Instrumented tools and algorithms for estimation of human joint mechanical impedance during tooling tasks

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Instrumented Tools and Algorithms for Estimation of Human Joint Mechanical Impedance during Tooling Tasks

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ABSTRACT

In recent years, robots have been successfully applied to automate repetitive, structured and non-contact tasks such as painting and welding. However, when it comes to contact tasks such as fine finishing tasks, these still cannot be performed by robots and often require the intervention of skilled human operators. Control strategies currently adopted for industrial robots are based on position/force control and do not clearly capture the skills developed by experienced human operators.

The main objective of this work is to develop tools and algorithms that capture human motor skills for the purpose of transfer to industrial robots. Human motor skills are here broadly intended as the coordination of multiple and redundant degrees of freedom (e.g. due to the kinematics of the human arm) and the regulation of forces and torques as well as the regulation of mechanical impedance (e.g. stiffness of the human arm).

This study uses available kinematic/dynamic information and applies stiffness estimation methods to infer the (neuro-)mechanical impedance of the human arm/wrist during motion, in particular during an industrial tooling task. This approach to stiffness estimation is validated on an impedance-controlled robot. The stiffness values estimated for human subjects, at different force levels, correlated positively with the muscular activity. The novelty of our method is that the perturbations originate from the stochastic nature of the task itself rather than from a dedicated, external system as in all previous works.

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INTRODUCTION

1.1 Background and Motivation

In recent years, industrial robots have been widely employed for automation of well-defined repetitive operations such as material handling, spray painting and drilling that necessitate null or weak interaction between the manipulator and working environments [1–3]. The general approach for such operations of industrial robots is through trajectory optimization control [4, 5]. However, a majority of industrial contact tasks such as surface finishing and grinding involve strong physical interaction with the workpiece and don't entirely depend on position information for task execution [6].

To automate such industrial contact tasks operations, e.g. by understanding and implementing human-like strategies [7], recent research has been looking into compliant robots, programmed via force/impedance control strategies, rather than traditional position-control [8]. One of the exciting challenges for the contact tasks is controlling a manipulator to follow exactly a workpiece's surface while maintaining a significant force on it for achieving the required quality of the surface roughness. When the tooling task and environment are well defined, the particular controller can be implemented to perform the function. For instance, in a polishing task with a given surface profile, a manipulator is controlled to regulate the magnitude of force at rough/uneven surface with corresponding to stiffness configurations. The contact forces are maintained in specific range to achieve system stability inspire of irregular surface area. However, the surface parts of a workpiece are usually complex, so the contact force is kept within a large range

of amplitude to make sure that the end-effector has adequate stiffness at the contact area. This broad range leads to an unstable situation of the manipulator. Many techniques have been proposed to maintain a significant force and compensate position error using a spring or some kinds of variable stiffness actuation. Migliore et al. [9] introduced an elastic actuation robotic joint with an angle and stiffness control; Zebardast et al. [10] and Park et al. [11] designed and implemented the passive compliance joint mechanism for collision safety. These techniques support manipulator to have more compliance, are simple in control and easily replaceable.

Process monitoring

Surface finishing operations involve material removal to improve product surfaces, with direct consequences on the product life [12]. Especially, free-form surfaces, often involve non-negligible and unpredictable interaction dynamics between the robot and the environment which do not allow to rely on motion planning alone, making sensing and feedback a necessity [13]. An extensive amount of literature has demonstrated the use of various force-sensing mechanisms to measure the forces/torques accurately during a finishing process. Earlier works revealed the use of *external sensors* (i.e., cutting force monitoring through sensors installed on machine tools) for force sensing. Byrne et al. [14] and Jun et al. [15] integrated force sensors into the spindle structure for monitoring and fault diagnosis of machining operations; Ohzeki et al. [16] installed integrated magnetostrictive torque sensor in a tool holder for sensing the cutting torque to monitor the milling process; Sarhan et al. [17, 18] estimated the performance of cutting forces for end milling process by using a spindle integrated with displacement sensors. *Internal sensors* (i.e. current sensors for servo and spindle motors installed on machine tools) are also widely employed for force/torque measurements, particularly for *numerical control* machine tools. In Altintas et al. [19], the use of the feed drive motor's current signal was proposed for face roughing and milling operation monitoring. It was pointed out that the cutting force can be tracked from the current measurements. In Lee et al. [20], the cutting force in numerical control milling process was measured by using currents of the AC servo drives and was applied to the online tool breakage detection. However, a majority of applications of force/torque measurements focus on process monitoring (i.e., capturing the machine state and device condition) rather than process automation, in particular, robotizing a labor intensive task like surface finishing. Understanding the significance of force-sensing in such tasks is an exciting, yet little-explored area.

For a robot to perform finishing tasks, it typically requires extensive programming

and repetitive testing phases with a high degree of detail for every single micro-motion and activity. With a given tool and workpiece, the results of the finishing tasks depend on the tool speed, the pressure on the workpiece, and the material removal rate¹. Once these variables information which are available from the manufacturers are defined, the result of the finishing tasks will be consistent. Early studies of Bausch [21] presented the feasibility of precision deburring using a 2 DoFs industrial robot with passive and active compliant end-effector. It also presents the two limitation points of using the robot for the deburring task is worst quality at end point position; large amplitude and high-frequency oscillation of robot reduces the surface finish quality. More recently, Erlbacher [6] proposed PUSHCORP *active force toolboxes* (see Fig. 1.1, taken from www.pushcorp.com) to be mounted on the end-effector of industrial robots such as KUKA [22], PUMA [23] combined with force control to provide process flexibility. To apply the desired force, the robot first pushes the PUSHCORP toolbox against the part surface and acquire the feedback signal from a mounted six-axis loadcell. Then, the controller compares the feedback force to the requested force to adjust if a force error exists. However, the system cannot adapt to ever-changing parts and unwanted burrs size which are not consistent as robot cannot learn overtime. Once the robot is programmed, it consistently repeats the program move day after day, so it cannot adapt to the changing parts or unwanted burr size. Moreover, most PUSHCORP toolboxes make use of pneumatic actuation to create a large force, leading to issues related to low-frequency and small bandwidth.

Skills transfer from humans to robots

In industrial contact tasks execution, achieving a perfectly finished part and not removing too much parent material is the most difficult task for robots. Robots are consistent but cannot easily adapt to varying conditions. On the contrary, humans are able to adapt to changing conditions, but lack in consistency. Expert operators are typically required to perform such tasks in spite of high labor cost, health concerns, and quality-control issues. Based on their experience, human experts to adjust the variations in the workpieces by adapting tooling parameters (such as a motion of the tool, orientation and applied forces) to achieve the desired level of output specifications such as surface roughness, cutting force, material removal rate (see Fig. 1.2). For example, blades of an aerospace fan or propellers of a vessel support to have a smooth surface to minimize drag and improve

¹Material removal rate (MRR) is the factor determining how fast the material is being removed during the surface finishing tasks.

Figure 1.1: PUSHCORP active force toolbox a) Air counterbalanced passive force device and its application in b) finishing, c) deburring, and d) polishing

the aerodynamics or the hydrodynamics. To achieve acceptable results in the surface roughness, the operator needs to observe the workpiece surface and use his perception to determine the amount, point of application, orientation of the applied force to the surface part. It usually takes much of time and costs for operators to get experience and become skillful in these contact tasks since an operator cannot become a master if they only observe the process. Although visual feedback remains a primary source of information, for during contact operations, force/tactile sensing becomes crucial in humans, who are known to rely highly on proprioceptive information for manipulation tasks. However, such operations are considered to be labor intensive, time-consuming and can cause impact on health [24, 25]. Furthermore, due to human errors, such operations can have inconsistent quality. Automation of such process can lead to significant cost reduction and quality improvement in the manufacturing, repairing, and overhauling industries. Implementing strategies that can allow a robotic device to adapt to variance in input in a similar manner as humans demands a clear understanding of underlying model used by skilled professionals. This can be achieved by capturing the operation skills from experienced workers during tooling task and then transforming this information into planning strategies for robot programming and control [26, 27].

Figure 1.2: Example of manual polishing with a hand-held tool.

Capturing human skills

Thus, one of the first steps in transitioning from manual to a robotized surface finishing process is developing a better understanding of a human operator's strategies in the interaction with the workpiece applied forces/torques, and the motion. However, it is challenging to identify the motor control mechanisms through which skilled operators dexterously manipulate tools and controls the interaction forces, because the highest stage of competence skills are often unconsciously applied [28]. This problem becomes even more significant when hand-held devices are used, as the motion and forces involved are not constrained to any dimensions or axis of rotation.

Manipulation requires information about the force, torque, contact location and geometry information of the tool-workpiece interaction. To my knowledge, works in literature focus on monitoring interaction dynamics in terms of process forces (typically normal and friction forces) arising during tool-workpiece interaction. However, for high-quality finishing, it is important to also monitor the contact point, i.e. where this interaction occurs, especially in the case of soft tools. Contact estimation based on force/torque sensing was initially proposed in the 80's [29–31] and later used in different scenarios. Salisbury [32] described how joint torque measurements in a robot arm might be used to determine the location of a contact on its links; Bicchi et al. [13] introduced the contact centroid for characterizing soft finger contact and emphasized the role of the *wrench axis* [33, 34], which will be described later in this thesis; Zhou et al. [35] formalized the method to localize the contact for robotic fingers and carried out an accuracy analysis based on noise levels in force/torque sensors; Benati et al. [36] developed a hand-held burr measurement device for trimming process based on a cantilever beam sensing burr height. In recent years, Charles et al. [37] presented a sensorised hand-held belt

grinder which allows capturing the *Key Process Variables*² used by the manual polisher. The changes of the geometry on the workpiece's surface are captured by using a 3D laser scanner. More recently, Prabhu et al. [38] and Tecchia et al. [39] used *Microsoft Kinect* camera to capture, digitize and simultaneously segment the human-workpiece interactions in three dimensional (3D) space.

In industrial applications such as tooling, specific motion paths are significant and unforeseen or unpredictable perturbations influence the final results. Over the last years, less expensive systems have been developed to measure human or robotic movement, this includes goniometers [40], accelerometers [41–43], inertia-based and electromagnetic sensors [44–46]. A variety of research has been conducted to report characteristics of selected systems and to validate new technical devices. Unlike robotic fingers, finishing and grinding tools are subject to high levels of mechanical vibrations which introduce additional errors referred hereafter as mechanical noise. Although the optical motion capture technology is a valuable tool when quantifying human movements, industrial applications require high system accuracy and quantifying small motion is a challenging task. This is significant in grinding tasks where vibrations occur regularly and affect the movement itself. To measure those vibrations, 3D motion capture can be used by applying local and global optimization techniques, but the system itself is associated with high costs and lower acquisition frequency compared to e.g. accelerometers. Therefore, the question arises, how do we measure accurately micromotions that are characterized by small amplitudes and high frequencies? Inertia-measurement Unit (IMU) can be used to measure orientations, accelerations, and the magnetic field. Then, the processing helps to combine the sources and detects translations and rotations. Both the IMUs and motion capture can detect the orientation of the tools in space, but a combination of both sources may be very useful. Each source has its system specifications, and while 3D motion capture system has the high 3D resolution at reasonably high acquisition frequency, they are outperformed by IMU in terms of temporal and technical resolution. Accelerometers and gyroscopes may have a high temporal resolution but are known to show signal drift over time. A combination of both systems could improve the acquisition of slow major movements and micromotions of the tools at the same time.

The operation of vibrating power hand tools can result in excessive grip force, which may increase the risk of cumulative trauma disorders in the upper extremities. Working with power tools is common either in professional or manual settings. While grinding

²A terminology closely related to contact force, tool path, feed rate, etc., is the "Key Process Variables (KPVs)"

or drilling, the tool interacts with the environment/workpiece and reaction forces have to be controlled by the user via eccentric³ dynamic muscle contractions [47–50]. The handling of the tool is controlled by joint stiffness [51, 52]. The joint stiffness is generated by viscoelastic properties of the joint, muscles and connective tissue and the reflex stiffness [51]. The influence of the muscles on joint stiffness is important as tooling involves large eccentric action which is directly linked to muscle damage and injury [53, 54]. The operators posture and the output capacity of the tool affect the forces and frequencies acting against the hand [47, 55, 56]. The stability depends on the relationship between externally imposed displacements of the hand and the generated response forces [57] and can be estimated by the inertial, viscous and elastic properties of the arm [58, 59].

A recent literature review [60] has revealed various methods and ways to estimate mechanical impedance defined as stiffness and damping characteristics of the system under consideration. Most studies involve well controlled postural perturbations using robotic manipulators (e.g. [57]) and the change in joint posture and torque are used to compute the joint impedance/stiffness. Joint impedance is the linearized relationship between joint torque and position [61]. Joint torque due to joint perturbation angle can be expressed as a second order parametric model that incorporates the inertia, viscous damping, and stiffness as parameters [62, 63]. In some circumstances these parameters can be directly measured [64, 65] or identified using e.g. regression methods, non-parametric methods fitting second order parametric models [66] and non-parametric methods in the frequency domain [67].

From a robotic perspective, one of the most interesting features of humans is their proficiency to operate a variety of tools in order to interact with and adapt to an often unpredictable environment. For example, artisans can skilfully use scalpels, hammers and grinders to carve, bend or polish different types of materials and geometries. While humans can cope with tooling tasks seemingly without effort and can flexibly adapt their motor strategies to different mechanical and geometrical constraints [68–70], for conventional industrial robots this type of tasks remain challenging.

Tooling an object with a robot is challenging for several reasons: i) the mechanical properties of the tooled object are usually unknown; ii) when tooling an object, its surface may deform or wear out and therefore the robot controller can no longer rely on the original CAD model and must continuously adapt to changes of the surface geometry; iii) friction and surface irregularities may result in large forces and to instability, especially

³Eccentric/Concentric dynamic contraction: muscle lengthens/shortens during force production.

for high gain feedback controllers typically adopted in industrial manipulators [71, 72].

Hybrid position/force control is often implemented for tooling tasks such as polishing whereby a position controller is used to align the tool with the relevant geometric features of the surface under tooling while a force controller applies desired forces in specific directions with respect to the surface [73]. Hybrid position/force control approaches, however, may fail in presence of *unstable contact tasks* such as drilling and carving and human operators are still required to carry out these so-called *fine finishing* tasks.

What mechanisms allow humans to perform such tasks? Several behavioural studies have shown that the success of humans to cope with unstable and unpredictable environments resides in their capability to adapt the endpoint mechanical impedance to the environmental conditions [69, 74–76]. These studies have also inspired novel bioinspired controllers mimicking the impedance characteristics of human operators performing contact tasks [71, 72, 77–80].

1.2 Objective and Scope of Thesis

The first step in transitioning from manual to a robotized surface tooling process is to develop a better understanding of a human operator’s strategies in the interaction with the workpiece. To address these issues, the general objective of the thesis is to investigate strategies to implement skilled tooling tasks on robotic manipulators. In order to accomplish the goal of the thesis work, it has been structured in two specific objectives which are presented as follows. Each objective consists of particular challenge that leads to the final goal of the thesis.

- ★ Objective #1: Investigate kinematic strategies and dynamic interaction between human operator and workpiece during finishing tasks.
- ★ Objective #2: Estimate joint stiffness from kinematic and dynamic data derived during finishing/polishing tasks.

In order to address the first objective, we propose an *instrumented rotating tool* in the *stationary* case that is capable of accurately monitoring force/torque and geometry of contact arising between a spinning grinding/polishing wheel and a workpiece. Then, similar concepts are applied to an *instrumented hand-held tool* which is more convenient for the human operator and capable of capturing 3D interaction dynamic in manual operation. The motion capture system is used to track the kinematics by attaching the infra-red markers on the tool. A filter algorithm is presented to solve the motion capture

signal problems, and to eliminate the gravitational biasing induced by the mass of the instrumented hand-held tool. For detecting the vibration's effect of the instrumented tool during operation, the additional acceleration and angular velocity signals from an IMU are presented. Followed by, a complementary filter that is able to optimize 3D motion capture data locally and remove the vibration's effect are introduced. The data after processed by the proposed complementary are used to estimate the contact point between the instrumented tool and workpiece. At the contact point, we present the first and second order geometry (i.e. tangent space and curvature directions) for the purpose of estimating a normal force, a friction force, a power of the hand-held tool, and contact ellipses (which would allow determining the area of contact).

To address the second objective, an algorithm which estimates the joint wrist stiffness of the operator using an instrumented hand-held tool is proposed. The algorithm is first validated with an industrial impedance-controlled robot (KUKA robot), deployed to perform a polishing task with a specific value of pre-set impedance. The same polishing task is then tested with a human subject using the power-tool and performing a similar contact task. Data from this experiment are analysed and the impedance values are shown to positively correlate with the muscular activity of relevant muscles, in a physiologically relevant range.

1.3 Organisation of Thesis

The remaining chapters of this thesis are organized as follows:

Chapter 2 presents the theoretical background on kinematics and dynamics. The devices and methods which allow measuring the kinematics and dynamics of the tool followed by the literature on a complementary filter for both devices are presented to improve the acquisition of gross and fine motions. The principle elements of differential geometry of surface which plays a vital role in machining operations are reviewed.

Chapter 3 addresses a novel method to capture both the force/torque and the geometry of contact during the interaction between an instrumented tool and a workpiece. The chapter first introduces the concept of an instrumented rotating tool along with the equations to derive forces and contact points from the readings of six-axis loadcell. This is followed by the algorithm which is allowed to measure the tool motion, eliminate the gravity's effect, and remove the vibration force is proposed. Finally, in addition to the contact point estimation, the first and second order geometry (i.e. tangent space and curvature directions) at the contact point are presented.

Chapter 4 describes the algorithm to qualify the wrist joint stiffness of the human operator during the tooling tasks. The experimental validation with an industrial impedance-control robot with pre-determined joint stiffness/damping are implemented to verify the proposed algorithm. The experiment to determine the wrist joint stiffness of a human is performed. Based on the results, the muscles impact joint stiffness and the electromyography (EMG) are analyzed.

Chapter 5 concludes the thesis, summarizes the contributions and outlines the future work.

Figure 1.3: Organisation of Thesis

GEOMETRY OF CONTACT BETWEEN RIGID BODIES: THEORETICAL ANALYSIS AND NUMERICAL ESTIMATION

The goal of this chapter is to i) introduce the means of devices and sensors that used in chapter 3 (for Objective #1) and chapter 4 (for Objective #2) for capturing the kinematic and dynamic features of the tool during the finishing task; ii) review the theoretical background of the algorithms employed in the chapter 3 and 4 for estimating the motion; detecting the intrinsic properties of the tool and its interaction with the environment; determining the contact point and analytically computing the geometry of contact.

In the machining operations, the motion of a tool (e.g. grinder, polisher) can be classified into i) *macromotion* which is the voluntary movement of a tool on a workpiece ii) *micromotion* which is the involuntary movement characterized by small amplitudes and high frequencies. The interaction between a tool and a workpiece such as the applied force/torque, the geometry of contact, the gravity's effect on the measurement decide the quality of the surface roughness. Kinematics and dynamics are parts of mechanics in which kinematics related to the motion of the tool without considering force/torque that cause the motion, while dynamics is concerned with the force/torque which influence to the movement of the tool. The kinematic and dynamic analysis of the tool during the operation are important and necessary for improving the quality of the final product, reducing the time process, avoiding injury to the worker, etc.

The tool is considered as a rigid body to facilitate the analysis. First, the primary mathematical constructs used to represent the rigid body motion in three dimensional

space are presented. The literature on rigid body motion is reviewed by using the *screw motion* theory, followed by a particular version of a screw in kinematics named as *twist* that provides a description of a linear and an angular velocity of a rigid body motion. Then, another case of the screw in dynamics called *wrench* where the act (force/torque) have the axis and yield a movement (translation or rotation) on a rigid body is introduced. The screw, twist, and wrench are used for explaining kinematics and dynamics of a rigid body because of two main reasons: i) enable a simplification of the analysis of mechanisms by using a geometric explanation. ii) provide an explanation of the rigid body motion which is not affected by singularities. The application of screw, twist and wrench plays a significant role in formulations of kinematics and dynamics of machining operations, which will be used through out the thesis.

Also in this chapter, an *active motion tracker* (optical) device and an *internal measurement unit* (IMU) are introduced to capture the kinematics information of the rigid body, i.e the *macromotion* and *micromotion*, receptively. The literature on complementary filter for both devices is presented to improve the acquisition of slow major movements and fast micromotion.

Besides capturing the kinematics information, a multi-axis force/torque sensor is used to measure a feedback information from the rigid body dynamics. Finally, the principle elements of differential geometry of surface which plays a vital role in machining operations are reviewed.

2.1 Rigid body motion

A rigid motion of an object is a continuous movement that maintains a distance between points. In other words, an object will keep the same shape and size after a proper rigid transformation. An unconstrained rigid body has 6 Degree of Freedoms (DoFs), i.e. 3 DoFs of translational freedom, and 3 DoFs of rotational freedom (see [81]).

2.1.1 Rotation and Transformation of a rigid body

The Special Orthogonal Group $SO(3)$, also known as the group of rotation matrices, is the set of all 3×3 real matrices R that satisfies:

$$(2.1) \quad SO(3) = \left\{ R \in \mathbb{R}^{3 \times 3} \mid RR^T = I, \det(R) = 1 \right\}$$

The associated *Lie-algebra* $so(3)$ is the set of anti-symmetric matrices (i.e. the tangent space to the group $SO(3)$ at the identity matrix) and is defined as:

$$(2.2) \quad so(3) = \left\{ R \in \mathbb{R}^{3 \times 3} \mid R^T = -R \right\}$$

Another way to represent for the rotation of the rigid body on $SO(3)$ is using *exponential coordinate*. The exponential coordinates parametrize a rotation matrix about a single rotation axis (represented by a vector ω of unit length), together with an angle of rotation θ about that axis. Consider a rotation of the rigid body about axis ω , the velocity of any point on the rigid body can be given by [73]:

$$(2.3) \quad \dot{\mathbf{q}}(t) = \omega \times \mathbf{q}(t) = \hat{\omega} \mathbf{q}(t)$$

where $\mathbf{q}(t) \in \mathbb{R}^3$ and $\times$ is the Euclidean cross product. Let $\mathbf{q}(0) = \mathbf{q}_0$ be the initial position of point $\mathbf{q}$ in the rigid body. Point $\mathbf{q}(t)$ is defined as:

$$(2.4) \quad \mathbf{q}(t) = e^{\hat{\omega}t} \mathbf{q}_0$$

where $e^{\hat{\omega}t}$ is the matrix exponential and is given as the sum of series:

$$(2.5) \quad e^{\hat{\omega}t} = I_n + \sum_{n \geq 1} \frac{(\hat{\omega}t)^n}{n!}$$

where $I_n \in \mathbb{R}^{n \times n}$ is the identity matrix. The exponential map $so(3) \rightarrow SO(3)$ is well-defined and surjective [81]. Using Eq. (2.5) for rotating rigid body on $SO(3)$, the rotation R can be represented as a rigid body rotating about the axis ω at unit velocity for θ units of time:

$$(2.6) \quad R(\omega, \theta) = e^{\hat{\omega}\theta}$$

where $e^{\hat{\omega}\theta} \in SO(3)$ and $\hat{\omega}$ is skew symmetric:

$$(2.7) \quad \omega = \begin{bmatrix} \omega_1 \\ \omega_2 \\ \omega_3 \end{bmatrix} \Rightarrow \hat{\omega} = \begin{bmatrix} 0 & -\omega_3 & \omega_2 \\ \omega_3 & 0 & -\omega_1 \\ -\omega_2 & \omega_1 & 0 \end{bmatrix} = \frac{1}{2\sin\theta} (R - R^T)$$

This leads to the following result also referred to as *Rodrigues's formula* [73]:

$$(2.8) \quad e^{\hat{\omega}\theta} = I_3 + \frac{\sin\theta}{\theta} \hat{\omega} + \frac{(1 - \cos\theta)}{\theta^2} (\hat{\omega}\theta)^2 = I_3 + \sin\theta \hat{\omega} + (1 - \cos\theta) \hat{\omega}^2$$

When $\|\omega\| \neq 1$, Eq. (2.8) becomes:

$$(2.9) \quad e^{\hat{\omega}\theta} = I + \frac{\hat{\omega}}{\|\omega\|} \sin(\|\omega\| \theta) + \frac{\hat{\omega}^2}{\|\omega\|^2} (1 - \cos(\|\omega\| \theta))$$

Together, the rotation matrix R and position vector $\mathbf{p}$ define the proper rigid body transformations. In kinematics, the set of proper rigid transformation is called *special Euclidean group*, denoted by $SE(n)$ for n -dimensional Euclidean spaces. A three-dimensional Euclidean space indicated as $SE(3)$ representing angular and linear displacement of a rigid body:

$$(2.10) \quad SE(3) = \left\{ G \left| G = \begin{bmatrix} R & \mathbf{p} \\ 0 & 1 \end{bmatrix}, R \in SO(3), \mathbf{p} \in \mathbb{R}^3 \right. \right\}$$

Rigid body motions are usually described using two frames of reference: the body frame

Figure 2.1: Coordinate frames for rigid body motions. $G^{\mathcal{A}}$ is the homogeneous matrix derived the point $Q^{\mathcal{A}}$ directly from the $\mathcal{A}$ frame into global $\mathcal{S}$ frame.

$\mathcal{A}$ that remains fixed to the body, and the other is the inertial frame (or global frame) $\mathcal{S}$ that remains fixed in inertial (or global) space (see Fig. 2.1).

Any point $Q = \begin{bmatrix} Q_x & Q_y & Q_z \end{bmatrix}$ attached to the body, located at the origin of the coordinate frame can be given by:

$$(2.11) \quad \begin{bmatrix} Q^{\mathcal{S}} \\ 1 \end{bmatrix} = G^{\mathcal{A}} \begin{bmatrix} Q^{\mathcal{A}} \\ 1 \end{bmatrix}$$

where $Q^{\mathcal{A}}$ and $Q^{\mathcal{S}}$ are the same point of the rigid body represented in the body frame $\mathcal{A}$ and in the global frame $\mathcal{S}$, respectively. $G^{\mathcal{A}}$ is the homogeneous matrix derived the point $Q^{\mathcal{A}}$ directly from the $\mathcal{A}$ frame into global $\mathcal{S}$ frame.

Every rigid transformation can be also expressed as a screw motion about some fixed axis in space. The detail and advantage of that approach are explained in the next section.

2.1.2 Screw and Twist

Screw motion:

A screw is a geometric entity that underlies the foundation of statics and instantaneous (first-order) kinematics. A screw motion is the motion of a rigid body from a position to another by a motion which consists of rotation about a straight line followed by translation parallel to that line.

There are two basic components in screw theory: i) *twist* representing a general helical motion of a rigid body about an instantaneous axis in three dimensional space, and ii) *wrench* describing an applied force/torque the rigid body [82]. Hunt [34] and Wilson [83] further developed the mathematical and geometrical representation of the screw systems for the analysis and synthesis of mechanisms.

In the remaining section, I first discuss the screw motion followed by the twist. In kinematics, a general spatial motion of a rigid body is a screw motion (rotation and translation) about a line in space called a screw axis. The Fig. 2.2 shows a rigid body undergoing a displacement in 3D space, where $S, \mathcal{A}$, and $\mathcal{A}'$ denotes the global frame, the initial and final configurations of the rigid body after transformation, respectively. According to the Chasles' theorem, there exists a screw axis represented by the line passing through the point Q and in the direction of the unit vector ω such that the displacement can be characterized as a screw motion about this axis. The screw motion consists of rotation about the screw axis by an angle θ , and a translation by a distance d .

Figure 2.2: The displacement of a rigid body can be characterized as a screw motion about a screw axis. The screw axis is represented by the line passing through the point Q and in the direction of the unit vector ω . The screw motion consists of rotation about the screw axis by an angle θ , and a translation by a distance d .

The relative displacement $G^{\mathcal{A}}$ of frame $\mathcal{A}$ and $G^{\mathcal{A}'}$ with respect to global frame $\mathcal{S}$ can be defined as:

$$(2.12) \quad G^{\mathcal{A}} = \begin{bmatrix} R^{\mathcal{A}} & \mathbf{p} \\ 0 & 1 \end{bmatrix} \quad \text{and} \quad G^{\mathcal{A}'} = \begin{bmatrix} R^{\mathcal{A}'} & \mathbf{p}' \\ 0 & 1 \end{bmatrix}$$

where the rotation matrix $R^{\mathcal{A}}$ and $R^{\mathcal{A}'}$ represent the axes of frame $\mathcal{A}$, axes of frame $\mathcal{A}'$, respectively. The translation vector $\mathbf{p}$ and $\mathbf{p}'$ represent the initial and final location of the origin of frame $\mathcal{A}$ in the global frame $\mathcal{S}$, respectively. Park [81] showed that for any given rotation matrix R , it is possible to find a unit vector $\boldsymbol{\omega} = \begin{bmatrix} \omega_1 & \omega_2 & \omega_3 \end{bmatrix}$ and scalar θ such that $R = e^{\hat{\boldsymbol{\omega}}\theta}$ (see Eq. (2.13) and Eq. (2.7)). From Fig. 2.2, we can express $R^{\mathcal{A}'}$ and $\mathbf{p}'$ as:

$$(2.13) \quad R^{\mathcal{A}'} = e^{\hat{\boldsymbol{\omega}}\theta} (R^{\mathcal{A}})$$

$$(2.14) \quad \mathbf{p}' = \mathbf{q} + e^{\hat{\boldsymbol{\omega}}\theta}(\mathbf{p} - \mathbf{q}) + h\theta\boldsymbol{\omega}$$

where h is the *screw pitch* denoting the ratio of translation and rotation $h = \frac{d}{\theta}$. The Eq. (2.14) verifies that vector $\mathbf{p}$ is the sum of the three vectors $\mathbf{q}$, $e^{\hat{\boldsymbol{\omega}}\theta}(\mathbf{p} - \mathbf{q})$ and $h\theta\boldsymbol{\omega}$ as point out in the Fig. 2.2. Combining the equations from Eq. (2.12) to Eq. (2.14) together, we have:

$$(2.15) \quad G^{\mathcal{A}'} = \begin{bmatrix} {}^{\mathcal{S}}R_{\mathcal{A}'} & \mathbf{p}' \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} e^{\hat{\boldsymbol{\omega}}\theta} & (I - e^{\hat{\boldsymbol{\omega}}\theta})\mathbf{q} + h\boldsymbol{\omega}\theta \\ 0 & 1 \end{bmatrix} \begin{bmatrix} R^{\mathcal{A}} & \mathbf{p} \\ 0 & 1 \end{bmatrix} = H(G^{\mathcal{A}})$$

The $SE(3)$ matrix H is the homogeneous transformation representation of the screw motion. Considering the pitch $h = \frac{d}{\theta}$ of the screw: i) if $\theta = 0$ which mean $h = \infty$ then the corresponding screw motion only consists of a pure translation along the axis of the screw by a distance $d\boldsymbol{\omega}$; ii) if $d = 0$ which mean $h = 0$ then the corresponding screw motion generates a pure rotation about screw axis.

Twist:

The screw theory underlies the foundation of both instantaneous kinematics and dynamics. The kinematic component of screw is referred as a *twist* dealing with the angular and linear velocity of the rigid body. It can be represented as:

$$(2.16) \quad \mathbf{K} = \begin{bmatrix} \mathbf{v} \\ \boldsymbol{\omega} \end{bmatrix} \in \mathbb{R}^6$$

From Eq. (2.11), the linear and angular velocity of point Q attached to the rigid body in the global coordinate can be defined as:

$$(2.17) \quad \begin{bmatrix} \mathbf{v}_Q \\ \boldsymbol{\omega}_Q \end{bmatrix}^S = \begin{bmatrix} R^{\mathcal{A}} & \hat{\mathbf{p}}^{\mathcal{A}} R^{\mathcal{A}} \\ 0 & R^{\mathcal{A}} \end{bmatrix} \begin{bmatrix} \mathbf{v}_Q \\ \boldsymbol{\omega}_Q \end{bmatrix}^{\mathcal{A}} = Ad_{G^{\mathcal{A}}} \begin{bmatrix} \mathbf{v}_Q \\ \boldsymbol{\omega}_Q \end{bmatrix}^{\mathcal{A}}$$

Here, the matrix $Ad_{G^{\mathcal{A}}} : \mathbb{R}^6 \rightarrow \mathbb{R}^6$ which maps the twist from frame $\mathcal{A}$ to frame S is referred to as the *adjoint transformation* associated with $G^{\mathcal{A}} \in SE(3)$.

2.2 Wrench-axis and Center of pressure at contact

2.2.1 Wrench-axis from dynamic measurements

The dynamic component of the screw is referred as a *wrench* consisting of two vectors representing a force and a torque acting on a rigid body. Any system of forces acting on a rigid body can be replaced by a single force $\mathbf{F}$ applied along a line, combined with a torque $\mathbf{T}$ about that same line. Such a force/torque is referred to as the wrench and the line is named as a *wrench-axis* [13], written as:

$$(2.18) \quad \mathbf{W} = \begin{bmatrix} \mathbf{F} \\ \mathbf{T} \end{bmatrix} = \begin{bmatrix} \mathbf{F} \\ \mathbf{r} \times \mathbf{F} \end{bmatrix} \in \mathbb{R}^6$$

$$(2.19) \quad \mathbf{r} = \mathbf{r}_0 + \lambda \mathbf{F}$$

where $\mathbf{r} = \begin{bmatrix} r_x & r_y & r_z \end{bmatrix}^T$ is any contact position along the wrench-axis, $\mathbf{r}_0 = \frac{\mathbf{F} \times \mathbf{T}}{\|\mathbf{F}\|^2}$ and λ is scalar constant [31]. Therefore, all the possible contact points are along the same line, depend on the value of λ . To compute the contact point, we just simply add a function of rigid body's surface $S(x, y, z)$ and find the intersection between the wrench-axis and the surface.

Applied force on the rigid body can be described at a microscopic and a macroscopic level. From a robotic sensing perspective, the focus will be on the latter and therefore rather than a distribution of micro contact forces $\mathbf{f}_i$, a macro resultant force $\mathbf{F} = \sum \mathbf{f}_i$ applied directly at the center of pressure (CoP) are considered. In this section, along with sensing the resultant force on the rigid body, estimation of the CoP using force/torque measurements is also presented (see Fig. 2.3).

The torque at any point on the surface in the rigid body frame $\mathcal{A}$ can be defined as:

$$(2.20) \quad \mathbf{T}^{\mathcal{A}} = \mathbf{r}^{\mathcal{A}} \times \mathbf{F}^{\mathcal{A}} = -\hat{\mathbf{F}}^{\mathcal{A}} \mathbf{r}^{\mathcal{A}} = \begin{bmatrix} r_y F_z - r_z F_y \\ r_z F_x - r_x F_z \\ r_x F_y - r_y F_x \end{bmatrix}^{\mathcal{A}}$$

Figure 2.3: Micro forces f_i , distributed over an area, result in a unique macro force $\mathbf{F}$ applied at the CoP. The CoP can be dynamically estimated from the resultant force $\mathbf{F}$ and moment $\mathbf{T}$ as the intersection between the wrench-axis ($\mathbf{T} = \mathbf{r} \times \mathbf{F}$) and surface of the rigid body

where:

$$(2.21) \quad \hat{\mathbf{F}}^{\mathcal{A}} = \begin{bmatrix} 0 & -F_z & F_y \\ F_z & 0 & -F_x \\ -F_y & F_x & 0 \end{bmatrix}^{\mathcal{A}}$$

Using Eq. (2.18), the same physical wrench can be expressed in different coordinate systems, for example with respect to the rigid body frame $\mathcal{A}$ and the global space $\mathcal{S}$, i.e., $\mathbf{W}^{\mathcal{A}}$ and $\mathbf{W}^{\mathcal{S}}$, respectively. According to Eq. (2.17), the two representations can be related to one another using the following transformation [73]:

$$(2.22) \quad \mathbf{W}^{\mathcal{A}} = \begin{bmatrix} R^{\mathcal{A}} & 0 \\ R^{\mathcal{A}} \hat{\Delta}^{\mathcal{A}} & R^{\mathcal{A}} \end{bmatrix} \mathbf{W}^{\mathcal{S}} = Ad_{G^{\mathcal{A}}}^T \mathbf{W}^{\mathcal{S}}$$

where the matrix $\hat{\Delta}^{\mathcal{A}}$ and $R^{\mathcal{A}}$ represent, the skew-symmetric matrix of the vector $\Delta^{\mathcal{A}}$ which is the displacement of the origin and the rotation of the axes of the $\mathcal{A}$ coordinate systems with respect to the $\mathcal{S}$ coordinate system, respectively.

$$(2.23) \quad \Delta^{\mathcal{A}} = \begin{bmatrix} \Delta_x \\ \Delta_y \\ \Delta_z \end{bmatrix}^{\mathcal{A}} ; \quad \hat{\Delta}^{\mathcal{A}} = \begin{bmatrix} 0 & -\Delta_z & \Delta_y \\ \Delta_z & 0 & -\Delta_x \\ -\Delta_y & \Delta_x & 0 \end{bmatrix}^{\mathcal{A}}$$

2.2.2 Center of Pressure

Literature provides us with mathematical models for localization of contact on the rigid (or soft) body. Bicchi [13] and Li [35] presented the notion of *contact centroid* for contacts modeled as a soft-finger contact using a loadcell mounted at the end of a fingertip to measure wrenches and used that information to estimate contact points

during the contact operation. The underlying idea is computing the intersection between the wrench-axis and the surface of the rigid body where λ is the only variable [29] (see Fig. 2.3).

$$(2.24) \quad CoP^{\mathcal{A}} = \mathbf{r}^{\mathcal{A}} \cap \mathbf{S}^{\mathcal{A}}$$

The main advantage of estimating the contact by using the wrench-axis is that the contact location is reduced to the contact point. However, the location of contact points which is estimated from Eq. (2.24) are only accurate if it satisfies the three following condition: i) the acquired data from the sensors is accurate, ii) the surface of the rigid body is well known and iii) the body does not move during the contact operation. For the first two conditions, one of the standard solutions is considering the sensitivities of the sensor [35, 84] in x, y and z-direction which leads to the *confident ellipse*⁴ defining the region of contact points. For the last condition iii), it is necessary to determine the center of mass of the rigid body and its movement during the operation. The purpose is to eliminate the effects of gravity on the loadcell reading. Therefore, the *sensitivities analysis* and the *elimination of gravitational biasing* method will be presented in the following sections.

2.3 Kinematic and Dynamic Measurements in 3D

To analyze the 3D motion of an object, it is necessary to obtain both kinematics and dynamics information. Kinematics information can be captured by using optical systems like cameras and markers, or using inertial measurement unit (IMU) or multi-electronic measurement system (MEMS). Dynamics information can be measured by using the analog devices such as force/torque sensor, pressure sensor. This section presents the characteristics of the motion capture system, IMU and loadcell devices which are used in this thesis to measure the kinematics and dynamics of the object.

2.3.1 Kinematics from redundant optical markers

Motion capture (abbreviated as *mocap*) system is a technology used to record motion by tracking position markers information in 3D and assembling the data into an approximation of a subject's motion. In general, there are two type of commercially available mocap systems: active and passive. The comparison of these systems in term of their disadvantages and advantages was reported by Richards [85].

⁴The confident ellipse is measured by using *Gaussian distribution* and sensitivities of the sensor.

The passive mocap systems use inert objects like white balls or painted dots as markers and utilize the reflected light from markers to the optical mocap. The accuracy of passive mocap systems is based on the number and the resolution of cameras, the space between cameras and markers, the quality and quantity of markers and the system's calibration [43, 86]. There are several commercially available passive systems such as Peak Performance's Motus, Vicon's 370, Qualisys' ProReflex.

The active mocap systems are developed using Light Emitting Diodes (LEDs) as markers for sensing the position and orientations of a subject. Each LED, when powered up, emits light pulses over relatively broad angles for the optical trackers to sense from different directions. The tracking unit, which has three cameras, detects the lights from an LED target, calculates its 3D position, and then transmits the computed position coordinates to the host computer immediately. This is carried out for each LED target in sequence, one at a time, at very high frequency (500 Hz).

In this research, the active mocap system type VZ4000 as shown in Fig. 2.4 was used for tracking the motion of rigid body objects, the implementation will be presented in Chap. 3, Sec. 3.3.1. This section mainly discussed the active system characteristics and problems encountered when measuring the 3D motion.

Figure 2.4: The active motion capture, type VZ4000, Poenix Technologies Inc

The VZ4000 active mocap device operates first with the user specifying the desired

motion capture operation modes and parameters (such as marker names, sampling period, intermission period between frames, coordinate reference frame, sensor exposure, data storage directory, occlusion handling, etc) according to application requirements through a suitable software using the device. Upon capture initiation, the software passes the mode settings and parameters to the trackers. The trackers, in turn, set up the LED-based (active) marker system either via a thin tether cable. Subsequently, the LED markers light up and the tracker(s) sense the LED lights to triangulate their 3D positions. Then the trackers stream the captured marker position data back to the software, thus completing the 3D motion capture operation. It is shown in the following drawing (see Fig. 2.5).

Figure 2.5: Implementation diagram for an active motion capture system

Although there are a lot of costly mocap systems, they sometime return error data or even no data because of marker occlusions or missing. Marker occlusions are a commonly known problem in mocap setup and to evade it: each marker must be visible to at least two cameras in each frame to establish its position. Many methods have been proposed to solve these problems. Dorfmueller [87] and Welch [88] used the Extended Kalman Filter [89] to effectively estimate and predict the missing marker by using marker information formerly. The method is only applicable if a marker is missing for only a very short period (i.e. less than 0.5 seconds). Chai [90] proposed a technique which uses the well-known neighbor markers to evaluate the missing markers. In the past few years, Andreas [91] proposed a prediction method being able to approximate the missing markers by combining the Kalman filter and neighboring visible markers methods.

Although a variety of research has been conducted to report characteristics of selected systems and/or to validate new technical devices, most of them often require manual intervention and not applicable to detect the micromotion. In industrial applications such as polishing or grinding, these micromotions (or vibrations) play a significant role

and unforeseen/unpredictable perturbation influence the final results. Quantifying small motion is a challenging task especially in tooling tasks where vibrations or micromotions regularly occur and affect the movement itself. To measure those vibrations 3D motion capture can be used by applying local and global optimization techniques [92] but the system itself is associated with high costs and lower acquisition frequency compared to e.g. accelerometers. Therefore, the question arises how to measure correctly micromotions that are characterized by small amplitudes and high frequencies. Inertial Measurement Unit (IMU) can be used to measure orientations, accelerations, and the magnetic field. Offline processing helps to combine the sources and detect translations and rotations on SE(3). A combination of both systems could improve the acquisition of slow major movements (3D motion capture) and vibrations (IMUs) simultaneously.

2.3.2 Higher-frequency motion capture from IMU sensor

An inertial measurement unit (IMU) is a single electronic module which can measure the angular velocity, linear acceleration and at times a magnetic field direction. The IMU contains two (or three) separate sensors that are useful for capturing kinematics: i) accelerometer which can measure three analog signals representing the accelerations along the sensor axes; ii) gyroscope which can acquire the change in orientation or rotational velocity in reference to an arbitrarily chosen coordinate system, also outputs three analog signals; iii) magnetometer (sometimes) which can collect the strength and direction of magnetic field which is useful for tracking orientation.

It is necessary to combine these sensors together because they output at different information, e.g. for the orientation, a signal from a magnetometer is not reliable in case of fast movement but nearly zero drift during operation. The angular velocity due to the integration scheme from the gyroscope's signal, on the other hand, reacts quickly and accurately to changes, but it accumulates large error over time and requires a well-known orientation at the starting point. Combining the inputs to these sensors allows for quick and accurate position and orientation determination with a low amount of drift over time. By incorporating IMU alone, the system behavior relative direction of gravity can be measured, which suffices most of the scenarios [93, 94].

In this thesis, a customized IMU described in the following is used together with motion capture to improve the acquisition of slow major movements (3D motion capture) and micromotions simultaneously. The IMU sensor unit (Fig. 2.6) is mainly composed of i) a 9-axis magneto-inertial sensor, the LSM9DS0 manufactured by STmicroelectronics, Inc., which embeds three axial accelerometers, gyroscopes, and magnetometers. The

LSM9DS0 is designed with a small outline (a 4x4 mm LGA24 package) and provides digital access to sensor data via I2C serial communication; ii) a 16-bit microcontroller, the dsPIC33FJ64GP202 by Microchip, Inc., which collects the data from the sensor, and sends it to the Bluetooth module for wireless transmission. The microcontroller also

Figure 2.6: The IMU sensor unit

processes the data with a quaternion-based complementary filter [95] in order to estimate the 3D orientation of the sensor, and transmits both raw data and computed quaternions with a sampling frequency of 200 Hz; iii) a Bluetooth module, the SPBT2632C2A, by STmicroelectronics, Inc., guarantees the wireless communication from the sensor unit to a remote laptop via a Virtual COM Port (VCP); iv) a rechargeable Li-Po battery with a capacity of 260 mAh, assures the power supply with at least 4 hours of continuous data streaming. The overall dimensions of the IMU sensor unit are 35x35x22 mm (see Fig. 2.6).

2.3.3 Sensor fusion via complementary filter on $SO(3)$

Complementary filters traditionally apply when redundant measurements are available [96] and combining all available information to minimize the instrumentation error. They are also used to fuse information from multiple sensors and correct the output based on the sensed inputs. Although the Kalman filters [89] can be extended to nonlinear cases, they fail in capturing the nonlinear structure of the configuration space of problems involving (e.g. rotations of a rigid body) which can be detected using complementary filters [97].

The complementary filter basically handle both *low-pass filter* and *high-pass filter* simultaneously [98]. The high-pass filter is a filter which passes signals having a frequency higher than a certain cutoff frequency, e.g. the accelerometer's signal in the case of vibration. The low pass filters filter low-frequency signals (such as the drift of the gyroscope). The idea of complementary filter is shown in Fig. 2.7-a where signals x and y , respectively, is noisy measurements in high frequency and low frequency of signal z ; and

$\tilde{z}$ is the estimated output of z operated by a complementary filter. Then, the filter $H(s)$ performs a high-pass filter to filter out the low-frequency noise in a x signal. Similarly, the filter $[1 - H(s)]$ is a low-pass filter to filter out the high-frequency noise in a y signal.

An alternate version of complementary filter can be presented in Fig. 2.7-b where the input signal is $x - y = (z + \eta_1) - (z + \eta_2) = \eta_1 - \eta_2$, hence, the filter $H(s)$ just filters out the noise in x and y .

Figure 2.7: a) The standard complementary filter: $H(s)$ is a high-pass (or low-pass) filter, $1 - H(s)$ is a low-pass (or high-pass) filter. b) Alternate version of complementary filter which filter only the noise.

The typical application of complementary filter is to estimate the rotational of the rigid body with one degree of freedom θ by combining measurement of angle θ_{mc} from motion capture device and angular velocity ω_{imu} calculated from IMU (see Fig. 2.8). For the simplest method is discussed, where gyroscope bias is not estimated, i.e. the 1st-order. Let $\tilde{\theta}$ be the estimate of angle θ . Assuming that the angular velocity measurement ω_{imu} is integrated ($1/s$) to produce the angle signal θ_{imu} . The integration attenuates the high frequency in the angle measurement, hence, the θ_{imu} is filtered by the high-pass filter, whereas the noise in θ_{mc} is filtered by the low-pass filter.

The transfer function gives:

$$(2.25) \quad \tilde{\theta} = \frac{1}{1 + \tau s} \theta_{mc} + \frac{\tau s}{1 + \tau s} \frac{1}{s} \omega_{imu} = \frac{\theta_{mc} + \tau \omega_{imu}}{1 + \tau s}$$

where τ determines the cutoff frequency of the filter.

Mahony et al. [99] presents an idea to correct the input which is the angle vector θ by some correction vector $\Delta\theta = \theta_{mc} - \tilde{\theta}$, which is provided by P controller (for the 1st - order) or PI controller (for the 2nd - order). For the P controller (see Fig. 2.9-a):

$$(2.26) \quad \tilde{\theta} = K_P \frac{1}{s} (\theta_{mc} - \tilde{\theta}) + \frac{1}{s} \omega_{imu}$$

Figure 2.8: Using Complementary filter to estimate position a) Basic Complementary filter b) Actual realization of Complementary filter

Figure 2.9: Mahony filter a) P controller b) PI controller

where $\theta_{mc} - \tilde{\theta}$ is the error input to the P controller. Rearranging Eq. (2.26) provides exactly the transfer function of the complementary filter (i.e. Eq. (2.25)):

$$(2.27) \quad \tilde{\theta} = \frac{K_P \frac{1}{s} \theta_{mc} + \frac{1}{s} \omega_{imu}}{1 + K_P \frac{1}{s}} = \frac{\theta_{mc} + \frac{1}{K_P} \omega_{imu}}{\frac{1}{K_P} s + 1} = \frac{\theta_{mc} + \tau \omega_{imu}}{1 + \tau s}$$

where $\tau := \frac{1}{K_P}$. Therefore, the complementary filter design is then reduced to the choice of K_P so as to meet a target break frequency that is entirely dictated by the physical characteristic of the sensors. The optimal value for K_P is determined by the characteristics of measurement noise [96].

For the PI controller (2^{nd} - order) when the gyroscope bias estimation is included

(drift estimation) (see Fig. 2.9-b), the transfer function gives:

$$(2.28) \quad \tilde{\theta} = (K_P + \frac{1}{s}K_I)\frac{1}{s}(\theta_{mc} - \tilde{\theta}) + \frac{1}{s}\omega_{imu}$$

Similarly, rearranging Eq. (2.28) leads to the transfer function:

$$(2.29) \quad \tilde{\theta} = \frac{1 + \frac{K_P}{K_I}s}{1 + \frac{K_P}{K_I}s + \frac{1}{K_I}s^2}\theta_{mc} + \frac{\frac{1}{K_I}s^2}{1 + \frac{K_P}{K_I}s + \frac{1}{K_I}s^2}\frac{1}{s}\omega_{imu}$$

In the previous application for estimation the rotation of rigid body which is considered in the linear condition, the $\Delta\theta = \theta_{mc} - \tilde{\theta}$ is a typical choice. However, $SO(3)$ is a nonlinear space, hence the quantities such as $(R_{mc} - \tilde{R})$ are no longer ensured belonging to $SO(3)$; where $\tilde{R}$ represents the estimate of R , and $R, \tilde{R} \in SO(3)$.

A complementary filter on $SO(3)$ for dynamic attitude estimation is presented by Campolo et al. [100] with the measurement input are the gravitational and the geo-magnetic, together with angular velocity from gyroscopes. Based on that, we use the measurement input are i) the angel of rigid body which is measured by motion capture and ii) the angular velocity which is measured from the IMU to estimate the kinematic of the rigid body on $SO(3)$. Let θ_{mc}^0 denote the angle of the rigid body at time t_0 as measured from motion capture. At time t , the orientation of the rigid body is the rotation matrix $R(t) \in SO(3)$; the measurements of ω_{imu} and θ_{mc} is expressed as:

$$(2.30) \quad \begin{cases} \hat{\omega}_{imu} = R^T \dot{R} = \hat{\omega} \\ \theta_{mc} = R^T \theta_{mc}^0 \end{cases}$$

where $\hat{\omega}$ is skew symmetric defined in Eq. (2.7), and the velocity vector $\dot{R}$ is tangent to the group $SO(3)$. Campolo et al. [100, 101] present and proof the theorem which is useful for estimation the orientation $\tilde{R}$ on $SO(3)$ space:

$$(2.31) \quad \begin{cases} \dot{\tilde{R}} = \tilde{R} \hat{\omega}^* \\ \omega^* = \omega_{imu} + K_P \sum_{i=1}^N (\theta_{mc} \times \theta_{mc}^*) \\ \theta_{mc}^* = \tilde{R}^T \theta_{mc}^0 \end{cases}$$

The diagram in Fig. 2.10 shows the complementary filter algorithm for dynamics estimation $\tilde{R}$. The main problems of rotation matrix are $|R| \neq 1$ and $RR^T \neq I$ because of numerical errors accumulate in a discrete time. Campolo et al. [100] proposed a technique which can avoid above problem, i.e. considering data from analog sensors are typically acquired via *Digital to Analog Converters* with a fixed sampling time ΔT . In the time

 Figure 2.10: Complementary filter for dynamic attitude estimation on $SO(3)$

interval $t_n \leq t \leq t_{n+1} = t_n + \Delta T$, data from motion capture and IMU are assumed constant, i.e. $\omega_{imu}(t) = \omega_n$ and $\theta_{mc}(t) = \theta_n$. This allows computing $\tilde{R}_{n+1}$ via the Rodrigues' formula which is guaranteed not to drift away from $SO(3)$:

$$(2.32) \quad \begin{cases} \omega_n^* = \omega_n + K_P (\theta_n \times (\tilde{R}_n^T \theta_{mc}^0)) \\ \alpha_n = \sin \|\Delta T \hat{\omega}_n^*\| / \|\Delta T \hat{\omega}_n^*\| \\ \beta_n = (1 - \cos \|\Delta T \hat{\omega}_n^*\|) / \|\Delta T \hat{\omega}_n^*\|^2 \\ \tilde{R}_{n+1} = \tilde{R}_n (I + \alpha_n \Delta T \hat{\omega}_n^* + \beta_n \Delta T \hat{\omega}_n^{*2}) \end{cases}$$

where $\|\cdot\|$ denotes the standard Euclidean norm.

The complementary filter using with motion capture and IMU for the tool during the tooling task will be presented in Sec. 3.3.3. The filter can estimate the motion on $SE(3)$ with the redundant measurements inputs are the angular velocity from motion capture, the acceleration and angular rate (6 DoFs) from the IMU. Suitable values K_P for rotation and translation is presented. An experimental validation is proposed to verify the filter algorithm [102].

2.3.4 Dynamic measurements from Multi-axis Force/Torque sensors

Multi-axis force/torque sensing also known as a multi-axis loadcell plays an important role to provide the feedback information in the rigid body dynamics. There are several works with some interesting ideas for optimal design and development of multi-axis force/torque sensors [103, 104]. In the tooling task applications (e.g. finishing, grinding), the ability to sense the interaction between the instrumented tool and workpiece requires the 6-axis loadcell (attached on the tool) to be able to measure the force F_x , F_y , F_z and

torque T_x , T_y , T_z . That measurement is necessary accurately to perceive movement, estimate type of contact, friction force, and power of the instrumented tool [105].

There are some multi-axis loadcells available in commercial such as Futek, Sunrise, ATI. Force/Torque sensors are used throughout industry for product testing, robotic assembly, grinding, and polishing [37]. In research, they are used in wide range of applications such as robotic surgery, haptics, rehabilitation, neurology, and many others applications [103]. In this thesis, I use the loadcell type ATI mini 40 [106] which has a compact, low-profile design, and high resolution (see Fig. 2.11-a) for measuring the dynamics of the instrumented tool and workpiece. The ATI Mini 40 loadcell can measure the outputting forces and torques from all three Cartesian coordinate: $F_{X,Y} : \pm 80N$, $F_Z : \pm 240N$, $T_{X,Y,Z} : \pm 4Nm$.

Each new loadcell comes with a high accuracy of *calibration matrix* which converts the measured signal from loadcell to the significant value of force and torque. However, the calibration matrix becomes impoverished after an interval of time. Therefore, it is necessary to re-calculate the calibration matrix to get accurate force/torque. In the following section, a calibration method for ATI loadcell will be presented based on the least square method.

2.3.4.1 Multi-axis loadcell calibration procedures

A high-performance loadcell is essential for any system, and an accurate calibration matrix is crucial for the loadcell. There are many works done with loadcell calibration [104, 107, 108]. The main idea is to use a well-known force/torque as the reference for loadcell.

Figure 2.11: a) Applied Force and Torque Vector on ATI loadcell b) Loadcell calibration procedures in horizontal direction $\vec{F}_z = -M\vec{g}$ c) in vertical direction $\vec{F}_y = M\vec{g}$

The Fig. 2.11-b and Fig. 2.11-c show the method to calibrate loadcell: i) the ATI

loadcell is fixed on a flat table which is parallel to the ground; ii) a symmetric plate is placed at the center of the loadcell (see Fig. 2.11-a); iii) eliminate the gravitational bias caused by the inertial of the plate and loadcell; iv) a well-known weight M used as the reference force is one by one displace on the $+X$, $-X$, $+Y$, $-Y$ axis of the loadcell and the distance from the weight M to the center is r . Then, the experiment is repeated in the vertical direction: the Y -axis of loadcell is parallel to the gravity vector $\vec{g}$.

The expected wrench $\mathbf{W}$ from the weight M after removing the gravitational biasing is defined as:

$$(2.33) \quad \mathbf{W}_{exp} = \begin{bmatrix} F_x \\ F_y \\ F_z \\ T_x \\ T_y \\ T_z \end{bmatrix} = \begin{bmatrix} +X_H & -X_H & +Y_H & -Y_H & +X_V & -X_V & +Y_V & -Y_V \\ 0 & 0 & 0 & 0 & 0 & 0 & -Mg & -Mg \\ 0 & 0 & 0 & 0 & Mg & Mg & 0 & 0 \\ -Mg & -Mg & -Mg & -Mg & 0 & 0 & 0 & 0 \\ 0 & 0 & -Mgr & -Mgr & 0 & 0 & 0 & 0 \\ Mgr & -Mgr & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & Mgr & -Mgr & Mgr & -Mgr \end{bmatrix}$$

where the first 4 columns ($+X_H$, $-X_H$, $+Y_H$, $-Y_H$) in the matrix are the estimated force and torque in the horizontal (plate parallel to ground), and the last 4 columns ($+X_V$, $-X_V$, $+Y_V$, $-Y_V$) are in the vertical. The calibration matrix is calculated from the expected wrench and the raw data using least mean square method:

$$(2.34) \quad \mathbf{W}_{exp} = \mathcal{C} * \mathbf{W}_{raw} \Rightarrow \mathcal{C} = \mathbf{W}_{raw} \setminus \mathbf{W}_{exp}$$

where $\mathbf{W}_{raw}$ is the raw data - voltage measured from the loadcell, and $\mathcal{C} \in \mathbb{R}^{6 \times 6}$ is the estimated calibration matrix for the loadcell.

2.3.4.2 Elimination of Gravitational Biasing

The wrench $\mathbf{W}^{\mathcal{L}} = \begin{bmatrix} \mathbf{F}^{\mathcal{L}} & \mathbf{T}^{\mathcal{L}} \end{bmatrix}$ contains the readings from the load-cell which, in addition to the interaction forces and torques, will also contain gravitational forces and torques due to the mass of the rigid body. Let call ζ is the center of mass, hence, the gravitational wrench $\mathbf{W}_{gr}^{\mathcal{L}}$ can be determined as:

$$(2.35) \quad \mathbf{W}_{gr}^{\mathcal{L}} = m \begin{bmatrix} R^{\mathcal{L}} \mathbf{g} \\ \zeta^{\mathcal{L}} \times R^{\mathcal{L}} \mathbf{g} \end{bmatrix}$$

where m is the mass of the rigid body, $R^{\mathcal{L}}$ is the orientation of the $\mathcal{L}$ frame as given by the motion tracker and $\mathbf{g} = \begin{bmatrix} 0 & 0 & 9.81 \end{bmatrix}^T$ is the gravitational acceleration (in space coordinates). Therefore, the significant force during operation can be estimated as:

$$(2.36) \quad \mathbf{F}_s^{\mathcal{L}} = \mathbf{F}^{\mathcal{L}} - \mathbf{F}_{gr}^{\mathcal{L}}$$

2.3.4.3 Sensitivity Analysis

The estimated contact location is a function of the force and torque measurements (see Eq. (2.24)). A sensitivity analysis is performed to study how the contact area is affected by the ranges and resolution of the load cell. This analysis allows assessing the effects and sources of uncertainties in the measurement, in the enabling for better interpretation of the obtained experimental results.

For a common 6-axis loadcell (3-axis of force and 3-axis of torque), let name the resolution specifications of each force channel is $\Delta \mathbf{f} = \begin{bmatrix} \Delta f_x & \Delta f_y & \Delta f_z \end{bmatrix}^T$, and each torque channel is $\Delta \mathbf{t} = \begin{bmatrix} \Delta t_x & \Delta t_y & \Delta t_z \end{bmatrix}^T$. These resolution specifications allow estimating the input distribution of each channel to compute the contact on the surface of the rigid body. From Eq. (2.18), the wrench is rewritten as:

$$(2.37) \quad \begin{aligned} \mathbf{W} &= \begin{bmatrix} \mathbf{F} \pm \Delta \mathbf{f} & \mathbf{T} \pm \Delta \mathbf{t} \end{bmatrix}^T \\ &= \begin{bmatrix} F_x \pm \Delta f_x & F_y \pm \Delta f_y & F_z \pm \Delta f_z & T_x \pm \Delta T_x & T_y \pm \Delta T_y & T_z \pm \Delta t_z \end{bmatrix}^T \end{aligned}$$

Hence, from Eq. (2.19), the wrench-axis is also rewritten as:

$$(2.38) \quad \mathbf{r} = \frac{(\mathbf{F} \pm \Delta \mathbf{f}) \times (\mathbf{T} \pm \Delta \mathbf{t})}{\|\mathbf{F} \pm \Delta \mathbf{f}\|^2} + \lambda(\mathbf{F} \pm \Delta \mathbf{f})$$

The Eq. (2.38) gives the multiple wrench-axis named as *wrench-tube* (see Fig. 2.12) the radii of ellipse of the tube is the confidence area measured by using *Gaussian distribution* and sensitivities (Δf , Δt) of the loadcell. Figure 2.12 shows that the size of confidence ellipses depend on the distance from the point of the applied force to the origin $\mathcal{L}$ of the loadcell, the larger ellipse are observed when the contact is further away from the load cell ($|r_1| > |r_2|$).

In the machining operations, along with the development of new machines, new sensors with high technologies, an analytical representation of a workpiece's surface is the required prerequisite. In the next section, I will briefly consider the principal elements of differential geometry of surfaces that are widely used in the machining operation.

2.4 Differential geometry of rigid surfaces at contact

In the preliminary discussion in Sec. 2.2.1, the relationship between wrench and surface of the rigid body can be used dynamically to estimate the contact point on both the workpiece and the instrumented tool surface. Once the contact point is determined, it is

Figure 2.12: The wrench-tube caused by using *Gaussian distribution* and the sensitivities of the loadcell, with the same applied force, the larger ellipse are observed when the contact is further away from loadcell

possible to analytically compute the *geometry of contact*, in particular, to carry out a first and a second order analysis [109]:

- *Tangent plane* Π (first order analysis): required to split the force $\mathbf{F}$ into a normal component and into a tangent component, the former being the normal force and the latter being friction. The normal to the surface is denoted as $\mathbf{n}$.
- *Curvature* (second order analysis): required to estimate the contact area once the normal force is known (e.g. based on Hertzian contacts model [110]). Curvature is encoded in terms of maximum and minimum curvatures ($\kappa_{max}, \kappa_{min}$). The curvature at contact is used in material removal models [111].

Giving a part surface P , at any 3D point M belong to P : $\mathbf{r}_P = \begin{bmatrix} x & y & P(x, y) \end{bmatrix}^T$ (all the quantities are with respect to the global frame S), it is possible to define two tangent vector $\mathbf{r}_x$ and $\mathbf{r}_y$ (see Fig. 2.13). These tangent vectors are in general not orthogonal, however, they define a base for the tangent space $\Pi := \{\mathbf{r}_x, \mathbf{r}_y\}$ at the point M . The first order analysis depends on the vector $\mathbf{n}$ normal to the surface P can be determined as:

$$(2.39) \quad \mathbf{r}_x = \frac{\partial \mathbf{r}_P}{\partial x}; \quad \mathbf{r}_y = \frac{\partial \mathbf{r}_P}{\partial y}; \quad \mathbf{n} = \frac{\mathbf{r}_x \times \mathbf{r}_y}{\|\mathbf{r}_x \times \mathbf{r}_y\|}$$

where $\times$ is the Euclidean cross product. For a second order analysis, also the second derivatives have to be evaluated:

$$(2.40) \quad \mathbf{r}_{xx} = \frac{\partial^2 \mathbf{r}_P}{\partial x^2}; \quad \mathbf{r}_{xy} = \frac{\partial^2 \mathbf{r}_P}{\partial x \partial y}; \quad \mathbf{r}_{yy} = \frac{\partial^2 \mathbf{r}_P}{\partial y^2}$$

Figure 2.13: Principal parameters of local topology of a surface P

Let $E(x, y)$, $F(x, y)$ and $G(x, y)$ be the coefficients of the *first fundamental form*; $e(x, y)$, $f(x, y)$, and $g(x, y)$ be the coefficients of the *second fundamental form* [109]:

$$(2.41) \quad \begin{cases} E(x, y) := \mathbf{r}_x^T \cdot \mathbf{r}_x \\ F(x, y) := \mathbf{r}_x^T \cdot \mathbf{r}_y \\ G(x, y) := \mathbf{r}_y^T \cdot \mathbf{r}_y \end{cases} \quad ; \quad \begin{cases} e(x, y) := \mathbf{n}^T \cdot \mathbf{r}_{xx} \\ f(x, y) := \mathbf{n}^T \cdot \mathbf{r}_{xy} \\ g(x, y) := \mathbf{n}^T \cdot \mathbf{r}_{yy} \end{cases}$$

With respect to the base Π it is possible to calculate at M the so called shape operator matrix N :

$$(2.42) \quad N = (EG - F^2)^{-1} \begin{bmatrix} fF - eG & eF - fE \\ gF - fG & fF - gE \end{bmatrix}$$

This is a 2×2 matrix and can be decomposed into a matrix of eigenvectors T and a diagonal matrix of eigenvalues K so that:

$$(2.43) \quad NT = TK$$

The eigenvectors $\mathbf{t}_1$ and $\mathbf{t}_2$ are the so called principal directions (at M), the eigenvalues κ_1 and κ_2 are the principal (normal) curvatures (e.g. the maximum and minimum normal curvatures at M) [109] and their inverses are the minimum and maximum principal radius of curvature respectively.

By re-scaling the eigenvectors by the principal radius of curvature, we define a new set of vectors: $\mathbf{d}_1 = \gamma \frac{\mathbf{t}_1}{\lambda_1}$ and $\mathbf{d}_2 = \gamma \frac{\mathbf{t}_2}{\lambda_2}$, with γ a constant that rescale the radius of curvature according to the rigid body dimensions as the radius of curvatures can

approach infinite values in the proximity of flat areas of the rigid body surface. The vectors $\mathbf{d}_1$ and $\mathbf{d}_2$ represent the main axes of an ellipse that is tangent at M to the surface P and can, therefore, be used to estimate the surface of contact at M . These (2D) vectors have coordinates that are expressed with respect to the base $\{\mathbf{r}_x, \mathbf{r}_y\}$. Let $J = \begin{bmatrix} \mathbf{r}_x & \mathbf{r}_y \end{bmatrix}$ be the 3×2 matrix containing the base vectors for the tangent space at M , we can rewrite the ellipse's axes as: $\mathbf{d}_1 = J\mathbf{d}_1$ and $\mathbf{d}_2 = J\mathbf{d}_2$.

It is also possible to approximate the ellipses by defining at M a set of unitary tangent vectors $\mathbf{w}_{M_i} = \begin{bmatrix} \cos(\theta_i) & \sin(\theta_i) \end{bmatrix}$. Each vector defines a specific direction in the tangent space at M along which it is possible to compute the normal curvature $\kappa_n(\mathbf{w}_{M_i})$:

$$(2.44) \quad \kappa_n(\mathbf{w}_{M_i}) = -\mathbf{w}_{M_i}^T N \mathbf{w}_{M_i}$$

note also that $\kappa_n(\mathbf{t}_1) = \kappa_1$ and $\kappa_n(\mathbf{t}_2) = \kappa_2$, i.e. the maximum and minimum curvatures are along the principal directions.

The ellipse can be approximated by the vectors $\mathbf{e}_{M_i}$:

$$(2.45) \quad \mathbf{e}_{M_i} = J \left(\gamma \frac{\mathbf{w}_{M_i}}{\kappa_n(\mathbf{w}_{M_i})} \right)$$

2.5 Summary

This chapter reviews the theoretical kinematics and dynamics of the rigid body, starts from the screw motion that has two fundamental concepts are twist and wrench. Twist represents a general helical motion of a rigid body an instantaneous axis in space which is kinematics. To capture a macro and micromotion of a rigid body, in this thesis, the motion capture system, and IMU are used. Wrench represents a forces/torques vector acting on a rigid body which is dynamics. Applied forces on a rigid body can be replaced by a single force applied on a line, combined with a torque about that same line defined as the wrench axis. The wrench axis, together with the surface of the rigid body allow measuring the contact point of the applied force/torque on a rigid body. The 6-axis ATI loadcell is used to measure force/torque in 3D. Together with motion capture and IMU, the elimination of gravitational biasing method for loadcell is discussed, following is a sensitivity analysis method which performs the estimated contact. The geometry of contact is presented to carry out a first and second order analysis, i.e., tangent plane and curvature. The first order analysis allows to split the applied force into a normal and tangent component; the curvature is used to estimate the ellipse at contact point which is useful for material removal models.

Based on the theoretical background presented in this chapter, a kinematics and dynamics of instrumented tools for machining operation are introduced. The instrumented tools are used to measure operator's behavior. A filter algorithm to eliminate the gravitation biasing and vibration affecting on the tool along with a method to estimate the accurate the geometry of contact between the tool and surface is discussed.

CONTACT DYNAMICS FOR INSTRUMENTED ROTATING TOOLS DURING FINISHING OPERATION

The goal of this chapter is to address the Objective #1 of the thesis: *Investigate kinematic strategies and dynamic interaction between human operator and workpiece during finishing tasks*. To achieve this, we propose a novel method [112] to capture both the *force / torque* and the *geometry of contact* during the interaction of an instrumented tool (polishing/grinding) with the workpiece.

Firstly, this chapter presents the interaction between the rotating tool and workpiece in the *stationary* case (the tool is fixed on a table-top): i) introducing the concept of an instrumented rotating tool along with the equations to derive forces and contact points from the readings of 6-axis loadcell ii) solving mechanical design issues of the tool iii) implementing an experiment to verify the accuracy of the tool.

Secondly, similar concepts are applied to an instrumented finishing tool in the *hand-held* case⁵ which is more convenient for operation along with the techniques that allow to obtain accurate results such as eliminating gravitational biasing and removing the vibration force.

Finally, in addition to the contact point estimation, the first and second order geometry (i.e. tangent space and curvature directions) at the contact point⁶ are presented for the

⁵Later on, the instrumented finishing tool in the hand-held case is named as the instrumented hand-held tool.

⁶Higher order geometry, in particular curvature, is required to estimate material removal [113, 114] although the review of such models is beyond the scope of this work

purpose of estimating i) normal force and in-plane component, i.e. friction, and estimating power ii) estimating contact ellipses, which would later on allow to estimate the area of contact (which however remains to be addressed in future work as it depends on the material properties).

3.1 Introduction

Contact estimation based on force/torque sensing was initially proposed in the 80's [29–31] and later used in different scenarios; Salisbury [32] described how joint torque measurements in a robot arm may be used to determine the location of a contact on its links; Bicchi et al [13] introduced the contact centroid for characterizing soft finger contact and emphasized the role of the *wrench axis* [33, 34]; Li et al. [35] formalized the method to localize the contact for robot fingers and carried out an accuracy analysis based on noise levels in force/torque sensors. Unlike robotic finger, finishing tools are subject to high levels of mechanical vibrations which introduce additional errors referred hereafter as mechanical noise.

Robots have been employed for a variety of industrial tasks such as material handling, welding, and spray painting; however those tasks necessitate weak interaction between the manipulator and its environment [1–3]. Automating such labor intensive surface finishing tasks require the robot to optimally adapt to unstable interactions with its dynamic workspace. These interactions generate contact forces that should be efficiently measured and controlled in order to achieve the desired end results. For a robot to handle a human-like adaptation of a finishing task typically requires a detailed programming and a repeated long-term testing with a high degree of detail for every single micro-motion/activity. Thus, one of the first steps in transitioning from manual to a robotized surface finishing process is developing better understanding of a human operator's knowledge in terms of the interaction with the applied forces/torques on workpiece, as well as the motion.

In order to address these issues, we propose instrumenting tools to assess interaction dynamics and geometry of contact. An extensive amount of literature has demonstrated the use of various force-sensing mechanisms to accurately measure the dynamic characteristics during the task. However, a majority of the research on force/torque measurements focus on process monitoring (i.e., capturing the machine state and tool condition) rather than assessing human skills for process automation, in particular, robotizing a labor intensive task like surface finishing. Understanding the significance of

force-sensing in such tasks is an exciting, yet little explored area.

3.2 Contact estimation for instrumented rotating tools: stationary case

Automating contact type tooling tasks demands clear knowledge of how human operator interacts with workpiece and the tool, including path information, force/torque interaction and point/area of contact with the workpiece. For capturing path information (kinematic data) motion capture systems and/or inertial sensors can be used. The main difficulty lies in estimating the interaction forces and contact point.

This section presents an instrumented rotating tool capable of capturing interaction 3D dynamics (in terms of contact points and interaction torques). In addition, accurate estimation of the application point of force is also made possible which, in general (in a manual operation) is derived using the haptic information. To this end, the friction at contact point is implemented to estimate the power of the rotating tool.

3.2.1 Estimating contact geometry for rotating tools

Contact between two surfaces can be described as a macro resultant force $\mathbf{F} = \sum \mathbf{f}_i$ applied directly at the center of pressure (CoP). In addition to measuring the resultant

Figure 3.1: Estimation of the centre of pressure (CoP) with a six-axis loadcell. The loadcell frame $\mathcal{L}$ is collocated with the workpiece (task) frame $\mathcal{T}$.

forces between the work piece and the tool, the estimation of CoP by means of above measured forces/torques is also presented (see Fig. 3.1). Although the interaction between tool and workpiece involves purely a resultant force at the contact, a torque $\mathbf{T}$ can be sensed at frames which are not co-located with the CoP. This shall always be the case,

since force sensors are practically always located far away from the CoP. Considering a generic finishing tool, a convenient task frame $\mathcal{T}$ can often be defined as having its z -direction aligned with the major axis of the mounting-bit and as being located opposite to the tooling surface.

A wrench $\mathbf{W}$ (i.e. a combination of force and torque components [33, 34]) sensed at the frame $\mathcal{T}$ can be written as:

$$(3.1) \quad \mathbf{W} = \begin{bmatrix} \mathbf{F} \\ \mathbf{T} \end{bmatrix}$$

where $\mathbf{T}$ is the torque arising at the origin of the frame $\mathcal{T}$ due to the force $\mathbf{F}$ applied at the CoP. In fact, the same wrench would be measured if the force $\mathbf{F}$ were applied at any position $\mathbf{r}$ along the *wrench-axis* [13, 35], i.e. a line defined by the following relationship:

$$(3.2) \quad \mathbf{T} = \mathbf{F} \times \mathbf{r}$$

where $\times$ is the Euclidean cross product. When written in $\mathcal{T}$ frame components, $\mathbf{r} = [r_x \ r_y \ r_z]^T$, $\mathbf{F} = [F_x \ F_y \ F_z]^T$ and $\mathbf{T} = [T_x \ T_y \ T_z]^T$, Eq. (3.2) leads to three *dependent* equations⁷ which define a line in 3D space:

$$(3.3) \quad \begin{bmatrix} T_x \\ T_y \\ T_z \end{bmatrix} = \begin{bmatrix} r_y F_z - r_z F_y \\ r_z F_x - r_x F_z \\ r_x F_y - r_y F_x \end{bmatrix}$$

In other words, Eq. (3.3) consists of three equations but only two are independent, and the solutions are all the points along a line parallel to $\mathbf{F}$ passing through CoP, as shown in Fig. 3.1-a as *wrench-axis*. Once the shape of the mounting-bit is known, in particular, when a point $\mathbf{r}$ on the surface S can be parameterized as $\mathbf{r} = [r_x \ r_y \ S(r_x, r_y)]^T$ in $\mathcal{T}$ frame coordinates, the CoP can be computed as the intersection⁸ between wrench-axis and the surface S , simply represented as:

$$(3.4) \quad r_z = S(r_x, r_y)$$

The CoP is determined as the intersection between wrench-axis (Eq. (3.3)) and tool surface (Eq. (3.41)), as graphically shown in Fig. 3.1-b. In this specific case, the surface $S(x, y)$ is the plane of the wheel surface, i.e. Eq. (3.41) is simply $r_z = 0$, which leads to the following dynamic estimation of contact point:

$$(3.5) \quad \mathbf{r}^* = \begin{bmatrix} -\frac{T_y}{F_z} & \frac{T_x}{F_z} & 0 \end{bmatrix}^T$$

⁷Eq. (3.2) can be seen as a linear system $\mathbf{T} = [\mathbf{F} \times] \mathbf{r}$, where $[\mathbf{F} \times]$ is a rank 2 matrix

⁸In general, as shown later, there will be two intersections but only one will have the force $\mathbf{F}$ pushing into the mounting-bit

3.2.2 Mechanical design of instrumented rotating tool

Various solutions have been proposed in literature to monitor interaction force between tool and the workpiece [28, 115]. This subsection presents a novel approach for measuring applied forces as well as deriving the point of contact. In principle, this is achieved by placing a multi-axis force/torque sensor between the spindle and the tool, mechanically in parallel to the rotating shaft (the sensor is therefore not rotating) (see Fig. 3.2). A bellows coupling is used to transmit spinning motion only from the spindle to the grinding wheel, while any other reaction forces or torques are transmitted through and sensed by the multi-axis force/torque sensor via a pair of rigid brackets fixed to the spindle casing and to the spinning tool holder. A set of bearings decouple the spinning tool from the tool holder, allowing the former to spin while the holder is stationary. The two brackets are then connected to each other via a force/torque sensor in the middle. This configuration, in particular the bearings between tool and tool holder, allow the loadcell to remain stationary while the tool is spinning. A major consequence of this de-coupling is that *the loadcell cannot sense any spinning torque*. For this reason, an alternative method is adopted to sense the spindle output torque. This consists of dynamic estimation of the spindle torque (e.g. through current readings) or by direct sensing of the torque transmitted through the flexible coupler (for this two encoders can be deployed, at the two ends of the flexible coupler), or by combination of both methods (sensor fusion). The compliance of the flexible coupler is such that all reaction forces/torques between tool holder and spindle casing are transmitted through the multi-axis force/torque sensor, as shown in Fig. 3.2. The force/torque sensor hereafter is also referred to as *loadcell*. The design approach is illustrated in Fig. 3.2 where the tool is assumed to be a rigid wheel, although more general tools (e.g. compliant wheels) can be considered. In Fig. 3.2, two reference systems are considered:

- The task coordinate system $\mathcal{T}$: located on the spinning axis of the tool and in-plane with the (tool) wheel. The z-axis of this coordinate system is assumed to point towards the workpiece.
- The loadcell coordinate system $\mathcal{L}$: the x-axis is defined parallel to the spinning axis, the z-axis of $\mathcal{L}$ is defined to be aligned with the x-axis of $\mathcal{T}$.

Fig. 3.2 shows the embodiment of instrumented tool used for later experiments. A Faulhaber DC motor 3863-024CR, equipped with an encoder (500 pulses-per-revolution), was used as spindle. A loadcell ATI mini 40 (range $F_{X,Y}: \pm 80N$, $F_Z: \pm 240N$, $T_{X,Y,Z}: \pm 4Nm$) measures interaction forces/torques. Two brackets made from AL6061 aluminium material were used for establishing the rigid connection between spindle casing and

Figure 3.2: a) The design approach for the instrumented tool. A force/torque sensor (loadcell) attached between the two rigid brackets captures the applied forces and torques while the flexible coupling links the spindle to spinning tool for torque transmission. Optical Markers and Inertial/Accelerometer shown in the figure are for kinematic data monitoring. b) CAD model of an implemented prototype.

the tool holder. Bearings were fixed inside the brackets for connecting the spindle shaft to the spinning wheel, via flexible coupler (bellows coupling CPBSC 25-10-10 from MISUMI). An additional encoder (HEDL 5400 #A12) is attached with motor to measure angular position/velocity of the tool (see Fig. 3.2). The two encoders can also sense the angular torsion of the bellows coupler, thus providing a direct measure of the transmitted torque but this feature shall not be used in this thesis. Fig. 3.3 shows the setup of the instrumented tool.

3.2.3 Estimation of interaction forces and contact point using the rotating tool

It is assumed that the spinning tool interacts with the workpiece at a very localized area, so that it can be described as a total force $\mathbf{F}_0$ acting at some point $\mathbf{r}^*$, with respect to the centre of the spinning tool (refer to Fig. 3.2). With respect to a coordinate system $\mathcal{T}$ located at the centre of the spinning tool, a *wrench* is generated and can be written as:

$$(3.6) \quad \mathbf{W} = \begin{bmatrix} \mathbf{F}_0 \\ \mathbf{T}_0 \end{bmatrix} = \begin{bmatrix} \mathbf{F}_0 \\ \mathbf{r} \times \mathbf{F}_0 \end{bmatrix}$$

where $\mathbf{T}_0 = \mathbf{r} \times \mathbf{F}_0$ is the torque with respect to the centre of the tool due to force $\mathbf{F}_0$ applied off-centre ($\mathbf{r}^*$). The same physical wrench can be expressed in different coordinate systems, for example with respect to the task (tool) space and the loadcell space, i.e $\mathbf{W}^{\mathcal{T}}$ and $\mathbf{W}^{\mathcal{L}}$, respectively. The two representations can be related to one another using the

Figure 3.3: The instrumented rotating tool: A Faulhaber DC motor 3863-024CR equipped with an encoder HEDL 5400 #A12 is used as spindle; a bellows coupler CPBSC 25-10-10 from MISUMI transfer spin from motor to the rigid wheel; two brackets made from AL6061 aluminium material were used for establishing the rigid connection between spindle casing and the tool holder. An additional encoder (HEDL 5400 #A12) is attached to the bracket to measure angular position/velocity of the wheel; a loadcell ATI mini 40 measures interaction force/torque

following transformation:

$$(3.7) \quad \mathbf{w}^{\mathcal{T}} = \begin{bmatrix} R & 0 \\ R \hat{\Delta}^{\mathcal{L}} & R \end{bmatrix} \mathbf{w}^{\mathcal{L}}$$

where the vector $\Delta^{\mathcal{L}}$ and the matrix $R = {}^{\mathcal{T}}R_{\mathcal{L}} \in \mathbb{R}^{3 \times 3}$ represent, the displacement of the origin and the rotation of the axes of the $\mathcal{T}$ coordinate systems with respect to the $\mathcal{L}$

coordinate system respectively (see Fig. 3.2).

$$(3.8) \quad \Delta^{\mathcal{L}} = \begin{bmatrix} \Delta x \\ 0 \\ \Delta z \end{bmatrix} \quad \hat{\Delta}^{\mathcal{L}} = \begin{bmatrix} 0 & -\Delta z & 0 \\ \Delta z & 0 & -\Delta x \\ 0 & \Delta x & 0 \end{bmatrix} \quad R = \begin{bmatrix} 0 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}$$

It should be noted that the wrench $\mathbf{W}^{\mathcal{L}}$ contains exactly the same force and torque components as measured by the ATI loadcell. Combining the Eq. (3.6) with the Eq. (3.7), we get both $\mathbf{T}_0^{\mathcal{L}}$ and $\mathbf{F}_0^{\mathcal{L}}$ from the loadcell readings. In order to determine the application point $\mathbf{r}^{\mathcal{L}}$, the equation $\mathbf{T}_0^{\mathcal{L}} = \mathbf{r}^{\mathcal{L}} \times \mathbf{F}_0^{\mathcal{L}}$ needs to be solved. However, this equation has multiple solutions, all lying on the wrench-axis. In particular, if $\mathbf{r}^{*\mathcal{T}}$ is a solution, also $\mathbf{r}^{*\mathcal{T}} + \lambda \mathbf{F}_0^{\mathcal{T}}$ is a solution, where λ can have any scalar value. As we are considering rigid tools (e.g. grinding wheels) we shall impose that the contact point stays on the wheel plane, i.e. $r_z^{\mathcal{T}} = 0$. Therefore, by imposing $\mathbf{r}^{\mathcal{T}} = [r_x \ r_y \ 0]^T$ and combining Eq. (3.6)-(3.21), we get:

$$(3.9) \quad \begin{bmatrix} r_x \\ r_y \end{bmatrix}^{(\mathcal{T})} = \begin{bmatrix} 0 & -F_{0z}^{-1} \\ F_{0z}^{-1} & 0 \end{bmatrix}^{(\mathcal{T})} \begin{bmatrix} T_{0x} \\ T_{0y} \end{bmatrix}^{(\mathcal{T})} = F_{0z}^{-1(\mathcal{T})} \begin{bmatrix} -T_{0y} \\ +T_{0x} \end{bmatrix}^{(\mathcal{T})}$$

From the equation above, we estimate the contact point on a rigid disk using component of force applied normal to the surface of the disk ($F_z^{\mathcal{T}}$) and corresponding torques ($T_x^{\mathcal{T}}$ and $T_y^{\mathcal{T}}$) produced.

The spindle of instrumented tool is set to rotate at 2000 *rpm* (revolutions per minute) to compare the accuracy of measured force from the instrumented tool and applied force from the pointer device's. There are two main problems with the measured force/torque of the loadcell in the dynamics case: *coupler's misalignment* and *system's stiffness*. In the following sections, the algorithms for removing these problems are proposed.

3.2.4 Removing the misalignment of the coupler

The difficulty in proper alignment of the coupler to be in line with the shaft of the spindle might result in a misalignment between the grinding wheel and the spindle. This misalignment effects the measured forces/torques by the loadcell as a sinusoidal function of angular position θ (from 0 - 2π *rad*) as shown in Fig. 3.4. To measure the coupler's effect in x , y and z -direction, we control the spindle's speed in the experiment at 2000 *rpm* and forces are recorded at task space. The raw data of force and torque measured at task space $\mathcal{T}$ under coupler misalignment's effect is shown in Fig. 3.4-i. The raw data of force and torque is filtered by using low-pass butterworth filter with cut-off frequency at

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Figure 3.4: i) The raw data of force and torque measured at task space $\mathcal{T}$ under coupler misalignment's effects at 2000 *rpm*. F_z^T approximately equal to zero shows the lowest stiffness is in z -direction. ii) The filtered data by using low-pass butterworth filter with cut-off frequency at 40 *Hz*. iii) The average force $\mathbf{f}_j^T$ and torque $\mathbf{t}_j^T$ derived from the filtered force $\mathbf{F}^T$ and filtered torque $\mathbf{T}^T$ in term of angle $[0 - 2\pi]$.

40 *Hz*. The filtered force and torque is named as $\mathbf{F}^T$ and $\mathbf{T}^T$, respectively. The coupler is in the cylindrical structure which has symmetric shaft, hence, the force $\mathbf{F}^T$ and torque $\mathbf{T}^T$ given by the effect of coupler during the rotation is in the sinusoidal function (see Fig. 3.4-ii). Therefore, the behavior (force/torque) of the system at specific velocity can be predicted by using *Fourier series*⁹.

The system behavior is analyzed in both the time and frequency domain and I compare the experimental data with a periodic signal made by using *fit* function of MATLAB (The Mathworks, Natwick USA) [116] to fit the sinusoidal function to the five-degree (specify the model type *fourier* followed by the number of term i.e. *fourier5*).

⁹Fourier series is a sum of sine and cosine functions which describes a periodic signal represented in either the trigonometric form or the exponential form [116].

Let $\mathbf{f}_j(j = x, y, z)$ be the average measured force by the loadcell caused by the couple's misalignment (see Fig. 3.4-iii). The coefficients of fourier series are computed by the average force for one cycle $[0 - 2\pi]$ of the rotating process of the spindle.

$$(3.10) \quad \mathbf{F}_j^* = a_0^f + \sum_{i=1}^5 \left(a_i^f \cos(\theta_j \omega) + b_i^f \sin(\theta_j \omega) \right) \quad j = x, y, z$$

where $a_0^f, b_0^f, a_i^f, b_i^f$, and ω are the coefficients of the fourier series measured by using *fit* function of MATLAB. The coefficient a_0^f model a constant (intercept) term in the data and is associated with the $i = 0$ cosine term, ω is the fundamental frequency of the signal, $\mathbf{F}_j^*$ is the predicted force for every cycle, θ_j denotes the angle $[0 - 2\pi]$ for every cycle measured by the encoder. The same analysis is used for the torque $\mathbf{T}_j^*$. The frequency components for both the measured data from loadcell and predicted data using Eq. (3.10) allows the comparison in both the time and frequency domain, as shown in Fig. 3.4-iii. The normalized root-mean-square deviation (NRMSD) as shown in Eq. (3.11) is used to derive a quantitative measure of the different between collected data and the predicted behavior, allowing the evaluation of the performance of the system.

$$(3.11) \quad NRMSD = \frac{\sqrt{\frac{\sum_{i=1}^n (\mathbf{F}_j - \mathbf{F}_j^*)^2}{n}}}{\mathbf{F}_{j\max}^* - \mathbf{F}_{j\min}^*}$$

where n is the length of samples, $\mathbf{F}_j^*$ is the predicted signal used as the reference and $\mathbf{F}_j$ is the measured signal undergoing the analysis.

Figure 3.5: The predicted method estimates the measured data with a good approximation along x, y, and z-axis, with a NRMSD < 3%.

Fig. 3.5 shows that the predicted force can be able follow the measured force with a good approximation along all x, y, z-axis with a NRMSD < 3%. By subtracting the predicted force $\mathbf{F}_j^*$, the coupler's misalignment problem is solved.

3.2.5 Eliminating the stiffness of the tool

From now, the contact force/torque at task frame is used with the assumption that they are already subtracted with the misalignment force/torque:

$$(3.12) \quad \mathbf{F}^{\mathcal{T}} = \begin{bmatrix} F_x - F_x^* \\ F_y - F_y^* \\ F_z - F_z^* \end{bmatrix} \quad \mathbf{T}^{\mathcal{T}} = \begin{bmatrix} T_x - T_x^* \\ T_y - T_y^* \\ T_z - T_z^* \end{bmatrix}$$

Previous equations are based on the assumption that the coupler will only transmit spinning torques ($T_z^{\mathcal{T}}$) and will be ideally transparent in terms of reaction force $\mathbf{F}^{\mathcal{T}}$ and remaining reaction torque ($T_x^{\mathcal{T}}, T_y^{\mathcal{T}}$) components (with respect to the $\mathcal{T}$ space). In practice, the coupler will have non-negligible stiffness which might affect reaction forces and torques as well. Considering a pure axial loading, a total axial force $\mathbf{F}^{\mathcal{T}}$ would be counteracted (and, at the same time, transmitted to the human operator) partly by the loadcell and partly by the coupler, i.e.

$$(3.13) \quad \mathbf{F}^{\mathcal{T}} = \mathbf{F}_{lc}^{\mathcal{T}} + \mathbf{F}_{cp}^{\mathcal{T}}$$

where $\mathbf{F}_{lc}^{\mathcal{T}}$ is the force going through the loadcell, and $\mathbf{F}_{cp}^{\mathcal{T}}$ is the force caused by the coupler which will be in proportion to the stiffness of the two components, i.e.

$$(3.14) \quad \frac{\mathbf{F}_{lc}^{\mathcal{T}}}{K_{lc}} = \frac{\mathbf{F}_{cp}^{\mathcal{T}}}{K_{cp}}$$

where K_{cp} is the axial stiffness of the coupler and K_{lc} is the effective stiffness of the loadcell-brackets assembly in the axial direction¹⁰ (see Fig. 3.6). The consequence is that the sensed force ($\mathbf{F}_{lc}^{\mathcal{T}}$) is lower than expected $\mathbf{F}^{\mathcal{T}}$ by the following factor:

$$(3.15) \quad \mathbf{F}_{lc}^{\mathcal{T}} = \alpha_f \mathbf{F}^{\mathcal{T}}$$

where $\alpha_f := \frac{K_{lc}}{K_{lc} + K_{cp}}$ is the attenuation factor of sensed axial forces.

Similarly, the robot creates an ideal torque $\mathbf{T}_R^{\mathcal{T}} = \mathbf{r} \times \mathbf{F}_R^{\mathcal{T}}$. Let α_t be the ratio between the ideal torque $\mathbf{T}_R^{\mathcal{T}}$ and the estimated torque from the loadcell on task space $\mathbf{T}_{lc}^{\mathcal{T}}$.

$$(3.16) \quad \alpha_t = \frac{\mathbf{T}_{lc}^{\mathcal{T}}}{\mathbf{T}_R^{\mathcal{T}}}$$

¹⁰The ATI loadcells are very rigid, in the order of 10^7 N/m but these values can be greatly reduced by parasitic compliance in the bracket-loadcell attachments.

Figure 3.6: Model accounting for coupler stiffness K_{cp} and parasitic stiffness from the bracket assembly K_b together with loadcell stiffness K_{lc} on force readings.

3.2.6 Sensitivity Analysis

The estimated contact location is a function of the force and torque measurements. A sensitivity analysis is performed to study how the contact area is affected by the ranges and resolution of the load cell (see Table 1). This analysis aid in assessment of the source and effect of uncertainties in the measurement, in the interest of better interpreting the obtained experimental results.

Table 3.1: The sensing ranges and resolution of each channel of the ATI SI-80-4 load cell

Calibration	Sensing ranges				Resolution			
SI-80-4	F_x, F_y	F_z	T_x, T_y	T_z	F_x, F_y	F_z	T_x, T_y	T_z
	80 N	240 N	4 Nm	4 Nm	1/25 N	2/25 N	1/1000 Nm	1/1000 Nm

The resolution specifications allow estimating the input distribution of each channel to compute the contact in the x- and y-direction:

$$(3.17) \quad X_P = \frac{-T_y \pm \frac{1}{1000}}{F_x \pm \frac{1}{25}} \quad ; \quad Y_P = \frac{T_x \pm \frac{1}{1000}}{F_x \pm \frac{1}{25}}$$

The applied force for the input of the sensitivity analysis was set to $F_x = 10N \pm 1/25$ and the values for T_x and T_y ranged from $0.1Nm \pm 1/1000$ to $0.9Nm \pm 1/1000$. For each condition the output variables (X_P and Y_P) were plotted against each other. The input variables (T_x , T_y and F_x) are randomly sampled and scaled based on its resolution using the randn function in MATLAB. The advantage of this approach is that it allows a visual indication of the sensitivity but also quantitative measures as the computed contact area. The contact areas was defined as the confidence ellipse where 95% of the data should lie, assuming a bivariate normal distribution.

Fig. 3.7 presents the orientation and size of confidence ellipses in the x, y and x-y direction and the confidence area as a function of distance of the contact point to the load

Figure 3.7: a) The sensitivity analysis shows the contact area represented as 95% confidence ellipse when computing the position in either the x-, y- and x-y direction b) The surface area of the confidence ellipse increases with distance from the origin of the load cell. The area stays below 4mm^2 at the outer part of the disk.

cell origin. Larger ellipses imply that contact is further away from the load cell. The area of the contact area is quite small and the radii of the ellipses are maximal one millimeter resulting in confidence areas smaller than 4mm^2 . The conducted sensitivity analysis shows that the contact area is relatively small and the computations are robust. From the simulation studies, it is concluded that force/torque-measurement based approach to contact localization is robust, and invariant to changes in point of contact.

3.2.7 Experimental Validation - Measuring the Force/Torque and the Contact geometry

Experimental tests for the proposed instrumented tool is implemented to verify the accuracy of measured contact force/torque as well as of estimated contact point during interaction with a workpiece when the tool is fixed. The setup used in the experiment is shown in the Fig. 3.8. For application of controlled force on the tool as a standard, we used a one degree of freedom cable driven robot with a pointer device attached at its end effector and actuated by current-controlled DC motors [117]. The robot is capable of generating forces up to 7 N and, for a detailed description, reader is referred to [117]. The robotic setup was programmed to apply forces on the disk with increasing steps of 0.3 N. The force on the wheel is measured by a 6-axis ATI loadcell embedded in the instrumented tool (see Fig. 3.2) and by a loadcell mounted on the pointer of the

Figure 3.8: Experiment setup: a pointer robot, bound to move on a linear guide, is cable-driven by a current-controlled motor is used to apply stepped forces on the wheel's surface. 6-axis (ATI) loadcell embedded in the instrumented tool, another ATI loadcell directly attached to the pointer is used to monitor applied forces.

robotic setup (see Fig. 3.8) with the sampling rate of 1 kHz. Accuracy of the contact forces as measured by the instrumented tool (with and without the effect of the coupler) is determined by comparing data captured by the two loadcells for different levels of applied force. The robot pointer was set¹¹ to make contact with the rigid wheel at a radial distance of 50 mm from the center of the wheel and was programmed to a step wise increasing force. Under the coupler's effect, from Eq. (3.9), (3.15) and (3.16), the application point is defined as:

$$(3.18) \quad \begin{bmatrix} r_x \\ r_y \end{bmatrix}^T = \frac{\alpha_t}{\alpha_f} \begin{bmatrix} -T_y/F_z \\ T_x/F_z \end{bmatrix}^T$$

where $\alpha_f = \frac{\mathbf{F}_{lc}^T}{\mathbf{F}_R^T} = \frac{\mathbf{F}_{lc-z}^T}{\mathbf{F}_{R-z}^T} = 0.77$ and $\alpha_t = \frac{\mathbf{T}_{lc}^T}{\mathbf{T}_R^T} = 0.8$ are the constant values and relates to instrumented tool. Fig. 3.9-a shows the applied stepped force $\mathbf{F}_R^T$ along z -direction by the pointer device and the force measured $\mathbf{F}_{lc}^T$ by the loadcell on the instrumented tool after transformation from loadcell frame $\mathcal{L}$ to the task frame $\mathcal{T}$. The accuracy of estimated force in z -direction is shown in the boxplot (Fig. 3.9-b). It shows that the grinder tool

¹¹The robot and the instrumented tool were manually set one in front of the other and grounded to the table.

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Figure 3.9: a) Comparison in the z -direction between the measured force F_{lc}^T by the instrumented tool and force applied by the robot device F_R^T at 2000 rpm. b) Force estimation error plot between force measured by the instrumented tool and applied force by the robotic setup for a range of applied forces at 2000 rpm after calibration.

can sense the applied contact force/torque reliably for different levels of forces/torques applied and the approximate range of error is within the range of 0.1 N.

Discrete captured data is filtered by using low-pass filter (second order Butterworth filter) with a cut-off frequency of 1 Hz to remove noise. The estimated application points are obtained from Eq. (3.18). Experiment result is shown in Fig. 3.10-a where the accuracy of contact point is presented by the error ellipse.

Figure 3.10: a) The accuracy of measured discrete point of application of force in polar coordinate when the wheel rotates at 2000 rpm. The confidence ellipse defines the region that contains 95% of all samples that can be drawn from the underlying Gaussian distribution. b) Error plot of contact point estimation for a range of applied forces when the wheel rotates at 2000 rpm.

The accuracy of force measured is shown in the boxplot (Fig. 3.10-b) which shows that at low levels of applied force, the contact point approximation has a higher degree of variation. However, as we increase the contact force, the accuracy of estimation of contact point increases and variability decreases. The application force which is used to estimate the contact point is greater than 3N.

Friction at the contact point and tool's Power: The power PWR of the instrumented tool can be estimated as:

$$(3.19) \quad PWR = \mathbf{F}_f^T \cdot \mathbf{v}^T$$

where $\mathbf{F}_f^T = \begin{bmatrix} F_x^T & F_y^T & 0 \end{bmatrix}^T$ is the vector of friction force during operation on task frame, $\mathbf{v}^T = \omega(\mathbf{r}^T \times \begin{bmatrix} 0 & 0 & 1 \end{bmatrix}^T)$ is the speed of the wheel at the contact points $\mathbf{r}^T$; and ω is the angular velocity of the wheel which is measured by the encoder.

Figure 3.11: Friction force vector in the task frame $\mathcal{T}$

Figure 3.12: a) The friction $\mathbf{F}_f = \sqrt{(F_x^T)^2 + (F_y^T)^2}$ and the angular velocity ω on the task frame $\mathcal{T}$. b) The estimated power based on friction, velocity and contact points.

The results from the experiment shows that the novelty of this approach lies in the fact that the proposed instrumented tool is capable of measuring forces/torques in three dimensions, as well as the application point. The task dynamics can be captured, the contact point, friction and power of the rotating tool can be estimated which is in fact considered as an initial step toward robotizing a manual complex surface finishing process. However, the instrumented rotating tool in the experiment is always fixed on the table-top, this leads to the limited space of the operation. Hence, in the next section, a more convenience instrumented tool which allow the operator engages in a finishing process will be proposed.

3.3 Contact estimation for instrumented finishing tools: hand-held case

This section presents a conceptual framework to capture human performance in terms of kinematics and interaction dynamics between a hand-held power tool and a workpiece. To this end, a hand-held power tool was instrumented to measure 3D kinematics and 3D interaction dynamics (i.e. 3D forces and torques) during manual finishing operations. Algorithms from literature were adapted to sense dynamically (i.e. based on force/torque measurements) the point of contact between a hard mounting-bit and the workpiece. Based on this estimation, from the shape of the mounting-bit we estimated important geometric features. Namely, a first order analysis allows splitting contact forces into normal force and friction components. The contact point along the mounting-bit surface determines the relative velocity at contact and, with friction, the mechanical power involved in the finishing process. A second order analysis at contact point, provides information about the curvature of the mounting-bit and of the workpiece at contact. Geometric curvature at contact is used in material removal rate models, although actual estimation of material removal is beyond the scope of this work.

Experimental results show that the contact point between the tool and the workpiece can be precisely estimated, as validated using 3D motion capture. The first and second order geometric features have been extracted from experimental data and compared with optical scans. The results of the study are promising and can potentially be programmed on robotic setups for facilitating operators during tooling tasks.

3.3.1 Designing of an instrumented hand-held tool

In this section, firstly, the instrumentation of a general-purpose, hand-held, rotary tool such as *Dremel 4000*, shown in Fig. 3.13-a and consisting of a spindle, a flexible shaft and a spinning tool hosting the mounting-bit and hand-held by the operator, see Fig. 3.13-b. The purpose of the flexible shaft is to transmit rotation, generated from a heavy spindle, to the mounting-bit while keeping the tool held by the operator lightweight. To be able to capture interaction forces/torques between the operator and tool, a custom made and 3D printed an ergonomic handle for the operator which would be attached to the spinning tool through a force/torque sensor, as shown in Fig. 3.13-b. In case the tool is operated by a robot, the ergonomic handle should simply be replaced by a proper attachment jig. In order to track the tool's motion, a marker-based motion capture system with the

Figure 3.13: a) Dremel tool including: spindle, flexible cable and spinning tool. b) Conceptual design of the instrumented tool: a loadcell attached between the spinning tool and handle captures the applied forces and torques while infrared markers allow capturing 3D position and orientation of the tool. c) Actual instrumented tool. 8 infra-red markers (from m_1 to m_8) for motion tracking; the spinning tool is clamped by two brackets; the loadcell is located between tool and handle to capture dynamic interaction during operation.

sampling frequency is at 100 frames/sec (see Chap. 2, Sec. 2.3) is used to sense the 3D location of several infra-red markers rigidly attached to the spinning tool.

Although, in theory, only 3 markers are necessary to determine position and orientation of a rigid body, I used a redundant set of 8 markers ($m_1, m_2, \dots, m_8$) to prevent problems such as occlusion, as one or more markers might not be seen by the cameras at some point in time. For this purpose and with reference to Fig. 3.13-c, the optical markers were rigidly attached onto two 3D printed brackets used to clamp the spinning tool. A force/torque sensor (ATI loadcell mini 40, range $F_{X,Y}: \pm 80N$, $F_Z: \pm 240N$, $T_{X,Y,Z}: \pm 4Nm$) is placed between the ergonomic handle and the spinning tool, to capture dynamic interaction (i.e. forces and torques) between operator and spinning tool.

All equations presented in previous section are written in $\mathcal{T}$ frame coordinates, which is located at the origin of the mounting-bit (i.e. opposite to the tooling end of the mounting-bit). However, since the mounting-bit is typically spinning, having a loadcell directly on the mounting-bit is often unpractical. In our case, the loadcell is mounted at a different location from task space $\mathcal{T}$, as shown in Fig. 3.13-b, which defines a new (loadcell) reference frame $\mathcal{L}$. As indicated in Fig. 3.13-b, the two main coordinate systems are:

- The task frame $\mathcal{T}$: located on the mounting-bit of the spinning tool, with z -axis

aligned with the major axis and pointing towards the workpiece.

- The loadcell frame $\mathcal{L}$: the x -axis of $\mathcal{L}$ is defined parallel to the z -axis of the $\mathcal{T}$ frame, the z -axis of $\mathcal{L}$ is defined to parallel to an axis of the handle.

In order to estimate the wrench $\mathbf{W}^{\mathcal{T}}$ in Eq. (3.1), in $\mathcal{T}$ frame coordinates, from the wrench $\mathbf{W}^{\mathcal{L}}$ as measured directly by the loadcell, the following transformation is used:

$$(3.20) \quad \mathbf{W}^{\mathcal{T}} = \begin{bmatrix} R & 0 \\ R \hat{\Delta}^{\mathcal{L}} & R \end{bmatrix} (\mathbf{W}^{\mathcal{L}} - \mathbf{W}_{gr}^{\mathcal{L}})$$

where the matrix $\hat{\Delta}^{\mathcal{L}}$ and the matrix R represent, respectively, the skew-symmetric matrix of the vector $\Delta^{\mathcal{L}}$ which is the origin of the $\mathcal{T}$ frame expressed in $\mathcal{L}$ coordinates; and the rotation matrix representing the axes of the $\mathcal{T}$ frame in $\mathcal{L}$ coordinates. In particular, as shown in Fig 3.13-b:

$$(3.21) \quad \Delta^{\mathcal{L}} = \begin{bmatrix} \Delta x \\ 0 \\ \Delta z \end{bmatrix}; \quad \hat{\Delta}^{\mathcal{L}} = \begin{bmatrix} 0 & -\Delta z & 0 \\ \Delta z & 0 & -\Delta x \\ 0 & \Delta x & 0 \end{bmatrix} \text{ and } R = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \end{bmatrix}$$

It should be noted that the wrench $\mathbf{W}^{\mathcal{L}}$ contains the readings from the ATI load-cell which, in addition to the interaction forces and torques, will contain gravitational forces and torques due to the mass of the spinning tool and clamping brackets. Therefore, it is necessary to eliminate the gravitational biasing to get the significant force/torque during the operation. The method to remove the gravity effect is presented in the following section.

3.3.2 Removing the gravity force from the hand-held tool

For capturing the macro and micromotion of the hand-held tool, a marker-based motion capture system type VZ4000, Poenix Technologies Inc, with a sampling frequency of 100 frames/sec (see Chap. 2, Sec. 2.3). This motion capture system is able to sense the 3D location of eight infra-red markers rigidly attached to the hand-held tool.

Marker occlusions are a commonly known problem and to evade it: must be visible to at least two cameras in each frame to establish its position. Dorfmueller in [87] used an extended Kalman filter (EKF) to predict the missing markers based on previous marker information while Welch et al. in [88] used the EKF to resolve occlusions based on the skeletal model. These methods require manual intervention or become ineffective in cases where markers are missing for an extended period of time.

In the following section, an algorithm named *damped least squares* capable of overcoming these shortcomings are presented. After filtering the motion capture signal, the proposed algorithm can detect the macromotion which allow to eliminate the gravitational biasing induced by the mass of hand-held tool. In the second part, the *complementary filter* algorithm which is used to detect the micromotion for removing the vibration of the tool is proposed.

3.3.2.1 Filtering motion tracker signal - damped least square algorithm

The configuration of the hand-held tool can always be represented by a rotation matrix $R \in \mathbb{R}^{3 \times 3}$, i.e. a matrix such that $R^{-1} = R^T$ and $\det R = +1$ (see [100]). The pose of a rigid object in task space $\mathcal{T}$ can be described in reference frame $\mathcal{S}$ via a homogeneous transformation matrix $G = \begin{bmatrix} R & \mathbf{p} \\ 0 & 1 \end{bmatrix} \in SE(3)$. Where $\mathbf{p} \in \mathbb{R}^3$ and $R \in \mathbb{R}^{3 \times 3}$, respectively, are the translation vector and the rotation matrix representing the axes of the object frame $\mathcal{T}$ in global coordinates $\mathcal{S}$.

In this work, eight infra-red markers are located on the hand-held tool with the relative position known based on computer-aided design (CAD) drawing (see Fig. 3.14). The position of i^{th} marker in the task space $\mathcal{T}$ is constant and can be defined as:

$$(3.22) \quad \mathbf{m}_i^{\mathcal{T}} = \begin{bmatrix} m_{ix} & m_{iy} & m_{iz} \end{bmatrix}^{\mathcal{T}}$$

The position of the i^{th} marker with respect to the global frame $\mathcal{S}$ changes with G and can be determined as:

$$(3.23) \quad \begin{bmatrix} \mathbf{m}_i^{\mathcal{S}} \\ 1 \end{bmatrix} = G \begin{bmatrix} \mathbf{m}_{0i}^{\mathcal{T}} \\ 1 \end{bmatrix}$$

One way to solve the marker occlusion problem, a model named *damped least square* (Fig. 3.15) which considers each marker as a spring with stiffness k_i is proposed. When the position of the marker changes there is a difference between its previous position $m_i(t-1)$ and its current position $m_i(t)$ and consequently k_i . The time interval between two samples $t_n \leq t \leq t_{n+1}$ is divided into N intervals with the same length. If the marker deviates from its correct position, due to the stiffness a force will pull each marker back to the correct position. The larger the interval N , the higher the accuracy of the algorithm.

Let $\mathbf{G}^*$ be the estimate pose of the tool frame $\mathcal{T}$, then from Eq. (3.23), the estimated position of the i^{th} marker is given as:

$$(3.24) \quad \begin{bmatrix} \mathbf{m}_i^{*\mathcal{S}} \\ 1 \end{bmatrix} = \mathbf{G}^* \begin{bmatrix} \mathbf{m}_{0i}^{\mathcal{T}} \\ 1 \end{bmatrix}$$

Figure 3.14: This figure shows the placement of markers on the top and side of the instrumented tool.

we can define this as:

$$(3.25) \quad \begin{cases} \mathbf{F}_i^S = k_i (\mathbf{m}_i^S - \mathbf{m}_i^{*S}) \\ \mathbf{M}_i^T = (R^{-1} \mathbf{F}_i^S) \times (\boldsymbol{\zeta}^T - \mathbf{m}_{0i}^T) \end{cases}$$

where $\mathbf{F}_i^S$ is the force in the reference space, $\mathbf{M}_i^T$ is the torque in task space of marker i^{th} and $\boldsymbol{\zeta}^T \in \mathbb{R}^3$ is the center of mass in task space $\mathcal{T}$ measured from the mechanical design.

Figure 3.15: Spring - Markers system: In a time interval, the different between the position estimated and position from CAD of each marker cause the force pull the tool back to the right position.

The angular velocity of the tool generated by this change can be defined as [100]:

$$(3.26) \quad \boldsymbol{\omega}^{\mathcal{T}} = b_r^{-1} \sum \mathbf{M}_i^{\mathcal{T}}$$

where $\boldsymbol{\omega}^{\mathcal{T}} \in \mathbb{R}^3$ is the tools angular velocity vector. The damping of rotation b_r will be identified later.

To avoid inconsistencies due to numerical integration, geometric integration is preferred, following [100]:

$$(3.27) \quad R_{n+1} = R_n \exp(\boldsymbol{\omega}^{\mathcal{T}} \Delta T)$$

The exponential $\exp(\boldsymbol{\omega}^{\mathcal{T}} \Delta T)$ can be computed via the Rodrigues' formula [73] which does not drift from $SO(3)$:

$$(3.28) \quad R_{n+1} = R_n \left(I + \alpha_n \frac{\Delta T}{N} \hat{\boldsymbol{\omega}}_n^{\mathcal{T}} + \beta_n \frac{\Delta T}{N} (\hat{\boldsymbol{\omega}}_n^{\mathcal{T}})^2 \right)$$

where:

$$(3.29) \quad \begin{cases} \alpha_n = \frac{\sin(\|\Delta T \hat{\boldsymbol{\omega}}_n^{\mathcal{T}}\|)}{\|\Delta T \hat{\boldsymbol{\omega}}_n^{\mathcal{T}}\|} \\ \beta_n = \frac{1 - \cos(\|\Delta T \hat{\boldsymbol{\omega}}_n^{\mathcal{T}}\|)}{\|\Delta T \hat{\boldsymbol{\omega}}_n^{\mathcal{T}}\|^2} \end{cases}$$

Similar to the rotation, a change in translation of the origin of $\mathcal{T}$ in the reference frame $\mathcal{S}$ for each time interval:

$$(3.30) \quad \mathbf{p}_i^* = \frac{\Delta T}{N} \frac{1}{b_p} \sum \mathbf{F}_i^{\mathcal{S}}$$

where b_p is damping of linear translation and N is the number of intervals between two samples of data.

The translation between current and previous position can be defined as:

$$(3.31) \quad \mathbf{p}_{n+1} = \mathbf{p}_n + \mathbf{p}_i^* = \mathbf{p}_n^{\mathcal{S}} + \frac{\Delta T}{N} \frac{1}{b_p} \sum \mathbf{F}_i^{\mathcal{S}}$$

For convergence with a time constant τ , set:

$$(3.32) \quad \begin{aligned} b_p &= \tau \cdot k \\ b_r &= \tau \cdot k \cdot L^2 \end{aligned}$$

where L is a characteristic length of the object, can be defined as:

$$(3.33) \quad L = \frac{\sum_i \|\boldsymbol{\zeta}^{\mathcal{T}} - \mathbf{m}_{0i}^{\mathcal{T}}\|}{N_{mrk}}$$

where ζ^T is the center of mass of the object and N_{mrk} is the number of markers.

For implementation purposes the Psuedo code is presented:

Data: $\mathbf{m}^S, \mathbf{m}_0^T, N_{mrk}, N, k, b_r, b_p, \Delta T, \zeta^T$
Result: $R, \mathbf{p}$
initialization;
for $j=1:N_{mrk}$ **do**
 for $i=1:N$ **do**
 $\mathbf{f}_i^S = k(\mathbf{m}_i^S - \mathbf{p}_n^S - R_n \mathbf{m}_{0i}^T)$
 $\boldsymbol{\tau}_i^T = (R_n^T \mathbf{f}_i^S) \times (\zeta^T - \mathbf{m}_{0i}^T)$
 $\boldsymbol{\omega}_n^T = \frac{1}{b_r} \sum \boldsymbol{\tau}_i^T$
 $\alpha_n = \sin(\|\Delta T \hat{\boldsymbol{\omega}}_n^T\|) / \|\Delta T \hat{\boldsymbol{\omega}}_n^T\|$
 $\beta_n = (1 - \cos(\|\Delta T \hat{\boldsymbol{\omega}}_n^T\|)) / \|\Delta T \hat{\boldsymbol{\omega}}_n^T\|^2$
 $R_{n+1} = R_n \left(I + \alpha_n \frac{\Delta T}{N} \hat{\boldsymbol{\omega}}_n^T + \beta_n \frac{\Delta T}{N} \hat{\boldsymbol{\omega}}_n^{T^2} \right)$
 $\mathbf{p}_{n+1} = \mathbf{p}_n + \frac{\Delta T}{N} \frac{1}{b_p} \sum \mathbf{f}_i^S$
 end
end

Algorithm 1: Damped Least Square algorithms

3.3.2.2 Removing gravitational biasing

Based on the results mentioned above, one can eliminate the gravitational biasing by assuming that the inertial and center of mass of the hand-held tool is well known from the CAD, and the movement is executed slowly to avoid inertial effects.

The loadcell measures all the applied force on the hand-held tool including the gravity. Meanwhile, the force caused by the gravity is estimated by the mechanical properties of the hand-held tool and the spatial information of the motion capture. The subtraction of these two vector of force presents the gravity's effect. The estimated gravity force from the markers at the origin of loadcell space $\mathcal{L}$ is:

$$(3.34) \quad \mathbf{F}_{gr}^{\mathcal{L}} = m R^{\mathcal{L}} g^S$$

where m is the mass of the spinning tool and brackets complex, $R^{\mathcal{L}}$ is the orientation of the $\mathcal{L}$ frame as given by the motion tracker and $g^S = \begin{bmatrix} 0 & 0 & -9.81 \end{bmatrix}^T$ is the gravitational acceleration (in $\mathcal{S}$ space coordinates, as defined by the motion tracker). The force error $\boldsymbol{\epsilon}^{\mathcal{L}}$ in the loadcell space after removing gravity's effect is defined as:

$$(3.35) \quad \boldsymbol{\epsilon}^{\mathcal{L}} = \mathbf{F}_{lc}^{\mathcal{L}} - \mathbf{F}_{gr}^{\mathcal{L}}$$

where $\mathbf{F}_{lc}^{\mathcal{L}}$ is the force measured by the loadcell in the $\mathcal{L}$ space. From Eq. (3.34) in the wrench formula with respect to Eq. (3.20), the gravitational wrench $\mathbf{W}_{gr}^{\mathcal{L}}$ can be determined as:

$$(3.36) \quad \mathbf{W}_{gr}^{\mathcal{L}} = m \begin{bmatrix} R^{\mathcal{L}} \mathbf{g} \\ \boldsymbol{\zeta}^{\mathcal{L}} \times R^{\mathcal{L}} \mathbf{g} \end{bmatrix}$$

The center of mass ($\boldsymbol{\zeta}$, as in Fig. 3.13-b) of the spinning tool and clamping brackets can be accurately estimated from CAD.

The experimental test is implemented in [102] to verify the *damped least square* filter algorithm.

3.3.3 Removing the vibration force from the hand-held tool - Complementary filter

In the previous section, a model is developed to i) filter the motion capture data and ii) to remove the gravitational effect on the loadcell. The motion capture can detect large rotations and translations at low frequencies but micromotions may stay undetected when the amplitudes are too small and the frequencies too high. This section proposes an algorithm capable to capture both the micro and macromotions on $SE(3)$.

Complementary filters traditionally apply when redundant measurements are available [96] and combining all available information in order to minimize the instrumentation error. They are also used to fuse information from multiple sensors and correct the output based on the sensed inputs. Although the Kalman filters can be extended (EKF) to nonlinear cases, they fail in capturing the nonlinear structure (e.g. rotations of a rigid body) which can be detected using complementary filters [97]. Therefore, the question arises how to properly measure micromotions that are characterized by small amplitudes and high frequencies. Inertia-measurement Unit (IMU) can be used to measure orientations, accelerations and the magnetic field.

Both the IMUs and motion capture can detect the orientation of an object in space. While motion capture system have high 3D resolution at reasonably high acquisition frequency they are outperformed by IMU in terms of temporal and technical resolution. Accelerometers and gyroscopes may have high temporal resolution but are known to show signal drift over time. A combination of both systems could improve the acquisition of slow major movements (3D motion capture) and micromotions (IMUs) at the same time. Both the motion capture device and IMUs are described in Chap. 2, Sec. 2.3. The

combination of motion capture, IMUs and the instrumented hand-held tool are shown in Fig. 3.16.

Figure 3.16: The instrumented hand-held tool with IMU sensor

Using complementary filter to remove the vibration force

Given the hand-held tool and defined an object frame $\mathcal{T}$ on it. As defined in Sec. 3.3.1, the rotation R_{MT}^S measured by using the motion tracker, presents the relative orientation of the tool frame $\mathcal{T}$ with respect to the global frame $\mathcal{S}$. The rotation R_{IMU} represents the estimated orientation of the tool and is defined by the following equations:

$$(3.37) \quad \begin{cases} \omega_e = \log(R_{IMU}^{-1} R_{MT}) \\ \omega^* = \omega_{gyr} + k\omega_e \\ \dot{R}_{IMU} = R_{IMU} \hat{\omega}^* \end{cases}$$

where k is a gain of the filter. The acceleration $\mathbf{a}^S$ in the global coordinate can be written as:

$$(3.38) \quad \mathbf{a}^S = R_{IMU} \mathbf{a}^T - \mathbf{g}^S$$

The algorithm of the complementary filter is shown in a block diagram in Fig. 3.17. The previous section allows us to have a rotation matrix R_{MT} and a translation vector $\mathbf{p}_{MT}$ of the tool from motion capture data. The gray block i) shows the procedure of an estimated rotation matrix R_{IMU} from both IMU and motion capture data. The integration block $1/s$ is a nonlinear integrator that requires a digital implementation.

Figure 3.17: Schematic diagram of Complementary filter

The digital implementation causes a numerical error, that leads the rotation matrix R_{IMU} to drift away from $SO(3)$, i.e. $\det(R) \neq 1$ and $R \cdot R^T \neq I$. To avoid this drift, Campolo et al. [100] proposed a technique that has been implemented to correct this phenomenon. The gray block ii) shows the verification of the estimated accelerations with measured accelerations from the loadcell. The measured force of the loadcell is the result of the acceleration and its moments of inertia. They are given by the hardware specifications and a multiplication with the estimated accelerations from the complementary filter will allow us to compare the estimated force with the measured force from the loadcell (see Eq. (3.39)). An estimated force from the complementary filter is defined as:

$$(3.39) \quad \mathbf{f}_{est}^{\mathcal{L}} = {}^{\mathcal{L}}G_T (R_{IMU}^{-1}) \mathbf{a}^S m_{Tool}$$

where m_{Tool} is the moments of inertia of the hand-held tool, ${}^{\mathcal{L}}G_T$ is an homogeneous transformation matrix computed from the CAD of the instrumented box. Therefore, the error between the measured force $\mathbf{f}_v^{\mathcal{L}}$ by loadcell and the estimated force $\mathbf{f}_{est}^{\mathcal{L}}$ by the complementary filter in the loadcell frame $\mathcal{L}$ can be determined as:

$$(3.40) \quad \mathbf{f}_e^{\mathcal{L}} = \mathbf{f}_v^{\mathcal{L}} - \mathbf{f}_{est}^{\mathcal{L}}$$

For implementation purposes, the Psuedo code is presented:

Data: $\mathbf{a}^\mathcal{T}, R_{MT}, \omega_{gyr}, \mathbf{g}^\mathcal{S}, \Delta T, \mathbf{f}_v^\mathcal{L}, {}^\mathcal{L}G_\mathcal{T}, m_{Tool}, f_{IMU}, f_{MT}$

Result: $R_{IMU}^\mathcal{S}, \mathbf{f}_\epsilon^\mathcal{S}$

initialization;

for $i=1:length(\mathbf{a}^\mathcal{T})$ **do**

$$\omega_\epsilon(i) = \log \left(R_{IMU}^\mathcal{S}(i)^{-1} R_{MT}^\mathcal{S} \left(\left\lceil \frac{f_{MT}i}{f_{IMU}} \right\rceil \right) \right)$$

$$\omega^*(i) = \omega_{gyr}(i) + k\omega_\epsilon(i)$$

$$\mathbf{a}^\mathcal{S}(i) = R_{IMU}(i)\mathbf{a}^\mathcal{T}(i) - \mathbf{g}^\mathcal{S}$$

$$R_{IMU}(i+1) = R_{IMU}(i)\exp(\omega^*(i), \Delta T)$$

$$\mathbf{f}_\epsilon^\mathcal{L}(i) = \mathbf{f}_v^\mathcal{L}(i) - {}^\mathcal{L}G_\mathcal{T} R_{IMU}^{-1}(i)\mathbf{a}^\mathcal{S}(i)m_{Tool}$$

end

Algorithm 2: Complementary filter algorithms

where $f_{IMU} = 200Hz$, $f_{MT} = 50Hz$ is the sampling frequency of the IMU and motion capture, respectively; the notation $\lceil \cdot \rceil$ denotes the ceiling function maps a real number to the smallest following integer.

3.4 Contact higher geometry via dynamic estimation

Contact between two surfaces can be described both at a microscopic and a macroscopic level. From a robotic sensing perspective, we shall be interested in the latter and therefore rather than a distribution of micro contact forces $\mathbf{f}_i$, we shall consider a macro resultant force $\mathbf{F} = \sum \mathbf{f}_i$ applied directly at the center of pressure (CoP). In the current study, I am not only interested in sensing the resultant force between the work piece and the tool but also in estimating the CoP itself (see Fig. 3.18) by means of force/torque measurements.

Although the interaction between tool and workpiece involves purely a resultant force, at the contact, a moment $\mathbf{T}$ can also be sensed at frames which are not co-located with the CoP. This shall always be the case, since force sensors are practically always located far away from the CoP. Considering a generic finishing tool, a convenient task frame $\mathcal{T}$ can often be defined as having its z-direction aligned with the major axis of the mounting-bit and as being located opposite to the tooling surface.

Once the shape of the mounting-bit is known, in particular when a point $\mathbf{r}$ on the surface S can be parameterized as $\mathbf{r} = [r_x \ r_y \ S(r_x, r_y)]^T$ in $\mathcal{T}$ frame coordinates, the CoP can be computed as the intersection¹² between wrench-axis and the tool surface S ,

¹²In general, as shown later, there will be two intersections but only one will have the force $\mathbf{F}$ pushing

Figure 3.18: Geometry of the contact between a rotating mounting-bit and a workpiece. Micro forces f_i , distributed over an area, result in a unique macro force $\mathbf{F}$ applied at the centre of pressure (CoP). The CoP can be dynamically estimated from the resultant force $\mathbf{F}$ and moment $\mathbf{T}$ as the intersection between the wrench-axis ($\mathbf{T} = \mathbf{F} \times \mathbf{r}$) and the mounting-bit surface S . Additional geometric features of the contact can be derived such as the tangent plane Π , the normal direction $\mathbf{n}$, and the principal curvatures ($\kappa_{min}, \kappa_{max}$).

simply represented as:

$$(3.41) \quad r_z = S(r_x, r_y)$$

The CoP can be determined as the intersection between wrench-axis (Eq. (3.3)) and tool surface (Eq. (3.41)), as graphically shown in Fig. 3.19-b. Once the CoP is determined, it is possible to analytically compute the *geometry of contact*, carry out a first and a second order analysis:

- *Tangent plane* Π (first order analysis): required to split the force $\mathbf{F}$ into a normal component and into a tangent component, the former being the normal force and the latter being friction. The normal to the surface is denoted as $\mathbf{n}$.
- *Curvature* (second order analysis): required to estimate the contact area once the normal force is known (e.g. based on Hertzian contacts model [110]). The curvature is encoded in terms of maximum and minimum curvatures ($\kappa_{max}, \kappa_{min}$).

The curvature at contact is used in material removal models [111].

As an example, we shall now apply previous equations to a specific *mounting-bit*: B52 abrasive mounted point from RS components. As for most of the tooling bits, S is a surface of revolution and can be determined from the profile. In order to estimate the surface of the mounting-bit, we used a photographic image of the tool itself and fitted

into the mounting-bit

Figure 3.19: a) The mounting-bit profile is estimated from a photographic image. b) At any time, the point is estimated as the intersection between the wrench axis (based on force and torque measurements) and the surface derived from the mounting-bit profile as a surface of revolution. c) Once the surface of the mounting-bit is known analytically, it is possible to estimate the normal and tangent vectors to the surface, as well as the Dupin indicatrix (an ellipse for this specific surface).

the profile of the tool to an 8-degree polynomial expression using the *Polyfit* function from MATLAB, as shown in Fig. 3.19-a. The equation of the surface can be obtained as a revolution of fitted profile around the z -axis. For a point $\mathbf{r} = [x \ y \ z]^T$ to be on the surface S , the height z (z -axis coordinate) is simply a function of its distance ($\sqrt{x^2 + y^2}$) from the axis, as follows:

$$(3.42) \quad z = S(x, y) = \sum_{i=1}^8 p_i \left(\sqrt{x^2 + y^2} \right)^i$$

where the $p_1, p_2, \dots, p_8$ are the fitting parameters. The fitted surface represents the actual surface only for points close enough to the central axis ($\sqrt{x^2 + y^2} \leq 5.3 \text{ mm}$). Using x and y as parameters, various geometric features of the point of contact can be estimated [109, 111]. For any 3D point $\mathbf{r} = [x \ y \ S(x, y)]^T$ on the surface $S(x, y)$, the first order analysis depends on the vector $\mathbf{n}$ normal to the surface and two vectors $\mathbf{r}_x$ and $\mathbf{r}_y$ tangent to the surface, which can be determined as:

$$(3.43) \quad \mathbf{r}_x := \frac{\partial \mathbf{r}}{\partial x} = \begin{bmatrix} 1 \\ 0 \\ \frac{\partial S(x, y)}{\partial x} \end{bmatrix}; \quad \mathbf{r}_y := \frac{\partial \mathbf{r}}{\partial y} = \begin{bmatrix} 0 \\ 1 \\ \frac{\partial S(x, y)}{\partial y} \end{bmatrix}; \quad \mathbf{n} = \frac{\mathbf{r}_x \times \mathbf{r}_y}{\|\mathbf{r}_x \times \mathbf{r}_y\|}$$

For a second order analysis, the second derivatives have to be evaluated:

$$(3.44) \quad \mathbf{r}_{xx} := \frac{\partial \mathbf{r}_x}{\partial x} = \begin{bmatrix} 0 \\ 0 \\ \frac{\partial^2 S(x,y)}{\partial x^2} \end{bmatrix}; \quad \mathbf{r}_{xy} := \frac{\partial \mathbf{r}_x}{\partial y} = \begin{bmatrix} 0 \\ 0 \\ \frac{\partial^2 S(x,y)}{\partial x \partial y} \end{bmatrix}; \quad \mathbf{r}_{yy} := \frac{\partial \mathbf{r}_y}{\partial y} = \begin{bmatrix} 0 \\ 0 \\ \frac{\partial^2 S(x,y)}{\partial y^2} \end{bmatrix}$$

Predictive models of polished surfaces require curvature information at the point of contact [111, 114]. For this, the coefficients of the *first fundamental form* $E(x,y) := \mathbf{r}_x^T \cdot \mathbf{r}_x$, $F(x,y) := \mathbf{r}_x^T \cdot \mathbf{r}_y$ and $G(x,y) := \mathbf{r}_y^T \cdot \mathbf{r}_y$ and of the *second fundamental form* $e(x,y) := \mathbf{n}_p^T \cdot \mathbf{r}_{xx}$, $f(x,y) := \mathbf{n}_p^T \cdot \mathbf{r}_{xy}$ and $g(x,y) := \mathbf{n}_p^T \cdot \mathbf{r}_{yy}$ should be evaluated. With respect to the tangent frame $\{\mathbf{r}_x, \mathbf{r}_y\}$, it is possible to calculate the so-called *Shape Operator* matrix N :

$$(3.45) \quad N = \frac{1}{EG - F^2} \begin{bmatrix} fF - eG & eF - fE \\ gF - fG & fF - gE \end{bmatrix}$$

The shape operator matrix can be used, among other things, to determine the so-called *Dupin indicatrix*, an approximation of the section of the tooling surface S cut by a plan parallel to the tangent plane Π at the contact point, and at an infinitesimal distance ϵ .

The Dupin indicatrix also contains important information about the contact area between tool and workpiece which, for elliptic points, i.e. points for which the curvatures have same sign as in typically mounting bits, is an ellipse [111, 114] and can:

$$(3.46) \quad 2\epsilon = \mathbf{w}^T N \mathbf{w}$$

It is possible to solve Eq. (3.46) for $\mathbf{w} = [w_x \ w_y]^T$ and therefore identifying the points belonging to the ellipse's orbit. The vector $\mathbf{w}$, that is a 2D vector of the tangent space at the contact point, can be transformed into a 3D vector by expressing its components with respect to the base $\{\mathbf{r}_x, \mathbf{r}_y\}$:

$$(3.47) \quad \mathbf{w} = w_x \mathbf{r}_x + w_y \mathbf{r}_y$$

Figure 3.19-c shows examples of ellipses at four different contact points.

3.5 Experimental validation

This section describes an experimental validation of the instrumented tool and algorithms presented above. In particular, we use a flat wooden surface as workpiece and the hard mounting-bit which is identified clearly in Sec. 3.4.

A major challenge in tooling operations, with respect to literature, is that we cannot compare our dynamic estimation method directly with kinematic measurements, for example from a motion tracker, because as the mounting-bit mills through the wooden surface, the geometry of the workpiece will change. For this reason, we shall also sensorize the workpiece, by placing a loadcell directly underneath the wooden surface, and use a 2-step validation:

- i. Validation of the dynamic estimation of contact by the instrumented workpiece *without mechanical vibrations* via simple contact with a rigid and non-rotating stylus. This will allow to use data from the motion tracker for validation since no abrasive phenomena are taking place.
- ii. Validation of the dynamic estimation of contact by instrumented tool in presence of mechanical vibrations, arising during an actual tooling process, by comparison with estimation from the instrumented workpiece.

It should be noted that, in the first validation step, the loadcell is mounted directly under the wooden surface, there will be no 'mechanical noise', e.g. due to vibrations of tool itself. The accuracy of contact point estimation by the instrumented workpiece is solely limited by the accuracy of the loadcell measurements. An additional loadcell is used for the instrumented tool, in the second validation step. However, in this case the process will involve a rotating mounting-bit and abrasive phenomena, adding considerable 'mechanical noise' to the measurements of the contact point. This will necessarily lower the accuracy of the estimation method. It is therefore plausible to use the instrumented workpiece (calibrated via motion tracker and in absence of mechanical noise) to calibrate the instrumented tool.

3.5.1 Instrumented workpiece

As described above, the first of the 2-step validation involves sensorizing the workpiece and validating the dynamic estimation of contact in absence of mechanical vibrations. For this purpose, we will use a loadcell mounted directly underneath the wooden surface, as schematically shown in Fig. 3.20. The wooden surface will act as 'touch pad' and, using the same method described in Sec. 3.4, we shall be able to estimate the contact point once a rigid, non-rotating stylus is in contact with the surface. The same equations (3.3)-(3.41) are hold, where the $\mathcal{T}$ frame is now on the centre of the wooden surface (see Fig. 3.20).

In this specific case, the surface $S(x, y)$ is the plane of the wooden surface, i.e. Eq. (3.41) is simply $r_z = 0$, which leads to the following dynamic estimation of contact

Figure 3.20: Calibration Loadcell Setup to compare the contact point measured from motion capture and loadcell: three markers are attached on the stylus and a 6-axis loadcell is located under the plane.

point

$$(3.48) \quad \mathbf{r}^* = \begin{bmatrix} -\frac{T_y}{F_z} & \frac{T_x}{F_z} & 0 \end{bmatrix}^T$$

At the same time, the point of contact between stylus and surface can be estimated via kinematic measurements derived from a set of markers mounted on the stylus itself and on the wooden surface.

In a validation experiment, the stylus was manually set in contact with the wooden surface in different quadrants of the wooden surface (areas I, II, III, IV, shown in Fig. 3.21-a), with different force levels and varying angles of contact. The accuracy of dynamic estimation in Eq. (3.48) will deteriorate at lower values of the signal-to-noise ratio of force (i.e. when no or little contact force is applied, the measurements from the loadcell are most corrupted by noise). This is apparent in Fig. 3.21-b, where the accuracy improves as the force levels increase. In particular, for forces above 10N, the estimation error is consistently below 2mm which indicates that the used loadcell is reliable for estimating the contact point with the applied force higher than 10N.

Figure 3.21: a) Contact points measured from motion capture and loadcell on the plane's surface. b) Distance error measured from motion capture and loadcell when increasing the force applied on the plane.

3.5.2 Instrumented tool validation

The second step of validation method, consists of comparing the dynamic estimation of the contact point, as derived from instrumented tool, with the estimation derived from the instrumented workpiece, validated in previous section. For this purpose the experimental setup shown in Fig. 3.22 was devised. The setup includes the instrumented tool, as described in Sec. 3.3.1, and an instrumented workpiece as described in Sec. 3.5.1. Note that the aluminum-frame is connected to the jig via a revolute joint, hence, it is able to slide left/right and achieve any specific angle. The position of the aluminum-frame is tracked by the motion capture system based on the infra-red markers attached on the workpiece. Both the tool and workpiece are instrumented with similar loadcells (respectively, loadcell 1 and loadcell 2 in Fig. 3.22) and with infra-red markers. As shown in Fig. 3.22, three major reference frames shall be considered:

- Task frame $\mathcal{T}$: located at the origin of the rotating mounting-bit (note that the frame $\mathcal{T}$ is not rotating but simply remains aligned with the mounting-bit at all times).
- Workpiece frame $\mathcal{P}$: attached to the centre of wooden workpiece, with the z-axis normal to the plane.
- Global frame $\mathcal{S}$: defined by the motion tracker, via external markers mounted on the workbench.

All the frames are defined by the motion capture system. The instrumented tool is fixed on a base; the workpiece can be manually slid on the jig and tilted to two different inclinations (150° , 175°) of the mounting. These various inclinations were chosen to

ensure contact points with different curvature on the mounting-bit. For each of these inclinations, an experimental session was conducted whereby the mounting-bit was brought into contact with the workpiece, set at the rotational speed of 5000 RPM and then the workpiece is slid horizontally (i.e. along the x-axis direction of the $\mathcal{T}$ frame). After each session, a horizontal trace was left on the workpiece due to the abrasive action of the mounting-bit. Care was taken to move the workpiece after each session so that any new trace would occur at a different location from the previous ones. As expected, the width of the trace would vary depending on the inclination of the mounting-bit, in particular due to the different contact point curvatures. When in contact, the mounting-bit will

Figure 3.22: Experimental setup: the instrumented tool is fixed on a workbench; the workpiece can be manually slid on the jig (i.e. along the x-axis direction of the $\mathcal{T}$ frame) and tilted to two different inclinations (150° , 175°) of the mounting. When in touch, the contact point is dynamically estimated by both the tool frame $\mathcal{T}$ and workpiece frame $\mathcal{P}$ coordinate related to one another via the motion tracker transformation.

be in touch with the wooden surface a point $\mathbf{r}$, which will be simultaneously estimated by the instrumented tool and by the instrumented workpiece. To be compared, the two estimations must be expressed in the same coordinate frame, (e.g. in $\mathcal{P}$). Denoting $\mathbf{r}_1$ the estimation of derived from the instrumented tool (via loadcell 1) via equations (3.3)-(3.41) in $\mathcal{T}$ frame and reported in $\mathcal{L}$ coordinates via the following coordinate transformation:

$$(3.49) \quad \begin{bmatrix} \mathbf{r}_1 \\ 1 \end{bmatrix} = (\mathbf{G}^{\mathcal{P}})^{-1} \mathbf{G}^{\mathcal{T}} \begin{bmatrix} \mathbf{r}^{\mathcal{T}} \\ 1 \end{bmatrix}$$

where $\mathbf{G}^{\mathcal{T}}$ and $\mathbf{G}^{\mathcal{P}} \in SE(3)$ are homogeneous matrices derived directly from the markers transforming, respectively, the components in $\mathcal{T}$ frame and $\mathcal{P}$ frame into $\mathcal{S}$ frame, (see Fig. 3.22).

The results of the analysis carried out on two experimental tests are shown in Fig. 3.23 and Fig. 3.24, respectively for the inclination of 150° (left panes) and 175° (right panes). For all plots, the horizontal axis represents the y-axis in the workpiece coordinates, i.e. the horizontal direction along which the sliding of the tool occurred. The tool first contacted the workpiece approximated at $y = 30\text{mm}$ and was then slid until $y = -50\text{mm}$.

Figure 3.23: The experiment results for 150° inclination i) Contact points measured from mounting-bit and from the workpiece, on the workpiece space $\mathcal{P}$. ii) Error between contact points from tool and from workpiece respects to the applied normal force. iii) The estimated friction force from the mounting-bit from the workpiece. iv) The estimated power due to friction.

The first row i) in Fig. 3.23 and Fig. 3.24 shows the contact point coordinates, during

Figure 3.24: The experiment results for 175° inclination

the whole experiment, as estimated from the sensors on the tool (dashed line) and from the workpiece (solid line). In this case, the estimation from the workpiece is considered more accurate, or less affected by mechanical vibrations. Previous experiments in Fig. 3.21 shows that the estimations from the workpiece sensors are subjected to less than 2 mm errors when the force is higher than 10 N. This information can be found in the second row ii) of Fig. 3.23 and Fig. 3.24 where both the error and the force magnitude (for both normal force and friction components, i.e. respectively the projection along the normal to the mounting-bit surface and the projection on the plane tangent to the surface at contact) are reported. It is possible to notice that the error increases when the contact force decreases.

The third row iii) of Fig. 3.23 and Fig. 3.24, shows the magnitude and direction of friction at different contact points. Both estimations from workpiece and mounting-bit are reported. It is clear that the friction forces as sensed by the workpiece are pointing in the opposite direction with respect to the friction forces as sensed by the mounting-bit.

Finally, the bottom row iv) of Fig. 3.23 and Fig. 3.24 plots the estimated power due to friction. In the hypothesis of a sufficiently localized contact, one can assume that the velocity of all abrasive grains on the mounting-bit have the same tangential velocity (as a result of tool rotation ω , in our case 5000 *rpm*). The tangential velocity $\mathbf{v}$ can then be estimated as:

$$(3.50) \quad \mathbf{v} = \omega \mathbf{r} \times \begin{bmatrix} 0 & 0 & 1 \end{bmatrix}^T$$

and the power PWR can then be estimated as:

$$(3.51) \quad PWR = \mathbf{F} \cdot \mathbf{v}$$

Finally, Fig. 3.25 shows the abrasive action of the mounting-bit on the workpiece. In particular, Fig. 3.25-a shows a photograph of the workpiece after the abrasive action with superimposed estimated contact points and computed contact ellipses. It can be seen that: 1) the estimated contact line (green line) matches with the trace on the wood-workpiece; 2) the width of trace, that depends on the contact area between the mounting-bit and the wood-workpiece, is well captured by the area of the estimated ellipses. Fig. 3.25-b shows a 3D scan obtained from an ATOS Triple Scan camera to visualize the depth of the 150° trace. This illustrates how the contact area can be visualized and the information used to evaluate the dimension of the contact ellipses.

Figure 3.25: The workpiece after the grinding process a) The projection of the computed ellipses onto the workpiece (150° trace). b) The depth of the contact area after the grinding is represented as a GOM picture.

3.6 Summary

This chapter presents a framework that allows capturing 3D contact dynamics, ‘dynamic touch’, during finishing operations with instrumented tools. In particular, we introduce the design of an instrumented hand-held power tool capable of online sensing, suitable to both manual and robotic operations. The instrumented rotating tool is capable of sensing contact geometry, applied normal/friction force on the wheel and the power of the tool. To accurate the sensing, this chapter suggested solutions for the mechanical design issues. i.e. eliminating the misalignment and the stiffness. The experimental validation is implemented, the experimental results in conditions show high accuracy in force detection, with force errors in the range of $\pm 0.1N$ (see Fig. 3.9 and Fig. 3.10). The results from the current study indicate high potential of designed setup to accurately capture applied force and estimate contact position when the tool was fixed.

For more convenient to the operator, the design of an instrumented hand-held power tool capable of online sensing during manual operations was proposed. Algorithms to carry out dynamic estimation of contact are adapted from literature and presented in the context of power tools, specifically considering the profile of hard mounting-bits. The complementary filter is proposed to eliminate the gravitational biasing and vibration force from the tool to accurate the task dynamic. From the estimation of contact point, first and second order geometric analysis is carried out to i) be able to split the sensed force into normal and friction components; ii) to estimate the curvatures of the mounting-bit and workpiece at contact. This type of information is critical for material removal estimates, although the evaluation of MRR is beyond the scope of this work. The results of study are promising and, although tested on data derived from manual operations, the proposed algorithms can be readily be applied to robotic applications.

ESTIMATION OF HUMAN JOINT MECHANICAL IMPEDANCE DURING A TOOLING TASK

In this chapter, we address estimation of the (neuro-)mechanical impedance of the human arm/wrist during motion, in particular during an industrial tooling task. This type of information would be very valuable, for example, to transfer skills from expert human operators to industrial robots.

Humans and robots are of course different, our standpoint is that they should have a similar behaviour from an operative perspective. For this reason, we instrumented a typical hand-held, abrasive tool used by humans during finishing tasks. In particular, we focused on the handle (through which both robots and humans are attached to the tool) to assess the 3D force/torque interactions between operator and tool during finishing task, as well as the 3D kinematics of the tool itself.

Building upon stochastic methods proposed in literature for human arm impedance estimation, the novelty of our approach is that we rely on the stochastic nature of the tooling task itself to estimate (neuro-)mechanical impedance during motion.

Our apparatus (hand-held, finishing tool instrumented with motion capture and multi-axis force/torque sensors) and algorithms (for filtering and impedance estimation) were first tested on an impedance-controlled industrial robot carrying out the finishing task of interest, where the impedance could be pre-programmed. We were able to accurately estimate impedance in this case.

The same apparatus and algorithms were then applied to a similar task performed by human operators. The stiffness values estimated for the human subject, at different

force level, correlated positively with the muscular activity, measured during the same task.

4.1 Current approaches to the estimation of human impedance

Mechanical impedance is a mathematical operator which predicts the force generated by a system in response to an imposed motion [118]. Impedance operators are typically defined for linear systems but can also be generalized to nonlinear systems once the system is linearized and under the assumption a ‘small perturbations’. When an external perturbation displaces the hand, a restoring force brings it back to the initial position [61, 119] or to the undisturbed trajectory [120–122].

By linearizing the system behaviour around a given equilibrium point or trajectory, the impedance can be decomposed into: *stiffness*, the resistance to a change in position; *damping*, the resistance to a change in velocity; and *inertia*, the resistance to a change in acceleration. For multiple-joint systems, such as a human arm, this process must be generalized to account for geometric factors, and the multi-dimensionality of interaction dynamics and kinematics [123–127]. In humans, while inertia due to the masses of bones and muscles cannot be controlled, stiffness and damping are due to the viscoelastic behaviour of muscles, tendons and ligaments and to reflexes, influenced by the motor commands [128].

In studies involving humans, the source of perturbation is usually a robotic manipulator whose end-effector is directly connected to the anatomical part of interest, such as the subject’s hand [61, 119, 129, 130]. Perturbations can be applied around an equilibrium configuration in static posture or during the undisturbed trajectory during movement. Several techniques have been proposed for the estimation of the hand impedance during movements. In this case, one of the main challenge, is the correct estimation of the unperturbed hand trajectory that is used to linearize the system dynamic [121, 122].

A first approach to multi-joint hand impedance identification was based on *displacement or force perturbations* along different directions of the transverse plane [61, 119, 131]. By recording the restoring force and the hand kinematic following the perturbations, linear least square method was commonly employed to identify the parameters of the hand mechanical impedance. Due to noise in the force measurement and error in the movement prediction [122], such an approach usually requires several experimental trials (each for every direction of perturbations).

An alternative approach was proposed by Perreault et al. whereby a stochastic force [132] or position [133] perturbation (rather than a single displacement [122] or force pulse [131]) was used. Potential advantages of this method include: i) the entire stiffness field could in principle be swept during a single or fewer trials ii) due to the stochastic nature, this kind of perturbation is less likely to evoke voluntary responses and hence alter the quality of the estimation. While the stochastic perturbation method was initially developed based on the assumption that the system of the arm controlled by the nervous system is a linear time invariant system, thus restricting its use to estimation of impedance in static postures, recent works have developed extensions to estimation in movements e.g. [27].

To our knowledge, all methods to estimate impedance in the literature were using a robot or a dedicated computer-controlled module [134, 135] to disturb movement or force, which restricts these methods to laboratory settings. However, these settings have different dynamics than the ecological scenarios we would be interested in investigating in order to understand how humans control movements and interactions in real-life situations. Here, we thus propose to rely on disturbance which come from the task itself due to the stochastic nature of contact during tooling task [136]. Building upon stochastic perturbation methods to assess impedance, we will use perturbations caused by the interaction of a tool with the environment in order to identify the mechanical impedance in real-life scenarios.

The task of interest in this paper is polishing, routinely performed via hand-held power-tools as illustrated in Fig. 4.1. For one of such hand-held power-tools we designed a custom made handle which allowed capturing (via multi-axis force/torque sensors) the 3D interaction dynamics between the tool and the operator. To capture the pose of the tool in 3D space, we used optical motion tracking with trackers affixed to the power-tool. The activity level of forearm/wrist muscles deemed relevant to the task was also monitored using surface electromyogram (EMG).

The method for extracting impedance values in contact is first tested with an impedance-controlled industrial robot, deployed to perform a polishing task with a specific value of pre-set impedance. The same polishing task is then tested with a human subject using the power-tool and performing a similar contact task. Data from this experiment are analysed and the impedance values are shown to positively correlate with the muscular activity of relevant muscles, in a physiologically relevant range. In the following, Section 4.2 describes the method of joint stiffness assessment and its validation on an industrial impedance-controlled robot. Section 4.3 describes the protocols

and experiments conducted on a human subject, data analysis and results.

4.2 Setup, methods and robotic validation

We consider tooling tasks which involve non-negligible contact forces, such as grinding or polishing. More specifically, we assume that the tooling operation is conducted by means of a power hand-held tool rigidly attached to distal end of a wrist joint. Our technique to estimate stiffness using this tool will be tested and validated on a robotic wrist in this section. As the goal is to estimate the stiffness of a worker's wrist when holding this tool the coordinates definition will follow the anatomy of a human wrist.

4.2.1 Instrumented tool: 3D kinematics, force and torque estimation

We present here a hand-held tool instrumented to assess 3D movements as well as forces and torques due to interaction with the work-piece transmitted to the operator via a handle. To measure 3D kinematics of the rigid tool, the tool was equipped with a redundant number of optical markers ensuring that at least three markers are always visible during operation. We consider a hand-held power tools operated with a single handle so that the interaction dynamics can be estimated using a single load cell capable of sensing 3D forces and 3D torques placed between the handle and the tool. For power tools, the spindle is usually the most heavy component and for some hand-held tools such as the Dremel 4000, it can be decoupled from the tool-bit via a flexible shaft, so that the user does not need to withstand the weight of the spindle during manual operations, as shown in Fig. 4.1-a).

In general, data relative to *tool pose* (3D positions and 3D orientations of a rigid body) and to *interaction forces and torques* [13] are acquired with respect to different reference frames, depending on the type of sensors (optical motion trackers and loadcells) and their placement. With reference to Fig. 4.1-b, for *human / robot joint impedance* analysis we shall refer all measurements to an anatomically relevant frame $\{\mathcal{W}\}$, rigidly *attached to the human / robot forearm and centred in the wrist*. In this paper, we shall consider a simplified kinematic model of the human wrist, which we assume to be a spherical joint with 3 degrees of freedom (dof) expressed as a vector $\mathbf{q} = [q^{RU} \ q^{FE} \ q^{PS}]^T$, with the joint angles q^{RU} , q^{FE} , and q^{PS} corresponding to RadioUlnar-deviation (RU), Flexion-Extension (FE), and Pronation-Supination (PS), respectively. Despite this simplification

Figure 4.1: a) Tool's description. Example of finishing task with a hand-held tool. b) Schematic and naming conventions for the instrumented tool shown in c).

of assuming a spherical joint, we shall still follow an anatomically correct sequence of rotations for the wrist joints (as in [137]) whereby PS is the most proximal joint and RU is the most distal. Defining the 'zero' configuration ($\mathbf{q} = [0 \ 0 \ 0]^T$) as the anatomically *neutral* position of the hand (i.e. the hand is aligned with the forearm, see [137] for details) the joint angles vector $\mathbf{q}$ can be derived from a 3×3 rotation matrix R , defined as the rotation of hand from its the neutral position. Following [137], the joint angles can be derived from R as:

$$(4.1) \quad \mathbf{q} = \begin{bmatrix} q^{RU} \\ q^{FE} \\ q^{PS} \end{bmatrix} = \begin{bmatrix} \text{atan2}(R_{1,3}, R_{1,1}) \\ \arcsin(-R_{1,2}) \\ \text{atan2}(-R_{3,2}, R_{2,2}) \end{bmatrix}$$

where $R_{i,j}$ represents the entry at the i -th row and j -th column of the matrix R .

The 3D force ($\mathbf{F}^{\mathcal{L}}$) and torque ($\mathbf{T}^{\mathcal{L}}$) measurements are directly provided by the loadcell in coordinates relative to its intrinsic loadcell frame $\{\mathcal{L}\}$ and conveniently merged into a 6D wrench vector $\mathbf{W}^{\mathcal{L}} := [\mathbf{F}^{\mathcal{L}} \ \mathbf{T}^{\mathcal{L}}]^T$, accounts for the interaction between the tool-bit and the work-piece, but is corrupted by the effects of the flexible shaft and of the gravity on the tool. In order to determine torques in the wrist joint, the wrench $\mathbf{W}^{\mathcal{L}}$ needs to be transformed into wrist coordinates $\mathbf{W}^{\mathcal{W}}$. Taking into account the *constant* rotation R_0 and displacement $\Delta^{\mathcal{L}}$ between loadcell and hand (from loadcell to hand coordinates), the hand rotation R (from hand to wrist coordinates, as shown in Fig. 4.2), the wrench transformation can be computed as [73]

$$(4.2) \quad \mathbf{W}^{\mathcal{W}} = \begin{bmatrix} \mathbf{F}^{\mathcal{W}} \\ \mathbf{T}^{\mathcal{W}} \end{bmatrix} = \begin{bmatrix} R R_0 & 0 \\ R R_0 [\Delta^{\mathcal{L}} \times] & R R_0 \end{bmatrix} \mathbf{W}^{\mathcal{L}}$$

where $[\Delta^{\mathcal{L}} \times]$ is the anti-symmetric matrix associated¹³ with the vector $\Delta^{\mathcal{L}}$. Finally, the

Figure 4.2: Neutral configuration of the hand.

anatomical joint torques can then be extracted from the wrench as

$$(4.3) \quad \begin{bmatrix} T^{RU} \\ T^{FE} \\ T^{PS} \end{bmatrix} := \mathbf{T}^{\mathcal{W}} = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \mathbf{W}^{\mathcal{W}}$$

4.2.2 Compliant robots: impedance-controlled joints

In contrast to conventional robotic manipulators that are typically stiff and position-controlled, modern service and industrial robots embed high-bandwidth current servos and/or joint-torque sensors allowing force/impedance control strategies. Several impedance/force control approaches have been proposed in the last two decades and the reader is referred to [138] for the literature on this subject. In this work, we shall refer to the impedance-control schemes available for commercial manipulators such as the KUKA lightweight robot [139].

The impedance-controlled robot used in this work was programmed in *operative (or Cartesian) mode*. In this modality, a Cartesian frame of reference is defined at the wrist of the robot, as shown in Fig. 4.3. The six degrees of freedom (dof) of this Cartesian frame formed of 3D translations and 3D rotations will hereafter be referred to as ‘joints’. Furthermore, as the rotations of the Cartesian frame will be used to mimic the wrist rotations of the human operator, we shall denote these axes as radial-ulnar deviation (RU), flexion-extension (FE), and pronation-supination (PS), as indicated in Fig. 4.3.

Using the subscript J to denote different joints (i.e. $J \equiv RU, FE, \text{ or } PS$), we shall consider an impedance-control mode with overlaid (i.e. superimposed) torques. Specifically,

¹³To any vector $\mathbf{a} \in \mathbb{R}^3$, one can associate a skew-symmetric matrix $[\mathbf{a} \times]$ defined such that $[\mathbf{a} \times] \mathbf{b} = \mathbf{a} \times \mathbf{b}$, for any vector $\mathbf{b} \in \mathbb{R}^3$ [73].

we shall assume that each robotic joint J is controlled according to

$$(4.4) \quad T^J = T_0^J + k^J (q^J - q_0^J) + b^J \dot{q}^J \quad J \equiv RU, FE, \text{ or } PS$$

where k^J is the *joint stiffness* and b^J *joint damping*, q_0^J is the desired trajectory, q^J is the actual trajectory, $\dot{q}^J$ denotes the velocity, T_0^J is the overlaid torque and T^J is the commanded joint torque. This scheme, also shown in Fig. 4.3, assumes that the robotic platform is force-controlled [140], i.e. forces at each joints are commanded based on the readings from encoders. The joint position q^J is measured via encoders and a control torque T^J is computed via Eq. (4.4) and then commanded to the joint actuator. To ensure stability, the control torque T^J should be updated at a very fast rate to quickly respond to changes in joint angle q^J , e.g. fast vibrations. Parameters such as T_0^J , q_0^J , k^J , b^J are meant to be input commands modulated at a much slower rate, e.g. comparable to human motions.

Also illustrated in Fig. 4.3, the interaction torque of the instrumented tool is measured at 1 kHz by an ATI mini 40 loadcell and its position at 100 Hz by motion capture. The anatomical joint torque and angle can then be determined using Eqs. (4.3),(4.1). The rate of torque is down sampled to 100 Hz to match the frequency of the motion capture. Finally, stiffness and damping of the KUKA robot are determined from the joint torque and angle, using the Eq. (4.6) which will be presented later in this section. Importantly, the stiffness k^J and damping b^J are assumed to be constant during a trial. This is certainly true for the robot experiment below but it is important to note that impedance can change during movement of a human operator.

4.2.3 Robotic impedance estimation during tooling tasks

Although robots generally provide access to joint angles q^J and commanded torques T^J , here we shall solely rely on measurements derived from motion capture systems and external loadcells, via Eqs.(4.1) and (4.3), as these will be the only source of information for experiments performed by humans. Furthermore, in this paper, we focus on the RU-axis so on the measurements T_0^{RU} , k^{RU} , and q_0^{RU} as per Eq.(4.4). We tested the estimation process illustrated in Fig. 4.3 on the KUKA lightweight robot, which was controlled in impedance to perform a tooling task kinematically similar to the human task described in next section. This task mainly involves a periodic, slow and self-paced oscillating motion about the FE-axis while maintaining a constant torque about the RU-axis. We focus here on estimating impedance only along the RU-axis.

Figure 4.3: Method to estimate a robot stiffness and damping during polishing while moving sinusoidally. The top left corner shows a diagram of a torque-controlled robotic joint.

To this end, the robot was programmed to be rotationally compliant (with rotational stiffness 10 Nm/rad and damping 1.9 Nm s/rad) along the FE- and RU-axis, as shown in Fig. 4.3, while maintaining maximum stiffness along the remaining dof (i.e. 300 Nm/rad rotational stiffness along the PS-axis and 5,000 N/m translational stiffness in all directions). With reference to Eq.(4.4), the following desired trajectories q_0^J ($J = FE, RU$) and overlaid torques T_0^J ($J = FE, RU$) where pre-programmed for the FE- and RU-axes: (4.5)

$$FE\text{-axis} \begin{cases} T_0^{FE} = 0 Nm \\ q_0^{FE} = \frac{\pi}{6} \sin(3t) rad \\ k^{FE} = 10 Nm/rad \\ b^{FE} = 1.9 Nms/rad \end{cases} \quad RU\text{-axis} \begin{cases} T_0^{RU} = 0.5 Nm \\ q_0^{RU} = 0 rad \\ k^{RU} = 10 Nm/rad \\ b^{RU} = 1.9 Nms/rad \end{cases}$$

The sinusoidal motion imposed to q_0^{FE} in Eq. (4.5) takes approximately 2 seconds for a whole period. In order to obtain 10 repetitions for statistical analysis, we performed the experiments for approximately 20 seconds, during which joint positions q_i^{FE} , q_i^{RU} where sampled from Eq.(4.1) at 100 Hz and joint torques T_i^{FE} , T_i^{RU} where computed from Eq.(4.3) at 1 kHz and downsampled at 100 Hz.

Considering a sequence measurements q_i^{RU} and T_i^{RU} , at each time sample t_i , Eq. (4.4) can be rewritten as:

$$(4.6) \quad \begin{bmatrix} T_i^{RU} \end{bmatrix} = T_{avg}^{RU} + \begin{bmatrix} q_i^{RU} & \dot{q}_i^{RU} \end{bmatrix} \begin{bmatrix} \hat{k} \\ \hat{b} \end{bmatrix}$$

to regress the impedance (formed of stiffness $\hat{k}$ and damping $\hat{b}$), or as

$$(4.7) \quad \begin{bmatrix} T_i^{RU} \end{bmatrix} = T_{avg}^{RU} + \begin{bmatrix} q_i^{RU} \end{bmatrix} \hat{k}'$$

to estimate only stiffness $\hat{k}'$. In these equations the scalar T_{avg}^{RU} represents the average torque T_i^{RU} over one period of time, which accounts for both the constant torque T_0^{RU} and the factor $k^{RU} q_0^{RU}$. The terms in square brackets represent matrices of measurements.

Figure 4.4: Result of impedance identification during the validation experiment with a robot. a) Measured torque T^{RU} vs. estimated torque $\hat{T}^{RU}$. b) Estimated torque $\hat{T}^{RU}$ using an elastic model. c) Estimated torque $\hat{T}^{RU}$ with visco-elastic model.

To assess the goodness of regression, the measured torques were compared with the estimated *viscoelastic* $\hat{T}^{RU}$ and *purely-elastic* $\hat{T}^{RU}$ torques, as predicted from Eq. (4.6) and Eq. (4.7), respectively, defined as follows:

$$(4.8) \quad \hat{T}^{RU} = T_{avg}^{RU} + \hat{k} q^{RU} + \hat{b} \dot{q}^{RU}$$

$$(4.9) \quad \hat{T}^{RU} = T_{avg}^{RU} + \hat{k}' q^{RU}$$

where q^{RU} and $\dot{q}^{RU}$ are the actually measured kinematics. T_{avg}^{RU} , $\hat{k}$, $\hat{b}$ and $\hat{k}'$ are regressed from Eq. (4.6) and Eq. (4.7). As reported in Fig. 4.4, when fitting only with an elastic model Eq. (4.7), the regression returned a value of $\hat{k}' = 10.34$ Nm/rad. When fitting with the viscoelastic model in Eq. (4.6), the regression returned a stiffness $\hat{k} = 10.28$ Nm/rad

and a damping $\hat{b} = 2.02 \text{ Nm.s/rad}$. In both cases, the stiffness and impedance estimates are accurate within a few percent with respect to the pre-programmed $k = 10 \text{ Nm/rad}$ and $b = 1.9 \text{ Nm.s/rad}$, as in Eq. (4.5) for the RU-axis.

It should be noted that the same data acquisition system (in particular the same instrumented tool in Fig. 4.1), algorithm and also a similar protocol as the one pre-programmed for the robot will be used to perform experiments with humans, so the same accuracy is expected in the estimation of impedance in humans.

4.3 Estimation of human operators's joint stiffness during tooling tasks

In this section we use the instrumented tool to estimate wrist kinematics and contact forces during a tooling task performed by a human operator. In addition, recording of muscle activity will enable us to study whether the identified impedance has properties expected from muscle physiology.

4.3.1 Experiments and setup

As shown in Fig. 4.5, a subject was seated in front of the workpiece (the metal square plate used for the robot experiment) while grasping the tool's handle with their right hand. Subject's forearm was supported against gravity to reduce fatigue and was strapped to the support's frame so as to confine the task to the wrist. The forearm height was adjusted for each subject to ensure that the tool's tip was in contact with the workpiece at the beginning of the experiment. This initial configuration was set as *neutral* reference configuration $q_{PS} = q_{FE} = q_{RU} \equiv 0 \text{ rad}$.

The subjects were instructed to move the tool periodically left-and-right across the horizontal workpiece surface shown in Fig. 4.5-b at self-paced speed while keeping a desired interaction force $F_y > 0$. No instruction was given regarding the speed and/or the range of horizontal movement. The tool tip rotated with a constant angular velocity of 15,000 rpm during the entire duration of the experiment. All subjects were naive to the task and provided informed consent.

We assume that the horizontal movement is mainly due to wrist flexion-extension and that the subject plans a constant reference trajectory $q_0^{RU}(t) = 0 \text{ rad}$ for the RUD joint, therefore focus on the estimation of RUD wrist stiffness. During the experiment, surface electromyography (EMG) was used to monitor the activation of muscles representing the

Figure 4.5: Setup of impedance identification experiment with a human subject performing the grinding task a). Panel b) shows the naming conventions.

control of the wrist RUD rotation: Extensor Carpi Radialis Longus (ECR), Extensor Carpi Ulnaris (ECU), Flexor Carpi Radialis (FCR), and the Flexor Carpi Ulnaris FCU [141]. EMG activity was collected with the BIOPAC MP150 Data Acquisition and Analysis System at 1kHz. The raw EMG signal was pre-amplified with a gain value of $G = 1000$ and band-pass filtered between 10 – 500Hz. This signal was rectified, low-pass filtered (using a 4th order Butterworth filter with 20Hz cut-off frequency) to yield the EMG envelope, which was normalized with respect to the maximum activity displayed by the muscle during a maximum voluntary contraction (MVC) task performed before starting with the experiment (Fig. 4.6). The mean normalised envelope was used as a measure of muscular effort and its contribution to the task.

4.3.2 Impedance and muscle effort dependence on force

One healthy subject (male, 29 years old, right-handed) participated in a first experiment. A trial consisted 10 forth and back rotational extension-flexion movements. Four conditions were tested corresponding to increasing levels of desired contact force: 3N, 5N, 7N, 9N. For each condition, the subject was asked to perform 12 trials consecutively. To enable the subject to apply a nearly constant level of force on the plate during movement, visual feedback was given to the subject consisting of a bar displaying the error between the applied force and the desired level of contact force. The subject was instructed to keep the error as small as possible for the whole duration of the experiment.

Fig. 4.7 shows the result for the flexion-extension task experiment, the estimated

Figure 4.6: Steps of EMG pre-processing illustrated on for an ECR muscle of a representative subject.

stiffness $\hat{k}^{RU}$ of the subject wrist from Eq. (4.7) for the applied force of 3N, 5N, 7N, 9N is: 5.10 *Nm/rad*, 6.07 *Nm/rad*, 7.87 *Nm/rad*, and 10.28 *Nm/rad*, respectively. Using the Eq. (4.6) presented above, the estimated torque from the estimated stiffness and damping is shown in Fig. 4.8. As shown in Fig. 4.9, the wrist stiffness of the subject increases in a roughly linear manner with the applied force for both methods of regression. In Fig. 4.10 it can be observed that the mean muscle activity increases with the desired force level to be maintained, in a similar way as stiffness, as can be expected from the muscle physiology [128, 142]. Among the wrist extensors and flexors, the ECR and FCR that are responsible for radial deviation show relatively higher activity as these muscles are used to hold the tool against the workpiece.

4.3.3 Inter-subject variability during the contact task

In a second experiment to estimate the mechanical impedance of the wrist and the inter-subject variability during the tooling task, eight healthy male subjects ($173 \text{ cm} \pm 5$ height, $78 \text{ kg} \pm 6$ weight, age of 24 ± 2 , all right-handed) participated in the experiment. Contact force was set to 7N and subjects were asked to maintain constant force throughout the

4.3. ESTIMATION OF HUMAN OPERATORS'S JOINT STIFFNESS DURING TOOLING TASKS

Figure 4.7: Results of the flexion-extension task. a) The stiffness estimation is given from Eq. (4.7), b) The measured angle given from the motion capture and c) The measured torque by the instrumented tool.

experiment using visual feedback of the force compared to a desired level. As mentioned in Section 4.3, joint stiffness k^{RU} , joint angles (q^{RU} & q^{FE}), and joint torque T^{RU} were analyzed.

Across all subjects the estimated joint stiffness k^{RU} ranges from 8.78 to 16.25 Nm/rad with a mean and standard deviation of 11.97 ± 2.93 Nm/rad. The range of motion of the q^{FE} is large 15.90 ± 3.64 degrees compared to 0.77 ± 0.36 degrees q^{RU} . In other words, subjects performed the task mainly using q^{FE} while the q^{RU} was not exploited. The corresponding joint torque T^{RU} ranges from 0.31 to 1.09 Nm with a mean and standard deviation of 0.81 ± 0.29 Nm. The detailed results of the variables affected by the experimental tooling task are presented in Table 4.1.

The results ($k^{RU}, q^{RU}, q^{FE}, T^{RU}$) of the experiment with eight subjects are shown in detail containing the maximum and minimum values for each variable except for k^{RU} .

Figure 4.8: Estimation of wrist visco-elasticity during wrist-flexion-extension task.

4.4 CONCLUSION and DISCUSSION

In this work, we propose a method based on stochastic perturbations to estimate stiffness during real-life tooling tasks. The novelty of our method is that the perturbations originate from the stochastic nature of the task itself rather than from a dedicated system as in all previous works, that is complex and would prevent its use during an actual contact task with a tool. Although the tool-bit spinning frequency is too high to identify stiffness (in fact a tool spinning at 15,000 rpm generates disturbances at 250 Hz, more than an order of magnitude higher than what found for a relaxed wrist [143]), the tooling action tends to destabilize contact between tool-bit and workpiece, triggering continuous adjustments at significantly lower frequency, thus giving us the opportunity to identify stiffness.

Figure 4.9: Results of the stiffness estimation for the radio-ulnar deviation. Stiffness distribution for four levels of applied forces: 3N, 5N, 7N, and 9N, respectively. a) Estimated scalar stiffness $\hat{k}^{RU}$ from Eq. (4.7) . b,c) Estimated scalar stiffness $\hat{k}^{RU}$ and damping $\hat{b}^{RU}$ from Eq. (4.6).

Table 4.1: Stiffness estimation from 8 subjects.

Subject		S1	S2	S3	S4	S5	S6	S7	S8
Stiffness k^{RU} [Nm/rad]		8.78	16.25	11.38	9.40	16.19	9.39	11.96	12.42
Range q^{RU} [degree]	max	0.80±0.32	0.67±0.31	0.40±0.16	0.87±0.23	0.22±0.39	0.71±0.28	0.35±0.38	0.30±0.41
	min	-0.42±0.37	-0.02±0.45	-0.34±0.23	-0.41±0.38	-0.53±0.23	0.04±0.7	0.21±0.62	-0.35±0.45
Range T^{RU} [Nm]	max	1.23±0.09	1.50±0.15	1.66±0.20	1.25±0.11	1.09±0.24	1.47±0.35	1.68±0.10	1.02±0.25
	min	0.50±0.07	0.37±0.10	0.58±0.16	0.45±0.11	0.43±0.16	1.16±0.22	0.59±0.09	0.45±0.16
Range q^{FE} [degree]	max	96.87±2.12	94.26±3.6	76.32±3.2	104.33±2.10	87.16±1.40	86.26±2.45	99.2±3.22	89.09±1.04
	min	76.81±1.08	78.45±2.34	65.24±3.23	85.99±2.01	71.89±1.87	68.86±1.03	80.11±1.08	78.95±0.87

The main objective of this work was to identify mechanical impedance at the (human) wrist during tooling tasks. For validation purposes, an impedance-controlled robot was used to carry out the same task a similar fashion and verify that our data analysis and regressions could correctly predict the pre-programmed robot impedance.

We were able to accurately predict the pre-programmed robot impedance which

Figure 4.10: Muscular effort increases with the applied force. FCR: Flexor Carpi Radialis, FCU: Flexor Carpi Ulnaris, ECRL: Extensor Carpi Radialis Longus, ECU: Extensor Carpi Ulnaris.

gave us confidence in the value estimated in the case of human subjects, presented in Table 4.1. For one subject, we also tested the electromyographic activation in relation to four different levels of exerted force (or RU torque), exhibiting a positive correlation as is expected from physiology. A first limitation of our work is that we assumed a constant impedance for the human throughout the motion. This is clearly an oversimplification, partly justified by a relatively contained range of Flexion-Extension motion (± 45 deg for the FE axis, as per Tab. 4.1) and the relatively contained exerted forces (3 - 9 N). One possibility is to ensure repetitive motions and regress impedance at different postures by averaging along ensembles, rather than along time, as recently suggested by Ludvig and Perreault [27].

A second limitation of our work is that we only focus on the RU joint, for which a constant angle and torque was maintained through the task. The reason is that, while for robots the intended periodic motion along FE axis (for this task) is pre-programmed and therefore known, for humans we cannot easily estimate it. So, at the present time, we only focused on the stationary axis (RU, for the given task). We are currently investigating the possibility of filtering out the voluntary, self-paced motion. If successful, this will allow extending identifying stiffness during motion.

CONCLUSION AND FUTURE WORK

In this thesis, the fundamental research issues of measuring human-workpiece interaction during tooling task such as grinding, polishing have been addressed. This final chapter summarizes the main contributions of this research work, followed by the possible future research directions.

5.1 Summary of Contributions

The broader aim of this thesis was to understand human-workpiece interaction during manual operation tasks. To accomplish this, the novel approaches for instrumenting tools for polishing/grinding used in monitoring the performance of skilled human operators in three-dimensional space are presented along with assessment of human wrist stiffness. The findings of research work presented in this thesis are summarized as follows:

Design of the Instrumented rotating tools: the instrumented finishing tools in the stationary case and in the hand-held case are designed to monitor interaction forces with the workpiece and point of contact, where these interaction forces arise. The key element in both designs is a flexible coupler/shaft which ideally only transmits rotation torques to spin the polishing/grinding wheel while all the remaining torque and force components are transmitted through a parallel structure and sensed by a 6-axis loadcell (ATI mini40). In this way, any reaction force and torque (other than spinning torque) is transmitted and sensed by the loadcell. Sensing torques, in addition to forces, allows estimating the geometry of contact. In our approach, the load cell is located as close as

possible to where interaction dynamics arise. In particular, our loadcell does not have to sustain the weight of the spindle, so it can have a much reduced dynamic range and therefore higher resolution, suitable for fine finishing tasks. While most works focus on measuring forces (typically only the normal force arising during finishing), our method measures 3D forces and 3D torques and is able to estimate the contact point where the interaction takes place. Together, a calibration method to overcome non ideal behavior of the flexible shaft assembly is also presented.

Implementation the Complementary Filter algorithm: The movement (macro-motion) and vibration (micro-motion) of the instrumented tool is measured by the motion capture system (the VZ4000 Tracker) and the IMU unit attached to the setup. The complementary filter algorithm is presented for the combination of both sources (motion capture, IMU) for accurate measurement. Each source has its own system specifications, and while the motion capture system has high 3D resolution at reasonably high acquisition frequency, they are outperformed by IMU in terms of temporal and technical resolution. Accelerometers and gyroscopes may have the high temporal resolution but are known to show signal drift over time. A combination of both systems could improve the acquisition of slow major movements (3D motion capture) and micromotions (IMUs) simultaneously. The complementary filter algorithm is able to detect the movements which the motion capture cannot such as the vibration with high frequencies and small amplitudes.

Estimation of contact geometry for an instrumented tool during operation: the instrumented tool can carry out the dynamic estimation of contact point by the sensed force/torque interaction from the 6-axis loadcell. Once the contact point is estimated, the first and second order geometric analysis is carried out to i) split the sensed force into the normal and friction components; ii) estimate the curvatures of the mounting-bit and workpiece at the contact which is important for material removal estimates. Moreover, the estimated friction force can be used with the spinning tool's velocity to calculate the power of the device.

Estimation of the human RU joint stiffness during tooling task: an algorithm based on stochastic perturbations to estimate stiffness during real-life tooling tasks was proposed and verified by the industrial impedance-control robot. The accurate prediction of the pre-programmed robot impedance gives us confidence in the value estimated in the case of human subjects. At the present time, we cannot easily estimate the intended motion along FE axis of human, so we only focus on the RU axis for the given task.

5.2 Future work

The research study presented in this thesis is based on the instrumented rotating tool with the rigid wheel which gives a special solution for estimating the geometry of contact. To apply this model for industrial surface finishing operations, the flexible wheel (e.g. paper wheel) need to be considered. When the wheel is not rigid, the equation $\mathbf{T} = \mathbf{r} \times \mathbf{F}$ will no longer be valid, and gives multiple solutions for the coordinates of contact point $\mathbf{r}$ all lying in the line of the application force (see Fig. 3.1-a). Therefore, to estimate the

Figure 5.1: a) Another embodiment with a cylindrical structure making use of a hollow loadcell b) CAD model of the symmetric implemented prototype.

geometry of contact for the flexible wheel precisely, its characteristics such as impedance and roughness should be accommodated in all formulation.

Similar to the instrumented rotating tool, Fig. 5.1 shows another embodiment with a cylindrical structure making using of a *hollow loadcell* [144]. The cylinder made from AL6061 aluminum material was used for covering the spindle casing and for establishing the rigid connection between loadcell and spinning wheel. The hollow loadcell (e.g. Sunrise 35XX series - 6-axis force/torque sensor) attached to spindle and cylinder for measuring interaction force/torque. The bearings were fixed inside the cylinder for connecting the spindle and spinning shaft. The main advantage of this embodiment is a cylindrical structure which has the symmetric shaft. Hence, it is easier for measurement and more convenience for operator doing tooling as well (see Fig. 5.1). However, it still

needs to be validated with the same experiment mentioned in Chap. 3, Sec. 3.2.4 and Sec. 3.2.5.

In Chap. 3, the integration of two measurement systems to detect micro and macro-motions is discussed. Multimodal sensor fusion is implemented using a complementary filter which is specialized to the nonlinear structure of the SO(3) group of rigid body rotations. This work is aimed to improve the estimation of acceleration, free from gravitational bias using a complementary filter. Both the numerical implementation and

Figure 5.2: Schematic diagram of Complementary filter with the estimation of velocity and position of the tool.

the experimental validation have been provided in three cases (Translation, Rotation, Combined) to complement the theoretical approach. Going on step further, future work could build up on the proposed algorithms and improve the determination of the position in SE(3) based on the determined accelerations. For instance, one could use the same principle with the schematic diagram of the complementary filter (as shown in Fig. 3.17) and add the additional block of translation (block *i* of Fig. 5.2) to the workflow. This would allow the user to integrate acceleration twice to obtain the position caused by the micromotions.

Measuring human-workpiece interaction during tooling task plays an important role in translating into planning strategies for robot programming and control, but that is only the first half of the story. What is equally important is the automation learning process of the robot while observing the human performance. Robotic programming is still a difficult process, even with CAD/CAM software for offline programming. Implementation of robotic programming not only requires careful determination of the process parameters

such as the features of material type, tool approach angle, amount of applied force, spindle speed, the feed rate, etc but also the cost factor because most robot approaches very slowly to the workpiece space from the free space, and this increases the overall cycle time. Thus, the time for programming could be even longer than the actual processing time of the robot. One of the recommended solutions is developing an in situ measurement system (instrumented tool) and process parameter adaptation algorithm to search for the optimal parameters automatically. In particular, while the human is performing the finishing task by using the instrumented hand-held tool, all the information captured from the instrumented tool is transferred to the processor of the robot and is converted to the parameters to replicated an expert human operator with the robotic manipulator (see Fig. 5.3).

Figure 5.3: Future work - The human is performing the finishing task by using the instrumented hand-held tool, all the information is transferred simultaneously to the processor of the robot and and is converted to the parameters to replicated an expert human operator with the robotic manipulator.

LIST OF PUBLICATIONS

PROVISIONAL PATENT FILE

- [1] D. Campolo, **Hoang G. Phan**, A.Hussain, "Instrumenting Tools For Monitoring Interaction Dynamics During Contact Task", *submitted to the NTUitive as Technical Disclosure, NTU Ref: TD/081/15, 2015*

INTERNATIONALS CONFERENCES

- [1] P. Tommasino, YN Eng, **Hoang G. Phan**, F. Widjaja, K. Gamage and D. Campolo, "Learning Coriolis-Type of Force Fields without Robot," in *The 3rd IFToMM International Symposium on Robotics and Mechatronics, 2013, Singapore*
- [2] **Hoang G. Phan**, P. Tommasino, M. Azhar, K. Welihena Gamage, A. Hussain, and D. Campolo, "Characterization of impedance rendering with a cable-driven agonist-antagonist haptic device," in *International Conference on Control, Automation, Robotics and Vision, IEEE, 2014, Singapore*
- [3] **Hoang G. Phan**, A. Hussain, and D. Campolo, "Preparation for capturing human skills during tooling tasks using redundant markers and instrumented tool," in *RCMME (8th Regional Conference on Mechanical and Manufacturing Engineering), Nov. 2015, Yogyakarta, Indonesia*
- [4] **Hoang G. Phan**, C. Hansen, P. Tommasino, A. Hussain and D. Campolo, "Instrumentation of a hand-held power tool for capturing dynamic interaction during finishing tasks," in *The sixth IEEE RAS/EMBS International Conference on Biomedical Robotics and Biomechatronics - BioRob 2016, Singapore*

INTERNATIONAL JOURNALS

- [1] **Hoang G. Phan**, P. Tommasino, A. Hussain, C. Hansen, S. Castagne and D. Campolo, "Geometry of contact during Tooling tasks via dynamic estimation", in *International Journal of Advanced Manufacturing Technology*, 2017, **Submitted**
- [2] **Hoang G. Phan**, C. Hansen, P. Tommasino, A. Hussain and D. Campolo, "Instrumentation of grinding/polishing tools for capturing dynamic interactions with the

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- [4] **Hoang G. Phan**, C. Hansen, P. Tommasino, A. Budhota, A. Hussain, E. Burdet and D. Campolo, "Estimation of human joint mechanical impedance during a tooling task", in *Journal of Bioinspiration & Biomimetics*, in 2017, **Submitted**
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