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Unrestrained Measurement of Arm Motion Based on Wearable Wireless Sensor Network

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Abstract – Techniques that could monitor human motion precisely are useful in applications such as rehabilitation, virtual reality, sports science and surveillance. Most of the existing systems require wiring that restrains the natural movement. To overcome this limitation, a wearable wireless sensor network using accelerometers has been developed in this study to determine the arm motion in the sagittal plane. The system provides unrestrained movements and improves its usability. The lightweight and compact size of the developed sensor node makes its attachment to the limb easy. Experimental results have shown that the system has good accuracy and response rate when compared to a goniometer.

Index Terms—Wireless sensor network, wearable sensor, human body motion, rehabilitation.

I. INTRODUCTION

TRACKING of human motion has attracted significant interest in recent years due to its wide ranging application such as rehabilitation [1], virtual reality [2, 3], sports science [4], and surveillance [5]. Existing methods include mechanical, visual, audio, radar, magnetic and inertial tracking [6]. Visual tracking involves the use of a single or multiple cameras. The captured images suffer from problems due to occlusion, lighting changes, clutter, shadow and noise [5, 7]. Single camera tracking is normally based on model, contour or feature but it generates ambiguity easily due to occlusion or depth. Multiple cameras can reduce the ambiguity and handle occlusion but are costly.

In recent years, inertial and magnetic tracking [8-12] have attracted much interest as they are source free approaches unlike the audio and radar that require an emission source. The development of Micro-Electro-Mechanical System (MEMS) technology has also made such sensors lighter, smaller and cheaper. Consequently, they are good candidates for an ambulatory measurement system used in telerehabilitation [13, 14] conducted in the patient's home or office. This will also greatly reduce the frequency to visit the hospital for patients undergoing physiotherapy. A good ambulatory system has to meet several design criteria: lightweight, easy attachment, little hindrance to natural movement, capability for long term monitoring, high accuracy and ideally low latency. Research work has also been conducted to make such system portable [15, 16] and wearable [17-20]. However, existing systems have many wiring and thus pose a constraint on the body movement. In this paper, a wearable wireless sensor system is proposed to overcome this limitation. The wireless feature enables the unrestrained motion of the human body as opposed to a wired

monitoring device and makes the system truly portable. This will also allow the system to be deployed in a cluttered home environment. The small form factor and lightweight feature of the sensor nodes also allow easy attachment to the limbs. The autonomous computing capability of each sensor node will also allow for distributed control architecture to be implemented. Such a system is also lower in cost as compared to a sophisticated visual tracking system with multiple tracking cameras. The low power consumption of each sensor node will also allow for long term monitoring.

The organization of the paper is as follows: Section II describes the configuration of the prototype system. This is followed by the measurement approach in Section III. The error modeling of the tilt measurement is investigated in Section IV. Calibration for the sensor node is presented in Section V. Section VI presents the results from the experiments conducted. The system performance in terms of accuracy and latency has been evaluated. Finally, we conclude this work in Section VII.

II. SYSTEM CONFIGURATION

Fig. 1 shows the configuration of the system. It is observed that the system consists of a number of sensor nodes that communicate wirelessly to a central coordinator in a star network topology. The coordinator is in turn connected to a personal computer via a RS232 wired link. Fig. 2 shows the coordinator with a PIC18LF2620 microcontroller. The coordinator may use either a mains power or a 9V rechargeable battery.

Fig. 3 shows the picture of a sensor node. Each sensor node is equipped with a capacitive micromachined accelerometer (Freescale MMA7261QT) that can be used to detect tilt angle of up to 3 axes. The sensor nodes are attached to the human limbs and operate completely untethered. They are powered by a 6V alkaline battery. The developed sensor node has a small form factor measuring $40 \times 39 \times 16$ mm. It weighs only 19g without battery. The battery will add another 14g to the system.

For this system, the MiWi network protocol [21] is used due to its small stack. It is based on the medium access control (MAC) and physical (PHY) layers of the IEEE 802.15.4 specification for low rate wireless personal area networks (LR-WPAN). A detail discussion on the choice of wireless standard, protocol and the implementation of the wireless platform is given in [22].

During operation, the accelerometer on each sensor node will measure the 3-axis (XYZ) acceleration. These measurements are then digitized via the analog-to-digital converter (ADC) module of the microcontroller and transmitted wirelessly using the RF transceiver to the network coordinator. The sampling

rate for the ADC is configurable and is set to 10Hz for a two-sensor node network system. The coordinator subsequently transfers the data to the personal computer (PC) via RS232 interface at a baud rate of 19200 bps for algorithmic computation and motion rendering. The PC used in the experiments runs on a Pentium 4 640 CPU with a clock speed of 3.2 GHz. The MatLab virtual reality toolbox is used for the motion rendering.

Fig. 1 General configuration of the system

Fig. 2 Photograph of a network coordinator

Fig. 3 (a) Photograph of a sensor node showing the front with a MCU and accelerometer and a 10 cent Euro coin (b) back is a Microchip RF module

III. MEASUREMENT APPROACH

Fig. 4 shows the attachment of the sensor nodes to the upper arm and the forearm. The figure also shows the corresponding

movements of the arm rendered in a virtual reality environment on the computer screen.

Fig. 4 Attachment of the sensor nodes on the human arm

In this paper, we investigate the movement of the human arm along sagittal plane, i.e. the plane that bisects the human body into left and right [23]. This corresponds to the flexion and extension movements of the forearm and the upper arm. Flexion is a bending movement in which the relative angle of the joint between the adjacent segments decreases. Extension is a straightening movement in which the relative angle of the joint between two adjacent segment increases as the joint returns to the reference anatomical position. For the physical therapist, the range of the elbow motion and shoulder joint of the patient is of particular interest for monitoring the rehabilitation progress. To capture the arm's rotational motion, an accelerometer is integrated to the sensor node as an inclinometer. An accelerometer, in general, can be used to measure the arm motion that is in static and dynamic conditions. The details are described in the following subsections:

A. Tilt/ Static measurement

Fig 5 shows an accelerometer mounted on the forearm. In the static conditions, i.e, the arm is not moving, the tilt angle θ of the accelerometer can be determined by measuring the acceleration due to the gravity g as shown in Fig 5.

Fig. 5 Tilt measurement in 2 axes (Y-Z)

From Fig. 5, the accelerations A_Y in the Y-axis and A_Z in the Z-axis that are due to the gravity can be determined as:

$$A_Y = g \sin \theta \quad (1)$$

$$A_Z = g \cos \theta \quad (2)$$

From (1)-(2), the tilt angle θ can be determined as:

$$\theta = \tan^{-1} \frac{A_Y}{A_Z} \quad (3)$$

The quadrant of θ can be determined by the sign of A_Y .

The output voltage V_{out} of the accelerometer is related to the acceleration, A_i , of a particular axis ($i=Y$ or Z) by the following relationship

$$V_{out} = V_{offset} + S \times A_i \quad (4)$$

where $S = \Delta V / \Delta g$ is the sensitivity of the accelerometer in $V/(m/s^2)$ and V_{offset} is the offset of the accelerometer at 0g.

The corresponding ADC value can be expressed as

$$\lambda_i = Q \left[\frac{2^n}{V_{REF}^+ - V_{REF}^-} V_{out} \right] \quad (5)$$

where n is the resolution bits of the ADC ($n=8$ in this case) and V_{REF}^+ and V_{REF}^- are the reference voltage levels and $Q[\]$ is the quantizer function. The accelerometer is ratiometric, i.e. the output voltage and sensitivity scale linearly with the reference voltage. From (4) and (5), it is observed that the supply induced errors are cancelled in the analog to digital conversion process.

Substituting V_{out} from (4) into (5), the acceleration A_i is approximately proportional to λ_i after subtracting an equivalent ADC offset. As such, (3) can be rewritten as follows:

$$\theta = \tan^{-1} \frac{\lambda_Y - \lambda_{Y0}}{\lambda_Z - \lambda_{Z0}} \quad (6)$$

where λ_Y and λ_Z are the ADC output values of the accelerometer in the Y and Z axis respectively, λ_{Y0} and λ_{Z0} are the offsets of the accelerometer at 0g.

B. Dynamic measurement

In the dynamic condition, modeling the rotation of the accelerometer in a circular motion yields

$$a_Y = g \sin \theta - A_Y(t) \quad (7)$$

$$a_Z = A_Z(t) - g \cos \theta \quad (8)$$

where a_Y and a_Z are the accelerations in the Y - and the Z - axis of the accelerometer.

In terms of derivatives of θ , we have

$$r \left(\frac{d\theta}{dt} \right)^2 = g \sin \theta - A_Y(t) \quad (9)$$

$$r \frac{d^2\theta}{dt^2} = A_Z(t) - g \cos \theta \quad (10)$$

where r is the distance of the accelerometer from the axis of rotation. Rearranging (9)-(10), we have

$$A_Y(t) = g \sin \theta - r \left(\frac{d\theta}{dt} \right)^2 \quad (11)$$

$$A_Z(t) = g \cos \theta + r \frac{d^2\theta}{dt^2} \quad (12)$$

From (11) and (12), it is observed that the value of $A_Y(t)$ is

affected by the angular velocity while the value of $A_Z(t)$ is affected by the angular acceleration. (11) and (12) are non-linear in nature and a solution is non-trivial. Since the target application of this paper is rehabilitation, the angular acceleration and velocity of the human arm motion are generally small. The maximum angular velocity of the arm for a patient undergoing rehabilitation is about 10 °/s or 0.17 rad/s [24]. For the angular acceleration, it is typically less than 1 rad/s [25] for most of the time during arm flexion and extension motion. This translates to an additional acceleration of 0.0043 m/s^2 in the Y -axis and 0.0043 m/s^2 in the Z -axis with $r=0.15m$ which is much less than the acceleration due to gravity (9.81 m/s^2). In addition, it is observed that the derivative terms are also multiplied by r . This suggests that the effects of the additional derivative terms can be minimized by placing the sensor close to the centre of rotation. Hence, the derivative terms can be neglected when determining the tilt angle. The error due to this assumption will be determined through experiments in section VI by subjecting the sensor to varying angular rates of rotation.

C. Latency measurement

Besides measurement accuracy, another important performance metric is the latency. The latency is the time between a motion is made and captured. In an ideal tracking system, the mean time delay after a motion is initiated until the corresponding data is transmitted should be less than 1 ms [6]. Moreover, the latency between the initiation of motion and the motion rendering should be less than 100 ms to avoid degradation of performance [26]. Thus, one of the challenges of the proposed wireless tracking system is to ensure acceptable latency when multiple sensor nodes are in use.

Fig. 6 shows the time components contributing to the latency of the system with one sensor node. The sampling interval, T_s , should be greater than the sum of the total latencies T_l . Thus, the latency of the system limits its maximum sampling rate. Given that the frequency spectrum of human body motion ranges from 2 to 20 Hz [27], the sampling rate of the system should ideally be greater than 40 Hz. However, for the case of arm flexion and extension motion, the FFT of the accelerometer signal mounted on a forearm undergoing normal and very fast flexion and extension motion shows that the majority of the frequency components fall under 1.0 Hz. Thus, an oversampling frequency at 10 Hz is more than sufficient. From Fig. 6, we have

$$T_s \geq T_l = T_{pn} + T_{dr} + T_{pc} + T_{ds} + T_{ps} \quad (13)$$

Fig. 7 shows the latency of a network with two sensor nodes and one coordinator. With multiple nodes, the figure shows that there are additional delays such as the time difference between different sensor measurements (t_{syn}), backoff time, serial and estimate (delay) etc. In this case, the sampling rate has to be greater than the latency of the system as below:

$$T_s \geq T_{block} \quad (14)$$

Fig. 6 Latencies involved in sample processing of real time motion wireless tracking system (single-node)

Fig. 7 Latencies involved with two wireless sensor nodes

IV. ERROR MODELLING

In this section, the error of the tilt measurement due to misalignment in attaching the sensor node onto the limb is investigated. The limb can be modeled as a cylindrical object with different base radii on both ends of the cylinder as shown in Fig. 8.

Fig. 8 Mounting errors of accelerometer on cylindrical limb model

From the top view of Fig. 8, it is observed that there is an error in mounting the sensor laterally. Consequently, the Y-axis of the accelerometer may not lie in the Y-Z plane. Instead, it is

inclined at an angle of $\Delta\alpha$ to the Y-Z plane along the X-Y plane. $\tilde{A}_y$ is the measured acceleration of the Y-axis of the accelerometer and is related to A_y , the projection of $\tilde{A}_y$ onto the reference Y-Z plane by

$$A_y = \tilde{A}_y \sqrt{(\cos \bar{\theta} \cos \Delta\alpha)^2 + \sin^2 \bar{\theta}} \quad (15)$$

where the angle $\bar{\theta}$ is the angle between the Y-axis of the accelerometer and the reference X-Y plane. The measured acceleration $\tilde{A}_y$ in the Y-axis of the accelerometer is given by

$$\tilde{A}_y = g \sin \bar{\theta} \quad (16)$$

Similarly, we have the following relationships for the Z-axis of the accelerometer:

$$\tilde{A}_z = g \cos(\bar{\theta}) \quad (17)$$

$$A_z = \tilde{A}_z \sqrt{(\sin \bar{\theta} \cos \Delta\alpha)^2 + \cos^2 \bar{\theta}} \quad (18)$$

From the side view in Fig 8, it is observed that as a result of the sloping surface of the arm model, there is a misalignment of A_y with respect to the reference Y axis. As such, the tilt angle $\hat{\theta}$ from the reference Y-axis about the X-axis is related to the true tilt angle θ from the arm by

$$\hat{\theta} = \theta + \Delta\theta \quad (19)$$

where $\Delta\theta$ represents the angle between A_y at 0g and the reference Y-axis. Hence, the true tilt angle θ can be related to $\bar{\theta}$, $\Delta\theta$ and $\Delta\alpha$ as

$$\tan \bar{\theta} = \tan(\theta + \Delta\theta) \cos \Delta\alpha \quad (20)$$

From (20), $\bar{\theta}$ approximates to θ if $\Delta\theta$ and $\Delta\alpha$ are small. The measured ADC values are given by

$$\tilde{\lambda}_y = Q[S_A g \sin \bar{\theta} + \lambda_{y0}] \quad (21)$$

$$\tilde{\lambda}_z = Q[S_A g \cos \bar{\theta} + \lambda_{z0}] \quad (22)$$

$$\text{where } S_A = \frac{2^n}{V_{REF}^+ - V_{REF}^-} S.$$

Therefore, the measured tilt angle can be modeled as

$$\tilde{\theta} = \tan^{-1} \frac{\tilde{\lambda}_y - \hat{\lambda}_{y0}}{\tilde{\lambda}_z - \hat{\lambda}_{z0}} \quad (23)$$

where $\hat{\lambda}_{y0}$ and $\hat{\lambda}_{z0}$ are the estimates of the 0g offset.

Using (20)-(23), the tilt angle error $\tilde{\theta} - \theta$ versus the variation in the values of $\Delta\theta$ and $\Delta\alpha$ is shown in Fig.9. The range of value for $\Delta\theta$ is from 0° to 10° and $\Delta\alpha$ is from -40° to 40° for an arbitrary value of $\theta = 45^\circ$.

Fig. 9 Variation of tilt angle error with $\Delta\alpha$ and $\Delta\theta$

The graph on the left of Fig. 9 shows the error plot with variation in $\Delta\theta$ and $\Delta\alpha$. The subplots on the right shows the error w.r.t $\Delta\alpha$ with fixed values $\Delta\theta = 0^\circ$ and 10° as well as the error w.r.t $\Delta\theta$ with fixed values $\Delta\alpha = 0^\circ$ and 40° .

From the plots, it is observed that the error is very close to the value of $\Delta\theta$ at $\Delta\alpha=0$ for fixed $\Delta\theta$. The error decreases as the absolute value of $\Delta\alpha$ increases, showing a parabolic curve centered at $\Delta\alpha=0$. The absolute value of the error ranges from 0° at $\Delta\alpha = 0^\circ$ to about 8° at $\Delta\alpha = 40^\circ$.

For a fixed value of $\Delta\alpha$, the error is minimum at $\Delta\theta = 0$. The error then increases linearly as $\Delta\theta$ increases. It is observed that the range of absolute value of the error is close to the range of value of $\Delta\theta$ while the value of the error is dependent on the value of $\Delta\alpha$. The combined effect of $\Delta\theta$ and $\Delta\alpha$ on the error produces the single-sheet paraboloid centered at the plane, $\Delta\alpha=0$, as shown in the 3D-plot. The results of these curves show the effect of the attachment errors on the tilt angle determination.

V. CALIBRATION

To improve the measurement accuracy, calibration is required to obtain the $0g$ offset values (λ_{y0} and λ_{z0}) for each accelerometer. One approach is to determine the ADC output when the accelerometer is at the $0g$ position or when it is positioned completely level. However, such measurement is difficult and is prone to error due to mounting or orientation as discussed in section IV. Calibration in $0g$ can be conducted by recording the ADC values during freefall. However, inaccuracies could arise due to unwanted rotation of the device during freefall.

From the sinusoidal relationship of $\tilde{\lambda}_y$ and $\tilde{\lambda}_z$ with respect to the tilt angle θ as in (21)-(22), it is observed that an estimate of λ_{y0} and λ_{z0} can be determined by taking the mean value of $\tilde{\lambda}_y$ and $\tilde{\lambda}_z$ over a 360° cycle in which the mounting or orientation error $\Delta\theta$ and $\Delta\alpha$ is cancelled out in the averaging process. This method yields more accurate result and requires no reference acceleration position that is difficult to determine in practice.

For our calibration process, the sensor node is mounted on a rotary stage as shown in Fig. 10. The rotary stage uses two ceramic motors. It has a resolution of 0.0001° and a maximum

allowable velocity of 250 mm/s. Fig. 11 shows the ADC values of the Y and Z axis of an accelerometer from 0° to 360° with a step size of 5° .

From the figure, it is observed that the ADC value for the Y and Z-axis follows a sine and cosine wave as in (21) and (22) respectively. The corresponding estimated $0g$ offsets, $\hat{\lambda}_{y0}$ and $\hat{\lambda}_{z0}$, are determined to be 127.8889 and 125.9306 respectively. This calibration can then be repeated for other accelerometers attached to the other limbs.

Fig. 10 Mounting of sensor node on high precision rotary motor for determination of angular displacement

Fig. 11 Calibration data for a typical accelerometer

VI. EXPERIMENTAL RESULTS

(a) Accuracy

To investigate the accuracy of the proposed approach, the sensor node is first mounted on a rotary stage as shown in Fig. 10. The stage is programmed to produce a swinging motion between $\pm 90^\circ$ with an angular speed varied from $10^\circ/s$ to $190^\circ/s$. The ADC accelerometer reading with respect to time is then captured. Fig. 12 shows the mean error and variances of the angle of rotation. From the experimental results, it can be observed that the mean error is close to 0° at very low speeds of oscillation ($< 20^\circ/s$). The mean error then fluctuates between 0.5° and 1.0° for increasing speeds of oscillation. The standard deviation on the other hand shows an increasing trend from 2° to 3.7° . This is due to the effect of neglecting the additional acceleration term besides the gravity in (11)-(12). From this test, it is concluded that an accuracy of 0.52° is achievable.

Fig. 12 Mean error and variance of accelerometer readings at various speed of oscillation

(b) Latency of sensor node

To estimate the latency of the system, 10,000 data samples have been collected from an experiment based on one sensor node with one coordinator. As shown earlier in Fig. 6, the latencies to be considered are the processing time of the sensor node T_{pn} , the processing time of the coordinator T_{pc} and the processing time of the computer T_{ps} in determining the rotation angle. These latency times can be determined using the timer module of the microcontroller and the CPU clock in PC. The data transmission time of the RF data link, T_{dr} , and the data transmission time over the serial link, T_{ds} can be calculated using the RF data rate and serial link baud rate. For this system, the data rate and baud rate are 250 kbps and 19.2 kbps respectively. The data propagation time over air can be ignored since the RF signal is transmitting at 3×10^8 m/s and the time over the typical distances (10-50m) is insignificant. The mean total latency time T_l obtained from this experiment is shown in Table I.

From Table I, the processing time of the PC is much greater than the coordinator and the sensor node. The major latency contributing to the system comes from the serial link. Thus, the total latency can be improved by employing a faster serial baud rate. A test on the system shows that the maximum supported baud rate is 57,600bps, which can give us a much improved total latency T_l of 2.083 ms.

TABLE I. LATENCIES ASSOCIATED WITH SINGLE SENSOR NODE

	T_{pn}	T_{pc}	T_{ps}	T_{ds}	T_{dr}	T_l
mean time (μ s)	107	90	3981	6250	1312	11028

Next, we investigate the latency of the system with multiple sensor nodes. The wireless system deployed here is a non-beacon multi-access network. Hence, all the nodes have equal access to the communication medium. Moreover, the nodes are allowed to transmit at any time as long as the channel is idle. Each sensor employs a CSMA-CA protocol to avoid wasteful collisions when multiple simultaneous transmissions might occur.

To determine the latency of the network with multiple sensor

nodes attached to the arm, we make use of the analysis in Fig. 7 which shows the case for two sensor nodes. Fig 7 showed that the latency, T_{block} , is just equivalent to the sum of $(t_{end} - t_{start}) + T_{header}$. T_{start} and t_{end} can be determined using the CPU clock in software while T_{header} can be obtained from the sum of T_{pn} , T_{dr} , T_{pc} , and T_{ds} as in the case for a single sensor node. The latency for three or more sensor nodes can be determined in a similar manner. 1000 block data samples are taken for each network with up to 10 sensor nodes in a star network configuration. The result from this experiment is shown in Fig. 13.

Fig. 13 Latency of system with multiple sensor nodes

From the figure, it is observed that the latency increases by about 20-40 ms with an addition of one sensor node to the existing network. From (14), the latency of the system must be less than the sampling period to meet the processing requirements. Thus, a sampling rate of 10 Hz is chosen for our two sensor node single arm network. The 50 to 90 ms latency for a 2 to 4 sensor node network is within the acceptable latency of 100 ms for a virtual reality based tracking system. There are several ways to improve the latency performance such as the use of a more advanced data collision avoidance algorithm with less time delay or the use of pipelining leading to a more efficient computation of data. These are some possible scopes that we will investigate in future.

(c) Power consumption

A breakdown of a typical average power consumption of a sensor node in operation (at a sampling rate of 10Hz) is given in Table II:

TABLE II BREAKDOWN OF POWER CONSUMPTION OF TYPICAL SENSOR NODE

	Average Current Consumption	Average Power Consumption
PICLF2620 microcontroller	11uA	36.3uW
MMA7261QT 3-axis accelerometer	500uA	1.65mW
MR24J40 RF transceiver	20mA	66mW
Entire sensor node	27mA	89mW

Using a 3.6V rechargeable battery with a nominal capacity of 500 mAh, the sensor node should ideally last for about 18.5 hours. As observed from TABLE II, the bulk of the power

consumption comes from the RF transceiver which consumes 20 mA of current in active mode. When placed in the sleep mode, the transceiver consumes only 2uA. As such, the power management can be further improved by configuring the RF transceiver module to sleep when it is not transmitting. In this case, the average current consumption drops to 8.4 mA. This would prolong the battery life to about 59.5 hours of continuous operation. Assuming a typical usage of 8 hours per day, a single charge of the battery would allow it to be used for one week.

(d) Comparison of proposed approach with goniometer measurements

In part (a) of the experimental study, the accuracy of the sensor node for angle determination has been demonstrated. In this section, we benchmark the performance of the sensor nodes on an actual human arm with the readings from a goniometer probe (PS-2137 from PASCO). The goniometer consists of two metal arm links and a potentiometer. As the angle between the arm changes, the resistance of the potentiometer changes. The accuracy of the goniometer is $\pm 1^\circ$ when calibrated, with a resolution of 0.042° at a sampling rate of 500 Hz.

The attachment of the goniometer and sensor node to the arm is as shown in Fig.14. The data logger for the goniometer is also shown on the left of Fig.14. The sensor nodes are attached to the side of the goniometer so that measurements can be made with respect to the same reference frame for comparison.

Fig. 14 Attachment of the sensor nodes and goniometer to a human arm

The subject is then asked to perform flexion and extension of his forearm for 100s. The flexion and extension motion is then repeated 15 times. The subject is instructed to vary the speed of his motion in each time from the slowest in the first trial to the fastest in the last trial using a metronome as a reference. The mean error and standard deviation over the computed mean angular speed from these experiments are shown in Fig.15. The offset in angle between the proposed system and the goniometer is found by taking the average of the difference in the readings at the maximum flexion and extension point of the forearm.

From Fig.15, the mean difference in angle between the goniometer and the proposed system shows a linear increasing trend from close to 0° at a mean angular speed of $10^\circ/\text{s}$ to 3.5° at a mean angular speed of $80^\circ/\text{s}$. The standard deviation also increases in a linear manner from 2.5° to 7° over the range of mean angular speeds. This result is similar to the experimental

results in Section VI(a) based on the rotary stage but is more pronounced when performed on the human arm. Several factors could have contributed to this effect. In the study, we have assumed that the flexion and extension of the arm can be modeled as a rotating motion about a fixed axis and that the arm is a rigid body. In reality, there will be momentary changes in rotation axis due to muscles and joint movements during flexion and extension movements. Furthermore, the arm rotation may not be restricted in a 2D plane.

Fig. 15 Angle between forearm and upper limb obtained using the sensor nodes and a goniometer attached to the human arm limb

VII. CONCLUSIONS

In this paper, an ambulatory and unrestrained measurement system based on a wearable wireless sensor network for tracking the human arm motion in the sagittal plane has been proposed. To study the performance of the prototype, controlled rotations of the prototype using a rotary stage show a mean error of only 0.52° . With the developed system mounted on a human arm and evaluated with a goniometer shows similar performance trend with slight increase in error. These experiments demonstrate that the accuracy of the system is sufficiently good for the targeted rehabilitation application where the angular velocity of the arm movement is less than $20^\circ/\text{s}$. Moreover, the latency of the system is less than 60 ms for a two-node network. Evaluation of the power consumption shows that the system can last for a week with a daily usage of 8 hours.

As compared to other existing approaches, the new system is portable and easy to use. It allows the patients to be monitored without restraint and rehabilitation can be carried out in a home environment instead of a specialized laboratory in the hospital. For future work, experiments conducted with stroke patients in collaboration with a hospital are being planned using the developed system. More tests can also be conducted to investigate the effect of RF interference from other patient monitoring devices and wireless systems.

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