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Ambulatory Measurement of 3-Dimensional Foot Displacement During Treadmill Walking Using Wearable Wireless Ultrasonic Sensor Network

Yongbin Qi¹, Cheong Boon Soh^{1*}, Erry Gunawan¹, Kay-Soon Low¹

Abstract—Techniques that could be used to monitor human motion precisely are helpful in various applications such as rehabilitation, gait analysis and athletic performance analysis. This paper focuses on the 3-dimensional foot trajectory measurements based on a wearable wireless ultrasonic sensor network. The system consists of an ultrasonic transmitter (mobile) and several receivers (anchors) with fixed known positions. In order not to restrict the movement of subjects, Radio Frequency (RF) module is used for wireless data transmission. The RF module also provides the synchronization clock between mobile and anchors. The proposed system measures the Time-of-Arrival (TOA) of the ultrasonic signal from mobile to anchors. Together with the knowledge of the anchor's position, the absolute distance that the signal travels can be computed. Then, the range information defines a circle centered at this anchor with radius equal to the measured distance, and the mobile resides within the intersections of several such circles. Based on the TOA-based tracking technique, the 3-dimensional foot trajectories are validated against a camera based motion capture system for 10 healthy subjects walking on a treadmill at slow, normal and fast speeds. The experimental results have shown that the ultrasonic system has sufficient accuracy of net root mean square error (4.2 cm) for 3-dimensional displacement, especially for foot clearance with accuracy and standard deviation (0.62 ± 7.48 mm) compared to the camera-based motion capture system. The small form factor and lightweight feature of the proposed system make it easy to use. Such a system is also much lower in cost compared to camera-based tracking system.

Index Terms—Ultrasound, wireless sensor network, foot clearance, wearable sensor, walking assessment, rehabilitation.

I. INTRODUCTION

IT is generally agreed that falls in the elderly population are serious healthcare issues due to their financial cost and associated mortality and morbidity rates [1]. Some researchers have investigated some basic gait variables such as stride length and walking speed [2] while others have studied joint kinematics to evaluate the ageing effects on gait [3]. In order to understand the complex relationship between gait and falls, an accurate method for the measurement of foot trajectory, such as foot clearance, is required [4]. Foot clearance is defined as the vertical displacement during walking, which has been shown to be an important kinematic parameter related to safe locomotion [5].

Foot movement can be measured using a wide variety of techniques and sensors [6], [7]. The most accurate measurement system is optical tracking system, which uses one or

more cameras to capture the displacement of reflective markers placed at specific anatomical sites on limb segments [8], [9]. The system allows for the assessment of a complete three-dimensional kinematic analysis of human movement only within restrictive laboratory environments [10]. In addition, it is sensitive to changes in lighting, clutter and shadow [11]. Therefore, it is not suitable for routine applications because of the complexity and cost.

An alternative method to the visual tracking system is to utilize inertial sensors, such as the accelerometer and gyroscope [12], [13]. An accelerometer can measure the component of its acceleration along its sensitive axis, which is suitable for measuring human movement [14]. A gyroscope is also a type of inertial sensor that is used to measure angular velocity [15]. Usage of inertial sensors have become more and more popular in a wireless sensor network due to its low cost and low form factor, which allow unrestrained natural movement of the human body limbs [16]. Although these inertial sensors do not suffer from the disadvantages of the visual tracking system, they are not ideal as well. The estimation of position and orientation requires integration of angular velocities or double integration of acceleration respectively. This is a cumulative procedure which in the presence of even small measurement errors could produce significant drift over long measurement durations. Thus, the integration should not be done over a long time or some other techniques should be applied to minimize error accumulation [4], [15].

Ultra-wideband (UWB) radio is an emerging technology that has attracted significant interest in recent years due to its robustness to fading, high temporal resolution, low loss penetration, and low power spectral density [17]. Particularly, wearable UWB radios are good candidates for human motion tracking, since they can provide high ranging and positioning accuracies and offer low-power consumption and robust performance in multipath environment [18], [19]. It is, however, difficult to sample the received signal in real time with current Analog to Digital Converter (ADC) technology due to its large bandwidth of UWB pulse. Furthermore, the clock between transmitter and receiver should be strictly synchronized, because even small clock drift would produce significant measurement error due to its high transmission speed [20].

It is therefore of interest to design a low cost and accurate motion tracking system for routine applications. In this paper, a wireless wearable sensor system based on ultrasound for monitoring foot trajectory during walking is proposed. The

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Fig. 1. The prototype of foot displacement measurement during gait [4].

objective is to allow patients to be monitored under an unrestrained environment. The proposed approach makes use of the wireless sensor network concept with all the mobile sensor nodes communicating wirelessly with the coordinator. These sensor nodes are light and small for attaching to the human foot. Furthermore, it is low cost as compared to the camera based motion capture system.

The paper is organized as follows: a brief overview of the configuration of the wireless wearable ultrasonic system is given in Section II. Section III describes the proposed measurement system using state-space methods to continuously track foot displacement during walking. This is followed by 3 steps tracking algorithm using the combination of Newton-Gauss method and extended Kalman filter to reduce the effect of range measurement errors on the foot displacement measurement in Section IV. Section V investigates the performance of the ultrasonic tracking system by comparing with camera based motion capture system during different walking speeds. Finally, conclusions are made in Section VI.

II. SYSTEM DESCRIPTION AND CONFIGURATION

A. System Description

The proposed foot displacement measurement system uses ultrasonic sensor to track and localize the foot motion during walking. As shown in Fig. 1, vertical displacement, also called foot clearance, is defined as the height between a foot and the ground during walking. The distance during walking is widely used in many fields extending from gait analysis to rehabilitation. General requirements for gait analysis are that the device attached to human body should be as small and as light as possible. Any bulky devices heavier than about 1-2 percent of the subject's mass may potentially disturb normal gait [21].

B. System Configuration

We developed a wearable ultrasonic motion analysis system using wireless sensor network. Fig. 2 shows the general configuration of the system. The system comprises of a number of sensor nodes, coordinator, data transmission module, anchors and mobiles. The mobile consists of an ultrasound generator board, as shown in Fig. 3(a), and a controller board, shown

Fig. 2. General configuration of the system

Fig. 3. (a) Photograph of Embedream ultrasonic transmitter, and (b) Embedream receiver module.

in Fig. 4, comprising of a microcontroller unit (MCU), a RF module and a temperature sensor. The RF module embedded in the controller board provides synchronization clock between mobiles and anchors. The RF module on transmitter will first send out a data package with Timer Starter Command (TSC) using broadcast address to notify the anchors that ultrasound signal has been transmitted. The anchors will then start the timers to obtain propagation delays of the ultrasound signal. Due to the characteristics of ultrasonic sensor, the speed of sound is sensitive to surrounding temperature, humidity, etc. In most cases, temperature has the most pronounced effect. Therefore, a temperature sensor is added in the controller board to measure the temperature, and compensate for the temperature effect on the velocity of ultrasound. The ultrasound velocity in air can be approximated by [10]

$$v_s = \sqrt{\kappa RT} \approx 20.05\sqrt{T} \quad (1)$$

where κ is the isentropic coefficient which is equal to 1.4 in air, $R = 287.14 \text{ m}^2/\text{s}^2\text{K}$ is the general gas constant, and T is the air temperature in degrees Kelvin.

An anchor is composed of an ultrasound receiver, as shown in Fig. 3(b), and a controller board. The anchor receives ultrasonic signals from the mobile device and computes dis-

Fig. 4. Embedream controller board comprising of microcontroller, a RF front end and a temperature sensor.

tance estimates to the mobile using time-of-arrival of the ultrasonic signal. These range information are forwarded to the coordinator. The coordinator node communicates with the data transmission module wirelessly to transfer data to computer for post-processing through RS232 wired link. The controller board can be made more compact to reduce its form factor, since the controller board was designed for both anchors and mobiles.

A single ranging cycle is shown in Fig. 5. Distance measurement is initiated by activating the trigger input with a pulse by a mobile. The RF module in the mobile target will send out its own address for coordinator to identify and synchronization signal for anchors to start its corresponding timer. Meanwhile, the ultrasound generator on the mobile target sends out a burst of 40 kHz ultrasound. The timer on the anchor will stop counting when the ultrasound receiver detects the transmitted signal. Then, a measurement of surrounding temperature by the temperature sensor is taken. Finally, the distance between the mobile and anchor can be calculated by:

$$D = t \cdot v_s \quad (2)$$

where D is the distance in meters, t is the ultrasound propagation delay from mobile to anchor in seconds, and v_s is the velocity of ultrasound in meters per second. After the anchor has completed the range calibration, the RF module in anchor transmits the distance information to PC via data transmission module for post processing. Using the distance information, the position of the mobile can be located by the following localization and tracking technique, Extended Kalman Filter (EKF) together with Newton-Gauss (NG) method, as described in Section IV.

III. SYSTEM MODELING

A. Motion Model

We assume that the mobile with position $\mathbf{p} = [x \ y \ z]^T$ sends out ultrasonic signals to anchors after each trigger signal. The positions of anchors are known with $\mathbf{p}_i = [x_i \ y_i \ z_i]^T$, respectively. Then, we design an EKF using a state vector with six components, three Cartesian coordinates (x, y, z) and their velocity components $(\dot{x}, \dot{y}, \dot{z})$. Therefore, the state of the mobile target for time step k can be expressed as

$$\mathbf{x}(k) = [x(k) \ y(k) \ z(k) \ \dot{x}(k) \ \dot{y}(k) \ \dot{z}(k)]^T \quad (3)$$

Fig. 5. Single ranging cycle. Distance measurement is initiated by sending a pulse to the trigger input. The receiver will respond with a pulse with a duration corresponding to the propagation delay.

Then the state transition equation from time step $k - 1$ to k is given by:

$$\mathbf{x}(k) = A\mathbf{x}(k-1) + \mathbf{q}(k-1) \quad (4)$$

where the state transition matrix A from the respective kinematics equations is

$$A = \begin{bmatrix} I_{3 \times 3} & T \cdot I_{3 \times 3} \\ O_{3 \times 3} & I_{3 \times 3} \end{bmatrix} \quad (5)$$

where $I_{3 \times 3}$ is the identity matrix and $O_{3 \times 3}$ is the matrix with all elements zero. T is the sampling interval. The process noise is $\mathbf{q}(k-1) \sim N(0, Q(k-1))$. The covariance matrix $Q(k-1)$ accounts for the un-modeled factors of the system that will be treated as random noise. It becomes:

$$Q(k-1) = \begin{bmatrix} \frac{T^3}{3} Q_s & \frac{T^2}{2} Q_s \\ \frac{T^2}{2} Q_s & T Q_s \end{bmatrix} \quad (6)$$

where $Q_s = \text{diag}(q_x^2, q_y^2, q_z^2)$. In most cases, q_x , q_y and q_z can be considered as standard deviations of the velocity noise in x, y and z directions, respectively.

B. Measurement Model

We let d_i denote the absolute distance measured at i th anchor using the following equation:

$$d_i = \|\mathbf{p} - \mathbf{p}_i\| + \tilde{d}_i = r_i + \tilde{d}_i \quad (7)$$

where $\tilde{d}_i$ is range measurement noise and r_i is actual distance. Stacking all the distance information, we have the measurement model expressed as:

$$D(k) = F(\mathbf{x}(k))\mathbf{x}(k) + \tilde{D}(k) \quad (8)$$

where

$$\begin{aligned} D(k) &= [d_1 \ d_2 \ \cdots \ d_n]^T \\ F(\mathbf{x}(k)) &= [F_1 \ F_2 \ \cdots \ F_n]^T \\ F_i &= \begin{bmatrix} \frac{\partial d_i}{\partial x} & \frac{\partial d_i}{\partial y} & \frac{\partial d_i}{\partial z} & 0 & 0 & 0 \end{bmatrix} \\ \tilde{D}(k) &= [\tilde{d}_1 \ \tilde{d}_2 \ \cdots \ \tilde{d}_n]^T \end{aligned} \quad (9)$$

n is the number of anchors, and $\tilde{D}(k) \sim N(0, R(k))$ is measurement errors. $R(k) = \text{diag}(e_1^2, e_2^2, \dots, e_n^2)$ is the covariance matrix of measurement errors. e_i is always considered as the standard deviations of the measurement error of anchor i .

IV. TRACKING ALGORITHM

We first apply pre-filtering of the range measurements to reduce the errors in tracking and localization. This is followed by the prelocalization algorithm using Newton-Gauss (NG) method and filtered by extended Kalman filter [22].

A. Prefiltering

Since the range measurements may have some large errors or outliers, these outliers can result in significant errors for mobile target tracking. It is not necessary to have a very rigorous pre-filtering since EKF is a robust estimator. Extremely large error in range measurements can be easily eliminated. The method used involves combining past distance measurements and the maximum moving speed at which the mobile is expected to move.

First note that the previous distance measurement for i th anchors is stored in d_i . The mobile target can either be moving away from the i th anchor or approaching it. In approaching case, the distance between the mobile and i th anchor will decrease as given by equation (10) for d_{imax}^- . Otherwise, the distance from the i th anchor will increase over time as indicated by equation (11) for d_{imax}^+ .

$$d_{imax}^- = d_i - T \cdot v_{max} \quad (10)$$

$$d_{imax}^+ = d_i + T \cdot v_{max} \quad (11)$$

where v_{max} is the maximum possible moving velocity of the mobile. Subtracting (11) by (10) results in the following equation:

$$\Delta d_i = d_{imax}^+ - d_{imax}^- = 2 \cdot T \cdot v_{max} \quad (12)$$

Equation (12) provides a threshold to eliminate large range measurement errors. The current range measurement is only used for tracking and localization when the absolute difference between the current range measurement and the previous measurement is smaller than the predefined threshold Δd_i , as illustrated by equation (13).

$$|d_{ik} - d_{i(k-1)}| \leq \Delta d_i = 2 \cdot T \cdot v_{max} \quad (13)$$

B. Pretracking using Newton-Gauss method

Newton-Gauss iterative method is commonly used to solve the nonlinear optimization problem (7) [23]. It begins with an initial guess and is followed by least-sum-square-error minimization [24]. For the j th iteration, we have

$$\mathbf{p}^{j+1} = \mathbf{p}^j - T^j \Theta^j \quad (14)$$

until the condition

$$\|\mathbf{p}^{j+1} - \mathbf{p}^j\| < \varepsilon \quad (15)$$

is satisfied.

$$\begin{aligned} T^j &= [\mathbf{F}^T(\mathbf{p}^j)\mathbf{F}(\mathbf{p}^j)]^{-1}\mathbf{F}^T(\mathbf{p}^j) \\ \Theta^j &= D^j - \|\mathbf{p} - \mathbf{p}_i\| \\ D^j &= \begin{bmatrix} d_1^j & d_2^j & \dots & d_n^j \end{bmatrix}^T \\ \mathbf{F}(\mathbf{p}^j) &= \begin{bmatrix} F(\mathbf{p}^j)_1 & F(\mathbf{p}^j)_2 & \dots & F(\mathbf{p}^j)_n \end{bmatrix}^T \\ [F(\mathbf{p}^j)]_i &= \left[\frac{\partial \|\mathbf{p}^j - \mathbf{p}_i\|}{\partial x} \quad \frac{\partial \|\mathbf{p}^j - \mathbf{p}_i\|}{\partial y} \quad \frac{\partial \|\mathbf{p}^j - \mathbf{p}_i\|}{\partial z} \right] \end{aligned} \quad (16)$$

where n is the number of anchors, and ε is a prescribed threshold. The initial value for k th step is

$$\mathbf{p}^0 = \begin{bmatrix} x^0 \\ y^0 \\ z^0 \end{bmatrix} = \begin{bmatrix} \hat{x}(k) \\ \hat{y}(k) \\ \hat{z}(k) \end{bmatrix} \quad (17)$$

where $[\hat{x}(k) \ \hat{y}(k) \ \hat{z}(k)]^T$ are the first three elements of the predicted state $\hat{\mathbf{x}}(k)$ of the extended Kalman filtering algorithm described in Section IV-C.

Initial guess is important to guarantee the convergence of such recursive method. Therefore, the position information of predicted state of the Kalman filter, which will be discussed in the following step, has been used as initial guess [25]. The experiment shows that such method converges after a few iterations when the predicted state of Kalman filter is used.

C. Extended Kalman Filter

While the Newton-Gauss method gives a pretracking position, we need to use the position information to update the measurement model in equation (7), where the new measurement is $\bar{d}_i = \|\mathbf{p}_{ng} - \mathbf{p}_i\|$ and $\mathbf{p}_{ng}$ is the prelocalization using Newton-Gauss method.

Using the measurement model of the system under study, the following equations can be used to evaluate iteratively to track the mobile.

- Prediction:

$$\begin{aligned} \hat{\mathbf{x}}(k) &= \mathbf{A}\mathbf{x}(k-1) \\ \hat{P}(k) &= \mathbf{A}P(k-1)\mathbf{A}^T + \mathbf{Q}(k-1) \end{aligned} \quad (18)$$

- Update:

$$\begin{aligned} \Phi(k) &= D(k) - F(\hat{\mathbf{x}}(k))\hat{\mathbf{x}}(k) \\ S(k) &= F(\hat{\mathbf{x}}(k))\hat{P}(k)F^T(\hat{\mathbf{x}}(k)) + R(k) \\ K(k) &= \hat{P}(k)F^T(\hat{\mathbf{x}}(k))S(k)^{-1} \\ \mathbf{x}(k) &= \hat{\mathbf{x}}(k) + K(k)\Theta(k) \\ P(k) &= \hat{P}(k) - K(k)S(k)K(k)^T \end{aligned} \quad (19)$$

where $\hat{\mathbf{x}}(k)$ and $\hat{P}(k)$ are the predicted mean and covariance of the state, respectively, for time step k before getting measurement result; $\mathbf{x}(k)$ and $P(k)$ are the estimated mean and covariance of the state, respectively for time step k after getting measurement result; $K(k)$ is the Kalman filter gain.

V. EXPERIMENTAL VALIDATION

In this section, we use the experimental results to compare the proposed ultrasonic motion analysis system with the camera based motion capture system. The foot 3-dimensional displacements are estimated using different approaches, such as Least Square approach, purely Newton-Gauss method, purely extended Kalman filter, and the combination of Newton-Gauss and extended Kalman filter.

A. Experiment Setup

TABLE I
INFORMATION OF SUBJECTS UNDER EXPERIMENT

Age (years)		Height (meters)		Weight (kg)	
mean	sd	mean	sd	mean	sd
24.8	2.25	176.4	6.26	65.4	6.59

In order to investigate the performance of the proposed system, various experiments have been conducted using the hardware platform described in Section II. The measurement was conducted in a motion analysis lab with eight high speed cameras in the School of Mechanical and Aerospace Engineering at Nanyang Technological University. The eight camera analysis system was used to provide independent reference measurements and used for the validation of the ultrasonic system. Ten healthy subjects were used to test the performance of the proposed system. The information of these subjects is given in Table I. All subjects were required to walk on treadmill without shoes or wear regular shoes without high heels, and repeat several times at slow, normal and fast speeds. The camera system tracked the position of three reflective markers placed on toe, heel and shank extremities of subjects' foot or shoe according to Fig. 6. Actually, one reflective marker on heel was enough to provide a reference data for validation. The other two reflective markers were used to create a template for better tracking in camera based motion capture system.

There were four anchors used in our experiment with positions ($p_1 = [0 \ 0 \ 0]^T$, $p_2 = [324 \ 0 \ 0]^T$, $p_3 = [324 \ 230 \ 0]^T$, $p_4 = [0 \ 230 \ 0]^T$). The ultrasonic transmitter was attached to the heel of the foot pointing towards the four anchors, using elastic straps. To benchmark the performance of the ultrasonic tracking system, we compare the 3-dimensional displacement estimated by the ultrasonic tracker with those from camera based motion capture system. Ultrasonic and camera based systems were synchronized to start recording at the same time and sampled at 50 Hz, same as [26], [27].

B. Parameters Identification

The process and measurement noise statistics should be estimated for the system models in Section III. We first conduct experiments with the mobile target moving at a given trajectory. These experiments help to find suitable values of process noise Q_s and measurement noise $R(k)$. We take a sensor and run M tests with the same trajectory. The actual distance for test i , r_i , is known, and there are N measurement samples m_i^j collected for each test, where $j = 1, \dots, N$.

Fig. 6. Wireless unit with embedded ultrasonic sensor attached on foot, and three reflective markers fixed on toe, heel and shank for reference camera based motion capture system.

1) *Process Noise Statistics in Kalman Filter*: As the process noise in EKF is an independent variable, it is difficult to get an exact value [28]. Here, we consider it as a velocity noise in x, y and z directions with mm/sec unit. A metric, Net Root Mean Square Error (Net RMSE), as defined by equation (21), is used to select a reasonable value of Q_s .

$$RMSE = \sqrt{\frac{\sum (Actual - Estimated)^2}{Number\ of\ Estimates}} \quad (20)$$

$$Net\ RMSE = \sqrt{X_{RMSE}^2 + Y_{RMSE}^2 + Z_{RMSE}^2} \quad (21)$$

The process noise Q_s was estimated by using numerical methods. By varying the values of q_x , q_y , and q_z , we will get

TABLE II
ERRORS OF FOOT MOVEMENT IN 3-DIMENSIONAL SPACE COMPARED WITH CAMERA BASED MOTION CAPTURE SYSTEM USING DIFFERENT APPROACHES

		Mean (mm)	STD (mm)	RMSE (mm)	Net RMSE (mm)
Horizontal	LS	7.89	66.37	66.83	
	NG	1.06	60.99	61.00	
	EKF	0.61	49.27	49.26	
	EKF-NG	-0.10	39.76	39.76	
Vertical	LS	-9.58	27.11	28.76	72.76
	NG	0.56	17.24	17.25	63.39
	EKF	0.52	13.01	13.02	50.96
	EKF-NG	0.62	7.48	7.50	40.46
Lateral	LS	Inf	Inf	Inf	Inf
	NG	-1.86	10.65	10.80	64.3
	EKF	1.29	9.75	9.83	51.90
	EKF-NG	-1.82	10.30	10.46	41.79

Fig. 7. Foot trajectory during walking in 3-dimensional space (a) Horizontal displacement, (b) Vertical displacement (foot clearance), and (c) Lateral displacement are compared with camera based motion capture system by using ultrasonic sensors.

the corresponding trajectory of the mobile to compute the Net RMSE value. Typical values of q_x , q_y , and q_z will be selected when their corresponding Net RMSE is minimal. The typical values of Q_s used in our experiments is $q_x = 36$, $q_y = 30$, $q_z = 9$.

2) *Measurement Noise Statistics in Kalman Filter*: It is reasonable to assume that all the anchors have independent distributed noise. Then, the mean and covariance of the measurement noise can be evaluated. Using the data obtained from the experiments, mean and variance of the measurement errors given by

$$u = \frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N (m_i^j - r_i) \quad (22)$$

$$e^2 = \frac{1}{M(N-1)} \sum_{i=1}^M \sum_{j=1}^N (m_i^j - u)^2$$

are computed. Typical value of $R(k)$ used in our experiments is $R(k) = \text{diag}(9, 9, 9, 9)$ with the units as mm^2 .

C. Performance Comparison

To validate our models, we first investigate the performance of purely EKF-based tracker, and then study the combination of EKF and Newton-Gauss (EKF-NG) for target tracking. Finally, by considering the four anchors, it was also possible to consider having multiple equations with three unknowns, and the whole TOA-based localization system was solved using a Least Square (LS) approach.

There are two metrics used for evaluate the performance of our system. One, RMSE, is described in section V This metric computes the tracking errors for x, y and z directions separately [28]. The other metric is the mean error and standard deviation of the discrepancy, considered as accuracy and precision, between the 3-dimensional displacement measured with the camera based system, for EKF, NG, EKF-NG, and LS approaches.

Good correspondence between proposed system and the reference camera based system is shown in Fig. 7. Table II provides numerical comparison of the 3-dimensional displacements in horizontal, vertical and lateral directions by applying different approaches (LS, NG, EKF, and EKF-NG). LS and NG approaches do not use the information of previous state and are sensitive to the geometry distribution of anchors, while EKF-based tracker uses prior knowledge of noise characteristics to filter out the noise. Furthermore, it is independent of the geometry distribution of anchors. Here, we combine the NG and EKF approach, our new method called EKF-NG, to offer superior tracking performance. It is shown in the numerical results that EKF-NG based tracker has a better performance to track the foot movement among all these approaches.

Horizontal displacement was obtained with an error of -0.10 ± 39.76 mm (expressed as the mean $\pm$ STD of the set of difference with the reference camera based system) for EKF-NG tracker and was smaller than other methods. The best absolute accuracy and precision observed was the vertical displacement with 0.62 ± 7.48 mm using EKF-NG tracker. The net RMSE value in 2D model ($\sqrt{X_{RMSE}^2 + Y_{RMSE}^2}$) of 40.46 mm shows the EKF-NG-based method gives a better estimate than the purely EKF- and NG -based methods of 50.96 mm and 63.39 mm, respectively, which are much better than LS-based estimation of 72.76 mm. LS-based approach fails to identify the displacement in lateral direction due to the setup of the 4 anchors in x-y plane. Therefore, there is no degree of freedom in the lateral direction. In other words, the result indicates that Kalman filters are robust and not sensitive to the geometry distribution of anchors. In addition, EKF-NG-based tracker can achieve net RMSE value of 41.79 mm in 3-dimensional space.

D. Influence of Walking Speed on Foot Displacement

The subjects are instructed to vary the speed of walking on treadmill at slow, normal, and fast speeds. Table III shows the mean and STD value of the difference between foot trajectory estimated using ultrasonic system and reference

TABLE III
FOOT MOVEMENT IN 3-DIMENSIONAL SPACE AT DIFFERENT WALKING SPEEDS

Speed (mile/h)		Slow (1.0)		Normal (2.0)		Fast (3.0)	
Horizontal (mm)		Mean	STD	Mean	STD	Mean	STD
	NG	1.01	48.31	-0.71	58.00	2.99	81.27
	EKF	0.86	43.01	2.39	47.50	0.32	58.68
	EKF-NG	0.13	39.55	0.93	40.73	0.23	38.57
Vertical (mm)	NG	-0.30	10.54	0.84	18.78	-0.22	30.52
	EKF	0.31	7.32	0.78	9.92	0.71	22.13
	EKF-NG	0.27	6.60	0.35	8.98	1.03	11.76
Lateral (mm)	NG	-0.99	9.65	-1.52	11.83	-5.49	14.53
	EKF	-0.18	9.00	-1.53	11.37	2.79	11.51
	EKF-NG	-1.00	9.38	0.38	11.85	-0.82	13.90
Net RMSE (mm)	NG	50.39		62.10		88.23	
	EKF	43.64		49.89		62.72	
	EKF-NG	41.19		41.52		42.99	

camera based system. The influence of speed on the 3-dimensional measurement of foot trajectory was found to be insignificant for Kalman filter, whereas it was significant for NG-based approach. Overall, the STD and net RMSE were found to be smaller with slight increase in our proposed EKF-NG method at all walking speeds. This can be interpreted as lower temporal resolution at higher speed. The results show the proposed EKF-NG method is more robust than purely EKF- and NG -based approaches.

VI. DISCUSSION AND CONCLUSION

We use state-space methods together with Newton-Gauss method to estimate the 3-dimensional displacements of foot during walking using one ultrasonic transmitter and four receivers. To estimate the 3-dimensional displacements of foot, we use the EKF which is more computationally efficient compared to other filters like Unscented Kalman Filter (UKF). This is because the EKF estimates for our system are as accurate as the estimates obtained with more complicated filters like UKF.

Some of the estimation errors might be attributed to the vibrations of reflective markers or sensors mounted on body, especially at high walking speed. Marker occlusion is another factor that affects the results of camera based motion capture system. The recording of the marker will be discarded when a significant percentage of markers have not been detected by more than 3 cameras. When one of the three markers is nonvisible, the position of such marker will be estimated from the other two markers by interpolation.

In our experiments, subjects are instructed to walk over several minutes period with slow, normal and fast speeds. Other researchers [29], [30] have also investigated foot displacement using inertial sensors (accelerometers, gyroscopes or both). Their experiments were conducted under slow movements or a limited number of consecutive strides to eliminate the error accumulation over time, since the displacements are estimated by either integrating the velocities or double integrating the measured accelerations. However, our proposed system does not have such limitations and does not have error accumulation even for prolonged measurement durations.

In summary, this study proposes a novel measurement system using wearable ultrasonic sensor to measure the foot displacement continuously during walking in 3-dimensional space. To evaluate the performance of the proposed system, the 3-dimensional foot displacement was measured and validated against the reference camera based motion capture system. The experiments have been conducted at different walking velocities with several healthy subjects. These experiments demonstrate that the results from the proposed ultrasonic measurement system have high correspondence with the results from camera based motion capture system over long walking period. Additionally, the proposed system is easy to wear and to use. It does not restrict the movement of patients or subjects with bulky cables.

REFERENCES

- [1] Rezaul Begg, Russell Best, Lisa DellOro, and Simon Taylor. Minimum foot clearance during walking: strategies for the minimisation of trip-related falls. *Gait & posture*, 25(2):191–198, 2007.
- [2] J.O. Judge, S. Ounpuu, RB Davis 3rd, et al. Effects of age on the biomechanics and physiology of gait. *Clinics in geriatric medicine*, 12(4):659, 1996.
- [3] S.J. Allin, C. Beach, A. Mitz, and A. Mihailidis. Video based analysis of standing balance in a community center. In *Engineering in Medicine and Biology Society, 2008. EMBS 2008. 30th Annual International Conference of the IEEE*, pages 4531–4534. IEEE, 2008.
- [4] B. Mariani, S. Rochat, C. Bula, and K. Aminian. Heel and toe clearance estimation for gait analysis using wireless inertial sensors. *Biomedical Engineering, IEEE Transactions on*, 59(11):3162–3168, 2012.
- [5] Andy Kerr, Danny Rafferty, Philippa Dall, Philip Smit, and Peter Barrie. Using an optical proximity sensor to measure foot clearance during gait: Agreement with motion analysis. *Journal of medical devices*, 4(3):31004–31009, 2010.
- [6] Weijun Tao, Tao Liu, Rencheng Zheng, and Hutian Feng. Gait analysis using wearable sensors. *Sensors*, 12(2):2255–2283, 2012.
- [7] Tao Liu, Yoshio Inoue, and Kyoko Shibata. A wearable ground reaction force sensor system and its application to the measurement of extrinsic gait variability. *Sensors*, 10(11):10240–10255, 2010.
- [8] H.A. Shaban, M.A. El-Nasr, and R.M. Buehrer. Toward a highly accurate ambulatory system for clinical gait analysis via UWB radios. *Information Technology in Biomedicine, IEEE Transactions on*, 14(2):284–291, 2010.
- [9] Yongbin Qi, Cheong Boon Soh, Erry Gunawan, Kay-Soon Low, and Arash Maskooki. A novel approach to joint flexion/extension angles measurement based on wearable UWB radios. *Biomedical and Health Informatics, IEEE Journal of*, 18(1):300–308, 2014.
- [10] Rita M Kiss, László Kocsis, and Zsolt Knoll. Joint kinematics and spatial-temporal parameters of gait measured by an ultrasound-based system. *Medical engineering & physics*, 26(7):611, 2004.
- [11] S. Bamberg, A.Y. Benbasat, D.M. Scarborough, D.E. Krebs, and J.A. Paradiso. Gait analysis using a shoe-integrated wireless sensor system. *Information Technology in Biomedicine, IEEE Transactions on*, 12(4):413–423, 2008.
- [12] Tao Liu, Yoshio Inoue, and Kyoko Shibata. Development of a wearable sensor system for quantitative gait analysis. *Measurement*, 42(7):978–988, 2009.
- [13] Rick A Hyde, Laurence P Ketteringham, Simon A Neild, and Rosie JS Jones. Estimation of upper-limb orientation based on accelerometer and gyroscope measurements. *Biomedical Engineering, IEEE Transactions on*, 55(2):746–754, 2008.
- [14] Carlijn VC Bouten, Karel TM Koekkoek, Maarten Verduin, Rens Kodde, and Jan D Janssen. A triaxial accelerometer and portable data processing unit for the assessment of daily physical activity. *Biomedical Engineering, IEEE Transactions on*, 44(3):136–147, 1997.
- [15] Angelo M Sabatini, Chiara Martelloni, Sergio Scapellato, and Filippo Cavallo. Assessment of walking features from foot inertial sensing. *Biomedical Engineering, IEEE Transactions on*, 52(3):486–494, 2005.
- [16] Guo Xiong Lee and Kay-Soon Low. A factorized quaternion approach to determine the arm motions using triaxial accelerometers with anatomical and sensor constraints. *Instrumentation and Measurement, IEEE Transactions on*, 61(6):1793–1802, 2012.
- [17] C.C. Chong, F. Watanabe, and M.Z. Win. Effect of bandwidth on UWB ranging error. In *Wireless Communications and Networking Conference, 2007. WCNC 2007. IEEE*, pages 1559–1564. IEEE, 2007.
- [18] Yongbin Qi, Cheong Boon Soh, Erry Gunawan, Kay-Soon Low, and Arash Maskooki. Measurement of knee flexion/extension angle using wearable UWB radios. In *Engineering in Medicine and Biology Society (EMBC), 2013 35th Annual International Conference of the IEEE*, pages 7213–7216. IEEE, 2013.
- [19] Yongbin Qi, Cheong Boon Soh, Erry Gunawan, Kay-Soon Low, and Arash Maskooki. Using wearable UWB radios to measure foot clearance during walking. In *Engineering in Medicine and Biology Society (EMBC), 2013 35th Annual International Conference of the IEEE*, pages 5199–5202. IEEE, 2013.
- [20] Y. Zhou, CL Law, and J. Xia. Ultra low-power UWB-RFID system for precise location-aware applications. In *Wireless Communications and Networking Conference Workshops (WCNCW), 2012 IEEE*, pages 154–158. IEEE, 2012.
- [21] Y. Wahab, A. Zayegh, and N.A. Bakar. Foot-to-ground clearance measurement: Analysis and modelling of mems applicability. *International Journal of Research and Reviews in Signal Acquisition and Processing (IJRRSAP)*, 2(1):56–64, 2012.
- [22] Jouni Hartikainen, Arno Solin, and Simo Särkkä. Optimal filtering with kalman filters and smoothers. *Department of Biomedical Engineering and Computational Sciences, Aalto University School of Science*, 16th August, 2011.

- [23] Y. Zhou, C.L. Law, Y.L. Guan, and F. Chin. Indoor elliptical localization based on asynchronous UWB range measurement. *Instrumentation and Measurement, IEEE Transactions on*, 60(1):248–257, 2011.
- [24] Yongbin Qi, Cheong Boon Soh, Erry Gunawan, Kay-Soon Low, and Arash Maskooki. An accurate 3D UWB hyperbolic localization in indoor multipath environment using iterative taylor-series estimation. In *Vehicular Technology Conference (VTC Fall), 2013 IEEE*. IEEE, 2013.
- [25] Xingbo Wang, Minyue Fu, and Huanshui Zhang. Target tracking in wireless sensor networks based on the combination of KF and MLE using distance measurements. *Mobile Computing, IEEE Transactions on*, 11(4):567–576, 2012.
- [26] Axel Mulder. Human movement tracking technology: resources. <http://xspasm.com/x/sfu/vmi/HMTT.add.html>, 1998.
- [27] Eric Foxlin and Michael Harrington. Weartrack: A self-referenced head and hand tracker for wearable computers and portable vr. In *Wearable Computers, The Fourth International Symposium on*, pages 155–162. IEEE, 2000.
- [28] Ali Shareef and Yifeng Zhu. Localization using extended kalman filters in wireless sensor networks. *Graduate Student Scholarly and Creative Submissions*, 2009.
- [29] G.X. Lee, K.S. Low, and T. Taher. Unrestrained measurement of arm motion based on a wearable wireless sensor network. *Instrumentation and Measurement, IEEE Transactions on*, 59(5):1309–1317, 2010.
- [30] H Martin Schepers, Edwin HF Van Asseldonk, Chris Baten, and Peter H Veltink. Ambulatory estimation of foot placement during walking using inertial sensors. *Journal of biomechanics*, 43(16):3138–3143, 2010.