Accuracy Improvement on the Measurement of Human Joint Angles

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Abstract—A measurement technique that decreases the root mean square error (RMSE) of measurements of human joint angles using a personal wireless sensor network (WSN) is reported. Its operation is based on virtual rotations of wireless sensors worn by the user, and it focuses on the arm, whose position is measured on 5 degrees of freedom (DOF). The wireless sensors use inertial magnetic units (IMU) that measure the alignment of the arm with the earth’s gravity and magnetic fields. Due to the biomechanical properties of human tissue (e.g., skin’s elasticity), the sensors’ orientation is shifted, and this shift affects the accuracy of measurements. In the proposed technique, the change of orientation is first modeled from linear regressions of data collected from 15 participants at different arm positions. Then, out of 8 body indices measured with dual-energy X-ray absorptiometry, the percentage of body fat is found to have the greatest correlation with the rate of change in sensors’ orientation. This finding enables us to estimate the change in sensors’ orientation from the user’s body fat percentage. Finally, an algorithm virtually rotates the sensors using quaternion theory with the objective of reducing the error. The proposed technique is validated with experiments on 5 different participants. In the DOF whose error decreased the most, the RMSE decreased from 2.20° to 0.87°. This is an improvement of 60%, and in the DOF whose error decreased the least, the RMSE decreased from 1.64° to 1.37°. This is an improvement of 16%. On average, the RMSE improved by 44%.

Index Terms—motion capture, joint angle, wireless sensor network, inertial magnetic unit, quaternion.

I. INTRODUCTION

DIFFERENT motion-capture (mocap) technologies have been developed in recent years. One of them is based on inertial/magnetic mocap systems that consist of electromagnetic, angular velocity, and acceleration sensors, also known as IMUs. IMUs are attached to a user using straps and move along with the body segments they are attached to, allowing the measurement of the motions.

The use of IMUs could have a positive impact on the future of rehabilitative medicine. For example, IMUs can provide real-time visual and audio biofeedback to patients during rehabilitation exercises. One of the principle steps in therapeutic rehabilitation is restoration of pre-injury ranges of motion [1], and biofeedback could be used to promote increased joint mobility by providing positive reinforcement to patients performing an exercise [2]. Correspondingly, negative reinforcement could be used to limit range of motion of patients following surgery where adequate time must be afforded for sufficient stabilization to take place relating to structural and procedural surgical fixations. Furthermore, successful rehabilitation often requires daily performance of exercises where only a small portion can be monitored by a clinician, and IMUs could eventually serve a role in tracking patient activity and progress during home rehabilitation for clinician review at subsequent follow-up appointments. In another example, the promotion of patient autonomy is essential to long-lasting efficacy and adherence of rehabilitative and preventative programming [3], [4].

However, the accuracy of measurements performed by IMUs is affected by the biomechanical properties of human tissue, and this limits the use of IMUs for rehabilitative medicine. The reason for the reduced accuracy is that human tissue, such as subcutaneous adipose tissue and skin’s elasticity, misalign the IMUs at different body positions causing errors in the measurements [5], [6], [7]. The objective of this paper is to reduce the effects of the human tissue properties on the accuracy of IMU-based mocap systems.

The focus of this paper is on the arm. Specifically, the problem addressed is the improvement of the accuracy of the measurements of IMU-based mocap systems on the human arm. This is achieved by applying the theory of quaternions [8] for mathematical modeling of the effects of tissue properties on the IMU mocap system measurements. This process can be summarized in three steps. First, the human-body index that most affects the accuracy of measurements is identified. The human indices considered in this paper are 8 in total:

- Body total mass: Total mass of user’s body
- Body fat mass: Total amount of fat in user’s body
- Body lean mass: Total mass without fat mass and bone mineral content
- Body fat percentage: Ratio of fat mass and total mass
- Arm fat mass: Total amount of fat in user’s arm
- Arm lean mass: Arm’s total mass without arm’s fat mass and bone mineral content
- Arm total mass: Total mass of user’s arm
- Arm fat percentage: Ratio of arm’s fat mass and arm’s total mass

Second, the effects of human tissue on the measurements of human joint angles are estimated using the identified body index. Third, the measurements are corrected by the estimated amount resulting in higher measurement accuracy.

The organization of this paper is as follows. In Section II, the related work and contributions are presented. Section III provides a description of the protocol followed to perform the joint-angle measurements of the arm. Section IV presents a description of the IMU-based mocap system in which the improvement on accuracy is implemented and evaluated.

Quaternions are four-dimensional vectors that can be used to perform rotations in three-dimensional spaces.
experimentally. This improvement and its implementation are explained in Section V. Finally, in Section VI, the experimental evaluation is performed.

II. RELATED WORK

A considerable amount of work has already been devoted to the problem of improving the accuracy of measurements of joint angles of the arm [9], [10], [11], [12], [13]. These mocap systems are based on reflective markers placed on the user's arm and tracked by the infra-red (IR) cameras. The measurements are affected by the skin deformation and displacement which causes marker movement with respect to the underlying bones. The measurements' accuracy is improved by modeling the marker movement with respect to landmark bones as the user performs selected movements. For example, in [9], an algorithm is proposed that compensates for the marker movement. Experimental results on six participants show that the RMSE decreases from 9° to 3° on the upper-arm.

In this paper, we address the same problem but for the case of IMU-based mocap systems.

Previous work on IMU-based mocap systems uses Kalman filters to measure human motion [14], [15], [16]. In [14], an arm-motion experiment was performed on 2 DOFs, but the accuracy of the measurements of the arm movements was not reported. It was only reported that the pitch, yaw, and roll of the IMU was measured with an RMSE of 0.2°, 1.5°, and 0.2° respectively. In [15], the design and testing of a portable magnetic system combined with IMUs was presented. The magnetic system consists of three orthogonal coils attached to the body. Experimental results showed that the orientation of the upper-arm could be measured with an RMSE of 2.3°. In [16], a Kalman-based fusion algorithm removed the effects of drifting error and error in the measurement of gravity. Experiments showed that head movements could be measured with an average RMSE of 3.3°.

Besides Kalman filters, the concept of quaternion [8] has also been widely used to measure human-body motion. In [17], [18], [19], [20], [21], quaternions were used to perform rotations of objects that represent body segments such as the upper-arm and forearm in a three-dimensional (3D) space. An extended Kalman filter for real-time estimation of rigid body orientation was presented in [17]. Experiments were performed by rotating an IMU along each of its three axes. However, the accuracy of the measurements was not reported. In [18], the problem of nonlinear relationship between estimated orientations, represented by quaternions, and expected measurements was addressed with an unscented Kalman filter. The filter was evaluated with the simulation of a random walk, but its accuracy was not reported either. In [19], a quaternion based extended Kalman filter was developed along with a procedure of sensor bias compensation. The objective was to reduce the effects that body motion and magnetic disturbance have on the measurements of the earth's gravity and magnetic fields respectively. Experimental results considered only one IMU whose pitch, yaw, and roll were measured with RMSEs of 1.40°, 4.13°, and 1.31° respectively. In [20], a 3-DOF orientation estimation algorithm was presented. Experimental results showed that the algorithm was able to track rotations of an IMU placed on a precision tilt table, but the accuracy of the measurements was not determined. In [21], a quaternion-based adaptive Kalman filter for drift-free orientation estimation was presented. Experimental results showed that an IMU's pitch and roll were measured with RMSEs of 0.75° and 0.65°.

As is the case with this paper, previous work [22], [23], [5], [24], [25] has focused on upper limbs. In [22], a protocol for measuring single-joint movements of the shoulder and elbow is evaluated. The measurements are found to have an RMSE no greater than 3.6°. In [23], an upper-limb motion estimation algorithm was developed that models the relationship between upper-arm and forearm movements. A link structure with 5 DOFs was proposed to model the upper-limb skeleton structure. Experimental results showed an RMSE of 2.3°, 0.88°, 2.90°, 6.18°, and 13.04° on the 5 DOFs respectively. In [5], the problems caused by noise and drifts in the IMUs and by the properties of human tissue were addressed. The proposed solution is a calibration process and a noise insensitive tracking algorithm. Experimental results on hand movements showed errors of 5°. In [24], a wearable WSN using accelerometers measured the arm motion in the sagittal plane only, and the focus was on flexions at the elbow. Experimental results showed that the standard deviation of the measurement error of the angle at the elbow increases linearly from 2.5° to 7.0° when the angular speed of the flexion increased from 10°/s to 80°/s. In [25], a factorized-quaternion approach for determining arm motions was proposed. It allows the implementation of anatomical arm constraints which match the range of motion of the human arm. Experiments were conducted using a WSN equipped with triaxial accelerometers attached to the arm under dynamical conditions. The standard deviation of the error for the upper-arm and forearm was 9.64° and 14.38° respectively.

Other mocap technologies different from IMUs have been developed as well. To the best of our knowledge, these include IR cameras [26], combination of IR cameras and IMUs [27], combination of ultrasonic sensors and IMUs [28], and optical linear encoders [29]. IR-camera mocap systems are characterized for having high levels of accuracy. Therefore, their measurements can be used as a reference when determining the RMSE of other mocap systems. For example, IR cameras were used with this purpose in [22], [15], [16], [19], [23], and in this paper. For the rest of the related work, the RMSE was measured using other techniques: a high-precision tilt table [14], a goniometer [24], and a commercially available IMU-based mocap system [25]. The method used to measure the RMSE in [21] was not reported.

Prior to this paper, its authors developed an IMU-based mocap system [6]. The focus of the system was on the upper-arm and forearm using 5 DOFs. As in [5], the experimental results showed that the RMSE is dependent on the positions of the arm. The RMSE was greater when the participant reached extreme positions. In the arm position that was most affected, the RMSE increased by 173% under static conditions.

In this paper, the problem of reducing the effects of human tissue properties is addressed under static conditions. The contributions are as follows.
The correlation between each of the eight body indices listed above and the variation of the RMSE is measured experimentally on 15 participants. The body index that correlates the highest is identified. This index is the body fat percentage.

The variation of the RMSE as a function of the arm position is modeled using quaternions. This model is parameterized with the identified body index, i.e., body fat percentage.

Using the parameterized model and the theory of quaternions, an algorithm is developed that reduces the effects that human tissue has on the RMSE. In order to use the algorithm, it is necessary that the body fat percentage be known a priori.

The improvement on the accuracy of the IMU-based mocap system using the proposed algorithm is experimentally evaluated on another 5 participants. The results show that with the algorithm, the RMSE decreases by 44% on average, from an average of 2.18° to an average of 1.23°.

III. PROTOCOL FOR THE MEASUREMENT OF UPPER-LIMB KINEMATICS

Based on the framework for the definition of standardized protocols for measuring upper-limb kinematics in [30], the following aspects specify the protocol followed in this paper.

The joints to be investigated are the shoulder (i.e., rotations of the humerus bone at the glenohumeral rotation centre) and elbow (i.e., movements of the forearm relative to the humerus).

The mechanical equivalent model of the selected joints is based on the recommendation of the International Society of Biomechanics on joint coordinate systems for the reporting of human joint motion [31]. The model consists of angles $\alpha_1$, $\alpha_2$, $\alpha_3$, $\sigma_1$, and $\sigma_2$ as shown in Fig. 1.

Movements of the upper arm relative to the thorax (i.e., at the shoulder joint) can be approximated with three rotations [31] that we represent with $\alpha_1$, $\alpha_2$, and $\alpha_3$ (Fig. 1a). These are rotations of the humerus bone (i.e., upper arm) at the glenohumeral rotation centre (i.e., shoulder joint). The elevation of the humerus as it moves away from and toward the thorax is $\alpha_1$ (i.e., flexion, extension, adduction, and abduction), the internal/external rotation of the humerus is $\alpha_3$.

Movements of the forearm relative to the humerus (i.e., at the elbow joint) can be approximated with two rotations [31]: the flexion and extension at the elbow (Fig. 1b) that we represent with $\sigma_1$, and the axial rotation of the forearm (Fig. 1c) that we represent with $\sigma_2$ (i.e., pronation, supination).

The arm movements to be measured are listed below along with the reference coordinate system which is based on the earth's gravity and magnetic north. The movements are such that only one angle is varied per movement (i.e., while one angle varies, all other angles are kept constant). This is for reducing cross-talk between the joint angle being varied and other joint angles [22].

- Movement 1 ($\alpha_1$): The arm is always kept straight (i.e., elbow fully extended). The arm’s initial position is to point down to the floor ($\alpha_1 = 180^\circ$). The arm moves at the shoulder (i.e., anterior movement of the humerus) along the sagittal plane in order to raise it completely ($\alpha_1$ decreases to $0^\circ$). When the arm is parallel to the floor, $\alpha_1 = 90^\circ$.
- Movement 2 ($\sigma_2$): The arm is always kept straight (i.e., elbow fully extended). The arm’s initial position is to point to the user’s right. The arm moves at the shoulder towards the user’s left along the transverse plane (i.e., transverse flexion of the humerus). When the arm points north, $\sigma_2 = 0^\circ$.
- Movement 3 ($\alpha_3$): The arm is always kept straight (i.e., elbow fully extended), parallel to the floor, and pointing to the user’s front. In the initial position, the user performs an internal rotation of the humerus to its maximum. Then, the user performs an external rotation. When the $Y$ axis of the shoulder sensor is parallel to the floor, $\alpha_3 = 0^\circ$.
- Movement 4 ($\sigma_1$): The upper arm is always kept parallel to the floor and pointing to the user’s front. In the initial position, the elbow is fully extended ($\sigma_1 = 0^\circ$), and then, it is flexed along the sagittal plane. When the forearm points up (Fig. 1b), $\sigma_1 = 90^\circ$.
- Movement 5 ($\sigma_2$): This movement is similar to Movement (Movt.) 3 with the difference that the rotation is performed at the elbow (Fig. 1c), i.e., the forearm is rotated.

The sensor configuration used to measure the joint angles is shown in Fig. 1. The location of the sensors was determined under two considerations. First, each sensor needs to be far from the joint that it measures because it follows arm movements more accurately in this way, and second, the effects of tensing and relaxing muscles and tissue (i.e., skin and fat) on the sensors’ orientation should be minimum. The sensors are attached to the arm with elastic cuffs that are tightened to the comfort of the user.

Finally, the last aspect of the protocol is the refinement that can be applied to the measurements in order to minimize the

\[\text{Movement 1 (}\alpha_1\text{): The arm is always kept straight (i.e., elbow fully extended). The arm’s initial position is to point down to the floor (} \alpha_1 = 180^\circ\text{). The arm moves at the shoulder (i.e., anterior movement of the humerus) along the sagittal plane in order to raise it completely (} \alpha_1 \text{ decreases to } 0^\circ\text{). When the arm is parallel to the floor, } \alpha_1 = 90^\circ\text{.}
\]

\[\text{Movement 2 (} \sigma_2 \text{): The arm is always kept straight (i.e., elbow fully extended). The arm’s initial position is to point to the user’s right. The arm moves at the shoulder towards the user’s left along the transverse plane (i.e., transverse flexion of the humerus). When the arm points north, } \sigma_2 = 0^\circ\text{.}
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\[\text{Movement 3 (} \alpha_3 \text{): The arm is always kept straight (i.e., elbow fully extended), parallel to the floor, and pointing to the user’s front. In the initial position, the user performs an internal rotation of the humerus to its maximum. Then, the user performs an external rotation. When the } Y \text{ axis of the shoulder sensor is parallel to the floor, } \alpha_3 = 0^\circ\text{.}
\]

\[\text{Movement 4 (} \sigma_1 \text{): The upper arm is always kept parallel to the floor and pointing to the user’s front. In the initial position, the elbow is fully extended (} \sigma_1 = 0^\circ\text{), and then, it is flexed along the sagittal plane. When the forearm points up (Fig. 1b), } \sigma_1 = 90^\circ\text{.}
\]

\[\text{Movement 5 (} \sigma_2 \text{): This movement is similar to Movement (Movt.) 3 with the difference that the rotation is performed at the elbow (Fig. 1c), i.e., the forearm is rotated.}
\]
error. This refinement is the main focus of this paper, and it is described in Section V.

IV. MOCAP SYSTEM DESCRIPTION

The mocap system considered in this paper consists of the mechanical model of the limb to be tracked described in Section III, a number of wireless sensors (i.e., one sensor per joint), and a software application that processes the measurement data in order to find the joint angles. The system is shown in Fig. 2 on a skeleton mannequin. Two wireless sensors are placed on each arm. The sensors connect wirelessly to the laptop forming a WSN, and the WSN connects through the Internet to the desktop computer where the joint angles are calculated. We refer to this system as the wireless IMU (WIMU) mocap system. Fig. 2 also shows the IR-camera mocap system that is used to determine the RMSE of the WIMU mocap system.

Each wireless sensor has an IMU, and the total number of sensors depends on the number of joints to be tracked. There needs to be one sensor per joint. This number of sensors is denoted by $M$. A wireless sensor is shown in Fig. 4. The IMU of the sensor is referenced to the 3D coordinate system shown in Fig. 4. The accelerometer and magnetometer measure the earth’s gravity and magnetic fields on the $X$, $Y$, and $Z$ dimensions at a rate $R_s$ that is configurable. We denote the $n$-th measurement of the fields by sensor $i$ with the following vectors.

\[
\vec{g}_i[n] \triangleq (g_{i,x}[n], g_{i,y}[n], g_{i,z}[n]) \\
\vec{m}_i[n] \triangleq (m_{i,x}[n], m_{i,y}[n], m_{i,z}[n])
\]

Each sensor in the network has an identification (ID) and transmits packets to the receiver connected to the laptop computer at a rate $R_t$ that is also configurable. In our experimental evaluation, $R_t$ and $R_s$ are equal. Therefore, each packet carries one sample of each field (i.e., gravity and magnetic) only. A packet also carries the sensor ID, packet length, packet number, and received signal strength indicator (RSSI). The ID is used to identify which sensor has been placed on each joint. The packet length and number are used for debugging, and the RSSI is used to guarantee that the user is close enough to the receiver for the wireless links to be reliable.

The angles are all updated with every packet reception according to the algorithm in Fig. 3. Before executed, the algorithm requires that all sensors be calibrated\(^4\). The input to the algorithm is the last $N$ received measurements $G_i[n]$ and $M_i[n]$ of every sensor as defined below, the ID of the sensor that transmitted the last received packet, and the body index $b$ (i.e., body fat percentage of the user). The output of the algorithm is the current joint angles $\alpha_1[n]$, $\alpha_2[n]$, $\alpha_3[n]$, $\sigma_1[n]$, and $\sigma_2[n]$.

\[
G_i[n] \triangleq (g_{i,x}[n-1], \ldots, g_{i,x}[n-(N-1)]) \\
M_i[n] \triangleq (m_{i,x}[n-1], \ldots, m_{i,x}[n-(N-1)])
\]

The algorithm operates as follows. The sensor that transmitted the received packet is identified first (see lines 2 and 3 in Fig. 3). The measurements performed by this sensor on every dimension are then normalized (see lines 4 and 5) as explained in [6] using the calibration data. Therefore, all coordinates vary in the interval $(-1, 1)$ indicating the alignment of the axis (i.e., $X$, $Y$, and $Z$ in Fig. 4) with the corresponding field. After the normalization, the orientation of the sensor is updated (see line 6). The orientation of sensor $i$ is given by its pitch $o_{i,p}$, yaw $o_{i,y}$, and roll $o_{i,r}$, which are calculated from the normalized gravity and magnetic-field measurements $(g_{i,x}, g_{i,y}, g_{i,z})$ and $(m_{i,x}, m_{i,y}, m_{i,z})$ as explained in [6]. In the algorithm in Fig. 3, the orientation of sensor $i$ is denoted by $\vec{o}_i = (o_{i,p}, o_{i,y}, o_{i,r})$. Once the sensor’s orientation is updated (see line 9), the joint angles are calculated [6] (see lines 10 and 11). However, in order to reduce the effects of human tissue and improve accuracy, the sensors’ orientation are virtually adjusted (see line 12) as explained in Section V. This is done using the user’s body index $b$ and the calculated joint angles because as the experimental analysis of the RMSE in

\footnote{A description of the implementation details of the algorithm and the calibration process can be found in [6].}
Section V-B shows, the RMSE correlates with the joint angles determined in lines 10 and 11 and the body index. With the adjusted orientations, the joint angles are finally recalculated, achieving better accuracy. This improvement in accuracy is evaluated experimentally in Section VI.

V. ACCURACY IMPROVEMENT USING QUATERNIONS

Due to the properties of human tissue, the sensors experience small changes in their orientation at certain arm positions. The accuracy improvement is achieved by virtually reorienting the sensors in order to counteract the effects of human tissue.

As shown in Fig. 4, each sensor has axes X, Y, and Z. Let these axes be represented in the 3D coordinate system formed by the following three orthogonal vectors: the earth’s gravity, the magnetic north, and the cross product between gravity and magnetic north. In this coordinate system, the X, Y, and Z axes of sensor i are represented by unit-length vectors \( \vec{s}_i,X[n] \), \( \vec{s}_i,Y[n] \), and \( \vec{s}_i,Z[n] \) respectively. Given that \( \vec{s}_i,Z[n] \) can be generated from the cross product between \( \vec{s}_i,X[n] \) and \( \vec{s}_i,Y[n] \), only \( \vec{s}_i,X[n] \) and \( \vec{s}_i,Y[n] \) are needed to represent the sensor’s orientation, and the coordinates of \( \vec{s}_i,X[n] \) and \( \vec{s}_i,Y[n] \) can be obtained as follows.

The spherical coordinates of \( \vec{s}_i,X[n] \) can be determined from the sensor’s pitch \( \alpha_{i,p} \) and yaw \( \alpha_{i,y} \):

\[
\vec{s}_i,X[n] = (1, \alpha_{i,p}, \alpha_{i,y}).
\]

The rectangular coordinates of \( \vec{s}_i,Y[n] \) can be determined by considering the plane in which \( \vec{s}_i,Y[n] \) lies when the sensor’s roll varies (i.e., the YZ plane in Fig. 4). Let \( \vec{d}_i = (\vec{s}_i,Y,n, -\vec{s}_i,X,n, 0) \) represent \( \vec{s}_i,Y[n] \) when the roll is zero (i.e., \( \alpha_{i,r} = 0 \)). Also, let the cross product of \( \vec{s}_i,X[n] \) and \( \vec{d}_i \) be \( \vec{c}_i = \vec{s}_i,X[n] \times \vec{d}_i \). Vectors \( \vec{d}_i \) and \( \vec{c}_i \) are orthogonal and lie on the plane. Therefore, \( \vec{s}_i,Y[n] \) can be determined from \( \vec{c}_i \):

\[
\vec{s}_i,Y[n] = \vec{c}_i \cos \alpha_{i,r} + \vec{d}_i \sin \alpha_{i,r}.
\]

A. Adjustment of Sensors’ Orientation using Quaternions

The adjustment of the sensors’ orientation is based on the concept of quaternion and its rotation operation [8]. A quaternion is a four-dimensional vector that can be used to perform rotations on objects in a 3D space.

From observations of the sensors on the arms of participants and the fact that \( \alpha_{i} \) had the smallest RMSE in the experimental results obtained in [6], it was concluded that the orientation of a sensor was mostly affected by the tissue properties on two directions of rotation: when the axes of rotation are X and Y in Fig. 4. In the WSN setup considered in this paper (Fig. 1), the effect on the orientation due to rotations along the Z axis was negligible due to the location of the sensors on the arms and the straps that attach them to the body. Therefore, as shown in Fig. 4 where the axes are vectors \( \vec{s}_i,X[n] \), \( \vec{s}_i,Y[n] \), and \( \vec{s}_i,Z[n] \), the orientation of a sensor is adjusted in those two directions of rotation that are affected:

- Adjustment 1 (Fig. 4a): This is an adjustment of the pitch, i.e., sensor \( i \) is virtually rotated around \( \vec{s}_i,Y \) by \( \theta_{i,1} \) degrees, which is equivalent to a rotation of the sensor’s XZ plane by \( \theta_{i,1} \) degrees. Let quaternion \( \mathbf{a}_{i,1} = \cos \frac{\theta_{i,1}}{2} + \vec{s}_i,Y \sin \frac{\theta_{i,1}}{2} \) represent the adjustment. Then, Adjustment 1 is performed as follows.

\[
\vec{s}'_{i,X} = \mathbf{a}_{i,1} \vec{s}_i,X \mathbf{a}_{i,1}^*.
\]

- Adjustment 2 (Fig. 4b): This is an adjustment of the roll, i.e., sensor \( i \) is virtually rotated around \( \vec{s}_i,X \) by \( \theta_{i,2} \) degrees, which is equivalent to a rotation of the sensor’s YZ plane by \( \theta_{i,2} \) degrees. Let quaternion \( \mathbf{a}_{i,2} = \cos \frac{\theta_{i,2}}{2} + \vec{s}_i,X \sin \frac{\theta_{i,2}}{2} \) represent the adjustment. Then, Adjustment 2 is performed as follows.

\[
\vec{s}'_{i,Y} = \mathbf{a}_{i,2} \vec{s}_i,Y \mathbf{a}_{i,2}^*.
\]

B. Correlation between RMSE and Body Indices

In order to perform the adjustments, it is necessary to have the values of \( \theta_{i,1} \) and \( \theta_{i,2} \) for every sensor in the WSN and every participant. The approach followed to obtain these values consists of 4 steps. In step 1, the values of \( \theta_{i,1} \) and \( \theta_{i,2} \) that made the measurement error equal to zero for 5 different arm movements on 15 different participants were measured.

In step 2, the correlation of \( \theta_{i,1} \) and \( \theta_{i,2} \) with each of the movements and for each of the sensors and participants was calculated; a linear regression of \( \theta_{i,1} \) and \( \theta_{i,2} \) as a function of the arm positions (i.e., joint angles) was also determined for each of the sensors and participants. In step 3, the correlation between the parameters of the regressions (i.e., slope and intersection with the Y axis) of \( \theta_{i,1} \) and \( \theta_{i,2} \) with the different body indices listed in Section I was calculated. Finally, in step 4, the parameters were modeled as functions of the body index using the body index of highest correlation so that they can be estimated for any user whose body index is known a priori.

The 15 participants were of the following characteristics: males, 19 - 23 years old, 1.71 - 1.89 m, and 59.93 - 88.83 kg. They were asked to perform the 5 movements described in Section III.

In order to measure \( \theta_{i,1} \) and \( \theta_{i,2} \) experimentally for step 1, the reference values of \( \vec{s}_{i,X} \) and \( \vec{s}_{i,Y} \) were measured using a Vicon IR-camera mocap system [26], which is a procedure similar to the one performed in [22]. The reflective markers of this system were placed on Vicon plastic plates of square

\[\text{Fig. 4. Adjustment of a Sensor’s Orientation}\]

\[\text{Adjustment 1}\]

\[\text{Adjustment 2}\]

\[\text{Participants were recruited from the undergraduate population of male students following Institutional Review Board for the Protection of Human Subjects approval. All potential participants were notified of all potential risks and benefits to participation and a written informed consent was obtained.}\]
shape. Each plate had 4 markers at the corners of the square. Two plates were used, which were attached to the upper-arm and forearm respectively. Also, the Vicon mocap system was calibrated using a digital compass and a level such that its coordinate system matched the coordinate system of the WIMU mocap system. This coordinate system is based on the earth’s gravity and magnetic north as explained previously.

For each movement, the participant was asked to take the arm to the movement’s initial position and then move the arm in the direction of the final position by an average of 7°. Measurements were taken at every 7°. The measurements were finished once the user reached the final position. For every measurement, the plates with reflective markers were adjusted manually to realign them with the humerus and radius bones. This was done by locating the bones manually and reorienting the marker plates so that two parallel sides of each plate were also parallel to their corresponding bones, i.e., humerus and radius. The attached sensors were adjusted in the same way, but only once. This was done prior to the measurements with the participant standing straight and with the arm at rest. Therefore, the shifts in orientation of IMUs with respect to the marker plates were measured at every arm position. For each measurement, the values of \( \hat{s}_{i,X} \) and \( \hat{s}_{i,Y} \) were obtained from both mocap systems: Vicon and WIMU. In the following, these are denoted by \( \vec{v}_{i,X} \) and \( \vec{v}_{i,Y} \) for Vicon and \( \hat{s}_{i,X} \) and \( \hat{s}_{i,Y} \) for WIMU. Therefore, \( \theta_{i,1} \) and \( \theta_{i,2} \) were determined according to

\[
\theta_{i,1} = \cos^{-1} \left( \frac{\vec{v}_{i,Y} \cdot \vec{v}_{i,Y}}{|\vec{v}_{i,Y}|^{2}} \right),
\]

\[
\theta_{i,2} = \cos^{-1} \left( \frac{\vec{s}_{i,X} \cdot \vec{s}_{i,X}}{|\vec{s}_{i,X}|^{2}} \right).
\]

In order to perform the measurements with the WIMU mocap system, the system was configured with the same parameter values given in [6]. These parameters are shown in Table I.

**Remark.** It should be noted that the previous procedure to measure \( \theta_{i,1} \) and \( \theta_{i,2} \) is susceptible to the following errors. First, \( \theta_{i,1} \) and \( \theta_{i,2} \) are based on the difference in orientation of the sensors and marker plates, not on the difference in orientation of the sensors and bones. The orientation of the bones is estimated with the IR-camera mocap system and marker plates which are realigned with the bones at every arm position in order to minimize the effects that human tissue has on the plates’ orientation [7], [9], [10], [11], [12], [13]. Second, the coordinate system of the IR-camera mocap system is referenced to the earth’s gravity and magnetic north with a level and digital compass respectively. Therefore, all measurements of vectors \( \vec{v}_{i,X} \) and \( \vec{v}_{i,Y} \) directly depend on the use and accuracy of these instruments. Finally, all measurements of vectors \( \hat{s}_{i,X} \) and \( \hat{s}_{i,Y} \) depend on the calibration of the WIMU mocap system described in [6].

Fig. 5 shows the measured values of \( \theta_{i,1} \) and \( \theta_{i,2} \) for 2 different participants and the adjustments selected in Table II. These are the participants of lowest and highest body fat percentage (i.e., 13.5% and 24.0%). The results show that \( \theta_{i,1} \) and \( \theta_{i,2} \) tend to vary linearly with the arm position. Therefore, at the extreme positions (i.e., initial and final positions of every movement), the orientation of the sensors is affected the most. This result is in accordance with the experimental results of [6] which show that when the user performs the greatest effort to achieve an arm position, the accuracy of the measurements of the human-joint angles is the lowest.

For step 2, the correlation coefficient of the linear regression of \( \theta_{i,1} \) and \( \theta_{i,2} \) as a function of the arm positions was calculated for all 15 participants, 5 movements, 2 sensors, and 2 adjustments (i.e., \( 15 \times 5 \times 2 \times 2 = 300 \) linear regressions). In order to find the general trend, the averages of the correlation coefficients among all participants were calculated (i.e., \( \frac{300}{15} \times 20 = 20 \) averages of correlation coefficients). These are shown in Table II. The results show that the 5 adjustments highlighted in Table II have a linear behavior. The highlighted adjustments include \( \theta_{1,1} \) and \( \theta_{2,1} \) in Movt. 1, \( \theta_{2,2} \) in Movt. 3, and \( \theta_{1,2} \) and \( \theta_{2,2} \) in Movt. 5. From now on, we refer to these 5 adjustments as the selected adjustments.

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For step 3, the parameters of the linear regressions of the selected adjustments (i.e., slope and intersection with the Y axis) are estimated from one of the body indices listed in Section I. This body index is identified from the correlation between the following two variables: the slope of the linear regressions of the selected adjustments and the body indices.

The 8 body indices were obtained using dual energy X-
Ray absorptiometry (DXA) (Fig. 6) which uses a 3-component model for estimation of lean mass, fat mass, and bone mineral. All body composition scans and analyses were performed by the same experienced and licensed Radiologic Technician using a densitometer (Hologic Discovery; Waltham, MA; USA). DXA is cheaper and more accessible than clinical reference techniques such as magnetic resonance imaging and computed-tomography. In addition, DXA is also more common and less reliant on subject compliance than other laboratory methods such as hydrometry and underwater weighing; furthermore, it provides for better precision than common field methods such as skin folds and electrical impedance [32].

Table III shows the correlation coefficients between the slope of the linear regression of each selected adjustment and each body index. The columns of Table III correspond to the selected adjustments, and the rows correspond to the body indices. The rows are in descending order such that the body index of strongest average correlation (i.e., body fat percentage) is listed first. Also, for each selected adjustment, the body index of highest correlation is highlighted. The results show that body fat percentage correlates the most for the first 4 selected adjustments, and it correlates almost equally to the body lean mass for the last selected adjustment, which is the body index of highest correlation in this case. Therefore, we selected body fat percentage to estimate the parameters of the linear model, i.e., slope and Y-axis intersection, of each of the selected adjustments for any person. For example, in the worst case scenario (i.e., \( \theta_{2,2} \) in Movt. 3), for every point increase in body fat percentage, the error’s magnitude increases by an extra 0.765° for every 1° the arm moves.

Fig. 5 shows how the slope of the linear regression changes when the body fat percentage changes from 13.5% to 24.0%. For the participant of higher body fat percentage (i.e., 24.0%), the magnitude of the error increases at a faster rate as the arm moves from the initial to final position. This trend is confirmed by the correlation coefficients in Table III. The error tends to change linearly with the arm positions, and the rate of change (i.e., the slope of the linear regression) is correlated with the body fat percentage as given in Table III.

Fig. 7 shows the linear regression of the rates of change of the selected adjustments as functions of the body fat percentage. The results show graphically that the magnitude of the rate of change of the selected adjustments increases with body fat percentage. Therefore, for people of higher body fat percentage, the necessary adjustments will be of larger magnitude in order to virtually reorient the sensors and improve the accuracy. This improvement is verified experimentally in the following section.

Finally, for step 4, the parameters of the linear models of the selected adjustments (i.e., slope and intersection with the Y axis) are determined from the linear regressions of step 3 (i.e., Fig. 7). This can be done for any user whose characteristics are similar to those of the 15 participants considered previously, i.e., males, 19 - 23 years old, 1.71 - 1.89 m, 59.93 - 88.83 kg. Remark. Table III shows that body fat percentage was found to be superior to arm-only indices (i.e., arm fat mass, arm lean mass, arm total mass, and arm fat percentage). The following reasons can be identified for this finding. First, it has been shown that DXA measurements of whole-body composition are more accurate than DXA measurements of regional-body composition [33]. Regional assessments in absorptiometry represent more recent additions to these machine capabilities. Second, body fat distribution and tissue variations might also play a role in sensors’ orientation. Adipose tissue occurs in two major categories: visceral or that which is in-between and covers deep internal organs and subcutaneous or the fat deposited underneath the skin and on top of underlying organs [34]. Subcutaneous fat, comprising the majority of total fat in the arms and legs is separated into two separate layers distinct in anatomy, location, and metabolic activity.
Table III also shows that the orientation of the sensor attached to the wrist is correlated to the body fat percentage. The following reason can be identified for this finding. Soft tissue elements, while proportionately decreased between the upper arm and forearm, comprise the vast majority of overall mass of both segments. Specifically, cadaveric dissection has revealed that skin and adipose tissue alone comprise a third of the overall mass of the forearm [38]. This value has further been shown to be almost identical to the proportion of skin and adipose tissue found in whole-body investigations [39], which also supports the finding that body fat percentage was the greatest indicator of adjustments. However, the notable contribution of skin, which was not directly assessed in the present study, might also play a significant role in the change of sensor orientation seen at the wrist. Regional differences in elastic properties of skin have been documented previously [40], [41] using non-invasive instrumentation with positioning similarities to the sensors in the present study. Perhaps more importantly, net elasticity of forearm skin could be higher than in the upper arm [40], a finding that could be a factor in the observed change in orientation of the sensor at the wrist. Furthermore, net elasticity as measured, is purported to be a strong indicator of solid, static components of the skin as it excludes viscous pull of extracellular fluid matrix components of the skin [40]. Future research could look at elucidating the differential effects of skin, adipose, and muscle elements on IMU precision.

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**VI. EXPERIMENTAL EVALUATION**

Two experimental comparisons were performed in order to quantify the improvement in accuracy of the proposed approach of estimating the values of the selected adjustments from the body fat percentage of the user. The two comparisons were done on 5 different participants of characteristics similar to those of the previous 15 participants. The first is a comparison of the estimated and actual selected adjustments, i.e., the adjustment estimated from the body fat percentage of the participant was compared with the adjustment measured on the participant with the procedure explained in Section V-B. The second is the comparison of the RMSE of measured joint angles with and without the estimated selected adjustments.

Fig. 8 shows the comparison of the estimated and actual selected adjustments for one of the 5 participants whose body fat percentage was 17.7%. The results show that the estimated adjustments follow the actual adjustments closely. The actual adjustments decrease with the arm positions around the estimated adjustments which vary linearly. The results of all estimated adjustments on the accuracy of the measurements of human joint angles on the 5 participants are summarized in Table IV. For Movt. 1, adjustments $\theta_{1,1}$ and $\theta_{3,1}$ decreased the RMSE of $\alpha_1$, $\alpha_2$, and $\sigma_2$ by 1.33°, 0.76°, and 1.19° on average respectively. These correspond to improvements of 60%, 36%, and 49% respectively. For Movt. 3, adjustment $\theta_{2,2}$ decreased the RMSE of $\sigma_2$ by 0.27° on average. This is an improvement of 16%, and for Movt. 5, adjustments $\theta_{1,2}$ and $\theta_{2,2}$ decreased the RMSE of $\sigma_3$ and $\sigma_2$ by 0.72° and 1.38° on average respectively. These correspond to improvements of 36% and 51%. The average RMSE reduction across all cases listed in Table IV is 0.95°, which is an improvement of 44%.

**VII. CONCLUSION AND FUTURE WORK**

An algorithm for wireless sensor networks was developed that improves the accuracy of measurements of joint angles of the human body. The focus was on measurements at the shoulder and elbow with 3 and 2 DOFs respectively. Its principle of operation is based on the virtual adjustment on the alignment of the sensors with the different body segments (i.e., upper arm and forearm) being tracked with the earth’s gravity and magnetic fields. The virtual adjustment is based on estimating the necessary rotations to reorient the sensors. This estimation is calculated from the user’s body fat percentage. This body index was found to have the highest correlation with the rate of change of the necessary rotations. A total of 8 body indices were considered in a group of 15 participants.
The indices are the body’s and arm’s total mass, fat mass, lean mass, fat percentage. Experimental results on another group of 5 participants of characteristics similar to those of the former group of 15 showed that the proposed algorithm improved the accuracy of the measurements of human joint angles. In the DOF whose error decreased the most, the RMSE decreased from 2.20° to 0.87°. This is an improvement of 60%, and in the DOF whose error decreased the least, the RMSE decreased from 1.64° to 1.37°. This is an improvement of 16%. On average, the RMSE improved by 44%.

Future research could look at elucidating the differential effects of skin, adipose, and muscle elements on IMU precision. Also, the problem of developing a more complete model that considers more than one body index (i.e., body fat percentage) should be addressed. This model can be developed using Multivariate Regression Analysis, in which the inputs to the model should consider several indices such as body fat percentage and skin elasticity and the outputs would include the adjustments on the orientation of the sensors. The impact on the practicality of the model should be addressed. This analysis requires an overview of the different instruments available for the measurement of the indices and a comparison of their accuracy, accessibility, and long-term side effects. Finally, the problem of extending the adjustments on sensors’ orientation to movements and participants not considered in this study should be addressed. The movements considered in this study limit the joint angles to be varied one at a time in order to minimize cross-talk between angle measurements.

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