Gait & Posture 49 (2016) 47–53

Contents lists available at ScienceDirect

Gait & Posture

journal homepage: www.elsevier.com/locate/gaitpost

Full length article

The feasibility of shoulder motion tracking during activities of daily living using inertial measurement units

Bryan Kirking[a,*], Mahmoud El-Gohary[b], Young Kwon[c]

[a] DJO Surgical, 9800 Metric Blvd., Austin, TX 78758, United States
[b] APDM, Inc., 2828 Southwest Corbett Ave, Portland, OR 97201, United States
[c] NYU School of Medicine, 333 E. 38th Street, New York, NY 10016, United States

ARTICLE INFO

Article history:
Received 18 January 2016
Received in revised form 6 May 2016
Accepted 8 June 2016

Keywords:
Shoulder
Motion
Angle
Kinematics
ADL

ABSTRACT

Measurements of shoulder kinematics during activities of daily living (ADL) can be used to evaluate patient function before and after treatment and help define device testing conditions. The purpose of this study was to demonstrate the feasibility of using wearable inertial measurement units (IMUs) to track shoulder joint angles while performing actual ADLs outside of laboratory simulations. IMU data of 5 subjects with normal shoulders was collected for 4 h at the subjects' workplace and up to 4 h off-work. An Unscented Kalman Filter (UKF) enhanced with gyroscope bias modeling and zero velocity updates demonstrated an accuracy of about 2° and was used to estimate relative upper arm angles from the IMU data. The overall averaged 95th percentile angles were: flexion 128.8°, abduction 128.4°, and external rotation 69.5°. These peaks angles are similar to other investigator's reports using laboratory simulations of ADLs measured with optical and electromagnetic technologies. Additionally, with a Fourier transform the 50th percentile frequency was determined and used to extrapolate the typical number of arm cycles in a 10 year period to be 649,000. Application of the UKF with the additional drift correction made substantial improvements in shoulder tracking performance and this feasibility data suggests that IMUs with the UKF are suitable for extended use outside of laboratory settings. The data provides a novel description of arm motion during ADLs including an estimate for the 10 year cycle count of upper arm motion.

1. Introduction

Due to the technical challenges of making 3D measurements, kinematic descriptions of three dimensional arm motion have been limited to laboratory studies. Studies such as those by Magermans [1] Andel [2], and Maier [3] used electromagnetic and stereophotogramatic systems to measure motion for simulated tasks such as hair combing, hand to back pocket, washing, and reaching above the shoulder. Inertial measurement units (IMUs) are sensors that contain combinations of gyroscope, accelerometer, and magnetometer technologies. The capabilities of these sensors have increased to where they appear suitable to use for joint biomechanics measurements. The purpose of this study was to demonstrate their feasibility to track three dimensional upper arm motion of usual activities in native environments. Such in-situ data can be used to characterize shoulder kinematics during activities of daily living (ADLs), help characterize how laboratory simulated activities compare with more general daily motion, and provide information for clinical evaluation of shoulders and their treatment.

El-Gohary et al. [4], presented an unscented Kalman filter (UKF) to estimate shoulder and elbow joint angles with a Root Mean Square (RMS) angle error of <8°. In this study, we modified that filter with random drift modeling of the sensor, natural range of motion constraints, and zero-velocity updates. We then used IMUs to collect measurements from subjects for up to 4 h of work and 4 h of recreational activities and present the distribution of arm angles. Finally, we estimate a representative frequency of motion and extrapolate the number of cycles performed by the upper arm for a 10-year period.

2. Methods

In this section, we describe the algorithms to track shoulder motion using IMUs attached to the sternum and upper arm of the

* Corresponding author.
E-mail addresses: Bryan.kirking@djoglobal.com (B. Kirking), mahmoud@apdm.com (M. El-Gohary), Young.Kwon@nyumc.org (Y. Kwon).

http://dx.doi.org/10.1016/j.gaitpost.2016.06.008
0966-6362/

Table 1
Robot maximum speed and range of motion used during evaluation of the tracker, and baseline and modified tracker root mean square errors.

Joint motion	Max rate (°/s)	Max range of motion (°)	Baseline tracker (°)	Modified tracker (°)
Shoulder internal/external	450	−180, +180	8.1	3.0
Shoulder flexion/extension	450	−160, +65	2.4	1.6
Elbow flexion/extension	514	−51, +225	2.6	2.0
Forearm supination/pronation	553	−200, +200	2.1	1.2
Wrist flexion/extension	553	−135, +135	2.2	1.5
Wrist twist	720	−360, +360	3.9	2.8

subject. We then describe the three different methods employed to mitigate the effect of sensor random drift. Finally we describe the protocol for attaching the IMUs and collecting upper arm motion during activities of daily living.

2.1. Algorithms

To describe angles and motions of an arm segment relative to its neighboring segments, we use a method of modeling based on a sequence of links connected by joints often used with robotic manipulators [5]. In our algorithm, we combine kinematic models of the trunk and arm with state space methods to estimate the joint angles. The trunk is modeled with three degrees of freedom (DOFs), and is connected to the arm with the shoulder joint also having three DOFs. This method does not represent the actual anatomy with the scapula and clavicle and the resulting angles are humeral – thoracic and not humeral – scapular.

We use the Newton-Euler equation of motions to recursively propagate the velocity and acceleration through the kinematic chain to create the measurement model. The process model represents the joint angles to be estimated as a function of the velocity and acceleration measured by the inertial sensors. The process and measurement models are then used with the unscented Kalman filter to estimate angles. Contrary to previous studies, our algorithm utilizes the rotational, translational and gravitational components of acceleration [4] but ignores magnetometer readings

2.2. Modeling sensor random drift

To reduce the random drift, we model the bias of the sensors. The 3D gyroscope bias and 3D accelerometer bias are modeled as random walk with zero-mean white noise. For more details on the state and observation equation used with the UKF, the reader is advised to refer to the description in El-Gohary and McNames [6].

2.3. Anatomical constraints in the shoulder and elbow

The state model equations incorporate prior knowledge of physical constraints on state estimates. Human shoulder internal and external rotation around the humerus rarely exceeds $\pm 90^\circ$. Similarly, the shoulder cannot attain more than 180° of abduction or flexion [7]. In this study, the constraint information is incorporated in the UKF during the time update step.

2.4. Zero-velocity updates

Only shoulder motions greater than 10 s were used to estimate angles. Since our algorithm uses gravity to estimate attitude, these estimates helped reduce the effect of gyroscope random drift on estimates of flexion/extension and abduction/adduction angles. However, the measurements lack an absolute reference for heading about the vertical axis. Therefore, we used an error correction technique known as zero-velocity updates, which has been used in gait analysis and pedestrian navigation [8]. When the rotational rate around the vertical axis was less than 3°/s for at least 0.25 s, the arm was considered static and the measurement equation is augmented with a pseudo-measurement of gyroscope vertical axis random bias. Putting pseudo-measurements into the UKF, provides additional benefits, such as estimates of the gyroscope bias.

2.5. Accuracy assessment

To evaluate the inertial tracking system, we compared the joint angles from the tracker with an industrial C3 robot arm (Epson Robots, California). The robot arm has 6° of freedom, with three segments attached to the robot stationary base: shoulder, elbow and wrist. The robotic arm was programmed to produce human-like motion, which involved rotation of the three joints at an average rotational rate range of 225–360°/s. Table 1 shows the arm range of motion and maximum operating speed. Three Opal sensors (APDM, Portland, OR), each containing triaxial accelerometers, magnetometers, and gyroscopes were placed on the robot segments to monitor motion for 15 min. The average root mean squared error (RMSE) between the angles was then calculated.

2.6. Activities of daily living assessment

A nonrandom sample of 5 subjects with normal shoulders was selected partly based on occupation. Subjects were volunteers from the local community and provided informed consent. The occupations were: dental hygienist, primary school teacher, mechanical engineer, administrative assistant, and retail associate. Subjects wore the OPAL IMUs (Fig. 1) for 4 h while at their workplace performing their normal activities and then for 4 h off-work. The IMUs were secured with a strap and two sided tape. The

Fig. 1. Placement of inertial measurement units on subject's manubrium and upper arm.