Determining Inertial Measurement Unit Placement for Estimating Human Trunk Sway while Standing, Walking and Running*

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Abstract—Inertial measurement units (IMU) are often used to estimate medial-lateral (M/L) trunk sway for assessing and treating gait disorders, and IMU sensor placement is an important factor effecting estimation accuracy. This study tracked multi-segment spine movements during standing and ambulation tasks to determine optimal IMU placement. Ten young healthy subjects, wearing markers placed along the spine, left/right acromion, and left/right posterior superior iliac spine performed standing and walking trials in a motion capture laboratory. Results showed that movement at the spine location T7-T8 most closely matched the clinical definition of M/L trunk sway for standing trials (0.5 deg error) and at the spine location T9-T10 for walking trials (1.0 deg error), while movement at the lower spine L2-L4 tended to be the least accurate for standing and ambulation tasks (1.5 deg error and 4.0 deg error, respectively). Based on these results, a second study was performed to develop and validate a trunk sway estimation algorithm during walking trials with a single optimally-placed IMU. IMU trunk sway estimation was compared to the clinical definition of trunk sway from motion capture markers and showed root-mean-square errors of 2.5 deg and peak trunk sway errors of 2.0 deg. The results of this study suggest that IMUs should be placed on the mid-back to reduce errors associated with spine movements not matching clinically-defined M/L trunk motion.

I. INTRODUCTION

Accurate trunk sway estimation is critical for assessing gait abnormalities in persons with vestibular loss, Parkinson’s disease and spastic diplegia [1]–[3]. Inertial measurement units (IMU) are commonly used to estimate trunk angles during standing and ambulatory tasks [4]–[8], and sensor fusion algorithms such as the complementary filter and Kalman filter have been shown to improve estimation accuracy [5]–[8].

Sensor placement is also critical to trunk sensing accuracy particularly when attempting to estimate overall multi-segment trunk kinematics with a single IMU as is commonly done in clinical applications. The clinical definition of trunk sway is typically defined by the deviation from vertical of a line between the seventh cervical vertebrae (C7) and the midpoint between left and right posterior superior iliac spines (PSIS) [9]. However, while optical motion capture systems can directly estimate these anatomical landmark positions, IMUs estimate angular displacement at a specific position. Because the trunk is flexible and multi-segmented [10]–[12], IMU placement along the trunk can have a significant impact on trunk sway estimation accuracy. However, currently the relationship between spine movement and the clinical definition of trunk sway is not well understood.

Thus, the purpose of this work was to study segmented spine movements during standing and ambulation tasks to determine which segments most closely follow a clinical definition of overall mediolateral (M/L) trunk sway. Based on these results, a second study was performed in which a single IMU was optimally placed on the trunk and a trunk sway estimation algorithm was developed and validated during walking trials for varying degrees of M/L trunk sway.

II. OPTIMAL IMU PLACEMENT

A. Subject Testing

Ten healthy subjects (age: 25.4±2.9 years, all male) participated in this study after giving informed consent in accordance with the Declaration of Helsinki. Subjects wore 14 reflective markers, and a VICON motion capture system (OML, Oxford, U.K.) was used to record marker trajectories. Markers were attached at C7, left and right acromion, left...
and right PSIS. Then nine markers were evenly placed from the midpoint of the left and right PSIS (S2) to the C7 marker, such that there were ten small vectors defined based on pairs of adjacent markers (Fig.1, left).

Subjects performed barefoot standing trials under the following conditions:

- eyes closed, Romberg (stand erect with feet together, hands by the sides), on a ramp (20° angle) with toes up
- eyes closed, Romberg, on a foam surface
- eyes closed, semi-tandem Romberg (partial heel-to-toe), on a foam surface
- eyes closed, tandem Romberg (heel-to-toe), on a firm surface

Each trial lasted 30 seconds and was performed three times. All subjects were required to keep the right foot forward for all semi-tandem Romberg and tandem Romberg trials. Subjects then performed walking trials on a treadmill (Bertec, OH, U.S.) while wearing their own walking shoes under the following conditions:

- walking (1.2 m/s) with:
  a) normal trunk sway
  b) slightly increased trunk sway
  c) significantly increased trunk sway
- walking (1.6 m/s) with normal trunk sway
- running (2.4 m/s) with normal trunk sway
- tandem walking at a self-selected speed

The subjects were required to bend their waists in M/L plane as they can to induce significantly increased trunk sway, and half of it to induce slightly increased trunk sway.

Each trial was performed one time and all trials lasted two minutes. Before each trial, subjects stood/walked/ran on the treadmill to become familiar with the required gait speed and walking condition for 30 seconds or longer as requested. Subjects rested for 30 seconds between each trial or longer as requested.

The root-mean-square error (RMSE) of the M/L sway angle was calculated to evaluate the errors between the clinically defined trunk vector (from S2 to C7) and each of 10 spine vectors. Matlab (MathWorks, MA, U.S.) was used to perform analysis of variance (ANOVA) to detect a difference among the results of 10 spine vectors, and Games-Howell analysis was used for post-hoc between position analysis.

B. Results

RMSE for the M/L sway angle computed from the 10 spine vectors and the trunk vector are shown in Fig. 2 for all standing trials. In standing trials, the 4th vector showed the minimum RMSE 0.54±0.47°, which corresponded to the T7-T8 level. There were no statistical significant differences between the 2nd to the 6th vectors (p>0.05), which corresponded to the T3-T12 level.

The results for all walking trials were showed in Fig. 3. In walking trials, the 5th vector showed the minimum RMSE 1.02±0.57°, which corresponded to the T9-T10 level. There were no statistical significant differences between the 4nd to the 6th vectors (p>0.05), which corresponded to the T7-T12 level.

III. TRUNK SWAY IMU ESTIMATION

A. Trunk Sway Sensor Fusion Algorithm

An IMU sensor fusion algorithm was developed to estimate M/L trunk sway during gait. An absolute reference frame, R0, was formed such that X0 was horizontal, pointing in the direction of forward progression and Z0 pointed vertically. The sensor frame Rs was attached to the sensor and the axes coincided with R0 before each trial began.
Acceleration measured on a body segment has two components, a gravity component, and a motion component. Subjects were required to stand up-right quietly for 10 seconds at the beginning of each trial to isolate the gravity component by eliminating motion. The gravity vector relative to the sensor was equal to the average acceleration value during the first 10 seconds of quiet standing, \( \mathbf{a}(0) \). This original trunk angle was then expressed as the quaternion, \( Q \):

\[
\theta_1 = \cos^{-1}(\mathbf{a}(0) \cdot -\mathbf{Z}0) \\
V_1 = \mathbf{a}(0) \times -\mathbf{Z}0 \\
Q = [\cos(\frac{\theta_1}{2}), \sin(\frac{\theta_1}{2}) \times \frac{V_1}{||V_1||}] 
\]

where \( \bullet \) and \( \times \) denote dot- and cross-products, respectively. \( \mathbf{Z}0 \) is the vertical axis of \( \mathbf{R}_0 \). \( \theta_1 \) is the rotation angle from \( \mathbf{R}_s \) to \( \mathbf{R}_0 \) rotated about the \( V_1 \) axis.

All sensor data was calibrated using \( Q \). When the sensor rotated, a rotation matrix rotated from calibrated magnetometer data \( \mathbf{m}(t) \) to \( \mathbf{m}(0) \) could be expressed as a quaternion \( \mathbf{q}(t) \). \( \mathbf{m}(0) \) was the average magnetometer vector over the first 10 seconds and \( \mathbf{m}(t) \) was the magnetometer vector at time \( t \). As the angle between the magnetic north and the gravity is fixed, the gravity vector \( \mathbf{g}(t) \) was calculated as follows:

\[
\theta(t) = \cos^{-1}(\frac{\mathbf{m}(t) \cdot \mathbf{m}(0)}{||\mathbf{m}(t)|| ||\mathbf{m}(0)||}) \\
V(t) = \mathbf{m}(t) \times \mathbf{m}(0) \\
q(t) = [\cos(\frac{\theta(t)}{2}), \sin(\frac{\theta(t)}{2}) \times \frac{V(t)}{||V(t)||}] \\
g(t) = q(t) \otimes \mathbf{g}(0) \otimes q^{-1}(t) 
\]

where \( \otimes \) denotes the product operator associated with quaternions. \( \theta \) is the angle between \( \mathbf{m}(t) \) to \( \mathbf{m}(0) \), rotated about the \( V \) axis.

A Kalman filter was then used to estimate the M/L tilt \( \phi \) and its drift \( d\phi \). The state vector \( \mathbf{X} \) was computed from \( \phi \) and \( d\phi \), while the observation vector \( \mathbf{Z} \) contained \( \phi_g \) determined from the gravity vector, \( \mathbf{g}(t) \):

\[
\phi_g(t) = \sin^{-1}(\frac{g_y(t)}{\cos(sin^{-1}(g_z(t))}) 
\]

where \( g(t) \) was scaled by 9.81 m/s².

The transition and observation equation were as follows:

\[
\mathbf{X}_t = [\begin{bmatrix} 0 & -T \end{bmatrix} \begin{bmatrix} \phi & T \end{bmatrix} \begin{bmatrix} 0 & T \\
0 & 0 \end{bmatrix} * g_{yo} \]

\[
\mathbf{Z}_t = [\begin{bmatrix} 0 & 1 \end{bmatrix} \begin{bmatrix} \phi & 0 \end{bmatrix} \begin{bmatrix} 0 & 0 \end{bmatrix} ] 
\]

where \( T \) is the sample rate and \( g_{yo} \) is the angular velocity of the x-axis measured from the gyroscope.

Given the initial state estimation with its associated variance, the tilt angle was calculated by the prediction and update formulas of the Kalman filter [15].

B. Subject Testing

A custom wearable sensor device, composed of a wireless microprocessor unit, 3-axis accelerometer, 3-axis gyroscope and 3-axis magnetometer (Fig. 4) was used to test the trunk sway algorithm accuracy.

![Fig. 4. Wearable sensor, size: 23.4mm × 21.5mm × 11.3mm (width × length × height) and weight 8.5g.](image)

The same ten subjects from the previous experiment participated in this experiment. Markers were attached at C7, left and right acromion, and left and right PSIS, and a sensor, with a T-shaped plastic bar (T-bar) taped on top, was taped at the middle of the 5th spine vector (T9-T10) based on findings from the first study (Fig. 1, right).

Subjects performed walking trials on a treadmill (Bertec, OH, U.S.) under the following conditions:

- walking (1.2 m/s) with:
  - a) normal trunk sway
  - b) slightly increased trunk sway
  - c) significantly increased trunk sway

Each trial lasted two minutes and was performed once. Before each trial, subjects walked on the treadmill to become familiar with the required walk speed and walking condition for 30 seconds or longer as requested. Subjects rested for 30 seconds or longer between each trial as requested.

Trunk error (RMSE and peak trunk angle on each step) was computed as the difference between the sensor calculation and VICON motion capture calculation (angle between a vertical line and a line between S2) to evaluate the accuracy of the sensor fusion algorithm in estimating M/L trunk sway.

C. Results

Error results are shown in Table 1. For all walking trials, the RMSE was 2.50±1.30°. The mean±SD of errors in peak trunk sway for walking normally, slightly increased trunk sway and significantly increased trunk sway were 0.45±0.70°, 2.48±1.51° and 3.31±2.15°, respectively. For all trials, the average peak trunk sway error was 2.07±1.98°.

IV. DISCUSSION

The aim of this study was to determine the optimal IMU placement for estimating human trunk sway while standing, walking and running. The first experiment studied segmented
spine movements during standing and ambulatory tasks to determine the segments which most closely followed the clinical definitions of overall trunk sway. Based on the results from the first study, a second experiment was performed to validate a trunk sway estimation algorithm for estimating M/L sway angle during walking.

For all standing trials (Fig.2), there were no statistical differences (p > 0.05) from the 2nd spine vector to the 6th spine vector (T3-T12), while the 4th spine vector (T7-T8) had the lowest numerical error value. This result seems reasonable given that subjects didn’t need to bend their trunk significantly to keep balance during standing tests. For walking trials (Fig.3), the 4th to the 6th spine vectors (T7-T12) were not statistically different (p > 0.05), and the 5th spine vector (T9-T10) had the lowest numerical error value. The result was different from the standing trials as trunk movement was more pronounced during walking and running.

In the second experiment, RMSE increased as trunk sway angles increased. Normal walking trials had the smallest error 1.37±0.42°, while the significantly trunk sway trials had the largest error 3.73±1.27°. The average peak trunk sway for walking normally, slightly increased trunk sway and significantly increased trunk sway were 1.44±0.64°, 5.63±2.00° and 10.72±3.89°. Increased peak trunk sway likely led to increased trunk sway error. Two factors were used to validate the accuracy of algorithm, the RMSE of all gaits over all subjects was 2.50±1.30°, and the error of peak trunk sway was 2.07±1.98°.

These findings could also inform standing balance studies for characterizing and treating postural disorders like vestibular loss [13], [14]. Accurate IMU placement could enable more accurate trunk sway estimation. A potential limitation is that the amount of trunk sway was not precisely controlled. Future work could use real-time feedback to train consistent slightly increased and significantly increased trunk sway angles.

In conclusion, the results of this study would suggest that a single IMU be placed at the T7-T8 location for standing tasks and T9-T10 for ambulation tasks for optimal estimation of human trunk sway. The sensor fusion algorithm may be appropriate for trunk sway applications that can tolerate estimation errors of 2-3°.

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**REFERENCES**


