Body Sensor Networks to Evaluate Standing Balance: Interpreting Muscular Activities Based on Inertial Sensors

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ABSTRACT

In this paper, we present a system that integrates inertial sensors and electromyogram (EMG) signals, which measures the muscular activities while performing motions. The objective of our study is to investigate the behaviour of the EMG signals to interpret the activity of standing balance. Quantitative parameters for balance are obtained from an inertial sensor through a body-sensor network. These parameters are further used to find the prominent features in the EMG signal. The inertial sensor used in this system is an accelerometer. The implementation details and effectiveness of using EMG signals are also provided.

Categories and Subject Descriptors

J.3 [**LIFE AND MEDICAL SCIENCES**]: Health

General Terms

Algorithms, Experimentation, Human Factors

Keywords

Balance, Inertial Sensors, EMG

1. INTRODUCTION

Balance evaluation finds applications in rehabilitation, sports medicine, gait analysis and fall detection. Inertial sensor based systems have been in use for such applications. As in other physiological activities, standing involves the prominent use of muscles. EMG signals have been the most effective source for measuring muscle activity. In this paper, we investigate how parameters for balance obtained from inertial sensors correlate with that of measurements from EMG signals.

We obtain the balance parameters mentioned in [1] from experiments conducted on different normal human subjects and classify each of the parameters as ‘low’, ‘medium’ and ‘high’. We find out if features measured from EMG signals can also be classified based on their correlation with the balance parameters. Linear Discriminant Analysis (LDA) is used for this purpose. Section 2 of this paper describes how the balance parameters are obtained from the accelerometer values. Section 3 provides the architecture of the system. The signal processing involved in the system to obtain this correlation is described in Section 4. Section 5 describes how the experiments were conducted. Analysis and interpretation of the experimental results including LDA are provided in Section 6.

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2. EVALUATION MODEL

We use the balance evaluation model described in [1] to derive performance metrics for standing balance. The system uses a single accelerometer placed at the approximate height of the centre of mass on the subject’s back. All three acceleration components are combined to build a vector and the path traced by this vector is recorded.

The calculation of the coordinates of the path traced, as depicted in Figure 1, is as follows: if a_x, a_y, a_z are accelerations in each direction, and g is acceleration of gravity, the combined accelerations, A is given by

$$A = \sqrt{a_x^2 + a_y^2 + a_z^2} \tag{1}$$

The directional angles between A and X, Y, Z are represented by,

$$\alpha = \cos^{-1}\frac{a_x}{A}, \beta = \cos^{-1}\frac{a_y}{A}, \varepsilon = \cos^{-1}\frac{a_z}{A} \tag{2}$$

From Figure 1,

$$\cos\varepsilon = -\frac{d_z}{D} \tag{3}$$

where D is the combined coordinates in the three directions, x, y and z and d_z represents the z coordinate of the end of A (distance to the ground from the sensor), which is assumed to be a constant. Hence the coordinates of A at floor level (d_x, d_y) can be expressed as:

$$d_x = D\cos\alpha, d_y = D\cos\beta \quad (4)$$

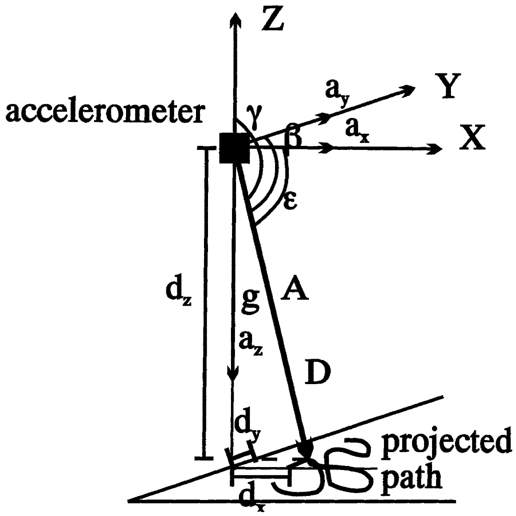

Figure 1. Obtaining the projected path.
Figure adopted from [1].

From this traced path, we can obtain the parameters used for evaluation. They are provided in Table 1.

Table 1. Five Quantitative Features

No.	Quantitative Feature
1	Mean Speed
2	Mean Radius
3	Mean Frequency
4	Anterior/Posterior Displacement (A/P)
5	Medial/Lateral Displacement (M/L)

Mean Speed, Mean Radius, Mean Frequency, A/P displacement and M/L displacement can be calculated. These parameters in combination give the measure of balance. The calculation of these parameters depicted in Figure 2 is as follows:

If the Total Distance covered in time t, is given by,

$$D_t = \sum_{n=startpoint}^{endpoint} \sqrt{(d_{y_n} - d_{y_{n+1}})^2 + (d_{x_n} - d_{x_{n+1}})^2} \quad (5)$$

then Mean Speed can be expressed as,

$$s_m = \frac{D_t}{t} \quad (6)$$

Mean Radius is given by,

$$r_m = \frac{1}{N} \sum_{n=startpoint}^{endpoint} \sqrt{{d_{x_n}}^2 + {d_{y_n}}^2} \quad (7)$$

where N is the number of points in the traced path.

Mean Frequency can be expressed as,

$$f_m = \frac{D_t}{2\pi r_m t} \quad (8)$$

A/P and M/L displacements are respectively given by,

$$d_{a/p} = \max_{\forall n}(d_{x_n}) - \min_{\forall n}(d_{x_n}) \quad (9)$$

$$d_{m/l} = \max_{\forall n}(d_{y_n}) - \min_{\forall n}(d_{y_n}). \quad (10)$$

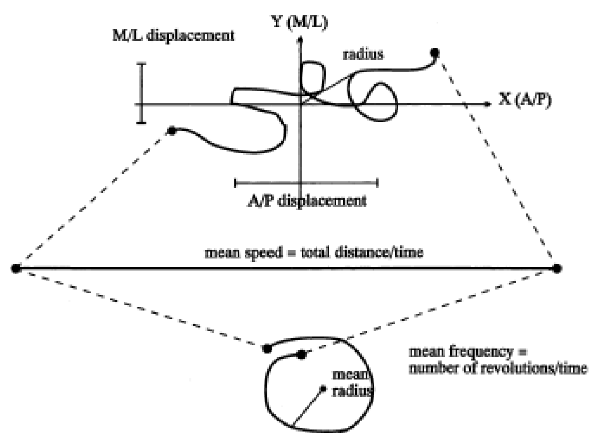

Figure 2. Extraction of features from the projected path Figure adopted from [1].

3. SYSTEM ARCHITECTURE

The system consists of two subsystems operating in parallel - the inertial sensor subsystem and EMG sensor subsystem. The inertial sensor subsystem is a body-sensor network of two nodes. One node is on the body of the subject and the other is connected to a desktop PC. Accelerometer values are transmitted to the node connected to the PC by the node on the body.

3.1 Inertial Sensor Subsystem

Our inertial sensor subsystem is a body sensor network consisting two sensor nodes (Moteiv Tmote Sky). The node placed on the body has custom-designed sensor board with a tri-axial 2g accelerometer as shown in Figure 3. It samples the sensor at 40Hz and sends data over a wireless channel to a base station. The base station is another mote that relays the information to a PC via USB port. The sensor readings are collected and processed in MATLAB.

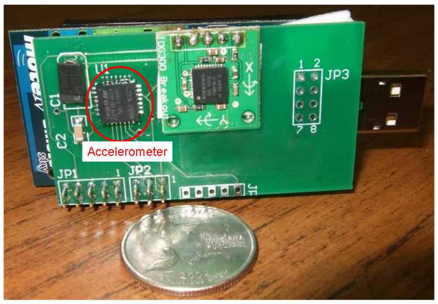

Figure 3. Mote with inertial sensors

3.2 EMG Sensor Subsystem

We use several EMG sensors to measure the electric activity generated during muscle contractions that occur while performing the motions. In the EMG suit we use (Delsys Myomonitor III), shown in Figure 4, the EMG signals are acquired using surface electrodes attached at the skin surfaces. Each electrode measures the electric flow in the associated muscles.

Figure 4. EMG system suit

The electrodes sample muscle signals in 1000Hz. The signals are amplified and band-pass filtered (20-450Hz) by the EMG suit. The data are transferred to a PC for offline processing.

3.3 Balance Platform

We use a balance ball as the platform for assessing the quality of standing balance. The platform is a "Both Sides Up" (BOSU) Balance Trainer which provides an unstable balance surface. This device has two functional surfaces integrating dynamic balance with functional or sports specific training. It can be used platform side up for push-up and seated exercises. We use this configuration which provides an unstable surface when subjects stand on the platform. Figure 5 shows the platform along with an experimental subject wearing motion and EMG sensors. We integrate a HUSKY Digital Level to control the experiment and for coaching purposes (i.e. the subject must tilt the ball 20 degree in an anterior direction). The digital level indicates the amount of inclination when swaying on the platform.

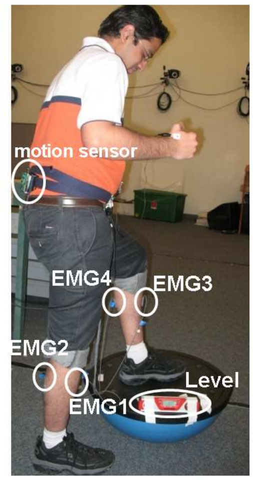

Figure 5. Balance platform and experimental subject wearing motion and EMG sensors

4. SIGNAL PROCESSING FOR FEATURE ANALYSIS

Signal Processing involves extracting parameters from the accelerometer and EMG signals, classifying the accelerometer parameters and analysis using LDA. These operations are divided into five stages as explained below.

Data Collection: Accelerometer values and EMG signals are continuously recorded for every trial for duration of 4 seconds. The sampling rates of the accelerometer and EMG signals are different. Data from accelerometer is sampled at 40Hz and that from the EMG sensors at 1000Hz.

Parameter Extraction: Five quantitative features are measured using accelerometer data as described in Table 1 of Section 2.

Quantization: For each quantitative feature obtained from the accelerometer values, the data obtained is divided into three classes-'low', 'medium' and 'high'. The set of values of a particular feature that is greater than the sum of the mean of the feature and standard deviation is categorized as 'high'. The set of values less than the difference between the mean and standard deviation is categorized as 'low' and the rest of the values as 'medium'.

Feature Extraction on EMG: To interpret the behavior of the EMG signals depending on the classes defined from accelerometer values, we need to have exhaustive set of EMG features. An exhaustive set of statistical features are extracted from each EMG signal such as S*ignal Energy*, *Maximum Peak*, *Number of Peaks*, *Average Peak Value*, and *Average Peak Rate*.

Feature Analysis: Significant features for EMG signals are extracted using Linear Discriminant Analysis (LDA). Given the quantitative metrics measured from the accelerometer, the purpose of feature analysis is to find out if the EMG signals are representative of the quantitative features for balance evaluation.

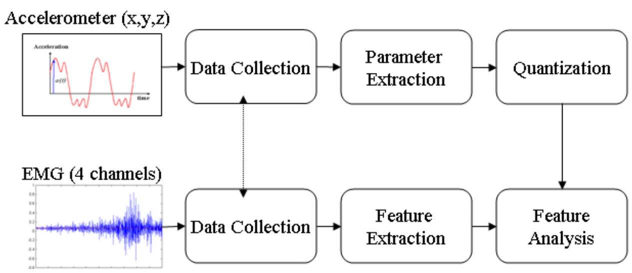

Figure 6. Signal processing flow

5. EXPERIMENTAL PROCEDURE

Experiments were conducted on five male subjects aged between 25 and 32 and height between 1.65m and 1.8m with no previous history of disorders. Subjects with corrected vision wore their glasses. Normal footwear was used for all subjects.

Table 2. Test conditions

Label	Description
S00	Quiet standing with tilt limited to less than 10 degree on either side
L10	Tilt the ball to the left. Limit the angle of tilt between 10 degree and 20 degree
L20	Tilt the ball to the left. Limit the angle of tilt to at least 20 degree
R10	Tilt the ball to the right. Limit the angle of tilt between 10 degree and 20 degree
R20	Tilt the ball to the right. Limit the angle of tilt to at least 20 degree
F10	Tilt the ball forward. Limit the angle of tilt between 10 degree and 20 degree
F20	Tilt the ball forward. Limit the angle of tilt to at least 20 degree
B10	Tilt the ball backwards. Limit the angle of tilt between 10 degree and 20 degree
B20	Tilt the ball backwards. Limit the angle of tilt to at least 20 degree

A sensor node with a tri-axial accelerometer was attached to a belt which was worn around the waist of the subject. The belt was worn such that the sensor node was positioned on the lower back of the subject. This node communicated with another node connected to the USB port of a desktop computer. A MATLAB tool was developed to read the data from mote connected to the USB and process it.

Although a number of muscles can be potentially active during and action, currently, we constrain our system in using only four EMG electrodes on lower leg muscles. The EMG sensors were placed on Right-Front leg (Tibialis Anterior muscle), Right-Back leg (Gastrocnemius muscle), Left-Front leg (Tibialis Anterior muscle), and Left-Back leg (Gastrocnemius muscle). The Delsys "Trigger Module" enabled the EMG subsystem to work synchronously with accelerometer. MATLAB behaved as a main controller that sends a trigger to EMG and accelerometer to start acquisitions through the trigger module (for EMG) and USB (for accelerometer).

The process of data collection was controlled and managed using our MATLAB tool. The EMG signals are obtained synchronously with the accelerometer signals. The data, however, are separately processed for the EMG and accelerometer.

The accelerometer and EMG data was recorded for 4 seconds for nine test conditions per subject. The test conditions are given in Table 2. Two trials for each condition were conducted for every subject. The angle of the tilt was measured from the level mounted on the balance platform.

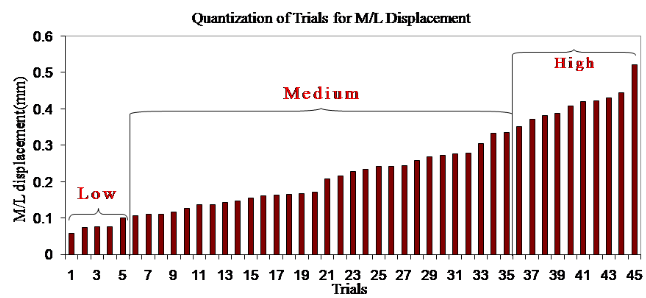

Figure 7. M/L displacement measured from acceleration data and quantized into three classes

For every trial, the projection of the centre of mass (COM) on the ground was obtained using the expressions we outlined earlier. From the projections, five quantitative features were extracted. These features, listed in Table 1, are the features described in [2]. The calculation of these features from the projected COM is shown in Figure 2. For each feature, the data obtained is divided into three regions as we described in Section 4.

EMG data was recorded for each trial. For each trial four channels of EMG data are obtained with each channel corresponding to a particular muscle. The data obtained from each channel was passed through a low-pass filter with a cut-off of 35Hz. From this filtered data, a set of statistical features were extracted as was describer earlier in Section 4.

6. EXPERIMENTAL RESULTS

In this section, we present our results on evaluation of standing balance using the performance metrics. The accelerometer data was obtained for ninety trials across five subjects as described previously. The three dimensional acceleration data was used to find projection of the center of mass on the plane. The five acceleration performance parameters were calculated based on the methods stated earlier. For each parameter, the ninety trials were mapped into three classes representing quality of observed action in terms of that given parameter. We subjectively quantized every trial into quality level 'low', 'medium' and 'high'. For example, with respect to the value of A/P displacement, measured for each trial, we assign a class label based on its magnitude. This process is done for every accelerometer parameter obtained in each trial. Each EMG feature set is given the same quality label as its corresponding accelerometer signal. The label assignment is accomplished because the accelerometer and EMG signals are available for the same duration of the trial.

Figure 7 shows a sample distribution of performance parameters across different trials. The values were obtained for M/L displacement and were sorted for quantization. The statistical approach explained before was used to find thresholds on each metric.

Table 2. Significant EMG features describing different performance metrics

Performance Metric	Significant Features
Low Speed	Maximum Amplitude (EMG2)
Medium Speed	Number of Peaks (EMG3)
High Speed	Maximum Amplitude (EMG2)
Low Radius	Number of Peaks (EMG4)
Medium Radius	Maximum Amplitude (EMG2)
High Radius	Number of Peaks (EMG4)
Low Frequency	Number of Peaks (EMG2)
Medium Frequency	Energy (EMG2)
High Frequency	Maximum Amplitude (EMG1)
Low A/P	Number of Peaks (EMG2)
Medium A/P	Number of Peaks (EMG2)
High A/P	Maximum Amplitude (EMG2)
Low M/L	Number of Peaks (EMG2)
Medium M/L	Average Peak Rate (EMG4)
High M/L	Maximum Amplitude (EMG2)

The next step in our system is to make EMG signals representative of performance parameters for balance evaluation. To achieve this, we determine those features from EMG signals that are prominent for each class. We used 50% of the input trials (training set) to find significant features for EMG and remaining trials (test set) for evaluation of the system. Each EMG trial consists of four signals corresponding to the four muscles. We extracted five features (Signal Energy, Maximum Peak, Number of Peaks, Average Peak Value, and Average Peak Rate) for each EMG signal. These features form a 20 dimensional space which represent some properties of muscle activities during the performed action. The obtained features are fed to our feature analysis box (shown in Figure 6) where only the most prominent feature is selected. The feature analysis was performed for each performance parameter. LDA is then used to select the most prominent feature from the subset. The list of prominent features is listed in Table 3.

To get insight into the effectiveness of the acquired EMG features, we used k-NN (k-Nearest Neighbor) classifier due to its simplicity and scalability. For each accelerometer parameter class, the corresponding significant feature (extracted from Table 3) was extracted. This feature was used in a binary classifier to differentiate between a certain quality levels from the rest. For example, to evaluate how accurate EMG sensors represent performance metric Low A/P, corresponding prominent feature (Number of Peaks by EMG2) was extracted and fed to the k-NN classifier to distinguish between Low A/P and other two levels of A/P displacement (Medium A/P and High A/P). The outcome of the classification for three values of k is illustrated in Figure 8 for a random set of classes.

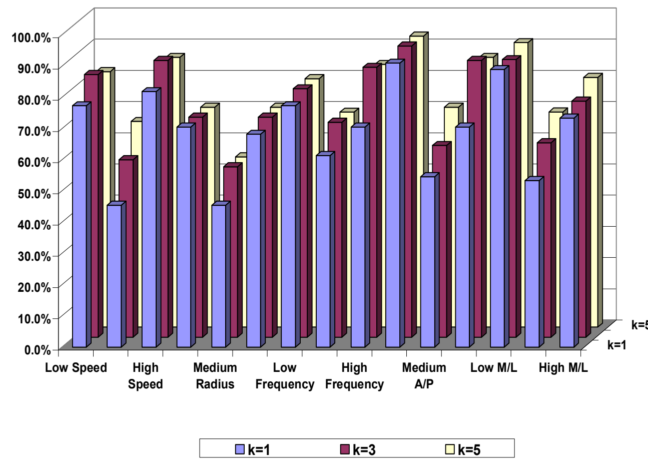

Figure 8. Classification accuracy for standing balance with respect to only EMG signals

7. RELATED WORK

Human performance in terms of quality of balance control system has been studied from different views each taking into account a certain model and its own evaluation metrics. Cybulski et al. [2] in their study of standing performance of paraplegia affected subjects, deduced and used statistical parameters from a center-of-force monitoring platform. Few authors have used accelerometer to measure the parameters used in [2] and study balance and control [3], [4] and [5]. Kamen et al. [3] used two uni-axial accelerometers, one each on the forehead and back. Mayagoitia et al. [1] used a single tri-axial accelerometer placed on the back at approximate height of the center of mass to evaluate standing balance. Maithe et al. [6] used this evaluation model to classify basic daily movements. Other authors ([7] and [8]) have concentrated on providing audio and/or visual feedback on the model parameters presented in [1] to improve balance. Winter et al. [9] present a kinematic model of upper body balance where EMG sensors were obtained to reinforce the conclusions from the moment of force analyses. A study on comparison of EMG and kinetic parameters during balance responses in children was presented by Sundermier et al. [10]. According to their results, the correspondence of muscle activity with measurements of center-of-pressure confirms that muscle activities contribute to the balance. In this paper, however, we investigate methods of learning from inertial sensors to interpret EMG signals for standing balance. To the best of our knowledge, this has not been studied before.

8. CONCLUSION AND FUTURE WORK

We introduced a physiological monitoring system that collects acceleration and muscle activity signals and performs analysis on those signals during standing balance action. The system quantifies performance in terms of five metrics which can be directly measured from accelerometer data. For the EMG signals, however, the quality of performed action is represented using a set of prominent features obtained after processing the EMG signals in conjunction with the accelerometer parameters. To provide a complete evaluation of the system, we plan to investigate methods of integrating a gold standard balance system with our experiments. We are also working on the deployment of our data processing techniques in real-time.

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