A Body Sensor Network With Electromyogram and Inertial Sensors: Multimodal Interpretation of Muscular Activities

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Abstract—The evaluation of the postural control system (PCS) has applications in rehabilitation, sports medicine, gait analysis, fall detection, and diagnosis of many diseases associated with a reduction in balance ability. Standing involves significant muscle use to maintain balance, making standing balance a good indicator of the health of the PCS. Inertial sensor systems have been used to quantify standing balance by assessing displacement of the center of mass, resulting in several standardized measures. Electromyogram (EMG) sensors directly measure the muscle control signals. Despite strong evidence of the potential of muscle activity for balance evaluation, less study has been done on extracting unique features from EMG data that express balance abnormalities. In this paper, we present machine learning and statistical techniques to extract parameters from EMG sensors placed on the tibialis anterior and gastrocnemius muscles, which show a strong correlation to the standard parameters extracted from accelerometer data. This novel interpretation of the neuromuscular system provides a unique method of assessing human balance based on EMG signals. In order to verify the effectiveness of the introduced features in measuring postural sway, we conduct several classification tests that operate on the EMG features and predict significance of different balance measures.

Index Terms—Accelerometer, body sensor networks, electromyogram (EMG), standing balance.

I. INTRODUCTION

H UMAN balance evaluation has many biomedical applications. Balance is maintained by the postural control system (PCS) that uses sensor input from the eyes, the proprioceptive system (body position awareness), and the vestibular system to evaluate the body's position and correct imbalance by sending corrective signals to muscles. PCS function can decrease because of problems in the sensory or disorders affecting the control system in the basal ganglia. Neuro-degenerative disorders such as Alzheimer's, Parkinson's, and Huntington's diseases often lead to a breakdown of PCS, while sports injuries can affect the sensor systems [1]. This results in increased postural sway [2] and can lead to falls [3] and decreased performance.

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The assessment of the PCS can aid in identifying the early detection of disease in children and fall detection in elderly population [4]. It also helps in gait analysis by finding shifts in the balance pattern [5]. Sports medicine is another area where postural stability testing helps in functional training and provides a useful tool for evaluating neurologic function following a sports-related concussion [6].

Balance evaluation involves assessment of relevant vestibular and neuromuscular system functions where the performance is quantified in terms of strength, range of motion, coordination and balance, mobility and risk of falls. Conventional methods of balance evaluation include clinical tests administered by trained therapists [7], assessment using force plates or other traditional sensory devices [8], and the use of on-body sensors such as inertial sensors [9]. Several clinical tests already exist but require the expertise of physicians. Force plates have been widely used in the past to investigate performance parameters of postural system by analyzing the time trajectory of center of pressure (COP) of the subject's feet in horizontal plan. Body sensor networks (BSNs) have become more promising in biomedicine, as they provide continuous monitoring with early detection, ambulatory monitoring, supervised rehabilitation and cost effective alternative of healthcare [10].

Multiple performance metrics are proposed that significantly describe the function of postural system during standing balance. Mostly, people with balance difficulties have greater sway velocity and greater anteroposterior (A/P) displacement during quiet standing [3], [11]. Such factors are commonly determined by means of either force plates [8] or inertial sensors [9]. With advancements in sensor technology, it is more feasible to use lightweight motion sensors such as accelerometers for balance evaluation [12]. In this case, certain parameters are extracted from movements of center of mass (COM) or COP. Despite the effectiveness of inertial information in detecting some abnormalities, other physiological signals may be required to monitor other diseases caused by reduction in balance abilities. Electromyogram (EMG) signals produce significant responses to changes in the PCS. In some applications, EMG sensors suffice to detect balance abnormalities. For example, the fall monitoring study in [13] discovers that parameters extracted from movements of COP poorly contribute to fall prediction, while measurements of muscular activities are the best factors to predict falls. In other applications such as pathophysiology of ataxia, EMG data are complementarily used with inertial information to monitor abnormal balance control [14]. Therefore, in

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addition to body sway, balance control is related to various muscle activities and their changing patterns. However, the absence of a set of standardized parameters for expressing the operation of the postural control system in terms of changes in muscle contraction system makes balance assessment challenging. In an effort to understand relationship between traditional performance metrics and muscular activities, we investigate how parameters obtained from inertial sensors correlate with that of EMG signal measurements. We obtain the balance parameters mentioned in [9] from experiments conducted on different healthy subjects and classify each parameter as *low, medium,* and *high*. We then find out if features measured from EMG signals can also be classified based on their correlation with the balance parameters.

In this paper, we make the following contributions: 1) we present a BSN platform for multimodal expression of postural stability using inertial and electromyogram sensors. The platform has potential for continuous and remote monitoring of the PCS; 2) we develop statistical learning algorithms that extract relevant information from EMG signals and identify appropriate features that interpret functions of muscle contraction during standing; and 3) we introduce a subject-independent classification model that uses the prominent EMG features and measures quality of PCS by assigning a standing movement to one of several predefined balance categories.

II. RELATED WORK

Human gait analysis is an important application of balance assessment. Gait analysis has been widely studied by researchers in different domains such as wireless sensor networks and computer vision. In [5], Moe-Nilssen et al. introduce an accelerometer-based system to measure linear acceleration of upper body in a horizontal-vertical coordinate during gait. Presentation of this instrument is motivated by the fact that parameters related to the movements of the COM are known as outcome measures of quire or perturbed balance. Helbostad and Moe-Nilssen [15] investigate the effect of gait speed on lateral balance control using inertial sensors. Sarkar et al. [16] introduce a video-based system for subject identification. Their statistical model, in particular, examines the impact of five covariates, namely camera angle, shoe type, grass or concrete surface, carrying of not carrying a briefcase, and time, on performance of the recognition system. Another vision-based gait recognition technique is proposed by Liu and Sarkar [17]. They use an HMMbased approach to build a unique dynamics-normalization model of walking patterns. Linear discriminant analysis (LDA) is further used to maximize intersubject silhouette distances and to suppress intrasubject stance shapes.

Human performance in terms of quality of the balance control system has been studied from different views, each taking into account a certain model with specific evaluation metrics. Cybulski and Jaeger [18], in their study of standing performance of paraplegia affected subjects, deduce and use statistical parameters from a center-of-force monitoring platform. Few authors have used accelerometer to measure the parameters used in [18] and study balance and control. Kamen *et al.* [2] use two uniaxial accelerometers on the forehead and back to measure characteristics of postural sway. They perform analysis based on amplitude and frequency of accelerometer data. Their results show that the system can discriminate among balance tasks and can differentiate between people with normal balance and those with tendency toward frequent falls. Mayagoitia et al. [9] use a single triaxial accelerometer placed on the back at approximate height of the center of mass to evaluate standing balance. Chiari et al. [19] present a system that measures trunk kinematic information using an accelerometer and provides acoustic feedback for balance improvement. The audio signals map anterior/posterior and medial/lateral accelerations into stereo sounds modulated in frequency, level and left/right balance. In [20], Wall and Weinberg employ inertial sensors to design a prosthesis improving postural stability for those elderly prone to falls. The system provides feedback to the subject via an array of tactile vibrators. In [21], Bonnet et al. mount a sensor suit of accelerometer and magnetometer on the subject's trunk to estimate the 3-D orientation of the trunk for balance assessment. They illustrate existence of several balance-related performance parameters by analyzing measured angles. Asseldonk et al. [22] study the effect of external and internal forces on standing balance. They measure kinematic reactions of a subject to sudden forward and backward movements while standing on two force plates.

Several techniques for evaluating balance control in terms of muscular activities are presented in literature. Winter et al. [23] 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 is presented by Sundermier et al. [24]. According to their results, the correspondence of muscle activity with measurements of COP confirms that muscle activities contribute to the balance. Another study by Jeong et al. [25] stresses the effectiveness of lower body muscular activities in classifying several perturbations affecting postural balance. They use a waist pulling system to generate horizontal classes of perturbations in five directions. A neural network classifier is then used to classify EMG signals into the five categories. In [26], Fraser et al. investigate the effect of balance status on muscle activities. In their study, individuals with different balance capabilities perform two task including treadmill walking and semantic judgment simultaneously. The results demonstrate increase in muscle activity of those subjects with poor balance during dual task. Laughton et al. [27] study relationship between muscle activity and postural sway during standing. For each traditional measure of postural sway obtain from force platform, they determine corresponding EMG parameters using stepwise regression techniques.

Most techniques addressed earlier derive evaluation information regarding balance control system using either inertial or EMG sensors. This paper is motivated by the fact that although sensor readings acquired from accelerometers provide a substantial indication of balance stability, interpretation of EMG signals with respect to these parameters can bring these sensors into a more structural way of evaluating balance based on muscular activities [12]. Therefore, we investigate methods of learning from inertial sensors to interpret EMG signals for



Fig. 1. Calculation of coordinates at ground level using an accelerometer placed on center of mass.

standing balance. To the best of our knowledge, this has not been studied previously by other researchers.

III. EVALUATION MODEL

We use the balance evaluation model described in [9] to derive performance metrics for standing balance. The system uses a single accelerometer placed at the approximate height of the COM 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 Fig. 1, is as follows: let a_x, a_y , and a_z denote accelerations in each direction, and g denote acceleration of gravity, the combined accelerations, A is given by

$$A = \sqrt{a_x^2 + a_y^2 + a_z^2}.$$
 (1)

The directional angles between A and each of X, Y, and Z coordinates are denotes by α , β , and γ , respectively. From Fig. 1, the term $\cos \gamma$ can be written as

$$\cos\gamma = -\frac{d_z}{D} \tag{2}$$

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). In this paper, we assume that the distance d_z is constant across all the subjects. In reality, however, it may vary from one person to another. Given the value of D, the coordinates of A at floor level (d_x, d_y) can be expressed as in (3) and (4)

$$d_x = D\cos\alpha \tag{3}$$

$$d_y = D\cos\beta. \tag{4}$$

From this interpretation, five performance parameters including *mean speed*, *mean radius*, *mean frequency*, A/P *displacement*, and M/L *displacement* can be calculated. These features in combination or individually give the measure of balance stability [3], [11].



Fig. 2. Sensor node with custom-designed inertial sensor board. Sensor board has a triaxial accelerometer and a biaxial gyroscope.

The total distance covered in time t is denoted by D_t and is given by

$$D_t = \sum_{i=0}^{N-1} \sqrt{(d_{y_i} - d_{y_{i+1}})^2 + (d_{x_i} - d_{x_{i+1}})^2}$$
(5)

where N denotes the total number of data points in the traced path in time t. Then the parameter *mean speed* can be represented as

$$s_m = \frac{D_t}{t} \tag{6}$$

and mean radius is given by

$$r_m = \frac{1}{N} \sum_{i=0}^{N-1} \sqrt{d_{x_i}^2 + d_{y_i}^2}.$$
 (7)

The parameter mean frequency can be expressed as

$$f_m = \frac{D_t}{2\pi r_m t} \tag{8}$$

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

$$d_{A/P} = \max(d_{x_i}) - \min(d_{x_i}) \tag{9}$$

$$d_{\rm M/L} = \max(d_{y_i}) - \min(d_{y_i}).$$
(10)

IV. 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 BSN of two nodes. One node is placed 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.

A. Inertial Sensor Subsystem

Our inertial sensor subsystem is a BSN consisting two sensor nodes. Basic platform for each node is a TelosB mote [28], which is commercially available from XBow. The node placed on the body has a custom-designed sensor board, shown in Fig. 2, with the triaxial LIS3LV02DQ accelerometer that has a sensitivity of 1024 LSb/g and is used in 2 g mode for our experiments. The node samples the sensor at 40 Hz and sends data over a wireless channel to a base station. The sampling rate is experimentally chosen to provide sufficient resolution of human motion data while compensating for bandwidth constraints on our sensor platform. The base station is another mote that relays the



Fig. 3. EMG system suit used for collecting muscle activity data.

information to a PC via USB port. The sensor readings are collected and processed in MATLAB.

B. EMG Sensor Subsystem

EMG sensors measure/record the electric activity generated during muscle contractions that occur while performing the motions. EMG sensors are in the form of Ag–Cl surface electrodes (as shown in Fig. 3) provided by Delsys, and each of these electrodes is directly attached on the skin of the human participant to collect an associated muscular activity. The effective sampling rate for human muscular activity is 1000 Hz. The acquired EMG signals from the surface electrodes are amplified and bandpass filtered (20–450 Hz) by the EMG suit. Data are transferred from EMG surface electrodes to a workstation in real time for further postprocessing and analyzing using Myomonitor III (provided by Delsys).

C. 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. Fig. 4 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 (e.g., the subject must tilt the ball 20° in an anterior direction). The digital level indicates the amount of inclination when swaying on the platform.

As mentioned previously, our system is composed of two major subsystems for simultaneous acquisition of inertial and EMG data. These systems are perfectly synchronized through a software module that functions on the base station. Practically, accelerometer and EMG sensors can be integrated within a single BSN platform for data collection and information processing. This feature is enabled by body-worn mote-based sensor platforms that accommodate multiple sensors. The focus of this paper is on development of effective signal processing techniques that establish applicability of EMG data for human balance eval-



Fig. 4. Balance platform and experimental subject wearing motion and EMG sensors.



Fig. 5. Signal processing flow for accelerometer and EMG sensors.

uation. For this reason, we use off-the-shelf components such as TelosB motes and Myomonitor III in this paper. This facilitates the prototyping and algorithm development. However, we are working on developing a unified multimodal BSN architecture that integrates both accelerometer and EMG sensors within the same platform.

V. METHODS

A. Signal Processing for Feature Analysis

Signal Processing involves extracting parameters from the accelerometer and EMG signals, classifying the accelerometer parameters and determining relationship between performance measures and muscle activities using stepwise linear feature extraction methods. These operations are divided into four stages for each one of the inertial and EMG subsystems as explained in the following and shown in Fig. 5.

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

Preprocessing on inertial data: Data are passed through a moving average filter to cancel high frequency noise. We determine the size of the moving window empirically as a compromise between noise reduction and step response [29]. In our system, a five-point window suffices to reduce the noise while retains sharp step response.

Preprocessing on EMG: For each trial, EMG data are normalized to the mean value of the entire trial. Data are then

TABLE I 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) |

TABLE II EMG Features

| Symbol | Name | Symbol | Name |
|----------|-----------------|----------|-----------------|
| F_1 | Signal Energy | F_{15} | Var. Peak Amp. |
| F_2 | Mean RMS | F_{16} | Med. Peak Amp. |
| F_3 | Activation Rate | F_{17} | Mean Peak Width |
| F_4 | Number of Peaks | F_{18} | Max. Peak Width |
| F_5 | Mean Peak Rate | F_{19} | Min. Peak Width |
| F_6 | Max. Peak Rate | F_{20} | Std. Peak Width |
| F_7 | Min. Peak Rate | F_{21} | Var. Peak Width |
| F_8 | Std. Peak Rate | F_{22} | Med. Peak Width |
| F_9 | Var. Peak Rate | F_{23} | Mean Peak Slope |
| F_{10} | Med. Peak Rate | F_{24} | Max. Peak Slope |
| F_{11} | Mean Peak Amp. | F_{25} | Min. Peak Slope |
| F_{12} | Max Peak Amp. | F_{26} | Std. Peak Slope |
| F_{13} | Min. Peak Amp. | F_{27} | Var. Peak Slope |
| F_{14} | Std. Peak Amp. | F_{28} | Med. Peak Slope |

low-pass filtered at 35 Hz using a Butterworth filter. Such filter has been shown to be effective for analysis of electrical activity of muscles [30].

Parameter extraction: Five quantitative features are measured using accelerometer data as described in Table I.

Quantization: For each quantitative feature obtained from the accelerometer values, the data obtained are 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 (see Table II).

Feature analysis: Significant features for EMG signals are extracted using forward stepwise discriminant analysis (FSDA) [31]. 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.

B. Experimental Procedure

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

A sensor node with a triaxial 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 was programmed to communicate with another node connected to the USB port of a

TABLE III Test Movements

| No. | Description | Tilt Angle (α) |
|-----|----------------------------|-------------------------|
| 1 | Quiet standing | $0 \le lpha < 10$ |
| 2 | Tilt the ball to the left | $10 \le \alpha < 20$ |
| 3 | Tilt the ball to the left | $\alpha \ge 20$ |
| 4 | Tilt the ball to the right | $10 \le \alpha < 20$ |
| 5 | Tilt the ball to the right | $\alpha \ge 20$ |
| 6 | Tilt the ball forward | $10 \le \alpha < 20$ |
| 7 | Tilt the ball forward | $\alpha \ge 20$ |
| 8 | Tilt the ball backwards | $10 \le \alpha < 20$ |
| 9 | Tilt the ball backwards | $\alpha \ge 20$ |

desktop computer. A MATLAB tool was developed to read and process the data from mote connected to the USB.

Although a number of muscles can be potentially active during an action, in this paper, we constrained 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 to send a trigger to EMG and accelerometer in order to start acquisitions through the trigger module (for EMG) and USB (for accelerometer).

The "trigger module" is a National Instrument USB-6501 Digital I/O device that can be connected to a computer or PDA via USB. As the data acquisition system transmits EMG data to the base station, the module communicates with the base station and detects start and stop times of data collection. The module outputs the start/stop times which can be further used by inertial subsystem to synchronize itself with the Myomonitor. This allows the EMG subsystem to function as primary component that controls the start and stop of a secondary data acquisition system. In our system, the controller in MATLAB operates at the base station and communicates with both EMG and accelerometer sensors for the purpose of synchronization.

The process of data collection was controlled and managed using our MATLAB tool. The EMG signals were obtained synchronously with the accelerometer signals. The data, however, were separately processed for the EMG and accelerometer. The accelerometer and EMG data were recorded for 4 s for nine test conditions per subject. The test conditions are given in Table III. 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.

For every trial, the projection of the COM on the ground was obtained using the expression we outlined earlier. From the projections, five quantitative features, shown in Table I and described in [18], were extracted. The calculation of these features from the projected COM is described in Section III. For each feature, the data obtained were divided into three regions as we described in Section V-A.

EMG data were recorded for each trial. For each trial, four channels of EMG data were obtained with each channel corresponding to a particular muscle. The data obtained from each channel were passed through a low-pass filter with a cutoff frequency of 35 Hz. The filtered data were then used to determine the onset of the EMG signal for each trial for each muscle.



Fig. 6. Extraction of EMG features.

The onset was calculated as twice the standard deviation of the baseline reference [32]. The baseline reference is the activity measured in the muscles when the participants stand idle. We used the first 10 ms of each trial as the baseline. For the purpose of feature extraction, the filtered data were processed to obtain a set of statistical features for each muscle and each trial. The feature signal energy (F_1) was measured over the portion of signal from onset to the end. The filtered data were processed using a 10 ms moving-window root mean square (rms). The mean rms (F_2) was calculated as the average rms values over all windows. The onset value was used to determine the percentage of a trail that each muscle was active. We named this feature as activation rate (F_3) . Given that higher contraction of muscles are indicated by high amplitude peaks in the EMG data streams, we extracted several parameters from the peaks within each acquired signal. The position, amplitude and width of each peak were determined using least squares curve-fitting techniques. The slope of each peak was defined by dividing the amplitude by the width. The peak rate was measured as duration between two consecutive peaks. From each set of peak rates, peak amplitudes and peak widths, six statistical features (mean, maximum, minimum, standard deviation, and variance) were obtained which are denoted by F_5-F_{28} in Table II. An illustration of the feature extraction from postprocessed EMG signal is given in Fig. 6.

For each quantitative feature measured from inertial sensor, our quantization technique induces three trial-disjoint categories. These classes (low, medium, and high) were used to divide the feature space on the EMG data into three categories. For instance, when evaluating balance for the *mean speed*, the EMG features are mapped into low speed, medium speed, and high speed. To determine relationship between the quantitative metrics and muscle activities, we used a stepwise feature selection technique. The purpose of feature selection is to find prominent features from the EMG data that provide descriptive information for each category for each quantitative metric. The FSDA [31] was used to select most useful features discriminating each category from the rest. Starting with the individual features which provides the greatest univariate discrimination, this method adds a new feature which, together with included features, produces largest discrimination.

Two classification techniques, k-nearest-neighbor (k-NN) and *neural network* [33], were chosen to verify the effective-



Fig. 7. Mean speed measured from acceleration data and quantized into low/medium/high classes.



Fig. 8. M/L displacement measured from acceleration data and quantized into low/medium/high classes.

ness of the selected EMG features in interpreting each category (e.g., *low speed*). The *k*-NN was constructed with three different configurations (k = 1, k = 3, k = 5, respectively) for binary classification. A two-layer feed-forward neural network was used to build a binary neural classifier [34], where hyperbolic tangent functions for the hidden layer and a logistic sigmoidal function for the output layer were chosen. We measured classification accuracy with two different values of the number of hidden units (NH = 2, NH = 5, respectively).

VI. RESULTS

A. Data Quantization

The accelerometer data were obtained for 90 trials across five subjects as described previously. The 3-D acceleration data were used to find projection of the COM on the plane. The fiveacceleration performance parameters were calculated based on the methods stated in Section III. For each parameter, the 90 trials were mapped into three classes representing quality of observed action in terms of that given parameter. We subjectively quantized every trial into quality levels *low*, *medium*, and *high*. For example, with respect to the value of A/P displacement, measured for each trial, we assigned a class label based on its magnitude. This process was done for every accelerometer parameter obtained in each trial. Each EMG feature set was then given the same quality label as its corresponding accelerometer signal. The statistical approach explained in Section V-A was used to find thresholds on each metric. Figs. 7 and 8 show

| Quantitative Feature | Significant Features |
|----------------------|---|
| Low Speed | $EMG2(F_1, F_{17}, F_3) \& EMG3(F_{15})$ |
| Medium Speed | $EMG2(F_{22})$ |
| High Speed | $\text{EMG1}(F_1)$ & $\text{EMG2}(F_{21})$ |
| Low Radius | EMG1(F_5) & EMG3(F_{16}, F_{25}) & EMG4(F_{28}, F_{22}) |
| Medium Radius | $EMG1(F_{22}) \& EMG3(F_{20}) \& EMG4(F_{28})$ |
| High Radius | $EMG1(F_1,F_{13}) \& EMG2(F_8,F_{24}) \& EMG4(F_6)$ |
| Low Frequency | $EMG3(F_{27}, F_9)$ |
| Medium Frequency | $EMG1(F_{16})$ |
| High Frequency | $EMG2(F_{21}) \& EMG3(F_{16})$ |
| Low A/P | $EMG3(F_{15},F_1) \& EMG4(F_6)$ |
| Medium A/P | $EMG2(F_{21},F_{10})$ |
| High A/P | $EMG1(F_{19}) \& EMG4(F_9)$ |
| Low M/L | $EMG2(F_{22}) \& EMG3(F_{28})$ |
| Medium M/L | $EMG2(F_{17})$ |
| High M/L | EMG2(F_{23}) & EMG4(F_6, F_7, F_3, F_{26}) |

TABLE IV SIGNIFICANT EMG FEATURES DESCRIBING DIFFERENT PERFORMANCE METRICS

sample distribution of performance parameters for one subject. For visualization, these values are shown only for *mean speed* and M/L *displacement*. An interesting observation is the existence of strong correlation between different balance parameters. That is, increase in speed is tightly coupled with the increase in M/L displacement. This property of the accelerometer data is highlighted by varying colors (e.g., movements have the same color in both Figs. 7 and 8, respectively, except for trials 7 and 15).

B. EMG Features

Once the quantization process is done, the next step is to make EMG signals representative of performance parameters for balance evaluation. To achieve this, we determined the features from EMG signals 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 28 features (see Table II) form each EMG signal. These features form a 112-D space, which represent some properties of muscle activities during the performed action.

The obtained features were fed to our feature analysis box (shown in Fig. 5) where only the most prominent features were selected. The feature analysis was performed for each performance parameter. FSDA was then used to select significant features from the subset. These features and corresponding EMG signals are listed in Table IV.

C. Classification

To get insight into the effectiveness of the acquired EMG features, we used *k*-NN and neural classifiers. For each category of an accelerometer parameter, the corresponding significant features (extracted from Table IV) were extracted. These features were used in a binary classifier to differentiate each quality level from the rest. For example, to evaluate how accurate EMG sensors represent performance metric *medium* M/L, the corresponding prominent feature (*mean peak width* from EMG2) was extracted and fed to the classifiers to distinguish between *medium* A/P and other two levels of M/L *displacement* (*low* M/L and *high* M/L). The outcome of the classification for three values of *k* (using *k*-NN) is illustrated in Fig. 9. In Fig. 10, the



Fig. 9. Classification accuracy of k-NN classifier using only EMG signals.



Fig. 10. Classification accuracy of neural network classifier using only EMG signals.

classification accuracy for the neural classifier for two values of *NH* is shown.

Classification results demonstrate existence of relatively consistent accuracy across the two classifiers. Several categories such as *high speed*, *low frequency*, *high frequency*, *high* A/P and *low* M/L achieve good classification accuracy (more than 84% for both classifiers) confirming that selected attributes from muscle activities provide meaningful description of postural sway. Multiple classes such as *low radius*, *low* A/P and *high* M/L obtain high classification accuracy on at least one classifier. Given the fact that, mostly, the performance of the balance control can be assessed using even one of the quantitative features (e.g., *speed* in [3], or *A/P* in [11]), the results reveal that the EMG features can be effectively used to evaluate postural stability.

D. Classifier Performance

While classification accuracy can be used to quantify ability of EMG data for balance assessment, more robust measures must be employed to compare performance of individual classifiers. When performing classification for a target category, a test movement that belongs to this category might be assigned to a different class (false negative). Furthermore, an unknown movement within any class other than the target class may be judged by the system to be in the target category (false positive). Classification accuracy gives equal weights to the both types of

TABLE V Between Subject Classification

| | | Training Subject | | | | |
|--------------|-------|------------------|--------|--------|--------|--------|
| | | S_1 | S_2 | S_3 | S_4 | S_5 |
| | S_1 | - | 89.19% | 97.62% | 85.32% | 86.27% |
| | S_2 | 99.11% | - | 97.15% | 92.35% | 89.86% |
| Test Subject | S_3 | 90.38% | 95.09% | - | 94.74% | 81.24% |
| - | S_4 | 92.26% | 94.25% | 96.10% | - | 81.35% |
| | S_5 | 92.37% | 95.00% | 86.41% | 85.49% | - |

misclassification. A more precise measure of classifier performance is the well-known *F*-measure [35] that is the harmonic mean of precision (*P*) and recall (*R*) and is defined as

$$F = 2 \times \frac{P \times R}{P + R}.$$
(11)

We calculated the value of F-measure for the five classifiers used for recognition of each balance parameter. Numbers ranged from 0.26 for the 1-NN classifier used to detect high frequency, to 0.97 for the neural classifier that assigns class labels for median radius. On average, k-NN and neural classifiers had F-measures of 0.63 and 0.71, respectively. This shows that the neural network classifier outperforms the k-NN.

E. Cross-Subject Validation

Through development of learning algorithms for interpretation of EMG signals and classification of balance parameters, our system aims to establish an expressive relationship between the PCS and muscular activities. Successful deployment of a learning system requires the results to be independent of the observations based on which the system has been developed. In case of our framework, the balance evaluation algorithms use data collected from five healthy subjects. In this section, we demonstrate the robustness of our system to changes in target population. For this purpose, we calculated classification accuracy on pairwise use of the subjects' data for training and testing. This allows us to estimate the amount of balance abnormality for a new subject without previous training data from that subject. For each one of the five subjects, we first trained a neural network classifier based on the collected data of that subject. The classifier was then used to recognize movements of other subjects as being within each balance category. The system was first trained with the first subject (S_1) and was tested on the rest of the subjects $(S_2, S_3, S_4, \text{ and } S_5)$. On average, the accuracy was 99.11%, 90.38%, 92.26%, and 92.37% for each of the test subjects S_2 , S_3 , S_4 , and S_5 , respectively. The overall accuracy of between-subject classification, with S_1 being used for training, was 93.53%, which was the highest overall accuracy among all the subjects used for training. We obtained the lowest overall accuracy (84.68%) when the fifth subject (S_5) was used for training and others $(S_1, S_2, S_3, \text{ and } S_4)$ for testing. Individual accuracies were 86.27%, 89.86%, 81.24%, and 81.35% for S_1 , S_2 , S_3 , and S_4 , respectively.

For each pair of subjects used for training and testing, Table V shows the classification accuracy averaged over all the 15 quantized balance categories. The lowest average accuracy is 81.24% which belongs to the classifier trained using S_5 and tested on S_3 . The highest accuracy (99.11%) was obtained when S_1 was used to train the classifier and S_2 was used to test it. This empirical study of between-subject classification clearly shows that the EMG features introduced by our system can actively express the quality of balance control without regard the experimental data used for development of our learning algorithms.

VII. 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. The objective of our system is to assess the behavior of the EMG signals to interpret the activity of postural control system in terms of balance control. Performance of postural control system is primarily quantified 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. In order to evaluate effectiveness of the extracted features, we conducted several classification tests on the EMG features. Our results showed that the introduced features can estimate, with high accuracy, significance of each quantitative parameter for balance assessment.

In this paper, we used off-the-shelf EMG sensor suits for data collection. These sensors have not been fully integrated with our mote-based BSN architecture that accommodates inertial sensors. As part of our ongoing research, we are working on development of a unified end-to-end system that consists of both EMG and motion sensors on the same hardware. Moreover, to provide a complete evaluation of the system, we plan to investigate methods of integrating a gold standard balance system with our experiments.

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