On the combined use of Electromyogram and Accelerometer in Lower Limb Motion Recognition

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***Abstract*— Analysis of motion of lower limbs is required in different fields including health monitoring, robotics, rehabilitation sciences, biometrics and consumer electronics. Motion sensors, such as accelerometers are prominently used in such analysis since they are non-invasive and are readily available in low cost. However, it is evident from literature that fusion of accelerometer data with those recorded from other types of sensors improves the recognition of human activities. In this paper, the use of surface electromyogram (sEMG) along with accelerometers is explored to recognize nine activities of daily living. The effect of the placement of the sEMG sensor on two of the most popularly reported muscle locations on leg, namely soleus and tibialis anterior, is studied in more detail to determine the appropriate positioning of such sensors for human activity recognition and hence, reduce the number of sensors that are required for classification. It is demonstrated using actual data that the use of sEMG along with accelerometer improves the overall classification accuracy to 98.2% from around 94.5%, which is obtained if only accelerometer is used. In particular, the classification of stationary activities is improved with the inclusion of sEMG. Moreover, the placement of the sEMG sensor on soleus muscle aids the classification more as compared to tibialis anterior muscle.**

Keywords—sEMG, activities of daily living, lower-limbs, accelerometer, soleus, classification

I. Introduction

Human motion analysis is widely studied in the field of robotics and medicine [1-6]. Ambulatory activities are studied in rehabilitation sciences to improve quality of life as well to improve context awareness in developing human-machine interfaces. In [1], for example, a smart assisted living system is proposed for elderly and disabled, where the person can interact with robot by means of gesture recognition and daily activity recognition. Such systems can be used in health monitoring for elderly and patients. A multi-sensor system is proposed in [2] to provide continuous monitoring during rehabilitation. Human gait analysis has been used to in diagnosing diseases, such as multiple sclerosis, Parkinson's and stroke [3]. Moreover, human gait has been used in designing indoor pedestrian navigation system to guide the user to a particular location or to monitor his daily activity levels [4]. Multimodal systems have been designed to perform gait analysis for biometric applications [5]. Analysis of motion of upper and lower limbs is also useful in designing prosthetics for amputees [6].

Various sensing technologies have been made use of in the aforementioned applications. For example, just accelerometers along with wireless transmission capability have been used for human motion monitoring [2]. Multiple triaxial accelerometers and triaxial gyroscopes have been used in recognition of hand gestures and daily living activities [1]. The combined use of accelerometer and gyroscope has been used in developing pedestrian navigation systems [4]. Accelerometers available in smart phones have been used for biometric applications by analysis of human gait [5]. Multiple accelerometers have been used to identify activities of daily living (ADL) [7]. Other sensors that are commonly available in smartphones such as magnetometer, microphone and global positioning system (GPS) have been used in analysis of human motion because of their easy availability [8, 9]. Non-wearable sensors, such as vision-based sensing using camera, infrared thermography and force platforms have been demonstrated in applications involving mobility tracking [3]. Biomedical sensors have also been integrated with motion sensors to enhance human activity recognition. Muti-lead electrocardiogram (ECG) has been shown to improve the accuracy with which ADL can be classified [10]. Multiple surface electromyogram (sEMG) sensors have been widely used to perform activity recognition for upper limbs [6]. However, the use of sEMG for analysis of the motion of lower limbs is still limited because it is easily affected by body gravity and muscle jitter [11].

In this paper, ADL classification has been performed with a single tri-axial accelerometer and a single sEMG sensor. Electromyogram is a recording of the biopotential generated as a result of activation of muscle being monitored when an activity is performed. The novelty of this works is the integration of the sEMG data with accelerometer data to identify activities which are particularly confusing, such as sitting and standing, which are not easy to identify with the considered placement of the accelerometer sensor. Also, most papers utilize multi-channel sEMG recordings for activity recognition [6, 11]. In this work, the appropriate location of the sEMG sensor is determined by comparing the performance achieved with the placement of sEMG sensor on two of the most prominently studied muscle locations for lower-limb analysis. The optimization of the sensor placement helps in reducing the number of sensors required for ADL classification, which is useful in reducing the cost of the system as well as improve the wearability of the system. The aim is to improve the accuracy of classification while keeping the required number of sensors to a minimum. Interesting findings about the similarity of the considered activities are revealed using statistical analysis if the corresponding signals.

The remaining paper is organized as follows. The basic signal processing required for extraction of commonly used features in the literature are described in Section II. Section III contains the details of the experimental setup used for recording signals from wearable sensors and the algorithm used for classification of the considered ADL. Experimental results demonstrating the utility of sEMG in ADL classification and the selection of the location for placement

Funding support received from SERB, DST (ECR/2016/000637).

of sEMG sensor are given in Section IV. Section V concludes the paper.

II. Signal Analysis for Classification of ADL

A. Review of ADL classification

In literature, a lot of work on ADL classification has been carried out using smartphone sensors [8,9]. The setup is popular because the sensors are readily available. In such setups, the objective is to identify the activities with flexible placement of the sensors such as in waist belt, pocket of shirt or trouser. Also, the sensors may experience motion during mobility of the subject because the smartphone may not be affixed firmly to the subject's body. The setup is suitable for developing assistive living or to obtain environment awareness. Hence, signal recorded using the microphone of the smartphone have been used to identify the environment.

In another setup, motion sensors, namely accelerometers and gyroscopes are placed firmly on the body of the subject using elastic bands [1,6,7,10,11]. This type of placement reduces the motion introduced in the sensors during mobility of the subject because of the motion of the device containing the sensor, such as a smartphone. Hence, the signals recorded by the motion sensors can be related to the motion of the subject with better reliability. Hence, the setup has been used in designing pedestrian navigation system and in health monitoring applications. In this work, as well, the accelerometer and the sEMG sensor are attached firmly to the lower limb of the subject using elastic straps.

Another aspect of the setup is the number of sensors used and their relative placement on the human body. In most researches, multiple accelerometers have been used. For instance, in [7], four inertial sensors have been placed on wrist, hip, chest and ankle for ADL classification, with an average classification accuracy of around 93%. Two inertial sensors have been used, one on the waist and one on the foot to recognize the ADL activities with an overall accuracy of 98.3% [1]. Here, most confusion is observed between level walking and walking down the stairs. In [6], data acquisition is carried out using 12 inertial measurement units and 12 sEMG sensors for forearm motion analysis. Single triaxial accelerometer sensors have also been used. For instance, in [12], the accelerometer is placed on the hip. In [11], a single triaxial accelerometer is used with a four-channel sEMG system, whereas in [10] the accelerometer is combinedly used with six-channel ECG recording. In this work, a single triaxial accelerometer and a single sEMG sensor are used for ADL identification. As the number of sensors are reduced, the classification task becomes more challenging. However, a suitable selection of features for classification and appropriate placement of the sensors is useful in maintaining the classification accuracies. In the following section, the features considered for the ADL classification are discussed.

B. Feature Extraction

The features extracted from the sEMG signal are listed in the following [13]. Since sEMG signals are stochastic in nature, statistical analysis is useful.

1. Mean absolute value (MAV) is defined as

$$\mathrm{MAV} = \frac{1}{n}\sum_{i=1}^{n}|x_i|, \tag{1}$$

where x_i characterizes the sEMG signal in a sample of i and n denotes the total length of sEMG signals. MAV indicates the strength of the signal.

2. Standard deviation (STD) is given by

$$\sigma = \sqrt{\frac{1}{n-1}\sum_{i=0}^{n}(x_i-\mu)^2}, \tag{2}$$

where

$$\mu = \frac{1}{n}\sum_{i=0}^{n}x_i \tag{3}$$

is the mean value of the signal. Since sEMG signals are expected to have zero mean value, μ is approximately zero.

3. Skewness is given as

$$\gamma = \frac{E\{x-\mu\}^3}{\sigma^3}, \tag{4}$$

where μ and σ are as defined in (3) and (2), respectively and E is the expectation operator.

4. Kurtosis is given as

$$\kappa = \frac{E\{x-\mu\}^4}{\sigma^4}, \tag{5}$$

where the symbols have the same meaning as given in (5) above. Higher-order moments have been shown to be useful for analyzing sEMG signals since sEMG signals are know to have non-Gaussian distribution [14].

5. Zero crossing (ZCR) is defined as

$$ZCR = \sum_{i=1}^{N-1}[sgn(x_i \times x_{i+1}) \cap |x_i - x_{i+1}|] \geq th, \tag{6}$$

where the threshold (th) is evaluated as the standard deviation of sEMG signal and sgn denotes the sign of the quantity inside the bracket. Features such as ZCR, SSC and STD are useful for determining the variation in the signal about the mean, which are mostly caused by the change in the firing rate of the muscle cells.

6. Slope sign change (SSC) is given as

$$SSC = \sum_{i=2}^{N-1}[f[(x_i - x_{i-1}) \times (x_i - x_{i+1})]], \tag{7}$$

where the function $f(x)$ is such that it is 1, if $x \geq th$ and zero otherwise. Here, the threshold th is again taken as the standard deviation of sEMG signal.

7. Waveform length (WL) is defined as

$$\mathrm{WL} = \sum_{k=1}^{n-1}|x_{k+1} - x_k|. \tag{8}$$

For sEMG signals, the time domain features considered above are known to provide good discrimination [13]. For the

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accelerometer, the signals recorded with each of the three axes are used to extract the following two features, the mean value, as defined in (3) and the autoregressive (AR) parameter with order one. The mean value of the accelerometer signal corresponds with the orientation of the sensor with respect to Earth's gravitational field. Hence, it is useful in identifying activities which are expected to have very distinct orientation of the body. The AR modeling of the signal with samples x_i is defined using

$$x_i = \sum_{k=1}^{K} a_k x_{i-k} + w_i, \tag{9}$$

where K is the model order, which is taken as one here. The AR spectrum of the accelerometer signal shows peaks at harmonically related frequencies if there is repetition in the signal, just like in different walking patterns. However, different walking patterns will result in fundamental peak at a different frequency. Hence, the AR(1) feature is useful for ADL classification. In the following section, the experimental setup for recording the signals and the algorithm for ADL classification are presented.

III. Integrated Use of Biomedical and Motion Sensors for ADL Classification

A. Data acquisition

Five healthy, able-bodied subjects, all males, between the age of 20-25 years participated voluntarily in this study. Delsys Trigno wireless system shown in *Fig.1* with following specification has been used for data acquisition- sampling frequency 1.111kHz and signal bandwidth 20-450 Hz for sEMG signal, sampling frequency of 148.148 Hz for accelerometer and 16-bit resolution depth for both the sensors. After following the basic skin preparation procedure, the Delsys sensors are placed on the skin surface using elastic bands and then covered with crepe bandage to keep the motion artifacts to a minimum. The sEMG sensors are placed on the right leg of the subjects on the muscles Soleus (SOL) and Tibialis Anterior (TA), as shown in *Fig.1*. The triaxial accelerometer (Acc) is at the location of the Soleus muscle. The sEMG and accelerometer data are transmitted wirelessly to the base-station (Delsys Trigno wireless system) which is connected to the computer via USB where the signals are stored for later processing.

Very Important

Here, the soleus and tibialis anterior muscles have been considered because these muscles have been studied in literature, particularly for their activation during daily walking activities [15, 16]. It has been shown that the muscle soleus is in general, displays higher sEMG activity as compared to tibialis anterior for ascending and descending the stairs, with more activity during ascending of stairs as compared to descending them [15]. Also, foot dorsiflexion, which is vital for proper balancing during walking, may be assessed using the activity of tibialis anterior muscle [16].

The nine ADL activities considered in this work are listed in Table I. Each activity has been recorded multiple number of times by each subject. So, a total of 100 observations, each of duration 3-5 sec of each activity are available and 120 observations are available for level walking activities (A4, A5). In A3, the subject lay down flat on the back. In level walking activity A4, the subjects were asked to walk at the pace comfortable with them and then increase the speed above their normal walking speed in A5. The wireless system has a range of 20m with line-of-sight, which is sufficient to record the considered activities.

Fig. 1. Experimental setup for data aquisition

TABLE I. ADL Activities

Stationary Activities		**Activities involving motion**	
A1	Sit	A4	Walk on level surface at normal speed
		A5	Walk on level surface at high speed
A2	Stand	A6	Walk down stairs
		A7	Walk up stairs
A3	Lay down	A8	Walk down a ramp
		A9	Walk up a ramp

B. Proposed ADL classification

Firstly, the raw sEMG and accelerometer signals are processed for missing samples. A simple linear interpolator is used, since the sample rates for the signals are high enough and the missing samples are observed to be few in numbers. Then, the baseline of the sEMG signals is removed using a moving average filter with 125 ms window length is selected to determine the baseline, which is removed from raw sEMG signals. Next, the recorded signals are segmented to generate the aforementioned number of observations. Then, feature extraction is carried out to obtain seven features for each of the sEMG signals and a total of six features (two from each axis) from the accelerometer signals.

Fig. 2 shows the block diagram of the approach followed for classification of ADL. A multiclass support vector machine (SVM) classifier with one-verses-all coding and radial basis kernel function is used for classification. A five-fold cross validation is used to avoid overfitting. The

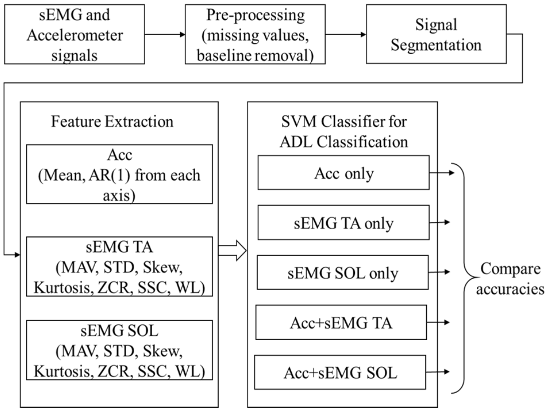


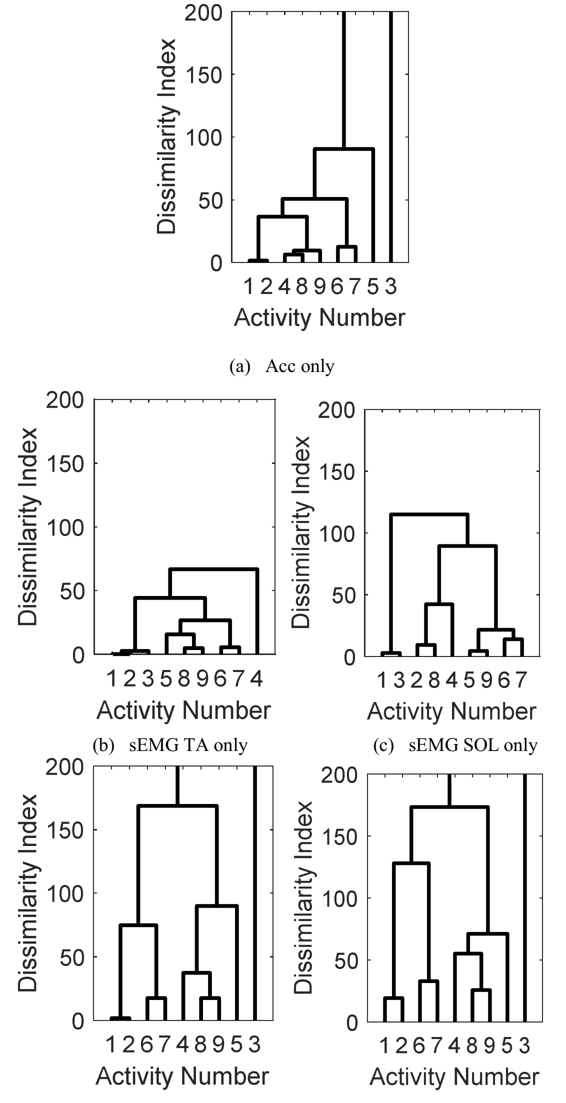
Fig. 2. ADL classification approach

classification accuracy obtained with only accelerometer (denoted as Acc in *Fig. 2*) signals is compared with that obtained using sEMG signals to determine their relative contribution towards identification of the considered activities. Then, the combined use of accelerometer and sEMG signals is evaluated to determine the combination of the sensors that will yield the best performance. The results are presented in the following section.

IV. Results

The dendrograms showing the relative dissimilarity between the considered ADL when different set of features are used to represent the ADL are plotted in *Fig. 3*. The nine ADL are recorded as accelerometer and sEMG signals and are processed in terms of the features extracted from the signals. Hence, the classification of the ADL depends on how discriminatory the features representing the ADL are. The range on y-axis has been kept uniform for all the dendrograms in *Fig. 3* to provide easy comparison. From *Fig. 3a* it is observed that the lying down activity (denoted by '3' in the figure) is completely different from all the others and this is because it does not contain any repetitive motion as observed in walking activities while the orientation of the accelerometer captured in terms of the absolute value is also different from the sitting and standing activities. However, the sitting and standing activities are most similar since they are stationary and orientations are also similar. The sitting and standing activities are difficult to distinguish if only accelerometer is used on the limb below the knee. The difficulty in identifying sitting and standing activities using accelerometer, as well as distinguishing between walking up and down the stairs has also been reported in literature [9, 12].

On the other hand, in *Fig. 3c* the sitting (A1) and lying down activities (A3) are grouped as similar, since both involve low muscle activity, but standing activity (A2) is distinct since the muscle activation is more than A1 and A3. This observation indicates that the sEMG signal for soleus muscle complements the accelerometer signals for classification purpose. However, as seen in *Fig. 3b,* the tibialis anterior muscle signals indicate all three stationary activities as similar and it may not enhance classification when fused with accelerometer signals. These interpretations are also supported by the dendrogram plots in *Fig. 3d* and *Fig. 3e*. When sEMG signals of soleus are used along with the accelerometer signals, the dissimilarity between any two activities, including the sitting and standing activities



(a) Acc only

(b) sEMG TA only

(c) sEMG SOL only

(d) Acc+ sEMG TA

(e) Acc+ sEMG SOL

Fig. 3. Dendrogram plots for considered activities using different sets of features

increases. The dissimilarity between activities is more with inclusion of sEMG signals of soleus muscle (*Fig. 3e*) as compared to that obtained with inclusion of the tibialis anterior muscle (*Fig. 3d*).

Similar observations are made from the confusion matrices given in *Figs. 4-6*. For activities A1, A2, A3 the confusion matrices for accelerometer only and sEMG of soleus muscle only indicate confusion between A1-A2 and A1-A3, respectively. When both sensors are used together, the confusion reduces drastically. Moreover, walking downstairs (A6) is confused with walking upstairs (A7) with accelerometer signals and vice versa when sEMG of soleus muscle are used. However, when both the sensor modalities are used together, the confusion decreases. The confusion of walking up the ramp (A8) is observed with walking at high speed (A5) since both activities involve more activation of muscles. However, the inclusion of accelerometer reduces this confusion.

A1	A2	A3	A4	A5	A6	A7	A8	A9	
82	18	0	0	0	0	0	0	0	**A1**
1	97	0	0	0	0	2	0	0	**A2**
0	0	100	0	0	0	0	0	0	**A3**
0	0	0	118	1	0	0	0	1	**A4**
0	0	0	1	119	0	0	0	0	**A5**
0	0	0	2	0	86	8	2	2	**A6**
0	0	0	0	0	1	94	0	5	**A7**
1	0	0	1	0	0	0	96	2	**A8**
0	0	0	1	0	0	0	1	98	**A9**

Fig. 4. Confusion matrix between output class and target class Acc features only. Average classification accuracy over all activities is 94.5%.

A1	A2	A3	A4	A5	A6	A7	A8	A9	
72	4	20	0	0	4	0	0	0	**A1**
4	94	0	0	0	2	0	0	0	**A2**
13	1	84	0	0	2	0	0	0	**A3**
0	0	0	120	0	0	0	0	0	**A4**
0	0	0	1	107	1	2	0	9	**A5**
0	0	0	0	0	93	5	0	2	**A6**
0	0	0	0	1	13	86	0	0	**A7**
0	0	0	0	0	0	0	95	5	**A8**
0	0	0	0	16	7	1	5	71	**A9**

Fig. 5. Confusion matrix between output class and target class for soleus muscle sEMG features only. Average classification accuracy over all activities is 87.1%.

A1	A2	A3	A4	A5	A6	A7	A8	A9	
98	1	0	0	0	1	0	0	0	**A1**
3	96	0	0	0	0	0	0	1	**A2**
0	0	100	0	0	0	0	0	0	**A3**
0	0	0	120	0	0	0	0	0	**A4**
0	0	0	0	119	1	0	0	0	**A5**
0	0	0	0	0	98	1	0	1	**A6**
0	0	0	0	0	4	93	0	3	**A7**
0	0	0	0	0	0	0	100	0	**A8**
0	0	0	0	0	0	0	0	100	**A9**

Fig. 6. Confusion matrix between output class and target class with Acc and sEMG (soleus muscle) features. Average classification accuracy over all activities is 98.2%.

The classification accuracies obtained with single modality or placement and those obtained using a fusion of two sensor modalities is given in Table II. The classification average accuracy for the considered ADL when only accelerometer is used is 94.5%. Here, the accuracies are affected by activities A1 and A6. For these activities, classification accuracy obtained with sEMG signals recorded from soleus muscle are more as compared to the tibialis anterior muscle. The inclusion of sEMG signals from the tibialis anterior muscle along with accelerometer signals does not yield any improvement in the overall accuracy. However, the use of sEMG sensor on soleus muscle with triaxial

TABLE II. ADL ACTIVITIES CLASSIFICATION ACCURACIES

Activity	Acc	sEMG on TA	sEMG on SOL	Acc+ sEMG on TA	Acc+ sEMG on SOL
A1	82.0	51.0	72.0	83.0	98.0
A2	97.0	62.0	94.0	81.0	96.0
A3	100.0	96.0	84.0	100.0	100.0
A4	98.3	95.0	100.0	100.0	100.0
A5	99.2	95.8	89.2	100.0	99.2
A6	86.0	87.0	93.0	95.0	98.0
A7	94.0	90.0	86.0	98.0	93.0
A8	96.0	85.0	95.0	96.0	100.0
A9	98.0	71.0	71.0	97.0	100.0
Average	94.5	81.4	87.1	94.4	98.2

accelerometer provides the best overall accuracy of 98.2%. Hence, an improvement of aroun 4% is achived on inclusion of the sEMG sensor on a carefully selected location on the lower limb.

V. CONCLUSION

A setup for classification of activities of daily living is proposed using minimum number of sensors. The complementary nature of accelerometer and surface electromyogram is utilized in improving the classification accuracies. The placement of the sEMG sensor is explored to determine the appropriate location that will contribute the most towards classification of the considered activities. In particular, the classification accuracies for stationary activities that are difficult identify using an accelerometer are improved with the inclusion of sEMG signal. The classification accuracy improves from 94.5% to 98.2% upon inclusion of sEMG sensor with accelerometer. The muscle location of soleus is determined to aid the classification more as compared to the tibialis anterior muscle.

ACKNOWLEDGMENT

The authors would like to recognize the funding support provided by the Science & Engineering Research Board, a statutory body of the Department of Science & Technology (DST), Government of India, SERB file number ECR/2016/000637.

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