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ORIGINAL ARTICLE

Accelerometer's position independent physical activity recognition system for long-term activity monitoring in the elderly

Adil Mehmood Khan, Young-Koo Lee, Sungyoung Lee and Tae-Seong Kim

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Abstract

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1 Introduction

Mobility refers to the amount of time we spend in the dynamic activities, such as walking or running, as well as the static activities, such as sitting, standing, and lying. Human health status and mobility are known to have a close relationship [32]. Increased mobility improves stamina and muscle strength. It promotes psychological well-being and quality of life by increasing the person's ability to perform a greater range of activities of daily living [1]. The changes in a person's health and psychological status affect his/her mobility levels [7]. Therefore, objective mobility data can be used to monitor health to assess the relevance of certain medical treatments and to determine the quality of life of an elderly patient [32].

Long-term, sensor-based monitoring performed in patients' natural home environment provides a clearer picture of their mobility than a short period of monitoring in an unnatural clinical setting [32]. First, it allows elderly patients to live independently in their own home and thus leads to a significant reduction in healthcare costs by avoiding unnecessary hospitalization. Second, it provides clinically useful trend data that can allow physicians to make informed decisions, to monitor deterioration in

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Long-term, sensor-based monitoring performed in patients' natural home environment provides a clearer picture of their mobility than a short period of monitoring in an unnatural clinical setting [32]. First, it allows elderly patients to live independently in their own home and thus leads to a significant reduction in healthcare costs by avoiding unnecessary hospitalization. Second, it provides clinically useful trend data that can allow physicians to make informed decisions, to monitor deterioration in chronic conditions, or to assess the response of the patient to a treatment. Thus, it ensures that those who need urgent care would receive it in a more timely fashion.

However, several issues need to be addressed to promote the use of long-term activity monitoring systems in the elderly. These include ease of use, discretion, cost, and the ability to perform daily activities unimpeded [32]. Any system which impedes subjects' daily physical activities or forces them into a fixed life pattern due to its size, communication methods or location is most likely to be rejected [27].

Wearable sensors are capable of measuring the mobility directly. They are well-suited to collecting data on daily activity patterns over an extended period of time as they can be integrated into clothing [3, 25, 26, 31], or worn as wearable devices. Since they are attached to the subjects they are monitoring, wearable sensors can therefore measure physiological parameters which may not be measureable using ambient sensors. However, the design of wearable systems is complicated by size, weight, and power consumption requirements [15].

Accelerometers are currently among the most widely used wearable sensors for long-term activity monitoring in the elderly [29]. Over the past decade, many human activity recognition systems have been developed that incorporate the use of triaxial accelerometers. Some studies investigated the use of accelerometers for differentiating different types of same physical activity, e.g., walking (along the corridor, upstairs, and downstairs) [17, 33]. Whereas others employed it for recognizing a wide set of daily activities such as lying, sitting, standing, walking, and running [2, 4, 6, 9, 11, 12, 16, 20, 21, 23, 30, 34].

In general, the output of any body-worn accelerometer depends on the position at which it is placed and can vary for different positions on a subject's body, even for the same activity. The output patterns for walking, for example, vary at three different positions as shown in Fig. 1. The high within-class variance caused by changes in orientation, magnitude, and frequency thus makes accelerometer's position free human activity recognition very challenging. Therefore, almost all previous works require accelerometers to be firmly attached to subjects' bodies. Most studies employed multiple accelerometers attached at different sites [4, 6, 9, 10, 12, 17, 21–23], whereas others investigated the use of a single triaxial accelerometer mounted on waist, chest, thigh, wrist, or sternum [2, 11, 13, 14, 16, 18–20, 24, 30, 33, 34]. Such configurations would force subjects into a fixed life pattern and hinder their daily

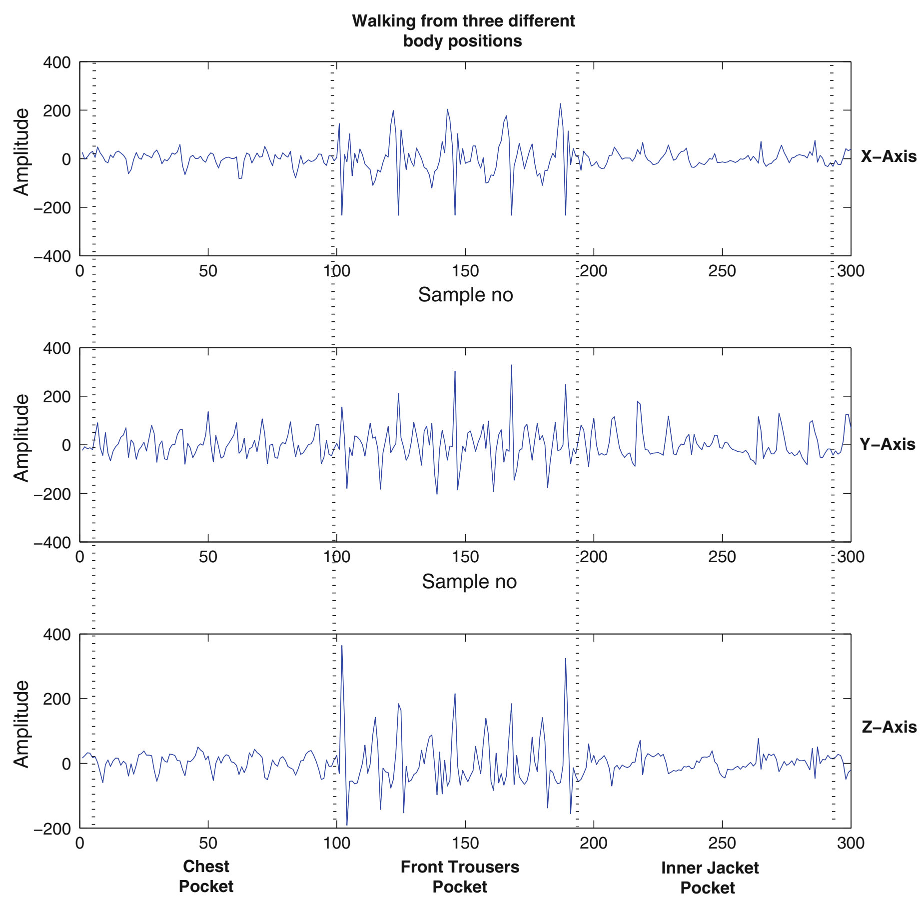


Fig. 1 Sample acceleration signals for walking from three different positions

physical activities and thus make these systems impractical for long-term activity monitoring during unsupervised free living.

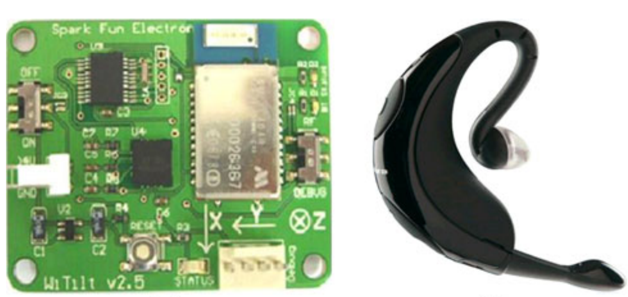
In our initial study on human activity recognition via a single triaxial accelerometer [13], we proposed the autoregressive (AR) modeling of the acceleration signals for the first time and proved the feasibility of the AR-analysis by achieving a recognition accuracy of 99%. However, the system required accelerometer to be firmly attached to a subject's chest. When tested for the position-independent case, the system's accuracy decreased significantly, i.e., 47%.

In this paper, we present a comprehensive approach to address the accelerometer's position-independent physical activity recognition problem. Our aim is to recognize daily physical activities without posing any preconditions on accelerometer's position and orientation relative to a subject's body but maintaining the same high standards in terms of accuracy. The proposed method allows subjects to carry accelerometer freely in any pocket without attaching it firmly to any body part, thereby allowing more flexibility in implementing a system for long-term activity monitoring. Our method also takes the approach of using single triaxial accelerometer for better conveniences of patients. We validated our approach using seven daily physical activities. Activity data was recorded from five body positions. The resulting high within-class variance and low between class variance was resolved by adopting a novel hierarchical recognition approach. The average accuracy of about 94% illustrates the effectiveness of our proposed method.

2 Methods

2.1 Sensor device and data collection

In this study, we used a 2.4 GHz wireless triaxial tilt sensor from Sparkfun called Witilt v2.5, previously used in [13, 14], shown in Fig. 2a. It employs a free scale MMA7260Q



(a) (b)

Fig. 2 **a** Witilt v2.5 triaxial accelerometer, **b** Jabra BT250v bluetooth headset

triaxial accelerometer and a class 1 bluetooth link from BlueRadios. MMA7260Q is a surface-mounted integrated circuit accelerometer that runs on low voltage (2.2–3.6 V) and is capable of measuring acceleration along the *X*-, *Y*-, and *Z*-axes. This accelerometer also features a 4-level sensitivity scale (1.5 g, 2 g, 4 g, and 6 g), with 1.5 g setting being the most sensitive. It measures both (+) and (−) acceleration.

About 24 h of activity data were collected in a home setting, outside the laboratory. The sensor, with a sampling frequency of 90 Hz, was placed on eight elderly subjects (six males, two females, age: mean = 65, SD = 3 years old) on five different positions, i.e., chest pocket, front left trousers pocket, front right trousers pocket, rear trousers pocket, and inner jacket pocket. The activities to be recognized were resting (lying/sitting/standing) (see Sect. 4 for the reason why these activities were combined into a single group), walking (along the corridor), walking upstairs, walking downstairs, running, cycling, and vacuuming. The cycling activity was recorded in a gym.

An approximate distribution of the data for each subject regarding the five body sites and the seven activities in our study were: resting (40 min, 8 min per site), walking (40 min, 8 min per site), running (25 min, 5 min per site), cycling (25 min, 5 min per site), vacuuming (25 min, 5 min per site), walking-upstairs (10 min, 2 min per site), and walking-downstairs (10 min, 2 min per site).

Annotations were performed using a bluetooth headset combined with speech recognition software. Our system marked the starting and ending points of each activity using a predefined set of commands. We used the Jabra BT250v bluetooth headset, shown in Fig. 2b. It offers a range of 10 m and a battery power for 300 h standby and 10 h active talking. The software for storing the annotations was developed following the idea presented in [35]. It is written in C and combines elements of the bluetooth API with the Microsoft Speech API.

This method proved very accurate and efficient as annotations were provided by the user on the spot. It also resulted in very little interference while performing activities. To minimize any mislabeling, data within 5 s of the start and stop times was discarded. Since the subject is probably standing still or sitting while he records the start and stop times, the data immediately around these times may not correspond to the activity label.

The subjects were trained on the use of data collection and annotation applications in the laboratory where they were given short definitions of the seven activity labels. Each subject then collected the data at home, without researcher's supervision, where he/she performed random sequences of the seven activities at their own pace and labeled the start and end points of each activity. We collected approximately 24 h of the activity data, i.e., 3 h per subject. The activity dataset for each subject was then divided randomly into the training and test sets in a roughly 40–60% split.

2.2 Signal processing

2.2.1 Feature extraction

The real time data from an accelerometer contains some noise that needs to be filtered out before using it for activity recognition. A moving average filter of order 3 was incorporated to filter out random noise. Signal features were then calculated for each second of the data collection, i.e., a window size of 90, with no overlapping between consecutive windows. A brief description of these features is given below.

Spectral entropy(SE): the SE of the acceleration signal for the frequency band $f_1 - f_2$, i.e., 0–45 Hz was calculated for each window as

$$S_N(f_1,f_2) = \frac{-\sum_{f_i=f_1}^{f_2} P(f_i)\log(P(f_i))}{\log(N[f_1,f_2])} \quad (1)$$

where $P(f_i)$ represents the power spectral density (PSD) value of the frequency f_i. The PSD values are normalized so that their sum in the band $[f_1 - f_2]$ is one. $N[f_1 - f_2]$ is the number of frequency components in the corresponding band in PSD.

Autoregressive (AR) coefficients: in our previous study on human activity recognition via triaxial accelerometer [13], we proposed the AR modeling of triaxial acceleration signals for the first time and proved the feasibility of using the AR-coefficients for activity recognition. An AR model can be represented as

$$y(t) = \sum_{i=1}^{p} \alpha(i)y(t-i) + \varepsilon(t) \quad (2)$$

where $\alpha(i)$ are the AR-coefficients, $y(t)$ the time series under investigation which in our case is the acceleration signal from the sensor unit, and p the order of the filter which is generally very much less than the length of the series. The noise term or the residue $\varepsilon(t)$ is assumed to be the Gaussian white noise. In other words, the order of an AR model refers to the number of past values of $y(t)$ used to estimate the current value of $y(t)$.

Model order is a key parameter of AR modeling, and yet in most cases, it is difficult to predict the optimum value of this parameter. A proper order for an AR model would yield a good data fitting effect while retaining a high data compression ratio. In order to determine the optimal AR model order we used root mean square error (RMSE). It is a measure of the differences between values predicted by a model or an estimator and the values actually observed from being modeled or estimated. In the case of AR models, as one increases the order of the model the RMSE generally decreases quickly up to a certain order and then more slowly. An order just after the point at which the RMSE evens out is usually an appropriate one. Although increasing the order of the AR model results in lower errors, in the case of RMSE, it does not always mean greater accuracy. Selecting a higher order can result in overfitting and therefore, does not always lead to realistic representation of the data. However, RMSE still provides a reasonable approximation for the study objectives.

The RMSE values were calculated for each activity against different model orders and then averaged to produce the final estimates. The behavior of the RMSE-curve against different model orders is presented in Fig. 3. One can observe a decreasing trend against the AR model order. The curve tends to even out near the model order of 10. This suggests that the optimum model order should lie in the neighboring values of 10.

Signal magnitude area (SMA): the SMA has been found as a suitable measure for distinguishing between static versus dynamic activities using triaxial accelerometer signals. In our previous study [13], we found that different dynamic activities, e.g., running and walking, register different SMAs. Therefore, the SMA when augmented with the AR-coefficients improved the recognition rate for the dynamic activities significantly. It is calculated according to the following equation:

$$\mathrm{SMA} = \sum_{i=1}^{N} (|x(i)|) + (|y(i)|) + (|z(i)|) \quad (3)$$

where $x(i)$, $y(i)$, and $z(i)$ indicate the acceleration signal along x- , y-, and z-axis respectively.

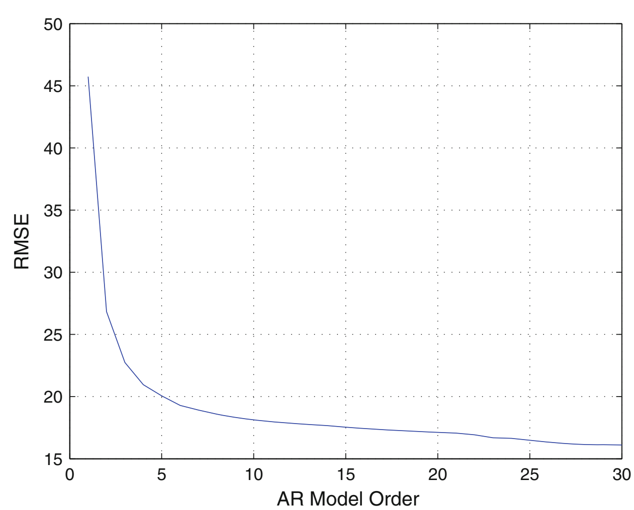


Fig. 3 RMSE versus AR model order for the whole activity set

2.2.2 Feature analysis

The feature extraction phase was proceeded by the feature analysis phase, which was performed in the following two steps.

- First, we analyzed the classification performance of the different configurations of the front-end features for a single sensor position. The purpose was to identify the feature(s) having the best performance in classifying activities from a single sensor-site (one of the 5 pockets/sites used for data collection). The features mentioned above were tested with the forward–backward search [28], which is a well-known feature selection algorithm. The classification was done using an ANN based on the feed-forward backpropagation algorithm. The training and testing datasets were composed of activity data from a single sensor position. This test was repeated five times, each involving the activity data from a different sensor position. The AR-coefficients augmented with the SMA, i.e., the AR–SMA proved to be the best discriminating features for all activity classes for all sensor positions, considering one at a time.
- Second, we combined the activity data from all five sensor positions into a single dataset and evaluated the classification performance of the AR–SMA. A significant decrease in the performance was witnessed due to high within-class variance resulting from positioning the sensor on five different sites. To minimize this variance, we proposed a two-level classification scheme, i.e., classifying the acceleration signal to be either from upper-body (chest and inner jacket pocket) or from lower-body positions (front and rear trousers pocket) before classifying the activity itself. Once again, the features were tested with the forward–backward search to identify the one having the best performance for this initial classification. The SE proved to be the best discriminating feature of all.

2.3 Classification scheme

Based on our findings, we devised a two-level recognition approach. Its architecture is illustrated in Fig. 4. At the lower level, the SE was employed to recognize three classes, i.e., the resting activity, dynamic-activity (upper-body), and dynamic-activity (lower-body). Such a division helped reducing the high within-class variance for a particular dynamic activity resulting from the upper- and lower-body sensor positions and avoiding the cost of computing the AR–SMA feature when the subject is at rest.

If the resting activity is not recognized at the lower-level, the system outputs the sensor position as upper- or

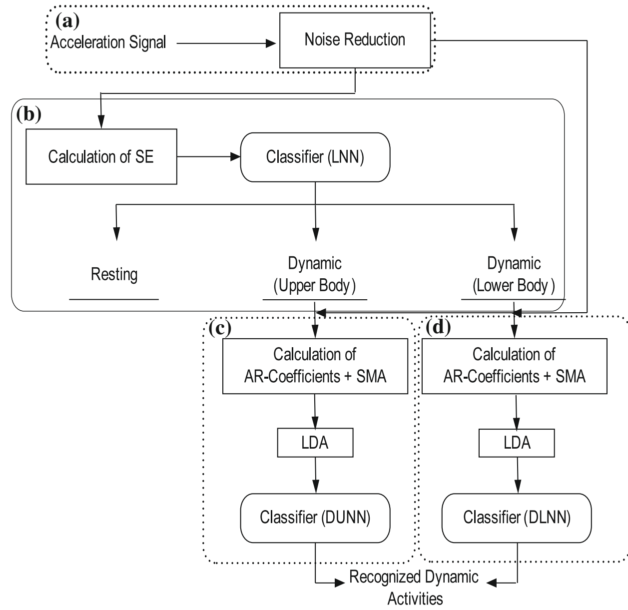


Fig. 4 Block diagram of the proposed recognition scheme: **a** A moving average filter of order 3 was used to filter out the random noise from the acceleration signal. **b** At the lower-level, the SE and the neural net (LNN) was employed to recognize three classes. The sensor position was outputted as lower or upper-body in the case of dynamic activities (absence of resting state). **c** Augmented features (AR-coefficients + SMA) were calculated, LDA (see the text) was applied and the neural net (DUNN) was employed to recognize dynamic activities in the case of upper-body. **d** DLNN was used to recognize dynamic activities in the case of lower-body

lower-body for a particular dynamic activity. The AR-coefficients and SMA are then calculated from the noise reduced acceleration signal to form an augmented feature vector. However, a high within-class variance and low between-class variance due to different sensor positions, i.e., front and rear trousers pockets in the case of lower-body whereas chest and inner jacket pockets in the case of upper-body, could still exist in this new augmented feature space.

2.4 Linear discriminant analysis (LDA)

The LDA, a second order statistical approach, is a supervised classification approach that utilizes the class specific information maximizing the ratio of the within and between class scatter information [5]. In order to obtain the maximum discrimination, it projects data onto the lower dimensional space so that the ratio of the between and within class distance can be maximized. The within-class S_{w} and between-class S_{b} class comparison is done by following equations:

$$S_{\mathrm{b}} = \sum_{i=1}^{c} J_i(\overline{m}_i - \overline{\overline{m}})(\overline{m}_i - \overline{\overline{m}})^T \tag{4}$$

$$S_{\mathrm{w}} = \sum_{i=1}^{c} \sum_{A_k \in C_i} (A_k - \overline{m}_i)(A_k - \overline{m}_i)^T \quad (5)$$

where J_i is the number of vectors in i-th class C_i. c is the number of classes and in our case it represents the number of activities. $\overline{\overline{m}}$ represents the mean of all vectors, $\overline{m_i}$ the mean of the class C_i and A_k the vector of a specific class. The optimal discrimination projection matrix D_{opt} is chosen from the maximization of ratio of the determinant of the between and within-class scatter matrices as

$$D_{\mathrm{opt}} = \arg\max_{D} \frac{|D^T S_{\mathrm{b}} D|}{|D^T S_{\mathrm{w}} D|} = [d_1, d_2, \ldots, d_t]^T \quad (6)$$

where D_{opt} is the set of discriminant vectors of S_{w} and S_{b} corresponding to the $c-1$ largest generalized eigenvalues λ and can be obtained via solving (7). The size of D_{opt} is $t \times r$ where $t \leq r$ and r is the number of elements in a vector.

$$S_{\mathrm{b}} d_i = \lambda_i S_{\mathrm{w}} d_i \quad i = 1, 2, \ldots, c-1 \quad (7)$$

where the rank of S_{b} is $c-1$ or less and hence the upper bound value of t is $c-1$.

The LDA produces an optimal linear discriminant function which maps the input into the classification space on which the class identification of the samples is decided. Thus, to acquire a better feature space, the LDA algorithm was applied on the extracted augmented feature vectors of different dynamic activities. The new feature vectors using LDA on the augmented feature space can be represented as

$$F_i = A_i D_{\mathrm{opt}}^T \quad (8)$$

where F_i and A_i represent the LDA-feature vector and augmented feature vector for the i-th dynamic activity sample, respectively.

2.5 Classifier

We decided to use the feed-forward backpropagation ANNs based on the findings of our previous study [13]. In that study, the performance of several automatic classification methods from the machine learning literature including the decision trees, nearest neighbor and Bayesian Networks [4, 9, 21, 30], support vector machines [30], neural networks [9, 10, 17], Gaussian Mixture Models [2], and Markov chains [12, 22, 34] were compared. Finally, the ANNs were chosen for their better performance.

In this study, different number of layers and neurons were tested in order to further optimize the performance. The training of ANNs was also repeated several times by changing the input order in a random fashion. The training and the testing datasets were composed of mixture of activity data collected from the five sensor positions.

For the lower-level recognition, only one network (LNN) was trained. The inputs to LNN were the SE-features. We used one hidden layer with 10 neurons and one output layer with three neurons corresponding to three classification outputs, i.e., the resting activity, dynamic activity (lower-body), and dynamic activity (upper-body). For the upper-level recognition, we trained two networks, i.e., an ANN to recognize the dynamic activities from the lower-body positions (DLNN) and an ANN to recognize the dynamic activities from the upper-body positions (DUNN). The inputs to each of these networks were the LDA-features. Each of these ANNs had one hidden layer with 10 neurons and one output layer with six neurons corresponding to the six dynamic activities.

We adapted the classical cross-validation [8] to evaluate the between-subject accuracy of the system. In other words, the ANNs were first trained with data from all subjects except few and then tested with data from the excluded subjects. The accuracy was then calculated as the proportion of correctly classified windows of data across all activities. This process was repeated until all subjects had participated in the testing datasets. The final overall accuracy was then calculated as the average accuracy across all train-test cycles.

3 Experimental results

Performance of the proposed hierarchical recognition system was then validated in the following three studies.

3.1 Single-level recognition without LDA

In this study, we used a single ANN to recognize all seven activities without employing the proposed hierarchical recognition scheme. The ANN had one hidden layer with 15 neurons and an output layer with seven neurons corresponding to seven activities. Features including the AR-coefficients, SMA, and SE were calculated to form a single feature vector. The 3D-representation of the feature space is shown in Fig. 5, only four classes are shown for the sake of visualization. Severe non-linearity and a high within-class variance could be observed. These features were used to train the ANN. During testing, each test activity was modeled in a similar fashion and the ANN was used for recognition. The recognition results are summarized in Table 1, showing an average recognition of only 47% only.

3.2 Single-level recognition with LDA

In this study, after calculating the AR-coefficients, SMA, and SE we applied the LDA on the extracted feature space. The LDA-features were then used to train the ANN used in

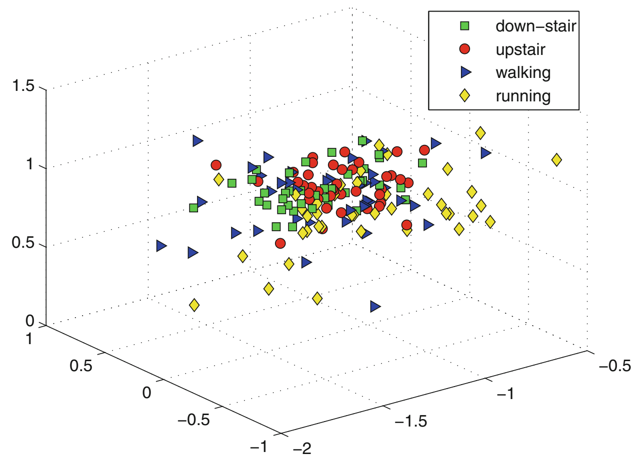


Fig. 5 3D-feature plot for four dynamic activities recorded from five different body positions, showing a high within-class variance

Table 1 Average recognition results (%) for three studies

Activity	Single-level (S-L)	S-L with LDA	Hierarchical scheme
Resting (lying/sitting/standing)	72	89	98
Walking downstairs	42	53	96
Walking upstairs	39	51	94
Walking	44	56	96
Running	52	68	96
Cycling	44	50	94
Vacuuming	36	44	87
Total	47	58.7	94.4

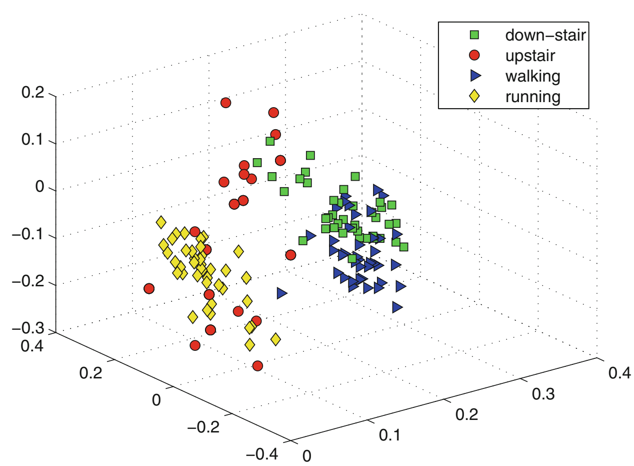


Fig. 6 LDA feature space for four dynamic activities, recorded from five different body positions, after applying the single-level recognition system

the previous study. The LDA-features for the four activities are shown in Fig. 6. They show improved class separability. However, a high within-class variance could still be

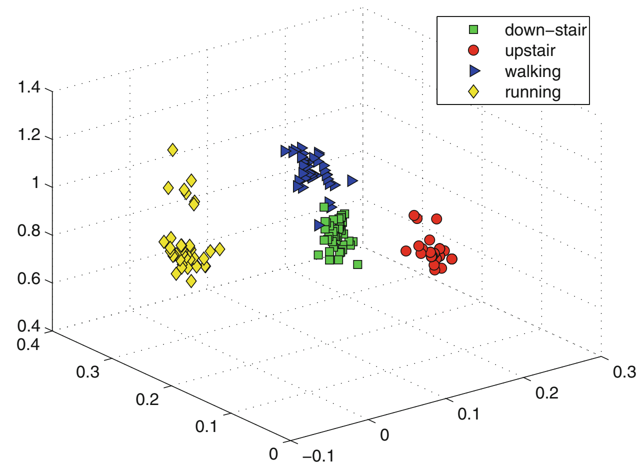


Fig. 7 LDA feature space for four dynamic activities, from lower-body, i.e., front and rear trousers pockets, after applying the proposed hierarchical recognition system

observed. During testing, each test activity was modeled in a similar fashion and the ANN was used for recognition. The recognition results are summarized in Table 1, showing an average recognition rate of 58.7% only.

3.3 Proposed hierarchical recognition

In this study, the proposed hierarchical recognition scheme was used to achieve accelerometer's position-independent activity recognition. Figure 7 demonstrates the LDA-features for the four dynamic activities collected from the lower-body sensor positions, i.e., front and rear trouser pockets. A significant improvement in class separability and a very low within-class variance could be observed. The recognition results for this study are summarized in Table 1, showing an average recognition rate of 94.4% which is a significant improvement over the recognition rates of the two previous studies.

4 Discussion and conclusion

Elderly patients, particularly those with chronic conditions, require continuous long-term physical activity monitoring. Several wearable accelerometer-based systems have been proposed in the past for such use. However, most of these systems require accelerometers to be firmly attached to specific body-parts, thereby forcing subjects to live into a fixed life pattern. Moreover, most prior studies have used the activity data collected under controlled laboratory settings, typically where the researchers have hand-annotated the collected data.

The aim of this study was to implement a single-triaxial-accelerometer-based human activity recognition system without posing any preconditions on accelerometer's position and orientation relative to a subject's body. We collected 24 h of activity data on seven activities of the daily living from eight elderly subjects at home, outside the laboratory. Activities were recognized from the data by loosely placing a triaxial accelerometer in five different pockets, without attaching it firmly to the subjects' bodies. Annotations were performed on the spot by the subjects using a bluetooth headset together with speech recognition software which resulted in very little interference while performing the activities.

In our previous study [13], we used the tilt angle (TA) as a part of an augmented feature vector to recognize three static activities, including lying, sitting, and standing, with an above 90% average recognition accuracy. The TA refers to the relative tilt of the body in space and its computation requires accelerometer's firm attachment to the body. In our new system, since the sensor's orientation can undergo arbitrary changes while performing an activity, it is therefore very hard to compute a reliable estimate of the TA. Moreover, since the body is at rest, the three activities register almost the same frequency components and the SMA. Therefore, these activities were combined into a single group, i.e., the resting activity.

However, a higher level analysis can be employed to achieve further classification of the resting activity as lying, sitting, and standing. For instance, by employing an improved knowledge of the transitional movements, such as lie-to-sit, sit-to-lie, sit-to-stand, and stand-to-sit, these activities could be distinguished from each other with a greater accuracy. In other words, if the system recognizes that the subject is currently resting and he/she has just undergone a sit-to-stand transition, then it can infer that the subject is now standing.

A high within-class and a low between-class variance, caused by change in sensor orientation, magnitude, and frequency, makes accelerometer's position free human activity recognition very challenging. Therefore, extracting discriminating features, which minimize and maximize these variances respectively, was crucial for our system. We employed the LDA for this use. However, it is a linear technique in nature and does not perform well when severe non-linearity is involved. The experimental results of our second study, i.e., single level recognition with LDA, support this fact.

To improve the recognition accuracy, we used a hierarchical recognition approach to separate the dynamic activities from the upper and lower-body sensor positions using their SE-values. Consequently, the high within-class variance resulting from these positions was removed, which reduced the complexity of the classification task. A better feature space was then created by applying the LDA on the augmented feature space, i.e. the AR-coefficients augmented with the SMA.

There are clear limits on what can be achieved in a free-living activity monitoring environment using a single accelerometer, without posing any pre-conditions on its position and orientation. A greater number of sensors, attached firmly to different body-parts allow more accurate activity classification. However, our proposed system is more practical for continuous long-term activity monitoring in the elderly because of its simplicity, ease-of-use, compliance, lower cost, and the ability to recognize some important dynamic activities of daily living with a 94.4% average recognition accuracy.

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