Feature Selection and Activity Recognition System Using a Single Triaxial Accelerometer

Piyush Gupta* and Tim Dallas

Abstract—**Activity recognition is required in various applications such as medical monitoring and rehabilitation. Previously developed activity recognition systems utilizing triaxial accelerometers have provided mixed results, with subject-to-subject variability. This paper presents an accurate activity recognition system utilizing a body worn wireless accelerometer, to be used in the real-life application of patient monitoring. The algorithm utilizes data from a single, waist-mounted triaxial accelerometer to classify gait events into six daily living activities and transitional events. The accelerometer can be worn at any location around the circumference of the waist, thereby reducing user training. Feature selection is performed using Relief-F and sequential forward floating search (SFFS) from a range of previously published features, as well as new features introduced in this paper. Relevant and robust features that are insensitive to the positioning of accelerometer around the waist are selected. SFFS selected almost half the number of features in comparison to Relief-F and provided higher accuracy than Relief-F. Activity classification is performed using Naïve Bayes and k-nearest neighbor (k-NN) and the results are compared. Activity recognition results on seven subjects with leave-one-person-out error estimates show an overall accuracy of about 98% for both the classifiers. Accuracy for each of the individual activity is also more than 95%.**

Index Terms—**Accelerometer, activity recognition, detrended fluctuation analysis (DFA), error estimates, feature selection, k-nearest neighbor (k-NN) classifier, leave-one-person-out (LOO) error, Naïve Bayes classifier, Relief-F algorithm, sequential forward floating search (SFFS) wrapper algorithm.**

I. Introduction

FALLS are a major problem associated with old age. Falls can force elderly people to depend on others, severely affecting their quality of life. Therefore, it is important to develop a technology that can monitor gait of elderly people that looks for precursors to falls. Lack of physical activity and loss of muscle strength is often associated with falls [1]. Therefore, a cost-effective system is needed that can investigate the relationship between probability of fall with the fitness and total count of daily living activities of the elderly person. The first step in this direction is to develop an autonomous system that can classify a gait data-set into different daily living activities. Moreover, with such a system, elderly people (and caregivers/medical personnel) can keep track of the level of activities being performed by them on a regular basis.

Some of the gerontology literature investigates the association of level of daily living activities with the occurrences of falls in elderly population. Graafmans *et al*. [2] and Smee *et al*. [3] related levels of daily physical activities performed by elderly population to the falls. Graafmans *et al*. [2] utilized validated questionnaires to collect falls and daily activity level data on 694 elderly subjects. The study concluded that the elderly people with the highest activity level had significantly lower risk of falls. Moreover, Smee *et al*. [3] concluded in a study on 32 independent living elderly people that lower physical functionality was strongly (independent of age) related to greater risk of falls. Therefore, a lot of time and money has been invested world-wide by different organizations, both public and private, to classify activities of daily living (ADL) and fall detection. A number of systems have been proposed and sometimes tested [4]–[27]. A few of these systems are discussed in this section to allow our proposed system to be put in context.

Bao and Intille [4] utilized 5 biaxial accelerometers, worn on different parts of the body, to classify 20 different ADL. Four features were calculated specifically for each axis (mean, energy, frequency-domain entropy, and correlation of acceleration data) and different classifiers were tested. Data from 20 subjects was used for the experiments and the best performance of 84% was obtained using decision tree classifiers. The system provided a strong case for detection of ADL. However, the limitations are the number of accelerometers that can be used on one's body and the need of accelerometers to be put in a prescribed orientation.

Khan *et al.* [5], [6] utilized a single triaxial accelerometer to distinguish between the different ADL. In [5], a triaxial accelerometer was attached to the chest of the user in a particular orientation and was able to classify fifteen activities with an average accuracy of 97.9%. However, when the system was tested with the sensor at five different positions, the accuracy of the system was reduced to 47%. In [6], a new system is proposed which can detect activities irrespective of the position of the sensor with an accuracy of 94.4%. However, all of the transitional activities (sit-to-stand, etc.) were excluded from these newer experiments.

He *et al.* [7], [8] utilized a single, triaxial accelerometer in various body locations in an orientation independent setting. The paper identifies four different activities as walking, running, jumping and being still (stationary). The system reports

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*P. Gupta is with the Department of Electrical and Computer Engineering, Texas Tech University, Lubbock, TX 79409-3102 USA (e-mail: piyushgupta.2@gmail.com).

T. Dallas is with the Department of Electrical and Computer Engineering, Texas Tech University, Lubbock, TX 79409-3102 USA (e-mail: tim.dallas@ttu.edu).

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97.51% of overall accuracy in identifying the four activities. However, the system did not include any transition states in the experiments.

Atallah *et al*. [9] utilized six wearable accelerometers, in addition to the ear-worn activity recognition sensor (e-AR), at different body positions to evaluate the best sensor position and relevant features. Filter-based feature selection approaches: Relief [28], Simba [29], and minimum redundancy maximum relevance (mRMR) [30], were evaluated for selecting the features for each sensor. k-Nearest neighbor (k-NN) (with $k = 1$, 5, and 7) and Bayesian classifier were tested for activity classification. The activities were classified into five broad groups as: very low level, low level, medium level, high level, and transitional activities. Outcomes of the three feature selection algorithms were relatively similar, as were the classification performance of k-NN ($k = 5$ and 7) and Bayesian classifier. However, results showed that none of the sensor positions, in isolation, could provide high precision and recall for all the groups.

More systems have been proposed for monitoring the gait of an individual to determine falls and the daily living activities, some of which are listed in [10]–[27]. However, most of these systems require accelerometers to be in a particular orientation and position on the human body or else exclude transitional events such as sit-to-stand, stand-to-kneel-to-stand, etc.

This study is focused on utilizing minimum number of sensors and analyzing data from young, age-matched subjects to determine if data corresponding to different physical activities tends to form different clusters. This study uses feature selection algorithms to carefully select the best features, from a range of newly developed features and previously published features, such that the new system is independent of the accelerometer position around the waist. The paper proposes an activity recognition system that requires less training of the user and, therefore, is a step towards utilizing it in a more realistic environment. Moreover, our study aims to classify the transitional events in ADLs.

II. System Components and Overview

A. Belt-Clip Accelerometer

A MEMS triaxial accelerometer is used to measure acceleration in three orthogonal directions at all times. This research utilizes a custom made belt-clip device that can be easily worn at waist level on a belt. A Freescale MMA7260 accelerometer is used in the belt-clip device to report acceleration in the range of ± 4.0 g. The belt-clip is 15 cm $\times$ 11 cm $\times$ 4.5 cm in size and weighs about 100 g. The belt-clip accelerometer sampled data at a sampling rate of 126 Hz during this experiment. The belt-clip accelerometer transmits nine ZigBee packets in one second (each containing 14 time-stamped samples). These packets are de-packaged at the server into individual samples as they are received. Consistent sampling allows time and frequency domain analysis. Previous research studies have demonstrated that human movements can be modeled by signals at and below 18 Hz. Therefore, a sampling rate of 126 Hz was considered to be more than sufficient.

Fig. 1. Belt-clip triaxial accelerometer.

Fig. 2. Gateway provided by AT&T Labs.

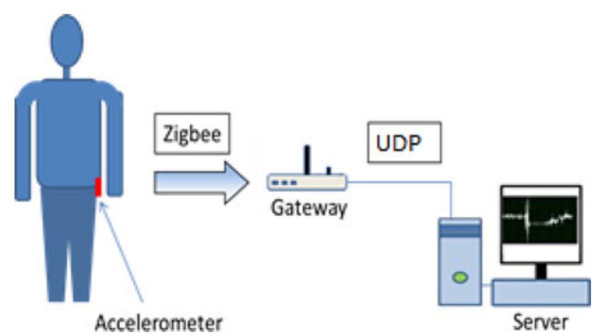

Fig. 3. Graphical depiction of experimental setup.

The belt-clip accelerometer, as shown in Fig. 1, utilizes ZigBee protocol for wireless communication to the gateway. The belt clip is supported by a rechargeable battery which lasts a couple of days before requiring recharge. The belt-clip has a battery indicator and is a preproduction prototype model to be used for geriatric gait study in this research project.

B. AT&T Gateway

An AT&T supplied Actuarius gateway converts a message received in ZigBee protocol to User Datagram Protocol (UDP). ZigBee protocol is used by the accelerometers for sending the data to the gateway. Once received by the gateway, the data packets are sent to the server side processing unit utilizing UDP protocol. The gateway is shown in Fig. 2. The complete system implementation is shown in Fig. 3.

C. MATLAB

MATLAB was used to record and analyze the data on the server. Each activity of each individual was recorded in a separate spreadsheet file and labeled so as to be used to calculate training or test vectors later.

Fig. 4. Positions of three belt-clip accelerometers for feature selection.

Algorithm development for the activity recognition system was done in two steps. The first step identifies and selects features that can reliably classify activities irrespective of where the belt-clip is worn on the waist. The second step was to train and test those features using two separate classifiers (k-NN and Naïve Bayes) and evaluate the error estimates from data on more diverse subjects. The following sections explain the feature selection process followed by the activity recognition experiment and its results.

III. Feature Selection

A. Experimental Setup for Feature Selection

Data were collected in an area that consisted of a room and a small corridor closely resembling an apartment/home or office setting. Data were collected on two young healthy subjects, one male and one female, aged 28 years with no walking impairment. Subjects were asked to wear three triaxial accelerometers at their waist at three different positions. All the belt-clip accelerometers were tested before the experiments (on turntable/pendulum) for noise, repeatability and reproducibility to ensure the data from the three independent belt-clips are consistent. Positions of the triaxial accelerometers on the waist are shown in Fig. 4. This was done to ensure that the data for the same activity is simultaneously collected by three accelerometers having different orientation for their X and Z axes with respect to the human body. Therefore, if the set of final selected features are able to correctly identify activities from all three accelerometers independently, the accuracy of the features can be said to not depend on the location of the belt-clip around the waist. The design of the belt-clip accelerometer, when worn on belt at the waist, allows the Y-axis of the accelerometers to mostly align with the vertical direction (longitudinal axis) of human motion. Though there might be some minor tilt with respect to the Y-axis when a user wears it on his/her belt, the features selected are expected to be robust enough to accurately recognize the gait event.

B. Data Setup and Feature Computation

Two subjects were asked to perform six activities (including transitional events) namely walking, jumping, running, sit-to-stand/stand-to-sit, stand-to-kneel-to-stand, and being stationary (sitting or standing at one place). Standing-to-kneeling-to-standing is to simulate the instances when a user is putting down or picking up an object from the ground. The two subjects performed all the daily living activities at comfortable, yet varied speeds and manners such that a more diverse data can be collected to select the best features possible. The acceleration data signals are segmented into windows of 6 s each with a 50% overlap between two consecutive windows. Therefore, every decision made about the activity is for the duration of the six seconds window. Previous literatures have utilized window sizes ranging from 2 s to 6.7 s for the purposes of activity detection [4]–[27]. Since the transitional events have variable completion/execution time, a longer window size (6 s) was chosen such that even the slowest of the stand-to-kneel-to-stand or stand-to-sit events performed in the experiments are completely contained in a window. Moreover, prior work published in [4] has demonstrated success with 50% overlap in windows. It should be noted that the stand-to-sit/sit-to-stand transitions and standing-to-kneeling-to-standing events were not performed in isolation. The user was also walking before or after performing these tasks to simulate a more realistic scenario. Even though the 6 s window that entirely contained the transitional event was kept and labeled appropriately into sit-to-stand or standing-to-kneeling-to-standing, there were instances when the window of transitional event data contained some part due to walking, too.

TABLE I
Initial Set of Features for Activity Recognition

Features	Time-series
Energy (Spectral) [4]	E_y $E_{x,z}$ $E_{x,y,z}$
Entropy (Spectral) [4]	H_y $H_{x,z}$ $H_{x,y,z}$
Mean [4]	μ_y $\mu_{x,z}$ $\mu_{x,y,z}$
Variance [4]	σ^2_y $\sigma^2_{x,z}$ $\sigma^2_{x,y,z}$
Mean Trend	μT_y $\mu T_{x,z}$ $\mu T_{x,y,z}$
Windowed Mean Difference	μD_y $\mu D_{x,z}$ $\mu D_{x,y,z}$
Variance Trend	σT^2_y $\sigma T^2_{x\text{-}z}$ $\sigma T^2_{x\text{-}y\text{-}z}$
Windowed Variance Difference	σD^2_y $\sigma D^2_{x\text{-}z}$ $\sigma D^2_{x\text{-}y\text{-}z}$
Detrended Fluctuation Analysis coeff.	α_y $\alpha_{x,z}$ $\alpha_{x,y,z}$
X-Z Energy Uncorrelated (Spectral)	EU_{xz}
Max. Difference Acceleration [10]	dA_y $dA_{x,z}$ $dA_{x,y,z}$

A large set of features were calculated using the raw accelerations recorded during the activity. Some of these features are previously shown to be effective for activity recognition in the published literature. However, according to our best knowledge, some of the unique features presented in this paper have not been used previously for activity recognition using a triaxial accelerometer. These features will be explained in more detail in this paper, whereas references are provided for the more commonly used/cited features. A list of all the features is provided in Table I. All the features were evaluated for the longitudinal axis (Y–vertical), resultant acceleration ($X-Y-Z$), and for the acceleration in horizontal $(X-Z)$ plane.

The details of mean trend, windowed mean difference, variance trend, detrended fluctuation analysis (DFA) coefficient, and uncorrelated energy are given below. These newly evaluated features were intuitively discovered and included since we need a high accuracy for transitional events from activities like walking and being stationary (sitting or standing). As mentioned before, the 6 s sample of transitional event might contain some data corresponding to walking or being stationary that followed or preceded the transitional event. In such cases, energy, entropy, mean and variance of these samples were expected and observed to be closer to those of walking or being stationary. Therefore, following new features were developed which will break this 6-s data into smaller windows and analyze it to capture the transitions.

1) Mean Trend and Windowed Mean Difference: The 6 s long acceleration series is further divided into 12 windows (0.5 s each) with no overlap. The mean of each of these 0.5 s windows is calculated and subtracted from the mean of the succeeding window. Therefore, a trend of mean (slope) for every half second is found for the entire 6 s window. The sum of absolute values of these slopes is calculated to be a feature called mean trend.

$$\mu T = \sum_{i=2}^{12} (|\mu_i - \mu_{i-1}|).$$

Also, the mean of each of these 0.5 s windows is subtracted from the overall mean of the 6 s data. The sum of absolute values of these distances is called the windowed mean difference feature

$$\mu D = \sum_{i=1}^{12} (|\mu - \mu_i|).$$

2) Variance Trend and Windowed Variance Difference: Variance trend and windowed variance difference is computed similarly to the mean trend and windowed mean difference, except variance is calculated instead of mean for each of the windows

$$\sigma T^2 = \sum_{i=2}^{12} \left(\left| \sigma_i^2 - \sigma_{i-1}^2 \right| \right)$$

$$\sigma D^2 = \sum_{i=1}^{12} \left(\left| \sigma^2 - \sigma_i^2 \right| \right).$$

3) DFA Coefficient: DFAs [31] provide us with a methodology to examine long-range correlation of a time series data. While DFA does not account for spurious correlations introduced by external nonstationary trends, it investigates fluctuations from the linear local trends. DFA leads to the value of alpha (α) that can be used to examine the relationship between the amount of fluctuations in a subset of a time series to the length of the subset [26]. An uncorrelated time series such as white noise will have a value of 0.5 for the alpha. An alpha value of less than 0.5 indicates that the fluctuations in one direction are likely to be followed by the fluctuations in the opposite direction. An alpha value more than 0.5 reflects self-similarity such that the fluctuations at one time scale are similar to the fluctuations at the other time scale.

To perform DFA and compute the scaling exponent α of a time series given by $x(i)$ (where $i = 1, 2, \ldots, N$), the time series should first be integrated [32]

$$y(k) = \sum_{i=1}^{k} x(i) - \bar{x}, \quad k = 1, 2, \ldots, N.$$

Once the integrated time series $y(k)$ is evaluated, it is divided it into N/n boxes of equal length (n) with no overlap. Then, a best-fit local trend y_n is fitted onto the each box. Calculate the average fluctuations $F(n)$ by the following equation:

$$F(n) = \sqrt{\frac{1}{N} \sum_{i=1}^{N} [y(i) - y_n(i)]^2}.$$

The same procedure is repeated for different box sizes and the average fluctuations $F(n_m)$ as per different scales is evaluated. As deviations becomes larger with the time scale, $F(n)$ is expected to increase with the increase of box sizes n. After plotting log $F(n_i)$ with respect to log n_i, the value of α can be estimated by the slope of the least squares fitted line [32].

4) $X-Z$ Energy Uncorrelated: Energy of X- and Z-axis accelerations (E_x and E_z) are calculated and added together. Cross-correlation factor (r_{xz}) is calculated between the X- and Z-axis acceleration series. Then, *X–Z* energy uncorrelated is found, shown as follows:

$$EU_{xz} = 2 * (E_x + E_z) - r_{xz} * (E_x + E_z).$$

5) Maximum Difference Acceleration: Difference between maximum and minimum acceleration experienced on each axis (*dx*, *dy*, and *dz*) during the 6 s window is calculated [10]. Difference acceleration for the Y–axis ($dA_y = dy$) is considered as one feature. The other features are simply calculated for the *X–Z* plane and the $X-Y-Z$ space as [10]

$$dA_{x,z} = \sqrt{(dx^2 + dz^2)} \text{ and}$$
$$dA_{x,y,z} = \sqrt{(dx^2 + dy^2 + dz^2)}.$$

C. Feature Selection

A total of 31 features were computed for the 6 s window of data from each triaxial accelerometer. Two people performed all six activities of walking, running, jumping, standing-to-kneeling-to-standing, sitting-to-standing/standing-to-sitting, and being stationary (sitting/standing). Since transitional activities, standing-to-kneeling-to-standing and sitting-to-standing/standing-to-sitting, are single events rather than continuously performed activities, the number of samples for these two gait events is lower than the other four activities. Feature selection was performed in filter-based approach using Relief-F [28], [33], and Wrapper-based approach using a variant of sequential forward floating search (SFFS) [34]. k-NN (10 neighbors) and Naïve Bayes classifiers were utilized for error estimation. Moreover, since different features are on different scales, all the features were normalized to obtain best results for k-NN. This ensures equal weight to all the potential features, while using k-NN classifier.

1) Filter-Based Feature Selection Using Relief-F: Kira and Rendell [28] came up with a Relief algorithm in 1992 for a general problem with a high number of features. Kononenko [33] improved the basic Relief algorithm, into Relief-F, by improving noise immunity and introducing support for multi-class problems. The Relief and Relief-F algorithms use a statistical approach rather than heuristic search for finding the feature subset. Relief-F provides a relevance weight to each of the

TABLE II
RESULTS FROM FEATURE SELECTION USING RELIEF-F

Classifier	Features Selected	Re-substitution error
k-NN	21	8
Naïve Bayes	30	29

potential feature and the ones above a set relevance threshold are selected.

In our approach, we determined the threshold as the number of features that provide best resubstitution accuracy with the classifiers. For evaluating resubstitution accuracy, the same dataset is used for training and testing purposes. The features were sorted according to their relevance in decreasing order. The most relevant feature was first added and resubstitution error on the given data-set was found using k-NN and Naïve Bayes classifiers. Then, the next relevant features were added one by one and resubstitution error was calculated each time until all the 31 features were added. Now, the least number of features that provided minimum resubstitution errors were selected. The minimum resubstitution error and number of features selected for each of k-NN and Naïve Bayes classifier using Relief-F is shown in Table II. The errors are out of 1740 samples calculated for the two subjects.

2) Wrapper-Based Feature Selection Using SFFS: The Wrapper-based approach for feature selection has certain advantages and disadvantages over the filter-based approach. The filtering methodology is based on data processing and data filtering and does not use a particular classification approach as a standard. Therefore, they are more generalized features and can be implemented using any of the classification systems. However, the Wrapper approach uses a classification scheme as a wrapper around which the whole feature selection is carried out. The features that provide high accuracy when included in the learning scheme of the wrapper are picked in the subset. Though they have poor generalization across different learning methods and are computationally expensive, they tend to provide higher accuracy than the filter-based approaches.

Our implementation of SFFS approach starts with an empty set for the desired selected features "X." The features are to be selected from a larger set of features "S." Let's say the most significant feature in S, with respect to X, is the one which provides the least resubstitution error when included in the X. At each iteration, the most significant feature in S is included into X if its inclusion does not increase the resubstitution error. Similarly, the least significant feature in X is found and removed if its exclusion helps improve the accuracy. Moreover, if there is a tie between two or more features to be the most significant feature in S, the one having higher weight from Relief-F is selected. Also, since special conditions are required to prevent the SFFS algorithm from getting into an infinite loop, resubstitution error and the new set of X after each iteration was verified. If the error became zero, the desired X has been selected and, therefore, the program can safely be terminated. However, if the error is not zero, but the set X before and after iteration is equal, the program has reached its limit for the dataset and the resulted X can be assumed to be the most optimum set for the given implementation. Therefore, this is the final selected set of features and the program should be safely terminated.

TABLE III
RESULTS FROM FEATURE SELECTION USING SFFS

Classifier	Features Selected	Re-substitution error
k-NN	11	5
Naïve Bayes	12	6

TABLE IV
FINAL FEATURES SELECTED FOR ACTIVITY RECOGNITION USING SFFS

Classifier	Selected Features
Common to both	$H_{x,z}$ $\sigma^2_{x,y,z}$ EU_{xz} $\mu D_{x,y,z}$ $\mu T_{x,y,z}$ α_y
k-NN	E_y $E_{x,y,z}$ $H_{x,y,z}$ σ^2_y $dA_{x,z}$
Naïve Bayes	μ_y $\mu_{x,y,z}$ μD_y σ^2_y $\sigma^2_{x,z}$ $\alpha_{x,z}$

Our SFFS implementation was carried out twice using Naïve Bayes and k-NN, respectively. The minimum resubstitution error and number of features selected for each of k-NN and Naïve Bayes classifier using SFFS is shown in Table III.

Clearly, SFFS provided much better estimates for resubstitution error at less than half the number of features as compared to Relief-F-based filtering. Even though k-NN performed marginally better than the Naïve Bayes classifier, the performance of the two classifiers is considered to be equal and, therefore, both the classifiers are evaluated for activity recognition in multiple subjects using their correspondingly selected features. The features selected by SFFS for NB and k-NN are given in Table IV.

It is interesting to note that the mean trend, windowed mean difference, and DFA coefficients for one or more axis were included as relevant features by both the classifiers. The preference in inclusion of these features over overall mean and energy proved that our hypothesis for further breaking the windows is justified.

IV. ACTIVITY RECOGNITION

Once the feature set and classifier is known for a classification problem, the system requires training and a testing dataset for evaluating the efficacy of features in a more practical scenario. The feature validation and, therefore, activity recognition was performed on data from seven subjects.

A. Experimental Setup for Activity Recognition

Data were collected in the same area where data were collected on the two subjects for the feature selection process. Data were collected on seven young healthy subjects, including the two previously recruited subjects, between 22 and 28 years of age with no walking impairment. Subjects were asked to wear the triaxial accelerometer at their waist. No specific instructions were given about how to wear the accelerometer and where exactly around the waist it should be worn. Each subject was asked to perform the six previously mentioned activities. All individuals conducted these activities in their own preferred speed for about 2–3 min each.

Different individuals wore the accelerometer on different positions around the waist. It was also interesting to note during

TABLE V
ACCURACY IN CLASSIFICATION FOR INDIVIDUAL ACTIVITIES

Activity	k-NN	Naïve Bayes
Jump	95.6%	95.6%
Run	98.6%	99.1%
Walk	100%	99.2%
Sit	99.2%	97.4%
S2S[a]	95.4%	97.7%
SKS[b]	97.3%	96.3%
Total	98.4%	97.8%

[a]S2S: Sit-to-stand/stand-to-sit.
[b]SKS: Stand-to-kneel-to-stand.

TABLE VI
CONFUSION MATRIX FOR ACTIVITY RECOGNITION USING NB

	Run	Jump	Walk	Sit	S2S	SKS	True count
Run	347	3	0	0	0	0	350
Jump	12	259	0	0	0	0	271
Walk	0	0	479	0	3	1	483
Sit	0	0	0	589	16	0	605
S2S	1	0	1	0	127	1	130
SKS	3	0	2	0	2	180	187

the experiment that the left handed individuals (2 out of 7) wore the sensor on the left side of the waist whereas right handed individuals wore it on the right side. Though this behavior might not be true for the entire left-handed and right-handed population, we expect our algorithm to eliminate any errors due to difference in positions of accelerometer around the waist and, therefore, reduce the training and efforts of the real subjects.

B. Feature Computation and Activity Classification

Hereby, all the feature vectors are calculated separately for NB classifier and k-NN classifier. Since data were collected on seven individuals, the leave-one-person-out (LOO) strategy was used to train and classify the daily living activities. Therefore, data collected on six individuals was used to train the system and then the system was tested by classifying the data of the seventh individual accordingly. This was repeated seven times until data from all the individuals was classified.

V. RESULTS

The results from the activity recognition on seven subjects showed high accuracy for all the activities. Samples or feature vectors computed on seven subjects totaled to be 2026. The overall accuracy of the system was about 98% from both the classifiers. The result for each individual activity using the LOO error estimation is provided in Table V for both the classifiers. Classification results showed accuracy of more than 95% for all the activities.

Tables VI and VII show the confusion matrix of activity classification using k-NN and Naïve Bayes classifiers, respectively. The system showed excellent classification results for all of the activities considered in this experiment. As per the confusion matrix, there were misclassifications of jumping into running, and vice versa, for both the classifiers. The system misclassified

TABLE VII
CONFUSION MATRIX FOR ACTIVITY RECOGNITION USING k-NN (10 NEIGHBORS)

	Run	Jump	Walk	Sit	S2S	SKS	True count
Run	345	5	0	0	0	0	350
Jump	12	259	0	0	0	0	271
Walk	0	0	483	0	0	0	483
Sit	0	0	0	600	5	0	605
S2S	1	0	4	1	124	0	130
SKS	1	0	4	0	0	182	187

four samples each from transitional events, and stand-to-kneel-to-stand into walking for the k-NN classifier. The reason for this is due to the fact that these events were not performed in isolation but added with walking as explained in Section III. Since the window size is fixed at 6 s, the windows of the transitional gait event also contained the walking movement of the subject prior to or after the transition is over. Therefore, at times when the transition is completed very quickly, there is a good portion of the windowed data that includes data from walking. Even though the new features performed well in classifying them correctly, 3%–4% samples were still misclassified.

VI. CONCLUSIONS AND FUTURE WORK

Even though the activities were performed by different individuals at different speed and style, it was observed that the system can classify different activities with high accuracy. The system, thus, provides a foundation towards a more robust system that will require minimum training of the users and provide least errors due to orientation and positioning offsets. The overall accuracy of the system is 98%; however, the future work requires testing on more subjects.

Moreover, both the classifiers, k-NN classifier (10 neighbors) and Naïve Bayes classifier, provided high accuracy and comparable results for their respective feature sets. It was shown that different classifiers work better with different features for activity recognition and, therefore, wrapper-based feature selection might provide better results than the filter-based approach. Though there are some commonly used features for activity classification using accelerometers in previously published literature, this paper introduces more features that are shown to be relevant for the activity recognition. Mean trend, windowed mean difference, energy uncorrelated, and DFA are introduced as features showing good results for activity classification. These features were chosen ahead of other popular features, energy and mean, by feature selection algorithms.

The system showed excellent results in LOO test scenario for seven different young healthy subjects performing activities in their own preferred manner. However, it will be interesting to analyze results on more diverse population. Furthermore, the system can be utilized to perform further investigations in the differences in ADL between elderly and young subjects or people with different weights. It is likely that different training sets are required for people in different age groups or weight groups. Moreover, since the feature vectors and classifiers are known, it will be an interesting exercise to evaluate if 6 s (and 50% overlap) is an optimum window length or if the results for transitional events can be improved, without compromising accuracy of other activities, by reducing the size of the window.

The system can also be used in monitoring elderly people. This may help to better understand the events prior to the falling cases when the elderly fell while unattended. It may also help relate the falls in the elderly people to the amount of activities performed by them on a daily basis. Furthermore, it might help quantify the amount of activities that are required by an individual to reduce the chances of falling.

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