Sensor Placement for Activity Detection using Wearable Accelerometers

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***Abstract*—Activities of daily living are important for assessing changes in physical and behavioural profiles of the general population over time, particularly for the elderly and patients with chronic diseases. Although accelerometers are widely integrated with wearable sensors for activity classification, the positioning of the sensors and the selection of relevant features for different activity groups still pose interesting research challenges. This paper investigates wearable sensor placement at different body positions and aims to provide a framework that can answer the following questions: (i) What is the ideal sensor location for a given group of activities? (ii) Of the different time-frequency features that can be extracted from wearable accelerometers, which ones are most relevant for discriminating different activity types?**

***Index Terms*—Wearable sensors, Body sensor networks, feature selection, sensor positioning.**

I. Introduction

The last decade has seen increasing maturity of pervasive sensing, largely due to miniaturisation of sensor hardware and steady advances in wireless technologies. The technical focus and challenges have now moved from obtaining wearable sensor data in laboratory settings to that of efficiently analysing large amounts of data using intelligent pattern recognition and data mining techniques. In this regard, developing on-node processing and data abstraction techniques, whilst minimising the number of sensor nodes to facilitate practical deployment and avoid activity restriction has become an important research topic.

Wearable accelerometers have played an important role in inferring metabolic energy expenditure [1], [2], [3], measuring gait parameters [4], [5], predicting falls [6] and detecting activities of daily living [7], [8]. Their extensive uptake is mainly due to the small size, relatively low cost, as well as their ease of integration with existing platforms for sensor networks.

Existing research has shown that activity recognition by using accelerometers could improve the quality of care provided to patients as well as being used as a means of observing lifestyle and behaviour changes for healthy subjects. An increase of activity can indicate improvement after surgery [9], quantify the positive effect of medication and provide carers with a measurement indicating general ‘well-being’.

One of the limitations of using wearable accelerometers for activity recognition is that it is often difficult to predict which locations on the body can provide the most relevant features with respect to activity classification. Placing the accelerometers on too many positions can be cumbersome and prone to errors. Another limitation is that accelerometers alone may not be enough to provide sufficient contextual information and they need to be combined with other sensors such as microphones [10], gyroscopes [11], [12] and ECG sensors [13] to provide more accurate activity classification. Table I summarises some of the recent work using accelerometers on their own for activity recognition. It is evident from current studies that the position of the sensors is important for activity classification. Although sensor location depends on the activity being monitored, there are thus far no comparative studies investigating optimal sensor placement for activities of daily living.

Reference	**Position**
Bao *et al.* [14]	hip, wrist, ankle, arm and thigh
Mathie *et al.* [15]	several body positions (survey)
Mathie *et al.* [16]	waist
Karantonis *et al.* [17]	waist
Yang *et al.* [8]	wrist
Lo *et al.* [18]	ear-worn
Hester *et al.* [19]	ankle

TABLE I
RECENT APPROACHES OF USING ACCELEROMETERS (ON THEIR OWN) FOR ACTIVITY RECOGNITION WITH THE BODY POSITIONS USED.

The practical requirement for home monitoring is that it is preferable to have a small, light-weight sensor embodiment that can provide maximum information content. This would increase wearability and avoid the use of manual labelling of different activities, as adopted by some of the current systems. Therefore, sensor positioning plays an important role in assessing the pervasiveness and wearability of devices. This paper addresses two questions related to optimal sensor placement: the first is that of sensor feature relevance for activity classification and the second is that of investigating optimal accelerometer positions for the detection of different groups of daily activities.

II. Experimental Setup

In order to gather data simultaneously from a large number of wearable sensors, we have integrated 3D accelerometers with the BSN platform [20] and a light-weight rechargeable battery board. 11 subjects were recruited (9 males, 2 females) to wear these sensors on 6 body positions shown in figure II. Subjects also wore the e-AR (ear worn activity recognition) sensor (Figure II) [7], also based on the BSN platform, while performing the circuit of activities given in Table II for 2 minutes each. The activities are classified into 4 main groups of activity as given in the compendium of physical activity [21]. Figure II shows some of the subjects while performing the circuit of activities. The sampling frequency used throughout the exercises is 50 Hz.

Fig. 1. Sensor placement for the experiment. The left figure shows the wearable sensors on the chest, arm, wrist, waist, knee and ankle. The right figure shows a subject wearing the e-AR sensor.

(a)

(b)

Fig. 2. Example activities of daily living used for this study; (a) eating, walking and wiping tables, (b) food preparation, vacuuming and lying down.

Activity	Activity group
1. Lying down	Very low level activity
2. Preparing food	Low level activity
3. Eating and drinking	Low level activity
4. Socialising	Low level activity
5. Reading	Low level activity
6. Getting dressed	Low level activity
7. Walking in a corridor	Medium level activity
8. Treadmill walking at 2 km/h	Medium level activity
9. Vacuuming	Medium level activity
10. Wiping tables	Medium level activity
11. Running in a corridor	High level activity
12. Treadmill running at 7 km/h	High level activity
13. Cycling	High level activity
14. Sitting down and getting up (repeat 5 times)	Transitional activity
15. Lying down and getting up (repeat 5 times)	Transitional activity

TABLE II
LIST OF ACTIVITIES AND THEIR CLASSIFICATION INTO ACTIVITY GROUPS AS GIVEN IN THE COMPENDIUM OF PHYSICAL ACTIVITIES [21].

III. Analysis Methodology

A. Feature extraction

Although significant care was taken to place all the wearable accelerometers at similar positions for all subjects, there were inevitable variations while attaching the sensors. Thus, the features extracted were chosen to be features that would not be highly affected by changes in orientation. These features are summarised in Table III and include standard features that are generally used for activity recognition including variance, entropy and frequency features. The windows used for feature extraction were selected to be 5 sec each with no over-lap.

Feature number	Description
1	Averaged variance over 3 axes
2	RMS of signal derivative
3	Mean of signal derivative
4	Average entropy over 3 axes
5	Average Cross correlation between each 2 axes
6	Average range over 3 axes
7	Average main frequency of the FFT over 3 axes
8	Total signal Energy averaged over 3 axes
9	Energy of 0.2 Hz window around the main frequency over total FFT energy (3 axis average)
10	Averaged skewness over 3 axes
11	Averaged kurtosis over 3 axes
12	Averaged range of cross covariance between each 2 axes
13	Averaged mean of cross covariance between each 2 axes

TABLE III
LIST OF FEATURES EXTRACTED FROM RAW ACCELEROMETER SIGNALS.

B. Feature Selection

To assess the relevance of features for discriminating activities per sensor, feature selection was used to investigate the importance of each type of feature in predicting activity classes. In this work, we used 'filter' rather than 'wrapper' feature selection methods as the former does not depend on classifiers used for classification. It generally assesses the contribution of each feature to increasing class distances or margins between classes. Three methods of feature selection were investigated and are summarised as follows.

1) RELIEF Feature Selection: There are 2 types of margins that are used in machine learning to define classifier confidence when making a decision. The first is the *distance margin* which looks at maximising the distance between an instance and the decision boundaries, and the second is the *hypothesis margin* which is the distance between the hypothesis and the closest hypothesis that assigns an alternative label to the given instance [22]. The RELIEF algorithm for feature selection [23] is an iterative algorithm that utilises hypothesis margins to assign weights to features in order to increase the margin between samples in different classes. The following update rule is used per iteration:

$$w_i = w_i + (x_i - nearmiss(x)_i)^2 - (x_i - nearhit(x)_i)^2 \quad (1)$$

In equation 1, w_i refers to weights per feature i, x_i is the value of the instance for i, $nearhit(x_i)$ and $nearmiss(x_i)$ refer to the nearest point to x_i with the same and different labels respectively. RELIEF has been used extensively in literature due to its speed and simplicity in weighting relevant features. However, it does not have mechanisms for eliminating redundant features.

2) Simba Feature Selection: The Simba (Iterative Search Margin Based Algorithm) for feature selection [22] is similar to RELIEF in terms of updating feature weights to provide maximum margins. However, unlike RELIEF, Simba performs a gradient ascent over weights to re-evaluate distances according to the weight vector w. This allows it to cope better with redundant features. Correlated features could be chosen by Simba if they contribute to overall performance.

3) mRMR (minimum Redundancy Maximum Relevance) Feature Selection: The mRMR framework for feature selection [24] aims to find features that provide the maximum relevance (equivalent to maximum dependency between features and class labels) as well as the minimum redundancy. These two criteria are combined in an incremental selection scheme using mutual information to assess relevance and redundancy. Mutual information between two random variables x and y can be defined in terms of their probabilistic density functions $p(x)$ and $p(y)$ as well as their joint probability $p(x, y)$:

$$I(x, y) = \int\int p(x, y) log \frac{p(x, y)}{p(x)p(y)} dxdy \quad (2)$$

Incremental search methods are used to find feature sets (S) that satisfy the mRMR operator $\Phi(D, R) = D - R$ where D and R are the relevance (approximating dependency) and redundancy respectively. Features that satisfy both of the following criteria are selected (c is the class label and x_i the feature):

$$maxD(S, c), D = \frac{1}{|S|} \sum_{x_i \in S} I(x_i, c) \quad (3)$$

$$minR(S), R = \frac{1}{|S|^2} \sum_{x_i, x_j \in S} I(x_i, x_j) \quad (4)$$

C. Classification

In this work, we opted for classifiers known for their speed as the datasets were relatively large when all subjects were combined. For this reason, we have used the knn classifier (K-nearest neighbour) with different values of k to assess the effect of outlier points. We have also used a Bayesian Classifier where Gaussian distributions were used to model the priors of classes and the posterior probability of a point x belonging to a class (C_k) calculated as:

$$P(C_k|x) = \alpha P(x|C_k)P(C_k) \quad (5)$$

The normalising constant α, is expressed as follows for a total number of classes K:

$$\alpha = \frac{1}{\sum_{k=1}^{K} P(x|C_k)P(C_k)} \quad (6)$$

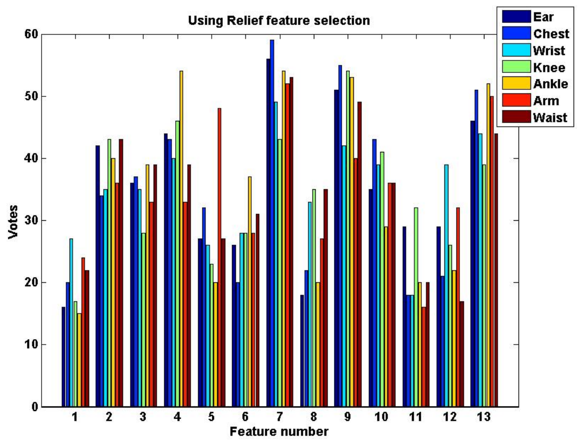
IV. Results

A. Optimal Features for Activity Discrimination

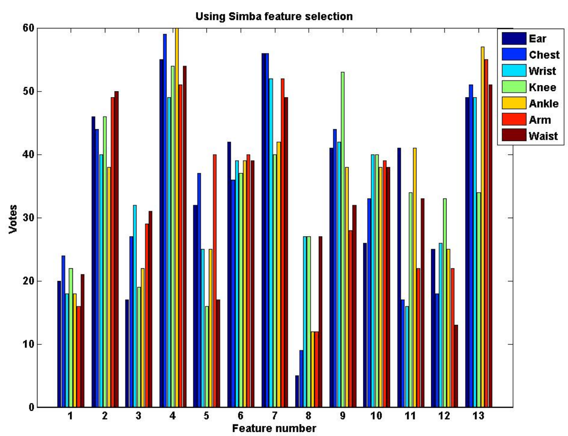
For optimal feature selection, features (given in Table III) were extracted for all 11 subjects, 15 activities and 7 wearable sensors. The 15 activities were combined into the 5 groups of activities given in Table II. The 11 subjects were integrated in one dataset and the three feature selection algorithms were used per activity group per sensor. The results of the feature selection algorithms were used to rank features from most relevant to least relevant, and weights were assigned according to this ranking. The weighting used per feature f_i, w_i was:

$$w_i = N - rank(f_i) \quad (7)$$

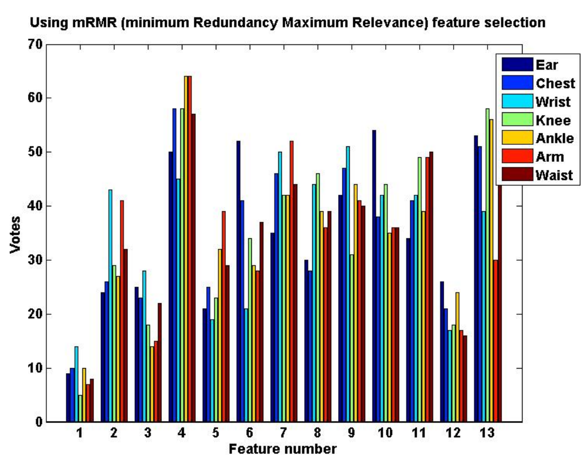
where N is the total number of features. The high weights provide an indication of features that were highly ranked by the algorithms. The results were averaged over all activities per sensor leading to a weighting (or voting) reflecting the relevance of each feature for overall discrimination of activity. Results of using RELIEF, Simba and mRMR are shown in Figures 3(a), 3(b) and 3(c) respectively. Feature numbers in these figures refer to the numbers in Table III. As indicated in [22], the RELIEF feature selection method could fail to remove redundant features. Despite this, the results for the 3 algorithms are relatively similar. Feature 4, namely the averaged entropy over 3 axes is highly ranked by all algorithms, especially for the ankle-worn sensor. Feature 13, the averaged mean of cross covariance between each 2 axes, is also highly ranked especially for the ear and chest worn sensors. Frequency features, especially feature 9, the energy of 0.2 Hz window around the main frequency divided by the total FFT energy, are also ranked highly for the knee, ankle and ear worn sensors, as they reflect repetitive walking and running patterns.



(a)



(b)



(c)

Fig. 3. Feature relevance as voted by the feature selection algorithms. The averaged weighting (or voting) for using RELIEF, Simba and mRMR is shown in Figures 3(a), 3(b) and 3(c) respectively.

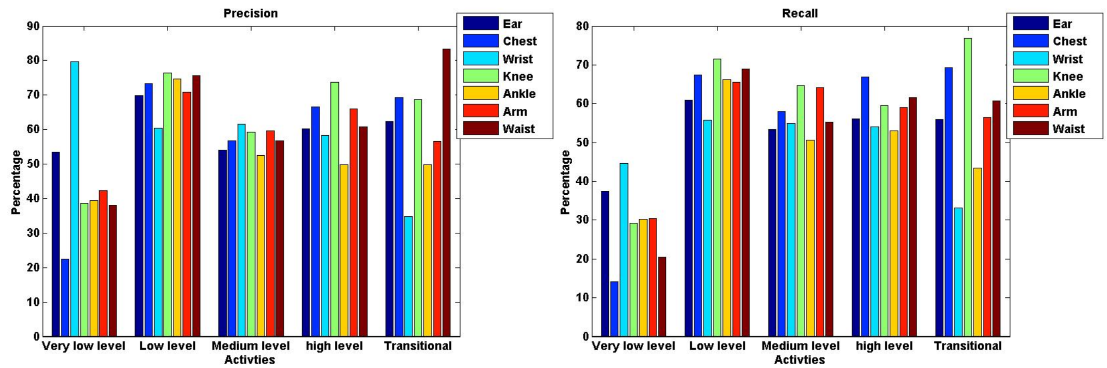
B. Optimal Positions for Activity Discrimination

The aim of this section is to assess the relevance of each sensor position in discriminating activity groups. For this purpose, we used one-versus-all classification per sensor and activity group, where each subject's data was used for testing and the others for training. The classifiers that were tested were KNN with k=1, 5, and 7 as well as the Bayesian classifier with Gaussian priors. Results are shown in Figure 4. There is a general agreement between the KNN (with k=5 and 7) and the Bayesian classifier. The KNN with k=1 is prone to outliers as it considers only one neighbouring point rather than considering a group of points for classifying new points. The observations for each group of activities are as follows:

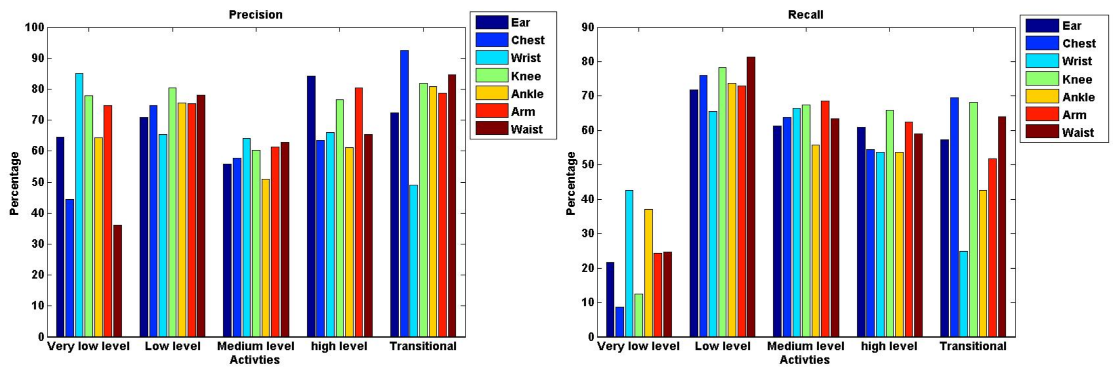
- Very low level activities: Although precision rates are reasonable, recall rates are generally low for this group for all sensor positions used. This is probably caused by the variation between subjects as they were lying down, as some were moving around whereas others were more still. Wrist and ear worn sensors provide reasonable rates in general.
- Low level activities: For this group, the waist sensor is selected by all classifiers as the one providing maximal precision and recall between this activity group and others. This group of activities is relatively varied, including eating, reading and socialising where body positions and motions could differ significantly.
- Medium level activity: For this group, the chest and wrist sensor provide the best precision rates. The result is not surprising as the activities include walking and housework involving wiping tables and vacuuming. Recall is high for these sensors as well as the arm sensor and the ear worn sensor (especially from the Bayesian classifier).
- High level activities: These activities are picked up mostly by the ear worn sensor as it measures the change in body posture while walking and running. The arm and knee sensors also perform well.
- Transitional activities: As these activities involve both sitting (from standing) and lying down (also from standing), the waist, chest and knee sensors reflect the parts of the body that are moving most. The ear sensor also gives good rates for both precision and recall over all the classifiers.

V. Conclusion

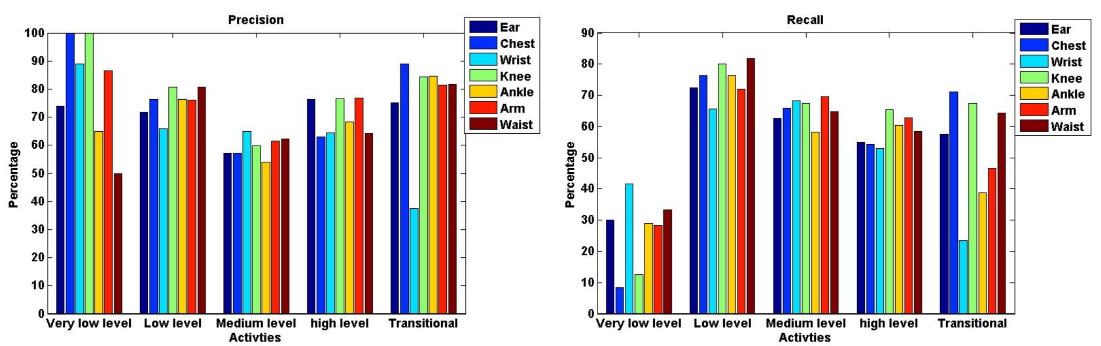
In this paper, we have presented a framework for the investigation of feature relevance as well as sensor positioning for a set of wearable accelerometers. It is evident that if more accelerometers are worn, classification results would improve and that the ideal scenario would include as many sensors as possible around the body to track subtle changes in gait and activity. This, however, is not practical and minimising the number of sensor used is of great practical importance for many pervasive sensing applications. Unlike previous work presented in [25], this paper investigates the use of accelerometers only rather than combining other types of sensors, but



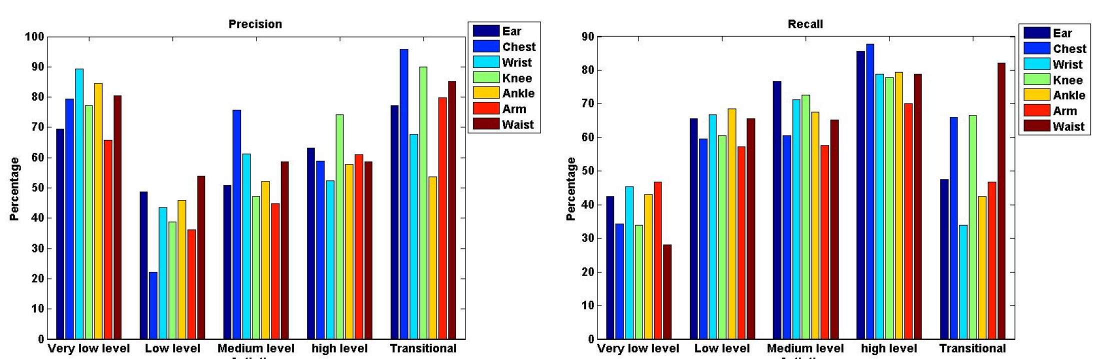
(a)



(b)



(c)



(d)

Fig. 4. Results of one-versus-all classification, showing precision and recall for each group of activity using the wearable sensors. Results for the KNN classifier are shown in (a) for k=1, (b) for k=5 and (c) for k=7. Results for the Bayesian classifier with Gaussian priors are shown in (d).

the general principle of optimal sensor placement as described in this paper applies.

The results of feature selection presented in this work also indicate the importance of choosing the most discriminative features for each sensor location. For the current study performed, the features that provide the best discrimination between activity groups are entropy, cross covariance between axes and frequency features.

The classification investigated in this work is one-versus-all classification, which aims to assess how generalisable the results are across all subjects. It is also worth noting that sensor locations were used separately and not in combination, as the question was finding the optimal location rather than the best combination of locations. Since most studies only require the differentiation of a sub-class of activities involved in daily living, the classifiers used show that different activity groups could require the use of different sensors, depending on limb motion and body posture for each type of activity. In this regard, a study of specific sensor optimisation is necessary, and the framework presented in this paper provides a systematic way for resolving such issues.

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