Sensor Positioning for Activity Recognition Using Wearable Accelerometers

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***Abstract*—Activities of daily living are important for assessing changes in physical and behavioral profiles of the general population over time, particularly for the elderly and patients with chronic diseases. Although accelerometers have been used widely in wearable devices for activity classification, the positioning of the sensors and the selection of relevant features for different activity groups still pose significant research challenges. This paper investigates wearable sensor placement at different body positions and aims to provide a systematic framework that can answer the following questions: 1) What is the ideal sensor location for a given group of activities? and 2) Of the different time-frequency features that can be extracted from wearable accelerometers, which ones are the most relevant for discriminating different activity types?**

***Index Terms*—Body sensor networks (BSNs), feature selection, sensor positioning, wearable sensors.**

I. Introduction

PROMOTING physical activity plays an important role in improving public health and well being [2] as well as preventing diseases, such as cardiovascular disease and diabetes. An increase in activity levels after surgery can be used to indicate overall improvement [3], [4] as well as the efficacy of therapeutic procedures. So far, many assessment criteria have been proposed for quantifying patients' activity levels after surgery. These include, for example, the Barthel index and the Nottingham extended activities of daily living scale which relies heavily on patient compliance, recall, and memory [5]. Pervasive technologies, on the other hand, have the potential to provide continuous monitoring without affecting patients' normal activity patterns. Existing research has shown that activity recognition by using accelerometers [6] could improve the quality of care provided to patients and be used as a means of observing lifestyle and behavior changes for healthy subjects.

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

Reference	Position
Bao *et al.* [23]	hip, wrist, ankle, arm and thigh
Mathie *et al.* [24]	several body positions (survey)
Mathie *et al.* [25]	waist
Karantonis *et al.* [26]	waist
Curone *et al.* [14]	waist
Lee *et al.* [27]	back
Bouten *et al.* [22]	lower back
Yeoh *et al.* [28]	waist and thighs
Lyons *et al.* [29]	thigh and trunk
Ravi *et al.* [30]	pelvic region
Song *et al.* [31]	torso
Yang *et al.* [13]	wrist
Lo *et al.* [32]	ear-worn
Bonomi [33]	lower back

In recent years, wearable accelerometers have played an important role in inferring metabolic energy expenditure [7]–[9], measuring gait parameters [10], predicting falls [11], and detecting activities of daily living [12]–[14]. Their recent uptake is mainly due to the small size, relatively low cost, as well as their ease of integration with existing platforms for sensor networks. Their use is also due to their strength in providing features indicative of human movement responding to frequency and intensity of motion as well as tilt, which is important to assess static posture characteristics. Although the use of a cluster of sensors forming a body sensor network (BSN) is interesting as a technical pursuit, particularly for controlled laboratory experiments, placing accelerometers on too many positions can be cumbersome, prone to errors, and impractical for patient deployment. Repeatability of experiments using exactly the same positions could be difficult in practice to ensure as a change in position could lead to a variation in the received signal. 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 [15], gyroscopes [16]–[18], and electrocardiogram (ECG) sensors [19] to provide more accurate activity classification. Table I summarizes some of the recent work using accelerometers alone for activity recognition. Although there is a large amount of work on the use of sensing for activity monitoring and behavior profiling (some of which is summarized in the survey [12]), there are, so far, no comparative studies investigating optimal sensor placement for activities of daily living.

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. Table I shows a large variety

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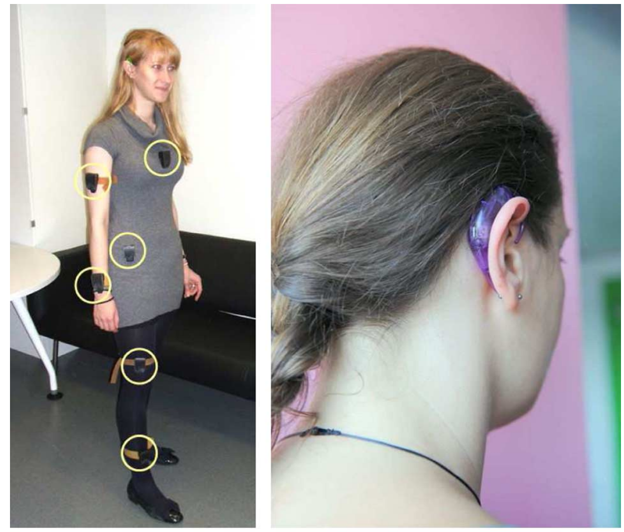
of positions used in recent studies for activity recognition with accelerometers. It may sound surprising that the best location for sensor placement is not where the symptom or abnormality manifests itself, as shown in studies investigating gait detection for limb impairment where head-worn sensors provided optimal locations for gait-feature detection rather than placement on the legs [20], [21]. For practical applications, the problem is further complicated by consistent sensor placement and subject compliance issues (e.g., it is difficult to ensure that waist sensors are always placed at the same location/orientation, and the position is often inconvenient for female subjects not wearing a belt).

It is therefore important to realize that sensor placement is far from being a solved problem. Consistent, yet practical positioning of the sensor(s) plays an important role in the accurate classification of low-level activities, which are particularly difficult to detect [22]. A waist-worn sensor, for example, could fail to detect activities involving head motion, body tilt, and hand motion. In addition to that and for the purpose of minimizing the number of sensors worn, it is important to know the capability of a certain position to classify a set of activities. Is a sensor worn on the chest, for example, capable of distinguishing walking and running, although the knee is an obvious choice?

Elderly and frail patients, as well as those recovering from surgery, cannot be asked to wear a multitude of sensors for long periods of time. The practical requirement for home monitoring is that it is preferable to have a small, lightweight sensor embodiment that can maximize the underlying information content. This would increase wearability and avoid the use of manual labelling of different activities, as adopted by many of the current systems. Therefore, sensor positioning, although dependent on the type of activity being observed, plays an important role in assessing the pervasiveness and wearability of devices.

All of the problems mentioned before suggest the need for a systematic framework for optimal sensor positioning for activity recognition. The purpose of this paper is to address 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. The remainder of this paper will be structured as follows. The experimental setup will first be presented, followed by the analysis methodology for feature selection and classification. Results will then show the use of the framework for deriving the optimal set of features for all sensors as well as the most important sensor positions for each group of activities.



(a) (b)

Fig. 1. Sensor placement for the experiment. The figure shows a subject wearing the wearable sensors on the ear, chest, arm, wrist, waist, knee, and ankle in (a) and a closeup of a subject wearing the ear-worn sensor in (b).

TABLE II
LIST OF ACTIVITIES AND THEIR CLASSIFICATION INTO ACTIVITY GROUPS AS GIVEN IN THE COMPENDIUM OF PHYSICAL ACTIVITIES [34]

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

II. Experimental Setup

3-D accelerometers (ADXL330, with sensitivity range $\pm 3g$) and a lightweight rechargeable battery board were integrated with the BSN platform [35] in order to gather data simultaneously from a large number of sensors. Eleven subjects (2 females and 9 males) wore the sensors on six body positions as well as the e-AR (ear-worn activity recognition) sensor [12] behind their right ear as shown in Fig. 1. Subjects performed a circuit of activities as defined in Table II for 2 min each. In order to identify a large range of activities, the sampling frequency used throughout the experiment was selected as 50 Hz. The sampling rate is chosen with consideration of battery life and bandwidth constraints as well as with reference to previous studies [17], [30], [36] addressing similar activities. In practice, too low sampling frequencies would fail to pick up details of high-level activities, such as running. During the experiment, data were wirelessly transmitted and marked by an observer.

The activities are classified into four main groups of activity as given in the compendium of physical activity [34]. In [34], activities are classified by the rate of energy expenditure in order to provide a coding system that would enable direct comparison to other studies. Energy expenditure is of importance in long-term monitoring, where clinicians would be able to observe overall activity and exertion over time. Fig. 2 shows some of the activities performed in the experiment as well as their grouping into different activity levels. In addition to standard activities of daily living, we have introduced additional transitional activities, such as lying down and getting up. Although transitional activities are generally overlooked in behavioral studies, they offer a means

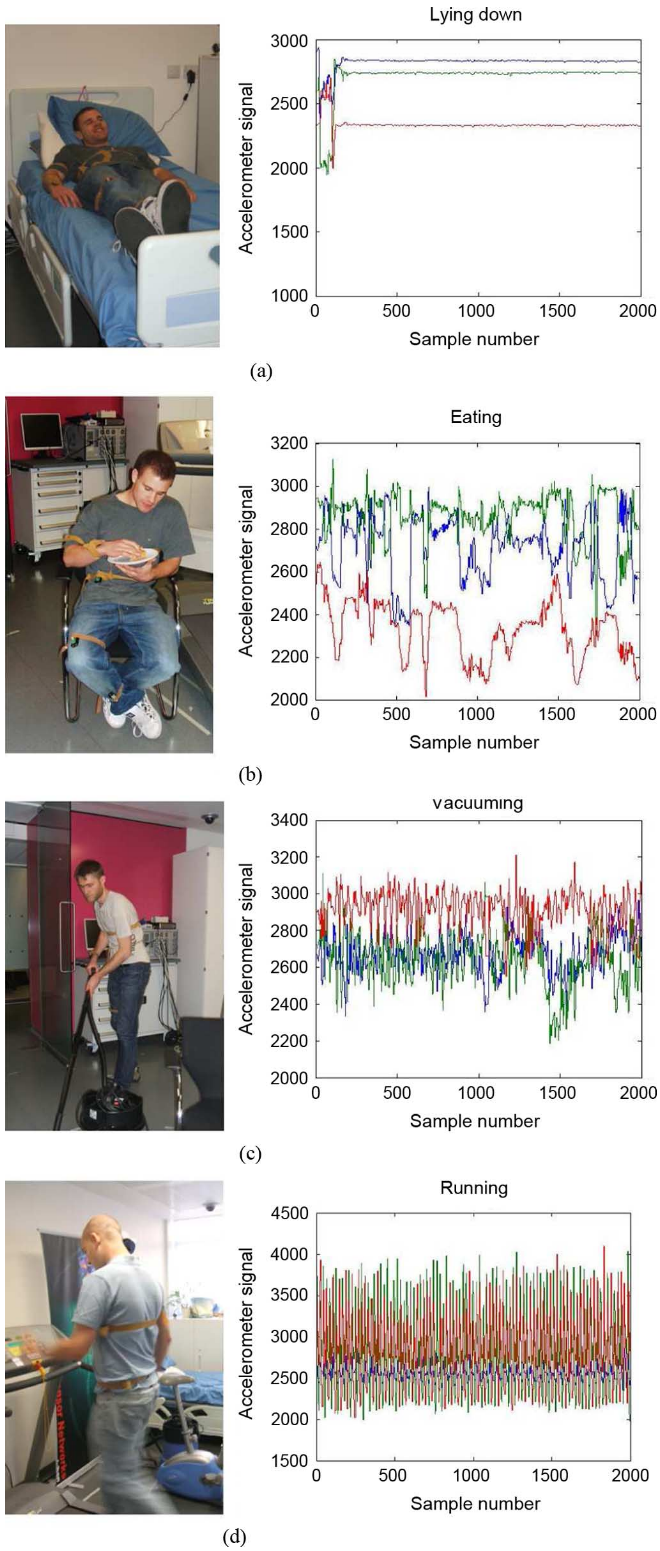


Fig. 2. Example activities of daily living used for this study also showing raw accelerometer signals (in millivolts) from the wrist-worn sensor. (a) Very low level activity-lying down. (b) Low level activity-eating. (c) Medium level activity-vacuuming . (d) High level activity-running.

of observing subtle patterns of motion that could be indicative of health changes due to surgery or disease progress.

TABLE III
LIST OF FEATURES EXTRACTED FROM RAW ACCELEROMETER SIGNALS

Feature number	Description
1	Averaged variance over 3 axes
2	Averaged RMS of signal derivative
3	Averaged mean of signal derivative
4	Averaged Shannon entropy over 3 axes The entropy per axis is: $H(X) = -\sum_{i=1}^{n} p(x_i) log_b p(x_i)$
5	Averaged cross correlation between each 2 axes
6	Averaged signal range (maximum-minimum) over 3 axes
7	Averaged main frequency of the FFT over 3 axes
8	Total signal Energy averaged over 3 axes
9	Energy of 0.2 Hz window centred 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 (range is defined as: maximum-minimum value)
13	Averaged mean of cross covariance between each 2 axes

III. ANALYSIS METHODOLOGY

A. Feature Extraction

Despite significant care being taken to place all of the wearable accelerometers at similar positions for all subjects, there were inevitable variations in sensor attachment during the experiment. Therefore, the features extracted were chosen to be features that would not be highly affected by changes in orientation. These features are summarized in Table III, which includes 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 s each with no overlap applied on the 3-D accelerometry signals in millivolts. The choice of window size was empirical, and presents a good compromise between very small windows that just pick up an action or a part of an activity and large windows that could confuse several activities.

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 paper, we used the "filter" rather than "wrapper" feature selection methods since 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 summarized as follows.

1) Relief Feature Selection: There are two 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 maximizing 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 [37]. The RELIEF algorithm for feature selection [38] is an iterative algorithm that utilizes 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:

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

In (1), w_i refers to weights per feature i, x_i is the value of the instance for i, and $nearhit(x_i)$ 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 the literature due to its speed and simplicity in weighting relevant features. However, it does not have mechanisms for eliminating redundant features. The time complexity of Relief is $\Theta(Nm)$ for a dataset with m instances and N features.

2) Simba Feature Selection: The iterative search margin-based algorithm (Simba) for feature selection [37] 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. The time complexity of Simba is $\Theta(Nm^2)$ for a dataset with M instances and N features [37].

3) Minimum Redundancy Maximum Relevance (MRMR) Feature Selection: The mRMR framework for feature selection [39] 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 is the feature)

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

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

C. Classification

In this paper, we opted for classifiers known for their speed since the datasets were relatively large when all subjects were combined. For this reason, we have used the classifier K-nearest neighbor (KNN) 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 normalizing constant α is expressed as follows for a total number of classes K:

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

IV. Results

A. Optimal Features for Activity Discrimination

Features that are 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, leading to a dataset of 11 subjects, 5 activity groups, and 7 sensors. The results of the feature-selection algorithms (Relief, Simba, and mRMR) were used to rank features from most relevant to least relevant, and weights were assigned according to this ranking. The weighting (or votes) used per feature f_i, w_i was

$$w_i = N - rank(f_i) \quad (6)$$

where N is the total number of features. The high weights provide an indication of features that were given a high rank (corresponding to a low number) by the algorithms.

Fig. 3 shows the averaged weights (*votes*) over all activities and highlights the importance of features per sensor. Results of using RELIEF, Simba, and mRMR are shown in Figs. 3(a)–(c), respectively. Feature numbers in these figures refer to the features described in Table III. As indicated in [37], 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-, ankle-, and chest-worn sensors. Frequency features, especially feature 9, the energy of the 0.2-Hz window centered around the main frequency divided by the total fast Fourier transform (FFT) energy and feature 7, the averaged FFT frequency over 3 axes, are also given high weights.

Fig. 4 shows the averaged weights over all sensors and highlights the importance of features per activity type. The overall weighting of features is very similar to that of analyzing them per sensor in Fig. 3. The features that are given an overall high ranking are 4 and 13 as well as frequency features 7 and 9. However, there are some discrepancies between the three algorithms. Feature 4, for example, is given a higher ranking for high-level activities in the Relief and Simba algorithms. mRMR, on the other hand, ranks it as a more important feature for low-level activities. Frequency features 7 and 9 are given a high rank for high-level activities and transitions for all feature-selection methods, along with feature 13.

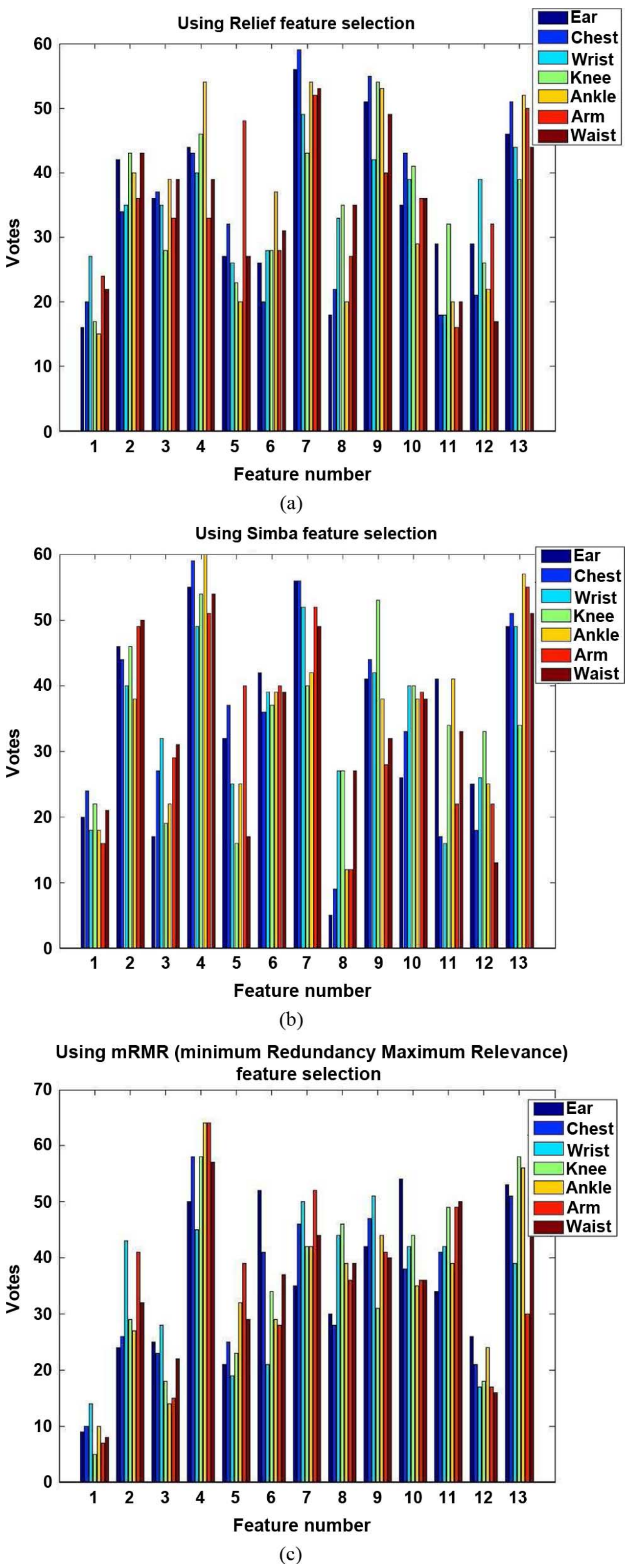


Fig. 3. Analysis of feature relevance per sensor (the figure appeared in [1]). The figure shows the feature relevance as voted by the feature-selection algorithms. The averaged weighting (or voting) for using RELIEF, Simba, and mRMR is shown in subfigures Figs. 3(a)–(c), respectively.

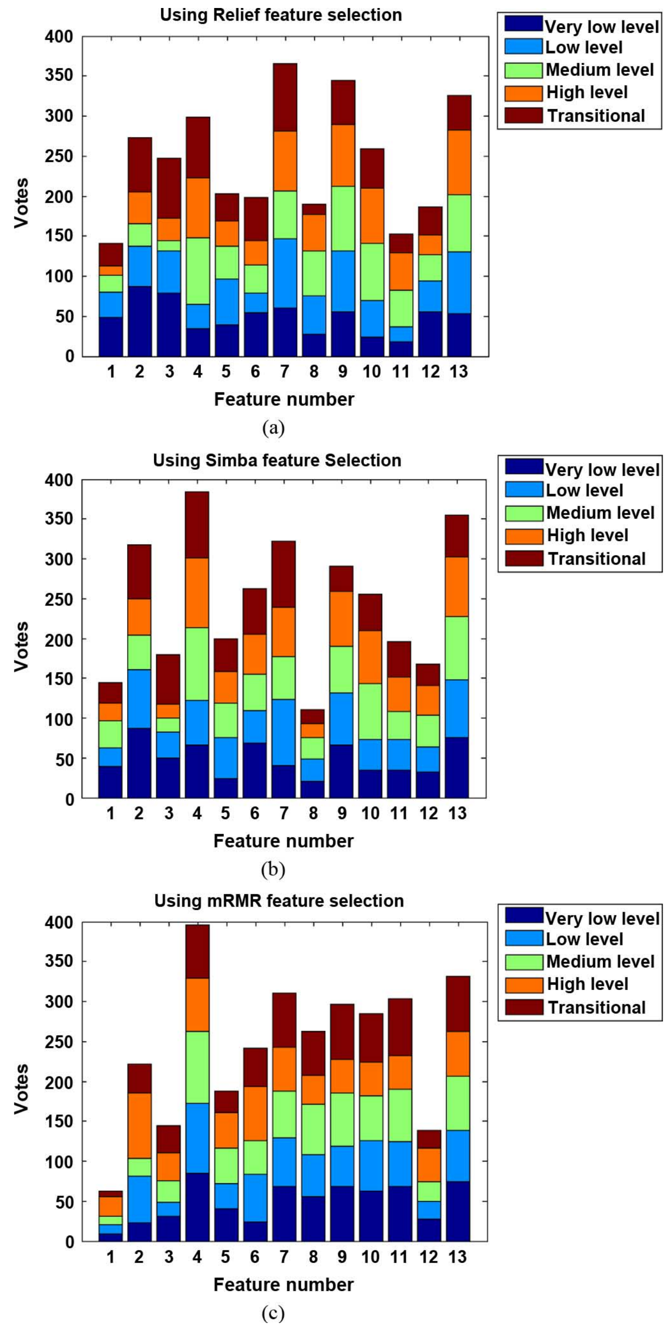


Fig. 4. Analysis of feature relevance per activity type. The figure shows feature relevance as voted by the feature-selection algorithms. The averaged weighting (or voting) for using RELIEF, Simba, and mRMR is shown in Figs. 4(a)–(c), respectively.

One of the highly ranked features in Figs. 3 and 4, average mean cross covariance (feature 13) could indicate the relative motion between axes providing discrimination between different activity groups, in the forward-backward, right-left, and up-down plane, which is not captured when each axis is considered alone. Entropy (feature 4) is also given a high ranking. The reason could be that it provides a measure of change in the instantaneous probability density function (p.d.f.) of processes detecting motions that could distinguish activity groups. Since medium- and high-level activities are mostly composed of repetitive motion, such as running, walking, and wiping tables, frequency features (mainly features 7 and 9) provided informative features for classifying these activity groups and, thus,

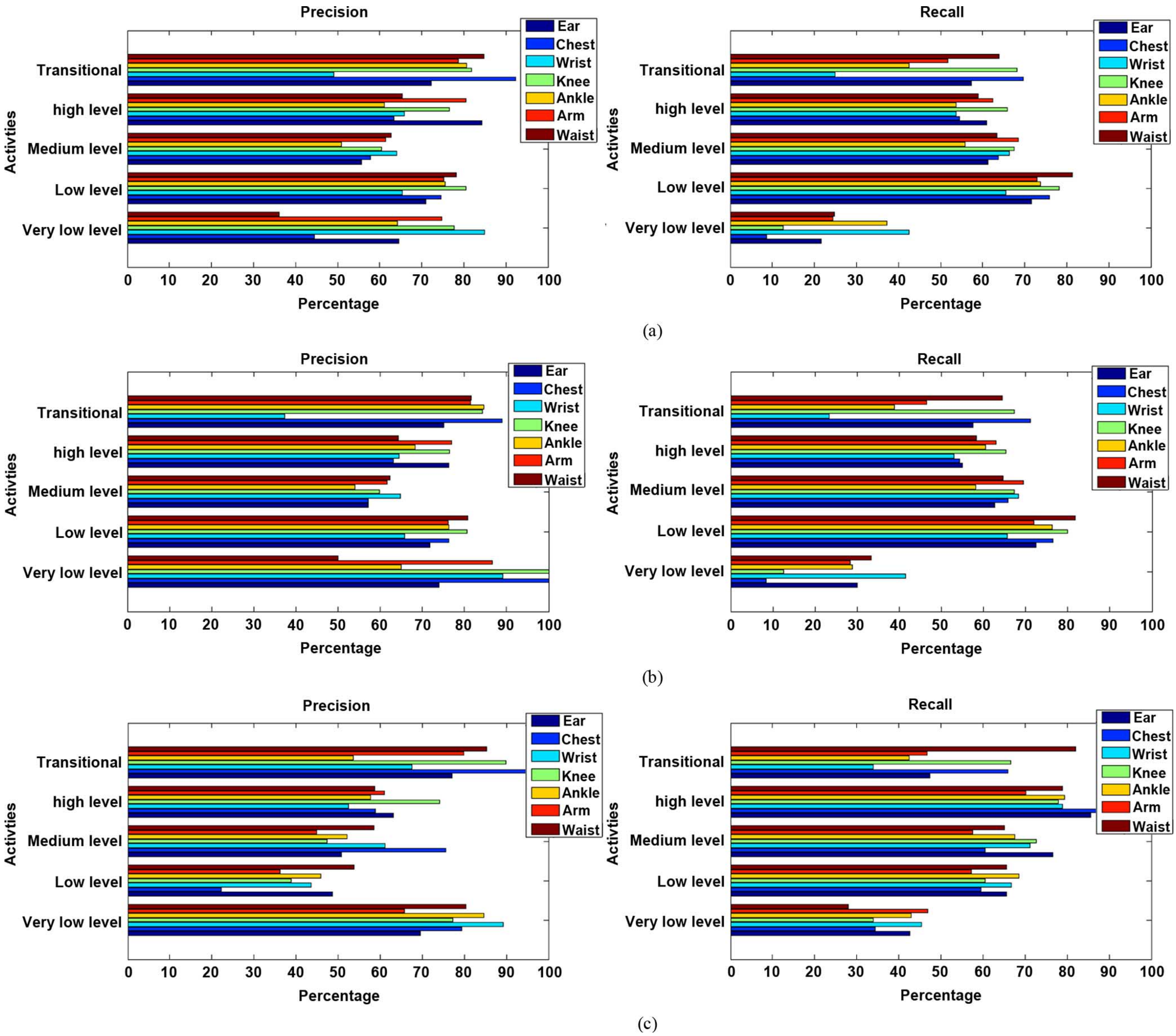


Fig. 5. Results of one-versus-all classification, showing precision and recall for each group of activity using the wearable sensors. This graph uses all 13 features per sensor. Results for the KNN classifier are shown in (a) for k = 5 and (b) for k = 7. Results for the Bayesian classifier with Gaussian priors are shown in (c). These results were previously presented in [1].

are ranked highly in Figs. 3 and 4. Although other activities, such as variance, generally provide good classification between activity types (based on activity levels), they were not given a high ranking since the features above were probably more specific to the activities chosen in this work.

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 = 5, and 7 (chosen empirically after testing a range of values for optimal rates) as well as the Bayesian classifier with Gaussian priors. The results are shown in Fig. 5. There is a general agreement between the KNN (with k = 5 and 7) and the Bayesian classifier. It is worth noting that for this section, we used all features per sensor to assess sensor relevance per activity. The observations for each group of activities are as follows.

1) **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. The wrist-worn sensor provides reasonable precision rates in general, with rates of more than 85%.
2) **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 socializing where body positions and motions could differ significantly.

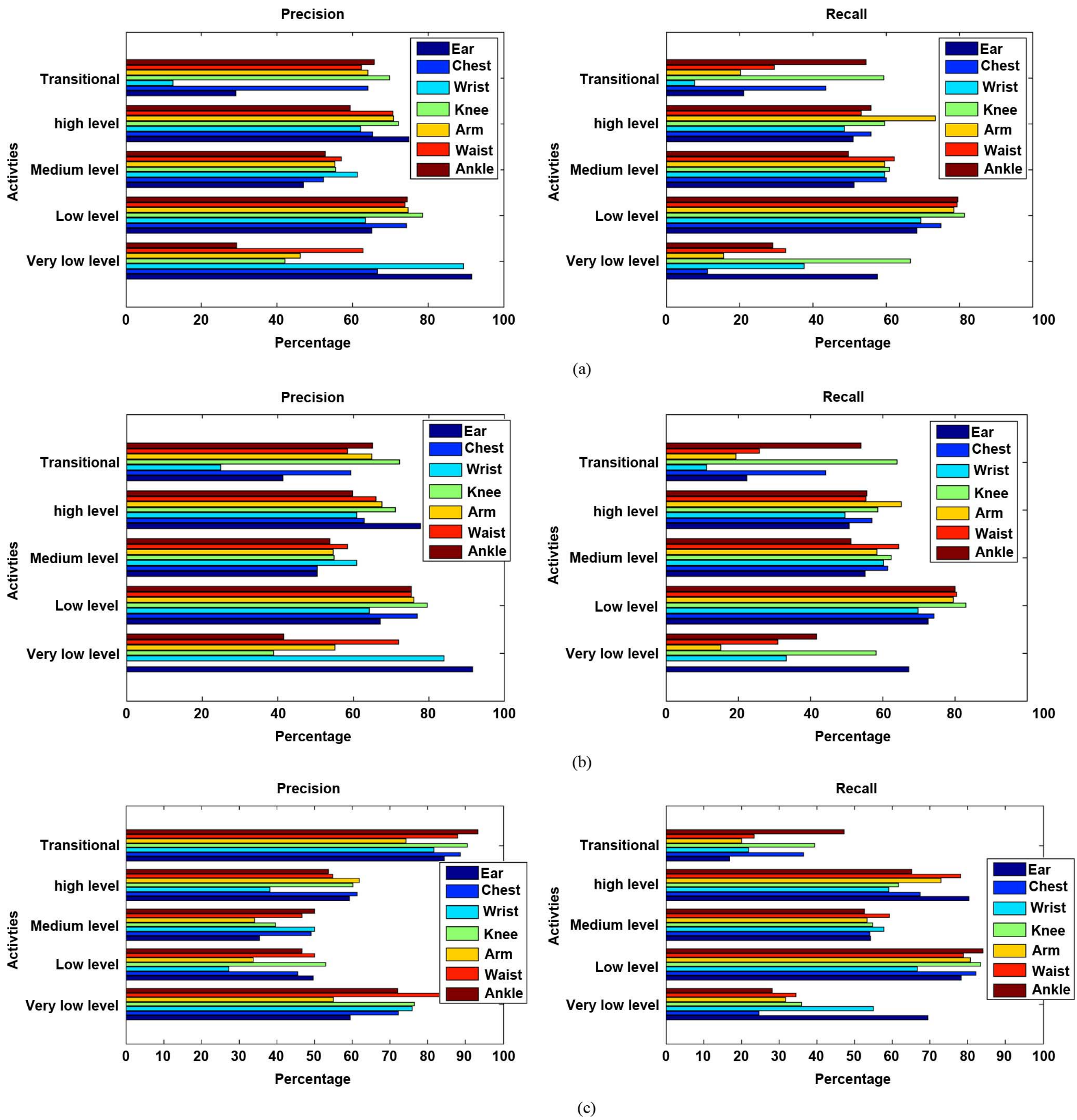


Fig. 6. Results of one-versus-all classification, showing precision and recall for each group of activities using only 4 features. Results for the KNN classifier are shown in (a) for $k = 5$ and (b) for $k = 7$. Results for the Bayesian classifier with Gaussian priors are shown in (c).

3) **Medium-level activities**: For this group, the chest and wrist sensors provide the best precision rates. The result is not surprising since 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).
4) **High-level activities**: These activities are picked up mostly by the ear-worn sensor since it measures the change in body posture while walking and running. The arm and knee sensors also perform well.
5) **Transitional activities**: Since these activities involve sitting (from standing) and lying down (also from standing), the waist, chest, and knee sensors reflect the parts of the body that are moving the most. The ear sensor also gives good rates for precision and recall over all of the classifiers.

In Fig. 5, all features were used per sensor to observe precision and recall. However, lowering the number of features used could enable on-node classification of activity groups, minimizing the data sent, and providing energy optimization. Given the features that were highlighted in Section IV-A, Fig. 6 shows the precision and recall rates using these four features. The features are:

- the averaged entropy over 3 axes (feature 4 in Table III);
- the averaged main FFT frequency over 3 axes (feature 7 in Table III);
- the energy of the 0.2-Hz window centered around the main frequency over total FFT energy—3 axis average (feature 9 in Table III);
- the averaged mean of cross covariance between each 2 axes (feature 13 in Table III).

Although the rates are lower than those obtained by using all features, reducing the number of features from 13 to 4 still provides reasonable values of precision and recall. The optimal number of features is that which provides the best classification rates. However, the optimal number varies with the type of sensor used, and we have included the 4 features as an indication that the observations highlighted for the whole set of features are generally still valid if we reduce the feature set in Fig. 6. Sensors that are shown to be relevant for each activity group are still of importance even when the feature number is minimized.

V. Conclusion

This work provides a framework for the analysis of sensor placement as well as feature relevance for activity recognition using wearable accelerometers. The method was evaluated with a protocol of activities of daily living, combined with transitional activities which could indicate subtle changes in gait and motion. Seven wearable accelerometer positions were investigated. With the current trend of applying wearable sensors for routine monitoring of activities of daily living, this work aims to investigate a framework for sensor positioning and feature relevance rather than sensor fusion with other types of sensors.

Several features can be extracted from accelerometers, ranging from statistical features to time–frequency features. However, a large number of features would generally have high computational cost, especially if we are simultaneously looking into miniaturization and on-node processing. In general, we noticed that four types of features were selected by three different feature-selection algorithms as features that could distinguish the 5 groups of activities. These features were the averaged entropy over 3 axes, the main FFT frequency (averaged) over 3 axes, the energy of the 0.2-Hz window centered around the main frequency over total FFT energy (3 axis average), and the averaged mean of cross covariance between each 2 axes.

In this work, we have chosen a set features that are not greatly affected by orientation. The analysis of sensor orientation poses an interesting research question on its own. For example, Thiemjarus [36] proposed a framework that could classify activities independent of sensor orientation (using a waist-worn sensor) but did not look into the effect of individual features. Lester *et al.* [40] investigated a framework that could classify activity regardless of positioning and orientation but used a combination of sensors, including accelerometers, microphones, and temperature sensors. An extension of this paper would be the use of a similar framework to investigate positioning of multiple sensors taking orientation into consideration.

One-versus-all classification has also been investigated, aiming to assess how generalizable the results are across all subjects. Sensor locations were used separately and not in combination, as the work aimed at finding the optimal location rather than the best combination of locations. The analysis of several wearable sensors for optimal classification is a well-addressed problem which normally aims to ensure that minimum cost is maintained (usually described in terms of energy/computational power) while observing prespecified performance criteria (defined as separation between activities). Since most studies only require the differentiation of a subclass 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 optimization is necessary, and the framework presented in this paper provides a systematic way for resolving these issues.

Considering each activity group separately, some of the results obtained were expected, such as the optimal sensor for high-level activities being the knee sensor. However, the next best sensors were selected as the ear and the arm sensors (Fig. 5) without a major loss in classification rates (using KNN for example). This indicates that these sensors could be used for this activity type rather than the wrist-worn sensor that ranks quite low as it lacks the relatively fixed position of the arm and the ear-worn sensors during running. For transitional activities that rely on leg motion and change of posture, both the chest and knee sensor were selected. Again, the wrist sensor did not rank very high as it probably did not reflect the range of motion as much as the knee and chest sensors. These results can give an indication on sensor selection when a single position is in question, especially when long-term monitoring is involved. If, for example, a healthy active cohort of athletes were to be monitored, the bias would be toward sensors that were selected for the high-level activity group. On the other hand, if postoperative patients with low levels of activity were to be observed, the bias would be toward sensors that can pick up low-level activities.

Although the results of this work give an indication of sensor positioning with respect to activity-group discrimination, practical issues have to be considered for long-term deployment [41]. It is difficult to use a waist-worn sensor for subjects that do not wear a belt or trousers (such as elderly female subjects) or subjects who are mostly in bed since it could limit their comfort. A chest-worn or a knee-worn sensor, on the other hand, could interfere with daily activities. These issues are of great importance when long-term studies are considered.

It is worth noting that although the method provides good generalization across the 11 subjects considered in this pilot study, all of them were young healthy adults. An extension of this work across a wider age group, including frail and elderly patients for example, would be required if the recommendations are to be applied to a larger population. A larger co-hort would be required if statistical conclusions are to be made. The activities chosen in this work are representative of daily activities, but it would be interesting to observe activity patterns over long periods, focussing on behavior profiling.

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