Activity Recognition System Optimisation Using Triaxial Accelerometers

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Abstract. Activity recognition is required in various applications such as motion analysis and health care. The accelerometer is a small, economical, easily deployed and high-performance sensor, which can continuously provide acceleration data from the body part it is worn. Previously, the human activity recognition system researches utilising tri-axial accelerometer have mainly focused on one placement of the sensor, and rarely states the reason for the choice of sensor placement. This paper presents an optimisation method utilising a tri-axial accelerometer when the sensor is placed on different body parts. The statistical characteristics-based algorithms use data from a motion captured database to classify six classes of daily living activities. Feature selection is performed using the principal component analysis (PCA) from a range of features. Robust and sensitive features that highly contribute to the classification performance are selected. Activity classification is performed using the support vector machine (SVM) and K-Nearest Neighbour (K-NN) and the results are compared. Based on the HDM05 Mocap database with six activity types (overall 89 motions) collected from five subjects, the best place for wearable accelerometers is the waist, followed by chest, head, left wrist, right wrist, humerus and femur. Based on the preliminary results, multi-accelerometers and data fusion methods are utilized for further increasing the accuracy of classification, where the accuracy increases by 6.69% for SVM and 7.99% for KNN. For two sensors, the best placements for sensors are the waist with the left wrist, followed by the waist with the right wrist, waist with chest, waist with the humerus, waist with head, and waist with femur. The result provides a guideline for sensor placement when developing an activity recognition system.

Keywords: Accelerometer, activity recognition, feature selection, support vector machine (SVM) classifier, *k*-nearest neighbor (*k*-NN) classifier, sensor position.

1 Introduction

People wish to increase their quality of life and live as long as possible, which is pushing towards new healthcare delivery models [1]. In recent years, the number of seniors who live alone keeps increasing. The risks of multiple chronic disease and critical events such as fall pose a significant issue to their life expectancy. The current worldwide condition is pushing towards new healthcare models, and different solutions have been trial to resolve these issues. The detection and recognition of human activities provide valuable information that can be leveraged as a part of the healthcare system. With advanced technology in micro-electromechanical system (MEMS), many connected objects, like a watch or a ring, can be designed with embedded sensors for monitoring the activities of an individual. The information of activity recognition can be looked at the macrolevel to infer the patter of life, finer information on gait metrics, and identify the person [5, 6]. Also, the human activity recognition technologies are extensively used in the entertainment industry, such as films, animations and games [7, 8]. Computing and sensing technologies can be combined with innovative perspectives to achieve a motion classification system and thus, three main types of technologies are applied in this field: wearable devices, camera-based [9] and radar sensor [10].

The camera-based or vision-based approach is one of the most researched, as it stems from the prominent field of computer vision, which provides a more complex and practical framework [9]. However, it is perceived as an invasion of privacy and potential dispute over image rights is a deterrent for the use of this technology for home use. Additionally, it is easy to be affected by lighting condition. In the case of both weak light and strong light, cameras cannot guarantee the quality of the images. In the night scenario, the vision-based method cannot work properly without a light source [11]. Radar systems are relatively new in this area, with the advantage of high-accuracy, safety and non-obstructive illumination [10]. It transmits a signal, that interacts with the target, and is backscattered to the radar [12]. The main approaches are using micro-Doppler signatures, range information, range-Doppler and Cadence velocity diagrams or combinations of those representations for activity classification. Radar sensors collect the signal instead of real image, which greatly reduces the risk of invasion of privacy. However, radar systems must be placed at a fixed location, and the classification performance heavily relies on the position and number of radars. Wearable devices are mobile sensors, where activities are monitored in a more first-person perspective. Concurrently, many wearable devices include both capabilities of data collection and data analysis. Compared with other methods, wearable sensors are considered as a more economical and more flexible approach in human activity recognition, with its ease of deployment, capability for providing continuous tracking and no invasion of privacy.

In this paper, we mainly focus on human activity recognition using accelerometers. Acceleration is one of the most direct ways of reflecting the movements of the human body. Over the last decades, accelerometers have become small, low-cost and high-performance. Their accuracy is continuously improving, due to the maturity of the manufacturing and measurement technology [13]. Accelerometers are available in single, dual and tri-axial sensors. The tri-axial accelerometers are most frequently used. They can output three mutually perpendicular directions, which means they can decompose any motion into three directions. This makes the recognition task more reliable and effective. Therefore, accelerometers are adopted in this project to achieve the task of human motion classification.

The studies based on using tri-axial accelerometer for human motion classification started several years ago and have made great achievements [2]. The recognition can be generally classified as two types [14]: threshold-based [3] and machine learning approach. Examples of machine learning approaches that are frequently used for human activity are Hidden Markov Model [3], support vector machine [3], and K-Nearest Neighbour [4]. Many studies focused on the algorithm optimisation and feature processing (extraction and selection) optimisation. However, the accuracy of results is also heavily dependent on sufficient raw acceleration data. Each body part has its own acceleration when people are doing activities, and one position may produce the same accelerations for completely different motions, which leads to false alarms. The model based on the acceleration data obtained from various body part has an entirely different performance. Thus, this study is aimed to place sensors on diverse body parts and utilise data fusion technology to optimise the performance of classification.

The organization of this paper is as follows: Section 2 presents a review of existing studies on accelerometer for activity recognition. Section 3 introduces the setup of data collection and processing. Section 4 reports the results. Section 5 provides the conclusion based on the result.

2 Related Works

A large body of research concentrates on activity recognition using accelerometers. Initially, the accelerometers were mainly placed at the waist because it was the central part of our body, providing more stable data than any other part. Mantyjarvi et al. [17], used a belt accelerometer to acquire signals and then generated feature vectors. The feature sets were very limited and only one classification algorithm was implemented. With the tendency of electronic device, such as e-watches and better hardware support, the placements of accelerometers were expanded, leading to the increase of classification accuracy [2]. Besides, more classification algorithms were introduced. Naranjo-Hernández et al. [18], designed a system, where they placed an accelerometer smart sensor at the lower back. The monitoring was achieved in a device's holistic manner with three processing modules.

With the improvement of classification due to the choice in sensor placement and advances in classification algorithm, more research tends to be more complex using more features, more locations and fusion to achieve better results. These works employed more complex algorithms such as supervised learning technologies to tackle classification problems. Lee et al. [19], proposed a one-dimensional convolutional neural network (1-D CNN) for recognising human activity using tri-axial accelerometer data.

Zhang et al. [20], compared the classification performance among four different classifiers (k-Nearest Neighbor, naive Bayesian classifier, Support Vector Machine and their sparse representation-based classification). Pannurat et al. [14], placed the sensors at different body parts. They ranked the performances of several joints for fall detection at different stages in certain conditions. They found that the waist had the highest accuracy of classification. Li et al. [3], used a wearable device with data fusion approach. The device involves an accelerometer, a gyroscope, a magnetometer, an inertial sensor and a radar sensor. The overall performance was much better after using data fusion technologies.

However, the study on classification optimisation and sensor placement is insufficient. Therefore, this paper is aimed to optimise the performance of recognition according to the placement of sensor and data fusion technologies with SVM and KNN algorithms. The more information about how the simulation is setup will be shown in the next section.

3 Data Description

HDM05 database provides researchers with both ASF/AMC (skeleton-based) format and C3D (3D trajectory-base) format. ASF/AMC format is chosen for two reasons. The bone length is a constant and, ASF/AMC does not have many redundant markers [15]. The ASF file records skeleton (see Fig.1) data and the AMC file records motion data.

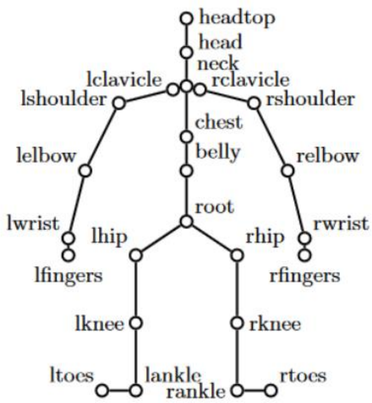

Fig. 1. Skeletal Kinematic chain model consisting of rigid bones that are flexibly connected by joints, which are highlighted by circular markers and labelled with joint names [15].

In this paper, seven joints are chosen: wrist, left wrist, head, chest, waist, right femur and right humerus. Five human subjects performed all the activities which were recorded at constant frequency 120 Hz. There are overall 89 motion files, including six types of activities, which are grabbing, jumping, sitting, standing, walking and running (Table 1).

Table 1. List of human activities.

Number	Activity Description
I.	Grabbing up
II.	Jumping
III.	Sitting
IV.	Standing
V.	Running
VI.	Walking

Acceleration data was obtained using MOCAP tool box [16]. Extracting the effective features from the original acceleration data guarantees that the result of classification is efficient and accurate. In this case, features were extracted from pre-processed acceleration data and were summarised in table 2.

Table 2. Table of features of acceleration for each joint (without feature selection).

Features	No.
Mean	3
Standard Deviation	3
RMS (root mean square)	3
Variance	3
Range	3
Minimum	3
Median Absolute Deviation	3
The Number of features	21

The principal component analysis is a common and effective data dimension reduction method in human activity recognition. The core of PCA is the principle of variance maximization of the covariance matrix. The original vectors can be replaced by fewer vectors using PCA. Those new transformed vectors are linearly independent, which are also called the principal component. Meanwhile, the information contained in the original vectors is preserved as much as possible. After using PCA, the dimension of feature space is reduced from 21 (Table 2) to 7.

4 Results and Analysis

The prepared dataset is first used to evaluate the performance of the SVM classifier. In this paper, a quadratic-kernel SVM classifier is used. Then, the classifier will be changed to a weighted KNN with K=10. The average classification performance is shown below. Note that all the training set was processed by PCA and the dimension of the feature space is seven.

Table 3. A running time comparison between before and after using PCA for both algorithms.

	Running time Before PCA	Running time After PCA
SVM	2.7562 s	2.1957 s
KNN	2.0795 s	0.9735 s

From table 3, it is clear that the principal component analysis greatly reduces the running time, 20.3% and 53.2% for SVM and KNN respectively.

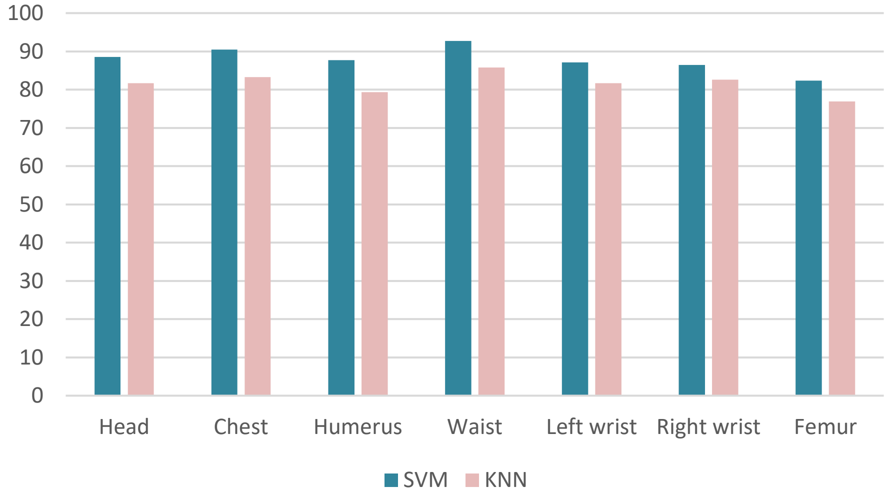

Fig. 2. A performance comparison on accuracy of classification for the SVM and the KNN.

Table 4. Confusion matrix for results from the waist and SVM algorithm.

	I	II	III	IV	V	VI
I	15					
II		10		2		
III			14	1		
IV		1	1	13		
V					15	
VI				1		14

Table 5. Confusion matrix for results from the waist and KNN algorithm.

	I	II	III	IV	V	VI
I	14					1
II		9		2	1	
III			12	2		1
IV		2	1	12		
V		1			14	
VI				1		14

Tables 4 and 5 show the confusion matrix of classification at the waist. Standing and jumping are the most difficult pair to recognise among all activities. Besides, sitting is also easily confused with these two activities. In fact, not only for the waist, but also for other sensor placements, there three activities are difficult to identify, especially for standing and jumping. To further improve our classification result, two accelerometers are concurrently utilized for collecting data. With data fusion technology, the features extracted from both accelerometers are fused at feature level and fed into SVM and KNN.

The waist is kept as it has been the best performance. The features extracted from the waist will be combined and fused with features from the other six parts. That is, there are six combinations, which are the waist with chest, the waist with head, the waist with left wrist, the waist with right wrist, the waist with humerus and the waist with femur.

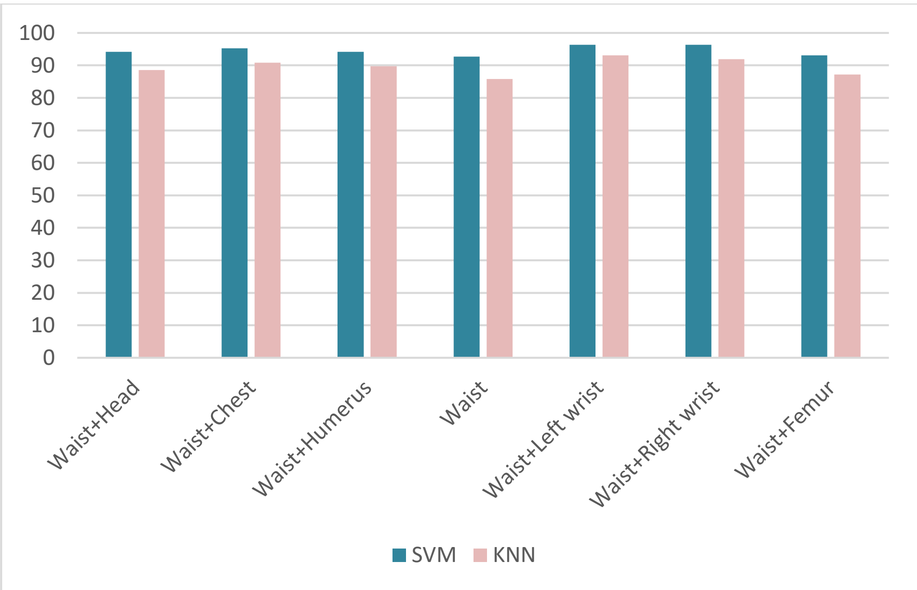

Fig. 3. A performance comparison on accuracy of classification for the SVM and the KNN (using data fusion).

Table 6. Confusion matrix for results from the waist and SVM algorithm (with data fusion).

	I	II	III	IV	V	VI
I	15					
II		11		1		
III			14	1		
IV		1		14		
V					15	
VI						15

Table 7. Confusion matrix for results from the waist and KNN algorithm (with data fusion).

	I	II	III	IV	V	VI
I	15					
II		11		1		
III			13	1		1
IV		1	1	13		
V		1			14	
VI						15

Fig.3 shows the accuracy of six combinations of sensor placements. The waist data remains as a control group to compare with fused data classification performance. The Waist+left wrist has the best performance, followed by the waist+right wrist, waist+chest, waist+humerus, waist+head and waist+femur. Generally, the SVM algorithm still has better performances than the KNN algorithm. After data fusion, the accuracy of classification is higher than the classification without data fusion.

Tables 6 and 7 are the confusion matrices for the waist+left wrist. From these two tables, it can be observed that the false alarms among standing, jumping and sitting has greatly decreased. Besides, for SVM algorithm, the grabbing, walking and running can be recognised perfectly, which means the accuracy is 100%. The accuracy of easily mis-recognised motions (standing, jumping and sitting) increase greatly, which increases by 5.00% and 10.1% for SVM and KNN, respectively.

The Left wrist and the right wrist are separately considered in this paper because we want to investigate the influence for wearing the sensor on different sides. The classification result shows that models trained by left wrist data and right wrist data almost have the same accuracy, where the difference of accuracy is less than 1%. That means, the effect for different sides is negligible.

5 Conclusion

In this paper, classification approaches and data fusion methods for discriminating human daily movement are proposed. All 89 data samples from the HDM05 database, including six classes, were used for acquiring accelerations and extracting features. Both SVM and KNN algorithms were used for classification. The preliminary results show that the performance of SVM is generally better than KNN. It is also clear that for the single accelerometer condition, the placement at the waist is optimum for putting the wearable devices, followed by the chest, head, wrist (both left and right), humerus and femur. After using data fusion methods, the overall accuracy at the waist is 92.75% for SVM and 85.82% for KNN. In addition, the average accuracy is increased to 94.60% and 89.60% from 87.91% and 81.61% for SVM and KNN, respectively. The proposed sensor placement for a single sensor is the waist. If wearing more than one sensor, the proposed placements would be the waist and the wrist (left or right). This paper gives a preliminary guideline on the detection performance for sensor positions.

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