On the Data Analysis for Classification of Elementary Upper Limb Movements

Dwaipayan Biswas[1], Andy Cranny[1], Ahmed F. Rahim[1], Nayaab Gupta[1], Koushik Maharatna[1], Nick R. Harris[1] and Steffen Ortmann[2]

[1] School of Elctronics and Computer Science, University of Southampton, Hampshire, UK

[2] IHP, Leibniz-Institute for Innovative Microelectronics, Frankfurt (Oder), Germany

Email: db9g10@ecs.soton.ac.uk

Abstract

Purpose. Body worn inertial sensors could be used to assess rehabilitation of patients with impaired upper limb motor control by detecting and classifying how many times particular arm movements (exercises) are made during normal activities. We present a systematic exploration to determine such a system.

Methods. Kinematic data was collected from 18 healthy subjects using tri-axial inertial sensors (accelerometers and gyroscopes) located at two positions on the dominant arm as four fundamental arm movements were repeated 20 times each. Ten time domain features were extracted from individual and combinations of sensor axes data, and were used to train a classifier. Three different classifiers were investigated: linear discriminant analysis (LDA), quadratic discriminant analysis (QDA) and support vector machine (SVM). Each was verified using a leave-one-subject-out technique for a generalized classification model, and a ten-fold cross validation technique for a personalized classification model.

Results. LDA repeatedly gave the better results when using features extracted from individual sensor axes data. When a personalized learning model is used with LDA, only a single tri-axial sensor (accelerometer or gyroscope) is required to classify all four of the upper limb movements with a sensitivity in the range 92-100%, using as few as 6-10 time-domain features. By comparison, the generalized model using LDA exhibited lower sensitivity and generally required more features (12-18), reflecting the greater variability inherent in a training set comprised of more than one individual's data.

Conclusions. We demonstrate that body worn inertial sensors can classify elementary arm movements using a low complexity algorithm.

Keywords: Accelerometer, activity recognition, gyroscope, movement classification, remote health monitoring, wireless body area network (WBAN).

1. Introduction

Advances in Wireless Sensor Networks (WSN) and Information and Communication Technology (ICT) are playing a key role in a wide array of applications such as remote health monitoring, human computer interaction and sports medicine using various forms of low-cost, body-worn, miniaturised inertial sensors that are capable of capturing kinematic data [1, 2]. The information extracted from such data can for example be used to produce a quantitative measure of a physical activity or a qualitative measure such as the classification of the type of activity, depending on the application area [3-5]. In healthcare, concerns regarding an ever increasing ageing population and their associated healthcare costs, particularly those related to the treatment of chronic arthritis, cardiovascular or neurodegenerative diseases have prompted an interest in telemedicine based systems that make possible rehabilitation within the home environment [3, 4, 6]. Wireless monitoring of various body parts is also being extensively used in a wide range of sporting activities [7]. Furthermore wireless sensing networks form a core part of ubiquitous computing and in particular, wireless body area networks (WBANs) are being developed as controllers for intelligent social user interfaces (ISUIs) [8, 9]. The use of wearable inertial sensors coupled with the advantages of wireless communication has become an integral part of many such applications.

From the long-term system operation perspective, when implementing a wireless body area network that comprises a number of various sensors, it is essential to select data analysis algorithms that are computationally of low complexity. The main reason is that in such a wearable system the data analysis primarily needs to be carried out at the sensor node, which has been shown to yield a more energy efficient solution compared to the more conventional continuous data transmission based remote monitoring approach [6]. Since the sensors are likely to be battery powered and because energy consumption is proportional to the computational complexity of the data processing algorithm used, the use of high-complexity algorithms (although they may be more 'accurate') will drain the battery faster, defying the objective of long-term monitoring.

In principle there are three steps for activity recognition using inertial sensors: 1) data capture by appropriate sensor; 2) segmentation of the captured data to identify the beginning and end of an activity and 3) recognition of the activity using appropriate classification techniques. Although the final two steps are in practise interrelated, individually they pose significant research challenges owing to the possible qualitative non-uniqueness of an activity pattern exhibited by an individual subject. Therefore these are treated as two individual research problems: event detection and activity recognition. In this paper we concentrate only on the second research problem, activity recognition, on the assumption that the start and stop time of the target activity is known. Sensor-based human activity recognition involves two phases – training a model with a given set of observations and evaluating the trained model with new sets of observations (testing).

In this paper we describe a systematic exploration to recognise four fundamental movements of the upper limb, that are associated with basic activities of daily living, using data collected from inertial sensors attached to the limb proximal to the wrist and elbow. These positions were chosen with respect to the arm movements being investigated, which were (along with examples of their daily occurrence): extension/flexion of the forearm (reach out and retrieve object); rotation of the forearm about the elbow (lift cup to mouth); rotation of the arm about the shoulder in the horizontal plane (reaching out for an object sideways); and rotation of the arm about the mediolateral axis (opening a door or using a key. Our aim was to investigate the appropriate data analysis and classification schemes to enable consistent and accurate detection of these basic arm movements using the minimum number of inertial sensors located at these two positions, with particular attention to developing a robust training model accounting for temporal and inter-subject variability. The detection and classification of particular arm movements (e.g. prescribed exercises) can over time provide a measure of arm rehabilitation progress in remote health monitoring applications, especially in neurodegenerative pathologies such as stroke or cerebral palsy. Enumerating occurrences of these movements over time can act as an indicator of rehabilitation progress since the frequency of these movements is more likely to increase as the motor functionality of the patient improves.

For this investigation, experiments were performed with 18 healthy subjects (age range 24 to 50, male and female, both left and right arm dominant) each completing the four tasks 20 times. From the kinematic data collected, 10 features were computed and used as the inputs for a number of different classification algorithms to determine the best combination of sensor type, features and classification algorithm to correctly identify each of the tasks. Our results show that under certain conditions, a tri-axial accelerometer or a tri-axial rate gyroscope placed near the wrist or elbow can independently recognise all four tasks performed by an individual.

The remainder of this paper is organized as follows. Section 2 presents a brief background study on human activity recognition and identifies the motivation for this research. The experimental protocol is discussed in Section 3 whilst Section 4 describes the data processing and feature extraction techniques. The classification methodologies used in our work are detailed in Section 5 and the analysis of the experimental results is provided in Section 6. Conclusions are drawn in Section 7.

2. Background

Human activity recognition in natural settings is an active research area that has been applied widely in the field of chronic disease management and rehabilitation [10-14]. Various types of wearable sensors have been used for activity recognition such as accelerometers, gyroscopes and magnetometers [5, 13-14]. Radio-frequency identification (RFID) has also been used to monitor the movement of objects within the home environment that are typically encountered during daily living [15]. Another approach being used is fusing data from vision systems and inertial sensors to complement each other. This approach is, however, mainly restricted to indoor activities within a defined region under the un-hindered surveillance of the vision system. Furthermore, the use of high complexity image processing algorithms can result in slower analysis which can be particularly challenging if real-time information gathering is required [12].

Analysis of collected data is generally performed using statistical signal processing involving the primary steps of feature extraction, feature selection and classification [16]. In terms of classification, a review of the literature shows that different machine learning techniques have been used depending on the application area, e.g. Support Vector Machines (SVM) [10, 13], Decision Trees (DT) [3, 10], Naive Bayes (NB) [10], Multi-Layer Perceptron (MLP) [11], Artificial Neural Networks (ANN) [3], or a combination of these techniques [12]. The accuracy of any classification technique will depend on the system requirements covering important areas – type of activities, number of activities, type of sensors, number of sensors, placement of sensors [17], multiple sensor fusion, etc.

Very little work has been reported in terms of activity recognition for elementary limb movements. By comparison, the majority of the published research on human activity recognition has been devoted to monitoring simple, gross, dynamic movements, such as sleeping, sitting, standing, cycling, running etc. [5] and monitoring of gestures involved during opening or closing curtains [18] and feeding motion [19]. However, it is not clear whether in these studies critical aspects such as optimising sensor selection and placement or the use of low-complexity data processing and classification techniques had taken priority. Further, an aspect which has not been investigated are the differences prevalent among individuals performing the same activities, which is essential considering the variability inherent within a subject population due to physical factors such as age, sex, body shape, etc. [20].

This therefore motivated us to make a thorough investigation on the basic requirements of a sensor-based arm activity recognition system which included selecting the best sensor type, investigating the effect of sensor location and determining the best sensor signals. This methodology was used to develop training models based on:

- a *generalized approach* where movement data is collected from a group of subjects and evaluated with a 'leave-one-subject-out' validation process,
- a *personalized approach* where data is collected from individual subjects and evaluated using a 10-fold cross validation process.

3. Experimental Protocol

In this investigation, experiments were performed at the University of Southampton (UoS) with 18 healthy subjects (age range 24 to 50, male and female, both left and right arm dominant) each completing the four movements 20 times. Experiments were performed within an open laboratory under the supervision of the research team.

3.1. Movement Selection

We selected four elementary types of arm movement that might typically be used during daily activities, these are:

- *Movement A* – Reach and retrieve an object monitoring extension and flexion of the forearm.
- *Movement B* – Lift cup to mouth and return to table focusing on rotation of the forearm about the elbow.
- *Movement C* – Reach out for an object sideways by swinging arm 90° in horizontal plane and return.
- *Movement D* – Rotate wrist with arm fully extended through 90° and return.

In principle, these simple movements also resemble task numbers 8, 9, 1 and 15 respectively of the standard Wolf Motor Function Test (WMFT); an established clinical assessment method for testing the functional ability of mild to moderate stroke patients [21-23].

All of the tasks were performed by the subjects in a seated position in the laboratory. Each subject performed 20 trials of each task separated into four groups of five repetitions with each group of trials being separated by approximately three minutes. This was done to avoid the generation and collection of unrepresentative data due to fatigue and/or boredom, as well as the effects of unconscious self-learning of the activities. The subjects were generally encouraged to perform the tasks in a natural way, as they would normally do when extending, lifting, bending or turning the arm during daily activities. In addition, there were no restrictions on the various physical factors of the experiment such as the seating position, height of the chair, distance between the chair and the table, position of the objects on the table and the time required to complete the tasks. Un-constraining the experiment in this manner helps to generate a wider range of variability in the data paving the way for a robust arm movement classification system.

3.2. Sensor Selection and Placement

The commercially available Shimmer 9DoF wireless kinematic sensor module, consisting of mutually orthogonal tri-axial accelerometers, rate gyroscopes and magnetometers, were used as the sensing platform (cf. Fig. 1) [24]. Two positions on the dorsal side of the dominant arm (forearm proximal to the wrist, and upper arm proximal to the elbow) were used as the sensing positions and were chosen as those locations were likely to produce the largest sensor responses to the arm movements being investigated. The XY plane of the sensor module was in contact with the dorsal side of the forearm, the X-axis points toward the hand and the Z-axis points away from the dorsal aspect. The Shimmer sensors were attached to the arm using elastic straps, providing an intimate, secure, yet un-constraining hold.

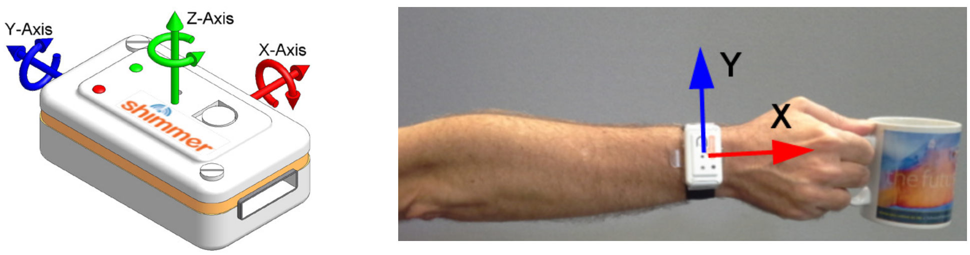

Fig. 1. Sensor module showing the coordinate system for the positive direction of the accelerometer axes and rotation for the gyroscope (left); when worn on the wrist showing the X and Y axis, the Z axis points away from the plane (right).

The Shimmer sensors have an internal 2 gigabyte data storage capacity (smart card) as well as low power radio communication capabilities (Bluetooth and IEEE 802.15.4) allowing both long-term data acquisition and real-time monitoring for experimental purposes. The Shimmer sensor module weighs 27g and measures 53 x 32 x 19 mm, thereby posing minimal obtrusion and discomfort for use over long periods [24]. For our experiments we only use the tri-axial accelerometer and the tri-axial rate gyroscope; we chose not to use the magnetometer since this can be affected by the presence of ferromagnetic materials which are expected to be present in the natural environment (e.g. cooker, wheelchair, etc.) [25]. Sensor data is collected at a rate of 50 Hz, deemed sufficient for assessing habitual limb movement which is on the higher side compared to assessing holistic activity as in [10, 11]. The accelerometer and gyroscope ranges are selected at ± 1.5g and ± 500^{o}/sec respectively. The sensors transmit kinematic data along with a time stamp to a host computer using the Bluetooth wireless standard. Data from multiple streaming sensor modules is synchronised with respect to their individual time stamps and each activity performed by a subject is marked to record the start and end of the task during the trial.

4. Data Processing and Feature Extraction

The key steps involved in our data processing are illustrated in Fig. 2 and described in detail in the following sections.

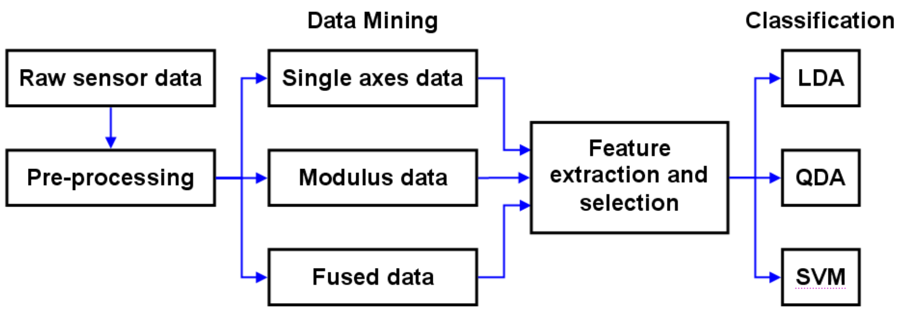

Fig. 2. Methodology used to evaluate data types and learning algorithms.

Acquisition & Pre-processing - The captured data is first pre-processed to get rid of any inherent noise and artefacts generally associated with the data acquisition process. The raw sensor data is low-pass filtered with a 3rd order Butterworth filter having a cut-off frequency of 12 Hz to attenuate the high frequency noise components. The resultant data is passed through a high-pass 3rd order Butterworth filter having a cut-off frequency of 0.1 Hz which attenuates the low frequency artefacts introduced in the data due to physical effects such as drift [10]. The filter order and cut-off frequency values were experimentally determined using Matlab.

Data Mining – The two Shimmer 9DoF sensor modules transmit data in real-time from a total of 12 individual sensors [(3 x accelerometers and 3 x gyroscopes) x 2 positions], providing a wealth of data from which to search for characterising patterns. Because one of our aims of this study is to determine which sensor position plays an important role in classifying arm movements, we also generate fused data signals that represent the modulus of the total acceleration or total rate of rotation experienced by these individual limb segments, as given by Eqn. (1). This results in 4 new signals, 2 each for the wrist and elbow sensor modules. Temporal variations in these signals indicate periods of activity of the underlying limb segment.

$$\begin{aligned} M_a &= \sqrt{AccX^2 + AccY^2 + AccZ^2} \\ M_g &= \sqrt{GyroX^2 + GyroY^2 + GyroZ^2} \end{aligned} \tag{1}$$

We further create fused signals, based on an a *priori* consideration of the expected trajectory of the subject's arm in relation to the sensor position on the arm and the orientation of the sensor axes when performing the required tasks. For example, Table 1 lists the specific accelerometer – gyroscope combinations that are expected to be the most active for each task as a function of their location on the arm. There are 3 unique sensor combinations for the wrist and 2 for the elbow to potentially identify the four tasks. Fusion of these signals takes the simple form of multiplying together the pre-processed data from the appropriate sensor combinations, thus creating 5 unique signals. We do not consider fusing data from different sensor nodes because we aim to find the minimum number of sensor locations.

Table I. Definition of fused signals for each arm movement.

Movement	Wrist	Elbow
A	AccX × GyroY	AccY × GyroZ
B	AccY × GyroZ	
C		
D	AccZ × GyroY	AccZ × GyroY

Feature Extraction – Although each of the sensors exhibits signal patterns that are distinctive for each of the arm movements and which may be recognisable to the human eye, in order for a machine to recognise these patterns a set of characterising features need to be extracted from the signals. Typical feature sets for human activity recognition include statistical functions, time and/or frequency domain features, as well as heuristic features [10].

In this investigation, we consider 10 time-domain features as follows: 1) *standard deviation,* 2) *root mean square (rms)*, 3) *information entropy* - measure of the randomness in a signal [26], 4) *jerk metric* - rms value of the second derivative of the data normalized with respect to the maximum value of the first derivative [27], 5) *peak number* - obtained from gradient analysis of the signal, 6) *maximum peak amplitude* - measure of the amplitude of the peaks obtained after gradient analysis, 7) *absolute difference* - absolute difference between the maximum and the minimum value of a signal, 8) *index of dispersion* - ratio of variance to the mean, 9) *kurtosis* - a measure of the 'peakedness' of a signal assuming a normal distribution in the data, 10) *skewness* - a measure of the symmetry of the data assuming a normal distribution in the data. Although the last two features are usually associated with defining the shape of a probability distribution, they can still be used as classifying features if they routinely return values that distinguish one pattern of data from another. All the 10 features are extracted from each of the individual sensor data streams (AccX, AccY, AccZ, GyroX, GyroY and GyroZ) and from the two modulus signals (M_a and M_g) as defined by Eqn. (1) for each of the wrist and elbow sensor modules, as well as from the five fused data signals described above in Table I.

Feature Selection – The most common multi-class feature ranking/selection algorithms in the field of human activity recognition are the RELIEF algorithm [28, 29] and the Clamping technique [11, 30-31], though both of these are computationally intensive. Accordingly, we choose not to use these algorithms due to our objective of utilising only low-complexity analysis algorithms. We normalize the extracted features and then follow the Wrapper approach using the sequential forward selection technique which selects various feature vector combinations to test for the minimal classification error probability and is computationally simple [32]. Therefore, depending on the purpose of our investigations, we select the best features for a given classification algorithm from: a). individual X, Y, Z data streams from each accelerometer and gyroscope placed on the wrist and elbow (a total of 120 features), b). modulus signals M_a and M_g from the wrist and elbow (a total of 40 features) and c). 3 fused signals from the wrist and 2 fused signals from the elbow (a total of 50 features). This process helps in feature reduction since we only select the optimal number of features thereby reducing the computational load and helps in achieving the best possible classification accuracy. However the number of optimal features depends strongly on the employed classification algorithm. Therefore we made a thorough exploration in this respect and the corresponding results are shown in Section 6.

5. Movement Classification Methodology

Although there are several well-known classification techniques used for human activity recognition, from the perspective of low/moderate computational complexity and to satisfy our own requirements we restrict our study to three different classifiers – Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA) and SVM. SVM is a very popular technique in machine learning community and generally produces high accuracy rates with moderate computational complexity (depending on the number of support vectors used) [11, 16]. In principle it is a binary classifier but has been extended to handle multiple classes using the 'one versus all' or the 'one versus one' scheme [33]. However both of these methods can be computationally intensive depending on the number of target classes. Hence we used the toolbox LIBSVM which is a library for SVM that is efficient for multi-class classification [34]. Overall (average) correct classification or accuracy is generally used to measure the performance of a binary classifier which might not always be applicable for multi-class classification because of possible dissimilar classification rates of different classes affecting the overall performance measure. Hence we measure the sensitivity of a given class from the confusion matrix N following the scheme proposed in [35]. The sensitivity S of class i estimates the number of patterns correctly predicted to be in class i with respect to the total number of patterns in class i [35]:

$$S_i = \frac{N_{ii}}{f_i} \times 100 \tag{2}$$

$$f_i = \sum_{j=1}^{c} C_{ij} \tag{3}$$

where, i = 1…c and c is the total number of classes. The diagonal and the off-diagonal elements of the confusion matrix correspond to correctly classified and misclassified patterns respectively. C_{ij} represents the number of times that the patterns are predicted to be in class j when they really belong to class i. A sample confusion matrix N is shown in Fig 3. This example shows near perfect classification since all diagonal elements approach unity and all off-diagonal elements approach zero.

	Predicted 'A' $j = 1$	**Predicted 'B'** $j = 2$	**Predicted 'C'** $j = 3$	**Predicted 'D'** $j = 4$
Actual 'A', i = 1	0.95	0.05	0	0
Actual 'B', i = 2	0	0.9	0	0.1
Actual 'C', i = 3	0.02	0	0.98	0
Actual 'D', i = 4	0.05	0	0.05	0.9

Fig. 3. A sample structure of a confusion matrix for four classes.

The sensitivity (S) of a class (i) can be calculated from the confusion matrix as follows:

$$S_i = \frac{N_{(i,i)}}{\sum_{j=1}^{c} N_{(i,j)}} \tag{4}$$

Therefore, the sensitivity of class A (expressed as a percentage), can be computed as $S_A = \frac{0.95}{(0.95 + 0.05)}$ = 95%.

Given the huge degree of inter-person/temporal variability for the same movement within the human population, and in particular, for people undergoing rehabilitation, the classifier needs to be robust enough to identify the same type of movements in the presence of large scale variability. Therefore the strategic choice of training the classifier is of utmost importance and hence the target classifier was developed using two types of approaches: generalized and personalized.

5.1. Generalized approach

The fundamental assumption behind this approach is that if a pool of data encompassing large variability of a particular type of movement from a population is used to train a classifier then it would be able to successfully identify that particular type of movement for a single subject as there is very high probability that the characteristics of the movement of that subject is already embedded within the training dataset. To test this hypothesis, as shown in Fig. 4, we perform a 'Leave-one-subject-out' validation methodology wherein we leave one subject out of the training data set.

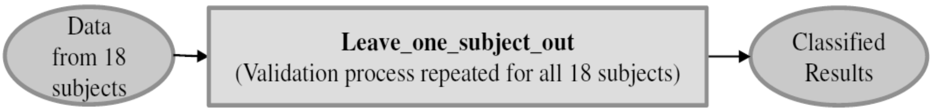

Fig. 4. *Generalized* classification approach.

This process was repeated for all 18 subjects. Since each subject carries out one type of movement 20 times, following the description provided in Section 4, for each sensor signal we have a data set consisting of 1440 samples (18 subjects × 20 trials × 4 movements). We keep one subject's data of 80 samples (1 subject × 20 trials × 4 movements) as the testing set and the remaining 1360 samples as the training set in each iteration to evaluate each of the three generalized classifiers (using LDA, QDA and SVM algorithms) for each of the 12 individual sensor signals and 9 fused data signals.

5.2. Personalized approach

In contrast to the generalized classification methodology, the basic hypothesis in the personalized approach is that the movement patterns have characteristic associations with specific subjects which may not be possible to capture in a generalized scenario. Personalized approach is a further testimony to the fact that each person undergoing any sort of rehabilitation will have different forms and levels of impairment and thus would be prescribed different exercises which would pertain to classifying individual movements. Therefore, a classifier based on the training set of the movement data of a subject (in a person-centric way) may yield more accurate classification results for that specific subject. The main steps for developing the personalized classification strategy are shown in Fig 5.

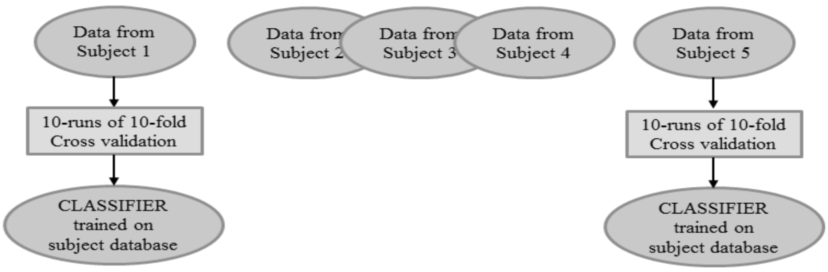

Fig. 5. *Personalized* classification approach.

To test this hypothesis in our experiment five subjects were asked to perform the same four movements 120 times each under the same experimental conditions. The collected dataset from a subject is labelled as the training database specific to that particular subject and 10 runs of 10-fold cross validation are carried out on the data collected for each subject. The cross-validation process creates 10 segments of the data sample (120 samples for each task) with each segment having 12 samples. In each run of the stipulated 10 runs, one segment is used as the testing set while the rest of the 9 segments are used as the training set. The whole process is repeated for each subject as shown in Fig 5 and for each of the 12 individual sensor signals and 9 fused data signals.

6. Results

The classification results (sensitivity for each arm movement recognised) of the *Generalized approach* using the individual sensor data, their moduli and the fused data for each of the learning algorithms LDA, QDA and SVM for the wrist and elbow are presented in Fig. 6 and Fig. 7 respectively. The sensitivity for each movement using the individual sensor signals for both the accelerometer and the gyroscope placed on the wrist and elbow is better than the modulus and the fused signals. The sensitivities and number of features for classification in each case are presented in Table II.

Table II. Generalized classification results.

		Wrist					Elbow				
Classifier	**Signal**	**A (%)**	**B (%)**	**C (%)**	**D (%)**	**Features**	**A (%)**	**B (%)**	**C (%)**	**D (%)**	**Features**
LDA	Acc_mod	58	58	51	73	9	63	77	48	87	8
	Acc_xyz	85	91	84	90	18	77	84	56	85	11
	Gyr_mod	82	78	39	80	7	76	50	65	81	8
	Gyr_xyz	96	83	83	88	12	81	81	79	84	15
	Fused	81	74	60	75	13	63	67	66	64	9
QDA	Acc_mod	49	61	54	72	4	56	76	45	86	7
	Acc_xyz	89	92	78	91	15	81	78	70	74	18
	Gyr_mod	82	71	36	85	7	74	54	64	67	7
	Gyr_xyz	94	91	95	89	12	76	72	86	85	15
	Fused	86	72	54	74	11	59	33	69	68	11
SVM	Acc_mod	42	53	55	70	5	57	76	35	82	4
	Acc_xyz	89	87	82	90	8	86	82	55	84	8
	Gyr_mod	90	74	35	80	5	76	49	58	77	5
	Gyr_xyz	97	85	90	89	11	88	81	78	83	14
	Fused	75	71	50	69	9	55	71	56	44	9

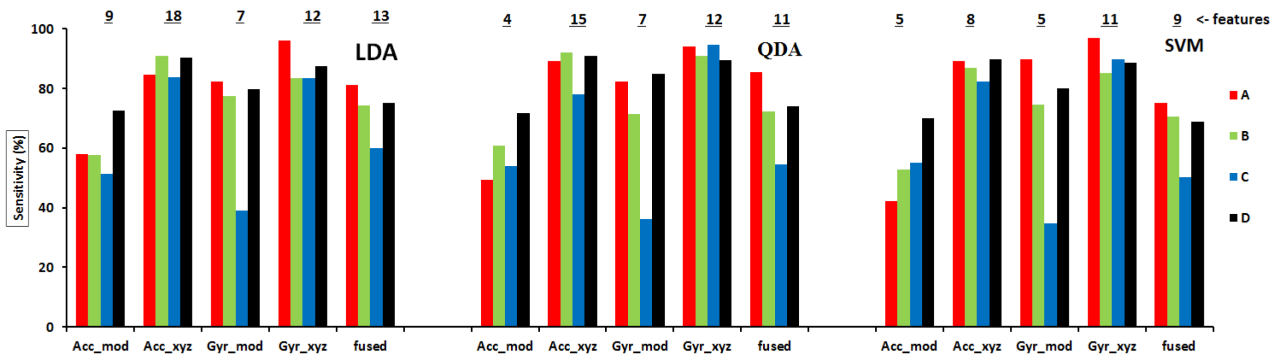

Fig. 6. *Generalized* classification - sensitivities for each task using the wrist accelerometer and gyroscope modulus signal (mod), individual sensor signals (xyz) and fused signals with LDA, QDA and SVM. The number of features required for each signal and sensor type is shown at the top of each group.

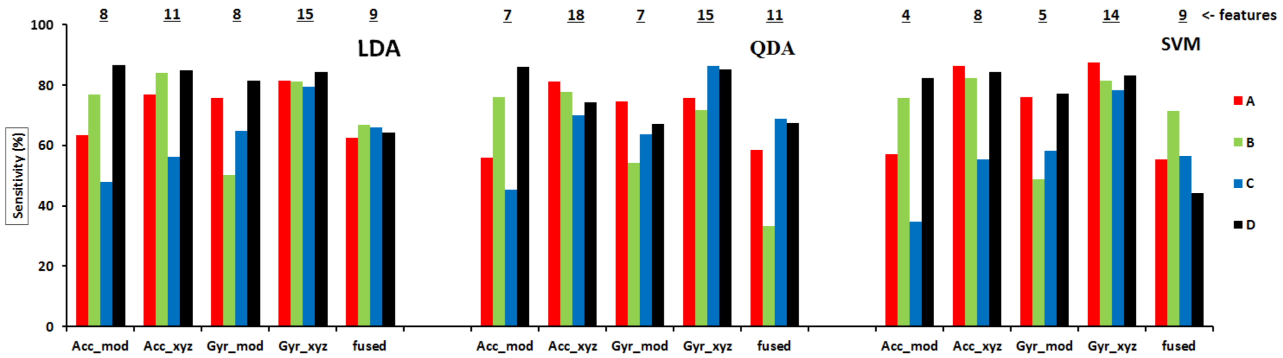

Fig. 7. *Generalized* classification - sensitivities for each task using the elbow accelerometer and gyroscope modulus signal (mod), individual sensor signals (xyz) and fused signals with LDA, QDA and SVM. The number of features required for each signal and sensor type is shown at the top of each group.

The sensitivity as discussed in section 5 represents the success rate of the classifier in detecting each respective arm movement. The classifier using the least number of features from a specific data source for successfully classifying each arm movement is the obvious choice as it involves less computation. The difference in the recognitions rates between modulus and individual signals is due to the fact that when we consider individual sensor signals we retain any bipolar information present in the raw data, whereas the generation of a modulus signal creates, by definition, only unipolar data. Hence, using the individual sensor signals provides the classifier an opportunity to select the optimum number of features from a wider pool of features and hence the recognition rate for the movements is reflected in the higher sensitivities achieved. For the fused signals the sensitivity is generally lower when compared to results obtained from individual sensors, but better than results obtained when considering the moduli signal. Considering fused signals from the wrist sensors, the sensitivity falls within 60-81% for the four movements with LDA and lies within 54-86% with QDA and 50-75% with SVM whereas for the elbow the sensitivities for the fused are within 60-81% with LDA, 33-69% with QDA and 44-71% with SVM. Considering LDA with individual sensor signals, the wrist gyroscope recognises the four movements with sensitivities in the range of 83-96% across all movements while the wrist accelerometer also has a similar detection rate with sensitivities in the range of 84-91% across all movements. However, the gyroscope uses only 12 features as compared to the 18 used by the individual sensor signals of the accelerometer (out of a total of 30 - 3×10 features) and hence is the obvious choice with regard to a lower complexity solution. We can achieve a higher sensitivity (91%) for Movement B using the accelerometer but that involves a cost of computing 6 extra features.

A further comparison of the wrist gyroscope results using individual sensor signals with QDA and SVM illustrates that the results for QDA and SVM are marginally higher than LDA, and the number of features required for the three algorithms is nearly the same. Hence, in view of the trade-off between the recognition rate and the complexity involved, LDA being computationally less complex [36] appears as the best choice.

The sensitivities achieved using the individual signals from the elbow gyroscope for LDA (A: 81%, B: 81%, C: 79%, D: 84%), QDA (A: 76%, B: 72%, C: 86%, D: 85%) and SVM (A: 88%, B: 81%, C: 78%, D: 83%) are lower than those achieved with the individual signals from the wrist gyroscope LDA (A: 96%, B: 83%, C: 83%, D: 88%), QDA (A: 94%, B: 91%, C: 95%, D: 89%) and SVM (A: 97%, B: 85%, C: 90%, D: 89%). In fact, a close examination reveals that in general the sensitivity for each movement for the signals from the wrist are better than those from the elbow, which is because the wrist is expected to produce the largest sensor response to the arm movements investigated.

Having established the effectiveness of the individual sensor signals over the moduli and fused signals we present here the classification results (sensitivity for each task) for the *Personalized* approach comparing 5 subjects using the individual signals for the different sensor-position combinations and the three learning algorithms in Table III. In general, all the three classifiers (LDA, QDA and SVM) applied on data from all sensor-position combinations give high levels of classification results across all tasks (above 90%). For sake of brevity we present here a comparative illustration of the classification results for the gyroscope signals from the wrist in Fig 8. In view of its low computational complexity, we focus on LDA where the sensitivities achieved for all the four sensor-positions combinations are similar within a range of 92-100%. Furthermore, sensors placed on the wrist require fewer features than the sensors placed on the elbow for similar levels of sensitivity, thus computational complexity can be reduced further selecting the former location for sensor positioning.

Table III. Personalized classification results with individual signals.

		Wrist					Elbow				
Sensor	**Subject**	**A (%)**	**B (%)**	**C (%)**	**D (%)**	**Features**	**A (%)**	**B (%)**	**C (%)**	**D (%)**	**Features**
LDA											
Acc	Subject 1	99	100	100	98	7	100	100	100	99	7
	Subject 2	100	100	100	99	3	100	99	96	98	5
	Subject 3	98	99	97	99	7	98	100	97	99	7
	Subject 4	94	100	96	99	7	94	97	96	98	9
	Subject 5	100	100	100	99	5	98	99	98	100	5
Gyr	Subject 1	100	100	100	100	6	100	99	92	98	8
	Subject 2	100	100	99	100	4	100	100	100	100	5
	Subject 3	98	100	99	99	5	100	100	99	99	7
	Subject 4	98	100	99	99	6	98	99	93	97	7
	Subject 5	99	100	100	98	7	99	99	97	100	10
QDA											
Acc	Subject 1	100	100	100	98	7	95	99	98	98	5
	Subject 2	100	100	99	99	3	100	98	100	100	4
	Subject 3	99	99	99	99	7	99	99	100	99	5
	Subject 4	94	98	81	91	7	79	95	84	96	5
	Subject 5	100	100	100	100	5	98	98	99	99	5
Gyr	Subject 1	99	100	100	100	6	99	98	99	96	7
	Subject 2	100	100	100	100	3	99	100	100	100	5
	Subject 3	98	98	100	99	6	100	100	100	98	9
	Subject 4	99	100	100	98	6	100	97	100	100	7
	Subject 5	98	99	99	98	5	98	100	98	100	8
SVM											
Acc	Subject 1	99	100	100	99	7	100	95	99	98	6
	Subject 2	100	100	100	99	3	100	99	98	99	4
	Subject 3	98	100	97	99	6	98	100	98	98	8
	Subject 4	91	100	90	99	6	93	98	90	99	10
	Subject 5	100	100	100	100	5	99	100	98	100	5
Gyr	Subject 1	100	100	100	100	7	100	99	92	98	8
	Subject 2	100	99	100	100	5	100	100	100	100	5
	Subject 3	99	100	100	100	7	99	99	100	99	8
	Subject 4	98	100	100	98	7	93	98	93	99	10
	Subject 5	98	99	98	98	6	94	98	93	99	5

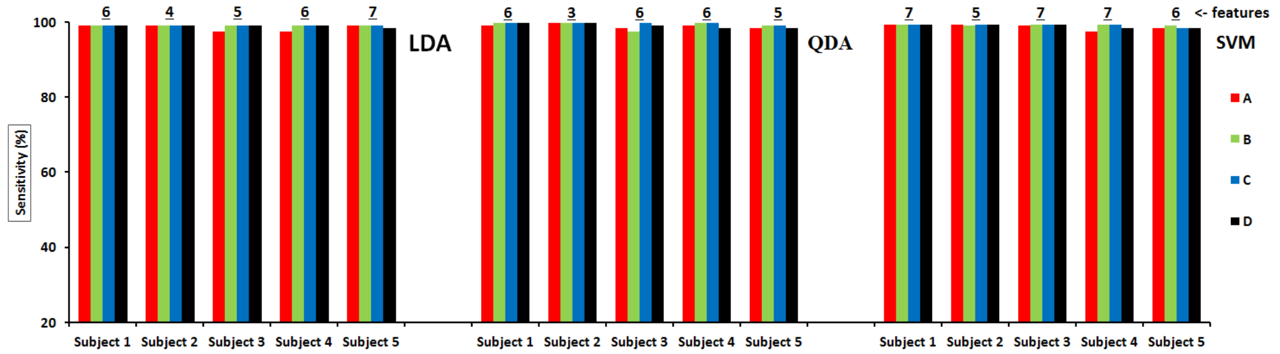

Fig. 8. *Personalized* classification – sensitivities for each task using the wrist gyroscope individual signals, with LDA, QDA and SVM for each of the 5 subjects. The number of features required for each subject is shown at the top of each group.

7. Conclusion

In this paper we have made a systematic exploration regarding developing a training model based on a group of subjects doing similar movements and in a subject specific manner to cater to inter-subject variability and verify the model using cross validation methodologies with attention on the selection of sensor type and position, and appropriate classification strategies for detecting four fundamental types of upper limb movements that are used in daily life activities. We show that a tri-axial accelerometer or tri-axial rate gyroscope placed near the wrist or elbow can independently classify all four movements with sensitivity in the range 92-100% when a small set of features (6-10) is extracted from the data from individual sensors and a *Personalized* learning approach is adopted in conjunction with the LDA classifier algorithm. Therefore any of these two types of sensor or locating positions can be used for the target classification.

For the *Generalized* approach, the accelerometer and the gyroscope placed on the wrist can classify all the four tasks with accuracy in the range 83-96% when data from individual sensors is used with LDA as the learning algorithm. However, the number of features required to achieve it is on the higher side (12-18) as compared to the *Personalized* approach which implies higher computational complexity involved in feature computation. This can be partly explained by the fact that the classifier requires more feature-specific information to cater to the wider variability inherent in the *Generalized* database as compared to the *Personalized* approach where generally there is a high degree of repeatability in the tasks performed by each individual subject and hence can be represented by fewer features.

By comparison, when we consider the modulus of the accelerometer and gyroscope signals, or the fused signals we achieve lower recognition rate. This is due in part to the fact that when we consider individual sensor signals we retain any bipolar information present in the raw data, whereas the generation of a modulus signal creates, by definition, only unipolar data. Using all the individual sensor signals, rather than a single processed signal (i.e. moduli or fused), provides the classifier an opportunity to select from a wider pool of features and hence the recognition rate for the tasks is reflected in the higher sensitivity achieved.

We further found that LDA gives comparable results when compared with more computationally intensive classification methods such as QDA and SVM. Therefore from the system realization point of view, being of low computational complexity LDA is a better choice when the training dataset is chosen in a personalized way. The methodology described can be used in remote healthcare systems in a resource constrained environment such as home-base rehabilitation of stroke patients. Typically, stroke patients are encouraged to perform particular exercises during normal daily life that are targeted at improving their specific impairments. Hence, a remote system that employs activity recognition as described here would be capable of detecting and recording the occurrences of such exercises (arm movements), and the analysis of their number and quality over time will provide a measure of rehabilitative progress.

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CONFLICT OF INTEREST STATEMENTS

The authors declare that they have no conflict of interest in relation to the work described in this article.

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