Development of fall detection and activity recognition using threshold based method and neural network

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Article Info

ABSTRACT

Falls are dangerous and contribute to over 80% of injury-related hospitalization especially amongst the elderly. Hence, fall detection is important for preventing severe injuries and accidental deaths. Meanwhile, recognizing human activity is important for monitoring health status and quality of life as it can be applied in geriatric care and healthcare in general. This research presents the development of a fall detection and human activity recognition system using Threshold Based Method (TBM) and Neural Network (NN). Intentional forward fall and six other activities of daily living (ADLs), which include running, jumping, walking, sitting, lying, and standing are performed by 15 healthy volunteers in a series of experiments. There are four important stages involved in fall detection and ADL recognition, which are signal filtering, segmentation, features extraction and classification. For classification, TBM achieved an accuracy of 98.41% and 95.40% for fall detection and activity recognition respectively whereas NN achieved an accuracy of 97.78% and 96.77% for fall detection and activity recognition respectively.

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1. INTRODUCTION

The population of elderly citizens in Malaysia is expected to increase significantly by the year 2030. The number of senior citizens aged 60 and over will grow from 6.2 % of the population in 2000 to 13.6% of the population in 30 years [1]. According to the World Health Organization (WHO) [2], falls can be defined as involuntary, unexpected and uncontrollable events resulting in a person impacting and coming to rest at a lower level [3] and it is estimated that 28-35% of people aged 65 and above fall each year. This statistic increases to 32-42% for those over 70 and the likelihood of a fall occurring is higher with as age increases. Falls are the leading cause of injury and accidental death for those over 75. In fact, they account for 70% of the accidental death occurrences [4]. The most common consequences of these injuries are fractures, loss of independence, and even death. This situation will usually worsen if the elderly person lives alone.

Recognizing human activity is a significant part in human life as it can be applied in monitoring a person's health and quality of life. It is a significant factor for assessing the activity of the subject subjects living. The assessment of physical activities of daily living (ADLs) of the elderly is very important to study and understand the relationship between ADLs and their health [5-8]. An activity recognition system enables the classification of an ADL which can be recorded for the purpose of healthcare monitoring [9-11].

However, the sensors for such a system would usually collect redundant information, as well as noise, which are produced due to involuntary movements of the person being monitored. From the literature review, it was observed that the low pass filter could be used to overcome the noise problem. However, both low and high pass filters should be implemented for different types of signal analysis. Also, sensor data segmentation is one of the critical stages of fall classification. Without signal segmentation, the signal sent will consume a very long time to process, causing the system to perform slowly.

Furthermore, raw sensor data are usually filled with meaningless information. Without extracting the useful features, it will affect the performance of classification [12]. Most fall detection systems focus on extracting one single feature which is the magnitude of the accelerometer sensor [13]. However, more features should be extracted to provide more information related to the ADLs of the elderly [14]. For classification, the most popular method is Threshold Based Method (TBM) [15-17] and Machine Learning Methods (MLM) such as Artificial Neural Networks (ANN) [18-20]. With sufficient data for training and testing, ANN could potentially produce highly accurate classification results with the only downside being the computational complexity it requires could lead to long processing times, making real time fall detection impossible [21]. On the other hand, TBM has the advantages of having low power consumption and fast processing speed [22] but might not be able to match the ANN in terms of accuracy.

The aim of this project is to develop an effective algorithm for fall detection and human activity recognition in MATLAB. The classification performance for the system will be compared between the TBM and ANN classifiers. It should be noted that this project is also one of the subsystems for a wearable fall detection system which incorporates two other subsystems which are the Wearable Detector and Notification System. These subsystems will only be described briefly in this paper since the focus is on the classifier design and output performance.

2. RESEARCH METHOD

For this project, it is focusing on the development of fall detection as well as the activity recognition. Besides propose and develop the fall detection algorithm for the wearable fall detection system mentioned above, this project develops the activity recognition using TBM and NN as well. The overview block diagram for the project is as shown in Figure 1.

Intentional falls and sequential ADLs were performed by 15 healthy volunteers: ten male and five female subjects whose ages ranged from 20 to 25, height from 160 to 190 cm, and weight from 50 to 95 kg. The falls were performed using a soft mattress. Each subject performed 3 sets of activities during testing. There are 7 types of activities to be performed as shown in Table 1.
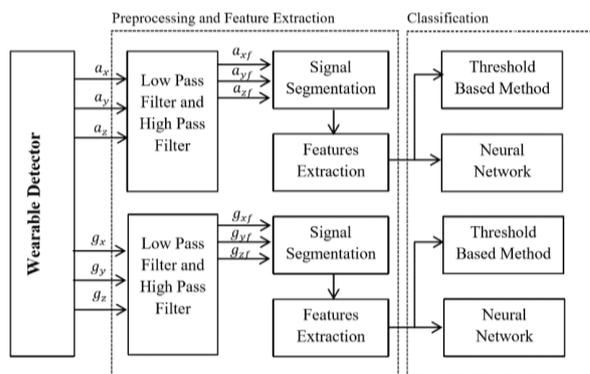

Figure 1. Block diagram of the fall detection and activity recognition system

Table 1. The Summarized Test Activities and Descriptions

Activities	Description
Falling	Stand for 2 seconds then fall forward
Running	Running at normal speed of 2.53 step per second for 8 seconds
Jumping	Jumping for 8 seconds
Walking	Walking at normal speed of 1.67 steps per second for 8 seconds
Standing	Standing for 8 seconds
Lying	Stand first then sit then lying on the bed
Sitting	Stand 2 seconds and sitting on the chair

During the testing, the subjects are asked to follow short instructions to perform intentional falls and ADLs. A total of 270 ADLs (45 sets for 6 kinds of ADLs) and 45 falls were tested. The device is mounted on the belt at the waist of the test subjects.

For this project, it mainly focuses on fall detection and activity recognition algorithm which the steps start from signal processing to the fall classification. The data collected during experiments are processed in a irtual environment in a computer using MATLAB software. The algorithm that discriminates the fall from ADLs consists of four important process stages:

a) Signal Filtering: Sensor data is both low pass and high pass filtered
b) Segmentation: A sliding window or time frame is used to segment the signal stream into frames of fixed length
c) Feature extraction: Different features are extracted from segmented signals
d) Fall Classification: The system uses the features extracted from the previous step as input for classification

2.1. Filtering Method

A low pass filter and a high pass filter are designed and implemented to remove the unnecessary and redundant information connected to involuntary human movements as well as to filter the noise if assumes that there are existences of noises on the accelerometer and gyroscope sensors. The second order Butterworth filters are selected for filtering the signal. Then, the cut off frequency for low pass filter is selected and the filter is implemented to check if the filter designed suitable or not. If the filter implemented does not meets the requirement which is produce less ripple signal and remove the noise, it go back to reselect the cut off frequency. The same approaches are applied for designing and implementing the high pass filter. As a result, the cut off frequency selected is 25Hz and 3Hz for low pass filter and high pass filter respectively.

For every second (200 samples of data), a high pass and low pass filter are applied to the accelerometer and gyroscope data. The high pass filtered values correspond to acceleration values which are due to the movement of the user whereas the low pass filtered values correspond to acceleration due to gravity [23]. The data received were low-pass (cut-off frequency = 25Hz) and high-pass filtered (cut-off frequency = 3Hz) with a digital second-order Butterworth filter for posture detection and dynamic analysis respectively. From that, the high pass filter is mainly used to eliminate the low-frequency acceleration (gravity) that captures information about the orientation of the sensor with respect to the ground. The high pass filtered data is used for the extraction of features relevant for dynamic activities, such as jumping and running. The low-pass filter is used to eliminate most of the signals generated by dynamic human motion, preserving the low-frequency component such as gravity. The low-pass-filtered data contains sensor orientation information, which is relevant for the recognition of static activities (postures), such as lying, sitting and standing.

2.2. Segmentation Method

Classification errors are often a result of inappropriate segmentation due to poor window size selection. Short time length will allow avoiding delay from continuously real-time processing while providing a reasonable recognition rate. Hence, the window size selected is 2.5 seconds. The technique used is non-overlapping window sizing which depends on the peak of the signal. Time frame of 1 second before and 1.5 seconds after the peak of the signal is selected as shown in Figure 2. The signal is segmented into frame with 2.5 seconds (500 samples) which mainly depend on the time of peak value of the signal, T_p, the time frame has interval of $[T_p-1s, T_p+1.5s]$, in which it take 1 seconds before the peak value and 1.5 seconds after the peak value.
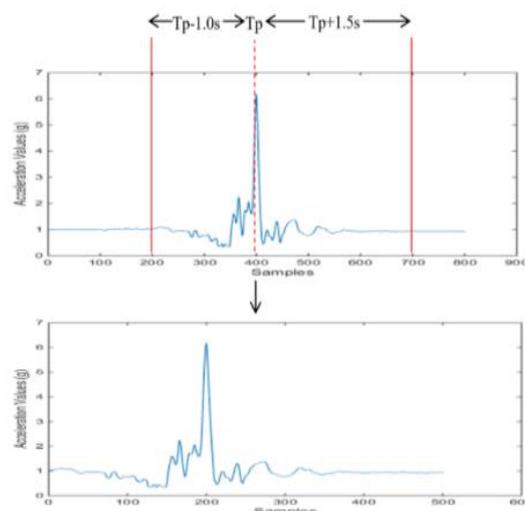

Figure 2. The steps of segmenting a signal into 2.5 seconds

2.3. Features Extraction Method

The features are extracted from both the low pass filtered signal and high pass filtered signal. Multiple potential features are tested but only eight optimized features are selected for achieving high accuracy result as shown in Table 2. From these 8 selected features, 6 are used to classify a fall from ADLs and 2 are included to recognize the other six ADLs (jumping, running, sitting, lying, walking and standing).

Table 2. Lists of Features

No	Features	Descriptions	Formulas
1	SVM_a	Sum vector magnitude of acceleration. It is calculated from high pass filtered acceleration values, also known as dynamic sum vector. This feature describes the spatial variation of acceleration during the falling interval [24].	$SVM_a = \sqrt{a_x^2 + a_y^2 + a_z^2}$ (1) *where a_x, a_y and a_z are the acceleration of x-axis, y-axis, and z-axis respectively*
2	SVM_w	Sum vector magnitude of angular velocity. It is calculated from high pass filtered angular velocity values. It is used to detect fall related impact [25].	$SVM_w = \sqrt{w_x^2 + w_y^2 + w_z^2}$ (2) *where w_x, w_y and w_z are the angular velocity of x-axis, y-axis, and z-axis respectively*
3	$NormAcc$	L1 norm of acceleration, which is the total acceleration exerted on the device. This feature is calculated each second from the high pass filtered acceleration values. It directly corresponds to the amount of acceleration that a user has exerted on the accelerometer [24].	$NormAcc = |a_x| + |a_y| + |a_z|$ (3) *where $|a_x|$, $|a_y|$, and $|a_z|$ are the absolute acceleration of x-axis, y-axis, and z-axis respectively*
4	Z_{min}	Minimum value of vertical acceleration Z_2 for impact detection. It is applied for impact detection the acceleration at the absolute vertical direction [5]. It is calculated from high pass filtered acceleration values.	$Z_{Min} = \sqrt{\dfrac{SV_{TOT}^2 - SVM_a^2 - G^2}{2G}}$ (4) *where SV_{TOT} is total sum vector (g) which is using formula in (1) but extracted from raw acceleration values without filtering, SVM_a is sum vector magnitude or dynamic sum vector (g), and G is gravitational component = 1g.*
5	SV_{yzh}	High pass filtered acceleration on horizontal plane y-z. It means the body tilts during the fall [24]. It will larger than certain threshold if there is a fall. It is calculated from high pass filtered acceleration values.	$SV_{yzh} = \sqrt{a_{yh}^2 + a_{zh}^2}$ (5) *where a_{yh} and a_{zh} are the high pass filtered acceleration of y-axis and z-axis respectively.*
6	SV_{yzl}	Low pass filtered acceleration on horizontal plane y-z. It means the body tilts during the fall [24]. It will larger than certain threshold if there is a fall. It is calculated from low pass filtered acceleration values.	$SV_{yzl} = \sqrt{a_{yl}^2 + a_{zl}^2}$ (6) *where a_{yl} and a_{zl} are the low pass filtered acceleration of y-axis and z-axis respectively.*
7	$MaxMin$	Differences between maximum and minimum acceleration values in last 0.5 seconds. The values are obtained during the interval time of last 0.5 second of the signal. It is to test the orientation of the user by determine if the user is in static phase after the fall.	$MaxMin = a_{max} - a_{min}$ (7) *where a_{max} and a_{min} are the maximum and minimum values from sum vector magnitude of acceleration signal which is filtered by low pass filter.*
8	θ_{ratio}	Ratio of polar angle. It describes the posture of body and when the body is in static. This angle reflects the body-tilt and a sudden change could be indicative of a fall [4].	$\emptyset_{ratio} = cos^{-1}\left(a_x / \sqrt{a_x^2 + a_{y+}^2 a_z^2}\right)$ (8) *where a_x, a_y and a_z are the acceleration of x-axis, y-axis, and z-axis respectively.*

There are seven features extracted from accelerometer signal and one feature from gyroscope signal. For acceleration, there are 4 features are selected from high pass filtered acceleration signal and 3 features are extracted from low pass filtered acceleration signal. For angular velocity, the feature is extracted from high pass filtered angular velocity signal.

2.4. Fall Classification

TBM is implemented for fall detection and activity recognition. This technique distinguishes between the falls and ADLs when the peak values are above or below certain predefined threshold value. Threshold based method has advantage of low power consumption and fast processing speed which is suitable for the wearable fall detector system. There are two algorithms are developed in this step. The first one is fall detection algorithm and second is fall detection algorithm with activity recognition. Firstly, a two-level threshold MATLAB algorithm is implemented for classifying a fall from ADLs. This algorithm consists of two processing stages, in which the first stage is to detect the impact of the fall and the second stage is to determine the orientation of the user when a fall occurs.

This method is introduced to reduce the false alarm, which can be a serious problem for caregiver and the family member of the user. The algorithm uses mainly tri-axial accelerometer and tri-axial gyroscope

sensors data collected from the waist to distinguish between fall, non- fall, and even the activity of daily living (ADL). The algorithm will involve multiple processing phases, for example, the sum vector magnitude of sensor signals is checked if exceed the threshold value in the first phase, then the next feature is checked if exceed the predefined threshold value in the next phase, and until the final phase is verified. Finally, a fall is detected if the threshold value is exceeded for all the phases and an immediate alert message will be sent. The fall detection algorithm is briefly explained as shown in Figure 3.

Total of six features (features 1, 2, 3, 5, 7, and 8) are used for detecting a fall. There are four features used in the first stage and two features used in the second stage. However, for the second algorithm, there are two additional features (features 4 and 6) are added to the fall detection algorithm for recognizing the other six kinds of ADLs, which also known as activity recognition. Hence, a fall detection algorithm with activity recognition is developed using total of 8 features. The flow of the second algorithm is briefly explained in Figure 4. It integratescanous developed fall detection algorithm with activity recognition algorithm by using 8 features. Hence, the algorithm is able to detect fall and recognize other six kinds of ADLs.
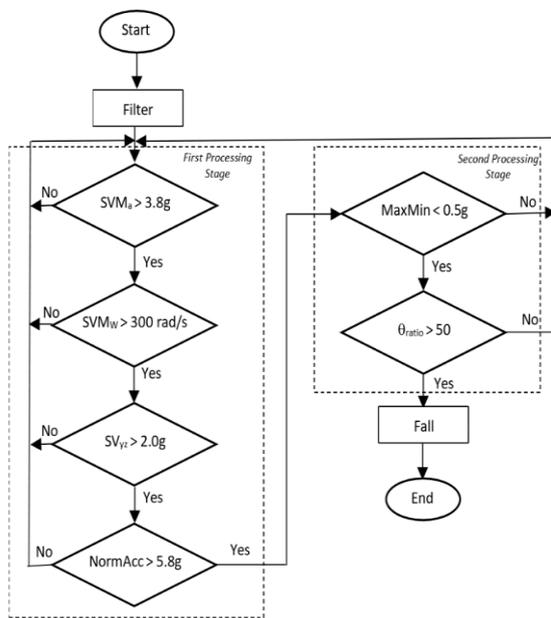

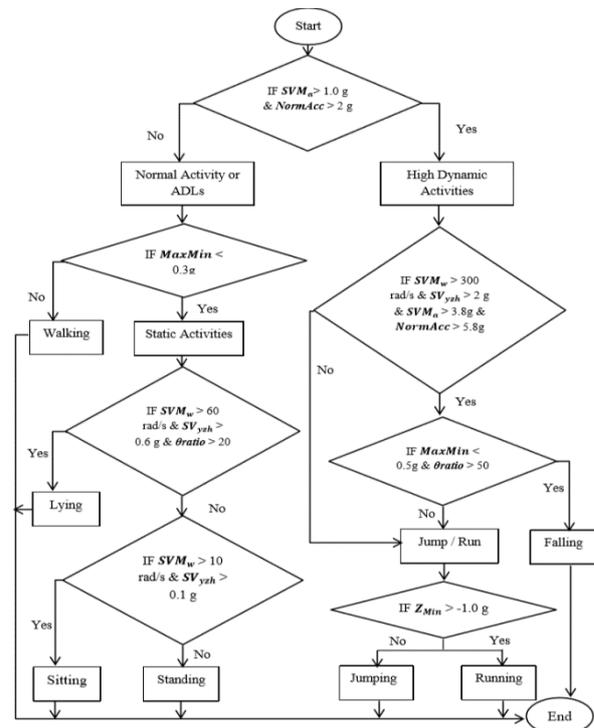Figure 3. The flowchart of fall detection algorithm

Figure 4. The flowchart of fall detection algorithm with activity recognition

Fall detection and activity recognition also can be achieved through Neural Network (NN). It overcomes the limitations of the conventional techniques but it has several disadvantages that make it less attractive to be a classification method for fall detection and activity recognition, these drawbacks are requirement of high mathematical skills and use of more computation resources. However, NN is applied in this project in order to compare the performance with the threshold-based method. NN is fed with the data collected so that it was able to classify a fall and ADLs. For the input of classification, the same eight features from the previous classification are applied. For neural network, the input data will pass into the hidden later then go through the output layer for producing output. The network architecture consists of input, 20 hidden neurons in hidden layer, output layer and output which as shown in Figure 5.

For validation and test data, total of 60% (189 samples) of the samples data is for training, 20 % (63 samples) of the samples data is for validation and 20 % (63 samples) of the samples data is for testing. The samples data is divided into three kinds of samples which are training samples, validation samples, and testing samples. For training, these are presented to the network during training, and the network is adjusted according to its error whereas for validation, these are used to measure network generalization,

and to halt training when generalization stops improving. For testing, it has no effect on training and so provides an independent measure of network performance during and after training.
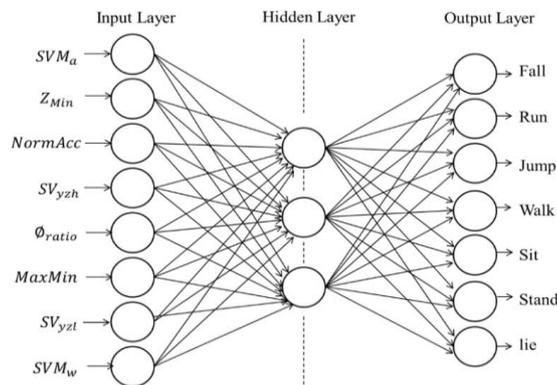

Figure 5. The network architecture of the neural network (NN)

3. RESULT AND ANALYSIS

The performance of the threshold based algorithm is evaluated by calculating accuracy, specificity and specificity. The algorithm performance was tested and validated by collecting the fall and ADL data as mentioned above. For fall detection, the sensitivity reached to 97.78% and specificity reached to 98.41%. Table 3 and Table 4 show the detailed information considering the sensitivity and specificity of the algorithm. Accuracy of the fall detection is 98.41% as shown in Table 5. Since the output of the fall detection is binary, there are four possible results:

a. True Positive (TP): a fall happens and the algorithm detects it.
b. False Positive (FP): an ADL is performed and the algorithm detects as a fall.
c. True Negative (TN): an ADL is performed and the algorithm detect as nonfall.
d. False Negative (FN): a fall occurs but the algorithm does not detect it.

Besides using TBM for classify the fall and other six kinds of activities, Neural Network (NN) also is used to compare the performance of the classification of fall detection and activity recognition. The NN is trained and applied using Neural Network Matlab Toolbox based on the same set of fall and ADLs data collected (315 tests). For input of the neural network classifier, the same eight features are used which are SVMa, SVMw, NormAcc, SVyzh, MaxMin, θratio, SVyzl and Zmin. The sensitivity, specificity and accuracy of detecting a fall using neural network are summarized in Table 3, Table 4, and Table 5 respectively. The sensitivity and specificity of fall detection using NN are reached 95.56 % and 98.15% respectively. The accuracy of the fall detection using neural network is 97.78%. For the activity recognition, the sensitivity and specificity for recognize each activity is calculated in Table 6 and Table 7. The accuracy of recognizing an ADL from 6 kinds of activities is as shown in Table 8.

Table 3. Sensitivity of the Fall Detection using TBM and NN

Falls (number of falls)	Fall detected (TP)		Fall not detected (FN)		Sensitivity (TP)/(TP+FN)	
	TBM	NN	TBM	NN	TBM	NN
Falling(45)	44	43	1	2	97.78%	95.56%

Table 4. Specificity of the Fall Detection using TBM and NN

ADL (number of tests)	Fall not detected (TN)		Fall detected (FP)		Specificity (TN)/(TN+FP)	
	TBM	NN	TBM	NN	TBM	NN
Running (45)	43	44	2	1	95.56%	97.78%
Jumping(45)	43	41	2	4	95.56%	91.11%
Walking(45)	45	45	0	0	100%	100%
Standing(45)	45	45	0	0	100%	100%
Sitting(45)	45	45	0	0	100%	100%
Lying(45)	45	45	0	0	100%	100%
Total(270)	266	265	4	5	98.52%	98.15%

Table 5. Accuracy of the Fall Detection using TBM and NN

Nnumber of tests(Fall and ADLs)	(TN+TP)		(FN+FP)		Accuracy (TN+TP)/(TN+TP+FN+FP)	
	TBM	NN	TBM	NN	TBM	NN
315	310	308	5	7	98.41%	97.78%

From the results based on TBM, the average sensitivity of the recognize all 6 types of activities is 86.67% where running, jumping, walking, standing, sitting, and lying have sensitivity of 75.56%, 62.22%, 93.33%, 100%, 95.56%, and 93.33% respectively. The average specificity of the activity recognition has reached 97.10% which consists of running (94.07%), jumping (93.33%), walking (97.78%), standing (100%), sitting (98.89%), and lying (98.52%). The average accuracy of activity recognition from 6 ADLs is 95.40%, where the accuracy of recognising running, jumping, walking, standing, sitting, and lying are 91.43%, 88.89%, 97.14%, 100%, 98.41%, and 97.78% respectively. The sensitivity and specificity of fall detection using neural network are reached 92.22 % and 97.53% respectively. The average accuracy of the activity recognition using NN is 96.77% where the accuracy of recognising running, jumping, walking, standing, sitting, and lying are 95.23%, 92.70%, 99.04%, 100%, 97.78%, and 94.87%.

The performance of the TBM and NN is evaluated by comparing the algorithms in terms of accuracy and specificity. The algorithm performance was tested and validated by collecting the fall and ADL data as mentioned above. The sensitivity, specificity and accuracy of the algorithm are as shown in Table 9. For fall detection, the accuracy of the NN (97.78%) is slight lower than TBM (98.41%). However, the accuracy of the activity recognition using NN is 96.77% which is higher than the accuracy of TBM of 95.40%. Theoretically, the NN classifier should has better classification performance for fall detection and activity recognition than the TBM. The unexpected result of NN classifier might due to there are less samples data are used for training, validating, and testing in neural network and the features used for NN might not be optimized for achieve high accuracy result.

Table 6. Sensitivity of the Activity Recognition using TBM and NN

ADL (number of tests)	Activity recognized (TP)		Activity not recognized (FN)		Sensitivity (TP)/(TP+FN)	
	TBM	NN	TBM	NN	TBM	NN
Running (45)	34	40	11	5	75.56%	88.88%
Jumping(45)	28	37	17	8	62.22%	82.22%
Walking(45)	42	44	3	1	93.33%	97.78%
Standing(45)	45	45	0	0	100%	100%
Sitting(45)	43	42	2	3	95.56%	93.33%
Lying(45)	42	41	3	4	93.33%	91.11%
Average	266	249	4	21	86.67%	92.22%

Table 7. Specificity of the Activity Recognition using TBM and NN

ADL (number of tests)	Activity not recognized (TN)		Activity recognized (FP)		Specificity (TN)/(TN+FP)	
	TBM	NN	TBM	NN	TBM	NN
Not Running (270)	254	260	16	10	94.07%	96.30%
Not Jumping(270)	252	255	18	15	93.33%	94.44%
Not Walking(270)	264	268	6	2	97.78%	99.26%
Not Standing(270)	270	270	0	0	100%	100%
Not Sitting(270)	267	266	3	4	98.89%	98.52%
Not Lying(270)	266	261	4	9	98.52%	96.67%
Average	1573	1580	47	40	97.10%	97.53%

Table 8. Sensitivity of the Activity Recognition using TBM and NN

ADL (number of tests)	(TN+TP)		(FN+FP)		Accuracy (TN+TP)/(TN+TP+FN+FP)	
	TBM	NN	TBM	NN	TBM	NN
Running	288	300	27	15	91.43%	95.23%
Jumping	280	292	35	23	88.89%	92.70%
Walking	306	312	9	3	97.14%	99.04%
Standing	315	315	0	0	100%	100%
Sitting	310	308	5	7	98.41%	97.78%
Lying	304	302	11	13	97.78%	94.87%
Average	1803	1829	87	61	95.40%	96.77%

Table 9. The Sensitivity, Specificity and Accuracy of TBM and NN for Fall Detection and Activity Recognition

Task	TBM			NN		
	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity	Accuracy
Fall Detection	97.78%	98.52%	98.41%	95.56%	98.15%	97.78%
Activity Recognition	86.67%	97.10%	95.40%	92.22%	97.53%	96.77

4.   CONCLUSION

Fall detection with activity recognition is successfully developed and implemented using TBM and compare with NN classifier. There are eight optimum features: SVMa, SVMw, NormAcc, SVyzh, MaxMin, θratio, SVyzl and Zmin. The accuracy for fall detection is 98.41% for TBM and 97.78% for NN whereas for activity recog-nition, the accuracy is 94.48% for TBM and 96.77% for NN. These high accuracy results might due to the test subjects in-volved are young people and the activities (intentional fall and 6 kinds of ADLs) are performed in simulated environment which is follow by certain instruction as there is a lot of different move-ment in real life might affect the actual outcome of the classifica-tion. The fall detection algorithm using TBM is suggested for wearable fall detection system as it has better accuracy for detect-ing fall and has advantages of low power consuming and fast processing speed. In future work, there should be a greater varia-tion in the sample data in terms of age range for the purpose of training and testing for both methods.

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