Towards Robust Classification of Human Activities and Motion Disorder

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Overview

Human Activity Recognition (HAR) systems play a key role in remote patient activity monitoring, particularly for the disabled and old adult people. In this project, we introduce a robust HAR system capable of identifying six different classes of body movements with high accuracy. Figure 1 shows the pipeline of the proposed HAR system. A smart phone worn on the subject's waist is used as a sensing unit to record the accelerometer and gyroscope signals.

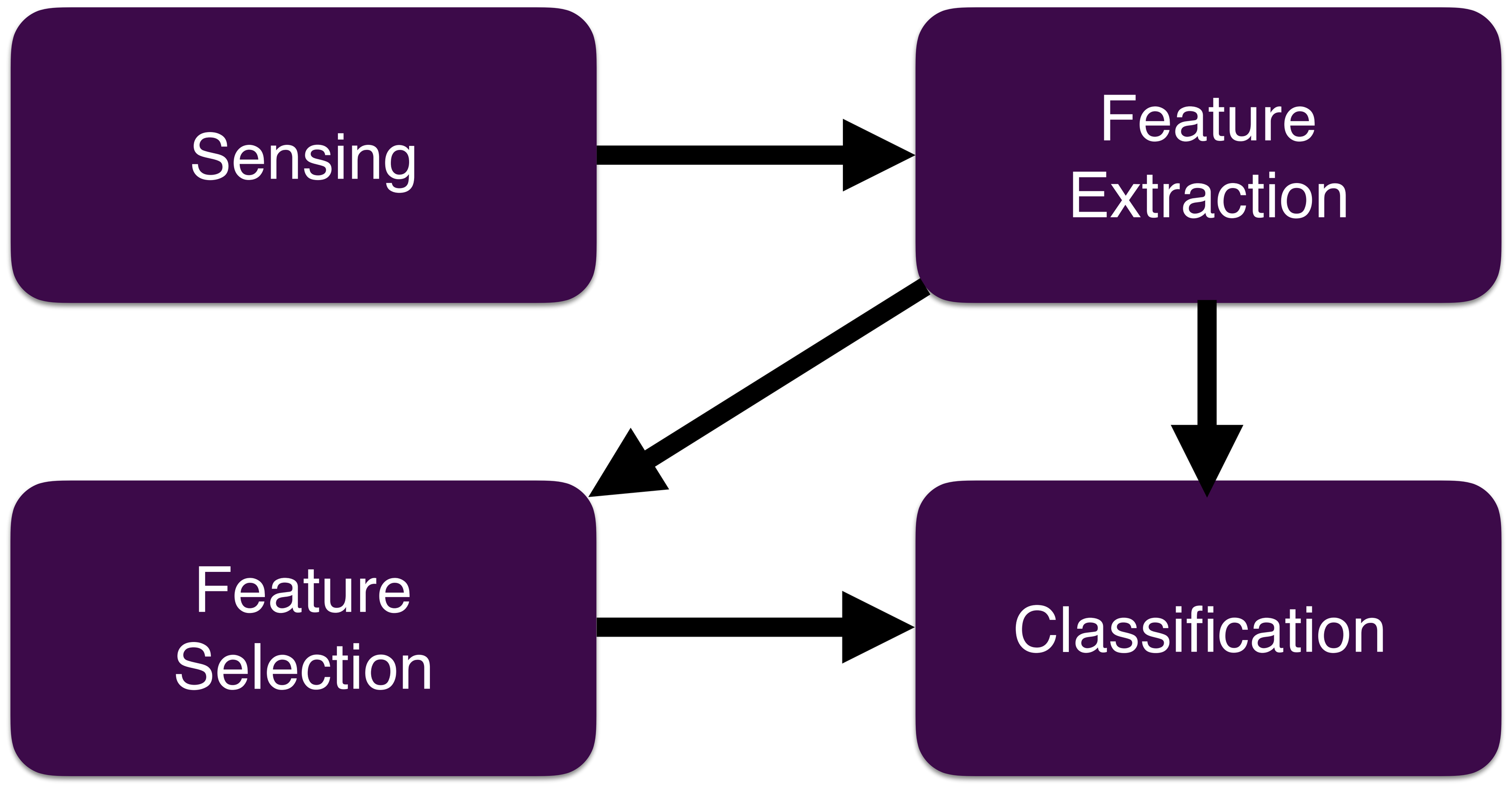


Figure 1. Overall System Description

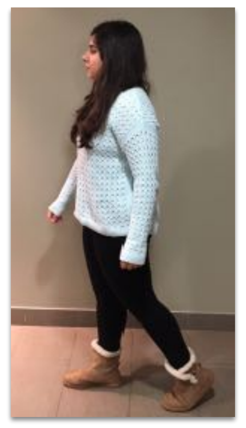
Then, a robust feature extraction method is proposed to effectively select the most discriminant features of HAR signals. These features are then fed into the classifier and the detection accuracy is evaluated. Six different classification models are used to examine the effectiveness of extracted features. Experimental results on a publicly available HAR dataset [1] verify the robustness of the proposed method for human activities recognition, as it achieves a classification accuracy of ~98.50%. We also adopted a feature selection method based on LASSO regression; the classification time is significantly reduced and an overall classification accuracy of 97.56% has been achieved.

Movement Classifications

Laying

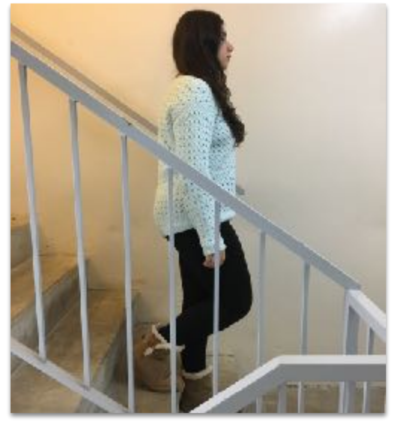
Sitting

Standing



Walking straight

Walking upstairs



Walking downstairs

Method

Data Acquisition

MATLAB IOS is installed on iPhone and MacBook for data acquisition. Data of accelerometer and gyroscope signals for six different positions are captured and logged through built-in sensors from iPhone. Figure 2 illustrates the recording of six activities/ positions on MATLAB.

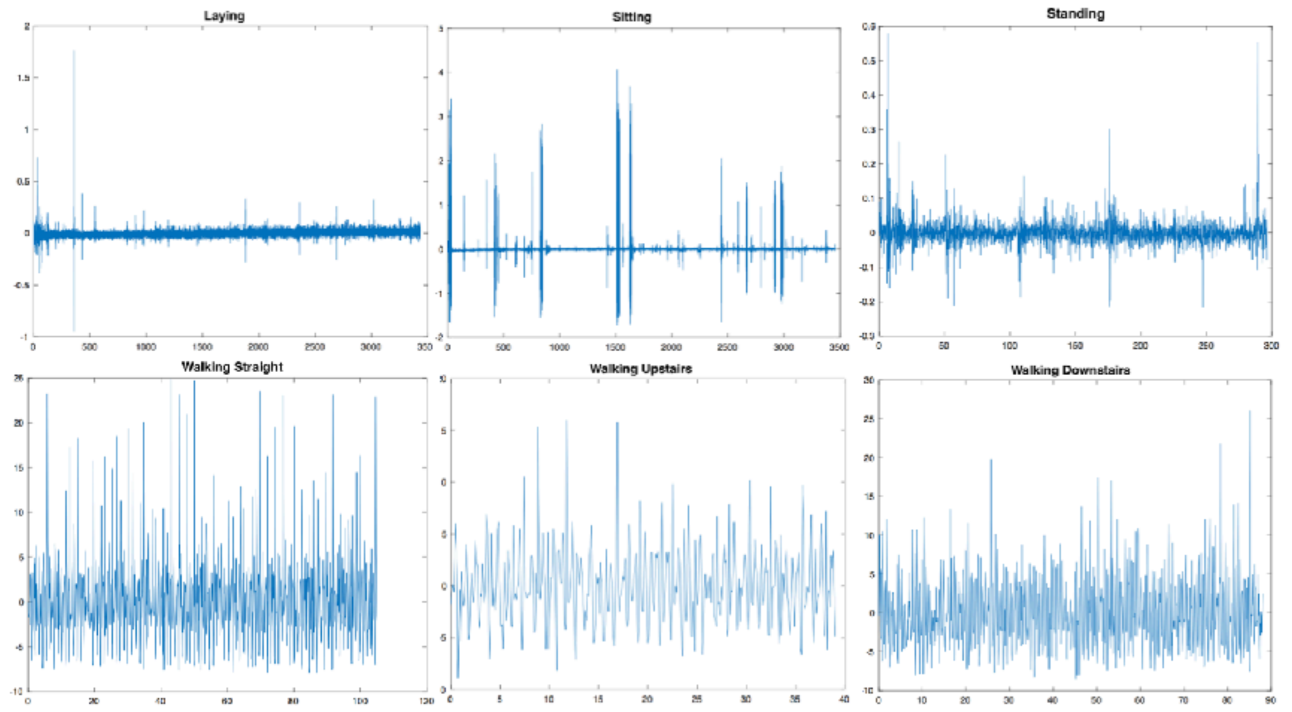


Figure 2. Examples of Time series Accelerometer signals for the 6 Activities.

Feature Extraction

Features used for the recognition processes are extracted from the captured accelerometer and gyroscope signals. Sampling frequency is initially set to 50Hz, then median filter is applied to eliminate the embedded noise. Furthermore, jerking signals are obtained by deriving the accelerometer and gyroscope signals with time. The magnitudes of these signals are computed using the Euclidean norm. The frequency spectrum of these signals is obtained as well. From the time-domain signals, jerking signals, magnitude signals and the frequency-domain signals, some features have been extracted. These features are mean value, standard deviation, median absolute deviation, largest value in signal, smallest value in signal, magnitude area, signal energy, interquartile range, signal entropy, autoregression coefficients, cross-correlation coefficients, indices of the frequency components with largest and smallest values, mean frequency, skewness, kurtosis and the energies of the frequency bands. The total number of extracted features are 561.

Feature Selection

The quantity of selected attributes has positive correlation with time required to build model. Hence, LASSO Regression method is introduced to optimize accuracy while reducing the number of selected features required [2]. The LASSO constrains the sum of the absolute values of the regression coefficients to be less than a fixed value, and constrains certain coefficients to be exactly zero. LASSO improves prediction accuracy when covariates have a strong relationship and reduces negligible data. Only 149 attributes are selected after application of LASSO Regression technique.

Classification

WEKA, which integrates various machine learning algorithms for data mining, is introduced to analyze and compare different classification models according to the same training dataset and test data, in order to select the best algorithm for fall detection. Macbook Pro with a 2.6 GHz processor is selected to run WEKA.

Results

The results acquired in this research demonstrated the feasibility of performing HAR in real-time with smartphones, attaining an accuracy approaching 98%. Priori to the adoption of feature selection technique, 98.50% accuracy was accomplished with Functions-SMO algorithm, although having a longer training time of 17.92 seconds. Table 1 shows the comparison on different learning algorithms with 561 attributes.

Table 1. Classification Accuracies based on Feature Extraction

Classification Model	# of Features	Training/Testing	Accuracy (%)	Training time (s)
Functions-SMO	**561**	**Cross-validation 5-fold**	**98.47**	**17.92**
Lazy-ibk	561	Cross-validation 5-fold	97.10	0
Meta-random.committee	561	Cross-validation 5-fold	96.98	2.82
trees -J48	561	Cross-validation 5-fold	93.98	15.68
trees-random.forest	561	Cross-validation 5-fold	97.81	14.93
trees-reptress	561	Cross-validation 5-fold	93.32	4.82

For the proposed smartphone HAR system to be applied in highly advanced and essential healthcare sectors such as remote ambulatory monitoring of people with disabilities and elderly people, it is essential that it accomplishes a high precision and accuracy and on the other hand work within a reasonable and convenient timeline. Thus, the Random Forest algorithm post LASSO Regression feature selection was found to be the best compromise between Accuracy (97.56%) and training time (8.19 s). Table 2 shows the comparison on different learning algorithms with 149 attributes.

Table 2. Classification Accuracies based on Feature Extraction and Selection

Classification Model	# of Features	Training/Testing	Accuracy (%)	Training time (s)
Functions-SMO	149	Cross-validation 10-fold	96.67	2.11
Lazy-ibk	149	Cross-validation 10-fold	92.96	1.43
Meta-random.committee	149	Cross-validation 10-fold	97.15	1.44
trees -J48	149	Cross-validation 10-fold	93.33	3.1
trees-random.forest	**149**	**Cross-validation 10-fold**	**97.56**	**8.19**
trees-reptress	149	Cross-validation 10-fold	92.96	1.43

Future Research

Falling is one of the major health risks among the senior community due to its tendency for mortality and morbidity. Falls and fall-induced injuries account for over 80% of all injury-related hospital admissions among people over 65 [3]. For further research, a software for fall detection could be programmed on the bias of current data analysis. Sensory data could be obtained from smartphone and have its time-domain, jerking, magnitude and frequency-domain signals commutated. Then, the program could calculate the similarity between the instance and training sample in the training dataset. If the instance is classified to be fall, then the system will send an alarm to notify caretaker. Else, it is not classified as a fall pattern.

References

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[3] Shumway-Cook, M. A. Ciol, J. Hoffman, B. J. Dudgeon, K. Yorkston, and L. Chanl, "Falls in the Medicare population: incidence, associated factors, and impact on health care," *Physical Therapy*, vol.89, pp. 324-332, 2009.

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