Using Machine Learning Techniques for User Specific Activity Recognition

Jaideep Chawla, Matthias Wagner
Research Group WSN & IOT
Frankfurt University of Applied Sciences
Frankfurt Am Main, Germany
Email: j.chawla|mfwagner@fb2.fra-uas.de

***Abstract*—This paper explores the possibility of using wireless sensor networks and a machine learning based approach to classify activities performed by the wearer. The network consists of inertial sensors mounted on the non-dominant wrist of a user. This wrist mounted module sends data to a smartphone present in the user's pocket via Bluetooth Low Energy (LE). The sensors present in the smartphone themselves are used to collect movement data of the user. In addition to this network structure no particular care is given to the orientation of the wrist based device and smartphone. The motivation behind this network structure is to develop a Human Activity Recognition (H.A.R.) system which causes minimal to no inconvenience to the user. Movement data (acceleration and orientation) was collected from 8 subjects for movement based activities like walking, jogging, running, cycling and some basic weight training based exercises and features were extracted from the raw data. The extensive list of features was reduced using a correlation based subset evaluation method. The performances of four different classification algorithms namely the K Nearest Neighbor, Support Vector Machine, Artificial Neural Network and Classification and Regression Tree (CART) was evaluated for classification accuracy. Classification accuracy in excess of 90 percent was obtained which points to the possibility using such a system for Real Time Human Activity Recognition while causing minimal inconvenience to the user.**

Keywords: human activity recognition, body area networks, inertial sensors, wearables, machine learning, classification

I. Introduction

Human activity recognition (H.A.R.) is the capture and analysis of various types of movement that a human can exhibit. It includes but is not limited to locomotion(translation), gestures, change of orientation of the body or a limb (via movement of joints). Capturing different types of human movement has its uses in fields like medicine, sports, surveillance and gesture recognition. We focus on macro level movements of the body such as locomotion, change of orientation and movement of the joints. Traditionally such forms of motion capture and analysis was done using video motion capture but with advancements in sensor and the ubiquitous nature of inertial sensors which are now available in almost all the smart devices (phones and digital watches) it is equally feasible to use a wireless sensor network on the human body for the purpose of H.A.R.

If done in a reliable manner, implementation of human activity recognition can be used for medical purposes. A good example is tracking of patient activity while performing a 24 hour ambulatory blood pressure monitoring. Patients are required to maintain a diary and note all the activities performed by them over a 24 hour period. This process could be automated with better accuracy if combined with an activity recognition system. Another possible application area is the monitoring of generalized tonic-clonic seizures(GTCS). This type of seizure manifests itself as rapid jerking movements in the limbs of the patient. Biniczky et al [1] assessed the reliability of a wrist worn wireless accelerometer for detecting generalized tonic clonic seizures and were able to achieve an accuracy of 89.7% in detecting GTCS with a false alarm rate of 0.2 false alarms per day. Automatic tracking of daily activity levels can also help in managing caloric expenditure especially if combined with a daily reporting and notification system.

We considered various locations sensors could be placed on the body and the subjects involved in the data collection phase of the experiment were also questioned as to where they would prefer (if at all) to have sensors on the body and amongst the 8 users all of them unanimously agreed to having a sensor placed on the non dominant wrist. It is also important to note that smart watches and fitness bands which are mounted on the non dominant wrist of the user themselves contain accelerometers and have been widely accepted by the demographic of consumers who use smart devices.

The prime motivation behind this paper is to evaluate the accuracy of a two node sensor network for H.A.R. for various fitness based activities (not limited to running,walking or bicycling as is the case with current fitness tracking systems). H.A.R. has been of interest to researchers since the 1980's and the field has seen two distinct approaches for implementation:

- Sensor based
- Vision based

Vision based activity recognition involves the use of some form of video as an input in order to detect the activity being performed. Inspite of its merits a video based approach cannot be implemented in a pervasive manner i.e. it cannot be used to track daily activity of a person because a person cannot be recorded everywhere she/he is present. This paper focuses on a sensor based single user activity recognition. This approach is based very strongly on statistically modeling the data being recorded by the sensors and using it as an input for a machine learning based algorithm. The second motivational factor behind the research is do develop a system which is able to learn various types of activities, hence the term "user specific has been used to highlight the fact that the research is not limited to analyzing if the approach can classify a fixed set of activities but rather a wide variety of activities so that the system is as versatile as possible while still not hindering any day to day activity of the user.

The research was conducted in a four step process

1) **Set up a wireless sensor network and collect data from 8 different users for 6 activities**: A wireless sensor network was built with a focus on ease of use and comfort therefore only a single wrist mounted module was built as a prototype which communicates with a smartphone present in the user's pocket.
2) **Extract features from the raw data collected**: The data itself generated by the sensors and collected by the smartphone cannot directly be used for the purpose of training a data mining model for activity recognition. The data needs to be converted into features.
3) **Select features using a correlation based subset filter**: An initial set of 75 features was reduced to 13 features using this approach.
4) **Evaluate 4 data mining models for accuracy**: The data mining algorithms were evaluated using a split of 66% towards the training data set and 34% towards the validation data set.

II. Related Work

The devices currently present in the market are dependent on human input of the data required to track the activity performed by a user. A fair amount of research on H.A.R. has been performed using various types of devices containing a different mix of sensors. Accelerometers are utilized by many researchers as they can provide information that is significantly distinct for different types of activity[3]. With the proliferation of accelerometers in devices like smartphones and smart watches it is theoretically possible to implement activity recognition in a way that can be made available out of the box. Such implementations also make it easy to provide solutions geared towards a specific use case for example assistance of an elderly population. Chernbumroong et al.[8] conducted a survey on 18 participants regarding the usefulness,effectiveness, adoption willingness and the concerns of using smart home technologies for assisting elderly people. Their study was inconclusive towards the willingness of adoption of such technology but it does raise the question of the user friendliness of such devices. It is also important to consider that a for the purpose or a survey a count of 18 participants is a very small sample space to derive any conclusions. If H.A.R. is to be used to assist daily living of any population demographic it becomes important to keep psychological factors also into consideration along with the technology used in such a system. Although Gao et al.[2] evaluated the difference in accuracy of a single versus multi sensor approach and came to the conclusion that a multi sensor approach is able to achieve higher accuracies using limited features(using only mean and standard deviation) the feasibility of using multiple sensors on a human body without hindering day to day activities needs to be evaluated before such a system is to be made commercially available.
Chernbumroong et al.[4] used a single wrist mounted accelerometer present in a sports watch to identify activities of daily living (ADL) like lying, walking, sitting, standing and running. Data was transmitted to a laptop and features were extracted from the data. The list of features consisted of 13 features. Two data mining models (Decision tree and artificial neural networks) were evaluated for classification accuracy. The researchers were able to achieve an accuracy of maximum 94.13%. There are multitudes of options available when it comes to data mining model all with their own merits and demerits. Kao et al.[5] used a similar setup of a wireless node on a user's wrist and collected data for ADL. In their case activity classification was performed using fuzzy basis function based classifiers. System performance was also evaluated by them in order to calculate the amount of time required by an embedded system to perform various calculations. The system in question was an Intel®Xscale PXA270 which was running at 520 MHz. A common criticism to both these approaches is that none of these venture to analyze the feasibility of their system when it comes to activities beyond those performed in daily living. If a user is performing activities other than walking or running then the systems proposed by these authors holds no merit to these types of users.

In order to use a data mining model it is essential to extract features from the data. Accelerometers provide a continuous stream of data therefore it is required transform the stream into a discrete form. The most popular way of doing so is to "window" the data and calculate features from the data. Windowing is the most popular technique for feature extraction.[3],[5],[6],[7],[4] and [9] use an overlapping window method to segregate the data and extract features from it. The windows are then labeled according to the activity that was performed. We chose a window size of 2 seconds as per Nyan et al[10] and Wang et al[11]. It also makes computational sense to use as small a window of data without it being too small leading to loss of information of the movement in the selected window size. Real time implementation of H.A.R. will be less computationally expensive on a smaller window size since the algorithm that calculates features works over a smaller sample size hence using less time and computing power.

III. Data Collection and Preprocessing

A. System description

The prototype consisted of a board (Adafruit ^{TM} Flora), a 3 axis sensor (consisting of an accelerometer, gyroscope and magnetometer) and a Bluetooth module working on the Bluetooth 4.0 low energy protocol as shown in Figure 1.

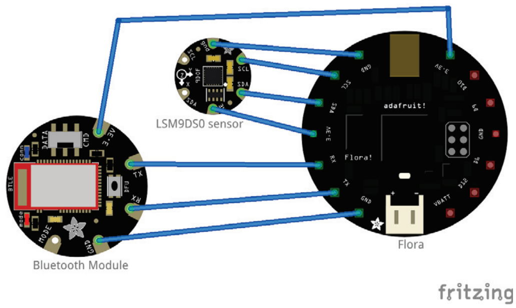

Fig. 1: Schematic of the wrist mounted prototype.

The phone used for data collection was a One Plus One™ which has a battery capacity of 3100 mAh. Battery consumption was calculated by running the application along with the prototype connected to the phone via Bluetooth LE. This resulted in a battery consumption of about 2 -4 % per hour. On a 100% charge that results theoretically in a battery life of **25 hours** for the smartphone. In actual day to day usage it can be much less depending upon multiple factors that can affect the battery life of a smartphone. These include (but are not limited to):

- Signal quality of cellular network : lower signal strengths results in higher battery consumption as the phone tries to lock on to the strongest possible signal.
- Use of mobile internet instead of Wi-Fi can possibly lead to increased battery consumed
- Use of Sensors : More the sensors being used by the smartphone more the battery consumption will be
- Power consumption by applications running in the background

All of these factors combined could possibly reduce the battery life of the smartphone being used in such an application. More research is required to have an accurate estimate of power consumption of a smartphone being used.

B. Data Collection

Implementation of Human Activity Recognition requires a trained classification algorithm. In order to train a data mining algorithm it was necessary to first collect data which is as close as possible to data which will be generated in real life usage of our application. To make sure the data was as close as possible to real life we took the following measures :

- No cables were used. The prototype and the smartphone communicate in a wireless manner using bluetooth even during the data collection phase.
- When it comes to the orientation of the devices set up on the body no particular care was taken regarding the orientation of the devices in order to make sure the data generated is as close as possible to how it will be generated in real life.

Data for the following movement was collected in an environment as close to real life as possible with the prototype mounted on the left wrist and the data collection device kept in the right pocket. Movement was initiated after clicking the data collection button on the smartphone. No pre processing of the data occured at this stage. The data was stored in a CSV file. The following data was gathered by application present on the smartphone

- Timestamp when the reading was taken
- Orientation values : roll, pitch and heading(yaw)
- Acceleration experienced by the sensor over the three axes (x,y,z). Please note that these are the axes of the sensor present on the device
- end of line character

TABLE I: Data format

timestamp	pitch	roll	heading	acc_x	acc_y	acc_z
1446921069	-81.12	-38.21	-8.39	0.14	-0.59	0.75

The phone based sensors were programmed to collect data at the rate of 25 Hz and the wrist mounted prototype collected data at a rate of 5 Hz. On trying a faster refresh rate for the prototype the bluetooth connection between the phone and the prototype used to terminate. A possible explanation could be because the communication happens via Universal Asynchronous Receive and Transmit (UART). Such communication requires a UART buffer which is of a limited size. Higher refresh rates possibly lead to an overflow in the UART buffer which then results in the communication being terminated.

The accelerometer on the wrist based prototype was set to a range of +-6G. As per Chen et al[12] the peak G's measured while collecting data while measuring falls were 6.9 G's for falling backwards and 12.7 G's for falling sideways. Should we choose to extend our system to be able to detect falls the LSM9DS0 sensors allows a range of measurement of 16 g's.

C. Feature Extraction

To calculate features a complete signal of duration 12 seconds for a particular activity was taken and was divided into windows of 2 seconds each using a sliding window method. These two second windows were then used to calculate features. The initial list consisted of 75 features which involved performing the following operations on the data for acceleration and orientation collected for the different axes of movement:

- mean
- standard deviation
- maximum and minimum amplitude
- root mean square
- inter-quartile range

From a list of 75 features a final set of 17 features was chosen using a correlation based filter method. Correlation based feature selection is dependent upon the concept of 'merit' of a feature. Good feature subsets contain features highly correlated with the classification, yet uncorrelated to each other [14]. Correlation here refers to the Pearson's correlation coefficient. Pearson's correlation coefficient is defined via

$$R(i) = \frac{Cov(X_i,y)}{\sqrt{var(X_i)var(y)}}$$

where cov refers to the covariance and var reference to the variance The acceptance of a feature calculated via ”Merit”

$$M_S = \frac{k\bar{r_{cf}}}{\sqrt{k+(k-1)\bar{r_{ff}}}}$$

where $\bar{r_{cf}}$ is the correlation of the feature to the classifier , $\bar{r_{ff}}$ is the correlation of the feature to other features and k is the number of features

There is no ‘one size fits all’ approach to feature selection. It depends a lot on the type of features we are working with. Wherever possible it is a good practice to involve the use of a subject matter expert to get a better insight into the set of features to make sure the feature selection techniques are not skipping features which could be important.

IV. Evaluation

In order to select the best possible algorithm for H.A.R. the algorithms chosen were evaluated for classification accuracy and the time required to train the algorithms.

A. Algorithms considered for evaluation

We evaluated the following models :

- kNN: K nearest neighbor classification
- ANN:Artificial Neural Network(Single layer perceptron)
- SVM:Support vector machines
- CART:Classification and Regression Tree

B. Protocol for evaluation of algorithms

In order to evaluate the algorithms for their accuracy of classification data was collected from 8 different subjects each performing the following activities:

1) walking
2) jogging
3) running
4) push-ups
5) squats
6) bench press
7) deadlifts
8) cycling

The activities performed by the subjects were dependent on their discretion and no care was taken to by the subjects to perform the activities in a certain standard manner since our focus is to provide a user specific solution to cater to the activities performed by an individual. The data of all the users was then collected and aggregated into a single file and features were extracted for the various activities. A total of 522 instances of data were generated after extracting features from the raw data streams of various users. These were split into 66 % towards training the data mining algorithm and 34 % towards validation of the model. The results of the evaluation have been provided in table 2.

NA refers to the fact that the time required to build the model was less than a second. Further evaluation was done to assess the classification accuracy corresponding to different activity types performed. The first column consists of percentage of correctly classified instances with all the features and the second column consists of classification accuracy of the algorithm after correlation based feature selection was performed. In three cases using a smaller set of features extracted using correlation based subset selection led to a minor decrease in accuracy of classification but led to a significant decrease in the time required to build the model. These metrics however are preliminary and more testing needs to be done with a wider population to be able to properly analyze the accuracy this approach can realize.

V. Conclusion

Looking at the algorithm evaluation table it can be observed that when all the features were used for the purpose of model evaluation the artificial neural network provided the highest accuracy(96.77%) but also took the longest time to train. The training dataset itself consists of 522 instances of data of which 66% were used to train the model. Even though the machine on which the models were trained is not as powerful as the servers which are used today it nevertheless can be inferred that using the ANN classifier with all the features is not feasible to use for an activity recognition system which needs to learn new types of movements continuously during it’s operating lifetime. Using the reduced set of features decreased the training time to 1.42 seconds which is a significant amount but still does not compare to the K nearest neighbor algorithm which took very little time to train yet providing an accuracy of 96.16% when all features were used and 95.31% on the reduced set of features.

For a limited dataset the results point to the feasibility of KNN as a classifier of choice for the problem of classifying human activity but given the small size of the study certain points/limitations need to be taken into consideration:

- The data was collected mostly in a fitness studio with subjects who are well trained and perform the movements with the correct form. This can lead to similarities in the data collected from different users. It is imperative to collect data from a general population to properly determine the accuracy of the algorithm.
- The quantity of data collected needs to be more in order to accurately analyze the time taken to train the models.
- The reliability of data transmission for Bluetooth low energy needs to be analyzed to see if is feasible to use when deploying the system to run on a real time basis.

Deploying such a system on a real time basis presents the challenge of having not only a reliable classification but the right hardware also needs to be used.The hardware tasked with measuring data for H.A.R. can be preferred to have the following characteristics

- Non pervasive: should not hamper with day to day activities of the wearer
- Long battery life: should not consume a lot of power or need frequent charge cycles
- Reliable connectivity:connection with a smartphone or ay other data collection device should be reliable

TABLE II: Algorithm Evaluation

Activity—Algorithm	KNN		CART		ANN		SVM	
	All	CFSS	All	CFSS	All	CFSS	All	CFSS
Time to train	NA	NA	0.25 seconds	0.06 seconds	13.64 seconds	1.42 seconds	0.21 seconds	NA
Jogging	89.6%	87.2%	93.2%	88.9%	91.3%	92.7%	86%	82.6%
Running	100%	100%	92.1%	94.4%	100%	97%	100%	89.2%
Walking	94.6%	95.9%	94.6%	90.9%	95.9%	86.4%	95.9%	95.8%
Pushups	100%	100%	92.3%	100%	100%	100%	93.3%	100%
Squats	100%	100%	100%	77.8%	100%	100%	100%	88.9%
Bench Press	91.6%	89.3%	100%	95.3%	91.6%	90.1%	89.3%	86.4%
Deadlifts	100%	100%	98.7%	97%	100%	96.9%	98.7%	96.3%
Cycling	93.5%	90.1%	91.6%	90.1%	95.4%	93.5%	92%	94.3%
Average accuracy	**96.16%**	**95.31%**	**95.31%**	**91.8%**	**96.77%**	**94.57%**	**94.4%**	**91.68%**

- Storage: some form of storage on the device(for example flash memory) could be useful to store data in the event that no connectivity options are available.

An all round device which exhibits all the features mentioned above is significantly difficult to come by in the market.Wrist devices which use the Android wear^{TM} operating system are possible options as they provide a sensor API that allows us access to raw data stream of sensors and include accelerometers,gyroscopes and magnetometers. Another option is to develop a custom board with all the requisite sensors and communication modules. The advantage of developing a custom board is the flexibility in developing your own firmware. The obvious disadvantage is that the equipment required to fabricate such boards is not cost friendly and will not be feasible for a home user looking to implement H.A.R. As future work we are looking to analyze the power consumption of our approach while using three distinct devices:

- A smart watch.
- A fitness band.
- a microcontroller mounted with sensors on a small printed circuit board

We believe that given the right hardware it is possible to implement a reliable and accurate human activity recognition system in the near future to assist users for a myriad of purposes and with the collection of more data and advancements in smart devices it is looking increasingly feasible.

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