

Activity Recognition using Actigraph Sensor

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ABSTRACT

Numerous accelerometers are being extensively used in the recognition of simple ambulatory activities. Using wearable sensors for activity recognition is the latest topic of interest in smart home research. We use an Actigraph watch with an embedded accelerometer sensor to recognize real-life activities done in a home. Real-life activities include the set of Activities of Daily Living (ADL). ADLs are the crucial activities we perform everyday in our homes. Actigraph watches have been profusely used in sleep studies to determine the sleep/wake cycles and also the quality of sleep. In this paper, we investigate the possibility of using Actigraph watches to recognize activities. The data collected from an Actigraph watch was analyzed to predict ADLs (Activities of Daily Living). We apply machine learning algorithms to the Actigraph data to predict the ADLs. Also, a comparative study of activity prediction accuracy obtained from four machine learning algorithms is discussed.

Categories and Subject Descriptors

H.2.8 [Database Management]: Database Applications – *data mining*; I.2.6 [Artificial Intelligent]: Learning – *knowledge acquisition*; H.4.m [Information Systems]: Information system Application – *Miscellaneous*.

General Terms

Algorithms, Performance, Experimentation, Human Factors.

Keywords

ADL, Activity, Actigraph, Wearable Sensor, Smart Home.

1. INTRODUCTION

As the world's population ages [1], those suffering from diseases associated with dementia will increase. Smart homes can assist their residents by acting as a cognitive prosthesis, by handling various appliances/objects and also by facilitating emergency communication. Being able to automate activity recognition from human motion patterns using unobtrusive wearable sensors can be useful in monitoring older adults in their homes and keeping track of their Activities of Daily Living (ADL) and behavioral changes [2]. This could lead to a better understanding of

numerous medical conditions and treatments. Wireless sensors provide continuous monitoring capability that traditional methodology lacks. Also in addition, the assessments performed in the clinical setting may not give the actual representation of the patient's behavior. Real life assessments can provide a better understanding of the patient than assessments performed in a clinical setting. Health care effectiveness in several situations has improved significantly using current wireless communication technologies. Traditionally, the sensors for these instruments are attached to the patient by wires. This eventually makes the patient become bed-bound. In addition, whenever a patient needs to be moved, all monitoring devices have to be disconnected and then reconnected later. In current technological advancements, all of these time-consuming tasks are terminated and patients could be liberated from instrumentation and bed by wireless technology. The future aims at the integration of the existing smart home sensors with pervasive, wireless networks. They will co-exist with the installed infrastructure, augmenting data collection and ultimately providing real-time responses. Also, integrated wireless devices could communicate with a gateway that connects to the medical center's network and transmits data to health data stores for monitoring, control, or evaluating in real time.

Unobtrusive, wearable sensors will allow vast amounts of data to be collected and mined for next-generation clinical trials. By using wearable sensors, data will be collected and reported automatically, reducing the cost and inconvenience of regular visits to the physician. With the growing technological advancements, we aim to provide telecare which allows elderly people to remain living in their own home. Furthermore, researchers are also aiming at integrating the knowledge gained from wearable (wireless) sensors with the wired smart home sensors. This will give a big picture of the physical behavior of the person. Also, by integrating this knowledge with information collected by object sensors we can get a picture of the person's physical interaction with the surroundings. By collecting this data for a longer duration, we can predict physical interactions and provide necessary prompting when the person forgets to do an activity. Also, wearable sensors could be used to provide accurate measures of motor abilities in the home and community settings. Their use could tremendously facilitate the implementation of tele-rehabilitation protocols. The wearable devices must also be lightweight enough to be worn without much inconvenience. With demographic changes of the aging population and an increasing number of people living alone, smart homes are set to play an important role in maintaining the independence and improving the quality of life for elderly persons at a lower cost. The present development of the demography of elderly people in the U.S as well as the other parts of the world will generate a shortage of caregivers for

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Conference '10, Month 1–2, 2010, City, State, Country.
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elderly people in the near future. The new concept of health monitoring is advanced by which health parameters are automatically monitored at home without disturbing daily activities. The recording of sensor data over extended periods of time is necessary to design and implement an efficient activity recognition algorithm.

In Section 2, we analyze previous work done in the field of wireless wearable sensors. Section 3 describes the Actigraph watch which we used for our experiments. Section 4 explains the process of feature extraction from the datasets. Section 5 gives a brief description of the machine learning algorithms we have considered for testing our dataset. In Section 6, we present the results of our experiments and compare the accuracy and time performance of activity prediction by different algorithms.

2. RELATED WORKS

Actigraph watches are used as effective data collection tools in the study and clinical assessment of sleep disorders [3]. Apart from Actigraph, various other accelerometer-based sensors have been used to detect activity behaviors. The eWatch system [4] proposes a wearable sensor and computing platform for context aware research for activity recognition and a related health monitoring system. Assessing sleep disruption is the most significant contribution that wrist Actigraphy has made. Previously, Actigraph sensors have been used primarily for sleep studies. The Actigraph device has also been used in finding circadian activity rhythms in healthy individuals as well as people with primary and co-morbid insomnia. Explicit focus on identifying which location the wearable has to be placed was concentrated by many researchers. By placing wearable sensors at different locations, researchers have tried to evaluate the accuracy of activity recognition [5][6]. Also, predicting the activity based on the user-annotated data has been carried using wearable Biaxial accelerometers [7]. Further, the prediction of complex activities performed inside a woodshop was recognized by attaching wearable accelerometers and a microphone on the human body [8]. Today most wearable systems are based on conventional notebook architectures integrated into some sort of belt or a device tied around the body that will make the participant to be easily spotted among the common public. Embedding sensors into garments is an idea that was first pursued by a research team at Georgia Tech. Research work by this team eventually led to a wearable system referred to as the *Smart Shirt* [9]. This approach appears to be ideal for very long-term monitoring (i.e. months to years) of individuals in the home and community settings. Alarmnet [10] being developed at University of Virginia is also targeting remote healthcare monitoring [11]. Recognizing activities with wrist-worn watches is the latest area of focus due to its portability and ease of use. Further these devices do not draw unwanted attention to the people who wear them. Wearable health monitoring systems integrated into a telemedicine system represent novel information technology that will be able to support early detection of abnormal conditions and prevention of its serious consequences.

3. ACTIGRAPH SENSOR DESCRIPTION

Actigraphs are wristwatch-like devices with an accelerometer inside. They are small, portable devices that detect physical motion, generate an internal signal each time they are moved, and store that information. Typically, it is used for measuring general or random motor restlessness in order to evaluate the rest-activity cycle. Actigraphy is a method in which the user

places accelerometers on different parts of the body to measure physical acceleration at each location and to estimate the level of human activity. Actigraphy is a relatively non-invasive method of monitoring human rest/activity cycles. Actigraphy has been shown to best estimate sleep duration. In sleep research applications the periods of low activity are considered as sleep. Actigraphs are generally worn on the wrist of the non-dominant arm. They may be worn for weeks at a time. The Actigraph watch used in our experiments is the Motionlogger Actigraph. This sensor can collect data for 21 days. Once the data is collected, it is downloaded to a computer. Actigraph devices are very practical, because of their low power consumption and the small size of the electronic components. The accelerometer records movement that will indicate when someone is active and quiet. It should be worn for 24-hours regardless of the activity. It is waterproof and can be worn in the shower, hot tub or when washing dishes. It can also be worn while swimming which involves partial submersion.



Figure 1. Actigraph wrist watch sensor.

The Motionlogger Actigraph monitor shown in Figure 1, contains a piezoelectric bimorph-cantilevered beam, which generates a voltage for each movement made. The voltage generated is passed on to the Analog circuitry, second essential element of the Motionlogger circuit. Here, the signal received is modulated and filtered through a 2-3 Hz bandpass filter. This conditioned analog signal can be processed in two different ways based on the mode of operation i.e., either Zero Crossing (ZC) Mode or the Proportional Integral Mode (PIM). Zero Crossing mode logs the number of times that the acceleration value exceeds a threshold amount, while PIM mode keeps track of more basic movement values. The derived information obtained based on the mode of operation is accumulated over the epoch and is stored in the memory of the device. Our Motionlogger Actigraph utilizes an epoch which is of 1 minute duration. The Actigraph watch should be set in the ZC or PIM mode well before the participant wears it in the wrist. The mode once set cannot be changed till the data collection stops. After setting the sensor in one of the two modes of operation, the time we want to start the data collection can also be defined with the help of the Actigraph software [12]. After selecting the start time for the watch, it is given to the participant. The sensor will be collecting data for next 21 days from the prescribed time of start. When the memory gets full, the data collection stops. The Actigraph watch is connected to a data collection system and the data stored in the memory of the device is extracted using the Actigraph software. The memory of the device should be refreshed for further usage. The Actigraph software also has the capability to generate the sleep and wake cycles just from the raw data. The software was hard-coded to predict sleep/wake cycles to a better extent and reduce the false positives generated by the software. The data finally got from the software is used for manual annotation.

4. FEATURE EXTRACTION

We plotted Actigraph values for various activities used in our experiments on a time scale to observe the patterns that are generated by the different activities. In order to generate these graphs we apply curve fitting to Actigraph data using a least squares method [13]. With curve fitting, we try to find the best fit to a series of data points. It can serve as an aid for data visualization, to approximate the values when no data are available, and to express the relationships between different data points. The line generated will be the pattern that corresponds to the particular ADL.

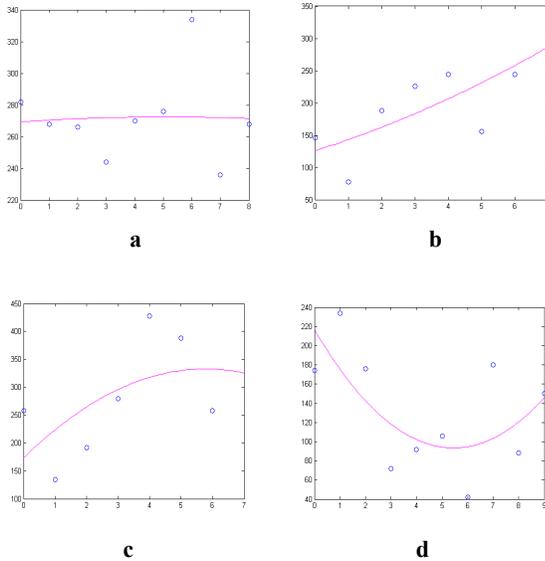


Figure 2. Curve fitting of ADLs for ZC values. (a. Cooking; b. Eating; c. Hygiene; d. Watching Movie)

From Figure 2, we can observe that each ADL follows a specific time-varying pattern. As a result, we hypothesize that we can use selected machine learning algorithms to recognize each pattern. The raw dataset was not given as input to the machine learning algorithms. The raw data extracted from the Actigraph watch contains only numerical information of the participant's motion in the form of ZC values. This value cannot be easily used by themselves in their raw form to predict activities. We have two more parameters in the dataset which we can integrate with the ZC value to extract features. The three parameters in the raw dataset are thus: Date, Time and ZC value. In order to obtain even more information from the existing dataset we consider that fact that the clock time of an activity can vary each time it is being performed in a real-life scenario. Thus, we extract additional specific information such as the amount of time spent for an activity, which hour of a day was the activity performed, what were the previous & next activities, and so forth. We extract features [14] from the raw dataset to get the processed data. The features extracted from the dataset were:

Min ZC value – The minimum zero-crossing value of an activity. This value is calculated for every instant of the activity.

Max ZC value – The maximum zero-crossing value of an activity for every instant of the activity.

Sleep status – The sleep/awake status of the participant. This value is generated through the Actigraph software after extracting the raw data.

Time length – The amount of time taken for the completion of an

activity. This value is calculated for every instant of the activity.

Begin hour – The time of day is split into a 24 parts with each part denoting an hour. The begin hour of every activity is calculated for each occurrence of the activity.

Number of events – The total number of actigraph events per activity calculated for every instance.

Bin – We discretized the raw ZC value data into five interval sizes by equal width binning [15].

Total ZC value – The total ZC value obtained for each activity for every instant.

Pre-Activity – We note every activity's previous activity.

Post-Activity – The following activity of every activity is taken as the post activity.

The processed dataset with the value of all the extracted features was used for our testing. By using the data mining and machine learning concepts, we can perform pattern recognition to predict the ADLs.

5. PREDICTION ALGORITHMS

Machine learning algorithms have been used exclusively to learn and recognize complex patterns and classify objects based on sensor data. Hence, we use these techniques to identify the appropriate ADLs. The following parts give a brief description of four machine learning algorithms used in our experiments.

5.1 BayesNet

Bayesian belief networks are based on the work of the mathematician and theologian Thomas Bayes. Bayesian belief networks [16] were introduced by Judea Pearl in 1985. BayesNet belongs to the family of probabilistic graphical models which represent a set of conditional independence assumptions by a directed acyclic graph. Each of the variables in the Bayesian belief network is represented by a node in the graph and the edges represent direct dependence among the variables. Bayesian belief networks offer consistent semantics for representing uncertainty and an intuitive graphical representation of the interactions between various causes and effects, thus they are a very effective method of predicting uncertain situations that depend on cause and effect. ADLs of an individual have a great extent of uncertainty. Hence, we use the BayesNet for predicting them.

5.2 Artificial Neural Network

Artificial neural networks (ANNs) [17] are composed of interconnecting artificial neurons. They are abstract computational models based on the organizational structure of the human brain. ANNs provide a general and robust method to learn a target function from input examples. The multilayer perceptron (MLP), a type of ANN, is a feedforward artificial neural network that maps the input to appropriate output. In our experiments we choose, MLP because it is one of the commonly used algorithms for any supervised-learning pattern recognition process.

5.3 Sequential Minimal Optimization

In a traditional Support Vector Machine (SVM), the quadratic programming problem involves a matrix, whose elements are equal to the number of training examples. If the training set is large, the SVM algorithm will use a lot of memory. To solve such a problem, Sequential Minimal Optimization (SMO) [18] decomposes the overall quadratic programming problem into a series of smaller quadratic programming problems. During the training process, SMO picks a pair of Lagrange multipliers for each iteration and solves each small quadratic programming

problem, then repeats the same process until it converges to a solution to the overall quadratic programming problem. SMO significantly improves scaling of training set size and computation time for SVMs.

5.4 LogitBoost Ensemble

Boosting is another most commonly used supervised learning algorithm. Boosting algorithms have become very successful in machine learning. The idea of boosting is to combine many "weak" classifiers to create a "strong" classifier. LogitBoost [19] combines the aspect of AdaBoost (Adaptive Boosting) and Logistic regression. Considering AdaBoost as a generalized additive model, if we apply the cost functionalities of Logistic Regression then we arrive at the LogitBoost algorithm.

6. EXPERIMENTS & RESULTS

In our experiment, we have used the Actigraph watch in the ZC mode. Previously the ZC mode has been used for detecting sleep studies. Here we explore its use for activity recognition. The watch was worn for 21 days by one participant. The participant noted down the activities of only 17 of the days. So, we considered only those days of the data. The ADLs performed by the participant was noted down manually. The participant performed a well-defined set of activities regularly. After the data collection stops, the data was extracted from the Actigraph watch and the dataset was manually annotated.

The participant performed the following set of activities for 17 continuous days: Hygiene, Cooking, WebCam Chat on Laptop, Working on Laptop, Watching movies on Laptop, Sleeping and Eating. Recognition results are calculated using 3-fold cross-validation to generalize the results. We analyzed recognition results using four Machine Learning algorithms: 1) LogitBoost, 2) BayesNet, 3) NeuralNet, and 4) SMO.

We use graphs to analyze the performance of the algorithms and also discuss the overall accuracy obtained in recognizing all the ADLs using the four algorithms. We also discuss the accuracy obtained for individual ADLs using the chosen machine learning techniques. Further, we plot the accuracy of an algorithm with its execution time to find the algorithm which runs in optimal time when compared to others. All the three plots are used to support our conclusion as to which algorithm outperforms the other three.

From Figure 3, we observe that LogitBoost performs better than the other three algorithms. This is because of the fact that the LogicBoost classifier estimates the accuracy by combining the performance of many "weak" classifiers. We also find that the next best algorithm is SMO and the accuracy rate is the same for NeuralNet and BayesNet. We cannot conclude that both of the algorithms have poorer accuracy than the others. This makes it very difficult to judge which one is better than other on the basis of accuracy performance alone.

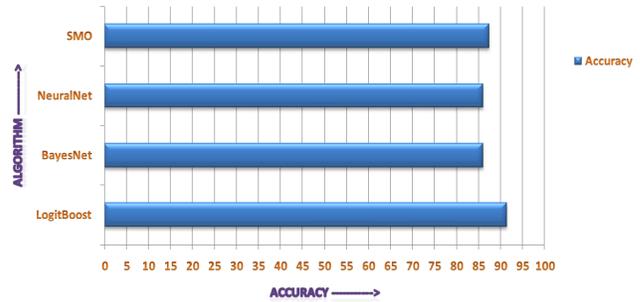


Figure 3. Overall Accuracy predicted by different algorithms.

Figure 4 shows the accuracy of each individual activity along the lines of every classifier used. SMO is not considered to be the best classifier for this task because it could not adequately differentiate three activities Watching Movie, Using WebCam chat and Working on Laptop. The activities Watching Movie and Using WebCam chat were also classified under working in Laptop. This prevented the algorithm from becoming the overall best algorithm. Also, we find that all the algorithms were able to recognize three activities more efficiently than others: 1) Cooking, 2) Sleeping, and 3) Eating. The activity Working on Laptop had a few instances misclassified either as Using WebCam chat or as Watching Movie in Laptop. This led to the lowered performance of the Working on Laptop. The ADL which was poorly recognized by all the algorithms is Watching Movie on a Laptop. This may be due to varied reasons like the lowered activity level when the participant watches a slow movie and the raised activity level when the participant watches a thriller or horror movie.

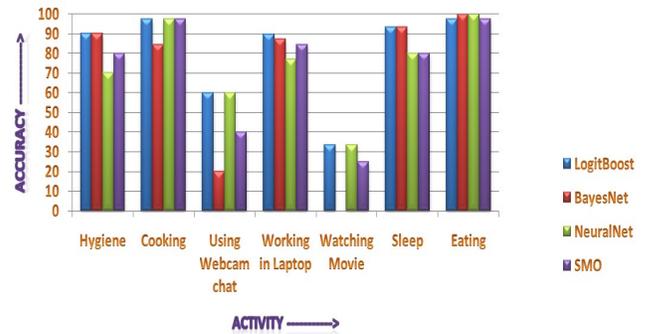


Figure 4. Individual Accuracy of ADLs predicted by different algorithms.

In Figure 5, we observe that the BayesNet performs the fastest in terms of the running time of the algorithm. BayesNet was not the overall best because it was not able to predict even one instance of the activity of WatchingMovie. The activity of watching movie didn't have a noticeable uncertainty in its behavior and also the algorithm was not able to differentiate between the activities Watching Movie and Using WebCam Chat.

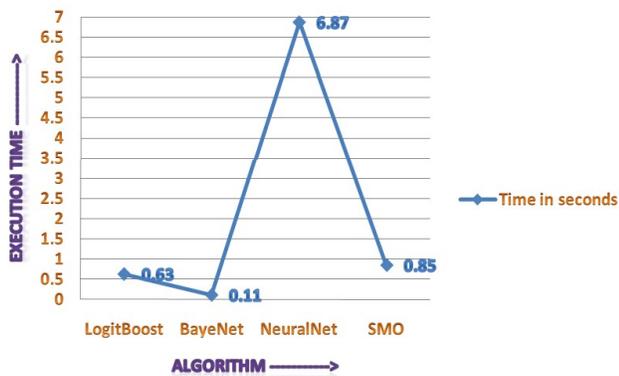


Figure 5. Execution Time of different algorithms.

Also, NeuralNet is not ranked as our overall best algorithm as it failed to meet the requirement of smaller execution time. The left out algorithms are LogitBoost and SMO. However, SMO takes a running time of 0.23 seconds more than LogitBoost. In this criterion also, LogitBoost outperforms all other algorithms. Hence LogitBoost becomes the overall efficient algorithm for our activity prediction.

7. FUTURE WORK & CONCLUSION

Constant monitoring using wearable sensors will allow patients to engage in normal ADLs, rather than relying upon specialized medical services outside their homes. From the viewpoint of the industrial sector, the addition of constant monitored data into the medical databases will allow an integrated analysis of all data to optimize individualized care and provide knowledge discovery through various data mining approaches. Typically, accelerometers are used to consider only simple ambulatory movements like sitting, standing and walking. In this paper we have considered complex ambulatory movements. The ambulatory movements considered are functional Activities of Daily Living (ADL). We were able to achieve an accuracy of 91.39% using the LogitBoost algorithm. Previous works had concentrated on using multiple sensors in different body locations to recognize activities. The main advantage over the previous works is we have used only one sensor placed in one location of the body (non-dominant wrist). We will try to use few more sensors like pulse rate detectors and energy sensors to predict activities. Continuous monitoring has the capability of pro diagnosis of disease at early stage of occurrence and it likely has the potential to provide patients with an increased level of confidence, which in turn may improve quality of life We are also planning to integrate wearable sensors with wired sensors used in the CASAS Smart home to predict activities. In the CASAS Smart Home, we also aim at using object sensor in a smart home along with the wearable sensors to predict the physical behavior of a person in that environment of living and try to use it to predict the behavior of the same person in another environment.

REFERENCES

- [1] <http://www.census.gov/population/www/projections/>
- [2] Cook, D.J., *Health monitoring and assistance to support aging in place*. Journal of Universal Computer Science, 2006. **12**(1): p. 15–29.
- [3] de Souza, L., et al., *Further validation of actigraphy for sleep studies*. Sleep, 2003. **26**(1): p. 81–5.

- [4] Maurer, U., et al., *eWatch: a wearable sensor and notification platform*, in *Wearable and Implantable Body Sensor Networks, 2006. BSN 2006. International Workshop on*. 2006. p. 4.
- [5] Maurer, U., et al., *Activity recognition and monitoring using multiple sensors on different body positions*, in *Wearable and Implantable Body Sensor Networks, 2006. BSN 2006. International Workshop on*. 2006. p. 4.
- [6] Lee, S.W. and K. Mase, *Activity and location recognition using wearable sensors*. IEEE Pervasive Computing, 2002: p. 24–32.
- [7] L. Bao and S. S. Intille. *Activity Recognition from User-Annotated Acceleration Data*. In A. Ferscha and F. Mattern, editors, *Pervasive*, volume 3001 of *Lecture Notes in Computer Science*, pages 1–17. Springer, 2004.
- [8] Lukowicz, P., et al., *Recognizing workshop activity using body worn microphones and accelerometers*. Pervasive Computing, 2004: p. 18–32.
- [9] Park, S. and S. Jayaraman, *Enhancing the quality of life through wearable technology*. IEEE Engineering in medicine and biology magazine, 2003. **22**(3): p. 41–48.
- [10] Wood, A., et al., *ALARM-NET: Wireless sensor networks for assisted-living and residential monitoring*. University of Virginia Computer Science Department Technical Report, 2006.
- [11] Istepanian, R.S.H., E. Jovanov, and Y.T. Zhang, *Guest editorial introduction to the special section on M-health: beyond seamless mobility and global wireless health-care connectivity*. IEEE Transactions on Information Technology in Biomedicine, 2004. **8**(4): p. 405–414.
- [12] Jean-Louis, G., et al., *The actigraph data analysis software: I. A novel approach to scoring and interpreting sleep-wake activity*. Perceptual and motor skills, 1997. **85**(1): p. 207.
- [13] Sage, A.P. and G.W. Masters, *Least-Squares Curve Fitting and Discrete Optimum Fitting*. IEEE Transactions on Education, 1967. **10**(1): p. 29–36.
- [14] Pirttikangas, S., K. Fujinami, and T. Nakajima, *Feature selection and activity recognition from wearable sensors*. Ubiquitous Computing Systems: p. 516–527.
- [15] Liu, H., et al., *Discretization: An enabling technique*. Data Mining and Knowledge Discovery, 2002. **6**(4): p. 393–423.
- [16] Uusitalo, L., *Advantages and challenges of Bayesian networks in environmental modelling*. Ecological modelling, 2007. **203**(3-4): p. 312–318.
- [17] Zornetzer, S.F., *An introduction to neural and electronic networks*. 1995: Morgan Kaufmann.
- [18] Platt, J., *Sequential minimal optimization: A fast algorithm for training support vector machines*. 1998.
- [19] Schapire, R.E., *The strength of weak learnability*. Machine learning, 1990. **5**(2): p. 197–227.