A BAYESIAN APPROACH FOR INDOOR HUMAN ACTIVITY MONITORING

Gamze Uslu , Özgür Altun , Sebnem Baydere
Department of Computer Engineering,
Yeditepe University, Istanbul, TR
{guslu, oaltun, sbaydere}@cse.yeditepe.edu.tr

***Abstract*—Activity monitoring plays a crucial role in ambient living environments for assessing changes in the normal behavioral pattern of elderly people. In this paper, we present a composite action description and detection model for activity monitoring. The model accomplishes real time continuous monitoring of composite actions by detecting the transitions from one simple action to another and determining the types of those actions. It utilizes a wearable TI Chronos watch with a built-in tri-axial accelerometer for data acquisition and uses naive Bayes classifier for the classification of simple actions; *walk*, *sit stand* and *lie*. The unique feature of these actions is that the transition between walk, sit and lie are the most likely causes of fall event in a home environment for elderly people. The early results of an experimental study conducted for the detection of the composite actions; *walk-after-sit* and *sit-after-lie* are very encouraging in terms of detection success rates.**

I. INTRODUCTION

Assistive technologies provide solutions to people with disabilities and aging population in performing tasks without being helped by another person. Even if a person is not suffering from disabilities or aging, they still can benefit from assistive technology tools and services. As a branch of assistive technologies, ambient care systems are emerging. To aid everyday life of people in need, ambient care systems contain a network of objects used in people's daily routines. Ambient care systems are capable of sensing the environment through sensors and reacting to certain conditions reasoned in the network mentioned. The ultimate goal of an ambient care system is presenting the assistive technology by meeting the following criteria: Devices in the system should be embedded in the surroundings. The constituents of the system should be able to detect the person being serviced and his conditions, the so-called context awareness principle. The system should be adjustable to the personal needs. It should adapt itself depending on the reactions of the person. It should understand when it is needed and consequently act as needed without the person's intrusion, namely principle of being anticipatory.

In the field of ambient care systems and more generally assistive technologies, activity monitoring plays a vital role in terms of taking decisions on when to make the system respond in what way.If the action performed by a person can be identified, this reveals the information regarding what the person needs or wants, so that his needs are met by the ambient care system.The person can be reminded of taking his medication if he forgets to do so or if the detected action reveals that *he is about to fall*, he may be prevented from falling or from a more severe situation.

There are various technical challenges for the design of activity monitoring systems. Since even the same person does not perform the same activity in the same way all the time and some different actions may exhibit similar characteristics, there is a potential deterioration in the recognition accuracy. Noise in the activity signal, namely differentiating between the noise and the actual signal causes problems as well. Enhancing an activity monitoring system includes detecting abnormal activities defined in accordance with the context and providing the appropriate actuation facilities in response.

Activity monitoring can be achieved in two phases; data collection followed by data classification. Data collection process is carried out through wireless sensors, cameras, PDA's or other health care monitoring devices[1]. The devices which do not intrude into the privacy of the person to be monitored can have an advantage over the devices like cameras. Wireless sensor network (WSN) technology can also improve the efficiency of this phase. For data classification, least squares[2], k-nearest neighbor (k-NN)[3], hidden markov models, artificial neural networks (ANN)[4] and support vector machines (SVM)[5] can also be used.

In this experimental study, an indoor human activity monitoring system is designed and implemented to recognize the simple actions performed by a person and the transitions between them in real time. For data acquisition, sensor readings from a tri-axial accelerometer built-in the TI Chronos watch[6] is used. The watch is worn by the person on the left wrist for the walk action, and worn to the left thigh for the sit, stand and lie actions. The resulting sensor data obtained in the form of unsigned integers varying in the range [0,255] are converted to their 2's complement equivalents. The acceleration values in 2's complement form are classified by using naive Bayes classifier into a simple action. Naive Bayes classifier has training and prediction phases. In the training phase, the training data are exposed to normal distribution to extract unique intervals of average posterior probability.

These intervals create the pattern for the specified action. Patterns for all simple actions are recorded into a database. In the prediction phase, real time data sample of a composite action with unknown type is detected by comparing the differentiated simple actions to the patterns in the database to produce a posterior probability value. The action of which

978-1-4577-2152-6/11/$26.00 ©2011 IEEE

average posterior probability value is included in one of the distinct intervals is marked as the corresponding action.

The content of the following sections is as follows: In Section II related work is reviewed. In Section III, methodology is explained and in Section IV, early results of the experimental study and future work are given.

II. Related Work

PIR sensors and cameras are widely used for activity monitoring tools in the areas of applications like surveillance, navigation and smart environments. Despite their accuracy, cameras can be a cause of drawback in operations like determining number of people and direction or position information related to motions in terms of computational load by requiring feature extraction. Furthermore, cameras can be regarded as intrusion into private life, so people may reject using them. PIR sensors can help determine whether a person exists in a certain area or not, which is beneficial in commercial applications in security point of view. One sensor can be sufficient for intrusion detection whereas video surveillance and tracking necessitate multiple PIR sensors. A video surveillance system has been put forward, containing a wireless sensor network equipped with PIR sensors and cameras. There exists a study supporting each sensor node with two PIR sensors to synchronize the data which are sampled from PIR sensors and communication cost problem[7].

Accelerometers are started to be embedded in wrist bands, bracelets, adhesive patches due to the advances in miniaturization. There is a great number of previous works which show 85% to 90% correct detection rates for ambulation, posture and other activities utilizing acceleration data. The energy originated from the acceleration helps telling the difference between stationary actions such as sitting or sleeping, temperately intensive activities such as walking and typing and high intensity activities such as running. According to a recent work done on 30 wired accelerometers on the body, increase in the number of sensors will usually improve correct detection rate. However wired sensors are not practical to use. It is also claimed that experiments done in laboratory environment and the real world may exhibit different characteristics since walking indoors shows repeating patterns while walking outdoors shows remarkable fluctuation resulting from the gait properties of the person and variations in traffic[8].

III. Methodology

In this experimental study, continuous activity monitoring is achieved through detecting which actions are performed following each other in a real time sample containing acceleration values obtained from the accelerometer in Chronos watch worn buy the human subject. The watch is wearable on various parts of the body. The real time sample is composed of lines each of which contain a vector of X,Y and Z axis acceleration values.Simple actions, which can not be split into other actions, are stored in database and actions contained in a real time sample are classified into these actions by utilizing naive Bayes classifier. The simple actions are ***walk***, ***sit***, ***stand*** and ***lie***, whose content are implied by their names. Real time sample holds a composite action since it contains multiple simple actions. The composite actions experimented with are ***sit- after-lie*** and ***walk-after-sit***. The formal definitions of simple and composite actions can be seen as finite state automata as given in Figure 1. The state S represents a simple action in the automata. At the end of the process, the real time sample is divided into chunks which are labeled as one of the actions recorded in the database. The size of each chunk is determined dynamically and the size value is used to figure out how long the action related to that chunk lasts. This is where the innovation of the proposed approach is. Figure 2 illustrates a picture of the test environment.

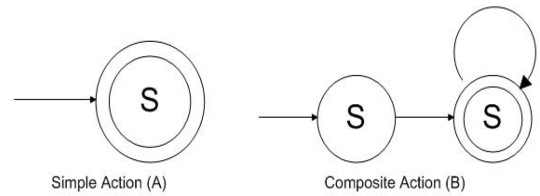

Fig. 1. Formal Representation of Simple and Composite Actions

Fig. 2. Walk and Sit-after-Lie Actions

Naive Bayes classifier has two phases, namely training and prediction. Training phase consists of performing the same action many times, acquiring distinct intervals for every simple action, finally storing these intervals in database. In this work, every action is repeated 25 times. The intervals contain average posterior probability values. Once the training phase is complete, the prediction process takes place. The algorithm which generates the distinct intervals in training phase is also used in the prediction phase to generate an average posterior probability value.In the prediction phase, real time sample is processed by extracting a chunk from it in each iteration. **n** being the current iteration number, C_n being chunk at iteration n, c_i being ith line in the real time sample, iteration number ranging from one to number of lines in real time sample, C_n = $[c_1,c_2,c_3,...,c_n]$ shows the structure of a chunk extracted from real time sample at any iteration. Chunk at iteration number one is exposed to the same interval generation scheme in training phase and depending on the resulting average posterior probability value is in which interval, the chunk is classified into the corresponding action.As long as the following iterations generate the same action classified as the first iteration, the iterative procedure continues, otherwise iteration terminates. The chunk at the instance of termination is the ultimate structure representing a simple action classified in real time sample and the iteration number at the instance of termination is the size of that chunk. After the first chunk is classified, real time sample is truncated so that it starts with the vectors right after the first chunk and chunk classification continues until there are no vectors left in real time sample.

Average posterior probability of training sample T or a chunk C from real time sample is calculated as in the following algorithm:

1) An array named A_1 is created from Z axis acceleration values in T or C.
2) t_j being *i*th value in T and c_i being *i*th value in C, an array named A_2 is created such that $A_2=[a_1, a_2, ..., a_{i+j}]$ where a_i is *i*th element of A_2 , $C=[a_1, a_2, ..., a_i]$ and $T=[a_{i+1}, a_{i+2}, ..., a_{i+j}]$.
3) The population created from A_2 is fit into normal distribution, generating mean and variance.
4) Normal probability density function values are calculated for each value of A_1 by using mean and standard deviations found via Step 3. Each normal probability density function value found represents the posterior probability. The average of the normal probability density function values is calculated.

While naive Bayes classifier can be implemented as assigning the action yielding greatest posterior probability as the action detected, this work follows the approach that generating unique intervals for every action out of posterior probability values and regards these unique intervals as the differentiating parameter.

There are a number of reasons why normal distribution is chosen in this work during posterior probability generation process: first, the normal distribution provides simplicity since practically there are many cases where a population who does not fit normal distribution is successfully processed under the normal distribution. Second, as the size of the population increases, the probability distribution becomes more similar to the normal form. Particularly the second point is a strong reason because of the length of the training data can reach the order of thousands[9].

Acceleration vs time relationship for the composite action ***walk-after-sit*** are depicted in Figure 3 and Figure 4. Here, time is represented virtually by the number of the acceleration vectors collected during the action. Higher number of vectors resembles an action of longer duration. With the transmission frequency of 33 packets per second, approximately 2.5 s corresponds to 45 vectors. During this approximate calculation, lost packets caused by Chronos are ignored. Figure 3 and Figure 4 illustrate the real time data for the ***walk-after-sit*** action. In these plots, the action occurs as the combination of simple actions sit, stand and walk respectively. Since the aim is detecting walk after sit rather than the sequence of sit, stand and walk, during the tests, the section of the signal showing the stand action is ignored by filtering that segment, regarding stand as the transition. The data is obtained by appending walk samples to the end of sit samples. The training data related to the simple walk action are collected by wearing sensor on the left wrist whereas in real time tests the composite action is performed with the sensor on the left thigh. The transition signal samples for the ***sit-after-lie*** action are also illustrated in Figure 5 and Figure 6.

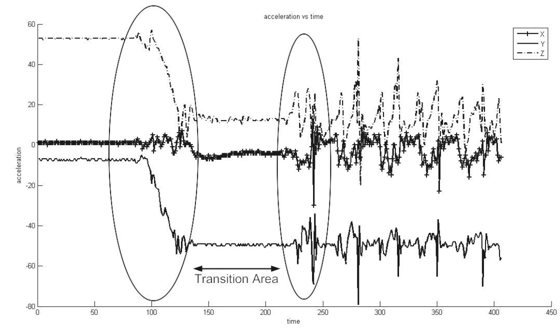

Fig. 3. Walk-after-Sit Data Sample 1

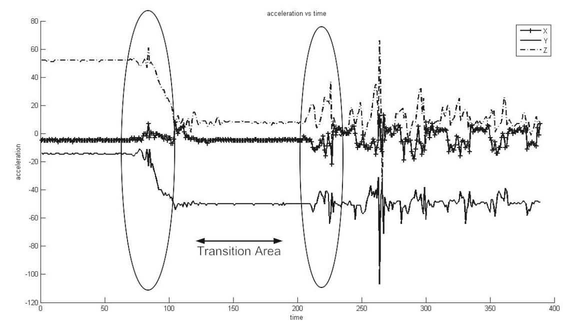

Fig. 4. Walk-after-Sit Data Sample 2

A. Training

Training data are exposed to normal distribution to extract mean and standard deviation for the Z axes. These values are used to calculate average posterior probability which form the pattern of an action. A pattern is created for every action and all patterns are inserted to a database to be used in the prediction phase later.

B. Prediction

A real time sample of an action whose type is unknown is compared to all of the action patterns in the database, producing a posterior probability value. In posterior probability calculation, normal probability density function values found the Z axes is used. To evaluate a normal probability density function value, the acceleration data obtained from the real time sample, the mean and standard deviation values related to the specified axis are used.

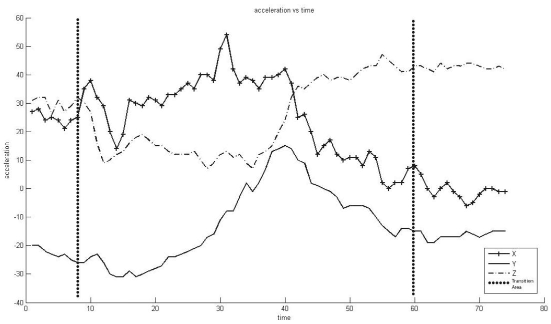

Fig. 5. Sit-after-Lie Data Sample 1

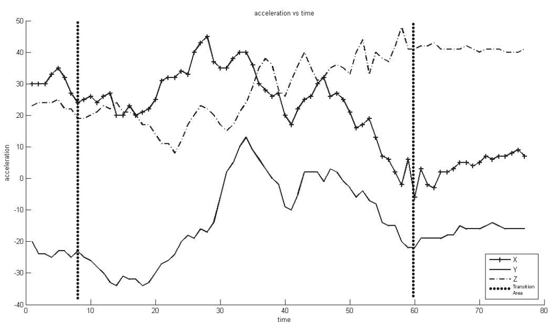

Fig. 6. Sit-after-Lie Data Sample 2

IV. RESULTS AND CONCLUSION

This study covers the design and implementation of a real time indoor human activity monitoring system by addressing the two phases namely data acquisition and classification. As the data collection device TI Chronos watch which has wireless communication capability with the PC is used. Naive Bayes classifier is implemented for the data classification subsystem. Naive Bayes classifier has training and prediction phases. Unique intervals of average posterior probability of the training data in 2's complement form are calculated with the normal distribution in order to complete the training phase. In the prediction phase, the real time sample is partitioned into chunks at the points where chunks show the simple actions and the chunk size shows the representative duration of classified action by means of calculating average posterior probability for each chunk. As a result of the experimental study, following success rates are achieved: walk 92%, sit 100%, lie 88% and stand 96% as tabulated in Table I. Based on these simple actions, various numbers of tests are performed for the detection of composite actions. The early results reveal that high detection success rates can be achieved using the proposed model based on Bayesian classifier. In 15 out of 25 tests, the model classified the ***walk-after-sit*** action successfully.

Future work includes increasing the correct detection rate by using other classification techniques and data networks.

TABLE I
DETECTION SUCCESS RATES FOR SIMPLE ACTIONS

Action Name	Detection Success Rate
Walk	92%
Sit	100%
Lie	88%
Stand	96%

A filtering mechanism will be tested so that variations of *walk*, *sit*, *lie* can also match the single actions defined. *i.e.* Walking with a walking stick can be detected as walk action. Generating meaningful information from raw sensor data in sensors[10] and physical activity monitoring implementation through wireless sensor networks [11] have the potential to further improve the activity monitoring so that the task can be done in environments left unattended. Detection of the abnormal activities such as fall and bump will be integrated to the model in the next step of the study. Further studies on the integration of the model to the mobile infrastructures such as GSM networks are also planned.

REFERENCES

[1] Y. Lin, E. Becker, K. Park, Z. Le, and F. Makedon, "Decision making in assistive environments using multimodal observations," in *PETRA 09 Proceedings of the 2nd International Conference on PErvsive Technologies Related to Assistive Environments*. ACM, 2009, pp. 1–8.
[2] Herve Abd, "Least Squares." [Online]. Available: http://www.utdallas.edu/ herve/Abdi-LeastSquares-pretty.pdf
[3] P. Cunningham and S. J. Delany, "k-Nearest Neighbour Classifiers," *Multiple Classifier Systems*, pp. 1–17 (UCD–CSI–2007–4), 2007. [Online]. Available: http://www.csi.ucd.ie/content/k-nearest-neighbour-classifiers
[4] Jha G. K., "Artificial Neural Networks," New Delhi, p. 10. [Online]. Available: http://www.iasri.res.in/ebook/EB_SMAR/e-book_pdf files/Manual IV/3-ANN.pdf
[5] S. R. Gunn, "Support Vector Machines for Classification and Regression," *The Analyst*, vol. 135, no. 2, pp. 230–267, 1998. [Online]. Available: http://eprints.ecs.soton.ac.uk/6459/
[6] T. Instruments(2010), "eZ430-ChronosTM development tool user's guide ," http://focus.ti.com/lit/ug/slau292c/slau292c.pdf.
[7] F. R. M. L. S. M. T. Hung P., Tahir M., "Wireless Sensor Networks for Activity Monitoring using Multi-sensor Multi-modal Node Architecture," *Proceedings of the 1st ACM international conference on PErvasive Technologies Related to Assistive Environments PETRA 08*, 2009.
[8] L. Bao and S. S. Intille, "Activity Recognition from User-Annotated Acceleration Data," *Pervasive Computing*, vol. 3001, pp. 1–17, 2004. [Online]. Available: http://www.springerlink.com/index/9AQFLYK4F47KHYJD.pdf
[9] "Normal distribution." [Online]. Available: http://www.nd.edu/ rwilliam/stats1/x21.pdf
[10] K. Römer, "Discovery of Frequent Distributed Event Patterns in Sensor Networks," in *European Conference on Wireless Sensor Networks EWSN*, vol. 67322, no. 5005. Springer-Verlag, 2008, pp. 106–124. [Online]. Available: http://portal.acm.org/citation.cfm?id=1786014.1786024
[11] S. Bosch, M. M. Perianu, R. M. Perianu, P. Havinga, and H. Hermens, *Keep on Moving! Activity Monitoring and Stimulation Using Wireless Sensor Networks*, ser. Lecture Notes in Computer Science. Springer-Verlag, 2009, vol. 5741, pp. 11–23. [Online]. Available: http://portal.acm.org/citation.cfm?id=1813045