ELSEVIER

Available online at www.sciencedirect.com

SciVerse ScienceDirect

Procedia Computer Science 19 (2013) 56 – 63

Procedia Computer Science

The 4th International Conference on Ambient Systems, Networks and Technologies (ANT 2013)

Frequent Bit Pattern Mining Over Tri-axial Accelerometer Data Streams For Recognizing Human Activities And Detecting Fall

C.Sweetlin Hemalatha[a], V.Vaidehi[b]a*

[a]*Research Scholar, Department of Information Technology, Madras Institute of Technology, Chennai 600044, India*
[b]*Professor, Department of Information Technology, Madras Institute of Technology, Chennai 600044, India*

Abstract

Human fall causes injuries and may even lead to death in the case of older age. Due to increasing elderly population every year to the total population and the health problems and risks caused by fall especially among the age group of 60 and above, detecting fall at the earliest is essential in order to avoid human loss. Basically, fall detection is considered as a classification problem which requires developing a classifier model that recognizes and classifies normal human activities and abnormal activity like fall. Most of the existing fall detection methods are based on classifiers constructed using traditional methods such as decision trees, Bayesian Networks, Support Vector Machine etc. These classifiers may miss to cover certain hidden and interesting patterns in the data and thus suffer high false positives rates. This paper presents a novel algorithm called Frequent Bit Pattern based Associative Classification (FBPAC) that maps the tri-axial accelerometer data streams to bit patterns and mines the frequent bit pattern occurring for normal activities like sitting/standing, lying and walking within a time-sensitive sliding window. Unlike normal activities, fall have significant peak acceleration and it is detected by setting most significant bit of bit pattern and thus clearly distinguishes fall from lying activity, thereby reducing false positive rates. Empirical studies are conducted by collecting real time tri-axial accelerometer data from a wearable and unobtrusive sensing device. Experimental results show that within a time-sensitive sliding window of 10 seconds, the proposed algorithm achieves up to 92% overall accuracy.

Selection and peer-review under responsibility of Elhadi M. Shakshuki

Keywords: data streams; fall detection; frequent pattern mining; sliding window

* Corresponding author
E-mail address: sweetlinh@gmail.com, vaidehi@annauniv.edu.

Selection and peer-review under responsibility of Elhadi M. Shakshuki
doi:10.1016/j.procs.2013.06.013

1. Introduction

Due to increasing elderly population every year to the total population and the health problems and risks caused by falls especially among the age group of 60 and above demands the need for a reliable and robust system for detecting falls. In India, number of people in the age 60 and above is expected to increase to 100 million in 2013. Most of the elderly people are left alone at home as both male and female members in the family are earning members. Falls not only cause physical injuries but may even lead to death. This may develop psychological fear within oneself resulting in reduced confidence and independent living.

With rapid growth in wireless sensor network technology, recognizing human activity for detecting falls has created a platform for research in pervasive and ubiquitous computing. Earlier approaches for fall detection uses computer-vision techniques like video based fall detection in which video camera are deployed in the home environment for collecting data. Recently, many works on fall detection have been reported using wearable wireless sensors like accelerometer and gyroscope. Most of the existing fall detection methods are based on classifiers constructed using traditional methods such as decision trees, Bayesian Networks, Support Vector Machine etc. These classifiers may miss to cover certain hidden and interesting patterns in the data and thus suffer high false positives rates. This paper presents a novel method for constructing a classifier for detecting falls based on mining frequent patterns in tri-axial accelerometer data streams.

Mining sensor data streams is a challenging problem in data mining as large amount of data are generated continuously with high speed in real time. Mining sensor data stream possesses different characteristics compared to traditional database model [1] such as (1) Each data element should be examined only once. (2) Though data gets generated continuously, memory usage for mining data streams is limited. (3) Each data element should be processed faster. (4) The outputs generated by online classifier algorithms should be instantly available when user requested. The proposed approach addresses the problem of detecting fall event from accelerometer sensor streams as pattern based classification problem. And hence, a classifier model is built based on Associative Classification (AC) [2] by mining frequent bit patterns for recognizing human activities like sitting/standing, lying and walking with an ultimate aim to detect human fall events.

The paper provides the following contributions.

- A novel fall detection algorithm based on frequent pattern mining that maps the sensor values to either 0 or 1 bit and mines the frequent bit pattern for normal activity classes such as sitting/standing, lying and walking. The most significant bit of frequent bit pattern is set to 1 when fall is detected and 0 otherwise. Thus, fall is clearly distinguished from lying posture.
- Sensor data is acquired from human volunteers and the proposed algorithm is evaluated using both activities of fixed time slice and arbitrary activity sequence.

The rest of the paper is organized as follows: Section 2 discusses the related work. Sensor Device and Data collection protocol are presented in section 3. Section 4 gives the overview of fall detection system and the proposed algorithm. Section 5 presents the implementation and experimental results. Section 6 concludes the paper.

2. Related Work

There exist significant research works on human activity recognition with an objective of detecting falls. Noury et al. [6] presented a survey of systems, algorithms and sensors for early diagnosis of fall conditions occurring in elderly persons automatically. Accelerometry is a low-cost, reliable, and practical method for monitoring human movements in order to analyze gait patterns, physical activities and falls. Most of works have extensively used one or more accelerometers for detecting falls. Other devices such as gyroscopes and tilt sensors are also used along with accelerometer for deciding fall. Authors in [3] have used motion, sound and visual sensors for human activity interpretation and emergency detection.

Bianchi et al. [4] have used barometric pressure sensors with accelerometer for detecting fall events. The location where the accelerometer sensor is placed plays a major role in activity recognition.

Yang et al. [5] embedded Naïve Bayes algorithm in Sun SPOT wireless sensors to implement a wearable real-time system to detect forward, backward, leftward and rightward falls. A hierarchical scheme for detecting static, transition and dynamic states to which a human physical activity belongs, was proposed by Khan et al. [7]. The authors have used single tri-axial accelerometer placed on the person's chest and have shown that auto regression coefficients augmented with signal magnitude area and tilt angle improve average classification accuracy. Acceleration and vital sign based activity recognition in mobile phone was proposed by Lara et al. in [8]. Associative classification or classification based on association rules which integrate classification and association rule mining was proposed by Liu et al. [2]. Su et al. [9] have proposed a new classification algorithm for data steam based on lossy counting and landmark window model. Lin et al. [10] presented a novel approach for mining frequent itemsets from data streams using time-sensitive sliding window model. An efficient window sliding technique for mining frequent itemsets over data streams was proposed by Li et al. [11]. Tao Gu et al. [12] presented an algorithm for recognition interleaved activities from sequential activities using a pattern mining approach.

The proposed approach is different from the above mentioned methods as normal activity and fall are detected based on frequent bit pattern based classifier that maps the frequent values in sensor data streams to bit patterns and they are mined to extract rules which forms the classifier model.

3. Sensor Device and Data Collection Protocol

BioHarness 3 sensor with chest strap manufactured by Zephyr [13] shown in Fig 1(a) is used for data collection. The dimension and the weight of the device are 28x7 mm and 18 grams. The device includes a tri-axial accelerometer and class II Bluetooth link from Bluetooth Radios. Hence it is unobtrusive, lightweight and harmless and can be worn by any person. The sampling frequency is 50 Hz and the range of sensor output is ±16g, where g stands for acceleration due to gravity. For every 400 ms, the device generates one acceleration data packet and each packet contains 20 acceleration data measured in all three dimensions. That is, it generates 50 samples per second. Accelerometers are normally placed in the part of the body such as wrist, thigh, arm etc. whose movement is to be monitored and analyzed. But, to analyze the whole body data, placing the accelerometer sensor closer to person’s chest is found to be suitable. Fig 1(b) depicts how the raw sensor data generated by the device on the chest reaches PC.

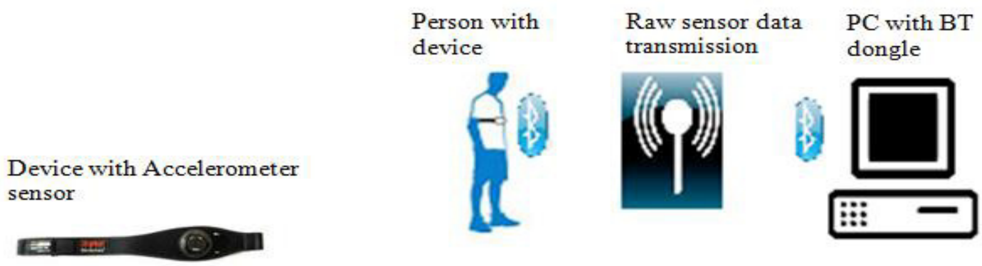

Fig. 1. (a) Sensing Device; (b) Sensor data stream Collection in PC

4. Fall Detection System Overview and the Proposed Algorithm

The overview of activity recognition and fall detection system is illustrated in Fig 2.

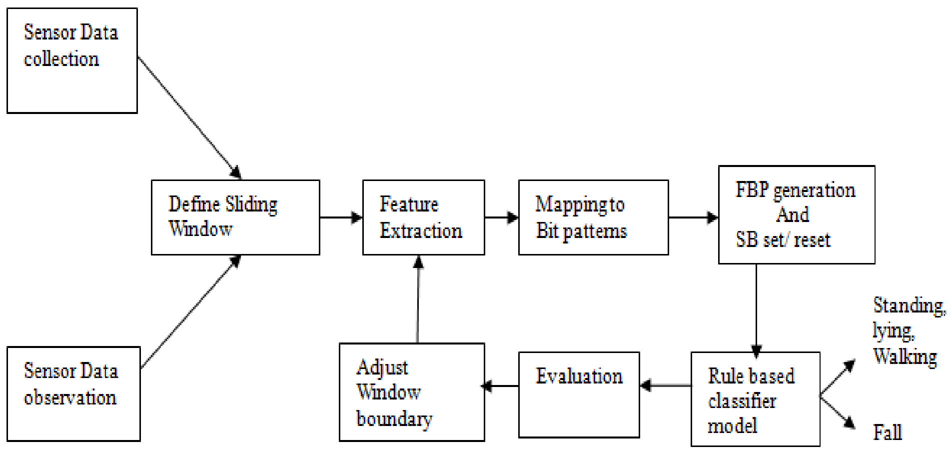

Fig. 2. Overview of Activity Recognition and Fall Detection System

4.1. Sliding window

As mentioned in section 3, Bioharness 3 generates 20 data samples every 400 milliseconds. So, each block contains 20 samples. A non-overlapping sliding window of 10 seconds is chosen. The sliding window contains 25 blocks and thus, 500 data samples are processed. After every 10 seconds, the window boundary is adjusted for processing next block set of data. Fig 3 illustrates with sample graph plotted for tri-axial acceleration data for normal actions and abnormal action like fall.

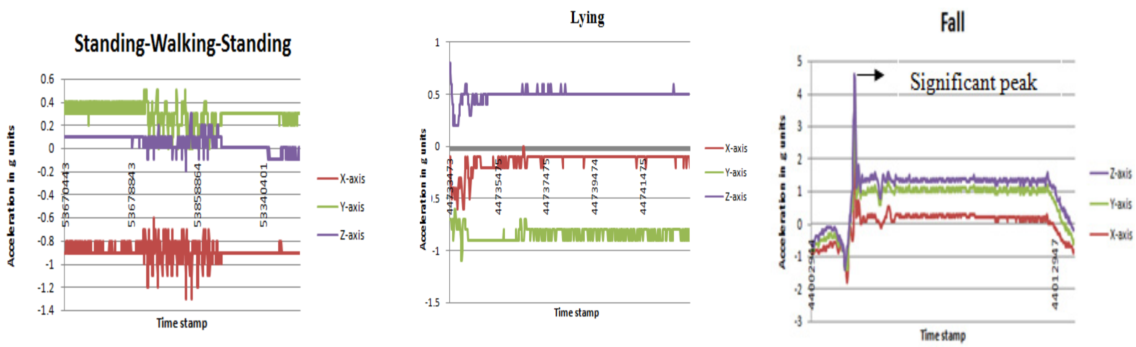

Fig. 3.Acceleration data plotted for standing-walking-standing, lying and fall

4.2. Feature Extraction

Two basic statistical features such as mean and standard deviation are extracted from three axes –X, Y, and Z axis of accelerometer.

- ***Mean*** – mean value of accelerometer data within the sliding window gives the DC component of the signal. This feature helps in separating sitting/standing classes from lying class.

- ***Standard deviation*** – gives the amount of deviation of the tri-axial data from the mean of data within the sliding window. This feature helps in distinguishing static activities like sitting/standing, lying from dynamic activity like walking and abnormal activity like fall.

Thus, totally six features are extracted and fed to the next module, bit pattern mapping.

4.3. Bit Pattern Mapping

Frequent pattern mining requires discretized data for processing. Accelerometer data streams contain continuous values and certain values along the axes are frequent. Proper analysis of data for each activity type enables mapping continuous feature vector to bit patterns. Thus, each feature is mapped to either bit 0 or 1 depending on the range it covers for each activity type. Support of each feature is determined by just counting the no. of 1's along each feature. The features whose support is greater than user specified minimum support are mapped to 1 and 0 otherwise and this gives Frequent Bit Pattern (FBP) for each activity class. Table 1 presents the sample frequent bit pattern obtained and pattern rules discovered for normal actions and fall. The first column shows the set/reset part of significant bit in the bit pattern and it is 0 for normal activities and 1 for fall. The second column shows the frequent bit pattern which is obtained by considering only the features whose support exceeds minsupport threshold. For example, for walking, only mean_x, standarddeviation_x, standarddeviation_y and standarddeviation_z satisfies minsupport criteria and thus the bit pattern obtained is 100111. Pattern rule in the next column specifies the column number of features whose support exceeds minsupport threshold preceded by significant bit. The last column gives the meaning of pattern rules.

Table 1. Sample Frequent Bit Patterns and Rules discovered for normal activities and fall

Significant bit	***Frequent bit pattern***	***Pattern Rules***	***Meaning***
0	100000/100100	00->sitting/standing 030->sitting/standing	(mean_x,1)->sitting/standing {(mean_x,1),(standarddeviation_x,1)}->sitting/standing
0	0100111	041->lying	{(mean_y,1),(standarddeviation_x,1),(standarddeviation_y,1), (standarddeviation_z,1)}->lying
0	100111	05430->walking	{(mean_x,1),(standarddeviation_x,1),(standarddeviation_y,1), (standarddeviation_z,1)}->walking
1	100000	10-> fall but recovered	(mean_x,1}->fall but recovered
1	0100111	1541- >fall and lying	{(mean_y,1),(standarddeviation_x,1),(standarddeviation_y,1), (standarddeviation_z,1)}->fall & lying

4.4. Significant Bit (SB) set/reset

Like normal activities such as sitting, walking etc. abnormal activity like fall cannot be determined using frequent pattern mining as fall will have significant peak that last for few seconds compared to other normal activities as shown in Fig 3 and later part of the fall data is same as that of lying activity data. Hence, a separate field called significant bit which forms the most significant bit of frequent bit pattern is set if significant peak is detected in the incoming data streams. Thus, fall which is often confused with lying activity can be distinguished from it by checking whether the significant bit is set or reset and hence true positive rate of fall is increased.

4.5. Rule Based Classifier Model

In this section, an algorithm called FBPAC (Frequent Bit Pattern based Associative Classification) is presented, which discovers the set of rules from frequent bit patterns for classifying normal activities and abnormal activity like fall as mentioned in Table 1. The basic idea of CBA [2] is used to mine frequent bit patterns for discovering rules for activity classification and for detecting fall. The proposed algorithm is shown in Fig 4.

```
Training phase:

Input: Accelerometer Sensor Data Stream (ADS), Sliding
       Window size (SW_size in time units), block size
       (blksize), User specified minimum support
       threshold (minsupport)

Output : Rules for detecting normal activities like
         sitting/standing, lying and walking and abnormal
         activity like fall.

Begin
        for each Sliding Window SW_size_t do
          for each block blksize_i do
           if Accelerometer Sensor Data Stream ADS in
              blksize_i contains peak then
              set significant bit in blksize_i sigbi_i for detecting
                                                        fall
           end if
            Extract feature to obtain Feature Vector FV_i
          end for
          Map the Feature Vector FV_i to Bit Pattern Vector
                                                      BPV_i
          Compute support for each feature using Bit Pattern
                                                 Vector BPV_i
          Obtain Frequent Bit Pattern Vector FBPV_i whose
                                      support > minsupport
          Obtain the feature list whose support > minsupport
          Generate pattern rules for recognizing activities and
          for detecting falls // Classifier Model
        end for
end
```

Fig. 4.Frequent Bit Pattern based Associative Classification (FBPAC)

5. Implementation and Result Discussion

The data set for the experiment was collected in a supervised manner at home. Five healthy persons i.e., three females and 2 males with an average age of 37, participated in the experiment. Data are collected for totally 3 normal activities such as sitting/standing, lying and walking and an abnormal activity like fall. The data set are manually annotated by the person. A sample sequence of activities performed by the subjects for normal activity category is sitting- standing- walking -sitting -lying. Each activity is performed approximately for 1 minute. For fall, subjects are asked to perform the sequence such as standing ->fall backward, standing ->fall sidewise etc. Approximately, 10 hours of activity data, i.e. 2 hours per person, are collected during experiment.

The module of activity recognizing and fall detection is coded in Java Net Beans environment. Table 2 shows the random activity sequence performed by 3 subjects who did not participated in training and the corresponding classification accuracy obtained for each subject. Accelerometer data stream is processed for every 10 seconds as in training phase with user specified minimum support as 80% and activity performed for that duration is reported. It is shown that with this frequent bit pattern approach, it is possible to achieve 92% overall accuracy for random activity sequence.

Table 2. Overall Accuracy for arbitrary activity sequence

Subject	Activity sequence	Overall Accuracy (%)
1	standing-walking-sitting-lying-sitting-standing-walking-fall-lying	91
2	walking-sitting-lying-sitting-standing-fall-lying	100
3	standing-walking-sitting-walking-fall-lying	85

Fig 5 depicts the mean classification accuracy obtained for traditional algorithms such as Naïve Bayes (NB), Bayesian Belief Network (BBN), Multi-layer perceptron (MLP), C4.5 Decision tree using Weka tool and the proposed algorithm FBPAC with the six features mentioned in section 4. It is observed that the proposed algorithm outperforms traditional methods.

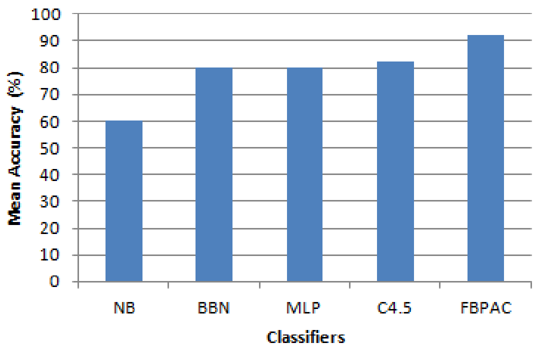

Fig. 5.Comparison of traditional algorithms with the proposed FBPAC method for classification accuracy

6. Conclusion

The proposed Frequent Bit Pattern based Associative Classification (FBPAC) algorithm reduces the false positive rates for fall events which are normally confused with lying posture. Because of mapping the feature vector to bit patterns, calculating support of features for all the activities covered under the sliding window is eased and is done faster. The algorithm is evaluated by observing sensor data streams of arbitrary activity sequence performed by three subjects who did not participated in training phase. The highest overall mean accuracy achieved is 92% for a sliding window size of 10 seconds.

Acknowledgements

This work is supported by NRDMS, Department of Science and Technology, New Delhi. The authors would like to extend their sincere thanks to NRDMS-DST for the support.

References

[1] R. Agrawal, T. Imielinski and A. Swami. Mining association rules between sets of items in large databases. *ACM SIGMOD Conference on Management of Data, Washington, D.C;* 1993; 22: p. 207-216.
[2] B. Liu, W. Hsu and Y. Ma. Integrating classification and association rule mining. *4th International Conference on Knowledge Discovery and Data Mining;* 1998; p. 80-86.
[3] C. Doukas and I. Maglogiannis. Emergency fall incidents detection in assisted living environments utlilizing motion, sound and visual perceptual components. *IEEE Trans. on Information Technology in Biomedicine;* 2011; 15(2):p. 277– 289.
[4] F. Bianchi, S.J. Redmond, M.R. Narayanan, S. Cerutti and N.H. Lovell. Barometric Pressure and Triaxial acclerometry based falls event detection. *IEEE Trans. on Neural systems and Rehabilitation engineering,* 2010;18(6) :p. 619-627.
[5] X. Yang, A. Dinh and L. Chen. A wearable real-time fall detector based on naïve bayes classifier. *23rd Canadian conference on Electrical and Computer Engineering;* 2010; p. 1-4.
[6] N. Noury, A. Fleury, P. Rumeau, A.K. Bourke, G.O. Laighin, V. Raille and J.E. Lundy. Fall detection – principles and methods. *29th Annual International Conference of the IEEE EMBS* ; 2007; p. 1663-1666.
[7] A.M. Khan,Y.K. Lee and T.S. Kim. A triaxial acceleerometer based physical activity recognition via augumented signal features and a hierarchical recognizer. *IEEE Trans. on Information Technology in Biomedicine;* 2010;14(5): p.1166– 1172.
[8] D.O. Lara, J.A. Perez, A.M. Labrador and D.J. Posada. Centinela: A human activity recognition system based on acceleration and vital sign data. *Pervasive and mobile computing;* 2012; 8(5):p. 717 – 729.
[9] L. Su, H.Y. Liu, Z.H. Song and ShiJiaZhuang. A new classification algorithm for data stream. *International Journal of Modern Education and Computer Science;* 2011; 4:p. 32-39.
[10] C.H. Lin, D.Y. Chiu, Y.H. Wu and A.L.P. Chen. Mining frequent itemsets from data streams with a time-sensitive sliding window. *SIAM International Conference on Data Mining* ; 2005.
[11] H.F. Li and S.Y. Lee. Mining frequent itemsets over data streams using efficient window sliding techniques. *Expert systems with applications;* 2009; 36(2):p. 1466-1477.
[12] T. Gu, L. Wang, Z. Wu, X. Tao and J. Lu. A pattern mining approach to sensor based human activity recognition. *IEEE Trans. on Knowledge and Data Engineering;* 2011; 23(9):p.1359 – 1372.
[13] Zephyr Bioharness 3 website, http://www.zephyr- technology.com/products/bioharness_bt.html.