Patient Fall Detection using Support Vector Machines

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Abstract This paper presents a novel implementation of a patient fall detection system that may be used for patient activity recognition and emergency treatment. Sensors equipped with accelerometers are attached on the body of the patients and transmit patient movement data wirelessly to the monitoring unit. The methodology of support Vector Machines is used for precise classification of the acquired data and determination of a fall emergency event. Then a context-aware server transmits video from patient site properly coded according to both patient and network status. Evaluation results indicate the high accuracy of the classification method and the effectiveness of the proposed implementation.

1 Introduction

The telemonitoring of human physiological data, in both normal and abnormal situations of activity, is interesting for the purpose of emergency event detection or long term data-storage for later diagnosis or for the purpose of medical exploration. In the case of elderly people living on their own, there is a particular need for monitoring their behavior. The first goal of this surveillance is the detection of major incidents such as a fall, or a long period of inactivity in a part of their area. The early detection of fall is an important step to alert and protect the subject, so that serious injury can be avoided. Fall detection is an important part of human body movement analysis; it is considered as an area of increasing importance and interest to practitioners, researchers, and health industry and most importantly, it is vital for indication of emergency cases. Accelerometers have been proposed as a practical, inexpensive and reliable method for monitoring ambulatory motion in elderly subjects for the detection and prediction of falls. Robust classification of motion and postures from accelerometer data enable the development of more reliable methods for monitoring long term change in physiological indicators such as parameters of gait, balance, energy expenditure and general well-being.

This paper presents a patient fall detection platform based on accelerometer data. Body sensors collect the movement data and transmit them wirelessly to the monitoring unit. Appropriate data classification using Support Vector Machines 19, can classify the recorded movement into three categories; fall, walk and run. Then the deployment of additional context awareness based on the previous activity detection may enable the proper coding and transmission of video images from the patient to remote monitoring units (i.e alarm triggering and high quality video transmission). The rest of the paper is organized as follows; Section 2 discusses related work in the context of patient activity and fall detection. Section 3 describes the acquisition of the patient movement data using sensors, whereas Section 4 presents that data classification using Support Vector Machines. The whole system architecture is described in Section 5 and Section 6 presents the evaluation results. Finally, Section 7 concludes the paper.

2 Related Work

Although the concept of patient activity recognition with focus on fall detection is relatively new, there exists related research work, that may be retrieved from the literature (1-16). Information regarding the patient movement and activity is frequently acquired through visual tracking of the patient's position. In 6 and 15 overhead tracking through cameras provides the movement trajectory of the patient and gives information about user activity on predetermined monitored areas. Unusual inactivity (e.g., continuous tracking of the patient on the floor) is interpreted as a fall. Similarly, in 10 omni-camera images are used in order to determine the horizontal placement of the patient's silhouettes on the floor (case of fall). Success rate for fall detection is declared at 81% for the latter work. Head tracking is used in 13 in order to follow patient's movement trajectory with a success rate of fall detection at 66.67%. The aforementioned methods that detect falls based on visual information of the user require capturing equipment and thus are limited to indoor environment usage. In addition, some of the methods require also the a-priori knowledge of the area structure (e.g., obstacles, definition of floor, etc.), or user information (e.g., height in 10). A different approach for collecting patient activity information is the use of sensors that integrate devices like accelerometers, gyroscopes and contact sensors. The decrease of sensors size and weight, in conjunction with the introduction of embedded wireless transceivers allows their pervasive placement on patients and the transmission of the collected movement information to monitoring units wirelessly. The latter approach is less depended on the patient and environmental information and can be used for a variety of applications for user activity recognition (1, 3, 9). Regarding fall detection, authors in 2, 7, 8, 12 use accelerometers, gyroscopes and tilt sensors for movement tracking. Collected data from the accelerometers (i.e., usually rotation angle or acceleration in the X, Y and Z axis) is used in order to verify the placement of the patient and time occupation in rooms and detect abrupt movement that could be associated with fall. Detection is performed using predefined thresholds 1, 3, 4, 7 and association between current position, movement and acceleration 2, 8, 12. Finally, area sensors have been used in order to track and analyze patient movement; authors in 11 describe a vibration-based detector that can detect falls based on the vibration caused on the floor. In 5 infrared sensors are used that provide thermal information regarding the patient's location and movement. The latter approaches do not require from the user to wear or carry sensor devices, however they demand more expensive equipment to be installed on the surrounding environment.

Most of the related work based on accelerometers for fall detection, focuses on the elderly and may not be used for general classification of the patient movement activity or usage in younger ages (e.g. interpretation of running has not been assessed against falling). In addition, detection is usually performed through predefined thresholds and thus results can be depended to the movement patterns of the users. The presented system is using a state of the art classification methodology, the Support Vector Machines, for data classification and fall detection. The proposed system may be used for a variety of patient activity recognition since it can successfully distinguish movement between run and fall. In addition it is not biased by the movement pattern or the physiology of a specific patient (i.e. it can perform successfully with movement data from different individuals) and it does not apply restrictions to the user's environment (e.g., it can be used in outdoor environments as well). A context-aware framework deployed within the system enables the proper transmission of video images from the patient in case of emergency events, optimizing the whole telemonitoring procedure.

3 Patient Movement Data Acquisition

This section provides information on the acquisition and pre-processing of the patient movement data. The MC13192 [2] sensor has been used in our system. The latter contains a 2.4 GHz wireless data transceiver RF reference design with printed circuit antenna, which provides all hardware required for a complete wireless node using IEEE 802.15.4 (ZigBee) 17 packet structure. It includes an RS232 port for interface with a personal computer, background debug module for in-circuit hardware debug, four switches and LEDs for control and monitoring, a low-power, low-voltage MCU (MicroController Unit) with 60KB of on-chip Flash which allows the user flexibility in establishing wireless data networks and two 3D Accelerometers for X, Y and Z axis. Fig. 1 shows the SARD ZigBee node 18. ZigBee has been chosen as communication technology for a number of reasons:

- Low cost and very low power consumption: its data rate is at 250 kbps and its power consumption is 30mA in Transmit mode and only 3μA in StandBy mode respectively. A ZigBee node can thus have a very long battery life (2-3 years with a AA cell).

- Low complexity that makes the protocol ideal for integration on sensor nodes.
- Higher range compared to Bluetooth (up to 100 meter).
- Can be used for automatic creation of mesh networks.
- Contains built-in security measures.

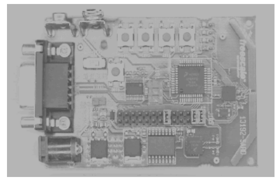

Fig. 1. The SARD ZigBee node. The node acts as both receiver and transmitter. The RS232 interface provides connectivity with the monitoring device (e.g., a laptop or a PDA) when the node is used as receiver. The transmitter is attached on user and sends data through the ZigBee wireless protocol.

The user's foot has been selected for acquiring movement data due to the fact the majority of human movements require the movement of the feet at one of the three axes (i.e. X, Y and Z). Thus the placement of the sensor on the foot allows the collection and association of accelerometer data with a wider range of human activity (e.g., walk, run, lie, etc.) The acquired data contain information about the patient's movement in the context of acceleration in the X, Y and Z axis and are transmitted wirelessly to the monitoring node. Fig. 2 illustrates an association between acceleration data on the X, Y and Z axes for the cases of normal movement, fall and run.

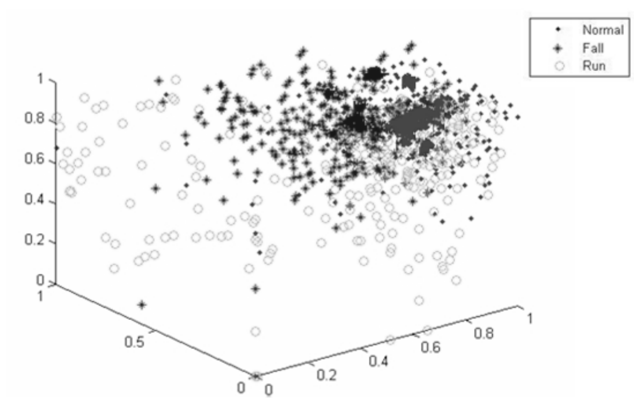

Fig. 2. Graphical association of the acceleration data on the X, Y and Z axis for three different movement types; Normal (i.e. walk), Fall and Run. Values have been normalized to [0,1].

4 Data Classification using Support Vector Machines

This Section provided information regarding the classification method used, parameters and data modeling. The Support Vector Machines (SVMs) is a popular algorithm for data classification into two classes 19, 20. SVMs allow the expansion of the information provided by a training data set as a linear combination of a subset of the data in the training set (support vectors). These vectors locate a hypersurface that separates the input data with a very good degree of generalization. The SVM algorithm is based on training, testing and performance evaluation, which are common steps in every learning procedure. Training involves optimization of a convex cost function where there are no local minima to complicate the learning process. Testing is based on the model evaluation using the support vectors to classify a test data set. Given a training set of instance-label pairs:

$$(x_i, y_i), i = 1, \ldots, l \ where \ x_i \in R^n \ and \ y \in \{1, -1\}^l$$

The SVM require the solution of the following optimization problem:

$$\min_{w,b,\xi} \ \frac{1}{2} w^T w + C \sum_{i=1}^{l} \xi_i \quad , \qquad \text{Equation 1}$$

subject to $y_i(w^T \phi(x_i) + b) \ \geq \ 1 - \xi_i, \ \xi i \geq 0,$ Equation 2

The training vectors x_i can be mapped into a higher dimensional space by the function φ. Then SVM finds a linear separating hyperplane with the maximal margin in this higher dimensional space. $C > 0$ is the penalty parameter of the error term. Furthermore, $K(x_i, x_j) \equiv \phi(xi)^T \phi(xj)$ is called the kernel function. The most commonly used kernels are the following:

- Linear: $K(x_i, x_j) = X_i^T x_j$
- Polynomial: $K(x_i, x_j) = (\gamma x_i^T x_j + r)^d, \gamma > 0$
- Radial Basis Function (RBF): $K(x_i, x_j) = e^{(-\gamma \|xi - xj\|^2)}, \gamma > 0$
- Sigmoid: $K(x_i, x_j) = \tanh(\gamma x_i^T x_j + r)$

where γ, r and d are kernel parameters.

In order to make an efficient selection of the most suitable kernel type for the presented platform, the aforementioned kernel types have been validated against input data from the accelerometer sensors. Three classification classes have been defined according to corresponding movement cases; fall, run and walk. A SVM train model has been created from the latter data using the tool presented in 21. The input data has the following form:

Class_ID X Y Z,

where Class_ID $\in [1,3]$ and represents the movement case (i.e. 1 for walk, 2 for run and 3 for fall), X the acceleration value in the X axis, Y the acceleration value in Y axis and Z the acceleration value in Z axis respectively. For simplicity, acceleration values were normalized to [0,1]. The same data have been used in order to verify the accuracy of each kernel. Fig. 3 illustrates the accuracy of each kernel type for different *C* values. As results indicate, the RBF kernel behaves much better in terms of accuracy (approaches 98.2% accuracy for C=1000) for proper classification of the test data into the three defined classes, and thus has been selected for data classification in the presented platform. A second experiment was conducted in order to evaluate the RBF kernel's performance against different γ values. Fig. 4 presents the accuracy results for a range of γ value between [1,100].

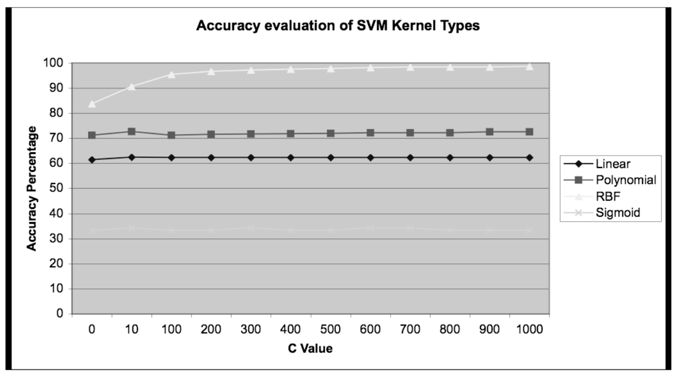

Fig. 3. Accuracy Evaluation of different SVM Kernel types for different C values. X axis represents the C value range between [1, 1000] and the Y axis the accuracy percentage.

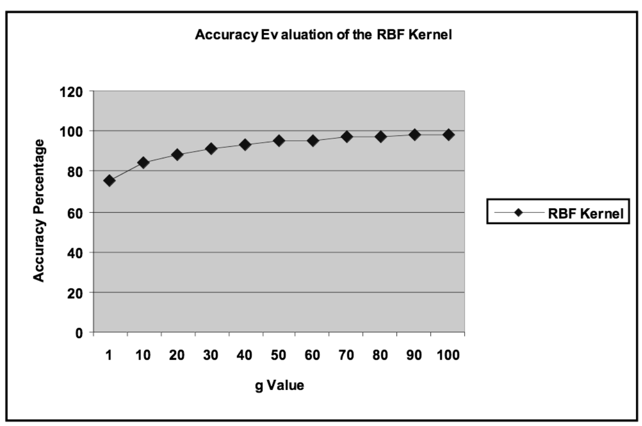

Fig. 4. *Accuracy Evaluation of the RBF kernel for different g values.*

Based on the aforementioned results, RBF with C=1000 and γ=100 was selected for creating the classification (i.e. train) model of the platform.

5 The System Architecture

The presented system follows the architecture illustrated in Fig. 5. Accelerometer data are collected through the sensor attached on the user's foot and are transmitted wirelessly to the monitoring node. The data is properly transformed in a suitable format for the classifier and the classification phase begins. Based on a predefined classification model (i.e. train model), the patient status is detected (i.e. emergency status when fall detected, normal status otherwise). A network status monitoring module determines the quality of the underlying network infrastructure and decides for the proper coding and transmission of the patient video images using H.263 22 video compression.

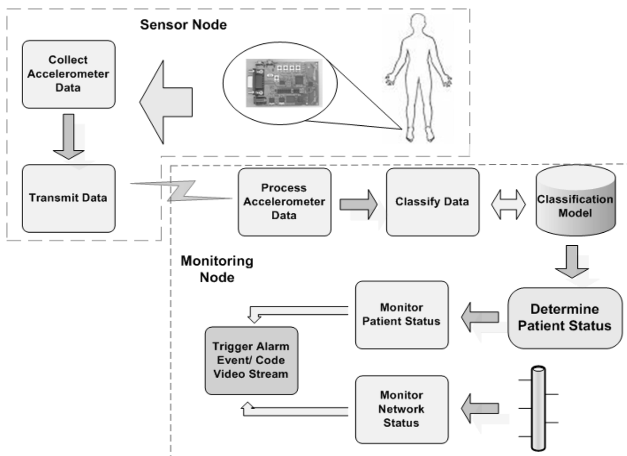

Fig. 5. Platform Architecture and Data interaction between the sensor and monitoring node.

6 Fall Detection and Evaluation Results

In order to evaluate the efficiency and accuracy of the presented platform in the context of detecting patient falls, three different experiments were conducted; two volunteers wearing the sensors devices described in Section 3 performed three combinations of movement types; a) simple walk, b) simple walk and fall, c) simple walk and run. The classification model with parameters and data described in Section 4 was used in order to validate the acquired accelerometer data. Each acceleration value in X, Y and Z axis was validated runtime and a corresponding movement type

was associated with it. Based on the number of sequential occurrence of a specific movement type, decision regarding a patient fall is taken. In order to improve the accuracy of the latter decision, Kalman filtering 23, 24 has been applied on the sequence of the movement type association of each acceleration data set.
Fig. 6 represents the classification results from the conducted experiments using the trained SVM model. Blue lines represent original results whereas purple lines results after applying Kalman filtering. Actual run and fall events are also annotated on the diagrams. As it is indicated, Kalman filtering improves the overall detection by smoothing the sequential occurrences of run or fall events respectively. A threshold $t = 10$ has been selected for determining the occurrence of a fall or run event from the total sequence of classified movement types (i.e. if sequential occurrence of fall movement types > 10 then a fall is detected). Using the aforementioned classification and the latter threshold value, fall events were detected with an average accuracy of 98.2% for both users, whereas run events were successfully detected at 96.72%.

7 Conclusions

In this paper a platform for detecting patient falls is presented. User movement is monitored using sensor devices that provide information regarding the acceleration in the X, Y and Z axis. Proper data classification based on Support Vector Machines provides fall detection with accuracy up to 98.2%. Fall detection indicates an emergency status for the patient. In conjunction to network status awareness proper patient video image coding and transmission is applied optimizing this way the telemonitoring procedure. Future work might include the enhancement of the platform with fall detection using computer vision processing of the patient's site for even more accurate results.

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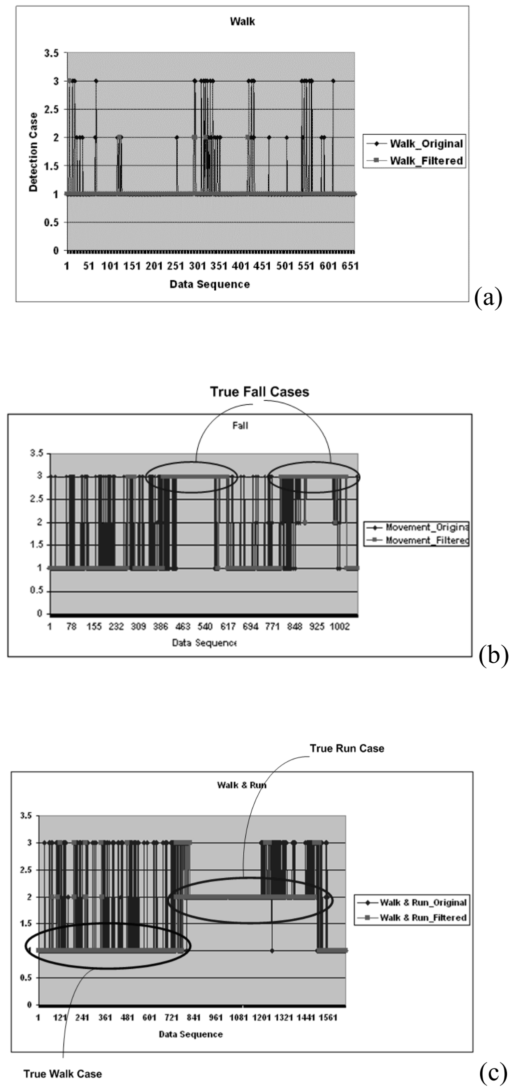

Fig. 6. Classification results based on the SVM trained model for three different types of movement: (a) simple walk, (b) walk and fall, (c) walk and run. X axis represents the acceleration data sequence and Y axis the corresponding movement type (i.e. 1 for walk, 2 for run and 3 for fall). Light lines represent original results whereas dark lines results after applying Kalman filtering. Actual run and fall events are annotated on the diagrams.

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