주성분 분석 기반의 노약자 응급 모니터링

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Principal Component analysis based Ambulatory monitoring of elderly

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요 약

일반인의 건강상태를 모니터하는 간편 착용 임베디드 장치가 홈 헬tm케어의 용이한 해법으로 소개되어지고 있다. 본 논문에서는 매일 일상 활동을 검사하고 활동성을 분류하는 방법을 보여주고 있다. 노약자나 장애인에 대한 일상 모니터링은 일반적인 건강상태 뿐 만아니라 넘어지거나 도움이 필요한 상황 등 비상시에 경보를 알려주게 된다. 이 같은 위기 상황에서 적시의 도움은 생명 손실을 줄여줄 수 있다. 본 연구에서는 3축 가속도계를 탑재한 흉부 착용센서로부터 수신되는 데이터를 분석하고 어떤 특징 값들이 인체활동분류에서 중요하게 되는가를 알려줄 수 있음을 보여주었다. 주성분 분석법은 특징 세트를 수정하거나 동일 정보에 대한 크기를 줄이는데 유용하다. 마지막으로, 신경망 분류기법이 정확도 분류를 분석하기 위해 적용되었다. 넘어짐에 대해서는 86%의 측정 정확도를 얻을 수 있었고, 일일 생활 활동에 대한 전체 활동성 분류 정확도는 94%를 얻을 수 있었다.

ABSTRACT

Embedding the compact wearable units to monitor the health status of a person   has been analysed as a convenient solution for the home health care. This paper presents a method to detect fall from the other activities of daily living and also to classify those activities. This kind of ambulatory monitoring of the elderly and people with limited mobility can not only provide their general health status but also alarms whenever an emergency such as fall or gait has been occurred and a help is needed. A timely assistance in such a situation can reduce the loss of life. This work shows a detailed analysis of the data received from a chest worn sensor unit embedding a 3-axis accelerometer and depicts which features are important for the classification of human activities, How to arrange and reduce the features to a new feature set so that it can be classified using a simple classifier and also improving the classification resolution. Principal component analysis (PCA) has been used for modifying the feature set and afterwards for reducing the size of the same. Finally a Neural network classifier has been used to analyse the classification accuracies. The accuracy for detection of fall events was found to be 86%. The overall accuracy for the classification of Activities of daily living (ADL) and fall was around 94%.

I. Introduction

A recent study has shown that the number and share of the population aged 65 and over will continue to grow steadily over the next decades [1]. With less number of care givers, the healthcare of elderly population living

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independently, is a challenging task for the modern healthcare system. So, the modern healthcare system suggests a more active life style by making the people aware of their general health status and providing emergency help whenever needed. Activity monitoring from a remote location is such an indication of the health status while alarming the emergency fatal events. In the series of studies for ubiquitous healthcare the use of compact, low-cost sensors can help in long term care with less expenditure without disturbing the daily routine activities. The major risk factor associated with elderly is fall which can be fatal when no immediate care is available.

One of the pivotal work by D.M. Karantonis et al. [2] presented an algorithm to classify the rest, movement, fall and posture of the person (Standing, Lying sub postures, sitting) using accelerometer sensor in single hop communication environment. The system proposed majority of signal processing on the wearable unit. While the classification algorithm was performed on the base station after the separation of bodily and gravity acceleration components.

Ning Wang et al. [3]used Wavelet transform for simultaneously analyzing the time and frequency domain features for walk patterns and neural network for classification. The use of neural network classifier implied the generalization to the new user's data and hence making the system more flexible.

The most recent work is presented by Jafari et al. [4][5] which uses the structural pattern recognition with angle from the vertical axes. The work shows the performance of K-nearest neighbor method and neural network to match the received pattern with the fall pattern[5]. In an another work,[4] they used the linear feature set minimization for activity classification. They used a number of sensor at different body positions for this.

This work shows an accelerometer sensor based system for the classification of daily activities like rest, walk and run along with the detection of simple forward fall events. Both the time and frequency domain features were analysed to form a single feature set. A feature reduction method is also shown using the principal component analysis (PCA). A

neural network was designed, trained and tested to show the final classification accuracies.

II. System Hardware and Software

The system hardware has been divided in two parts: User's end and the care-giver's end. Fig. 1 is showing the complete system architecture. The user's end consists of a single chest worn 3-axis accelerometer sensor unit. This is used to capture the acceleration data associated with the activity being performed by the user. The care giver's end consists of a similar sensor node and the base station PC. Both the nodes have CC2420 2.4 GHz ISM band radio which is capable to transfer the data at a rate of 250Kbps and connected to each other by an IEEE 802.15.4 compliant radio module. The use of wireless communication between the two ends enable the user with mobility in the range. The base station node receives the data sent by the accelerometer sensor node and sends the data to the base station PC via an RS-232 interface.
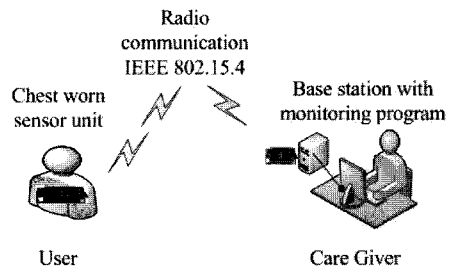

그림 1. 시스템 구조
Fig. 1 System Architecture

In this work, Telos type sensor node, TIP710 (Maxfor, Korea) has been used as a resource for computation and communication while the Capacitive type Microelectrome-chanical Sensors (MEMS) tri-axial accelerometer MMA 7260 (Freescale Inc. USA) has been used for capturing the acceleration signal of the movement. The accelerometer sensor has a range of -6g to +6g and sensitivity of 200 mV/g, g is here the acceleration due to gravity in m/s2. The sampling frequency was chosen as 50Hz[6].

III. Methods

MATLAB 7.4.0 has been used as a software platform for analyzing, preprocessing and classifying the data at the base station PC. The following section discusses this in detail:
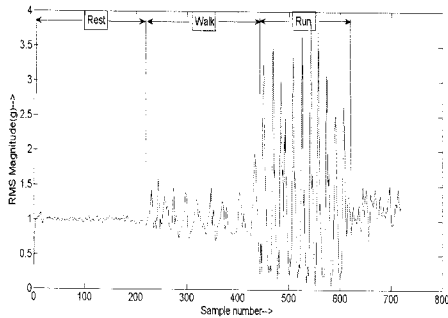

그림 2. 쉬기, 걷기, 달리기에 대한 3축 가속도
데이터의 RMS
Fig. 2 RMS of the three axis acceleration data for
Rest, Walk and Run

a. Data calibration and preprocessing: The de-packetized three axis acceleration data, at the base station PC are the equivalent acceleration values in terms of voltage levels. These are needed to be converted back to the equivalent acceleration values in terms of gravity acceleration 'g'. This process is called as calibration. A linear calibration was performed on data[6]. The filtered three axis accelerometer data was then combined to get a root mean square (RMS) value of the acceleration[7]. The RMS data, so obtained, consists of bodily acceleration data, the gravity acceleration data and the spurious noise due to environment or circuitry involved. The bodily acceleration data consists of the acceleration associated with the movement of the user and hence can give the information regarding the activity being performed. The gravity acceleration data consists of the information regarding the user's orientation with respect to the vertical and hence can help in detection of the fatal fall event. So the next step is to remove the unwanted noise spikes from the acceleration data. A moving average filter of order 3 has been used to smoothen the data [7]. The smoothened RMS acceleration data for a sequence of rest, walk and run is shown in fig. 2.

b. Data classification: After the calibration and basic preprocessing the data was needed to be classified on the basis of the acceleration anomalies present in itself. A machine learning technique for the classification not only gives a higher resolution in the presence of some level of noise but also generalizes the classification for any unforeseen activity data. The activity data captured by the accelerometer sensor node has been found to consist of so many data constraints to be satisfied. A neural network can satisfy the multiple constraints due to the parallel organization of neurons. Therefore, a neural network classifier was selected as compared to other machine learning approaches.

For an efficient learning it is required that the data features should be selected so as to be able to generalize the results with a less complex and faster machine. The next section discusses the feature set preparation and then reduction for an efficient classification.

IV. Feature set preparation

For the classification, the preprocessed data was divided into a sequence of 256 samples to form one data block. The 256 data samples create a block of 5.1 seconds(for the sampling frequency=50 Hz) and hence a single activity can be considered to appear in this small duration. Also the choice of the size of 256 samples(a power of two) is also suitable for the fast computation of the Fourier transform[9]. The selection of features from each data block is shown below:

a. Time domain features from data: As shown in fig.2, the three activities i.e. Rest, Walk and Run differ in their magnitude of accelerations and their ranges. This is also shown in fig. 3 for mean, standard deviation, minimum and maximum value of the acceleration for the three activities involved. It is clear from the figure that these values can be used for classification of Rest, Walk and Run.

For the detection of the fall event, the angle from vertical axis has been found to be a more accurate observation as sometimes the magnitude of the same has been found to be overlapped with that of a run activity[7]. So the angle from

the vertical at each sample point is also included as the feature parameter in the time domain feature set.
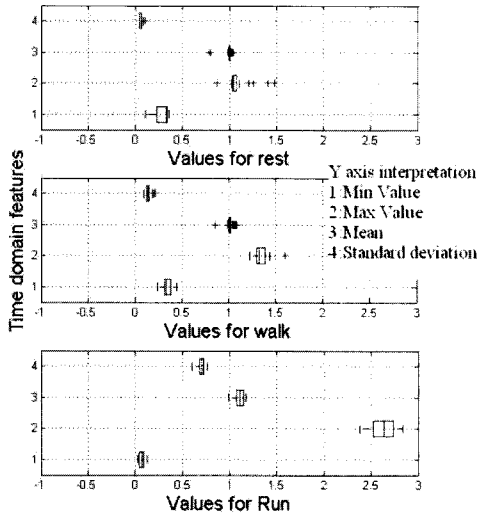

그림 3. 쉬기, 걷기, 달리기에 대한 시간영역 특징 값들
Fig. 3 The time domain feature values for Rest, Walk and Run

Including all the above observations a time domain feature set has been prepared including the Mean, standard deviation, minimum value, maximum value of the block and the 256 points of angle from the vertical at each sample point in the block. Therefore the total size of the time domain feature set is 260 points.

b. Frequency domain features: The frequency has been found to be a more accurate parameter for classification of ADL [8]. So a 256 point FFT has been calculated for the data block. The 256 FFT coefficients, so calculated, contain redundant information around the zero frequency. Therefore, only the half part i.e. 128 points have been included as a frequency domain feature set.

c. Total feature set: The total feature set was created by combining the two sets i.e. time and frequency domain feature sets. So the total feature set can be expressed as

$$X = (x1, x2, x3, ... xn)$$ (1)

where X is the Total feature set, xi is the value of i-th feature. For the activity data, the total feature set size n=388.

d. Feature reduction: If the classification were performed using a data set of size 388 points(for each of the observed data block), It would have taken a long time to train a neural network as well as a large number of neurons in each of the hidden layers. So a feature reduction is required to reduce the size of the feature set and simultaneously retain the motion anomalies present in the feature set.

Feature reduction can be performed either by using a feature subset from the original feature set or by a feature transformation. The former method is simple but requires a lot of data statics to be analysed to count the importance of each feature for the classification while the latter one involves transformation of the feature set to new plane such that the transformed feature have a more descriptive power to order than the original feature set.

A feature transformation using principal component analysis (PCA) has been analysed for the reduction purpose[10]. A new set of variables $Z = (Z_1, Z_2, ... Z_n)$, called the principal components, were calculated so that they are the linear combination of the original features.

The first principal component is calculated so that as below:

$$Z_1 = a_1^T X$$ (2)

$$Z_1 = \sum_{i=1}^{n} a_{i1}^T X$$ (3)

Here the vector

$a_1 = (a_{11}, a_{21}, a_{31}, ... a_{n1})$ is so computed that the variance of Z_1 is maximized.

where, X is the total feature set as given by eq. (1) and superscript T in equations (2) and (3) signifies the transposition of the matrix.

The next principal components were so computed that they are orthogonal to each other and maximize the variance for that axis for all possible choices of axes. Due to orthogonality of the calculated principal components they do not contain any redundant information. The calculated number of principal components were the same as the original number of features in the feature set. But for

the reduced feature set only those principal components were included which were found to have a variance of more than 0.2% of the total variance of the original data set. An analysis for principal component#1 and principal component#2 is shown in fig.4 for data of only rest, walk and run activity. The figure also shows the grouping of similar activities on the two dimensional plane.
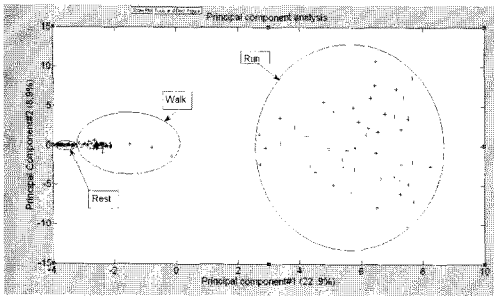

그림 4. 주요 컴포넌트 #1 대. 주요 컴포넌트 #2
Fig. 4 Principal component#1 versus Principal Component#2.

During the observation it was found that only 55 components were giving a variance of more than 0.1% of the original data and only 28 of them were giving a variance of more than 0.2%. We have used 28 principal components having a variance greater than 0.2% to form the feature vector for classification. Also from the manual retrogression it was possible to classify the data using a composite plot of different combinations of the principal components on plane.

Ⅴ. Experimental set up and results

The data were collected from the three test persons by wearing the prototype sensor unit on chest. The test person was asked to perform the activity of Rest, Walk, Run and Simple forward fall. A neural network(NN) has been designed for the classification of the accelerometer data to one of the four categories i.e. rest, walk, run and fall. The network was designed empirically by performing the training and testing with different number of layers and neurons in each of the layers. The classification accuracy for the various training and testing data sets with three fold cross validation have been observed to find the best design of the network iteratively. The Table 1 records the implementation results for each of the activity using Principal components, contributing more than 0.2% of the variance. The classification results using various approaches have been recorded in Table 2. A comparison of the above mentioned approach with other existing approaches shows a higher classification resolution.

표 1. PCA 축소를 이용하여 얻어진 분류결과
Table 1. The classification results obtained using the PCA reduction

Activity Performed ↓	Total number of data blocks considered	Number of data blocks classified correctly
Rest	57	57
Walk	57	51
Run	57	56
Fall	29	24
Rest, Walk, Run and Fall	200	188

표 2. 다양한 접근으로부터 얻어진 분류 결과값 비교
Table 2. A comparison of the classification results obtained from various approaches

Method used	Activities considered	Classification Accuracy
Tilt Angle	Fall	66.6%
PSD and Median Frequency	Walk and Run	81.25%
NN Classifier (Using FFT coefficients only)	Rest, Walk and Run	83.96%
NN Classifier with Tilt angle	Rest, Walk, Run and Fall	83.2%
PCA of feature set including the time and frequency domain features	Rest, Walk, Run and Fall	94%

Ⅵ. Conclusion

The activity monitoring and fall detection system has been implemented using an accelerometer sensor node in a wireless sensor network environment. Both the time and frequency domain features were analysed for achieving the best possible classification. A feature reduction using the principal component analysis has been shown. The overall classification accuracy of implementation was recorded as 94%.

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