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Mobility Pattern Classification for a Bed Activity Monitoring System

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Abstract

Bed Activity Monitoring System (BAMS) monitors and assess the mobility of people on a bed. This is a useful and critical application for patients with mobility issues after stroke or traumatic brain injury. The system is based on processing of data collected from a piezoelectric pressure sensor for discriminating mobility patterns. There are four different types of motion that were simulated by non-patient volunteers and data was collected. In this paper, two methods were used to extract feature parameters (autoregressive and cepstral coefficients) from the acquired data. Two classification algorithms, Euclidean Distance Measure (EDM) and Weighted Distance Measure (WDM) were used to classify and discriminate the mobility patterns of normal person (healthy subject) from people with mobility issues (patient subjects). Experimental result shows that the recognition rate using cepstral parameters was more effective compare to autoregressive parameters.

Keywords: *Feature Parameter, Euclidean Distance Measure (EDM), Weighted Distance Measure (WDM), Burg's method, Autoregressive Coefficients (AR), Cepstral Coefficients (CEP), piezoelectric sensor*

1. Introduction

An individual following stroke or traumatic brain injury experience functional impairments that impede their body movement or mobility. Bed mobility refers to the movements on the bed by people while trying to get up from the bed, lying down onto the bed or tossing and turning. The movement or motion pattern of a normal person getting up from the bed is uniquely different from person affected by stroke with various degrees of loss of mobility. There are many functional assessments have been used to evaluate mobility in the elderly and people with neurological disorders. Traditional assessment methods mainly depend on the examiner's visual observation and they are not effective enough to detect the patient's movement pattern in bed while performing a specified task. The approach used in this study is based on non-invasive sensors to discriminate the mobility patterns of normal persons (healthy subjects) from people (patient subjects) affected by stroke or others who have limited mobility. The assessment can effectively provide a measure of evaluating the mobility of the person before and after physical therapy sessions. Though some research has been conducted for gait analysis of stroke patients and for monitoring foot patterns, there is very little work done on bed mobility after stroke.

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An instrumented assessment method using a wireless infrared sensor and vibration sensors was utilized to identify human behavior in bed (Cho *et. al.*., 2012). Pressure sensitive mats have been used along with data processing unit to develop a system that automates Hierarchical Assessment of Balance and Mobility (HABAM) assessment to assess balance and mobility to perform 5 scenarios (representing each of the 5 scores) in the elderly (Bennett *et. al.*2012). Linear predictive coefficients (conventional autoregressive (AR)) and Cepstral coefficients are successfully used along with classification algorithms (Euclidian Distance Method (EDM and Weighted Distance Method (WDM)) for electromyographic (EMG) signal classification and pattern recognition . In speech processing, the distance measure between cepstral coefficients evaluated recursively from Linear Prediction Coefficients (LPC) is proved to be most effective method for speaker identification and verification (Atal, 1974; Gray and Markel, 1976). The similar process is being applied to pressure signal to discriminate the mobility patterns. Weighted cepstral distance measure is superior to Euclidean cepstral distance and the log likelihood ratio distance measures across two different data bases in word recognition system (Tohkura, 1987).

This study is focused on the processing of recorded data from pressure sensor mat placed under a thin (1 to 3 inches) bed mattress positioned beneath the arm on the side of the bed to implement a system that automates the process of mobility pattern discrimination. Non-patient subjects were asked to perform specific task of getting up from the bed to analyze the pattern. The data was sampled at 100 Hz using an A/D and stored. The acquired data was divided into intervals of equal length to check the local stationarity of the signal (Akhouayri *et. al.*2011). Feature parameters of the signal were extracted and used with pattern classifier module for mobility pattern classification and discrimination. From the experiments, we can conclude that the system was able to distinguish the movement patterns.

2. Theoretical Background

A. Autoregressive (AR) Model

Autoregressive model is a linear stationary model where the present value of the output depends on its past values. For pressure sensor signal, the frame size is assumed to be 0.15 sec (15 samples) to get the stationary signal. AR model can be defined as (Orfanidis, 1988):

$$y(n) = \sum_{k=1}^{p} a_k y(n-k) + \varepsilon(n), \quad n = 0,1,\ldots p \qquad (1)$$

$y(n)$ is the model output, a_i denotes the filter coefficients, $\varepsilon(n)$ is the prediction error, and p represents the order of the filter. Transfer function of the model (1) can be obtained by taking the z-transform. The transfer function of the system is:

$$H(z) = \frac{1}{1+\sum_{k=1}^{p} a_k z^{-k}} \qquad (2)$$

B. Cepstral Analysis

The cepstrum is defined as the inverse Discrete Fourier Transform (DFT) of the log magnitude of the DFT of a signal (Oppenheim and Schafer, 1975).

$$c[n] = F^{-1}\{\log|F\{x[n]\}|\} \qquad (3)$$

Where F and F^{-1} are Discrete Time Fourier Transform (DFT) and Inverse Discrete Time Fourier Transform (IDFT).

If all the poles of H (z) are inside the unit circle, then the logarithmic transfer function ln{H(z)}can be represented by the expansion of the power series (Oppenheim and Schafer, 1975).

$$\ln\{H(z)\} = C(z) = \sum_{m=1}^{\infty} C_m Z^{-m} \tag{4}$$

Differentiating both sides of (4) with respect to z^{-1};

$$\frac{d}{dz^{-1}} \ln\left[{}^{1}\!/\!\{1 + \sum_{m=1}^{\infty} q_k z^{-k}\} \right] = \frac{d}{dz^{-1}} \sum_{m=1}^{\infty} c_m z^{-m} \tag{5}$$

Simplification of (5) gives following recursive relationship between AR coefficients and cepstral coefficients (Atal, 1974):

$$c_1 = -q_1$$

$$c_m = -q_m - \sum_{k=1}^{m-1} \left(1 - \frac{k}{m}\right) q_k\, c_{m-k}\,, \quad 1 < m < p \tag{6}$$

C. Classification Algorithms

Body movement pattern classification and discrimination is accomplished by using the classifiers. Let $F_1, F_2, \ldots, F_m$ are the reference frame (signal feature vector) of $P_1, P_2, \ldots, P_m$ pattern classes. If F_t is the test frame (signal feature vector) associated with the unknown pattern class then Euclidean distance between test feature matrix and reference feature matrix is defined as:

$$d_{EDM}^2\,(F_t, F_m) = \|F_t - F_m\|^2 = (F_t - F_m)'(F_t - F_m) \tag{7}$$

Subscript in (7) denotes the transpose operation of a vector. It computes the distance between the test frame of the unknown pattern and the reference frame of each classified pattern. The pattern category that is closest or has the minimum distance assigned to the unknown pattern. The Euclidean distance measure (EDM) between cepstral coefficients is another important spectral distance measure that can be used for pattern recognition.

There is another classifier called Weighted Distance Measure (WDM) with weights equal to the inverse variance of the cepstral coefficients that is widely used for speech recognition process (Tohkura, 1987). It is defined as:

$$d_{WDM}^2 = (F_t - F_m)' W_m^{-1} (F_t - F_m) \tag{8}$$

Where W_m is the covariance matrix of the m^{th} reference feature vector.

3. Method

A. Equipment Setup and Data Collection

The setup included a data pressure mat, data acquisition device, computer and the software to process on data. Non-patient subjects participated in this study voluntarily. They were asked to perform specific movement pattern on the bed as specified in Table 1.

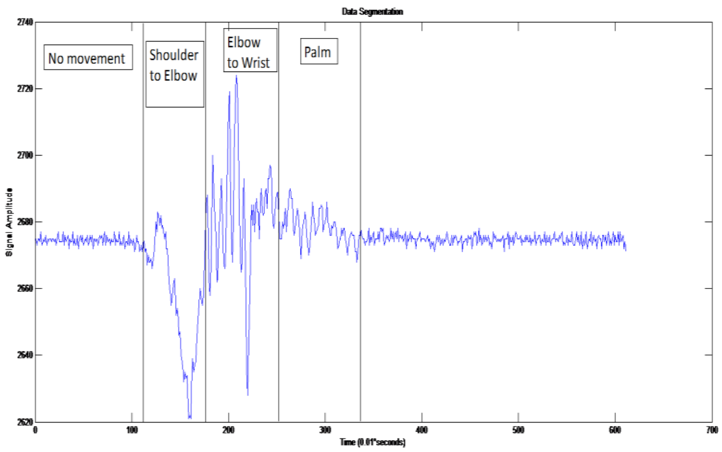
Table 1. Movement Patterns Simulated in the Experiment

1.	Normal person getting up (NP)
2.	Patient getting up using good arm (GA)
3.	Patient getting up using bad arm alone (BA)
4.	Patient getting up using bad arm but with support from good arm (BGA)

Table 2. Data Segmentation

1.	No Movement (Patient is lying onto bed)
2.	Pressure applied from shoulder/upper arm to elbow.
3.	Pressure applied from elbow to wrist
4.	Pressure applied by palm

The pressure sensor mat was placed under the bed mattress positioned underneath the arm on the side of the bed while movement patterns, as specified in Table 1 were recorded. The data was sampled at 100 Hz. Recorded data was analyzed then divided into number of segments specified in Table 2 and shown in Figure 1. The first segment of the data indicates no movement or the subject lying still in the bed. Pressure applied by shoulder to elbow portion of the body while getting up is represented by second segment. Third segment indicates the pressure applied by elbow to wrist part of the body and the fourth segment shows data when subject is in sitting posture on the bed and almost constant pressure is being applied by the palm.



Segments are specified in Table 2

Figure 1. Segmented Signal for Normal Person

B. Signal Processing and Classification

The collected data shows that the amplitude and time duration of the signal varies for each pattern specified in Table 1. The block diagram of the procedure is shown in Figure 2.

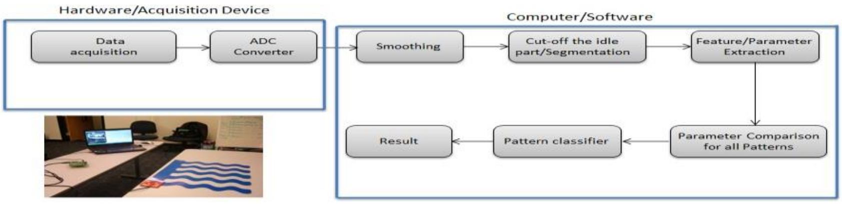


Figure 2. Block Diagram of the Proposed Algorithm

The digitized raw signal was low-pass filtered using the 5th order simple moving average filter to suppress the high frequency noise that was present in the raw signal. Idle period in a subject's motion indicates that there is no motion while the person is lying down on the bed. To remove this idle period, the variance of sensor readings was calculated and idle periods were removed when the variance of sensor readings is less than predefined threshold value. The resultant signal was then analyzed using the Burg's algorithm to extract the AR feature parameters. Burg's method is based on minimizing the sum of both the squared forward and backward prediction errors [9]. Local stationarity of the recorded signal was analyzed and then the interval for signal was chosen to be 0.15 seconds (15 samples) to make sure that the sampled data was stationary in the interval. 5th order filter was used for Burg's method to extract the feature parameters. There is negligible change in mean square error after 5th order as shown in Figure 3. The AR coefficients for higher order are more variant and less significant in estimating the Euclidian distance between two different patterns (Kang *et. al.*, 1995).

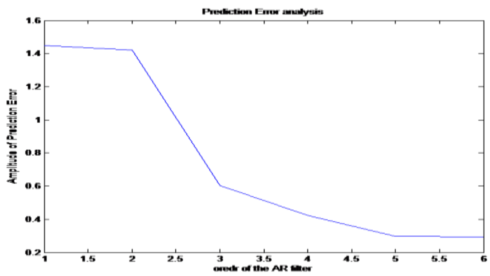


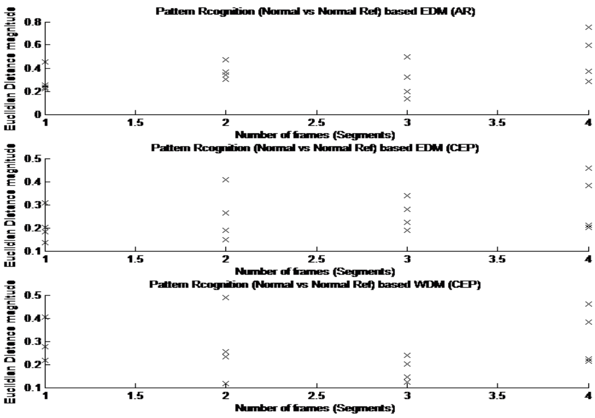
Figure 3. Mean Square Analysis for Burg's Method

Cepstral coefficients were extracted using (6) that is based on AR coefficients. Both AR and cepstral coefficients vectors were then used in pattern classifier module to classify and discriminate movement patterns between normal and patient subjects for each segment individually specified in Table 2.

4. Experimental Results

A. Classification of Mobility Patterns

First the comparison was performed by assuming the normal person's feature vector as test frame. EDM and WDM were computed between reference frame and the test frame for each segment, as specified in Table II. Results for all three proposed methods (EDM classifier based on AR coefficients (EDM-AR), EDM classifier based on cepstral coefficients (EDM-CEP) and WDM classifier based on cepstral coefficients (WDM-CEP)) are shown in Figure 4.



Seg1-4 as specified in Table 2

Figure 4. Pattern Classification for Normal Person.

'x' – Indicates the pattern for normal person (NP)

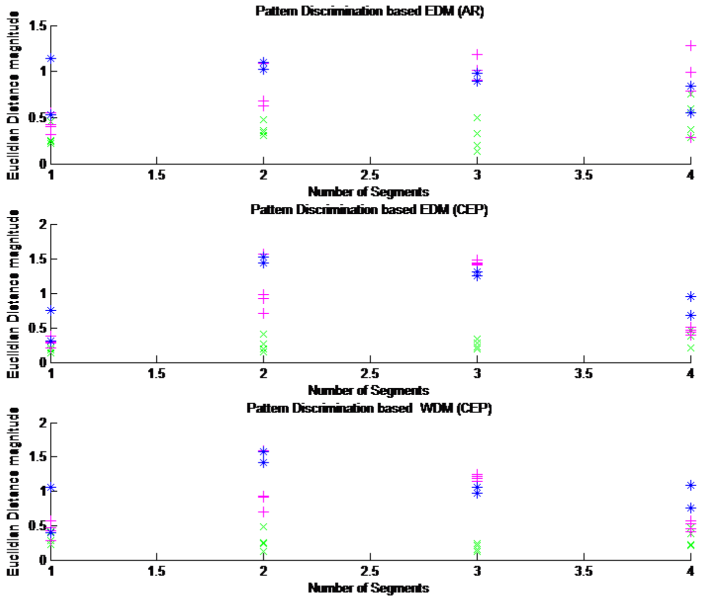
Similar steps were repeated for other patterns as specified in Table 1 to identify the mobility pattern. Table 3 lists statistical analysis result (mean and standard deviation) for each distance measure method. Results in Figure 4 and data in Table 3 show that EDM-AR is less effective for pattern identification compare to the EDM-CEP and WDM-CEP. In addition, for AR coefficients the variance is larger than the variance of cepstral coefficients. And for ceptral coefficients, WDM classifier has less variance in comparison to EDM classifier. High variability is not the desired property of the classifier. Therefore, WDM-CEP is superior among all the proposed classifier.

Table 3. (Mean ± SD) measurement for the classifier

Feature	Classifier	Method	mean ± SD of distance
AR	EDM	EDM-AR	0.3626 ± 0.1137
Cepstral	EDM	EDM-CEP	0.2576 ± 0.063
Cepstral	WDM	WDM-CEP	0.246 ± 0.0558

B. Pattern Discrimination

For pattern discrimination, the recorded data for all patterns listed in Table 1, was tested against the reference frame of the Normal person's data. Mobility Pattern for the normal person (NP) was well discriminated by all classifier methods as shown in Figure 5.



Seg1-4 as specified in Table II
'x' – Indicates the pattern for normal person (NP)
'+' – Indicates the pattern for patient getting up using good arm (GA)
'*' – Indicates the pattern for patient getting up using bad arm (BA)

Figure 5. Pattern Discrimination of patient's movement from normal person's movement

WDM-CEP achieves significant improvement in the process of pattern discrimination when compared with EDM-AR and EDM-CEP. The same steps were repeated to discriminate the patient's movement pattern (GA, BA and BGA).

5. Conclusion

This study is primarily based on instrumented assessment method where the pressure sensitive mats along with processing algorithms were used to monitor the motion assessment on the bed. The experimental results show that the movement patterns can be uniquely identified. The classifier module is efficient enough to discriminate the normal person's movement (NP) from patient's movement (GA, BA, BGA). WDM-CEP provides superior results compared to the EDM-AR and EDM-CEP. However due to the similarity in patient's motion data (GA and BA), the current extracted parameters do not produce the same result as in the case of discriminating the normal person's motion. The current work is being extended to extract more information or parameters from the patient's data that can distinguish the pattern more effectively and finally to automate the monitoring system that would assist physiotherapist to identify the impact of physical therapy sessions for the patients.

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References

[1] S. L. Bennett, R. Goubran, A. Arcelus, K. Rockwood, F. Knoefel, ‘Pressure Signal Feature Extraction for the Differentiation of Clinical Mobility Assessments’ IEEE Trans. Medical Measurements and Applications Proceedings, **(2012)**
[2] W. Kang, J. Shiu, C. Cheng, J. Lai, H. Tsao ‘The Application of Cepstral Coefficients and Maximum Likelihood Method in EMG Pattern Recognition’ IEEE Transactions on Biomedical Engineering, 42, **(1995)**
[3] S. Cho, B. Moon, R. Sankar, ‘NiBeMS: A Non-Invasive Bed Monitoring System Using Multiple Sensors’ Asia-Pacific Conference on Fundamental Problems of Opto- and Microelectronics (APCOM 2012), **(2012)** August 21-24, Dalian, China
[4] E. Akhouayri, E.H.A. Laasri, D. Agliz, A. Atmani, ‘Signal Stationarity testing and detecting of its abrupt change’ IEEE Transactions SIECPC, **(2011)**
[5] Atal, B. S. ‘Effectiveness of linear prediction characteristics of the speech wave for automatic speaker identification and verification’ Journal of Acoust. Soc. Amer., 55, 6, **(1974)**
[6] A. H. Gray, J. D. Markel ‘Distance measures for speech processing’ IEEE Transactions on Acoustics, Speech, Signal Processing’, 24, **(1976)**
[7] Y. Tohkura, ‘A weighted cepstral distance measure for speech recognition’ IEEE Transactions on Acoustics, Speech, Signal Processing, 35, **(1987)**
[8] Oppenheim A. V., Schafer, R. W. Digital Signal Processing, Prentice-Hall, Englewood Cliffs, New Jersey **(1975)**
[9] S. J. Orfanidis, Optimum Signal Processing: An Introduction, Macmillan Publishing Company, New York **(1988)**

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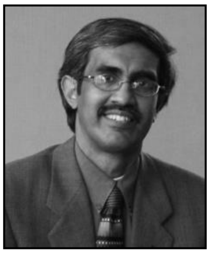

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