

STABLE AND CRITICAL GESTICULATION RECOGNITION IN CHILDREN AND PREGNANT WOMEN BY WEIGHTED NAÏVE BAYES CLASSIFICATION

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Abstract

The healthcare monitoring on a remote care taking base involves many implicit observations between the subjects and the care takers. Any deficit in domain knowledge and carelessness leads to unpleasant situations thereafter. A wearable attire system can precisely interpret the implicit communication of the state of the subject and pass it to the care takers or to an automated aid device. Casual and conventional movements of subjects during play and living condition can be used for the above purpose. The proposed system suggests a novel way of identifying safe and unsafe conditions of playing for the children where a rapid warning assistance is required. The same system is used in the case of the normal and contraction time identification of pregnant women. Naive Bayes classifier was applied on features created by different algorithms and on the combinations of features constructed by algorithms like Fractal Dimension, Fast Fourier Transformation, Singular Value Decomposition. The result shows in general that the combinational features with point system results in better classification. Especially the FFT and SVD were more supportive in all three sets of experiments and better classified by Navie Bayes classifier than the other combinations and individual features. But the complexity is high when going through the point system. When a priori based point system is introduced with a reduced complexity to replace the conventional point system, the enhanced results show a well-distinguished realization of different body movement activities using a wearable attire array and the interpretation consistently results in significant and identifiable thresholds.

Keywords:

Bio-Signal Processing, Fractal Dimension, Naïve Bayes, Remote Monitoring, Wearable Computing

1. INTRODUCTION

The ever increasing demand for care takers of children and the lonely staying pregnant women is alarming the need for a technical solution. At the same time the cost involved and the complexity of such system also posing a demand of technical support from research community. The high demand for such personal care takers and the scarcity of expertise and the wage cost involved makes it always an unfeasible target for the families, care homes and healthcare organizations. To overcome this issue of care givers, an automated care taking and or a robotic support would be of a precise and appropriate solution. In order to achieve this best classifier is essential. In our preliminary experiment we used naive bayes to classify different types of features. The ultimate aim of this proposed work is to identify the best classified feature types suitable for the naive bayes classifier. Hence in this proposed work, electrodes-

embedded wearable attire is used to capture the gait [22] and body movements of a subject. The aim of this proposal is to capture the variations precisely communicated during the desired and undesired states of a subject to the care taker. It includes passing information to automated care taking system or a robotic assistance in modern healthcare, by reading the gesture signals made by the subjects.

The usage of such digital conversions from the body and limbs movements can go beyond human visual understanding or mere communication interfaces. The proposed system consists of an array of electrodes embedded in a wearable jacket which captures the postures of the body and their movements continually. This system can overcome the limitations of human's aid due to tiredness and lack of timely service in taking care of children and pregnant women. The dress can be worn on or under the normal dress of the subjects and the data are continually transmitted through the wireless transmission and recorded on desired intervals of monitoring space. The Naïve Bayes (NB) classifier is used to classify the feature components extracted by assorted methods like Fractal Dimension (FD), Singular Value Decomposition (SVD), Fast Fourier Transformation (FFT) and their combinational features to analyze the strengths of the signals during safe and unsafe zone gestures of toddlers as well as the best suitable feature for this purpose which can be precisely classified by the Naïve Bayes [4] [10] [19]. The purpose of the work is to identify the best feature extraction method to suit the Naïve Bayes classifier by the best percentage of classification. All the feature set values were calculated based on the differences in danger zone gestures that are different from safe zone gestures.

2. METHODS

2.1 RELATED WORK

The technology supporting the analysis of human motion have provided us with significant knowledge about the accuracy of tests performed, the understanding of the process of human locomotion, and how clinical testing can be used to evaluate medical disorders and affect their treatment. Gait analysis is now recognized as clinically useful and financially reimbursable for some medical conditions [23]. Gait analysis has had its greatest clinical value as a test for individuals with central nervous disorders associated with spasticity, especially children with cerebral palsy (CP). To prevent deformity and increase mobility, various medications, non-surgical therapy regimens, bracing, assistive devices, and/or orthopaedic and neurosurgical

procedures are prescribed for these children. Minimizing the testing time and applying analytic methods and computer programming techniques to the evaluation and reporting of locomotor disorders is feasible and will greatly enhance the proficiency of gait laboratories [15]. The paper also refers to a brain computer interface (BCI) system provides a communication channel between a brain and a computer by passing the need for muscular means [26]. Electroencephalography based BCI systems that utilize the P300 speller paradigm are commonly used but due to the nature of the P300 speller paradigm; these systems are prone to erroneous classification [25].

Data were collected using 64 electrodes. In order to reduce the dimensionality of the samples and extract their significant analysis, principal component analysis (PCA) was applied to the training set for each of the selected electrodes independently [17] [26]. This paper also relates a Wireless Wearable EEG/ECG Biometric System based on the ENOBIO Sensor. The results show that the authentication of people from physiologic data can be achieved using techniques of machine learning. Concretely it shows that the fusion of two (or more) independent biometric modules increases the performance of the system by applying a fusion stage after obtaining the biometric scores. It also shows that processing the different physiological modalities separately on different processing modules, and introducing a data fusion step, the resulting performance can be increased. Applying a very similar approach, we could easily adapt the system to do emotion recognition from physiological data, or develop a Brain Computer Interface, just starting from different ground truth data. From our point of view, this easy to extend feature of our system is the more interesting part of our study along with the ‘personal classifier’ approach which improves considerably the performance of the system [23]. Video cameras, Optoelectronic systems, Electromyography (EMG), Inertial systems are various technologies which are used to capture Gait analysis techniques. In this paper we have captured signals using wearable attire/jacket as the technologies used previously are not accurate and cost and time consuming.

Data captured from five subjects of toddlers and 5 subjects of pregnant women and using feature extraction of FFT and classified as safe and unsafe for toddlers and Normal and contra for pregnant woman using the classifier Smithies has been explained briefly in the forthcoming sections.

The number of subjects is not a criterion for accuracy or procedural validity. Since the experiment is dealing with every individual on a customized basis. Only the difference between a particular subject’s states does matters.

2.1.1 Setting up Wearable Attire and Experiments:

Wearable attire, also known as body-borne computers are miniature electronic devices that are worn by the bearer under, with or on top of clothing. Wearable computers are especially useful for applications that require more complex computational support than just hardware coded logics. The main feature of a wearable computer is consistency. There is a constant interaction between the system and user, i.e. there is no need to turn the device on or off. It can therefore be an extension of the user’s mind and/or body. The interaction between the human and computer technologies increasingly provides natural ways to operate and communicate with machines. Ranging from speech to vision, all the standalone to

wearable interaction technologies help to change the way how people operate computers [3]. With all these interaction methods, Gait analysis takes an important and unique role in human locomotion[1]. Gait analysis is the systematic study of human motion, using the eye and the brain of observers, augmented by instrumentation for measuring body movements, body mechanics, and the activity of the muscles[21]. Gait analysis involves measurement, where measurable parameters are introduced and analyzed, and interpretation about the subject is drawn.

As an enhancement to the concept, here in this research work we took the gait and gesture combinations by capturing the body movements of the subjects in different states of their routine day to day activities. All normal actions of conventional daily life environments were used to show the contrast in the emergency state where it is classified as danger zone activities for toddlers/children and contra pain timing for pregnant woman respectively. Data from five healthy subjects, including one female subject, in the case of children and all 5 female in the case of pregnant subjects were taken into account. The average age of Children is 3 and the average age of pregnant women is 30.5. The electrode embedded attire is worn as a jacket by all ten subjects involved in both the category. In all experimental paradigms, an electrodes-embedded wearable jacket is used to capture the body movements of the subjects.

The Electrodes used are Ag electrodes embedded on Lycra material, and the positions of its impression may vary from subject to subject based on the dimensions of their abdomen for pregnant women and in the body of the toddler as shown in Fig.1 and Fig.2. A set of 14 electrodes fixed on the wearable attire of the subjects were used to record the body movement signals and measurements were taken for 5000 milliseconds (5seconds) in regular intervals. The raw signal data were recorded from the wearable monitoring interface of the subjects by 14 electrodes. Data obtained from 14 electrodes have larger values hence the data has to be normalized. Linear techniques limit the feature values in the range of [0, 1] or [-1, 1] by proper scaling [12] [13] [20]. The data captured from the 14 electrodes has been normalized to -1 to +1 range to fit to a scale. Secondly, the data were down sampled to an effective sampling frequency of 64 Hz from 1024Hz [15] [9]. The dimension of each feature signal, A was n by m , where n was the number of electrodes and m was the number of sequential samples in one signal set. N and m were fixed as 14 and 250 throughout the experiment. The gait and body movements are categorized by capturing the signals from the electrodes of the smart attire for all five subjects into safe and unsafe or critical states. The captures sample size of each sample matrix for five seconds varies between 250 to 256, and the column size is 14. In this experiment a uniform row size 250 is taken throughout.



Fig.1. Position of the sensors embedded in the body of Children



Fig.2. Position of the sensors embedded in the body of pregnant Women

2.1.2 Feature Extraction Varieties:

Feature extraction for this work is done to significantly simplifying the representation of input signal by reducing its dimensionality while acquiring its relevant characteristics to the maximum for the desired task. After the pre processing butter worth band pass filter the signals were subjected to four categories of feature extraction. The fourth category of combinational features follows the third methods.

2.1.2.1 Fast Fourier Transformation:

The application of FFT on these signals is to compute the Discrete Fourier Transform (DFT) and its inverse using the butterfly method is explained in the Eq.(1) & Eq.(2) [11]. It is much faster than the DFT and it supports for the huge datasets where N may be thousands or millions. In this novel method the FFT is applied to the first two channel values as a sampling method [6]. The FFT features were in turn representing the actions of the subjects. This helps to represent the presence of the important gesture component and its strength.

Each signal is represented as the best electrode selection and forms the feature by

$$A = a + bW_N^k \quad (1)$$

The product bW_N^k is added to the feature a to form new feature vector AW_N^k is a phase factor. The product bW_N^k is subtracted from feature a to form new feature vector B.

$$B = a - bW_N^k \quad (2)$$

2.1.2.2 Fractal Dimension:

The Fractal Dimension of the pre processed signals was done using the Katz's method for estimating the features. The sum and average of the Euclidean Distance between the successive points of the sample (L – sum of Euclidean Distance between successive points of samples and an average of Euclidean Distance between successive points of samples) are calculated as well as the maximum distance between the first point and any other point of sample (d) [2] [24]. The fractal dimension of the sample (D) then becomes [18]

$$D = \frac{\log(L/a)}{\log(d/a)} = \frac{\log(n)}{\log(n)+\log(d/L)} \quad (3)$$

where, n is L divided by a .

Fractal dimension (FD) is a very effective tool applied in many quantification processes which helps to evaluate feature

spaces. The results of FD in time domain depend on the algorithm and window length [2, 7]. One of the advantages of fractal analysis is the ability to describe irregular and complex objects. Fractal analysis wearable attire signals were carried out and used as the features for this experiment.

2.1.2.3 Singular Value Decomposition:

SVD is a matrix factorization technique commonly used for producing low-rank approximations. Usually SVD calculated for a matrix results in a feature vector of reduced dimension. Given an $m \times n$ matrix A , with rank r , the singular value decomposition, SVD (A), is defined as,

$$SVD(A) = USV^T \quad (4)$$

where, U , S and V are of dimensions $m \times m$, $m \times n$, and $n \times n$, respectively. Matrix S is a diagonal matrix having only r nonzero entries, which makes the effective dimensions of these three matrices $m \times r$, $r \times r$, and $r \times n$, respectively [8]. U and V are two orthogonal matrices and S is a diagonal matrix, called the singular matrix [1]. The SVD method is used to reduce the overlapping noise artifacts. The use of SVD also reduces the feature size and simple distance based classifier (with two thresholds) is capable of availing this reduced feature set [14]. The SVD is applied on the two channels of raw signals derived out of filtered signals from the 14 channel, attire and are classified by Naïve Bayes.

2.1.2.4 Combinational Features:

While composing combinational features like FD-FFT and FFT-SVD we used the creation method as referred in Eq.(4). We formed the combinational feature by adopting the fusion technique with the partial feature component of FFT along with FD and SVD. The contribution of these two techniques to the new feature is given by,

$$f_c = \left\{ \frac{f_1}{2} + f_2 \right\} \quad (5)$$

where, $f_{1/2}$ is the feature of the signal by FFT and f_2 is the feature through FD or SVD. So the f_c is the combinational feature used for clustering in the third part of the experiment. In the case of FD and SVD combination, we used FD feature as f_2 and SVD feature as f_1 and used the same Eq.(5) to construct the feature f_c .

2.1.2.5 Naive Bayes Classification:

The Naive Bayes classifier combines this model with a decision rule. One common rule is to pick the hypothesis that is most probable; this is known as the maximum a posteriori decision rule [4]. The advantage of Naïve Bayes classification is that the precise number of features falls under both the categories can be found. The corresponding classifier, a Bayes classifier, is the function *Classify* defined as follows:

$$Classify(x_1, x_2, \dots, x_n) = \arg_c \max p(C = c) \prod_{i=1}^n p(X_i = x_i | C = c) \quad (6)$$

where, C is a dependent class variable and x_i is a feature variables.

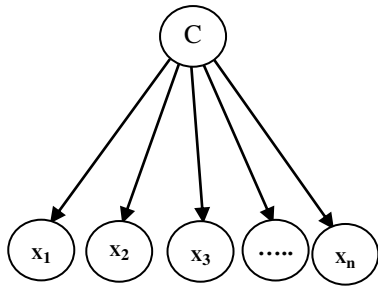


Fig.3. Naïve Bayes Classifier

The simple structure of Naïve Bayes is shown in Fig.3. Where, the root node C represents different classes and the child nodes are X_1, X_2, \dots, X_n represent different components or features of a sample. NB assumes all the feature nodes are independent of each other given the class, and typically, the feature variables are assumed to have Gaussian distribution if they are continuous. NB has worked quite well in many complex real-world situations. Compared to other complex graphical models, it requires smaller amount of training data to accurately estimate the parameters necessary for the classification [5].

3. RESULTS

In the first experiment with pointing system, the results of feature sets FFT, FD-FFT, FFT-SVD, FD, SVD and FD-SVD combo features based classification of safe and danger zone of children as well as the normal and contra situation of the pregnant women are shown in Table.1. The results are from individual and the other combinational features that were classified through Naïve Bayes Classifier.

It is found and shown in Table.1, that the performance of FFT-SVD is better than all the other four features.

In the Naïve Bayes classification percentage error is subtracted from 100% and is taken as percentage of classification. Table.1 showing that the classification rate is increased in the combinational feature FFT-SVD and this is the good result as compared to the other features set. The point values of Naïve Bayes classifier for danger and safe zone were taken from all the feature sets and the point value is used for the percentage calculation.

A twofold training and testing was conducted by dividing the feature sets by interchanging the test features on both iterations. The average classification percentage is given in Tables.1, 2 and 3.

Table.1. Classification by Naïve Bayes

| Feature Set | Points | Naïve Bayes % of classification |
|-------------|--------|---------------------------------|
| FFT | 46 | 80.5 |
| FFT&FD | 46 | 79.6 |
| FFT&SVD | 48 | 99 |
| FD | 48 | 76 |
| FD&SVD | 46 | 94 |

The percentage of classification is given in the Table.1 is based on the pointing system that is used to enhance the results. The point system support is act as a priori that supports the classification decisions. When the points are removed the

weights fall under the actual percentage of classification with reduced in Table.2.

Table.2. Classification by Naïve Bayes without Pointing System

| Feature Set | Naïve Bayes % of classification |
|-------------|---------------------------------|
| FFT | 76.6 |
| FFT&FD | 76.6 |
| FFT&SVD | 80 |
| FD | 80 |
| FD&SVD | 76.6 |
| SVD | 67 |

In the Table.2 it is observed that the classification of features by naïve bayes classifier in the case of FFT&SVD combination and for the feature constructed only through FD seems equal. While considering a complexity in the use of combinational features the single feature FD seems beneficial more than one way. Hence a new priori may be set and applied to FD alone and the results can be enhanced. Such an experiment is carried out and the enhance results of FD with the new priori is given in Table.3.

Table.3. Classification by Naïve Bayes with- Priori Pointing System

| Feature Set | Points | Naïve Bayes % of classification |
|-------------|--------|---------------------------------|
| FFT | 48 | 76 |
| FFT&FD | 40 | 80 |
| FFT&SVD | 47 | 79.6 |
| FD | 50 | 90 |
| FD&SVD | 40 | 80 |
| SVD | 48 | 76 |

4. DISCUSSIONS

The basic idea of this work is to find the abnormal gestures through the emergency situation recognizing system which clearly specifies the situation of the children, and pregnant woman from their usual normal activities. The differences in gesture activities which result in a significant deviation in classification distance are found to be the key in the identification of the emergency situation. These differences in terms of signal features helps to distinguish the condition of the subject from their safe or unsafe zone in the case of children, normal or contra pain in the case of pregnant women. The proposed work is capable of initiating crucial responses by an automated care taking system or a robotic assistance or a remote assistance.

5. CONCLUSION

To conclude, all the features including the proposed combinational features confirms that the perfect classification rate improved significantly in both the paradigms of children and pregnant women. This is realized based on the exact positioning and normal-contra, safe-unsafe differences reflected in the features. As compared with FFT-SVD combinational feature the FD is the best than all the other features used in this experiment.

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