Research Journal of Applied Sciences, Engineering and Technology 7(23): 4917-4926, 2014
DOI:10.19026/rjaset.7.883
ISSN: 2040-7459; e-ISSN: 2040-7467

Submitted: December 18, 2013 Accepted: January 20, 2014 Published: June 20, 2014

Research Article

Stable and Critical Gesture Recognition in Children and Pregnant Women by SVM Classification with FFT Features of Signals from Wearable Attires

[1]A. Sheryl Oliver, [2]N. Maheswari and [3]Andrews Samraj
[1]Department of Computer Science and Engineering, St. Joseph's College of Engineering,
[2]School of Computing Science and Engineering, VIT University,
[3]Department of Information Technology, Mahendra Engineering College, India

Abstract: The aim is to identify stable and critical recognition in children and pregnant women by wearable interface based monitoring system. The objective of this research proposal is to identify safe and danger zone prediction in toddler and normal and contra pain in pregnant women. The technology supporting this analysis of gesture has advanced dramatically. Past decades of remote health care monitoring have provided us with significant knowledge about the accuracy of tests performed. Mainly motivated by increasing healthcare costs and propelled by recent technological advances in miniature bio sensing devices, smart textiles, microelectronics and wireless communications, the continuous advance of wearable sensor-based systems will potentially transform the future of healthcare by enabling proactive personal health management and ubiquitous monitoring of a toddler and pregnant women health condition.The remote healthcare monitoring on a care taking base involves many implicit observations between the subjects and the care takers. Any ignorance and negligence leads to unpleasant situations thereafter. A simple 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 methodology suggests a novel way of identifying safe and unsafe conditions of playing for the children as well as normal and critical situations of pregnant women where a medical assistance is desperately required. The experimental results show a well-distinguished realization of different body movement activities using a wearable attire array medium and the interpretation results always show significant and identifiable thresholds.

Keywords: Affective-gesture computing, bio-signal processing, remote monitoring, wearable computing

INTRODUCTION

The demand for care takers for children and the lonely staying pregnant women is so essential and of high importance. At the same time the cost involved and the scarcity of expertise is also started increasing. 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. Hence in this proposed study, electrodes-embedded wearable attire is used to capture the gait 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.

LITERATURE REVIEW

The technology supporting the analysis of human motion have provided us with significant knowledge about the accuracy of tests performed, the

Corresponding Author: A. Sheryl Oliver, Department of Computer Science and Engineering, St. Joseph's College of Engineering, India

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. 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 (Stacy and Paradiso, 2002). Minimizing the testing time and applying analytic methods and computer programming techniques to the evaluation and reporting of loco-motor disorders is feasible and will greatly enhance the proficiency of gait laboratories (Ng *et al*., 2009). After signal acquisition the processing steps such as pre-processing, dimensionality reduction. Dimensionality reduction methods are innovative and important tools in machine learning (Scholkopf *et al*., 1996, 1995). Beckmann *et al*. (2010) investigated the characteristics of textile electrodes for measuring ECG and made a specification comparison between different textile electrodes. Lin *et al*. (2011) developed dry foam electrodes to monitor long-term EEG. Although these novel dry electrodes can measure bio-potentials without conductive gels, contact with the user's skin and thus risk of irritation, is still necessary. Different from the conventional wet electrodes and dry electrodes, which tend to minimize the skin electrode interface impedance, non-contact electrodes, developed by the concept of coupling capacitance, were also proposed for wearable sensing devices recently. Oehler *et al*. (2008) developed capacitive electrodes on a multichannel portable ECG system. Matsuda and Makikawa (2008) proposed a capacitive coupled electrode for ECG monitoring in car driving. Baek *et al*. (2012) also used active electrodes to develop a health monitoring chair for long-term ECG monitoring. Eilebrecht *et al*. (2010) designed a 3 X 3 electrode matrix for monitoring ECG. Chi *et al*. (2010) combined the input capacitance cancellation circuit and the bootstrap circuit with the active electrode to develop non-contact electrodes for ECG and EEG monitoring. Due to the advantages of measuring bio-potentials across clothing, it may be practicable to embed non-contact electrodes in a user's normal clothing to monitor the user's ECG in daily life (Lin *et al*., 2009). A wide variety of techniques and algorithms are found in the literature to classify measurements for posture and movement recognition. Most of them are based on traces collected using accelerometers and gyroscopes. Techniques range from feed-forward back propagation neural network (Scholkopf *et al*., 1996, 1995) discrete wavelet transforms (Xu and Lu, 2006), Support Vector Machine (SVM) techniques and hidden Markov models. In this study, SVM classification technique is implemented to recognise different activities, due to its success in many classification problems (Zhang *et al*., 2009; Kamel *et al*., 2008). SVM is both a linear and a nonlinear classifier which has been successfully applied in many areas such as handwritten digit recognition and object recognition (Scholkopf *et al*., 1996, 1995). SVM has been exploited to do channel and modulation selection, signal classification and spectrum estimation (Blanz *et al*., 1996). Xu and Lu (2006), a method for combining feature extraction based on spectral correlation analysis with SVM to classify signals has been proposed.

In this study, SVM method will be explored as a classifier for measured signal data. Data captured from 5 subjects of toddlers and 5 subjects of pregnant women have used to extract the features using FFT and classified as safe and unsafe for toddlers and Normal and contra for pregnant woman using the classifier. Smithies have been explained briefly in the forthcoming sections. Our purpose is not to present a finely tuned and well-engineered algorithm, but to show that standard classification methods have the potential to solve the problem with acceptable accuracy.

METHODOLOGY

Wearable attire and experiments: The latest innovations in wearable attire and systems have resulted from significant research efforts to fabricate wireless, unobtrusive devices.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 computer 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. With all these interaction methods, Gait analysis takes an important and unique role in human locomotion (Guraliuc *et al*., 2011). 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 (Sergios and Konstantinos, 2009). 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 study we took the gait and gesture combinations by capturing the body movements of the subjects in different states of their routine day to day

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

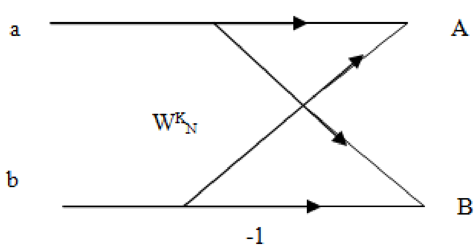


Fig. 3: Flow graph of fast Fourier transform

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 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 (5 sec) 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. 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 1024 Hz (Sheryl *et al*., 2013). 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 of the 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.

The feature extraction is done on all the captured signal samples by Fast Fourier Transformation (FFT). The data signals due to its sampling rate are voluminous (Ibarguren *et al*., 2010) in nature and the use of 14-electrode attire is also another cause for the volume; hence to reduce the dimensionality of the data signals to be used for comparison the FFT is applied on the signal window taken by omitting the first 10% and the last (Lee and Verleysen, 2007). In this feature vector estimation the Squared Euclidean Distance is calculated among the set thresholds and are considered as features for SVM classification of classes (Ng *et al*., 2009). The thresholds were selected based on our preliminary experimental simulation trials.

Fast Fourier Transform (FFT): A Fourier Transform converts a wave in the time domain to the frequency domain. The Fast Fourier Transform (FFT) is the most common method for determining the frequency spectrum of the signal. FFT is a simply a method of laying out the computation, which is much faster for large values of N, where N is the number of samples in the sequence. The FFT is a faster version of the Discrete Fourier Transform (DFT). The FFT utilizes some clever algorithms to do the same thing as the DTF, but in much less time. The FFT butterfly is a graphical method of showing multiplications and additions involving the samples. Standard graph flow notation is used where each circle with entering arrows is an addition of the two values at the end of the arrows multiplied by a constant. The constant is a number which appears beside the arrow, if there is no value then the constant is taken as one. Here's a simple example that multiplies the two inputs and adds them together. Figure 3 shows the fundamental building block of a butterfly. It has two input values x(0) and x(1) and the result in two output values F(0) and F(1).

Fast Fourier Transform is used to approximate the given data to plot the support vectors:

Let, S be the set of discrete items with N items as maximum:

$$S = \{s^{k}_{i,} s^{k+1}_{i+1}, \ldots s^{K}_{N}\} \quad (1)$$

The Fast Fourier Transform of set S can be calculated as:

$$\text{FFT}(S) = \{A, B\} \quad (2)$$

where,

$$A = a + bw^{k}_{N} \quad (3)$$

$$B = a - bw^{k}_{N} \quad (4)$$

where,

a = s^{k}_{i}
b = s^{k+1}_{i+1}
w^{nk}_{N} = $e^{-j2\pi nk/N}$
i = The number of elements in S taken for calculating FFT (Bruce *et al*., 2002)

Here, radix-2 FFT algorithm is employed based on the stage of computation the K value varies from 0, 1, 2, 3 and N is the total number of available data.

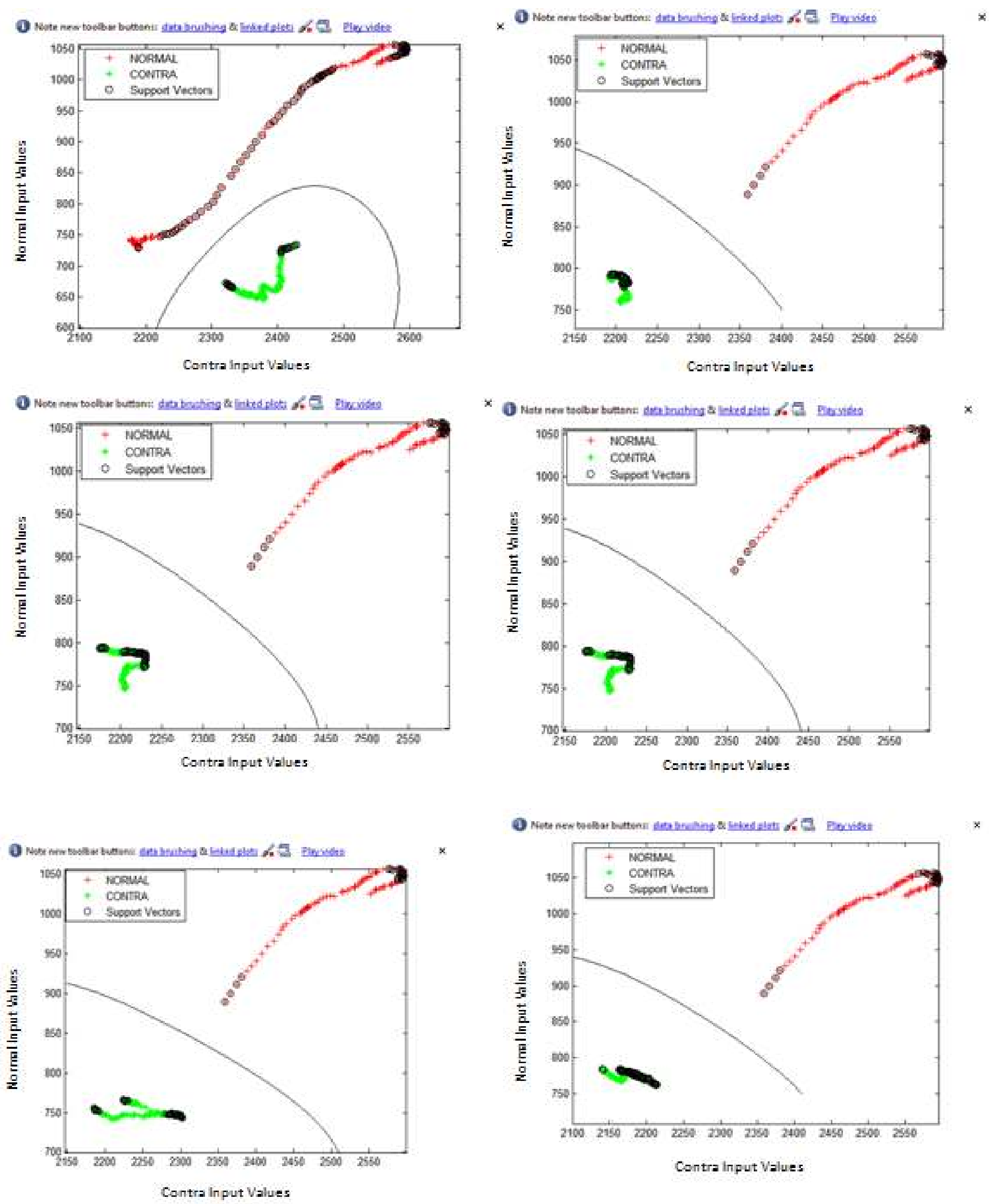


Fig. 4: Classification of average FFT features of normal and contra of subject 1, subject 2, subject 3, subject 4 and subject 5

Support Vector Machines (SVM): Classification is a procedure that assigns a given object to a given number of classes. A classifier is trained using a training dataset, where the class of each object is known. After training, the classifier should be able to assign a new object to its right class: in the testing phase, the classifier is applied to a testing dataset. By comparing the classifications made on the testing dataset, the performance of the classifier is evaluated. Most classifiers work in a feature space, which is a multidimensional space, where each object is represented by a point (Stephen, 2009).

In the feature space, the coordinates of the point are the values of the object's features. A feature can be any quantity that is significant for the object. Usually, features are normalized, so that all points lie in the unity hypercube of the feature space. The most important step in classification problems is the choice of relevant features. The number of features should be as low as possible to avoid over fitting and reduce computational complexity. Their number should be sufficient to distinguish the objects, namely to assign each trace point to the right class (Guraliuc *et al*., 2011).

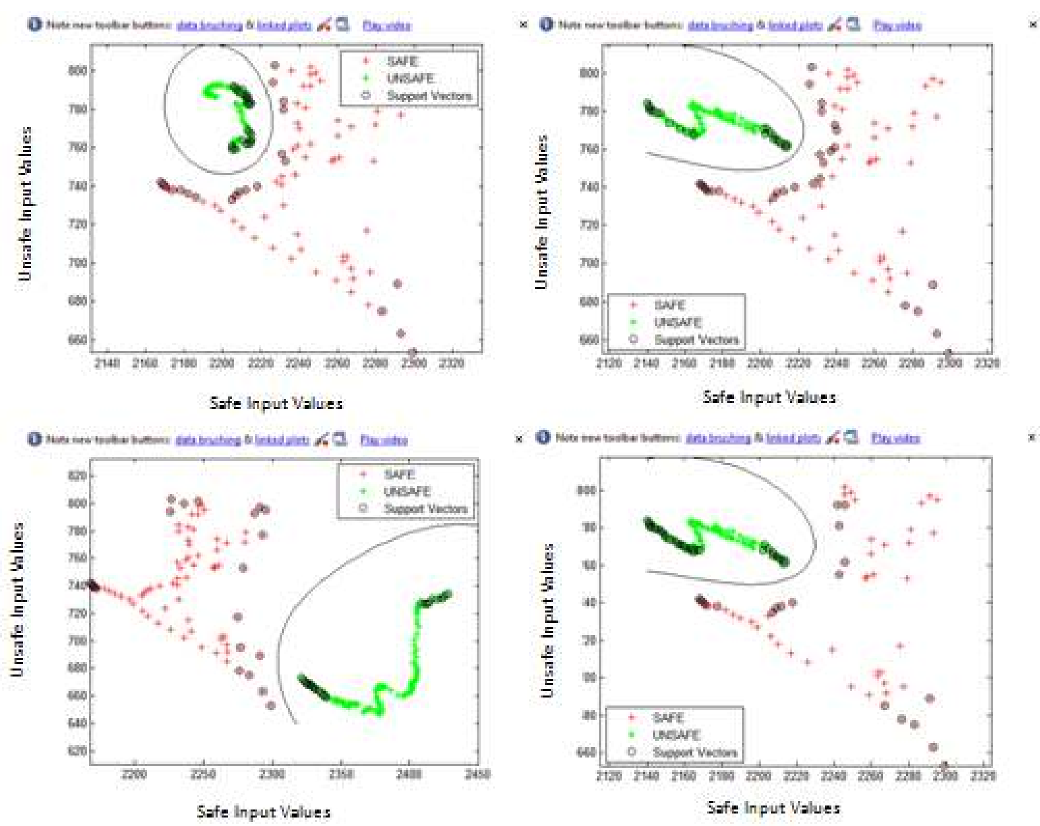
The techniques used here are based on Support Vector Machines (SVM). SVMs are machine learning strategies which use a robust cost function. A support vector machine is a distinctive approach to pattern classification and regression, since it tackles the principle of structural risk minimization. The central idea of SVM is the adjustment of discriminating function so that it optimally uses the severability information of the boundary patterns (Cortes and Vapnik, 1995). A linear discriminating function and two linearly separable classes with target values +1 and -1.

A discriminating hyper plane will satisfy:

$$w'x_i + w_0 \geq 0 \text{ if } t_i = +1 \quad (5)$$

$$w^{\prime xi} + w_0 < 0 \text{ if } t_i = -1 \quad (6)$$

The distance of the closest pattern to it is called margin of seperation. When a data exactly have two classes we can apply SVM classification. The classification is done by finding out the best hyper plane that separates all data points between one class and another class. For that first we have to train the data then use the trained data to classify new data. The encircled data shown in Fig. 4 to 8 are the support vector that is close to the hyper plane. Radial Basis Function (RBF) method of SVM is based on the exact interpolation method of determining a function h(x) that will fit the target values t_i. RBF has the best approximation property and it is used to classify the data in this study. In order to make the outputs more finely grained, RBF is added at relevant positions and reduce the radius of respective fields. It maybe also recognized as the squared Euclidean distance.



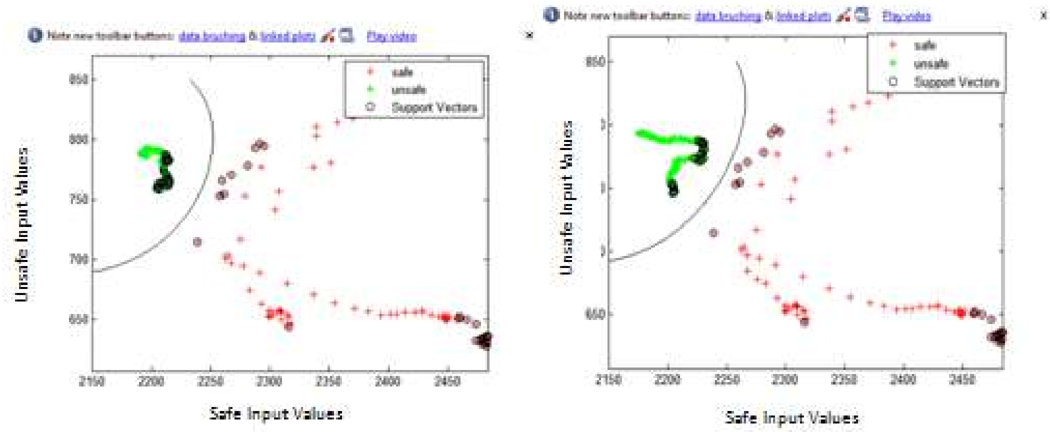


Fig. 5: Classification of average FFT features of safe and unsafe average of subject 1, subject 2, subject 3, subject 4 and subject 5

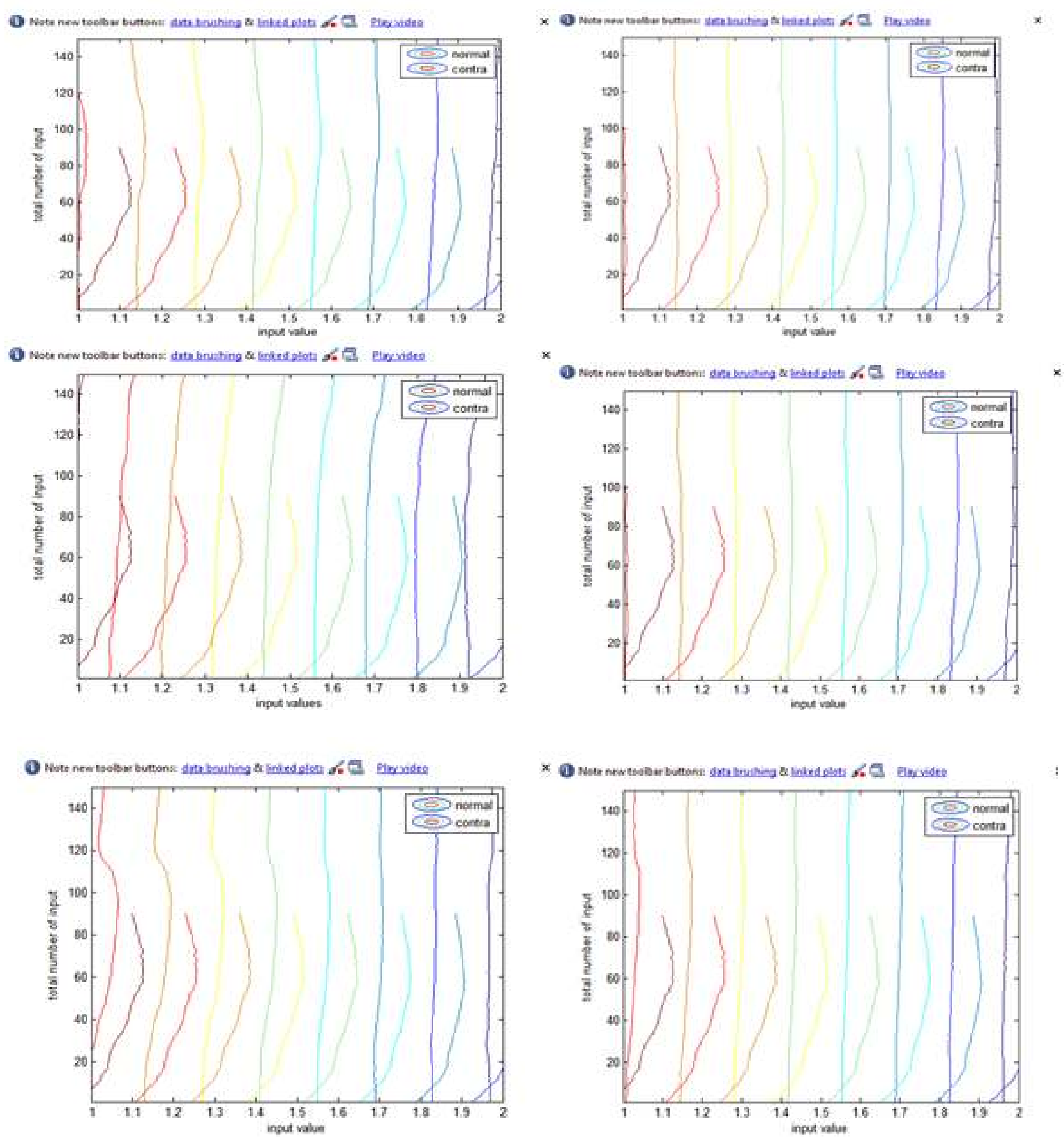


Fig. 6: Comparision of average FFT features of normal and contra of subject 1, subject 2, subject 3, subject 4 and subject 5

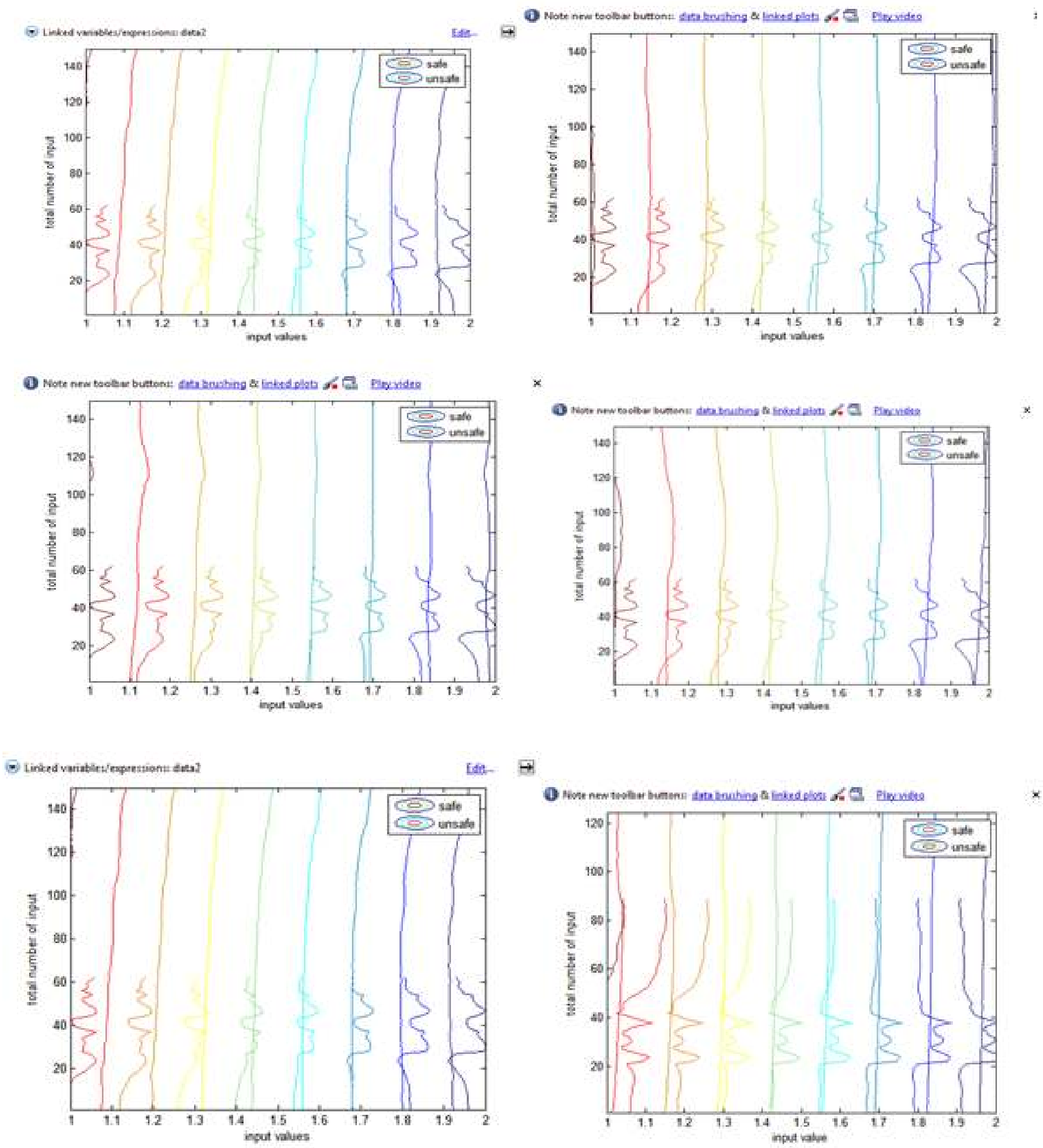


Fig. 7: Comparison of average of FFT features of safe and unsafe of subject 1, subject 2, subject 3, subject 4 and subject 5

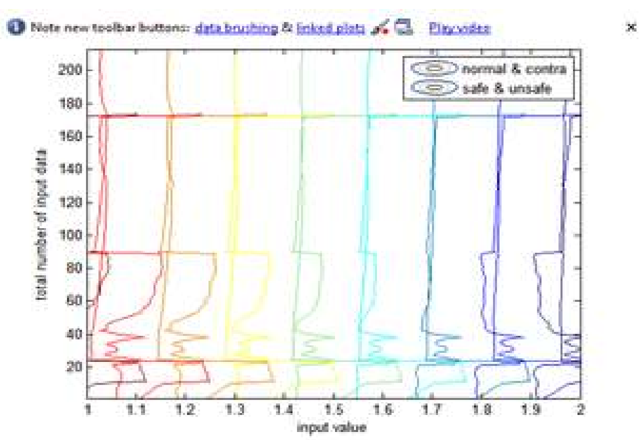


Fig. 8: Comparison of Average FFT features of all subject normal, contra, safe and unsafe

EXPERIMENTAL RESULTS

The FFT features were calculated for each subject of Normal, Contra, Safe and Unsafe subjects. The FFT features of all signal samples were calculated. The input parameters are divided into training,crossvalidation and the graphs were plotted by SVM classification technique using the Squared Euclidean Distance. In general the Square Euclidean distance between two points, *a* and *b*, with *k* dimensions is calculated as:

$$\sum_{j=1}^{k} (a_j - b_j)^2 \tag{7}$$

The analysis for match or overlap possibilities were ardently observed by comparing the classification distance among various paradigms of intra as well as inter subjects.

Squared Euclidean Distance is used to measure the distance between each set of FFT values. In general, the Squared Euclidean space is given as, (Ibarguren *et al*., 2010):

$$K(x, x') = \exp\,(\gamma||x - x'||_2^2) \tag{8}$$

Here the points x and x' represents the set of FFT values extracted using the signals during the experimental calculations. Squared Euclidean Distance is calculated for the reference and the other FFT values using the Eq. 3 and 4. The work has been carried out using MATLAB.

Group = svmclassify (SVMStruct, Sample, 'Show plot', Show plot Value) Group = svm classify (SVMStruct, Sample, 'Showplot', Showplot Value) controls the plotting of the sample data in the figure created using the Show plot property with the svmtrain function.

The following figure shows the classification of Support Vector machine (SVM), average Squared Euclidean distance between the FFT features of Normal and Contra belongs to subjects including all experimental trials.

Figure 4 shows the classification of Support Vector Machine (SVM), the average Squared Euclidean distance between the FFT features of Normal and Contra belongs to Subject 1 to Subject 5 in all experimental trials is given.

Figure 5 shows the classification of Support Vector Machine (SVM), the average Squared Euclidean distance between the FFT features of Safe and Unsafe belongs to Subject 1 to subject 5 in all experimental trials.

Figure 4 and 5 shows the support vectors and the hyper plane which separates both the classes. A hyper plane is a linear decision surface that splits the space into two parts. The distance separating the classes is 2/|w|, the optimal hyper plane therefore is the one for which |w| is minimal. The hyper plane which divides the two classes and there is good margin which separates two classes gives the accuracy in identifying the Normal and contra of a pregnant woman and safe and danger zone for the movement of toddler.

The following figures show the comparison of average FFT features of all the subjects. Figure 6 clearly shows the comparison of Normal and Contra when it's plotted against total number of input and the input values (Fig. 7).

The graph in Fig. 8 represent the average comparison Squared Euclidean distance of FFT values of the Normal, Contra, Safe and Unsafe belongs to all subjects.

The average of FFT features of each subject is computed and then the average of all subjects is taken and graphs are drawn.

DISCUSSION

The research idea of this study 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 expected normal activities. The difference in gesture activities which result in a significant deviation in Euclidean distance are found to 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.

The FFT features for every single subject were calculated for both the safe-unsafe, normal-contra paradigms and the results were produced. The average FFT are calculated for all the five subjects under all paradigms and individually represented in graphs. For in depth study and verification, the produced results are further compared in various combinations with all subjects inter relatively and the results ensure a clear diversification of features between different gestures.

The maximum diversification in squared Euclidean distance by means of non overlapping features of different gestures were identified to select gesture that are suitable to be adopted for an error free automated care taking and/or robotic assistance system developments.

It is evidently shown for subject 5 in Fig. 4 that the Normal and Contra are set apart in a wide range of distances, the same trend continued to all other subjects and is important to note here. The reason for cross comparison done between different paradigms of different subjects is to ensure the uniformity of gesture variations irrespective of subjects.

Another important point to note is the FFT features behave in the same direction when used in calculating the Squared Euclidean distance for classification and provide the same end result.

CONCLUSION

The affective gesture movements capturing suggested in this study during Normal, Contra, Safe and Unsafe among two types of users like children and the pregnant woman are found to be a successful way of implicit response communication by the acquired experimental results. The proposed method is free from any training, learning or brain activity etc. and no complex functions involved. Hence wearable attire with sufficient electrodes is much useful for this implicit safety monitoring system for the toddlers and pregnant women who need protective surveillance system as it captures the signals that are generated by the mere physical gestures and body movements. The experimental results obtained by the methodology show the significant variation among the signals when the subject is under different state. This system can be simplified in terms of cost, enhanced as a people-friendly and easy accessible robotic control system in healthcare, for increasing confidence in people for taking care of their kith and kin in any challenging situations when left alone.

ACKNOWLEDGMENT

We acknowledge ASTRC, India for providing the dataset for our research.

REFERENCES

Baek, H.J., G.S. Chung, K.K. Kim and K.S. Park, 2012. A smart health monitoring chair for nonintrusive measurement of biological signals. IEEE T. Inf. Technol. B., 16(1): 150-158.

Beckmann, L., C. Neuhaus, G. Medrano, N. Jungbecker, M. Walter, T. Gries and S. Leonhardt, 2010. Characterization of textile electrodes and con-ductors using standardized measurement setups. Physiol. Meas., 31(2): 233-247.

Blanz, V., B. Scholkopf, H. Bulthoff, C. Burges, V. Vapnik and T. Veter, 1996. Comparison of view-based object recognition algorithms using realistic 3D models. Lect. Notes Comput. Sci., 1112: 251-256.

Bruce, L.M., C.H. Koger and L. Jiang, 2002. Dimensionality reduction of hyperspectral data using discrete wavelet transform feature extraction. IEEE T. Geosci. Remote, 40(10): 2331-2338.

Chi, Y.M., T.P. Jung and G. Cauwenerghs, 2010. Dry-contact and noncontact biopotential electrodes: Methodological review. IEEE Rev. Biomed. Eng., 3: 106-119.

Cortes, C. and V. Vapnik, 1995. Support-vector networks. Mach. Learn., 20(3): 273-297.

Eilebrecht, B., A. Schommartz, M. Walter, T. Wartzek and M. Czaplik, 2010. A capacitive ECG array with visual patient feedback. Proceeding of annual International Conference of the IEEE Engineering Medicine and Biology Society (EMBC, 2010), pp: 6539-6542.

Guraliuc, A.R., P. Barsocchi, F. Potort`ı and P. Nepa, 2011. Limb movements classification using wearable wireless transceivrs. IEEE T. Inf. Technol. B., 15(3): 474-480.

Ibarguren, A., I. Maurtua and B. Sierra, 2010. Layered architecture for real time sign recognition: Hand gesture and movement. Eng. Appl. Artif. Intel., 23(7): 1216-1228.

Kamel, N.S., S. Sayeed and G.A. Ellis, 2008. Glove-based approach to online signature verification. IEEE T. Pattern Anal., 30(6): 1109-1113.

Lin, B.S., W. Chou, H.Y. Wang, Y.J. Huang and J.S. Pan, 2009. Development of novel non-contact electrodes for mobile electrocardiogram monitoring system. IEEE J. Translat. Eng. Health Med., Vol. 1, ISSN: 2168-2327.

Lin, C.T., L.D. Liao, Y.H. Liu, I.J. Wang, B.S. Lin and J.Y. Chang, 2011. Novel dry polymer foam electrodes for long-term EEG measurement. IEEE T. Biomed. Eng., 58(5): 1200-1207.

Lee, J. and M. Verleysen, 2007. Nonlinear Dimensionality Reduction. Springer Verlag.

Matsuda, T. and M. Makikawa, 2008. ECG monitoring of a car driver using capacitively-coupled electrodes. Proceeding of 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBS, 2008), pp: 1315-1318.

Ng, H., W.H. Tan, H.L. Tong and J. Abdullah, 2009. Extraction of human gait features from enhanced human silhouette images. Proceeding of the IEEE International Conference on Signal and Image Processing Applications (ICSIPA, 2009), pp: 425-430.

Oehler, M., V. Ling, K. Melhorn and M. Schilling, 2008. A multichannel portable ECG system with capacitive sensors. Physiol. Meas., 29(7): 783-793.

Scholkopf, B., C. Burges and V. Vapnik, 1995. Extracting support data for a given task. Proceeding of the 1st International Conference on Knowledge Discovery and Data Mining. AAAI Press, Menlo Park, CA.

Scholkopf, B., C. Burges and V. Vapnik, 1996. Incorporating invariances in support vector learning machines. In: von der Malsburg, C., W. von Seelen, J.C. Vorbr´luggen and B. Sendhoff (Eds.), Artificial Neural Networks ICANN'96. Lecture Notes in Computer Science, Springer, Berlin, 1112: 47-52.

Sergios, T. and K. Autrombas, 2009. Pattern Recognition. Elsevier Inc., ISBN: 978-1-59749-272-0.

Sheryl, O.A., A. Amraj and N. Maheswari, 2013. Fuzzy ARTMAP based classification feature for danger and safety zone prediction for toddlers using wearable electrodes. Proceeding of IEEE International Conference on High Performance Green Computing.

Stacy, J.M. and J.A. Paradiso, 2002. A compact wearable sensor package for clinical gait monitoring. OFFSPRING, 1(1).

Stephen, M., 2009. Machine Learning: An Algorithmic Perspective. CRC Press a Chapman and Hall Book, Taylor and Francis Group.

Xu, G. and Y. Lu, 2006. Channel and modulation selection based on support vector machines for cognitive radio. Proceeding of International Conference on Wireless Communications, Networking and Mobile Computing (WICOM, 2006), pp: 1-4.

Zhang, F., X. Jiaotong, Z. Geng and W. Yuan, 2009. The algorithm of interpolating windowed FFT for harmonic analysis of electric power system. IEEE T. Power Deliver., 16(2): 160-164.