Analysis of Chronic Joint Pain using Soft Computing Techniques with Feature Extraction and Classification based on sEMG Signals

[1]Mrs. Shailaja S. Patil, [2]Prof. Dr. Shubhangi B. Patil[2]

[1]Ph.D. Scholar, Shivaji University, Kolhapur, Maharashtra, Assistant Professor, [2]Professor,

[1]Electronics and Telecommunication Engineering Department

[1]Rajarambapu Institute of Technology, Sakharale, Sangli,Maharashtra, , India,415414.

Dr. J. J. Magdum College of Engineering, Jayasingpur, Maharashtra, 416101, India.

ABSTRACT

Joint pain is the one of the major health related problem reported by many numbers of patients. Accurate measurement of pain is not ever having universal standard reference unit of measure and overall subject's pain information solely depends on the survey form only. A study of finding the correlation between EMG signal and pain is the prime moto of current research work. Chronic joint pain especially in the area located at knee and ankle is a severe health concern today. Therefore, multiple clinical remedies have been suggested to get rid of these health problems. Level of pain measurement is a survey type questionnaire on ten-point scaling. Electroencephalogram (EEG) signal is best correlated with the physiological symptoms and overall pain related information, which is global in nature.

Support Vector Machine on processed sEMG data is used for the classification of pain in three different categories like Normal, Moderate and Severe. Performance analysis of present method is validated with the survey pain diagnostic feedback forms.

Keywords: *sEMG signals, SVM, Feature Extraction, Principal Component Analysis*

I.INTRODUCTION

EMG biomedical signal has become more popular to measure muscular activity. Surface electrode method is non-invasive, painless and easy to use with the 0.5 – 1% of the full-scale deflection and no risk to patients. EMG is the basically a technique of obtaining the electrical activity of the contracted muscles. Surface electrode EMG method is used to obtain the data that can be best realized using randomized static stochastic process. Localized muscle fatigue is the sustained contraction and variation in the EMG pattern related with the muscles [103]. This is further leading to time stretching and variation in shape of EMG signal. In addition to these, the EMG signal is used for the various cases such as assessment of physiological muscles, rehabilitation of muscles, medicine related to sports and evaluation of muscles performance. Power spectrum analysis reflects the time stretching and shape variation upon the reception of pain related signals but very difficult to separate this indirect information.

Electromyograms (EMG) signal obtained from localized muscle from the area where the pain is sensed having information of related parameters especially in the power spectrum domain. Chronic pain related pattern of localized muscles can be investigated using frequency domain and power spectrum analysis. However, EMG has the temporal and amplitude information in the pattern of muscles but does not have the linear relationship with the pain. In fact, the indirect information of joint pain in the muscle is hard to isolate from EMG signal. Independent Component Analysis (ICA) of EMG signal is able to distinguish the various data obtained from the surface electrodes and separating the pain related data from EMG signal. The main objective of EMG signal is to investigate muscle activity to access joint pain related patterns.

In the present work sEMG data is directly obtained from patients, hereafter called as subjects that undergoing into some kind of join pain ranging from normal to severe pains. The subjects are from different age ranging from below 20 years to above 71 years and there are total 257 males and 290 females. There are total 150 healthy subjects were recruited for this work that to explore the normal data and contributing a normal type of healthy database. However, the subject's analysis is complex and critical that require even large type of datasets. Datasets classification with or without prior information has been used in many research problems of unsupervised classification. Problem of classification is hard in case of joint pain assessment [81].

II LITERATURE REVIEW

The papers referred for the research work are reviewed here.

Xin Shi, Pengjie Qin et al. proposed feature extraction method based on Principal Component Analysis to improve speed of the classification model and got 3-dimensional eigenvectors and Wavelet Packet Transform to decompose SEMG signals of three muscles of lower limb and got 24 –dimensional eigenvector. Authors adopted scale unscented Kaltman filter (SUKF) and neural network (NN) for lower limb motion classification and showed average accuracy of 93.7%. [2].

J. Mendes, M. Freitas et al. presented comparative study between dimensionality reduction and feature selection to classification problem of six hand gestures by SEMG signal.[3]. The armband with 8 channels was used to acquire signals. Total 29 features from time and frequency domain were extracted. Two methods were presented, first method used Quadratic Discriminant Analysis (QDA) classifier for dimensionality reduction and 80 attributes from Principal Component Analysis (PCA) resulting in 84% accuracy. In second method with 112 attributes and a non-linear SVM with Gaussian Kernel resulted in 91% accuracy. After comparison it is concluded as dimensionality reduction approach presented less computational cost whilst has a lower accuracy compared with feature selection approach.

Somayeh Aftasiabi, Reza Boostani et al. did Quantitative pain measurement using Electroencephalogram (EEG) in five levels.Participants were executed the Cold-Pressor Test (CPT) along with the EEG recordings. Bayesian Optimized support vector machine (BSVM) is was trained at each node of decision tree. Result provided 93.33 % accuracy for five classes. Total 12 features from ALPHA rhythm of EEG namely Mean, Median (. 5 quantile), Trimmed Mean, Skewness, Standard Deviation, Kurtosis, Trimmed SD,α band power, Variance, Area under curve, Negentropy, Range were extracted.[4]

Zengyi Qin, Zhenyu Jiang et.al.proposed deep learning based approach for quantifying the tremor severity of Parkinson's disease (PD) based on surface electromyography sEMG. They designed the S-Net, a light weight and computational efficient convolutional neural network. They used MDS-UPDRS- Movement disorder society-Unified Parkinson's Disease Rating Scale evaluation metrics for quantification of PD tremor severity using sEMG signals.[5]

Wei Song, Qingquan Han et al. proposed wearable smart sEMG recorder integrated gradient boosting decision tree (GBDT) based hand gesture recognition.SEMG signal is collected using a neural signal acquisition analog front end (AFE) chip. The GBDT based neural signal processing unit (NSPU) was implemented on FPGA near the AFE. Extracted features were classified into four categories viz, Time Domain Related Features, Frequency domain features, Autoregression coefficient, Wavelet transformation and others. Selected features were Mean Absolute Value, Simple Square Integral, Minimum Value, Maximum Value, Standard Deviation, Average Amplitude Change, Zero Crossing, Slope Sign Change, Willison Amplitude. Total 12 gestures were recognized with 91% accuracy.[6]

Wenjing Du , Olatunji Mumini Omisore et al. used SEMG surface Electromyography to recognize Chronic Low Back Pain in persons with non-specific symptoms.[7] subjects are asked to perform four functions as forward and backward bending and forward bending, right lateral and left lateral flexion. Total 31 features (19 time-domain and 12 frequency domain) have been extracted from SEMG signals and support vector machine classification is used. The method achieved CLBP accuracy of 98.04%,91.3%,96.15% and 93.33% respectively.

J. Ryu, B. H. Lee et a. presented lower-limb motion detection with top and slope (TAS) feature extraction algorithm using SEMG. The system was divided gait sub phase detection, locomotion mode recognition and mode change detection with detection accuracy 8%,5% and 4% respectively. They implemented sEMG feature extraction algorithm such as Mean Absolute Value, Root Mean Square, Variance, Zero Crossing,simple linear Slope Sign Change, Willison Amplitude and Integrated EMG. They also implemented Linear discriminate analysis classifier. It applied a sEMG activity variation of the EMG signal to a feature value which reflected into better timing characteristics of sEMG signal.[8]

Youngjin Na, Changmok Choi et al. proposed new method to estimate joint Force using a biomechanical muscle model and peaks of Surface Electromyography. The SEMG measurement was carried out from the first dorsal interosseous muscle during isometric index finger abduction. The SEMG peaks were used as the input of the biomechanical muscle model which is a transfer function to generate the force. The developed method was compared with mean absolute value (MAV) and it is concluded as performance of the developed method is (0.94 ± 0.03) was better than MAV (0.90±0.02). The author recommended developed method for quantitative analysis of muscle activities based on SEMG. [9]

III SURFACE EMG ACQUISITION

Surface EMG acquired with Four-electrode array (Spes Medica, Battipaglia, Italy), 5 ×1 mm with10-mm Inter-Electrode Distance (IED) electrodes and spacing between each electrode was 10mm covering surface of skin. Signal sampled with 1024 sampling rate with resolution of 5 mV and 8-bit bit Analog to Digital Converter (ADC). Band-pass filter of second order is used with cut of frequency of 20 Hz to 500 Hz. A surface electrode type of EMG has a set of array pattern of surface electrodes, EMG signal amplifier and Computer system along with analog to digital converter. Surface electrodes available in the different shape, sizes and diameters, may be unipolar or bipolar in nature [10].

IV EXPERIMENTAL PLATFORM FOR DATA ACQUISITION

HARDWARE METHODOLOGY

National Instruments Educational Laboratory Virtual Instrumentation Suite II Series (NI ELVIS II Series) is used for data acquisition. The hardware, software approach is vital in order to implement the SEMG in real time. NI ELVIS II Series has provided optional Lab-VIEW-based software instruments and a custom-designed workstation and prototyping board to provide the functionality of a suite of common laboratory instruments. NI ELVIS II Series has two-Wire and Three-Wire Current Voltage Analyzer with variable power supplies as shown in figure 1. NI ELVIS II Series having full supports for the various fields of engineering, physical sciences, and biological sciences laboratories, basic electronics and circuit design etc. Also supports full testing, measurement, and data-logging capabilities of NI ELVIS II Series Prototyping Board that provides greater flexibility to build any electronic circuits. It has tools such as the Bode Analyzer and Dynamic Signal Analyzer for real time analysis. There are sets of sensors and transducer measurements along with the signal conditioning. [11]

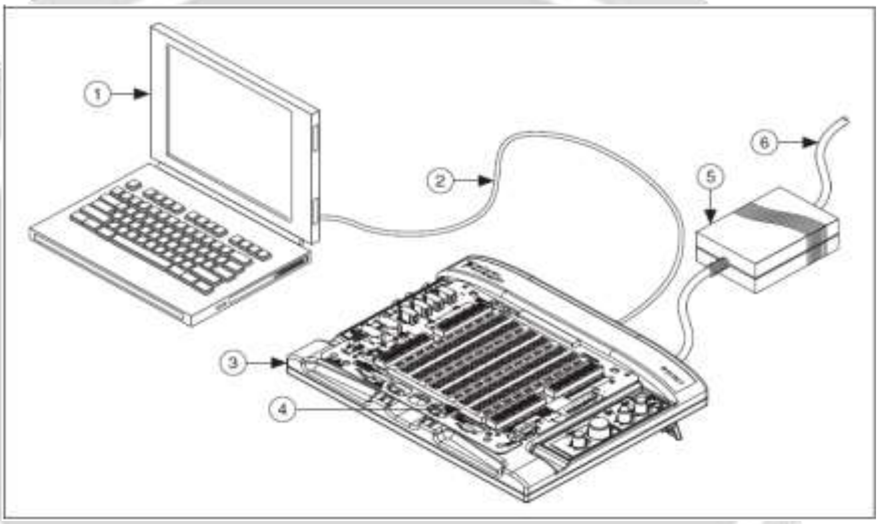

Figure 1:- Typical NI ELVIS II Series System

SOFTWARE METHODOLOGY

Electromyography, or EMG, involves acquiring and studying the electrical activity of muscles. The instrument used to measure the contraction of muscles is called an electromyography but the term EMG sensor is often used as well. An electromyography measures the electric potential generated by muscle cells and this recorded voltage is called an electromyogram. EMG signals are of interest to the developers of prosthetic devices, such as artificial limbs, and this is called myoelectric prosthesis. EMG is also found in bio-instrumentation, as a clinical diagnostic tool to identify neuromuscular diseases, assisted control in aircrafts, and unvoiced speech recognition. The QNET Myoelectric trainer shown in Figure 2 includes a two-electrode electromyography with a grounding strap and a servo. The on-board processed EMG signal can be measured and the servo can be driven by the PWM. Through EMG signal processing and control, the clamp on the servo can be opened and closed through muscle contraction, similarly to myoelectric prosthesis.

Figure 2. Myoelectric board to acquire SEMG

The electromyogram acquired from the EMG is very qualitative. It depends greatly on how the sensor is placed, how close it is to the muscle, and what muscle is being measured. EMG signals are very noisy and have a small amplitude, usually ranging around 5 mV. It can contain frequencies ranging from 10 Hz to 1 kHz.

To remove some of the noise, the electrodes on the myoelectric board include a differential amplifier as well as a local band-pass filter. The EMG signal received from the instrument is isolated and amplified on the myoelectric board. The set-up is shown in figure 3.

Figure 3. Setup to acquire sEMG signal

EMG SENSOR SETUP

The electromyogram acquired from the EMG is very qualitative. It depends greatly on how the sensor is placed, how close it is to the muscle, and what muscle is being measured. A typical EMG signal is shown in the first plot of Figure 4. As illustrated, EMG signals are very noisy and have a small amplitude, usually ranging around 5 mV. It can contain frequencies ranging from 10 Hz to 1 kHz. To remove some of the noise, the electrodes on the QNET myoelectric trainer include a differential amplifier as well as a local band-pass filter. See Reference [12] for the common mode rejection ratio (CMRR) and filter specifications of the electromyograph. The EMG signal received from the instrument is isolated and amplified on the QNET myoelectric trainer circuit

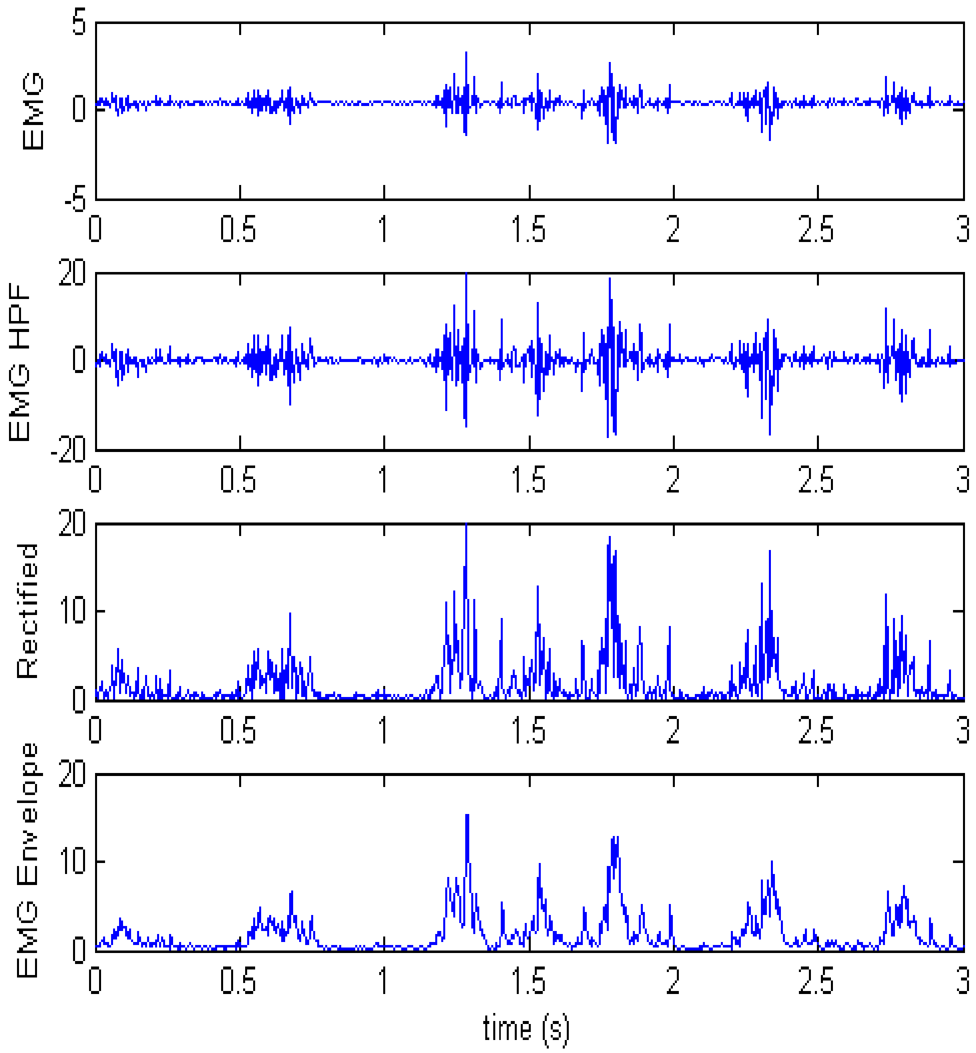

Figure 4:- Measured and processed EMG signal

V FEATURE EXTRACTION

Principle Components Analysis (PCA)

PCA is one of the most used linear dimensionality reduction technique. When using PCA, we take as input our original data and try to find a combination of the input features which can best summarize the original data distribution so that to reduce its original dimensions. PCA is able to do this by maximizing variances and minimizing the reconstruction error by looking at pair wised distances. In PCA, our original data is projected into a set of orthogonal axes and each of the axes gets ranked in order of importance. PCA is an unsupervised learning algorithm; therefore it doesn't care about the data labels but only about variation. This can lead in some cases to misclassification of data.

Independent Component Analysis (ICA)

ICA is a linear dimensionality reduction method which takes as input data a mixture of independent components and it aims to correctly identify each of them (deleting all the unnecessary noise). Two input features can be considered independent if both their linear and not linear dependence is equal to zero. Independent Component Analysis is commonly used in medical applications such as EEG and MRI analysis to separate useful signals from unhelpful ones.

VI ANALYSIS AND INTERPRETATION FOR CATEGORIZATION OF CHRONIC JOINT PAIN

Generating EMG Data file

Surface Electrode EMG signal have been acquired using NI ELVIS board for varied range of patients categorized into normal, medium and sever chronic join pain. The real time EMG signal data has been exported to excel file and file is saved in computer memory for further processing. Normal category has total 150 patient data. Medium category has total 190 patient data. Sever category has total 207 patient data. Thus, the database has 547 patient data those are categorized into three categories. Precautions have been taken during recording and data exporting of Surface EMG signal data to the excel file, so that signal to noise ratio become moderate and optimum. Data from excel file is imported using MATLAB scripting program and extracted data is saved as mat file for further processing of data. Thus, the systematic database file is created for the chronic pain detection.

Analysis and Processing of EMG Signal Data file

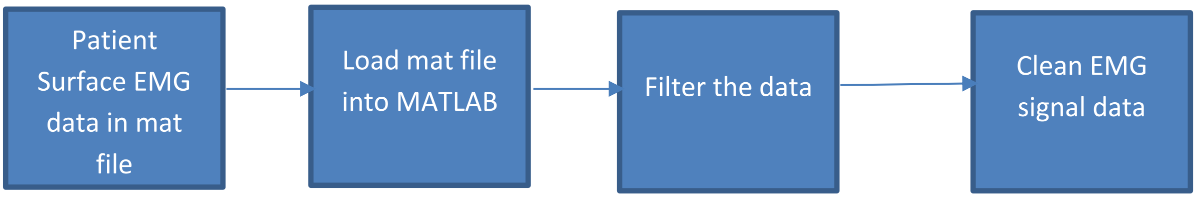

Figure 4:- Obtaining clean EMG signal data

Surface Electrode EMG signal have been acquired using NI ELVIS board for the pain detection. Surface EMG signal data file is loaded into the MATLAB environment for the detection and category of chronic join pain as shown in figure 4. Sampling frequency set to 1024 Hz during acquisition of surface EMG signal. A band pass filter is designed to remove out noise present in the EMG signal. The parameters of the band pass filter are given in table 1.

Table 1:- Band Pass Filter Parameters

Fstop1	15	First Stopband Frequency
Fpass1	25	First Passband Frequency
Fpass2	450	Second Passband Frequency
Fstop2	490	Second Stopband Frequency
Dstop1	0.001	First Stopband Attenuation
Dpass	0.057501127785	Passband Ripple
Dstop2	0.0001	Second Stopband Attenuation
dens	40	Density Factor
N	50	Order of filter
f_0	[0; 0.0292968750000000; 0.0488281250000000; 0.878906250000000; 0.957031250000000; 1]	pair of normalized frequency points
A_0	[0; 0; 1; 1; 0; 0]	Desired amplitude at point
W	[57.5011277850000; 1; 575.011277850000]	Weights

VI FEATURE EXTRACTION AND ANALYSIS

Features are extracted from the three type of EMG data categorized (table 2) are clean EMG data, Normalized EMG data and Extracted function EMG data (see table 3). 10 features have been extracted (table 4) for the three set of three data-set mention above.

Mean: - Average or mean value of data set.

$$mean = \frac{1}{N}\sum_{i=0}^{N-1} x_i \tag{1}$$

N = Total Number of data or Length of Sequence.

Standard Deviation: - Standard deviation of data sequence is calculated. The $\bar{x}$ is the mean value of data sequence, calculated using equation number (5.5).

$$s = \left(\frac{1}{n-1} \sum_{i=1}^{n} (x_i - \bar{x})^2 \right)^{\frac{1}{2}} \tag{2}$$

Mean of absolute values of first difference: - Mean value of absolute of difference between two successive sample data is calculated.

$$mean\_abso\_First\_diff = \frac{1}{N} \sum_{i=0}^{N-1} abs\,|(x_{i+1} - x_i)| \tag{3}$$

Mean of absolute values of Second difference: - Mean value of absolute of difference between two alternate successive sample data is calculated.

$$mean\_abso\_Second\_diff = \frac{1}{N} \sum_{i=0}^{N-1} abs\,|(x_{i+2} - x_i)| \tag{4}$$

Maximum Value: - Maximum value of EMG signal data set.
Minimum Value: - Minimum value of EMG signal data set.
Range: - Difference between Maximum and Minimum value is the range of EMG signal Data set.
Minimum to Total Sample Ratio: - It is the ratio of Minimum value of EMG signal data to the total number of samples in that data set.
Maximum to Total Sample Ratio: - It is the ratio of Maximum value of EMG signal data to the total number of samples in that data set.

Median: - Median value of EMG data set.

Table 2:- Three Data-Set of EMG signal

Sr. No.	MATLAB Variable Name	Description
1	X(:,1)	EMG data
2	X(:,2)	Normalized EMG data
3	X(:,3)	Extracted Function EMG Data

Table 3:- 10 Features Extracted from EMG data-Set

Sr. No.	MATLAB Variable Name	Description
1	Feature(P,1)	mean
2	Feature(P,2)	Standard deviation
3	Feature(P,3)	mean of absolute values of first difference
4	Feature(P,4)	mean of absolute values of second difference
5	Feature(P,5)	minimum value
6	Feature(P,6)	maximum value
7	Feature(P,7)	range

8	Feature(P,8)	minRat
9	Feature(P,9)	maxRat
10	Feature(P,10)	median
P=1 for EMG data set.		
P=2 for Normalized EMG data set		
P=3 for Extracted Function EMG Data set		
Feature is a 3 by 10 matrix data set.		

VII Classification performance of SVM

Classification of feature into the normal, medium and severe category is done by using the Support Vector Machine (SVM). Performance of each of classifier is the vital key for final classification of patient. It has categorized into groups and SVP trained for the detection of three kind of features corelated to classification of patient. Validation of classifier is essential that guarantees the performance of support vector machine. Initial performance evaluated and then training is started for each of cross indices (k=50). The performance of support vector machine after training is given in table 4. The performance for the three-group problem is not provide the enough information of the patient pain category but performance of detecting Severe patients from the selected population is higher than the other two population. Finally, the confusion matrix is obtained where the column represents three-groups of pain (15 each) and row represents the classifier prediction (see table 5 to7). The standard set of databases for the training of support vector machine creates the alpha parameters and every time training is repeated produces the approximate same parameters with minimum error and with few cases of exceptions. It is conformal training data used to classify the patient into three groups using SVM classifier after the successful training.

Table 4:- Accurate performance of SVP

Patient Code	Normal SVM CP	Medium SVM CP	Severe SVM CP
1	53.33	46.66	60
2	53.33	46.66	60
3	46.66	46.66	66.66
4	53.33	46.66	60
5	53.33	46.66	60
6	53.33	46.66	60
7	53.33	46.66	60
8	53.33	46.66	60
9	53.33	46.66	66.66
10	60	46.66	53.33
11	53.33	46.66	60
12	53.33	46.66	60
13	53.33	46.66	60
14	53.33	46.66	60
15	53.33	46.66	60

Table 5:- Alpha parameter for SVM classifier after training (Patient Normal)

Rows	Normal SVM	Medium SVM	Severe SVM
1	-0.267416554293535	0.123894629795402	0.153918914085087
2	-0.218187456663535	0.162021770110978	0.102497754293909
3	-0.202715096879748	0.121221926374909	0.113578124728895
4	-0.204297907088344	0.128759051798433	0.106934602489861
5	-0.294268890202384	0.155365146300526	0.139437448373366
6	0.128096987526808	-0.273241877536594	0.139341640819491
7	0.134424074184706	-0.258605133727450	0.129150647367751
8	0.147634689909611	-0.275088869590729	0.130932618231246
9	0.134644102528691	-0.263695568092367	0.134723730009765
10	0.142779925296704	-0.267257488231639	0.102818575785441
11	0.113735816546234	0.130937398596178	-0.275056669222009
12	0.143742181562357	0.119828442979816	-0.214144179118535
13	0.129261510136715	0.155866435925627	-0.316266309821667
14	0.112566617435720	0.115397116052185	-0.225359861501617
15	0.110566617435720	0.124597019244726	-0.222507036520986

Table 64:- Alpha parameter for SVM classifier after training (Patient Medium)

Rows	Normal SVM	Medium SVM	Severe SVM
1	-0.295070755712072	0.123894629795402	0.153918914085087
2	-0.267563649347735	0.162021770110978	0.102497754293909
3	-0.218157872552098	0.121221926374909	0.113578124728895
4	-0.219017729704853	0.128759051798433	0.106934602489861
5	-0.316310570224463	0.155365146300526	0.139437448373366
6	0.125281683231226	-0.273241877536594	0.139341640819491
7	0.129745819798153	-0.258605133727450	0.129150647367751
8	0.142210851455694	-0.275088869590729	0.130932618231246
9	0.130905442693735	-0.263695568092367	0.134723730009765
10	0.161595353471049	-0.267257488231639	0.102818575785441
11	0.139794246642182	0.130937398596178	-0.275056669222009
12	0.112499130372277	0.119828442979816	-0.214144179118535
13	0.138695118028576	0.155866435925627	-0.316266309821667
14	0.123883459394967	0.115397116052185	-0.225359861501617

15	0.111509472453361	0.124597019244726	-0.222507036520986

Table 7 5:- Alpha parameter for SVM classifier after training (Patient Severe)

Rows	Normal SVM	Medium SVM	Severe SVM
1	-0.295070755712072	0.123894629795402	0.153918914085087
2	-0.267563649347735	0.162021770110978	0.102497754293909
3	-0.218157872552098	0.121221926374909	0.113578124728895
4	-0.219017729704853	0.128759051798433	0.106934602489861
5	-0.316310570224463	0.155365146300526	0.139437448373366
6	0.125281683231226	-0.273241877536594	0.139341640819491
7	0.129745819798153	-0.258605133727450	0.129150647367751
8	0.142210851455694	-0.275088869590729	0.130932618231246
9	0.130905442693735	-0.263695568092367	0.134723730009765
10	0.161595353471049	-0.267257488231639	0.102818575785441
11	0.139794246642182	0.130937398596178	-0.275056669222009
12	0.112499130372277	0.119828442979816	-0.214144179118535
13	0.138695118028576	0.155866435925627	-0.316266309821667
14	0.123883459394967	0.115397116052185	-0.225359861501617
15	0.111509472453361	0.124597019244726	-0.222507036520986

VII TESTING THE CLASSIFIER FROM TRAINING DATABASE

Testing of the classifier using the training data for the individual cases have been carried out and it is given in the table no.8. The accuracy of the support vector machine classifier is 86.66% and the value is quite satisfactory. The performance mark is tagged for the each of selected training databases.

Table 8:- Testing classifier from training database

Patient	Severe SVM classifier	Medium SVM classifier	Normal SVM classifier	Actual Patient pain category	Predicted Patient pain category by SVM classifier	Performance Mark
1	0	0	1	Normal	12.5 to 25	1
2	0	1	1	Normal	25 to 37.5	1
3	0	0	1	Normal	12.5 to 25	1
4	0	0	1	Normal	12.5 to 25	1
5	0	1	0	Normal	37.5 to 50	0
6	0	1	0	Medium	37.5 to 50	1

7	0	1	0	Medium	37.5 to 50	1
8	0	1	0	Medium	37.5 to 50	1
9	0	1	0	Medium	37.5 to 50	1
10	0	1	1	Medium	25 to 37.5	0
11	1	0	0	Severe	87.5 to 100	1
12	1	0	0	Severe	87.5 to 100	1
13	1	0	0	Severe	87.5 to 100	1
14	1	1	0	Severe	50 to 62.5	1
15	1	0	1	Severe	75 to 87.5	1

VIII CONCLUSION

This paper aims to address the method of quantification of pain intensity using Surface EMG based system. It proves that SVM algorithm is an efficient solution to categorize pain intensity. On the basis of obtained result, the SVM algorithm resulted into accuracy of 86.66%. It can be concluded that chronic joint pain recognition using sEMG is a promising alternative to conventional methods. This paper could inspire to use the system as a pain measurement tool in the medical field.

IX ACKNOWLEDGMENT

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