Quantification of Pain using EEG and Fuzzy Logic

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Abstract

This paper aims to quantify and calculate the pain level of the volunteers experienced during cold pressure test with the help of electroencephalogram (EEG). The experiment was done on 20 volunteers having age group of 20 to 60 years. The EEG of 20 people was taken in normal (No Pain) condition and in Pain state. The pain was induced by cold pressure test. The acquired EEG contains noise and other artifacts which were removed with the help of filters. Various features of EEG signal were extracted. Three features viz. amplitude (RMS value), Power Spectral Density (PSD), and Higuchi fractal Dimension (HDF) responded well to pain and had the ability to separate pain and non-pain signals efficiently. These three parameters were fed as input to a fuzzy inference system (FIS). Fuzzy rules were made very carefully after experimentation at different pain levels. The output of FIS is the pain index ranging from 0 to 10, where 0 is for No Pain, 5 is for Medium Pain, and 10 is for High Pain.

Keywords

Pain estimation, EEG, Power Spectral Density (PSD), Higuchi Fractal Dimension (HDF), Fuzzy Logic, Fuzzy Inference System (FIS)

1. Introduction

The estimation of pain is a major problem for the physicians since many years. It is very difficult to assess the pain level of deaf, children, patients in ICU, paralyzed patients, semi anaesthetized patient, and patients who can't communicate due to some injuries or suffer from mental health problem. Generally, automated pain intensity detection is very beneficial for low Glasgow comma scale (GCS) for measurement of consciousness level [1].For patients who cannot communicate about their pain level with physician, there is urgent need of pain detection device so that doctors can treat their patient with the right amount of dose [2]. During surgery, analgesic drug is given to the patient to alleviate pain. But in some cases, surgery takes long time and the patient does feel pain but he cannot speak out because he is paralyzed. With the help of pain detection device, physician can easily monitor patient's pain level and accordingly, analgesic drug can be given whenever required [3]. Similarly, children or patients with mental problem are also not able to tell how much pain they are feeling [4]. Then there are some criminals who try to fake pain in court to escape hearing of their case. ICU patients are given sedatives to tolerate the pain level for their comfort [5] [6] but there is no pain detection device to measure their pain.

The pain is the unpleasant sensation to body due to inflammation or tissue damage [7]. It can be detected by many methods. First method for pain detection is by verbal communication to the patient [8]. We can ask the patient about the grade of his pain i.e. very high pain, low pain, or having no pain at all. But this method fails when the patient is deaf, ICU patient, or children etc. who cannot communicate. Second method of pain detection is by heart rate variability. It can be done with the help of electrocardiogram (ECG). When the patient feels pain, it causes variation in the heart rate; this variation is calculated with the help of the ECG and thus, pain can be detected [9] [10]. But problem with this method of pain detection is that the heart rate is a fragile parameter, ready to undergo change

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on the slight pretext. It cannot be relied upon for diagnosing any non-cardiac event. Third method of pain detection is by analyzing facial expressions [11]. But problem with this method is that there are some patients who are in coma or ICU and are not able to give expressions [12].

One of the most effective methods of pain detection is EEG based. Whenever patients feel pain, its sensation goes directly to brain. The brain signals are reflected in EEG. In this work, pain was induced in volunteers and EEG signals were acquired. It was filtered using low pass filter to remove noise and other artifacts [13]. Various time-domain and frequency-domain features were extracted. Their efficacy was evaluated vis-à-vis pain sensation [14] [15]. Those parameters which showed excellent correlation with pain were selected to estimate the pain index. These parameters, being imprecise in value, were given to a fuzzy inference system whose output was a crisp number corresponding to Pain Index. In place of fuzzy logic we can use KNN (K- Nearest Neighbors), SBS (Sequential Back Selection), SVM (Support Vector Machine) [16], and Neural Network techniques as a classifier. However, Fuzzy Logic classifier is easy and efficient method of EEG signal classification [13].

2. Material and Method

In the experiment, 20 volunteers in the age group of 20 to 60 years (male +female) were included. These volunteers were teetotaler and non-smoking. The weight of volunteer ranges from 45 to 80 Kg, the experiment was performed on 32 channel EEG machine (Recorders and Medicare System, Chandigarh, India). The data format was 24 bit and sampling rate was 1024 samples/sec. There were 8 electrodes which were placed at different position of brain viz. Fp1, Fp2, C3, C4, P3, P4, Ground, and Reference. These EEG electrodes were in the shape of cup and made up of silver (Ag) and silver chloride (AgCl) [17]. The EEG was taken using EEG machine and analyzed on AD Instrument Lab Chart. The EEG of volunteers was taken first in normal state i.e. No Pain condition. Then EEG of patient is taken in Pain state. The pain is produced by using cold pressure method [18]. In this test, ice cube of size 4.5 × 3 × 1.8 cubic centimeters were added to 3 liter water baths and right hand of volunteer was dipped into it to generate pain. With the passage of time, the volunteer felt pain and thus EEG in pain condition was recorded. This process was repeated for every volunteer [14].During this, they were asked the pain level verbally which was marked so that later EEG signals at different level can be recognized. The schematic of the signal processing is shown in Figure 1. The flowchart appears in Figure 2.

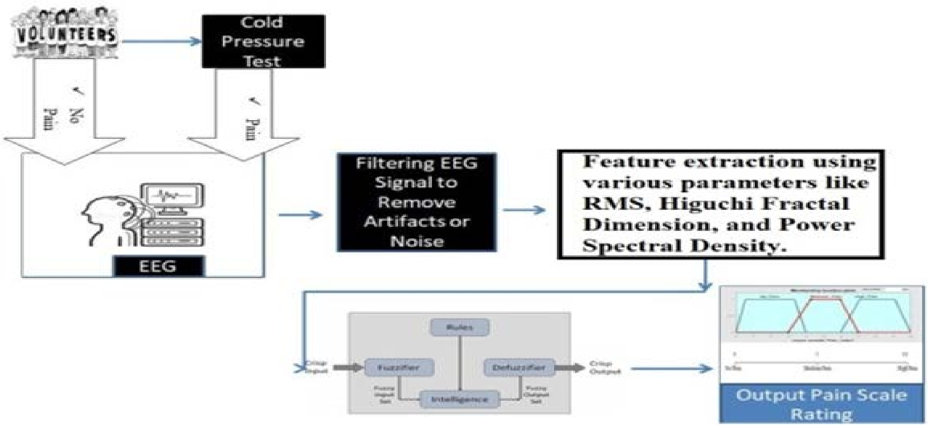


Figure1: The schematic of signal processing.

- **EEG in Pain and Non Pain condition**: The EEG of every volunteer is taken in Pain and No-Pain condition. For inducing pain, the cold pressure method is used.
- **Artifact removal and Filtering of EEG signal:** Raw EEG recorded with the help of the EEG machine setup contains noise and other artifacts due to eye blinking, 50-60 Hz electrostatic interference, muscle contraction or expansion etc. To get clean EEG signal, these unwanted signals must be removed. Raw EEG signal was passed through a notch filter of 50 Hz and a low pass filter

with a cut-off frequency of 70 Hz. This reduced electrostatic interference and noise significantly. If EEG signal is badly affected then adaptive filtering can also be used [19].

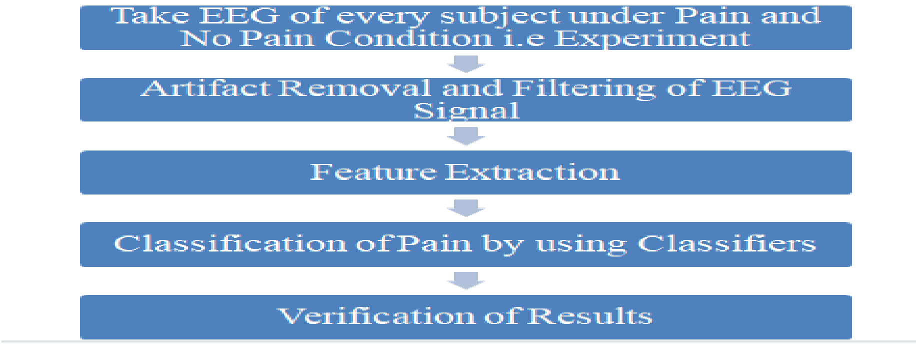


Figure 2: Flowchart of operation.

- **Feature Extraction:** The EEG data was divided into epochs of 4seconds each. Various parameters were calculated for these epochs. Linear discriminant analysis was applied to identify parameters which were highly related to pain. Table 1 gives the list of these parameters.

Table 1
Calculated EEG parameters

S.No.	Calculated Parameter	Comments
1	RMS Value	Root mean square value of every epoch
2	Power Spectral Density	Measure of signal irregularities in frequency domain
3	Higuchi Fractal Dimension	Calculation of fractal dimension of a time series directly in time domain

The method of calculation of above parameters is given below:
1. RMS value: RMS is the Root Mean Square value of signal. It can be calculated as:

$$RMS = \sqrt{\frac{1}{N}\sum_i x_i^2} \qquad (1)$$

where, N = the number of measurements and x_i = the sample amplitude value.

2. Power Spectral Density: Spectral Density (PSD) describes the distribution of the signal power with frequency. The significant frequency components of signal which can be considered for further study is decided by its Power Spectral Density (PSD). It is determined by using Welch's method. In this method first periodogram is calculated and then PSD is calculated by taking average of periodogram as described below in equation 4 and 5.

$$Periodogram = \frac{1}{MU}|FFT|^2 \qquad (2)$$

Where, U is the normalization factor and M is the window *hop size*. Welch's estimate of PSD is given as:

$$Power\ Spectral\ Density\ (PSD) = S(f) = average\ (Periodogram) \qquad (3)$$

3. Higuchi Fractal Dimension (HFD): In 1988, Higuchi published a research paper on nonlinear measurement of magnetic field change which was based on fractal theory [16]. However, this method is sensitive to noise and other random signals. Therefore, for getting good results, artifacts and other noise random signals must be removed efficiently from EEG signal. The various steps for determination of HFD of a time series x(1), x(2), ……. x(N) are:

Step 1: The new time series is generated by using the equation:

$$x_m^k = \left\{x(m), x(m+k), x(m+2k)\ldots\ldots\ldots x(m + \left[\frac{N-m}{k}\right])k\right\} \quad (4)$$

m = 1, 2, 3, 4….k

where, m is the initial time and k is the initial time interval respectively.In this way, there will be k new time series.

Step 2: Calculate average length of each new time series $L_m(k)$ which can be calculated as:

$$L_m(k) = \frac{1}{k}\left\{\left[\left[\sum_{i=1}^{\left[\frac{N-m}{k}\right]} \left|x(m+ik) - x(m+(i-1)k)\right|\right] \frac{N-1}{\left[\frac{N-m}{k}\right]k}\right\} \quad (5)$$

This process is repeated for almost all values of k from 1 to $k_{\max}$. N is the number of samples. In some research papers, it was taken as 11 or 17 or 25 but in this study the value of K_{max} is taken 6and N ≥125 because at this value accurate and faster algorithm for fractal dimension is obtained [20].

Step 3: The mean length of the actual time series is calculated as the average of $L_m(k)$ by the equation:

$$\textit{Mean length} = \textit{Average}\ [\ L_m(k)\ ] \quad (6)$$

The Fractal dimension of the signal is obtained as the slope of the curve *ln(Mean length)* vs. *ln(1/k)* by using the polynomial curve fitting method [21].

- **Classification of pain**

Once all the above features are calculated for various EEG epochs, the next step is to feed these parameters as input to the classifier. There are many classifiers available viz. KNN, SBS (Sequential Backward Search), SVM (Sequential Vector Machine), Neural Networks, Fuzzy Inference System (FIS), and PKSVM (Polynomial Kernel Support Vector Machine)) etc [22]. All these classifiers except Fuzzy Inference System need large amount of data. As we have EEG data of only 20 patients so we made use of Fuzzy Inference System (FIS). FIS is easy to use and gives reliable and accurate results. In this work, “Mamdani” type of FIS is used with trapezoidal (trapmf) membership functions. The FIS containing three inputs viz. RMS, Power Spectral Density and Higuchi Fractal Dimension is schematically shown in Figure 3. All these inputs are processed by the fuzzy rule set mentioned in Table 2.

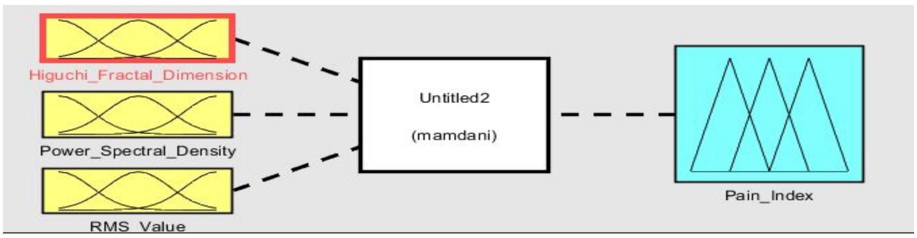


Figure 3: Fuzzy Inference System with Input, Mamdani, and Output state.

The design of rules was done as follows:

Rule 1: If two or more input parameters show a high pain value then it is considered as high pain.

Rule 2: If two or more input parameters show a medium pain value then it is considered as medium pain.

Rule 3: If two or more input parameters show a low pain value then it is considered as low pain.

Rule 4: If all parameters show different pain levels then it is taken as medium pain.

It must be kept in mind that the RMS and Power Spectral Density are directly correlated with pain level while HFD is inversely correlated with pain.

Table 2

The rule base used in fuzzy inference system (FIS).Calculated EEG parameters.

Rule No.	RMS Value	Power Spectral Density (PSD)	Higuchi Fractal Dimension (HFD)	Output Pain Index
1	Low RMS	Low PSD	Low HFD	Low Pain
2	Medium RMS	Low PSD	Low HFD	Medium Pain
3	High RMS	Low PSD	Low HFD	High Pain
4	Low RMS	Medium PSD	Low HFD	Medium Pain
5	Medium RMS	Medium PSD	Low HFD	Medium Pain
6	High RMS	Medium PSD	Low HFD	High Pain
7	Low RMS	High PSD	Low HFD	High Pain
8	Medium RMS	High PSD	Low HFD	Medium Pain
9	High RMS	High PSD	Low HFD	High Pain
10	Low RMS	Low PSD	Medium HFD	Low Pain
11	Medium RMS	Low PSD	Medium HFD	Medium Pain
12	High RMS	Low PSD	Medium HFD	Medium Pain
13	Low RMS	Medium PSD	Medium HFD	Medium Pain
14	Medium RMS	Medium PSD	Medium HFD	Medium Pain
15	High RMS	Medium PSD	Medium HFD	Medium Pain
16	Low RMS	High PSD	Medium HFD	Medium Pain
17	Medium RMS	High PSD	Medium HFD	Medium Pain
18	High RMS	High PSD	Medium HFD	High Pain
19	Low RMS	Low PSD	High HFD	Low Pain
20	Medium RMS	Low PSD	High HFD	Low Pain
21	High RMS	Low PSD	High HFD	Low Pain
22	Low RMS	Medium PSD	High HFD	Low Pain
23	Medium RMS	Medium PSD	High HFD	Medium Pain
24	High RMS	Medium PSD	High HFD	Medium Pain
25	Low RMS	High PSD	High HFD	Low Pain
26	Medium RMS	High PSD	High HFD	Medium Pain
27	High RMS	High PSD	High HFD	Low Pain

There are a total of 27 rules that were made to quantify the pain level of the patient. IF part of the rule is the premise and THEN part is the consequent. Membership functions for RMS value are shown in Figure 4 with Low, medium, and high values ranging from 0.05 to 0.15, 0.14 to 0.25, and 0.23 to 0.5 respectively. Figure 5 shows the membership functions for PSD having low, medium, and high value of PSD ranging from 0.001 to 0.014, 0.015 to 0.02, and 0.02 to 0.08 respectively. Figure 6 shows the low, medium, and high value of HFD ranging from 1.25 to 1.4, 1.38 to 1.48, and 1.45 to 1.6 respectively. These values are taken based on the experiment done and parameters calculated. Figure 7 shows the membership functions of the output i.e. the Pain Index. The crisp Pain Index shows the pain in the range 0 to 10, 0 for the No Pain, and 10 for High Pain (extreme). Figure 8 shows Pain rating scale

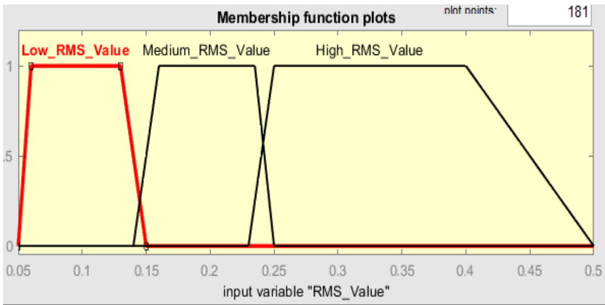


Figure 4: Membership functions for RMS value

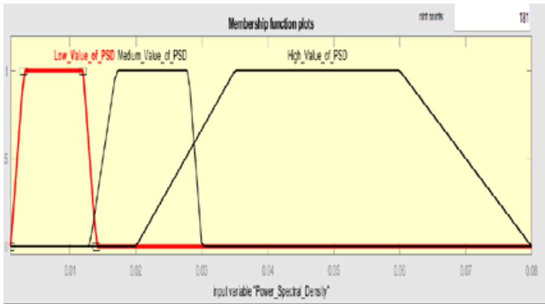


Figure 5: Membership functions for PSD

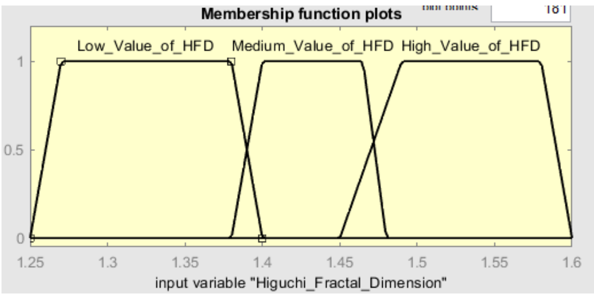


Figure 6: Membership functions for HFD

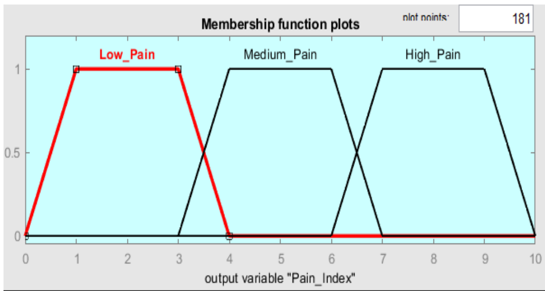


Figure 7: Membership functions for Pain Index

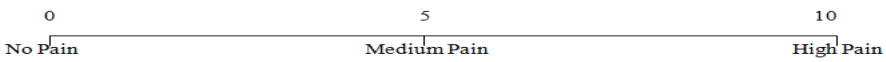


Figure 8: Pain rating scale.

- **Verification of Result**

After processing the inputs and defuzzyfying the output, crisp value of “Pain Index” is obtained. The Pain Index has a range of values from 0 to 10. Output 0 is for Low Pain, 5 is for Medium Pain, and 10 is for High Pain. The result obtained can be verified by comparing calculated result to the actual verbal pain estimation.

3. Result and Discussion

The raw EEG is obtained by using EEG machine. The electrostatic noise is removed by passing it through a notch filter of 50 Hz as can be seen in Figure 9.

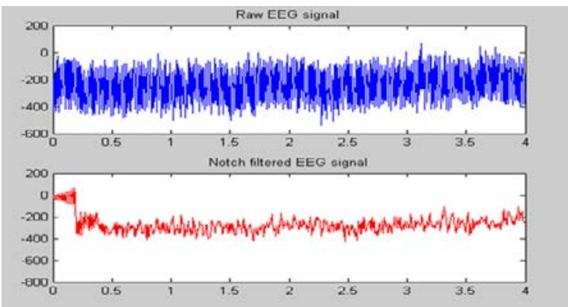


Figure 9: Raw and notch-filtered EEG signal.

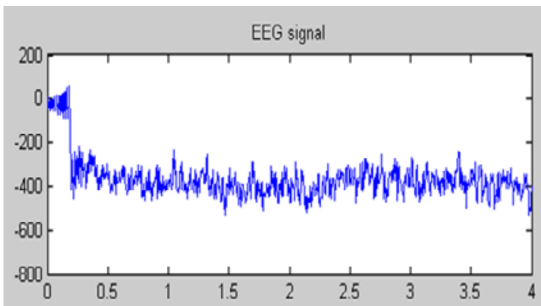
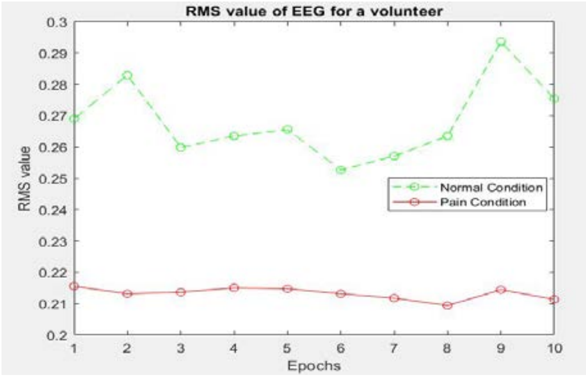


Figure10: EEG signal after passing through LPF

Passing signal through a low pass filter, clean EEG output is obtained which is shown in Figure 10. All the parameters viz. RMS value, PSD, and HFD were calculated in both pain and no-pain states. All these parameters are shown below in Figure 11-13.



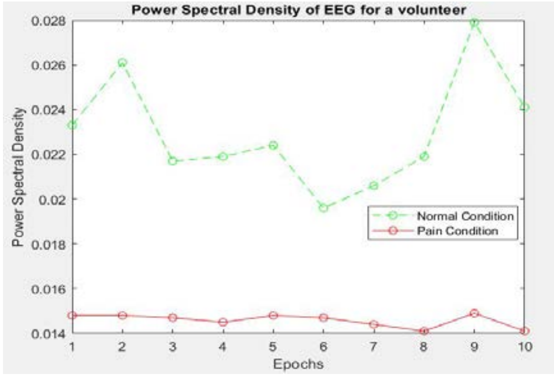


Figure 11: RMS value of one of volunteer EEG. **Figure12:** PSD of one of the volunteer's EEG

Figure 11 shows the typical RMS values of the EEG signal. The hard line shows Pain Condition and dotted line shows Normal or No-Pain state. The maximum value achieved is 0.5 (High Pain) and lowest value achieved is 0.05 (Low Pain). It can be seen that RMS parameter of EEG has great ability to separate the Pain and No-Pain signals from each other. Low values show low pain while high values show the high pain states. Figure12 shows the PSD of one of the volunteers. The continuous line shows the Pain Condition and dotted line shows the Normal or No-Pain Condition. The maximum achieved value of PSD is 0.08 corresponding to Normal or No-Pain Condition and 0.001 for High Pain condition.

Figure 13 shows HFD parameter values of the EEG. The hard line) shows the Pain condition of the volunteer and dotted line shows the Non Pain or Normal Condition of the patient. It is clear that Pain and No-Pain signals are clearly separated by HFD parameter. In this case, the lowest value obtained is 1.25 (High Pain) while highest value is 1.6 (Low Pain).One caution that must be kept in mind is that Higuchi's method only works at very low noise. Large noise signals may not give desired results. However, it is considered one of the best parameters for the analysis of biomedical signals. Based on the above-mentioned parameters, a fuzzy rule base was made. All these input parameters are given to FIS. The FIS processes them on the basis of fuzzy rule base.

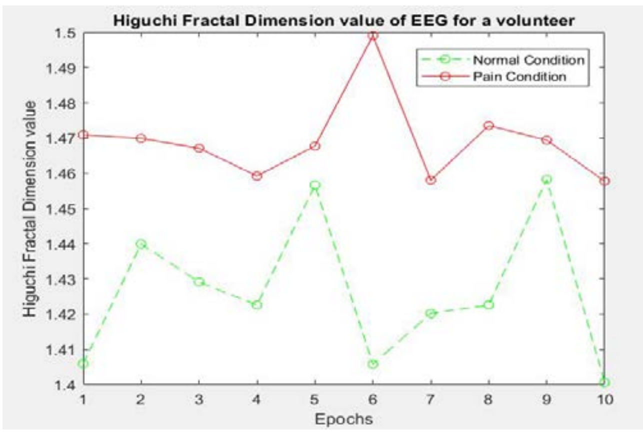


Figure 13: HFD of one of the volunteer's EEG.

The fuzzy rule check is shown in Figure 14. The output Pain Index has three ranges- High Pain, Medium Pain, and Low Pain. In Figure14, when RMS parameter has a value of 0.392 (High Value), PSD has a value of 0.01966 (Medium value) and HFD has a value of 1.31(Low value), the firing of rules and the resulting defuzzified output can be seen. After defuzzification was done by the Centroid

Method, the crisp output Pain Index obtained is 8 (High Pain). The output obtained for the FIS was got confirmed by patients at different levels of pain.

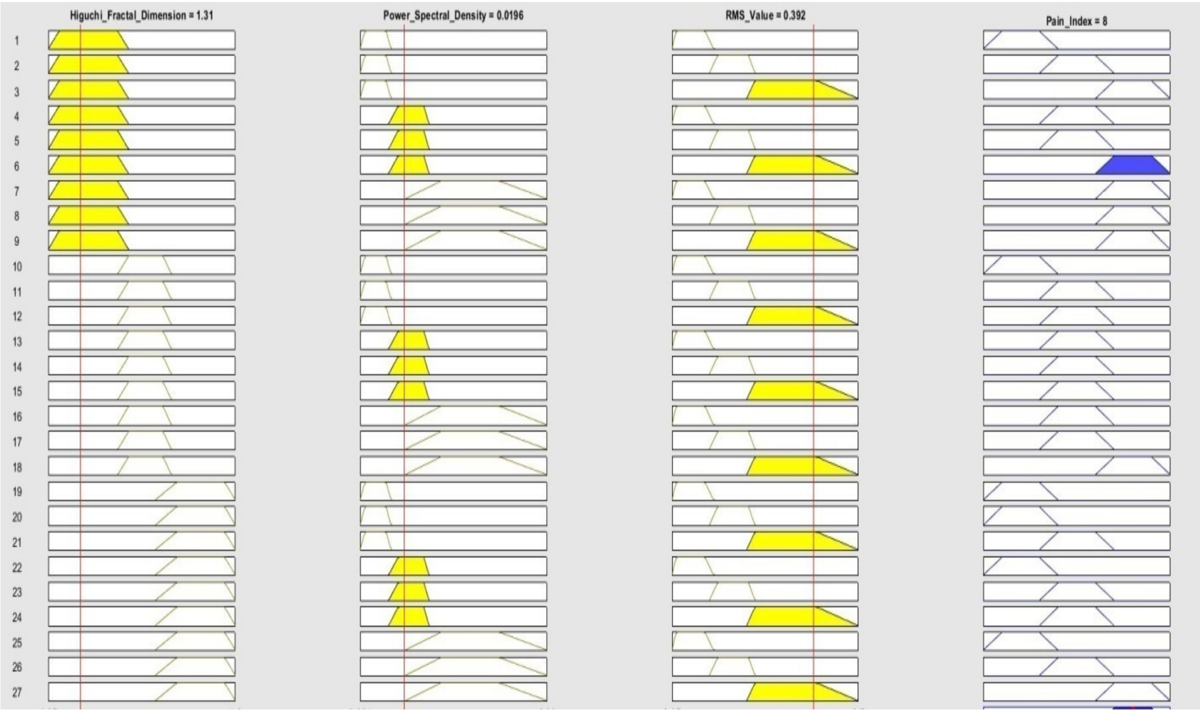


Figure 14: Fuzzy Rule check for output Pain Index.

4. Conclusion

At present, there is no scientifically proven pain estimation technique. By conventional methods, pain of a patient is not determined with accuracy and still there are some irregularities and limitations in these methods. The EEG based method is very promising for the pain detection. High accuracy is achieved by this technique because the extracted pain defining parameters are highly sensitive to pain. One point to be kept in mind is that to achieve high accuracy, noise and artifacts must be removed to the maximum possible extent from the EEG signal.

Fuzzy inferencing is probably the best classification technique when the data is limited. In fact, more accurate classification techniques like neural networks or tree based methods would not achieve better results here because there is no Gold standard method available for pain measurement which can help learning of these classification methods. Impreciseness of the pain scale having rating from 0-10 from no pain to high pain goes well with Fuzzy inferencing. The designed system can be used in Operation Theatre (OT) so that underdose or overdose of analgesic dose can be avoided. It may also be used by the physicians to diagnose and treat diseases associated with pain. Subjects with chronic pain should be separately investigated since EEG recording in the non-pain state is not accessible in such cases.

Further work is required in this area to investigate the efficacy of the technique in case of different pain sources. Before testing the system clinically, it must be evaluated by simulating pain externally through different methods e.g. with the help of a pin, by giving thermal or mechanical stress to the human body, etc.

5. Acknowledgment

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