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Umace Filter for Detection of Abnormal Changes In Eeg: A Report of 6 Cases

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Abstract: It is well known that the UMACE filter is mostly used for face detection system, text recognition and fingerprint verification. However, in this study, the potential of UMACE to detect changes in EEG data from epilepsy monitoring routine is explored using only one channel of EEG recording. A novel method to analyse and detect variances in scalp EEG is performed by comparing the abnormal region to the normal segment of the patient's EEG. The changes occurred in the zero plot is examined and initial results showed that these changes can be employed to distinguish irregularities in EEG. The proposed method is capable to produce first rate results too.

Key words: Unconstrained Minimum Average Correlation Energy (UMACE) . Electroencephalogram (EEG)

INTRODUCTION

The application of EEG signals as inputs for epilepsy detection, Brain Computer Interface (BCI) and wake-sleep studies has gained interest from researchers in this field. Basically, EEG is used to detect the electrical activity of the brain. In BCI, EEG signal of the patients is used as a communication medium to aid lock in syndrome patient to communicate with the outside world. EEG is the only responses that can be monitored and read by the clinicians in order to see the responses of the lock in syndrome patient. In early days, EEG is employed for detection of tumor and epilepsy. Nowadays, it is mostly utilize to examine the EEG signal recorded by the epilepsy monitoring unit for localizing the epilepsy. This is achieved by monitoring the EEG pattern and behavior during the occurrence of epilepsy. This procedure required the EEG to be recorded for a few days. A few series of epilepsy attack need to be scrutinized for confirmation purpose before surgical treatment.

Numerous researches are done to enhance the detection, prediction and understanding of epilepsy. On going researches are performed to perk up the existence methods. Improvements and suggestions on the existing methods due to arguments are still in discussion term. Earlier work done by other researchers on EEG detection was algorithm development that is based on pattern recognition of spike and sharp wave detection. The shape and duration of the events is critical for detection. However, the disadvantage of this method is to identify the spike and sharp waves in real situation since both waves are implicated with the background and along with the noise and this make it difficult to obtain the defined pattern [1]. Mohseni *et al.* [2] proved that the variance method is the best algorithm as compared to other methods namely the time frequency distributions and lyapunov exponent. However, the threshold value needs to be studied and set for processing. Ramachandran [3] studied the detection method and stated that the previous method are not comparable since the term used by this method are mostly different and not standardized. In essence, most researchers prefer ease of implementation technique that can produce moderate result in contrast to complicated method that engendered excellent effect.

Research of epilepsy frequently used EEG as an input. Till now, EEG is still being used and has gain more attention such as seizure prediction purpose. The reason is because EEG is ease to obtain, non invasive and the inexpensive technique to acquire signal from the brain. Some of the previous methods in processing EEG used intracranial EEG (iEEG) [4-7]. Many problems arisen as a result of using iEEG. IEEG is limited to only acute epilepsy cases. It is invasive and only certain infirmaries practiced iEEG. Therefore, to avoid the occurrence of these problem via iEEG, scalp EEG are utilized in our work instead of iEEG.

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In this study we dealt with scalp EEG data from the EEG monitoring lab. The epilepsy patient will need to go through the monitoring session to localize and produce more accurate result before the epilepsy surgery. Patient has to stay for a few days in the monitoring lab and a few episodes of seizure attacks will be recorded. This procedure is mandatory before surgical. Hence, the specialists will have to examine long hours of recording due to series of attack. Therefore, there is a call for computerized screening to assist them in localize the time of seizure attack. This can also shorten the duration needed for diagnosing [1, 8, 9]. Further, dealing with huge amount of EEG data requires fast and trouble free implementation for producing accurate and prompt result. Thus in this study, the UMACE filter is chosen for processing the EEG data since it can be employed to handle huge amount of data and produce punctual result.

Advanced correlation filter namely MACE and UMACE are usually applied in the filed of image processing. It is mostly used in authentication and identification process. The advantage of MACE is that it has the ability to provide good discrimination without the need for imposter training images [10]. In image processing, it can be designed to accommodate the intrinsic amplitude variability of the images in training set while being tolerant to noise pervading the image [11, 12]. MACE filter has been improved and can produce the quick result. It can also be applied on limited memory device such as PDA [13]. Further, UMACE is being considered due to ease of implementation, first rate result and does not require large number of training images [10, 14].

As we know, the EEG signal is complex and changes rapidly. For certain cases such as epilepsy, it is still unknown and there is no specific pattern for specific situation. Some difficulty when handling the biomedical signal such as EEG data; is inter-subject variability [15]. In epilepsy, the potential of UMACE filter to detect abnormal condition is possible since generally, seizure of an individual usually exhibits a similar pattern. However, this pattern could not be compared with other patient since no two patients' exhibits similar pattern of seizure [4]. Since the UMACE method can tolerate the inter and intra-variability for a certain degrees of changes as mentioned by Savvides and Kumar [10], hence the UMACE method will be investigated in this study.

MATERIAL AND METHODS

MACE and Umace Filters: According to Savvides *et al.* [12], MACE filter is developed by Mohalanobis *et al.* in (1987) in the effort to reduce the large sidelobes observed from equal correlation peak synthetic discriminant filter (ECP SDF) filter. MACE is developed to help the detection of sharp correlation peak produced for easier detection method in one region on the plane. MACE filter minimizes the average correlation output due to the training images while simultaneously satisfying the correlation peak constrain at the origin. In this way, the correlation planes value will be closed to 0 all over except at the location of the trained object and it will produce a strong peak. The closed form equation of a MACE filter is given by:

$$h = D^{-1}X(X^{+}D^{-1}X)^{-1}u \tag{1}$$

D is a diagonal matrix with the average power spectrum of the training image placed along diagonal elements; X consists of the Fourier transform of the training images lexicographically re-ordered and placed along each column; u is a column vector containing the desired correlation output at the origin for each training images. UMACE is minimizing the average correlations output while maximizing the correlation output at the origin. Further, the equation for a UMACE is as:

$$H = D^{-1}m \tag{2}$$

where, m is a column vector containing means of the Fourier transform of the training images. UMACE filters are computationally more attractive as the inversion of only a diagonal matrix is required. Noise tolerance can be built in to the filters as described in [10]. This is done by substituting D with D' and D'= aD + sqrt (1-a2)C, where C is a diagonal matrix containing the noise power spectral density. For white noise, C is the identity matrix and a ranges from 0 to 1 and is chosen to trade-off noise tolerance for discrimination. Note that an a of 1 yields a MACE filter.

The EEG data used in this study were recorded using Medelec-Profile system by Medelec, Oxford Instruments, United Kingdom. This analysis using EEG data recorded using bipolar montage. The EEG signals were digitally sampled at 256 Hz and band pass filtered settings of 0.5 to 70 Hz. The subjects used in this study involved six patients of the Science University of Malaysia Hospital in Kubang Kerian. The patients ages ranged from 13 to 33 years old. Patients were admitted for video EEG monitoring for evaluation prior to an epilepsy surgery. The results are tested against the time of seizure observed through video observations.

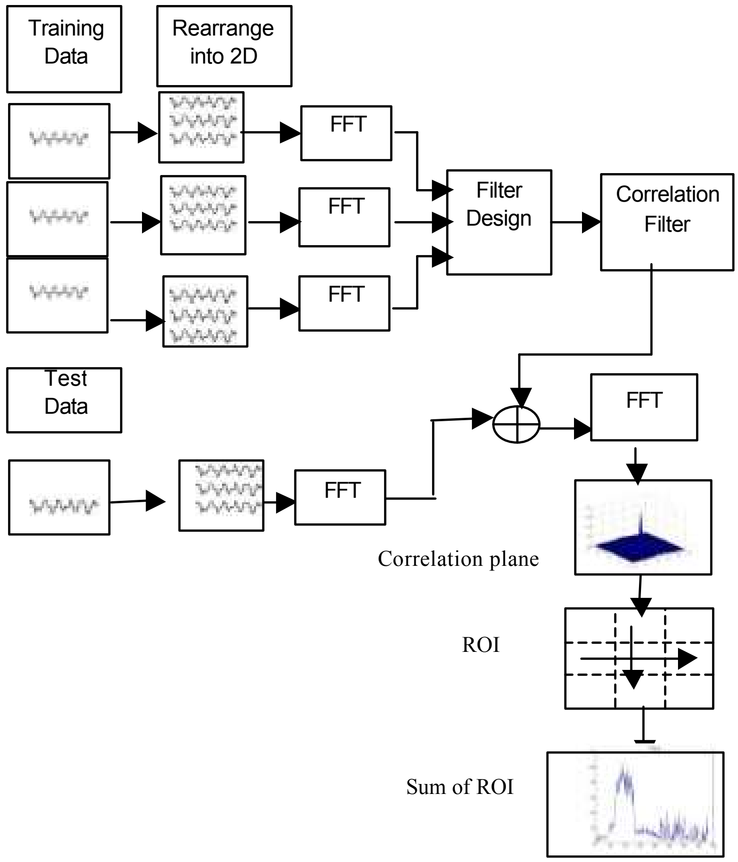


Fig. 1: Application of UMACE method

During the video-EEG monitoring process, all 19 channels of data were recorded. For clinical onset analysis, both video and EEG data recordings were synchronized so that the stored video EEG data can be used for offline analysis. In this preliminary research, we only used and analyzed EEG data from one channel, the most prominent channel based in the recording. EEG data from the Medelec system is changed into.txt before it can be processed using matlab function. The most affected channel chooses as an input based on amplitude changes in EEG data. Three seconds from the normal EEG data is choose as a training portion for the filter then tested with the rest of the input from that channel using UMACE method.

UMACE and MACE usually used 2 dimensional data for inputs such as images. In this analysis, UMACE filter is used on one dimension scalp EEG signal. In order to create a 2-D signal from 1-D format, time delayed methods is utilized to develop the signal to a 2-D data. Firstly, the training data are selected from the normal region of the EEG recording. This is done by choosing three consecutive seconds from the normal region as the training data. Next, the selected training data is rearranged to a 2-D data. Figure 1 depicted the overall system of our method. A specific number of training data acted as input to the filter. Test data is then correlated with the designed filter to produce correlation output. Peak to side lobes ratio (PSR) measurements from correlation output have been used in most researches as an indicator for discrimination or classification [11, 12, 14, 16]. However, instead of considering PSR value, we monitor the consistent changes exist in the correlation output. Some small changes exist in the correlation output as different segment or situation of the EEG data is compared. Consistent changes appeared in the middle row of the plot and this is called the region of interest (ROI). The changes in the ROI are calculated and used as an input to produce the final plot labeled as the Sum of ROI shown in Fig. 1. Normal segment is usually around 0 whereas the abnormal part will produce a very high peak value as compared to the normal part.

Figure 2 showed the correlation output in the 2-D and the 3-D format. The first top row diagram is the outcome for the normal region as both training and testing data. Next is the output of the epilepsy region as the testing data and finally the last row indicated the result of the correlation output for

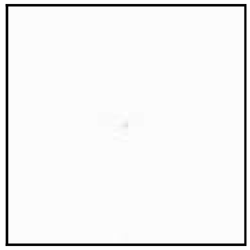
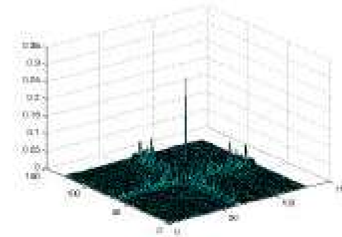
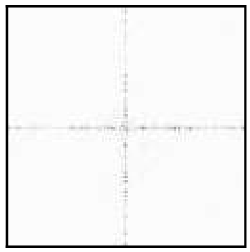
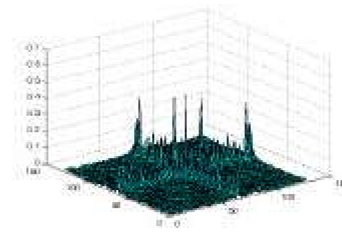
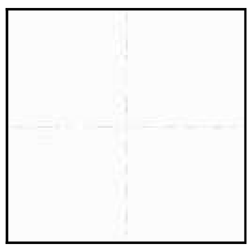
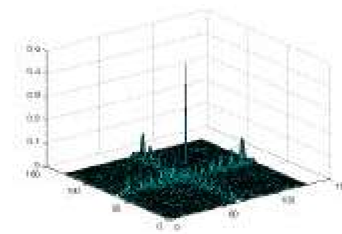
	2 Dimension	3 Dimension
Training		
Epilepsy		
Post epilepsy		

Fig. 2: Output of correlation plane

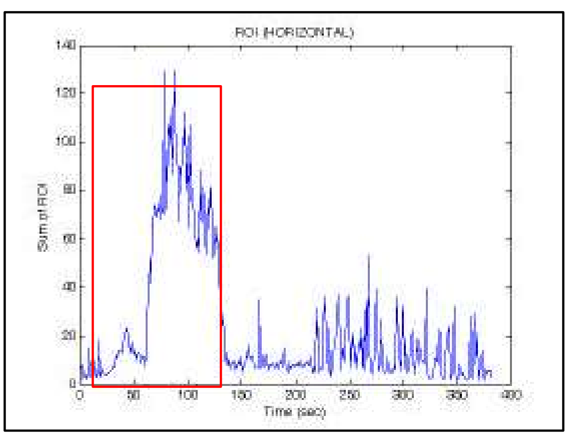


Fig. 3: Result of patient 1

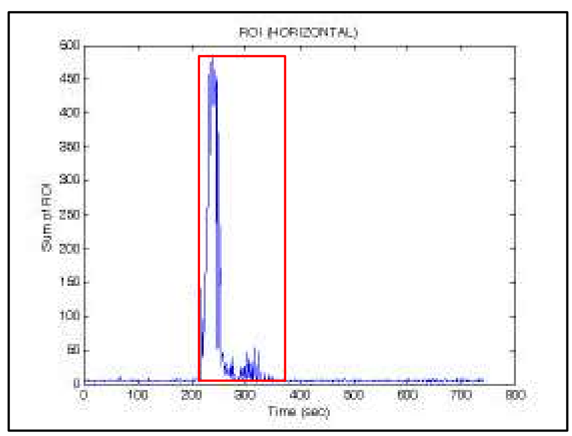


Fig. 4: Result of patient 2

the post epilepsy region as the testing input. As can be seen, the results of the 2-D plot are unobvious for all testing inputs. However, some distinctions are observed in the 3-D plot for dissimilar training and testing data due to occurrence of some clear peaks in the 3-D plot. These peaks will indicate certain value of the plot. It is also observed that using epilepsy segment as the testing input produced mainly sharp peaks whilst for post epilepsy as testing data, spiky peak are also produced but less than the epilepsy region. However, the peak due to normal region is the least. The sum of these peaks in the ROI region will be recap to produce the concluding graph as illustrated in Figure 3 through Figure 8. The characteristic of the epilepsy region is highlighted in the red box.

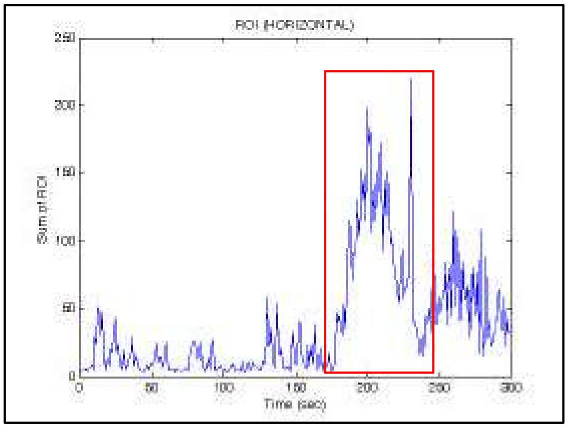


Fig. 5: Result of patient 3

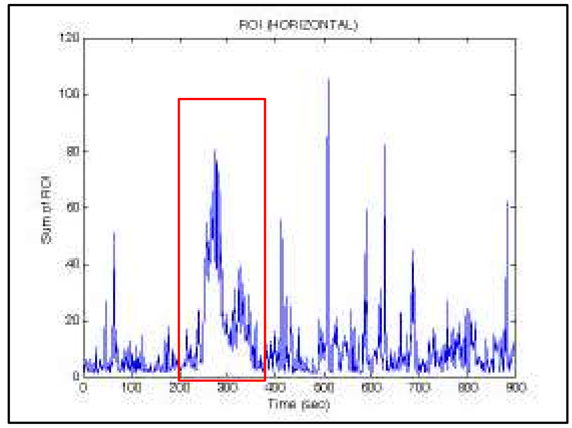


Fig. 7: Result of patient 5

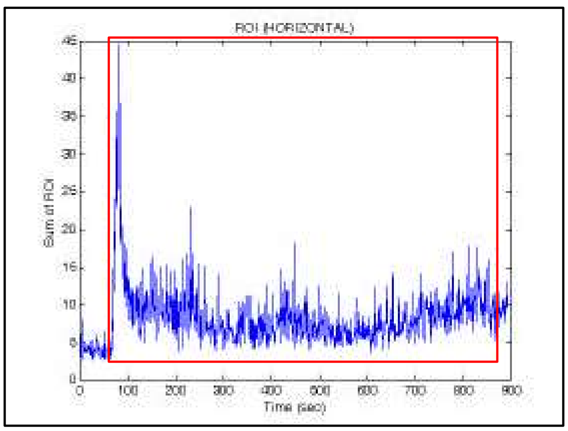


Fig. 6: Result of patient 4

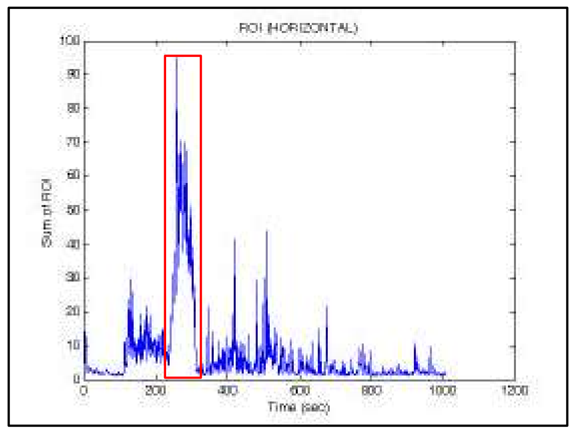


Fig. 8: Result of patient 6

It can be seen from Fig. 3 through Fig. 8 that these plots has demonstrated the ability of UMACE filter in discriminating the percentage changes in the ROI region when the normal segment is compared to the epilepsy portion and the changes can be calculated and depicted in graph form. The training data is chosen using empirical method based on recorded data. Consistent results are achieved when using this technique for selecting the training data. Results showed that low value is achieved for normal region acted as training and testing data and reflected small changes in the plot. As for the epilepsy part, the variations in the plot are distinct with high value shown in these plots in contrast to plot during normal region. It is observed that the obvious feature in the seizure region are the high lofty values and this pattern continue for a certain period of time without decreasing to near zero (not fluctuate to 0) as highlighted by the red boxes in Fig. (3 to 8). Next, for the post-epilepsy, some EEG data of patients will change to normal EEG state but for other patients, it will depict a new EEG pattern. This can be seen in the graph of Figure 5 for patient 3 where the post epilepsy value is between the normal and epilepsy value. Additionally, other patients may exhibit the changes of EEG data before the epilepsy attacked; as illustrated in the Fig. 8. It is observed here that the changed value increased to 50 seconds before the real epilepsy attack.

Table 1 showed the comparison of UMACE and video observation. In patient 1, 2 and 6, the UMACE method is unable to detect the duration perfectly as compared to the video. As for patient 3, 4 and 5, the UMACE detect accurately and better than the video observation (Fig. 4, 5). Next, for patient 4, the UMACE could categorize all the EEG data as seizure at 66 seconds although from the video observation there are some unknown responsive performed by the patient as predicted by the medical practitioner during 95 to 764 seconds. Though the UMACE filters produced late detection for several cases, but the strength of

Table 1: Estimation of epilepsy attack

Patient No	VIDEO EST Seizure start	VIDEO EST Seizure end	UMACE EST Seizure start	UMACE EST Seizure end
1	22	145	21	135
2	199	337	214	350
3	180	240	180	240
4	64	95	66	892
	764	892		
5	256	319	245	350
6	242	335	242	305

Table 2: CPU time for UMACE method

Patient No	Data length (sec)	UMACE	1 sec of data
1	384	11.546	0.030
2	742	16.032	0.022
3	300	9.703	0.032
4	889	22.922	0.025
5	900	18.468	0.021
6	900	20.969	0.023

evaluating and comparing the changes without using huge training data required makes them a suitable technique to aid diagnosing and as a guideline to assess a patient has recovered from an attack or vice-versa.

Furthermore, it can be stated that the UMACE is capable to produce prompt result from the time tabulated in Table 2. The average processing time for one second of data with 256 as the sampling frequency is 0.0255 second. Thus, the UMACE is suitable as an online method in screening the EEG data to assist the neurologist or medical practitioner for faster diagnosis.

CONCLUSION

As a conclusion, from the results obtained, it is proven that the UMACE filter is applicable to detect changes in the scalp EEG data that are recorded using bipolar montage. In EEG, we are aware that the data from the same person and the changes in the normal and abnormal state of the same individual is the matter that is highlighted to distinguish between normal and epilepsy portion of the data. UMACE can be used to detect these changes in a group of data from the same source. Next, same condition of the EEG signal produced minimum changes in the UMACE output while for different state, immense changes is observed in the plot. Since this method is suitable for bipolar montage, the database from hospitals can directly be applied without any conversion of the original database.

Further, the proposed method only utilized 3 consecutive seconds of the normal data as the training input and this made implementation effortless. The results between normal and epilepsy state of EEG data are distinguishable too. Thus, our method is acceptable since seizure detection usually suffered certain limitation; for instance accurate prediction required careful patient-specific tuning and usefulness for poorly localized epilepsies is limited. Besides, seizure data is costly to collect. Therefore, the results of the UMACE filter obtained can be used as an aided diagnosis tools in reading the EEG, assisting specialist to produce faster result and accurate diagnosis.

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