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Asmat Zahra, Nadia Kanwal, Naveed Ur-Rehman, Shoaib Ehsan, Klaus D. McDonald-Maier

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Seizure Detection from EEG signals using Multivariate Empirical Mode Decomposition

[1]Asmat Zahra,[1*]Nadia Kanwal, [2]Naveed Ur-Rehman, [3]Shoaib Ehsan and [3]Klaus D. McDonald-Maier

[1] *Department of Computer Science, Lahore College for Women University, Lahore, Pakistan*
[2] *COMSATS Institute of Information Technology, Islamabad, Pakistan*
[3] *3School of Computer Science and Electronic Engineering, University of Essex, UK*

Abstract

We present a data driven approach to classify ictal (epileptic seizure) and non-ictal EEG signals using the multivariate empirical mode decomposition (MEMD) algorithm. MEMD is a multivariate extension of empirical mode decomposition (EMD), which is an established method to perform the decomposition and time-frequency ($T-F$) analysis of non-stationary data sets. We select suitable feature sets based on the multiscale $T-F$ representation of the EEG data via MEMD for the classification purposes. The classification is achieved using the artificial neural networks. The efficacy of the proposed method is verified on extensive publicly available EEG datasets.

Keywords: , EEG Signals, Epilepsy, MEMD, Time-frequency algorithm

1. Introduction

Epileptic seizure is a chronic neurological brain disorder that impacts people worldwide. With reference to World Health Organization (WHO) epileptic seizure is one of the most common non-communicable neurological brain disorder affecting approximately up to fifty million people worldwide [1]. As per the WHO fact sheet, nearly 80% of the people with epileptic seizure disorder belong

Email address: asmat.pucit@yahoo.com, *nadia.kanwal@lcwu.edu.pk, nrehman.comsats@gmail.com, sehsan@essex.ac.uk, kdm@essex.ac.uk ()

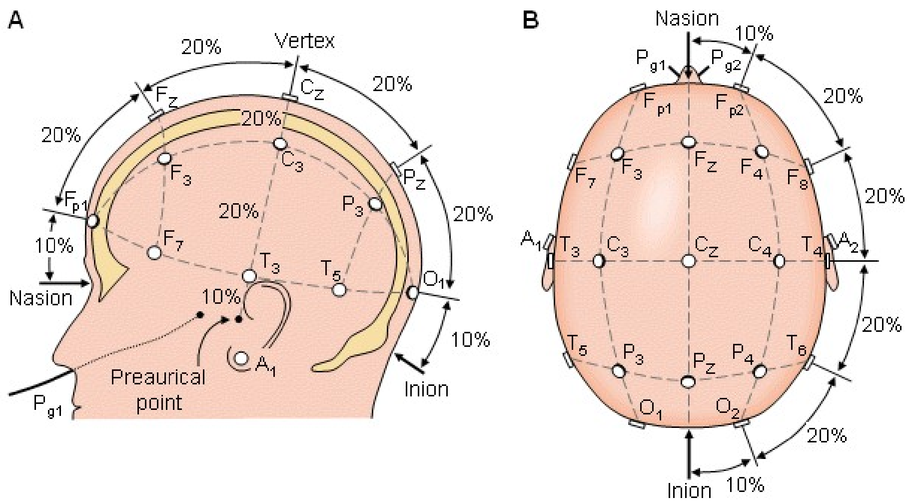


Figure 1: Internationally accepted 10-20 system initially presented in1958

to countries with low and middle income. During seizure there is abrupt rush of electrical and magnetic field activity because of the sophisticated chemical changes in the nerve cells of the brain. In a normal human brain, there exists a state of equity between nerve cells that excite and those that inhibit (stop). However, when an epileptic seizure takes place, an inequity can be seen clearly between excitation and inhibition neurons present in the brain. This leads to frequency changes (high / low) in message passing among brain cells. In clinical terms, this imbalanced discharge of electrical activity is often stated as paroxysmal activity that occurs may be in the course of epileptic seizure (ictal period) or in the intervals of epileptic seizures (inter-ictal periods) [2]. Mainly there are two stages of seizure. First one is the onset stage and second one is the event stage. Onset stage shows the earliest start of seizure hyperactivity while event stage is the accurate occurrence of seizure.

In clinical practice neurophysiologists visually scan long recordings of Electroencephalogram (EEG) to detect epileptic seizures. A German psychiatrist Hans Berger was the first person who recorded the electrical field of human brain in 1924 in Jena [3]. Communication activity of neurons in the brain is

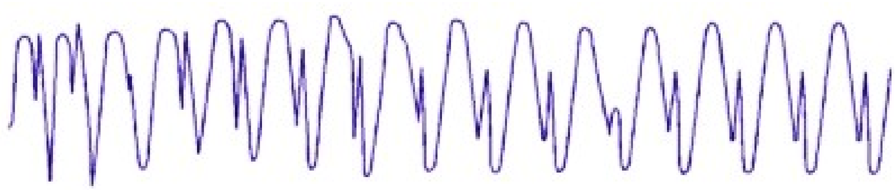
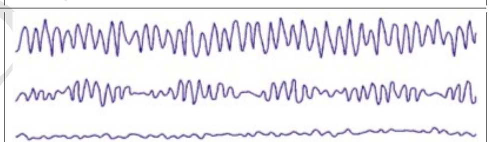
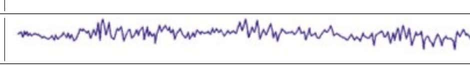
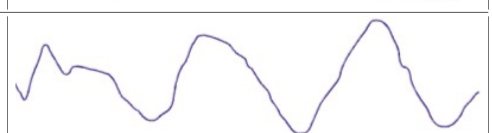


Figure 2: Epileptic spikes of 3Hz measured via EEG

recorded via placement of electrodes on scalp. An Internationally recognized 10-20 system [3] with 21 electrodes has been followed for the settlement of electrodes on the surface of scalp as shown in Figure 1. Nasion is the point at the top of the nose leveled with eyes, whereas Inion is the point in the mid-back of the head and is actually the bony lump which is located at the base of the skull. From these points other parameters are measured in the axial and longitudinal plane.

Table 1: Description of Alpha, Beta, Delta and Theta waves

Wave type	**Frequency Band** (Hz)	**Brain Region**	**Person state**	**Example**
Alpha (α)	8-13	Occipital	Awake with eyes closed	
Beta (β)	13-30	Parietal, Frontal		
Delta (δ)	0.5-4		Infants, sleeping adults	
Theta (θ)			Children, sleeping adults	

One of the rich feature of EEG is the sparking points (or epochs) linked to epileptic seizures and other waves usually classified as alpha (α), beta (β), delta (δ) and theta (θ) waves. Properties of each wave may differ depending upon the state of consciousness of a subject under investigation. Properties like amplitude, frequency and noise may vary when a person is awake, performing Rapid Eye Movement (REM), in the state of sleep (state of dream with active eye movement) and deep sleep [3]. The frequency spectrum (or band) of each type of wave is different and each wave type can be measured effectively from different brain regions as shown in Table 1. However pattern of epileptic spikes of 3Hz can be seen in Figure 2, these are more synchronized as compared to the signals in Table 1.

EEG signals are highly complex in nature due to inherent non-linear and non-stationary (comprised of two or more bands of frequency contents that changes with time) properties. Therefore, for both clinical and research purposes there have been many techniques proposed in literature that are used to analyze non-linear and non-stationary EEG data. As EEG signals are formed when cluster of neurons interact with each other, so it is important to seperate the frequencies/scales for appropriate interpretation and further processing. For seizure detection, many single- and multi-channel algorithms have been proposed: In [4] authors have used the energy, entropy and standard deviation as features extracted from EEG signal after applying the wavelet transform and Support Vector Machine (SVM) to classify the epileptic signals with 91.2% of accuracy rate. In [5, 6], Fourier transform has been used to classify seizure in EEG data; though no significant improvement was noted due to the inefficacy of Fourier based representations to handle non-stationary data, such as EEG. In [7], wavelet transform was implemented to extract energy and normalized coefficient of variation as features to distinguish normal and ictal EEG signals. He has used simple Linear Discriminant Analysis (LDA) for classification and reported 92% accuracy.

In [8], Singular Value Decomposition (SVD) was implemented to quantify seizure and non-seizure signals. Authors have selected r-singular values and Euclidean distance as features, and then inspected the final results visually, reliability and scalability is big question due to visual perception of humans. In [9], SVD has also been applied and used dipole parameters and Relative Residual

Energy (RRE) as features. They have classified the signals via visual inspection of parameters. Implementation of EMD using single channel input with Instantaneous Frequency (IF), amplitude, skewness, kurtosis and Shannon's entropy as features has been studied in [10]. In this study Linear Bayes classifier was applied and reported accuracy was 98%. In [11], EMD was implemented with modified central tendency as a feature to classify seizure and non-seizure EEG signals with 90% accuracy. In [12], normal and epileptic seizure signals were distinguished by deploying EMD algorithm. He used Multilayer Perceptron Neural Network (MPNN) and Self-Organizing Map (SOM) to classify the final results with 95.42% success rate. In [13], the MEMD was implemented with Hilbert Transform and used mean frequency as feature to classify seizure and non-seizure signals. In order to mark the significance level they used Kruskal Wallis test as classifier [12]. In [14], the effectiveness of MEMD has been investigated motor imagery Brain Computer Interface (BCI) and reported the comparative results of extensions of EMD *i.e.* Ensemble EMD (EEMD), Noise-Assisted EMD (NA-EMD), MEMD and Noise-Assisted MEMD (NA-MEMD). It was shown that MEMD and its variations provide efficient results for multi-channel analysis of non-stationary signals. Furthermore, other clinical uses of MEMD include removal of unwanted artifacts from electrooculography (EOG), electromyography (EMG) and electrophysiology.

In this paper, we employ instantaneous amplitude and frequency of multiple data scales of EEG data, obtained from MEMD, as features to detect seizure. MEMD was used to obtain the multiple IMFs from the input multi-channel EEG signals. t-test has been applied after adjusting the alpha value according to Bonferroni correction. t-test has been applied to only select the IMFs having most significant p-value. To classify seizure and non-seizure signals, frequency and amplitude information extracted from particular IMFs is then passed to Artificial Neural Networks. Final results have shown improved identification of seizure and non-seizure signals than the method proposed by Rehman *et al.* [13]. The rest of the paper is organized as follows: The EEG dataset, the Multivariate Empirical Mode Decomposition (MEMD) method, extraction and selection of Intrinsic Mode Functions (IMFs), computation of parameters, and ANN classifier are presented in Section 2. Obtained results and discussion of results are presented in Section 3. Finally, Section 4 concludes the paper.

2. Methodology

2.1. Multivariate Empricial Mode Decomposotion

EMD algorithm can decompose an input EEG signal into different frequency bands called Intrinsic Mode Functions (IMFs). The algorithm follows an iterative method to identify frequencies by calculating local mean from maxima and minima points of the signal. If the difference of IMF and mean is equal to the stopping criteria, it is selected as an IMF, otherwise the process repeats itself. In this way, a number of IMFs can be extracted. In its original formulation, EMD can only handle single-channel data sets. To extend the algorithm for multivariate data, Multivariate Empirical Mode Decomposition (MEMD) algorithm has been proposed [15]. MEMD is an improved extension of EMD which supports the computation of IMFs of multivariate (comes from multi-channel) data. MEMD not only solves the mode mixing issue but it also computes the mean value in an efficient way. It projects the multi-channel signal along multiple directions of multi-variate space and then computes the envelopes. After successful computation of envelopes it calculates the local mean of input signal.The steps of the MEMD algorithm are listed in Algorithm 1.

MEMD performs better than EMD due to the following exceptional properties:

- MEMD supports multi-channel input, contrary to EMD which only processes single channel data.
- MEMD efficiently deals with the mode mixing problem, which is resolved via combined breakdown of multiple oscillations present in a complex (higher dimensional) signal [16]. Hence, guaranteeing that the IMFs are matched in properties of both number and scale modules.

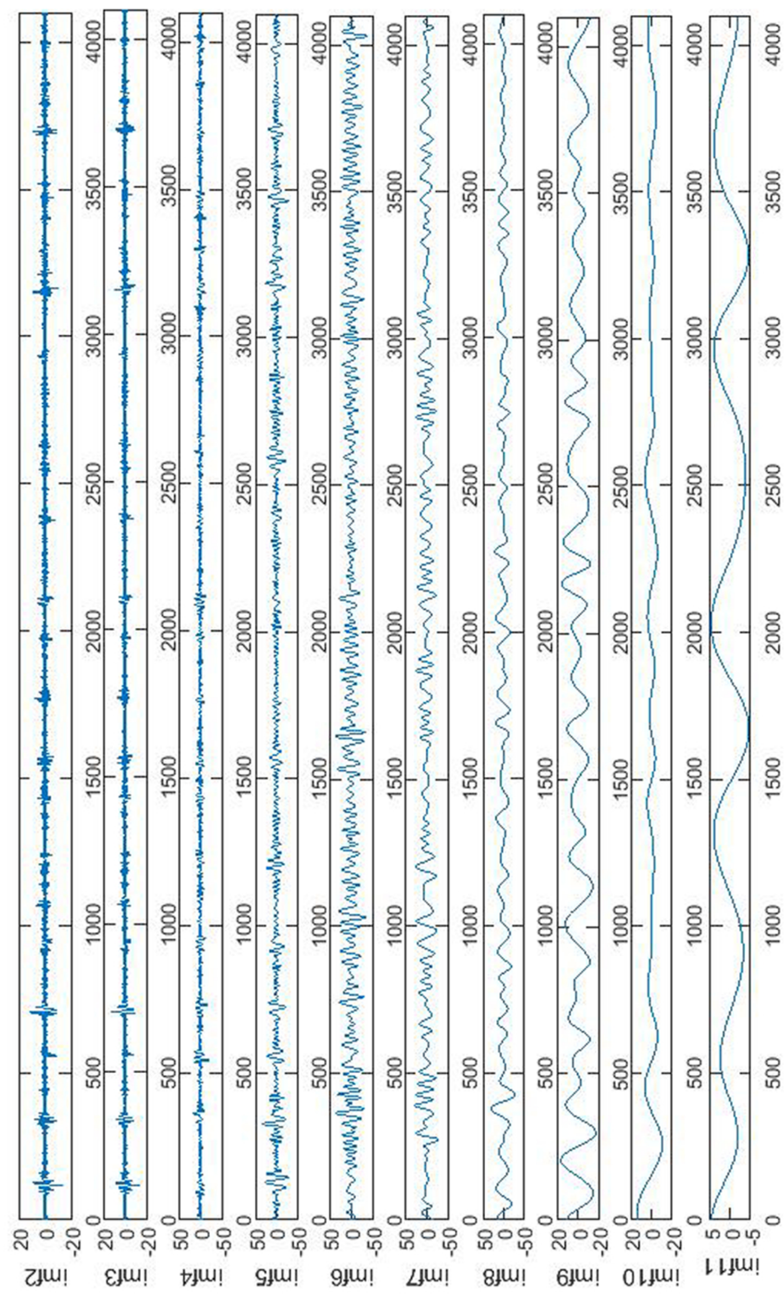


Figure 3: IMFs of random EEG signal obtained via MEMD

During IMFs computation, EMD faces the mode mixing issue i.e. when you repeatedly apply EMD on a particular signal, each time the resultant IMFs are different. Due to this issue feature extraction becomes unreliable thus a major limitation of EMD. However, IMFs shown in Figure 3 are obtained via MEMD and are free of mode mixing issue.

A repetitive process with a concerned threshold is required to bring out the meaningful information from a non-stationary EEG signal. MEMD follows the sifting process to obtain the IMFs. The first IMF contains unclear information; due to this ambiguous detail, the first IMF is not very useful in analysis. Similarly, IMF 12 and IMF 13 are residuals, hence they do not contain any considerable information. Therefore, these two IMFs are also ignored and the remaining set i.e. IMFs 2-11 are used for analysis and are shown in Figure 3.

Algorithm 1 Algorithm 1: MEMD Algorithm

1: Select an appropriate set of points in order to have sampling on (n-1) range.

2: Compute a projection, represented by $P^{(}\theta_n)\ (t)\}_{i=1}^{T}$, of contributed signal $v(t)_{i=1}^{T}$ along the direction vector $x\theta_n$, for all n (the complete set of direction vectors), giving $P^{\theta_n}(t)_{i=1}^{N}$ as the set of projections.

3: Discover the time instants $\{t_j^{\theta_n}\}$ matching to the maxima points of the set of projected input signals $P^{\theta_n}(t)\}_{i=1}^{N}$.

4: *Interpolate* $[t_j^{\theta_n}, v(t)_{i=1}^{T}]$ *to get multivariate envelop curves* $e^{\theta_n}(t)\}_{i=1}^{N}$.

5: For a set of N direction vectors, the mean represented by $m(t)$ of the envelope curves is computed as

$$m(t) = \frac{1}{N}\sum_{i=1}^{N} e\theta_n(t) \tag{1}$$

6: Collect the detail represented by $d(t) using d(t) = x(t) - m(t)$. If the 'detail' $d(t)$ meets the given stoppage criterion for a multivariate IMF, apply the above given procedure to $x(t) - d(t)$, else apply it to the extracted detail $d(t)$.

The termination condition is same as that presented by [17] except for the number of points. Further, zero crossings are not implemented due to undefined extrema points for multivariate signals [16]. IMFs of a random EEG signal obtained using MEMD are shown in Figure 3.

In the proposed method, we first obtain a multivariate signal by combining channels from different EEG sources to obtain an m channel data set. The multivariate m-channel data is then decomposed using the MEMD algorithm which results in N number of multichannel IMFs. However, not all IMFs are processed and used in the proposed method: the first few IMFs which contain high frequency information may contain noise, while the last few IMFs are mostly residuals and hence can be discarded. For the remaining IMFs, feature extraction is performed before classification through the neural network approach. The block diagram of the proposed methodology is shown in Figure 5.

In order to have multi-channel dataset, we have combined 5 signals from each dataset (Z, O, N, F and S). Hence dataset is now of 5-channel EEG which is then decomposed by MEMD. MEMD insures the formation of IMFs of multiple channels in the same frequency range for consistent results. Same frequency range of multiple channels is important to compare the features extracted from multi-channel data with some common bases. Hence, for classification purpose feature set from IMFs can be extracted from mulit-channel data on common bases.Note that mode mixing issue is resolved here because all the frequency ranges for each channel is same. Graphs shown in Figure 4 clearly demonstrate the same frequency distribution of IMFs belonging to first two channels of EEG dataset. As first IMF of channel 1 and channel 2 have same frequency distribution (each having same number of frequency bins (3 bars in first IMF of channel 1 and channel 2)) obtained via MEMD's sifting process (frequency scale in each corresponding graph is same i.e. frequency scale in IMF1 of channel 1 and IMF 1 of channel 2 is same. Similarly, frequency scle in IMF2 of channel 1 and IMF2 of channel 2 is similar)

Total numbers of obtained IMFs after implementing the MEMD are 13. Hence total number of IMFs when computed against each dataset:

$$\#ofIMFs = 13 \times 500 = 6500 \tag{2}$$

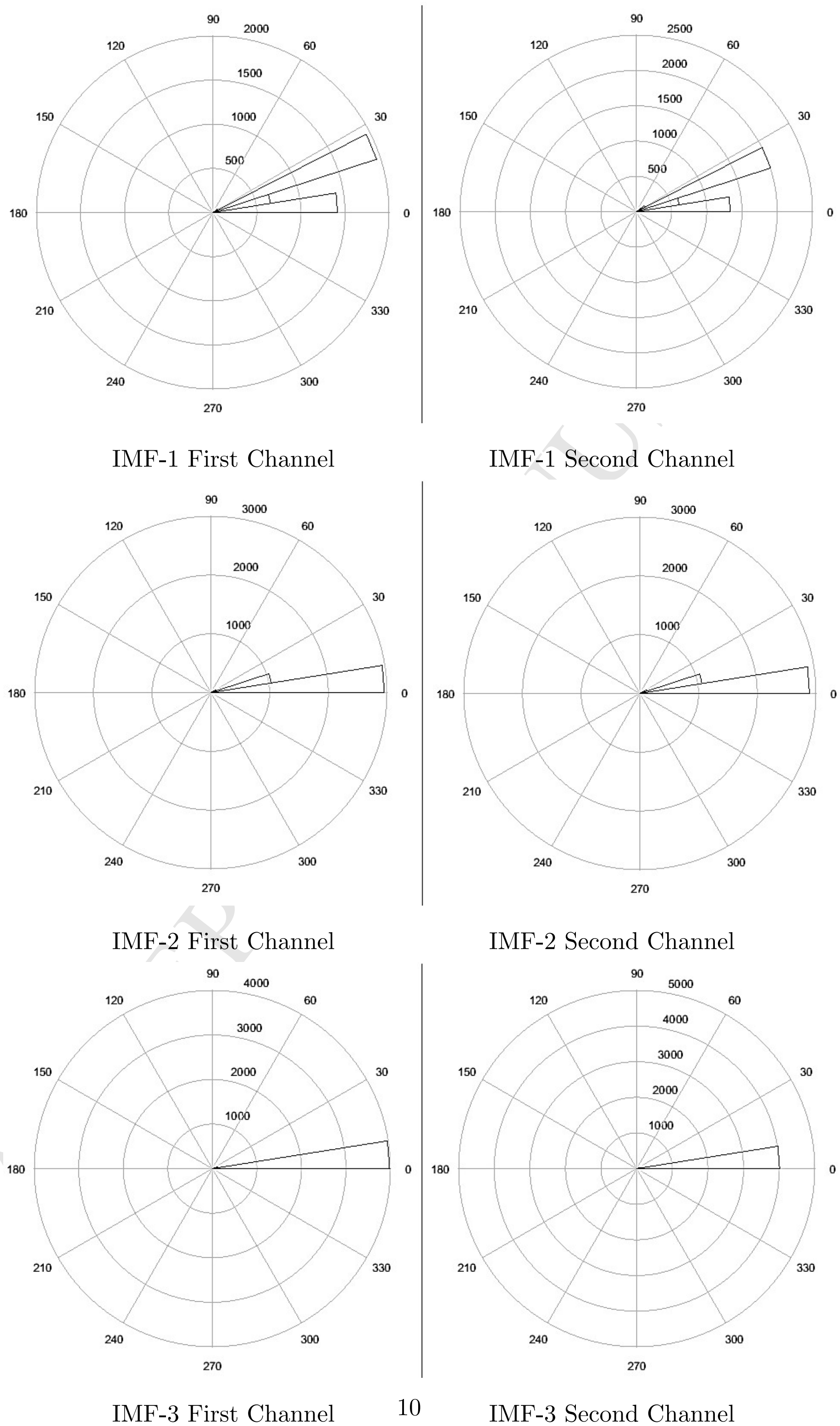


Figure 4: MEMD ensures the same range of frequency in IMFs of each channel hence for classification purpose feature set from IMFs can be extracted. Same range of frequencies among IMFs has been shown in Figure 3 for first three IMFs

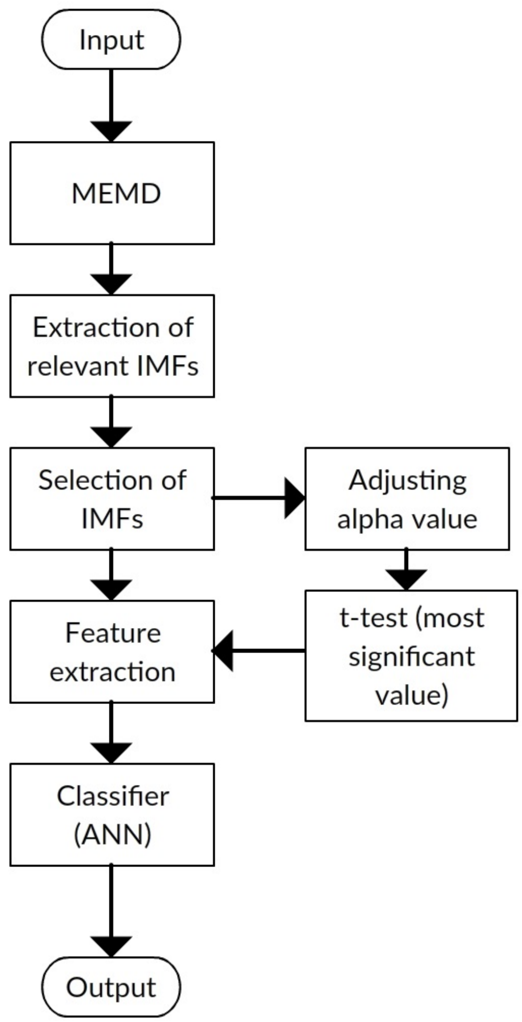


Figure 5: Block Diagram of the proposed system

It has been shown in [18] that only first four IMFs yields the important information content about the signal, rest of the lower IMFs indicates artefacts of lower frequency and trend. And the first IMF contains more noise as compare to others. Hence, we have chosen 2-4 IMFs because of the valuable information content present in them. Now the total size of dataset after removing noisy and IMFs with lower frequency remains:

$$Size\ of\ dataset\ = 3 \times 500 = 1500 \tag{3}$$

2.2. Feature Extraction

As discussed in the previous section that IMFs with lower frequency information and noise has been removed. On the rest of the selected IMFs, Hilbert transform is applied to extract the information about instantaneous frequency and amplitude. In order to compute the weighted mean frequency we have used the equation 4 [18].

$$f' = \frac{\sum_{i=1}^{n} a(i) f^2(i)}{\sum_{i=1}^{n} a(i) f(i)} \tag{4}$$

Here f is the instantaneous frequency and a is the instantaneous amplitude obtained via Hilbert transform. Instantaneous frequency has also been used as a feature.

2.3. Selection of IMFs for Classification

For rapid classification purposes, the number of IMFs is still too large and therefore, selecting statistically significant IMFs makes the dataset considerably small yet useful. Therefore, t-test has been applied here to find IMFs with significant P-value as shown in Table 2. The use of any statistical test includes calculating test statistics interpreted as statistically significant value or non-significant value if it is greater or less than some threshold known as level of significance denoted by α. The most common value of is 0.05 with no identified reason [20]. Therefore, a number of researches urged to adjust this threshold as per number of samples under comparison. A well-known of such adjustment is known as Bonferroni correction [19] where it is suggested that

0.05 should be divided by total number of samples to find corresponding level of significance. Hence if the number of samples under comparison are 3 then appropriate will be $0.05/3 = 0.0167$. This adjusted value of alpha has been used in the t-test. In order to get the most significant feature vector, IMFs with most significant corresponding p-value have been selected. Table 2 shows the p-values against top three IMFs of first subset of input channel. P-values are collected via implementation of t-test. IMFs with maximum P-value have been selected for classification using features. After the selection of IMFs two feature i.e. instantaneous amplitude and instantaneous frequency has been computed which are then used as input to the classifier.

Table 2: p-values of selected IMFs

IMF - # - dataset	**p-value**	**t-test (h)**
IMF-2-Z	0.0476	0
IMF-3-Z	0.8095	0
IMF-4-Z	**0.9045**	**0**
IMF-2-O	0.3041	0
IMF-3-O	**0.8265**	**0**
IMF-4-O	0.6951	0
IMF-2-N	0.4259	0
IMF-3-N	0.3967	0
IMF-4-N	**0.9498**	**0**
IMF-2-F	0.1949	0
IMF-3-F	**0.6461**	**0**
IMF-4-F	0.3858	0
IMF-2-S	0.0907	0
IMF-3-S	**0.5464**	**0**
IMF-4-S	0.0077	1

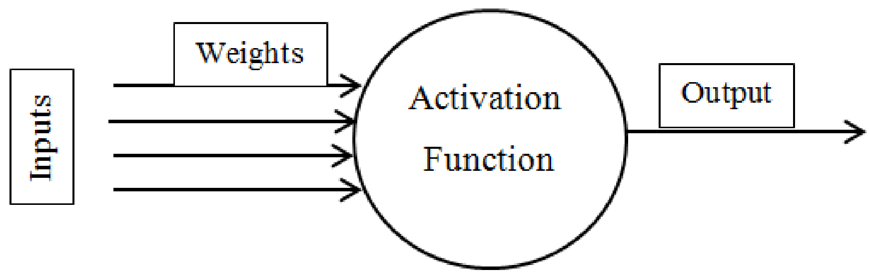


Figure 6: An Artificial Neural Network

2.4. Classification using ANN

Once we get the IMFs, next step is to classify the EEG signals into ictal events(seizures) or otherwise. A number of classification algorithms have been used for this purpose however, the use of Artificial Neural Network (ANN) is more common [20]. Traditional work in ANN began approximately 50 years ago, to use machines that simulate the working of human brain. ANN works similar to that of real neuron (composed of dendrites, soma (cell body), axon and synapses) and all of the neurons collectively work to respond against particular stimulus. Similarly, ANN is the generalization of human neural biology (related to human cognition). Abstract mapping of biological neuron on artificial neuron is shown in Figure 6 and follows the following description:

- ‘Synapse’are replaced with ‘inputs’
- ‘Activation of neuron’is replaced with weights (higher weights, stronger the input with which it is multiplied) computed by particular mathematical function

All of the artificial neurons combined (or linked) together to process the particular information. Various ANN models have been used to classify different kind of data. However, a simple (basic) ANN is comprised of an input layer, an output layer and one or more than one number of hidden layers. Multi-layer (composed of one or more hidden layers) model is formed by growing the count of hidden layers. Multi-Layers increase the complexity of neural network but provide better output in complex problems. There are two variation of ANN; feed-forward multi-layer ANN and back propagation ANN. In feed-forward, artificial neurons are arranged in multiple layer and send signals in forward direction, if errors exist then they are sent back to the previous layer so that model learns them again (by adjusting weights) to decrease the chances of error. The process of weight adjustment in a neural network to get better output is known as 'training'or 'learning'. However, backpropagation is one that uses the error to learn such weights effectively using a method called gradient descendent. In order to test each dataset (Z, O, N, F, S) against collected feature set, we have implemented neural networks. Weights are randomly initialized among the connections of nodes (neurons). After then they are learned using back propagation method. In order to determine the error, input value is compared with the given target value. Computed error is then propagated back to the input of neural network, here the weights are then learned again and training phase continuous. Training loop stops when the cost function is minimized. Here cost function used by artificial neural network is:

$$J(w) = \frac{1}{n}\sum_{(i=1)}^{n}(y^i log(h_w(x^i)) + (1-y^i)log(1-h_w(x^i))) \tag{5}$$

Here 'w'are the weights of all the connections present in the neural network. Back propagation algorithm uses equation 6 to compute the partial derivative of cost function (given in equation 6) with respect to each weight (assigned randomly). This partial derivative is then used by gradient descent algorithm to minimize the cost function given in equation 5.

$$\frac{\delta}{\delta_{ij}^{l}}J(w) \tag{6}$$

Here l is the index of hidden layer.

3. Results and Discussion

3.1. Datasets

The electroencephalogram (EEG) readings taken from publicly available Bonn University's database [15]. Database consists of five sets denoted as Z, O, N, F, S, containing 100 single-channel EEG recordings each of 23.6s duration with 173.6Hz of sampling rate. The annoying artifacts due to activity of muscles and eye movements had already been removed on the basis of visual inspection of data sets (This visual inspection has been done by the providers of the database. Database source: Bonn's University Dataset) [15]

- Set Z and O are comprised of surface EEG recordings of healthy volunteers in the wakeful state with eyes open (Z dataset) and eyes closed (O dataset) respectively. A standardized electrode placement technique was used for recording. See Figure 1.
- Set N EEG recordings were recorded for five patients in seizure-free interims from the region of hippocampal formation of opposite hemispheres of the brain.
- Set F came from seizure recordings in the epileptogenic zone.
- And the set S only contained recordings of the patients showing seizure activity.

All of the EEG data was recorded using 128-channel amplifier system. After 12-bit conversion (analogue to digital), data was written to disk with 173.61Hz of sampling rate. 0.53-40Hz was the pass band range for the band-pass filter used to record the frequencies in certain range.

Table 3: Details of datasets division into training, validation and testing sets

Division	**Training**	**Validating**	**Testing**
Percentage	60%	5%	35%
Samples	12291 samples	1024 samples	7170 samples

In order to obtain the results dataset has been divided into training, validation and testing sets as shown in Table 3.

3.2. Classification Results

Results obtained by deploying our proposed method are quite good in comparison to other methods of decomposition like SVD, EMD. Confusion matrix shown in Figure 7 shows the training, validation and testing results, classified by ANN using back propagation algorithm.

In Figure 7 first five (each representing the individual dataset i.e. Z, O, N, F and S respectively) diagonal cells (in green color) of training confusion matrix depict the number and percentage of correct classifications by the trained network. For example, 2205 cases are correctly classified as samples of Z dataset. 2126 cases are correctly classified as part of O dataset. And 1635 cases are correctly classified as part of N dataset. Similarly, 2325 and 2444 are correctly classified as part of dataset F and S respectively. No cases of the dataset O are incorrectly classified as part of Z dataset. 802 cases are incorrectly classified as part of Z dataset. 0 cases from datasets N, F and S are incorrectly classified as part of Z dataset. Total of 73.3% cases have been correctly identified as part of Z dataset and rest of the 26.7% are wrong. And out of Z dataset 89.0% cases are correctly classified as Z dataset and 11.0% are classified as from other datasets i.e. O, N, F and S.

Overall, 87.3% of the predictions are correct and 12.7% are wrong classification in training dataset. Same distribution as of training set has been considered for Validation and Testing sets. And collectively correct identification is 87.2% for all datasets. Furthermore, Receiver Operating Characteristics curves commonly known as ROC curves, have also been used to demonstrate the performance of algorithm. Closer the curve to the top-left edge of the plot box the better is the classification of each specified class present in the dataset. However, diagonal line represents the random performance of the classifier. ROC of our obtained output classes are shown in Figure 8.

Best validation performance at particular epoch (period of time) has been

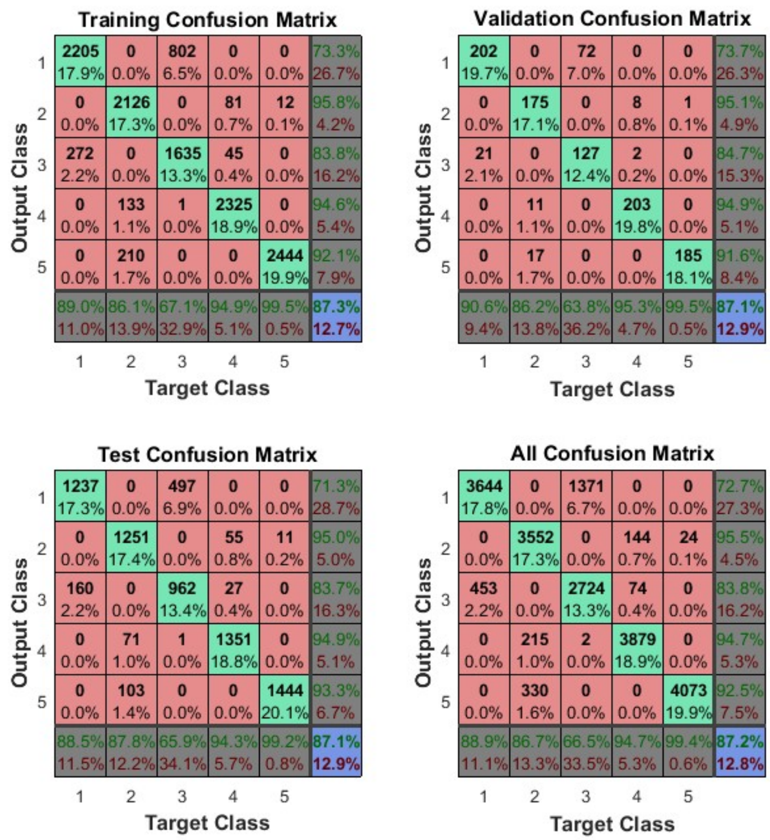


Figure 7: Confusion matrix showing results of classification. Accuracy (upper value in each cell) and error rate (lower value in each cell) of each dataset is quite good. Here 1, 2, 3, 4, 5 are depicting data set Z, O, N, F, and S respectively

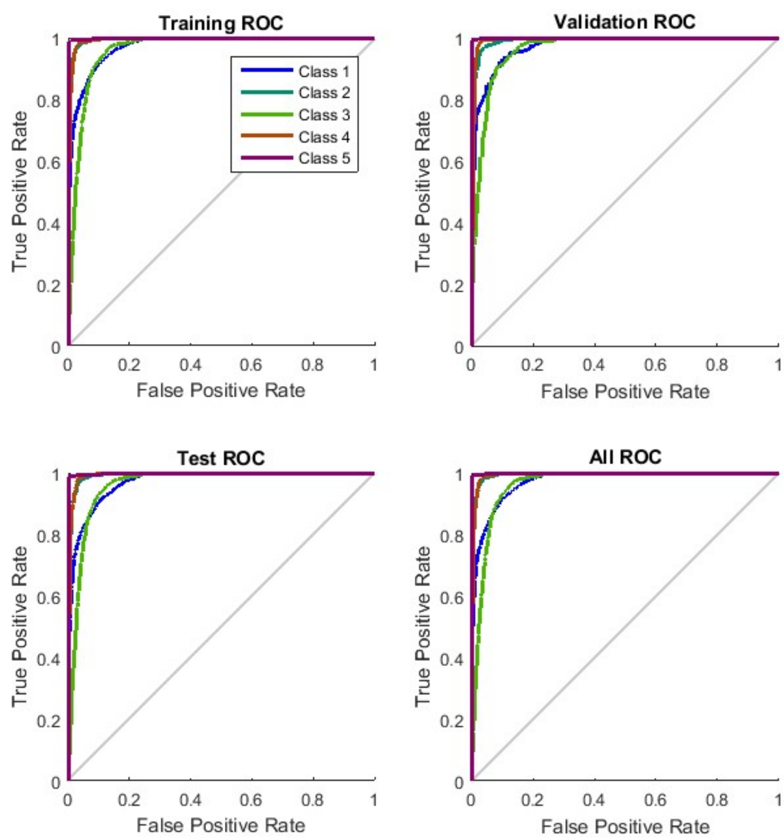


Figure 8: Receiver Operating Characteristics of each phase i.e. Training, Validation and Testing. Here Class 1, 2, 3, 4, 5 are depicting classification accuracy of dataset Z, O, N, F and S respectively

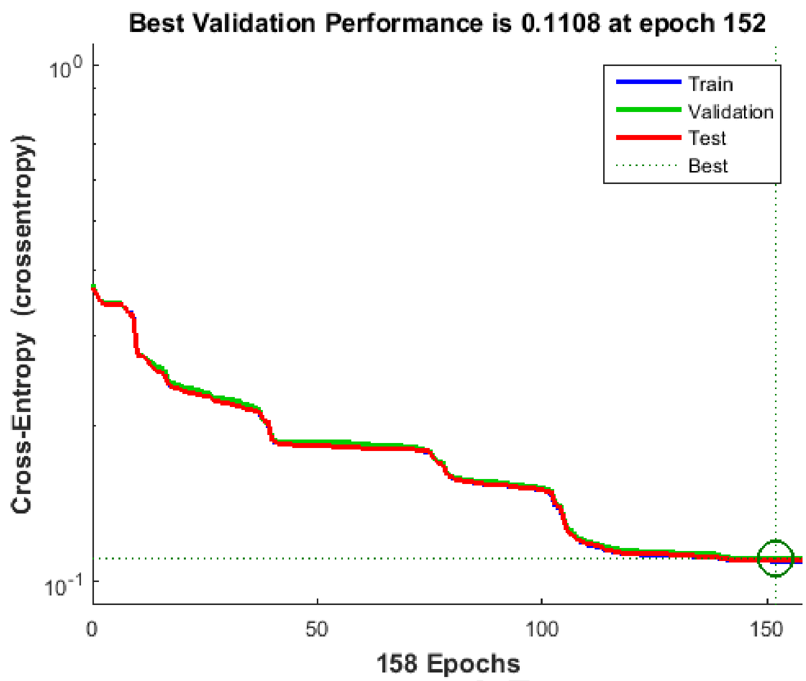


Figure 9: Showing best validation performance at epoch 152

shown in Figure 9. Error histogram of each state i.e. training, validation and testing has been shown in Figure 10 . Error histogram shown in Figure 10 presents a clear sketch of network authentication of each phase i.e. training, validation and testing. It represents the outliers, where the authentication is not as good as the best set of data points. Part of histogram that is showing the zero line error provides the grounds for setting the threshold, further used to categorize the outliers based on perfection or imperfection of selected feature values.

Table 4: Comparison of current research with other researches

Paper	Dataset	Algorithm	Classifier	Accuracy
[13]	Bonns University	MEMD	Kruskalwallis test	Efficient but ignored time information
[21]	Bonns University	EMD	LS-SVM	86.00%
Our findings	Bonns University	MEMD	ANN	87.2% (overall for all datasets i.e. Z,O,N,F,S)

Proposed method is different in the selection of features and on the basis of

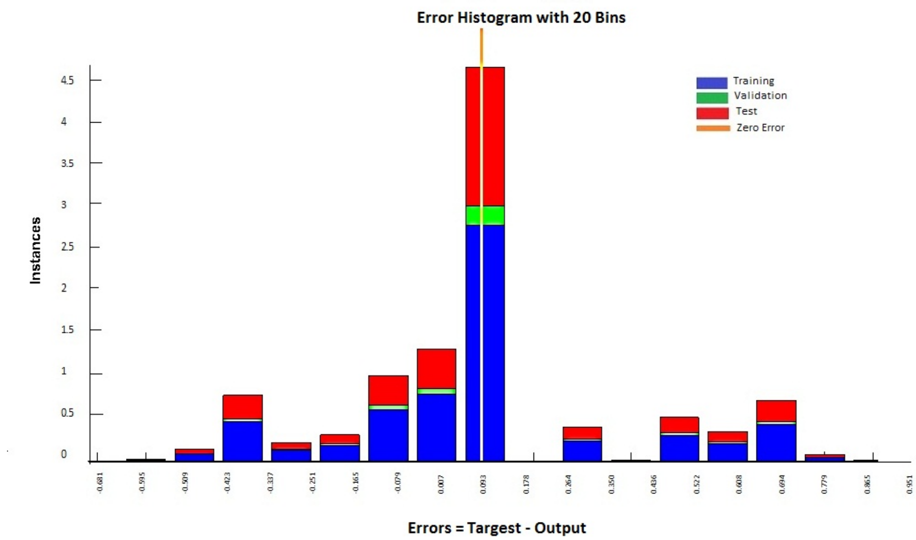


Figure 10: Histogram of each training, validation and testing state

methodology and classification as compared to feature selection in [13].We have used MEMD to extract the IMFs from multichannel EEG dataset. As standard EMD produces misaligned IMFs (corresponding to different frequency bands) for multi-channels and hence make their comparison meaningless. This issue has been resolved using MEMD. MEMD process the signals directly in higher dimensional spaces where it resides. This results in matched IMFs in terms of frequency, facilitating comparison of individual or summed IMFs. After the extraction of IMFs, only those IMFs have been considered with maximum frequency linked information. Only the first four IMFs yields the important information content about the signal, rest of the lower IMFs indicated artefacts of lower frequency and trend [18]. And the first IMF contains more noise as compare to others. Hence we have chosen 2-4 IMFs because of the valuable information content present in them.In [13], no such reduction has been done. On the rest of the IMFs, Hilbert Transform is applied to extract the instantaneous frequency and amplitude. In order to compute the weighted mean frequency equation 4 has been used [18]: t-test has been applied on the IMFs to choose the IMFs with most significant P(probability) value. Level of significance in t-test denoted by has been adjusted using Bonferroni correction [19]. There has been no such adjustment in [13]. After then dataset has been divided into training, validation and testing sets. Spectral features from the IMFs with most significant p-value have been used to train the ANN with back propagation algorithm. Overall obtained accuracy using ANN is 87.2% as shown in Table 4. However no such detailed information is given in [13].

4. Conclusion

We have proposed a data adaptive multiscale algorithm for the classification of EEG signals for seizure detection. For that purpose, multichannel input EEG data is first decomposed to its multiple intrinsic scales using the multivariate empirical mode decomposition algorithm. After removing the IMFs belonging to noise and other unnecessary artifacts, classification on the remainder of IMFs has been performed by employing a feature vector based on instantaneous frequency and amplitude via artificial neural network framework. We have shown comprehensive results obtained from extensive simulations on real world EEG data sets to show the effectiveness of the proposed method. The results have been very promising since the proposed method has been shown to provide excellent classification of seizure from EEG data.

The computational complexity of the MEMD algorithm is a concern though. The method is compositionally very expensive especially for signals with large number of input channels. The computational complexity of MEMD has been discussed in detail in [22]. Recent parallel implementation of EMD and multivariate EMD could pave the way for a faster online implementation of EMD and MEMD based algorithms.

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Asmat Zahra
Department of Computer Science, Lahore College for Women University, Jail Road, Lahore, Pakistan

Asmat Zahra received her MSc (IT) degree from Punjab University College of Information Technology in 2012 and has completed her MSCS degree from the Lahore College for Women University in 2016. Currently she is working as Lecturer of Computer Science at Punjab Group of Colleges which she joined in 2016.

Her research interests include developing and analyzing adaptive multivariate T-F algorithms, Signal processing, Computer vision, and their applications in biomedical engineering.
She has also been nominated for government's Laptop scheme on merit basis in 2012 and 2015, and she is also the recipient of Gold medal on completion of her MSCS degree from the Lahore College for Women University in 2016.

Nadia Kanwal
Department of Computer Science, Lahore College for Women University, Jail Road, Lahore, Pakistan

Nadia Kanwal received her M.Sc. and PhD degrees in computer science from the University of Essex, Essex, U.K., in 2009 and 2013 respectively. Currently she is working as Assistant Professor at Lahore College for Women University which she joined in 2001.

Her research interests include performance characterization of vision algorithms and local image features detection, description and matching techniques for tracking and navigation applications. Currently, she is involved in research to develop a navigation system for visually impaired people using Microsoft Kinect sensor. Mrs. Kanwal remained a student member of the IEEE Computer Society, the Institution of Engineering and Technology, and the British Machine Vision Association. She has been involved in reviewing for conferences and journals.

Naveed ur Rehman
Comsats Institute of Information Technology, Islamabad, Pakistan

Naveed ur Rehman received the B.Eng. degree in electrical engineering from the National University of Sciences and Technology, Pakistan. He completed his Ph.D. degree in signal processing in 2011 from Imperial College, London, United Kingdom. He is currently working as an assistant professor in COMSATS Institute of Information Technology, Islamabad, Pakistan. His research interests include developing data adaptive multivariate T-F algorithms, nonlinear methods, and their applications in biomedical engineering, communications, remote sensing, data fusion, and renewable energy.

Shoaib Ehsan

School of Computer Science and Electronic Engineering, University of Essex, Colchester, U.K.

Shoaib Ehsan received the B.Sc. degree in electrical engineering from the University of Engineering and Technology, Taxila, Pakistan, in 2003, and the Ph.D. degree in computing and electronic systems with a specialization in computer vision from the University of Essex, Colchester, U.K., in 2012. He has extensive industrial and academic experience in the areas of embedded systems, embedded software design, computer vision, and image processing. His current research interests are in intrusion detection for embedded systems, local feature detection and description techniques, image feature matching, and performance analysis of vision systems. He is a recipient of the University of Essex Post Graduate Research Scholarship and the Overseas Research Student Scholarship. He is a winner of the prestigious Sullivan Doctoral Thesis Prize by the British Machine Vision Association.

Klaus D. McDonald-Maier
School of Computer Science and Electronic Engineering, University of Essex, Colchester, U.K.

Klaus D. McDonald-Maier received the Dipl.Ing. degree from the University of Ulm, Ulm, Germany, the M.S. degree in electrical engineering from the École Supérieur de Chimie Physique Électronique de Lyon, Lyon, France, in 1995, and the Ph.D. degree in computer science from the Friedrich Schiller University, Jena, Germany, in 1999.
He worked as a Systems Architect on reusable microcontroller cores and modules with Infineon Technologies AG's Cores and Modules Division, Munich, Germany, and as a Lecturer of electronic engineering with the University of Kent, Canterbury, U.K. In 2005, he joined the University of Essex, Colchester, U.K., where he is a Professor with the School of Computer Science and Electronic Engineering. His current research interests include embedded systems and system-on-chip design, development support and technology, parallel and energy efficient architectures, the application of soft computing, and image processing techniques for real-world problems.