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Selection of Artificial Neural Network Training Algorithms in the Detection and Classification of Wavelet de-noised Musical Tone Stimulated EEG Signals

Roy Francis Navea and Elmer Dadios

***Abstract*—The human brain can be stimulated by internal and external factors with which the effect of these can be traced from brainwaves or EEG signals. The natural complexity of EEG signals calls for methods by which information can be extracted and used for a particular purpose. In this study, musical tones were used to stimulate the brain and an attempt was made to detect and classify these stimulations from the EEG signals. An Artificial Neural Network (ANN)-based classifier was employed to do this task. Wavelet based de-noising was used to smoothen the musical tone stimulated EEG signals and among the 110 known mother wavelets, the reverse biorthogonal 'rbio3.1' and 'rbio3.3' using the 'rigrsure' thresholding method satisfied the selection criteria for better de-noising effects.**

Detection and classification were performed using ANNs implementing four different training algorithms. Results show that *trainbr* or *trainlm* is good for detection while the *trainlm* was found to be better than the other training algorithms used when it comes to classification. The metrics for selecting the training algorithm were based on the F-score and the rejection rate having the condition that F-score should be high while the rejection rate should be low.

***Keywords*—Electroencephalogram, musical tone stimulation, wavelet de-noising, training algorithms, Artificial Neural Networks**

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I. Introduction

THE relaxed state of the mind can be disturbed by different stimulation causing a response that can be mapped and viewed through electroencephalography (EEG). The stimulation can be assessed and characterized [1] using different signal processing techniques. Not just stimulations, inherent motions [2],[3] and other regular activities of the human body [4]–[6] are deeply registered and appear in different patterns in the brain. Different attempts were made to understand brainwave patterns according to a specific task or stimulation [6]–[8] and this brought about a variety of approaches that addresses the nature of the task and stimulation.

In this study, an attempt was made to detect and classify the disturbance caused by musical tone stimulation by utilizing different algorithms in an artificial neural network. Musical tones are the building components of a melody when they are arranged in a specific timing pattern guided by a time signature. Lyrics were added to give meaning to these arrangement, thus, producing a song. The uniqueness of this study is that it focuses on the music itself, specifically the pitch, and not on the song which is a short piece of music with lyrics that comes with different genres. Stimulated EEG signals were used to investigate the relative effect of the musical tones [1] through the different features which can be extracted from it. EEG signals in its raw form requires a number of processing techniques in order reduce its complexity and utilize it into something useful and informative.

Processing EEG signals poses challenges in developing algorithms by which they can be utilized for a specific purpose. EEG signal patterns can be used as a basis for diagnoses [5], [7], [9]–[12] and a control signal for actuators and motors [13], [14]. Before doing so, preprocessing has to take place to remove unwanted details in the EEG stream. Hence, filtering techniques have to be performed.

One of the best de-noising methods is wavelet-based filtering due to its capability to deal with both time and frequency maps of the given signal simultaneously as compared to Fourier-based filters which suffer from substantial loss of EEG data [15]. It is an important matter how mother wavelet (MW) and thresholding method is selected.

Detection and classification are always paired with feature extraction. Features are the characteristics of the signal of interest which discriminate it from the others. Features can be extracted using different algorithms which includes both time-domain, frequency-domain and statistical characteristics [4], [16]–[19]. For as long as these features and characteristics can possibly differentiate one segment from another, they are good inputs to the classifier engine. Power and energy features [1], [2],[20] are useful features since stimulation is basically a transfer of energy from the stimuli to the receptors (or human sensory organs) which generate impulses that travel through the nerves to the brain.

Features are fed into classifiers that come in a variety of types and algorithms used. Some of the well-known classifiers include Artificial Neural Networks (ANN), Naïve Bayes (NB) classifiers, k-nearest neighbor (k-NN) classifiers and Support Vector Machines (SVM). In [21], EEG signals from epileptic patients were used. The features are based on Discrete Fourier Transform (DFT) coefficients and results show that NB classifiers is better than k-NN when it comes to classification accuracy and computation time. In [22], single EEG channel was used to classify levels of drowsiness. Features used are based on Fast Fourier Transform (FFT) coefficients and results show that ANN is better than SVM in terms of accuracy and receiver operating characteristic (ROC) curve. Each classifier may perform better than the other depending on the application and type of signal used [21]–[23].

This study focuses on the implementation gradient descent, quasi newton, conjugate gradient and Bayesian regularization ANN algorithms using the training functions (TF), *trainrp*, *trainlm*, *trainscg*, and *trainbr*.

I. METHODS

A. Audio Stimulus and Data Gathering Procedures

The audio stimulus is composed musical tones in the key of C. The tones are C, F, and G are located at the 4th octave of a standard piano keyboard. The tones are arranged in a musical piece [1],[20] as shown in Figure 1. Rests (whole, half and quarter rests) are periods of silence while the notes (half notes) are the tones. The long series of rests before the first tone establishes the baseline (baseline1) while the rests that come immediately after a note is the secondary baseline (s-baseline).

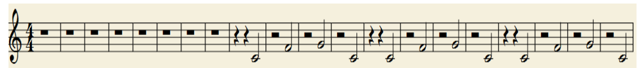


Fig. 1. Audio Stimulus Piece

A timing table [1],[20], as shown in Table I, was used to easily determine where in time a tone was played and stimulated the brain. No delays were assumed. The timing table is the summary of the audio stimulus in terms of the stimuli, time stamp, period, number of samples and sample series. The stimuli were named baseline1, s-baseline, C, F, and G. The audio was played for 3 minutes and 48 seconds. Baseline1 has the longest period with 180 seconds. S-baseline and the notes have a period of 2 seconds for each occurrence. The EEG signal was sampled at 128 samples per second. Baseline 1 has the largest number of samples with 23040. S-baseline and the notes have 256 samples each. There are 29184 samples corresponding to the total period of the audio stimulus. Each stimulus was mapped in the sample series for segmentation purposes.

The data used were taken from 15 undergraduate students with ages typically ranging from 18 to 21. As in [20], the data gathering was performed in a dim-lighted acoustically prepared room. The respondents were seated one at a time and were asked to close their eyes to minimize eye-related artefacts. An ear phone was used for optimal audio reception. A 14-channel Emotiv EPOC neuroheadset was used and its signal quality and data transmission functionality was carefully monitored through its graphical user interface.

B. Detection and Classification Procedures

The general detection and classification process follows the flowchart in Figure 2. The raw EEG signals obtained from the neuroheadset were loaded in Matlab®.

The signals were bandpass filtered within the alpha (8Hz–13Hz) and beta (13Hz–30Hz) bands, and smoothened using wavelet de-noising techniques. Two classifiers were used. The first one (ANN1) was for detecting the tone-stimulated EEG signal and the second one (ANN2) is to classify it according to C, F or G tone. The display process is an indicator of what has been detected or classified. There is a possibility that a certain signal might not be classified [24] and to address this, rejection ratios were indicated in the results.

TABLE I
Audio Stimulus Timing Table

Stimuli	baseline 1	s-baselline	C	s-baseline	F	s-baseline	G
Time Stamp	0-3:00	3:01-3:02	3:03-3:04	3:05-3:06	3:07-3:08	3:09-3:10	3:11-3:12
Period	180 sec	2 sec	2 sec	2 sec	2 sec	2 sec	2 sec
No. of Samples	23040	256	256	256	256	256	256
Sample Series	1-23040	23041-23296	23297-23552	23553-23808	23809-24064	24065-24320	23421-24576

Stimuli	s-baseline 1	C	s-baseline	C	s-baseline	F	s-baseline
Time Stamp	3:13-3:14	3:15-3:16	3:17-3:18	3:19-3:20	3:21-3:22	3:23-3:24	3:25-3:26
Period	2 sec	2 sec	2 sec	2 sec	2 sec	2 sec	2 sec
No. of Samples	256	256	256	256	256	256	256
Sample Series	24577-24832	24833-25088	25089-25344	25345-25600	25601-25856	25857-26112	26113-26368

Stimuli	G	s-baseline	C	s-baseline	C	s-baseline	F
Time Stamp	3:27-3:28	3:29-3:30	3:31-3:32	3:33-3:34	3:35-3:36	3:37-3:38	3:39-3:40
Period	2 sec	2 sec	2 sec	2 sec	2 sec	2 sec	2 sec
No. of Samples	23040	256	256	256	256	256	256
Sample Series	26369-26624	26625-26880	26881-27136	27137-27392	27393-27648	27649-27904	27905-28160

Stimuli	s-baseline	G	s-baseline	C
Time Stamp	3:41-3:42	3:43-3:44	3:45-3:46	3:47-3:48
Period	2 sec	2 sec	2 sec	2 sec
No. of Samples	256	256	256	256
Sample Series	28161-28416	28417-28672	28673-28928	28929-29184

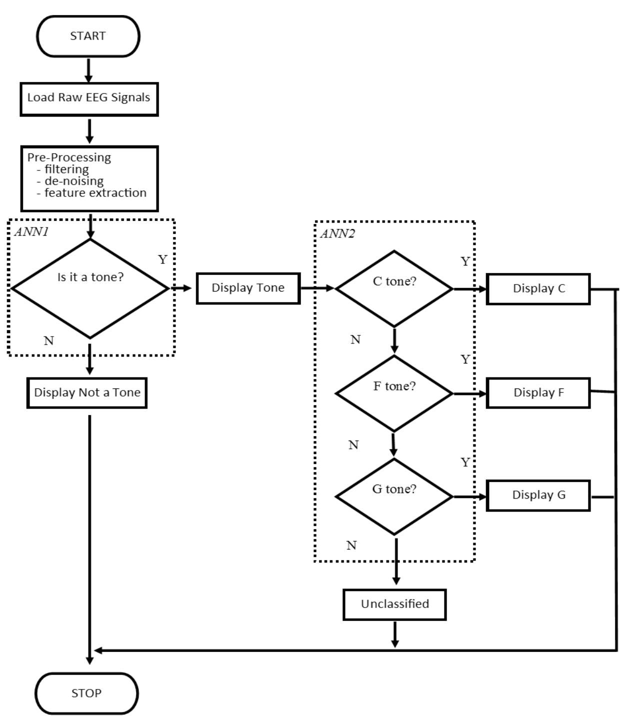


Fig. 2. Detection and Classification General Flowchart

C. Wavelet-based De-noising

This filtering technique is a three-step process that includes signal decomposition using DWT by selecting a mother wavelet and the number of decomposition levels, perform thresholding in the wavelet domain and shrink the coefficients by thresholding, and then reconstruct the signal from the thresholded DWT coefficients.

TABLE II
Wavelet Families

Wavelet Family	Wavelet Tag	Count
Daubechies	db1 - db45	45
Coiflet	coif1 - coif5	5
Biorthogonal	bior1.1 - bio6.8	15
Reverse-Biorthorthogonal	rbio1.1 - rbio6.8	15
Discrete Meyer	dmey	1
Symlets	sym2 - sym30	29
Total		**110**

There are 110 known mother wavelets, as shown in Table II, and these were all tested using a soft thresholding algorithm implementing four thresholding methods namely: "rigrsure," "heursure," sqtwolog," and "minimaxi" [25],[26]. A 2-level decomposition was implemented since the baseband signal ranges from 8 Hz–30 Hz covering the alpha and the beta bands. This results to alpha waves ranging from 8Hz–13.5 Hz and beta waves ranging from 13.5 Hz to 19 Hz and 19 Hz to 30 Hz.

Mother wavelet and thresholding method selection was based on the following: signal-to-noise ratio (SNR), peak signal-to-noise ratio (PSNR), mean square error (MSE) and the correlation coefficient (R). These parameters were calculated using (1)–(4), respectively. The original EEG signal is $x(n)$ while the de-noised EEG signal is $x_d(n)$. As a selection requirement, SNR, PSNR and R should be at maximum while MSE should be at minimum [25].

$$\mathrm{SNR} = 10\log\left[\frac{\sum_{i=1}^{N}\left(x_d(n)\right)^2}{\sum_{i=1}^{N}\left(x(n)-x_d(n)\right)^2}\right] \tag{1}$$

$$\mathrm{PSNR} = 20\log\left[\frac{\max\left[x(n)\right]}{RMSE}\right] \tag{2}$$

$$\mathrm{MSE} = \left[\frac{\sum_{i=1}^{N}\left(x(n)-x_d(n)\right)^2}{N}\right] \tag{3}$$

$$\mathrm{R} = \left[\frac{cov\left(x(n)-x_d(n)\right)}{\sqrt{var\left(x(n)\right)}\, var\left(x_d(n)\right)}\right] \tag{4}$$

D. Feature Extraction

Feature extraction is the process of determining a unique characteristic, a special feature or a distinct feature vector from a pattern vector. Features are usually divided into the statistical characteristics and the syntactic descriptions. Not all features are good discriminants and all features need not to be used for classification. Large feature vectors require more processing time and are computationally expensive. Best features can be identified according to various criteria and optimization techniques [27]. In classification tasks like using ANN, feature extraction and selection plays an important role.

In this study, four features were considered. The features were based on the statistical characteristics of the power spectrum vectors of the EEG signal and the signals' energy obtained from autocorrelation.

- Kurtosis: This is a statistical measure of the flatness or peaks of a signal distribution. The kurtosis of the power spectrum vector of the EEG signal was used as a feature [1].
- Skewness: This is another statistical measure that deals with the asymmetry of a signal distribution. As with kurtosis, the skewness of the power spectrum vector of the EEG signal was used [1].
- Power Spectrum Vectors: These are derived from the Hamming-windowed Fourier transform coefficients of the EEG signal. The power spectrum vectors were decomposed using Singular Value Decomposition (SVD) to represent a single feature [20].
- Signal Energy: This is obtained by taking the element at the origin of the autocorrelation sequence of the signal. The autocorrelation of the signal x(n) is defined by

$$r_{xx}(l) = \sum_{n=-\infty}^{\infty} x(n+l)\,x(n), \quad l = 0, \pm1, +2, \ldots \tag{5}$$

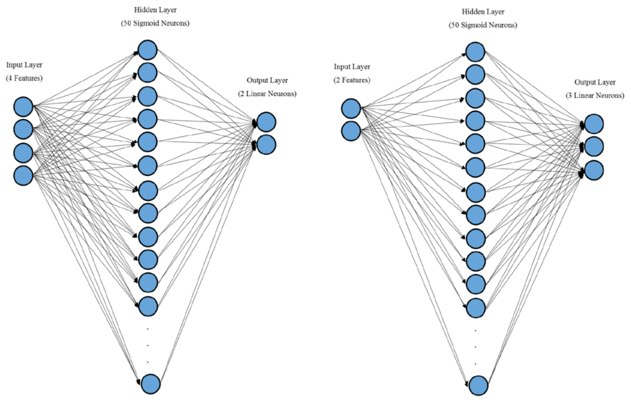
where the signal energy is $r_{xx}(0)$.

E. Artificial Neural Networks (ANN)

An artificial neural network is composed of 'neurons' or 'cells' which are linked together by weighted connections. [28]. These units receive input signals from other units or sources and use it to compute for an output signal which is transmitted to other units.

ANNs have three useful layers: the input layer (which receives data from external sources), the hidden layer (which contains internal network input and output data) and the output layer (which sends the output/resulting data). A three-layer feed-forward neural network was used in this study [19]. Feed forward networks are straight forward networks in which data flow from the input side to the output side of the ANN.

The architecture of the network is shown in Figure 3. There are two networks used, one for detection and one for classification. For detection, the input layer is composed of 4 neurons which correspond to the 4 features of the EEG signals. Each input neuron is linked to the 50 sigmoid neurons that forms the hidden layer. The hidden neurons are linked to the output layer which is composed of 2 linear output neurons that correspond to Not Tone (Baseline) or Tone. Same hidden layers were used for classification except that the input layer has 2 neurons corresponding to the energy and power of the signal, and the output layer with three neurons, corresponding to the tones C, F, and G.



a. b.

Fig. 3. Neural Network Architecture, a) detection; b) classification

The network was trained using gradient descent, quasi-newton, conjugate gradient and Bayesian regularization by implementing the training functions *trainrp*, *trainlm*, *trainscg* and *trainbr*, respectively [29]. These training functions has the property to deal with the non-linear nature of the EEG signals using non-linear activation or kernel functions. In resilient backpropagation (trainrp), the weight and bias values were updated by using the sign of the partial derivatives leaving its magnitude of no significant effect. This performs faster than a standard steepest descent algorithm. For scaled conjugate gradient Bayesian regulation backpropagation, the weight and bias values are updated according to the Levenberg-Marquardt (LM) optimization method [30] which minimizes squared errors and weights combinations [31]. In Bayesian regulation, weights are introduced into the training objective function denoted by

$$F(w) = \alpha S_w + \beta S_D \qquad (5)$$

where S_w is the sum of the squared network weights and S_D is the sum of the network errors. The objective function parameters are defined by the variables α and β. The weights of the network are randomly selected and a Gaussian distribution of the network weights and training set is assumed.

The objective function parameters, α and β, are defined using the Baye's theorem which basically shows the relationship between two variables, say A and B, according to their prior and posterior probabilities [32]. The posterior probability of A with respect to B is defined by

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \qquad (6)$$

where P(B | A) is the prior of B conditional to A, P(A) and P(B) are the prior probabilities of A and B not equal to zero, respectively. The optimal weight space can be obtained by minimizing the objective function in (5) which means maximizing the posterior probability function which is given by

$$P(\alpha,\beta|D,M) = \frac{P(D|\alpha,\beta,M)P(\alpha,\beta|M)}{P(D|M)} \qquad (7)$$

where α and β are the variables to be optimized, D refers to the weight distribution, M is the specific neural network architecture, P(D|M) is the factor of normalization, P(α, β|M) is the regularization parameters' constant prior density and P(D|α, β, M) is the similarity function of D given α, β, and M. This process results to optimum values of α and β for a given weight space. The LM phase calculates the squared second-order partial derivatives of the objective function (the Hessian) and minimizes the objective function by updating the weights. For non-convergence, the algorithm makes an estimation for new values of α and β. This process repeats itself until convergence is reached [33].

F. *Confusion Matrices*

Confusion matrices are used to assess the performance of different classifiers [34],[35]. These matrices provide information that leads to determining the sensitivity, specificity, precision, accuracy and F-score of the classifier. Precision tells how many of the positively classified were relevant, sensitivity / recall tells how good a test is in detecting the positives, and specificity is an indicator of how good a test is in avoiding false detections. The harmonic mean of precision and sensitivity is known as the F-score. This is commonly used as a discriminating factor to describe a good classifier. There were instances in which not all of the samples were classified. Hence, the rejection rate of the classifier has to be considered [24].

III. Results and Discussion

As a requirement, higher SNR, PSNR and correlation coefficient, and lower MSE indicates better de-noising effect. Table III shows the maximum values for the SNR, PSNR and R, the minimum values for the MSE, and the mother wavelet where they were obtained with respect to the five segments. Among the four thresholding methods, the "rigrsure" outperformed the other methods. Results show that the mother wavelet that mostly satisfied the conditions were 'rbio3.1' and 'rbio3.3.'

The two identified mother wavelets were then used to de-noise the EEG signals using the 'rigrsure' thresholding method. A sample of an original signal and de-noised signal is shown in Figure 4.

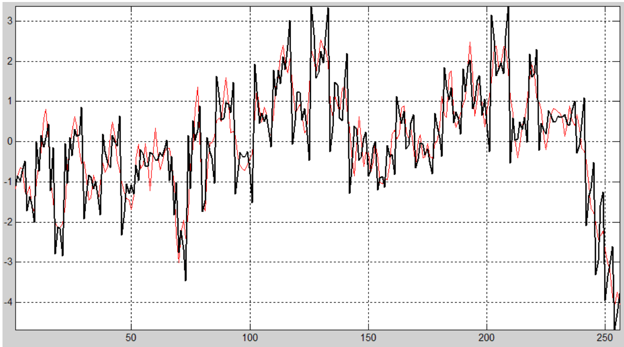


Fig. 4. Original (light) and de-noised (dark) signal

Four features were used to detect whether the EEG is tone stimulated or not, and two features (power and energy) were used to classify the tones whether C, F, or G. Two ANNs (ANN1 and ANN2) were used to perform detection and classification, respectively, implementing the training functions *trainrp*, *trainlm*, *trainscg* and *trainbr* one at a time. Ten training repetitions were performed and the trained network with the highest F-score and lowest rejection rate was selected. Results are shown in Table IV and Table V for detection and classification, respectively.

For detection, the *trainbr* function has the lowest rejection rate and has 0.8571 (85.71%) F-score for both mother wavelets. However, this training algorithm took more time (more or less 120 sec) to converge during simulation.

TABLE III

Segment Parameter Values and Significant wavelets

Thresholding	Parameters	Segments									
		BL		sBL		C		F		G	
Heursure	SNR(dB)	22.0950	rbio3.3	23.0178	rbio3.1	25.2446	rbio3.1	23.5344	rbio3.1	25.8607	rbio3.1
	PSNR (dB)	51.4410	bior3.9	47.4349	rbio3.1	48.8130	rbio3.1	49.1932	rbio3.1	51.7892	rbio3.1
	MSE	0.2455	rbio3.3	0.3368	rbio3.1	0.2729	rbio3.9	0.3043	rbio3.1	0.2421	rbio3.1
	R	0.9956	rbio3.3	0.9945	rbio3.1	0.9959	rbio3.1	0.9934	rbio3.1	0.9966	rbio3.1
Minimaxi	SNR(dB)	20.6370	db39	18.8722	db43	19.4585	db1	17.6053	db1	18.8816	db1
	PSNR (dB)	50.6617	db37	45.6015	db43	42.8141	db31	44.1963	db20	45.7596	db43
	MSE	0.3091	db39	0.4860	db43	0.4481	db1	0.5558	db23	0.5942	db1
	R	0.9944	db39	0.9926	db43	0.9886	coif4	0.9884	db38	0.9903	db41
Rigsure	SNR(dB)	22.3970	rbio3.3	23.9690	rbio3.1	25.8157	rbio3.1	24.5010	rbio3.1	26.1473	rbio3.1
	PSNR (dB)	51.5537	bior3.9	48.6092	rbio3.7	49.1534	rbio3.1	50.4841	rbio3.3	53.4510	rbio3.1
	MSE	0.2251	rbio3.3	0.2299	rbio3.9	0.1756	rbio3.1	0.1750	rbio3.3	0.1459	rbio3.3
	R	0.9958	rbio3.3	0.9961	rbio3.1	0.9957	rbio3.1	0.9963	rbio3.1	0.9978	rbio3.3
sqtwolog	SNR(dB)	15.6564	bior3.9	14.2099	bior3.7	12.7085	bior3.7	12.4987	bior3.7	12.6978	bior3.9
	PSNR (dB)	45.0140	bior3.9	40.2942	bior3.9	36.7208	bior3.7	38.6902	bior3.7	38.5500	bior3.9
	MSE	1.2286	bior3.9	1.5163	bior3.7	1.7650	bior3.7	1.8006	bior3.9	1.9498	bior3.9
	R	0.9753	bior3.9	0.9755	bior3.7	0.9606	bior3.7	0.9669	bior3.7	0.9690	bior3.9

TABLE IV

Precision, Sensitivity, Specificity, Accuracy, F-score, and Rejection rate Table for Detection

MW	TF	Precision	Sensitivity	Specificity	Accuracy	F-score	Rej. Rate
rbio3.1	train1m	76.27%	100.00%	51.72%	81.08%	86.54%	1.33%
	trainscg	75.00%	100.00%	50.00%	80.00%	85.71%	0.00%
	trainbr	75.00%	100.00%	50.00%	80.00%	85.71%	0.00%
	tainrp	76.79%	100.00%	53.57%	81.69%	86.87%	5.33%
rbio3.3	train1m	79.63%	95.56%	63.33%	82.67%	85.86%	0.00%
	trainscg	75.86%	100.00%	51.72%	80.82%	86.27%	2.67%
	trainbr	75.00%	100.00%	50.00%	80.00%	85.71%	0.00%
	tainrp	76.27%	100.00%	48.15%	80.56%	86.54%	4.00%

An alternative training function, *trainlm*, can be considered because this is faster and has an F-score and rejection ratio not significantly far from *trainbr*. The mother wavelet 'rbio3.3' is a better choice because of minimal rejection rate.

For classification, the *trainlm* function has the lowest rejection rate and has highest F-score among all the other training algorithms for both mother wavelets. Hence, 'rbio3.3' is a better choice since it has higher F-score and lower rejection ratio when classified using the *trainlm* function.

The detection and classification of the disturbance caused by the musical tones was successfully performed using the ANN *trainlm* function with de-noised EEG signals using the 'rbio 3.3' mother wavelet. The response of the brain as shown in the EEG signals were characterized in terms of the features extracted from them. These features describing the response were found to be useful enough to differentiate each stimulation whether there is a tone or none and if there is a tone stimulation, whether C, F, or G.

TABLE V
Precision, Sensitivity, Specificity, Accuracy, F-score, and Rejection rate Table for Classification

MW	TF	Segments	Precision	Sensitivity	Specificity	Accuracy	F-score	Rej. Rate
rbio3.1	train1m	C	100.00%	60.00%	100.00%	85.19%	75.00%	9.71%
		F	55.56%	76.92%	61.90%	67.65%	64.52%	
		G	63.64%	58.33%	80.00%	71.88%	60.87%	
	trainscg	C	60.00%	30.00%	81.82%	57.14%	40.00%	9.71%
		F	30.00%	75.00%	30.00%	42.86%	42.86%	
		G	75.00%	27.27%	90.00%	57.14%	40.00%	
	trainbr	C	100.00%	13.33%	100.00%	60.61%	23.29%	0.00%
		F	38.46%	100.00%	17.24%	45.45%	55.56%	
		G	75.00%	20.00%	94.44%	60.61%	31.58%	
	trainrp	C	100.00%	36.36%	100.00%	73.08%	53.33%	12.37%
		F	48.15%	100.00%	30.00%	57.58%	65.00%	
		G	100.00%	22.22%	100.00%	73.08%	36.36%	
rbio3.3	train1m	C	83.33%	76.92%	91.67%	86.49%	80.00%	5.17%
		F	73.33%	91.67%	84.00%	86.49%	81.48%	
		G	96.67%	78.57%	95.45%	88.89%	84.62%	
	trainscg	C	87.50%	58.33%	94.12%	79.13%	70.00%	8.65%
		F	50.00%	91.67%	52.17%	65.71%	64.71%	
		G	83.33%	41.67%	94.74%	74.19%	55.56%	
	trainbr	C	*	0.00%	100.00%	50.00%	0.00%	0.00%
		F	33.33%	100.00%	0.00%	33.33%	50.00%	
		G	*	0.00%	100.00%	50.00%	0.00%	
	trainrp	C	100.00%	45.45%	100.00%	76.00%	62.50%	15.96%
		F	54.55%	92.31%	41.18%	63.33%	68.57%	
		G	66.67%	33.33%	94.44%	79.17%	44.44%	

The confusion matrices for detection and classification using the training algorithms *trainbr* and *trainlm* are shown in Table VI and Table VII. The inputs here served as the bases for the computation of the parameters in the previous tables. One noticeable information is the total summation of the horizontal data. Not tone (NT) has a total of 30 hits while tone (T) has 45 hits. The tones C, F and G has a total of 15 hits each. In the event that the sum of the horizontal hits are less than as mentioned, then, the difference was accounted and was used to determine the rejection rate of the classifier.

IV. CONCLUSION AND FUTURE DIRECTIVES

Wavelet based de-noising was implemented to smoothen the musical tone stimulated EEG signals. It was found out that the mother wavelets 'rbio3.1' and 'rbio3.3' using the 'rigrsure' thresholding method satisfied the selection criteria in order to provide a better de-noising effect.

Detection and classification were performed using ANNs implementing four different training algorithms. Results show that *trainbr* is good for detection but converges slower. Hence, the *trainlm* is recommended to be an alternative training algorithm. For classification, the *trainlm* was found to be better than the other training algorithms used. The metrics used for selecting the training algorithm were the F-score and the rejection rate which accounts the missed hits of the classifier. F-score should be high while the rejection rate should be low.

Future works may consider other training algorithms for ANN and other classifiers such as SVM, NB and k-NN for detection and classification of musical tone stimulated EEG signals.

TABLE VI
CONFUSION MATRICES FOR DETECTION

		Target Class	
		NT	**T**
Output Class	NT	15	15
	T	0	45

a. Detection using rbio 3.1 (trainbr)

		Target Class	
		NT	**T**
Output Class	NT	15	14
	T	0	45

c. Detection using rbio 3.1 (train1m)

		Target Class	
		NT	**T**
Output Class	NT	15	15
	T	0	45

b. Detection using rbio 3.3 (trainbr)

		Target Class	
		NT	**T**
Output Class	NT	13	16
	T	0	45

d. Detection using rbio 3.3 (train1m)

TABLE VII
CONFUSION MATRICES FOR CLASSIFICATION

		Target Class		
		C	**F**	**G**
Output Class	C	10	3	0
	F	0	11	1
	G	2	1	11

a. Classification using rbio 3.1 (train1m)

		Target Class		
		C	**F**	**G**
Output Class	C	10	3	0
	F	0	11	1
	G	2	1	11

b. Classification using rbio 3.1 (train1m)

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