On the use of EEG features towards person identification via neural networks®

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Abstract: Person identification based on spectral information extracted from the EEG is addressed in this work - a problem that has not yet been seen in a signal processing framework. Spectral features are extracted non-parametrically from real EEG data recorded from healthy individuals. Neural network classification is applied on these features using a Learning Vector Quantizer in an attempt to experimentally investigate the connection between a person's EEG and genetically - specific information. The proposed method, compared with previously proposed methods, has yielded encouraging correct classification scores in the range of 80% to 100%, (case - dependent). These results are in agreement with previous research showing evidence that the EEG carries genetic information.

Keywords: EEG, Person Identification, Neural Network, LVQ

1. Introduction

The objective of this work is to extract genetically-specific information from a person's EEG and to use this information for the development of a person identification method based on features extracted from the EEG recording. This work is mainly addressed to informaticists and computer scientists, aiming to investigate new approaches in the field of EEG analysis. However, it is our belief that results of this study would be of interest to clinicians as well. Potential applications of the proposed person identification method are, for example, information encoding and decoding or access to secure information. EEG recording is non-invasive and medically safe; it therefore constitutes a viable and, under certain conditions, attractive alternative to currently existing forms of person identification based on fingerprints, blood test or retinal scanning. It should be noted, however, that the proposed method is merely indicative rather than deterministic in its classification results, in comparison to DNA identification, e.g., because the biochemical bases of the EEG phenomena are, as yet, completely unknown. Thus, it is not legitimate to claim that EEG identification is equivalent to DNA identification.

Research aiming to extract genetic information from the human EEG began as early as 1938, [1]; however, first results became available only after 1955, [2, 3]. More specifically, the research carried out was focused on three different cases. In the first case, EEGs from members of the same family were investigated and compared, [3, 4, 5]. In the second case, the common characteristics between the EEGs of monozygotic and of dizygotic twins were sought, [2, 6, 7, 8]. In the third case, different EEGs were compared, which came from the same person; the objective was to extract more or less invariant characteristics that would characterise the individual, [9].

Pioneering research into brain activity in the alpha and beta rhythms of the EEG was conducted by Juel - Nilsen, [2] and Vogel, [3], and subsequently by other researchers, [4, 7, 8, 10, 11, 12]. In these works it has been shown that alpha and beta rhythms contain significant brain activity frequencies, in the sense that individual genetic characteristics are contained therein.

® Partial results of this work have been presented in ICASSP'99, Arizona, USA, March 1999, [20].

The methods used to reach that conclusion were initially supported by teaching aids which, were observed by sight. Therefore, the results were unreliable. Thanks to the progress in computerised data processing, it became possible for the EEG signal to be analysed digitally with parametric and non-parametric methods, [8, 9, 13]. Further progress was made possible thanks to the development of artificial neural networks (see, e.g., [13]) and other methods of pattern recognition.

Most of the previous research effort, however, has been focused on the classification of pathologically induced EEG variants due, for example, to epilepsy or schizophrenia, for diagnostic purposes. Along this line, recent research including linear and non-linear approaches with a neural network classification scheme has reached a 71% classification score, [13]. A key observation in these approaches is the fact that a given pathology induces a pathology -specific variation pattern on the "healthy" EEG signal. Diagnosis of the pathology is therefore based on the detection of the specific variation pattern, which thus serves as a classification feature.

On the contrary, the present work focuses in principle on healthy as opposed to pathological cases and aims to establish an one-to-one correspondence between the genetic information of the individual and certain appropriate features of the recorded EEG signal. A neural network classifier, Learning Vector Quantizer, (LVQ), is employed to classify unknown EEGs as belonging to one of a set of known individuals. Neural network based classification has received considerable attention recently in a wide variety of research fields and experimental set-ups (see, e.g., [14] for an introduction to neural networks and applications). The specific type of neural network employed here, namely the LVQ, offers the advantage of classifying input vectors of high dimensionality, which is desirable in our tests. A more detailed description of its architecture and operation is given in section 2 (Feature extraction). Spectral values obtained non parametrically from the alpha rhythm spectral band of the EEG signal are used as features to form the input vectors. This is a continuation of our previous work on the same subject, using non-linear processing (computational geometry algorithms, [9]). Certain limitations of the computational geometry approach, however, as discussed in [9]– mainly complexity issues and the need for an unambiguous output class decision in the classification step - have prompted the neural network approach taken here.

2. Feature extraction and classification

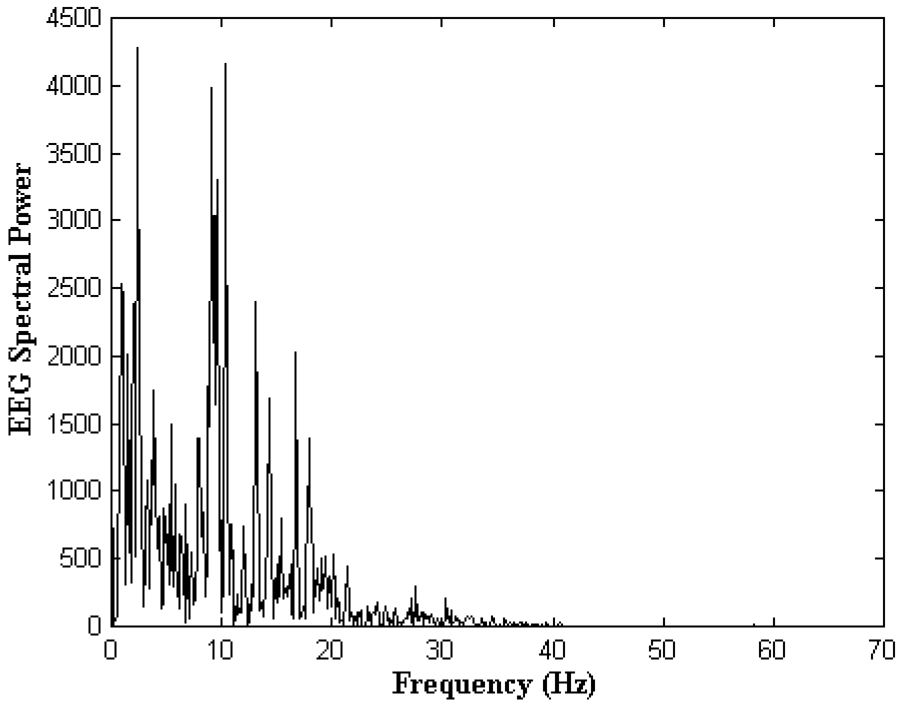

Figure 1: *Example of an EEG spectrum obtained via Fourier Transform, EEG signal sampling rate is 128 Hz. EEG spectral power versus normalized frequency points from 0 to ½ (point 64)*

Although parametric linear or non-linear processing of the EEG signal for feature extraction is also to be investigated, the non-parametric Fourier Transform based spectral analysis was chosen first, due to its obvious physical interpretation in terms of EEG rhythms (figure 1). Fourier Transform is implemented via the Fast Fourier Transform (FFT), which is a family of fast implementations of the basic transform. When the FFT is applied to successive segments of an EEG signal, the frequency spectrum is observed to vary over time as the Fourier coefficients vary [15]. It is generally accepted that the EEG is a non-stationary signal. This makes the use of the FFT for the analysis of an EEG signal problematic, because the classical Fourier analysis method assumes stationarity of the signal. It can be modified or suitably adapted to process a non-stationary signal, (e.g., short time Fourier Transform); however, the interpretation of the results can be complex. This is particularly the case when the aim of analysing a signal is to extract features for further processing, such as classification or prediction. Thus the use of the FFT or its modifications to process a non-stationary signal may result in an excessive number of parameters or "features".

However, for the purposes of this work the FFT (with appropriate modifications) was selected for the following reasons:

1. The coefficients of the non parametric FFT have an advantage over those of parametric methods in that they describe the signal spectrum more accurately.
2. The problem of assessing the range of stationarity of the background EEG [16] has already received attention by researchers. The activities, which represent slowly changing parameters, are the alpha rhythm plus variants, theta rhythm and various kinds of beta activity [17]. Thus, in the proposed method, the use of the alpha rhythm along with the use of per segment processing only is an acceptable compromise in order to employ the FFT. The consideration of the alpha rhythm FFT coefficients only, reduces the number of significant FFT coefficients; however, the number still remains higher than desirable in view of the classification step to follow. This problem can be overcome either by reduction of the frequency resolution, or stage, or by a combination of both by the use of the appropriate choice of neural network in the classification stage.

Step1: Feature extraction from the EEG signal.

As referred to in the Introduction, basic research carried out in order to detect a particular spectral area of an EEG carrying "genetic" features, resulted to specify this to be the alpha rhythm spectral band. As it is known, the alpha rhythm is the spectral band of 7-12 Hz, extracted from the original EEG spectrum and recorded mainly from the occipital part of the brain, when the subjects are at rest, with eyes closed. Thus in our case, the spectral values of the EEG signal are obtained and then restricted to the alpha rhythm band values only. These values are further segmented into three overlapping sub-bands, namely (7-10 Hz) (see figure 2), (8-11 Hz) and (9-12 Hz) respectively, in order to investigate whether one of these sub-bands is informative enough to represent the whole EEG spectrum, for person identification purposes. The segmentation of the alpha rhythm activity into three sub-bands is based on the findings of previous researchers, [5].

As referred to in the Introduction, basic research has been carried out on the genetic information found in the EEGs of specific groups of individuals, such as members of families or monozygotic twins. In [5] are compared the EEG spectral power and mean frequency values from two groups of subjects. The first group consists of members of a real family, whereas the second group consists of members, of a non-real family. It was found that the correlations of mean frequenting among family members were greater than those among non-family members for the alpha rhythm sub-bands. These results were consistent with the findings for the spectral power data but, except for the alpha band, these findings were not as statistically strong as those found for the spectral power measures [18]. Similar results were obtained in the cases of monozygotic twins, [3].

Using this evidence, our next step was to assume that a relationship exists between the EEGs of the same individual taken at different times. This was our motivation for segmenting the alpha rhythm in sub-bands, in order to isolate the significant amplitudes of each sub-band (figure2).

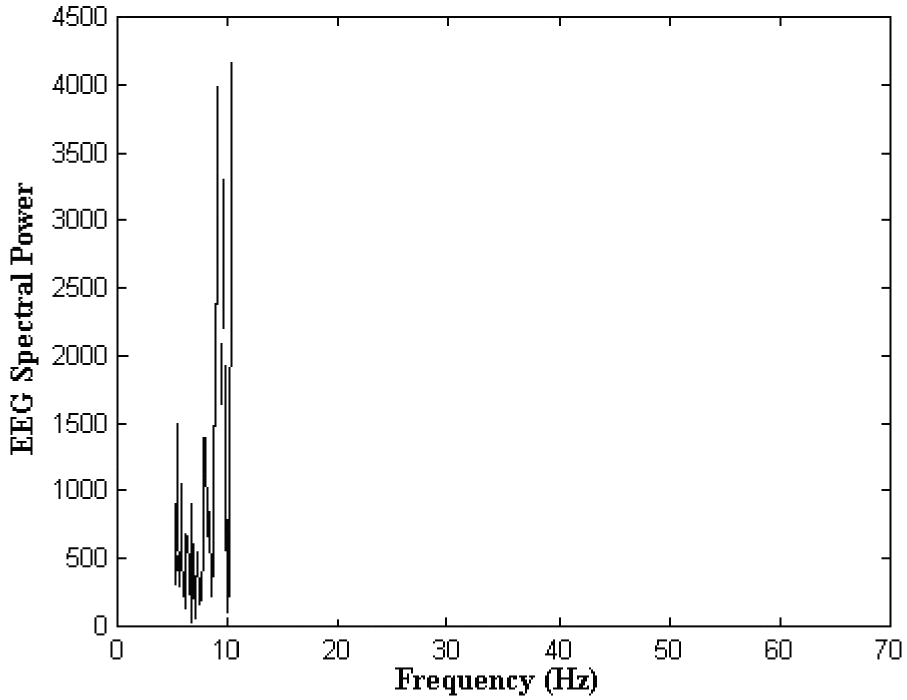

Figure 2. *The (7-10 Hz) EEG spectral sub-band, isolated from a subject A EEG spectrum.*

Step2: Neural network classification.

The spectral values obtained in Step 1 are used as feature vectors for classification (FFT vectors). These vectors (codebook) are fed into an LVQ classifier, [13], first for training and then for the actual classification of unknown input vectors. During the training process, the codebook vectors are directed towards the data vectors of the same class and distanced from those codebook vectors of a different class. The adaptation of the weights of the neurons is carried out iteratively, based on the Euclidean distance measure.

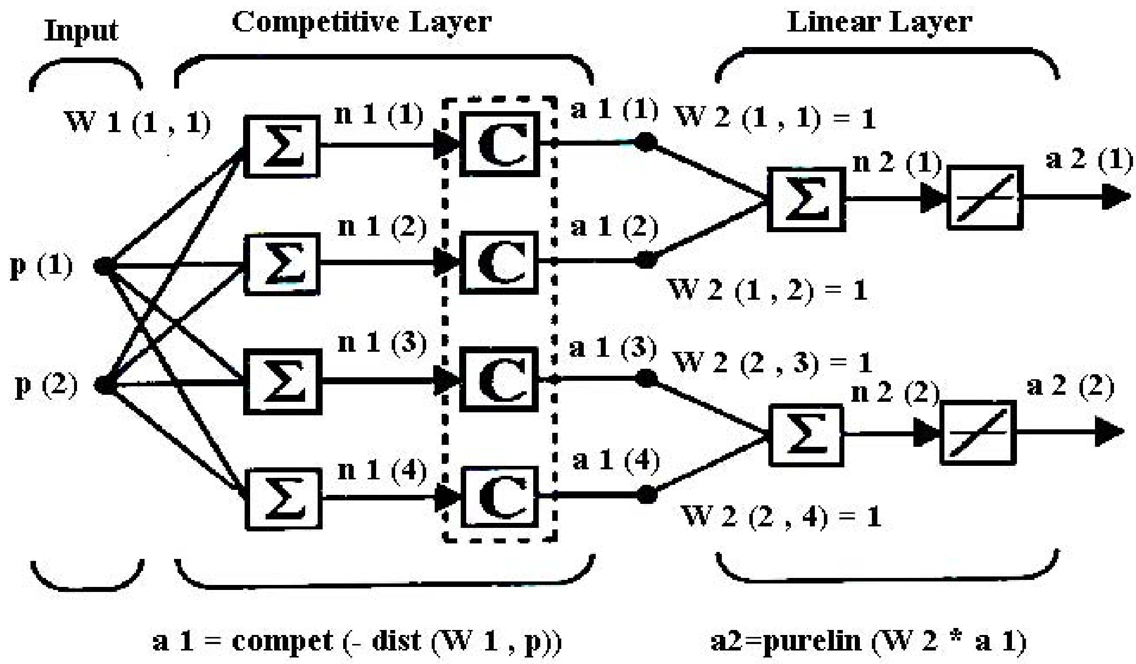

Figure 3. *The architecture of a simplified 2x2 LVQ neural network*

A detailed description of the LVQ training algorithm can be found in [19]. Here, the basic functionality of an LVQ neural network is outlined. An example of a (2x2) LVQ structure is used for simplification (figure 3), which means that the input vectors consist of two parameters [p(1), p(2)] while there are also two target classes [a2(1), a2(2)]. The basic LVQ architecture consists of two layers of neurons, the competitive layer and the subsequent linear layer. The competitive layer classifies inputs into subclasses, while the linear layer group subclasses into target classes and produces the output. In figure 3, the first two competitive neurons are connected to the first linear neuron (with connecting weights of 1), while the other two competitive neurons are connected to the second linear neuron. All other connecting weights between the competitive neurons and linear neurons have values of 0, and are not shown. Thus, each of the two target classes is in fact the union of two subclasses.

Taking into account the properties of the various available neural network architectures, the LVQ network was selected for two reasons:

1. It has the ability to successfully classify input vectors of high dimensionality, such as the FFT vectors, because the LVQ represents the most characteristic structures of the input density function in a lower-dimensionality space, [19].
2. It has the ability to classify incoming vectors (codebook vectors) into classes that are not linearly separable in a n-dimensional space, where n is the number of the parameters - a clearly desirable property given the nature of our feature space. Such an example of non-linear class separation is shown, e.g., in figure 5. An LVQ type of network would adequately handle this problem, which cannot be solved, e.g., by other types of neural networks such as the perceptron.

3. Experimental part - Results

Two different experiments are conducted using real EEG data, in order to exhibit the potential of the proposed method for person classification and, furthermore, for person identification. The first test case focuses on identification of a given person among a group (pool) of others. Its purpose is to show that the proposed method works and that the tools chosen are appropriate for the problem at hand. The second test case focuses on a more realistic, multi-class set-up, where a group of four persons are classified. For test case 1 experiments, presents the identification results are tabulated for each subject along with the values of the Sensitivity and Specificity parameters calculated.

3.1 Signal acquisition and feature extraction

In our study five data types were selected. For each one of four (4) subjects, named A B, C and D, a set of forty five (45) EEG recordings were taken. In addition, one EEG recording was taken from each one of seventy-five (75) different subjects to form a group named X. The final pool of EEG recordings thus contained (4 x 45 + 75 x 1 = 255) recordings. Both male (76%) and female (24%) subjects formed group X, subjects A, B and C were male and subject D was female. Ages ranged from 19 to 60 years and it was determined that none of these subjects had chronic or acute health problems or used any prescribed medication. Furthermore EEG recordings including non-typical parts, such as artefacts, are excluded from the set after inspection by a physician.

All recordings were taken using a digital electroencephalograph with the PHY-100 Stellate software. Subjects were at rest, with closed eyes. Voltage difference (in μVolts) was recorded between leads O2 and CZ. All EEG recordings lasted for three (3) continuous minutes, thus producing a 23040 samples long record each, at a 128 Hz sampling rate. Further processing was carried out off-line, in Matlab 5.2, on a Pentium PC. As an example, in figure 4 can be seen a full EEG waveform from subject A, recorded over a 3 min or 180 sec period.

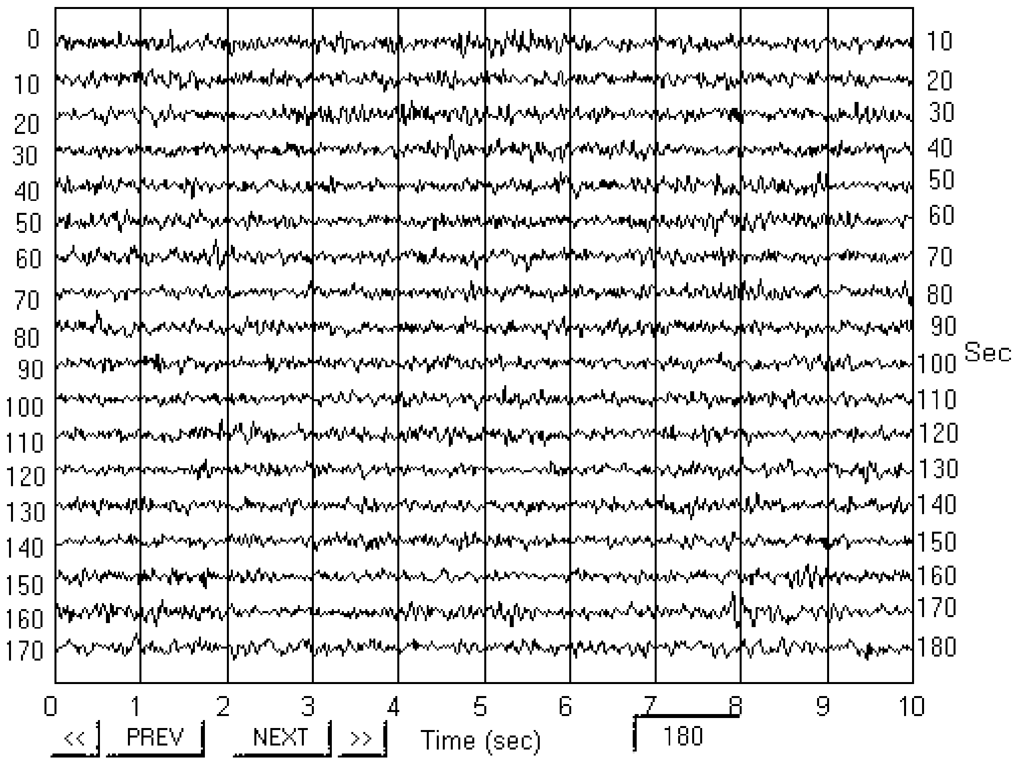

Figure 4. *A 3 min (180 sec) EEG, recorded from subject A (sampling rate 128 Hz)*

Spectral values of the EEG signal were computed and the alpha rhythm frequency band (7-12 Hz) was retained for further processing. Alpha rhythm frequencies were next partitioned into three overlapping frequency bands of 3 Hz each (7-10 Hz, 8-11 Hz, 9-12 Hz), each band containing 540 spectral values at the frequency resolution employed. It must be noted that in this procedure, each recorded EEG was used in its entirely for feature extraction, while segmentation into three sub-bands takes place only at the 3 spectral (and not the signal) level. Thus, 255 FFT vectors, of 540 elements each, were obtained for each of the three selected frequency sub-bands, as outlined in section 2, step 1 (Feature extraction and classification).

3.2 Test case 1

Test case 1 aims to differentiate between individual A and 'non-A' individuals, the group X members serving as the 'non-A' class in that case. The same experiment was subsequently carried out for individuals B, C and D and for each one of the three alpha rhythm sub-bands mentioned above. In every case members of group X served as the "non-B", "non-C" or "non-D" class, respectively. Let us note here that, although this four-ply experiment was not absolutely necessary, we present here the results of all four tests, because of the indicative nature of this test. In every case, twenty five (25) feature vectors from the individual of interest (A or B or C or D, respectively) along with twenty five (25) feature vectors from group X formed the training set, which thus consisted of fifty (50) feature vectors. The LVQ neural network which was used in the aforementioned training procedure is described in section 2, step 2 (Feature extraction and classification) and was trained for a total of 1500 cycles (epochs) with a learning rate in the order of 10^{-3}. In figure 5 can be seen the clustering of the two classes of FFT input vectors, those of subject A and those of members of group X, respectively (in sub-band 7-10 Hz), after training the LVQ neural network.

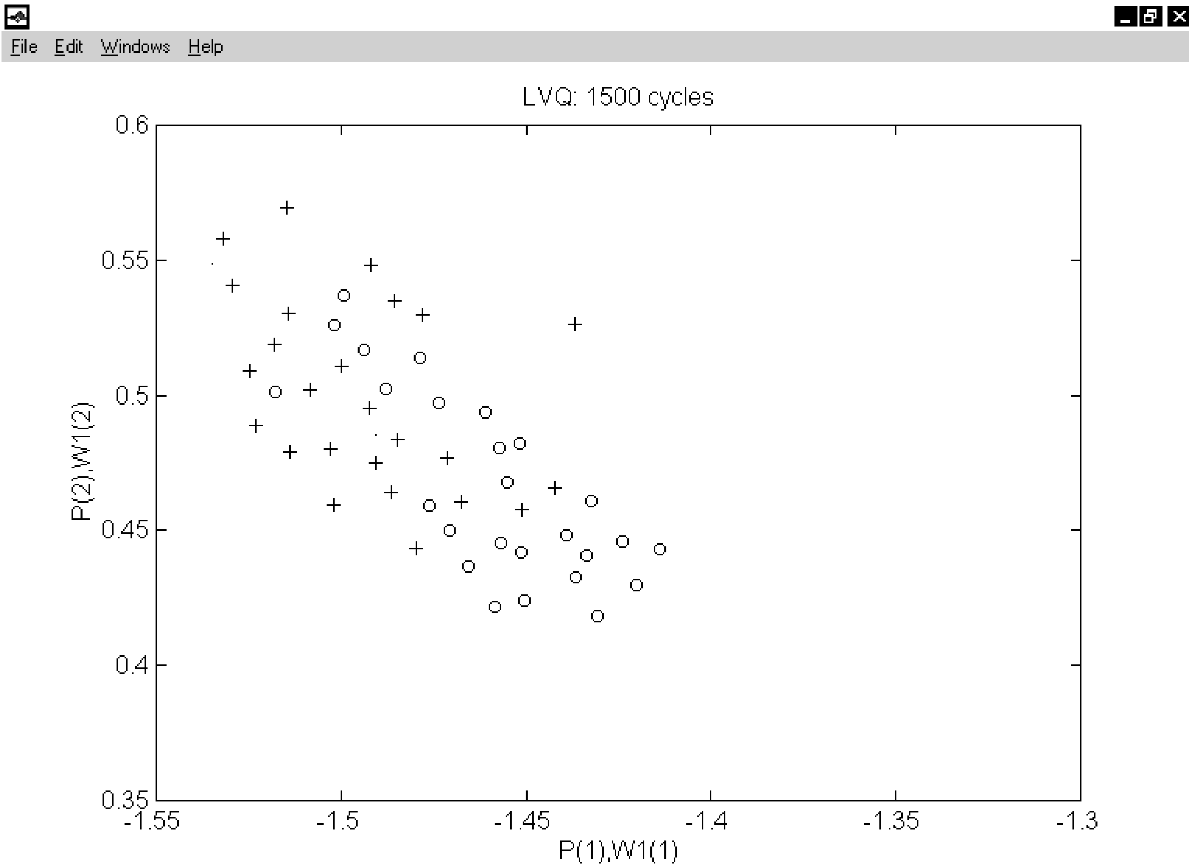

Figure 5. *A plot of the input / target vectors of subject A and members of group X. the 25 '+' markers represent the input vectors of subject A, while the 25 'o' represents the input vector of members of group X. Input vectors are based on the (7-10 Hz) sub-band only. Note that for 2-D visualization purposes, only the first two coefficients of the input vector are plotted.*

In the testing procedure, the remaining twenty (20) out of the total of forty five (45) feature vectors of subject A, along with the remaining fifty (50) vectors of members of group X, formed the test set for subject A (seventy (70) vectors in total). Test sets for subjects B, C and D were formed accordingly, each consisting of seventy (70) feature vectors.

The neural network was trained by the (A, X) training set and then classification was performed using the (A, X) training set as the test set, for each one of the three alpha rhythm sub-bands. Individuals B, C, and D were treated analogously. The results obtained are used to assess the appropriateness of the specific neural network architecture for the problem at hand.

Subsequently, the actual classification experiments were performed, where the test set consisted of twenty (20) EEGs of each one of the subjects A, B, C and D, and fifty (50) EEGs of members of group X. This test set was disjoint to the training set. Results shown in tables 1, 2, 3 and 4, respectively, illustrate the generalising property of the network when facing unknown EEGs.

In all four tests (A versus X, B versus X, C versus X and D versus X) we consider either the true positive result or the true negative result on an input vector to be a correct classification result. For example, in table 1, (sub-band 7-10 Hz), the true positive recognition score for subject A is 19/20 or 95%, the number of true recognition cases being a=19. The true negative recognition score for group X is 44/50 or 88%, the number of true recognition cases being d=44. In the same table and sub-band, the false positive recognition score for subject A is 1/20 or 5%, the number of false recognition cases being b=1. While, the false negative recognition score for group X is 6/50 or 12%, the number of false recognition cases being c=6. Consequently we can calculate the Sensitivity and Specificity values of the results in table 1.

According to the above notation, Sensitivity is the proportion of positive cases correctly identified by the test while Specificity is the proportion of negative cases correctly identified by the test. For the results of table 1, sub-band (7-10 Hz), e.g., these values are calculated as follows:

$$\text{Sensitivity} = \frac{a}{a + c} = 0.76$$

$$\text{Specificity} = \frac{d}{b + d} = 0.98$$

In the same way in tables 2-4 are shown the correct negative or positive classifications scores along with calculated values of Sensitivity and Specificity, for all sub-bands.

	7-10 Hz		8-11 Hz		9-12 Hz		
classified as: ⇒ belong to class: ⇓	A	X	A	X	A	X	Total Per band
A	19/20 (95%)	1/20 (5%)	19/20 (95%)	1/20 (5%)	20/20 (100%)	0/20 (0%)	20
X	6/50 (12%)	44/50 (88%)	5/50 (10%)	45/50 (90%)	8/50 (16%)	42/50 (84%)	50
Sensitivity	0.76		0.79		0.71		
Specificity	0.98		0.98		1		

Table 1: *Test Case 1: Subject A against members of group X: classification scores in the 3 alpha rhythm subbands (results obtained using test set disjoint to training set).*

	7-10 Hz		8-11 Hz		9-12 Hz		
classified as: ⇒ belong to class: ⇓	B	X	B	X	B	X	Total Per band
B	19/20 (95%)	1/20 (5%)	20/20 (100%)	0/20 (5%)	20/20 (100%)	0/20 (0%)	20
X	5/50 (10%)	45/50 (90%)	6/50 (12%)	44/50 (88%)	7/50 (14%)	43/50 (86%)	50
Sensitivity	0.79		0.77		0.74		
Specificity	0.98		1		1		

Table 2: *Test Case 1: Subject B against members of group X: classification scores in the 3 alpha rhythm subbands (results obtained using test set disjoint to training set).*

	7-10 Hz		8-11 Hz		9-12 Hz		
classified as: ⇒ belong to class: ⇓	C	X	C	X	C	X	Total Per band
C	16/20 (80%)	4/20 (20%)	18/20 (90%)	2/20 (10%)	19/20 (95%)	1/20 (5%)	20
X	10/50 (20%)	40/50 (80%)	5/50 (18%)	41/50 (82%)	8/50 (16%)	42/50 (84%)	50
Sensitivity	0.62		0.78		0.70		
Specificity	0.91		0.95		0.98		

Table 3: *Test Case 1: Subject C against members of group X: classification scores in the 3 alpha rhythm subbands (results obtained using test set disjoint to training set).*

	7-10 Hz		8-11 Hz		9-12 Hz		
classified as: ⇒ belong to class: ⇓	D	X	D	X	D	X	Total Per band
D	17/20 (85%)	3/20 (15%)	18/20 (90%)	2/20 (10%)	18/20 (100%)	2/20 (10%)	20
X	5/50 (10%)	45/50 (90%)	5/50 (10%)	45/50 (90%)	8/50 (16%)	42/50 (84%)	50
Sensitivity	0.77		0.78		0.69		
Specificity	0.94		0.95		0.95		

Table 4: *Test Case 1: Subject D against members of group X: classification scores in the 3 alpha rhythm subbands (results obtained using test set disjoint to training set).*

As can be seen in tables 1-4, the overall results of all four tests in test case 1 show that the correct classification scores (positive or negative) range between 80% and 100%, the values of Sensitivity range between 0.62 and 0.79 and the values of Specificity range between 0.91 and 1.00. These results, depending on the individual and on the frequency band, are promising as to the potential of the proposed method.

3.3 Test case 2

Test case 2 addresses a more realistic, multi-target setup, where four individuals of interest, namely A, B, C and D, are to be classified (as opposed to identified), in contrast to test case 1. This test is carried out to ascertain that the proposed neural network has the ability to correctly classify EEG features within a multi person group. Twenty (20) feature vectors of each one of the classes A, B, C and D were used as the training set, whose size was thus eighty (80) vectors. For the training procedure, we used an LVQ architecture of four target classes A, B, C and D, respectively. This LVQ was trained for a total of 1500 cycles (epochs) with a learning rate in the order of 10^{-3}. In figure 6 can be seen the clustering of the four classes of FFT input vectors, those of subjects A, B, C and D (in sub-band 7-10 Hz), after training via the LVQ neural network.

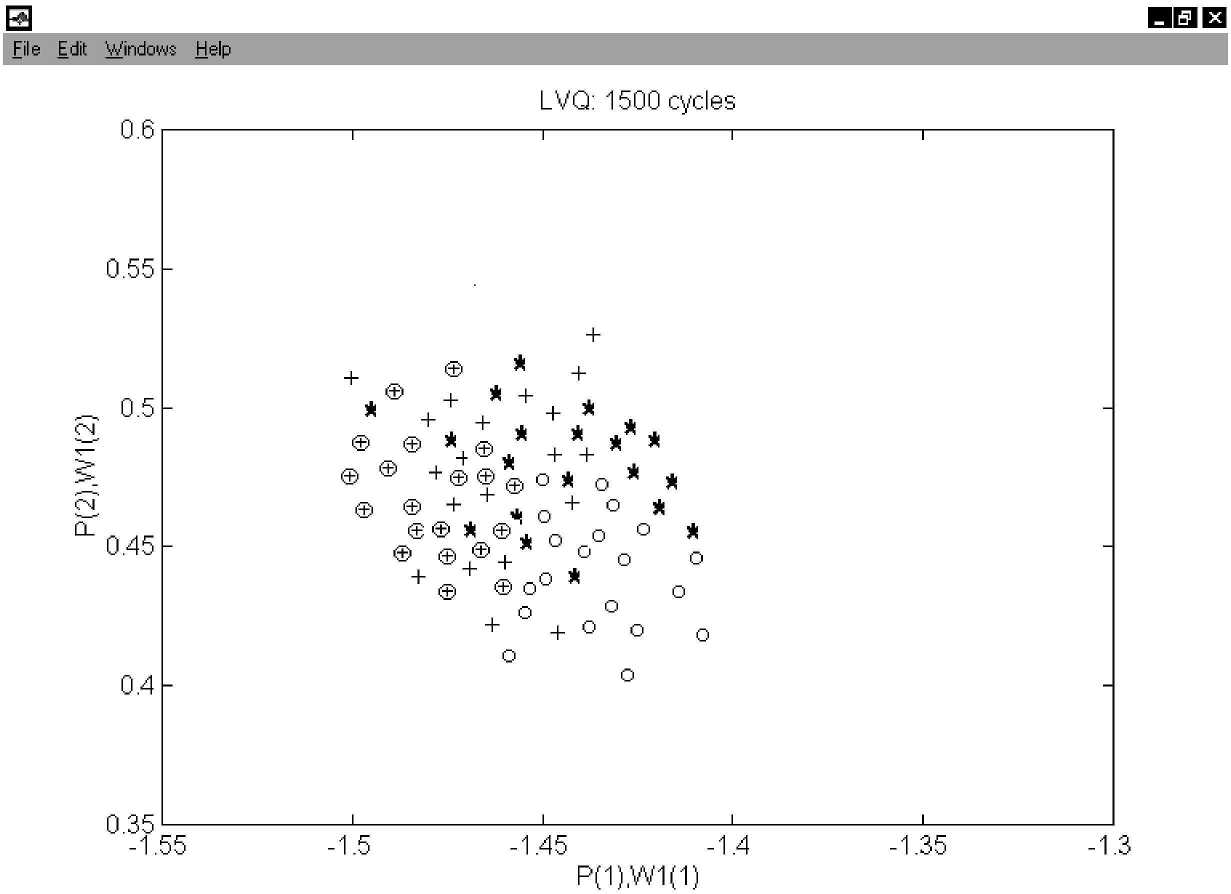

Figure 6. *A plot of the input / target vectors of subjects A, B, C and D. The 20 '+', 'o', '*' markers represent the input vectors of subject A, B, C and D, respectively. Input vectors are based on the (7-10 Hz) sub-band only. Note that for 2-D visualization purposes, only the first two coefficients of the input vector are plotted.*

In the testing procedure, the remaining twenty-five (25) vectors of each one of the classes A, B, C and D, one hundred (100) vectors in all, were used as the test set. The classification scores obtained after training are shown in tables 5-7, for the three frequency sub-bands (7-10 Hz), (8-11 Hz) and (9-12 Hz), respectively. As in test case 1, in our statistical evaluation we consider the true positive or true negative recognition of an input vector to be a correct classification result. For example, in table 5 (sub-band (7-10) Hz), the true positive recognition scores are shown along the diagonal of the table entries. Therefore, for subject A correct positive score is 21/25 or 84%, for subject B it is 23/25 or 92%, for subject C it is 22/25 or 88% and for subject D it is 25/25 or 100%. In the same table the false positive recognition scores are also shown in the off-diagonal entries. For example, four (4) input vectors of subject A were recognised falsely as belonging to subject D, two (2) input vectors of subject B were recognised falsely as belonging to subject D, three (3) input vectors of subject C were recognised falsely: two (2) of them as belonging to subject D and one (1) of them as belonging to subject A. Finally for subject D no false positive recognition score occurred.

7-10 Hz band				
out: ⇒ in: ⇓	A	B	C	D
A	21/25 (84%)	0/25 (0%)	0/25 (0%)	4/25 (16%)
B	0/25 (0%)	23/25 (92%)	0/25 (0%)	2/25 (8%)
C	1/25 (4%)	0/25 (0%)	22/25 (88%)	2/25 (8%)
D	0/25 (0%)	0/25 (0%)	0/25 (0%)	25/25 (100%)
Total: 100				

Table 5. *Test Case 2: Common pool classification experiment for subjects A, B, C and D. Classification scores for the (7-10 Hz) alpha rhythm subband (test set disjoint to training set).*

8-11 Hz band				
out: ⇒ in: ⇓	A	B	C	D
A	22/25 (88%)	0/25 (0%)	0/25 (0%)	3/25 (12%)
B	0/25 (0%)	24/25 (96%)	0/25 (0%)	1/25 (4%)
C	0/25 (0%)	0/25 (0%)	23/25 (88%)	2/25 (8%)
D	0/25 (0%)	0/25 (0%)	0/25 (0%)	25/25 (100%)
Total: 100				

Table 6. *Test Case 2: Common pool classification experiment for subjects A, B, C and D. Classification scores for the (8-11 Hz) alpha rhythm subband (test set disjoint to training set).*

9-12 Hz band				
out: ⇒ in: ⇓	A	B	C	D
A	23/25 (92%)	1/25 (0%)	0/25 (0%)	2/25 (8%)
B	0/25 (0%)	24/25 (92%)	0/25 (0%)	1/25 (4%)
C	0/25 (0%)	1/25 (4%)	23/25 (92%)	1/25 (4%)
D	0/25 (0%)	0/25 (0%)	0/25 (0%)	25/25 (100%)
Total: 100				

Table 7: *Test Case 2: Common pool classification experiment for subjects A, B, C and D. Classification scores for the (9-12 Hz) alpha rhythm subband (test set disjoint to training set).*

In the same way, in tables 6 and 7, the correct negative or positive classification scores for the sub-bands (8-11 Hz) and (9-12 Hz), are calculated respectively._Again, these results are promising, in the range of 80% to 100%, depending on the individual and the frequency band.

No frequency band shows any clear advantage over the others as to the classification scores obtained; rather, they are all equally informative regarding the problem at hand. This conclusion limits the field for the feature extraction step; it can result, therefore, in considerable computational savings regardless of the specific algorithm used for feature extraction.

3.4 Comparison with existing methods

Previous research conducted by the same authors has investigated the use of various methods, aiming to validate the conjecture that the EEG carries genetic information which, can be exploited for person identification. The methods tested varied in (i) features extracted from the EEG signal and (ii) the classification method employed, as follows:

1. Fast Fourier Transform features - Computational Geometry (CG) classification [9].
2. Fast Fourier Transform features - LVQ (Learning Vector Quantization) classification [20].
3. AR modeling features - LVQ (Learning Vector Quantization) classification [21].
4. AR modeling features - Computational Geometry (CG) classification [22].

The common and contrasting elements of the above methods in the areas of data acquisition, signal preprocessing, and classification should be noted and are as follows:

1. All EEGs used were common to all methods.
2. In the signal preprocessing stage all the EEGs used were of 3-m duration and alpha rhythm extraction was carried out for each method in the following way:

a. In the FFT - CG method, the alpha rhythm was segmented into sub-bands of 0.3 Hz width each.

b. In the FFT - LVQ method, the alpha rhythm was segmented into 3 sub-bands of 3 Hz width each.

c. In the AR - LVQ method the alpha rhythm was used in its entirety, (7 - 12 Hz).

d. In the AR - CG method the alpha rhythm was segmented into sub-bands of 1 Hz width each.

3. In the classification stages of both methods that employed LVQ, (FFT- LVQ, AR-LVQ) the same architecture LVQ neural network and experimental settings were used.
4. In the testing and training procedures of both methods that employed LVQ, (FFT-LVQ, AR-LVQ) the same input classes and subjects were used for training. However, there was a significant difference in the dimensionality of the feature vectors used. Specifically, the order p of the AR vectors was 8 (a p=8 order AR model was fitted to the data) in contrast to the FFT vectors which were 540 points long.
5. The settings of the Computational Geometry algorithm were the same in both methods that employed CG, (FFT - CG, AR - CG).

Our practical experience has shown that the segmentation of each EEG in sub-bands in the FFT method depends on the ability of the subsequent classification method to classify feature vectors of high dimensionality, such as the FFT vectors are; for example, a sub-band of 0.3 Hz width yields a vector of 54 amplitudes, in contrast to a sub-band of 3 Hz width which yields a vector of 540 amplitudes. Specifically, Computational Geometry method showed the ability to classify vectors of a dimensionality not higher than 54 elements whereas the LVQ was capable of classifying vectors of up to 540 elements.

In the experimental phase of the present work, a Multi-layer Perceptron (MLP) neural network was fed with the same input vectors and it was again verified that this neural network was not able to classify vectors of dimensionality 540, reaching only a 55% to 65 % recognition score. In the cases where AR parameters were used as features, and therefore the input vectors were of a lower dimensionality (1 x 8), the LVQ and CG methods showed virtually the same classification ability.

Comparative results of all four methods are shown in table 8. In particular, this table is divided into 2 main columns, the correct positive classification column and the correct negative classification column. Each of these columns is again divided into two sub-columns, the Minimum and the Maximum sub-columns. In the Minimum sub-column are presented the lowest correct recognition scores, either positive or negative, over for all four (4) methods. In the Maximum sub-column are presented the highest correct recognition scores, either positive or negative, over all four (4) methods. This table shows, in an aggregate form, results already tabulated in tables 1-4 (test case 1). Note that in table 8 no results from test case 2 are shown, because no comparison can be made between results of test case 2 and test case 1, as they test different hypotheses and use different neural network architectures. In particular, in test case 2 a classification method, involving four (4) target classes, was employed, in contrast to test case 1, a two target classes set-up was employed. Moreover test case 1 represents an identification hypothesis while test case 2 represents a classification hypothesis.

METHOD	CORRECT POSITIVE CLASSIFICATION		CORRECT NEGATIVE CLASSIFICATION	
	MIN	MAX	MIN	MAX
FFT - CG	90%	100%	96%	100%
FFT – LVQ (Test case #1)	80%	100%	84%	90%
AR – CG	91%	97%	81%	95%
AR - LVQ	72%	82%	76%	83%

Table 8: *Comparative results of the proposed method - (1st row) plus three alternative methods already investigated by the same author four methods applied.*

As it can be seen in table 8, the cases where the CG method is employed for the identification step show percentages of positive and negative classification scores higher than those where the LVQ method is employed. Moreover, the best results obtained under the CG method are those combined to the FFT, where the correct (positive and negative) classification scores range between 90% - 100%. We should note, however, that the use of multi-sub-bands in the CG method increases the computational complexity of the method. For more details on this problem, the interested reader is referred to [9]. Furthermore, according to the results in table 8, the FFT-based, non-parametric spectral analysis is seen to be more efficient than the AR parametric modelling.

4. Conclusions - Further research

Person identification based on spectral information extracted from the EEG is addressed in this work - a problem that has not yet been seen in a signal processing framework, to the best of our knowledge. Neural network classification was performed on real EEG data of healthy individuals, in an attempt to experimentally investigate the connection between a person's EEG and genetically -specific information. The proposed method has yielded correct classification scores in the range of 80% to 100%. These results are in agreement with previous research showing evidence that the EEG carries genetic information and also show the potential of our approach for person identification. The reduction of the feature space dimensionality using parametric linear methods, [21, 22], has not given satisfactory results compared to the non-parametric FFT based spectral analysis. It might be argued, however, that an improvement in correct classification scores is expected via non-linear processing, which would exploit the information carried in the non-linear components of the EEG. Finally, more extensive experimentation is necessary, in order to obtain statistically significant results and thus verify the conjecture of the existence of an one-to-one correspondence between the EEG and the genetic code of the individual.

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Captions of Figures

Figure 1. Example of an EEG spectrum obtained via Fourier Transform. EEG signal sampling rate is 128 Hz. EEG spectral power versus normalised frequency points from 0 to 1/2 (point 64).

Figure 2. The (7-10 Hz) EEG spectral sub-band, isolated from a subject A EEG spectrum.

Figure 3. The architecture of a simplified 2x2 LVQ neural network.

Figure 4. A 3 min (180 sec) EEG signal, recorded from subject A (sampling rate 128 Hz).

Figure 5. A plot of the input/target vectors of subject A and members of group X. The 25 '+' markers represent the input vectors of subject A, while the 25 'o' markers represent the input vectors of members of group X. Input vectors are based on the (7-10 Hz) sub-band only. Note that for 2-D visualisation purposes, only the first two coefficients of the input vectors are plotted.

Figure 6. A plot of the input/target vectors of subjects A, B, C and D. The 20 '+' ,'o', '*', and '⊕ markers represent the input vectors of subjects A, B, C and D, respectively. Input vectors are based on the (7-10 Hz) sub-band only. Note that for 2-D visualisation purposes, only the first two coefficients of the input vectors are plotted.

Captions of tables, Page 1

Table 1. Test Case 1: Subject A against members of group X: classification scores in the 3 alpha rhythm sub-bands (results obtained using test set disjoint to training set).

Table 2. Test Case 1: Subject B against members of group X: classification scores in the 3 alpha rhythm sub-bands (results obtained using test set disjoint to training set).

Table 3. Test Case 1: Subject C against members of group X: classification scores in the 3 alpha rhythm sub-bands (results obtained using test set disjoint to training set).

Table 4. Test Case 1: Subject D against members of group X: classification scores in the 3 alpha rhythm sub-bands (results obtained using test set disjoint to training set).

Table 5. Test Case 2: Common pool classification experiment for subjects A, B, C and D. Classification scores for the (7-10 Hz) alpha rhythm sub-band (results obtained using test set disjoint to training set).

Table 6. Test Case 2: Common pool classification experiment for subjects A, B, C and D. Classification scores for the (8-11 Hz) alpha rhythm sub-band (results obtained using test set disjoint to training set).

Table 7. Test Case 2: Common pool classification experiment for subjects A, B, C and D. Classification scores for the (9-12 Hz) alpha rhythm sub-band (results obtained using test set disjoint to training set).

Captions of tables, Page 2

Table 8. Comparative results of the proposed method, 2nd row, with three alternative methods already proposed by the same authors.

	7-10 Hz		8-11 Hz		9-12 Hz		
classified as: ⇒ belong to class: ⇓	A	X	A	X	A	X	Total Per band
A	19/20 (95%)	1/20 (5%)	19/20 (95%)	1/20 (5%)	20/20 (100%)	0/20 (0%)	20
X	6/50 (12%)	44/50 (88%)	5/50 (10%)	45/50 (90%)	8/50 (16%)	42/50 (84%)	50
Sensitivity	0.76		0.79		0.71		
Specificity	0.98		0.98		1		

	7-10 Hz		8-11 Hz		9-12 Hz		
classified as: ⇒ belong to class: ⇓	B	X	B	X	B	X	Total Per band
B	19/20 (95%)	1/20 (5%)	20/20 (100%)	0/20 (5%)	20/20 (100%)	0/20 (0%)	20
X	5/50 (10%)	45/50 (90%)	6/50 (12%)	44/50 (88%)	7/50 (14%)	43/50 (86%)	50
Sensitivity	0.79		0.77		0.74		
Specificity	0.98		1		1		

	7-10 Hz		8-11 Hz		9-12 Hz		
classified as: ⇒ belong to class: ⇓	C	X	C	X	C	X	Total Per band
C	16/20 (80%)	4/20 (20%)	18/20 (90%)	2/20 (10%)	19/20 (95%)	1/20 (5%)	20
X	10/50 (20%)	40/50 (80%)	5/50 (18%)	41/50 (82%)	8/50 (16%)	42/50 (84%)	50
Sensitivity	0.62		0.78		0.70		
Specificity	0.91		0.95		0.98		

	7-10 Hz		8-11 Hz		9-12 Hz		
classified as: ⇒ belong to class: ⇓	D	X	D	X	D	X	Total Per band
D	17/20 (85%)	3/20 (15%)	18/20 (90%)	2/20 (10%)	18/20 (100%)	2/20 (10%)	20
X	5/50 (10%)	45/50 (90%)	5/50 (10%)	45/50 (90%)	8/50 (16%)	42/50 (84%)	50
Sensitivity	0.77		0.78		0.69		
Specificity	0.94		0.95		0.95		

7-10 Hz band				
out: ⇒ in: ⇓	A	B	C	D
A	21/25 (84%)	0/25 (0%)	0/25 (0%)	4/25 (16%)
B	0/25 (0%)	23/25 (92%)	0/25 (0%)	2/25 (8%)
C	1/25 (4%)	0/25 (0%)	22/25 (88%)	2/25 (8%)
D	0/25 (0%)	0/25 (0%)	0/25 (0%)	25/25 (100%)
Total: 100				

8-11 Hz band				
out: ⇒ in: ⇓	A	B	C	D
A	22/25 (88%)	0/25 (0%)	0/25 (0%)	3/25 (12%)
B	0/25 (0%)	24/25 (96%)	0/25 (0%)	1/25 (4%)
C	0/25 (0%)	0/25 (0%)	23/25 (88%)	2/25 (8%)
D	0/25 (0%)	0/25 (0%)	0/25 (0%)	25/25 (100%)
Total: 100				

9-12 Hz band				
out: ⇒ in: ⇓	A	B	C	D
A	23/25 (92%)	1/25 (0%)	0/25 (0%)	2/25 (8%)
B	0/25 (0%)	24/25 (92%)	0/25 (0%)	1/25 (4%)
C	0/25 (0%)	1/25 (4%)	23/25 (92%)	1/25 (4%)
D	0/25 (0%)	0/25 (0%)	0/25 (0%)	25/25 (100%)
Total: 100				

METHOD ANALYSIS - IDENTIFICATION	CORRECT POSITIVE IDENTIFICATION		CORRECT NEGATIVE IDENTIFICATION	
	MIN	MAX	MIN	MAX
FFT - CG	90%	100%	96%	100%
FFT – LVQ (Test case 1)	80%	100%	84%	90%
AR – CG	91%	97%	81%	95%
AR - LVQ	72%	82%	76%	83%