Spatial Patterns Underlying Population Differences in the Background EEG

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Summary: A method is described which can be used to extract common spatial patterns underlying the EEGs from two human populations. These spatial patterns account, in the least-squares sense, maximally for the variance in the EEGs from one population and minimally for the variance in the other population and therefore would seem to be optimal for quantitatively discriminating between the individual EEGs in the two populations. By using this method, it is suggested that the problems associated with the more common approach to discriminating EEGs, significance probability mapping, can be avoided. The method is tested using EEGs from a population of normal subjects and using the EEGs from a population of patients with neurologic disorders. The results in most cases are excellent and the misclassification which occurs in some cases is attributed to the nonhomogeneity of the patient population particularly. The advantages of the method for feature selection, for automatically classifying the clinical EEG, and with respect to the reference-free nature of the selected features are discussed.

Key words: Electroencephalogram; Eigenanalysis; Spatial patterns; Classification

Introduction

The mapping of probability scores has become the standard for the quantitative detection of differences in the characteristics of the normal and abnormal EEGs (Duffy et al. 1981; Nuwer 1988a,b). The approach has generally been to extract parameters such as, for example, the spectral powers from the potential variations at the electrode sites in a recording montage and to compile these for the EEG populations available. Differences in these parameters at each electrode site are then often measured as 't' scores between populations or as 'z' scores between an individual and a population. These scores are then interpolated and displayed as maps to reflect the topography of any spatial differences which might exist.

There are several drawbacks to this approach. The first, and probably most important of these is that the statistical scores are computed at different electrode sites as if the EEG processes at these sites are independent. Because the spatial covariance of the EEG is not taken into account and because of the multitude of electrode sites involved, the calculated statistical scores may indicate differences that are due to chance alone. These spurious results, when interpolated, can appear to be well defined on a significance-probability map and thus lead to misleading conclusions about the differences between the populations.

The second drawback to the probability-scores approach is that due to the active recording reference which is inevitable in electroencephalography. Probability scores related to the background EEG are usually derived from a temporal analysis of potential variations at individual electrode sites which occur with respect to a common reference electrode. Probability maps are then constructed by spatial interpolation. This approach of temporally then spatially analyzing the referential EEG is exactly contrary to Lehmann's observation (1987) which makes it clear that to avoid ambiguities in topographic mapping due to the reference, the spatial analysis must be applied first.

We present here a method of discriminating EEGs which is based on the covariance between the potential variations at the electrode sites in a multichannel EEG. This method extracts spatial patterns in the EEG which can then be interpreted free from the confounding effects of an active-recording reference. Therefore, these patterns can also be interpreted unambiguously in terms of

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EEG source geometry and thus can have important functional significance. In addition, the statistics applied more properly reflect the nonindependent nature of the EEG between electrodes. We have chosen a population of normal EEGs and a population of abnormal EEGs obtained from neurologic patients to illustrate our method.

Methods

We have assembled a database of 31 channel (referential recording with respect to the left ear) EEGs from some 75 normal volunteers and some 30 neurologic patients. The volunteers were of both sexes, ranged in age from 17 to 50, and had passed a cursory neurological examination. This examination did however not include the routine clinical EEG. Individuals with any otherwise apparent systemic disease or on medication known to affect the EEG were not included in the normal population. The patients included in the abnormal population had been routinely diagnosed as either epileptic, stroke or tumor in the neurology department of an adjoining hospital. Not all of the patients had received a routine clinical EEG. Recordings lasting several minutes during each of the eyes open and eyes closed conditions were obtained from all of the subjects. The arrangement of electrodes in the recording montage covered the entire scalp and was as has been described previously (Koles et al. 1989). Scalp potentials were amplified in the .5Hz to 50Hz bandwidth into the ± 1 volt range and sampled using a 12 bit analog to digital converter at the rate of 120/s.

The digitized recordings were reviewed visually using a high-resolution (1024x1024) graphics monitor. Epochs consisting of 1024 samples from each channel (about 8.5s) which were free from obvious artifacts were selected and stored for subsequent analysis. In all, 594 epochs, 3 from each subject, during each of the eyes open and eyes closed conditions, were used. Whenever possible, the epochs chosen from a subject were not consecutive in the available record. To test the classification method, a supervised-learning method was used and 420 of the 594 epochs were used as the training set and 174 epochs were used as the testing set. All epochs from a particular subject were placed in either the training or the testing set. Of the 420 epochs in the training set, 300 were from the normal population and 120 were from the patient population. Subjects were placed in either the training or testing set on a random basis. All epochs were digitally prefiltered into the 1.5Hz to 37.5Hz band prior to the analysis.

Our method for discriminating EEGs is based on the eigenfunction approach summarized recently by Hjorth and Rodin (1988). This approach has been extended as suggested by Fukunaga (1972) to extract spatial components which are common to two populations but which account, in the least-squares sense, for maximally different proportions of the variances present in the EEGs of the two populations.

Each selected epoch of the EEG was represented by a 31x1024 matrix **X** with each row of this matrix containing the samples from a single channel in the recording montage. An estimate of the spatial covariance in the EEG during this epoch was obtained as:

$$R = X\,X^t / trace\,(X X^t) \tag{1}$$

where the denominator in this expression is the sum of the squares of the samples from each channel, $\mathbf{X}^t$ is the matrix transpose of **X** and **R** is the 31x31 covariance matrix. The normalization of **R** with respect to the trace was done to eliminate magnitude variations in the EEG between individuals. The diagonal elements of **R** thus represent a measure of the fractional variance (or fraction of the total power) of each EEG channel in an epoch and the off-diagonal elements the fractional covariance.

From the covariance matrix $\mathbf{R_i}$ for each selected epoch, a population covariance matrix $\mathbf{R_p}$ was computed as:

$$R_p = \frac{1}{N_p} \sum_{i=1}^{N_p} R_i \tag{2}$$

where N_p is the number of EEG epochs in the population 'p'.

To study the basic spatial patterns underlying the EEG in each of our populations, the respective population covariance matrices were factored into the product of 3 matrices using the method of eigenanalysis. That is:

$$R_p = B_p\,\lambda_p\,B_p^t \tag{3}$$

where $\mathbf{B_p}$ is constrained such that:

$$B_p^t\,B_p = I \tag{4}$$

using routines in the MATLAB™ software package. $\mathbf{B_p}$ and λ_p are 31x31 matrices with $\mathbf{B_p}$ containing, as its columns, the eigenvectors of $\mathbf{R_p}$ and λ_p, a diagonal matrix, containing the corresponding eigenvalues. The eigenvalues are a measure of the variance in the composite EEG which can be accounted for by each of the

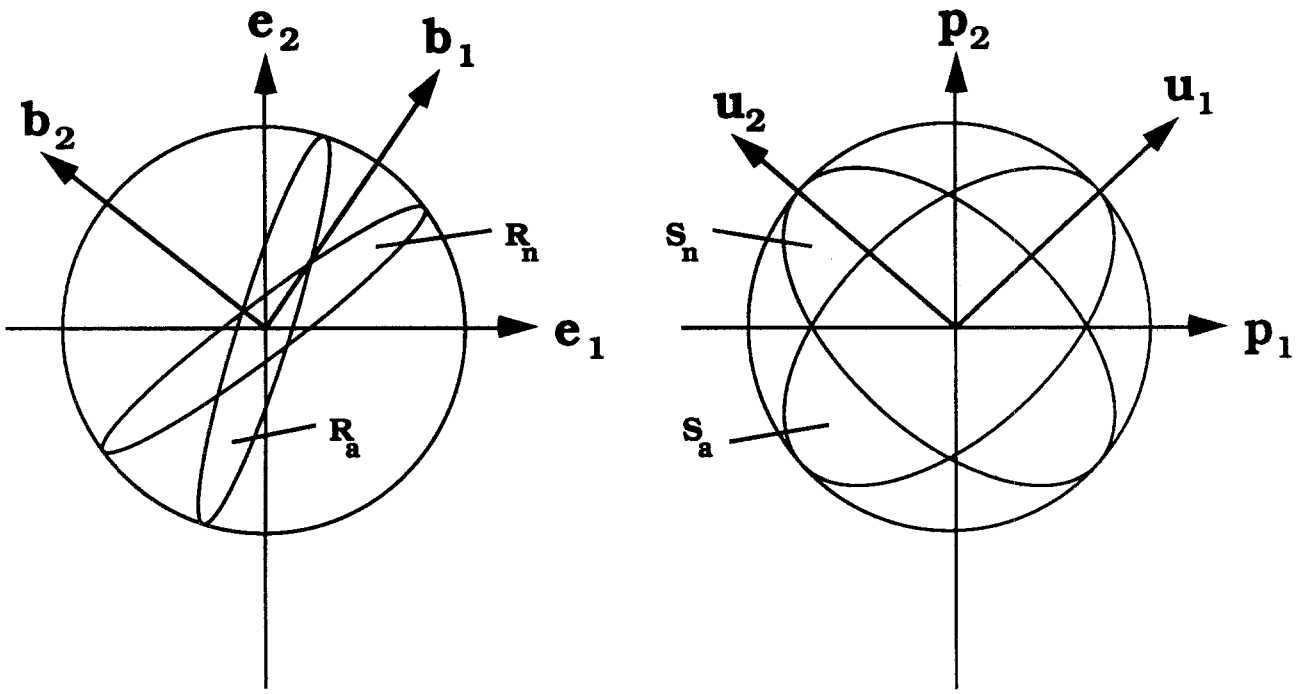

Figure 1. The ellipses R_n and R_a indicate covariance patterns between two electrode potentials e_1 and e_2 which might exist in the normal and abnormal EEG respectively. The principal directions (sometimes called principal components) of the composite covariance pattern which includes both R_n and R_a are b_1 and b_2. If the variance in the measurement space is whitened using equation 7 the resulting whitened covariance patterns S_n and S_a have the same principle components u_1 and u_2. However, the component u_2 which accounts for the maximum variance in S_n accounts for the minimum in S_a and vice versa.

eigenvectors. The eigenvectors themselves represent an orthonormal set which spans the 31 dimensional EEG measurement space. They can also be viewed as the basic spatial patterns which underlie the EEGs in the population.

To determine if two populations exhibit spatial patterns which enable them to be discriminated, we first formed a composite covariance matrix:

$$R_c = 0.5 * (R_a + R_b) \tag{5}$$

where the subscripts p=a and p=b indicate the two populations. $\mathbf{R_c}$ was then factored as before:

$$R_c = B_c \ \lambda_c \ B_c^t \tag{6}$$

and a composite transformation $\mathbf{P_c}$ formed as:

$$P_c = \sqrt{\frac{1}{\lambda_c}} \ B_c^t \tag{7}$$

so that $\mathbf{P_c}$ is a whitening transformation which equalizes the variances in the space spanned by the eigenvectors in $\mathbf{B_c}$.

The transformation $\mathbf{P_c}$ was then applied to the two population covariance matrices to form $\mathbf{S_a}$ and $\mathbf{S_b}$ where:

$$S_i = P_c R_i \ P_c^t \qquad \text{for } i=a,b \tag{8}$$

It can be shown that $\mathbf{S_a}$ and $\mathbf{S_b}$ share the same eigenvectors and that the sum of the corresponding eigenvalues for these two matrices will always be 1 (Fukunaga 1972). In other words, if $\mathbf{S_a}$ is factored as:

$$S_a = U_a \ \Psi_a \ U_a^t \tag{9}$$

and $\mathbf{S_b}$ as:

$$S_b = U_v \ \Psi_b \ U_b^t \tag{10}$$

then if the eigenvectors in $\mathbf{U_a}$ are ordered so that the corresponding eigenvalues in Ψ_a are in decreasing order, the same arrangement of eigenvectors in $\mathbf{U_b}$ will result in an increasing order of the corresponding eigenvalues in Ψ_b and:

$$\Psi_a + \Psi_b = I \tag{11}$$

This result is extremely valuable for the classification problem since the eigenvectors which span a measurement space are known to be optimal, in the least-squares sense, for the amount of variance in the measurements they can account for. With respect to the whitened measurement space spanned by $\mathbf{U_a}$, the variance accounted for by the first 'm' eigenvectors (as given by the corresponding eigenvalues in Ψ_a) will be maximal for population 'a'. Because of the constraint on Ψ_b (equation 11), the variance accounted for by these eigenvectors must then be minimal for population 'b'. The reverse will of course be true for the last 'm' eigenvectors (for which the eigenvalues in Ψ_b are maximal). Therefore, it would appear that an approach which is based on the projection of whitened EEG epochs on $\mathbf{U_a}$ will yield feature vectors which are optimal for discriminating between two populations. The steps involved in obtaining $\mathbf{U_a}$ are illustrated graphically in figure 1.

To test this method for 2 populations 'a' and 'b', each epoch in the EEG database was first normalized by the trace of its own covariance matrix. That is:

$$\overline{X} = X / trace(XX^t) \tag{12}$$

The variance in $\overline{X}$ was then whitened with $\mathbf{P_c}$ obtained from the composite 2-populations covariance matrix (equation 7) and projected along the eigenvectors of its own whitened population covariance matrix $\mathbf{S_a}$ (equation 8). The overall transformation applied to $\overline{X}$ was therefore:

$$F = U_a^t \; P_c \; \overline{X} \tag{13}$$

A 31-element feature vector **f** consisting of the variance projected along the transformed dimensions was obtained from:

$$f = \frac{1}{1024} \sum_{j=1}^{1024} f_{ij}^{\,2} \tag{14}$$

where the f_{ij} are the elements of **F** (i^{th} row, j^{th} column).

The first and last 5 elements of **f**, as they represent most of the variance in the respective populations, were selected and subjected to discriminant analysis. The software used was that provided in the MGLH module of the SYSTAT ™ statistical software package.

Table I. The percent variance in the EEGs accounted for by the first 5 eigenvectors of the covariance matrix obtained separately for the normal and patient populations.

Eigenvector	Percent Varaince	
	Normal	Patient
1	57	53
2	21	22
3	7	8
4	3	4
5	2	3
Totals	90	90

Results

Figure 2 shows the first 5 eigenvectors obtained from the population covariance matrices of the normal and patient EEGs (using equations 1 and 2). The left-hand column, from top to bottom, contains the normal eigenvectors while the right-hand column, from top to bottom,

Table II. Comparison of the normal and patient populations with the eyes-open and eyes-closed conditions combined. A multivariate statistical analysis of the feature vectors from the normal and patient populations in the training set indicated a significant difference at the $p << .001$ level ($F=25.4$, $df=10, 409$).

Population	Predicted		Totals	% Correct
Training	Normal	Patient		
Normal	268	32	300	89
Patient	34	86	120	72
Totals	302	118	420	81
Testing				
Normal	118	26	144	82
Patient	12	18	30	60
Totals	130	44	174	71

Table III. Comparison of the normal and patient populations during the eyes-open condition. A multivariate statistical analysis of the feature vectors from the normal and patient populations in the training set indicated a significant difference at the p <<.001 level (F=15.7, df=10, 199).

Population	Predicted		Totals	% Correct
Training	Normal	Patient		
Normal	139	11	150	93
Patient	17	43	60	72
Totals	156	54	210	83
Testing				
Normal	55	14	69	80
Patient	8	4	12	33
Totals	63	18	81	57

Table IV. Comparison of the normal and patient populations during the eyes-closed condition. A multivariate statistical analysis of the feature vectors from the normal and patient populations in the training set indicated a significant difference at the p <<.001 level (F=15.9, df=10, 199).

Population	Predicted		Totals	% Correct
Training	Normal	Patient		
Normal	126	24	150	84
Patient	13	47	60	78
Totals	139	71	210	81
Testing				
Normal	59	16	75	79
Patient	2	19	21	90
Totals	61	35	96	85

contains the patient eigenvectors. The topographic maps shown in the figure were obtained by describing the average position of each electrode in the recording montage over the subjects in terms of spin and tip angles as if they were located on the surface of a sphere. These positions were then projected azimuthally onto a plane (with C_z as the origin) and the elements of the eigenvectors corresponding to each electrode interpolated using 3^{rd}-order natural splines (Perrin 1987).

The two sets of maps are surprisingly similar indicating that the basic spatial patterns which underlie and account for most the variance in the EEGs of the two populations are essentially the same. The proportion of the variance in the EEGs of the two populations accounted for by the eigenvectors in figure 2 are given in table I.

The table shows that the first 5 eigenvectors can account for approximately the same proportion of the variance in the EEGs in both populations. This probably indicates that the gross geometries of the EEG generators in both populations were very similar and that any consistent differences, if they exist, will be contained in the minor details.

The results of the discriminant analysis on the first and last five elements of the feature vectors obtained from equations 13 and 14 are given in table II. Of the 420 epochs in the training set, 300 were from the normal population and 120 were from the patient population. Of the 174 epochs in the testing set, 144 were from the normal population and 30 were from the patient population. The discriminant function was calculated from the training set and the table shows the results of a retrospective classification of this set. Application of this function to the testing set produced the results given in the bottom portion of the table.

The table shows an overall correct classification rate of 81% for the training population and 71% for the test population. Tables III and IV show similar classification tables for the normal and patient populations separated into the eyes-open and eyes-closed conditions. Normal-

Table V. Comparison of normal populations during the eyes-closed and eyes-open conditions. A multivariate statistical analysis of the feature vectors from the eyes closed and eyes open conditions in the training set indicated a significant difference at the p <<.001 level (F=21.8, df=10, 289).

Population	Predicted		Totals	% Correct
Training	Closed	Open		
Eyes closed	108	42	150	72
Eyes open	20	130	150	87
Totals	128	172	300	76
Testing				
Eyes closed	59	16	75	79
Eyes open	1	68	69	99
Totals	60	84	144	89

Table VI. The percent of the totalvariance from the combined normal and patient populations in the eyes-closed condition accounted for by the common eigenvectors in each of the two populations separately. Top and bottom portions of this table correspond to the left and right columns respectively of figure 3.

Eigenvector	Percent Variance	
	Normal	Patient
1	79	21
2	73	27
3	72	28
4	71	29
5	69	31
31	20	80
30	23	77
29	26	74
28	29	71
27	30	70

Table VII. The percent of the total variance from the combined eyes-closed and eyes-open conditions accounted for by the common eigenvectors in each of the two conditions separately. Top and bottom portions of this table correspond to the left and right columns respectively of figure 4.

Eigenvector	Percent Variance	
	Eyes Closed	Eyes Open
1	73	27
2	70	30
3	66	34
4	66	34
5	61	39
31	16	84
30	23	77
29	25	75
28	27	73
27	29	71

patient discrimination is similar during the two conditions except for the patients in the testing set during the eyes-open condition. The correct classification for this group was only 33%.

Table V shows the classification of the normal population based on the eyes-closed and eyes-open conditions. Clearly, in both the training and testing sets, the eyes-open condition is better discriminated. This is true particularly in the testing set where a remarkable 68 of the 69 available EEG epochs were correctly classified.

Figure 3 shows the eigenvectors of the whitened population covariance matrix used for the normal-patient discrimination during the eyes-closed condition. The left column shows, from top to bottom, the 5 eigenvectors which account, in decreasing order, for the maximum variance in the normal population and which account, in increasing order, for the minimum variance in the patient population. The right column shows, from top to bottom, the 5 eigenvectors which account, in decreasing order, for the maximum variance in the patient population and, in increasing order, for the minimum variance in the normal population. The figure indicates that these eigenvectors are dominated by only a few electrodes. Generally, the electrodes responsible

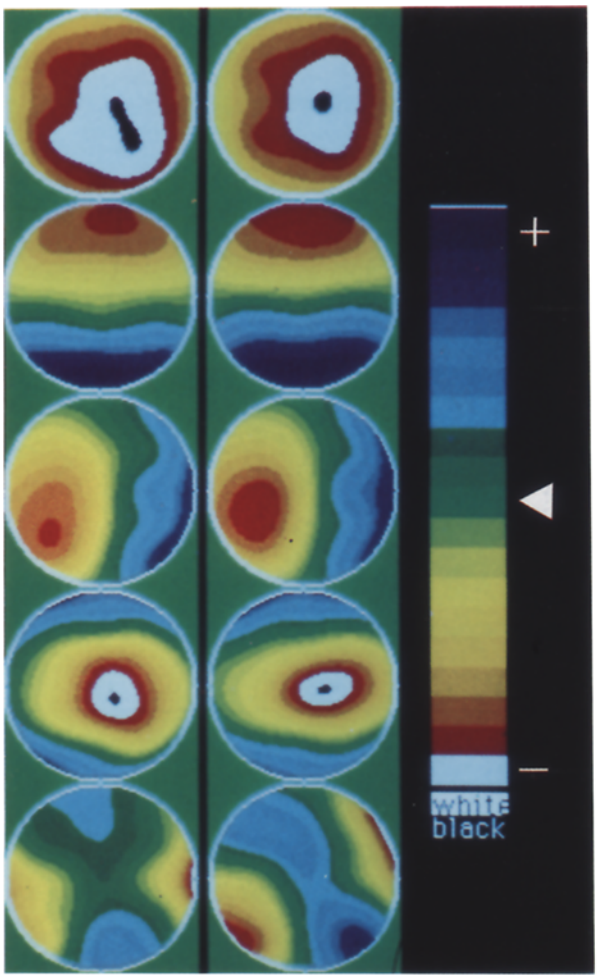

Figure 2. Eigenvectors computed separately from the covariance of the normal and abnormal EEG populations. The left-hand column contains the eigenvectors of the normal population while the right-hand column contains the eigenvectors of the patient population. The top to bottom arrangement of eigenvectors is such that the variance accounted for in the EEGs of the populations becomes progressively less. The percent variance accounted for by each eigenvector is given in table I. The background green used for the maps which is also indicated by the white arrow on the color bar indicates the zero level for the pattern while the darker greens to blues indicate a relatively more positive scalp potential and the lighter greens to yellows, red, white and black indicate a relatively more negative scalp potential.

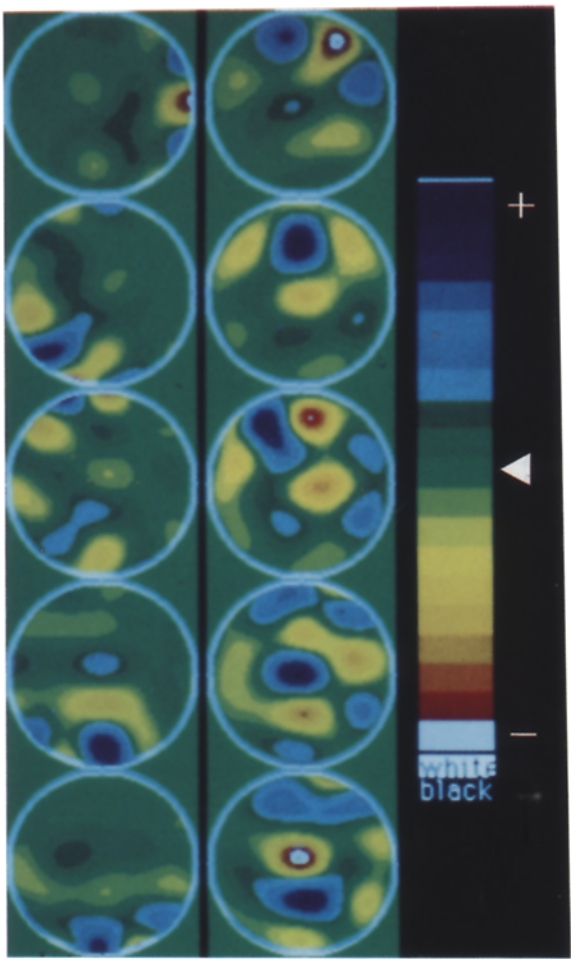

Figure 3. Spatial patterns in the EEG which contribute most strongly to the normal-patient discrimination. The eyes open and eyes closed conditions have been combined in each population. The top-left pattern accounts for the maximum variance in the normal population and minimum variance in the patient population. The top-right pattern accounts for the maximum variance in the patient population and the minimum variance in the normal population. These proportions with respect to variance tend to equalize for each map down the figure. The values for the variance proportions are given in table VI. The background green used for the maps which is also indicated by the white arrow on the color bar indicates the zero level for the pattern while the darker greens to blues indicate a relatively more positive scalp potential and the lighter greens to yellows, red, white and black indicate a relatively more negative scalp potential.

for the variance in the normal EEGs which is minimally present in the patient population tend to be the peripheral electrodes while the electrodes responsible for the variance in the patient EEGs which is minimally present in the normal EEGs tend to be located in the interior of the mapped region. The percent variance from each population accounted for by each of the eigenvectors in figure 3 is given in table VI. Eigenvectors 1 to 5 relate to the maps, from top to bottom, in the left-hand column of figure 3 and eigenvectors 31 to 27 relate to the maps, from top to bottom, in the right-hand column of figure 3.

As expected, the eigenvectors which account for most of the variance in one population and the least in the other are 1 and 31. Figure 3 indicates that electrodes along the right temporal perimeter of the recording

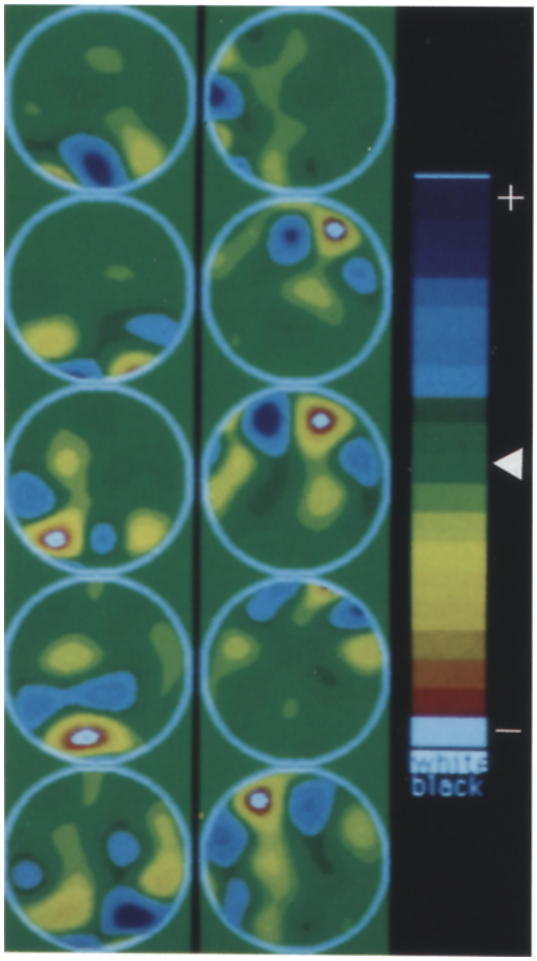

Figure 4. Spatial patterns in the EEG which contribute most strongly to the eyes open-eyes closed discrimination in the normal population. The top-left pattern accounts for the maximum variance in the eyes-closed condition and the minimum variance in the eyes-open condition. The top-right pattern accounts for the maximum variance in the eyes-open condition and the minimum variance in the eyes-closed condition. These proportions with respect to variance tend to equalize for each map down the figure. The values for the variance proportions are given in table VII. The background green used for the maps which is also indicated by the white arrow on the color bar indicates the zero level for the pattern while the darker greens to blues indicate a relatively more positive scalp potential and the lighter greens to yellows, red, white and black indicate a relatively more negative scalp potential.

montage most strongly discriminate the normals from the patients, while the right frontal electrodes most strongly distinguish the patients.

Figure 4 shows the eigenvalues of the whitened population covariance matrix used for the normal eyes closed-eyes open discrimination. Generally, the electrodes contributing to the variance in the EEGs in the eyes-closed condition tend to be the posterior ones while the electrodes contributing to the variance in the eyes-open condition tend to be the anterior ones. Table VII shows the percent variance from the eyes-closed and eyes-open conditions accounted for by each of the patterns in figure 4. Eigenvectors 1 to 5 relate to the maps, from top to bottom, in the left-hand column of figure 4 and eigenvectors 31 to 27 relate to the maps, from top to bottom, in the right-hand column of figure 4.

Eigenvector 31 is particularly large in the eyes-open condition compared to the eyes-closed condition and figure 4 shows that the variance in the EEGs in the eyes-open condition comes mainly from the electrodes along the left-hand periphery. Eigenvector 1 in figure 4 shows that the variance in the EEGs in the eyes-closed condition that most strongly distinguishes it from the eyes-closed condition originates in the occipital region. This pattern seems reasonable in view of the known increase in the strength of the alpha rhythm in this region which accompanies the eyes-closed condition in the normal population.

Discussion

Using the methods of eigenanalysis, we have been able to quantitatively extract spatial patterns which underlie the differences in the EEGs of two populations. The results, we think, are quite impressive yielding classification statistics in many cases which are well over 80%. In addition, since the number of features used for the classification was small compared to the number of epochs in the training set and since the retrospective classification of the training set could, in many cases, be replicated with the testing set, the results are probably very meaningful and applicable to independent normal and patient populations. While the classification rate of the patients in the testing set was not always high, this may be due to the fact that this population was either not very homogeneous or that the numbers involved were too small. For example, the numbers problem may have been the factor responsible in the results obtained for the testing set in table 3 where only 33% of the patients were classified correctly.

We find the result of very similar basic spatial patterns underlying and accounting for 90% of the variance in the EEGs from both the normal and patient populations to be somewhat surprising. In our minds, the EEGs from the two populations should be very different as every individual in the patient population has had some otherwise identified and probably severe neurological disorder. Yet, figure 2 indicates that the source geometries responsible for most of the EEGs in the two populations are not what would be called distinctive. This indeed may be the reason that the visual (and qualitative) recognition of the abnormal EEG is sometimes so difficult. The patterns in figures 3 and 4 because of their relative com-

plexity (compared to figure 2) and which serve to distinguish two populations must therefore account for only a small proportion of the variance present in the EEGs of the two populations. It therefore seems that that the features in an EEG which make it abnormal or which occur with the eyes-open or eyes-closed conditions in a normal EEG are very minor making the development of quantitative methods such as the one described here vital for most discriminations. Figures 3 and 4 would also suggest that the details which serve to discriminate EEGs tend to be quite local in origin.

Gevins (1984) in a review of the methods of quantitative analysis of the EEG has discussed the problems related to the extraction of features from the EEG as these are relevant to the classification problem. Three approaches are discussed, the first being the heuristic approach which utilizes the expert knowledge obtained from the traditional visual assessment of the strip chart. The second is the principal components analysis approach which attempts to account for most of the variance (information) in the EEG in terms of a minimum number of factors (features). The third is the classifier-directed approach particularly stepwise-discriminant analysis which attempts to select, one at a time, those features from the heuristic set which maximize a separation criterion between the populations.

The heuristic approach is clearly not satisfactory in general since the salient features apparent in a visual examination of an EEG are not necessarily relevant or in any way optimal for a particular classification problem. In addition, there is no way of limiting the number of features selected in this way, a situation which is exemplified in commercial brain-mapping systems some of which apparently offer some 1500 features with which to describe a 19 channel recording of the EEG.

The principal components approach has been criticized because the factors which account for most of the variance in any one EEG may not be useful for discriminating between two EEGs. The validity of this criticism becomes apparent after examination of figure 2. Stepwise discriminant analysis is effective in solving the feature explosion problem that can evolve from the heuristic approach but does not solve the problem of the selection of features which are in some way optimal for the classification problem. In addition, it has been found that a set of features chosen one at a time may not be as effective for the classification as another set of features chosen together. Therefore, because it additionally requires other methods to select features, stepwise discriminant analysis would not seem to be an extemely useful approach to the problem of classifying EEGs.

The method we have described in this work, which is a modification of the principal components approach, would seem to have overcome all of the problems which exist with the previous approaches. First of all, the features are not heuristically selected and those which are extracted are only those which are relevant to the particular classification problem at hand. These features are, in the least-squares sense, optimal in the proportion of the variance they can account for in two EEGs or two EEG populations. Furthermore, features for discriminant analysis can be selected in combination and only the number of features selected is arbitrary. The method, in effect, sorts the features into the order in which they are most effective for the discrimination.

Although the results obtained classifying the EEGs from normal and patient populations are impressive, even these, we feel, could be improved if the populations involved were more homogeneous. The neurologic patients, in particular, would seem to be particularly nonhomogeneous as their EEGs are due to different pathological conditions and these in individual cases probably affect different regions of the brain. We note that the normal EEGs are almost always more successfully classified than the patients. Also, within the normal population itself, classification during the eyes-open condition is more successful suggesting that there is less consistency in the EEG during the eyes-closed condition. It seems, therefore, that the methods developed here may have greatest utility distinguishing a single 'normal' EEG from one which is suspected of being abnormal. In view of this, population studies like the one described here may be most useful in psychiatry where individual differences may be too subtle to be detected directly. Averaging over individuals which according to psychiatric criteria are affected by the same mental disturbance might be the only way possible to elucidate an abnormality in the EEG. The results obtained in this work suggest that the eyes-open condition may be better than the eyes-closed condition for doing this.

The main value of the results presented in this work is probably related to the normal population and indicate some kind of average difference in source-generator geometry between the eyes-open and eyes-closed conditions. Indeed, it is worth emphasizing that the maps presented here are free from any confounding effects produced by an active recording reference. This comes from the fact that the spatial patterns are derived from a spatial analysis of the EEG and that these patterns are presented as topographic maps. While the absolute elevation at any point on the map may be reference dependent, the general topography is not and this topography represents an unambiguous view of the source geometry within the brain which must be responsible for the differences between the two conditions.

In conclusion, we feel that further work using methods similar to those described here could lead to the development of an important tool for the detection and surface

localization of the abnormal EEG. We suggest however, that this should be done with more electrodes and by using a carefully assembled and homogeneous normative data base.

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