AUTOMATIC ADAPTIVE SEGMENTATION OF CLINICAL EEGs 1,2

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In the visual analysis of clinical electroencephalograms as a basis for interpreting and reporting them, the clinical electroencephalographer searches for different types of activity. Although it may happen that only a single type of activity is present in a particular record, it is more frequently the case that several different types of activity are encountered, which may or may not be accompanied by different behavioral states. Examples include the waking EEG with eyes closed and with eyes open, the EEG during drowsiness, sleep, intermittent slow activity, paroxysmal spike-wave activity, and so on.

In computer analysis, for the most part, particular portions of EEGs having specific types of activity or which correspond to specific behavioral states are visually selected prior to the analysis. Operator intervention is thus usually necessary in the selection of the particular portions of EEGs for computer analysis, in order to avoid mixing different types of activity of different behavioral states, in any particular period of analysis.

Recently, computer programs have been developed for automatic adaptive segmentation of EEGs, so that boundaries between different types of activity are automatically identified and demarcated (Bodenstein and Praetorius 1977; Praetorius et al. 1977; Michael and Houchin 1979). We report now on our experience with one of these programs (Michael and Houchin 1979) for a group of clinical EEGs. A preliminary report on some aspects of this work has been presented to the German EEG Society (Michael and Houchin 1980).

Materials and Methods

For this investigation, 20 EEGs representing a diversity of normal and abnormal patterns were selected from a library of 70 EEGs previously recorded at the Max Planck Institute for Psychiatry in Munich. Of these 20, 9 were further selected for additional detailed analysis. The original 8-channel ink recordings were also available. The EEGs had been simultaneously recorded onto analog magnetic tape, of which 4 channels, selected because of their interest as normal or as abnormal patterns, were digitized and stored on magnetic disks. These in turn were transferred to floppy disks.

The principle of adaptive segmentation is schematized in Fig. 1A (one channel at a
time is analyzed). A difference measure that includes both frequency and amplitude changes is obtained for the EEG as ‘seen’ through two different 1.2 sec windows. The first, the reference window, is stationary and immediately follows the last segmentation boundary. (In the case of no prior segmentation, the initial 1.2 sec of EEG is taken.) The second window, the test window, moves along the EEG in time. If the difference measure, which is based on the autocorrelation functions of the EEGs within the two windows, respectively, exceeds the preset threshold (see below), a new segment boundary is signaled. The exact placement of the latter is determined by a separate algorithm that determines the point along the EEG at which the change leading to the segmentation actually began.

For each segment, the mean amplitude and ‘mean frequency’ (the latter is an approximate measure, derived as is the former from the autocorrelation function) are computed and can be written out adjacent to the segmented EEG itself, as shown in Fig. 1B. (Further details on the method of segmentation can be found in Michael and Houchin 1979).

The segments are clustered by means of Ward’s hierarchical cluster algorithm (Ward 1963), with the same measures of amplitude and frequency differences as were used in the segmentation algorithm. The clustered segments are then written out (Fig. 2A) together with the associated dendrogram (Fig. 2B). From visual inspection of these, the number of desired principal clusters (states) is chosen. A temporal profile (Fig. 3A) is then plotted that indicates which of the principal types of activity were obtained at any given time during the recording. Overall mean amplitude and ‘mean frequency’ for all segments within a given principal cluster are computed and displayed alongside the temporal profile.

For comparison with the latter, power spectra are computed from the respective averaged autocorrelograms. For this purpose, inverse filter coefficients for the respective autoregressive filter model are first computed directly from the autocorrelation functions. The power spectrum is then determined from the inverse of the filter coefficients (Fig. 3B). An 8th order autoregressive model (see Barlow 1979) was used, corresponding to 9 autocorrelation coefficients including the one for zero lag.

Computer programs were written in a combination of Fortran and Basic, and were run under the RT-11 operating system. The analyses were carried out on an RT-11 based multi-computer system (Hammond 1980) consisting of several PDP-11’s. A later version of the programs permitted their being run on an LSI-11.

Results

At the onset, it was necessary to optimize the segmentation parameters. As a first step, a specific EEG was chosen which included a normal background as well as both intermittent slowing and intermittent spike-wave activity. It was then found that the optimal segmentation parameters for this EEG were also satisfactory for the entire set of 20 EEGs. The optimal segmentation parameters were (a 50 Hz sampling rate was always used): length of window, 1.2 sec; length of autocorrelation function, 100 msec (i.e., 5 autocorrelation coefficients, including the one for zero lag); interval along the EEG between successive comparisons of reference and test windows, 100 msec; threshold for differences between reference and test autocorrelation functions, 120% for frequency, 120% for amplitude. The segmentation algorithm operated in such a way as to be less sensitive to amplitude changes for amplitudes less than a pre-specified threshold, thus avoiding excessive segmentation at low amplitudes. For this purpose, a linear rather than a percentage amplitude test was used as the determining factor for segmentation.

An example of the clustered segments for an EEG showing 4 principal types of activity
is shown in Fig. 2A (the same EEG as for Fig. 1A and 1B). The corresponding dendrogram is shown in Fig. 2B, the numbers on which (i.e., 1 through 4) correspond to those in Fig. 2A. The temporal profile for the 4 types of activity (i.e., the 4 major clusters) is shown in Fig. 3A, the mean amplitude and 'mean frequency' for each state being shown at the right in the figure. It is evident that there are two kinds of background activity, one with a 'mean frequency' of 8.7 c/sec and the other of lower amplitude 12.6 c/sec. The paroxysmal activity is also divided into two groups, the first with a 'mean frequency' of 4.4 c/sec

Fig. 1. A: schema of method of adaptive segmentation. The original EEG is shown at the top, the lighter vertical lines at the left enclose a just segmented paroxysm. The new reference window is at the left, the moving test window at the right. The difference measure (for amplitude and frequency combined) is shown below, together with the threshold for segmentation (horizontal line). (In actuality, there are separate thresholds for frequency and for amplitude.) Note that the point at which the threshold is exceeded lags the actual beginning of the change; a separate algorithm is therefore used to determine the latter point in time. Note also that the small spike component hardly affects the difference measure. The same EEG (No. 007, channel 2 (F4-C4)) is also used in Figs. 2–5. B: segmented EEG (No. 007) with normalized autocorrelation function of 5 terms, mean amplitude (in this and in the subsequent figures amplitude in microvolts is twice the indicated value) and 'mean frequency' for each segment. Note that the latter are numbered in sequence.
Fig. 2. A: principal clusters (types of activity) for EEG 007. The 4 clusters were chosen from the EEG segments shown, in combination with the corresponding dendrogram shown in B. The numbers of the first segment in each cluster (i.e., 13, 1, 3 and 4, respectively) in this and in the subsequent illustrations are shown enlarged in the clustered EEGs and in the corresponding dendrograms. Note that there are two groups of faster activity, differing primarily in amplitude, and two groups of slower activity of which one is paroxysmal. B: dendrogram for EEG 007. The ordinate indicates the degree of difference among the various subclusters. Note that with progressively decreasing values of the ordinate (i.e., measure of difference), 2 clusters or branches emerge at a level of 30, 3 at a level of 7, 4 at a level of 6, and so on.
and of moderate amplitude, and the other of a 'mean frequency' of 3.5 c/sec and an appreciably higher amplitude. Closer inspection of the temporal profile (Fig. 3A) and the clusters (Fig. 2A) shows that several of the lower amplitude slow-wave events are associated with (i.e., either immediately precede or follow) the higher amplitude paroxysms.

To visual analysis, this EEG channel was interpreted as showing brief (1–1.5 sec) paroxysms of high amplitude, somewhat irregular, approximately 3 c/sec slow-wave activity, often with an associated spike component, amid a background of some average amplitude 8–10 c/sec alpha, some low amplitude fast, and with additionally occasional low to medium amplitude slow (5–6 c/sec) activity.

For comparison, the power spectra (Fig. 3B) showed the following peaks (in decreasing order of prominence): state 1: 8.6, 15.3, 20.5 c/sec; state 2: 8.3, 14.9; state 3: 2.6, 8.5;

![Table]

### A

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**Fig. 3.** A: temporal profile for EEG 007, showing the type of activity or state (major cluster) present at any given time during the recording. Mean amplitude and 'mean frequency' is shown for each state at the right. In 4 instances, the lower amplitude slow activity (state 3) was adjacent to a paroxysm (state 4). Note that the paroxysmal activity is relatively uniformly distributed in time. B: power spectra for each of the 4 states of A, computed from the respective averaged autocorrelograms. The principle peaks are at 8.6, 8.3, 2.6 and 3.1 c/sec. Frequencies of other peaks are given in the text.
state 4: 3.1 c/sec. To the extent that the spectra can be represented by a single number for frequency, it is evident that the ‘mean frequencies’ given by the profile program (Fig. 3A, right side) provide a good summary of the different types of activity in the original EEG. Moreover, it is apparent that for this EEG, the computer segmentation, clustering, and determination of mean amplitude and ‘mean frequency’ compare favorably with the visual evaluation and that the further specific information provided by the frequencies of the peaks in the power spectra for the different states yields little additional important information, nor are the spike events themselves segmented, as is to be expected (see Discussion).

In the normal EEG shown in Figs. 4A and B, 3 principal types of activity are apparent: a relatively large amplitude alpha with a ‘mean frequency’ of 13.5 c/sec (state 1 in Fig. 5A); a lower amplitude background with some slower activity, having a ‘mean frequency’ of 11.4 c/sec (state 2); and a still lower amplitude background with some slower activity, having a ‘mean frequency’ of 5.3 c/sec, probably representing a pattern of drowsiness (state 3). Note that the latter state is apparent at intervals throughout the recording, but with a preponderance in the very last part of the recording. By visual analysis, a 12–13 c/sec alpha activity of moderate amplitudes was noted, with lower amplitude irregular faster activity being present at times. Intermittent irregular slowing typical for drowsiness was also noted.

The power spectra (Fig. 5B, left), computed from the averaged autocorrelation functions for all of the segments within each of the principal 3 clusters, showed the following: state 1, peak at 11.9 c/sec; state 2, peak at 11.8; state 3, a peak at the low frequency end and a low peak at 12 c/sec.

For this EEG, there is rather good agreement between the results of visual analysis, and those of segmentation and clustering and the summary parameters derived therefrom. The power spectra provide little additional helpful information.

The 3 principal clusters (states) for a different type of EEG that has abnormal slowing are shown in Fig. 6A together with the corresponding dendrogram. From the temporal profile (Fig. 6B) the ‘mean frequency’ of the background is 7.3 c/sec. Both the irregular lower amplitude slow activity with admixed faster activity (having a ‘mean frequency’ of 5.1 c/sec — state 2) and the higher amplitude more rhythmic slowing (having a ‘mean frequency’ of 3.9 c/sec — state 3) occur more frequently in that part of the recording that is somewhat beyond the midpoint. By visual analysis, this channel of this EEG was interpreted as having a number of brief paroxysms of high amplitude irregular approximately 3 c/sec slow-wave activity, often with a spike component, amid a background of some average amplitude 8–10 c/sec alpha, some low amplitude fast activity, together with occasional low to medium amplitude slow activity at 5–6 c/sec.

For comparison with these results, the power spectra (Fig. 5B, right side) showed the following for the different states and types of activity, respectively: state 1 (background activity), a very broad peak at 7 c/sec; state 2 (irregular lower amplitude slow activity), a peak at 4.6 c/sec; state 3 (higher amplitude rhythmic slowing), a higher peak at 4.0 c/sec. It is evident that these values are in good agreement with the ‘mean frequencies’ for the respective state as shown at the right in Fig. 6B (i.e., 7.3, 5.1 and 3.9 c/sec, respectively). The ‘mean frequencies’ therefore provide a good summary of the formal power spectra in this instance.

An additional 6 EEGs (one channel each) were studied in similar detail. Included were 1 normal and 5 abnormal EEGs with the following findings upon visual evaluation, respectively: (1) normal alpha activity, (2) frequent episodes of irregular 3–5 c/sec slowing with a normal alpha background, (3)
Fig. 4. A: cluster for a normal EEG (010) having a relatively high amplitude alpha background (state 1) interspersed with lower amplitude slower and faster activity (state 2), and at times with some still slower activity probably consistent with drowsiness (state 3). B: dendrogram corresponding to the cluster shown in A.

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Fig. 5. A: temporal profile for the EEG of Fig. 4. Note that the different types of activity are relatively randomly distributed in time during the recording. B: power spectra for the different states of the EEG of Figs. 4 and 5A (left, EEG 010), and for the different states of the EEG of Fig. 6 (right, EEG 037).
Fig. 6A.
paroxysms of irregular high amplitude spike/sharp wave activity with a normal background of alpha activity and occasional eye-roll artifact, (4) brief paroxysms of irregular 4 c/sec spike-wave or slow-wave activity with a normal alpha background, (5) numerous paroxysms of 3–4 c/sec sharp/slow wave complexes amid irregular lower amplitude slowing and a normal alpha background, (6) occasional 4 c/sec spiking or spike-wave activity with intermittent low amplitude slowing and a background of somewhat irregular alpha.

For all 6 of these EEGs, the segmentation and clustering were found to be satisfactory from a clinical standpoint (i.e., with respect to the different types of activities in the records), and for 3, the summary descriptors of mean amplitude and 'mean frequency' were found to provide an adequate evaluation, in comparison with the results of visual analysis. However, for the remaining 3, the 'mean frequency' parameter did not adequately indicate the presence of two different frequency bands within the same cluster (e.g., alpha and slow), although the original autocorrelation functions used in segmentation, clustering and estimation of power spectra did of course indicate their presence. Further, as expected, in no EEG was spike/sharp wave activity adequately reflected in the results. On the other hand, it was found that eye-roll artifacts could be separately segmented and clustered, thus facilitating their exclusion from real EEG activity, and at the same time, facilitating their identification in the original record.

Discussion

The principal parts of the present analysis of the EEG include: (1) segmentation, (2) clustering with computation of the associated dendrogram, (3) plotting of the temporal profile and determination of mean amplitude and 'mean frequency' (the inclusion of quotes indicating that only an approximation to the actual mean frequency is obtained), and (4) computation and plotting of the power spectrum corresponding to each type (state) of activity. Initially, therefore each of these steps will be discussed separately.

(1) Segmentation. Although the adaptive segmentation technique would not have been practical had it been necessary to establish a new set of segmentation parameters for each new EEG, it is perhaps remarkable that a single set of parameters (see Materials and Methods) was found to be satisfactory for a number of EEGs. The fact that this was the case suggests that a segmentation technique based on changes of amplitude and frequency in relation to the respective thresholds is a good approximation to the process that the clinical
electroencephalographer uses in the visual analysis of records.

As was previously noted, a segmentation technique based on comparison of autocorrelation functions of EEGs, at least for EEG samples of the duration employed in the present technique (i.e., 1.2 sec) cannot be expected to segment in relation to spike/sharp-wave activity since even a relatively high amplitude spike of for example 80 msec will contribute relatively little to the autocorrelation function for the portion of the EEG within which the transient appears. Indeed, it is probably desirable that a segmentation technique be sensitive to wave changes alone, and that a separate technique (or techniques) be employed for spike/sharp-wave detection. For example, mean amplitude, 'mean frequency,' and power spectra would be meaningless for such brief transients. A separate spike-recognition algorithm is therefore under consideration.

(2) Clustering. For the present work, the number of principal clusters was chosen from visual inspection of the clustered EEG segments and of the associated dendrogram. In fact, it was found that for all of the 20 EEGs studied, at most 5 clusters sufficed to sort out the clinically significant types of activity. Indeed, for the EEGs in the accompanying illustrations, 4 clusters sufficed. Accordingly, the delineation of the principal clusters could be carried out by visual selection from the temporal profiles, mean amplitudes and 'mean frequencies' for 3, 4 and 5 principal clusters, respectively, generated automatically by the computer.

Alternatively, a fixed level of dissimilarity could be specified for the dendrogram. Fig. 7 shows that for a group of 20 EEGs (among which the ones already discussed were included), a level of dissimilarity within the range 7.1–9.6 would have resulted in at least 2 but not more than 4 clusters. Thus, for all 20 EEGs, the levels of dissimilarity for the first bifurcation of the dendrogram (i.e., for 2 clusters only) fall to the left of the shaded bar, whereas the levels of dissimilarity for 4 bifurcations (clusters) to be obtained lie to the right of the shaded bar. The shaded bar then represented the range of levels of dissimilarity to obtain at least 2 but not more than 4 clusters. Such a fixed value for the dissimilarity level might not, however, result in the appropriate clinical clusters for every EEG. (A possible further refinement would be for the algorithm to take into account the lengths of the successive branches of the dendrograms (Bodenstein, personal communication) in the automatic determination of the number of clusters.) Therefore, a computer algorithm yielding 2, 3 and 4 clusters for each EEG, as previously mentioned, might be more suitable than an algorithm using a fixed level.

(3) The temporal profile. Indicating as it does the specific portions of a recording during which the particular types of activity (states) found by the clustering process were present, the temporal profile is very useful for displaying the distribution in time of particular types of activity in the recording. For example, the appearance of the EEG of drowsiness may become more frequent in the course of a recording, or, paroxysmal activity may occur only during drowsiness. The mean amplitude and 'mean frequency' then provide a summary for each state. The 'mean frequency' parameter has advantages and disadvantages, as previously indicated. If the spectrum of the particular cluster is characterized by a relatively well defined single peak, or is relatively broadband, then the 'mean frequency' provides a reasonable single-parameter summary. However, if there are two (or more) distinct peaks in the frequency spectrum, the 'mean frequency' value can be expected to lie somewhere between the two (or more) peaks in the spectrum, and hence only an inadequate picture can be given. Unfortunately, it is not possible to ascertain from the 'mean frequency' parameter itself whether the aforementioned is the case; inspection of the original autocorrelation function or of the power spectrum is necessary.

(4) Power spectrum. As noted previously,
the power spectrum was computed from the averaged coefficients of the autocorrelation function for the respective cluster (state), the inverse filter coefficients corresponding to the respective autoregressive model serving as an intermediary. The power spectrum corresponding to the inverse filter coefficients is then determined, from which the desired power spectrum is obtained by inversion. This procedure is a more reliable one than simply taking the Fourier transform of the autocorrelation function, since appreciable errors can be expected from directly transforming an autocorrelation function of only 9 terms. In contrast, an autoregressive model (see Barlow 1979) of 8 terms, which is computed from the corresponding 9-term autocorrelation function (including the point at zero lag), provides a good representation of EEGs, and the corresponding power spectrum provides a good representation for spectra having up to 4 peaks (strictly speaking, 4.5 peaks, or half the number of coefficients). (For smoothness of the final spectral curves, 128 or 256 points may be plotted.) From the discussion in the preceding section on the temporal profile, it is evident that computation of the power spectrum may be desirable for further evaluation of the significance of the ‘mean frequency’ as indicated in the temporal profile plot.

The present work has been entirely confined to the analysis of a single EEG channel at a time. With this approach, problems
increase rapidly when multichannel analysis is considered. (The interactive data processing of two channels has been accomplished by Bodenstein et al. 1980). Indeed, a very sizable quantity of processed data would be generated for, for example, a 16-channel clinical recording. However, it should be possible in principle to carry out a data-reduction process by computer, so that the essential information of a multichannel recording is summarized in tabular form. At the same time, the technique as it now stands is immediately applicable to the analysis of a small number (say 1–4) of selected channels in a multichannel recording, as an aid to the investigator or the clinical electroencephalographer.

Summary

A method of automatic adaptive segmentation of EEGs, whereby the boundaries between different patterns of activity appearing in a given channel are identified and demarcated, has been applied to a group of clinical EEGs. The EEGs were especially selected from a library of 70 recordings so as to include a diversity of normal and abnormal EEG patterns. In the subsequent steps of the analysis, like segments were automatically clustered and a dendrogram plotted, from which the principal clusters or types of activity were visually selected. For the latter, a temporal profile was then plotted, indicating which type of activity was present at any given time during the respective recording. Summary parameters of mean amplitude and a measure of mean frequency were plotted alongside the temporal profile.

The findings are as follows. (1) A single set of segmentation parameters was found to be clinically satisfactory for the entire group. (2) The inappropriateness of adaptive segmentation for the isolation of spikes and sharp waves, which had been anticipated in view of the short duration of such transients in relation to the length of the window (1.2 sec) used for the autocorrelation functions employed in the segmentation algorithm, was confirmed. A separate spike/sharp-wave detection algorithm is therefore planned. (3) Longer transients (i.e., some 300 msec or greater) are segmented and separately clustered. (4) For an individual EEG, the number of clinically significant clusters was 5 or less. (5) If a given cluster included activity in more than one frequency band (for example, simultaneous alpha and slow activity) the simple summary parameters of mean amplitude and a measure of mean frequency may not be sufficient for a clinically adequate description; however, the original autocorrelation function, or, more conventionally, the power spectrum (which can be estimated from the autocorrelation function) provides the necessary information. (6) The use of automatic adaptive EEG segmentation minimized human bias in the selection of portions of EEG recordings for computer analysis.

Résumé

Segmentation automatique souple des EEGs cliniques

Les auteurs appliquent à un groupe d'EEGs cliniques une méthode de segmentation automatique adaptive des EEG, au moyen de laquelle les frontières entre différents patterns d'activité apparaissant dans une dérivation donnée sont identifiées et démarquées. Les EEG ont été sélectionnés à partir d'une bibliothèque de 70 enregistrements afin d'inclure toute une diversité de patterns EEG normaux et anormaux. Dans les étapes suivantes de l'analyse, des segments semblables ont été réunis automatiquement et un dendrogramme a été tracé, à partir duquel les groupements principaux de type d'activité ont été sélectionnés visuellement. Pour ces derniers, un profil temporel a été ensuite tracé, indiquant quel type d'activité était présent à un moment donné au cours de l'enregistrement concerné. Des paramètres résumés d'amplitude moyenne et une mesure
de fréquence moyenne ont été relevés parallèlement au profil temporel.

Les résultats sont les suivants: (1) Un seul ensemble de paramètres de segmentation s'est avéré cliniquement satisfaisant pour l'ensemble du groupe. (2) L'inadéquation de la segmentation adaptive pour isoler des pointes et des ondes pointues, qui avait été prévue étant donné la brève durée de ces transitoires par rapport à la longueur de la fenêtre (1,2 sec) utilisée pour les fonctions d'auto-corrélation employées dans les algorithmes de segmentation, a été confirmée. Un algorithme distinct de détection des pointes ou des ondes pointues est donc envisagé. (3) Les transitoires de plus longue durée (i.e. voisines ou supérieures à 300 msec) sont segmentés et réunis à part. (4) Pour un EEG donné, le nombre de groupements cliniquement significatifs ne dépasse pas 5. (5) Si un groupement donné inclut une activité située dans plus d'une bande de fréquence (par exemple alpha et activité lente simultanée) les paramètres résumés simples d'amplitude moyenne et une mesure de la fréquence moyenne peuvent ne pas suffire pour une description clinique adéquate; cependant la fonction d'auto-corrélation originale ou, plus conventionnellement, le spectre de puissance (qui peut être estimé à partir de la fonction d'auto-corrélation) fournit l'information nécessaire. (6) L'utilisation de la segmentation EEG automatique souple minimise l'élément subjectif dans le choix de fragments d'enregistrements EEG destinés à l'analyse par ordinateur.

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References


