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SESSION 14	Biomedical Computing
	Signal processing and analysis - neurology
Chairman	Prof. B. McA. Sayers
Co-chairman	Prof. M. Saito

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DETECTION OF CHANGES IN AMPLITUDE AND PHASE OF THE EEG

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EEG changes due to photic stimulation are studied by the method of complex demodulation. Individual (not averaged) EEG is first subjected to band-pass filtering and then changes in amplitude and phase are calculated in terms of a demodulation technique implemented on a digital computer. Applicability of the method to the evoked response analysis is examined.

EEG data of 2.5 sec length (1 sec pre-stimulus and 1.5 sec post-stimulus) are digitized with 512 samples. Peak frequencies of EEG are first sought by the FFT. Then individual EEG are digitally band-pass filtered around the peak frequencies (Non-phase-shifting Ormsby filter is used). Finally the filtered data are demodulated; envelope and phase of dominant frequency components are calculated by the demodulation technique incorporated with the moving average.

EEG data are taken, by the monopolar connection, from the occipital region of normal human subjects kept quiet with eyes closed.

Our attention is paid principally to changes in amplitude of the alpha activity. One of the main results is 'alpha enhancement' provoked by photic flashing: Figure 1 shows average and superposition of alpha envelopes. A decrease in amplitude of the alpha activity (alpha blocking with the minimum at about 200 msec after the stimulus) is followed by an increase (alpha enhancement with the first maximum at about 650 msec).

Other results and remarks are summarized as follows:

1) Although there is a difference in evoked responses among individuals, we can observe alpha enhancement as well as alpha blocking by the present method.
2) Each individual EEG should be processed to get provoked changes quantitatively. Averaging may cancel out some part of EEG changes.
3) Sorting of data according to the pre-stimulus EEG state makes the blocking or enhancing process more clear.
4) Detection of alpha phase changes is critical. Much more demodulated data should be accumulated to fix the problem such as 'the alpha phase coherency'.
5) Changes of low or high frequency components can also be studied by the present method. However, further examination is required for components with relatively small stimulus-provoked changes.

EEG data are taken, by the monopolar connection, from the occipital region of normal human subjects kept quiet with eyes closed.

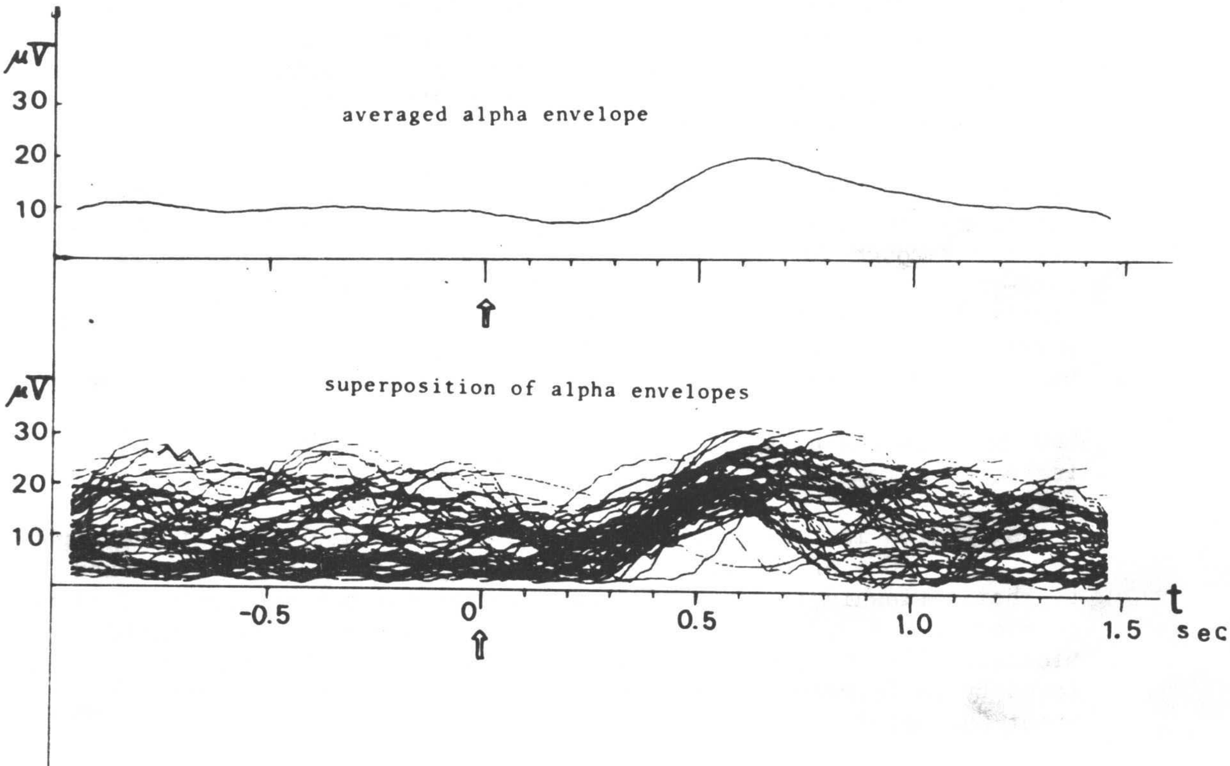

Fig.1 Average and superposition of alpha envelopes for 50 EEGs

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FEATURE EXTRACTION OF THE ELECTROENCEPHALOGRAM BY ADAPTIVE SEGMENTATION WITH APPLICATIONS TO PATTERN RECOGNITION

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A general structural model for EEG generation has not yet been established. We must be guided therefore by the diagnosing physician. His experience tells us that the human classifying process involves at least three stages: (i) detection of pattern boundaries (segments of particular interest); (ii) classification of segments; (iii) diagnostic classification of the whole process.

If efficient classification algorithms are to be employed we must extract as few features as possible. If we were to restrict ourselves to power spectra, for example, we would need to find a parametric description of these spectra. It would be of little use if our exercise merely substituted the vast amount of EEG data, which the physician can in fact interpret very well, by a lesser but still vast amount of descriptors nobody understood. Therefore, the final pattern to be classified should be the whole EEG record; the result of the classification should be the clinical diagnosis.

The method we use is essentially nonlinear but makes extensive use of the linear method of Wiener filtering. The Wiener filter gives us a representation of the power spectra which depends on a preset number of parameters. We use the autocorrelation function of the filter output to construct a measure for spectral changes in the EEG. This allows the detection of pattern boundaries as follows: the output of the filter is uncorrelated as long as no new pattern is encountered. As the spectrum of the EEG changes, the filter output becomes correlated, the spectral measure grows and finally passes a preset threshold, thereby indicating a pattern boundary. The whole process is then repeated: a new Wiener filter is computed, the autocorrelations calculated, and so on. Proceeding in this manner we get a new process with segments each represented by a constant number of parameters, namely length, power, and power spectrum of the original process segments.

A comparison of Wiener's linear prediction method for the smoothing of short-time power spectra with the "direct" FFT methods shows that there is no loss in spectral information, but a substantial saving as regards data reduction.

The information loss in the process was investigated and the original EEG was simulated from the segmental process. Data reduction by this method is about 1:20. Current and possible applications of the method to pattern recognition and to clinical diagnosis will be discussed.

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EEG SPECTRAL PARAMETER ESTIMATION USING A LINEAR MODEL

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Nowadays very often the spectralanalysis is used for EEG-investigations. That means that first the periodogram is calculated from an EEG using the Fast Fourier Transform and then the power density (power spectrum) is estimated after the choice of a window function. To obtain a small number of parameters from the spectrum the average power and average frequency are calculated in the EEG frequency bands. This procedure is very simple, but has the disadvantage that the power and frequency parameters obtained in this way depend on the chosen lower and upper limits of the frequency bands. Furthermore also an average α - power and α - frequency are estimated if there exists no α- rhythm, for example.

Another and more objective description of the different activities in an EEG can be obtained if an autoregressive model is introduced. For this linear discrete model the assumption is made that the amplitude of a sampled EEG at time t can be expressed by a weighted linear summation of the past amplitudes at times t-1, t-2,....., t-p. The weighting coefficients are the autogressive parameters and the number of it (p) is the order of the model.

The autoregressive parameters are estimated from the auto-correlation function and can be transformed in spectral-parameters like average powers, dominant frequencies and bandwidths.

In this way every dominant rhythmic activity in an EEG can be described by the three parameters average power, dominant frequency and bandwidth. The bandwidth thereby is a measurement for the stability of the rhythm. The random component can be described by the two parameters average power and bandwidth.

The two different methods of spectralparameter estimation have been applied to EEG data recorded from many subjects, during different experimental situations and tasks. Generally it was found that the spectralparameters estimated with the autoregressive model are more suitable to describe the EEG than the parameters calculated from the powerspectrum.

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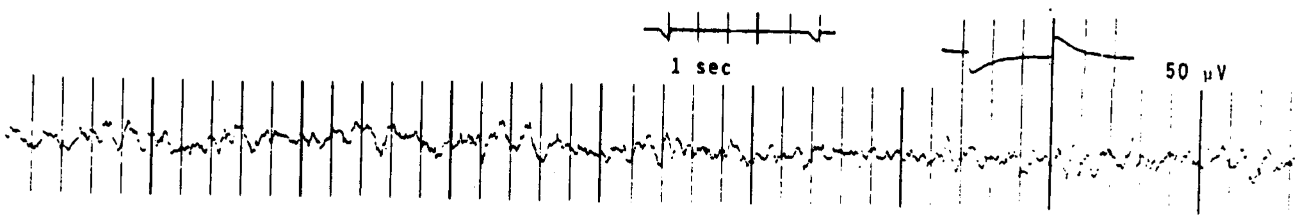
An example of the results of analyses using the spectralanalysis and the autoregressive model is shown in fig. 1. An EEG of 21.3 sec was sampled with 60/sec and analysed. Some seconds of the primary record are illustrated on the top of fig. 1. Below that is the table with the results of the parameter calculation from the powerspectrum. These coefficients were used to calculate the powers and frequencies, as illustrated in the middle of fig. 1. It can be seen that e.g. for the α - band different results were obtained with both methods. A dominant α - frequency of 9.7 HZ and a α - power of 22% using powerspectrum and a α - frequency of 11.86 HZ and a α - power of 12% with the autoregressive model were calculated. In the EEG and the powerspectrum respectively can be recognized that the frequency of 11.86 HZ is more accurate than that of 9.7 HZ. Because the spectrum is rather flat the dominant frequency in the α - band (7 - 12 HZ) is about in the middle of this band, that means in the near of 9.5 HZ.



CH. 4 TOTAL POWER 0.48777+003 PSF 0.48777+003 SCH/20/5

HZ	.0- 3.0	3.0- 7.0	7.0-12.0	12.0-20.0	C_3-P_3
%	16.5	38.5	21.9	14.1	21.3sec
POWER	80.5913	187.8483	106.6148	68.9353	
FO/FS HZ	1.7 / .70	5.6 / 1.10	9.7 / 1.52	15.0 / 2.32	N=1280

FILTER PARALLEL TYP 2

NR	FRE	FREDEV	BAND	POWER	POWABS	SYM	POWTOP	POWUP/90
1	24.67	.92	9.69	.046	23.00	-.013	.009	.011
2	9.63	.47	6.34	.838	418.93	.035	.093	.115
3	11.86	.59	8.08	.116	58.13	-.053	.036	.043

AUTOREGRESSIV-COEFFIZIENTS

0.6383+000 -0.9558-001 -0.1386+000 0.1803-001 0.4853-001 -0.7629-001 -0.3468-002 0.6546+000

AR-COEFF. DEVIATIONS

0.2803-001 0.3318-001 0.3326-001 0.3348-001 0.3326-001 0.3318-001 0.2803-001 0.6650-002

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APPLICATION OF EMPIRICAL DISTRIBUTIONS TO EVALUATE BIOELECTRIC SIGNALS

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A basic problem in the evaluation of EEG and evoked potentials, both for the physician and the investigator, is to determine precisely the symmetry or asymmetry of the two hemispheres with respect to their electric activity, as well as to distinguish among the simultaneous changes in different brain structures.

We have employed a non-parametric, probabilistic approach to cope with the problem of pattern indentification, because attempts to parameterize EEG and evoked signals have had little success. The method compares the empirical distribution of the EEG amplitudes according to a given pattern from a certain interval of the recording. Sampling has been triggered either by a stimulus or by a predetermined voltage-level of the EEG signal. The program determines in each sample relative magnitude of each amplitude, labelling them with their position in the sample. From a family of such patterns a matrix was generated, where the first row represented the empirical distribution of positions taking up by the highest magnitude throughout the samples, the second row contained the empirical distribution characteristic for the second highest magnitude and so on. Matrices derived from different conditions were compared quantitatively by characterising the similarity of two matrices with values ranging from 0 to 1. The number 1 was assigned to the comparison when all elements of both matrices were identical and lower values increasing dissimilarity. Calculation and matrix generation were done on a digital computer (Siemens 4004/150); FORTRAN IV was used as source.

In animal studies we have used our program to identify EEG responses recorded in different structures and elicited by positive, negative and conditioned inhibitory stimuli. The method was successful in recognising the EEG patterns in 52% of the cases, which is seven times the probability of random prediction; it was impossible to distinguish between the EEG records by conventional qualitative analysis.

In another application the program proved to be a valuable tool in identifying with about 98% probability corresponding structures in the two hemispheres, or the parallel activity of different structures in certain pathological cases from human EEG records. The method of "empirical distribution" was also a good measure of the reproducibility of the bioelectric activity registered over different brain regions.

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EVALUATION OF VIGILANCE LEVEL BY AUTOMATIC ANALYSIS OF EEG DURING RECORDING OF CONTINGENT NEGATIVE VARIATION AND READINESS POTENTIAL

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Contingent negative variation (CNV) and readiness potential (RP) have been used recently in clinical neurology, psychiatry and psychology to obtain information on brain activity. As they depend on vigilance level of the subjects, it also should be evaluated during CNV and RP measurement before discussing their amplitudes.

In testing CNV over 15 seconds, randomly spaced series of light pairs (2.5 second interval) were used as warning and task signals. Normal subjects were ordered to clench the fist as fast as possible after the task signal. EEG and forearm flexor EMG were recorded together with timing pulses for later analysis.

EEG with the faster reaction time (RT) were selected from the tape and averaged on the computer, as well as those with the shorter RT in the same subject. The amounts of delta, theta, alpha, beta 1 and 2 during the 1 second period preceding the voluntary movement in these responses were averaged on the computer.

In recording RP, the subject was instructed to clench the fist voluntarily at irregular intervals for more than 10 seconds. In the same way, with retrospective computation we obtained RP, and averaged the amounts of delta, theta, alpha, beta 1 and 2 waves during 1 second period preceding the voluntary movement. We tested CNV, RT and RP preceding the voluntary lateral gaze using the same method.

Results showed that when the amplitude of RP preceding the unsignaled voluntary movement is great, the amounts of beta 1 and 2 waves increase and delta and theta waves reduce. When the amplitude of slow negative potential preceding the signaled voluntary movement (CNV) is great, the RT is short and the amounts of beta 1 and 2 waves increase and delta and theta waves reduce.

Variations of amplitude in CNV and RP under some disease condition or during some tasks are widely studied in normal subjects, neurological and psychiatric patients. But from the results obtained the amplitude of CNV and RP changes with the amounts of faster and slower brain waves in the same person. EEG frequency should therefore be analysed simultaneously with CNV and RP recording in order to discuss the amplitude of CNV and RP.

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SESSION 15 — Biomedical Computing

Signal processing and analysis - clinical

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PROCESSING ELECTRO-MYOGRAPH SIGNALS

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The electrical activity of muscles is a complex phenomenon which can be viewed only indirectly by electro-myography. It is obviously dynamic and furthermore the electrical waves at separate points in the muscle volume are never identical even over the same time period. An electro-myogram is thus only a restricted window on reality and as such is critically dependent on the electrodes used.

Although methods of processing the e.m.g. should ideally be designed only with regard to the aims of the investigation and the electrodes chosen to suit, in practice it is strongly influenced by the shortcomings of the electrodes and the existence of electrical noise in the signal. Investigations, with any type of electrode, will generate signals having a high probability of corruption from four types of noise:-

1. Low frequency noise, e.g. due to electrode movement;

2. Mains frequency noise, e.g. from internal power supplies or nearby electrical equipment;

3. High frequency noise, e.g. due to thermal effects in amplifiers or recording tape hiss;

4. Fast transient via the mains or by aerial pickup from sparking contacts.

Reducing these noise levels on the raw recording depends on an engineering understanding of their causes with proper steps taken and, where appropriate, some on-line analog filtering. Mitigation of their effects on processed data depends on successful filtering procedures after recording.

An efficient way of dealing with e.m.g. signals is to record on an analog tape recorder and later to digitise and filter on a digital computer. Techniques for processing the filtered signals can be classified into three broad categories:-

1. Generation of macroscopic statistics as a function of time, e.g. running rectified average or mean square;

2. Generation of significant event markers as a time series, e.g. location of pairs of turning points;

3. Wave form analysis, e.g. examination of frequency spectra.

All of these methods require the use of processing procedures which can be implemented on a digital computer and they generate data which can be correlated with other physiological data; again digitally if required.

The first and second areas can be related by regarding functions of the event markers as statistics of the signal. Wave form analysis is, in practice, predominantly spectral analysis and open to a wide variety of interpretations depending on the resolution and averaging times used, but under certain circumstances also could be regarded as a statistic which changes with time. For low levels of activity and by the use of wire electrodes it is possible to pursue wave form analysis directly by obtaining non-overlapping action potentials.

The topics discussed have been investigated and, where appropriate, used in an examination of e.m.g.s from the muscles of the pelvic floor.