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A model-based detector of vertex waves and K complexes in sleep electroencephalogram

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Summary A model of sleep phasic events such as vertex waves, K complexes, delta waves and sleep spindles is proposed. It consists of feedback loops that are driven by white noise (simulating tonic delta and sigma activity) and by isolated random impulses, simulating vertex waves or K complexes, depending on the background tonic activity.

A model-based method for the detection of sleep phasic events was implemented in a personal computer. Its performance was investigated using simulated and real whole-night EEG signals. The method was able to detect K complexes and vertex waves in a reliable way in spite of their variable shapes and in the presence of a variety of background activities.

The detector appears to have superior performance to those so far reported in the literature.

The performance of the detector was also compared to that of an electroencephalographer using normal sleep EEG records of 8 h duration from 6 subjects. The performance was satisfactory both in terms of accuracy and reliability. The problem of detecting K complexes in stages 3 and 4 of sleep is discussed.

Key words: Sleep EEG; Model-based detector; Vertex wave; K complex

In sleep studies vertex waves and K complexes are usually evaluated only in a qualitative way. Quantitative evaluation of these phasic events has been rare (Bremer et al. 1970; Sheriff et al. 1977; Othmer et al. 1980). It is difficult to distinguish K complexes from delta waves. The usual ways of defining vertex waves, delta waves and K complexes are as follows:

Vertex waves consist of triphasic sharp waves with 50–200 msec duration, localized over the precentral area and observed in stages 1 and 2 of non-rapid eye movement (NREM) sleep. According to the official definition (Chatrian et al. 1983) these waves can occur spontaneously during sleep or in response to a sensory stimulus during sleep or wakefulness. They may be single or repetitive, and their amplitude may vary, but rarely exceeds 250 μ V. Delta waves consist of monophasic or polyphasic rhythms of frequency below 4 Hz and amplitude between 10 and 300 μ V (Dutertree 1977). A K complex consists most commonly of a large amplitude diphasic slow wave frequently associated with a sleep spindle. Its amplitude is generally maximal near the vertex. K complexes occur during sleep, apparently spontaneously or in response to sudden sensory stimuli.

They are not specific for any particular sensory modality (Chatrian et al. 1983). Nevertheless these definitions do not provide a sufficiently clear basis for an automatic sleep analysis method (Davis et al. 1939; Gastaut 1953; Roth et al. 1956; Johnson and Karpan 1968; Rechtschaffen and Kales 1968; Bremer et al. 1970; Kugler 1973; Sheriff et al. 1977; Othmer et al. 1980; Pal et al. 1985; Declerck et al. 1987).

We describe here how automatic analysis can be based on models that simulate the generation of these phenomena. We also report the performance of such analysis.

Model

A model of delta waves, K complexes and vertex waves (DKV model) should ideally be related to physiologically meaningful phenomena. However, the required precise physiological knowledge is, as yet, not available. Therefore a general model already used in the analysis of sleep spindles and alpha rhythms was chosen (Kemp and Blom 1981; Kemp 1983, 1987; Kemp et al. 1985, 1987).

The basic idea is that EEG phenomena are generated by excitatory and inhibitory neuronal populations interacting by means of feedback loops. Such models were

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proposed by Freeman (1972a,b, 1975, 1979) for the rhythmic generators in the olfactory system of the rabbit and cat and for the generation of the alpha rhythm in the thalamus by Lopes da Silva et al. (1973, 1974, 1976) and generalized to the cortex by Van Rotterdam et al. (1982). The behavior of the alpha model was analyzed by Zetterberg et al. (1978) using a system theory approach. A simplified version of this model was successfully applied to the alpha attenuation latency measurement, to the sigma state detection and to the monitoring of sleep stages (Kemp et al. 1987).

The extrapolation from alpha resonance to delta resonance is suggested by the works of Başar (1980) and Rush et al. (1976, 1977). Başar (1980) analyzed evoked responses during sleep by characterizing the spectral activities of the EEG before and after a stimulus. The conclusion from the point of view of systems theory is the existence of a striking similarity between the manner of occurrence of delta resonances during slow wave sleep and of alpha resonances. Corner (1984) proposed a neuronal model for delta wave generation, which also includes feedback loops.

Averaged evoked potentials and K complexes in cats were studied using intracortical recordings by Karmos et al. (1986) and Jurko and Andy (1978). Both groups suggested that K complexes are generated by multiple thalamo-cortical feedback loops. Sensory evoked potentials increase in amplitude from wakefulness to sleep and show a transition from vertex waves during light sleep to K complexes and delta waves during deep sleep. These 3 types of event have similar power spectral densities and spatial distributions, with a maximum over the vertex (Davis et al. 1939; Brazier 1949; Yasoshima et al. 1984; Ujjaszsi and Halasz 1988). Therefore, we assume that vertex waves and K complexes may be considered as transient, and delta waves as stationary responses of neuronal networks of the type

Two Rhythms (Delta and Sigma) Feedback Model

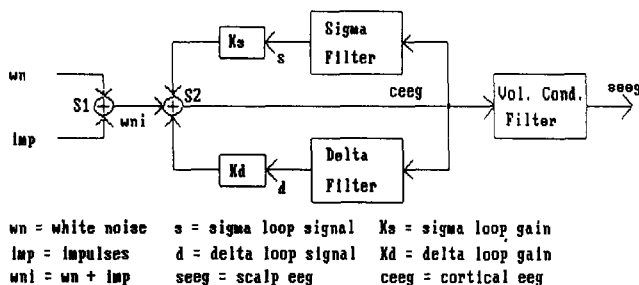


Fig. 1. K complex, vertex wave and the two rhythm feedback models for NREM sleep EEG. The figure shows the simplified structure of the model, with only two rhythm generators (delta and sigma feedback loops) and a propagation effect filter. The model assumes that the noise input is the excitation of the tonic activity and the impulses elicit vertex waves or K complexes depending on the delta loop gain in the vicinity of the impulses.

Model-based K-complex Detector

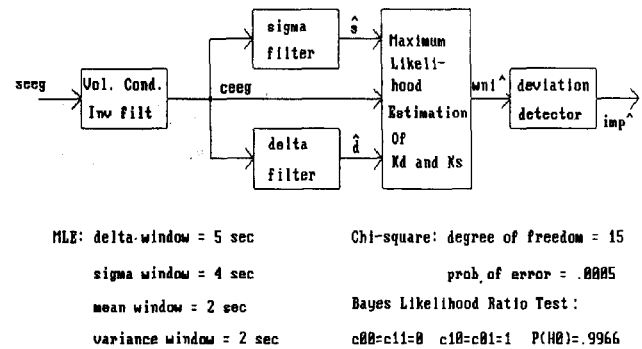


Fig. 2. Model-based K complex detector. The detector is the inverse of the model which gives an estimate of the noise and impulse input with the aid of a maximum likelihood estimator of the loop gains. The non-stationarities in the input process are detected using a combination of chi-square and Bayes likelihood ratio tests. The filter characteristics of the detector are the same as for the model in Fig. 1.

described above, the basic characteristics of which depend on the frequency response of the network.

Fig. 1 shows the general structure of the model. It consists of 2 feedback loops, with a bandpass filter and a variable gain. Each bandpass filter represents the resonance behavior of the neuronal network for a specific frequency band (e.g., delta and sigma). The gain simulates the general effects of the inhibitory and excitatory action on the feedback loops. The gain can also be interpreted as the level of synchrony within the neuronal network. The noise input (wn) represents the ongoing background neuronal external activity. The pulse input (imp) represents the phasic activity afferent to the neuronal network which is responsible for evoking vertex waves and K complexes.

A lowpass filter represents the effect of the volume conductor from the cortex to the scalp (Pfurtscheller and Cooper 1975).

Detector

The detector corresponds to the model working in the inverse way. By means of the detector, the input signal (wni) can be estimated from the scalp EEG. The block diagram of the detection process is shown in Fig. 2.

At the second summing point (S2) in the model (Fig. 1) we have the following relationship:

$$\begin{aligned} wni &= wn + imp \\ wni &= cEEG - (Kd \cdot d) - (Ks \cdot s) \end{aligned} \quad (1)$$

By passing the scalp EEG (sEEG) through the inverse volume conductor filter L^{-1} , the cortical EEG (cEEG) is obtained. The delta and sigma loop signals (d and s) result from filtering cEEG by the corresponding

bandpass filters. Taking into consideration that *imp* is a rare and short event, in a first approach its influence can be neglected; it is also assumed that *w_{ni}* is a stationary white gaussian process during the observation period. The gains (*K_s* and *K_d*) are estimated using the maximum likelihood (ML) approach as follows:

The joint probability of a sequence of *N* samples of an independent gaussian process with the mean μ (zero) and variance σ (known) is given by

$$p(w_{ni}) = \frac{1}{2\pi\sigma^2} \exp - \left\{ \frac{(w_{ni} - \mu)^2}{2\sigma^2} \right\} \quad (2)$$

$$p(w_{ni1}, \dots, w_{niN}) = p(w_{ni1})p(w_{ni2}) \dots p(w_{niN}) \quad (2a)$$

Substituting equation (1) and equation (2) in (2a) and taking the two partial derivatives in relation to *K_d* and *K_s* of this new equation and equating the derivatives to zero, the ML estimators are obtained by resolving the set of two equations. The symbol ($\hat{}$) denotes estimates.

$$\hat{K}_d = \frac{\text{sum}(d \cdot cEEG) \cdot \text{sum}(s \cdot s) - \text{sum}(d \cdot s) \cdot \text{sum}(s \cdot cEEG)}{[\text{sum}(s \cdot s) \cdot \text{sum}(d \cdot d) - \text{sum}(s \cdot d) \cdot \text{sum}(s \cdot d)]} \quad (3a)$$

$$\hat{K}_s = \frac{\text{sum}(s \cdot cEEG) \cdot \text{sum}(d \cdot d) - \text{sum}(d \cdot s) \cdot \text{sum}(d \cdot cEEG)}{[\text{sum}(s \cdot s) \cdot \text{sum}(d \cdot d) - \text{sum}(s \cdot d) \cdot \text{sum}(s \cdot d)]} \quad (3b)$$

$$\text{sum}(x \cdot y) = x_1 \cdot y_1 + x_2 \cdot y_2 + \dots + x_N \cdot y_N \quad (3c)$$

In the case where the assumption of zero mean ($\mu = 0$) does not hold the corresponding ML estimators change slightly. In the expressions of the gains estimators (3a, 3b) all the $\text{sum}(x \cdot y)$ terms must be changed to $n\text{sum}(x \cdot y)$ given by expression (3d).

$$n\text{sum}(x \cdot y) = \text{sum}(x \cdot y) - [\text{sum}(x) \cdot \text{sum}(y)]/N \quad (3d)$$

The estimation errors of the gains decrease with the increase of the number of observations used in the estimator (estimation window). But the increase of the window also affects negatively the capability of the estimates to track fast changes. The optimal estimation windows have to be established experimentally using an independent learning set as described in detail in Rosa (1989).

The optimal values for the windows were obtained from the learning set, consisting of 2 h of normal night sleep record (stages 2 and 4 NREM). These values are used in all detections and are indicated in Fig. 2.

The extraction of the unknown pulses (*imp*) from *w_{ni}* may be accomplished in different ways. A possibility is to use a matched filter detector but this is not feasible since the mean duration of the impulses can be estimated only roughly and their amplitude is unknown. Another possibility is to consider the impulses as deviations from gaussianity of the input process, and to detect them by means of a chi-square test (Lopes da Silva and Mars 1987). To apply the chi-square test, the normalized sum of a set of squared *w_{ni}* must be compared to a threshold. A deviation of gaussianity is decided whenever the threshold is surpassed. The threshold depends on the significance level desired. The

power of the test depends on the number of observations in the set (degree of freedom) which has to be adapted to the average duration of the deviations from gaussianity.

The occurrence of a sudden change of the mean value of the process may indicate the existence of an impulse at the input. The occurrence of such a change in the mean value is detected by using a Bayes likelihood ratio test (Whalen 1971). In this test the normalized estimated mean of the input for each epoch is compared to a threshold. The latter depends on the probability of occurrence of the impulses and the cost factors of true and false detections. The estimation window, like the chi-square test, depends on the average duration of the change in mean values. Taking into account the duration of the phasic events, and by trial and error in the simulations, the average duration of the change in the mean around 150 msec was established.

In the development of the likelihood ratio test two possibilities were considered: according to hypothesis H1 the input process *w_{ni}* is the noise *w_n* and a superimposed constant value *m* and according to H0 the value of *m* is zero:

$$H0: w_{ni} = w_n$$

$$H1: w_{ni} = w_n + m$$

The likelihood ratio (*lr*) is given by the ratio of the probability density (*p₁*) of H1 conditioned to the mean value *m* and the probability density (*p₀*) of H0 conditioned to a zero mean value:

$$lr = \frac{p_1(w_{ni}|m)}{p_0(w_{ni}|0)} \quad (4)$$

By substituting (2a) in (4) and taking the logarithms (*ln*) of both sides gives:

$$\ln(lr) = (N \cdot \mu^2) / 2 \cdot \sigma^2 \quad (4a)$$

This ratio is compared to a threshold (*L0*) which depends on a risk criterion. The minimum risk in the Bayes criterion (Whalen 1971) is given by

$$L0 = \frac{P(H0) \cdot [c10 - c00]}{[1 - P(H0)] \cdot [c01 - c11]} \quad (5)$$

where *P(H0)* is the a priori probability of hypothesis H0. The cost decisions are indicated as follows: *c00* and *c11* are the true negative and positive cost decisions, and *c01* and *c10* are the false negative and positive cost decisions respectively.

Since the interest is to minimize either the false positives or the false negatives, both *c01* and *c10* are set to 1, and disregarding the true positives and true negatives, both *c00* and *c11* are set to 0. The value of *P(H1) = 1 - P(H0)* is related to the ratio of the impulse duration and the mean time between impulses (inverse of phasic events density). In the visual classification of the normal subjects, a global mean phasic events density of 1.3/min was found, corresponding to a value of 0.9966 for *P(H0)*. The degree of freedom of the chi-

square test is 15; it corresponds to the estimated duration of the change in the mean of 150 msec (15 samples of 10 msec interval). In order to achieve a low level of error, the level of confidence chosen was 0.9995.

If $\ln(I_r)$ is smaller than $\ln(L_0)$ one decides for H_0 , otherwise H_1 is accepted.

Fast activities like spindles, beta and EMG artifacts can be expected to induce a large number of false positives when using the chi-square method. Slow activities, such as a short burst of delta rhythm or eye movement artifacts and electrode movements are expected to cause problems with the likelihood ratio test, because in these cases the means are not zero. The combined use of the two tests gives a better performance because the sets of false positives of the two methods do not overlap.

The estimation windows of the mean and variance of the input noise process reflect the amount of background activity of the same duration. Both windows were set to 2 sec because, according to the first criterion, the observer manually compared the amplitude of the phasic event to the preceding 1 or 2 sec of background activity. The estimation windows used for the sigma and delta gains were tuned to the characteristics of these rhythmic activities. In preliminary trials, using a learning set, it was found that the performance of the detector was not very sensitive to changes of the window length in the range from 2 to 8 sec; thus intermediate values were chosen: 4 sec for the sigma window and 5 sec for the delta window. The threshold levels should correspond with visual scoring amplitude threshold criteria. The adjustment of these thresholds was necessarily a trade-off between false positives and false negatives. The final choice was a result of a trial and error procedure.

Simulations

The behavior of the model is evaluated using simulated signals.

The depth of slow wave sleep (SWS) was simulated by adjusting the amount and the amplitude of the delta waves. This was controlled by the value of the corresponding feedback loop gain. The same procedure was used for the sigma rhythm. Vertex waves and K complexes were simulated by applying impulses at the input of the model, using different delta loop gains.

The model was simulated digitally by using a personal computer. The bilinear filters in the feedback loops were of second order with center frequencies at 2 Hz and bandwidth (-3 dB) of 3.5 Hz for the delta rhythm and at 14 Hz and bandwidth of 6 Hz for the sigma rhythm. The low pass first-order filter had a cut-off at 2 Hz. The noise was generated by transform-

ing a pseudorandom binary sequence with uniform density into a gaussian distribution.

Simulations were done in the following way: the background activity was simulated using the estimated delta and sigma loop gains calculated from the sleep EEG of a normal subject (8 h); simulated K complexes were obtained by superimposing random impulses on the noise input at a mean frequency of 2.4/min. This frequency is arbitrary and it is the average of values reported by several authors (Halasz 1985; Gaillard 1987).

Comparison of the performance between the detector and the independent visual scorer was done by using the two simulated EEG records with different squared impulse amplitude to noise variance ratios (A/N).

Subjects

Six adult normal subjects, with ages between 21 and 26, 5 females and 1 male, spent 3 nights at the laboratory (1 for adaptation and 2 for recording) in a soundproof and temperature controlled room. Only the third night was scored.

Polygraphic recording consisted of 9 channels of EEG with linked ears as reference, filtered by analog filters with 0.3 sec time constant and 30 Hz cut-off frequency, 1 submental EMG channel, 1 channel of EOG from the outer canthi of both eyes, plethysmography of the index finger, respiration from nostrils and mouth thermistors and ECG. The EEG signals were digitized at 100 Hz; the other channels at different sub-sampling frequencies; all channels were stored on digital cartridge tape. Continuous paper recording was also used.

The records were scored visually in digitized and analog form using Rechtschaffen and Kales (1968) criteria.

K complexes and vertex waves were scored in one EEG channel C4-A1, using the criteria of Paiva and Rosa (1989) adapted from Declerck (1987): non-stationary event; peak-to-peak amplitude twice that of the background activity measured peak to peak within the preceding 1 sec in stages 1 or 2 and 2 sec in stages 3 or 4; bi- or triphasic morphology with asymmetrical slopes; duration between 500 and 3000 msec; isolated or in pairs.

The detector, with the same set of estimation windows and threshold levels used for the simulated signals, was applied to the real signals (C4-A1).

During paradoxical (REM) sleep, waking and arousal periods the detections were not considered. The detector is only sensitive to the transient part of the longer non-stationarities since it adapts quickly to the new characteristics of the EEG; that is, to the first segment of an arousal, a movement or an awakening period.

Results

The dependence of the simulated delta activity on the delta feedback loop gain has been examined. For simplicity and in order to eliminate the influence of other loops, only the delta frequency band feedback loop was considered. Fig. 3 shows that larger gains provoke greater amounts of low frequency activity as expected. Superficial SWS stages (1 and 2) were simulated using gains below 0.5 while deeper SWS stages (3 and 4) were simulated using gains between 0.5 and 1.

The possibility for the model to generate phasic events in response to pulse inputs has been investigated.

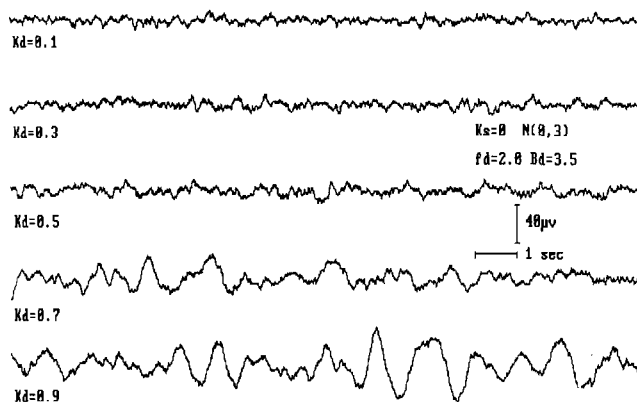


Fig. 3. Simulation of slow wave sleep (SWS). The figure shows simulated examples of SW sleep EEGs of 15 sec duration. The SWS depth is controlled by the delta loop gain K_d of the model.

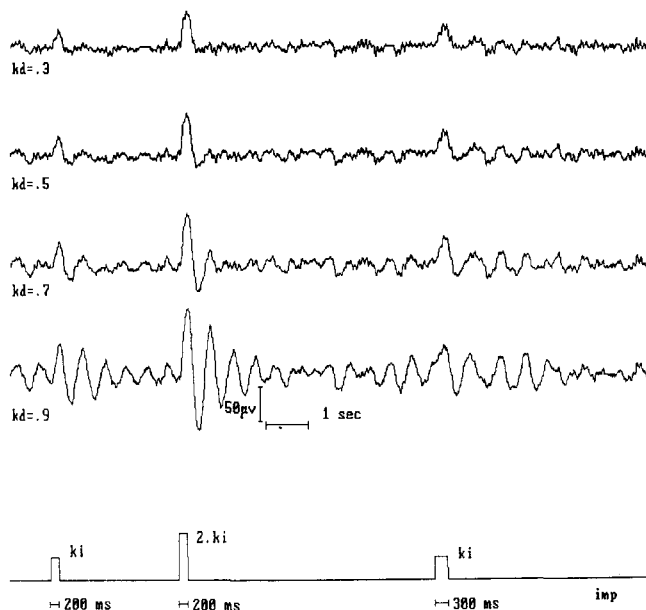


Fig. 4. Simulation of K complexes. The figure shows simulation examples, when square impulses of 200 msec and 300 msec duration are added to the noise input of the single loop model. The squared amplitude of the impulse to the noise variance ratios (A/N) are 12 and 15 dB. For the same impulse the response changes from monophasic to polyphasic with the increase of the delta gain.

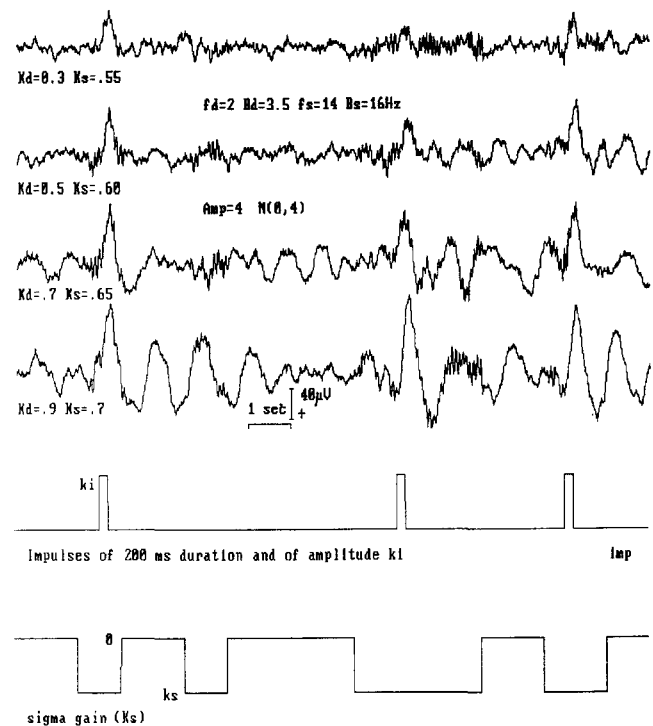


Fig. 5. Simulation of spindles and K complexes. The figure shows simulation examples, when impulses of 200 msec duration and A/N ratio of 6 dB are added to the noise input of the 2-loop feedback model. A pair of constant delta and changing sigma gains is used for each trace.

Fig. 4 shows simulations with varying gains and constant input pulses. Different types of input pulses were tried. The response of the model to a single volley, represented in a simplified form by a square wave input pulse of 100 msec duration, simulated either monophasic vertex waves or biphasic or polyphasic K complexes. It depended mainly on the ongoing background activity which was related to the delta feedback loop gain and also to the ratio of the pulse amplitude and duration.

The model with two feedback loops was used in the simulations. The inclusion of the sigma loop not only allowed the simulation of sleep spindles but also added more variability to the simulated sleep EEG signals. Fig. 5 demonstrates the occurrence of simulated sleep spindles, either isolated or associated with K complexes. A realistic simulation of burst-like sleep spindles of variable duration was achieved by modulating the sigma loop gain with square wave forms.

The performance of the automatic detector and of the visual scorer applied to simulated K complexes has been analyzed. Table I shows the results of visual scoring and automatic detection using as reference the known impulses. In both simulations the detector performed better than the visual scorer. The performance of visual scoring and automatic detection decreased with decreasing A/N ratios. In the lower part of Table

TABLE I

Both tables show the visual scoring and automatic detection performance to simulated signals. In the upper part the reference is the known added pulses. The detector performs slightly better than visual scoring. Both visual and automatic detection deteriorates with decreasing A/N ratio. In the lower part of the table the visual score is used as reference. It is curious to find that the performance of the detector is very similar to that obtained in the case of real signals.

	Simulation a (A/N = -8.75 dB)					Simulation B (A/N = -10.51 dB)				
	T	M	F	T/R (%)	F/R (%)	T	M	F	T/R (%)	F/R (%)
Detect.	1070	81	48	92.9	4.2	836	315	48	72.3	4.2
Visual	938	213	31	81.5	2.7	790	361	25	68.6	2.1
Detect.	902	67	216	93.0	22.2	641	174	243	78.6	29.8

T = true positive; F = false positive; M = false negative.

I, the visual scorer was used as reference; for simulation B the performance of the detector is similar to the results obtained from normal sleep signals (Table II). Fig. 6 shows examples of typical situations.

The performance of the detector was analyzed by applying it to the night sleep records of 6 normal subjects. Table II shows the performance for 6 normal subjects, using as reference the visual scores obtained by an experienced electroencephalographer. The global true detection rate for all sleep stages was 89%, varying between 83 and 92%, and the number of false positives was 49%, ranging between 32 and 157%. For K complexes in stages 1 and 2 the true detection rate was 94%, ranging between 87 and 97%, whereas the false detection rate was 13%, varying between 7 and 23%. Fig. 7 shows the true detection (T), false positive (F) and false negative (M) rates in percentages, using as reference the visual score ($R = T + M$). The upper part shows K complex detection performances in percentages in stages 1 and 2, where the contribution of the K complex for

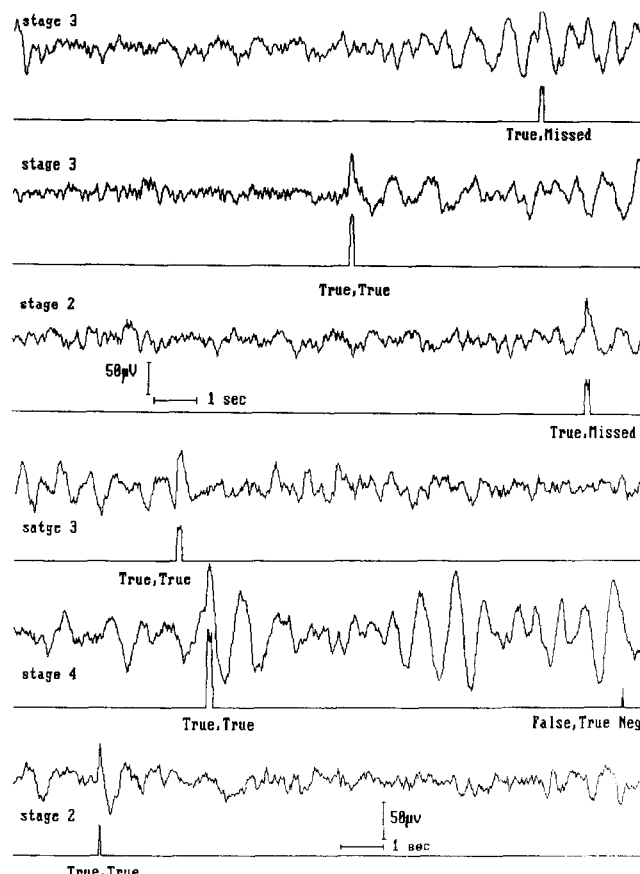


Fig. 6. Automatic and visual detection of simulated signals. The figure shows typical situations. The first symbol of the detection pair refers to the automatic detector and the second to the visual scorer. The reference is the known added impulse. Most of the misses in visual scoring are caused by vertex waves in stage 1 and K complexes in stage 4.

stage classification is more important; the true detection percentages are in most cases over 90% and the false positives are in most cases below 20%. The lower part of

TABLE II

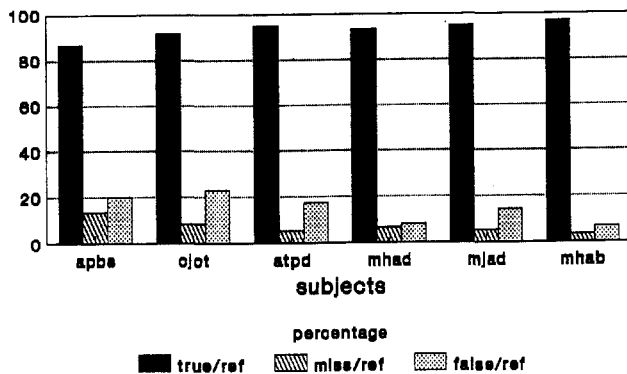
Performance of automatic detection of real EEG signals. Individual and group values are presented. The true positive to reference percentage (T/R) is 94% for K complexes in stage 2 and 89% for vertex waves and K complexes in all SWS stages. The false positive to reference percentage (F/R) is 13% for K complexes in stage 2 and 49% for vertex waves and K complexes in all SWS stages.

	K-compl. stage 2			Vertex and K compl. all			K compl. stage 2 (%)		All events (%)	
	T	M	F	T	M	F	T/R	F/R	T/R	F/R
APBS	26	4	6	94	18	176	86.7	20.0	83.9	157.1
CJCT *	151	14	38	293	52	135	91.1	23.0	84.9	39.1
ATPD	237	13	44	695	76	384	94.8	17.6	90.1	49.8
MHAD	323	23	28	769	158	349	93.3	8.1	82.9	37.6
MJAD	466	26	71	978	82	662	94.7	14.4	92.3	62.2
MHAB	341	12	24	698	68	247	96.6	6.8	91.1	32.2
Total	1544	92	211	3527	454	1953	94.3	12.9	88.6	49.0

T = true detection; F = false positive; M = false negative; R = reference (T + M).

* Only 5 h of recording.

K-complexes Stages 1 and 2



V-wave and K-complex all subjects

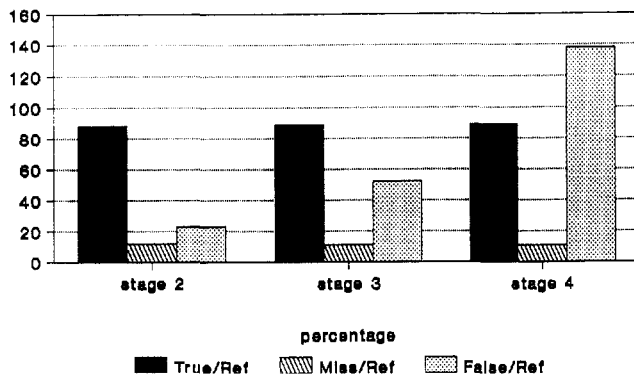


Fig. 7. Performance of the automatic detector. The upper part of the figure shows the performance of the detector in detecting K complexes in stages 1 and 2. The individual rates are homogeneous across the normal subjects analyzed. The detection performance for vertex waves and K complexes in all SW sleep stages for all subjects is also homogeneous except for the false detection rate, which increases with the depth of the sleep stage.

the figure shows the detector performance for vertex waves and K complexes in stages 2, 3 and 4. The true detection and false negative percentages were homogeneous in all 3 stages, but the false detection percentage increased with deepening of the SWS. Fig. 8 shows examples of typical situations in stages 2 and 4. The false positives were found mainly (about 90%) in stages 3 and 4.

Discussion and conclusions

According to this simple model the description of sleep EEG activity may be reduced to a combination of 3 parameters. The slowly varying statistics of the background (tonic) slow wave activity are characterized by

smooth changes in the delta feedback loop gains. The transient (phasic) K complexes and vertex waves are described by pulses added to the input of the model. The sudden changes of the sigma feedback loop gain simulate sleep spindles.

From the simulation results one may conclude that the two phasic events, K complexes and vertex waves, are basically the same phenomenon. The different morphologies depend on the state of one parameter, the delta gain, closely associated with the NREM sleep stages. The noise input causes the simulated phasic events to have variable shapes even when the gains are kept constant. This corresponds closely to what can be seen in the real EEG. Accordingly, one can state that vertex waves and K complexes belong to the same family of low frequency phasic events. Impulses (or micro-arousals) occurring during low levels of tonic activity result more probably in vertex waves, while K complexes are more likely to appear during moderate levels of tonic activity.

Using simulated signals it was shown that the detection performance level depends on the S/N ratio; the automatic true detections were 72 and 93%; false positives were both 4% for the two cases investigated (records A and B) respectively. Visual scoring of the same records yielded slightly lower accuracy of detection, 69

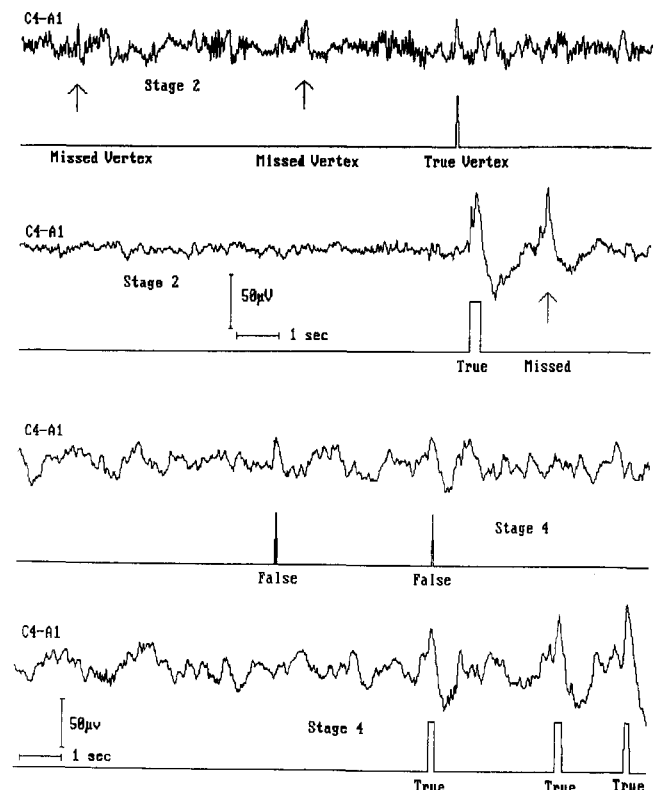


Fig. 8. Automatic detection of real EEG signals. The figure shows examples of typical situations of V wave false negatives (vertex waves missed) and K complex true detections (true), false positives (false) and false negatives (missed) in stages 2 and 4.

and 82%, and the false positives were similar, 2% and 3%. These results demonstrated the validity of the model; most of the simulated events were recognized as real and gave some confidence in the model-based detector. The simulated signals, albeit artificial, provided a precise and objective reference for the pulse inputs (imp).

In real sleep signals from normal subjects, the number of detections in which automatic and visual scoring agreed reached levels of 94% and 89% for K complexes in stages 1 and 2 and for vertex waves and K complexes in all NREM stages respectively. The average number of false positives was 13% for K complexes in stages 1 and 2 and 49% for all events. As shown in Fig. 7 the false positive rate increased with the depth of the SWS, 90% of the false detections being found in stages 3 and 4. These figures are not surprising, because in stages 3 and 4 it is very difficult to distinguish visually the phasic events due to large amplitude delta activity, part of which, at least, can be detected as K complexes by the automatic detector.

Three automatic K complex detectors were previously reported in the literature. Bremer et al. (1970) described a deterministic wave form detector implemented in hardware. The agreement between the automatic detection and two scorers was 63% and a large number of false positives, especially in stages 3 and 4, was reported. Sheriff et al. (1977) presented a detector based on matched filters designed from a template wave form which was tested using a small sample. The maximum number of K complexes scored was 142 by the automatic detection and the true detection and false positive percentages were 67 and 154% respectively for one of the scorers and 85 and 52% for the second scorer. Othmer et al. (1980) reported a detector based on the slopes and peak amplitudes of the delta waves. The data presented in these papers are not in a suitable form for direct comparison.

A difficulty in performance comparison of human scorers and automatic detectors is the lack of consistency of the former. In the case of K complexes, Bremer et al. (1970) found an agreement between two scorers of only 50 and 57% and Sheriff et al. (1977) found still lower values, 32 and 61%. This means that the reference set is poorly defined. For this reason we restricted our comparison to one electroencephalographer only; however, the performance of the automatic detector can be changed easily to suit other EEGers by changing its parameters. An essential advantage of the automatic method is that such a change is always carried out in an explicit and quantitative way, so that the results are always reproducible.

It was shown that the detector using a model-based approach is able to detect quite accurately K complexes and vertex waves in stages 1 and 2 NREM and can achieve the goal of substituting for visual scoring in

these stages. However, for stages 3 and 4, the level of true detections was preserved, but because of the large number of false positives the detector can only be used as a guide for visual selection, thereby reducing drastically the visual detection effort. In future studies the performance may be improved further by using the a posteriori knowledge of the statistical properties of the estimated gains and of the input pulse; another step will be the inclusion of theta and alpha rhythm loops in the model, in order to prevent their recognition as non-stationarities.

The parameters of the feedback loop filters can be tuned to any individual sleep EEG, but the results showed that in the normal population studied the detector is robust for inter-individual variations and tuning was not needed.

A further improvement may be achieved by adopting a self-adaptive estimation scheme for the feedback loop gains, where the windows are sensitive to the respective activity. In this way the problem of obtaining a satisfactory compromise between accuracy of estimation and tracking speeds may be optimized.

It is expected that technological improvement of the detector, advances in the understanding of the physiological functions and more experience in detecting and scoring K complexes in a variety of EEG sleep records may contribute to better performances, especially during the deeper slow wave sleep stages.

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