A Multistage System to Detect Epileptiform Activity in the EEG

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***Abstract*— A PC-based system has been developed to automatically detect epileptiform activity in sixteen-channel bipolar EEG's. The system consists of three stages: data collection, feature extraction, and event detection. The feature extractor employs a mimetic approach to detect candidate epileptiform transients on individual channels, while an expert system is used to detect focal and nonfocal multichannel epileptiform events. Considerable use of spatial and temporal contextual information present in the EEG aids both in the detection of epileptiform events and in the rejection of artifacts and background activity as events. Classification of events as definite or probable overcomes, to some extent, the problem of maintaining high detection rates while eliminating false detections. So far, the system has only been evaluated on development data but, although this does not provide a true measure of performance, the results are nevertheless impressive. Data from 11 patients, totaling 180 minutes of sixteen-channel bipolar EEG's, have been analyzed. A total of 45–71% (average 58%) of epileptiform events reported by the human expert in any EEG were detected as definite with *no* false detections (i.e., 100% selectivity) and 60–100% (average 80%) as either definite or probable but at the expense of up to nine false detections per hour. Importantly, the highest detection rates were achieved on EEG's containing little epileptiform activity and *no* false detections were made on normal EEG's.**

I. Introduction

Electroencephalography is a well established clinical procedure which can provide information pertinent to the diagnosis of a number of brain disorders (e.g., epilepsy or brain tumors). However, despite its widespread use, it is one of the last routine clinical procedures to be fully automated [1].

Analysis of the electroencephalogram (EEG) includes the detection of patterns and features characteristic of abnormal conditions. For example, asymmetries in the amplitude or frequency of background activity suggest a lesion, while the presence of epileptiform activity supports a clinical diagnosis of epilepsy [2]. Over half the EEG referrals relate to epilepsy, with the EEG being the most useful procedure in its diagnosis.

Recording the EEG during a seizure is particularly helpful in determining whether a patient has epilepsy. Because seizures usually occur infrequently and unpredictably, obtaining such a recording might require an EEG extending over several days (long-term EEG monitoring). Techniques have been developed for the automated detection of petit mal seizures [3]–[5] and grand mal seizures [6], which have proven relatively successful.

Between seizures, the EEG of a patient with epilepsy may be characterized by occasional epileptiform transients (spikes and sharp waves) and, consequently, relatively short recordings can still be useful in the diagnosis of epilepsy. A routine recording typically lasts 20–30 minutes, during which some 40 m of paper record are produced. An electroencephalographer (EEGer) detects epileptiform transients by visual inspection of the recording, which requires considerable skill and is time consuming. Hence, automation of this process could save time, increase objectivity and uniformity, and enable quantification for research studies.

Automated detection of epileptiform transients has two primary areas of clinical application. The first is in long-term EEG monitoring, where it acts essentially as a data reduction process [7], [8]. A segment of EEG is recorded only when a transient is detected and all segments are reviewed by an EEGer. Thus, the goal is to detect a high proportion of epileptiform activity while minimizing false detections. The second area is in routine clinical recordings, where a major objective is to minimize the visual inspection process as far as epileptiform transients are concerned. In this case, it is important not to precipitate a misdiagnosis of epilepsy and, therefore, the aim is to eliminate false detections while detecting a satisfactory proportion of epileptiform transients.

Spikes and sharp waves are defined as transients clearly distinguished from background activity with pointed peaks at conventional paper speeds [9]. Spikes are defined as having durations of 20–70 ms, while sharp waves have durations of 70–200 ms. Throughout this paper, no distinction is made between spikes and sharp waves and, therefore, they are collectively termed epileptiform transients. Due to the wide variety of morphologies of epileptiform transients and their similarities to waves which are part of the background activity and to artifacts (i.e., extracerebral potentials from muscles, eyes, heart, electrodes, etc.), the detection of epileptiform activity in the EEG is far from straightforward.

Several techniques have been applied to the detection of epileptiform activity in the EEG. These include: a) template matching, where a detection is made whenever the cross

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correlation of the EEG with a template exceeds a threshold [10], [11]; b) parametric methods, where a detection is made when the difference between the EEG and its predicted value (based on the assumption that the background is stationary) exceeds a threshold [12]–[14]; c) mimetic methods, where one or more parameters of each wave are calculated and thresholded [15]–[17]; d) syntactic methods, where detections are based on the presence of a structural combination of features [18]; e) artificial neural networks trained to detect epileptiform transients [19]; and f) expert systems, which detect epileptiform activity by mimicking the knowledge and reasoning of the EEGer [20], [21]. Most of these systems are still in the developmental stage, and those in clinical use are restricted to long-term EEG monitoring with all detections being reviewed by an EEGer. Due to a high number of false detections, these systems cannot perform satisfactorily in the routine EEG setting.

It is now generally accepted that the only way to separate epileptiform from nonepileptiform waves is to make use of a wide spatial and temporal context [20], [22]. Several groups are implementing this approach in an effort to minimize false detections. Glover *et al.* [20] have developed a system that relies on a wide spatial context, with 12 EEG channels being analyzed together with additional contextual information provided by EKG, EOG, and EMG channels. Conversely, the system developed by Gotman and Wang [22] implements a wide temporal context, where sections of EEG are classified into one of five states (active wakefulness, quiet wakefulness, desynchronized EEG, phasic EEG, or slow-wave EEG) before state-dependent rules are applied to reject nonepileptiform activity.

We have developed a system that makes considerable use of both spatial and temporal contextual information. This system has proven particularly successful at rejecting nonepileptiform activity in awake resting EEG's [23]–[25]. It uses a mimetic approach to detect candidate transients, which are subsequently confirmed or rejected as epileptiform by an expert system. The current system integrates both spatial and temporal contextual information to detect definite and probable epileptiform activity and to reject nonepileptiform waves. Preliminary results indicate that this system should be capable of performing reliably in the routine clinical EEG setting.

II. System Objectives and Philosophy

Our aim was to develop a real-time PC-based system to reliably detect epileptiform activity in the routine clinical EEG recording. We firmly believe that if a system for detecting epileptiform activity is to be of real value in assisting the EEGer with routine EEG recordings, it must have *no* false detections. Otherwise, the EEGer must inspect all activity reported (to prevent a misdiagnosis of epilepsy), which could well take longer than reviewing the entire record independently. Thus, it is essential to eliminate false detections while, at the same time, maintaining reasonable detection rates.

The approach we took was to replicate, as far as possible, the knowledge and reasoning of a single EEGer (GJC). An expert system is ideal for the implementation of such an approach because it provides a convenient way of representing knowledge and encoding reasoning or logic. Extensive collaboration with the EEGer was required to extract relevant knowledge. In distinguishing epileptiform from nonepileptiform activity, the EEGer makes extensive use of spatial and temporal contextual information. The *spatial context* of a wave includes the presence of synchronous waves on adjacent channels, the background activity on all channels, and any artifacts that are present. The *temporal context* of a wave is: a) the background activity upon which it occurs; and b) the occurrence of other suspicious waves with similar distribution during the EEG. This type of information can be conveniently represented in an expert system.

Because epileptiform transients do not usually occur in isolation, but arise synchronously on several channels, the EEGer detects epileptiform *events* rather than individual epileptiform transients. The EEGer classifies these events as focal (localized) or nonfocal (generalized) based on the spatial relationships between transients. Therefore, we decided that the final output of the system should be the epileptiform events detected rather than individual epileptiform transients and that a distinction should be made between focal and nonfocal events.

We have developed a system that detects focal and nonfocal epileptiform events in a manner similar to the EEGer. The system consists of three stages: 1) a data collection stage, which samples and digitizes EEG data; 2) a feature extractor, which detects candidate epileptiform transients; and 3) an expert system, which detects and classifies epileptiform events.

Because of the difficulty of reliably distinguishing epileptiform events from all background activities and artifacts, and because of sometimes conflicting clinical requirements or priorities, we decided to allow two types of output. The first is *definite* epileptiform events. For these, it is essential that all artifacts and background activity are rejected and, therefore, the subsequent detection rate of epileptiform events may not be particularly high. The second type of output is *probable* events. The aim here is to detect a higher proportion of epileptiform events, but this is likely to be at the expense of several false detections.

This approach should prove satisfactory for most situations. When a data reduction process is required (e.g., in long-term EEG monitoring), probable events can be used to trigger data storage. In the routine EEG setting, it is intended that the EEGer need only look at the probable event results if there are few or no definite events detected.

III. Data Collection

The EEG is recorded by placing electrodes on the scalp according to the International 10–20 system [26]. Sixteen channels of EEG are recorded simultaneously for both referential montages, where all electrodes are referenced to a common potential (e.g., ear, vertex, average), and bipolar montages, where each electrode is referenced to an adjacent electrode. Recordings are made while the patient is awake but resting and include periods of eyes open, eyes closed, hyperventilation, and photic stimulation. Amplification is provided by an EEG machine (Siemens Minograph Universal).

The EEG is bandpass filtered between 0.5 and 70 Hz using a five-pole analog Butterworth filter, sampled at 200 Hz and digitized to 12 b. At present, all data are stored for off-line processing.

IV. Feature Extractor

The first stage of analysis is the feature extractor, which essentially acts as a data reduction process extracting pertinent information for use by the expert system. Therefore, the feature extractor needs to detect a high proportion of epileptiform transients and provide information about their context, without detecting an unnecessarily large number of nonepileptiform waves.

A mimetic approach was adopted and implemented in the procedural language C. The EEG is divided into halfwaves (a wave consists of two contiguous halfwaves) by a simple peak detection algorithm. Parameters of the wave and its constituent halfwaves are calculated, thresholded, and compared with measures of the background activity. Waves whose parameters exceed all thresholds are reported as candidate epileptiform transients.

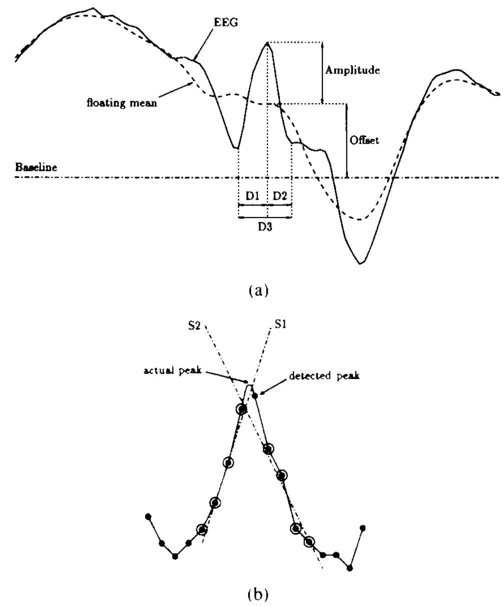


Fig. 1. Definitions of parameters calculated for each wave. (a) Halfwave durations (D1, D2), wave duration (D3), amplitude and offset of floating mean from baseline. (b) Halfwave slopes (S1, S2).

A. Parameters

The parameters calculated for each wave are duration, amplitude, and sharpness which are defined as follows.

1) *Duration* of a wave [Fig. 1(a)] is the sum of the durations of its halfwaves. The duration of each halfwave is the duration from the peak to the point where the slope of the halfwave (calculated over three samples, 15 ms) changes rapidly (i.e., changes direction, or more than a 50% drop in slope). This duration measurement ensures muscle spikes (even those superimposed on slow waves) have short halfwave durations.

2) *Amplitude* of a wave [Fig. 1(a)] is the difference between the peak and a floating mean (the average EEG value over 75 ms centered on the peak). The amplitude measure is, therefore, dependent on wave duration.

3) *Sharpness* of a wave is the sum of the peak slope magnitudes of each of the two halfwaves [Fig. 1(b)]. The peak slope of each halfwave is: a) the peak-to-peak slope when the halfwave duration is less than 20 ms; or b) obtained by a least squares estimation based on four samples (excluding peak).

Epileptiform transients are defined to be clearly distinguished from background activity. Therefore, parameters of each wave need to be compared with those of the background activity. The following measures of the background activity are calculated.

1) *Background amplitude* is the average difference between the EEG and the floating mean. This measure of background amplitude means that slow activity (e.g., delta waves, slow waves of spike-and-wave activity) do not contribute significantly to the background activity.

2) *Background slope* is the average magnitude of the slope of the EEG between consecutive samples.

3) *Background duration* is the average peak-to-peak duration of the halfwaves.

4) *Background rhythmicity* is defined by two parameters: the coefficient of variation (standard deviation/mean) of halfwave durations and the coefficient of variation of halfwave amplitudes.

Measures of the background activity are calculated over 1 s centered on the wave under consideration. In our experience, a 1 s background is sufficiently long that an epileptiform transient cannot dominate the background measure but is sufficiently short that bursts of alpha or muscle activity have a substantial effect. Therefore, waves making up such a burst do not appear significantly larger than the background.

Parameters of each wave are compared with those of the background activity by determining the relative amplitude and sharpness. The relative amplitude of each wave is calculated by dividing the amplitude of the wave by that of the background, while the relative sharpness is obtained by dividing the wave sharpness by the background slope. The background duration and rhythmicity are used by the expert system in determining the background activity (e.g., alpha rhythms).

Suitable measures for parameters of both the individual waves (amplitude, sharpness, and duration) and the background activity (amplitude, slope, duration, and rhythmicity) were determined by statistical analysis (in preparation). A number of different measures of each parameter were calculated (e.g., peak-to-peak halfwave amplitude, amplitude to a floating mean, average halfwave slope, maximum halfwave slope) and several techniques employed to compare the parameters of individual waves with those of the background activity (e.g., wave parameter/background parameter, wave parameter—background parameter, [wave parameter—background parameter] / standard deviation). A discriminant analysis was used to determine the measures that best distinguished epileptiform transients from nonepileptiform waves of similar morphology.

B. Thresholds

Epileptiform transients do not usually occur in isolation but arise synchronously on several channels. To detect a high proportion of synchronous transients, a two-threshold system is employed. When a wave whose parameters exceed the thresholds is detected, waves on all channels within 50 ms are reconsidered using a lower set of thresholds. This ensures that most epileptiform transients are detected, while smaller nonepileptiform waves throughout the EEG are rejected. Ideally, the higher set of thresholds allows at least one epileptiform transient from every event to be detected while the lower set of thresholds enables all transients constituting the event to be detected.

C. Contextual Information

In order to replicate the reasoning of the EEGer, the expert system requires knowledge of the spatial context in which candidate transients occur. The spatial context of a wave includes knowledge of activity on adjacent channels. Thus, whenever a group of candidate epileptiform transients is detected, measures of the background activity (amplitude, slope, duration, and rhythmicity) on all channels are recorded. This information can be interpreted spatially by the expert system if the recording montage is known. The montage can be determined (for a given recording protocol) by detecting the times when the montage was changed (i.e., when no EEG is present). To ensure that measures of the background activity do not include periods when no EEG is present, it is necessary to have a 0.5 s refractory period on either side of a montage change.

Artifacts, such as eyeblinks and electrode movement, are characterized by substantial prolonged deviations of the EEG from baseline. Therefore, whenever the offset of the floating mean from baseline exceeds a threshold of 50 μV, this fact is reported to the expert system.

V. Expert System

The expert system is the final stage in the detection of epileptiform activity and rejection of artifacts and epileptiform-like background activity. The expert system is written in Prolog (a declarative artificial intelligence language) and attempts to replicate the knowledge and reasoning of the EEGer.

When reading an EEG, the EEGer tends to mark epileptiform events (rather than the individual epileptiform transients) and classifies these as focal (localized) or nonfocal (generalized). In distinguishing epileptiform activity from artifacts and background activity, the EEGer makes use not only of the amplitude and sharpness of waves but also of contextual information. Thus, for automated detection of epileptiform activity, the parameters of the individual waves must be used in conjunction with: a) spatial information (i.e., location of electrodes on the scalp, channel derivations, presence of transients or artifacts on adjacent channels); and b) temporal information (i.e., the presence and distribution of abnormal activity during the EEG). When EEGers observe suspicious activity, they carefully review the electrodes involved searching for similar activity. This approach can be implemented by detecting all likely epileptiform events (based purely on spatial information) and grading them as definite, probable, or possible. Probable and possible events can then be upgraded or rejected based on the presence and distribution of events elsewhere in the recording.

A. Knowledge

In general, an expert system applies rules to facts and data to infer new facts and arrive at conclusions. Our expert system is provided with a number of facts concerning the location of electrodes and the channel derivations for each montage. These facts constitute the permanent knowledge of the system. Further knowledge is derived through application of rules to the data and these facts. At present, only bipolar montages are included because of multichannel artifacts which frequently arise on referential montages due to artifacts occurring at the reference electrode. Presently, four bipolar montages are included in the knowledge base.

B. Use of Spatial Context

Knowledge of electrode locations and channel derivations allows the expert system to interpret information spatially. Measures of the background activity on individual channels can, therefore, be combined to describe the distribution of EEG activity over the scalp.

The first task of the expert system is to eliminate artifacts due to muscle contraction, eyeblinks, and electrode movement. A series of rules, which take into account channel location and background activity on adjacent channels, eliminates most of these artifacts. These rules take the following form.

1) *Bursts of muscle spikes* are detected when the background activity on any channel is of high frequency ($\geq$25 Hz) and large amplitude (background amplitude $\geq$12.6 μV). All waves within 200 ms possessing characteristics of muscle spikes (i.e., short halfwave durations, high frequency background) are disregarded.

2) *Eye blinks* are detected when the floating mean drops significantly below baseline ($\geq$80 μV) on at least two frontal channels. Waves on all frontal channels within 200 ms are rejected as being a result of eyeblink.

3) *Electrode movement* is detected when the offset of the floating mean from baseline exceeds 50 μV for more than 400 ms and reaches a maximum offset of at least 100 μV. All waves on this channel within 200 ms are disregarded.

These rules successfully eliminate waves due to overt movement, sustained muscle activity, electrode movement, and eye blinks.

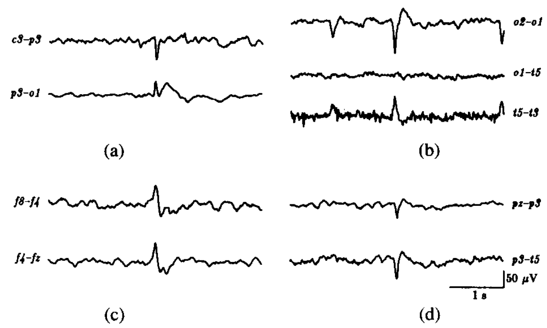


Fig. 2. Four possibilities for focal events. (a) Phase reversal on adjacent channels (focus at $p3$). (b) Phase reversal separated by a null channel (focus between $o1$ and $t5$). (c) Focus at beginning of an electrode chain ($f8$); no phase reversal is observed with all transients being negative (upward). (d) Focus at end of an electrode chain ($t5$); no phase reversal is seen with all transients being positive (downward).

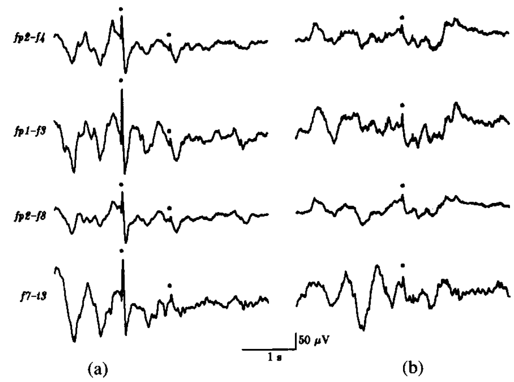


Fig. 3. Examples of nonfocal events from one EEG in which grading on spatial grounds led to (a) a definite followed by a possible event and (b) a probable event.

Waves are also eliminated if they appear to be part of the background activity. For example, a wave is considered to be part of an alpha rhythm if its duration and background duration fall within the alpha frequency range (8–13 Hz) and there are rhythmical waves of alpha frequency on occipital channels.

The next stage of the spatial analysis is the detection and grading of epileptiform events. An epileptiform event comprises one or more synchronous epileptiform transients. There are two types of epileptiform event: focal and nonfocal. Focal or localized events arise from a center of negativity (i.e., a focus) at the surface of the brain. On bipolar montages, focal events are typically characterized by phase reversal on adjacent channels [Fig. 2(a)], although there are several other possibilities. For example, the phase reversal may be separated by a null channel [Fig. 2(b)]; this occurs when the focus arises between two electrodes. No phase reversal is observed when the focus is at the beginning [Fig. 2(c)] or end [Fig. 2(d)] of an electrode chain. On the other hand, constituent transients of nonfocal events do not have any fixed polarity relationships, although negative waves tend to hold greater significance, especially on referential montages.

We define an epileptiform event to consist of all epileptiform transients that arise within 40 ms of each other. To avoid multiple detections for a single event, only one event every 125 ms is reported. Therefore, waves occurring within a window of 125 ms are grouped together and each group of waves must satisfy a number of criteria in order to be put forward as an epileptiform event.

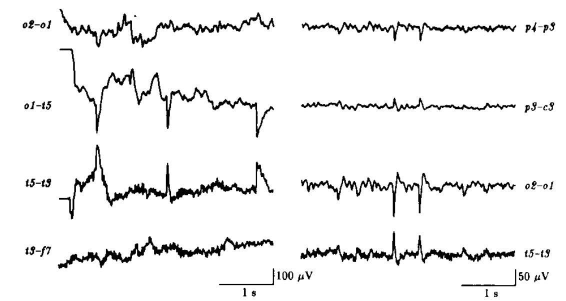
For a focal event to be detected, a distinct focus must be found and all waves in the group must support its presence. A focus is defined by two synchronous waves (Fig. 2) which: a) are on adjacent channels with opposite polarity; b) have opposite polarity but are separated by a null channel; c) are both negative and at the beginning of an electrode chain; or d) are both positive and at the end of an electrode chain. The phase reversal must be such that the waves arise from a center of negativity and *not* from a center of positivity. Waves which appear to be due to a positive surface potential are invariably electrode artifacts. Two synchronous foci can be detected if they arise over opposite hemispheres or at nonadjacent electrodes.

A nonfocal event is detected when there are at least two synchronous negative epileptiform transients and may include any number of positive transients. No fixed polarity relationships between waves are necessary.

Although events usually require at least two synchronous transients, a single epileptiform transient can be detected if it is particularly large and sharp. Single negative waves are detected both as focal and nonfocal events, while single positive waves are detected only as focal. Allowing a single wave to constitute an event enables the detection of: a) nonfocal events that consist of only one epileptiform transient; and b) focal events where one of the waves defining the focus has escaped detection by the feature extractor (either because it is of very low amplitude, is insufficiently sharp, or occurs during a burst of muscle activity).

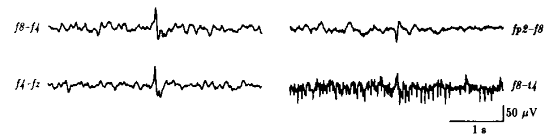
Focal and nonfocal events are graded as definite, probable, or possible corresponding to their level of certainty. The grading of events is determined from the amplitude and sharpness of constituent epileptiform transients. For focal events, the grading is based on the two waves defining the focus while, for nonfocal events, it is based on the two largest negative waves. Classification of focal events is less stringent than for nonfocal events because of the well-defining polarity relationships which must exist between constituent waves. An example of the grading of nonfocal events is shown in Fig. 3. Events consisting of a single wave are classified more stringently and can, at most, be probable.

A major problem has been distinguishing between isolated spikes due to muscle activity and epileptiform transients. Such muscle spikes tend to be characterized by short halfwave durations or a high-frequency background. However, many epileptiform transients share these characteristics. To overcome this problem, the grading of events as definite, probable, or possible is based on waves which do not have characteristics of muscle spikes. Therefore, events consisting of transients with similarities to muscle spikes may be rejected or have a lower level of certainty.



(a) (b)

Fig. 4. An example of artifact rejection in which (a) an electrode artifact was initially detected as a definite focal event (focus at $t5$) but was rejected due to lack of supporting evidence on adjacent channels, whereas (b) a definite focal event (focus between $o1$,$t5$) also manifested itself on nearby channels ($p4$-$p3$ and $p3$-$c3$).



(a) (b)

Fig. 5. An example of resolving classification difficulties during temporal analysis (a) a definite event detected as focal (focus at $f8$) and nonfocal, (b) another event in the same EEG on another montage which is focal (focus at $f8$). Thus, (a) is also classified as focal ($f8$).

The classification of events is followed by a further artifact rejection stage. Electrode artifacts may give rise to large waves of opposite polarity on adjacent channels [Fig. 4(a)], which may initially be detected as definite focal events. Events of this type are rejected on the basis that definite focal events should manifest themselves on more than two channels [Fig. 4(b)].

Based purely on spatial contextual information, it is not always clear whether a group of waves constitutes a focal or nonfocal event (the reasons for this become more evident in Section V-C). Each group is searched for both focal and nonfocal events and, hence, a group of waves may be detected as both focal and nonfocal. More than one focus may arise during an EEG. Our system, in addition to being able to detect all foci occurring separately, can discriminate two synchronous foci but may be unable to determine whether they are related or independent (based purely on spatial information). These classification difficulties are resolved by the temporal analysis stage.

C. Use of Temporal Context

Temporal information is defined to be the presence of abnormal patterns occurring with the same spatial distribution during the EEG. This information is used to upgrade or reject probable and possible epileptiform events and to resolve any classification problems encountered during spatial analysis.

Probable and possible events are upgraded if there is temporal support for their existence, otherwise they are rejected. Events are upgraded if their constituent transients arise with the same distribution as those of a definite event, or if there is a group of at least three probable events with the same distribution. For example, the probable event and possible event of Fig. 3 arise on the same channels as the definite event and so are upgraded to definite and probable events, respectively. Therefore, in the final output there are only two categories of event—definite and probable.

When a group of waves has been classified as both focal and nonfocal, temporal information is used to determine the most likely event type. For example, the definite event of Fig. 5(a) was initially detected as both focal (focus at $f8$) and nonfocal because all transients are negative and arise at the beginning of an electrode chain. The temporal analysis is able to resolve this difficulty because events detected on another montage exhibit phase reversal at $f8$ [e.g., Fig. 5(b)]. Similarly, the events of Fig. 3 were initially classified as both nonfocal and focal (focus at $fp1$) but, as there is no phase reversal at this electrode at other times in the EEG, these events are classified as nonfocal. In cases where correct classification is still unclear, focal events take precedence unless all constituent transients are negative.

If two synchronous foci are detected, temporal information is used to determine whether they are independent. For example, foci may be detected at $f3$ and $f4$. These may be independent or may be due to a single focus at fz (i.e., between $f3$ and $f4$). By considering similar events detected on montages that include fz or by determining whether the foci also arise independently, it is possible for the system to decide the number of foci present.

VI. System Performance

To date, system performance has been evaluated only on data used for development (i.e., the evaluation and training data are the same). Although this does not provide a true measure of performance, the results are nevertheless impressive.

Data from 11 patients aged 4–64 years (mean 25 years) have been analyzed, totaling 180 minutes of sixteen-channel bipolar EEG's. The data covered a wide range of EEG's—three normal, four with only focal epileptiform activity, and four with predominantly nonfocal epileptiform activity. A variety of background activities also occurred (e.g., alpha, delta) and most EEG's contained significant amounts of artifact (e.g., eyeblink, electrode movement, and muscle), particularly during periods of hyperventilation and photic stimulation. All bipolar EEG data available were used and no EEG's (or segments of EEG's) were rejected because of excessive artifact or "difficult" background activities (e.g., sharp alpha activity).

Results obtained from the system were compared with those of a single EEGer (GJC). Throughout the development process, the EEGer was consulted regarding events detected by the system. Thirteen events not initially detected by the EEGer were subsequently confirmed as being unequivocally epileptiform. These events tended to arise on page boundaries or during sections of EEG that contained considerable artifact. Thus, although the EEGer was considered to have 100%

TABLE I
SYSTEM PERFORMANCE ON 11 EEGS: 3 NORMAL (N), 4 WITH ONLY FOCAL ACTIVITY (F), AND 4 WITH PREDOMINANTLY NONFOCAL ACTIVITY (NF)

EEG (Type)	Duration (mins)	EEGer Events	Events Detected															
			Definite					Probable					Total					
			True	(%)	Quest	False	(/hr)	True	(%)	Quest	False	(/hr)	True	(%)	Quest	False	(/hr)
1 (N)	20	0	0	(-)	0	0	(0)	0	(-)	0	0	(0)	0	(-)	0	0	(0)
2 (N)	20	0	0	(-)	0	0	(0)	0	(-)	0	0	(0)	0	(-)	0	0	(0)
3 (N)	20	0	0	(-)	0	0	(0)	0	(-)	0	0	(0)	0	(-)	0	0	(0)
4 (F)	20	8	4	(50)	0	0	(0)	3	(37)	4	2	(6)	7	(87)	4	2	(6)
5 (F)	20	3	2	(67)	0	0	(0)	1	(33)	0	0	(0)	3	(100)	0	0	(0)
6 (F)	20	5	3	(60)	1	0	(0)	2	(40)	1	0	(0)	5	(100)	2	0	(0)
7 (F)	15	267	121	(45)	2	0	(0)	38	(15)	8	2	(8)	159	(60)	10	2	(8)
8 (NF)	15	70	50	(71)	1	0	(0)	4	(6)	2	1	(4)	54	(77)	3	1	(4)
9 (NF)	5	62	40	(64)	1	0	(0)	9	(15)	2	0	(0)	49	(79)	3	0	(0)
10 (NF)	5	37	20	(54)	0	0	(0)	8	(22)	0	0	(0)	28	(76)	0	0	(0)
11 (NF)	20	10	5	(50)	0	0	(0)	1	(10)	0	3	(9)	6	(60)	0	3	(9)
Totals	180	462	245	(53)[1]	5	0	(0)	66	(14)	17	8	(3)	311	(67)[1]	22	8	(3)
Best Case				(71)			(0)							(100)			(0)
Worst Case				(45)			(0)							(60)			(9)
Average Case				(58)[2]			(0)							(80)[2]			(3)

[1] Average over all events.
[2] Average per EEG.

selectivity and 100% sensitivity (i.e., was the "gold standard"), this was in part facilitated by his being able to reconsider his "independent" scoring on viewing the system's results. Events detected by the system that the EEGer agreed were related to other epileptiform activity in the EEG, but that would not normally be reported, have been termed questionable events.

Results obtained from the system are detailed in Table I. The system detected 45–71% of epileptiform events in an EEG as definite with *no* false detections (i.e., 100% selectivity) and 60–100% as either definite or probable but at the expense of up to nine false detections per hour. On average, 58% of the events in an EEG were detected as definite and 80% as either definite or probable. Because slow wave activity does not contribute significantly to the background amplitude measure, bursts of spike-and-wave activity are detected as several events (Fig. 6).

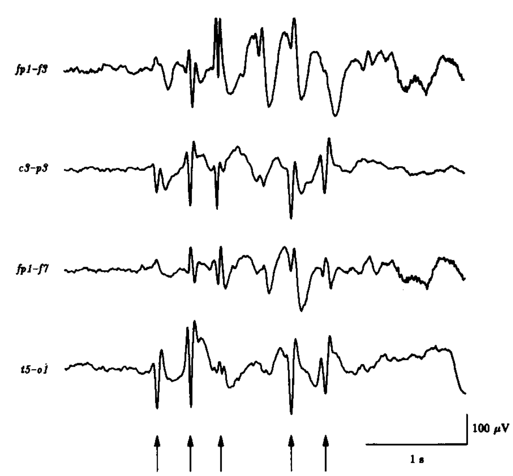


Fig. 6. A generalized burst of spike-and-wave activity detected as five events.

VII. DISCUSSION

We have developed a system that makes considerable use of spatial and temporal contextual information in detecting epileptiform activity in the EEG. All synchronous transients (i.e., arising within 40 ms) are considered to constitute a single event. Epileptiform events are reported as either focal or nonfocal based on the polarity relationships between their constituent transients. Two categories of event—definite and probable—are employed to overcome the problem of maintaining high detection rates while minimizing false detections and to enable the system to be applied in different clinical situations.

The highest overall detection rates were achieved on EEG's containing little epileptiform activity. When classifying an EEG as normal or epileptiform, the number of events detected is only of importance when there are very few of them, but it is not so critical when the EEG contains a large amount of epileptiform activity. Therefore, it is of little concern that the total detection rate is only 60% for EEG #7 in which there were over 250 focal events. Of more concern is that only 60% of events were detected for EEG #11, which contained only 10 events. However, three of the events in this EEG were unable to be detected because they arose within 0.5 s of a montage change. Although it would be possible to remove the refractory period around montage changes by estimating measures of the background activity, we do not feel that implementation of this feature is warranted (e.g., if the montage had been changed 0.5 s earlier the events would not even have appeared on the chart).

False Detections: No events were reported for any of the normal EEG's. Thus, false detections only occurred in EEG's containing epileptiform activity and then only in the probable category. All false detections had the same distribution as epileptiform events but were generally too low in amplitude or insufficiently sharp to be considered epileptiform by the EEGer.

Missed Detections: Missed detections fall into two classes: 1) those completely missed; and 2) those falsely rejected as artifacts or background activity. Our system is unable to detect epileptiform events that arise within 0.5 s of a montage change or during sustained muscle activity and reports a maximum of one event every 125 ms. The feature extractor may not detect epileptiform transients if they are of very low amplitude, are insufficiently sharp, or have muscle spikes superimposed on them. The expert system tends to miss events if only one epileptiform transient has been detected by the feature extractor, because thresholds for the detection of a single transient as an event are very high. In addition to missing events completely, the expert system may also reject true epileptiform events if all constituent transients have characteristics of muscle spikes or appear to be part of the background activity. Only 14 events were rejected by the expert system, and 11 of these were due to their similarities to muscle spikes. The temporal analysis stage of the expert system rejects nondefinite events if they do not arise with the same spatial distribution as other detected events. Overall, only four events were rejected by temporal analysis.

Comparison with Other Systems: Comparisons between systems for detecting epileptiform activity are made difficult by the wide range of "gold standards" used for evaluating their performance. In particular, different definitions are used for both false detections and missed detections. For example, false detections can be defined as detections made by the system that were: a) obviously artifact [27]; b) not marked by any of n EEGers [19]; or c) marked by fewer than m of n EEGers [10]. Similarly, missed detections may be: a) those not detected by the system but marked by at least m of n EEGers [19]; or b) those falsely rejected by the system as nonepileptiform [27]. Despite these difficulties, we have made an effort to compare the performance of our system with that of others.

Most systems for the detection of epileptiform activity are still in the developmental stage and, consequently, studies of their performance tend to be limited. The most extensive system evaluation has been performed by Gotman *et al.* [27], who recorded 2–3 minutes of EEG from 110 patients while they were relaxed with eyes closed. An attempt was made to obtain recordings as artifact-free as possible. During a total of 255 minutes of sixteen-channel bipolar EEG, an average of seven false detections per hour were reported. No account was made of the number of transients entirely missed by the system, but 16% of events were rejected as nonepileptiform. This system, which adopts a mimetic approach, has since been modified for long-term EEG monitoring and is now in regular clinical use as a data reduction system. It is only used during typical hours of sleep (11 p.m. to 5 a.m.) in an attempt to reduce movement, muscle, and eyeblink artifacts. However, Gotman [7] reported its performance to be "highly variable" and stated that "the variety of morphologies of artifacts appeared to preclude a total automatic elimination." Recent modifications [22], which implement a wide temporal context, have considerably reduced the number of false detections (by up to 90%) with a minimal further loss of true epileptiform transients (<5%). However, they still expect approximately 15 false detections per hour during periods of wakefulness (due mainly to eyeblink artifacts).

Glover *et al.* [21] used a similar approach to ours, with a mimetic stage being followed by a rule-based expert system. Twelve channels of bipolar or referential EEG were analyzed and additional information was available from EMG, EOG, and EKG channels. The recordings analyzed included periods of sleep, and results were reported for three patients. For development data, 56% of events were detected with an average of 15 false detections per hour while, for evaluation data from the same three patients, 21–57% (average 40%) of events were detected with 9–34 (average 16) false detections per hour. Walters *et al.* [18] use a syntactic approach and report that, for three EEG's, their system detected 70% of epileptiform transients but reported 30 false detections in the 30 minutes of EEG processed. Fischer *et al.* [10] use a parametric method to detect transients in the EEG and follow this with template matching. The system detected 73% of transients marked by at least four of seven EEGers in both a training and test set with seven false detections (i.e., marked by no EEGers) in 8.3 minutes (50/hour) and three false detections in 8 minutes (23/hour) on the training and test sets, respectively.

The overall detection rate for our system of 67%, with an average of three false detections per hour, compares very favorably with the results of other systems. The outstanding feature of our system is, however, its ability to detect, on average, 58% of events in an EEG as definite with *no* false detections.

It is this ability to eliminate false detections that will make our system applicable to routine clinical recordings. However, more data are required to further evaluate its performance and a blind clinical study is in progress. Further stages of development include processing referential montages, application to recordings with periods of sleep (long-term monitoring), and integration of the data collection, feature extraction, and expert system stages to achieve a system capable of real-time on-line detection of epileptiform activity in the EEG.

It is only a system such as ours, which is able to eliminate false detections and, thus, remove the need for manual checking, that will find its way into routine clinical use.

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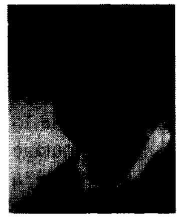

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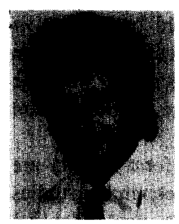

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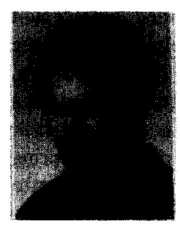

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