KNOWLEDGE-BASED ENHANCEMENT AND INTERPRETATION OF EEG SIGNALS

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ABSTRACT

The need to automate the interpretation of the EEG to provide a more efficient and reliable assessment is widely recognised. Techniques developed thus far however, neither adequately deal with the uncertainty in the knowledge, which is linguistic in nature, or deal with contamination of the EEG by artefacts. By developing models to interpret the EEG based on fuzzy logic, and integrating many years of research for the reliable processing of artefacts, this work aims to develop a reliable technique for the purpose of developing a decision support system for EEG staff to ensure accurate interpretation of the EEG. Results include an automatically generated factual report of an EEG which deals with uncertainty in manner akin to the human reasoning. The results also show a reduction in bias in the factual report introduced by artefact contamination.

INTRODUCTION

The electroencephalogram (EEG), the recording of electrical activity of the brain, is used in hospitals world-wide for the analysis and diagnosis of various normal and diseased states of the brain such as sleep, dementia and epilepsy. Typically it is recorded for 15 - 60 minutes from 21 locations on the scalp. A report is then written describing the relevant features of the EEG, and finally an interpretation is made in the light of the clinical problem. The waveforms of interest in the EEG are often called *activity* and can be classified as either background or transient. Background activity is on-going and rhythmic and is usually classified by frequency into the bands: delta (0 - 4Hz), theta (4 - 8Hz), alpha (8 - 13Hz) and beta (> 13Hz). Transient activity is short duration and is usually described in terms of waveform such as spikewave or sharpwave. Figure 1 shows 4 seconds of EEG and the electrode positions from where each EEG channel was recorded. An alpha rhythm is clearly discernible, particularly at the back of the head. This rhythm is characteristic of the normal adult.

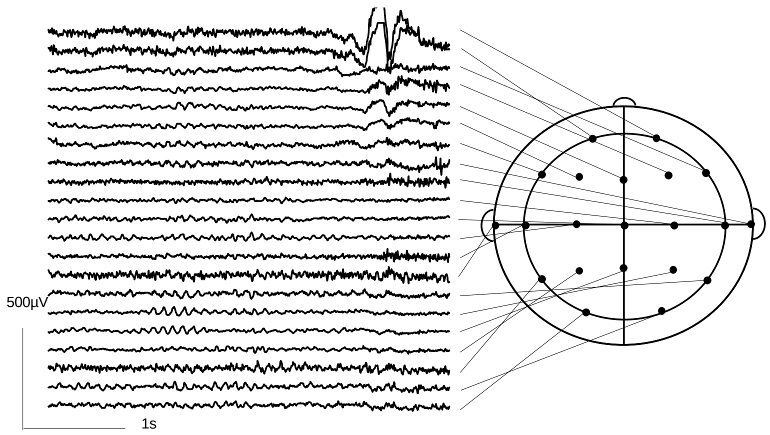

Figure 1. The normal EEG.

Although some knowledge of the origin of EEG signals exists, much is still unknown. As a consequence, the interpretation of these signals is based partly on an empirical as well as physiological understanding, making EEG interpretation a subjective procedure requiring many years of experience. Further, to interpret the EEG, features such as frequency and amplitude need to be analysed both in time and spatially on the scalp. This makes EEG interpretation a difficult, time consuming and laborious task, especially when carried out on the routine 15 - 60 minute recording. Interpretations consequently differ between clinicians, leading to variable and sometimes erroneous assessments [Kiloh *et al*. 1981].

The need to automate the interpretation of the EEG to provide a more efficient and reliable assessment is widely recognised, but is complicated by 2 factors: the presence of artefacts which contaminate the EEG, making interpretation difficult, and the adequate capture of subjective expertise which is ill-suited to conventional methods of artificial intelligence. Techniques developed to interpret the EEG thus far [Nakamura *et al*. 1992, Jagannathan *et al*. 1982], neither adequately, if at all, deal with the uncertainty in the knowledge which is linguistic in nature, or deal with the contamination of the EEG by artefacts, which seriously biases or invalidates system results. Unlike certainty factors, fuzzy logic deals with uncertainty in a manner akin to human reasoning, that is linguistically (e.g. very normal, somewhat normal, extremely abnormal) rather than numerically (e.g. normal [0.7], normal [0.3], abnormal [1]). By developing models to interpret the EEG based on fuzzy logic, and integrating many years of research for the reliable processing of artefacts, this work aims to develop a reliable technique for the purpose of developing a decision support system for EEG staff to ensure accurate interpretation of the EEG and provide some relief to the clinical work load.

DATA COLLECTION

For the development of a reliable technique to interpret the EEG the collection of appropriate data in sufficient amounts is paramount. The data required is 21 channel EEG taken from awake Alzheimer's disease patients and age-matched normal controls and for screening purposes, age, medical history, family medical history and a mental state assessment. For the initial study, a collection system and protocol was integrated into the hospital environment and 8 normal control volunteers and 3 Alzheimer's EEGs were recorded.

FEATURE EXTRACTION

To characterise each activity in each channel in each 4 second segment, 6 basic time and frequency domain features were extracted. The features *frequency*, *power*, *amount* and *frequency variability*, were taken from the power spectral density (PSD), where frequency was the frequency of a PSD peak maximum, power was the area of a PSD peak, amount was the area of a PSD peak as a percentage of the whole PSD and frequency variability was the width of a PSD peak (Figure 2). The features *amplitude* and *amplitude variability* were taken from the time domain by isolating the activity in time using a digital filter whose passband was defined by the width of the PSD peak (Figure 3). Amplitude was defined as the maximum peak to peak swing and amplitude variability was defined as the mean standard deviation of the maxima and minima. To produce a value that was amplitude independent, the maxima and minima values were first divided by their mean value.

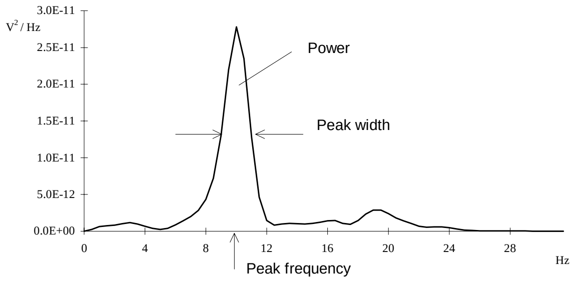

Figure 2. Frequency domain features using power spectral density estimation.

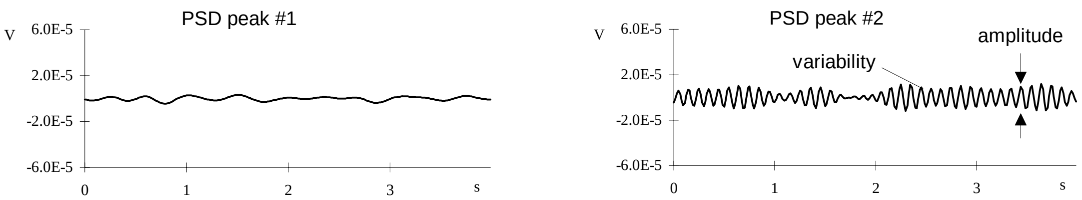

Figure 3. Time domain features using frequency band filtering.

DATA REDUCTION

PSD peak detection is a highly sensitive method for identifying activity in the EEG, typically identifying around 100 activities in a 4 second epoch. Many of the activities however are of the same origin, in fact, the clinician rarely identifies more than 10 activities in the entire EEG record. Because background activity is usually classified according to frequency, activities were clustered by frequency using the leader cluster algorithm. This procedure usually produces about 9 - 15 clusters, each corresponding to unique activities in the EEG.

INTELLIGENT SIGNAL ANALYSIS

Some of the features used to describe the EEG can and are expressed *quantitatively*. For example, amplitude is often measured by the clinician as the maximum peak-peak swing (in μV), and frequency is often measured by counting the number of peaks contained in a 1 second window (in Hz). Other features such as the organisation of activity or the location of activity on the scalp cannot quantitatively be measured without additional computerised analysis. Instead, these features are measured by the clinician *qualitatively* using pattern analysis expertise obtained through training and experience.

Table 1 shows 7 features used to describe each activity in the EEG. Also shown are the extracted features from which these features will be calculated. For the quantitative features: amplitude, frequency and symmetry, the extracted features can be used directly. For the qualitative features, location, organisation and change on eye opening, an intelligent technique is necessary to model the pattern analysis expertise of the clinician.

Features	Example	Extracted features
Frequency	10Hz	mean cluster frequency
Amplitude	50μV	maximum cluster amplitude
Amount symmetry	1 : 0.6	ratio of the cluster power in the left and right hemisphere
Frequency symmetry	10Hz : 10.6Hz	mean cluster frequencies in the left and right hemisphere
Location	right anterior	distribution of cluster power across the scalp normalised to 1
Organisation	irregular	mean cluster frequency variability and mean cluster amplitude variability
Change on eye opening	attenuates	difference between eyes closed cluster power and corresponding eyes open cluster power

Table 1. Features used to describe activity in the EEG.

FUZZY SYSTEM DEVELOPMENT

The development of a fuzzy system to model imprecise expertise is typically carried out in 4 stages:

- *define rules*
- *define fuzzy relations* to model each rule and fact
- *perform compositional rule of inference* to calculate the deduction
- *utilise deduction* e.g. for a crisp output perform defuzzification, for a linguistic output perform linguistic approximation or for forward chaining assert the deduction as a new fact

To model the pattern analysis expertise to extract the features organisation and change on eye opening, fuzzy models were developed using the stages described above. For a detailed example of performing these stages see [Riddington *et al*. 1996].

Organisation

Organisation is an important feature, particularly when assessing the dominant rhythm in the EEG. Defined as the degree to which an activity conforms to certain ideal characteristics [Chatrian *et al*. 1974], and measured in this case as variability in amplitude and frequency. The relationship between the organisation of an activity and the features frequency variability and amplitude variability is described by the rules in Table 2. Each fuzzy proposition were defined using s, z or pi shaped fuzzy sets. From these, rule models were constructed using the Mamdani implication and the deduction calculated using the compositional rule of inference. Finally a linguistic approximation to the deduction was calculated using primary sets *regular*, *moderate* and *irregular* and hedges *extremely*, *very*, *somewhat*, and *more or less*. Each hedge performed a power operation of 3, 2, 0.5 and 0.333 on the primary sets respectively.

IF frequency variability is organised AND amplitude variability is organised THEN organisation is regular	IF frequency variability is organised AND amplitude variability is disorganised THEN organisation is moderate
IF frequency variability is disorganised AND amplitude variability is organised THEN organisation is moderate	IF frequency variability is disorganised AND amplitude variability is disorganised THEN organisation is irregular

Table 2. Knowledge-base modelling expertise to calculate the feature organisation.

Reactivity To Eye Opening

Another important feature for assessing the dominant rhythm in the EEG is its reactivity to eye opening. For example, in dementia, the lack of alpha rhythm reactivity can be a highly sensitive diagnostic sign [Visser 1991]. To calculate the change of an activity between eyes open and eyes closed states, clusters needed to be identified in each state which corresponded to the same activity. This was carried out using a measure of similarity. The difference between the average power in each cluster pair was then used to give the change on eye opening. Similarity between eyes closed and eyes open clusters was measured using frequency (mean cluster frequency) and location (distribution of power across the scalp normalised to 1) by the rules shown in Table 3. Defuzzification of the deduction from these rules provided a numerical measure for similarity. Eyes open / eyes closed cluster pairs having the maximum measure of similarity were thus selected as clusters corresponded to the same activity. Change on eye opening was calculated using cluster average power using the rules in Table 4. Finally, a linguistic approximation to the deduction was calculated using primary sets *attenuates*, *does not change* and *increases* and hedges *extremely*, *very*, *somewhat*, and *more or less*.

```
IF eyes open frequency equals eyes closed frequency
AND eyes open location equals eyes closed location
THEN similarity is high
IF eyes open frequency does not equal eyes closed frequency
AND eyes open location equals eyes closed location
THEN similarity is moderate
IF eyes open frequency equals eyes closed frequency
AND eyes open location does not equal eyes closed location
THEN similarity is moderate
IF eyes open frequency does not equal eyes closed frequency
AND eyes open location does not equal eyes closed location
THEN similarity is low
```

Table 3. Knowledge-base modelling expertise to measure similarity between eyes open and closed activity.

```
IF difference between eyes closed and eyes open power as a
percentage is positive
THEN activity attenuates on eye opening
IF difference between eyes closed and eyes open power as a
percentage is zero
THEN activity does not change on eye opening
IF difference between eyes closed and eyes open power as a
percentage is negative
THEN activity increases on eye opening
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Table 4. Knowledge-base modelling expertise to calculate the feature reactivity to eye opening.

Location

The calculation of location of activity on the scalp was based on the distribution across the channels of power in a cluster. Normalising the distribution to 1 provides the membership values of the location of the clusters for each channel. Linguistic approximation was then calculated using primary fuzzy sets *posterior*, *anterior*, *frontal*, *central*, *post-central*, *parietal*, *occipital*, *left-temporal*, *right-temporal*, *temporal*, *right-laterally*, *left-laterally* and *diffuse* and hedges *left*, *right*, *more-on-the-left* and *more-on-the-right*.

ARTEFACT PROCESSING

An important issue in visual EEG examination is the effect of artefacts, which are mostly non-cerebral activities. Artefacts can seriously affect the interpretation of EEG since they could have similar waveforms as genuine activities. The importance of artefact processing to automated EEG is widely recognized to ensure that the interpretation takes place in the proper context.

In general, artefact processing includes two major steps: artefact identification and artefact removal/rejection. The former detects the existence of artefacts in EEG and identifies their types. The latter removes the contamination caused by artefacts from EEG signals with minimal distortion of important clinical information or rejects the signal if no appropriate removal procedure can be found.

In this paper, we use an artefact processing system based on neural networks (NN) and expert system, whose structure is shown in Figure 4. Time and frequency domain features are extracted from EEG. The phase I identification involves classifier design using multilayer feedforward networks. The networks are trained using the data selected by medical experts. The phase II identification employs the expert knowledge to analyse the outputs from the NN classifiers to further increase the successful rate of classification. The detailed description of feature extraction and classifier design can be found in [Wu *et al*. 1994].

The output of the artefact processing system is a table which labels each channel of EEG with the artefact type or as artefact-free.

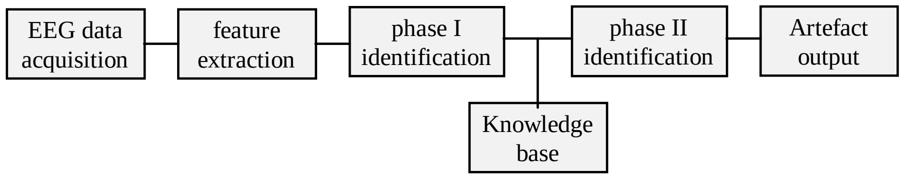


Figure 4. Artefact processing system.

These labels can then be used to exclude from the clustering procedure the PSD peaks suspected of artefact contamination (Figure 5).

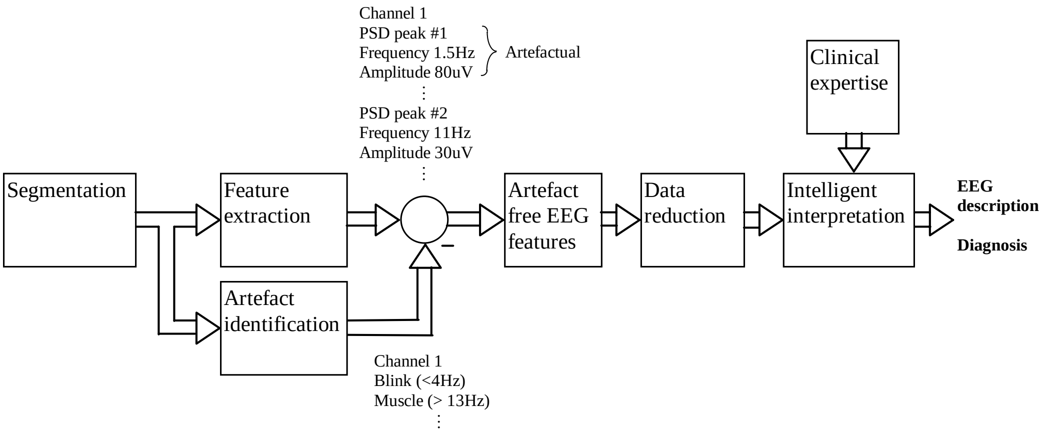


Figure 5. System for intelligent enhancement and interpretation.

RESULTS

Quantitative features calculated during feature extraction and qualitative features calculated during intelligent signal analysis, when combined, produce a description which efficiently characterises the entire EEG. Table 5 shows the generated description produced from the EEG of volunteer #2. Significant activities and artefacts for volunteer #2 are a regular dominant alpha rhythm, located in the posterior region, 10Hz, 50µV, which is symmetrical and attenuates on eye opening; beta activity, located diffusely, 20Hz, up to 20µV, which is symmetrical; muscle, located in the frontal region, approx 22Hz upwards, 50µV, which reduces on eye opening; muscle, located temporal regions - more on the left, approx 20Hz upwards, 30-50µV, which does not change on eye opening and small eye movements, up to 40µV, which increases considerably on eye opening.

The canonogram, the display of the distribution of power for each cluster, verifies the effectiveness of the linguistic approximation technique for describing activity location. Cluster #6 describes the alpha rhythm well. The large and artefact prone frequency range of beta activity (> 13Hz) has resulted in the sharing of beta activity between clusters #1, #3 and #4. All other clusters are probably artefact. Only PSD peaks ≤ 4Hz were removed by the system when eye movement or blinks were identified. As a consequence cluster #7 which is > 4Hz have not been removed. Cluster #2 is very low power and is probably insignificant. Cluster #5 represents eye movements not identified by the artefact processor.

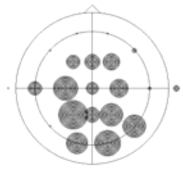
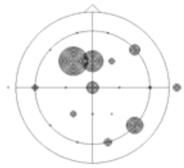
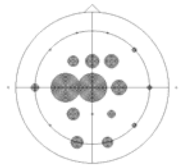
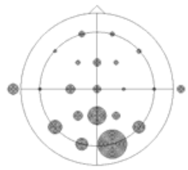
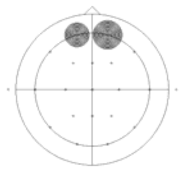
Computer generated factual report				
#	**Description**	**Amount symmetry**	**Frequency symmetry**	**Canonogram**
1	somewhat-regular **beta**-activity, 19Hz, 18μV, located-post-central-more-on-the-left, attenuates-on-eye-opening	0.9 : 1	18.9 : 19	
2	moderately-organised **beta**-activity, 25.1Hz, 8.8μV, located-diffuse-more-on-the-right, attenuates-on-eye-opening	0.9 : 1	25 : 25	
3	somewhat-moderately-organised **beta**-activity, 22.2Hz, 12μV, located-central, attenuates-on-eye-opening	1 : 0.9	22.3 : 22.2	
4	regular **beta**-activity, 15.1Hz, 19μV, located-posterior-more-on-the-right, attenuates-on-eye-opening	0.6 : 1	15.2 : 15.2	
5	somewhat-regular **delta**-activity, 1.8Hz, 20μV, located-frontal-more-on-the-right, increases-on-eye-opening	1 : 1	1.6 : 1.9	
6	more-or-less-regular **dominant-alpha**-rhythm, 9.8Hz, 44μV, located-posterior-more-on-the-right, attenuates-on-eye-opening	0.9 : 1	4.5 : 5.1	
7	regular **delta-theta**-activity, 4.8Hz, 23μV, located-frontal-more-on-the-right, increases-on-eye-opening	0.9 : 1	4.5 : 5.1	

Table 5. Factual description of the EEG for volunteer #2.

The effects of artefact processing on the interpretation are shown in Table 6. Prior to artefact processing, muscle activity found in the frontal, and left temporal regions have biased many of the features of the beta activity. Artefact processing removes PSD peaks suspected of muscle, blink or eye movement corruption and has thus removed some of the bias in the results.

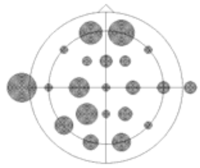
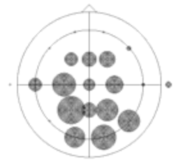
Description	Amount symmetry	Frequency symmetry	Canonogram
Without artefact processing somewhat-regular **beta**-activity, 20Hz, 24μV, located-diffusely-more-on-the-left, attenuates-on-eye-opening	1 : 0.9	19.9 : 19.9	
With artefact processing somewhat-regular **beta**-activity, 19Hz, 18μV, located-posterior-central-more-on-the-left, attenuates-on-eye-opening	0.9 : 1	18.9 : 19	

Table 6. Effects of artefact processing.

CONCLUSIONS

Salient features of the EEG are both quantitative and qualitative. Quantitative examples are amplitude where the clinician measures the parameter using a ruler, or frequency, where peaks in a 1 second segment are counted. Qualitative examples include organisation where the amplitude and frequency of a rhythm are assessed with regard to uniformity and descriptions such as *regular* or *irregular* are subjectively applied. Similar situations exist for location, change on eye opening and overall abnormality.

Fuzzy sets enable such descriptions to be formally represented by allowing objects such as frequency variation measurements to be members to subjective terms such as *organised* or *disorganised* to a degree. Inference in formal systems have long been based on truth. How does one however represent the truth of the proposition *the rhythm is organised* if *organised* is ill-defined? Fuzzy logic represents the truth of such propositions with equally ill-defined measures of truth such as *somewhat true*. Reasoning with fuzzy logic modifies the conclusion of a rule given the truth of the rule antecedent by increasing the vagueness for decreasing truth. A procedure called linguistic approximation then identifies the changes made in the conclusion and applies *hedges* such as *the rhythm is very irregular* or *the rhythm is somewhat regular* to represent these changes.

The qualitative nature of EEG interpretation was represented using these techniques to provide a factual report of the EEG which accurately describes the qualitative features such as organisation and location of activity e.g. descriptions such as *organisation is very irregular, location is posterior - more on the left*. This is in stark difference with existing published techniques to interpret the EEG which portray uncertainty to the clinician numerically, and being incompatible to the clinician, require experience to understand and interpret.

To take into account the effects of artefacts, the system omits from the clustering procedure, frequency peaks which are suspected of having artefact origin by incorporating work from [Wu *et al*. 1994]. Rather than omitting the PSD peak, further work will correct the effects of artefacts in a PSD peak, particularly if it contains information of cerebral origin by incorporating work from [Ifeachor *et al*. 1990].

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