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Attribute Ranking for Lateralizing Focal Epileptogenicity in Temporal Lobe Epilepsy

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Abstract— **A consensus feature-ranking approach has been applied to the study of localization-related temporal lobe epilepsy (TLE) in order to evaluate the relative discriminative power of individual attributes. Cases were selected on the basis of a postoperative outcome free of disabling seizures (i.e., Engel class I) in order to establish a definitive laterality of focal epileptogenicity. Several quantitative measures made available by imaging and electrographic studies are considered and the most discriminative of these are quantitatively prioritized for the lateralization of focal epileptogenicity. Cases requiring extraoperative electrocorticography were examined as a subgroup to establish whether the current method of analysis could distinguish laterality sufficiently well to avoid the requirement for intracranial electrode implantation.**

Keywords- feature ranking; temporal lobe epilepsy; lateralization; data mining; machine learning

I. Introduction

Computer methods provide a means for assimilating clinical, electrographic and imaging data, quantifying salient attributes and optimizing their application in clinical decision-making. Data mining techniques have been successfully applied in various biomedical domains to study complex diseases [1]. However, the gathering of several diagnostic features from multiple sources results in the creation of high-dimensional sample spaces which are common characteristics of medical databases. It is known that the presence of features that are irrelevant or have low relevancy to the desired outcome reduce the accuracy and reliability of the prediction model. Therefore, prioritization of individual attributes is an important aspect of any effort towards computer-aided decision-making [2]. Additional benefit of such assessment is the achievement of knowledge on the comparative value and reliability of each feature with respect to diagnosis.

In this study, a data-mining methodology has been applied to the study of localization-related temporal lobe epilepsy (TLE) [3] in order to evaluate the discriminative power of individual attributes. Several quantitative measures are made available by imaging and electrographic studies undertaken in this condition. Such studies could be the foundation by which determination of laterality can be made with the greatest efficiency.

A clinical and imaging archive of TLE patients, namely the human brain image database system (HBIDS) [4], provides several clinical attributes including risk factors underlying the condition, semiology, both pre- and postoperative neuropsychological profiles, location of surgery, pathology and outcome according to the Engel classification. Descriptive electrographic features include interictal waveforms, their location and predominance as well as ictal onset location. Both magnetic resonance (MR) and single photon emission computed tomography (SPECT) (ictal and interictal) imaging is included with the provision for quantitative semi-automated assessment of compartmental volume, fluid-attenuated inversion recovery (FLAIR) mean signal and standard deviation and texture analysis [5]. Compartmentalized ictal SPECT subtraction image analysis is also available [6].

Five established classifiers were utilized to assess the individual value of each feature in predicting laterality. From patients who attained Engel class I surgery outcomes, cohorts were delineated representing those who were operated following standard preliminary investigation (i.e., inpatient scalp video-electroencephalography (vEEG), MR and SPECT imaging, sodium amobarbital study) and those who required extraoperative electrocorticography (eECoG) because of discordance of preliminary findings.

The present study undertakes an analysis of the above comprehensive clinical and imaging features and uses a data mining ranking technique to aid in the prioritization of these features for the purpose of lateralizing the focus of epileptogenicity in TLE. The approach adds further to prior attempts at analysis of a similar clinical group of mesial TLE [7] [8]. In particular, it addresses those cases that present with confounding features requiring further intensive electrographic study with implanted electrodes, an approach that bears greater risk and adds significantly to the economic burden of health care delivery.

II. Methods

There are multiple feature selection and attribute ranking methods in data mining, machine learning, pattern recognition, and statistical analysis domains [9]. Most of these methods are optimized for specific purposes inheriting

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certain limitations. Recently emerged consensus feature selection and ranking methods, where attributes are ranked based on fusion of analysis from multiple perspectives, tend to show superior results with respect to accuracy [10]. Since attribute scores are calculated from several sources, consensus feature rankings are less dependent on prediction models and do not suffer from classifier bias.

In the application of any data mining approach to medical datasets, certain common characteristics of such domains, unbalanced distributions of data and missing values should be taken into consideration. Missing values, in particular, are a consistent problem in medical databases as not all studies can be necessarily carried out in all patients. The target cohort is also often not proportional to the control population rendering difficulty in assigning certain features sufficient priority. As a trivial example, noncancer-bearing patients outnumber cancer patients.

In our study, missing values were avoided to promote the reliability of the results. To this end, the study was based only on properly recorded values. This, however, might have resulted in the elimination of certain parts of the dataset thus causing adverse effects on data distribution. We used the area under the receiver operating characteristic (ROC) curve (AUC) as a performance evaluator for individual features to handle the balance problem.

Individual features were evaluated using five classifiers and their AUC calculated using leave-one-out cross validation. The classifiers included in this study were those of decision trees, naïve Bayes, support vector machine, 3-nearest neighbors, and multilayer perceptron. The average AUC from all classifiers was considered as the final discriminative score of each feature.

$$D.Score(f_i) = \sum_{c_k \in C} AUC(c_k, f'_i)/5 \qquad (1)$$

where all the missing values of the feature f_i are removed to generate f'_i and c_k is the classifier that belongs to the classifier pool C of the classifiers mentioned above.

III. EXPERIMENTAL RESULTS

The dataset used in the following experiments is from HBIDS, developed in the Radiology Department of Henry Ford Health System (Detroit, Michigan USA). The database contains 89 patients with Engel class I outcome (36 males, 56 females) having 197 medical features. The patients have an average age of 38y (S.D. 12.2). Temporal lobe epileptogenicity was found to be on the left in 47 patients and the right in 42 patients. In 50 patients, standard noninvasive evaluations lateralized the TLE sufficiently well to proceed with resection of the site of epileptogenicity directly, whereas, 39 patients required eECoG. Missing values were identified for EEG features in 21% of cases, for Wada studies in 31% and for imaging features in 46% of cases. The missing values of the remaining features were found in about 20% of cases on average.

In the first study, clinical attributes were analyzed in groups and the discriminative score of the best indicator in each group was considered the score of the whole group. The group discriminative score was formulated in Eqn (2).

$$G.D.Score(G_j) = max(D.Score(f_i)) \mid f_i \in G_i \qquad (2)$$

Patients who were lateralized based on standard noninvasive investigation and patients who were lateralized based on eECoG are placed in the same cohort for this study. Results are summarized in Table I. The best indicators in each group of patients are reported with their discriminative scores.

TABLE I. DISCRIMINATIVE POWER OF DIAGNOSTIC FEATURE GROUPS IN ALL PATIENTS (PATEINTS LATERALIZED BASED ON STANDARD PRELIMINARY INVESTIGATIONS AND PATIENTS LATERALIZED BASED ON EECOG).

Group	Best Discriminative Feature	D. Score
Imaging	Ictal SPECT subtraction (right-left)	0.88
EEG	Sharp wave 1 activity location (waveform less than 200ms in duration on EEG identified at site 1)	0.88
Wada	Memory score (right-left)	0.70
Neuro-psychology	Boston naming test	0.55
Handedness	Habitual hand used for writing	0.55
Medication	Medication dosage	0.50
Seizure description	Aura without seizure (the occurrence of a simple partial event without the succeeding habitual ictus)	0.54
Medical history	Family history of febrile seizure (seizures with fever)	0.55
Semiology	Olfactory	0.53
Age	Age at surgery	0.49
Exam	Speech dysarthria (poor articulation of speech)	0.49
Psychiatric history	Past depression	0.47

While the AUC at around 0.50 is an indication of a random decision, it could be seen that imaging, EEG and Wada test groups contain most discriminative features.

In the second study, only patients who eventually underwent eECoG for lateralization are included in the investigation. Results from this study are reported in Table II. As lateralization of the patients in this study group is known to be harder, predictive power of attributes are reduced. EEG, imaging and Wada test remain the top three discriminative features. Interestingly, EEG Sharp wave 1 location and Boston naming test from neuropsychology demonstrate slightly better results in comparison with the previous study. Limited number of cases and presence of missing values might be a source for this change.

TABLE II. DISCRIMINATIVE POWER OF DIAGNOSTIC FEATURE GROUPS IN PATIENTS LATERALIZED BASED ON EECOG.

Group	Best Discriminative Feature	D. Score
EEG	Sharp wave 1 activity location (Waveform less than 200ms in duration on EEG identified at site 1)	0.93
Imaging	Ictal SPECT subtraction (right-left)	0.79
Wada	Memory score (right-left)	0.59
Neuro-psychology	Boston naming test	0.65
Semiology	Olfactory	0.50
Psychiatric history	Past depression	0.51
Seizure description	Duration of epilepsy	0.49
Handedness	Habitual hand used for holding a hairbrush	0.48
Age	Duration of latency	0.52
Exam	Motor side (Side of loss of power)	0.44
Medical history	Family history of febrile seizure (seizures with fever)	0.44
Medication	Medication frequency (Number of times drug is taken during the day)	0.44

Here, features in the top three groups are reported from the studies to provide a comparative ground in each section. Subtraction or ratio (whichever is superior) of each imaging feature for the left and right hippocampus is used in these analysis. Features performances in the first study are plotted in Figure 1.

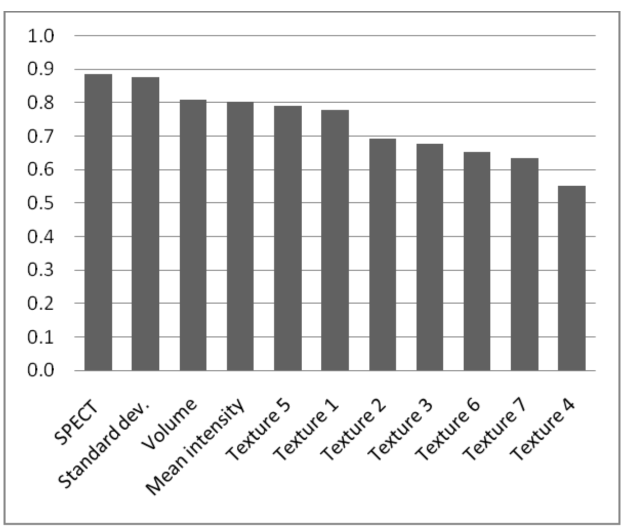

Figure 1. Discriminative power of diagnostic imaging features in all patients (patients lateralized based on standard preliminary investigations and patients lateralized based on eECoG).

In this study, compartmentalized ictal SPECT subtraction is the most discriminative feature. FLAIR MR imaging standard deviation and mean signal intensity perform as the second and the forth with the hippocampus volume in the middle as the third best indicator. Texture analysis of the FLAIR MR imaging signal [5] demonstrate lower discriminative powers.

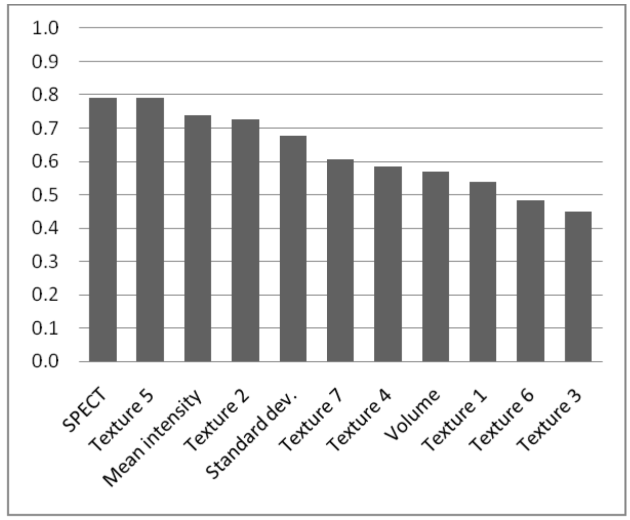

Figure 2. Discriminative power of diagnostic imaging features in patients lateralized based on eECoG.

Study of the imaging features in the second cohort revealed interesting results. While SPECT imaging remains the best indicator for lateralization, hippocampus volume performs with average AUC around 0.57 demonstrating no significant discrimination based on comparative hippocampus volumes for patients in this group.

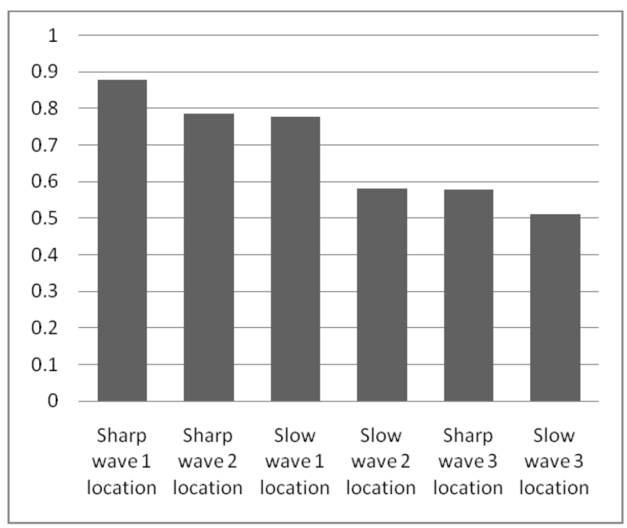

Figure 3. Discriminative power of diagnostic EEG features in all patients (patients lateralized based on standard preliminary investigations and patients lateralized based on eECoG).

Regarding the EEG data, sharp and slow wave locations and their relative frequencies were discriminative. They are listed by order of their frequencies from wave 1 through wave 3 thus specifying the relative activities in their respective locations. Sharp wave 1 location being the most discriminative EEG feature in this study, corresponds accordingly with the clinical belief (Figure 3).

In the second study, the location of the sharp wave 1 demonstrated a higher average AUC while sharp wave 2 location remained the second best indicator. Interestingly, sharp wave 1 location performed slightly better for this group of patients with respect to the previous study. Results from this study are reported in Figure 4.

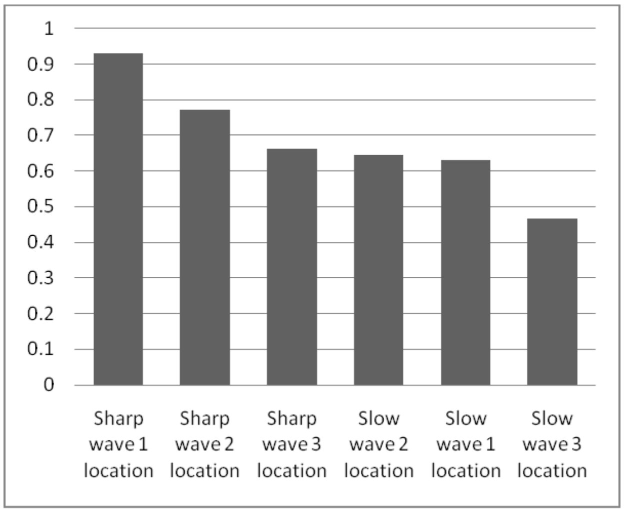

Figure 4. Discriminative power of diagnostic EEG features in patients lateralized based on eECoG.

Regarding the Wada test, the memory score (subtraction of number of correct answers from each side) is the best discriminative feature with an average AUC of 0.70 for the first study. In the second study, this indicator performed with an average AUC of 0.59, showing reduction of discriminative power. Language representation side from the Wada test performed similar to a random feature for all studies, indicating no significant correlation with laterality of the TLE.

IV. CONCLUSION

A consensus feature ranking method is applied to quantitatively prioritize feature groups for lateralizing TLE patients based on Engel class I outcome and the need for eECoG. Both electrographic and imaging attributes provided the highest discrimination of laterality, despite symmetry of hippocampal volumes in a significant number of patients. More detailed features in each of these groups have also been studied to demonstrate their predictive power in terms of laterality.

A high average AUC in some features such as SPECT, FLAIR MR imaging and EEG (sharp wave 1 location) for those patients who underwent eECoG suggests that avoidance of eECoG would have been possible in a number of cases. Computer based applications employing data mining and pattern recognition methodologies and providing quantitative rigor to the analysis of several electrographic and imaging features in TLE are shown to be beneficial not only in the identification of laterality but in potentially reducing the requirement for eECoG.

In the continuation of this work, we will study combinations of features from several diagnostic groups with multiple data mining classifiers to build a model with higher confidence and accuracy. Preliminary results based on the combination of EEG and imaging features indicate a strong likelihood that eECoG can be avoided in a good number of cases. However, to strengthen the reliability of the studies, greater numbers of patients with fewer missing values are desirable.

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