Automatic identification of epileptic focus on high-frequency components in interictal iEEG

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***Abstract*—The localization of the seizure focus affected by epilepsy is crucial for epilepsy treatment due to observing long-term interictal intracranial electroencephalogram (iEEG) for categorizing the patterns of seizures by the neurological experts. Therefore, a computer-aided system based on machine learning method for automatic localization of focal patterns is promising future. In this study, we presents a filter-bank entropy-based feature-extraction approach in high-frequency components to detect epileptic focus, which consider a valid biomarkers to guide epilepsy surgery. The experimental results on real-world interictal iEEG recorded from eight patients demonstrate that our proposed method can achieve average AUC 0.79, which can reduce the workload of clinical experts for detection of epileptic focal.**

***Index Terms*—Epilepsy, interictal iEEG, high-frequency components, filter-bank analysis, entropy**

I. Introduction

Epilepsy is a chronic brain disease, defined by repeated and unpredictable seizure caused by abnormal brain neuronal firing [1]. In the surgical treatment of epilepsy, localization of focal patterns from long-term iEEG is very important. The long-term interictal iEEG signals are recorded over several days to determine the epileptic focus by visual inspection of neurological experts. This type of visual inspection is an extremely time consuming and difficult process. Therefore, a computer-aided automatic detection of epileptic focus is required to reduce the workload of clinical experts by some new methods.

Many approaches for automatic identification of epileptic focus characterizing dynamic nature of brain signal have been proposed using signal processing and machine learning methods [2]–[4] For instance, Sharma et al. proposed the combination of five entropies as features extracted from iEEG data to identify the focal patterns using various classifiers such as k-nearest neighbour (KNN), probabististic neural network (PNN), fuzzy classifier, and least squares support vector machine (LS-SVM) [1]. These above studies used the Bern-Barcelona dataset [5], which consists of 3750 pairs of focal and 3750 pairs of non-focal signals judged by clinical experts. The frequency bandwidth of the iEEG signals was between 0.5 to 150 Hz, which partially exclude high-frequecy oscillations (HFOs) including the ripple (80-250 Hz) and fast ripple (250-600 Hz) bands. Recent studies in epilepsy have shown that HFOs are the valid biomarkers to guide the epilepsy surgery [6], [7]. Multiple reports indicate that the fast ripple bands with repetitive waveform pattern are more localized compare to ripple bands distinguishing seizure onset zone (SOZ) [8].

In this study, the high-frequency components so called high-frequency oscillations (HFOs) in interictal iEEG data are decomposed into multiple subbands and various entropies estimated from each subband as features. Finally, support vector machine (SVM) with radial basis function kernel is used for identifying the focal patterns.

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II. Methods

A. Dataset

Eight patients with temporal lobe epilepsy caused by focal cortical dysplasia (FCD) are used in this study collected from Juntendo university Hospital, Tokyo. This study was approved jointly with the ethics committee of Juntendo University Hospital and Tokyo University of Agriculture and Technology, Japan. All the patients signed the informed consent. The eight patients labelled as Pt192, Pt375, Pt359, Pt088, Pt816, Pt421, Pt749, and Pt074. Three epileptologists identified the seizure onset electrodes from sufficient number of habitual seizures. A positive label was assigned to a channel judged to be a seizure onset and a negative label was given to the rest of the channels.

B. Proposed Method

We divided a 30 minutes interictal iEEG from each patients into 20 seconds segments resulting into 90 segments in total. The high frequency components in iEEG were analyzed dividing them into 10 sub-bands from 100 Hz to 600 Hz with 50 Hz interval. We used eight types of entropy estimating approach such as approximate, sample, permutation, shannon, Renyi, Tsallis, and phase 1 and 2. Finally, support vector machine was used for classifying the epileptic from non-epileptic foci. For epilepsy focal identification, the number of non-focal electrodes is much higher than focal electrodes, which cause imbalance learning problem. In this study, an oversampling with adaptive synthetic (ADASYN) approach was used in the training stage of the SVM for each cross-validation to handle imbalance learning problem. We calculated sensitivity, specificity, positive predictive value, false positive rate and AUC from ROC graph in each subject. We also assessed the relationship between clinical factors and each value.

III. Experimental Result

To evaluate the performance of the automatic detector, the accuracy of our method was evaluated by 10-fold cross validation, consisting of 9-training sets and 1-subset as a test. The localization results of focal and non-focal channels for the eight patients are presented in Fig.1. Note that, the number of focal and non-focal channels are previously defined with neurological experts for the evaluation of the proposed system. It is observed from Fig. 1 that the detected focal epochs at the focal channels were much higher (red peaks) than the non-focal channels.

Automated detection using our method resulted into a higher value of AUC was 0.98 for the patient pt074. Age, seizure duration, seizure frequency, location, and pathology were not related to AUC values. False-positive ratio from the subjects with bottom of sulcus type of FCD were over 10%.

IV. Discussion and Conclusion

This study developed an effective focal detection method from high-frequency bands in interictal iEEG data. We evaluated the proposed method with eight epilepsy patients caused FCD. Considering the real time implementation, the proposed filter-bank method need little computational cost as well as reduce the system complexity compare to other multivariate decomposition methods such as wavelet and empirical mode decomposition (EMD). The deep sheeted FCD shows widely distributed chronological change of HFO and lowers the AUC. Generally, our method is good enough for epileptic focus detection.

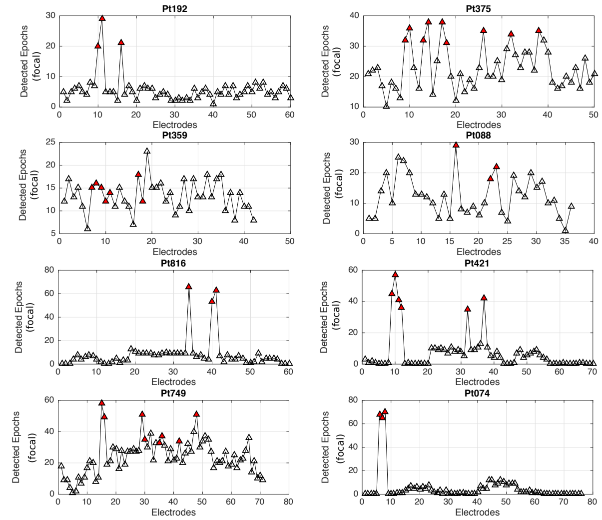

Fig. 1. The Localization results of eight patients. The focal channels are detected with prominent peaks (red arrow) using our proposed method.

References

[1] R. Sharma, R. B. Pachori, and U. R. Acharya, "An integrated index for the identification of focal electroencephalogram signals using discrete wavelet transform and entropy measures," *Entropy*, vol. 17, no. 8, pp. 5218–5240, 2015.

[2] G. J. Ortega, L. Menendez de la Prida, R. G. Sola, and J. Pastor, "Synchronization clusters of interictal activity in the lateral temporal cortex of epileptic patients: Intraoperative electrocorticographic analysis," *Epilepsia*, vol. 49, no. 2, pp. 269–280, 2008.

[3] D. Gajic, Z. Djurovic, J. Gligorijevic, S. Di Gennaro, and I. Savic-Gajic, "Detection of epileptiform activity in EEG signals based on time-frequency and non-linear analysis," *Frontiers in Computational Neuroscience*, vol. 9, p. 38, 2015.

[4] R. Sharma and R. B. Pachori, "Classification of epileptic seizures in EEG signals based on phase space representation of intrinsic mode functions," *Expert Systems with Applications*, vol. 42, no. 3, pp. 1106 – 1117, 2015.

[5] R. G. Andrzejak, K. Schindler, and C. Rummel, "Nonrandomness, nonlinear dependence, and nonstationarity of electroencephalographic recordings from epilepsy patients," *Phys. Rev. E*, vol. 86, p. 046206, Oct 2012.

[6] J. Jacobs, P. LeVan, R. Chander, J. Hall, F. Dubeau, and J. Gotman, "Interictal high-frequency oscillations (80-500 Hz) are an indicator of seizure onset areas independent of spikes in the human epileptic brain," *Epilepsia*, vol. 49, no. 11, pp. 1893–1907, 2008.

[7] M. Dmpelmann, J. Jacobs, K. Kerber, and A. Schulze-Bonhage, "Automatic 80-250 Hz ripple high frequency oscillation detection in invasive subdural grid and strip recordings in epilepsy by a radial basis function neural network," *Clinical Neurophysiology*, vol. 123, no. 9, pp. 1721 – 1731, 2012.

[8] K. Kerber, M. Dmpelmann, B. Schelter, P. L. Van, R. Korinthenberg, A. Schulze-Bonhage, and J. Jacobs, "Differentiation of specific ripple patterns helps to identify epileptogenic areas for surgical procedures," *Clinical Neurophysiology*, vol. 125, no. 7, pp. 1339 – 1345, 2014.