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Seizure Prediction Based on Classification of EEG Synchronization Patterns with On-line Retraining and Post-Processing Scheme

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***Abstract*— Epilepsy is one of the most common brain disorders in the world. The spontaneous seizure onset influences the daily life of epilepsy patients. The studies on feature extraction and feature classification from Electroencephalography(EEG) signal in seizure prediction methods have shown great improvement these years. However, the variation issue of EEG signal (being awake, being asleep, severity of epilepsy, etc.) poses a fundamental difficulty in seizure prediction problem. The traditional off-line training method trains the model using a fixed training set, and expects the performance of the model to remain stable even after a long period of time, and thus suffers from variation issue. In this paper, we propose an on-line retraining method to leverage the recent input data by gradually enlarging the training set and retraining the model. Also, a simple post-processing scheme is incorporated to reduce false alarms. We develop our method based on the state of the art machine learning based classification of bivariate patterns method. The performance of the method is evaluated on Electrocorticogram(ECoG) recording from Freiburg database as well as long-term scalp EEG recording from CHB-MIT EEG Database and National Taiwan University Hospital. The proposed method achieves 74.2% sensitivity on ECoG database and 52.2% sensitivity on scalp EEG database, while improving the sensitivity of off-line training method by 29.0% and 17.4% in ECoG database and EEG database respectively. The experimental result suggests that on-line retraining can greatly improve the reliability and is promising for future seizure prediction method development.**

I. INTRODUCTION

A. Epilepsy and Seizure Prediction

Epilepsy is the world's second most common brain disorder with over 40 million people worldwide suffering from it [1]. It is a neurological disorder characterized by *seizures* [2]. These seizures are transient symptoms of abnormal, excessive or synchronous neuronal activity in the brain [3]. Two-thirds of the patients achieve sufficient seizure control from medication, and another 8-10% could benefit from resective surgery. For the remaining 25% of patients, no sufficient treatment is currently available [4].

Even if epileptic seizures are rare in a given patient, the constant fear of the next seizure and the feeling of helplessness often have a strong impact on the daily life of a patient [5]. A method reliably predicts the occurrence of seizures could significantly improve the quality of life for these patients, and open new therapeutic possibilities such as on-demand drug delivery or on-demand electrical stimulation which resets brain dynamics [6].

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B. Seizure Prediction Problem

Great efforts have been spent on seizure prediction through EEG monitoring for more than 3 decades. It has long been observed that the transition from the interictal state (far from seizures) to the ictal state (seizure) is not sudden and may be preceded from minutes to hours by clinical, metabolic or electrical changes [7]. The goal of seizure prediction problem is to predict an upcoming seizure based on the analysis of biomedical signal recorded from patients. In seizure prediction problems, there are some basic terms as follow:

1) The *ictal state* is a period of time in which seizure onset is identified by epileptologists through EEG or ECoG waveform examination.
2) The *preictal state* is a period of time before the seizure onset occurs.
3) The *postictal state* is a period of time after the seizure onset ends.
4) The *interictal state* is other than the above three states.

Note that in seizure prediction problem, the duration of each state is decided by human speculation rather than an objective value since the true mechanisms of spontaneous occurrence of seizures are not completely understood. Generally, the data corresponding to ictal and postictal is discarded in this setting, because the task is to predict a upcoming seizure. *Prediction Horizon* is the period after an alarm within which a seizure is expected to occur. If a seizure occurs within the prediction horizon, the alarm is classified as a true alarm, otherwise it is regarded as a false alarm. Prediction horizons reported in the literature range from several minutes to few hours [6].

C. Seizure Prediction Methods

Most current seizure prediction approaches can be summarized into two steps. The first is extracting measurements such as similarity or synchronization from EEG over time. The second is classifying them into a preictal or interictal state using statistical analysis or other machine learning techniques such as neural network and support vector machine [8]. An extensive review of these methods can be found in [1]. Recently, a machine learning based method proposed by Mirowski and et al. predicts seizures by doing pattern recognition on high-dimensional bivariate synchronization features has achieved outstanding sensitivity and low false alarm rate [9]. We found that the method is very promising and proposed our method based on this work. However, it should be noted that our proposed method is not limited to the machine learning based pattern recognition method. We will briefly review this method in Section II.

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D. Challenges of Seizure Prediction Problems

There is a fundamental issue in seizure prediction problem that has not been properly resolved, which is *variation* issue. A model trained from several seizures may have no predictive power for the upcoming seizures in next few days or even few hours. It is too optimistic to expect the performance of the trained model to persist while the patient condition varies constantly. Also, the amount of past seizures that a trained model needs to learn remains a basic issue in seizure prediction problem. On the other hand, it is also important to reduce false alarms to relieve patients from being worried about nonexistent upcoming seizures.

In Section III, we elaborate the proposed *on-line retraining method* to deal with the variation issues by making most use of available data. A simple post-processing scheme has also been incorporated to reduce false alarms. The simulation results on ECoG database as well as long-term EEG database as case studies are shown in Section IV, and Section V concludes this work.

II. REVIEW OF MACHINE LEARNING BASED CLASSIFICATION OF PATTERNS METHODS

The machine learning based method is proposed by Mirowski and et al. [10]. The method follows a similar methodology in traditional methods, that is, feature extraction followed by binary classification of features into preictal or interictal states. The breakthrough of this method is that machine learning enables classification of high-dimensional feature vectors which aggregate into patterns. In contrast, the traditional method restricts feature to a low-dimensional vector or a scalar value. We briefly describe the steps of this method below.

A. Feature Extraction

Figure 1 shows an example of feature extraction.

1) Bivariate Feature: First, the frequency-specific phase of EEG signal of each channel is extracted by continuous wavelet transform at each band [11]. Then, statistics which measure the synchronization of the phase between two channels (such as wavelet coherence [12]) are computed for all pairs of channels and frequency bands. In our study, we adopt a window of length 5 seconds to compute one wavelet coherence value between two channels.

2) Feature Aggregation: After extracting synchrony features from raw data, these features are further aggregated into certain size of matrix(i.e. pattern). The number of rows in the pattern corresponds to the number of pairs times the number of frequency bands. The number of columns in the pattern corresponds to the duration of one pattern divided by 5 seconds. In this study, we adopted the convention of [9] using 7 bands and 5 minutes as our baseline method. For 6 channel ECoG data, each pattern is a matrix with dimension 105 (7 bands for 15 pairs) by 60 (5 minutes / 5 seconds), which is a 6300-dimension vector in vector form.

B. Feature Classification

After feature aggregation, classifiers such as neural network or support vector machine (SVM) can be used to classify the patterns into preictal and interictal states. The development in machine learning enables the classification task for high-dimensional feature vectors. Support vector machine is a popular technique for data classification. Generally, for high-dimensional data, the performance of Linear SVM is comparable with SVM using kernel of higher order, while the time complexity is much smaller.

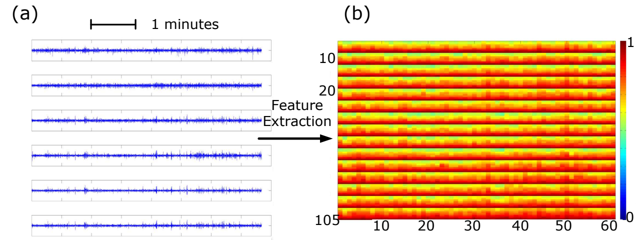

Fig. 1. The illustration of feature extraction. (a) The input data is 5 minutes of 6-channel EEG data. (b) The pattern extracted from (a). There are 105 rows in the pattern(7 bands x 15 pairs). Each row contains 60 wavelet coherence values. Every wavelet coherence value is computed from 5 seconds data of one pair of channels.

III. THE PROPOSED METHODS

A. On-line Retraining Method

The main idea of on-line retraining method is to learn the preictal and interictal patterns while performing seizure prediction. In the traditional off-line method as shown in figure 2, a fixed portion of the data serves as training set, and the rest as testing set. The testing data can not be used to refine the model parameters. In on-line retraining method, the size of training set gradually increases as more and more data becomes available. With more recent data, the method is more capable of dealing with variation issue in seizure prediction problem than off-line method. The block diagram of on-line retraining method is shown in figure 3. In this scenario, we assume an on-line seizure labeling feedback is available through push-button from patients or from a seizure detection module. The assumption is practicable since many EEG recording devices are already equipped with push-buttons to mark the event, and seizure detection method has been widely studied. The state of the art seizure detection method can achieve sensitivity higher than 96%, while merely few false alarms happen [13]. The extracted patterns can be stored in a buffer, and be labeled by the detection result/push button later after prediction horizon. The patterns which have already been labeled can serve as training data and refine the classifier.

Figure 4 shows the timing diagram of on-line retraining method. Each row shows the duration of training data and valid prediction region of each retraining iteration. Every two consecutive rows are separated by a duration of retraining period. Assuming the prediction horizon is 2 hours (green segment), and the EEG signal is being recorded with detection feedbacks. Then the data up to last 2 hours can be labeled according to the detection feedbacks. Therefore, the training set duration should start from the oldest available recording to last 2 hours (blue segment). Each retrained model is only responsible for the prediction in a near future (red segment). The duration of the valid prediction is the same as retraining period. The retraining period can be set

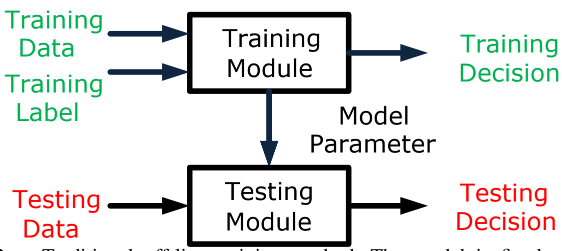

Fig. 2. Traditional off-line training method. The model is fixed after training, and the testing data is obsoleted after testing.

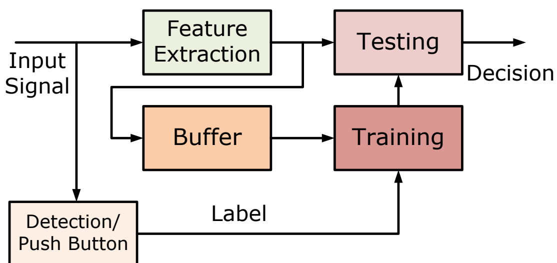

Fig. 3. On-line retraining method. The input data can be labeled by detection/push button input, and the model can be refined through retraining.

considering the computing throughput and the variation of EEG data. For example, in our study, a retraining period of half an hour is feasible with SVM training algorithm implemented on a RISC processor.

B. Classification for On-line Retraining: Linear Support Vector Machine Classifier

In [9], both convolutional neural network (CNN) and support vector machine exhibit certain ability to do classification on synchronization patterns. Neural network can support both on-line learning and batched learning. However, there are some difficulties in both modes. There may be very few preictal patterns while most of the patterns are interictal. In on-line learning mode, neural network classifiers may gradually loose the ability to recognize preictal patterns after learning a long series of interictal patterns. In batched learning mode, neural network classifiers can successfully learn the patterns, but it requires a long time (up to several hours) to obtain a stable model. In [9], the author addressed this problem through an off-line training stage, which is not suitable in our proposed scenario. Support vector machine requires less time in training stage (within several minutes), so it is more applicable for on-line retraining method. There is an on-line learning extension of SVM called incremental SVM [14]. However, there is no well-established implementation of this algorithm so far, so we prefer the traditional SVM provided by libsvm [15] in our study. In our simulation setting, we store all the patterns from the beginning since the total length of recordings is less than 48 hours for a given patient. Practically, to meet hardware constraints, we can set two individual FIFO queues for preictal patterns and interictal patterns.

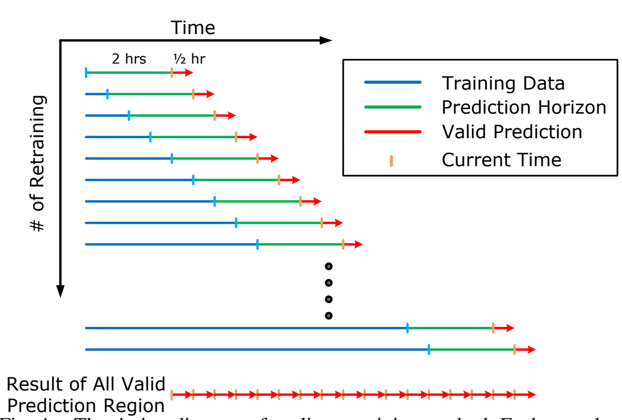

Fig. 4. The timing diagram of on-line retraining method. Each row shows the training data segment(blue segment) and the period of time in which the decision of the trained model is valid(red segment). Each retrained model is only responsible for a near future. The result of on-line retraining method can be obtained by aggregating decisions in all the valid prediction regions.

C. post-processing

We adopt a simple two-in-a-row post-processing technique to reduce false alarms. The alarm would be generated only if there are two consecutive patterns classified as preictal. This technique can neglect the false alarm generated alone once in a while and reduce the false alarm rate.

IV. RESULTS & DISCUSSION

We evaluate our proposed method on Freiburg ECoG database as well as long-term scalp EEG database.

A. Experimental Setup

In each testing condition that follows, we compare the performance of three algorithm flows as shown in figure 6. In off-line training flow, the classifier can only be trained using data in the training set, as shown in figure 6(a). In on-line retraining flow and on-line retraining with post-processing flow, the classifier can be retrained using more and more recent data, as shown in figure 6(b),(c). In all the experiments, the input data is first filtered by a band-pass filter of 1-100 Hz, and a notch filter of power-line frequency (50Hz or 60 Hz). The flow for off-line training method is basically the same as [9] except that the classifier is linear SVM in our experiment. Specifically, we use complex Gaussian wavelet for wavelet coherence feature extraction, and set the prediction horizon and postictal duration to be 2 hours.

B. Freiburg ECoG Database

The Freiburg database is a publicly available intracranial EEG database provided by the Epilepsy Center of the University Hospital of Freiburg, Germany [16]. The database contains 6-channel intracranial EEG recording of 21 patients. Each of the recording is composed of ictal part and interictal part. The number of electroencephalographic seizure onsets in ictal part is between 2 and 5. At least 50 min of preictal data for most seizures is available. The interictal part contains about 24 hours of recording without seizure activity. To test the concept of on-line retraining, we arrange the data segments of preictal and ictal states into long term interictal states such that the durations of interictal states between seizure onsets are approximately the same. Figure 5 illustrates the example of arrangement.

We evaluate the proposed method on two different testing sets, that is, original testing set and enlarged testing set. In *original testing set*, we separate the data before the specified

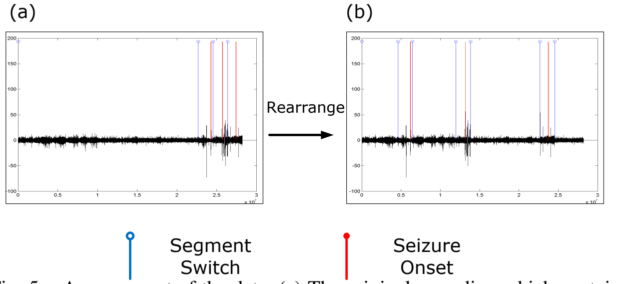

Fig. 5. Arrangement of the data. (a) The original recording which contains both interictal part and ictal part (with preictal and postictal). (b) After arrangement, we can simulate long-term ECoG data in which spontaneous seizure onsets occur from time to time.

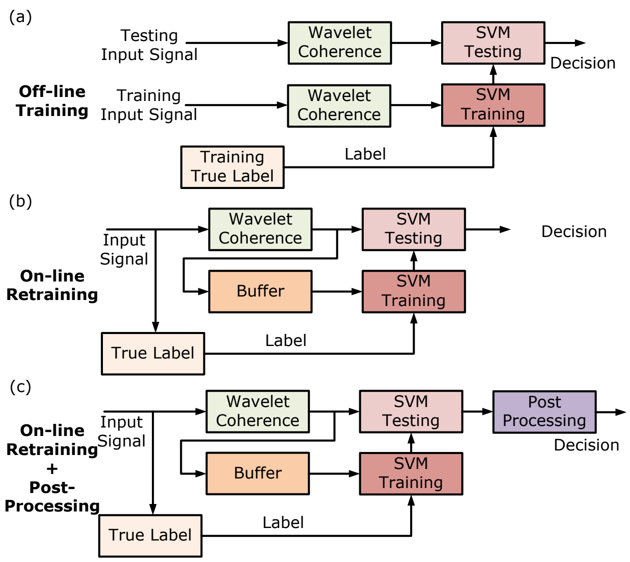

Fig. 6. The algorithm flows. (a) Off-line training method. (b) On-line retraining method. (c) On-line retraining method with post-processing scheme.

number of seizure onsets as shown in table I into training set and the data after that number of seizure onset into testing set. Note that in [9], a fixed portion of 2/3 interictal data is assigned to training set, which is different from our setting, although the result is generally comparable. On the other hand, using on-line retraining method, we expect the model to have certain prediction ability before learning all the data in the original training set. Ideally, the model should be able to predict the next seizure onset after learning the preictal data corresponding to the first seizure onset. We use *enlarged testing set* to evaluate the prediction ability under this condition.

C. Result on ECoG Database

1) Original Testing Set: As shown in table I, the original testing set is composed of certain number of seizure onsets

TABLE I

ORIGINAL TESTING SET AND ENLARGED TESTING SET

Number of Total Seizure Onsets	Original Training Set for off-line	Original Testing Set	Enlarged Training Set for off-line	Enlarged Testing Set
2	1	1	1	1
3	2	1	1	2
4	2	2	1	3
5	3	2	1	4

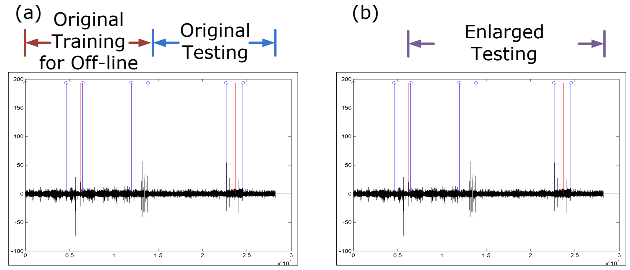

Fig. 7. (a) An example of original testing set for number of total seizure onsets equals to three. In off-line training method, the classifier can only be trained once using the data before the first and the second seizure onset. In on-line method, the training set can gradually increase the size and retrain the classifier. Only the response in original testing set region is taken into evaluation. (b) An example of enlarged testing set for number of total seizure onsets equals to three. We expect the model to be functional right after it learns the first seizure.

TABLE II

SIMULATION RESULTS OF ORIGINAL TESTING SET

Method	Off-line	On-line	On-line+Post-Processing
Successful Patient	9/21	13/21	16/21
Successful Prediction	14/31	19/31	23/31
Failed Prediction	17/31	12/31	8/31
Successful Rate	45.2%	61.3%	74.2%

according to the total number of available seizure onsets. Note that the second column (original training set for off-line) is only for off-line method, as shown in figure 7(a). In contrast, on-line method can gradually enlarge the training set in each retraining iteration. Only the patients whose results satisfy the following two conditions would they be counted as successful patients.

- False positive rate less than 0.2 per hour.
- At least one alarm is generated in the preictal period.

The results of different methods are shown in table II. The on-line retraining method boosts the successful rate from 45.2% to 61.3%, and post-processing scheme further enhances it to 74.2%. An typical example is shown in figure 8. The figure is obtained through aggregation of all valid prediction regions as shown in the bottom of figure 4. The post-processing scheme reduces false alarms and results in more successful patients, and hence enhances successful rate.

2) Enlarged Testing Set: As shown in figure 7(b) and specified in table I, all the seizure onsets other than the first

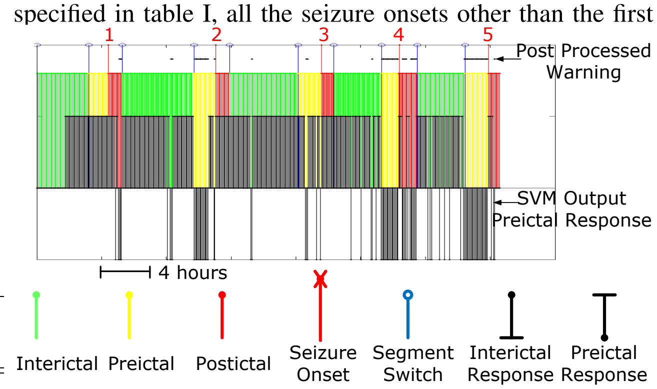

Fig. 8. The result of on-line retraining method with post-processing scheme of patient 17 in Freiburg database. The legend is shown below. There are some isolated false alarms between the fourth and the fifth seizure onset. However, they can be neglected by post-processing scheme.

TABLE III

SIMULATION RESULTS OF ENLARGED TESTING SET

Method	Off-line	On-line	On-line+Post-Processing
Successful Patient	8/21	13/21	16/21
Successful Prediction	24/66	37/66	45/66
Failed Prediction	42/66	29/66	21/66
Successful Rate	36.4%	56.1%	68.2%

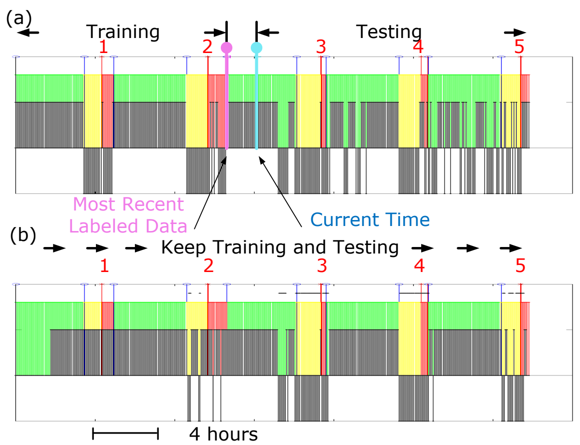

Fig. 9. The result of patient 10 in Freiburg database. (a) The response of the on-line retrained classifier right after learning the second seizure onset. The pink segment marks the right boundary of the training set for this retraining iteration. The cyan segment marks the current time. Although the response is perfect in training set, there are many false alarms between the fourth and the fifth seizure onsets if the classifier were used to make decision during that time. (b) The result of the on-line retraining method with post-processing scheme. The figure is obtained through aggregation as shown in the bottom of figure 4. The false alarms are greatly reduced since the classifier can gradually learn interictal patterns.

one can serve as testing objects. Therefore, the size of testing set is enlarged from 31 to 66.

The results of different methods are shown in table III. The on-line retraining method boosts the successful rate from 36.4% to 56.1%, and post-processing scheme further enhances it to 68.2%. A typical example of the learning process of the classifier in on-line retraining method is shown in figure 9. In figure 9(a), we examine the response of the retrained classifier for all data segment to judge the prediction ability, although every retrained classifier is only accountable for a short period of time right after specified current time. In figure 9(a), the classifier has learned the preictal data of the first and the second seizure onsets and the interictal data before the second seizure onset. However, if this classifier stops learning, and we use this classifier to predict next three seizure onsets, there would be many false alarms generated by this classifier. On the other hand, figure 9(b) shows the response if the classifier keeps retraining. Although there would be some false alarms between the second and the third seizure onset, the false alarms after the third seizure onset could be greatly reduced since the classifier can learn recent interictal data. Another typical example of the learning process of the classifier is shown in figure 10. The classifier does not gain prediction ability after learning the first seizure onset as shown in figure 10(a). However, after learning part of preictal patterns of the second seizure onset, the classifier gains prediction ability of the third and the fourth seizure onsets as shown in figure 10(b).

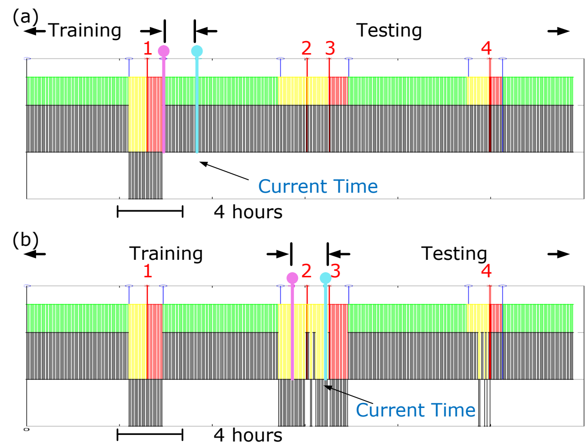

Fig. 10. The two snapshot of patient 11 in Freiburg database. (a) The response of the retrained classifier right after learning the first seizure onset. It shows that the classifier has no prediction ability of the future seizure onsets. (b) The response of the retrained classifier after learning part of preictal data of the second seizure onset. The classifier gains the ability to predict the third and the fourth seizure onsets.

TABLE IV

SENSITIVITY VERSUS NUMBER OF LEARNED SEIZURES FOR ENLARGED ECOG TESTING SET OF ON-LINE RETRAINING AND POST-PROCESSING SCHEME

Number of Seizures in Training Set	1	2	3	4
Successful Predictions	12	13	12	8
Total Predictions in Successful Patients	16	16	13	8
Sensitivity in Successful Patients	75.0%	81.3%	92.3%	100%
Total Predictions in All Patients	21	19	16	10
Sensitivity in All Patients	57.1%	68.4%	75.0%	80.0%

3) Number of Learned Seizure Onsets for Enlarged Testing Set: We further explore the relation between prediction ability and the number of learned seizure onsets. We examine the relation within only successful patients and among all patients. The result is shown in table IV and figure 11. For successful patients, the sensitivity achieves 100% as the number of learned seizure onsets accumulates to 4. From this result, we expect that the number of preictal patterns to be stored in order to retain prediction ability would be finite.

D. Long-term Continuous EEG Recording

We also evaluated the method on CHB-MIT Scalp EEG Database [17]. The CHB-MIT scalp EEG database is composed of long-term scalp EEG recording of 24 patients. Most of the recording contains more than 22 channels.

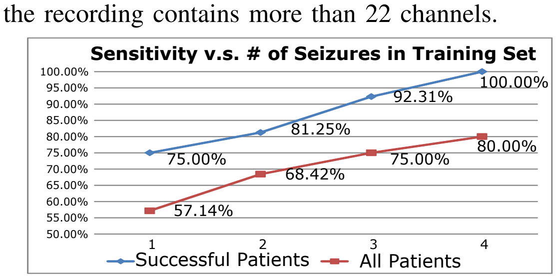

Fig. 11. For successful patients in invasive EEG database, the on-line retraining method achieves 100% sensitivity as the classifier learns 4 seizure onsets.

TABLE V

TRAINING SET AND TESTING SET IN EEG DATABASE

Patient	1	3	6	7	9	10	22	NTUH	Total
Training for off-line	2	4	3	2	1	1	1	3	17
Testing	5	3	4	1	3	1	1	5	23
Total	7	7	7	3	4	2	2	8	40

TABLE VI

SIMULATION RESULTS OF EEG DATABASE

Method	Off-line	On-line	On-line+Post-Processing
Successful Patient	2/8	4/8	5/8
Successful Prediction	8/23	11/23	12/23
Failed Prediction	15/23	12/23	11/23
Successful Rate	34.8%	47.8%	52.2%

Some of the recordings are not suitable for seizure prediction problem. We select 7 patients (patient 1, 3, 6, 7, 9, 10, 12) satisfying the following conditions for seizure prediction problems.

1) There is at least one interictal state longer than 4 hours between two seizure onsets.
2) The recording of above interictal state is not disrupted by more than one hour.

We also evaluate one long-term EEG recording of a patient at National Taiwan University Hospital (NTUH). The training set and the testing set of these patients are shown in table V. Note that the second row (Training for off-line) is only for off-line method. On-line method can gradually enlarge the training set in each retraining iteration.

E. Result on EEG Database

The results of different methods on these 8 patients are shown in table VI. The criterion of successful patient is the same as stated in IV-C.1. The on-line retraining method improves the successful rate from 34.8% to 47.8%, and post-processing scheme further enhances it to 52.2%. The performance is weaker on EEG database than on ECoG database because the information provide by 6 channel ECoG on focal and non-focal region is more direct in comparison with the information from 22-channel scalp EEG without knowledge of focal and non-focal region. Also, the pattern size becomes larger and deteriorates the performance of classifier due to *curse of dimensionality*.

Five (patient 1,3,10,12 from CHB-MIT database, and the patient from NTUH) out of eight selected patients exhibit good prediction results. A typical example of successful result of on-line retraining with post-processing scheme is shown in figure 12. After learning the first preictal state, the proposed method can successfully predict the 2nd to the 7th seizure onset, although the 2nd seizure onset is not counted in testing set in table V. The false alarms are rare, and the single false alarm generated by SVM can be neglected by post-processing.

V. CONCLUSIONS

In this paper, an on-line retraining method with simple post-processing scheme based on bivariate feature extraction and machine learning method is proposed. The proposed on-line retraining method aims to solve variation issue in seizure prediction problem by leveraging the input information and detection/push-button input. Also, simple post-processing scheme helps to reduce false alarms. The proposed method is compared with traditional off-line training method using benchmark Freiburg ECoG database as well as multi-channel scalp EEG data from CHB-MIT database and NTUH. The comparison and discussion show that online-retraining successfully enhances the sensitivity and reduces false alarms by incorporating more recent data into classifier retraining. Further, the proposed method leads to a promising foundation for future seizure prediction method development.

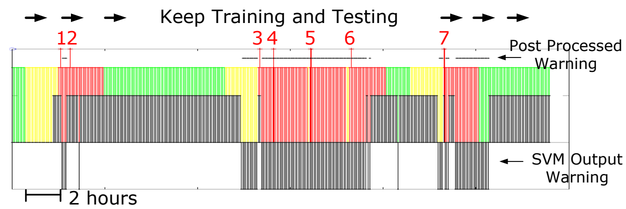

Fig. 12. The result of on-line retraining method on patient 1 in CHB-MIT database. The classifier can successfully predict all the seizures after learning part of the preictal data of the first seizure onset.

REFERENCES

[1] N. Sivasankari and et al., "An extensive review of significant researches on epileptic seizure detection and prediction using electroencephalographic signals," *Advances in Biomedical Research*, 2010.

[2] International League Against Epilepsy, "Guidelines for epidemiologic studies on epilepsy," *Epilepsia*, vol. 34, pp. 592-596, 1993.

[3] R. S. Fisher and et al., "Epileptic seizures and epilepsy: definitions proposed by the International League Against Epilepsy (ILAE) and the International Bureau for Epilepsy (IBE)," *Epilepsia*, vol. 46, pp. 470-472, 2005.

[4] F. Mormann and et al., "Seizure prediction: the long and winding road," *Brain*, vol. 130, pp. 314-333, 2007.

[5] R.S. Fisher and et al., "The impact of epilepsy from the patient's perspective I. Descriptions and subjective perceptions," *Epilepsy Res.*, vol. 41, pp. 39-51, 2000.

[6] Florian Mormann, "Seizure prediction," *Scholarpedia*, vol. 3, no. 10, pp. 5770, 2008.

[7] K. Lehnertz, M. Le Van Quyen, B. Litt "Seizure prediction," in *Epilepsy: A comprehensive textbook*, 2nd ed., Lippincott Williams & Wilkins, Philadelphia, pp. 1011-1024, 2007.

[8] C. Cortes and V. Vapnik., "Support-vector network," *Machine Learning*, vol. 20, no. 3, pp. 273-297, 1995.

[9] P. Mirowski and et al., "Classification of patterns of EEG synchronization for seizure prediction," *Clinical Neurophysiology*, vol. 120, no. 11, pp. 1927-1940, Nov. 2009.

[10] P. Mirowski and et al., "Comparing SVM and convolutional networks for epileptic seizure prediction from intracranial EEG," *IEEE Proc. Machine Learning and Signal Processing*, 2008.

[11] M. Le Van Quyen and et al., "Comparison of Hilbert transform and wavelet methods for the analysis of neuronal synchrony," *J. Neurosci Method* vol. 11, pp. 83V98, 2001.

[12] A. Grinsted, J. C. Moore, and S. Jevrejeva, "Application of the cross wavelet transform and wavelet coherence to geophysical time series," *Nonlinear Processes in Geophysics*, vol. 11, pp. 561-566, 2004.

[13] Ali Shoeb, John Guttag. "Application of machine learning to epileptic seizure onset detection," *27th International Conference on Machine Learning (ICML)*, 2010.

[14] G. Cauwenberghs and T. Poggio. "Incremental and decremental support vector machine learning," *Advances in Neural Information Processing Systems*, vol. 13, 2001.

[15] C.-C. Chang and C.-J. Lin, "LIBSVM: a library for support vector machines," 2001, Software available at http://www.csie.ntu.edu.tw/ cjlin/libsvm.

[16] Freiburg invasive EEG database, Epilepsy Center of the University Hospital of Freiburg, available at https://epi-lepsy.uni-freiburg.de/freiburg-seizure-prediction-project/eeg-database/.

[17] A. L. Goldberger and et al., "PhysioBank, PhysioToolkit, and PhysioNet: Components of a New Research Resource for Complex Physiologic Signals," *Circulation*, vol. 101, pp. e215-e220, Jun. 2000