

# Exploration of Instantaneous Amplitude and Frequency Features for Epileptic Seizure Prediction

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**Abstract**—For the purpose of effective epileptic seizure prediction, this paper presents a new representation for the electroencephalogram (EEG) signal by recurring to their primary amplitude and frequency components. This formulation is then applied on an epoch-by-epoch basis to the preictal and interictal states of EEG signals in order to extract the most dominant amplitude and frequency characteristics. Through inspecting and identifying the distinctive EEG signal changes and stage transitions revealed by these extracted feature vectors, upcoming epileptic seizures could be predicted in due course. Machine learning approaches have been employed to construct patient-specific classifiers that can divide the extracted feature vectors into preictal and interictal groups. In this context, our work is distinguished from most currently adopted feature extraction process which employs time-consuming high-dimensional parameter sets. We have made special efforts to derive discriminative and comprehensive features for the front-end of the epileptic seizure prediction algorithm. To reduce false alarms due to trivial signal fluctuation, a simple yet effective post-processing step is incorporated thereafter. Performance of the prediction algorithm is assessed through out-of-sample evaluation on the intracranial EEG (iEEG) recordings provided by the publicly available Freiburg data set. It has been shown by simulation results that the proposed feature estimation method leads to promising prediction results in terms of sensitivity and specificity. In particular, only four out of the 83 seizures across all the patients included in our experiment were missed by the prediction, which means that a sensitivity as high as 95.2% has been achieved.

**Index Terms**—Epileptic seizure prediction, electroencephalogram signal representation, instantaneous amplitude and frequency modulation features.

## I. INTRODUCTION

Epilepsy is one of the most common neurological disorders worldwide, second only to stroke. Around 1% of the world's population are affected by various types of epilepsy. Epilepsy characterized by recurring seizures are resulted from sudden disturbances of brain function. For people with epilepsy, apart from the embarrassing situations that may happen at unpredictable occasions, they are threaten by sudden lapse of attention or convulsion. The aftermath of seizures such as dyspnoea or serious injuries usually does the most harm to them. Two thirds of patients can achieve sufficient seizure control with the help of anti-convulsive medication, another 8 ~ 10% people could get benefit from resective surgery. However, for the remaining 25% of patients, no adequate treatment is currently available [1].

There are several major phases of seizures. By the definition given by the epilepsy foundation of America [2], preictal is a period of time before the seizure onset occurs, which can

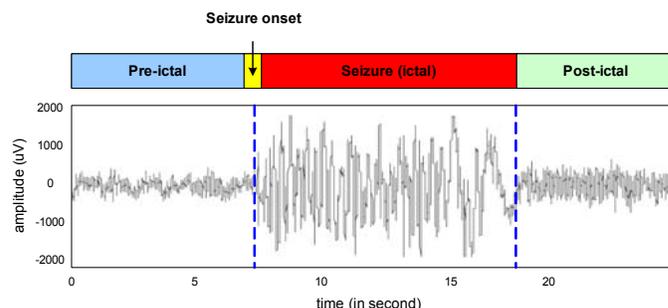


Fig. 1. EEG preictal-postictal transition.

last from minutes to days. Ictal is the period during which the seizure takes place. Postictal is the period after the seizure ends, which can sometimes take several hours. Interictal is the time between seizures. In Figure 1, the preictal-postictal stage transition for an example seizure cycle is illustrated. Recent clinical studies have found premonitory symptoms for seizures from a certain portion of patients with epilepsy [3], [4]. There are also evidences showing that the interictal-ictal transition is not abrupt. During this period of time, the person with epilepsy manifests changes in medical measurements such as cardiovascular, metabolic, and EEG recordings [5]. These changes will help a neurologist to predict an upcoming seizure. The most common way for epilepsy diagnosis is through analysis of EEG. The EEG is typically described in terms of rhythmic activity and transients [6]. The rhythmic activity is divided into bands by frequency like those shown in Figure 2.

Epileptic seizure onset detection algorithms aim to raise alarms as soon as a seizure occurs on a patient from examining his/her EEG data [7]. These alarms will startup devices that are capable of quickly reacting to a seizure by delivering therapy or notifying a caregiver, thus alleviating fatal consequences of seizures.

On the other hand, there is the challenge of predicting epileptic seizures, which is approached by searching for distinctive changes in the EEG before seizure onsets. An epileptic seizure prediction algorithm has to forecast an upcoming seizure by raising an alarm prior to seizure onset. The time interval after an alarm within which a seizure is expected to take place is called Seizure Prediction Horizon (SPH) in the context of seizure prediction characteristic. SPH ranges from several minutes to few hours [8]. If a seizure occurs within the SPH, the alarm is regarded as a correct prediction; otherwise,

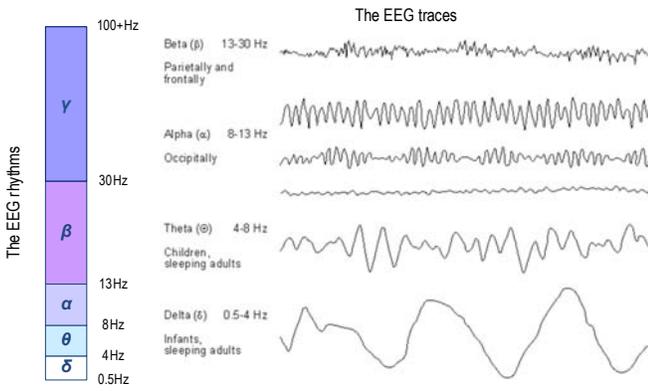


Fig. 2. Typical rhythmic activities in an EEG signal.

it is counted as a false alarm.

Current seizure prediction approaches mostly adopt a two-step strategy: extracting measurements from EEG signals along the time line, and then determining their phases to be either preictal or interictal within a binary classification framework. The machine learning based approaches have been employed in state-of-the-art seizure prediction and detection algorithms [7], [9], [10], [11], [12], [13], [14], [15]. The studies on feature extraction and classification for EEG data in seizure prediction methods have achieved noticeable improvement throughout these years. However, considering the variation issue and non-stationary nature of EEG signals, hardly any systematic analytical models have been accounted in expressing essential epilepsy-related EEG characteristics in a comprehensive yet compact way. In [7] and [10], the spectral structure, the channels on which a seizure manifests, and its short-term temporal evolution, in total 432 parameters from 6 second windows of EEG waveforms, were produced by the front-end feature extractor for a support vector machine (SVM) classifier. Mirowski *et al.* in [11] and [12] proposed a bivariate pattern method to capture the brainwave synchronization measures, where the spatio-temporal bivariate features constitute vectors with dimension as high as 6300 for a 5-minute time span. The power spectra of time- and space-differential EEG signals have been employed as seizure prediction characteristics in [14]. Spatio-temporal correlation structure of multi-channel EEG data were also taken as seizure indicators [15]. Besides these spectral, temporal information, and their correlation, the auto-regression parameters were proven discriminative in distinguishing ictal/preictal states from others [13]. Current seizure prediction patterns mostly consist of a large number of parameters. Although sophisticated machine learning tools can alleviate the computational burden caused by feature classification in a very high dimensional data space, the high complexity of feature extraction process still greatly increase the operational cost of these algorithms. Besides, it is known that the amplitude-frequency modulation theory provides an apposite way to study the dynamic mechanism of narrow-band signals like EEG rhythms. Dáaz *et al.* have reported their findings in characterizing preictal, ictal, postictal and interictal phases within a recurrent seizure cycle through

the instantaneous amplitude modulation (AM) and frequency modulation (FM) components of a given EEG signal [16]. They also gave a graphical and analytical description of epileptic seizures based on multi-band AM, FM parameters. The AM-FM representation of EEG signals helps to visualize the phase-transition of an epileptic seizure as well as to probe the underlying epilepsy mechanisms.

Consider the fact that few research efforts have been specialized in extracting amplitude-frequency modulation patterns of EEG signal for seizure prediction purposes. In this paper, with the attempt to derive amplitude-frequency related patterns as epileptic seizure indicators, a pertinent representation for the dominant rhythms present in the EEG signal is first developed. The representation is then applied to epochs of the EEG signal to derive effective epilepsy-related characteristics. Finally, these features are evaluated on a patient-specific basis under state-of-the-art machine learning based epileptic seizure prediction algorithms.

## II. SEIZURE PREDICTION FEATURES

This section first observes the primary amplitude-frequency modulation components in an EEG signal, and then introduces the feature extraction process.

### A. Amplitude-frequency modulation signal representation for the EEG signal

A narrow-band signal, whose bandwidth is sufficiently small, can be viewed as a monocomponent amplitude and frequency modulating (AM-FM) signal. Among the frequencies spanning over the signal spectrum, there is one frequency bin assuming a majority of the signal energy. The two determining parameters in an AM-FM signal is *amplitude* and *phase*. The  $k$ th EEG rhythm  $s_k(n)$  as shown in Figure 2 could be formulated as an AM-FM term by Equation (1):

$$s_k(n) = A_k(n)\cos[\Theta_k(n)], \quad (1)$$

with the EEG rhythm being characterized by two sequences:

- $A_k(n)$  – Amplitude of rhythm;
- $\Theta_k(n)$  – Phase of rhythm.

Teagers proposed to employ a multicomponent AM-FM model in exploring amplitude-frequency modulation patterns in speech resonances [17]. Likewise, considering the multiple characteristic bands of EEG, we can also interpret it as a multicomponent AM-FM signal. An EEG signal can thus be written as a linear combination of amplitude and frequency modulated components which we call the primary components,

$$\begin{aligned} s(n) &= \sum_{k=1}^K A_k(n)\cos[\Theta_k(n)] + \eta(n) \\ &= \sum_{k=1}^K A_k(n)\cos\left\{\left[\Omega_c(k)n + \sum_{r=1}^n q_k(r)\right]\right\} + \eta(n), \end{aligned} \quad (2)$$

where  $A_k(n)$  denotes the instantaneous amplitude of the  $k$ th primary component and  $\Theta_k(n)$  denotes its instantaneous phase. With the backward difference between  $\Theta_k(n)$  and

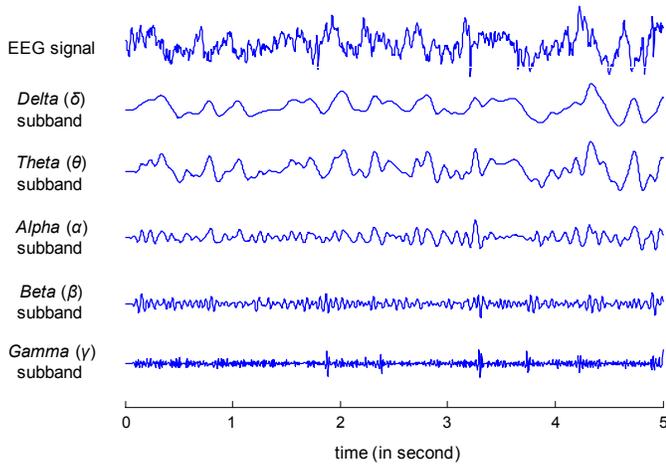


Fig. 3. Detection of the present rhythms in a 5-second long EEG epoch.

$\Theta_k(n-1)$ , the instantaneous frequency sequence is defined as  $\Omega_k(n) = \Omega_c(k) + q_k(n) = \frac{2\pi}{f_s} f_c(k) + q_k(n)$ , where  $f_s$  is the sampling frequency,  $q_k(n)$  is the frequency modulation component. Note  $\eta(n)$  takes into account additive noise and errors of modeling, especially those errors due to finite summation. The dominant rhythms in an EEG signal are therefore captured by the primary AM-FM components in the corresponding frequency bands. Depending on applications, the number of primary components required for processing may vary. For epileptic seizure prediction purposes, the necessary components are identified as the existing constituent brain waves.

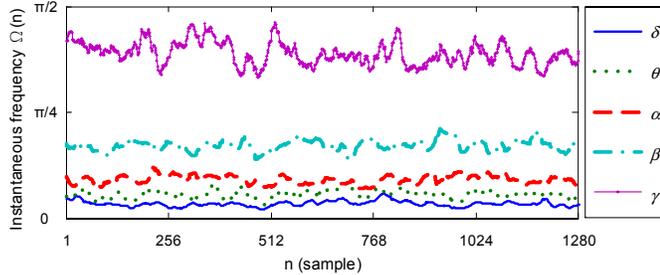


Fig. 4. The instantaneous frequency estimate  $\Omega(n)$  in the detected EEG rhythms.

Figure 3 gives an example of a 5-second long EEG signal from the 3rd preictal stage of patient 1 in the Freiburg database [18] and the present rhythms detected through band-pass filtering. In Figure 4, instantaneous frequencies of these subbands have been shown. From Figure 4, it is obvious that a primary component dominates the frequency variation in each subband, and this principal value differs from one subband to another. Similar observations could be found for the instantaneous amplitude quantities. An effective feature extraction process can therefore be considered as to identify and estimate these constituent primary components from the AM-FM EEG representation.

### B. Feature extraction overview

A common approach of getting these inclusive components in EEG signals is through nonlinear signal decomposition.

Consequently, we employ the multi-band AM-FM model on the EEG signal to extract the averaged instantaneous envelope (AIE) and averaged instantaneous frequency (AIF) feature vectors. The process of computing the AIE and AIF features is summarized as follows:

- 1) *Signal segmentation*: The EEG signal in each channel is segmented into 5 second epochs with no overlap.
- 2) *Signal decomposition*: Each epoch is divided into 5 subbands: *delta* (0-4 Hz), *theta* (4-8 Hz), *alpha* (8-13 Hz), *beta* (13-30 Hz), and *gamma* (>30 Hz) through a bank of 48th ordered finite impulse response (FIR) filters, where a 48-point Hanning window is applied before the filtering process.
- 3) *Multi-band demodulation*: Teager's energy separation algorithm [19] is employed to obtain the instantaneous envelope (IE) sequence  $|A(n)|$  and the instantaneous angular frequency (IF)  $\Omega(n)$  one epoch by another for each subband signal.
- 4) *Sequence smoothing*: A 21-point median filter is applied to remove the abrupt impulses in the epochs of IE and IF sequences, where the order 21 is empirically determined.
- 5) *Spatio-temporal averaging*: This process is conducted on each subband epoch by following a two-step calculation:
  - *Temporal averaging*: The averaging operation is undertaken on the smoothed IE and IF sequences first to remove the fluctuations over time.
  - *Spatial averaging*: These temporal IE, IF mean values are then averaged across different channels to compensate for possible channel variability.

## III. EVALUATION METHODOLOGY

In this section, the Freiburg EEG data set employed in the evaluation is described first, and the examination metrics of the relevant amplitude-frequency modulation feature vectors are introduced thereafter.

### A. Database

Our epileptic seizure prediction algorithm is evaluated on the Freiburg EEG database [18]. It is a publicly available intracranial EEG data set, which contains invasive EEG recordings of 21 patients suffering from medically intractable focal epilepsy. The data were recorded during an invasive pre-surgical epilepsy monitoring at the Epilepsy Center of the University Hospital of Freiburg, Germany. The epileptic focus was located in neocortical brain structures for 11 patients, in the hippocampus for eight patients, and in both for two patients. In order to obtain a high signal-to-noise ratio with fewer artifacts, and to record directly from focal areas, intracranial grid-, strip-, and depth-electrodes were utilized. The EEG data were acquired using a Neurofile NT digital video EEG system with 128 channels, 256 Hz sampling rate, and a 16-bit analogue-to-digital converter.

For each of the patients, there are two sets of data that contain EEG signals from ictal and interictal stages, respectively. For prediction purposes, at least 50 minutes preictal data were retained prior to each epileptic seizure. As for the interictal

states, approximately 24 hours of EEG recordings without seizure activity were provided. At least 24 hours of continuous interictal recordings are available for 13 patients. For the remaining patients, interictal invasive EEG data consisting of less than 24 hours were joined together, so as to end up with at least 24 hours of interictal recordings per patient. For each patient, the recordings of three focal and three extra-focal electrode contacts are available.

### B. Performance metrics

We measure the performance of our epileptic seizure prediction algorithm in terms of sensitivity and specificity. Sensitivity refers to the number of seizures that have been predicted correctly. Once an alarm of seizure has been raised in the preictal stage, and there is seizure occurring in the subsequent SPH, it is regarded as a correct prediction. Specificity in the seizure prediction task is counted as the number of false alarms generated during the interictal period per hour.

### C. Cross-validation and classification

The epileptic seizure prediction is to classify the feature vectors into two groups: preictal, where a seizure is about to take place in the following SPH; or interictal, where no seizure could be foreseen so far. The patient-specific binary classification of feature vectors is implemented with a support vector machine through employing the Libsvm software package [20]. Nonlinear decision boundaries are generated to separate the preictal and interictal data by using radial basis function (RBF) kernel.

In order to estimate the prediction performance in an in-sample optimization and out-of-sample evaluation manner, 5-fold cross validation is applied to obtain the optimal parameters during the training stage. Suppose there is  $N_S$  50-minute preictal records, and  $N_{NS}$  1-hour interictal records included in a patient's data. In measuring the prediction sensitivity, one classifier is trained from  $N_S - 1$  preictal records, and another classifier is trained from all  $N_{NS}$  interictal records. The predictor is then tasked with determining the class of samples in the withheld preictal record. This process is repeated  $N_S$  times until all preictal records are tested. True positive (TP) and false negative (FN) measurements are counted in the process. To estimate the predictor's specificity, the classifiers are trained from the  $N_S$  preictal records and  $N_{NS} - 1$  interictal records, respectively. The withheld interictal record is used as testing data, and this process is repeated  $N_{NS}$  times such that all interictal records are tested. The false alarms (FA) which have occurred are noted as well.

In general, for disease prediction tasks, the samples falling into the two classes are usually unbalanced in number. The overall accuracy in these scenarios sometimes cannot make good trade-off with the loss due to missing detection and false alarm errors; consequently, the  $F_\beta$  measurement might be a good choice instead.  $F_\beta$  is a performance metric for binary classification functions that is weighted on the harmonic mean for the classifier's TP, FN, and FA, its definition is denoted by

Equation (3):

$$F_\beta = \frac{(1 + \beta^2) \cdot TP}{(1 + \beta^2) \cdot TP + \beta^2 \cdot FN + FA}, \quad (3)$$

where we set the weighting factor  $\beta$  to be 2 in this paper. In each cross-validation training round, the target function is optimized by choosing SVM cost parameter  $C$  and RBF kernel parameter  $\gamma$  through a  $21 \times 21$  grid search, where  $\log_2 C$  and  $\log_2 \gamma$  range from -10 to 10, respectively. The parameter set  $[C, \gamma]$  chosen in the training stage is subsequently adopted in the respective evaluation round. Two sets of parallel experiments have been conducted. One set is to maximize the overall accuracy, and is noted as  $\text{Exp}_{Acc}$ , while the other one that optimizes the  $F_2$  measurement is noted as  $\text{Exp}_{F_2}$ .

## IV. PERFORMANCE

The epileptic seizure prediction algorithm is evaluated on 19 out of 21 patients in the Freiburg iEEG data set. The other two patients that contain less than 3 seizures are discarded. The seizure numbers and interictal period for patients included in the evaluation set are tabulated in Table I. The SPH is set to be 50 minutes in this study.

### A. Feature aggregation

The short-term parameter sets AIE and AIF are generated from the characteristic bands of EEG signals on an epoch-by-epoch basis. They capture the dominant amplitude and frequency components in the concerned temporal span and spatial range of these bands. The dimension of AIE and AIF feature vectors depend on the number of subbands that are included, which is five for both AIE and AIF in this study. The number of data samples extracted from a fixed set of EEG data depends also on the epoch length, which is empirically set to be 5 second. In order to achieve a more comprehensive description of the distinct amplitude and frequency components with respect to the prediction results, two aggregation procedures are taken. First, a 0-1 weighting scheme is employed to decide the AIE weight  $w_{AIE}$  and that of AIF  $w_{AIF}$  for a feature combination consideration. When  $[w_{AIE}, w_{AIF}] = [1, 0]$ , AIE is the only information source that is taken into account; on the other hand, AIF is fully emphasized when  $[w_{AIE}, w_{AIF}] = [0, 1]$ . AIE and AIF are concatenated one after the other in a vector form when  $w_{AIE}$  and  $w_{AIF}$  are both set to be 1. These newly generated AIEF vectors are therefore of a dimension which equals to the sum of those of AIE and AIF vectors.

Furthermore, as the physiological situations of epilepsy patients in a way transit between regimes of the seizure and non-seizure states, and the patients may be in many possible scenarios, like awake or sleep, when a seizure is forthcoming, the EEG data are therefore a nonstationary process. To eliminate the false decisions caused by insufficient inspection time and scarce evidence, the short chunks of EEG features are concatenated sequentially in time to form a longer observation interval [12]. In order to search for a suitable aggregation degree for these newly derived parameters, we have taken a

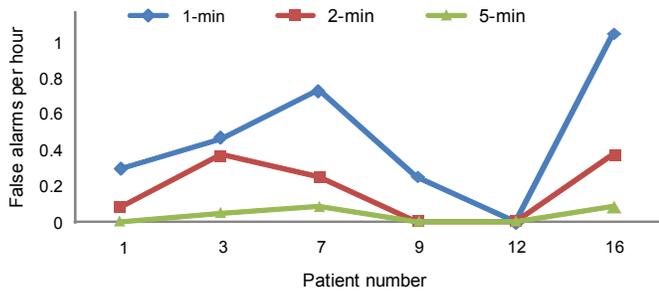


Fig. 5. False alarm performance of the temporally integrated AIEF feature vector.

performance-driven method. Having the preictal stage roughly containing 50 minutes of EEG data each, we set the maximum vector duration to be 5 minutes so that each preictal testing record includes at least ten vectors in the set. In Figure 5, six patients' epileptic seizure prediction performance by the AIEF parameter sets that temporally integrated into 1-minute, 2-minute and 5-minute vector forms are shown. It is found that the false alarm performance of the AIEF features are evidently improved when the integrating length increases from 1 to 5 minutes. Meanwhile, their corresponding sensitivity results show no degradation. Therefore, the feature vectors employed in the following evaluation are set to be of 5-minute's duration for all three sets of features.

### B. Sensitivity of prediction

Figure 6 illustrates the prediction sensitivity averaged over 19 patients for the AIE, AIF, and AIEF parameters respectively, in the  $Exp_{Acc}$  tests. It is observed that the dominant frequencies in the EEG signals have shown greater discriminative power than that of the amplitude parameters and even the combination of both of them in terms of sensitivity. It has also been revealed that, for some patients, the feature performance achieved in  $Exp_{Acc}$  could be considerably improved by using  $F_2$  metric instead. In pursuit of an accurate prediction as per patient, the best performing features from this  $Exp_{Acc}$  experimental findings are then re-evaluated by the  $Exp_{F_2}$  tests in a patient-specific manner. The final sensitivity results for all 19 patients are thuswise determined from these two sets of experiments.

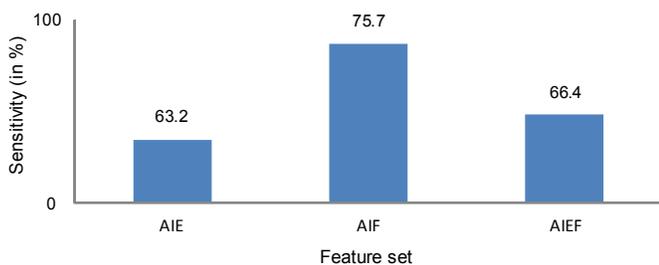


Fig. 6. Epileptic seizure prediction sensitivity by individual feature sets: AIE, AIF, and AIEF (in %).

Figure 7 records the prediction sensitivity achieved patient by patient. The overall sensitivity achieved across all patients is 95.2%, which means 79 out of 83 seizures in the evaluation

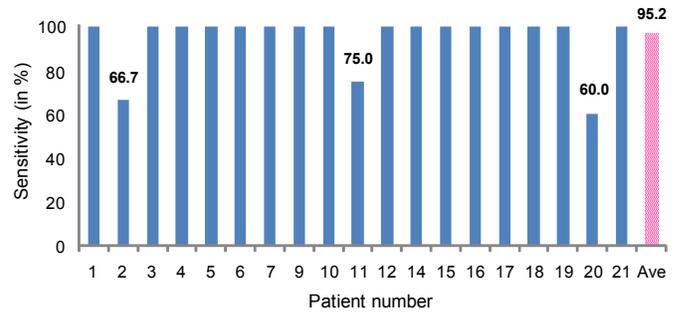


Fig. 7. Epileptic seizure prediction sensitivity on individual patients (in %).

set have been successfully predicted. For 16 out of 19 patients, all seizures are correctly forecasted in advance.

### C. Specificity of prediction

The specificity of the epileptic seizure prediction algorithm is inspected through measuring the average false alarms occurred per hour. Considering the observation that a majority of isolated positive detections happen to be falsely generated alarms, we employ a simple one-step post-processing scheme to filter out these single positives. Figure 8 shows the FA/hr results before and after taking this two-in-a-row filtering step for individual patients. As a consequence, we have obtained a specificity result of 0.130 FAs per hour on average.

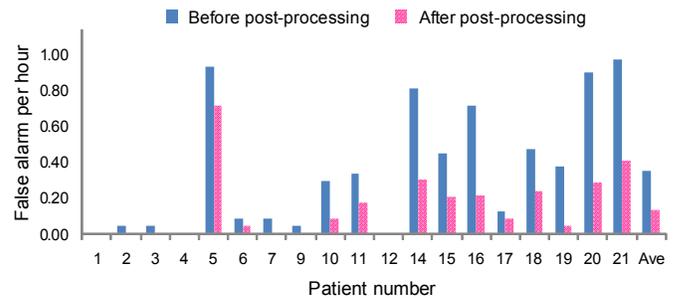


Fig. 8. Epileptic seizure prediction specificity measured in FAs per hour.

### D. Overall performance

The epileptic seizure prediction performance on a patient-specific basis is indicated in detail by Table I. In comparing our approach with other published parameter sets that were evaluated under similar classification methods, which are represented by [14] and [15] as a typical approach, the sensitivity results we achieved are found to be excellent for both of them. Note, however, that our approach has been articulated with an interpretation of the physical meaning of the involved parameters. For the specificity performance, our method which involves only a one-step post-processing operation has obtained a comparable result with that reported in [14], where a collaborative patient-specific post-processing operation was undertaken. This means our approach requires less assumption in post-processing, and leaves room for improvement in future.

## V. DISCUSSIONS AND CONCLUSION

Machine learning based feature classification approaches have been adopted in epileptic seizure prediction for EEG

TABLE I  
PATIENT-SPECIFIC SEIZURE PREDICTION RESULTS.

Patient Id.	Seizure No.	Interictal Hr.	Sensitivity (%)	FP/hr
01	4	24	100	0.000
02	3	24	66.7	0.000
03	5	24	100	0.000
04	5	24	100	0.000
05	5	24	100	0.708
06	3	24	100	0.042
07	3	25	100	0.000
09	5	24	100	0.000
10	5	25	100	0.082
11	4	24	75.0	0.166
12	4	25	100	0.000
14	4	24	100	0.294
15	4	25	100	0.200
16	5	24	100	0.208
17	5	24	100	0.083
18	5	26	100	0.232
19	4	24	100	0.041
20	5	25	60.0	0.284
21	5	25	100	0.401
Total			Mean	
19	83	461	95.2	0.130

signals. In pursuing high prediction accuracy, discriminative epileptic indicators from EEG signals are much desirable. This paper deals with the epileptic seizure prediction problem from a feature-based perspective. An amplitude and frequency modulation modeling technique that fits well for narrow band signals is employed to produce lower-dimensional feature vectors which are capable of distinguishing preictal and interictal EEG stages for the current classifiers in use. To work out an effective formulation for characterizing the primary preictal/interictal stages of an EEG signal, the pertinent representation for most dominant components present in the EEG signal is first developed. It is then applied to epochs of the EEG rhythms to extract concerned pre-seizure and interictal attributes, respectively. By evaluating these extracted parameters in the binary classification system implemented with support vector machine, it has been found that: (1) the amplitude-frequency modulation signal representation is capable of capturing the changes of EEG signal characteristics both with and without upcoming epileptic seizures; (2) the feature derivation method can provide promising epileptic seizure prediction performance in the context of standard machine learning approach; and (3) the derived parameters perform well in detecting pre-seizure attributes manifested by the EEG signal, which leads to a perfect sensitivity performance for most patients in the experimental data set. As observed, a simple one-step post-processing method has led to noticeable specificity improvements for most of the patients. It is therefore considered that by attaching a more relevant post-processing step, the promoted feature derivation front-end

could be refined for further improvement.

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