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Output regularization of SVM seizure predictors: Kalman Filter versus the "Firing Power" method

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***Abstract*— Two methods for output regularization of support vector machines (SVMs) classifiers were applied for seizure prediction in 10 patients with long-term annotated data. The output of the classifiers were regularized by two methods: one based on the Kalman Filter (KF) and other based on a measure called the "Firing Power" (FP). The FP is a quantification of the rate of the classification in the preictal class in a past time window. In order to enable the application of the KF, the classification problem was subdivided in a two two-class problem, and the real-valued output of SVMs was considered.**

The results point that the FP method raise less false alarms than the KF approach. However, the KF approach presents an higher sensitivity, but the high number of false alarms turns their applicability negligible in some situations.

I. INTRODUCTION

Among the patients that suffer from epilepsy, 30% are resistant to medication and surgery is not an option [1]. The unique way to improve the quality of life of these patients would be by seizure anticipation methodologies that could predict efficiently, and with a comfortable time in advance, the upcoming seizures. In a next step, the time between the prediction and the seizure onset time would be used to take preventive actions, such as drug administration.

Seizure prediction is usually based on the processing of the raw EEG data. This processing result in a set of descriptors, the so-called features, that are expected to present coherent changes before seizures. Several descriptors from time, frequency and time-frequency domains have been considered (see [2]). Traditionally features were considered independently and alarms were raised when the selected feature crosses an optimized threshold level [3]. More recently, seizure prediction was faced as a classification problem. This approach is based on the labeling of feature samples in several brain states[4], [5], [6]. The classification is implemented in first place by considering a high dimensional feature space, i.e., by feeding the classifier with several features simultaneously. It was reported that feature combination has the potential to improve the seizure prediction performance [7], [5], [8]. Having in mind to increase the separability between patterns, the dimensionality of the input space is usually augmented by applying non-linear classifiers. Among the available non-linear classifiers, support vector machines (SVMs)[9] with Gaussian kernels have been pointed as prospective classifiers for seizure prediction [5], [8]. The output of the SVM classifiers can be directly used to predict seizures [5]. However, in order to reduce the number of false alarms a post-classification stage is usually employed [8], [10]. In [8] a Kalman Filter was applied to regularize seizure prediction by SVM. In [10], a new methodology to regularize the output of SVM, and also of artificial neural networks, was introduced as part of the EPILAB package. This methodology computes a measure that discriminated the rate of classification in the preictal class, called the "Firing Power (FP). If FP crosses a predefined threshold under some pre-established conditions then an alarm is raised.

In this paper we explore the output regularization of SVMs by two different approaches: by the technique proposed in [10] and by the Kalman Filter (KF) technique. For this purpose we implemented a dual SVM classification schema that enables trustworthy comparisons.

II. METHODS AND DATA

A. Database

In this paper a group of 10 patients from the European Database on Epilepsy [11] was considered. We selected patients that were monitored non-invasively (scalp EEG), and according to some quality conditions, such as the patients data should have at least for five days and the EEG data should not present intervals in the recordings (more than 99.5% of effective recording time). Fifteen patients fulfil these conditions, and 10 were randomly selected. All the selected patients suffer from temporal epilepsy. Particular data details are listed in Table II.

B. Methodology overview

The methodology applied is presented in Fig. 1. The 50 Hz power-line interference is removed from the raw EEG data by applying a notch filter. The filtered EEG signals are then subjected to feature extraction. Twenty-two univariate features were extracted per channel. The selected features are listed in Table I, and were selected based on previous studies that reported successful seizure prediction performances using SVM and ANN classifiers, and also because of their low computational cost, enabling real-time operation [10], [12]. In this paper all the features were computed using consecutive five-second windows without overlap.

After feature extraction, six electrodes were selected by two different strategies. In one, three electrodes that were over the seizure-onset-zone (SOZ), and three that were not

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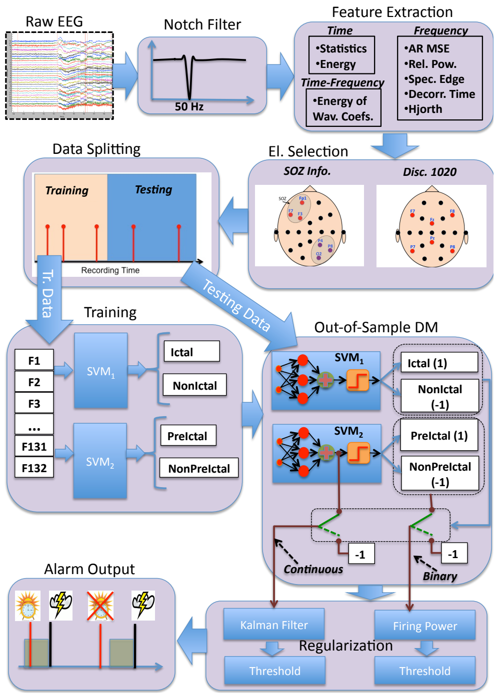

Fig. 1. General overview of the employed methodology.

TABLE I

FEATURES THAT ARE POSSIBLE TO EXTRACT FROM RAW DATA

Feature	
First Coef. of AR Models	
Decorrelation Time	
Energy	
Entropy	
Hjorth	Mobility Complexity
Relative Power	Delta Band (0.1-4 Hz) Theta Band (4-8 Hz) Alpha Band (8-15 Hz) Beta Band (15-30 Hz) Gamma Band (30-2000 Hz)
Spectral Edge	Power Frequency
Statistics	1^{st} Moment (Mean) 2^{nd} Moment (Variance) 3^{rd} Moment (Skewness) 4^{th} Moment (Kurtosis)
Energy of the Wavelet Coefficients	Several mother Wav. and decomposition levels

related with the SOZ were selected. The other selection approach aims to maximize the scalp coverage with a reduced number of electrodes and is based on the discretization of the international 10-20 system. This selection resulted in the selection of the electrodes F7, Fz, F8, P7, Pz, P8. After the identification of the electrodes to be used a set of 132 (6 electrodes $\times$ 22 features) features were available as inputs of the classifiers.

Here we consider cost-sensitive SVM classifiers with Gaussian kernels that by default have as free parameters the cost (C) and the spread of the Gaussian kernel (γ). The portion of data that contained the first three seizures was used for training, and the remaining data containing the last seizures were selected for out-of-sample validation. This strategy simulates a real-time scenario, where just a first part of the data is known at first place. Each patient had eight different training sets consisting on four different preictal periods, or seizure occurrence periods (SOPs), and two different electrode selection methods. Three classes were considered: interictal, related with seizure free intervals; preictal, i.e., the time epochs just before the seizure onsets; and ictal, related with the seizure episodes. To determine the best SVMs parameters we used a *grid-search*. Here we considered exponentially growing sequences for the SVMs parameters (C and γ), i.e., $C = \{2^5, 2^8, 2^{10}, 2^{13}, 2^{15}\}$ and $\gamma = \{2^{-10}, 2^{-5}, 2^3, 2^5, 2^{10}\}$.

Two SVM classifiers were considered, one (SVM_1 in Fig. 1) is designed to label feature samples as ictal or non-ictal, and the other SVM (SVM_2) is trained to classify the feature samples as preictal or non-preictal. This dual classification solution decomposes a multi-class problem in two binary problems, enabling the output regularization methodology implemented in this paper and that is explained next. After training, the classifiers were evaluated in out-of-sample data. The SVM_1 classifier was designed to distinguish the ictal samples from the other ones, and acts in this paper as a decision mechanism. On one hand, if the SVM_1 classifies a sample as ictal then the sample is not a preictal one, and the outputs of the SVM_2 are forced to be as negative as possible, i.e., to be -1 in both continuous and binary versions. On the other hand, if SVM_1 classify a sample as to be non-ictal, then the final continuous and binary outputs are the output of SVM_2.

To reduce the number of false alarms the output of SVM_2 should be regularized, i.e., should be filtered by taking in account the past classification dynamics. As presented in Fig. 1 the KF regularization technique is based on the continuous SVM_2 output, i.e., the signal just before the standard SVM threshold and that is the distance between a given input sample in the high dimensional space and the hyperplane defined. The FP regularization is based on the binary classification output, i.e., the usual SVMs output.

C. Firing Power regularization

The FP method generates alarms taking into account the temporal dynamics of the classification output in the testing set. Considering the continuous output of the classifier, the first step is to binarize the output y_k according to:

$$o_k = \begin{cases} 1, & \text{if } y_k \geq 0 \\ 0, & \text{if } y_k < 0 \end{cases} \tag{1}$$

Then, a sliding window with size equal to the preictal period was settled aiming to quantify the number of samples classified as preictal according to:

$$fp[n] = \frac{\sum_{k=n-\tau}^{n} o_k}{\tau} \tag{2}$$

Where $fp[n]$ is the "firing power" at the discrete time n, τ corresponds to the number of samples considered in each window, and o_k is the binary output of the classifier. A firing power of one (a full firing power) means that all the samples in the past preictal time were classified as preictal, therefore strongly suggesting a preictal state. The alarms are generated using the $fp[n]$ values and according to:

$$a[n] = \begin{cases} 1, & \text{if } fp[n] \geq L \\ 0, & \text{if } fp[n] < L \end{cases} \tag{3}$$

where L is an arbitrary threshold value, which in this work assumed the values $\{0.10, 0.15, ..., 0.85\}$, i.e., a fraction of the full "firing power". After an alarm, a new one can only be raised after the a time equal to the preictal time and if $a[n]$ crosses the threshold in an ascending way.

D. Kalman Filter regularization

In [6] an alternative approach based on the Kalman Filter (KF) was used to reduce the number of false positives obtained using the decision variable, i.e., the real-valued signal just before the SVM threshold. The KF underlying idea is the estimation of the states s_k of a linear dynamic system defined by [6]:

$$\begin{cases} s_{k+1} = \begin{bmatrix} 1 & T_p \\ 0 & 1 \end{bmatrix} s_k + w_k \\ y_k = \begin{bmatrix} 1 & 0 \end{bmatrix} s_k + z_k \end{cases} \tag{4}$$

where s_k is the state of the system at instant k; y_k is the measured variable; w_k and z_k are zero mean white noise vectors. Let y_k denote the real-valued SVM_2 output and $s_k = [y_k, \dot{y}_k]$ the state vector ($\dot{y}_k$ represents the rate of change of y_k). T_p is the prediction interval (we considered a 5 seconds interval) and w_k the process noise. In the same way as considered in [6], the unique tunable filter parameters was the standard deviation of the random fluctuations of $\dot{y}_k$, denoted as σ_w, and assumed to be equivalent to the Kalman gain ($\sigma_{\text{KF}} \triangleq \sigma_w$). In this paper we assumed the values $\{10^{-2}, 10^{-3}, 10^{-4}, 10^{-5}\}$ for σ_w.

An alarm is raised whenever the KF output is classified as a preictal sample. In the same way as for the FP, a new alarm can only be raised if the KF output crosses the zero-threshold in an ascending way.

III. RESULTS

Taking into account the different datasets (originated by considering different SOP periods and different electrode selection methods), the grid search considered for SVM optimization, and the two suggested regularization methods, the total number of predictors developed for each patient was 6400. In this paper we evaluate the results based on the sensibility (SS), i.e., the percentage of predicted seizures, and based on the number of false predictions per hour, or false prediction rate (FPR). The best predictors for each patient and for each regularization method was selected as the one that presents SS and FPR close to the optimal performance point, i.e., SS=100% and FPR=0 h^{-1}.

Table II summarizes the best results obtained for each patient using the two different regularization approaches.

The prediction results using the two regularization methods produced different results reflecting in general the trade-off between sensitivity and false positive rates.

The results using KF as a regularization strategy produced higher sensitivities. In average the sensitivity was 84%, but with a high false positive rate of 1.51 h^{-1}, in average. In fact, for some patients (1,2, and 9) the best predictor based in KF present such a huge number of false predictions that its usefulness is negligible. The FP regularization yields significant improvement in the false positive rate, i.e., a reduction to 0.23 h^{-1}, in average. These results were associated to a slight decrease in the sensitivity to 77% in average (note that patient 9 had an important contribution to this decrease). Three patients presented a sensitivity of 100% with a rate of false predictions inferior to 0.15/h.

The best models according to our results favored datasets with longer preictal periods. No particular pattern was found in the electrode array selection (slightly advantage to the "1020" selection).

Taking a closer look to the KF approach, it is noticeable that σ_w was related to the FPR. The lower is σ_{KF} the smoother is the filtered output, and less false predictions are raised . More precisely, σ_{KF} values higher than 10^{-5} were related to FPR>1 h^{-1}.

The threshold associated to the best result obtained with FP was in general low. Five of the patients analyzed presented a threshold of 0.1, i.e., 10% of the samples in a preictal duration window should be classified as preictal to generate an alarm.

Fig. 2 presents the output regularization by KF (A) and by the FP (B) in the testing data for one exemplary patient. It can be noticed that the KF output is more fluctuating than the FP, rising more false alarms. The rule impose in the FP method that a new alarm is only possible after a preictal time also contributes to the decrease of the number of false alarms.

IV. CONCLUSIONS

We compare two regularization approaches to improve the seizure prediction performance of predictors based on SVM classifiers: the Firing Power (FP) and the Kalman Filter (KF) methods. On one hand, the FP approach presented better results concerning the false positive rate. On the other hand, KF produced results with higher sensitivities. However, the number of false alarms raised by KF makes its applicability insignificant for some of the analyzed patients. It can be concluded that the FP approach is more "conservative" concerning the raising of alarms, because it considers a longer memory, and because of its particular constraints (rules) on the times were alarms are possible to be raised. While FP considers a past window equal to the preictal time, which can range form 10 minutes to 40 minutes, the KF approach is based on just the past output sample and on its derivative (rate of change), i.e., a much more shorter memory is considered.

Another important issue was the optimization of the preictal period for each patient. The use of different targets in

TABLE II

INFORMATION AND RESULTS FOR THE 10 STUDIED PATIENTS. *Total Rec.* IS THE TOTAL RECORDING TIME IN DAYS HOURS:MINUTES:SECONDS, I.E., INCLUDING TRAINING AND TESTING DATA. *N. Sz* IS THE TOTAL NUMBER OF SEIZURES IN THE TESTING DATA. *Testing Dur.* IS THE TESTING DATA DURATION IN HOURS. *SS* STANDS FOR SENSIBILITY, AND *FPR* FOR FALSE PREDICTION RATE. *El. Sel.* FOR ELECTRODE SELECTION METHODOLOGY, WHERE "ORIG" MEANS THAT THE BEST PREDICTOR WAS BASED ON ELECTRODES SELECTED BASED ON THE SEIZURE ONSET ZONE, AND "1020" MEANS THAT THE BEST PREDICTOR WAS BASED ON ELECTRODES SELECTED ACCORDING TO THE DISCRETIZED 10-20 METHODOLOGY.

Pat.	Total Rec.	N. Sz.	Testing Dur(h)	Kalman Filter				Firing Power			
				SS (%)	FPR (1/h)	SOP (min)	El. Sel.	SS (%)	FPR (1/h)	SOP (min)	El. Sel.
1	07 22:40:14	5	106.80	60.00	4.98	40	1020	40.00	0.25	40	1020
2	08 05:03:49	5	42.30	80.00	2.34	20	1020	80.00	0.07	40	1020
3	05 00:15:59	3	69.03	66.67	0.52	40	orig	66.67	0.20	40	1020
4	06 20:47:58	1	43.40	100.00	0.23	40	1020	100.00	0.12	40	orig
5	06 19:05:56	6	108.14	83.33	1.43	40	orig	100.00	0.40	40	1020
6	19 19:41:59	1	29.96	100.00	0.30	20	1020	100.00	0.10	40	1020
7	05 20:49:06	3	40.84	100.00	0.69	30	orig	100.00	0.07	40	orig
8	06 15:20:37	4	77.38	75.00	0.79	40	1020	75.00	0.25	20	1020
9	06 16:20:07	24	134.40	75.00	2.70	40	orig	41.67	0.30	40	orig
10	06 00:01:44	6	99.02	100.00	1.10	40	1020	66.67	0.21	40	1020
Avg.	-	5.8	75.13	84.00	1.51	35	-	77.00	0.20	38	-

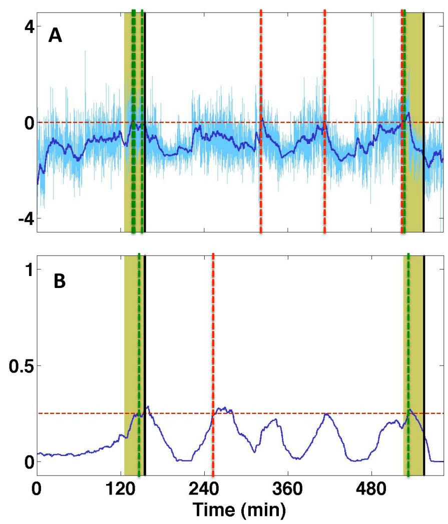

Fig. 2. Kalman Filter (A) and the Firing Power (FP) outputs. The horizontal dashed lines represent the considered threshold levels. Vertical green lines indicate true alarms, while vertical red lines represent false alarms. The seizure onset is marked by full vertical black bars, and the considered preictal time by green regions. In (A) the KF output is the dark-blue curve, while the light-blue curve represents the continuous SVM output. In (B) the firing power is described by the dark-blue curve.

the training stage of our study indicates that longer preictal periods may help the classifier to discriminate preictal from nonpreictal samples.

Future steps will encompass the validation on a larger number of patients from the EPILEPSIAE database [11] and the comparison of both regularization methods in a real-time environment.

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