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Selection of Variables by the F-Score Algorithm for Radiated Magnetic Field Signals Discrimination of Electrical Discharges

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Abstract—**This paper proposes the use of a hybrid variable selection method called F-Score with proposed threshold, which reduces the duration of the training and the testing phases while improving the accuracy of recognition for radiated magnetic field signals discrimination of electrical discharges generally taking place in insulation systems and in particular in insulators of high-voltage lines and power transformers. The classifier used is based on support vector machines (SVMs). The experimental analysis was carried out on a basis of data containing 161 signals which 106 signals were reserved for the training and 55 signals for the testing. The obtained results show that the proposed algorithm combined with the SVMs, allows a substantial reduction in the number of variables and a high improvement of the recognition rate compared to the pre-selection rate.**

Keywords—Electrical Discharges, insulation systems, Support Vector Machines (SVMs), Variable Selection, F-Score

I. INTRODUCTION

We can distinguish two types of discharges: dangerous that can lead to a breakdown and consequently the partial or total destruction of the insulation system and equipment, and not dangerous that extinguish themselves [1], [2]. The radiated magnetic field signals associated with these acquired electric discharges are represented by 25,000 variables. It is a question of discriminating the two types of discharges and mainly of focusing on the detection of the radiated magnetic field signals linked to dangerous type discharges. To do this, we use a recent classifier, namely support vector machines or SVMs, whose robustness in the field of pattern recognition has been proven [3]-[7], Moreover, unlike the neural networks [8]-[10], used in the past which, moreover, are binding in terms of the number of parameters to be adjusted, the SVMs require them to adjust only two parameters, which is a great advantage.

The performance of the classifier strongly depends on the quality of representation of the examples or in our case of the signals to be recognized: harmless or dangerous, which generally implies the obligation to represent them by means of a large number of variables [11]. It is therefore common for some of these to contain only redundant, noisy or irrelevant information to the classification, thus making the training of the recognition system more complex [11].

The variable selection is a process that aims to filter the basic characteristic-vector, so that only the discriminant information is extracted and presented to the classifier in a relevant way.

Several methods have been developed. We can divide them into two categories: Filtering methods (Filters) and enveloping methods (Wrapper).

The Filter approach is performed as a pre-processing since the variables are selected independently of the classifier and regardless of its influence on system performance. This model is characterized by its speed. Nevertheless, the effectiveness of this type of method is questionable.

The Wrapper approach depends on the classifier used which contributes to the evaluation of the quality of the subset of selected variables. For each subset found, it is necessary to train a classifier until the empirical error is validated. This model is efficient but is characterized by a high calculation time [3], [11], [12].

We propose to use a combination of filter and wrapper methods using a Fisher-based measure called F-Score [15] that assigns a score for each variable, which allows the variables to be ranked by importance. Once the redundant variables are eliminated, we will search for the optimal percentage of the number of remaining variables sorted in decreasing order leading to the best recognition rate.

The rest of this paper is organized as follows:

In Section II, we give a brief description of the SVMs classifier, which are currently the best in terms of performance [3]. In Section III, we will analyze the variable selection by the F-Score algorithm as it was designed and then describe in details this algorithm applied to our system.

In section IV, we will be presented the experimental results and their interpretation.

Finally, we conclude on the work done and the remarks that can be made.

II. SVMS CLASSIFIER

Support vector machines or SVMs were developed in the 1990s by Vapnik [3] and supplanted other types of classifiers such as neural networks. They have become popular with the scientific community of learning machines and have since become widely used, particularly in the field of pattern recognition. In fact, we have a set $\{(x_i\,,\ y_i)\}_{i=1}^{n}$ where $x_i \in R^m$ are the n examples of training while m is the number of variables for each example, for their part, y_i are the labels corresponding to the two classes: $\{-1, +1\}$.

Originally, the purpose of the SVMs is to separate two classes of data, for this purpose we search for the best

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separation plan that maximizes the margin between the data of the two classes by calculating a decision function whose expression is the next one :

$$f(x) = sign(\sum_{k=1}^{S_v} \alpha_k \, y_k K(x_i, x_k) + b) \qquad (1)$$

Where α_k are the parameters of Lagrange, S_v is the number of support vectors x_k which are the border points of the margin such as $0 \leq \alpha_k \leq C$, where C is the regularization parameter to be adjusted, that constitutes a trade-off between the maximization of the margin and the error due to the non-separable data. Finally x_i and b represent respectively the variable vector and the bias.

In practice, the data is nonlinearly separable, so a kernel function $K(x_i, x_k)$ is used.

The kernel function used is the RBF known for its better performance compared to other kernels [3]-[7] whose expression is:

$$RBF(x, x_k) = exp\left(-\frac{1}{2\,\sigma^2} \|(x - x_k\|^2\right)$$

Where σ is the kernel parameter. It will be a question of adjusting then of finding the optimal couple (C, σ) which allows to find the best recognition rate. In addition, the kernel function must satisfy the conditions of Mercer.

III. Variable Selection Using the F-Score Algorithm

Variable selection is a method of choosing a subset of relevant variables that is optimal or sub-optimal from a set of original variables according to the evaluation criterion .

The goal is to make a selection from the original feature vector $X_n = [x_1, x_2, \dots, x_n]'$ while trying to improve performance or failing to preserve them. The vector obtained after selection will therefore be:

$$X_m = [x_1, x_2, \dots, x_m]' \qquad \text{with} \qquad m < n$$

The authors set out a list of three goals for making a variable selection [3], [11] :

1/ Reducing the size of the training and the testing set.

2/ The reduction of the training and the recognition times.

3/ Improvement of the recognition rate.

The F-Score technique is used to calculate the discrimination between two classes by calculating a score called Fisher score from the training data.

It is useful to specify that Fisher's criterion consists of calculating the distance between the average values of a variable established for two classes of data, and of normalizing it by the average of the variances, in order to estimate the discriminative power of the variable considered between these two classes [15].

This criterion is written for a given variable i :

$$F(i) = \frac{(\mu_i^{(1)} - \mu_i^{(2)})^2}{(\sigma_i^{(1)})^2 + (\sigma_i^{(2)})^2} \qquad (2)$$

For two classes designated by (1) et (2) whose number of examples are respectively n_1 and n_2 , this criterion $F(i)$ for the ith variable is defined by [15] :

$$F(i) = \frac{\left(\bar{x}_i^{(1)} - \bar{x}_i\right)^2 + \left(\bar{x}_i^{(2)} - \bar{x}_i\right)^2}{\frac{1}{n_1-1}\sum_{k=1}^{n_1}\left(x_{k,i}^{(1)} - \bar{x}_i^{(1)}\right)^2 + \frac{1}{n_2-1}\sum_{k=1}^{n_2}\left(x_{k,i}^{(2)} - \bar{x}_i^{(2)}\right)^2} \qquad (3)$$

Where $\bar{x}_i$ is the mean of the variables of rank i for the two classes (1) and (2) combined or what amounts to the same at the training base.

$\bar{x}_i^{(1)}$ and $\bar{x}_i^{(2)}$ are respectively the means of variables of rank i of classes (1) et (2).

$x_{k,i}^{(1)}$ and $x_{k,i}^{(2)}$ are the variables of the kth example of rank i respectively of each of the two classes (1) and (2).

The numerator indicates the discrimination between the two classes, while the denominator indicates the discrimination within each of the two classes. Thus, the higher the $F(i)$, the more the variable is discriminant [15].

This score is therefore used as a variable selection criterion in our problem of discriminating radiated magnetic field signals, that is to say that starting from the expression (3) of the F-Score, we propose to select and retain only the most relevant variables, which will also allow elimination of the redundant variables, i.e., those with the same value of the Fisher score, all this leads to a reduction in the number of the variables and consequently a reduced calculation time for both the training and the testing [7].

VI. Description of the F-Score Algorithm

A. Progress of the F-Score Algorithm

Knowing that the highest $\mathrm{F}(i)$ score corresponds to the most discriminating variable, the F-Score algorithm consists of six steps described as follows:

- F-Score calculation for each variable i.
- Elimination of the redundant variables.
- Sort F-scores of the remaining variables in decreasing order from the most discriminating variable to the least discriminating variable.
- Choice of several thresholds for the F-Score.
- Calculation of the rate of recognition of dangerous signals for each chosen threshold.
- Retention of the threshold corresponding to the best recognition rate.

B. Choice of the Threshold

The difficulty of the F-Score method lies in the choice of a threshold that can determine the optimal subset of the variables to be selected.

Several empirical thresholds must be used to find the best approach for choosing the F-Score threshold to give the best recognition rate.

C. Prioritization of the Fisher's scores

The approach for which we have opted was to take as a threshold a variable percentage of the number of variables (amputated redundant variables) from the variable with the best F-score to the one with the lowest and to determine experimentally the optimal threshold leading to the subset of variables corresponding to the best recognition rate.

IV. Experimental Results

We present in this section an experimental analysis of the performances of the F-Score method in the selection of variables for the discrimination of radiated field signals. To do this, we proceeded in two steps. The first is to perform the recognition of these signals, using the original signals i.e. without selection of variables; classification is done using support vector machines (SVMs).

The second is to carry out the recognition after implementation of the F-Score algorithm on the original signals which allows to obtain vectors of reduced dimension, where the number of variables passes to a much smaller number than that of the original variables.

The database which was generated at electrical and industrial systems laboratory (EISL-USTHB), contains 106 examples for the training and 55 for the testing.

The classes of the harmless type and dangerous type signals are formed respectively by 100 and 61 signals.

We note that our database is formed mainly of signals associated with discharges of low voltages and not dangerous while the signals associated with discharges of high voltages and dangerous are a minority. Signals numbered from 1 to 100 consist of non-dangerous signals and constitute the first class while those numbered from 101 to 161 are dangerous and constitute the second class.

We have taken 2/3 of the database of each class of signals for the training and 1/3 remaining were reserved for the testing.

Let designated DSTEST As the rate of recognition of dangerous signals of the testing; an illustration for the 106 examples of the training matrix, the values of the F-Score as a function of the rank i of the variable are as follows:

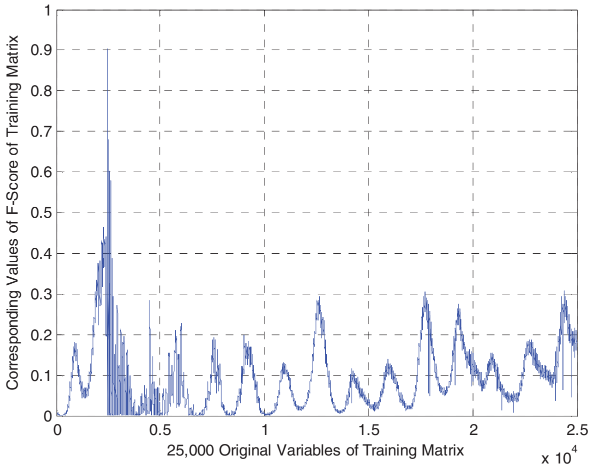

Figure.1: Score F (i) according to the rank of the variable i

A careful examination of the curve in Fig. 1 shows that there is a large variation in the values of some variables. Some have the same score: these are the redundant variables, which led us to keep only one of them having an identical F-Score value. Finally, the selection process that we have adopted takes place in five steps :

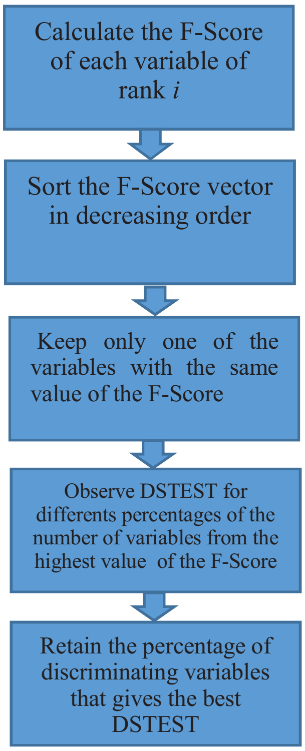
Calculate the F-Score of each variable of rank i
Sort the F-Score vector in decreasing order
Keep only one of the variables with the same value of the F-Score
Observe DSTEST for differents percentages of the number of variables from the highest value of the F-Score
Retain the percentage of discriminating variables that gives the best DSTEST

Figure.2: Diagram explaining the progress of the F-Score Algorithm with proposed threshold for selecting the best DSTEST

Fig.3 below, shows the evolution of the dangerous signal recognition rate DSTEST, as a function of the percentage of the number of the most discriminating variables.

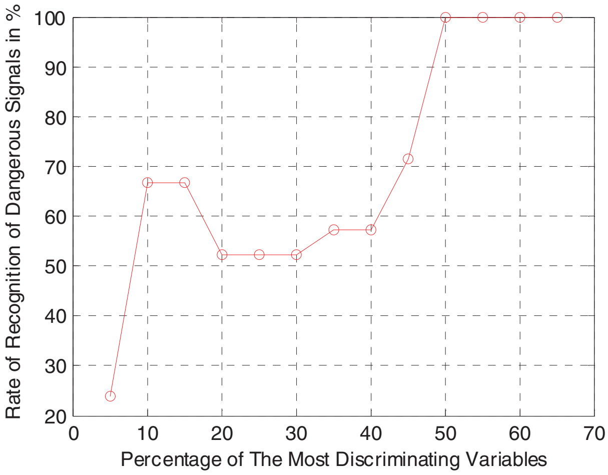

Figure.3: Rate of recognition of dangerous signal after selection according to the percentage of the most discriminating variables

From Fig. 3, we find that the best recognition rate after selecting variables is 100%, which corresponds to several percentages corresponding to 50, 55, 60 and 65 respectively, of number of variables from the variable which have the highest value of F-Score.

The threshold of 50% of total number of non-redundant variables corresponds to the optimal threshold because it corresponds to the minimum of variables, i.e. exactly 1,178 most discriminanting variables selected. In total, out of 25,000 variables, a total of 22,645 redundant variables were eliminated while only 2,355 variables underwent a selection process, among them, only 1,178 were selected and retained corresponding to an optimal threshold of 50% of the proposed percentage, i.e. almost 4.7% of all the original variables.

In TABLE.I below, the DSTEST recognition rate, the duration of the training and the testing, and the number of variables used before and after the application of F-Score selection are summarized respectively.

TABLE I. RECOGNITION RATE DSTEST, DURATION OF THE TRAINING AND THE TESTING AND THE CORRESPONDANT NUMBER OF VARIABLES

Recognition Rate DSTEST before and after application of the F-Score Algorithm	Duration of the Training and the Testing	Number of Variables
SVMs : 33.33%	66h 14' 54''	25,000
F-Score + SVMs : 100 %	11h 35' 8''	1,178

V. CONCLUSION

This paper is an alternative hybrid approach to the filter and wrapper models using two selection criteria, one independent of the classifier (the $F(i)$ score), while the second criterion corresponds to the recognition rate for dangerous signals in the insulation systems.

Before the application of the F-Score selection algorithm, the SVMs alone, were able to recognize only 7 of the 21 dangerous signals of the testing, which is a low recognition rate of 33.33%. The presence of a very large number of redundant variables, exactly 22,645 variables, provide no additional information to the classifier and also the non-redundant but irrelevant variables that may be noisy.

To solve this problem, we made a variable selection; we opted for the application of Fisher's F-Score algorithm before classifying the signals in two classes by SVMs.

The strategy of the threshold proposed above, has led to very good results. The F-Score algorithm combined with the SVMs not only reduced the number of variables very significantly but also leads to the recognition of all dangerous type signals (SDTEST = 100%) with a significantly reduced computation time for the training and the testing, almost six times less than pre-selection.

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