Fault Detection System with Non-Invasive Magnetic Passive Sensor and a Support Vectors Machine

Journal:	*Transactions on Magnetics - Conferences*
Manuscript ID:	Draft
Manuscript Type:	Compumag 2011
Date Submitted by the Author:	n/a
Complete List of Authors:	Carvalho, Alexandre; UNINOVE, Ciencias Exatas - Engenharia; Primeira Opção Engenharia Elétrica, Engenharia Sartori, Carlos Antonio Franca; Escola Politécnica da Universidade de São Paulo, Programa de Pós-graduação PEA/EPUSP. Laboratório de Eletromagnetismo Aplicado LMAG-PEA. Sevegnani, Francisco; FCET/PUC/SP, Faculdade de Ciências Exatas e Tecnologia
Keywords:	non-invasive fault detection system, magnetic signature, support vector machines

Fault Detection System with Non-Invasive Magnetic Passive Sensor and a Support Vectors Machine

Alexandre Miguel de Carvalho[1], Carlos Antonio França Sartori[2] and Francisco Xavier Sevegnani[3]

[1]Dep. de Ciências Exatas da Associação Educacional Nove de Julho, Av. Dr. Adolpho Pinto, 109, São Paulo, SP, Brazil
[2]Dep. de Eng. de Energia e Automação Elétricas - Escola Politécnica da USP PEA/EPUSP, 05508-900 São Paulo, SP, Brazil
[3]Faculdade de Ciências Exatas e Tecnologia FCET/PUC/SP, 01303-050 São Paulo, SP, Brazil

***Abstract*—A robust high impedance fault detection approach is presented in this work. This methodology consists of classifying faults, by applying a support vector machines pattern recognition system based on magnetic signals captured by non-invasive sensors. Faults were simulated experimentally taking into account various parameters, such as sensor distances and loads. The classification process achieved 98% accuracy.**

***Index Terms*—non-invasive fault detection system, magnetic signature, support vector machines.**

I. Introduction

THE USE OF NON-INVASIVE measurement techniques in electrical power systems to detect faults is quite new [1], [2]. In a previous work, a new approach suitable for fault detection and classification by analyzing the related magnetic signature was presented [1]. In this paper, the support vector machine technique is presented to classify fault´s magnetic signature.

The use of support vector machine for high impedance fault detection is not new. Some authors have already presented works in this field but, the main difference between those works and this, is that fault detection is not non-invasive [7],[8]. Another difference is that, the direct method presented here is simpler and easier to apply and has good classification results (98.7%).

II. Support Vector Machines

A. Introduction

Support Vector Machines (SVM) constitute a pattern-classification technique with supervised learning algorithms, capable of solving linear and non-linear classification problems. The SVM approach, computationally, offers many advantages like less CPU consumption and massive data processing ability when compared with other approaches, such as back-propagation neural networks [3],[5],[6]. This property means SVM can be used to classify very large datasets with great performance in time training and quality results.

A support vector machines architecture is presented in Haykin [5] and Bishop [6]. Basically, when training support vector machines, the designer has to define the kernel function and its parameters, such as the penalty parameter C [3], [5], [6]. Concerning the kernel function, many functions can be used [3], [5] and [6]. In this paper the so-called radial-basis kernel is used for learning performance [9]:

$$K(x_i,x_j) = e^{-\gamma\|x_i-x_j\|^2}, \gamma > 0 \qquad (1)$$

Where C is user-specified upper bound on the Lagrange multipliers, x_i and x_j are input vectors and γ parameters are defined in training processes [4], [10].

III. Methodology

The methodology implemented here has six steps: experimental data acquisition; data pre-processing; SVM kernel choice and the training process; the cross-validation process; fault classification, and analysis of results.

First of all, as described in [1], the experimental data acquisition is performed. Fault type, fault current and magnetic flux density were acquired. Fig. 1 shows the sketch of the experiment setup used to acquire the experimental data.

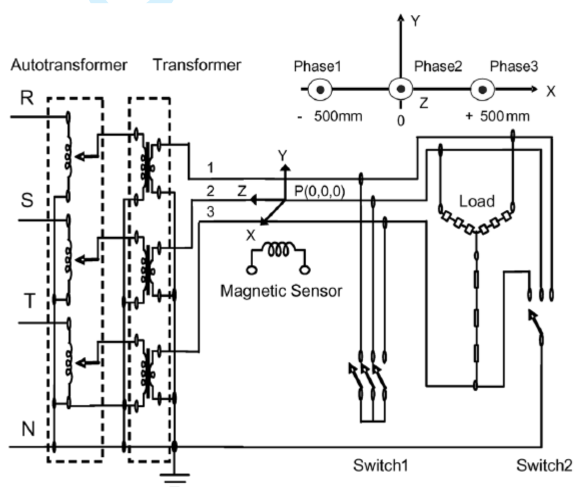

Fig. 1. Diagram of the experimental setup. Resistive Load.

Manuscript received July 1, 2011.
Corresponding Authors: Alexandre Miguel de Carvalho. (email: engenheiro.alexandre.carvalho@gmail.com);
Carlos A. F. Sartori. (email:sartori@pea.usp.br);
Francisco Xavier Sevegnani(e-mail: fransev@pucsp.br)

Waveforms of magnetic flux density generated by short-circuits were detected by unidirectional magnetic sensors. These sensors were located close to the lines in a variety of distances h1 (distance between line and magnetic sensors) and d2 (distance between magnetic sensor 3 and magnetic sensor 4). Fig. 2 shows the configuration of the magnetic sensors. The sampling frequency used was 10 kHz, corresponding to 2000 stored samples, for each of the 220 measurement experiments. The second step consists of data processing, i.e., the manipulation and organization of data. This step defines how data can be organized for classification system. Classifications are defined and described as in table I, and training vectors are prepared to use with support vectors machines training processes [3], [4], [5] and [6].

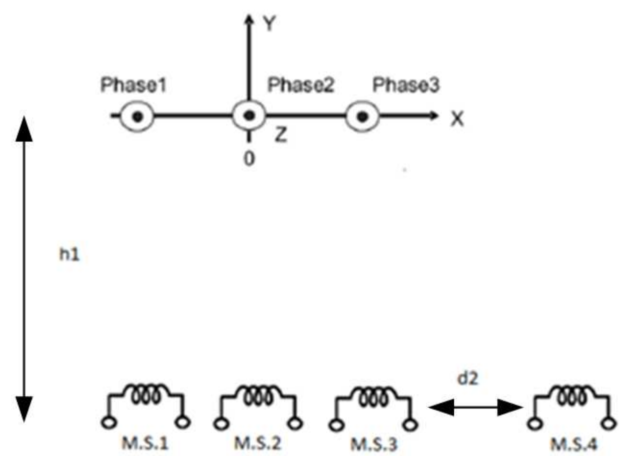

Fig. 2. Diagram of magnetic sensor positions.

The main goal of this work is to create a robust fault detection system beyond detect fault types, such as phase to phase or phase to earth etc. For this work, codification of faults is necessary.
Table I shows the fault type codification used in this work.

TABLE I
FAULT TYPE CODIFICATION

Type	*Fault Type Code (F.T.C.)*	Fault Explanation
Normal	0	No fault
F3N	1	phase 3 - neutral
F2N	2	phase 2 - neutral
F1N	3	phase 1 - neutral
F2F3	4	phase 2 - phase 3
F2F3N	5	phase 2 - phase 3 - neutral
F1F3N	6	phase 1 - phase 3 - neutral
F1F2	7	phase 1 - phase 2
F1F3	8	phase 1 - phase 3
F1F2N	9	phase 1 - phase 2 - neutral
F1F2F3	10	phase 1 - phase 2 - phase 3

Thus, in step I – experimental data acquisition – the fault signal were stored, i.e., 220 x 2000 vectors.

Step II connects the fault-type codification with these 220 vectors. Table II illustrates this step.

On the other hand, the supervised training algorithms need correlations between data and results, to do this, for example, when a short-circuit type 10 (F1F2F3) is under study, experimental vector data and fault type must be stored in a suitable format, like in the table II. With this data file format, the algorithm will let us know that signal 1, for example, is a type 10 fault short-circuit, etc.

TABLE II
TRAINING VECTORS: FAULT TYPE CODIFICATION LINKED WITH MAGNETIC FLUX DENSITY **B** FAULT VECTOR

ELEMENT	***0***	*1*	*2*	.	.	.	*2000*
SIGNAL 1	***FAULT TYPE CODE***	$B_{1,1}$	$B_{1,2}$	.	.	.	$B_{1,2000}$
SIGNAL 2	***FAULT TYPE CODE***	$B_{2,1}$	$B_{2,2}$	.	.	.	$B_{2,2000}$
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
SIGNAL 220	***FAULT TYPE CODE***	$B_{220,1}$	$B_{220,2}$	.	.	.	$B_{220,2000}$

In step III – SVM kernel choosing and training process – the kernel type must be specified and the training process must be started. Here, data need to be randomly separated in three datasets: the training data, the final test data set and cross-validation data set. The final test data set represents 15% of all vectors. The cross-validation dataset represents 20% of all vectors and the training data set, 65% of all vectors available [10].

These data sets must be separated randomly in each training process to guarantee generalization of the support vector machine engine and trusted results.

The training data set is used to train the support vector machine engine. After engine has been trained, the cross-validation dataset is presented to verify engine quality (step IV). If the engine has a good classification accuracy, final test data is presented for classification, step V.

Choosing the kernel function is an empirical approach. In this work, the radial-basis function kernel has presented good quality classification and computational performance [9]. LIBSVM was used to train the SVM engine, [4].

For the training process, datasets must be separated as previously explained. For the robustness training process, this work does the training process 50 times with 50 random datasets. The cross-validation and classification processes were also done 50 times. This value was chosen based on the Cross Validation literature [10]. Average accuracy was considered satisfactory at 98%. Figure 3 summarizes the SVM classification processes.

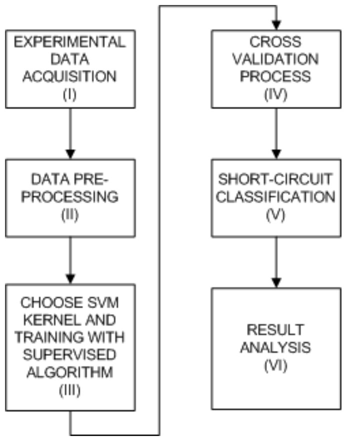

Fig. 3. Data pipeline for short-circuit fault classification.

IV. Application and Results

The main goal here is to show the suitability of the proposed method for building a fault classification system. The results presented here regard a classification engine as capable of identifying fault types as described in Table I with 98.65% average accuracy.

TABLE IV
ACCURACY AND PARAMETERS IN 50 SVM TRAINING PROCESS

Training	*C*	*γ*	*Accuracy %*
1	32	0.125	98.4848
2	32	0.125	100
3	32	0.125	95.4545
4	128	0.125	96.9697
5	32	0.125	99.2424
6	128	0.125	99.2424
7	32	0.125	100
.	.	.	.
.	.	.	.
.	.	.	.
29	128	0.125	100
30	32	0.125	99.2424
31	32	0.125	99.2424
32	128	0.125	99.2424
33	128	0.125	100
34	128	0.125	100
35	512	0.03125	97.7273
.	.	.	.
.	.	.	.
.	.	.	.
42	128	0.125	100
43	128	0.125	96.2121
44	128	0.03125	97.7273
45	32	0.125	100
46	128	0.125	100
47	32	0.125	100
48	128	0.125	100
49	128	0.125	100
50	32	0.125	99.2424
		Average accuracy	*98.6515*

Experimental Results - Poor classification

Initially, a first attempt of the classification process was to classify 220 vectors with 2000 **B** (magnetic flux) samples each. In this experiment, poor accuracy was found (less than 60% accuracy). Other strategies were used to improve accuracy quality. Wavelet transform [1] was used in this work to try to increment accuracy but classification results were less than 45%. Two methods with wavelet transform (Daubechies 4, Level 10) were used. First, wavelet coefficients (cD1[1003], cD2[505], cD3[256], cD4[131], cD5[69], cD6[38], cD7[22], cD8[14], cD9[10]) were calculated for all 220 **B** signals and, with these coefficients, training vectors were constructed as in table V. Each new vector has 2048+1 points. The classification engine with table V training vectors had a poor classification accuracy (less than 40%). A second wavelet transform, with 220 **B** signals (Daubechies 4, Level 10) was calculated and standard deviation [1] was used for all 10 levels. With this method, less than 20% accuracy was found. Table VI shows how standard deviation training vectors were constructed. In the three cases above, some support vector machines kernels were tested but poor results were find. Further studies will be carried out in order to test other data organization.

TABLE V
TRAINING VECTORS
WAVELET COEFFICIENTS FOR **B** SIGNAL (DAUBECHIES 4, LEVEL 10)

ELEMENT	*0*	*1*	2	.	.	.	*2048*
TW SIGNAL 1	***F.T.C.***	[$CD_{1,1}$]	[$CD_{1,2}$]	[$CD_{1,3}$]	[$CD_{1,4}$]	...	[$CD_{1,9}$]
TW SIGNAL 2	***F.T.C.***	[$CD_{2,1}$]	[$CD_{2,2}$]	[$CD_{2,3}$]	[$CD_{2,4}$]	...	[$CD_{2,9}$]
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
SIGNAL 220	***F.T.C.***	[$CD_{220,1}$]	[$CD_{220,2}$]	[$CD_{220,3}$]	[$CD_{220,4}$]	...	[$CD_{220,9}$]

TABLE VI
TRAINING VECTORS
STANDARD DEVIATION (SD) WAVELET TRANSFORM FOR ALL 10 LEVELS
(DAUBECHIES 4, LEVEL 10)

SIGNAL	*0*	*1*	*2*	*3.*	*4*	...	*10*
1	***F.T.C.***	$SD_{1,1}$	$SD_{1,2}$	$SD_{1,3}$	$SD_{1,4}$	...	$SD_{1,10}$
2	***F.T.C.***	$SD_{2,1}$	$SD_{2,2}$	$SD_{2,3}$	$SD_{2,4}$	...	$SD_{2,10}$
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
220	***F.T.C.***	$SD_{220,1}$	$SD_{220,2}$	$SD_{220,3}$	$SD_{220,4}$	...	$SD_{220,10}$

Experimental Results - Good Classification Quality - 98.7%

Results shown in table IV were found with direct method classification with some work on data sets. To increase the number of vectors, each **B** vector with 2000 samples was transformed into four vectors with 500 samples. As a result, 220 signals with 2000 samples are transformed into 880 vectors with 500 samples. Table VII show how 220 x 2000 changed to a 880x500 vector format. Table VIII shows the final signals with which the support vector machine was trained, giving 98.6515% accuracy in the classification process.

TABLE VII
DATASET EXPANSION- 220X2001 TO 880X501

SIGNAL 1	***0***	*1*	*2*	*3*	*4*	...	*2000*
	F.T.C.	B1	B2	B3	B4	...	B2000

SIGNAL 1.1	***0***	*1*	*2*	*3*	*4*	...	*500*
	F.T.C.	B1	B5	B9	B13	...	B1997
SIGNAL 1.2	***0***	*1*	*2*	*3*	*4*	...	*500*
	F.T.C.	B2	B6	B10	B14	...	B1998
SIGNAL 1.3	***0***	*1*	*2*	*3*	*4*	...	*500*
	F.T.C.	B3	B7	B11	B15	...	B1999
SIGNAL 1.4	***0***	*1*	*2*	*3*	*4*	...	*500*
	F.T.C.	B4	B8	B12	B16	...	B2000

V. CONCLUSION

In this work a robust detection system for high impedance faults was presented combining non-invasive magnetic passive sensors and a support vector machines classification system. A 98.7% fault classification accuracy was obtained. These results demonstrate that this combination of techniques has great potential for non-invasive fault classification.

Future work will study the application of this technique to fault location apart from the detection and classification of faults.

TABLE VIII
FAULT TYPE CODIFICATION LINKED WITH MAGNETIC FLUX DENSITY **B** FAULT VECTOR (880X500)

ELEMENT	***0***	*1*	*2*	.	.	.	*500*
SIGNAL 1	***F.T.C.***	$B_{1,1}$	$B_{1,2}$	.	.	.	$B_{1,500}$
SIGNAL 2	***F.T.C.***	$B_{2,1}$	$B_{2,2}$	.	.	.	$B_{2,500}$
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
SIGNAL 880	***F.T.C.***	$B_{880,1}$	$B_{880,2}$	.	.	.	$B_{880,500}$

REFERENCES

[1] C.A.F. Sartori and F. X. Sevegnani, "Fault Classification and Detection by Wavelet-Based Magnetic Signature Recognition", IEEE Transactions on Magnetics, VOL.46,NO.8, AUGUST 2010.

[2] S. L. Avila, O. Chadebec, B. Raison and G. Vernau, "Currents identification in overhead lines from radiated magnetic field knowledge" in Proc. 16th Int. Conf. Comput. Electromagn. Fields (COMPUMAG´07), Aachen, Germany, 2007.

[3] N. Cristianini and J. Shawe-Taylor, "An Introduction to Support Vector Machines and Other Kernel-based Learning Methods", Cambridge university Press, 2000.

[4] Chih-Chung Chang and Chih-Jen Lin, LIBSVM: a library for support vector machines, 2001, Software available at http://www.csie.ntu.edu.tw/~cjlin/libsvm

[5] S. Haykin, "Neural Networks – A Comprehensive Foundation", 2nd edition, 1999, Prentice Hall.

[6] C.M. Bishop, "Pattern Recognition and Machine Learning", Springer, 2006.

[7] M. Sarlak and S. M. Shahrtash, "High Impedance Fault Detection in Distribution Networks Using Support Vector Machines Based on Wavelet Transform", IEEE Electrical Power & Energy Conference, 2008.

[8] S. R. Samantaray, L. N. Tripathy and P. K. Dash, "Combined EKF and SVM based High Impedance Fault Detection in Power distribution feeders", Third International Conference on Power Systems, Kharagpur, INDIA, December, 27-29, Paper Identification Number-30.

[9] Xuehua Li and Lan Shu, "Fuzzy Theory Based Support Vector Machine Classifier", Fifth International Conference on Fuzzy Systems and Knowledge Discovery, 2008, IEEE Computer Society.

[10] J. Han and M. Kamber, "Data Mining Concepts and Techniques", 2nd edition, 2006.