TIME-FREQUENCY DISTRIBUTION FOR AUTOMATIC FAULT CLASSIFICATION IN POWER ELECTRONICS

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Abstract

A new method of fault analysis and detection by signal classification in industrial frequency converters is presented. The Wigner-Ville time frequency distribution is used to produce the representation of the signal and the probabilistic neural network as a classifier. The accuracy and robustness of the proposed method is investigated on signals obtained during the different fault mode operations of the industrial frequency converter.

1. INTRODUCTION

In this work the problem of classification of signals obtained from the industrial power frequency converters is considered. Object of the signal classification is the control of the modern frequency power converters, which generate a wide spectrum of harmonic components. Especially, the task of fault detection is difficult. A subset of faults, which is usually not discovered by the protections (in under-load conditions), is particularly hard to classify. In large converter systems, which generate not only characteristic harmonics typical for the ideal converter operation, but also a considerable amount of non-characteristic harmonics and interharmonics, the task of fault detection is particularly difficult [4],[2].

The characteristics of the signal can be better analysed and understood if the correct representation is chosen. In case of the heavily distorted signals, which contents change with time, it can be expected that the time and frequency characteristics are the most important.

The Wigner–Ville transformation is especially appropriate for the analysis of non-stationary signals due to its good temporal resolution, excellent performance in the presence of noise, better frequency concentration and less phase dependence than Fourier spectra.

In the case of the Wigner-Ville distribution it is possible to study simultaneously the time and frequency characteristics of the signal with best possible resolution of all non-parametric time-frequency distributions [3].

The signal classification is the assignment of the time-series to a specific class with given characteristics.

The process of signal classification consists of the following steps.

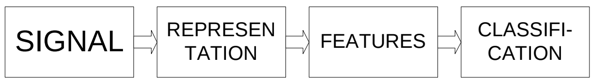

Figure 1. Signal classification approach.

It exists no correct mathematical definitions of the signal classes in the above-presented problem, because the inherent structure of the signal is unknown.

The signal classification should be based on robust and distinguishable features. The time and frequency moments of the signal time-frequency representation are chosen as robust and compact features. It is known that moments are robust to disturbances like noise. Another point is that the dimensionality of the feature vector should be as low as possible in order to obtain better results of classification [9].

In this paper the probabilistic neural network performs the task of classification. This subgroup of radial neural networks is most suitable for classification task.

2. WIGNER-VILLE REPRESENTATION

The Wigner –Ville transformation is especially appropriate for the analysis of non-stationary signals due to its good temporal resolution, excellent performance in the presence of noise, better concentration and less phase dependence than Fourier spectra [8].

What makes the representation of the signal important, is that the characteristics of the signal could be better understood in an appropriate representation.

The signal obtained during the operation of the frequency converter carries the temporal and spectral information. In order to obtain the best possible results of classification it is important to consider both *temporal* and *spectral* information, especially when dealing with dynamic and non-linear systems.

Time-frequency distributions are two-dimensional representations of temporal signals, which describe the time-varying spectral contents of the signal.

Most of the time-frequency distributions belong to the Cohen's Class, which members are covariant of time and frequency shifts of the signal. It is possible to change the properties of the time-frequency distribution by choosing the appropriate two-dimensional kernel function $\Phi(\xi,\tau)$.

$$C_x(t,\omega) = \iiint_{\mathbb{R}} x\left(t+\frac{\tau}{2}\right) x^*\left(t-\frac{\tau}{2}\right) \times \\ \times \Phi(\xi,\tau) e^{-j\xi t + j\xi u - \omega\tau} du\, d\tau\, d\xi \quad (1)$$

The Wigner-Ville distribution (WVD) is obtained for $\Phi(\xi,\tau)=1$. It is the member of Cohen's class with the best resolution of all time-frequency representations [7] and is expressed by:

$$W_x(t,\omega) = \int_{-\infty}^{\infty} x\left(t+\tfrac{\tau}{2}\right) x^*\left(t-\tfrac{\tau}{2}\right) e^{(-j\omega\tau)} d\tau \quad (2)$$

where t is a time variable, ω is a frequency variable and * denotes complex conjugate.

For a discrete-time signal $x(n)$ the discrete pseudo-Wigner-Ville distribution (PWD) is evaluated using a sliding symmetrical finite-length analysis window $h(\tau)$ [8].

$$W_{xh}(n,k) = 2\sum_{\tau=-L}^{L} x(n+\tau)\, x^*(n-\tau) \times \\ \times h(\tau)\, h^*(-\tau)\, e^{-j4\pi k\tau/N} \quad (3)$$

where $h(\tau)$ is a windowing function that satisfies the condition: $h(\tau)=0; |\tau|>L$. Variables n and k correspond respectively to the discrete time and frequency variables.

One main deficiency of the WVD is the cross-term interference. WVD of the sum of signal components is a linear combination of auto- and cross-terms. Each pair of the signal components creates one additional cross-term in the spectrum, thus the desired time-frequency representation may be confusing.

Traditionally, the cross-terms are considered as something undesired in the WVD [8] and should be removed. But, when a cross-term is discarded, the resulting representation will leave significant energy out. One way of lowering cross-term interference is to apply a low-pass filter to the WVD. The smoothing, however, will reduce the frequency resolution of the WVD and cause the loss of many useful properties of the transformation [7].

3. MOMENTS AS FEATURES

When using two-dimensional signal representation it arises the dimensionality problem. For an *N*-point time series, when the frequency axis of the time-frequency distribution has *M* points, the signal representation has $\mathrm{N}\times\mathrm{M}$ points. To describe the signal with as few variables as possible, the use of geometric moments is proposed [1]. By using the moments, the reduction of dimensionality is achieved without loosing the classification accuracy.

The time and frequency moments are calculated from the Wigner-Ville distribution of the signal.

$$m_t = \int_{-\infty}^{+\infty} \omega^p W_x(t,\omega)\, d\omega \quad (4)$$

$$m_f = \int_{-\infty}^{+\infty} t^p W_x(t,\omega)\, dt \quad (5)$$

The adequate classification requires a relatively small set of moments [1]. For the purpose of fault signal classification we used first and second order moments.

4. PROBABILISTIC NEURAL NETWORK

Probabilistic Neural Networks [4] as a subgroup of Radial Basis Neural Networks are good suited for classification problems. Design of the network structure is straightforward and does not depend on training. The network consists on an input layer, radial basis layer and competitive layer. When an input vector is presented, the first layer computes distances from the input vectors to the training vectors. The first layer produces a vector showing how close the input is close to the training data. The second layer produces a vector of probabilities, which show how close is the input vector to each trained class. Output function picks the maximum of these probabilities and produces *true* for a vector belonging to specific class and *false* for other classes. The network architecture is shown in the Figure 2.

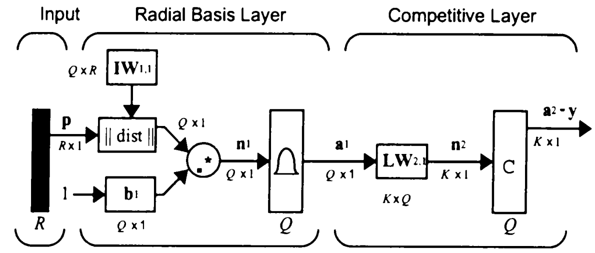

Figure 2. Architecture of the probabilistic neural network [6].

When an input vector is presented the distance function (|dist|) produces the measure how close the input vector is to the training vectors.

5. INVESTIGATION RESULTS

5.1. Simulation of the fault operation

. In the paper we show investigation results of a 3 kVA-PWM-converter simulated with the *Power System Blockset* of MATLAB®. Figure 4 shows the waveforms of the currents at the converter output for the frequency 50 Hz during a short circuit between phases A and B with a small fault resistance.

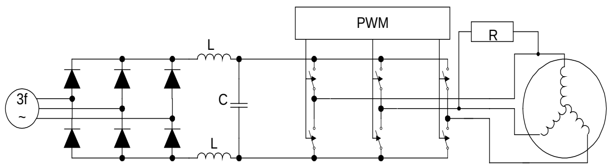

Figure 3. Simplified scheme of the simulated converter configuration. R – resistance of the short-circuit.

5.2. Space-phasor

The complex space-phasor of the converter output currents is investigated using the WVD.

The motor is provided with a positive-sequence 3-phase voltage system.

Complex space-phasor $\underline{f}_p = f_\alpha + j \cdot f_\beta$ of a three-phase system f_R, f_S, f_T is given by [4]

$$\begin{bmatrix} f_\alpha \\ f_\beta \end{bmatrix} = \sqrt{\tfrac{2}{3}} \begin{bmatrix} 1 & -\tfrac{1}{2} & -\tfrac{1}{2} \\ 0 & \sqrt{\tfrac{3}{2}} & -\sqrt{\tfrac{3}{2}} \end{bmatrix} \begin{bmatrix} f_R \\ f_S \\ f_T \end{bmatrix} \quad (6)$$

It describes, in addition to the positive-sequence component, existing negative-sequence component, and harmonic and non-harmonic frequency components of the signal.

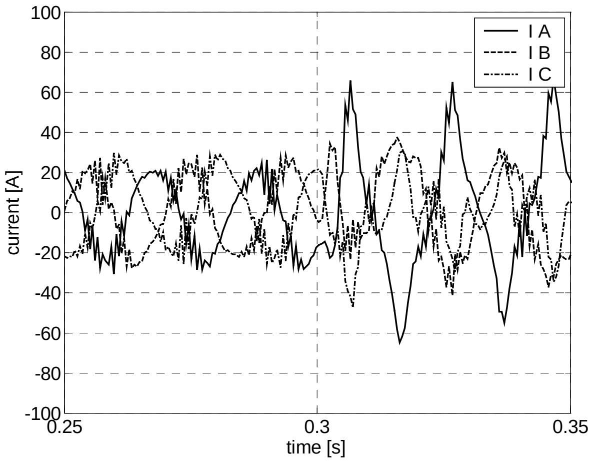

Figure 4. Inverter output currents. Short-circuit between motor leads occurs at the time point *t*=0.3 s.

5.2. Classification process

The three-phase signal representing the currents at the output of the frequency converter is combined with the help of the equation (5) to the compact form of the complex space phasor. Its Wigner-Ville representation is calculated. From this time frequency representation the time and frequency moments of the first and second order are obtained, to serve as inputs of the probabilistic neural network. The algorithm of classification is shown in Figure 5.

The signal at the converter output was sampled with the frequency of 20000 Hz. For the training vector the time sequence of 200 samples was chosen. From this time sequence the Wigner-Ville distribution with dimension in time-frequency plane equal to 200×200 was calculated. As the input vectors to the neural network served:

- first order time moment – averaged frequency
- second order time moment – frequency band
- first order frequency moment – averaged time
- second order frequency moment – squared time duration

The input vector of the probabilistic neural network has the dimension 4×200. Input weights (**IW**) (Figure 6) are set to the transpose of the matrix formed from the training vectors. Training vectors are composed of eight vectors containing four moments of the signal obtained during normal operation of the converter and four moments of the signal obtained during the fault operation. Target matrix contains ones in the rows corresponding to the fault operation. The second layer weights (**LW**) are set to the matrix of target vectors. The competitive layer produces 'true' for the largest value of the output of the a^2 vector in Figure 2. Finally, the network classifies the input vector into one of two classes, by choosing the class, which has the maximum probability of being correct [6].

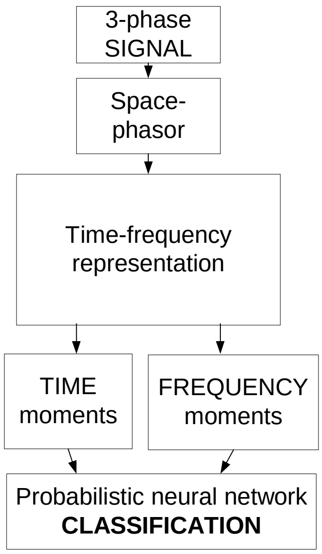

Figure 5. Classification algorithm.

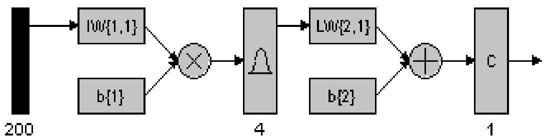

Figure 6. Structure of trained probabilistic neural network [6].

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For the classification process two classes of signals were investigated: signal obtained during normal operation of the inverter drive and signal obtained from the output currents of the inverter drive during short-circuit between the motor leads with a resistance. For each of the two signal classes 100 realizations were made.

From the three-phase signal obtained from the output currents of the frequency converter a complex space phasor was calculated, using (6). Then, the Wigner-Ville representation of the complex space phasor was calculated, according to (3).

The classification algorithm took randomly 70 realizations for training and the remaining 30 realizations for testing.

Before the training of the network the inputs and targets were scaled so that they always fall in a specified range [-1,1]. An advantage of this method is the lower estimation error [5]. The results of investigations showing the classification rate for different values of the fault resistance is shown in Figure 7.

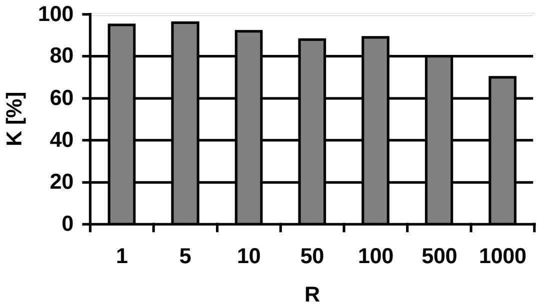

Figure 7: Classification rate K for two class classification (*fault mode operation-normal operation*) for different values R [Ω] of the fault resistance.

The classification rate using the time-frequency distribution and probabilistic neural network averages 85% of correct classifications for input vectors other than training vectors obtained for different resistances of the short-circuit connection between output leads of the frequency converter.

6. FUTURE WORK

Introduction of the optimised time-frequency distribution based on data-dependent kernel could lead to the improvement of the classification rate. It is possible to handle the optimisation by maximising the classification rate over different kernel designs [1]. For instance, it is possible to use the two-dimensional Gaussian kernel in the form [10]:

$$\Phi(\xi,\tau)=\left(1+\frac{1}{\sqrt{\pi}\xi_0}\right)e^{-\left(\frac{\xi_0}{\xi}\right)^2}\left(1+\frac{1}{\sqrt{\pi}\tau_0}\right)e^{-\left(\frac{\tau_0}{\tau}\right)^2} \tag{7}$$

Representation of the signal and properties of the time-frequency representation strongly depends on the chosen kernel $\Phi(\xi,\tau)$. Since it exist no simple model of the signal in question, a practical way of design of the optimal kernel can be chosen. After the process of kernel optimisation is completed, another important step is the validation of reliability of classification. The optimisation process must properly handle synthetic signals with defined limit properties. Another approach to classification problem could be based on class-dependent kernels, which accentuate the regions in TFD [12], where the maximum difference between the classes of the signal occurs, or the use of adaptive neuro-fuzzy interference system with clustering [11].

An extension of this work could be the design of a classifier with more than two classes handling different fault mode operations of the inverter drive.

7. CONCLUSIONS

In this paper a new method of classification of electric signals was presented, based on the time-frequency representation and automatic signal classification with the help of probabilistic neural network. The investigations prove the validity of the proposed approach, however this method needs further improvements to increase correct classification rate. Further work will lead to design of the classification system with many classes, corresponding to different faults of the drive.

ACKNOWLEDGEMENT

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