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Adequacy of the Map SOM for Defects Detecting in Inverter Switching

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***Abstract*— This article presents a model of an IGBT inverter switching time, its switching defects and the ability of neuronal strategy using the map SOM (Self Organizing Map) in detecting defects resulting. This approach involves the most significant parameters of SOM such as the topological structure of the map, the learning algorithm of Kohonen, and also the activity diagram UML (Unified Modeling Language).**
Eventually, a simulation is made on Matlab with an experimental measurement of the stator current at the NDC (Non Destructive Control) laboratory, followed by a treatment stage before applying to the SOM map which gives a more meaningful result.

Key words- Neural network SOM, modeling of the inverter, IGBT switching anomalies.

I. INTRODUCTION

The diagnoses of industrial processes with neural networks play actually an important part in preventive maintenance. It can target the types and origins of abnormalities that may affect them. Indeed, the associations of induction machines and static converters are more and more in application. Particularly, the electrical drive systems based on induction machine are widely used in industrial applications because of their low cost, their performance and robustness. In fact, these converters are ubiquitous in many applications , especially in high-tech sectors such as aerospace , nuclear , chemical industries , in transport (metro, trains, vehicle and propulsion of ships , elevators) in industry (machine tools , winches) .

However, degraded modes of operation may occur during the life of the converter. One of the main reasons for these failures remains the switching abnormalities control. To improve the dependability of these inverters, monitoring systems and smart modern diagnosis based on neural networks can be established [1] [2].

Many published research [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13] treat neural systems dedicated for the anomalies detection, such as the Kohonen map SOM designated by self organizing map, and which represents a powerful tool for diagnostic tasks in various fields. This map is able to represent as many input information having multidimensional data, as the number of unit or hierarchy that develops. It acts simultaneously as classifier and quantifier, and this is where the very purpose of this paper is to further develop the efficiency of this method and apply it to detect anomalies and identify the converter by following the SOM map performance.

II. THE INVERTER MODELING

A. Possible state vectors of the inverter

The opening and closing of the inverter switches depend on the state of control signals (C1, C2, and C3).

Owing that, we can have eight possible combinations and eight positions of the vector rotating.

We note the existence of two zero vectors $\vec{V}_0$ and $\vec{V}_7$. The six other all have the same module, $(\sqrt{2/3})U$, and a regular offset of $\pi/3$. The vector representation of these tensions

($\overline{V}_0 \ldots \overline{V}_7$) is given by the following figure1:

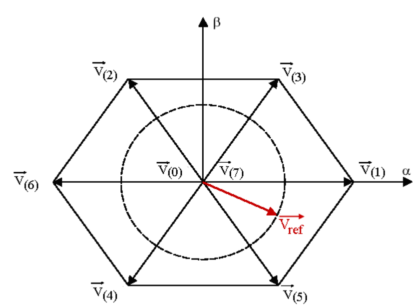

Fig. 1 Vector representation of the tensions generated by the inverter

With the technique PWM (pulse width modulation), control voltage vector is generally calculated and approximated on a modulation period Tm by an average voltage vector.

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The reference vector or the control one is expressed in polar coordinates by:

$$V_{ref} = r.\sqrt{\frac{2}{3}}.\frac{U}{2}.\exp(j\theta) \qquad (1)$$

With, $\theta = \omega_s.t$; $\omega_s = 2\pi f_s$ (fs is the fundamental frequency).

The Vref voltage vector control is approached on the modulation period Tm by generating an average voltage vector <V> developed by applying the status of the inverter vectors $\vec{V}_i$, the adjacent $\vec{V}_{i+1}$ and the zero vectors $\vec{V}_0$ and $\vec{V}_7$. For this, the reference vector is sampled at the frequency $f_m = \frac{1}{Tm}$.

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$$V_{ref\ m} = <\vec{V}>_m = \frac{1}{T_m}(T_i'.\vec{V}_i + T_{i+1}'.\vec{V}_{i+1}) \qquad (2)$$

So, $Tm = T'_i + T'_{i+1} + T'_0$ with T'_i **:** Application time of $\vec{V}_i$ and T'_{i+1} **:** Application time of $\vec{V}_{i+1}$

T'_0 **:** Application time of $\vec{V}_0$ and $\vec{V}_7$

$$T'_0 = T_m - (T'_i + T'_{i+1}) \qquad (3)$$

Vectors $\vec{V}_i$ and $\vec{V}_{i+1}$ are chosen by industry in what is the Vref vector.

- Calculation T'i and T'i+1

$$\vec{V}_i = \sqrt{\frac{2}{3}}.U.\exp(j(i-1)\frac{\pi}{3}) \qquad (4)$$

$$\langle\vec{V}\rangle_m = \frac{T'_i}{Tm}\vec{V'}_i + \frac{T'_{i+1}}{T_m}\vec{V'}_{i+1} \qquad (5)$$

$$\langle\vec{V}ref\rangle_m = \langle\vec{V}_m\rangle = \sqrt{\frac{2}{3}}U\left[\frac{T'_i}{T_m}\exp(j(i-1)\frac{\pi}{3}) + \frac{T'_{i+1}}{T_m}\exp(\frac{ij\pi}{3})\right] \qquad (6)$$

According to the two expressions (1) and (6) we can write the following equation:

$$r.\sqrt{\frac{2}{3}}.\frac{U}{2}.\exp(j\theta) = \sqrt{\frac{2}{3}}\frac{U}{T_m}\left[T'_i\exp(j(i-1)\frac{\pi}{3}) + T'_{i+1}\exp(\frac{ji\pi}{3})\right] \qquad (7)$$

Where:

$$r.\frac{3}{4}.T_m.\exp(j\theta) = T'_i\exp(j(i-1)\frac{\pi}{3}) + T'_{i+1}\exp(\frac{ji\pi}{3}) \qquad (8)$$

If we divide this expression by $\exp(j\frac{i\pi}{3})$ we get:

$$r.\frac{3}{4}.T_m.\exp(j(\theta - \frac{i\pi}{3})) = T'_i\exp(-\frac{j\pi}{3}) + T'_{i+1} \qquad (9)$$

By breaking this third relationship by real and imaginary part is deduced the following matrix relationship

$$r.\frac{3}{4}.T_m.\begin{bmatrix}\cos(\theta - \frac{i\pi}{3}) \\ \sin(\theta - \frac{i\pi}{3})\end{bmatrix} = \begin{bmatrix}\cos(-\frac{\pi}{3}) & 1 \\ \sin(-\frac{\pi}{3}) & 0\end{bmatrix}\begin{pmatrix}T'_i \\ T'_{i+1}\end{pmatrix} \qquad (10)$$

For identification, determining the terms of application time of state vectors:

$$\begin{aligned} T_i' &= \frac{\sqrt{3}}{2}.r.T_m.\sin(\frac{i\pi}{3} - \theta) \\ T_{i+1}' &= \frac{\sqrt{3}}{2}.r.T_m.\sin(\theta - (i-1)\frac{\pi}{3}) \\ T_0' &= T_m - (T_i' + T_{i+1}') \end{aligned} \qquad (11)$$

B. *Control switches*

If the reference vector $\vec{V}ref$ is located in sector1, between the two vectors $\vec{V}_1$ and $\vec{V}_2$. In this case, it takes $\vec{V}_1$ during part of the interval, $\vec{V}_2$ during another part and $\vec{V}_0$ or $\vec{V}_7$ for the rest, because the inverter allows for the states represented by $\vec{V}_0, \vec{V}_1, \vec{V}_2, ...\vec{V}_7$.

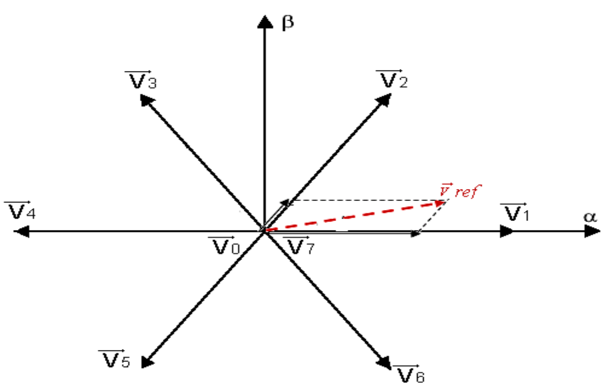

Fig. 2 The reference vector is located in the sector1

III. The Inverter Defects

A defect is characterized by functional impairment, either partial or total. Within the inverter, the most common and the most critical defects mainly concern the control of the transistors. These may result from a degradation caused by electrical stress, heat or excessive mechanical. Their origins can be internal and related to the same operation, or external and linked to the environment or use outside specifications. In particular, a control history of failure can induce failure of a transistor.

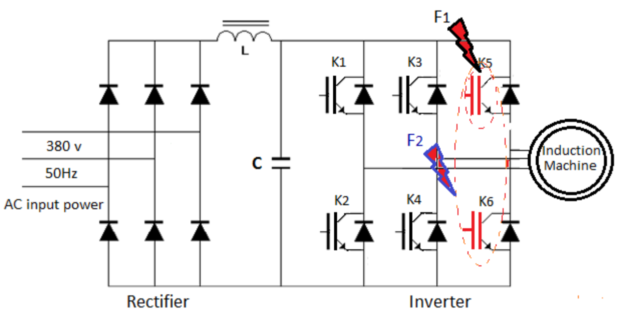

Fig. 3 Equivalent circuit diagram of a fault (F1) in open circuit of a transistor and a fault (F2) of a switching cell

A. Simulation result

1) Failures (F1) "high impedance type" of a transistor

The maintenance in the open state of a transistor, for example due to a failure of grid causes a loss of reversibility power switch (only the freewheel diode remains). It manifests itself in inverter mode by the loss of alternating phase current. Thus, in the case where the upper transistor of a cell remains open and the current in the corresponding phase is positive, the phase remains connected to the negative potential of the bus by the lower - diode freewheel . The phase current remains zero until the current reference is positive (Figure4) , and when the phase current changes sign , the faulty transistor is no longer involved in the modulation and the current can then be controlled

Significant distortion of current results in a significant fluctuating power and involves an increase in the effective current from the normal regime since the resulting harmonics generate only losses.

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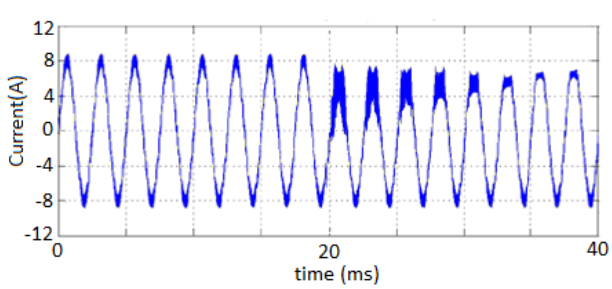

Fig. 4 Simulation of the inverter output current with malfunction 20ms

2) Failure (F2) to "high impedance" kind of the two transistors of a switching cell

The default mode is the loss of control of an arm, its two remaining transistors open. The phase is no longer connected only through the antiparallel diode of the switching cell. Spontaneous conduction of a fault in the diodes arm depends on the currents developed by the filter cell and controls the remaining arm. The deterioration of the waveform of current is further increased compared with the previous case. The current in the phase concerned is rather low or almost zero.

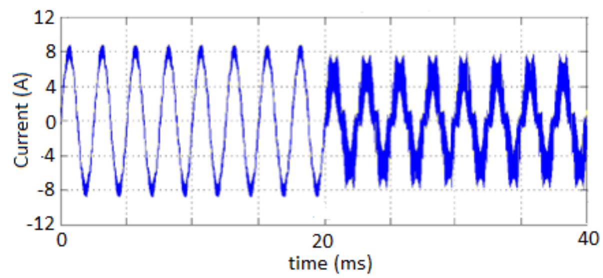

Fig. 5 Simulation of the inverter output current with malfunction of a cell 20ms

IV. Strategy of Anomalies Detection by the Map SOM

Based on modeling by biologically inspired networks, Teuvo Kohonen achieved a particular neural network map called SOM. The implementation of a number of formal neurons working in parallel and massively interconnected, gives them learning skills and decision-making to the detection of abnormality. The activation function is usually nonlinear. Each function is suitable for well-defined purposes. [4] It is said that the constituted network is enriched by a form of generalization after learning a definite database.

In the model of Kohonen, it is possible to say that the self-organizing maps learn to classify input vectors depending on how they are grouped in this space. This differs from competitive networks where neurons and their neighbors learn to recognize groups in the input space. In fact, the neuron weight evolution rule follows the rule Kohonen except that instead of activating the single winner neuron, all the neurons located in the vicinity, and placed at a certain distance will also be activated (figure 6). These networks are also used for data analysis. However, the Enabling a whole neighborhood at once makes this type of less selective network in terms of classification [5], [6].

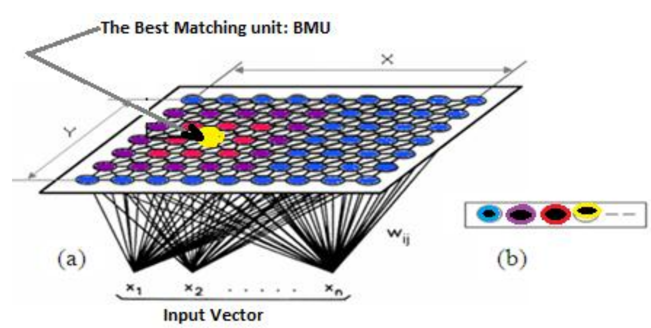

Fig. 6 Representation of the SOM map ; (a) in 2D and (b) in String

The weight vector of a neuron #i unit, designated by Vpi is shown, for j input data, as follows:

$$V_{pij} = \{w_{i1}; w_{i2}; w_{i3}; \ldots; w_{ij}\} \qquad (12)$$

Each neuron will receive elements characterizing the input vector. The nearest neuron representation by minimizing a Euclidean distance, the input vector is called the BMU 'Best Matching Unit'. At the end of each iteration "learning cycle or test map" each neuron has a weight vector, which will be compared by calculating the distance to the input vector to give a single winner neuron [4], [8]. This is the one that is the closest distance from the input vector.

The BMU is, then, the neuron unit that can best join the input vector. It is still the unity of winning neuron owing to every iteration. The quantization error associated with the neuron i is given by the Euclidean distance:

$$E_i = \| x(t) - w_i \| \qquad (13)$$

Thus, for a given input vector, the winner neuron "v" is the unit that minimizes the quantization error from which we will have:

$$E_v = \min E_i \quad ; i \in N \qquad (14)$$

For each learning or test iteration, a single neuron is activated; it is the BMU; this is the neuron whose prototype vector (weight vector) best represents the input vector. This activation propagates along the map SOM by following the form of a Mexican hat; this is described in Kohonen algorithm by updating equation of synaptic weights of the neurons. The learning rule updates the weight of neurons in the vicinity of activated neuron ' winner ‘, bringing them close to the input vector :

$$\Delta w_i = \gamma . h_{iv} (x(t) - w_i) \qquad (15)$$

With: γ is a learning report and hiv is a neighborhood function, which decreases with the distance between units i and v on the map.

- SOM settings by detecting anomalies

The Kohonen map has many parameters that can influence the detection rate such as:

- The size of the data vector to recognize, presented to the input of the classifier SOM. In this case a sample of the received signal is converted into a matrix of coefficients characteristic MFCC which has twelve windows (12 columns). Each line of this matrix means an anomaly wording.

- The size of the card that is the vector quantization space 2D or 1D.

- The number of neurons in the SOM map. A judicious choice of the size of the SOM map must be based on the number of anomalies in question and the number of neurons of the map. The total number of Nn neural map is approximated by Nn = 2.5C. Where C corresponds to the number of individuals employed in learning.

- The topological structure of the map: The mesh at the base of the neural network is generally square, rectangular or hexagonal. A hexagonal mesh is particularly suitable for the visualization of classes.

Fig. 7 Illustration of the topology of the SOM map after learning

- **The type of learning is sequential or parallel.**

The variables displayed by the SOM map are indicators of anomalies [1], [2], [3]. They are represented by their appropriate frequency, indicated as follows:

- h : healthy
- fr is the rotor rotation frequency
- fs is electric network frequency
- fb is the rotational frequency of the ball
- fc is the cage rotation frequency
- fbi the rotational frequency of the inner ring
- fbo the rotational frequency of the outer ring
- fes is the frequency of static eccentricity
- fed is the frequency of dynamic eccentricity
- feg is the frequency of global eccentricity
- fco is the commutation frequency
- fbg is the bearing frequency
- fbr is the frequency of broken bar rotor
- fsb is the frequency of Short rotor bar circuit
- fic is the frequency of short - circuit portion of the rotor ring
- fsc is the frequency of short circuit coil
- fps is the frequency of phase short-circuit
- fim is the frequency of imbalanced
- fsa is the frequency of short circuit between phase and batie
- fre is the frequency resonances

- **The extension of neighborhood**: the extension of the neighborhood is measured in number of neurons in the vicinity of the BMU winning neuron.
- **The number of iterations** of the learning algorithm. For good convergence condition of the SOM map to optimal results, Teuvo Kohonen chose very long learning periods between 1000 and 100000 iterations. An iteration corresponds to a presentation of the data sample at the

entrance to the SOM map. All times the condition remains dependent on the size of the input sample.

- **The initialization mode** of the SOM map. Three modes of initialization vectors weight (references) to the SOM map can be adopted: random, linear and using selected samples from the training set. Studies done in 2003 showed that the generated maps converge to the same performance whatever the initialization procedure.
- **The update rule of weight vectors** (prototypes).

V. Kohonen Learning Algorithm

The Kohonen algorithm simultaneously pursues two goals [4], [5], [6]:

- Find the best prototypes representatives of the signal data set. This is called vector quantization.
- Find a configuration such as two neighboring prototypes in the data space are associated with neighboring neurons on the map , this proximity being generally interpreted in the sense of Euclidean metric , or that topologically close neurons on the map react to similar input data.

This algorithm is described as competitive: in the presentation of an individual's network, neurons compete, so only one of them, the "winner" is finally active. In the Kohonen algorithm, the winner is the neuron whose prototype now the shortest distance, in the sense of Euclidean metric, with the individual presented to the network.

The neuron having won the competition determines the center of an area of the map called neighborhood area whose extension (radius) varies over time. The next phase, called update or adaptation, changes the position prototype to reconcile the individual presented to the network. The prototypes are even closer to the individual in question they are close on the map of the winner neuron. Weighting to determine the significance of changes in position in space is thus a function of distance on the map between the winner neuron and the considered neuron.

The steps of the Kohonen algorithm are as follows:

1. Initialization prototypes
2. Selecting an individual
3. Determination of the winner neuron for that individual; is the competition phase.
4. Modification of all prototypes of the map: stage adaptation and update.
5. Resume stepping 2 if the stop condition is not satisfied.

A. *Anomaly detection procedure flow chart by the SOM map*

The different stages of anomaly detection are given by the following diagram:

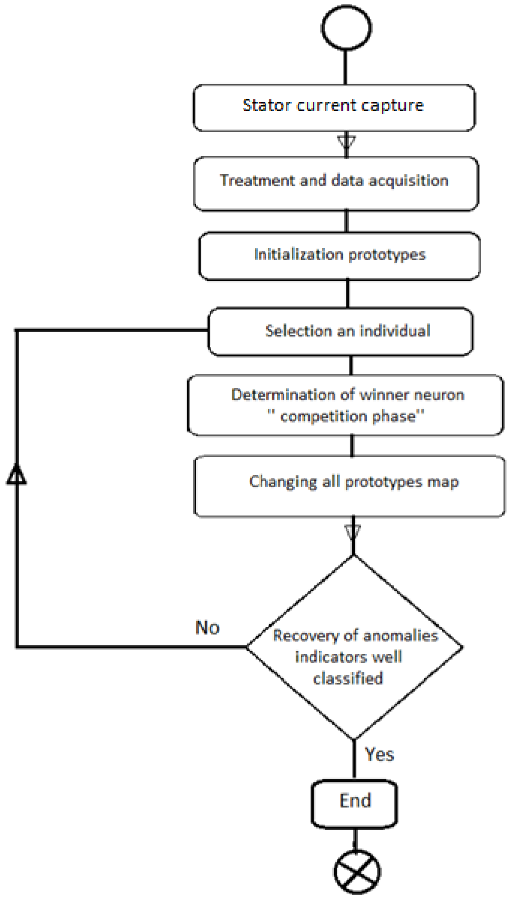

Fig. 8 UML activity diagram for the SOM map learning

VI. Experimental Results

A. *Detection result by the SOM map*

The entrance to the SOM map is the vector of the stator current from the experimental test after treatment and data acquisition, the result is given by the following topology:

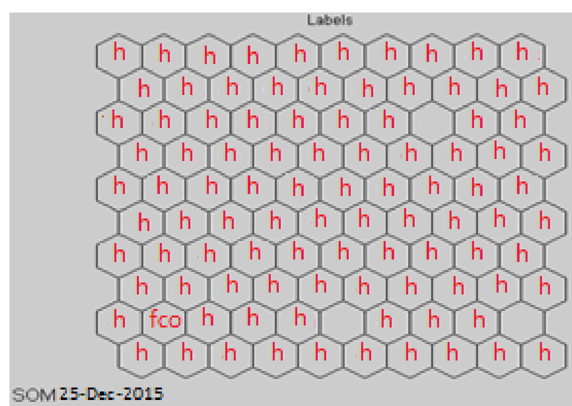

Fig. 9 Fault detection result of the inverter by the SOM map

- The result is given following an apprenticeship 97٪.

VII. EXPERIMENTAL BENCH

The experimental bench is composed of:

- A three-phase induction machine, the machine is controlled by an inverter ' OMRON ', the rotor shaft is coupled to a DC generator which feeds into a rheostat to control the load.
- Characteristic of the induction machine:
  - Nominal power 4 Kw
  - Nominal speed 1480tr/min
  - Moment of inertia J= 0.013kgm^2
  - Number of pair of stove P =2
  - Rolling type ball SKF 6208, to a mechanical rotational frequency from f_r = 25Hz, les frequency outer ring , inner ring , and ball cage are respectively f_{bext} =89.4Hz, f_{bint} =136Hz, f_c = 9.94Hz et f_{bille} = 58.4Hz.
- A light Microlog portable terminal for acquiring and storing from the sensor measurements.

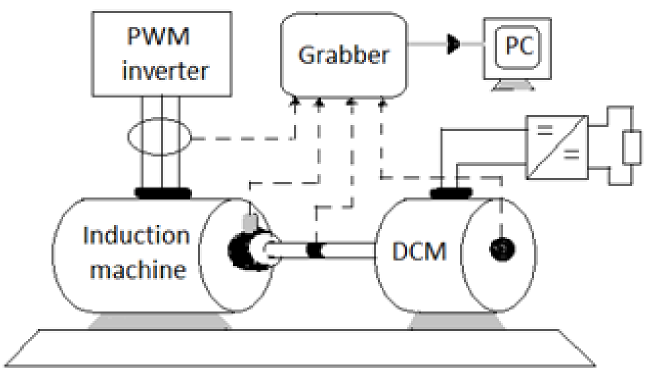

Fig. 10 Schematic block diagram of the experimental bench

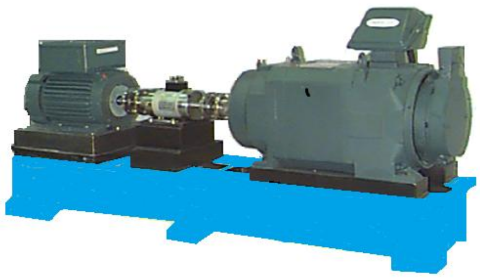

Fig. 11 Photography machines of experimental bench

VIII. CONCLUSION

The map SOM occupies a very advanced position in terms of robustness in adverse environments, and a universal recognition tool of static data. However, its operating rules related to Kohonen algorithm are an unsupervised one that can also be iterative, non-linear and self promoters.

Experimental results show that the SOM map is accurate. But the effectiveness of the anomalies recognition is strongly linked to the quality of learning in the developed system. Also, the segmentation of stator current signal in stationary atom is a very important factor to enhance the frequency characteristics of anomalies recognition rate.

However, the significant distortion of current results in a meaningful fluctuating power and involves then an increase in the effective current from the normal regime since the resulting harmonics generate only loss.

Various approaches and models have been proposed for the diagnosis. Each model suggests various solutions. However, they have limitations. A powerful tool that remains in this area is that the self-organizing map of Kohonen (SOM) and several variants of it were mentioned. The character of the unsupervised SOM algorithm gives it properties that are suitable for recognition in the presence of a large data volume. The experiment of SOM showed that it is effective in the representation of static data. This reality leads us to think about the design of integrating recurrent self-organizing patterns over time in line with the temporal variations of the sensed signals from our system.

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