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Growing Curvilinear Component Analysis (GCCA) for Stator Fault Detection in Induction Machines

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Abstract. Fault diagnostics for electrical machines is a very difficult task because of the non-stationarity of the input information. Also, it is mandatory to recognize the pre-fault condition in order not to damage the machine. Only techniques like the Principal Component Analysis (PCA) and its neural variants are used at this purpose, because of their simplicity and speed. However, they are limited by the fact they are linear. The GCCA neural network addresses this problem; it is nonlinear, incremental and performs simultaneously the data quantization and projection by using the Curvilinear Component Analysis (CCA), a distance-preserving reduction technique. Using bridges and seeds it is able to fast adapt and track changes in the data distribution. Analyzing bridge length and density, it is able to detect a pre-fault condition. This paper presents an application of GCCA to a real induction machine on which a time evolving stator fault in one phase is simulated.

Keywords: bridge; curvilinear component analysis; dimensionality reduction; electrical machine; fault detection; neural network; online algorithm; projection; seed; stator current; vector quantization.

Introduction

Data mining is more and more facing the extraction of meaningful information from big data (e.g. from internet), which is often very high dimensional. For both visualization and automatic purposes, their dimensionality has to be reduced. This is also important in order to learn the data manifold, which, in general, is lower dimensional than the original data. Dimensionality reduction (DR) also mitigates the curse of dimensionality: e.g., it eases classification, analysis and compression of high-dimensional data.

Most DR techniques work offline, i.e. they require a static database (batch) of data, whose dimensionality is reduced. They can be divided into linear and nonlinear techniques, the latter being in general slower, but more accurate in real world scenarios. See [1] for an overview.
However, the possibility of using a DR technique working in real time is very important, because it allows not only having a projection after only the presentation of few data (i.e. a very fast projection response), but also tracking non-stationary data distributions (e.g. time-varying data manifolds). This can be applied, for example, to all applications of real time pattern recognition, where the data reduction step plays a very important role: fault diagnosis, novelty detection, intrusion detection for alarm systems, speech, face and text recognition, computer vision and scene analysis and so on.
In recent years, research in the field of Fault Diagnosis (FD) and Condition Monitoring (CM) of electrical machines has attracted researchers all over the world. This because of its involvement in an endless number of industrial applications. The concept of FD and CM has always been a key issue for industries when it comes to maintaining the assets, especially large motors or generators, whose possible failures may pose serious repercussions in both monetary terms and non-monetary terms.
Early identification of incipient faults results in a quick maintenance and short downtime for processes under consideration. An ideal FD and CM system must be able to extract the required data and correctly detect and classify the fault incurred in the motor. In the most recent years, there has been a lot of research in the development of new CM schemes for electrical machines and drives, overseeing the downsides of the conventional techniques.
According to the authors of [2-4], the quantity of working machines in the world was expected to be around 16.1 billion in 2011, with a rapid development of 50% w.r.t. the preceding five years. Among these machines, Induction Machines (IMs) are the most common ones and are widely used in the industry. This derives from the fact that IMs are rugged, cheap, reasonably portable, sensibly high effective, and conform to the available power supplies. They are reliable in operations, yet are liable to various sorts of undesirable faults, which can be categorized as follows: mechanical faults, electrical faults and outer motor drive faults. In view of rotating magnetic field, the IMs are incredibly symmetrical electric systems, so any fault occurrence changes its symmetrical properties.
As per the statistics available from IEEE and EPRI for motor faults [5-7], stator-winding faults contribute to as much as 26% of the total number of failures in IMs. The stator winding faults begin as an inter-turn short circuit, which evolves over time into a short circuit between coils and phase windings. Thus, it is fundamental that a diagnosis be made able to track them in real-time [8, 9].
Working in real time requires a data stream, a continuous input for the DR algorithms, which are defined as online or, sometimes, incremental (synonym for non-batch). They require, in general, data drawn from a stationary distribution. The fastest algorithms are linear and use the Principal Component Analysis (PCA, [10]) by means of linear neural networks, like the Generalized Hebbian Algorithm (GHA, [11]) and the incremental PCA (candid covariance-free CCIPCA [12]). Nonlinear DR techniques are not suitable

for online applications. Many efforts have been tried in order to speed up these algorithms: updating the structure information (graph), new data prediction, embedding updating. However, these incremental versions (e.g. iterative LLE, [13]) require too a cumbersome computational burden and are useless in real time applications. Neural networks can also be used for data projection. In general, they are trained offline and used in real time (recall phase). In this case, they work only for stationary data and can be better considered as implicit models of the embedding. An example are the self-organizing maps (SOM) [14] and their variants [15 - 18].

For data drawn from a non-stationary distribution, as it is the case for fault and pre-fault diagnosis and system modeling, the online Curvilinear Component Analysis (onCCA, [19]) and the growing Curvilinear Component Analysis (GCCA) have been proposed in [20, 21]. They both track non-stationarity by using an incremental quantization synchronously with a fast projection based on the Curvilinear Component Analysis (CCA, [22, 23]).

The purpose of this paper is the presentation of an application of GCCA to the stator-winding fault problem previously described with the purpose of detecting and following in real-time the evolution of a fault in a phase of IM.

After the presentation of GCCA in Sec. 2, Sec. 3 shows the results of a fault simulation on a stator-winding on a real IM. Finally, Sec. 4 presents the conclusions.

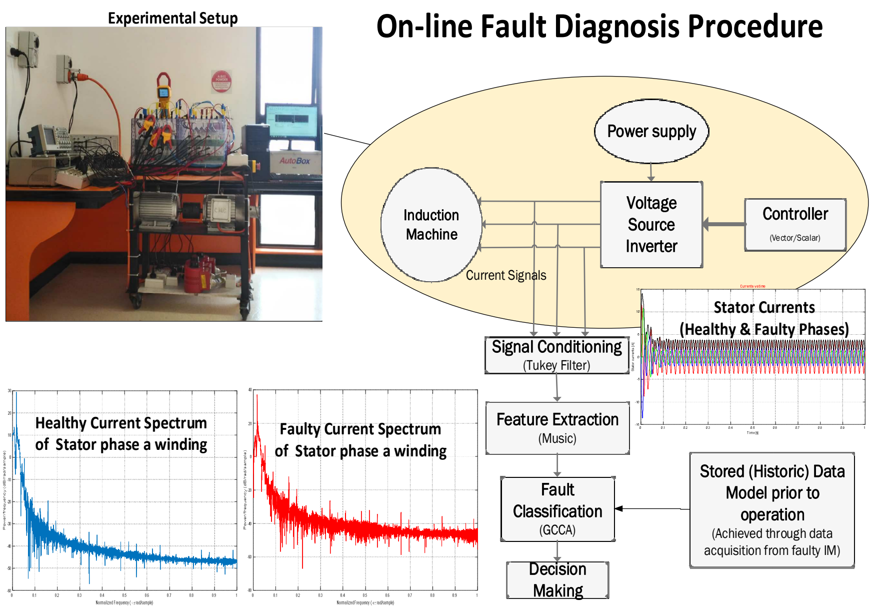

Fig. 1. Proposed Methodology

The Growing CCA (GCCA)

The growing CCA is an incremental supervised neural network whose number of neurons is determined by the quantization of the input space. Each neuron has associated two weight vectors: one in the input space (X-weight) and the other one in the latent space (Y-weight) which yields the data projection. Each neuron is equipped with a threshold which represents its Voronoi region in the data space. It is computed as the distance in the X-space between the neuron and its farthest neighbor (neighbors are defined by the edge graph) and is used for determining the novelty of the input data. If the input data passes the novelty-test a new neuron is created, otherwise the closest-neuron (the first-winner) in the X-space and its neighbors adjust their weight vectors according to the soft competitive learning (SCL, [19, 20]).

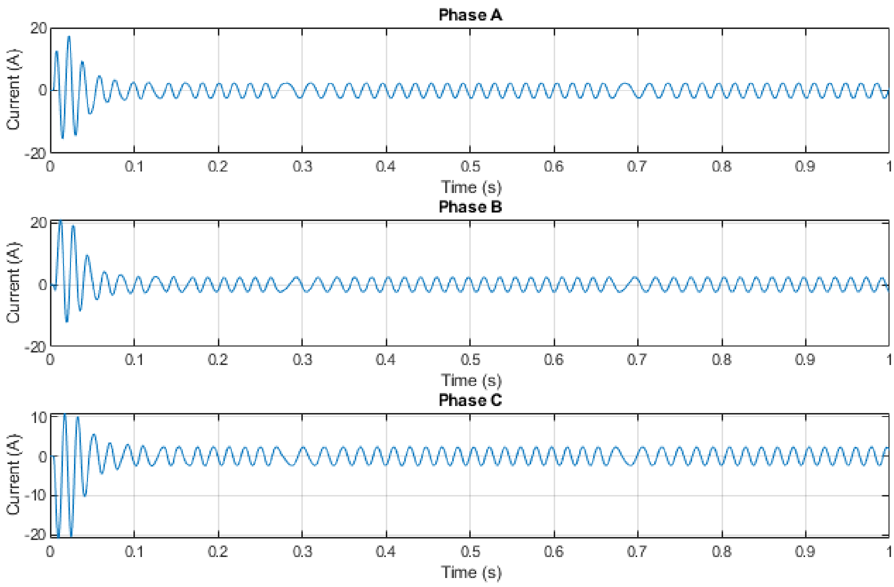

Fig. 2. Three Phase Current Signature of a Healthy IM

Neurons can be connected in two ways: through edges, which define the manifold topology according to the Competitive Hebbian Learning (CHL, [24]), or through bridges, which track a change in the input distribution (e.g. a jump). GCCA uses bridges and seeds to understand how the input evolves over time. A bridge is a particular kind of neurons link created to connect a new neuron to the already existing network. It is a directional link towards the new neuron. In this sense, it points toward the change in the input data. A seed is a pair of neurons made of a neuron and its doubled (whose weight is computed using the hard competitive learning, HCL, [19, 20]). Neuron-doubling is performed each time the first-winner is the top of a bridge with the second-close neuron (the second-winner). On the contrary, if the first-winner is the tail of the bridge, that connection becomes an edge.

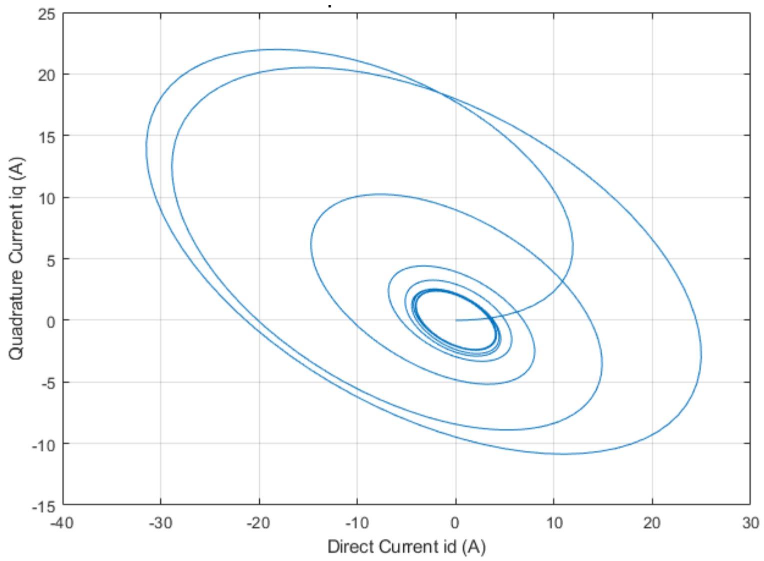

Fig. 3. Space vector loci of stator current for a Healthy IM

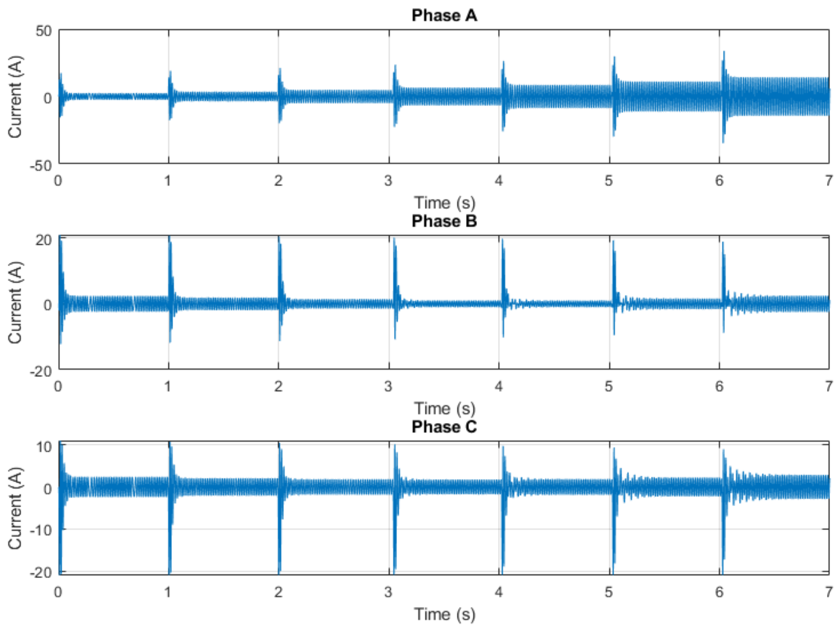

Fig. 4. Fault evolution in IM from healthy to 30% stator inter-turn fault

GCCA is incremental, it can increase or decrease (pruning by age) the number of neurons.

The projection algorithm is based on CCA. It uses a distance-preserving function which aim to preserve in the Y-space distances whose length is less than λ.

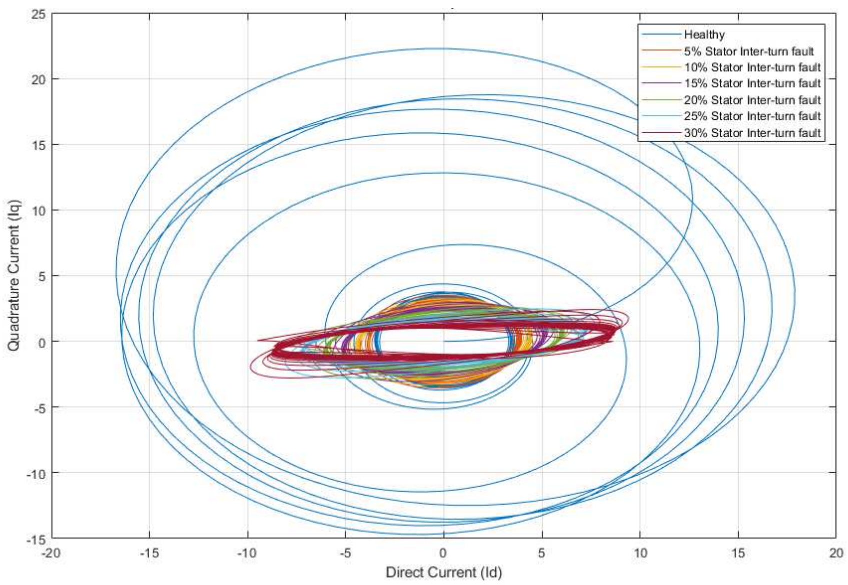

Fig. 5. Space Vector Loci – Fault Evolution from 0-30% stator inter-turn fault

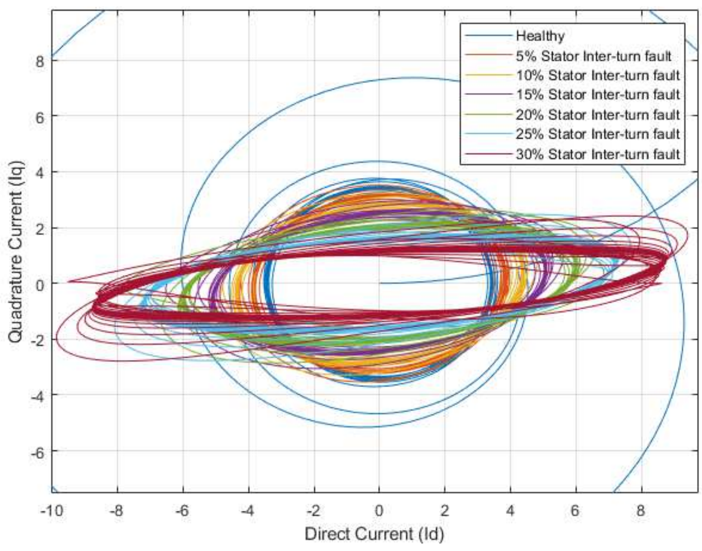

Fig. 6. Fault Evolution from 0-30% stator inter-turn fault: zoom around the origin

Stator-winding Fault Experiment

Using model based techniques, a stator fault has been modelled and the temporal-evolution of its current has been compared with the healthy case.

The dataset is generated for both the cases: healthy and faulty conditions of a 3-phase Squirrel cage IM which is of 1.1kW rating and connected to a 60Hz voltage supply. By using a pre-processing based on the Tukey filter, the signal to noise ratio (SNR) is increased from the acquired current signal. Thereafter, by using statistical signal processing, the frequencies of interest are extracted (see Fig. 1). Both the healthy and the faulty IMs are dynamically modelled in MATLAB® and the current signature acquired. The dataset consists of 35685 samples taken in a span of seven seconds.

Fig. 2 and Fig. 3 show, respectively, the three phase current of the IM and the space vector representation (i.e. a two-phase current transformation by means of direct and quadrature currents) in the healthy case. Both figures are characterized by an initial transient (large oscillations in the current signature and corresponding decreasing spirals in the space vector representation) followed by a steady state (regular oscillation in Fig. 2 and circles in Fig. 3).

The inter-turn short circuit fault is induced in the IM by introducing a variable resistor in parallel with the phase A of the IM. The resistance was varied to correspond to a percentage of fault in the stator. From the starting (t = 0), the IM is in healthy condition for one second and after every second, the percentage of stator inter-turn fault rises by 5%. In particular, the current signature (see Fig. 4) in phase A rises every second, first portraying a transient stage (a spike in current signature each second) and then moves to a steady state. The other phases are also affected by a transient stage as the fault severity changes as shown in Fig. 4.

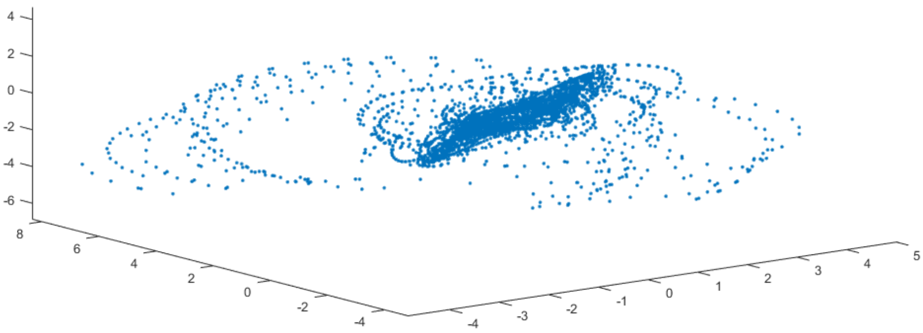

Fig. 7. GCCA - Fault Evolution from 0-30% stator inter-turn fault – X Space Quantization

The interchange between transient and steady phases, i.e. the fault evolution over time, is also observed in the space vector representation (see Fig. 5 and its zoom in Fig. 6). As in the previous case, the space vector trajectories follow the same loci as before but with larger radii (they are larger and larger as the fault evolves).

GCCA has been applied to this problem. The parameters of GCCA are the following: α=0.01, λ=0.5, α_1=0.2, α_n=0.04, age_{max}=4, epochs=5. GCCA is trained with the phase

current information and evolves with it. It also projects in the latent current space in real time.
Fig. 7 shows the quantization made by the first layer of weights of GCCA (connections are not shown for clarity)
The trajectories have been modelled (tracked) accurately, spirals and circles are visible. Fig. 8, instead, illustrates the linking phase of the neural network. The first transient is represented by small edges and bridges, which are also orthogonal to the true current projection. This is due to the rapidity of the transient which does not allow their pruning. However, they build a fine small size network, which is typical of self-organization. As the transient evolves more and more bridges track the changes in current, which are represented by their density. Indeed, the appearance of bridges detects the onset of a non-stationarity. If the time change is abrupt, more and more bridges are created in a correlated way. This is the reason that the inner part of the plot is denser and denser.
Unlike other neural networks which need constant parameters in order to track non-stationarity, GCCA does not only recognize the pre-fault situation, but also records the whole story of the machine.

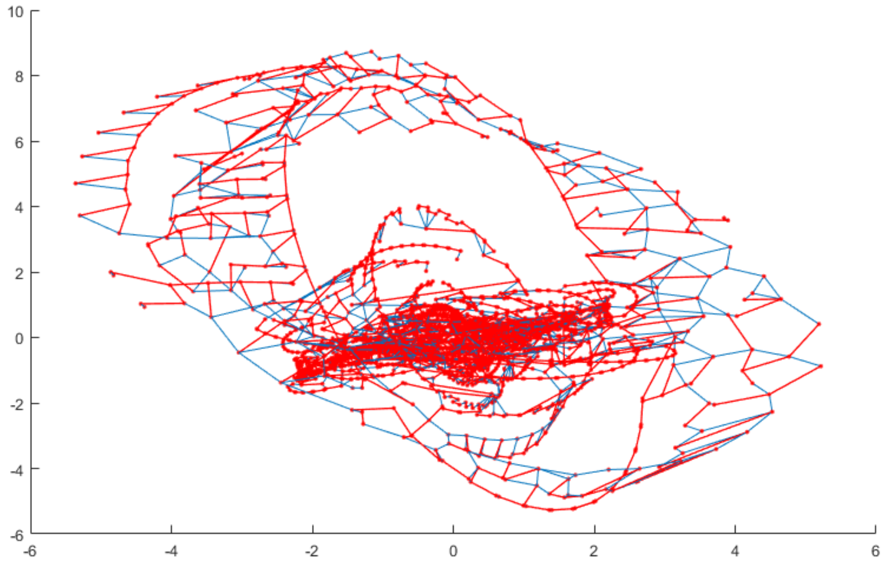

Fig. 8. GCCA - Fault Evolution from 0-30% stator inter-turn fault (edges in blue, bridges in red)

CONCLUSIONS

Time signals extracted from a non-stationary distribution, as in the case of the stator phase current, which evolves in the same way as the machine (faults and deterioration) are not easy to handle, above all in real time. This could have important applications, as, for instance, the possibility to stop the motor well before the fault or for maintenance. In the literature, only linear techniques are used, because of their speed and simplicity. Nonlinear techniques and neural networks are too cumbersome and time consuming. The GCCA neural network is the only neural method able to track a non-stationary input distribution and to project it in a lower dimensional space. In a sense, GCCA learns a time-varying manifold. It has been applied in a difficult test, like the tracking of evolutive faults on an electrical machine. It has been shown that it learns (and represents) the machine life, from the first transient to the last fault. However, this can be automatically exploited, by means of the bridge length and density estimation, in order to stop working for avoiding damages. Future work will deal with the exploitation of the stator current spectrum (by using algorithms like MUSIC) and observing the changes with respect to the stator current spectrum of a healthy IM. Because of this preprocessing step on the stator currents, GCCA should perform a faster and more reliable fault detection. It will also help in fault classification.

Acknowledgments

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