DEVELOPMENT AND EXPERIMENTAL EVALUATION OF A VISION SYSTEM FOR DETECTING FAULTS OF INDUCTION MOTOR STATOR WINDINGS IN STATOR ASSEMBLY LINES

BERNARDO CASSIMIRO FONSECA DE OLIVEIRA¹, RODOLFO CÉSAR COSTA FLESCHE², MIGUEL BURG DEMAY³, HIAGO ANTONIO SIRINO DANGUI⁴

1. Laboratório de Metrologia e Automatização (LABMETRO), Departamento de Engenharia Mecânica, Universidade Federal de Santa Catarina
Caixa postal 5053, 88040-970, Florianópolis, SC, Brazil
E-mail: bernardo.oliveira@labmetro.ufsc.br

2. Departamento de Automação e Sistemas, Universidade Federal de Santa Catarina
88040-900, Florianópolis, SC, Brazil
E-mails: rodolfo.flesch@ufsc.br, hiagodangui@gmail.com

3. Fundação CERTI
Caixa postal 5053, 88040-970, Florianópolis, SC, Brazil
E-mail: mbd@certi.org.br

Abstract— Several tests for quality control are performed in electric motors during their manufacturing. Even though most of the tests are automatic, some of them, mainly vision inspection tests, are typically done by human operators. It is well-known in literature that human operators are not reliable for repetitive inspections, since they are subjected to factors like subjectivity and lack of attention. In this sense, vision systems are an alternative to increase the reliability of the inspections. This paper presents the development of a vision system to inspect defects related to the windings of stators in a motor assembly line, before the rotor is assembled to the motor. Specifically, the proposed vision system was designed to identify defects characterized by one or more coil segments of the winding that are not properly fastened to the other coils and are placed in the projection of the orifice where the rotor will be inserted. This defect can become a failure if during the rotor insertion process the wire is broken, if it loses its insulation, or if the rotor cannot freely spin due to the presence of the wire. Two stator models were evaluated in a test rig in an industrial environment and, for the one used to tune the program parameters, the developed edge-detection algorithms achieved a success rate of 100%. The success rate for a stator model that was not previously used to tune the algorithm parameters was 82.7%. Based on the achieved results, improvements in the developed system are also discussed to enhance its reliability and ruggedness to allow its implementation in an assembly line.

Keywords— Electric motor, vision system, inspection, computer vision.

Resumo— Diversos testes para controle de qualidade são realizados em motores elétricos durante sua fabricação. A maior parte desses testes é automatizada, contudo alguns, em especial inspeções visuais, são tipicamente feitos por operadores humanos. É bastante difundido na literatura que esses operadores não são confiáveis para inspeções repetitivas, pois estão sujeitos a fatores como subjetividade e falta de atenção. Nesse sentido, sistemas de visão são uma alternativa de aumento da confiabilidade das inspeções. Neste artigo, apresenta-se o desenvolvimento de um sistema de visão para inspecionar defeitos relativos às bobinas do estator em uma linha de produção de motores elétricos, em um ponto anterior à inserção do rotor. Esse defeito se torna uma falha se, durante a inserção do rotor, o condutor é rompido, se o condutor perde o isolamento elétrico ou se o rotor eventualmente for travado devido à presença do condutor. Dois modelos de estatores foram avaliados numa bancada de testes num ambiente industrial e o algoritmo de detecção de bordas desenvolvido atingiu uma taxa de acertos de 100% com o modelo utilizado para ajuste dos parâmetros do algoritmo utilizado. A taxa de acertos foi de 82,7% para o outro modelo. Baseado nos resultados obtidos, melhorias no sistema são também discutidas visando o aumento da confiabilidade e robustez, permitindo uma futura aplicação diretamente na linha de montagem.

Palavras-chave— Motor elétrico, sistema de visão de máquina, inspeção, visão computacional.

1 Introduction

Electric motors are machines which convert electrical energy into mechanical energy, in the form of linear force or torque. They can be found in different topologies and sizes, and their applications are diverse (Lamin Filho, 2013). Because of their reliability and cost, alternating current squirrel-cage induction motors are widely used in industry (Pederiva, 2007). This type of motor is composed of two main parts: a stator and a rotor (Saidur, 2010). An example of single-phase induction motor with highlights to the (1) rotor and (2) stator can be seen in Figure 1.

Usually, the stator manufacturing process is more complex than the rotor one. Therefore, it is expected that the quality control for stators is more resource-consuming than for rotors.

After monitoring the production line of an electric motor manufacturer, different defects could be identified and classified according to their potential to cause a failure. The most relevant defects are broken wires in the stator windings, coils of the stator winding in the region of insertion of the rotor, short-circuit in the windings, and the disconnection of one or more stator power cables. A vision-based system for detecting the last defect is presented in Oliveira et al. (2016).
Many of these defects can be identified using electrical tests in the end of motor assembly lines, but there are some defects which do not change any electrical or mechanical property of the motor and, thus, cannot be identified by such tests. A relevant example is the presence of coils of stator windings in the region of insertion of the rotor (CIR), which can cause short-circuits, broken wires or even a locking of the rotor spinning. Since this defect may only become a failure sometime after starting the motor, it may not be identified by electrical tests. However, a coil that is not properly fastened to the winding and may cause such type of failure can be visually identified by human operators, before the insertion of the rotor.

On the other hand, human operators are subjected to factors as lack of attention, fatigue and subjectivity over time, in addition to being costlier than automatic solutions, since they require training and time for skill development (Gill, 2013; Malamas et al., 2003; Fu et al., 2016). Also, there are many environmental restrictions that must be also considered. For those reasons, the use of computer vision and vision systems (VS) has increased during the last years in many industrial tasks, such as object measurements, visual positioning, object location and defect detection, becoming progressively an interesting alternative for application in industry (Feliciano; Souza; Leta, 2005; Fisher et al., 2014; Gonzalez; Woods, 2008; Malamas et al., 2003; Fu et al., 2016). In addition, some examples from literature can be given regarding the reliability of VS in industrial applications, such as the works of Malamas et al. (2003), Golnabi and Asadpour (2007) and Liu et al. (2015).

Regarding the use of VS for inspecting electric motor parts, the work of Herakovi and Noe (2007) presents an experimental analysis of the required conditions to replace the human inspection of stators by VS. Sun, Tseng and Chen (2010) proposed a machine vision-based system for inspection of electric contacts of switches, breakers and relays, consisting of three sub-systems inspecting different types of defects from the top, side, and bottom surfaces of electric contact. Le, Hoang and Ngo (2016) proposed a method for inspecting the order of electrical colored wires in industrial connector cables manufacture. The work of Leo et al (2016) describes a two-camera image based measurement system for the online inspection of electromechanical parts. Roosileht (2014) developed a VS for measuring metal sheets used to build stators, thus avoiding errors due to thermal expansion caused by the difference on the temperatures in the storage and in the manufacturing environments. In Cognex (2015), the company shows its application of smart cameras inspecting stator production lines. So, it is noticeable the large applicability of VS in defect detection and process control for parts used in electric motors (Golnabi and Asadpour, 2007).

Considering that, this paper proposes the use of VS to inspect CIR when the rotor is not yet placed in the motor, i.e., it uses images of the stator acquired at the end of a stator assembly line. Experimental evaluation of the developed VS is performed considering a goal of 99.7 percent (three-sigma limit) of correct indications, showing the benefit of vision techniques in an industrial environment.

In section 2, CIR defect is detailed and solutions are described, including the developed VS algorithms and the proposed test rig. Following, in section 3, case studies are proposed, and their outcomes are presented. Finally, the conclusions in section 4 summarize the main ideas of this paper.

2 Problem characterization and proposed solutions

In this section, CIR is described in subsection 2.1, the test rig and its components in subsection 2.2, and the developed algorithms in subsection 2.3.

2.1 Defect description

CIR, shown in Figure 2, is characterized by a conductor which is not well fastened to its coil and is located into the rotor insertion area. This may lead to motor failures, since the wire can be damaged during rotor insertion or even lie in the airgap, causing short-circuits and rotor spinning locking.

It is possible to inspect this defect at two different moments during the production process: when the stator is finished but the rotor is not inserted yet, or when the rotor is already assembled. In this work, it is proposed to inspect just the stator, without the rotor, because in this situation it is possible to detect mispositioned wires along the whole inner surface (depth) of the stator. Even considering that the specification of

Figure 1. A model of single-phase induction motor.  

Figure 2. CIR example.
the lens and camera is more expensive and complex for this case, it is possible to use a cheaper equipment, which inspects only a small section of the stator at a time and rotates it. Furthermore, the detection of defective parts before inserting the rotor considerably simplifies the reworking process.

2.2 Test rig

A test rig was developed to capture images for detection of CIR. A picture of this test rig is presented in Figure 3. Its components are identified as: (1) camera; (2) camera positioning system; (3) stator positioning system; (4) light cover; (5) power source, and (6) light diffuser.

The camera was placed above the inspected part because it is the position more likely to be adopted in the production line. Additionally, the inspection can be done with one single picture. The VC was composed of a Pixelink PL-B777G camera and Fujinon HF9HA-1B lens, which is not the best match for the camera, but was the best option available for use. Parameters of the VS can be seen in Table 1.

2.3 Algorithm

An image captured by the camera using the proposed test rig is shown in Figure 4(a). A CIR can be seen in this case, and a detailed view of the defect is presented in Figure 4(b).

Based on that image, the algorithm, which has been implemented using LabVIEW® and its Vision Development Module, follows the steps shown in the flowchart in Figure 5.

In order to locate the stator on the captured image of Figure 4, a circumference detection tool based on gradient edge detection and least squares was used. Since the test rig is able to provide an image that is almost centered with respect to the motor axis, it is possible to determine an annular region that contains the circumference associated with the upper part of the stator hole. Then \( m \) lines are radially distributed along the center of this annulus and at each of those lines a border, which corresponds to the circumference of interest, is identified. A number \( m \) of 72 lines was arbitrarily chosen in this case, since it has provided a good line density on the inspection area. Each of these lines are the Regions Of Interest (ROI) of an edge-detection technique based on the gradient of gray level intensity used to determine the borders which represent the edge between the stator inner and upper surfaces. Each

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Interface</td>
<td>Gigabit Ethernet</td>
</tr>
<tr>
<td>Sensor type</td>
<td>CMOS</td>
</tr>
<tr>
<td>Sensor size</td>
<td>1/2.5&quot; (10.16 mm)</td>
</tr>
<tr>
<td>Sensor resolution</td>
<td>5 MP (2592 pixels × 1944 pixels)</td>
</tr>
<tr>
<td>Focal length</td>
<td>9 mm</td>
</tr>
<tr>
<td>Minimal working distance</td>
<td>100 mm</td>
</tr>
</tbody>
</table>

Figure 3. Test rig and its components: (1) camera; (2) camera positioning system; (3) stator positioning system; (4) light cover; (5) power source, and (6) light diffuser.

Figure 4. (a) Image captured with the test rig of an inspected stator with a defect. (b) Detail of the defect.

Figure 5. Flowchart of the proposed algorithm.
ROI is a vector \( l(i) \) with gray levels from the pixels of those lines, and \( i = 1, 2, \ldots, N \), where \( N \) is the number of pixels of each line. The algorithm used in this paper considers that a border is found in the first point at which the condition in Equation (1) is matched:

\[
l(i + 1) - l(i) \geq \Delta g, \quad (1)
\]

where \( \Delta g \) is the difference of gray levels which characterize a border. In the case studied in this paper, the best value \( \Delta g = 50 \) was obtained experimentally and is assumed in all cases. The coordinates of each of those border points with respect to the image reference point are represented as \( (x_{\text{meas}}, y_{\text{meas}}) \) and they are stored in a vector \( p(k) \), \( k = 1, 2, \ldots, m \). As a last step, a least-squares algorithm is used to define the best circumference considering all the points in \( p(k) \). This circumference is called ‘stator circumference’ and its parameters are the coordinates of its center point, \( (x_c, y_c) \), and its radius, \( R \). The parameters of the circumference are obtained by solving an optimization problem that minimizes the cost function \( \rho \) of equation (2):

\[
\rho = \sqrt{\sum_{k=1}^{m} d_k^2}, \quad (2)
\]

where

\[
d_k = \sqrt{(x_k - x_{\text{meas}})^2 + (y_k - y_{\text{meas}})^2},
\]

\( d_k \) represents the distance from the \( k \)-th point in \( p(k) \) to the point \( (x_c, y_c) \), which represents the intersection between the fitted circumference

\[
(x_c - x_k)^2 + (y_c - y_k)^2 = R^2
\]

and the \( k \)-th line.

After the location of the center of the stator in the acquired image, the next step is to find the position of the insulators, in order to guarantee that they will not be considered as defects when analyzing the internal region of the stator. However, finding the correct position of insulant slots turned out to be cumbersome, due to variations of the manufacturing process. As the stator block is formed by stacked isolated metal sheets, their alignment is crucial to have uniform inner surfaces and insulant slots. Any variation in this feature may jeopardize the algorithm performance. In addition, the different positions that insulators can assume may produce variations in the image parameters, making it more difficult to find their positions on the image. Finally, color variations, due to many factors such as dirt or material variation, may also have an influence on the performance of the algorithm. Then, in order to increase the algorithm accuracy for identifying insulant locations, another processing tool was required. It considers that the pixels inside a circular area with a diameter of 5 pixels centered at the identified points are points of interest, and by using this idea it was possible to correct determine the position of the insulators on the image.

The described tool uses a threshold filter on the stator internal region to produce a binary image where only the detectable insulant points are represented. The behavior of this tool is defined by equation (4):

\[
p'(x, y) = \begin{cases} 
0, & \text{if } p(x, y) < 220, \\
1, & \text{if } p(x, y) \geq 220,
\end{cases} \quad (4)
\]

where \( p'(x, y) \) is the gray level of the pixel \( (x, y) \) after the use of the filter and \( p(x, y) \) is its gray level in the original image. The value which was used to establish the threshold was 220, since it has presented a good result on preliminary tests and it also represents well the gray level of the insulant pixels. Then the circular areas around those points are drawn. The result can be seen in Figure 6, which presents in (a) a captured image, in (b) the virtual gauge resulting from (a), and in (c) a detail from (b). In (b), a circular ROI called ‘detection circumference’ is determined by using the center of the stator circumference and its radius subtracted by the arbitrary value of 5 pixels, obtained by previous experiments. Using this ROI with the previously described gradient edge detection tool, it was possible to determine the edges of the insulators.

The next step is to use a median filter to avoid non-homogeneities such as dust inside the stator. This filter is defined by a 5x5 kernel in which the central value is changed to the median of all the values of this sub-window. The kernel starts from the left upper corner of the image and scans it row by row from the left to the right. The value of each filtered pixel can be expressed as in equation (5), adapted from (Verma, Singh and Thoke, 2015):

\[
p'(x, y) = \text{median}_{i,j \in W}[p(x+i, y+j)], \quad (5)
\]

Figure 6. Procedure to estimate the location of the insulators on the image: (a) a captured image, (b) the virtual gauge resulting from (a), (c) a detail from (b).
where $W$ is a window, $i$ and $j$ are the row and column indices. After that, the ‘detection circumference’ and a gradient edge detection tool were used in the original image to determine potential defect points. As can be seen in Figure 7, in addition to the potential defects, this function detects the insulant borders. Since the edges of the insulants are already known, the algorithm ignores points which correspond to them and, therefore, each detected point can be identified as a defect.

### 3 Case study and results

A case study was proposed with the objective of analyzing the behavior of the developed algorithm. Special attention was given to the efficiency of the insulant position estimation, since it is the major key to correctly identify the presence of defects. Also, the test is valuable to better characterize the inspection and to find possible problems, which may affect the reliability of the algorithm.

Tests were first conducted in a laboratory environment. Four stators were used with artificially-introduced defects. Artificial defects were used in this phase because the number of stators with real defects was limited and they were reserved for the validation tests, which should use different stators than the ones used for tuning the algorithm. Even though the defects were not real ones for this first test, they were produced with the same characteristics of real defects observed in the production line, such as width, color and region of occurrence, and the same test rig used in manufacturing line was used to capture the images.

Those tests were important to determine algorithm parameters, such as threshold values and kernel sizes of the filters. Tests with different light intensities were also performed, since the illumination is one of the most important factors for capturing good images. With a good set of specifications, it was possible to proceed to the next phase: the validation test using real defects.

The tests in real conditions were performed in the production line of an electric motor manufacturer. The tested stators were removed from the manufacturing line to perform the inspection and tested in the test rig described in section 2.2. This procedure reproduces almost the same conditions that would be found in a real application. It was not possible to completely integrate the test rig in the line because a great amount of resources would be necessary for this first validation test, but the main difference from the ideal test scenario is that the positioning of the stator in the rig is not automatic, but done by a human operator. Once the algorithm is validated, it is intended to test the system in a running production line.

Two different models of stator were used to perform the validation tests, which will be identified as $\alpha$ and $\beta$. The difference between these two models is the diameter of the internal hole of the stator and also the height. Both are larger in model $\beta$. Even though it was clear that such differences could lead to differences in the best set of parameters, as the light intensity, those tests were performed as a way of evaluating the robustness of the proposed method to changes in the characteristics of the stators.

Twenty five stators of model $\alpha$ (four with CIR defect) and fifty two of model $\beta$ (eight with defect) were used for the validation tests. In all cases, stators were classified as defective or not based on a visual inspection by two skilled operators, which agreed upon the classification. For model $\alpha$ — the model used for tuning the algorithm parameters —, the algorithm could correctly classify all the stators as defective or flawless. On the other hand, for model $\beta$, as can be seen in Table 2, the algorithm produced nine incorrect indications (17.31%). All the incorrect indications were false positives, i.e. the algorithm classified as defective a stator that did not present any defect. To better understand the reasons for the incorrect indications, they were divided according to the most probable source of the error: light or insulant detection issues. The first one involves any problem related to illumination and was caused mostly because of the geometrical differences between the models, since the algorithm parameters were optimized for $\alpha$. The second one involves insulant detection problems also caused by geometrical differences.

Even though the number of tested parts was small, the inspections on the first model show that the proposed method has potential to be adopted in manufacturing. They also show that the $a$ priori tests in the laboratory were enough to correctly tune the parameters of the algorithm. This was not the case for the second model, thus illustrating the dependence of correctly tuning the algorithm parameters for each specific model of stator. For future reference, it is recommended that each model has a proper set of parameters in order to avoid algorithm mistakes.

Regarding the algorithm, it is important to notice that the detection may be compromised if the conductor is exactly above two insulant borders, since all the edges in those regions are ignored by the algorithm. However, it is clear that it is very unlikely that this situation happens.

From the results of this test, it was noticed that in all the proposed cases the test rig functioned properly, creating proper conditions for the image acquisition.
The observed problems were related to the tuning of the algorithm and not to the test rig itself, what indicates that the VS has potential to be integrated to assembly lines.

4 Conclusions

This paper proposes the use of VS to inspect the presence of coils of stator windings in the region of insertion of the rotor (CIR), a relevant defect of electric motor stators. An algorithm was developed to detect this defect and experimental evaluation of its performance was done considering real motors from a manufacturing line. A test rig was developed to capture images which were used to validate the algorithms for detection of CIR. Two different models of stator were used for testing. The algorithm presented 100% of correct indications for the first investigated model, but only 82.69% for the second. The main reason for this difference was that the algorithm was tuned considering stators of the first model, thus indicating a strong dependence of the proper tuning for each model. More tests need to be done for all cases to evaluate the effective success rate of the VS, but the preliminary results presented in this paper show that the target rate of 99.7% can be possibly reached.

The next activities of this research will be oriented towards optimizing the parameters of the algorithm for each investigated model, evaluating a larger number of samples, and integrating the test to a production line.

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