Inspection System with Neural Network and Vision Techniques for the Manufacture Industry

Sistema de inspección con redes neuronales y técnicas de visión para la industria manufacturera

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Abstract

The inspection of components with vision systems is a task that can be achieved with different methods, in this project the problem is solved applying artificial neural networks. This project uses the technique of image erosion against a mas-ter picture (connector) and neural network pattern recognition after erosion. The acceptability of connectors (Shells) is achieved using the recognition of elements by means of artificial vision, on this work explains how we can extract the key features of the image and we convert these to numbers and feed the neural net-work to determine if a connector meets the requirements or is a defective con-nector. The system was tested in the inspection area of receipt in local manufac-ture factory, where the first inspection of the components is carried out, against their drawing. The validation results of the vision system show that the wrong components, oval and those that did not have the angular guides on the position expressed in the supplier's drawing and established as necessary by design were rejected.

Inspection System, Manufacture Industry, Neural Network, Visión System

Resumen

La inspección de componentes con sistemas de visión es una tarea que se puede lograr con diferentes métodos. En este proyecto, el problema se resuelve aplicando redes neuronales artificiales. Este proyecto utiliza la técnica de erosión de imagen contra una imagen maestra (conector) y el reconocimiento de patrones de redes neuronales después de la erosión. La aceptabilidad de los conectores (carcasas) se logra mediante el reconocimiento de elementos por medio de visión artificial. En este trabajo se explica cómo podemos extraer las características clave de la imagen y las convertimos en números y alimentamos la red neuronal para determinar si Un conector cumple con los requisitos o es un conector defectuoso. El sistema se probó en el área de inspección de recepción en la fábrica local de manufactura, donde se realiza la primera inspección de los componentes, en contra de sus planos. Los resultados de la validación del sistema de visión muestran que se rechazaron los componentes incorrectos, el óvalo y los que no tenían las guías angulares en la posición expresada en el dibujo del proveedor y establecidas según sea necesario por diseño.

Sistema de Inspección, Industria de Manufactura, Red Neural, Sistema Visión

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Introduction

The lower labor cost in developing nations compared with that in developed economies often results in difficulty in justifying automation machinery. While such technology can improve the quality of product, and productivity as well as reduce the cost of the products, in developing and emerging economies there is often a need for manufacturing companies to ask for support to research center as the universities, address students to support the local industries [1].

Artificial Vision (AV) uses images that are captured by an industrial vision camera and later processed through the specific software. In this way, AV is able to measure, count, verify, select and identify faults and anomalies and, based on this processing, the technology also has the ability to make decisions such as expelling a determined product of the production line when this does not meet the quality standards required. These decisions are made based on pre-established parameters, so that everything that does not comply with these parameters, it is considered wrong [2].

In a local manufacture industry, 4000 harnesses are manufactured per day. The harnesses have a mean of two (2) connectors each, and a verification of these connectors is made daily. Due to a strict quality criterion, all cables are subjected to a double visual inspection. Even with these activities, there are losses of around 50,000 USD per year for rework and defects. Price of a vision system in the market tend to range of 2,000 to the 100,000 USD. The local manufacture industry has an area of inspection of receipt, so the cost for the system of vision could be as high as 60,000 USD.

The system would be expected to have inspection machine programmable optics, and also require the hiring of specialized personnel in the field or hiring support companies which would represent up to another 15,000 USD per year. The cost would be justified on the grounds that in certain applications the teams need to be constantly adjusted or retrained, due to the changing nature of the environment where they work.

The aim of this paper is to propose to develop a low-cost automatic inspection system using vision techniques and artificial neural networks trained with the backpropagation algorithm capable to reduce the human errors.

The inspection system would need to be fast and reliable, able to detecting orientation, diameter and defective machined keyways of connectors used in the automotive and military industry.

Background

Artificial Neural Networks (ANN) have been developed as generalization of math-ematical models of human cognition and have shown promise for solving difficult problems in areas such as pattern recognition and classification. A neural network consists of a group of simple elements called neurons which process input infor-mation. Using neural networks as a classifier requires a training phase and a testing phase. In the training phase, the neural network makes the appropriate adjustment for its weights (W) to produce the desired response. When the actual output response is the same as the desired one, the network has completed the training. In the testing phase, the neural network is asked to classify a new set of images and its success is evaluated [3].

In [11] the authors addressed the task of identifying surface defects or imperfections in foundry processes such as inclusion, cold lap and misruns. The authors used a segmentation method that marks the region affected by some of the defects, and then applied machine learning techniques to classify the incorrect regions. The researchers used the weka tool to perform the classification task with the algorithms NaiveBayes, SVM, J48 KNN, and RandomForest (RF). With RF, with a sample of 50 they achieved an approximately 95% accuracy. In a similar way, our work seeks to identify defects in a connector through the method of erosion to later predict using a neural network. In our work, the acuracy was 97%.

Maintaining quality standards is important in any company due to the rotation of employees in the inspection area. At work [12] the authors propose a neural network model to help industrial practitioners make decisions in the area of inspection with binary inputs.

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The experimentation was carried out using 70% of the data for training and 30% for testing. The authors conducted a two-stage evaluation. In the first, a neural network was allowed to decide if the product was a rejection. In the second stage, a second neural network model decided if the piece could be reworked or it was definitely scrap.

Unlike our work, the authors used input from experts, while this work takes information from the pieces through a camera. In phase 1, they reached 97% of pieces correctly classified and in phase 2 accuracy was 98%. Unlike our work, the authors used input from experts, while this work takes information from the pieces through a camera.

Development

Due to the strict quality requirement and lack of artificial vision inspection, it is necessary the inspect 100% of connectors. The company uses double inspection of connectors. During the manufacture process and final inspection by quality control, but still with double inspection the company rejected 16,000 connectors and 300 defective harnesses that were accepted by manufacture and quality control by January and March of 2017. The cost of bad quality has been estimated in 50,000 USD.

Our systems use the inspection camera Mighty Scope. The camera has integrated 6 high intensity LEDs; the LEDs help in 85% of cases to avoid the low illumination factor. Moreover, the camera was designed to inspection task. For this reason, the lens in dedicated to capture details on the picture, this is of helpful to obtain images for processing. The camera specifications are shown in Table 1.

Signal Output	USB 2.0
Magnification based on a 17" monitor	Resolution: 640 x 480 (Max. ~ 95X), Resolution: 1024 x 768 (Max. ~ 150X), Resolution: 2048 x 1536 (Max. ~ 300X)
Video format	AVI
Gain Control	Automatic
Snap Shot Mode	Hardware & Software controls
White Balance	Automatic
Power Source	5VDC through USB port
O/S	Windows XP, Vista, 7, 8, & 10 | Mac OSX 10.6 or above
Power Consumption	260mA (AVG)
LED Lighting	6 White LEDs
Working Distance	At 10x (112mm), At 20x (42mm), At 30x (19mm), At 40x (8.5mm)

Table 1 Camera Avent Mighty Scope specification

To obtain the image of the connector, the camera must remain stable. For this rea-son, it was necessary to use the camera stand " Migthy Scope View Stand". The design of fixure to place the connectors in the same position. This action helps to avoid the false rejection on the inspection. Figure 1 shows the camera and fixture together.

Figure 1 Inspection camera

Figure 2 shows the flowchart of our systems

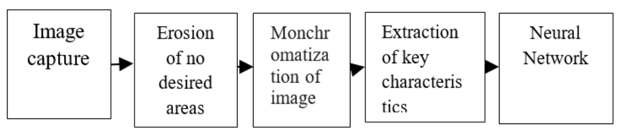

Figure 2 Flowchart of the system

Capture Interface: An application was developed in MATLAB which iterated with the camera and obtain the image as is shown in Figure 3.

Erosion of not desired areas: The erosion technique was used to obtain the clear and defined area of connector keyways, the area to be inspected, the erosioned image is show in Figure 4.

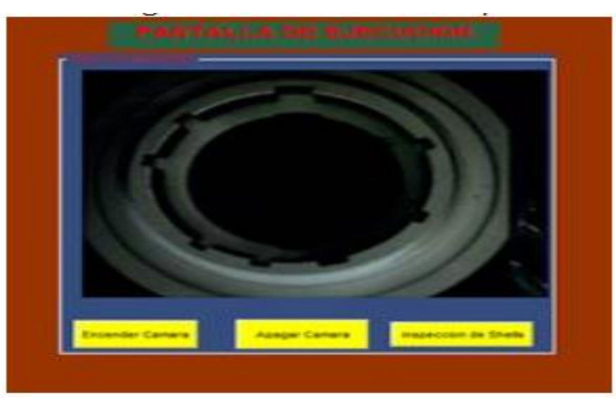

Figure 3 Workspace of the system

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Monocromatization of image: Figure 5 shows an image monocromatic of the connector under insepction, the keyways to be analyzed are shown in white.

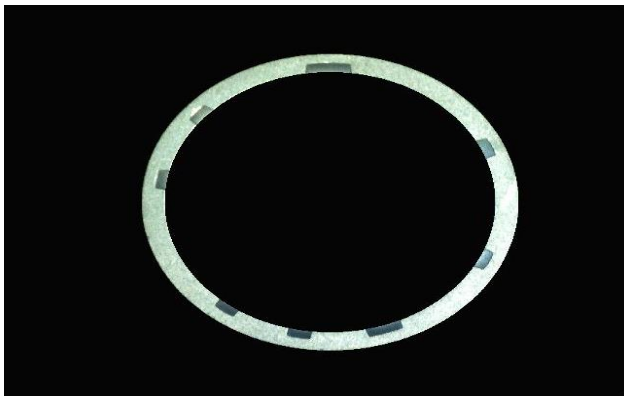

Figure 4 Aplication of erosion technique to original image

The extraction of the key characteristics, in our case the position of the keyways of the connector is achieved by sweeping 360° on the diameter of the connector. It requires sweeping the keyways position as a cicle. The output data of key characteristic extraction, are expressed as '1,' where it detects that the space is found and a '0' where it does not exist, Table 2 provides the information obtained.

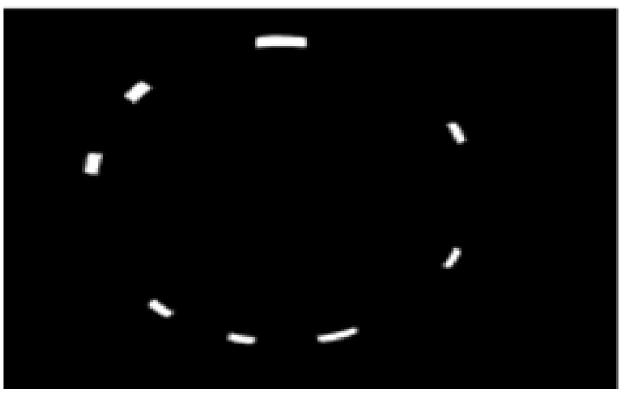

Figura 5 Monocromatic figure of conector, view of key characteristics

0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	1	1	1	1	1	1
1	1	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
1	1	1	1	1	1	1	1	1	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	1	1	1	1
1	1	1	1	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	1
1	1	1	1	1	1	1	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	1	1	1	1	1	1	1	1	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	1	1	1	1	1	1
1	1	1	1	1	1	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	1	1	1	1	1	1	1
1	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0

Table 2 Reading of 360 degress sweep binarizated

Artificial Neural Networks: As a result of the experiment, implementing an ANN trained with the backpropagation algorithm, such as the one shown in Figure 7, is proposed. A neuronal structure of this type gave the results with a higher degree of success.

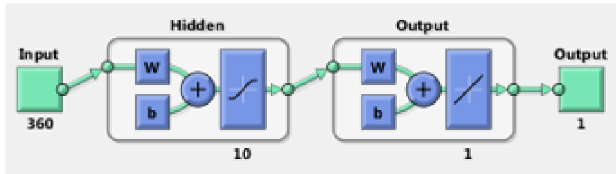

Figure 7 ANN structure

Results

The developed interface, which contains the capture process, image processing using artificial vision techniques and neural networks as an intelligent technique for image classification is shown in Figure 3. A multilayer perceptron RNA with a training back-propagation algorithm was used, with 10 neurons in hidden layer. The decision on the use of this type of neuronal structure is based on a test analysis of different topologies with a set of training and test data that satisfy the company's quality policy. Overall, 97% accuracy was obtained, using cross validation. Table 3 shows the number of connectors for the training and the test vector.

Descriptión	Quantity
Acceptable connectors	230
No acceptable connectors	50

Table 3 RNA Training set

Finally, a complete batch of the product was used as test vector. In this case, the connectors under test were used, which corresponded to the amount of 2,412 connectors in incoming area. Table 4 shows the results of the test inspection.

Lot of Connectors	Test Results
2,412	2,412 successful identifications
	0 rejections

Table 4 Inspection Results

The inspection time required was dramatically reduced, showing a great improvement when this proposed automatic process is implemented, as shown in Table 5.

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Inspection type	Time of Inspection
Manual	150 seconds
Automatic	8 seconds

Table 5 Comparative of inspection

After training different models of ANN with the same amount of data, we can see that the proposed model performs well, classifying without errors of inspection the number of connectors shown in Table 4, with a success rate of 100%. The results shown in Table 5 show a fast process, reducing the inspection time by 95%. One of the proposed objectives has been achieved in that we have a fast and reliable inspection system. This model also shows that it is possible to reduce the costs of implementing the system by 94%, making the comparison in what an industrial system costs and the development of the application. This proposed inspection device can be used to check the quality of other products using only the appropriate training data for the ANN and the results can be compared with each other.

Results and Conclusions

After training different models of ANN with the same amount of data, we can see that the proposed model performs well, classifying without errors of inspection the number of connectors shown in Table 4, with a success rate of 100%. The results shown in Table 5 show a fast process, reducing the inspection time by 95%. One of the proposed objectives has been achieved in that we have a fast and reliable inspection system. This model also shows that it is possible to reduce the costs of implementing the system by 94%, making the comparison in what an industrial system costs and the development of the application.

This proposed inspection device can be used to check the quality of other products using only the appropriate training data for the ANN and the results can be compared with each other. The use of high level programming languages facilitates the elaboration of interfaces that match or exceed the characteristics of the products of the industrial type used to visualize information. In addition, with the development of computing they facilitate the incorporation of artificial intelligence algorithms and vision processing techniques that, when used with comercial video cameras, we can desing automatic inspection systems.

Future work involves expanding learning and recognition with connectors that correspond to other models and implementing a set of automated inspection equipment throughout the manufacturing plant.

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