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Optimization of the Quality Control for Pieces Recognition in Manufacturing Flexible Cells by the Implementation of Neural Networks

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Abstract

The high levels of automation in the companies that use manufacturing cells for their fabrication processes guarantee a high efficiency in production with high quality standards. The main objective of this paper is to develop an optimization for the tasks performed by the quality control station through artificial vision belonging to the manufacturing cell FMS-200; the development of the proposal focuses on optimizing the inspection process and control of quality by adapting image processing techniques and adaptive resonance neural networks. For this particular case, a review of the location of the optical system and a detailed time study for each movement of the station actuators was carried out, attempting to determinate a better position for the optical detection system (artificial vision camera) and the possibility elimination of some components of the station; all of this in order to considerably reduce the operating time and increasing the efficiency for the quality control of the system.

Keywords: Quality control, optical detection system, ART2 neural network, flexible manufacturing cell, time study

1 Introduction

Nowadays the organizations that specialize in the manufacture of products require high quality standards entering to new market fields and ensuring the sustainability of the business over the time [1]. The quality controls have acquired importance for different stages of the manufacturing processes [2], seeking to detect and take action against the different errors or defects that may arise during the manufacture of a certain product [3], resulting at the end of the production chain an article in accordance with established standards; this highlights the importance of evaluating and rethinking the mechanisms used to perform these activities [4-6].

In the manufacturing process, there are several systems for quality control, each of them specialized in measuring the variables or attributes that need to be measured [7]; the most used ones today are electronic systems, since they have a great versatility and a wide coverage, greatly favoring the quality assurance in the industries [8]. The multiple alternatives offered by electronic systems make them a research and major improvement target; advances regarding this subject are increasingly surprising and seek to improve impact processes, making them more reliable and largely productive [9].

The flexible manufacturing system on which this work is developed is the FMS-200, this cell is divided by stations and is responsible for the process of a bearing assembly; based on this, the present paper establishes a proposal of optimization for the FMS-210 quality control station by using artificial vision, through modification, relocation and elimination of some operational elements, after previous studies and time analysis for each one of its components [10]. In addition to this operational analysis, it is intended to implement a pattern recognition algorithm supported on adaptive resonance neural networks (ART2), which would optimize the inspection process and quality control based on the validation of specific patterns associated with an optimal finished product [11, 12], thus substantially improving the operating times of the inspection and validation processes of a final product [13].

2 Methodology

The proposed development consists of three stages: the identification of the improvement opportunity, the times quantification for the station, and the development of a pattern recognition algorithm based on neural networks for the pieces recognition.

Identification of the improvement opportunity

In the continuous use of the flexible manufacturing cell, a series of possible delays and difficulties in the correct quality control of the station FMS-210 (station 6) were identified, see Fig. 1, this focused the attention on this point, keeping in mind that it is one of the most important units within the cell and it is susceptible to the application of improvements, since there are more appropriate ways of performing quality control.

Figure 1: FMS-210 artificial vision quality control station [10]

Fig. 2 shows the average times for all the stations that constitute the cell (operating times), as it can be seem the time of this station is one of the largest considering it is purely inspection, meaning no direct intervention in the product assembly. Homologating this situation to a real scenario in the manufacturing industry, would represent large losses due to generation of nonconforming products due to quality control failures and loss of productive capacity because of the large station times. In this way, it was determined the opportunity for improvement on which the present study is developed.

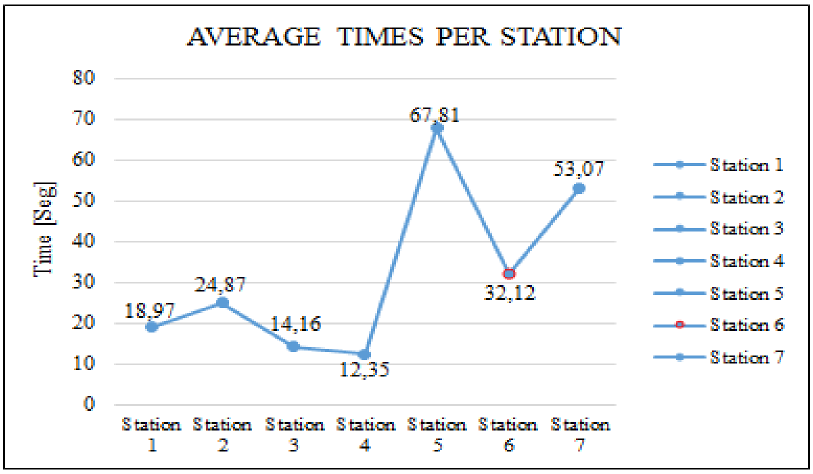

Figure 2: Average times per station.

Description and time analysis

Initially, a general sampling was performed with a sample size of n = 30 with the objective of identifying and tune up the line; establishing the general conditions for the study of this exercise, it was determined that the average number of units assembled per hour in the line are 16 and the participation percentage of the station regarding the total time of the cell was 14.38% (the data used are enunciated in Fig 2).

In order to quantitatively determine the delays in the detection system, extraction and rejection of pieces at the quality station, a specific sampling was performed for each of the movements of the components that coincide at station 6 (see Fig. 3), this in order to identify the areas with the greatest incidence of delays and to evaluate several possibilities to optimize the system correctly.

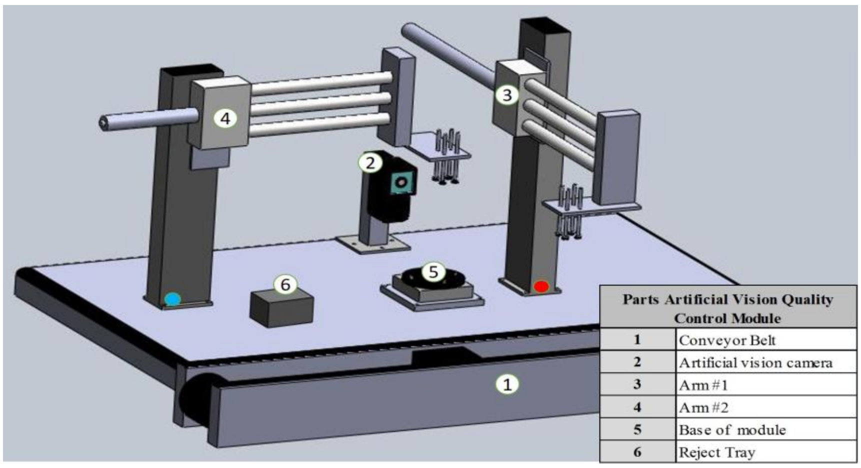

Figure 3: Components of station 6 (Station FMS-210).

To perform an optimal sampling, a sample with size n = 55 was determined, taking into account the time availability for each type of detailed sampling (4 hours after achieving the desired condition of the line).

Determination of the sample size (n)

Given the results obtained during the general sampling and the time available for sampling, the sample size for a finite population is determined by the following equation:

$$n = \frac{Z^2 pqN}{NE^2 + Z^2 pq} \tag{1}$$

Where each of the parameters involved in the sample size are defined in Table 1.

Table 1. Parameters for the sample calculation

Parameters for the calculation of the sample	
n	Sample size
Z	Confidence level = 1.96 (According to normal distribution table for 95% reliability and 5% error)
N	Universe = (average of units assembled per hour) * (Time in defined hours of sample in required condition) = (16 * 4) = 64 units
p	Positive variability = 0.50
q	Negative variability = 0.50

When replacing the parameters of Table 1 in the respective equation it is obtained:

$$54{,}86 = \frac{(1{,}96)^2\,(0{,}5)(1-0{,}5)(64)}{((64)(0{,}05)^2)+((1{,}96)^2(0{,}5)(1-0{,}5))} \tag{2}$$

Sample size = 54.86 = 55

Sampling was performed considering two scenarios: In the first of them, all the pieces that go through the station are compliant product, and meet the specification given. In the second scenario is quite the opposite, the pieces do not match, so they are rejected. This analysis was performed in order to observe the processing times and the activities the system performs the most, when the piece fulfills the quality specification.

Graphic study and analysis of movement

Below there is a graphical study of the movements analyzed during the sampling performed at the station. The movement times associated with the conformal product (see Fig. 4) and nonconforming product were analyzed (see Fig. 5).

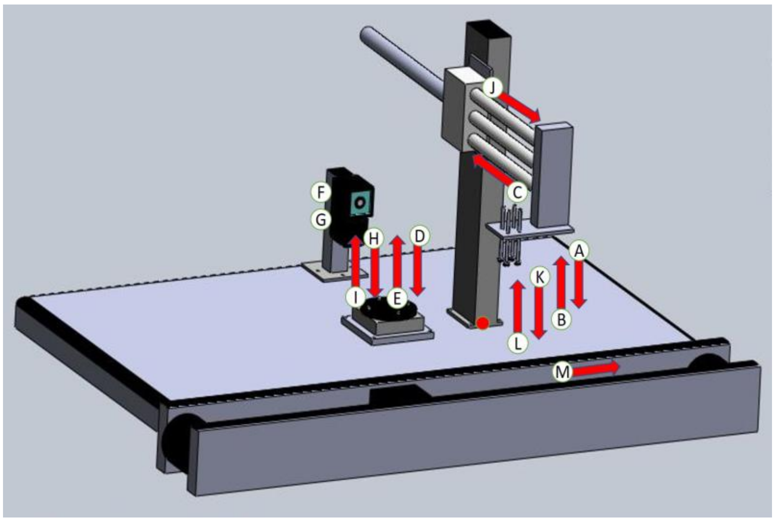

Figure 4: Movements at the station associated with conforming product.

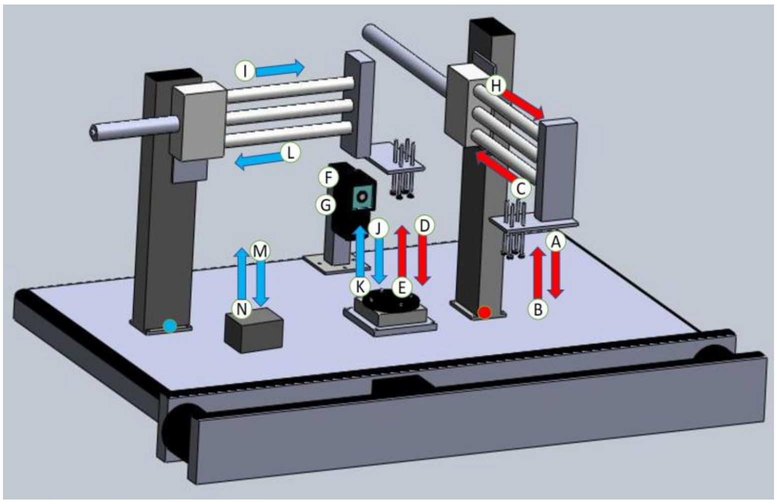

Figure 5: Movements at the station associated with nonconforming product.

Table 2 shows the results obtained during the sampling performed in each of the scenarios described above. As can be seen in Table 2, the G movement (Image Capture) shows a long hold representing 33% of the total time of the station; this is due to the location of the camera and the number of captures that must be made to identify the condition of the piece.
On the other hand, during the development of the sampling and recognition of the system it was possible to identify that some of the movement that the station does to accommodate the piece and make the capture of images do not add value to the activity.

Table 2: Average times in two scenarios

	Average movement times for defective parts		**Average times of movement of conforming parts**	
Movement	**Sec**	**Min**	**Sec**	**Min**
A	0,95	0,016	1,01	0,017
B	1,53	0,026	1,53	0,026
C	2,58	0,043	2,57	0,043
D	0,99	0,017	1,02	0,017
E	2,34	0,039	2,36	0,039
F	3,05	0,051	3,05	0,051
G	10,44	0,174	10,44	0,174
H	1,43	0,024	1,01	0,017
I	1,13	0,019	1,41	0,023
J	0,72	0,012	1,54	0,026
K	0,99	0,016	1,27	0,021
L	1,37	0,023	2,34	0,039
M	0,97	0,016	3,75	0,062
N	1,53	0,025	N/A	N/A
TOTAL	**28,48**	**0,475**	**34,30**	**0,572**

In Table 3 is found the added value study of each of the movements at station 6 in the two previously studied conditions; in this way, it is evident that some operating times can be eliminated through the adjustment of the capture angle and position of the camera, allowing that the station and the control process itself being made much more efficient. It can also be clearly evidenced that for the process of evacuation of the nonconforming piece it is necessary to continue making movements since the defective piece must be removed from the production line.

To perform the analysis of added value, 3 criteria are defined [14]:

- AV: Movement adds value to the process

- NAV: The movement does not add value to the process.

- NAVN: The movement does not add value to the process but it needs to be done.

Table 3. Value-added analysis

Movement	Movement Defective parts	Movement Conforming parts
A	NAV	NAV
B	NAV	NAV
C	NAV	NAV
D	NAV	NAV
E	NAV	NAV
F	AV	AV
G	AV	AV
H	NAV	NAV
I	NAVN	NAV
J	NAVN	NAV
K	NAVN	NAV
L	NAVN	NAV
M	NAVN	NAVN
N	NAVN	N/A

Neural Network ART2

An ART2 (Adaptive Resonance Theory) network is basically a continuous version of the adaptive resonance model. This new model, like its predecessor, is made up of two layers in which forward and backward connections are established, but for this particular case both weights connection values are the same [13,15].

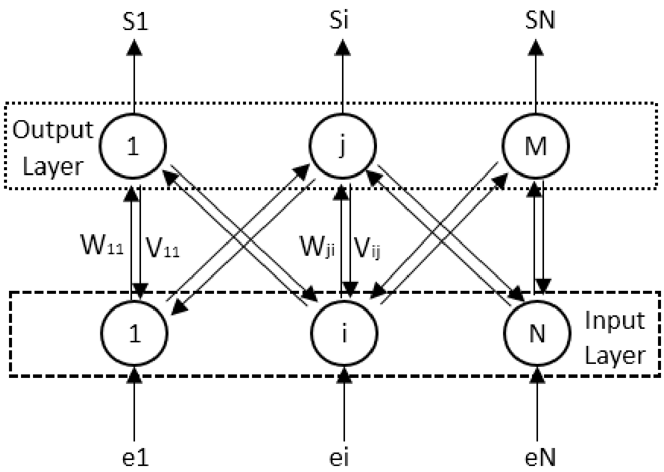

Figure 6: ART2 network architecture

This neural network working with continuous values, allows to maintain a high sensitivity to parameters such as noise, distortion or information shifts, providing this way a tool capable of processing real input values instead of binaries, keeping the same original architecture as an ART core network. The operating process is still oriented to competitive environments where only one of the output neurons is activated after being competing with others, performing a weight adjustment of the connections according to the neuron at the output layer that has been the winner or the activated one [15].

3 Implementation

The proposal focused on the optimization of quality control is centered in the reduction of operating times associated to the complete detection of pieces assembled in the FMS200 manufacturing cell; this quality control process focuses on the implementation of digital image processing techniques related to the model of adaptive neural networks for decision making, see Fig. 7.

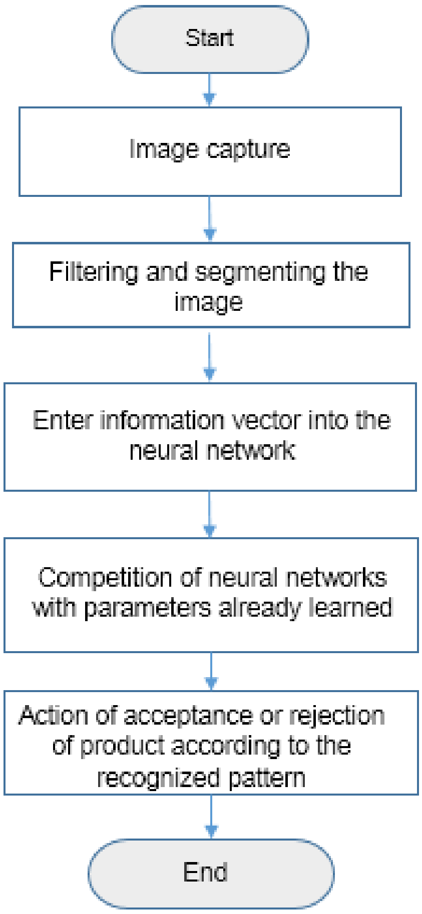

Figure 7: Flow diagram

As the adaptive resonance model with which the selected neural network works handles real values, it was proceeded to capture the image of the product to be analyzed by an HD camera; this information is filtered, conditioned and segmented, in such a way that only the necessary patterns are entered to carry out the validation process through the neural network.

Hilera and Martinez [15] detailed describe the implementation of the ART2 network in a simple way; in their description, once the input information vector is created, the data is entered into the neural network $E_k = \left(e_1^{(k)}, \ldots \ldots e_N^{(k)}\right)$, taking into account that all of the components $e_i^{(k)}$ are real values. Each neuron in the input layer receives the value of the component corresponding to the input vector E_k and sends it to the neurons at the output layer via W_{ji} connections.

The neurons at the output layer compete with each other until only one remains active; the winning neuron is the one that maintains a minimal difference or Euclidean distance between the input vector and the weights of the connections between itself and those of the layer of input; this is represented by the following equation:

$$MIN\left\|E_K - W_j\right\| = MIN \sum_{i=1}^{N}\left|e_i^{(k)} - W_{ji}\right| \tag{3}$$

For this neural network modified model, the concept of similarity relation is still maintained, which can be defined by the equation 4:

$$\|E_K - X\| = \sum_{i=1}^{N}\left|e_i^{(k)} - W_{j*i}\right| \tag{4}$$

The above implies the similarity relationship to determine whether the winning neuron adequately represents the input pattern $E_k = \left(e_1^{(k)}, \ldots \ldots e_N^{(k)}\right)$, proceeding to perform the weight adjustment for the incorporation of some of the input vector characteristics to the representative patterns of the winning neuron. The adjustment equation is defined by:

$$W_{j*i}(t+1) = V_{ij}(t+1) = \frac{e_i^{(k)} + W_{j*i}(t) * Num_{j*}(t)}{Num_{j*}(t)+1} \tag{5}$$

Where $Num_{j*}(t)$ is the number of input vectors considered until time *t* belonging to the category or pattern j^*.

One of the advantages of implementing this neural network is that a supervised learning procedure is not needed; this is achieved thanks to the influence of the monitoring parameter (ρ). In this new model, there will be a value of (ρ) defined in a range between 0 and the maximum value of the components of E_k, in which the minimum difference will be 0, as long as the input vectors and the reference patterns of the neural network match.

The implementation of this algorithm will allow a precise identification of whether the product is compliant or not. The generated quality control specifically recognizes if there is any failure in the finished product evaluated, because it has been previously taught to the network which are the optimal characteristics of a fully compliant product. In general terms, the implementation of an optical recognition system based on image processing and a pattern recognition algorithm supported on neural networks has been described.

4 Results

After the time and movements analysis performed on the quality control station (see Table 2), it was possible to show that this station generates a high execution time in its inspection activities, meaning the time of image recognition adds the time associated to its actuators displacements (pneumatic cylinders). The times obtained for the development of these activities gave an average value of 34.30 seconds for validation of conforming pieces and 28.48 seconds for defective pieces; it is worth emphasizing that in this station there is an average of 14 movement actions associated to quality control activities, see Fig. 4 and Fig.5.

The effectiveness of the optimization focuses on the implementation of the pattern recognition algorithm based on the use of the neural network ART2, since this network implements a competitive type unsupervised learning, highly depends on the reduced value that should be given to the monitoring parameter (ρ); for this specific case, a reduced value was used in which it did not accept pieces below 98% similarity to the original pattern. If the monitoring parameter handles a very high value, the neural network would increase the number of categories or references, because it is directly proportional to the membership conditions between a reference class and pattern. The specific time taken by the algorithm to perform the validation process is 220 milliseconds per piece; this processing stage is installed in a development interface on PHYTON which runs on 32-bits Windows 7 operating system, with an Intel Core I5-4200U CPU 2.3 GHz processor and 6 GB in RAM.

Taking into account the results obtained with the pattern recognition established by the neural network, this proposal also covers the making of a general modification to the workstation. This proposal consists of reducing the number of pneumatic cylinders or actuating elements involved in the inspection, likewise proposing a relocation of the artificial vision camera for the finished product image acquisition (see Fig. 8); these modifications would generate a reduction of elements equivalent to 60% and a considerable reduction regarding the operating time of the station.

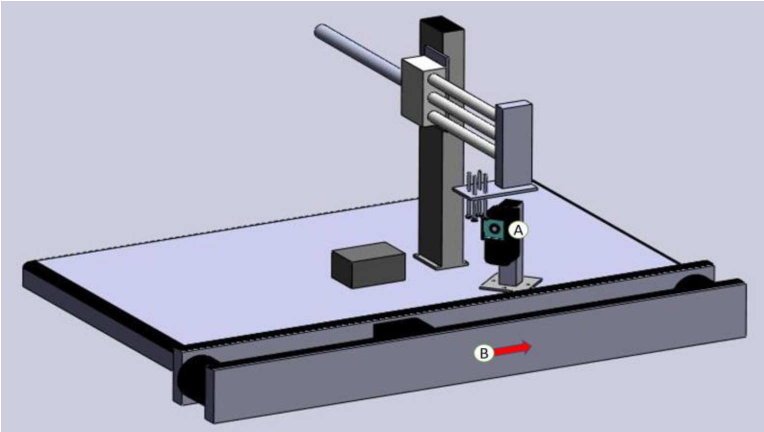

Figure 8: Movements of station 6 (Matching Product) implementing proposed improvements.

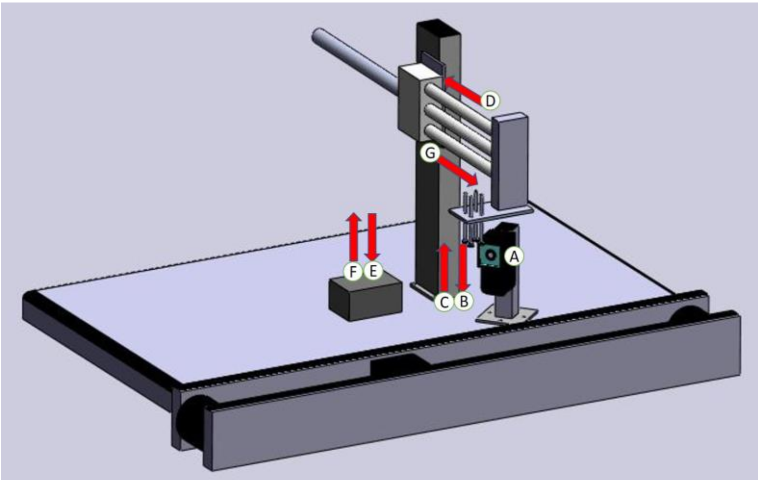

Figure 9: Movements of station 6 (Nonmatching Product) implementing proposed improvements.

With the improvement obtained with the neural network and the adequacy of the number of actuating elements in the station, it would be obtained a movement reduction equivalent to 84.62% in compliant products and a reduction of 50% of movements associated to noncompliant products. In general terms, the quality control inspection performed on an optimum product takes about 220 milliseconds, equivalent to only 0.7% of the total time taken in the preset configuration for the workstation.

5 Conclusions

The significant reduction of operating times in the quality control processes for the FMS-200 manufacturing cell highly depends on the successful selection of the pattern recognition algorithm; by establishing a suitable technological support to guarantee the correction of the detected faults in the production line, the neural network based on the adaptive resonance model showed a level of optimum effectiveness, depending on the quality of the processed image and on the luminosity control established for the piece to be inspected.

One of the main inefficiency sources in the quality station was the great amount of movement that the mechanisms performed to carry out the tasks of inspection and rejection. With the camera relocation, it was possible to reduce those movements and ensure the good work of the station (as shown in Fig. 8 and Fig. 9), avoiding alterations during its operation and the one of the cell; thus, confirming the positive impact of the optimization proposal.

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