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DEVELOPMENT OF A WORKPIECE CLASSIFICATION SYSTEM USING AN ELECTRO-PNEUMATIC ROBOT AND MACHINE VISION

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Abstract. *With the growing movement towards automation in industrial manufacturing and distribution, machine vision systems are quickly being adopted in different fields. Vision systems are used in different configurations, however, most applications use an optical system for image acquisition, a set of computer scripts for image processing and data interpretation and a hardware for computing data. In this work, the goal lies in the development of a methodology for workpiece recognition that allows shape identification, aiming the organization of production through a 3-axis electro-pneumatic robotic manipulator. For recognition of geometric form, both centroid and profile of workpieces are used; part dimensions can be compared through direct pixel comparison. After determination of workpiece characteristics, a positioning algorithm is applied on the robot, thus allowing its positioning for part classification.*

Keywords: *machine vision, image processing, image recognition, electro-pneumatic robot.*

1. INTRODUCTION

Machine vision systems are computational tools with growing industrial application. Basically, these systems include acquisition, processing and interpretation of image related data for some specific application (Groover, 2008). Their main applications involve automatization of complex or time consuming tasks, or even replace human labor in tedious or repetitive tasks. Among other areas, these systems are applied in astronomy, medicine, logistics and manufacturing (Marques and Vieira, 1999). Industrial applications of machine vision systems occurs especially in manufacture, robotics and productive systems (Rudek *et al*., 2001).

Golnabi and Asadpour (2007) classify the usual applications of machine vision systems in four categories: process control and monitoring (Pfeifer and Wiegers, 2000); parts classification and recognition (Rudek *et al*., 2001); inspection (Almeida *et al*., 2007; Yoon and Chung, 2004; Proença and Conci, 1999; Su *et al*., 1995); guidance and control of robotic manipulators and mechanisms (Meng and Zhuang, 2007; Gruver *et al*., 1985). Since each of these applications has different requirements for accuracy, dynamic response and processing, and the costs involved in the acquisition of a vision system can vary significantly with these parameters, their development should address the specific needs of the use to which it is intended.

The goal of this paper is to develop a part classification system for, through the utilization of image processing and part recognition techniques, reposition them using a three axis electro-pneumatic robotic manipulator.

2. EXPERIMENTAL PROCEDURE

According to Gonzalez and Woods (1992), digital image processing can be divided into three stages: low-level processing, intermediate processing and high-level processing. The former corresponds to the data acquisition (image) and pre-processing (filtering). The second step is the segmentation and description. From this procedure follows the division of the image in similar blocks and the extraction of relevant features. Finally, the high-level processing corresponds to the interpretation of the data. After the data interpretation, is possible to set the actions to be performed by the system. In this work, the system to be controlled is an electropneumatic three axis manipulator that will reposition the part according to its geometric shape. The development of computational routines was carried out with the software Matlab®, which has toolboxes especially developed for image processing and acquisition.

2.1 Experimental apparatus

The goal of this work is to develop a computer vision based image recognition system for classification of workpieces using a robotic manipulator (Fig. 1). The equipment used to classify the parts is an Festo electro-pneumatic manipulator, consisting on three prismatic links oriented according a Cartesian coordinate system X, Y, Z. Each link is a single rod double-action pneumatic cylinder, commanded by fast solenoid valves. The end-effector used to hold the parts is a pneumatic suction cup.

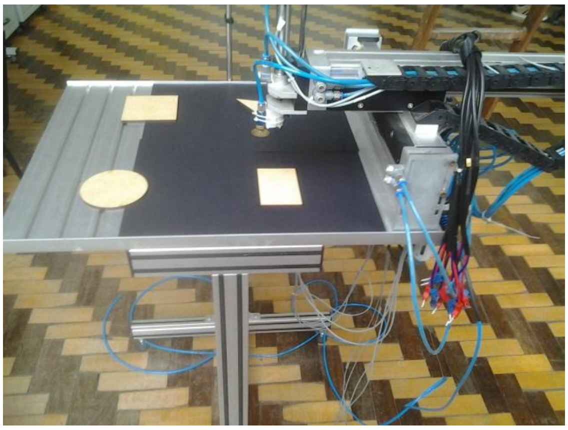

Figure 1. Three axis electropneumatic manipulator.

The communication of the robotic manipulator with the computer was carried out with an Arduino development platform. However, due to the 24 V necessary to the solenoid valves operation, it was necessary to develop a power board, since the Arduino supplies up to 5 V. For the activation of the solenoid valves, a power board made up of 5 V relays and CI 4N25 optocouplers was designed. Thus, the microcontroller can use its outputs with a voltage +Vcc (typically 5V) to activate the optocouplers which, in turn, close the relays by providing 24 V for solenoid valves.

For image acquisition a low cost USB camera, Microsoft Life Cam Cinema, is used. This device has a maximum video transfer rate of 30 frames per second and a maximum resolution of 1280 x 720 pixels and do not require acquisition board, thus making the communication with the computer easier. In addition, the camera features auto focus lens and high-precision lenses, ensuring sharper images.

2.2 Image pre-processing

According to Sonka *et al*. (1993), pre-processing is a common name for operations with images at the lowest level of abstraction, were both input and output are intensity images. Along with image acquisition, pre-processing is considered part of the low-level processing. This step involves several methods and procedures, among whose is possible to highlight color conversion, luminous intensity histogram analysis and noise suppression by filtering.

The image acquired by the camera follows the RGB standard, being composed by red, green and blue pixels. RGB images consists of three independent image plans, one for each color, that, combined, result on a composed color image (Gonzalez and Woods, 1992). Thus, the procedure adopted to simplify the representation of an image is its conversion to grayscale for posterior binarization. A grayscale image is represented by an 8-bit 2D matrix with values where each pixel is represented by its luminous intensity: while zero represents the absence of color (black), 255 is the maximum color value (white). In addition to this conversion, images are frequently converted to binary format in the segmentation step.

In addition to the conversion of images to grayscale, the image pre-processing procedures include filtering and enhancement. The main objective of the techniques of filtering and enhancement is to process an image turning it in a more suitable image for the desired application (Marques and Vieira, 1999).

In this work, the smoothing filter by median is used. This method has performed particularly well in situations where the image is contaminated by impulsive noise (salt and pepper), and consists on replacing the gray level of each pixel by the median gray level of its neighborhood (Jain, *et. al*., 1995).

2.3 Segmentation and description

After the image acquisition and pre-processing, occurs the intermediate processing step, consisting on segmentation and description. The former is one of the most widely used steps in the process of reducing images to information, and consist on dividing the image into basic elements or features. This process is often described through an analogy with visual processes as a foreground/background separation, implying that the selection procedure concentrates on a single kind of features and discards the rest (Russ, 1998). Thresholding is an important part of segmentation, and consists on the binarization of the image, with foreground and background being distinguished with black and white colors. This representation, as well as in grayscale image, also uses a two-dimensional array. However, this matrix has only two values (one bit): one (white) and zero (black). These values are set from the conversion of an image to grayscale, where pixels with light intensity below a threshold are set to zero and pixels with light intensity above this limit are set to one. This threshold is defined from the light intensity histogram analysis. Peaks in the histogram often identify the different homogeneous regions and thresholds can then be set between them (Russ, 1998).

Histograms are graphical representations of frequency distributions. They are constructed representing measurements or observations on an horizontal scale and mapping rectangles with base dimensions based on the class intervals and heights equal to the corresponding class frequencies (Freund, 2004). For the purposes of this paper, the histogram represents the frequency distribution with which certain light intensity appears on an image.

Still within the intermediate processing, there is the stage of description. This step consists in the identification and storing of key features of the image. These characteristics can also be called object descriptors. Object descriptors are usually represented as a set of numerical data and from these values is possible to establish a database where all the characteristics that determine the analyzed object will be stored (Gonzalez and Woods, 1992).

In this work, representation and description are carried out using the Signature method. This method consists on the identification of the distance between the part centroid and its edge for different angles. The extraction of these features creates a one-dimensional representation of a border, which is usually defined from a graph of the centroid/border distance versus angle (Zhang and Lu, 2002).

2.4 Part recognition

Part recognition is the stage where the system interprets the data obtained and refined through the previous processes by comparison with a database. Based on the interpretation results, specific actions can be determined. In this work, the main goal is the recognition of geometric shapes. After application of the Signature method, it is possible to obtain a set of data defining the behavior of each form. Recognition is done as follows:

- circular parts have the same distance from the center to the edge to any angle;
- square parts feature three equal peaks regularly spaced (90º) and with equal center-corner distances;
- rectangular parts have four peaks, with equal center-corner distances every 180º;
- triangular parts have three peak values.

Since the graph is composed by discrete data, smoother curves are related to smaller angular resolution. However, since this resolution is time and processing demanding, the center-peak distances for square and rectangular parts doesn't always have equal values, thus being the number of peaks a more reliable information, providing that the angular spacing is enough to represent all the peaks.

3. RESULTS

In order to evaluate the proposed methodology, an experimental procedure was carried out. These experiments included both machine vision and electropneumatic applications, with the goal of classifying parts according to their geometric shapes.

As previously stated, the initial step involves the image acquisition. For this, the USB camera was positioned with the electropneumatic robot in a location where the image sampling area does not contain unnecessary elements. In addition, the camera is positioned perpendicular to the piece, to reduce distortion. The parts used for this study are made of laser cut Medium Density Fibreboard (MDF). This material was selected due to several characteristics: economically, due to its low cost, allied with the fact that it is easy to cut; optically, due to its clear color and opaque tone, reducing reflexes that can induce to errors. These optical characteristics contribute to the reduction of noise and demand less computational power for image filtering and segmentation.

After the image acquisition, the data is sent to the computer for pre-processing (color conversion and filtering), segmentation (distinction between part and background), description (extraction of relevant features) and geometric recognition. Figure 2 presents images of the evaluated parts. These images were previously filtered through the median filter and converted to grayscale.

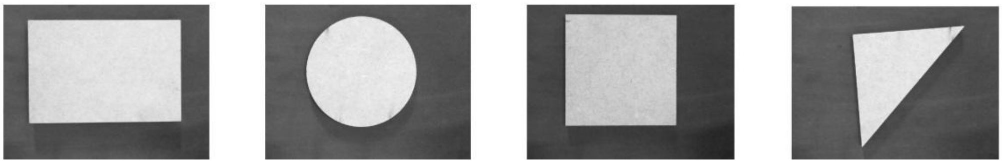

Figure 2. Grayscale representation of the evaluated parts.

Since the images contain only the parts and the background, the respective histograms have only two peaks. The histogram representing the light intensity of the circular part is presented in Fig. 3.

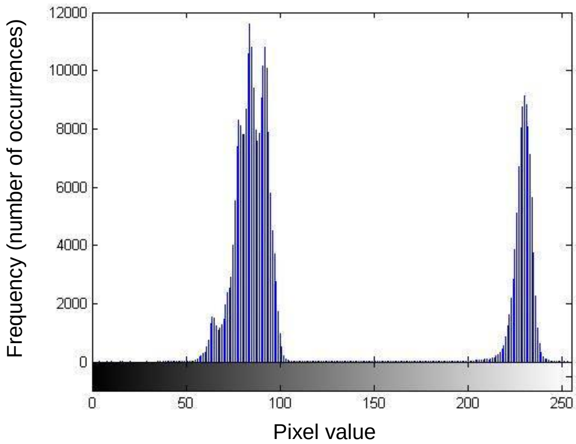

Figure 3. Histogram for the 8-bit circular part image shown in Fig. 2.

From the histogram analysis, one can determine the threshold. For Fig. 3, threshold must be defined between the two pikes, thus separating the image in two different colors. The threshold value was set in 127, and the binary images corresponding to the parts in Fig. 2 are presented on Fig. 4.

Figure 4. Binary images.

With the binary image, one can apply the signature method for extracting the characteristics of each geometric shape. As already shown, this method is to identify the distance from the centroid to the edge for different angles. This distance is identified by a counter that defines the amount of pixels between the centroid and the edge of the image. Figure 5 presents this analysis using a 30º angular step, whose values, in pixels, are shown in Tab. 1.

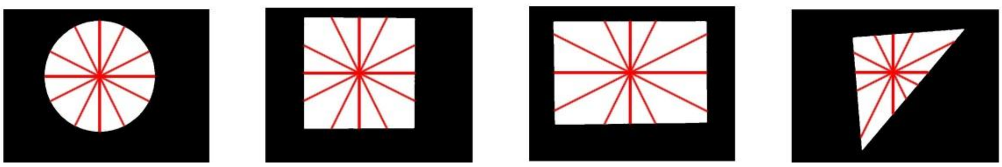

Figure 5. Signature method applied with a 30º angular step.

Table 1. Distance from the centroid to border (in pixels) measured at 30º intervals for the evaluated parts.

	Shape			
Angle	Circle	Square	Rectangle	Triangle
0º	172	172	102	107
30º	172	199	118	241
60º	172	197	80	140
90º	172	171	69	115
120º	173	199	80	128
150º	171	197	119	138
180º	171	171	102	115
210º	171	197	117	126
240º	171	199	80	200
270º	171	171	68	126
300º	171	197	78	87
330º	172	197	119	83

Figure 6 presents the centroid/border distance versus measuring angle for the parts presented in Fig. 2, with a 30º step.

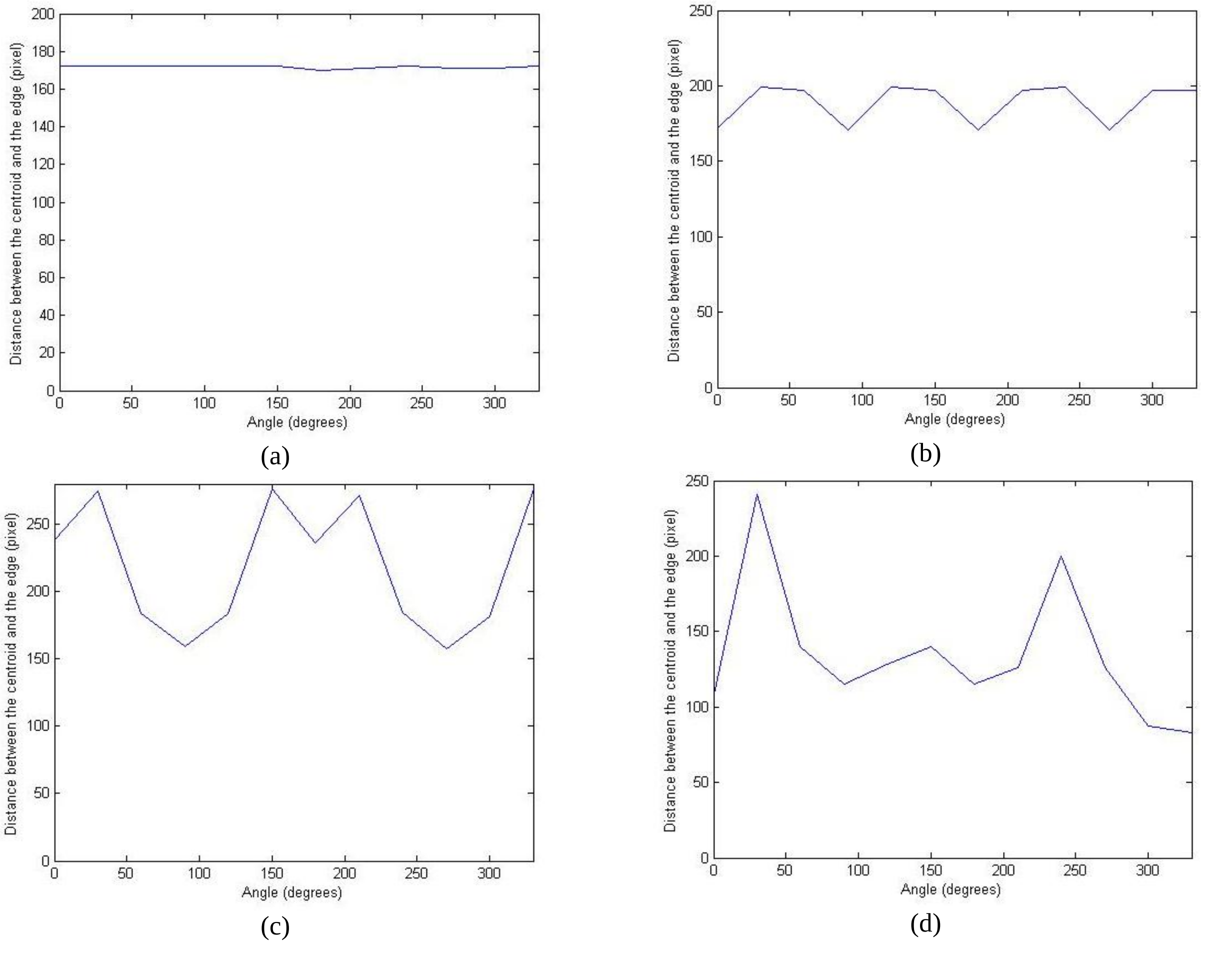

Figure 6. Centroid/border distance for the evaluated shapes: (a) circle; (b) square; (c) rectangle and (d) triangle using a angular step of 30º.

From the results presented in Fig. 6 is possible to identify the characteristics of the shapes. However, this low resolution, can lead to misinterpretations, especially in automated applications. Figure 7 presents an analysis carried out in the same images with an angular step of 5º.

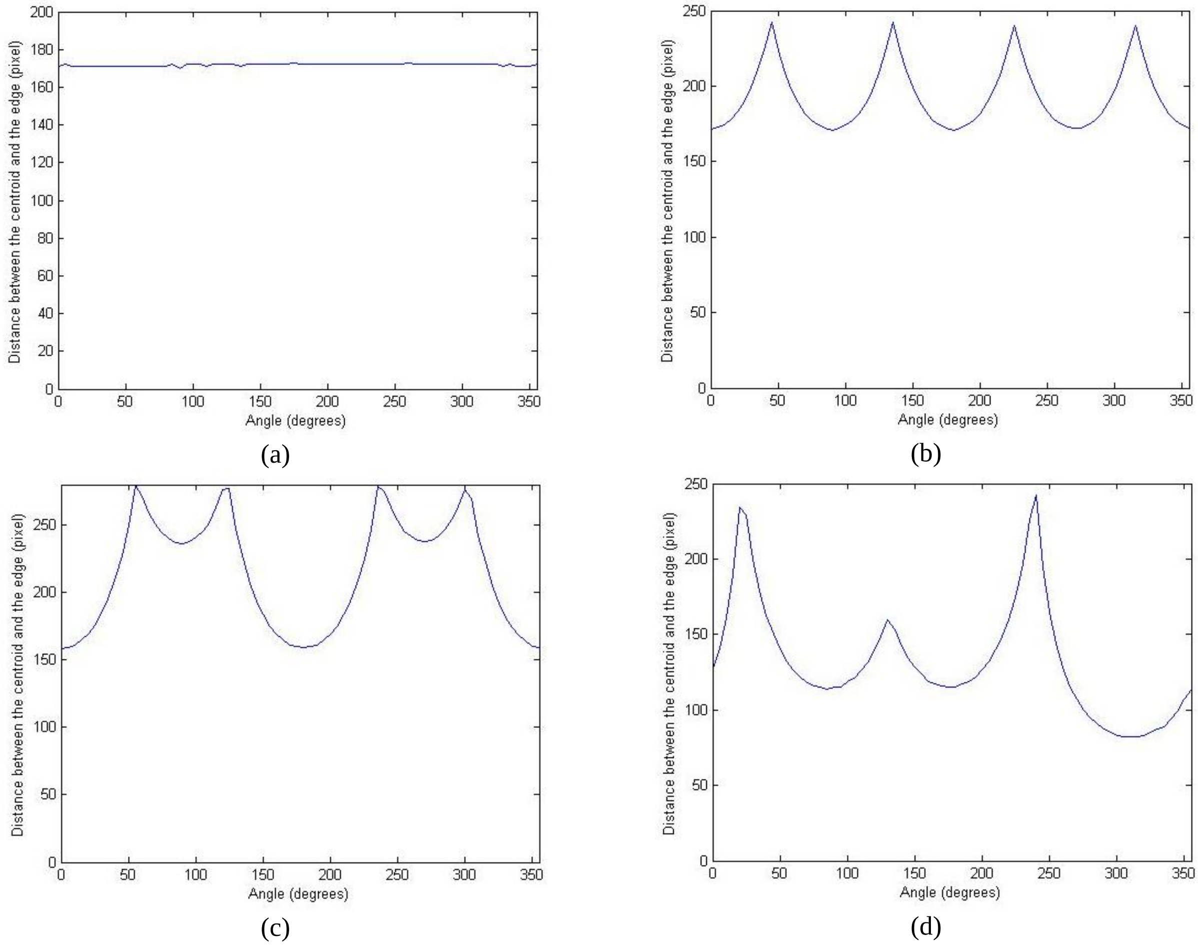

Figure 7. Centroid/border distance for the evaluated shapes: (a) circle; (b) square; (c) rectangle and (d) triangle using a angular step of 5º.

Part recognition is carried out through the comparison of the distance vectors intensity. Every time a vector length is repeated within a 10 pixel tolerance, a counter is incremented. Since each evaluated geometries has its specific value, it is possible to identify the respective part.

According to the identified geometric shape, a second routine is responsible for sending signals to trigger the robot valves in order to relocate the part from its initial location to the storage area dedicated to the corresponding shape (Figure 8).

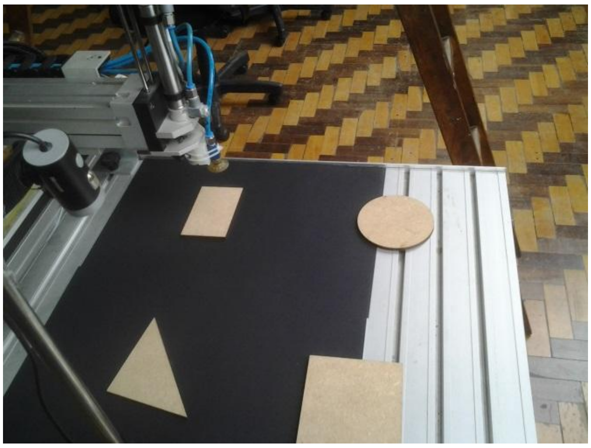

Figure 8. 3-axis electro-pneumatic robot classifying parts according to their geometric shape.

4. CONCLUSIONS

Through experimental procedure it was found that the methodology proposed in this paper is effective for the recognition of geometric shapes using a low cost camera. The results obtained through applying the developed vision system with the electro-pneumatic robot are especially promising, especially when considered the low cost of the equipment used. The proposed system is especially efficient when compared with processes where part inspection and repositioning is manual.

The result obtained from the application of the signature method showed great improve for smaller angular steps. However, this parameter has to be selected carefully, since it is time consuming due to the processing required.

5. REFERENCES

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6. RESPONSIBILITY NOTICE

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