Robust and Fast Algorithm for Artificial Landmark Detection in an Industrial Environment

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***Abstract*—This paper describes a solution to detect and gather information on artificial landmarks placed in an industrial floor. This solution is composed of an observation module (artificial vision plus a chamber for light conditioning) and a fast algorithm for detecting and extracting landmarks. It is applicable with two types of landmarks, which provide useful information and in the future the solution may be applied in Autonomous Guided Vehicles (AGVs) for locating or path following. The execution time and accuracy results of the detection and extraction algorithm are presented in this paper, when applied in landmarks in good and degraded conditions.**

***Index Terms*—Artificial Landmark, Artificial Vision, Autonomous Guided Vehicle (AGV)**

I. Introduction

According to David A. Schoenwald [1], autonomous unnamed vehicles (AUVs)" (...) need to understand enough about their surroundings so that they can function with minimal or no input from humans. This implies sensors are needed that are capable of "seeing" terrain (...)".

The fundamental motivation for this work is the development of a sensorial system based on artificial vision which can capture relevant information on artificial landmarks. The information acquired will be useful in the future for the vehicle localisation and for navigation purposes.

The presented observation module is composed of a camera inside a chamber, as shown in Fig. 1. The aim with the chamber is to perform light conditioning, making it possible to obtain quality images. The real chamber is shown at Fig. 2.

The software for landmark detection and extraction should be fast and capable of detecting and extracting data from two types of landmarks.

These landmarks will be subjected to degradation as they will be placed on the floor of an industrial site. Therefore, the detection and extraction algorithm should be robust and capable of performing its function properly in the presence of small degradations in the landmarks without the need for an additional computational effort. The entire solution needs be fast enough to be implemented in an embebed computing system with real time constrains.

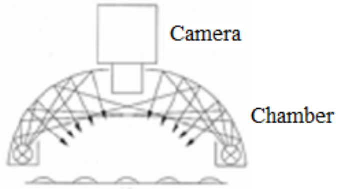

Figure 1. Observation Module (camera and chamber)

Figure 2. Observation Module (chamber is to perform light conditioning).

II. Literature Review

In modern flexible production systems [2], Autonomous Guided Vehicles (AGVs) can handle and store materials. The efficiency and effectiveness of production systems is influenced by the level of optimization of the materials' movement within the plant.

Document [3] provides a vision on the technologies and efforts around the AGV systems and their application in handling and logistics purposes in warehouses and manufacturing sites. In fact, if the logistics and material handling can be done with a high degree of autonomy, the material flux will be more effective and faster. Moreover, the worker will spend less time performing those tasks and less exposed to dangerous situations.

Examples of enterprises that successful develop AGVs are AGV Electronics [4] and Kiva Systems [5]. Expensive Laser Range Finders are used in the vast majority of these AGVs, while others use guided navigation as magnet-gyro guidance, inductive guidance or lines painted on the floor, which sometimes makes the overall system less flexible.

Artificial vision is one of the most common observation sensors used in robot localisation and navigation. It is cheaper than a Laser Range Finder and more flexible comparatively to guided navigation systems.

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However, it is not commonly applied in industrial environments with the purpose of detecting and extracting artificial landmarks to be used in AGV localisation and navigation.

III. Artificial Landmarks

Two types of artificial landmarks were created, an arrow, shown in Fig. 3 and in Fig. 4, and a line, shown in the Fig. 5.

When the developed sensorial system is applied to an AGV, it is possible to obtain the position and orientation of the vehicle relatively to the arrow. With regard to the line landmark, it is only possible to obtain information on orientation.

The arrow is an isosceles triangle. The vector that defines direction of the arrow is perpendicular to the small side of the arrow, indicated in Fig. 3, and intersects the arrow's vertex which contains the angle β.

The arrow has a code composed of a set of filled circles, as shown in Figure 4. This code identifies the landmark and is composed of six bits (bitA, bitF), which can be filled or not. For example, if a filled circle appears in the position of bitA, then the value of bitA is 1. Contrarily, if there is not a filled circle in the position of bitA, then its corresponding value is 0. The same rule is applicable to all bits from bitA until bitF. Therefore, the arrow's code can be computed as follows:

$$Code = \begin{bmatrix} 2^0 & 2^1 & 2^2 & 2^3 & 2^4 & 2^5 \end{bmatrix} \begin{bmatrix} bitA \\ bitB \\ bitC \\ bitD \\ bitE \\ bitF \end{bmatrix} \quad (1)$$

With this philosophy, it is possible to have 64 different arrows with different codes. These filled circles are printed in a smooth gradient to prevent the borders of the arrow from being detected by the edge algorithm, presented in the following section.

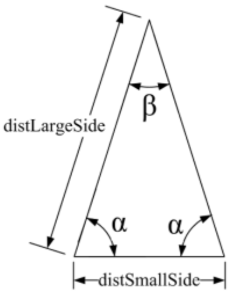

Figure 3. Landmark Arrow-Isosceles Triangle.

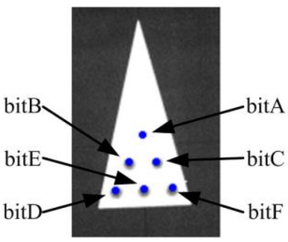

Figure 4. Arrow-Identification Code.

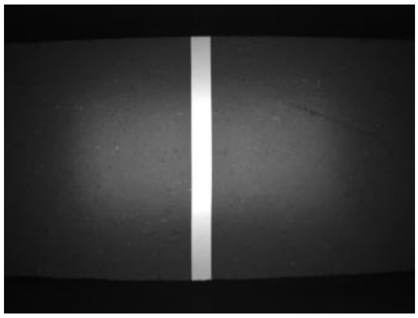

Figure 5. Landmark Line.

A suitable acquisition environment was developed in order to highlight the relevant information to be extracted from the landmarks and eliminate the undesirable reflections on the acquired image, as shown in Fig. 6. This is a chamber containing a fuzzy and frontal illumination circuit. The results obtained with this conditioning system are shown in Fig. 6.

Figure 6. Conditioning of the acquisition environment. Left: Image obtained with deficient lighting. Right: Image obtained with correct lighting.

IV. Artificial Landmark Detection

The detection of artificial landmarks is performed in three essential steps: edge detection and binarization; line detection using the Randomized Hough Transform; and feature extraction, as is example the arrow and line orientations; and the arrow position and code.

Several methods were considered to detect the edges and binarization phase. The algorithm of Edge Enhancement (Roberts) [6], followed by a binarization phase, proved to be the fastest method. On average, this method takes 16ms using an Intel Pentium, 1.7 GHz. The TABLE I contains a comparison between other approaches and this method. It is possible to confirm that all the alternatives require a higher execution time using the same computer comparatively to the Edge Enhancement (Roberts).

TABLE I. Comparison of Edge Detection algorithms –Image resolution of 1024x768.

Algorithm	Duration (ms)
Edge Enhancement (Roberts) [6]	16
Canny Edge Detector [7]	29
Marr-Hildreth Edge Detector [7]	17
Sobel Enhancement Edge detector + Binarization [7]	22
Enhancement Prewitt Edge detector + Binarization [7]	21
Gaussian Filter + Edge Enhancement Roberts + Otsu Method [7]	21

Fig. 7 shows the result of applying the chosen edge detection algorithm to an arrow, followed by a binarization.

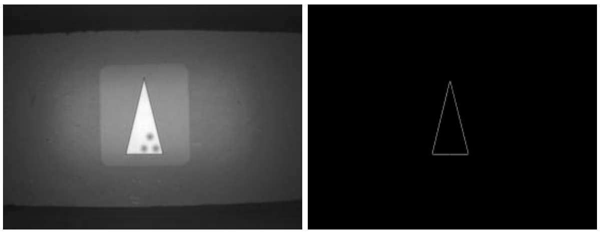

Figure 7. Arrow image (left), detected edges and binarization applied (right).

The Hough transform was used in the line detection phase [8]. The classical Hough transform is characterized by its robustness and efficiency; however, it is slow. Other variant of the Hough transform, which performs better in terms of execution time, is the Randomized Hough Transform (RHT).

Therefore, the classical Hough transform and the RHT were compared in this work. The execution time spent for both approaches in a 1.7 GHz Intel Pentium is presented in TABLE II.

The Hough transform extracts information about the lines in polar coordinates. Therefore, the extracted information is ρ and θ. The parameter ρ, represents the perpendicular distance between the referential origin and the line identified in the image, while θ represents the angle of that perpendicular and the referential origin. Both, the classical Hough transform and the RHT, were performed with a resolution in the Hough transform of $\Delta\rho$=1 pixel in the distance to the origin and $\Delta\theta$ =0.1º.

The results proved that the RHT is faster than the classical Hough transform; therefore, the Randomized Hough Transform (RHT) was the solution adopted to detect lines.

TABLE II. HOUGH TRANSFORM METHODS BASED ON TIME COMPARISON.

Algorithm	Image size	Duration(ms)
classical Hough transform	1024x768	480
randomized Hough transform	1024x768	3
classical Hough transform	512x384	180
randomized Hough transform	512x384	2

An experiment was conducted to classify the accuracy of the line detection algorithm. The TABLE III contains the average of the error in the angle and distance obtained during 10 tests, for each landmark type (arrow and line) and condition (good and damaged). This table proves the success of the obtained results, in terms of accuracy, even in the presence of damaged landmarks.

TABLE III. VALUES OF THE AVERAGE ACCURACY OF THE LINE DETECTION ALGORITHM

Landmark	Condition	Average Accuracy
Arrow	Good	0.9º; 2mm;
Arrow	Damaged	2º; 4mm;
Line	Good	0.1º; 1mm;
Line	Damaged	0.4º; 1mm;

The application of the algorithm of detection and extraction in the damaged landmarks is shown in Fig. 8 and Fig. 9. Successful results for line and arrow extraction can be seen in Fig. 8 and Fig. 9, respectively.

Finally, in the feature extraction phase, the orientation of the arrow and line landmarks is obtained using the lines detected with the RHT algorithm. The position of the arrow is obtained by computing the centre of mass of the intersection points. These intersection points are obtained from the detected lines. After that, a mask is used together with the knowledge on the position and orientation of the arrow, to obtain its code. This code computed through the equation (1), and entered in account if the bits, as explained in Section III, are or not filled.

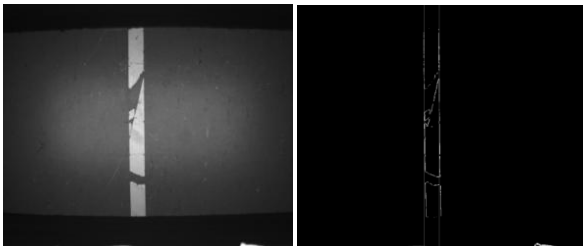

Figure 8. Damaged Line (left) and respective result of line detection (right).

V. CONCLUSIONS

The sensorial system and the algorithm developed for detecting and extracting landmarks is robust, accurate and fast. The entire solution always detected the landmarks, even when those landmarks were in degraded conditions.

The next step is using the information on the landmarks position and orientation, obtained using the algorithm described here, to implement a localisation and navigation routine for an autonomous guided vehicle (AGV).

The intention is also to implement the entire sensorial system in a smart camera, which carries a processor and a camera on the same board

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