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Geometric and Threshold Calibration Aspects of a Multiple Line-Scan Vision System for Planar Objects Inspection

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1. Introduction

The vision system proposed as support of this chapter is dedicated for inspection and localization of flat glass parts, in a robot-based automation of the unloading and packing stages in the flat glass industry. This vision system belongs to the class of the artificial Vision Systems dedicated for analyzing objects located on a moving scene (conveyor).

The Industrial Vision System described in the paper is designed for silhouette inspection of planar objects (it is a pure 2D Vision System, the volumetric characteristics of the analyzed objects being not relevant for the application).

Analyzing the functional system requirements can be identified a sum of characteristics that have to be achieved by the system, from which the most critical ones and also most relevant for this paper, are:

The response time – especially because this Vision System belongs to the class dedicated analyzing objects located on a moving scene (other parts are coming under camera) and also because it is part of an automation process were all the following application partners' components are piped along the conveyor.

The accuracy of the analysis results. The main purpose of including this Vision System into the automation system is to analyze and to provide decisional results on the inspection of the glass plates. The aspects to be analyzed are the accuracy of the edges and corners (resulted from the cutting process and/or from the previous handling process of plates).

The paper is focused on the *geometric calibration* and *threshold calibration* aspects of a multiple line-scan camera vision system (in particular a dual line-scan camera system).

In our specific vision system application the size of the image that has to be processed is very large. This is caused by the size of the inspected parts: lengthwise the conveyor up to 6500 mm and the width of the area of interests is 4000 mm in conjunction with the accuracy requirements (which is leading to a resolution of the acquired image of about 0.5 mm/pixel).

The major research and development efforts were to define, implement and test, for both geometric calibration and threshold calibration processes, methods with minimal negative

impact on the critical requirements of the vision system (the response time and the system accuracy).
The methods defined for the both calibration processes have to maintain an acceptable system Set-up time and also to provide the ability of moving the most of the vision system computational effort from on-line to off-line processing stage.

2. The Automation System Description

In Figure 1 is presented the architecture of this automation system. This architecture is often utilized in industrial applications (in palletizing of moving objects systems).

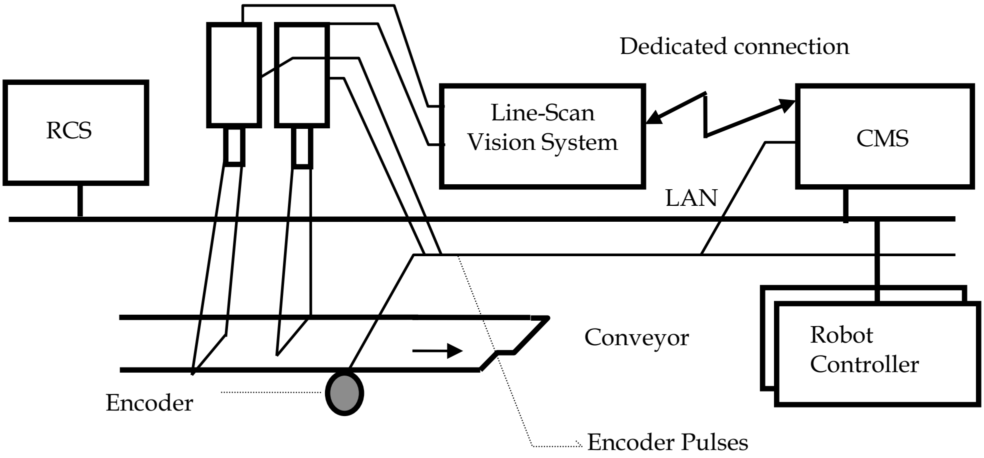

Fig. 1. The robot-based automation system for inspecting and handling moving glass plates from a conveyor

2.1 The Structural Aspects of the Automation System

The structural aspects of the automation system architecture are (Hossu & Hossu, 2008-c):
Active Elements: Control Management System (CMS), Routing Control System (RCS), Vision System and Robotic Cells.
Passive Elements: Conveyor, glass plates.
Infrastructure: Communicational Links: Vision System – CMS, CMS – Robots Controllers, CMS – RCS.
General assumptions: The plates are connected to the conveyor (the same speed and direction).

2.2 The Functional Aspects of the Automation System

The Routing Control System has to provide for CMS the Routing Data - a description of the possible destinations (one or more of the robotic cells) of each plate in the moment the plate is passing the Decision Point of the Vision System. The role of the Vision System is to inspect the cutting accuracy and the shape parameters of every plate. The vision system is analyzing the information provided by a Line Scan Acquisition System (a dual line scan camera system) in conjunction with the information provided by an encoder connected to the transport conveyor. The Vision Data, containing the data resulted from the inspection process, together with the data describing the location of the plate, are transmitted to CMS in the moment the vision system processing time ended. The moment (time-based) is called Vision Decision Point. Both sets of data (Routing Data and Vision Data) are merged by CMS. CMS will take the decision to send the pick plate command to a certain robotic cell only if Vision Data describe the plate having cutting accuracy and shape parameters inside the accepted tolerances for a certain packing destination and also if the plate is routed to that certain destination.

3. The Description of the Vision System

This system belongs to the class of the artificial Vision Systems dedicated for analyzing objects located on a moving scene (conveyor).

The Vision System main task is to inspect glass plates transported by a conveyor.

From the structural system architecture and its working environment we could identify a set of its general intrinsic characteristics, from which the most relevant in this point, are:

The system is using line-scan camera / cameras for the image acquisition and an encoder for estimating the motion of the object by measuring the motion of the transport support (the speed of the conveyor).

The image is obtained by reflection of the light from a linear light source (fluorescent) on the surface of the analyzed objects.

The plates have the same speed and direction as the conveyor, and the orientation of the conveyor is known relative to the acquisition line and constant in time.

4. Geometric Calibration Aspects of a Multiple Line-Scan Vision System for Planar Objects Inspection

This class of the Artificial Vision Systems dedicated for analyzing objects located on moving scenes (conveyor) presents some specific characteristics relative to the Artificial Vision Systems dedicated for static scenes. These characteristics are identified also on the image geometric calibration process (Borangiu, et al., 1995), (Haralick & Shapiro, 1992).

In Figure 2 is presented the model of the image obtained from a dual line-scan camera Vision System.

For this class of the Artificial Vision Systems we could identify as relevant for the geometric calibration process the following characteristics (Hossu, 1999):

The obtained image has significant geometric distortions on (and only on) the image sensors direction. The geometric distortions are along the acquisition line, but not from one line to the other.

There is an overlapped image area between the two cameras. The end of the acquisition line of the 1st camera is overlapping the beginning of the acquisition line of the 2nd camera. This overlapping area is significant in size and is a constant parameter estimated during the artificial vision system installation process.

There is a lengthwise conveyor distance between the acquisition lines of the two cameras. This distance is also a constant parameter and its value is also estimated during the system installation process.

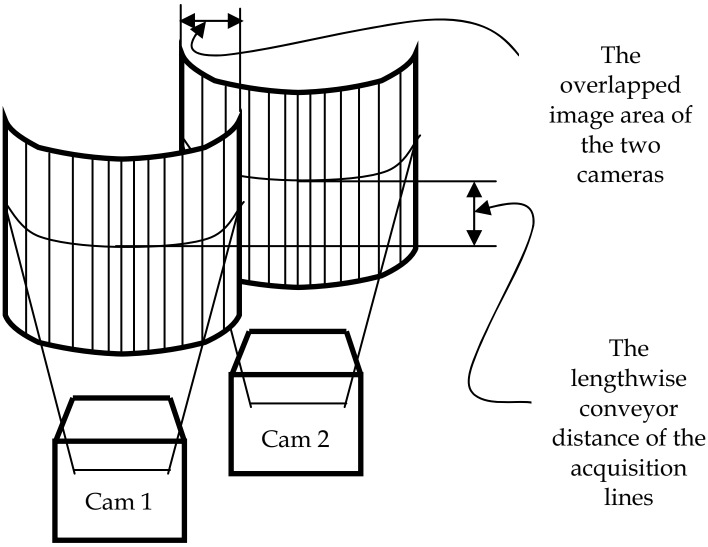

Fig. 2. The geometric distortions of the image acquired with a dual line-scan camera Vision System.

4.1 The Pattern based Calibration Tool

For the calibration process we adopted the method of using a Pattern based Calibration Tool.

This Pattern based Calibration Tool represent a set of blobs with a priori known dimensions and locations for the real world (millimeters and not image pixels) (Croicu, et al., 1998).

The outcome of using this type of calibration technique was to obtain the following:

- Estimation with the highest accuracy of the scene model parameters on the direction of the distortions.
- Estimation of the size of the overlapped image area for both cameras.
- The parallelism of the two acquisition lines is obtained during the installation process, using the support of the Calibration Tool.
- Achieving a high accuracy of mounting the cameras in such a way to obtain the perpendicularity of the acquisition lines on the moving direction of the scene (of the conveyor).
- Achieving a high accuracy on the distance lengthwise the conveyor of the acquisition lines (the acquisition lines of Camera 1 relative to the acquisition lines of Camera 2). The shape and the dimensions of the pattern adopted for the Calibration Tool force this characteristic.

4.2 The Calibration Tool Description

In Figure 3 is presented the pattern adopted for the Calibration Tool used for the dual line-scan camera Vision System (the dimensions are presented in millimeters) (Croicu, et al., 1998)., (Hossu, et al., 1998).

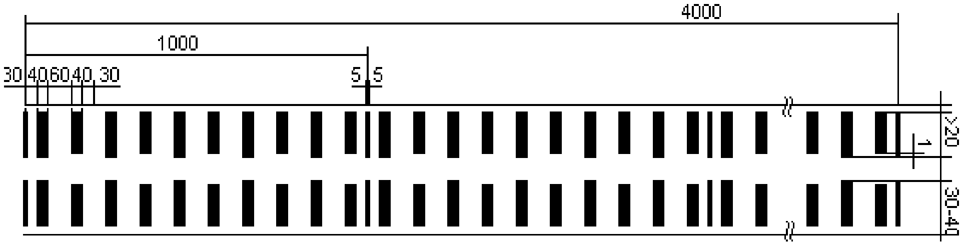

Fig. 3. The pattern of the Calibration Tool used for the dual line-scan camera Vision System.

The characteristics of the adopted Pattern are:

The pattern contains dark blobs (marks) placed on a bright background (with a high level of light intensity for the image).

The pattern is symmetrical on the vertical direction (lengthwise the conveyor). The two cameras have the acquisition lines parallel one each other but located on different position on the conveyor (due to the lighting system adopted – built from two fluorescent tubes used for obtaining the image from the reflection on the object surface). 1st Camera will have the acquisition line located on the top edge of the lower section of the pattern, and the 2nd Camera will locate its acquisition line on the bottom edge of the upper section of the pattern.

The pattern is partially homogenous on the horizontal axis (the direction crosswise the conveyor, the direction of the distortions)

The pattern contains a characteristic of a small difference (1 mm.) between the even and the odd marks. This will force the mounting process of the cameras to be very accurate in obtaining the parallelism of the acquisition lines of the cameras and also the perpendicularity on the conveyor direction.

4.3 Experimental Results of the Calibration Process

In Figure 4 are presented the results obtained from the Calibration process performed on the 1st Camera. (Hossu & Hossu 2008-c)

The Excel Cell used as support for representing the results of the Calibration on the 1st Camera contains the following:

The 1st column (called Mark) contains the number of the corresponding Mark existing in the pattern.

The 2nd column (called Cam1) contains the values of the coordinates of the marks on the Calibration Tool. These values are obtained from the “real world”, from direct measuring of the Pattern applied on the Calibration Tool (represented in millimeters).

The 3rd column (called Pixel) represents the coordinates of the existing Marks on the image. These coordinates are represented in pixel number.

For both cameras we chose a Polynomial Trend of order 3 for the approximation of the conversion function of the image coordinates values (pixels) into the conveyor coordinates values (millimeters). Using this type of trend the calibration method will provide results with a maximum approximation error inside the accuracy requirements of the particular Vision System.

a1	b1	c1	d1
1.448567E-09	-9.128585E-06	0.5088785	338.946

Mark	Cam1	Pixel	Estimated
1	429.1	175	427.7278
2	529.2	380	531.0810
3	629.3	576	629.3081
4	729.5	777	729.5128
5	829.6	979	829.7479
6	929.8	1181	929.5853
7	1033.1	1390	1032.5400
8	1133.3	1595	1133.2616
9	1233.6	1799	1233.3085
10	1333.9	2004	1333.7361
11	1434.7	2210	1434.6181
12	1535.1	2415	1535.0504
13	1635.4	2621	1636.0883
14	1735.8	2825	1736.3342
15	1836.2	3028	1836.3487
16	1936.6	3231	1936.6953
17	2042.2	3443	2041.9242
18	2142.6	3644	2142.1760
19	2243.1	3844	2242.4668
20	2343.7	4046	2344.3760

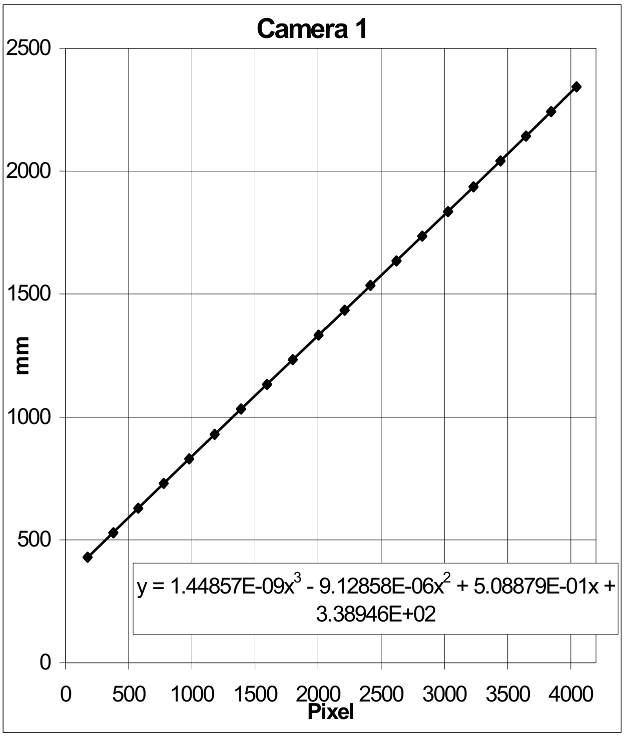

Fig. 4. Experimental results of the calibration process on the 1st camera.

On the top and right side of the Excel Cell (the first two rows and the last four columns) are stored the parameters of the 3rd Order Polynomial estimated as trend.

The last column (called Estimated) contains the estimated of the marks coordinates values (on the conveyor), obtained from applying the Polynomial trend of order 3.

In the bottom right side of the Excel Cell is presented the graphical chart of the trend of the coordinates values of the marks on the conveyor related to the pixel coordinates.

In the figure the following notations are used:

x coordinate value in image – (pixels),

y coordinate value on the objects scene (on conveyor) – (mm).

$$y = a_1 x^3 + b_1 x^2 + c_1 x + d_1 \text{ for the 1st Camera} \tag{1}$$

$$y = a_2 x^3 + b_2 x^2 + c_2 x + d_2 \text{ for the 2nd Camera} \quad (2)$$

In Figure 5 is presented the graphical chart of the evolution of the distortions estimated on the acquisition lines direction. The two cameras are covering around 4 meters wide view. The figure represents the behavior of the two acquisition cameras: in the area from 400 mm to 2250 mm it is represented the behavior of the 1st camera and in the area from 2250 mm to 4400 mm it is represented the behavior of the 2nd camera.

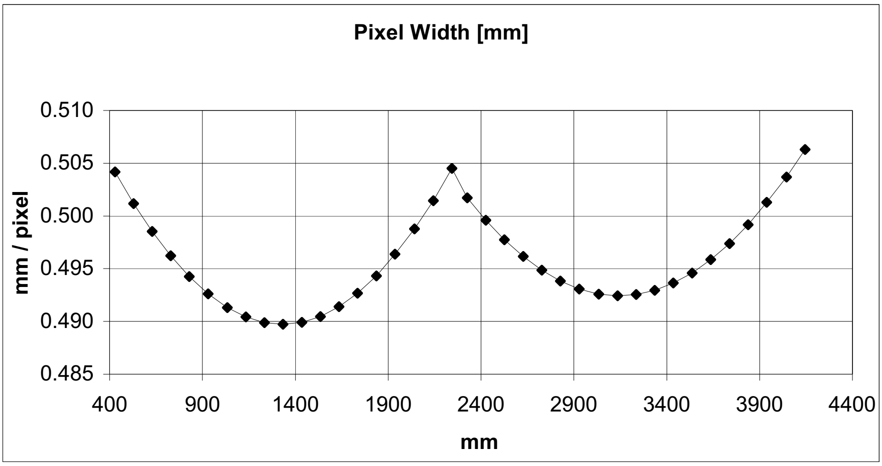

Fig. 5. The distortions estimated on the acquisition lines direction

We can notice the distortions are affecting the pixel width of the image form 0.49 mm/pixel to 0.507 mm/pixel. Ignoring this variation of the pixel width along the image acquisition line, would lead to accumulation of very high errors in some areas of the image, due to the fact the amount of pixels contained in an acquisition line is high (8096).

4.4 Using the Geometric Calibration Results

The most important achievement from estimating the scene parameters is the estimation of the image geometric distortions.

The end of the distortions estimation process leads to obtaining a table for conversion the image coordinates (pixels) in scene coordinates (millimeters) for each of all the 8096 pixels of the acquisition lines. This lookup table will contain 8096 values (of floating-point type) representing the real values of the scene (conveyor) coordinates of each pixel.

The CPU effort of the image processing algorithm will be minimal on converting the image coordinates into conveyor coordinates, using the pixel coordinate as the index of the offline-built lookup table.

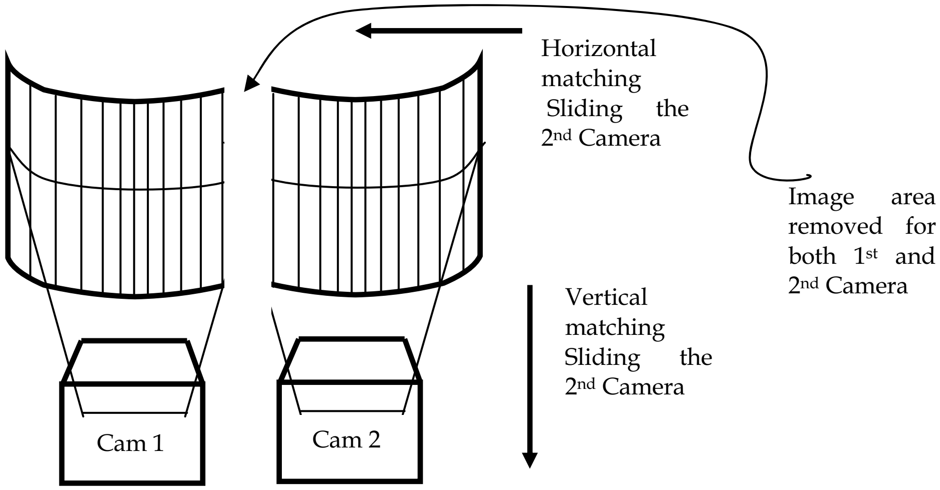

Fig. 6. Using the calibration results for a dual line-scan camera system.

In order to minimize the processing time of the image, the polynomial estimation is not used on-line. The polynomial estimation is used for building the pixel to millimeters lookup table, in the offline stage of the presented method. In fact using a polynomial trend of 3rd order or other type of trend is not relevant for the response time performances of the vision system but only for obtaining the required approximation error. This stage, being offline and using a relative small amount of data, another more sophisticated approximation method could be used.
In Figure 6 are presented the ways the last steps of the calibration process are performed.

5. Threshold Calibration Aspects of a Multiple Line-Scan Vision System for Planar Objects Inspection

For this specific vision system we could identify as relevant for the threshold calibration process the following structural characteristics:

The lighting environment (provided by the light source) is stable in time (from one acquisition line to the other). This is obtained using a high frequency controller for the control of the fluorescent lamp of the light source. This assumption of stability in time of the lighting environment is true for a short and medium segment of the lifetime of the light source.

The image is acquired on variable acquisition frequency. The consequence of this is that the intensity level of the same image element (pixel) under the same lighting conditions is dependent on the conveyor speed.

Taking into account the critical requirements of achieving the real-time characteristic (minimal response time), our choice was for a Binary Image Processing System. In order to obtain the binary image from the gray level image, we adopted a threshold method.
Threshold methods are defined as starting from the analyze of the values of a function *T* of the type (Gonzales & Wintz, 1981), (Borangiu, 2004), (Hossu, 1999):

$$T = T\,[x, y, p(x, y), f(x, y)] \tag{3}$$

Where:

$f(x, y)$ – represents the intensity value of the image element located on the co-ordinates (x, y),

$p(x, y)$ – represents the *local properties* of the specific point (like the average intensity of a region centered in the co-ordinates (x, y)),

T – is the *image threshold*

The goal is to obtain from an original gray level image, a binary image $g(x, y)$ defined by:

$$g(x,y) = \begin{cases} 1 & \text{for } f(x,y) > T \\ 0 & \text{for } f(x,y) \le T \end{cases} \tag{4}$$

For T a function only of $f(x, y)$, the obtained threshold is called *global threshold*.

In the case of T a function of both $f(x, y)$ and $p(x, y)$, the obtained threshold is named *local threshold*.

In the case of T a function of all $f(x, y)$, $p(x, y)$, x and y, the threshold is a *dynamic threshold*.

5.1 Image Segmentation using Global Threshold

Gray level histogram represents the probability density function of the intensity values of the image (Gonzales & Wintz, 1981), (Borangiu, 2004), (Hossu, 1999).

In order to simplify the explanations, we suppose the image histogram of the gray levels is composed from two values combined with additive Gaussian noise:

The first segment of the image histogram corresponds to the background points – the intensity levels are closer to the lower limit of the range (the background is dark).

The second segment of the image histogram corresponds to the object points – the intensity levels are closer to the upper limit of the intensity range (the objects are bright).

The problem is to estimate a value of the threshold T for which the image elements with an intensity value lower than T will contain background points and the pixels with the intensity value greater than T will contain object points, with a minimum error. For a real image, the partitioning between the two brightness levels is not so simple and also not so accurate. The partitioning is fully accurate only if the two modes of the bimodal histogram are not overlapped. The classification is defined as the process of the distribution of the pixels in classes. The goal of the process of finding a segmentation threshold is the minimization of the error of classification. The optimum segmentation threshold is located in the intersection position of the two normal distributions.

The estimation of the error of classification is obtained from the area of the overlapped segments:

$$E = \frac{A + B}{\textit{image size}} \tag{5}$$

Suppose the image contains two intensity level values affected with additive Gaussian noise. The mixture probability density function is:

$$p(x) = P_1 p_1(x) + P_2 p_2(x) \tag{6}$$

Where:

x – the random value representing the intensity level,

$p_1(x)$, $p_2(x)$ – are the probability density functions,

P_1, P_2- are the a priori probabilities of the two intensity levels ($P_1 + P_2 = 1$).

For the normal distribution case on the two brightness levels:

$$p(x) = \frac{P_1}{\sqrt{2\pi}\sigma_1}\exp\frac{(x-\mu_1)^2}{2\sigma_1^2} + \frac{P_2}{\sqrt{2\pi}\sigma_2}\exp\frac{(x-\mu_2)^2}{2\sigma_2^2} \tag{7}$$

Where:

μ_1, μ_2 - are the mean values of the two brightness levels (the two modes),

σ_1, σ_2 - are the standard deviations of the two statistical populations.

Suppose the background is darker than the object. In this case $\mu_1 < \mu_2$ and defining a threshold *T*, so that all pixels with intensity level below *T* are considered belonging to the background and all pixels with level above *T* are considered object points. The probabilities of misclassification an object point (classifying an object point as a background point) and similarly of misclassification a background point (classifying a background point as an object point) are:

$$E_1(T) = \int_{-\infty}^{T} p_2(x)dx \tag{8}$$

$$E_2(T) = \int_{T}^{+\infty} p_1(x)dx$$

The probability of error is given by:

$$E(T) = P_1 E_2(T) + P_2 E_1(T) \tag{9}$$

To find the threshold value for which the error is minimum, $E(T)$ is differentiate with respect to T:

$$P_1 p_1(t) = P_2 p_2(t) \tag{10}$$

Applying the result to the Gaussian density we obtain:

$$AT^2 + BT + C = 0 \tag{11}$$

Where:

$$\begin{aligned} A &= \sigma_1^2 - \sigma_2^2 \\ B &= 2(\mu_1\sigma_2^2 - \mu_2\sigma_1^2) \\ C &= \sigma_1^2\mu_2^2 - \sigma_2^2\mu_1^2 + \sigma_1^2\sigma_2^2 \ln\frac{\sigma_1 P_1}{\sigma_2 P_2} \end{aligned} \tag{12}$$

If the standard deviations are equal, a single threshold is sufficient:

$$T = \frac{\mu_1 + \mu_2}{2} + \frac{\sigma^2}{\mu_1 - \mu_2} ln\frac{P_2}{P} \tag{13}$$

If the probabilities are equal $P_1 = P_2$ the threshold value is equal with the average of the means.

A way of checking the validity of the assumption of bimodal histogram is to estimate the mean-square error between the mixture density, $p(x)$ and the experimental histogram $h(x_i)$.

$$M = \frac{1}{N}\sum_{i=1}^{N}[p(x_i) - h(x_i)]^2 \tag{14}$$

Where: N – number of possible levels of the image (usually $N = 256$).

The binary image is obtained changing the color attribute of each pixel according to its intensity level relative to the segmentation threshold. Characteristics of the global threshold methods (Borangiu, et al., 1995), (Hossu & Andone, 2005) for these classes of vision applications:

- The assumption that both classes have the same standard deviation is not correct in our vision system environment. The background pixels (dark) have much smaller standard deviation than the object pixels.
- The assumption the classes (two levels) have the same a priori probabilities in many applications is also not acceptable for this vision system application.

In the case of the artificial vision systems dedicated to object recognition for industrial applications there is a large amount of a priori information about the image that has to be processed. Better results of estimation of the distribution of the image elements of the scene (background image, without the objects) can be obtained. Usually, in robotic applications, the illumination environment is known and controlled and also the object classes with a probability of apparition in the image are known. In many robotic application an estimation of the ratio between the area of the objects to be analyzed and the total area of the image scene, can be made with good results (a better estimation than the assumption of $P_1 = P_2 = 0.5$ could be obtained).

5.2 Image Segmentation using Dynamic Threshold

There are some classes of scenes of artificial vision systems where using the global threshold methods is not acceptable:

- The case of the applications where the lighting system does not supply a uniform intensity all over the analyzed surface.
- Segments of the image (or sometimes image elements) do not have the same behavior in the same lighting conditions.

For these types of images, in order to obtain a binary image, the most often used are dynamic threshold methods. The methods are based on the local analyze of the image. The algorithm of the estimation of the dynamic threshold consist of:

- The original image is divided in regions of a prescribed size.
- For each region it is estimated the histogram
- For each histogram it is estimated the error induced from the assumption of bimodal histogram (a histogram built from two normal distributions)
- If the value of the error is less than an acceptable value, the global threshold for the region is estimated.
- If the value of the error is too big (the histogram is too far from a bimodal histogram) the threshold value is estimated from the interpolation of the neighbors' region threshold values (for which the assumption of a bimodal histogram is considered acceptable).

In the final stage, a second interpolation process is applied: for each image element is assigned a threshold value $T(x, y)$ from the interpolation of the values of the neighbor image elements.

This method is called dynamic threshold method because the value of the resulted threshold for each image element is dependent of the position of the element in the image - $T(x, y)$.

Characteristics of the dynamic threshold methods:

Lack of processing time consumption – each element of the image is used at least two times (the method requires multiple-pass of the image) in different steps of the algorithm (and the number of the elements is very large).

Estimation of the acceptable error value (or the validation of the bimodal histogram assumption) is a complex process.

To choose the size of the image regions we have to take into account:

Large size of the region makes the method to loose the dynamic threshold characteristics and to fail into a global threshold method

Small size of the region makes to loose the statistical characteristic of the population of the image elements contained by the analyzed region (and the accuracy of the results is poor).

The last comment on the method is the fact that this method does not solve the problem of the non-uniformity of the illumination system or of the acquisition sensor.

5.3 Image Segmentation using Statistical Estimated Local Threshold

The set of types of image intensity level distortions identified for this class of vision systems (Hossu, et al., 1998), (Hossu. & Hossu, 2008-b) contains:

Illumination non-uniformity (obtaining a uniform intensity of the light on the whole area of the scene where the image is analyzed – usually 2 m – it is practical impossible).

Sensor and optics non-linearity – for linear cameras with a large number of pixels per row and also on optics with wide ranges, can be identified areas of nonlinear behavior of the image sensor and/or lenses.

Sensor cells non-uniformity – in cameras with CCD sensor, the cells present a different response on sensitivity at light intensity related to their neighbors.

In Figure 7 are presented the image intensity level distortions.

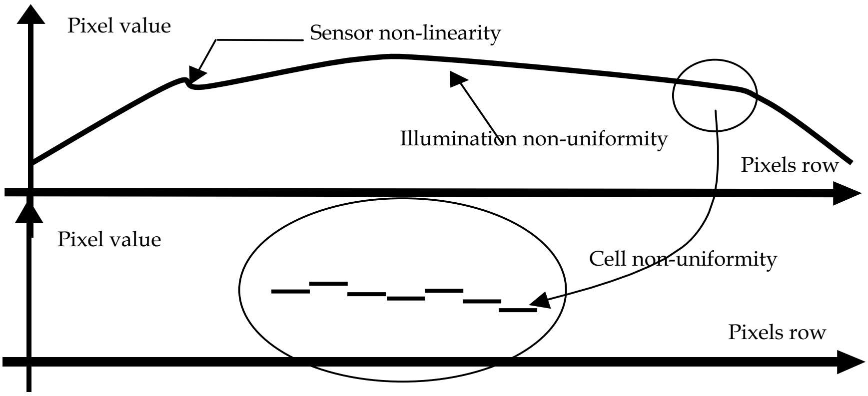

Fig. 7. Image intensity level distortions for CCD linear camera acquisition.

The main problem of the methods presented before represents the assumption that the image is a statistical population obtained from the addition of two ore more distributions (in the general accepted case normal distribution).

This assumption on the distribution of the intensity levels has the starting point the assumption that the insertion point of the noise is located on the transmission level of the information. In other words, the assumptions is that:

The acquired image is an ideal image (with only two gray levels: the gray level of the scene pixels and the gray level of the pixels corresponding to the object)

Then a global noise is applied, transforming the two levels in two normal distributions.

The assumption is false and using it we are analyzing a histogram, which is far away of two normal distributions, and from here the results are distorted. In reality the noise on the intensity level has its insertion point on the acquisition level and not on image transmission level. Intensity source has the meaning of intensity signal on the acquisition element and not only the lighting system. This implies the fact that the noise on the intensity source represents the whole chain of: lighting sources noise, reflective characteristics of the object surface and reflective characteristics of the scene surface, the sensitivity characteristics of the sensor and the vision system environment.

The vision system environment (the industrial environment the system it is dedicate for) is causing the most significant temporal intensity level distortions. This noise on intensity level is caused mainly by mechanical components of the system environment – causing vibrations of the mechanical support of the lighting source and/or vibrations of the object to be inspected (which are varying the reflection angle of the light).

For the image segmentation we adopted a local threshold estimated from temporal built statistical populations of every element in the image.

In the general case (an *array image*) an image represents a data set of:

$$\{f(x, y) \mid x \in [0,N], y \in [0,M]\} \tag{15}$$

Where:

N represents the number of image elements per row (number of image columns),

M represents the number of image elements per column (number of image rows).

In the *linear image* case, this data set becomes:

$$\{f(x) \mid x \in [0,N]\} \tag{16}$$

Where:

N represents the number of image elements per row (number of image columns).

Moving the insertion point of the noise we obtain: In the general case (an *array image*) an image represents a data set of:

$$\{f_i(x, y) \mid x \in [0,N], y \in [0,M], i \in [0,L]\} \tag{17}$$

Where:

L represents the number of the image frames (the size of the statistic population analyzed),

N represents the number of image elements per row (number of image columns),

M represents the number of image elements per column (number of image rows).

In the *linear image* case, this data set becomes:

$$\{f_i(x) \mid x \in [0,N], i \in [0,L]\} \tag{18}$$

Where:

L represents the number of the image frames (the size of the statistic population analyzed),

N represents the number of image elements per row (number of image columns).

In this way several temporal built statistical populations (from intensity levels of the same image element on a set of image frames acquired on different moments) replace the spatial built statistical population (made from image elements of the same image). The method of temporal histogram has the result the fact that each element of this set of histograms represents a bimodal histogram with two not overlapped modes (in case of a correct acquisition environment). It can be also introduced an estimation of the quality of the acquisition and image segmentation process using the estimation of the misclassification error analyzing the parameters of the two normal distributions. The method offers also the capacity of identification of the areas where some modifications should be done (on the lighting system) in order to improve the quality of the acquisition and image segmentation process. The lack of the proposed method is the memory consumption (it has to be built *N* x *M* different histograms in array acquisition, or *N* – in linear acquisition case). This problem is not so restrictive because at the end only the threshold values have to be stored and not the whole histograms. Another restriction is the fact that the method requires a large number of image frames acquired for construction of the statistical populations (in application set-up time). In the case of the systems dedicated to industrial applications usually this does not represent a real problem. This type of applications does not require a system response in condition of a small number of image frames a priori acquired. The vision systems dedicated to industrial applications can take the advantage on the fact that the image environment does not change a lot in time. In this way it can be initially reserved a certain time for acquiring a large enough number of image frames in order to be able to identify the permanent characteristics of the environment. All the intensity level distortions present permanent characteristics. This method has to be used in the case of the artificial vision systems dedicated to applications where the errors on image segmentation are not acceptable. In the applications dedicated exclusively to shape recognition the errors are accepted in a predefined range.

5.4 Local Threshold Values and the Acquisition Frequency

In moving scene applications, in order to maintain a constant resolution of the vision system along the direction of the scene movement, it is necessary the ratio between the acquisition frequency (the image lines rate – in the case of a line scan camera) and the scene speed to be constant. The acquisition frequency determines the exposure time of the CCD sensor cells. It can be notice an important influence of the speed (of the conveyor) on the intensity level of the same image element in the same lighting environment.

In Figure 8 are presented the experimental results obtained analyzing the influence on the intensity levels (for both: bright object and dark background) of the speed of the conveyor (acquisition frequency). The results were obtained on a statistical population from an image element on each measured speed. The second column represents the measured speed of the scene (conveyor) – V [m/min]. The 3rd to 8th columns represent image intensity levels estimated from the analyzed statistical population (temporal histogram). The values from the Threshold column are the image threshold values obtained from a global optimum temporal threshold method applied on the histogram built for each analyzed level of the speed.

In Figure 9 are presented graphical the explanations on the meanings of the data involved in the analysis of the influence of the speed (acquisition frequency) on the intensity levels. The artificial vision system benefits from these results using a relation between the value of the image threshold and the speed V of the scene.

$$T = T\,(x,\,V) \tag{19}$$

Because of the response time restrictions imposed to the artificial vision system, instead of using an explicit expression of the estimated function $T(x, V)$, a search method in an a priori filled table (at set-up time) is more appropriate.

The size of the table is 256 (the number of the possible values of the image thresholds), containing floating-point values of the speed of the conveyor (acquisition frequency) for which the value of the threshold has to be changed.

	V [m/min]	Object Min+	Object Max	Object Min-	Scene Min+	Scene Max	Scene Min-	Threshold
1	20.7	221.532847	203.810219	168.364964	66.459854	44.306569	22.153285	110.766423
2	25.9	174.338624	160.391534	132.497354	52.301587	34.867725	17.433862	87.169312
3	31.1	147.510373	135.709544	112.107884	44.253112	29.502075	14.751037	73.755187
4	36.2	130.479452	120.041096	99.164384	39.143836	26.095890	13.047945	65.239726
5	41.3	118.513120	109.032070	90.069971	35.553936	23.702624	11.851312	59.256560
6	46.4	109.644670	100.873096	83.329949	32.893401	21.928934	10.964467	54.822335
7	51.4	102.927928	94.693694	78.225225	30.878378	20.585586	10.292793	51.463964
8	56.5	97.474747	89.676768	74.080808	29.242424	19.494949	9.747475	48.737374
9	61.6	93.040293	85.597070	70.710623	27.912088	18.608059	9.304029	46.520147
10	66.7	89.363484	82.214405	67.916248	26.809045	17.872697	8.936348	44.681742
11	72.5	85.877863	79.007634	65.267176	25.763359	17.175573	8.587786	42.938931

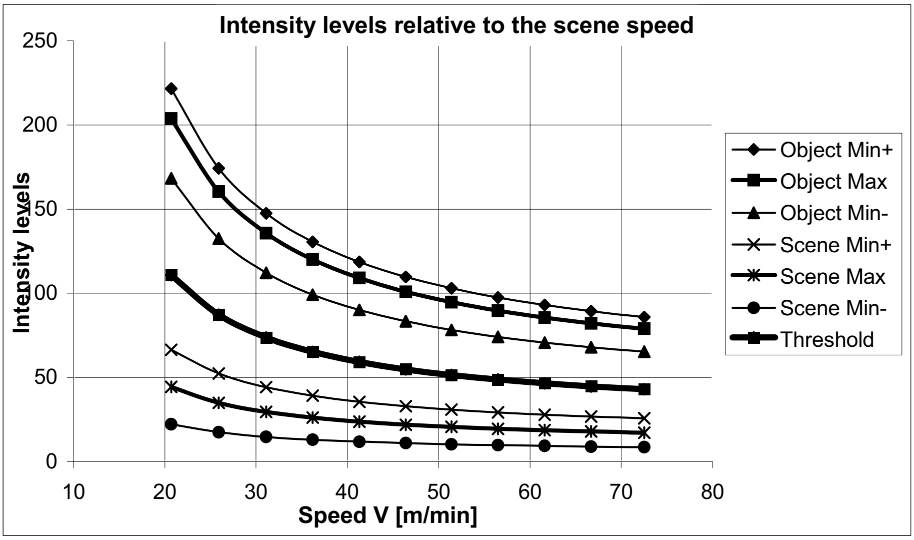

Fig. 8. The influence on the intensity levels of the acquisition frequency.

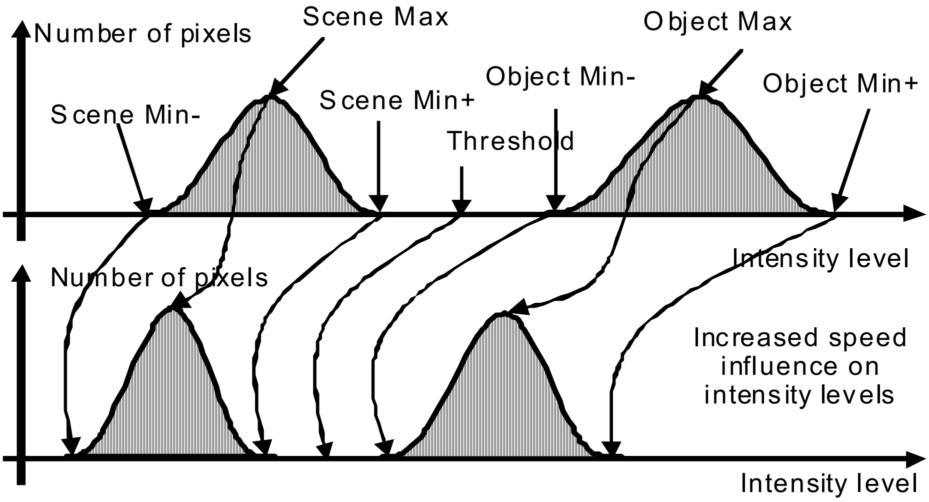

Fig. 9. The influence of the speed on the intensity levels

6. Conclusions

The proposed *geometric calibration* method is specific for multiple line-scan camera artificial vision applications for inspecting planar parts on moving scene. The system is a pure 2D Vision System. However the height of the object is varying in time (from one set of parts to another). Due to the fact the distance between the cameras and the objects is changing, the measuring results are affected. The proposed geometric calibration method allows the Vision System to self-adjust the calibration parameters for a known change in height of the objects, without affecting both the system accuracy and the response-time performances.

The presented geometric calibration method is moving all the computational effort from the vision system real-time to the off-line stage (setup stage of the system). The only process that remains quasi-on-line is the self-adjusting of calibration parameters on objects height change. This is done on the change production time (this is a time when the vision system is idle). The presented method doesn't cover the calibration aspects on the direction lengthwise the conveyor. This is not a trivial aspect for the real industrial parts-transportation systems (the objects are not following exactly the conveyor speed – causing a lower accuracy of the vision system on the lengthwise conveyor direction).

In the same way, the presented *threshold calibration* method is specific for line-scan camera artificial vision applications for inspecting planar parts on moving scene. For this class of vision systems, dedicated for inspection and measurement industrial applications the error on object segmentation process is not acceptable. In this case, classic methods of global and dynamic threshold are not applicable. Starting from these methods, for the gray level image segmentation we adopted a statistical estimated local threshold. In the industrial environment the vision system is dedicated for, slow but significant modification of the lighting environment during the lifetime of the light source is a normal process of aging. In the future research an efficient method has to be developed to provide the vision system the ability of self-adjusting to these environment changes.

In its implementation, the vision system subject of this paper has the acquisition frequency dependent on the speed of the moving scene (the speed of the conveyor). The paper proposes a processing time efficient method to estimate the modification on the threshold values for the case of an *error free* vision system in the case of variation of the acquisition frequency.

7. Acknowledgment

Parts of this paper are reprinted from 1. Hossu, A., Hossu, D. ,2008, A new approach of gray images binarization for artificial vision systems with threshold methods , *ICINCO 2008,* Vol. RA-2, pp. 11-16; and 2. Hossu, A., Hossu, D. ,2008, Calibration aspects of multiple line-scan vision system application for planar objects inspection, *ICINCO 2008,* Vol. RA-2, pp. 36-40.

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Contemporary Robotics - Challenges and Solutions

Edited by A D Rodi

ISBN 978-953-307-038-4
Hard cover, 392 pages
Publisher InTech

This book book is a collection of 18 chapters written by internationally recognized experts and well-known professionals of the field. Chapters contribute to diverse facets of contemporary robotics and autonomous systems. The volume is organized in four thematic parts according to the main subjects, regarding the recent advances in the contemporary robotics. The first thematic topics of the book are devoted to the theoretical issues. This includes development of algorithms for automatic trajectory generation using redudancy resolution scheme, intelligent algorithms for robotic grasping, modelling approach for reactive mode handling of flexible manufacturing and design of an advanced controller for robot manipulators. The second part of the book deals with different aspects of robot calibration and sensing. This includes a geometric and treshold calibration of a multiple robotic line-vision system, robot-based inline 2D/3D quality monitoring using picture-giving and laser triangulation, and a study on prospective polymer composite materials for flexible tactile sensors. The third part addresses issues of mobile robots and multi-agent systems, including SLAM of mobile robots based on fusion of odometry and visual data, configuration of a localization system by a team of mobile robots, development of generic real-time motion controller for differential mobile robots, control of fuel cells of mobile robots, modelling of omni-directional wheeled-based robots, building of hunter- hybrid tracking environment, as well as design of a cooperative control in distributed population-based multi-agent approach. The fourth part presents recent approaches and results in humanoid and bioinspirative robotics. It deals with design of adaptive control of anthropomorphic biped gait, building of dynamic-based simulation for humanoid robot walking, building controller for perceptual motor control dynamics of humans and biomimetic approach to control mechatronic structure using smart materials.

How to reference

Andrei Hossu and Daniela Hossu (2009). Geometric and Threshold Calibration Aspects of a Multiple Line-Scan Vision System for Planar Objects Inspection, Contemporary Robotics - Challenges and Solutions, A D Rodi (Ed.), ISBN: 978-953-307-038-4, InTech, Available from: http://www.intechopen.com/books/contemporary-robotics-challenges-and-solutions/geometric-and-threshold-calibration-aspects-of-a-multiple-line-scan-vision-system-for-planar-objects

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