The Analysis of Industrial Product External Surfaces: A Pattern Recognition Approach to the Situation of Imprecise Limits

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Abstract: The present study describes a model which, by using pattern recognition procedures, detects defects on the external surface of pieces and industrial products, especially those whose borders are indefinite. In addition to describing the model, a practical application and the results obtained are described, including an important extension of this work, i.e. the comparison of pieces with standards (defect control by means of matching procedures).

Key-words: Quality; External Surface Analysis; Pattern Recognition.

1 Introduction

This papers deals with quality control procedures related to identification and analysis of defects on products such as metal surfaces, materials derived from steel or iron, alloys, or even on the external area of products having these products in their composition, e.g., the surface of car shells, have made a considerable progress on account of automatization procedures.

Particularly, the use of what we call Quality Control Intelligent Systems, which deploy advanced techniques of Pattern Recognition, Artificial Intelligence or Fuzzy Logic, has made possible the development and application of highly efficient, reliable and practical procedures in defect detection, evaluation and classification for quite reasonable prices.

Some examples of pattern recognition techniques in a similar way we are using here and also similar kind of problems we are considering here can be seen in [1] and [2].

As we will see, the proposed model works in a very different way from the models described in these (and other) references.

Besides, the present study shows an extra outcome in this research line related to structuring a new method to carry out defect analysis on the external area of pieces or metallic materials.

The application of this method involves a specific situation, however rather common, i.e., cases where the borders of a given defect are not well defined.

This is the case of spots caused by finish imperfections, failures resulting from corrosion processes, cracks as a consequence of internal breaks or damage from handling, material accumulation as a result of warping, etc.

This study describes a method which, by making use of a relatively simple mathematical model, yields a precise quantitative analysis of the image of the piece under inspection.

This image is produced by means of simple devices (such as cameras connected to digitalizing boards).

The model has such characteristics that make possible not only to determine the presence of defects, but also to quantify their extension and seriousness.

Since it is operated by highly sensitive elements, the procedure is able to detect defects even in situations where the borders of the imperfection are extremely indefinite (which in general distorts the image of the product).

2 Detection Process

This paper focus on detecting defects imprecisely defined, or defects with low definition or, also, defects with indefinite borders. Defect analysis of the external areas of pieces and products under study will be carried out for the images representing these areas.

The process of obtaining information which makes up the image of the pieces consists of devices which will replace visual and tactile evaluation by inspectors, who normally do it in the traditional model. This procedure is called image capturing. Through this procedure, the image representation structures upon which the defect detection system is to work are be defined. The technical feasibility of the system structuring is, thus, ensured and at the same time the pieces of information are defined which will work as entries to the computer programs that make possible the recognition of defects.

This study involves a type of defect with no clear definition as regards its borderlines. Thus, it is important to highlight on the image of the piece the characteristics relevant for the detection of the defect and its subsequent identification.

Firstly, in order to determine such characteristics, it is necessary that the concept of pixel be taken into consideration, since the pixel is the basic element of any image (picture element). Hence, pixels are the fundamental aspects of a digital image. They are also the coordinates used to determine the location/position of the point on the image.

Linked to the pixels are basic characteristics of an image, such as its chromatic pattern and the level of gray, fundamental components of the analyses herein carried out, since these data provide cues as to the presence or absence of certain properties of an image – or of part of it – which determine the presence of defects on the piece.

The association of quantifiable values to the color of the piece (or its gray level in the case of monochromatic images) makes possible to determine the intensity of the property under study and, thus, by using an approach similar to that of quality evaluation by variables, to eliminate some of the basic restrictions imposed to quality evaluation by attributes, a typical situation as regards the occurrence of defects with indefinite borders.

The characteristics of the pixels of greatest interest for this study have to do with their chromatic properties. Therefore, we consider relevant such aspects as factors influencing color perception as well defined by Bonsiepe [3] or, in a classical way, by Swets, Tanner & Birdsall [4]; color classification (achromatic, chromatic and parachromatic, [3]), color description according to Swain & Ballard [5] and color models according to Wilson [6].

The best adapted color models to the scope of this investigation are of two types, according to what is considered by the mono and polychromatic analyses. Monochromatic models are those which allow the representation of an image in one single color.

Generally, a monochromatic image is represented by blacks and whites as maximum values of image coloring. In-between values are defined as gray levels, a fundamental concept for this study. Gray levels appear in the diagonal of the RGB cube (equal parts of red, green and blue), which produces the gray scale. White is the maximum value on the gray scale and black is the minimum.

Gray level C_I relates each pixel to such a color index that $C_I = r = g = b$ (points of the main diagonal of the RGB cube). Each point is identified by a position in the system of coordinates. Therefore, $f(x,y) = C_I$, $0 < C_I < 255$, where $C_I = 0$ (black) e $C_I = 255$ (white). The progression from 0 to 255 implies going from dark into light.

Occasionally we define, for convenience, a function $g(x,y)$ as $g(x,y) = 255 - f(x,y)$. This conversion is used in most of the models developed for defect detection.

The second type of models involves a polychromatic analysis. The polychromatic models of greater interest for the present investigation are the RGB and the HSI. Together with the models HSV, HLS and CMY, no less relevant, they make up the best-known cases. The RGB model is represented by a cube centered on the origin, where the axes represent the basic colors (blue – z; red – x and green – y).

The following notable points characterize the image for the cube of unitary measures: (0,0,0) : Black; (1,1,1) : White; (1,0,1) : Ciano; (1,1,0) : Yellow and (0,1,1) : Magenta.

The complementary colors ciano and magenta stand for, respectively, to bluish green and very deep red, slightly purplish, or carmine. Each pixel is represented by (r,g,b,), which are the projections of the point over the 3 axes of the cube and which produce the intensity of each color.

Models HSV, HLS and HSI represent five characteristics of a color, i.e. chromatic hue (H), saturation (S) luminance (L), value (V) and intensity (I). These are the models that best adapt to color description according to human perception. Chromatic hues are the pure spectral colors; saturation is the quantity of a chromatic component; luminance is the intensity with which a surface reflects waves, which can also be expressed by I and value is a color measuring parameter.

The most widely used model for the situation describe in this study is the HSI. This model consists of a more neutral way of describing colors than the traditional RGB model. The components of model HSI give important information in a straightforward way: chromatic hue is the effective color (blue or yellow, for example); saturation is the depth of the color (pink or dark red, for example) and intensity has to do with brightness.

The HSI system tend to save time insofar as the analysis of one single component has been enough for most of the applications developed, which does not happen in the case of the RGB system, where the three components have to be analyzed. For example, in order to check a car door, observing the chromatic hue value is enough. Saturation has to be examined in order to separate light blue from a darker shade of blue. Since intensity corresponds exactly to the monochromatic version of an image, this value can be used in any algorithm working with monochromatic situation processing.

There are systems which perform the conversion between the systems RGB and HSI. They operate by means of equations of transformation of a system into another (see [6] and [7]).

3 Capturing and Analyzing Images with Indefinite Borders

There are various image capturing methods and they depend on the type of environment one is working, i.e. monochromatic or polychromatic. In the case of monochromatic image capturing methods there are three possibilities: scanning and processing with the use of digitalizing boards.

For polychromatic images there are systems which scan color images, defining values associated with each pixel of the image. Scanning processes, in this case, tend to make use of a specific color scheme, as is the case of the systems RGB or HSI. The use of boards is considered a simpler means of digitalizing polychromatic images.

Image capturing systems involve in general the following elements: (a) A camera, which captures the image; (b) Image processing boards; (c) A computer; (d) Image processing software and (e) A system connecting the board to the PC.

According to the purpose, the system might require some adaptation of the image capturing procedures to the production procedures. In this case, there are specific devices thereto which must be used.

Image processing is a general term used to define a set of operations altering the basic data of a structure in order to obtain information from it adequate to a given application.

Such processing techniques make possible to improve an image in many ways, by highlighting its characteristics, reducing noises recorded during the capturing process, and eventually making it compatible with the analytical model selected. Image improvement takes place in many ways: it is possible to enhance contrasts, combine two images, highlight or minimize details, enhance edges, rotate, superpose or blend images, etc.

For the specific case herein studied, in view of the lack of definition, of the borders of the defect, image segmentation plays a fundamental role in the analysis of the area captured. In fact, image treatment aims essentially at enhancing specific situations found on it, providing more effective conditions for decision-making through the system of capture and analysis, taking into consideration particularities of the piece being studied. In the case of detecting defects with indefinite borders, what is aimed at in a preliminary analysis, in fact, is a segmentation process of the image 'read', where a partition of the structure (grid) of the points in the sample image is created.

This segmentation should highlight specific situations of the image, disregarding limits (which are fuzzy in defects with indefinite borders).

The following segmentation techniques are the most appropriate for this case:

a. Thresholding: If (x,y) stands for the coordinates x and y of an element of the image (pixel) and $S(x,y)$ and $f(x,y)$ stand for the segmentation and the basic aspect related to the characteristic under study at point (x,y) of the image ($f(x,y)$ could be, for example, the gray level – value related to the 'hue' characteristic), this thresholding could be defined as: $S(x,y) = k$ if $T(k-1)<f(x,y)<T(k)$ for

k=0, 1, 2, ..., m. T(0), ..., T(m) are ‘threshold’ values with T(0) = min and T(m) = max and m is the number of distinct labels associated to the segmented image. Notice: The model can disregard extreme values (borders) and concentrate on intermediate values.

b. Clustering: The grouping of the aspects connected with the characteristic being studied for a given piece (e.g.: gray level of a certain area if the characteristic under investigation is the hue of the piece) applied to a segmented image is the multidimensional extension of the concept of ‘thresholding’. The idea here is to bring together the points having a particular similarity, such as gray level lying within a given interval. These groupings would be mapped now back to the original space where the image was being studied in order to produce a segmentation of it. Notice: in the new mapping, borders are no longer relevant, with grouping density and intensity being given priority.

c. Edges: Edge detection aims at determining image discontinuity. It can be assumed that on the edges there are sudden alterations on the image gray level values, for example. Extraction of the edge elements can be carried out with the use of both parallel techniques and sequential techniques. When using the former, one decides whether a given point of the image belongs to the edge or not by studying the gray level of a given group and some surrounding areas. When using the latter, one studies the points in a given sequence and decides whether it still belongs to the edge or not any longer based on the previous results. Notice: at a certain point the system stops by itself, without requiring the determination of the borders of the area being analyzed.

The elementary techniques of captured image analysis refer, fundamentally, to the evaluation of specific characteristics or of the image as a whole.

In the first case, what is being sought is elements or details of the image which make possible to determine, firstly, the presence or absence of a given characteristic and, secondly, the depth (intensity) of its occurrence.

For example: consider a color image where we one is trying to determine whether there are green elements and, if so, what is the depth (intensity) of occurrence of the pixels for this color (value of the chromatic hue of all pixels lying around 120 degrees in the chromatic circle). The use of filters in this situation is highly adequate.

The evaluation of the image as a whole can be carried out based on such schemes as histograms, arrays of numbers and also continuous functions. Each representation has its own characteristics and can be useful, depending on the application.

There is a variety of software packages on the market which can be used for processing purposes and mostly image analysis. Such packages are compatible with image capturing procedures by means of digitalizing boards or scanners. They are more effectively useful in the case of boards, where it is even possible to have synchrony processes between production system and image capture and analysis procedures.

This aspect tends to be essential for areas such as Quality Control, where a prompt identification of defects and the quick and immediate correction and prevention of their causes are fundamental factors in evaluating the effectiveness of the whole system.

The analysis of the various software packages showed that, despite the fact that many of them are compatible with the general goals of image evaluation and analysis, not all of them do not meet the general objectives of the quality control system, especially in the case of a system such as the one used in this study.

4 Piece Analysis Scheme

The defect detection process begins with a piece being removed from a productive process. The analysis refers to the piece in a sample (‘static’ position) or being processed (dynamic situation – such is the case of pieces going through a belt, for example). Next, a specific procedure captures the image of the piece.

This procedure consists of an illumination system to throw light on the piece, cameras to photograph it and a device to store the image captured. In the following phase, a processor creates a structure associated to the image, such as a matrix or a histogram.

A second processor develops a given treatment for the image (this processor can be software or even the same device which created the structure of the image). The objective here is to enhance properties useful in detecting the defect on the piece. Having the image associated to a structure, in the form of a matrix, the structure can be submitted to an analytical procedure aimed specifically at detecting the defect.

This scheme – which can, for example, be software – will determine two aspects fundamentally: the presence or absence of defects and their possible classification. If a defect is identified, the system should propose a decision about the piece (accept/reject), a basic identification of the defect and relevant additional information about it. Corrective and preventive measures should be suggested for each defect found as well.

This whole system was set up experimentally. For the purpose of the application herein considered, an illumination system with optical fibers proved more adequate. In addition to their modular aspects, other aspects were considered to be essential for their adequacy to the system, such as their structure and the possibility of using specific lenses interacting with the boards.

We have selected a specific system that operates by means of boards. It has proved adequate for image processing in monochromatic environments. Even when operating in a monochromatic environment, this system supplies data enough for detecting basic defects, whether by immediate detection or by matching with a previously stored pattern. Additional software has been used for image treatment, depending on the application required.

The outputs of the processing are displayed on the screen, with the possibility of printing both the images recorded and the gray level values associated with a given situation. The outputs of the monochromatic processing are:

(1) Gray levels, row by row;
(2) Gray level histograms, row by row;
(3) Occurrence of edges on the rows studied;
(4) List of defects detected and (5) defects classified.

In the polychromatic environment some alterations are required. Hue control is carried out, essentially, in a supervised procedure, where a given piece is selected to set the standard so that the pieces under study can be compared with it. Thus, the image matching procedure is fundamental in the chromatic analysis of images. Individual analysis of pieces is no considered.

The system of capturing and processing of images must have some characteristics which are not required in other situations previously considered in the specific literature. The first is the necessity to store in a vast and easily accessible memory the images of the patterns with which the pieces studied are to be compared.

Next, in order to have a sound and objective comparison, a basic model of colors must be defined which will be used as a reference in the analysis of the image. Finally, arithmetical and logical operations which effectively carry out the comparison must be used. These aspects show characteristics that will be required from the system, which, as it can be seen, must have a better support in terms of software resources than in the monochromatic case.

Since there are several color models available, it is important to select that which best suits the objectives of this study in view of the specificity of the present investigation.

The HSI system was chosen both because of the independence that the analysis of each component makes possible to develop – which makes it more efficient in computation terms – and because of the greater proximity with form effectively used by humans to visualize color scenes.

Both aspects are relevant. In fact, the need of creating a system which can be adapted to the productive process in the simplest and most practical way and which facilitates a quick and objective evaluation of a piece, requires a computationally efficient system.

Additionally, it is desirable that the system act as a conventional inspector, i.e., that it imitate his procedures. This causes the system to consider the same values considered by the inspector in order to evaluate a piece. Hence we van observe the adequacy of the HSI system to the present project.

Lastly, the possibility of converting the HSI system to RGB shows that it is possible to use other types of analysis starting from the same representation of the image of a piece, since it is carried out according to the HSI model.

It is worth mentioning that the processing logic for polychromatic image matching is the same used for monochromatic environments.

This is only made possible because of the adoption of a color model – HSI – in which the basic elements identifying the colors are independent from one another.

The RGB system would have some difficulties to adopt the same processing model precisely because of the interdependence of the basic model coordinates.

We have selected the board to be used by the polychromatic analysis system. It has given the process of image capture and analysis considerable speed and making possible to reduce the time spent with capturing the image and carrying out the operations relevant for this study.

Additional software has been used for image treatment according to the application required.

The outputs of the polychromatic system can be displayed on the screen or printed. Both the images saved and the values of the levels of the various properties analyzed (with chromatic hue or saturation) related to a given situation, as well as functions, graphs, histograms and the results of the different operations carried out, are available for the two types of output (screen and printer).

The basic result of color image processing is a set of values representing the color of each pixel composing the image of the piece.

Fundamentally, such values are chromatic hue, saturation and intensity (in the case of the HSI model) and the values of the basic primary components – red, blue and green (in the case of the RGB model).

When working with the system we have selected, it is possible to convert from one system into another without difficulty. The values of each individual property are, in general, expressed in the form of matrixes, where each input of a matrix is the value of the property in the pixel with an equivalent position in the image representation structure.

From these basic values, it is possible to obtain other data of interest. Thus, for example, whenever the values of the components R, G and B of the pixel are equal ($r = g = b$), there is a point of the main diagonal of the cube representing the RGB space and, in this case, the value related to this point happens to be the pixel gray level.

Other relevant outputs of the processing are the histograms of the levels of the various properties of the pixels of the image as a whole or of specific areas on the piece, functions of these same levels, by row or by area, and specific results of the different types of software used.

5 Imprecise Limits Analysis Model

The general structure of the operations developed on image representation for the pieces studied can be divided into three well-defined phases, namely, determining the data necessary to carry out the operation, processing proper and producing results. Thus, we have:

(a) Inputs: They are the outputs of the image capture and analysis for the pieces studied;
(b) Processing: Operating the data. There are two types of processing: (1) Individual analysis of the structure and (2) analysis by matching structures;
(c) Outputs: There are two types of output: (1) Basic information: *there are* or *there aren't* defects and (2) general information that might be useful for an occasional classification and identification of defects (for example: borders around those pixel concentrations considered to be 'defective').

The operations are valid for the three modalities in which the systems works, i.e., they can be processed when the individual analysis of a single piece is required, as well as when pieces are analyzed in a continuous flow, or even we are dealing with pieces that are part of the process.

Their effectiveness, however, is higher for the third case, due to the greater feasibility of the image capture and analysis phase in the process of defect detection.

Once the operations to be executed on the image representation structures are defined, it is possible to define what the global processing of the defect detection system will be like.

The system develops along five basic activities:

(a) Capturing and analyzing the image;
(b) Executing operations on a structure which represents the image;
(c) Determining the results of the operation: (1) presence or absence of defects and (2) additional information useful for occasional defect classification and identification;
(d) Actions defined by the results of the operations: (1) classification of defects as crucial; acceptable and minor and (2) determining actions according to defect classification;
(e) Identifying defects and determining the actions to be taken: (1) Identifying the defect as to its nature and area of occurrence and (2) Determining corrective and preventive actions to be taken in the production line.

The model used in this study has well-defined elements. This model both checks whether a piece has basic defects, which here are indefinite, i.e. fuzzy surface defects which determine its immediate rejection, and determines whether the piece has such defects when compared with a given pattern.

Each analysis is carried out in a specific phase of the model: phase 1 gives a preliminary evaluation of the piece; in case the piece has no basic defects, it goes on to step 2, where the presence of defects is checked by means of image deviance shown by the piece when compared with a pre-established pattern.

Notice: in phase 2, the model does not consider spots as defects and tries to associate the piece with a given pattern. The comparison between the piece and various patterns in phase 2 also has characteristics of indefiniteness on the limits of the crucial areas of the images. The model also allows the creation of new patterns.

This model can be used both for monochromatic images, when only gray levels are being evaluated, and for polychromatic images, where matrix analysis are developed which associate parameters related to chromatic motivation to each pixel of the piece.

The model can be used for determining elementary surface defects, as well as to detect deviance of the piece in relation to a given pattern.

In both cases, analyses are carried out of the parameter being investigated by decomposing each matrix considered into singular values (piece or pattern).

This makes possible to proceed with the evaluation of the piece without relating a given image property to the place where it occurs, that is, it has to do with the situation where the occurrence of the property does not depend of the area of the piece, i.e., it is not relevant to take into consideration whether a certain area has always the same chromatic pattern.

Thus, here the piece uniformity is considered as whole regardless of observing the occurrence of certain chromatic motivations or figures or, still, specific parts of the image always in the same place.

The basic utilization of this model is restricted to cases where the image of the piece is subject to variations due to way in which the piece was photographed, the environment where it is or still the possibility of occurrence of frequent noises during the capturing process or even during the analysis of the image. The defect detection process, here, shows low sensitivity to such problems.

It is worth mentioning that, in general, these situations are typical of cases where defect borders are not clearly defined.

The model makes use of piece representation matrixes. In the monochromatic case, we have a matrix that relates gray levels to each pixel; in the polychromatic case we have matrixes which relate specific parameters to each pixel.

Generally, the most relevant parameters are chromatic hue, intensity, saturation and value in the case of the HSI and HSV systems; in the case of the RGB system, the parameters are the amount primary colors contained in each pixel (the primary colors here are green, blue and red). If necessary, the system can operate with complementary colors, such as ciano or magenta, for example. All one has to do is to alter the environment where the analysis is carried out.

The model works in a totally different way from the similar defect and identification models. The first aspect to point out is that visual characteristics of the piece are not observed, nor are parameter specific values of image representation transformed.

Another fundamental aspect that differentiates this model from the others is the fact that there is no statistical evaluation of individual image pixels.

What happens, in fact, is an algebraic evaluation of the characteristics of the image, where the piece is considered as a whole with no attention paid to specific areas to the particularization of properties or, still, to the borders of certain areas of the image.

Thus, this evaluation represents intrinsic attributes of the image, evaluated within a model which considers that, if an image can be represented by a matrix, then various algebraic transformations or decompositions of this matrix can be used to make possible the extraction of specific aspects of the image in question.

Particularly, the decomposition of the matrix into singular values can be used both because of adequacy of the technique to the usual space of matrixes and because of aspects that make it suitable for use in extremely common situations in the process of capturing and analyzing images. In fact, the technical support for decomposing the matrix into singular values has properties extremely desirable for the development of image recognition methods.

Such properties refer, fundamentally to the extreme stability of singular values, i.e., when small disturbances occur in the original matrix as a reflex of minor alterations on the image or noises during the process of retrieving its characteristics, there are no significant alterations on the singular values.

Furthermore, singular values are related to intrinsic attributes of the image, which are not deviated on account of visual problems. With a specific type of image characterization, singular values possess properties of geometrical and algebraic invariance, which are extremely useful. Such is the case, for instance, of invariance in relation to movements of rotation and translation of the piece [8]. In order for such methods to be used, it is enough to obtain the matrix of the parameters related to the piece.

In phase 1, the model dispenses with patterns and operates directly on a matrix representing the piece. All one has to do is provide the reference values for the singular values.

In phase 2, the matching procedure uses Frobenius's norm, of easy calculation, applied to the same representation matrixes of the pieces and of the patterns considered.

This way, an overall evaluation of the piece is also being carried out. Only this evaluation is more intimate to the piece and tends to have very little variation when there are noises of any nature associated with the procedure of capturing and analyzing the images or with border indefiniteness of certain areas of the pieces.

6 Conceptual Background of the Model

Matrix decomposition into singular values is a relatively well-known technique in classic algebra. In broad terms, the conceptual background applicable to this case can be summarized as follows:

Any symmetric real matrix can be converted into a diagonal matrix by means of orthogonal transformations and so can any general rectangular matrix A(m x n), through the decomposition of this matrix into its singular values, according to the following theorem:

Given a real rectangular matrix A(m x n), with rank k, then there are two orthogonal matrixes U(m x m) and V(n x n) and one diagonal S(m x n), so that $A = U.S.V^t$ (1), where S = diag(L_1,L_2,...., L_K, 0, 0, ..., 0) e L_1>L_2>...>L_K.

Hong [8] describes the basic elements U, S and V in detail and shows that L_i, i ranging from 1 to k represents the positive square root of the Eigen values of the product of matrix A multiplied by its transposed; Lawson & Hanson [9] give a detailed demonstration of this theorem.

Within the approach of this work, which considers a matrix to be a representation of an image, the formula (1) means that the original image A was decomposed into the three matrixes in an unequivocally defined operation. In particular, matrix S, i.e., the singular values L_1, L_2, ..., L_K plus the null values, can be represented on a single vector, $x(n \times 1)^t = S_e$=(L_1, L_2,.., L_K, 0, ..,0), where the column vector 'e' is formed by n x 1 components of equal value and all equal to a 1. x(n x 1) is called vector characteristic of singular values of image A.

Within the approach of this work, which considers a matrix to be a representation of an image, the formula (1) means that the original image A was decomposed into the three matrixes in an unequivocally defined operation. In particular, matrix S, i.e., the singular values

The following properties are relevant here:

(1) For any rectangular matrix A, under the restrictive condition that $L_1 > L_2 > L_3$ >...>L_K, the diagonal matrix S in formula (1) unique. Therefore, the original image A corresponds to a single vector characteristic of singular values x(n x 1) [see 9];

(2) The characteristic vector x(n + 1) is stable. This is one of the properties of greater interest. Thereby, it is assured that, since the original image and its characteristic vector x(n x 1) have a relation of single correspondence, this vector can be used to represent the image. Moreover, it is possible to prove that when the original image undergoes small variations, the characteristic vector does not get substantially altered, i.e., it remains stable as proved by Guang [10]. This property is supported by the following theorem: If R(m x n) represents the set of all the real matrixes m x n, and A(m x n) and B(m x n) belong to R(m x n), with $L_1 > L_2 > L_3$ >...>L_n e $G_1 > G_2 > G_3$ >...>G_n their respective singular values, then, for any norm $\|\cdot\|$ of unitary invariance over R(m x n), $\|\mathrm{diag}(L_1 - G_1, L_2 - G_2, ..., L_n - G_n)\| < \| B - A \|$

Particularly, if Frobenius's norm is employed, it is possible to ensure that the square root of the summation of the differences (L_i - G_i), for i ranging from 1 to n, will always be equal to or less than Frobenius's norm applied to the difference of the matrixes (A - B). As it is known, Frobenius's norm is given by the summation of the square root of the square of all the elements of the matrix [9].

Due to its high stability, the characteristic vector is little sensitive to noises from the image or minor alterations on gray level values caused, for example, by changes on the illumination system. This even makes possible that the image pre-processing phase, in this case, be disregarded. Experimental results are already available to show the validity of this property (see, for example, Tian [11]).

Other properties that might be of interest are those referring to spatial transformations of the image. It is possible to prove that the characteristic vector is invariant in face of the transformations of transposition, rotation, translation and reflex in mirrors [8].

The treatment of image used in this paper has been used, in a similar way, by Rashwan [12]; Neves at al. [13] and Dahabiah, Puentes and Solaiman [14].

7 Structure of the Model

In view of the decomposition properties of the matrix representing the image in its singular values, a model was structured which takes into consideration the matrix in question and, subsequently, decomposes it into its singular values.

Firstly, the model seeks to determine whether the matrix has basic defects. This is done by considering a relation proposed between the arithmetic average of the values of the property being studied (gray levels of the piece, for example) and the highest singular value of the characteristic vector.

Whenever this relation exceeds a certain limit, the piece has basic defects and is immediately discarded. The relation proposed is the following:

For a piece k, we determine W(k) as $W(k) = ABS [XM(k)* n - L_1]$, where XM is the average of the values of the properties studied, n the number of columns and L_1 the highest singular value of the matrix. The piece will present basic defects whenever $W(k)>(0.4)*L_1$.

If the piece does not have any basic defects, it is compared with a set of patterns. In this case, the procedure is the following:

(1) The decomposition into singular values is applied to each of the matrixes representing the patters;
(2) The decomposition into singular values is applied to each of the matrix representing the pieces;
(3) By using Frobenius's norm, the distance between a given piece and each pattern is determined;
(4) According to the distance values, it is determined whether the piece has, in relation to each pattern, total, great, reasonable or little adequacy or whether it is not adequate to any of the patterns available;
(5) in this last case, since the piece does not have any basic defect as shown by the test, the user shall decide if the piece will be regarded as a new pattern.

8 Structure of the Program

The computer program related to the model involves the following elements:

<u>Inputs</u>:

Phase 1 – Basic Indefinite Defects

(1) A matrix whose inputs are round numbers which lie between two specific values (for example, between 0 and 255). A matrix has a variable size.
(2) Reference values for decomposing the matrix which represents the image of the piece.

Phase 2 – Matching with standards

(1) A set of matrixes – called standard-matrixes – each perfectly identified by a code and a second set of matrixes – called piece-matrixes – also identified by a code. Both sets of matrixes have the same characteristics of the matrix in phase 1;
(2) A set of parameters consisting of round numbers which will be identified as the basic parameters for comparison between the pieces and the patterns. These parameters can be considered to be reference values.

<u>Processing</u>:

Phase 1 – Basic Indefinite Defects

(1) Each matrix represents a piece which will be decomposed into three other matrixes in such a way that the product of these three can reproduce the original matrix. The central matrix of the product will be that whose main diagonal lists in a decreasing order the singular values related to the original matrix;
(2) The evaluation of the image will be carried out by contrasting the singular values related to the piece representation matrix with the reference

values. Such values fix intervals within which the singular values must lie; thus, if this is not the case, a situation of presence of defects on the original image will have been characterized.

Phase 2 – Pattern Matching

(1) Processing Logic: The processing refers to matching the matrixes which represent the pieces with each pattern stored. The procedure is as follows: a given piece-matrix is considered and contrasted with the standard-matrix available from the system memory. A test determines the need (or not) of comparing the same piece-matrix with the next standard-matrix. The procedure is repeated until the last standard-matrix is analyzed, if necessary.

(2) Operations: (a) The singular values of the matrix representing the first piece are determined: (b) the singular values of the matrix representing the first pattern are determined; (c) by using Frobenius's norm, the distance between the singular values of both matrixes is calculated; (d) if this distance is less than the reference values specified for the norm in question, the piece is considered to be adequate for the standard and a specific message is issued (*'Piece XX fits standard YY'*). In this case, no basic indefinite defect was detected; (e) otherwise, the operation is repeated for the same piece and the next pattern; (f) if no piece fits any of the standards listed, it is necessary decide whether this piece will from then on be accepted as a new pattern. If not, the process restarts with the next piece. If so, a code is given to the piece which from then on will be regarded as a pattern and the process begins again with the next piece. In case there is no new piece to examine, the process stops at this point.

Outputs:

Phase 1 – Basic Indefinite Defects

(1) Singular values related to the image representation matrix;

(2) Diagnosis of the image as a whole.

Phase 2 – Pattern Matching

(1) Singular values related to each matrix representing the pieces under inspection and the patterns considered:

(2) Most adequate piece and pattern (or no adequacy in relation to all of the patterns stored and, if applicable, the new pattern created). In this case, there is no basic indefinite defect.

9 Application Examples

In order to test the program, 10,000 pieces were necessary, with 777 to make up a representative sample of the universe studied. The pieces were generated by a process of random simulation, according to experimental data obtained from the factory. The random generator which simulates the productive process underwent tests such as frequency, product-interval and sequencing [15], with good results.

These 777 pieces were divided into 5 groups and we tried to establish specific practical situations in each of them, such as when there is a high defective fraction or when the average quality of the process if low, cases in which pieces appear randomly distributed in the lot or after or after each perfect piece comes a defective one, and so on.

The program classified the 777 pieces into 640 as "perfect" (82.4%) and 137 into defective (17.6 %). As a matter of fact, there were 649 perfect pieces (83,5%) and 128 (16.5%) of defective ones. The error was of 9 pieces or 1.16%. This was the tendency for the 10,000 pieces observed: an error of 1 %, lower in the cases where the defective fraction was below 2.5% (the usual situation in practice).

As for the pieces regarded as inadequate in relation to all of the patterns, less than 0.77% in the real data (6 out 777), the program considered that 8 pieces, or 1%, were in this situation, i.e., a deviation of less than 0.3%. This error does not remain the same when the defective fraction is low. In the universe studied, for defective fractions below 3%, the percentage of error gets to values inferior to 0.1%.

Let us consider a small example. The first piece in group 5 has the following gray levels: 73 67 72 75 65 62 70 72 71. The average for these values is 69.667 and the singular values are: 209.1513; 7.9096 e 3.7647. Therefore, W(1) = 0.1503. Since this value is lower than 83.66, the piece does not have basic defects.

The program considered that the piece had no basic defects and more adequate to pattern 4, highlighting the fact that there was a great conformity between the piece and the pattern. It is important to point out that pattern 4 would be chosen (a difference of only 0.333).

10 Some Results

The results were satisfactory. Some analyses demonstrating this conclusion can be done in relation to each of the 5 groups considered, as follows:

- *Group 1*: 156 pieces. There are 3 classifications which can be discussed: piece 44, with an average of 77.8 was deemed adequate to pattern 2 (average 77.0); it could have been classified after pattern 3 (80.0). For pattern 1, with an average of 74.0, the norm would be 17.10. Piece 100 had an average of 71.3 and was deemed adequate to pattern 6, with an average of 65.0. It could have been allocated to pattern 4, with an average of 70.0. Here norm values are closer: 169.3 for pattern 9 and 215.6 for pattern 4. Piece 103, with an average of 72.6, was allocated to pattern 1 (its average is 74.0). It could have been allocated to pattern 4 as well. The norms were 212.6 for pattern 4 and 166.6 for pattern 1. Piece 106, with an average of 72.3, was allocated to pattern 1, with a norm of 170.9. It could have been allocated to pattern 4, which had a norm of 217.0.

- *Group 2*: 161 pieces. All classifications coincide with the average proximity principle, i.e., the pieces and patterns selected have considerably close averages. In this group there are 2 light pieces and 2 dark – spotless. The program considered – correctly – that they had no basic indefinite defect and rejected the adequacy of the pieces to any patters. Nevertheless, the program classified them correctly: it did not eliminate them – and, in fact, they had no basic indefinite defects – but it did not consider them adequate to any of the patterns listed. All pieces with a very low gray level, i.e. light, were considered to be free of basic indefinite defects and classified according to the value closest to the lowest reference value of the patterns (pieces 19, 29 and 71). Likewise, other pieces with high gray levels, i.e. dark, were deemed free of basic indefinite defects and classified according the value closest to the highest reference value of the patterns (pieces 39, 44 and 90). Notice that $g(x,y) = 255 - f(x,y)$ was the function used.

- *Group 3*: 159 pieces. Pieces 17, 29 and 104 were deemed non-compliant with the patterns of this group. The classification might have been rather strict. In fact, even when classified after pattern 1, according to the norm, piece 17 seems to be closer to pattern 3. The same is true for piece 29. Notwithstanding, the classification of piece 104 is adequate. It is worth pointing out, for example, that the average of the gray levels of piece 17 is 78.9, close to pattern 3 (average 80.0), whereas the average of piece 29 is 69.0, likewise closer to pattern 4 than to pattern 3 (average 80.0). The other classifications are adequate. High amplitudes were observed for the pieces of this group.

- *Group 4*: 150 pieces. Piece 34, with an average of 68.9, was allocated to pattern 6, with an average of 65.0. It could have been allocated to pattern 4, with an average of 70.0. However, it is worth pointing out the extreme proximity between the norms: 15.1 for pattern 4 and 14.8 for pattern 6.

- *Group 5*: 151 pieces. Piece 97 had an average of 61.4 and was deemed adequate to pattern 7, with an average of 57.0 and norm of 12.47. It could have been allocated to pattern 8, which had an average of 60.0. The difference between norms, however, was small: the norm for pattern 8 was 14.13. An identical situation occurred with pieces 55 (average 72.90 – allocated to pattern 4, with an average of 70 and norm of 12.27 – it could have been allocated to pattern 1, with an average of 74.0 and norm of 13.04) and piece 64 (average 63.44 – allocated to pattern 8, with an average of 60.0 and norm of 12.47 – it could have been allocated to pattern 6, with an average of 65.0 and norm of 14.13). Notice, for this two cases too, the small difference between norms. Piece 99 was deemed perfect, but id does have spots. Anyway, it was considered inadequate in relation to all patterns. Pieces with an average below 60 were all allocated to the pattern having the lowest value (pattern 8 – average 60.0). Likewise, pieces with an average above 95 were allocated to pattern 9, which has an average of 90.0.

The examples show that the model has obtained very good results. Also it is possible to observe how the media and the norm interact in each case. In fact, they compound two different measures that complement each other.

11 Conclusions

We have compared the different phases of the model with similar models in literature. We list some examples of these different techniques.

- Bereciartua et al have used Artificial Neural Networks Techniques to create an evaluation process of surface of polyurethane foam by image processing [16].
- Zanella and Vargas proposed some models to analyze face images in terms of active shapes and automatic morphing [17].
- Maher et al [18] have observed that early detection and measurement of the extent of road distresses coupled with prompt reactive measures are necessary to keep the pavement function at an acceptable level. For the objective, they have developed a method that uses a**pplication of image processing to measure road distresses.** This research paper performs image processing measurements to estimate areas of a pothole and alligator cracking, and sets a program for plane measurements of an area that experience rutting. The benefits of this method are well defined.
- In 2008, Rajab and Al-Hindi [19] investigated the analysis of feed-forward BP neural network that has been trained to detect noisy edge patterns, so as to achieve close insight into their internal functionality. The search for edges is a very critical pattern recognition method.
- Considered as showing great interest for us, Jurian et al [20] have developed a comparative study regarding certain methods of image processing by the texture characteristic, to find the optimum method for detecting color texture. It is important to point out that the study was based on the experiments. There are two main points in this paper: the quality of the detection and the response time. According to the authors, for the experiments have been used the co-occurrence matrix and the iso-segments matrix of the gray or color levels. These methods are based on processing the image at a pixel level and the making of matrix that contain certain spatial positions of pixels. This paper shows the resulting matrix analyzed and, based on the existing information, the characteristics vectors associated to the matrix was determined. WE have observed that each method was studied by analyzing the pixels of the image files in certain situations and directions and at certain distances. The authors have concluded that the co-occurrence methods had better results for the queries based on water, wood and grass textures and on the ones based on sand, ruble and clouds, better results were obtained using the iso-segment matrix. It is important to observe the analogous objectives of this paper when comparing with ours. And also the differences in the evaluation approach.
- Dynamic Background Subtraction is another method used in detection processes. Sundaraj [21] has used it to develop an automated method of recognizing a person’s face based on a physiological or behavioural characteristic, it means, face biometrics. According to the author, segmentation of novel or dynamic objects in a scene, often referred to as background subtraction or foreground segmentation, is a critical early step in most computer vision applications in domains such as surveillance and human-computer interaction.

We can observe that the image processing we have used here has similarity with the papers we have described above.

What becomes different is the software support, the general pattern recognition approach, the specific characteristics of the images and (mainly) the nature of the evaluation process. In fact: the model above is used whenever there are no guarantees that the resolution of the image captured is of good quality and there is interference on the image representation structure.

This is caused by the lack of clear-cut borders delimiting the defect. Also, the two-phase evaluation process (the search for basic defects and the comparison with some specific patterns) is an explicit attribute of the model we have developed.

Although it can be activated after there are reference values already defined and basic defects have not been detected, the model is self-sufficient in relation to these questions.

In fact, it both generates its own limits and determines, before comparing pieces with patterns, whether there are basic defects on the piece. Thus, the system starts to operate from the model, even though it is only activated if basic defects have not been detected and the reference limits have already been defined.

Thus, on grounds of the cases observed, we considered that the program yielded quite satisfactory results. According to the classifications performed, it seems important to remark that only three pieces, out of almost 600 making up this sample, got an effectively wrong classification but, as a mitigating aspect, were considered inadequate in relation to all patterns, having, thus, been rejected anyway. Before they are turned into new patterns, they will be removed from the production line

Thus, what could be noticed was a perfect adequacy of the model to the specific situation it was designed for.

It is important to mention also that the program is been used by the industrial organization where it has been tested since January, 2009.

Up to now, we have had around 1% of deviation in confronting the selection made by the model with the human evaluation.

The next step it to try to establish some synchrony between the model operation and the production line, in order to get, in the near future, a completely automated quality evaluation system.

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