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Localization and Fuzzy Classification of Manufacturing Defects in Sheets of Glass

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Abstract

Artificial Vision Systems are commonly used in industrial applications. The low cost of the equipment facilitates the development of new products. In this paper we describe the use of an artificial vision system in one of the phases of a quality control process related to automotive industries: the windshield manufacturing. We intend to localize and classify the defects that were originated while manufacturing the glass that forms the windshield. We will show that a fuzzy classifier, after being tuned with a genetic parameter adjustement procedure, outperforms a neural networks based classfier.

1 Introduction

Windshields are built by moulding with heat a plane sheet of glass. The quality of this glass is periodically checked, so we can detect defects that may affect the transparency of the glass or reduce its strength. The analysis of the sheets of glass is being carried out by specialized personnel, who visually examine every material sample. This is a hard and expensive process that is being automated. The CVSIM system, developed at Oviedo University, automates the whole process of search and classification, so the intervention of human operators is not necessary.

The quality control first detects the defects, and it classifies them later. The localization of the defects is solved by classical artificial vision techniques. And their classification uses an imprecise description of the characteristics of the defects, being based on fuzzy rules. In these rules, the parameters that define linguistic variables were automatically obtained by means of genetic procedures. These methods tune the fuzzy rule knowledge base so the classifier behaviour is optimal over a set of examples that were classified by hand. The structure of the rule bank was also designed by hand, using the aforementioned imprecise description.

The reasons that made us to choose a fuzzy rule based classifier instead of any other classical statistical method were two:

1. We were not provided with a number of examples high enough to design a statistical classifier system. The information conveyed about some of the classes by the set of examples was incomplete.

2. The expert knowledge of the operators about the characteristics of the defects cannot be easily incorporated to the design of a statistical classifier. This knowledge is necessary, since it allows us to decide on cases that cannot be related to one of examples in the initial set.

These circumstances are justified if we realise that the acquisition of representative examples of some of the least frequent kinds of defects is difficult and expensive, so the number of samples can be too low to characterise the properties of the defect. A fuzzy classifier can include additional linguistic information as well; this information will reduce the chance of a misclassification to happen when the system is confronted with one of these rare defects. In the last section we will present numerical results that empirically validate this asseveration.

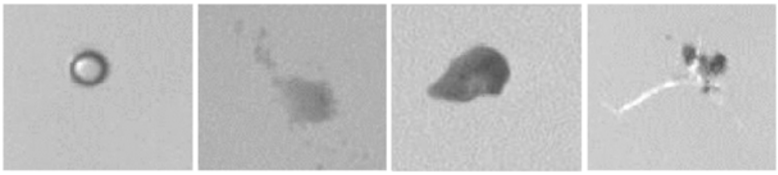

Figure 1: Categories of defects

2 The system

The quality control laboratory of the factory proposed the following system objectives:

1. The localization and classification of all defects with sizes greater than 50 microns.

2. The measurement of the depth of the defect, when it is embedded in the sheet.

3. The discrimination between four categories of defects: bubbles, stains of tin, stones and dust (see Figure 1).

3 Kinds of defects in glass manufacturing

We have just mentioned that four different defects will be separated: bubbles, tin, stones and dust. In this section, we will describe briefly their characteristics.

Bubbles are the most common defects. They are formed by gas that could not reach the surface of the glass while it was hardening. When light passes through

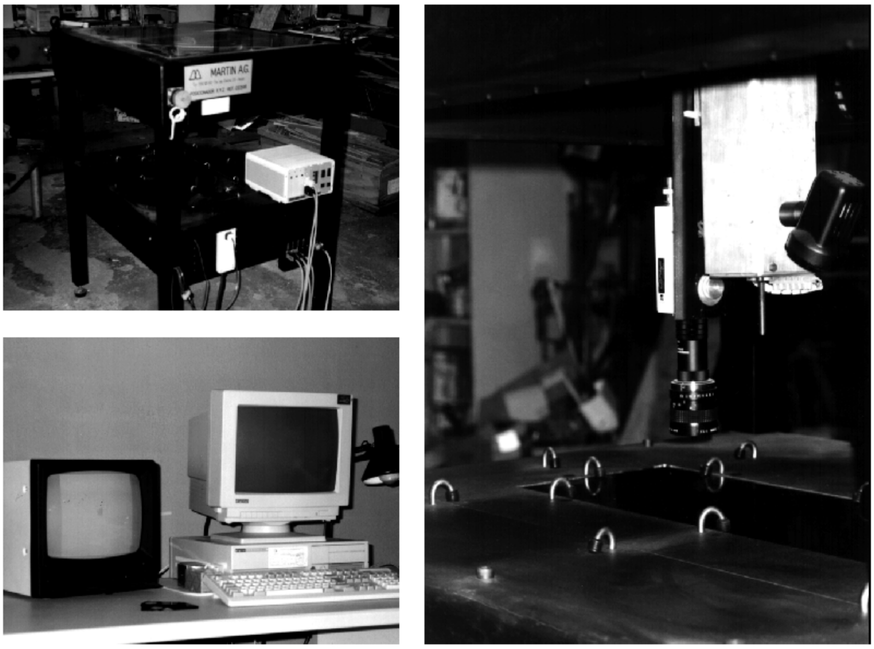

Figure 2: CVSIM system

them, multiple reflections occur and they can be seen as dark rings with some bright zones inside.

Stones are formed by strange materials that were not separated from the glass. They can originate in shortcomings during the melting process. They appear as dark zones with crisp edges.

Tin stains are due to small drops of metal that condense and fall on the surface of the glass, leaving a small mark.

Dust is not, strictly speaking, a defect. But the surface of the glass is seldom completely clean. Even it is possible that the glass gets dirty while it is being inspected. These particles frequently produce a wrong classification, because its shape can be very irregular and resemble a true defect.

4 The hardware framework

The hardware architecture in which the system has been implemented is shown in figure 1. It comprises a host computer (an old PC 486DX2), a commercial monochrome CCD camera (Cemtys CV-252C), an image acquisition card (DT2853-SQ) and a board, where the glass sample is anchored and the camera is settled so as to permit its movement. The xyz-axes of the camera stage are driven by three stepper motors and its position can be computer controlled with a resolution accuracy of $25 \mu m$.

The depth measuring requires a special treatment. In next sections we will discuss the depth estimation problem. The CVSIM system uses a depth from focus technique with a set of three images yielded at different distances of sample surface. In order to achieve that, a z-axis movement is incorporated to the system.

The spatial resolution of a 512x512 pixel image was 5.85 μm in horizontal and vertical directions. Therefore, an image covers a 3x3 mm^2 area, and defects with diameters greater than 50 μm (9 pixels) can be measured. This is the minimum size established for a correct recognition. About 13,000 images are processed to complete the initial analysis of the whole standard 600x200 mm^2 glass sample. When a defect is found two new images are necessary to carry out the depth measuring.

The optical illumination device can be adapted to the characteristics of the analysed glass. Light intensity is regulated to illuminate the whole shape of the defects with contrast enough with regard to the background. Glasses with different transmission degrees can be studied. Threshold has been used to decide whether an image is well illuminated and has brightness enough.

5 Functioning

In general, the procedure followed can be divided into six steps:

1. Glass sample placement and control illumination
2. Camera positioning
3. Image acquisition
4. Localization (xy) of posible defects
5. Depth (z) estimation for each defect
6. Classification

Steps II to VI are sequentially repeated until the whole sample analysis is completed.

6 Extraction of defect characteristics from one image

We will summarize the artificial vision techniques used to extract information from a digital image in order to locate and classify the described defects.

7 Localization of the defect

The horizontal positioning of the captured image is immediately calculated since the coordinates (xy) of the camera position are well known by the system. The detection of each defect is carried out in a simple way. The image is binarized using a threshold criterion, based on the mean brightness of the scene. The next step is the clustering and labelling of dark pixels. Various algorithms have been designed to accomplish a new group assembling because certain defects are composed by several items and a defect can be left divided in some images.

However, the problem is not so simple when we try to determine the situation of the defect inside the sheet of glass. We can apply several procedures to measure the distance from one object to the camera. The most common are the stereoscopy and the use of active sensors.

Since Pentland [1] exposed their new concept of depth of field, an alternative for the calculus of distances inferred from the computed blurring in an image, numerous works have been developed using this advanced technique. Blurring increases with the distance of the object from the plane of focus, and also depends of other factors like the camera parameters and lens [2]. Many authors [3] use motorized lens in order to determine precise scene depth maps with a wide range of distances. In those applications where the range of depths is narrow enough, it is possible (and it presents certain advantages [4]) to automate the movement of the camera leaving unchanged the rest of parameters. This model accommodates perfectly the profile of our system. The defect distance is computed from the defocus degree (measured using Tennengrad function [6]) of a set of three images focused on different planes.

8 Characteristics extraction

Determination of defect characteristics is basically a region analysis problem. Normally, the basic feature of a region is their form. However, in this case, all kinds of defects, excepting the bubbles, present very irregular forms. We will base our recognition procedure in other type of regions descriptors. We have selected a set of four basic functions: Contrast, a second moment that computes the similarity with a donut figure, grouping degree and shines areas. The depth is the fifth parameter that will determinate the class to which the defect belongs (see Table 1.)

9 Design of the classifier

Two facts conditioned the design of this classifier system:

- We could access a complete linguistic description of the defects (see Table 2).
- We were provided with only a few samples of defects, and some of the categories were very poorly represented.

It is clear that we need a classifier able to use the whole available linguistic information; we will show that a fuzzy rule based classifier is more suitable than a classical statistical method or a neural network based one. To improve the design, we tuned the parameters that define every rule by means of a genetic optimization procedure.

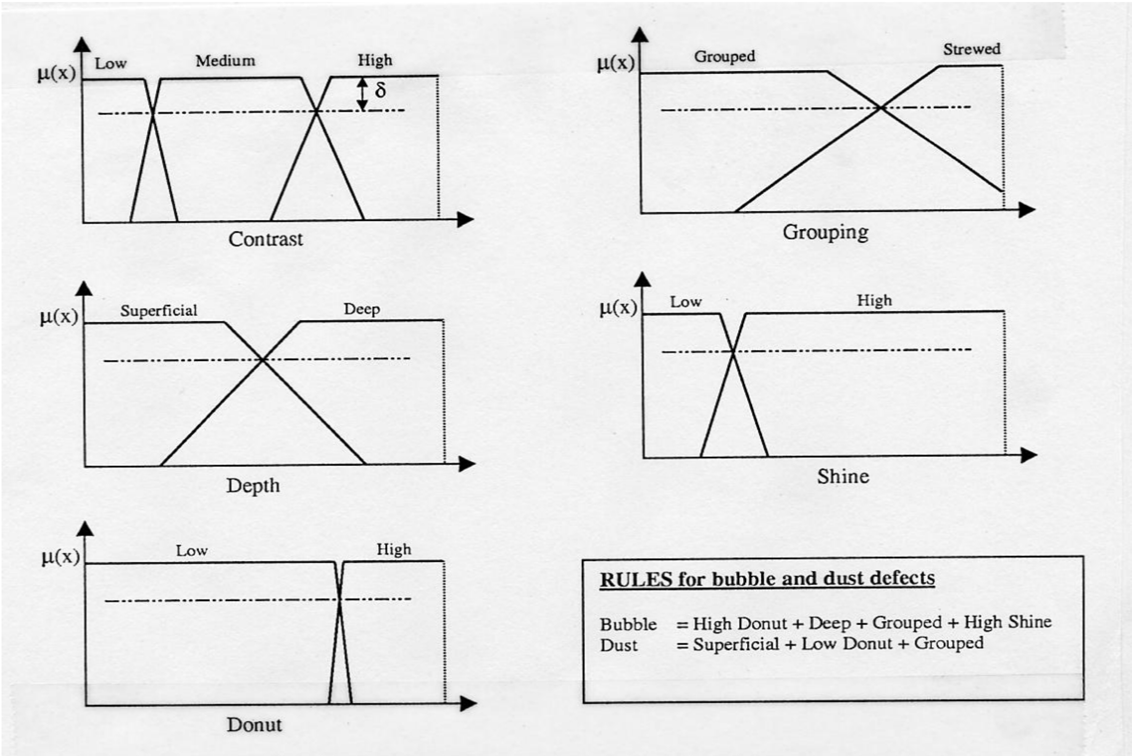

Figure 3: Memberships of linguistic labels

Table 1: Characteristics of the defects

Defect	Position	Form	Characteristics
Bubble	Inside	Ring	Shine Grouped
Stones	Inside	Low Irregular	High contrast inside Without bright Grouped
Stones in surface	Surface	Irregular	Shine Opaque, with lighter areas surronding Grouped
Tin	Surface	Irregular	Strewed Without shine Low Contrast
Dust	Surface	Irregular	Sometimes shine Grouped

Table 2: Defects classification percentage

	Fuzzy Classifier	Multilayer Perceptron
Training	90.20%	88.23%
Test	94.37%	77.46%

Let us suppose that there are N descriptors, whose supports are crisp sets $A_i, i = 1, \dots N$, and that we define m_i linguistic variables associated to fuzzy sets $\tilde{A}_i^j, j = 1, \dots m_i$, where $\tilde{A}_i^j \in \tilde{\mathcal{P}}(A_i)$. For instance, A_1 could be the set of values of the descriptor *depth*, $\tilde{A}_1^1$ be the fuzzy set related to the label *high*, $\tilde{A}_1^2$ related to the label *medium* and $\tilde{A}_1^3$ related to *low*. The sets $\tilde{A}_i^j, j = 1, \dots m_i$ form a fuzzy partition of A_i. We will use the definition of $\delta - \epsilon$–partition of S. Montes [5],

$$\begin{aligned} (\tilde{A}_i^j \cap \tilde{A}_i^k)_{\overline{\alpha}} = \emptyset, \quad \forall\, j,k = 1,2\dots m_i, \quad \forall\, \alpha \geq \delta \\ \left(\cup_{j=1}^{m_i} \tilde{A}_i^j\right)_\alpha = A_i, \quad \forall\, \alpha \leq 1 - \epsilon \end{aligned} \tag{1}$$

because is the most flexible definition we have found.

Let us also suppose that membership functions of $\tilde{A}_i^j$ depend on p parameters each

$$\tilde{A}_i^j(x) = f((a_i^j)^1, (a_i^j)^2, \dots, (a_i^j)^p, x), \quad x \in A_i \tag{2}$$

We will characterize the q type of defect by a tuple $(q_1, q_2, \dots, q_k, \dots, q_N)$, whose components are the indexes of the mentioned linguistic variables, $q_k \in \{1, \dots, m_k\}$; they are derived from the information given by the human expert. Since every defect x can be regarded as a point in $A_1 \times \dots \times A_N$, $x = (x_1, \dots, x_N), x_i \in A_i$, we can assess a degree of compatibility of x with the type of defect q, and this value will be

$$\mu_q(x) = \tilde{A}_i^{q_1}(x_1) \wedge A_i^{q_2}(x_2) \wedge \dots A_i^{q_N}(x_N). \tag{3}$$

Our rule of classification consists in assigning the type $T(x) \in \{1, \dots, N_c\}$ to the defect represented by x, where

$$\mu_{T(x)}(x) = \max_{q=1,\dots,N_c} \mu_q(x). \tag{4}$$

The classifier is completely defined by the $2 + \sum_{i=1}^N pm_i$ parameters that define the fuzzy sets $\tilde{A}_i^j$ and the values δ and ϵ. To estimate these parameters we use a set of examples $X = \{x^1, x^2, \dots x^{N_e}\}$, which we have classified by hand. If we know that every example x^k belongs to the class T_k, $k = 1 \dots N_e$, the efectiveness of the classifier system will be better when the number of correctly classified examples (those for which $T(x^k) = T_k$) is high. It will also be desirable that the confidence we have in the classification that the system has made is high. This confidence is measured by the value $\mu_{T(x_k)}(x_k)$, so the expression

$$E(X) = \sum_{\{x \in X : T(x) = T_k\}} \mu_k(x) - \sum_{\{x \in X : T(x) \neq T_k\}} \mu_k(x) \tag{5}$$

assess the behaviour of the classifier. We have used a genetic algorithm to maximize $E(X)$ with respect to a set of parameters.

10 Experimental results

We have chosen trapezoidal memberships, $N = 5$ descriptors (contrast, moment of inertia, grouping degree, brighness and depth) and $N_n = 5$ classes of defects (bubbles, stones in surface, stones inside, tin, dust) and we had access to $N_e = 51$ examples. Giving random initial values to the parameters, we could check that the chosen rules were coherent, because in a few hundred of generations we found a set of parameters that classified almost all the samples. This classifier was implemented in the prototype, and the results obtained after a week of functioning in the plant are summarized in Table 2, row "Test". The row labelled "Training" shows the percentages of correctly classified examples obtained in the laboratory, with the initial 51 examples.

In the same table we show the results obtained when we perform the classfication with a multilayer perceptron. We can observe that, besides the percentage obtained with the training data are similar, results obtained with test data are quite inferior. The explanation is simple if we realize that the linguistical description of the fuzzy rules was not obtained from the examples, so the neural network did not access this information and, consequently, generalizes poorly.

11 Conclusions

When we have a good linguistic definition of the rules that govern a classifier and we only have a reduced set of examples, the fuzzy classifier is a simple alternative that competes favourably with neural network based classifier systems. In this practical application we have used genetic algorithms to tune the parameters that define the fuzzy sets that partition the domain of the input variables.

Acknowledgements

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References

[1] A.P. Pentland. (1987) "A new sense of depth of field". T-PAMI Vol 9, No.4, pp. 523-531

[2] M. Subbarao, T.C. Wei, G. Surya. (1994) "Focused Image Recovery from Two Defocused Images Recorded with different Camera Settings". CVPR(94), pp. 786-791

[3] M. Subbarao, T. Choi. (1995) "Accurate Recovery of Three-Dimensional Shape from Image Focus". T-PAMI Vol 17 No.3, pp. 266-274

[4] K. Nayar, Y. Nakagawa. (1994) "Shape from focus: An effective approach for rough surfaces". Int. Conf. on Robotics and Automation, pp. 218-225

[5] S. Montes, M.J. Lopez-Palomo y P. Gil. (1995) "Las ϵ particiones difusas". ESTYLF 95

[6] G. Ligthart, F. Groen (1982) "A Comparison of different autofocus algorithms". Int. Conf. Pattern Recognition. pp 597-600.

[7] A. Gonzalez y R. Perez. (1993) "Un modelo experimental para determinar la estructura de una regla". Tercer Congreso español sobre tecnologías y lógica fuzzy. Santiago de Compostela. pp 9-16.