AUTOMATED VISUAL INSPECTION OF NON-SMOOTH SURFACES. APPLICATION TO CAST ALUMINUM.

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Abstract: In this paper a general, low cost, arquitecture is described along with a methodologie for on-line defect detection and analysis in flat surfaces continously produced. On-line inspection of 100% production, along with the proper characteristics of inspection when texture is present force up the development of optimized algorithms for both detection and classification. Also hardware platforms that permit pipelined processing along with high modularity and are needed with a cost that make them competitive in every kind of surface visual inspection applications. An industrial application is described for quality assessment and process driving in cast aluminum obtention.

Keywords: industry automation. Quality control. Image processing. Visual Pattern Recognition. Neural nets.

1. INTRODUCTION

Inspection for surface appearance (surface finishing, texture, presence of defects, ...) is not an easy task. The complexity of the inspection task is variable depending on several aspects like: kind of material, surface finishing, production rate, appearance of surface defects. In the following, the influence of this parameters is analysed to determine how they condition both inspection algorithms and image processing hardware development.

1.1. *Influence of surface finishing.*

Surface finishing determine lighting techniques, inspection algorithms and acquisition devices.

*Smooth surfaces.*This in the usual appearance of rolled metals, painted surfaces, composites, ... They show a very low dispersion of gray levels. In these cases the use of threshold-based segmentation techniques is advantageous (Jain, 1989).

Textured surfaces. Images from cast metals, wood, cork, ... are not suitable for threshold-based processing since the great amount of discontinuities these surfaces present. In this cases two alternatives show applicable: similarity-based inspection algorithms when the texture is homogeneous and defetcs implie a significat alteration. Texture-based inspection algorithms when the surface texture is not homogeneous.

1.3. *Influence of the production rate.*

The data volume to be processed dertermine the image processing hardware:

Data volume < 500 Kbytes/s. Posibility to use low performance DSPs on PC bus.

Data volume < 5 Mbytes/s. High performance DSPs along with pararell processing.

Data volume > 5 Mbytes/s. Great scale paralelism. Pipelined processing.

1.4 *Nature of surface defects.*

The kind of defects that can appear in the surface to be inspected determine the classification techniques to employ.

Structural approach. When defects can be described in terms of structure it is convenient to use sintactic methods for classification: rule-based methods in combination with expert systems and neural nets trained to recognize gramars from structural primitives.

Theoretical decition approach. When it is no possible to describe defects in terms of structure -this is the case of defects that present semi-deterministic texture- it is necessary to resort to multivariant or factorial analysis or what is more powerfull, neural nets: MLPs, LVQ, ART.

2. TEXTURE ANALYSIS

Texture analysis perform with good accuracy when inspecting objects that present non-smooth appearance. Nevertheless texture-analysis algorithms are great time consumers when implemented into artificial vision systems. This handicap has been solved in two different ways: when determining surface finishing -the whole image must be then analyzed- a convolution-based implementation of a gray level difference method has been hardware implemented for real-time operation. Another approach has been used when classifying different defect types that alter the surface texture; a mixed technique is used: similarity-based processing to detect the presence of defect in the surface, texture analysis to extract texture features from the defect and neural networks to determine the kind of surface defect.

The aim of the study is the analysis of manufactured product surfaces in order to achive both surface finishing meassurement and defect detection and classification in defective portions of the surface.

3. TWO-PHASES APPROACH FOR DEFECT DETECTION AND ANALYSIS

High-speed applications where automated visual inspection is demanded and low percentage of defective area is present -it is normal that many defects represent only an small portion of less than 1/20000 of the whole inspected area- advise the use of a two-phases approach as shown in figure 1.

Firstly, a similarity-based processing algorithm (Fernández, 1993) is used in order to detect the presence of defect.

Defective portions of the surface are then processed using texture analysis techniques in order to classify defects into types.

Surface appareance is enhanced by means of an adecquate lighting system. For this purpouse a light simulator has been developed to obtain the optimum configuration. Instead of physical optics models (Beckman & Spizzichino, 1963) -that show not very suitable when wavelenght of incident light is not despreciable compared with dimenison of surface imperceptions- geometrical optics model (Torrance & Sparrow, 1967) is used. With this model, threee kinds of relfection componenets: diffuse reflection halo, specular reflection halo and specular spike can be observed, depending on the material of which surface is made of.

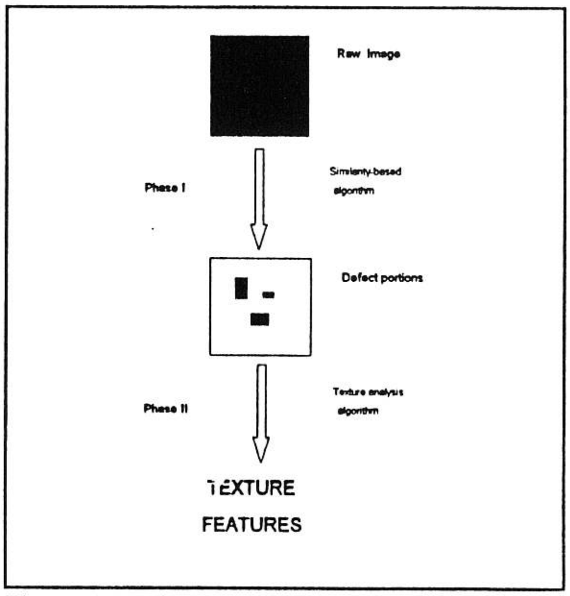

Fig. 1. Two phases approach.

Local analysis is used in order to avoid lighting non-uniformity. While no defect is detected, the lighting pattern is updated in òrder to avoid the influence of lighting conditions, presence of dust,...

Defect detection algorithms are based on simple statistical features methods, since this result into on-line implementations. Gray level distribution in one image coming from any surface can be considered as a set of gaussian distributions - one distribution by area unit- depending on incident light and surface composition. For a given homogeneous surface variance can be considered as a constant value. Every area unit with different average/variance values is considered as a defect.

4. TEXTURE FEATURES.

Considering that texture can be described by a function (Tamura & Mori, 1978):

$$f=S(e)$$

for its analytic study, for a region of interest in one image where S represents a distribution model in the region of a pattern element represented by e, S can be very significant- it is the case of heavily structured textures- or S can be very low significant -it this the case of random textures- and different techniques (Reed, 1993) (Fernández, 1992) can be applied that perform with more or less accuracy over textures belonging to one of the two texture types.

When inspecting for visual appearance of surfaces, both situations can arise inside defects: greatly structured appearance or randomness, although second situation is more frequent in many production processes: wooden surfaces, cast metals, leather preparation process, ... In such manufacturing processes statistical approach for texture analysis is widely used.

Common texture features extracted from images include: measurements for: coarseness, contrast, orientation, linearly, regularity, roughness.

First order statistics (like mean gray level) do not perform with accuracy enough for texture discrimination, being of more usefulness to implement techniques that consider both gray level along with gray level distribution over the image.

4.1 *Attribute matrix for feature extraction.*

Attribute matrices are made up of a set of real numbers obtained when performing some statistics operations over imagess (Wu & Chen, 1992)

Definition 1: let I be an image of m rows and n columns, G(x, y) the gray level at I(x, y) and g the mean gray level.

Definition 2: let $\nu(\Delta x, \Delta y)$ be the intersample spacing vector. A v statistical attribute is defined as a second-order statistical feature of an image I with intersample spacing distance vector v.

Definition 3: a statistical attribute matrix M is (r+1) rows by (2*c+1) columns whose (i, j) element is:

$$M_{con}(i,j) = E([g(x,y) - g(x+j-c, y+1]^2)$$

for the <u>contrast</u> matrix,

$$M_{cov}(i,j) = E([G(x,y) - \bar{g}][G(x+j-c, y+i) - \bar{g}])$$

for the <u>covariance</u> matrix and

$$M_{dis} = E(|G(x,y) - G(x+j-c, y+i)|)$$

for the <u>dissimilarity</u> matrix, where E() stands for the expectation operation.

c and r can vary from 1 to n and m, respectively, according to the method application. In the case of study we have adopted c=r=2 for on-line performance.

Some advantages derived from the use of attribute matrices include:

* Different sample distances can be adopted.
* When sample distance grows up, old data from lower distances calculations can be added to new data, since no variation is observed.
* Matrix components can be easily separated from the size of the analyzed portion -the defect in our study- of the image.

A main inconvenient arises when trying perform on-line implementation of this analysis into continuous production processes:

* Quite complex operations are needed, operations normally not implemented on available processing hardware.

On-line performance in the application has been achieved introducing two modification in the algorithm:

* The number of gray levels in the original image from defects -256 gray level- has been reduced until 11 to 7 gray levels using an equal probability histogram quantization method (Lázaro & Fernández, 1992), which allows to reduce the number of operation to calculate attribute matrices by significantly reduction of gray levels, maintaining most information of images.

* Matrix calculation operations have been reduced by single calculations without considering rotation-invariance, since in the application images are obtained using a non-varying camera-to-surface orientation.

5. SURFACE FINISHING MEASUREMENT IN METALLIC SURFACES

Surface finishing measurement is a main goal in many manufacturing processes where surfaces are involved. Conventional techniques, based upon tool-to-surface contact, present two main inconvenients:

* Low speed inspection due to physical contact.
* Only small portions of the whole surface can be inspected.

Electro-optical devices (Janson, 1984)(Stout, 1984) have been employed with success to measure the amount of reflected light from a surface, although texture can not be determined with accuracy -no texture characteristics are achieved-.

When inspecting for surface finishing in metallic strips obtained by casting, forging, lamination or tempering processes it has been found out that using and adequate lighting system, there is a great correlation rate between surface texture and the total amount of reflected light.

For a surface like the one shown in figure 2 where random irregularities can be observed, two surface models can be adopted in order to modelate the way in which light is reflected.

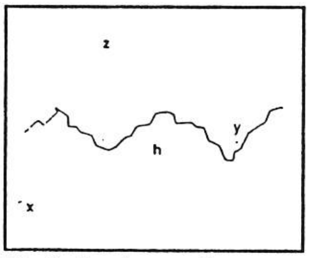

Fig. 2. Random surface.

5.1. Height distribution model.

Height coordinate of a given surface can be expressed as a random function depending on x and y variables, as shown in figure 3. Surface appearance can be expressed by means of the probability distribution function for height:

$$P_h(h)=\frac{1}{\sqrt{2\Pi\sigma_h}}e^{-\frac{h^2}{2\sigma_h^2}}$$

This model presents the problem illustrated in figure 3: two surfaces (a) and (b) with very different appearance may have the same height distribution function.

2. Slope distribution model.

Surface is considered as a microstructure containing a great number of micro-faces. These micro-faces have a privileged orientation, represented with a deviation in the normal vector n of angle alpha (see figure 4). Modelation can be assumed that:

$$P_\alpha(\alpha)=\frac{1}{\sqrt{2\Pi\sigma_\alpha}}e^{-\frac{\alpha^2}{2\sigma_\alpha^2}}$$

This is a simple model that simply explains light reflection more dependant on local slope than on irregularities height.

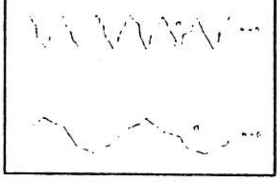
Fig. 3. Two different surfaces.

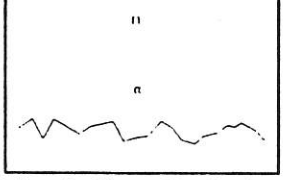
Fig. 4. Slope distribution model.

Assuming this surface model three algorithms have been developed:

Measurement of specular component of reflect light (Luk, 1987). A global histogram is obtained over images coming from the surface. It works with acceptable accuracy with magnified images and is not suitable for on-line 100% inspection in high-speed applications.

Measurement of number of microedges contained in the image. Surface roughness can be evaluated by measuring the number of micro-edges by area unit on the incoming image. As this number increases, smoother texture is present (Hayes, 1973). The following space filter to detect such micro-edges has been employed:

$$|A_{ij}-A_{i-1,j-1}|+|A_{i,j-1}-A_{i-1,j}|$$

This measurement technique is contrast dependant. This dependence can be partially avoided if incoming images are equalized -gray level normalization- although in this case on-line operation is more difficult to achieve.

Gray Level Difference. Finally, the best size detector from Rosenfeld (Luk, 1987) was chosen which has been implemented as shown in figure 5.

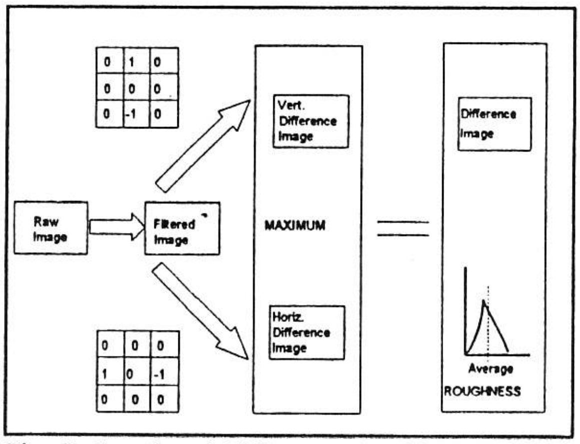

Fig. 5. Gray Level Difference algorithm.

Since in non-deterministic or half-deterministic textures (cast aluminum belongs to this second type) it is very difficult to set the size of the texture pattern, neighborhood size is chosen in a experimentally way considering the different levels of surface finishing present in the application. The algorithm performs over no-zoomed images, all of them acquired in same resolution conditions. For on-line performance some simplifications have been assumed:

* No gray level equalization is performed over raw images.

* A single-dimension algorithm (only in casting direction) has been implemented.

6. APPLICATION: ALUMINUM CASTER

These techniques has been applied to quality assessment in aluminum casting process.

In this process a 6-7 mm thick, 1500-2000 mm wide aluminum strip is obtained using a single, very compact casting line involving direct casting from molten aluminum at a speed up to 2 m/m. Aluminum strip so obtained can present different kinds of defects; some of these defects produce alteration in aluminum surface texture.

Images are taken by non-interlaced CCD matrix cameras (ten cameras cover the whole section of the aluminum strip by its both sides). The visual inspection system detects defects on the aluminum surface and then these defects must be classified into types. Figures 6 to 11 show the appearance of different defects.

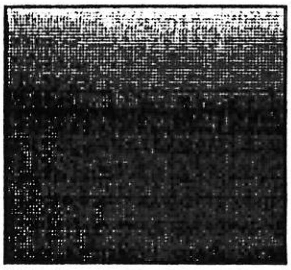

Fig. 6. No defect.

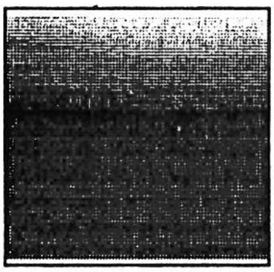

Fig. 7. Lack.

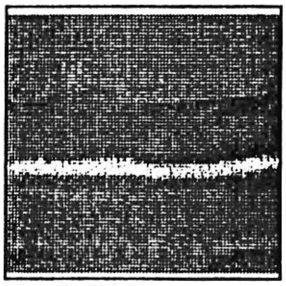

Fig. 8. Sticking.

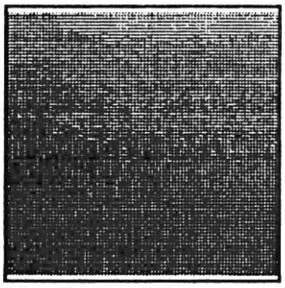

Fig. 9. Graphite inclussion.

6.1 Defect classification

For quality assessment, defect classification into known types is needed. For this purpose, statistical analysis by means of factor analysis was firstly implemented over extracted features with poor results -only three defect types could be accurate classified-. After, a neural net approach was tried which seemed to offer a better performance. Texture features resulting of attribute matrix applied over defective portions of the image acts as inputs for the neural net.

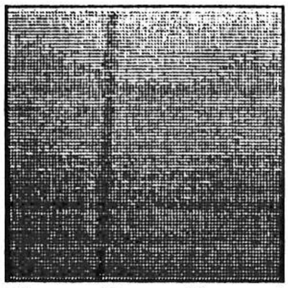

Fig. 10. Abnormal crystallization..

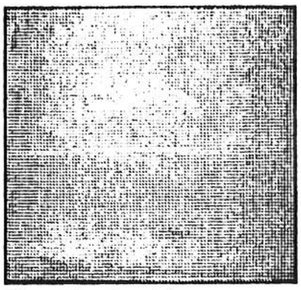

Fig. 11. Speckle.

Neural net architectures suitable for pattern classification include (Neural Inc., 1990): categorical learning, counterpropagation, learning-vector (Kohonen et al, 1992), probabilistic and self-organizing category map. Previous experience on similar problems (steel) advised us to try two architectures: backpropagation and learning-vector quantization.

Second solution was discarded in first stages of the study because although learning wa ready after 500 iterations reaching zero error level, when processing the test set, performance was quite poor.

The former led to better results. MPL + backpropagation has demonstrated good performance in similar classification problems (Sikka, 1992). It has been used since its good generalization properties. .Two thirds of the data file were used to train a backpropagation (27/18/6) net and the rest was used for testing. This network was compose of 27 input nodes ([3 matrices of 3 rows*5 columns]* 9 different elements each one), 6 output nodes (corresponding to 6 different defect types) and only on hidden layer of 18 processing elements. Several different configurations were tested (more processing elements, two hidden layers,...) presenting equal or worse results than the described configuration. The simplest one was chosen, which became in shorter training and smaller C code when net is "frozen".

Once the net structure has been set definitively, it has been "frozen" back and attached to hardware-implemented image processing algorithms for on-line performance.

Results vary from 80% and 95% accuracy depending on image quality, that is, uniformity of incident light over the aluminum strip.

6.2. Hardware implementaiton of algorithms

Image processing algorithms -for surface finishing measurement and texture features extraction- have been implemented into a low cost and modular hardware architecture highly suitable for visual inspection.
Every image processing board includes:

* Video digitizer, able to real time digitalization

of video signals up to 1024 pixels/line. (Also digital input is available).

* Master CPU based on RISC microprocessor Am29240.
* Image processors. Up to four (parallel or pipeline configuration) IGOR ASIC chips for real-time image processing.

Processing boards are stand-alone type with a network connection for program downloading, debugging and results transference. In figure 12 a single board prototype is shown.

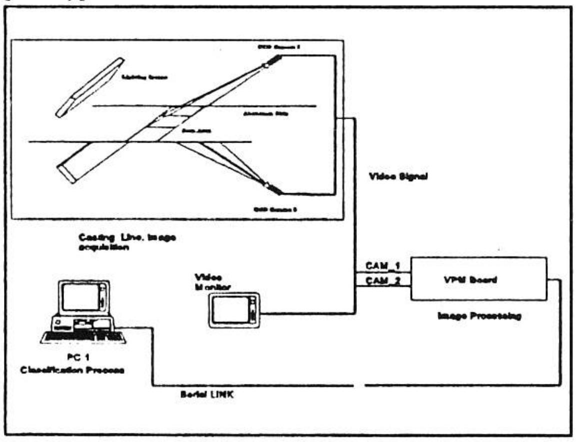

Fig. 12. Single board prtotype.

7. CONCLUSIONS

A combination of techniques is presented to face Automated Visual Inspection of flat products presenting surface texture, continuously produced, where on-line performance is required.

Texture analysis has been on-line achieved by means of a two-phases approach which allows process only small portions of images coming from surfaces, that is, only defects are processed.

A fast gray level difference algorithm has been implemented to on-line surface finishing measurement.

Quality assessment, applied to cast aluminum, relies on a supervised-way trained network which allows a preliminary success near to 96% well classified defects.

These results, along with some no-homogeneity detected in lighting devices show that a success near to 100% is possible.

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