A Quality Control System using Texture Analysis in Metallurgy

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***Abstract*—Object detection, recognition and texture classification is an important aspect of many industrial quality control systems. In this paper, we report on a system designed for the inspection of surfaces which has a range of applications in the area of metallurgy. The approach considered is based on the application of Fractal Geometry and Fuzzy Logic for texture classification and, in this paper, focuses on the manufacture of rolled steel. The manufacture of high quality metals requires automatic surface inspection for the assessment of quality control. Quality control systems are required for several tasks such as screening defected products, monitoring the manufactures process, sorting information for different applications and product certification and grading for end customers. The system discussed in this paper was developed for the Novolipetck Iron and Still Corporation in Russia and tested with images captured at a rolling mill with metal sheets moving at speed of up to six meters per second and inspected for several defect classes. The classification method used is based on the application of a set of features which include fractal parameters such as the Lacunarity and Fractal Dimension thereby incorporating the characterisation of surface surfaces in terms of their texture. The principal issues associated with texture recognition are presented which includes fast segmentation algorithms. The self-learning procedure for designing a decision making engine using fuzzy logic and membership function theory is also presented and a new technique for the creation and extraction of information from a membership function considered. The methods discussed, and the system developed, have a range of applications in 'machine vision' and automatic inspection. However, in this publication, we focus on the development and implementation of a surface inspection system that can be used in a iron and steel manufacture by non-experts to the automatic recognition system operators.**

***Keywords*-Computer vision; patterns analysis; segmentation; object recognition; self-learning; fuzzy logic; image morphology.**

I. INTRODUCTION

Pattern recognition is a part of image analysis, which involves the use of image processing methods that are often designed in an attempt to provide a machine interpretation of an image, ideally, in a form that allows some decision criterion to be applied [1], [2]. Pattern recognition uses a range of different approaches that are not necessarily based on any one particular theme or unified theoretical approach. This is because there is no complete and unique theoretical model available for explaining and simulating the processes of visual image comprehension by humans. Hence, machine vision remains a rather elusive subject area in which automatic inspection systems are advanced without having a fully operational theoretical framework as a guide. Nevertheless, numerous algorithms for understanding two- and three-dimensional objects in a digital image have and continue to be researched in order to design systems that can provide reliable automatic object detection, recognition and classification in an independent environment, [9], [10], [11] and [13].

Machine Vision can be thought of as the process of linking parts of the visual object's field with stored information or 'templates' with regard to a pre-determined significance for the observer. There are a number of questions concerning vision such as: (i) what are the goals and constraints? (ii) what type of algorithm or set of algorithms is required to effect vision? (iii) what are the implications for the process, given the types of hardware that might be available? (iv) what are the levels of representation required to achieve vision? The levels of representation are dependent on what type of segmentation and edge detection can and/or should be applied to an image. For example, we may be able to produce primal sketches from an image via some measure of the intensity changes in a scene. These are recorded as place tokens and stored in a database. Regions of pixels with similar intensity values or sets of lines are obtained by isolating the edges of an image scene and computed by locating regions where there is a significant difference in the intensity. Such sets are subject to inherent ambiguities when computed from a given input image and associated with those from which an existing data base has been constructed. These ambiguities can only be overcome by the application of high-level rules, based on how humans interpret images, but the nature of this interpretation is not defied. Parts of an image will tend to have an association if they share size, colour, figural similarity, continuity, shading and texture. For this purpose, one needs to consider how best to segment an image and what form this segmentation should take.

The identification of the edges of features on metal surfaces (as given in Figure 1, for example) is an important component for developing quality control system in metallurgy. This identification provides information on the basic topology of a feature from which an interpretative match can be achieved. Some edges can be detected only in terms of a representative view a whole image and have no connection with local pixels. Nevertheless, the segmentation of an image into a complex of edges is a useful pre-requisite for object identification and the solution may require analysis of the whole scene. Although many low-level processing methods can be applied for this purpose, the problem is to decide which object boundary each pixel in an image falls within and which high-level constraints are necessary. In many cases, a principal question is, which comes first, recognition or segmentation?

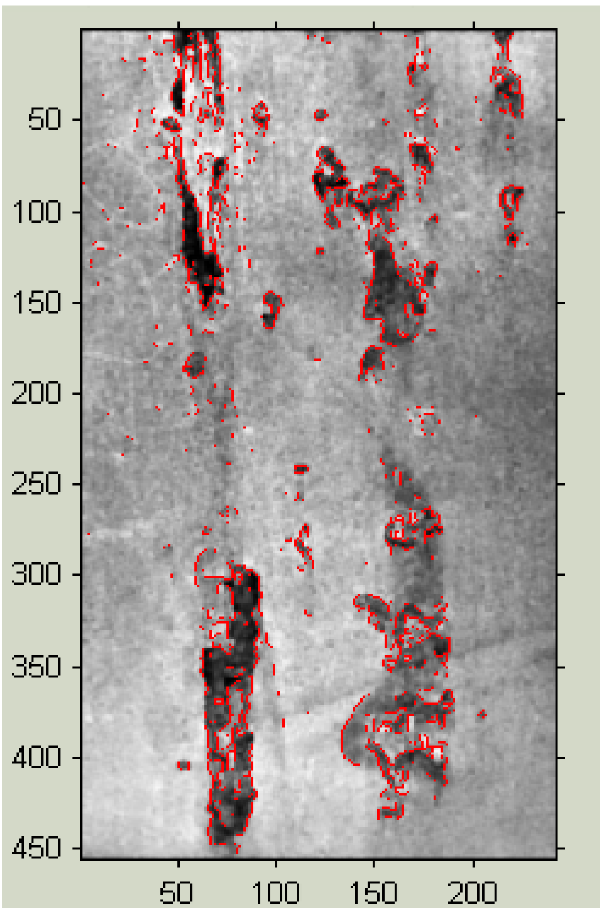

Figure 1. Example of a metal surface with edge-based features.

Compared to image processing, computer vision (which incorporates machine vision) is more than automated image processing. It results in a conclusion, based on a machine performing an inspection of its own. The machine must be programmed to be sensitive to the same aspects of the visual field as humans find meaningful. Segmentation is concerned with the process of dividing an image into meaningful regions or segments. It is used in image analysis to separate features or regions of a pre-determined type from the background; it is the first step in automatic image analysis and pattern recognition. Segmentation is broadly based on one of two properties in an image: (i) similarity; (ii) discontinuity. The first property is used to segment an image into regions which have grey or colour levels within a predetermined range. The second property segments the image into regions of discontinuity where there is a more or less abrupt change in the values of the grey or colour levels.

In this paper, we consider an approach to object detection in an image scene that is based on a new segmentation edge recognition or edge tracing or edge following algorithm. The segmented object is then analysed in terms of metrics derived from both a Euclidean and Fractal geometric perspective, the output fields being used to train a fuzzy inference engine with a supervised leaning technique, the recognition structure being based on some of the technologies for image processing, analysis and machine vision reported in [12]. The approach considered is generic in that it can, in principle, be applied to any type of imaging modality. The system developed includes features that are based on the textural properties of an image which is an important theme is patterns analysis.

II. Pattern Recognition

Pattern recognition can be considered to be a form of machine understanding based on assigning a particular class to an object. The tasks of construction and application of formal operations for numerical or character representation of objects of a real or ideal world is the basis of pattern recognition. This depends on establishing equivalence relations that express a fit of evaluated objects to any class with independent semantic units. The recognition classes of equivalence can be set by the user in the construction of an algorithm, which uses own pithy representations or external padding information on a likeness and difference of objects in the context of a solved task; the basis for phrase 'recognition with the teacher'. For a typical object recognition system, the determination of the class is only one of the aspects of the overall task. In general, pattern recognition systems receive data in the form of 'raw' measurements which collectively form a stimuli of 'feature' vector [3], [4]. Uncovering relevant attributes in the elements present within the feature vector is an essential part of such systems. An ordered collection of such relevant attributes which more clearly represent the underlying features of the object is assembled into the feature vector. In this context, learning amounts to the determination of rules of associations between the features and attributes of a pattern.

Practical image recognition systems generally contain several stages in addition to the recognition engine itself. The recognition represents information processing that is realised by some converter of the information (by an intellectual information channel), having an input and output. On input, such a system establishes information on the properties of an object. On output, the information shows which class or feature of an object is assigned. When a computerised system decides on the task of classification without engaging external learning information, it is called automatic classification - 'recognition without the teacher'. The majority of algorithms for pattern recognition require the engagement of a number of considerable computational capabilities, which can be provided only with high-performance computer equipment [5].

There are two principal methods for object recognition solutions with a parametric and non-parametric approach. Statistical voting and alphabetic propositions has been reviewed in [7][8][12]. The main disadvantage with this approach is that classes have to be clearly defined so that no overlapping is allowed. Methods based on a principal of separation and potential functions can be found in [6] and [11]. A large amount of training data or preliminary information about system is required which makes the recognition process less flexible. In general, there is no system which considers objects from the point of view of a superposition of global scenery. This leads to the following problem: how can we evaluate an object in terms of it being part of the 'bigger picture' without losing specific details on its particular texture for precise recognition? This paper attempts to solve this problem by merging concepts from Fractal Geometry [21] [22] [23] [24] [25] and Fuzzy Logic [15] [16] [17]. We start by considering the problem of object location.

III. Object Location

Recognition is the process of comparing individual features against some pre-established template subject to a set of conditions and tolerances. This task can be reduced to the construction of some function determining a degree of proximity of the object to a sample - a 'template' of the object. The process of recognition commonly takes place in four definable stages: (i) image acquisition and filtering; (ii) object location (with edge detection); (iii) measurement of object parameters; (iv) object class estimation and decision making.

Suppose we have an image which is given by a function $f(x,y)$ and contains some object described by a set of features $S = \{s_1, s_2, ..., s_n\}$. We consider the case when it is necessary to define a sample, which is somewhat 'close' to this object in terms of a matching set. The system discussed in this paper is based on an object detection technique that includes a novel segmentation method and must be adjusted and 'fine tuned' for each area of application. This includes those features associated with an object for which fractal models are well suited [1], [2], [21]. A conventional method consists of calculating some function of a pointwise coincidence between the map of the object and the image together with a search for the maximum of this function. In terms of a 'similarity function', this method can be represented in terms of metrics that include the sum of square deviations, the sum of the modulus of deviations or as a pair of sum of multiplications of values of brightness (function of the greatest transparency), for example. The first two similarity functions compute the 'smallness' of a functional pair; instead of searching for a maximum it is necessary to search for a minimum.

Not all fragments of an object are equally important for recognition and hence, a broadly distributed functional evaluation matched with weighted coefficients can be undertaken on separate parts. Appropriate similarity functions can be used as a sum of the weighted squares of deviations, a sum of the weighted modules of deviations and the sum of the weighted multiplication of pairs of brightness values. The correct selection of weight coefficients is important in the field of identification and can be calculated from a given set of samples. The common application for weighted comparisons occurs in the field of artificial neural networks. The advantage of usage of neural networks lies in the capability of introducing a flexible set of weights during operation (system training). This property becomes especially important if a set is based on a non-stationary model which varies in time while it is extended and updated.

The system described in this paper provides a decision using a knowledge database by subscribing different objects. The 'expert data' in the application field creates a knowledge database by using a supervised training system with a number of model objects [15]. At this stage, the learning technique uses positive feedback for the second step of object location and filtering. We consider an image of a metal surface as given Figure 1.

Figure 1 represents the result after applying a conventional filtering and edge detection procedure. The conventional method does not provide continuous edges in order to locate a feature. We have therefore designed a new object location procedure that considers the image in its entirety without detailing smaller features. This is based on a measure of weight coefficients to provide information about object connectivity. The result of this procedure can be given in Figure 2.

The calculation of weight coefficients for each pixel is defined as $k_{x,y}$:

$$f_{m,n} = f(x,y)k_{x,y}$$

where

$$k_{x,y} =$$

$$\left(\frac{1}{f(x,y)} \begin{bmatrix} k_{x-1,y+1} & k_{x,y+1} & k_{x+1,y+1} \\ k_{x-1,y} & p_{x,y} & k_{x+1,y} \\ k_{x-1,y-1} & k_{x,y-1} & k_{x+1,y-1} \end{bmatrix} \right) * p_{\mathrm{obj}(x,y)}$$

There is local dependency between the current pixel $f_{m,n}$ and the object pixels. The global evaluation is determined by $p_{\mathrm{obj}(x,y)}$ which is the probability that the pixel could be a part of an object. This probability is calculated from a fuzzy logic membership function which has a loop-back to the current object location. The function $p_{\mathrm{obj}(x,y)}$ is a two

ISBN: 978-1-61208-158-8

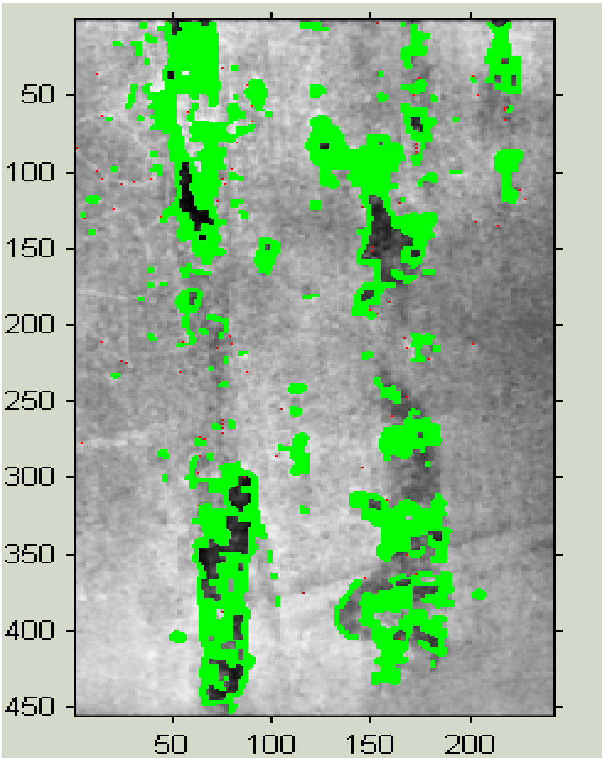

Figure 2. Metal surface with approximate object locations.

dimensional matrix and recalculates local values dynamically using the object table location $f_{m,n}$. The construction of this matrix is based on the following: The intensity level of the objects is computed. This level uses only those pixels which have not been recognised as a part of an object. To start with, the object level denoted by $\mathrm{L_{obj}}$ is higher than the background level $\mathrm{L_{bgr}}$ as the recognition process continues. As long as $\mathrm{L_{obj}} == \mathrm{L_{bgr}}$, all objects are recognised as having been indexed according to the equation [19], [20]

$$\mathrm{L_{bgr}} = \mathrm{mean}[f(x,y) - f(m,n)]$$

In order to obtain $\mathrm{L_{obj}}$, a probabilistic min-max equation, which has been experimentally tested for different surfaces, is used given by [19]:

$$L_{\mathrm{obj}} = \begin{cases} L_x, & L_x \geq L_y; \\ L_y, & \text{otherwise.} \end{cases}$$

where

$$L_x = \frac{1}{2}\left(\min_y\left(\max_x f(x,y)\right) - \langle \max_x f(x,y)\rangle_y\right) + \langle \max_x f(x,y)\rangle_y,$$

$$L_y = \frac{1}{2}\left(\min_x\left(\max_y f(x,y)\right) - \langle \max_y f(x,y)\rangle_x\right) + \langle \max_y f(x,y)\rangle_x.$$

In order to maintain simplicity, we do not include in this equation that component which is responsible for dividing previously defined objects in $f_{m,n}$. For more complex images, the user can define a region of interest *a priori*.

The second stage is to compute a particular value of membership function $p_{\mathrm{obj}(x,y)}$ according to the equation

$$p_{\mathrm{obj}(x,y)} = \int_{xy} (f_{x,y}\mathrm{L_{obj}} - \mathrm{L_{bgr}} + \mathrm{edge}_{xy})dxdy$$

for the closed border of the object. The function edge_{xy} is an edge detection function. Depending on the application, special filters including the 'Detour by object contour' and 'Convex Hull Spider' can be included [20]. Information from the application of these filters can be stored and used for the classification and decision making procedure. Each object is enumerated in terms of the procedural steps associated with the object recognition process.

IV. Decision Making Processes

Information about feature classes is stored in a Knowledge Data Base (KDB) which is composed of probability coefficients for a particular class. The class probability is a vector $\mathbf{p} = \{p_j\}$ which is estimated from the object feature vector $\mathbf{x} = \{x_i\}$ and membership functions $m_j(\mathbf{x})$ defined in the knowledge database. If $m_j(\mathbf{x})$ is a membership function, then the probability for each j^{th} class and i^{th} feature is given by

$$p_j(\mathbf{x}_i) = \max\left[\frac{\sigma_j}{|\mathbf{x}_i - \mathbf{x}_{j,i}|} \cdot m_j(\mathbf{x}_{j,i})\right]$$

where σ_j is the distribution density of values $\mathbf{x}_j$ at the point $\mathbf{x}_i$ of the membership function. The next step is to compute the mean class probability given by

$$\langle p \rangle = \frac{1}{j}\sum_j \mathbf{w}_j p_j$$

where $\mathbf{w}_j$ is the weight coefficient matrix. This value is used to select the class associated with

$$p(j) = \min\left[(p_j \cdot \mathbf{w}_j - \langle p \rangle) \geq 0\right]$$

providing a result for a decision associated with the j^{th} class. The weight coefficient matrix is adjusted during the learning stage of the algorithm.

The decision criterion method considered represents a weighting-density minimax expression. The estimation of the decision accuracy is obtained by using the density function

$$d_i = |\mathbf{x}_{\sigma_{\max}} - \mathbf{x}_i|^3 + [\sigma_{\max}(\mathbf{x}_{\sigma_{\max}}) - p_j(\mathbf{x}_i)]^3$$

with an accuracy determined by

$$P = \mathbf{w}_j p_j - \mathbf{w}_j p_j \frac{2}{\pi}\sum_{i=1}^{N} d_i.$$

 ISBN: 978-1-61208-158-8

The overall accuracy depends on the level of confidence of an expert. In some cases, an expert is unable to make clear decisions about which class belongs to an object. In such cases, it must be 50/50 in order for the system to consider this case as overlapping, but not to delete it and use extra data from the KDB to make a decision.

Consider a sample belonging to one of three groups: Scale, Cleavage crack or Cusping. We then undertake the same operations as those during the training session. The system then finds the object, computes its fractal dimension which, in this case study, is 2.58, for example, and the convexity factor (0.69). The degree of confidence determined by all the parameters functions is displayed in Figure 3.

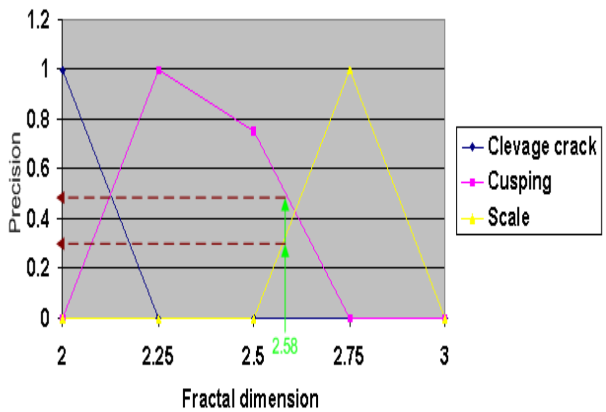

Figure 3. Precision definitions

We compute the degree of confidence for each class as:

(Scale)=0.27+0.87=1.14

(Cusping)=0.46+0.42=0.88

(Clevage crack)=0+0=0

The maximum of these values characterizes that class to which the given image corresponds. In the example given, the output is *Scale*. For industrial systems with many reference classes, it is possible to utilise scaling factors for each of the computed parameters in conformity with a measure of influence (weight coefficient) on a parameter for a class definition. The weight coefficients will be automatically readjusted with the next teaching input. Once the expert decides to correct some class performance, then the corresponding input parameters will be reconsidered for chosen class only.

The computation time depends on the image resolution, normally varying from 2 to 10 seconds in the MatLab environment. For a metal surface moving at 6m/sec, the algorithm described above would need to be implemented by means of a field-programmable gate array (FPGA), which will lead to the computation fitting within frames.

V. Conclusion and Future Works

This paper has been concerned with the task of developing a methodology and applications that are concerned with two key tasks: (i) the partial analysis of an image in terms of its fractal structure and the fractal properties that characterize that structure; (ii) the use of a fuzzy logic engine to classify an object based on both its Euclidean and fractal geometric properties. The combination of these two aspects has been used to define a processing and image analysis engine that is unique in its modus operandi but entirely generic in terms of the applications to which it can be applied.

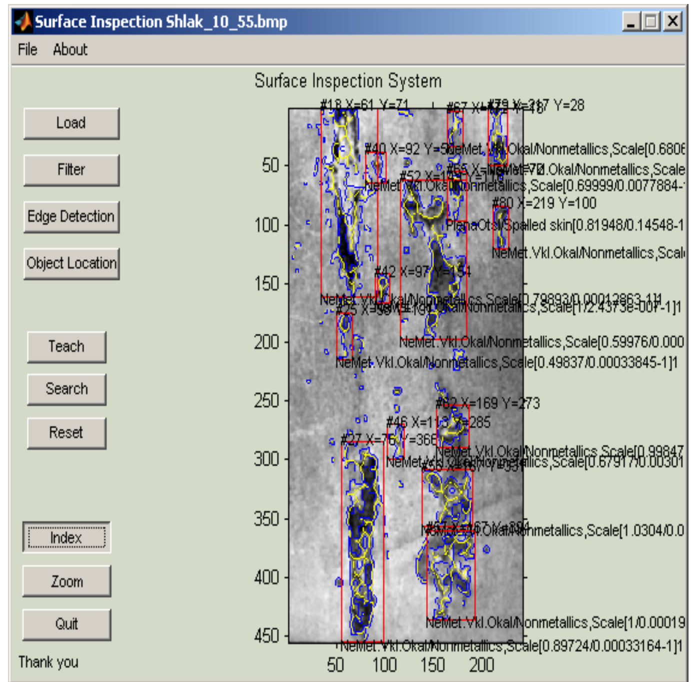

Figure 4. Result of surface inspection.

The work reported in this paper is part of a wider investigation into the numerous applications of pattern recognition using fractal geometry as a central processing kernel. This has led to the design of a new library of pattern recognition algorithms including the computation of parameters in addition to those that have been reported here such as the information dimension, correlation dimension and multi-fractals [21]. The inclusion or otherwise of such parameters in terms of improving vision systems such as the one considered here remains to be understood. However, from the work undertaken to date, it is clear that texture based analysis alone is not sufficient in order to design a recognition and classification system. Both Euclidean and fractal parameters need to be combined into a feature vector in order to develop an operational vision system, which includes objects that have textural properties such as those associated with medical imaging.

The creation of logic and general purpose hardware for artificial intelligence is a basic theme for any future development based on the results reported in this paper for the applications developed and beyond. The results of the

 ISBN: 978-1-61208-158-8

current system can be utilized in a number of different areas although medical imaging would appear to be one of the most natural fields of interest because of the nature of the images available, their complex structures and the difficulty of obtaining accurate diagnostic results which are efficient and time effective. A further extension of our approach is to consider the effect of replacing the fuzzy logic engine used to date with an appropriate Artificial Neural Network. It is not clear as to whether the application of an ANN could provide a more effective system and whether it could provide greater flexibility with regard to the type of images used and the classifications that may be required.

ACKNOWLEDGMENT

The authors are grateful for the advice and help of Dr P.P. Chernov (Novolipetsk Iron and Steel Corporation), Professor V. Deviatkov and Professor A. Chernikov (Bauman Moscow State Technical University).

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