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HYBRID SYSTEM
APPLICATION TO DEFECT CLASSIFICATION IN CAST ALUMINUM

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Abstract - This paper describes some A. I.-based techniques applied to the interpretation of images from aluminum surface. The whole process includes defect detection and defect classification into five to eight different types. The whole process is on-line performed. The developed Visual Inspection System includes: a defect detection module, a feature extraction module and a classification module.

Images coming from the aluminum surface are preprocessed by means of local analysis to seek for defects. A local analysis is necessary due to the presence of texture and to the appearance of defects where clear points appear mixed up with darker ones. The image acquisition is performed by a set of CCD cameras and these are supported by a specially developed lighting system. Image processing for defect detection consists on getting simple statistical parameters, averages in the neighbourhood and local comparison with correct patterns.

Also, we discuss about feature extraction and the use of direct and indirect methods for syntactic analysis and extraction of the feature vector. At this point, we put emphasis on transforming the set of defect primitives into a feature vector to reduce the spatial dimension of the input to the classifiers. Several classifiers are used together to improve the performance of the classification module. On-line classification is achieved.

A hybrid system has been developed for the structure recognition of defects in cast aluminum.

1. INTRODUCTION

Quality control is the one aspect more important in industrial competitive. The high cost in the inspection performed by humans forces up the development of automatic systems since they can solve the task accurately. One of the biggest difficulties in inspection is the visual appearance supervision and this activity is traditionally entrusted to human inspectors. The human vision system is adequate for variety and change, while industrial visual inspection requires to observe repetitive scenes for learning what is defect or not. The vision human accuracy decreases with repetitive and monotone works. The result is slow, high cost and erratic inspection. Automatic vision inspection is the alternative to human inspectors.

During the last years several architectures for defect detection in woods, webs, steels, aluminum,..., have been developed, but defect classifiers are still hold by research field. Classification problems carry out a great variety of clusters, defects belonging to same class may have different appearances and however inspection demands on-line learning systems able to create new classes.

Cast aluminum strip is a process that requires visual inspection along with other variables for the quality determination of final product. Figure 2 shows the block diagram containing an image processing, interpretation and display system; and an expert system which uses information from visual system, thickness measurement and temperature information. Expert system generates control actions over the casting process along with quality reports of produced coils. This paper follows the aim of presenting a novel architecture for real-time detection and classification of defects over images coming from the inspection devices.

The visual inspection system developed includes a detection module and a defect analysis module (figure 1).

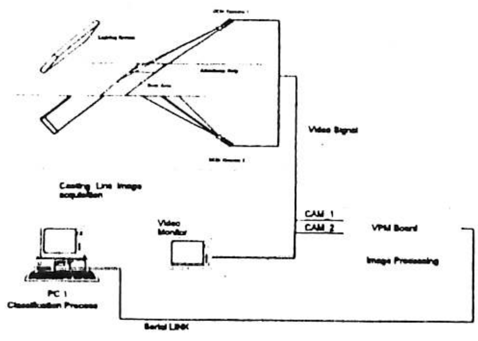

Fig. 1. Visual Inspection System

2. DETECTION MODULE

Its aim is to determine the presence/absence of defect in the aluminum surface; it includes a lighting system, an image adquisition and image processing module.

Lighting system & image adquisiton

Defects in metallic surfaces are characterized for alterations in its micro-structure. Since the defects that appear in metallic surfaces imply a material alteration, the observation of the specular component of the reflected light gives as result defect enhancing. Due to the high reflectance coefficient of the aluminum surface, it is a necessity to design a system able of uniformly lightening the surface, avoiding any type of reflection. With this purpose, lighting simulator was designed for getting the optimal configuration by means of optical models from Torrance-Sparrow [1].

CCD matrix cameras have been adopted as the most appropriate for the application, mainly for two reasons: the maximum speed of the strip doesn't overcome the 2 m /m, which permits acquisition times of 50 [msg] and, the most important reason, the necessity of neighbourhood processing, since the surface contains quite a great amount of texture that does not permit local threshold-based processing (principal feature of linear cameras). The initial specifications for the inspection system are:

- 1 [mm²] the size of the minimum defect.
- Strip width: up to 2000 [mm]
- Speed: up to 2 m/mim.

Using a resolution of 2 pix./mm with 752 x 528 [pixels] CCD cameras, eight cameras (four cameras for each side of the strip) are necessary in order to cover the width of 2 m. In this case the time of analysis for each one of the images rounds 2.1 seconds; the surface of cast strip covered by each camera is of 376 [mm] of width for 291 [mm] in the casting direction.

Image processing

Once got, images from aluminum are processed to find defects. A local analysis is carried out to localize defects, since it is not possible a global focus due to the presence of texture. Due to high roughness of cast aluminum, clear points appear mingled with darker ones, some defects do not produce a significant variation in the absolute gray level values, but produce an alteration in the space distribution of gray levels.

Previous to image processing, an image is acquired setting the diaphragm to the maximun opening possible, avoiding saturations, maintaining the maximal range of measuring with the best quantification of the analog signal. Then images are displaced n gray levels to avoid overflows in the processing step.

Similarity-based algorithms as well as texture analyses [2] have been developed for defect detection. According to previous conclusions of simple statistical parameters methods, they seem to perform quite accurately in real-time artificial vision applications[3]. The detection algorithm is carried out considering that the distribution of gray levels in the aluminum surface under an uniform light is a Gauss density function, which average depends on the quantity of illumination and the nature of the material, maintaining approximately constant its variance. A pixel will be considered no faulty, when it observes:

$$m(x,y) - X_1 \leq p(x,y) < m(x,y) + X_2$$

m(x,y) is the grey level average (3 x 3) from correct pixel and $\mathbf{X_1}$, $\mathbf{X_2}$ the grey values around the average and **p(x,y)** is the average from image to analyze. The processing steps are minimal (average in the neighbourhood environment and local comparison with patterns) and allow to define defects with appearance "clear" or "dark". Subsequently, it is passed to detection of presence /absence of defects with a simple image histogram result.

The absence of defects permits light pattern updating, with the aim of removing potential defects produced by the waste in the lamps, presence of powder, or variation in the levels of natural light of the plant.

The presence of defects will originate an object labelling stage into clear and dark objects. In the case that the number of objects were excessive (case of the sticking defect which envolves many images) the local thresholds will be increased (X1, X2) carrying the formation of a new light pattern. The experience has demonstrated that the identification of defects does not require an excessive number of objects, as the presentations of these maintain space characteristics well differentiated. Therefore, the local thresholds is a dynamic characteristic and its value will depend on the aluminum appearance.

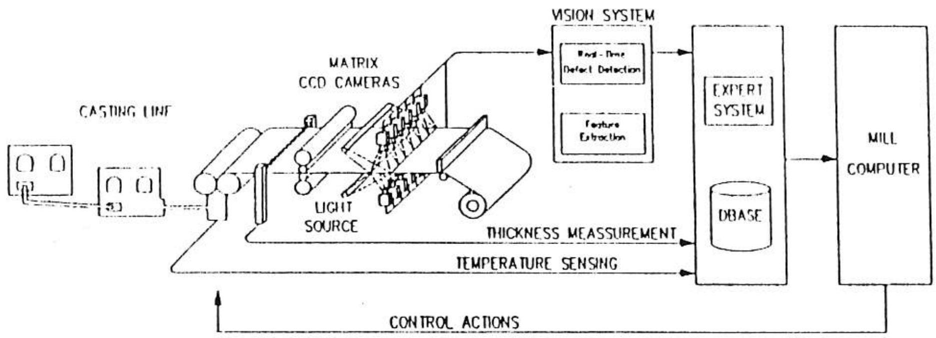

Fig. 2. Developed Architecture.

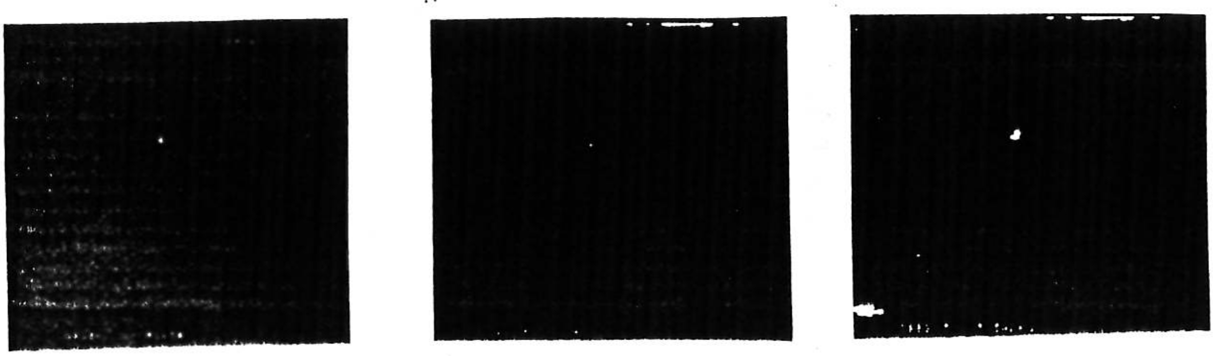

Fig.3. Defect Detection Process.

3.IMAGE ANALYSIS MODULE

Feature extraction

One of the main problems in pattern recognition is the optimal selection of features . We have used syntactic methods for defect representation, therefore direct methods are employed to describe defects with primitives. Once defects are segmented into object as shown above, the use of syntactic methods carry out the descriptive selection of the objects and defines the stage of feature extraction.

In a first development, the all possible number of object attributes were extracted, characteristics of edges and regions with techniques of scalar transformation, attending to the Pavlidis classification [4]. The knowledge of defect privileged directions involving traverse or longitudinal bands as well as speckles, forced up the development of a continuous algorithm based on defect mass mass and to perform a transformation from object information into terminal elements that are common to all grammars. Terminal elements has been used to associate object attributes with spatial features. Theses primitives act as sources for parametric and non parametric classifiers.

Primitive obtention Method

Objects grouping in primitives

Figure 4

Once a defect is detected and analyzed, features belonging to every object are capable to act as input vectors to the grouping algorithm. Objects are classified by their area in very ROI (region of interest in the image), and then objects are labelled into predefined shapes (points, speckles, longitudinal bodies and traverse bodies) and compactness level is calculated. Then, objects are associate to terminal elements starting from the most significant objects (acting as seeds), following rules of of continuity and vecinity, starting from gravity centres and searching along privileged orientations. This operation ends with labelling and getting features for the medium-level terminal elements (figure 4).

For each defect an information tree is obtained following the previous steps; each node of this tree contains the terminal elements and the information of lower level, for each of the images in witch the defect was detected.

At this moment, we have a terminal element collection ready to use as the input vector for classifiers based on concatenation rules, composed by the primitives sequence, but we also need an input vector for data-based classifiers. For this reason, the primitives information requires a transformation from terminal element sequences to pattern vector with n dimension. Feature selection can be approached by separating the problems of optimal clustering and dimension reduction.The latter problem is solved by a transformation

$$x = \Lambda z$$

where Λ is chosen to diagonalize the covariance matrix of the sample, z features proposal from pattern primitives and x will be result pattern vector.The features are ordered according to the increasing size of the covariance eigenvalues. Larger eigenvalues of the covariance matrix imply more spread in the samples in that direction, which in turn implies less confidence in that feature. The directions corresponding to the n smallest covariances are then chosen as the feature [5]. With pattern space chosen, we had used Sammon mapping for deducing the best grouping that solves the second problem and it allows to reach optimal feature selection.

Sammon's mapping showed as the label samples of same clusters were close or not. And we had good results with normalized vector

$$x_{ij} = \frac{X_{ij} - \overline{X}_j}{\sqrt{S_j}}$$

where $X_{i,j}$ is the j feature of the i sample, X_j and S_1 is average and covariance of j feature.

Another idea is where we can obtain the measurement space from primitives pattners. Firstly, we consider that if the interpretation through primitives is possible and reliable then they would fit as input sources for classifiers based on data. The objective is to condense primitive information into a vector. For this reason, we got some features as invariant moments, area for every primitive, perimeter of primitives,... to be included in the pattern vector. The set configure the measure vector, z.

This method offers multiple advantages. First, if there is not uncertainity in defect representation through primitives, the information volume is smallest and its conclusion is smallest n dimension by pattern space.Second, the quality of pattner vector depends of quality of primitives, therefore if terminal elements information contains information about defect structure then our descriptors will have higher cualification than classical descriptors. Third, the pattner vector is gotten with the whole images that includes defect, and it is independent on the numers of images. Fourth, vector dimension is smallest because each descriptor has cualitive information and not cuantitative one. All theses reasons permits to use togheter serveral classifiers in real time, because we only need a vector with 18-dimension in our application.

4.CLASSIFICATION MODULE

Defect recognition problem is not an easy task; the solution can be obtained using a conjunction of several Artificial Intelligent techniques, v.g. Laveen Kanal introduces the concept 'hybrid system' [6]. It seems necessary to use several tools for the recognition; in this case we have used paramentric and non parametric classifiers. The output data from the primitive recognition becomes as the common input vector to all the subsystems that build up the classification module. Each subsystem performs a separate classification by itself, having all of them complementary features. Output vectors from these classifiers act as inputs for a neural net which acts as supervisor and decides what type the defect belongs to.

The techniques employed were selected as a result of searching for classification subsystems with supplementary features. Primitives have conditioned the use of free-context grammars for each defect type, so a rule-based production system has been implemented and in addtion we tried to increase performance including concepts about fuzzy clasifiers[7]. Several nets have been used to perform at this stage[8]. Also statistical decision is used[9]. As a result of this research the following combination of tools has been chosen:

1. Rule-based systems: use of a free-context grammar for each defect type, along with supervising system and fuzzy classifiers.

2. MLPs with backpropagation learning algorithm, useful by their high capacity of generalization.

3. LVQ Net with nearest neighbor based classifier.

4. ART Net for the determination of new defect types.

5. Statistical decision

At the top, acting as a supervising system, a neural system selects the most accurate classification. In the following ,every subsystem is showed in detail.

Rule-based Production subsystem

The aim is to justify the presence of primitives according to spacial situation and defect topology. Every grammar, one by defect type, generates a particular type of rule set. In most of the cases grammars are not well-known and they should be inferred from a patterns set. The basic idea of grammatical inference is to find out the rules from a sample set belonging to the same defect type. This task is carried out for each defect type, which results into a non-recursive grammar. Redundant productions are swapped out and grammar is converted into a recursive one in order to generate an infinite number of words The rules are based in the connectivity between primitives, by continous area and sudmodel finding. It concludes into grammars as:

$$G_i = (V_{N,i}, V_{T,i}, S_i, F_i, R_i) \qquad 1 \leq i \leq m$$

where m is five or eigth class and $V_{N,i}$, $V_{T,i}$, S_i are independent of grammar, only rules, F_i and classifier functions, R_i, depends on the class. It is used to search up-down, firstly it begins searching a submodel and then it tries to chain themselves and it gives an interpretation logic. When it is finished, the resulting string is passed to the supervisor and it decides what kind of defect owns the string model [10].

Introducing fuzzy variables in production rules

We try to get fuzzy connectivity in order to words that are representative of defect, have ownership levels to diferent grammars. If we used a conventional classifier, as above, a sample P belongs to grammar ω_i if :

$$P \in \omega_i = \omega_i(V_{N,i} \cup V_{T,i})$$

but if the classifier is syntactic fuzzy, the sample P belongs to ω_i when ownership level, $gr(P/\omega_i)$, is upper than the rest of the grammars

$$\{P \in \omega_i \mid gr(P/\omega_i) > gr(P/\omega_j) \quad \forall i \neq j\}$$

First stage consists of fuzzy equivalents to deterministic values of inputs assignation. For each input variable it is necessary to define the discourse universe and the linguistics labels that are going to be used, as well as the ownership function associated to each one. Polynomics ownership functions are simple to calculate and they are similar to normal density functions, easier to calculate, so they have been chosen in the fuzzing phase.

Fuzzy variables are suggested under descriptive conceptions of defect topology and they are partially obtained from the experience extracted from the above classifier. For instance, a material lack is introduced by dark primitives near to and clears ones, sharing similar masses. This is presented as a production rule:

IF((objects are near between themselves) && (have similar masses)) THEN defect is possibly a lack

After deterministic values of input variables have been translated into fuzzy values, the system make use of those rules that could be started out. Each vector acting as input to our system must be assigned to a set of m classes, that is, it must be divided into m parallel problems or sub-classifiers to be applied to every input vector x. In the case of study, aluminum strip, there are five main defect types, that is, classes:

- longitudinal bands
- traverse bands (dark and clear)
- sticking
- lacks
- abnormal crystallization

An useful tool for the rule-based system construction is the so called Questions Matrix, which, if completely specified, involves all the possibilities of clauses combination.However, in the actual problem, as well as in most of real systems, the enumeration of all the possibilities in clauses combination usually makes the system unaffordable, besides of introducing a great number of unmeaningful or impossible combinations. That is the reason why a partial matrix, with only the meaningful clauses combinations, is usually built. Implementation of the different sub-classifiers is carried out by means of rules association to each box with affirmative answer of ownership or exclusion.

The sub-classifiers set in our application takes the fuzzy production rule-based systems structure, where consequents are not purely fuzzy sets but fuzzy elements representing ownership confirmation or exclusion for the input vector to a defect type.

IF fuzzy antecedent THEN (μ^c,μ^e)

being μ^c,μ^e confirmation and exclusion indexes to a defect type. When indexes are calculated at every rule evaluation, the totality takes effect by combining confirmations and partial exclusions for the complete rules set; in this way the ownership or exclusion rate for the input vector is obtained for each defect type.

Regarding the increase in the computational time for fuzzy classifier and the not more significative results obtained in comparison with conventional syntactic classifier, it has been only implemented the conventional syntactic classifier in the final software.

Methods based on neural nets

Starting out from data described in previous points (from output syntactic filter) the input for neural net based classifiers will be got. These inputs are formed by some general characteristics about the defect to be classified; and by the internal structure such as the whole weigh of the primitive that forms the defect:

- general data: The width and length of the whole defect will be specified; also the 'y' coordinate of the gravity center; also the inertia moments of the whole defect are taken into account These five features are separately calculated for the part of the defect that is dark and for that which is clear, resulting in the first 10 input features to the net.

- Internal structure data: Theses features will give the information about the structure of the defect according to its primitives. For this objective, the sum of the areas of eigth different primitives is calculated.

We started from a set of labelled samples near 200 and they were separate into five or eigth classes , and the representatives of each class resulted not of the same size. This set was divided into two random groups, one of them for learning and the other for test purpose.

Several architectures has been tested (MADELINE, MLPs + Backpropagation, SOM, LVQ and ARTs); MLP, LVQ and Fuzzy ART have shown as the most suitables for the application.

MPL + backpropagation have been adopted by their good generalization properties. Using a growing technique [11] the hidden layer was increased from 2 to 30 elements. These nets were trained with numbers of renovation cycles of the weighs of 2000, 3000, 4000, 6000, 8000 10000, with a moment =0.4 and a size epoch of 16. The objective was to generate a net that enough learns in order to generalize well with minimum number of elements. The conclusions with six neurons in the hidden layer and a training between 4000 to 6000 epochs are shown in the figure.

When applying Kohonen Maps for pattern recognition, accuracy can be improved if cells are adjusted following supervised training principles, LVQ [12]. The input vector was normalize by zero average and unit covarianze, it give more results than without treatment input.The total number of tried codevectors has varied between 20 and 30, and best results correspondended to 25 and 26 codevectors. Training for codevector has been accomplished by means of OLVQ1 algorithm; but it was experiment by LVQ2 and LVQ3 too, although theses algoritms represents not significant improvement [13].

As alternative to MLP and LVQ nets, a fuzzy net topology ART is adopted. This option is justified by some properties of this net: ability to detect new defect types and posibility to use an analog input vector. At this stage of development we have not achieved significant results with this kind of topology so this is the reason why results are not shown in Tables I and II.

Classifier based on probability distribution

Starting from a labelled sample set, several histograms for each feature in each class are obtained, that is, the expected ranges for each feature for every defect type; so wew obtain n-histogram set by class

$$H^k = \langle h_1^k(x),\ h_2^k(x),\ \dots\ ,\ h_n^k(x)\rangle$$

where x is the feature vector and h_i^k is the i-feature histogram of k class. If we normalize the distribution, then ^{Hl} can be regarded as the probability distribution of the feature value. Since we have only a finite number of training images, p^k represents an approximate probability distribution.

$$P^k = \langle p_1^k(x),\ p_2^k(x),\ \dots\ ,\ p_n^k(x)\rangle$$

The classification rule will contain the maximum probability of ownership x^* to ω_k. Then, if it demonstrates the independency between features (covariance matrix of sample set), $p(x/\omega_k)$ it will be the product of probabilities for each feature of the vector,

$$c(x^*) = k \ Si \ \prod_{i=1}^{n} p_i^k > \prod_{i=1}^{n} p_i^l \quad \forall k \neq l$$

beeing c the decision function. The features are the number of primitives, total area of defect, number of ROI, height of longitutional bands, width of traverse bands,.... The results of this classifier are the best under typical defects but it has uncertainr behaviour with irregular defects.

Results of the classifiers

The preliminary results of the different classifiers can be contemplated in the table I and table II (see appendix).

Configuration of the hybrid system

Considering that the success of the control for the casting process depends on the rigth detection of the defect type, the truthfulness of the data is needed, therefore the artificial vision inspection system must give a successfull classification. If we look at Tables I and II in Appendix I, it was not possible to reach the 100 % success from any of the isolated classifiers. This forces up the use of a hybrid system.

In other hand, previous classifiers have only the aim of identifying the topology of the defect. But the defect type can be caused by past patterns, that is to say, it is necessary to keep present the history of the defects of the reel. If all these assumptions must be considered, recurrent nets design is necessary along with rule based systems that keep also the history of the process. The objective is divided into two phases, one that identifies the type of topology of the defect and other that, considering the past history and information system, decides about the defect type. For instance, a defect of type sticking is characterized by the presence along several meters of traverse dark bands; these ones will be not classified as dark bands but as sticking based on the mantained history about the aluminum strip.

The presented configuration implements neuronal nets, rules based systems and statistical decision in order to reach the 100% accuracy when determining the defect topology, which is confirmed by a supervisor net. In the second level an expert system is founded that will infer which is the action to be taken in the casting process with data coming from the vision system, the thickness measurement system and from the temperature measurement system.

5. CONCLUSIONS

A pattern recognition system for surface defect identification in cast aluminum, based on several artificial intelligent techniques, has been presented. Artificial vision algorithms has been implemented for the description of the process and for feature extraction; the presence /absence of defect in the aluminum surface is on-line detected. The absence will provoke the renovation of the light pattern and the presence of defetc starts the classification process.

Syntactic methods are used for representation of the defect. The information primitives are transformed into a feature vector. It was discussed about the construction of the syntactic analyzer and the advantages/disavantages when introducing fuzzy models into production rules. Several neural nets and statistical classifier acts toghether for defect clasification. All together give information to a supervisor net, implement by a MLP with backpropagation learning algoritm. The conclusion is transmited to an Expert System which decide the control actions to be taken over the casting process and the quality of the product.

Image Processing algorithms have been implemeted into commercial Matrox's IMAGE 1280 board and the interface man-machine is supported with an application in Windows 3.1. The neural nets are absorbed int he final sotware and they had been devoloped with NEURALWORKS II tool. The fuzzy clasifier was built by GURU and it is not present in the aplication. The results are between 99.7% sucess for five classes and 95.7% sucess for eight classes. The final sotware incoprporates supervisor tools for classifiers improvement.

6. BIBLIOGRAPHIE

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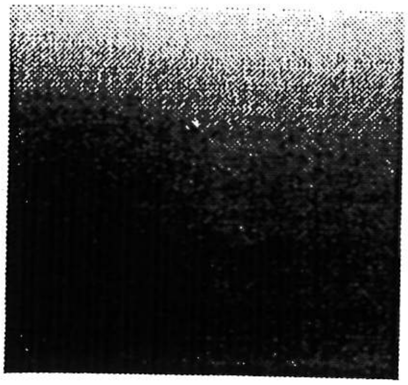
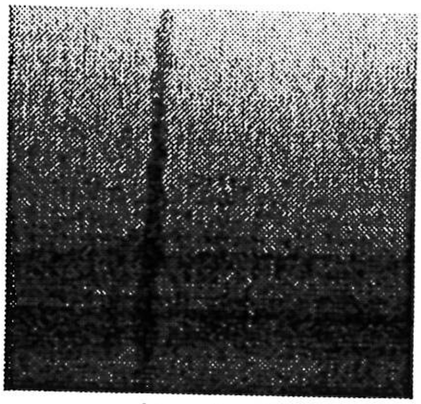
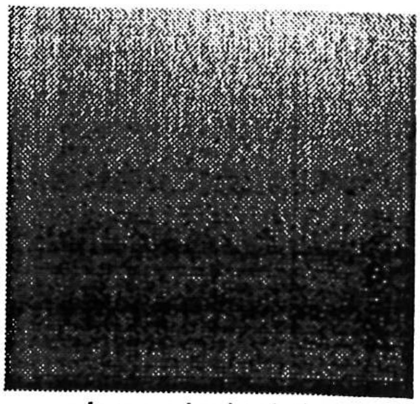
APPENDIX



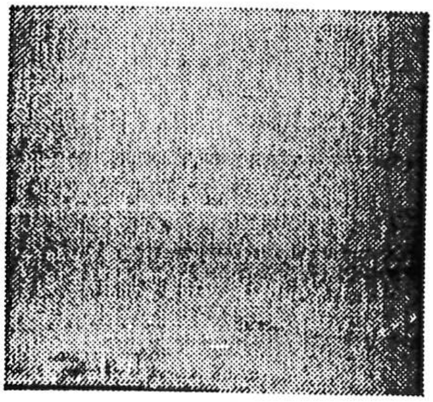
Lack



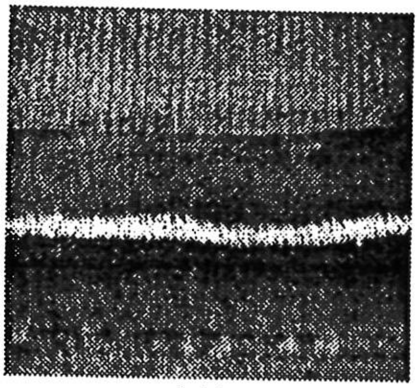
long. band



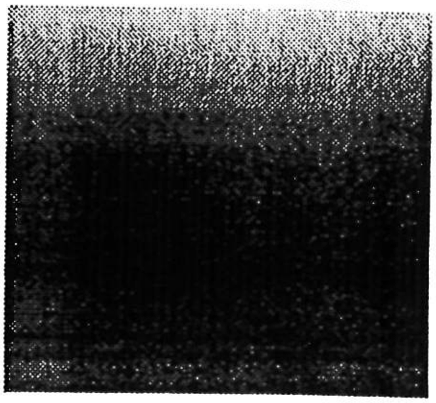
abnormal cristalation



traverse bands



sticking



without defect

Defect name	MLP	LVQ	F_ART	Syntactic	Statitistical	Supervisor
Sticking	88	66		100	100	100
Lacks	86	89		100	100	100
long. bands	100	94		100	89	100
traverse	97	100		94	100	100
ab.crist.	89	89		68	94	94

Table I

Defect name	MLP	LVQ	F_ART	Syntactic	Statitistical	Supervisor MLP
Sticking	88	66		88	100	100
Lacks I	86	89		100	100	100
Lacks II	83	50		66	100	100
long. bands	84	94		68	68	94
scratch	72	59		100	100	100
traverse	97	100		94	100	100
clear bands	100	87		100	100	100
ab.crist.	89	89		68	94	94

Table II