IAPR Workshop on CV - Special Hardware and Industrial Applications OCT.12-14, 1988, Tokyo

AN AUTOMATED SYSTEM FOR METAL STRIP INSPECTION

Timo Piironen[1], Olli Silvén[2], Toni Laitinen[2], Esko Strömmer[1] and Matti Pietikäinen[2]

[1] Technical Research Centre of Finland, P.O. Box 181, SF-90101, Oulu, Finland
[2] Department of Electrical Engineering, University of Oulu, SF-90570, Oulu, Finland

ABSTRACT

A prototype of an automated visual on-line metal strip inspection system is described. The system is capable of both detecting and classifying the surface defects of copper alloy strip. It has been installed on a production line in a rolling mill for evaluation. The inspection algorithms are based on morphological preprocessing and combined statistical and structural defect recognition. The image acquisition part of the system is based on a CCD line scan camera and bright-field lighting. The image processing hardware consists of commercial modules. An analysis of this implementation and a proposal for a full-scale industrial system are presented.

INTRODUCTION

Metal strip is typically a 0.3 - 2.0 m wide and 0.1 - 5.0 mm thick shiny metallic band. It is basic material in the fabrication of a large variety of products in, e.g., electronic and electrical, automotive and construction industries. This naturally subjects the strip to automatic forming and surface finishing steps, that require correct metallurgical and surface properties.

In rolling mills the surface quality of strip is currently controlled mainly by human on-line visual inspection before cutting the strip into variable length sheets for delivery. Human inspectors classify the defects according to their cause and origin because the inspection results are used as feedback to correct the manufacturing process.

Defect recognition is not always straightforward; occasionally the real nature of a defect comes to the fore only after examination with a magnifying glass. Thus, flaws that appear similar to the naked eye, or a visual inspection system, may fall into different defect categories. Also the large number of defect types may cause difficulties for non-experts, for example, a copper strip manufacturer recognizes well over twenty surface defect classes.

The experience of the inspector is essential, because there are seldom any fixed defect criteria. The inspector's pass/reject decisions seem to be based on the types of the defects, the maximum number of defects per unit of surface area and the total number of defects on the entire inspected strip. In addition, the inspector's knowledge of the customer and the use of the strip have a great impact on the decisions.

Automatization of the visual inspection of metal strip is an acute problem because the human visual inspection is an unreliable, tedious and boring task. Several automatic inspection systems have been designed for this purpose, but they are generally only defect detection devices /1,2/. The methodology of these systems is usually based on thresholding the image signal and applying a region growing algorithm to the scan lines. Defect recognition and assessment are performed by a human operator that is notified of discrepancies found .

The computational requirements of strip inspection are severe. In a typical copper strip case, the strip to be inspected is 1 m wide and moves at the speed of 1.5 m/s, and the required minimum size of the defects to be detected is of the order of one millimeter. This amounts to over 3 million pixels per second because both strip surfaces must be inspected.

OVERVIEW OF THE EXPERIMENTAL SYSTEM

The inspection system prototype described in this paper employs an image acquisition system that is sensitive to most strip discrepancies. Image acquisition is followed by a preprocessing stage based on grey-scale morphological erosion and dilation operations that enhance the interesting features and suppress noise. The preprocessed image data is thresholded and subjected to binary connected components analysis that is equivalent with the region growing procedures of current industrial systems.

All the defect candidates are submitted to an automatic defect analysis stage because even the smallest ones may give valuable clues. A preliminary recognition is performed with a fast tree classifier by using the size, shape, and orientation features computed for the possible defects. However, some flaws in the binary image may consist of several blobs with loosely defined spatial relationships. In these cases the analysis stage continues with a structural analysis that compares the relationships of each defect candidate with structural models.

The computational requirements of this sequence are several orders of magnitude larger than those of simple defect detection devices. However, the additional cost is well covered by the significantly lower need for operator intervention.

IMAGE ACQUISITION

The metal strip defects are either distortions of surface colour or have a finite depth or height. The sizes of the flaws in every class vary greatly.

The most common two-dimensional defects are irregularly shaped oil, water or oxide stains. Foreign particles or dirt rolled into the surface, usually observed as discolored spots and streaks, are also 2-D faults.

Surface lamination defects often consist of metal flakes partially attached to the surface or shallow pits. Both transverse and longitudinal versions of these defects exist. Also surface scratches have these two dominating orientations but their width is smaller. Chevron cracks are chevron-shaped defects that usually appear in groups where the defects have a common orientation.

The detection of these defects on shiny metallic surfaces is a difficult problem from both illumination and imaging standpoints. The surface must be examined at specific viewing angles in order to detect defects and often the viewing angles of different defects vary. Special illumination arrangements are necessary even for human inspection.

Condensing bright field imaging arrangement with a 1024 pixel line scan camera was adopted in the prototype system. The illuminator is implemented by using a large fresnel lens and a halogen light source as depicted in Figure 1.

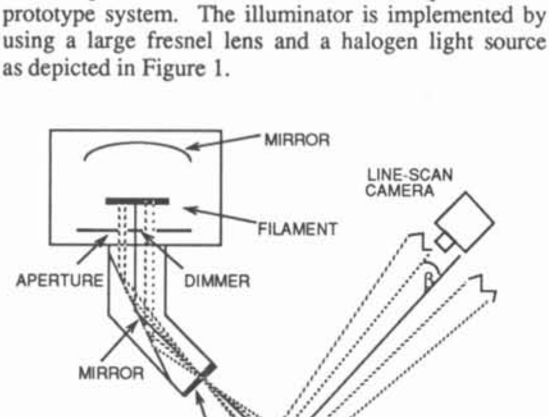

Figure 1. Illumination and imaging system.

The fresnel lens acts as a condenser and forms the image of the halogen filament on the entrance pupil of the camera lens together with the specularly reflecting defectless metal surface. The illumination system permits the control of the direction of the incident light to the surface and the viewing angle of the camera relative to specular reflection. Direction control is achieved with the fresnel lens and the viewing angle control by the dimmer installed in front of the filament. The viewing angle can be tuned for the detection of the most critical defect types depending on the surface roughness of the defects.

The maximum width of the inspected strip is 600 mm with the current illumination device but can be expanded to 1000 mm by using a wider fresnel lens and a longer CCD camera array.

INSPECTION ALGORITHM

The purpose of the inspection algorithms is the detection and classification of possible defects. Knowledge about the defects can be used for alarming the operator or controlling the production machinery.

The inspection algorithms are invariably a compromise between recognition accuracy and available computational power. Very good recognition accuracy may be achieved if the implementation issues are ignored /3/. However, any practical inspection system is a product of optical, and illumination hardware, and algorithmic solutions. Every part of the system must be designed to fit the whole.

The ideal copper strip has a homogeneous specularly reflecting smooth mirror-like surface and the defects are detected as aberrations of the reflection properties. However, any change in the strip reflectance function can not be flagged as a defect because a defectless strip is normally not completely homogeneous but varies locally due to the raw material and manufacturing process.

Due to the bright-field lighting scheme used in the prototype system, defects generally reduce the light intensity reaching the camera and are registered as areas darker than their surroundings. Some defects may have locations that are brighter than the defectless areas of the strip. However, this phenomenon is not very common and so far no purely bright defects have been encountered.

The overall algorithmic structure of the prototype system is similar to most previous pattern recognition and visual inspection systems. The most notable differences from these solutions are the used morphological preprocessing and segmentation, and the structural classification of defect candidates.

The image created by the image acquisition system is first subjected to non-linear morphological filtering to remove noise. This step deletes all small regions brighter than their background and enhances the small dark areas. The preprocessed image is segmented by thresholding and the produced binary image is used in subsequent analysis steps. An adaptive thresholding scheme is used in order to prevent larger and smoother variations from being detected.

Our tests showed that a binary image generally provides enough information for a human inspector to carry out defect classification. Thus, the performance of automatic defect classification should not suffer significantly if binary image analysis is used. The advantage of this approach is the possibility to use available commercial hardware.

After segmentation the typical strip surface defect appears as a small blob or a group of blobs, that may be organized near the same vertical or horizontal line. Stripe-like defects are common, too.

The next step analyzes the connected components of the segmented image and calculates several shape and orientation features for each blob. This data is fed to a tree-classifier to obtain the tentative defect classes for the blobs. Most of the defects are correctly recognized by this stage. However, the statistical classification is not an adequate solution.

Some defects consist of several disconnected blobs whose spatial relations are important for determining the correct type of the flaw /4/. For example, a typical longitudinal spill consists of several shallow, possibly elongated blobs at irregular intervals as demonstrated in Figure 2. Also scratches are often detected as lines of small blobs.

These kinds of defects are searched for at a structural recognition stage based on measuring the similarity of semantic nets /5/. A human inspector seems to perform this kind of recognition task effortlessly but in the inspection system significant computational resources have been allocated for this step.

Figure 2. Examples of a larger defect (left) and a defect consisting of many small blobs.

After defect recognition the applied basic acceptability criteria are very similar to the human inspection: The number of defects per unit of surface area must be below a defined maximum and no fatal defects are tolerated. After this initial pass/fail decision the quality class of the strip is determined more accurately based on the types and density of defects.

The defect classification of experienced human inspectors and the prototype system differ from each other as the humans use metallurgical classification. However, the prototype system can only use the classes that can be discriminated from the image. According to our experience, a metallurgical defect class may have several differing appearances and the visually similar defects may have different metallurgical properties.

REAL-TIME IMPLEMENTATION

In order to achieve rapid implementation the inspection system prototype is built from system level modules. Its current throughput is approximately half a million pixels per second that is satisfactory for testing the system in a production line. On-line tests are necessary to gather data of the acceptability and defect criteria for further development of the analysis stage.

Due to hardware compatibility reasons the inspected images consist of 512x512 8-bit pixels. Each pixel corresponds to an area of about 1 mm x 1 mm or less on the strip. Most image processing and analysis operations are performed with hardware support. They include: morphological grey scale erosion and dilation, arithmetic and logical operations on pixel-by-pixel basis for combining the result of the morphological operations with the original image, connected components analysis of the defect candidates and the extraction of their features. Further classification of the blobs is performed with software algorithms.

The block diagram of the image processing system is shown in Figure 3. The system is realized by Maxvideo® (Datacube Inc., Peabody, MA.) and APA-512 (Vision Systems Ltd., Adelaide, Australia) machine vision modules /6/. The CPU is based on the Motorola M68020 microprocessor.

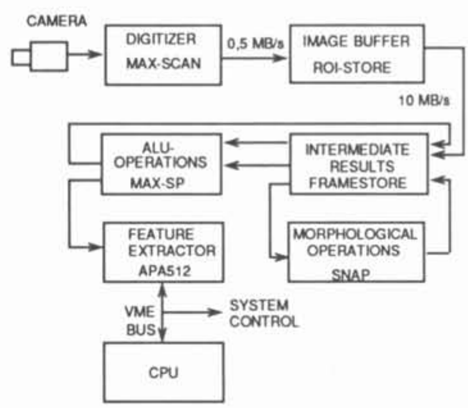

Figure 3. Functional structure of the system.

The system is based on a pipelined architecture. Each processing unit in the pipeline reads data from the previous unit and sends its output to the next unit. Memory units are used as temporary storage for the intermediate results. A control unit synchronizes the operation of the units.

In order to reduce the number of the processing units, the image data is circulated from the intermediate result storage via the morphological unit or the ALU-processor back to the intermediate storage. Then the control unit can re-load the operation instructions to the processing units and start a new re-circulation cycle. Each cycle takes 26 ms. The disadvantage of this scheme is reduced speed, but this is offset by a lower number of processing units and reduced cost. The classification time of the blobs by the CPU depends on the number of the blobs.

Typically the inspection time for one 512 by 512 image in the current system is 450 ms. The system throughput can be improved by providing extra morphological units and thus reducing the number of re-circulation cycles. The maximum throughput attainable in this way is approximately eight times the current one. This would only double the cost of the system.

EXPERIMENTAL RESULTS

Laboratory tests were carried out by inspecting 150 test sheets sized 500 mm by 800 mm. A sample sheet typically contained several different defect classes: defects created during the manufacturing process and small scratches, fingerprints and dirt caused during the cutting, transferring and handling of the sheets. On-line tests were carried out on a manufacturing line of cold rolled copper strips.

The performance of image acquisition and segmentation stages are promising. All critical defects are visible in the image and are segmented reliably. The system is insensitive to mechanical vibrations and harmless reflectance patterns on the strip resulting in a low false alarm rate.

The classification of larger defects like longitudinal and transverse scratches and colour defects by a tree classifier works well but is not reliable with flaws formed by several small area defects, such as spills. Structural defect analysis improves the identification performance in these cases. Nevertheless, advances are still needed to achieve fully automatic operation.

Extensive testing of defect identification and classification algorithms is in progress.

SUMMARY

An experimental inspection system capable of real time algorithm testing in a manufacturing environment has been developed by using commercially available image processor components. In its current form the system can inspect only a part of the strip width. However, it should be possible to expand the system by adding standard hardware.

The illumination arrangement used can be tuned to optimize the contrast of different defects depending on the surface roughness of the base material and defects. The good performance of the lighting solution has greatly simplified the analysis algorithms.

Defect recognition is based on the analysis of blobs in bilevel images that is a rather conventional solution. However, morphology based adaptive thresholding enables the control of local contrast, shape and size of the blobs to be detected resulting in a low false alarm rate.

Statistical defect identification based on the features calculated from each blob in the segmented image is reliable for large defects only. The use of structural pattern recognition techniques for defects consisting of several components has given promising improvements in classification accuracy.

The classification process is complicated by large variations in the appearance of particular defect types and the lack of exact models for the shape of the defects. The experimental system is used to collect defect data in a process environment and as a testbed for further algorithm development.

ACKNOWLEDGMENTS

The financial support provided by the Technology Development Centre, Outokumpu Oy, Nokia Oy and Rautaruukki Oy is gratefully acknowledged. The authors also wish to thank Mr. Tapani Westman from the University of Oulu, and Messrs. Pekka Ruuska and Martti Elsilä from the Technical Research Centre for their contributions.

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