A System for Real-Time Fabric Inspection and Industrial Decision

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ABSTRACT

This work presents an application of software engineering to fabric inspection. An inspection system has been developed for textile industries that aims automatic failure detection. Such as wood, paper and steel industries, this environment has particular characteristics in which surface defect detection is used for quality control. This system combines concept from software engineering and decision support. Detection of defects within the inspected texture is performed in a first step acquiring images by CCD cameras, then extracting texture features and, finally by classifiers being trained a priori on database of defective and non-defective samples. The extracted data depend on the type of method selected for image analysis. The used types are based on segmentation or fractal dimension. Two usual segmentation techniques were adapted and improved. A new algorithm was developed to calculate efficiently fractal dimension of textures. Experiments show the accuracy and applicability of the proposed techniques for a real factory environment.

Categories and Subject Descriptors:

G.1.0 [**Numerical Analysis**]: General; H.5.2 [**Information Interfaces and Presentation**]:User Interfaces; I.3.6 [**Computer Graphics**]: Methodology and Techniques; I.4.0 [**Image Processing**]: General; J.6 [**Computer Applications**]:Engineering.

General Terms:

Algorithms, Management, Measurement, Performance, Design, Economics, Reliability, Experimentation, Verification.

Keywords:

Industrial application, decision support systems, real-time quality control.

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1. INTRODUCTION

All industries aim to produce competitive goods. This is possible if these goods conquer the consumer and maintain their profit. The competition enhancement depends mainly on productivity and quality. With the advances in electronic technologies, much can be done to improve productivity by using automation as an integral part of manufacturing systems [20, 21, 22]. The primary benefits of automation are reduction in organisation time, improvement on equipment utilisation, better processing and reduction in manual intervention.

Industrial quality control is designed to ensure that defective products do not reach the customer. For this reason, it forms essential information for the whole industrial process, with influence from the design to logistic planning, as well as on manufacturing. Moreover, the quality control must be automated too. Therefore, automatic quality control has become one of the major business strategies and perhaps the most important way to achieve success in a highly competitive world market.

Industry should expect effective support of quality assurance activities by a complete Quality Information System (QIS). Usually, QIS should cover three stages: pre-production stage (the needs of the customer and design), production stage (equipment maintenance, statistical control and inspection) and post-production stage (distribution, sales and product performance). However, sometimes it is impossible to do a complete QIS. Generally, commercial software available in the area of quality refers to: (1) statistical process control, (2) statistical quality control, (3) in-process inspection control, or (4) computer-aided simple quality tools for recording and storing data [2].

Visual inspection constitutes an important part of quality control in many industries. Until recent years, this job has heavily relied upon human inspectors. The use of multimedia advances and the development of fast and specialised equipment for image capture have stimulated applications of new information resources to QIS. Resources such as knowledge acquisition, knowledge-on-demand and service-on-demand technologies enable QISs enter the information technology age [15].

In this paper we describe how net-communication, databases, knowledge representation, and image processing techniques can be combined by software engineering to create an automated visual inspection systems [1]. Many attempts to combine these techniques have been performed [5-8] and, finally, were successfully achieved here. The starting point was the search of an algorithm for surfaces identification that was efficient enough for applications in real textiles (a point where the traditional approaches [11,18] fail). Reference [5] describes the algorithm developed in order to satisfy the characteristics of this application. Then this algorithm had its potentialities and limitations studied in details [6], which showed the necessity of combining techniques to supply the high precision need to real industrial systems [7]. It is important to point out that other researches in the same subject [13] are still in such a initial phase, of searching a single method that can be used in textile quality control. Reference [8] showed that multiple resolution analysis, time and flexibility are fundamental for the textile inspection. It drove to the new ideas presented here for a definitive solution of the problem of textile inspection: the use of multiple resolution acquisitions and multiple learning divisions.

1.1 Structure of the Paper

Organisation of this paper is as follows: Section 2 gives a brief overview of the factory environment and how intranet and multimedia resources can be included in this kind of industry without dramatically changing its configurations. Section 3 describes the proposed defect detection system sketching its structure. Sections 4 and 5 discuss the used methods and some particular details of the implemented techniques. A critical review of the results, some conclusions and progresses on next QIS implementations end this paper (section 6).

2. PRESENTING THE ENVIRONMENT

The structure of a weaving plant is variable and influenced especially by the types of raw materials, the degree of industrial automation and the final produced textiles. In general, the textiles are produced passing the raw materials throughout several steps like cleaning, preparing, combining fibres, spinning and finally weaving.

In this paper we propose automatic detection of fabric faults as a first step for a future complete industrial Quality Information System (QIS) in textile industries. We consider the production stage, inspecting the final product, the woven textiles, as greige (or gray goods) or after submitted to the bleaching and dyeing process. That is, this quality control occurs at the end of manufacture process. When the inspection is done by the usual manual form, the operator/inspector makes a report with information like: size (width and height), type of textile produced, loom, worker's name, inspector's name, quantity and types of faults, and others.

The manual textile quality control usually goes over the human eye inspection. Notoriously, human visual inspection is tedious, tiring and fatiguing task, involving observation, attention and experience to detect correctly the fault occurrence. The accuracy of human visual inspection declines with dull jobs and endless routines. Sometimes slow, expensive and erratic inspection is the result [4]. Therefore, the automatic visual inspection protects both: the man and the quality.

The first point for the introduction of information resources in visual inspections is to simulate the highly complex human skill of image understanding [1]. The current advances in artificial intelligence and computer vision are a long way from achieving the image-classification and pattern-recognition ability of humans. This does not deter researches from trying to achieve automatic visual inspection, as there are many applications that can be tackled effectively by automatic technique [3]. Automatic inspection systems must perform several steps from image acquire and processing to image analyse, comparison and final decision [18]. Figure 1 shows these steps.

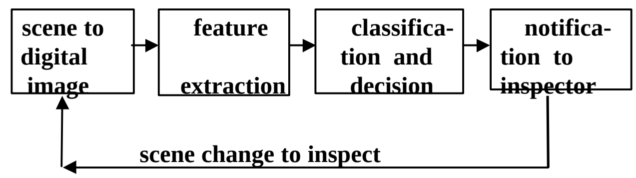

Figure 1 - Image inspection chain

There are many simpler computer vision softwares, where inspection using only a digital video (for acquisition of the image) and a computer (for image storage and processing) can be executed effectively [4]. However, this is not the case of fabrics. The term fabric fault covers all faults occurring in the fabric resulting from all previous stages of woven processing. It presents defects as small as its yarns and as large as the whole cloth width (figure 2-4).

To identify small imperfection the camera uses specific lens and must be properly positioned enabling the distinction between each fabric thread. But different type of lens and position are needed for others faults, like the stripe fault (ST) and thin place (TH), that usually extend across the full width of the fabric. Moreover there are other imperfections like holes (HO), interlacing faults (IF) and warp-end repair (WR) presenting medium size (figure 3), where for defect detection, it needs intermediate position and lens.

For plain weaves (like those showed on figure 2 to 4) at least 2 pairs of monochromatic (or gray level) cameras and lenses must be used [7]. When printed fabric or textiles with patterns or stamps are in the inspecting process (figure 5) this number can increase and, of course, for colourful fabrics, additional colour cameras (RGB or other 3 chromatic channel) are necessary (figure 6) [10].

3. SYSTEM ARCHITECTURE

An textile inspection system must have capability of storage and improvements in the decision learning in addition to those steps of usual visual inspection systems, showed in figure 1. The images are analysed and stored (for review or future reference) in real-time (the inspections process must not change the times in the industry) together with relevant data such defect location and dimensions [23].

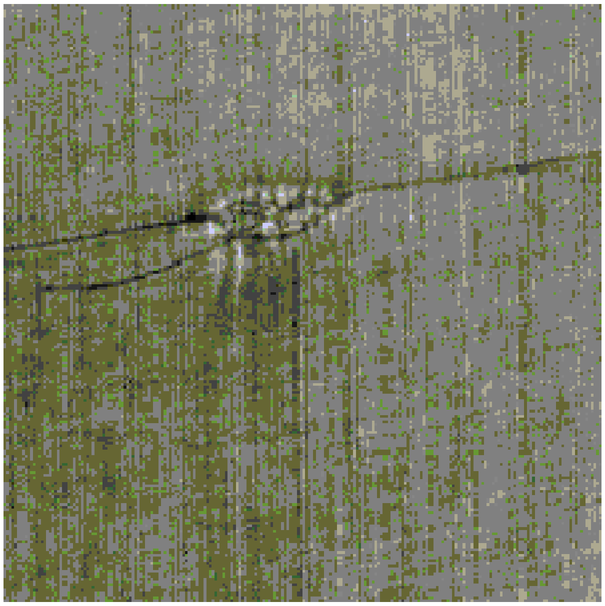

Figure 3. Medium size (WR) fault in woven fabric before the finishing process (Greige).

Figure 2. All width drill imperfection: thread pull off.

If the use of automatic fabric inspection machines with electronic fault classification is employed, there is an obvious need of many cameras to archive precision in fault detection. In big plants various inspection units, one per each moving fabric in real-time inspection, can be integrated with common databases of defects or documentation and human supervisor. Some types of defects can trigger directly a stop signal to machines or produce a supervisor interaction, as well as can only trigger a fabric marker

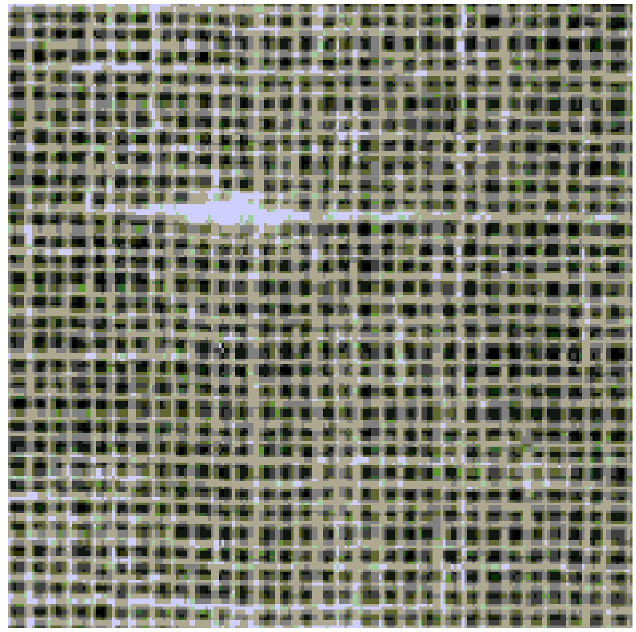

Figure 4. Greige with small (YD) defects.

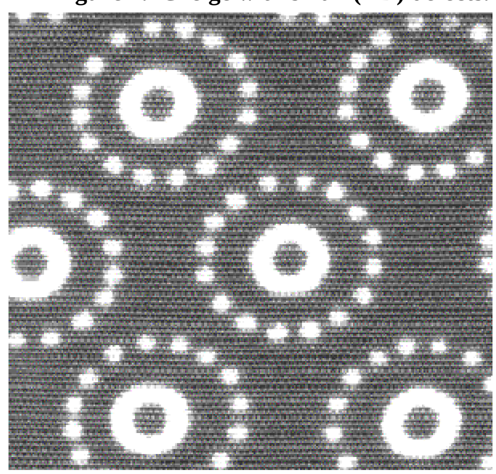

Figure 5. Faults in finished fabric.

Figure 6. Defective colourful textile.

device and register the defect (for documentation and printed defect report).

Images acquired by each inspection unit are displayed in real-time on supervisor video monitor, enabling the supervisor locate the rotary fabric machine and performing the required corrective action. Figure 7 illustrated a global view of our system's components.

4. USED TECHNIQUES

Such as birch wood board and steel slab, textile industries has particular characteristics in which texture feature extraction can be used for visual quality control. The computer vision techniques applied to textile automatic inspection in this paper can be classified in two groups: Segmentation Techniques and Fractal Dimension.

Segmentation is defined as "the process which subdivides an image into constituent parts or objects" [11]. It is a common and successful technique used for examining traditional images on inspection. However, to detect textile fault we can not subdivide the textile's image exactly into objects perfectly defined [13]. The main idea is: (1) use segmentation technique to subdivide the gray scale information in black or white points; (2) identify the pattern of the normal fabrics texture; (3) use pattern recognition techniques to identify textures that are different from textile without fail; and (4) find the fault associated with the imperfection in the database of defect patterns (Album of defects).

Many different techniques are available for image segmentation. The most commonly used include threshold and edge detection. Threshold is simplest and fastest, it has been used widely in the field of defect detection. There are various techniques to edge detection [18]. Typically the efficiency on estimating the imperfection of each approach depends on its characteristic: whether it uses image first or second derivatives, how the derivatives are approximated, how the two components of gradient are combined, and the threshold used to determine edge points. Both, threshold and edge detection have been used in this work, details of how they were implemented can be found in http://www.ic.uff.br/~cproenca/rb.html [8].

There are various numbers, associated with fractals, which can be used to compare them. They are generally referred to as fractal dimensions. These numbers are important because they can be defined in connection with real-world data, and they can be measured approximately by means of experiment [14]. There is not yet a broadly accepted unique way of associating a Fractal Dimension (FD) with a set of experimental data. Several approaches exist to estimate the FD in digital images (set of pixels). For example: the $\in$-Blanket method [16], which is a 2D generalisation of the original approach [17]; the estimation of FD from Fourier power spectrum of the image intensity surface [9, 12]; or the used variations of box-counting [19] approach to estimate FD, which is named differential box-counting approach (DBC) [5]. For applications in fabric the last one has been implemented because related studies have shown it more accurate [6].

However, as we will see in the next sub-section, no technique is the best in all cases. A good idea is combine approaches [8]. Moreover, each camera is related to a specific focus distance, that shows different details on fabric surface. The number of pattern (to recognise) is a function of used approaches; normal textile pattern; and the focus distance used to acquire the fabric sample. Defect identification is more easily performed than the recognition of the type of defect [7]. For identification of defect type, on gray level image, all possible pattern of this defect have to be learned before. For colourful fabrics, depending on the used colour space (which is three-dimensional), this database patterns could be multiply for 3. Colour as part of the information of a document is described by 3 channels, it need special hardware and other way of organising the patterns recognition process. Each new pattern will be associated with the representation of the image intensity on each colour of the base vector component [10].

4.1 Experiences

Experimentation has been developed (using 100 fabrics) for test these techniques on fault detection. Now the question is: Which is (considering the 3 commented in section 4) the best technique? These techniques are compared by the efficiency in no producing false alarm and in accuracy of correct defect identification on figure 8 and 9, respectively. The defects used on figure 8 and 9 are Hole (HO), Interlacing Fault (IF), Reed Mark (RM), Slack Thread (SK), Stripe (ST), Thin place (TH), Tight Thread (TT), Warp end Break (WB), Yarn Defect (YD), and Warp end Repair (WR). The abbreviations in parents are used in these figures for their identifications. The names of various fabric defects are not unique (universal) yet, which is a difficulty for automatic fault classification. It is possible to see sample of each type of this defect in http://visual.ic.uff.br/mvv.html [6].

In these experiments traditional threshold and edge detection methods were compared with the approach based on fractal dimension (FD) for textile surface recognition. The edge detection approach presented low average of correct identification of good samples (67%) if compared with the others (72% for threshold and fractal dimension). Threshold showed detection accuracy greater than 70% on average. Fractal dimension presents the better average results at both, good (72%) and defective (96%) samples identification. Results have shown also that the computation complexity and processing time of the FD approach, is much lower than that of the others approach [7].

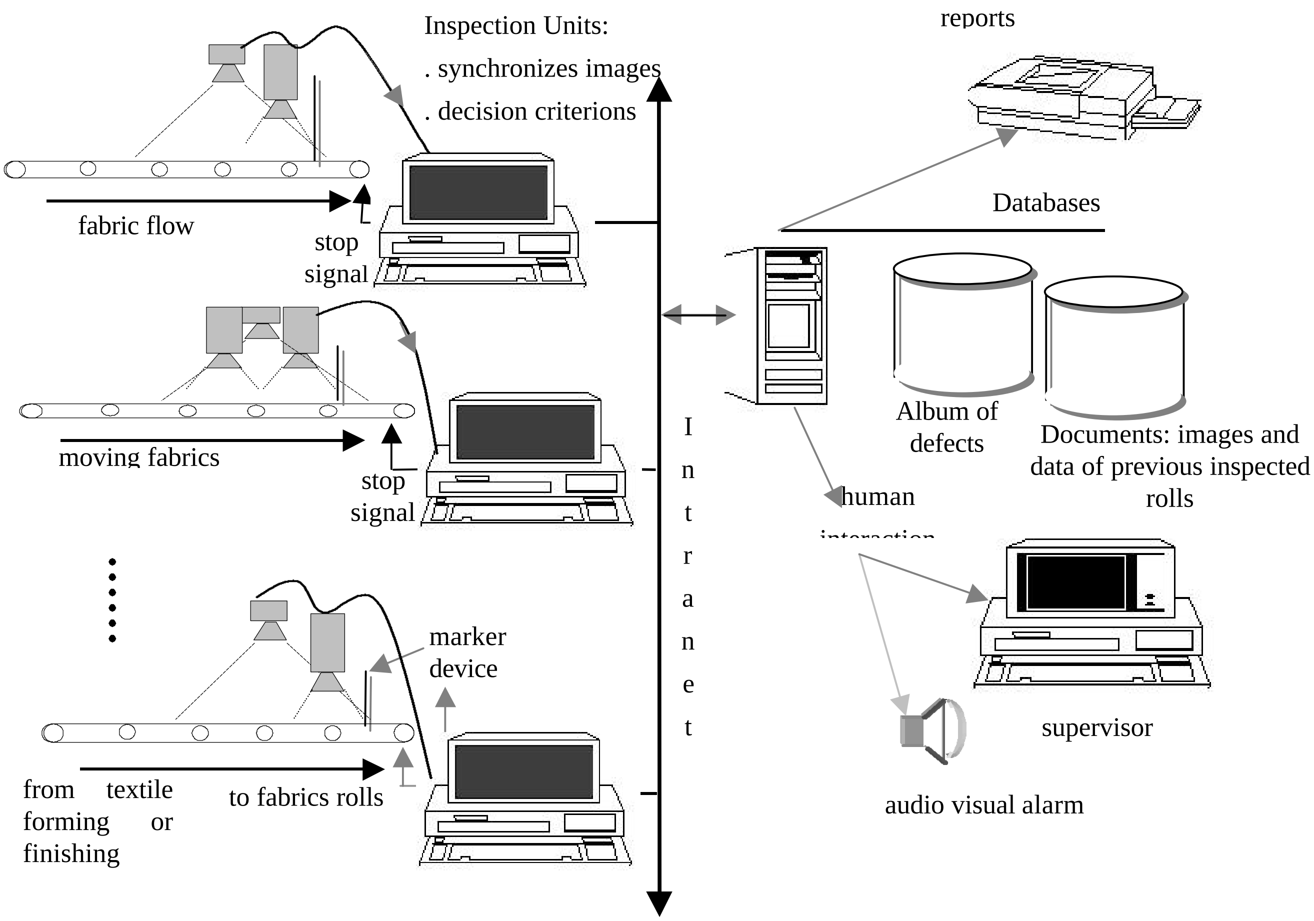

Figure 7. Overall inspection system.

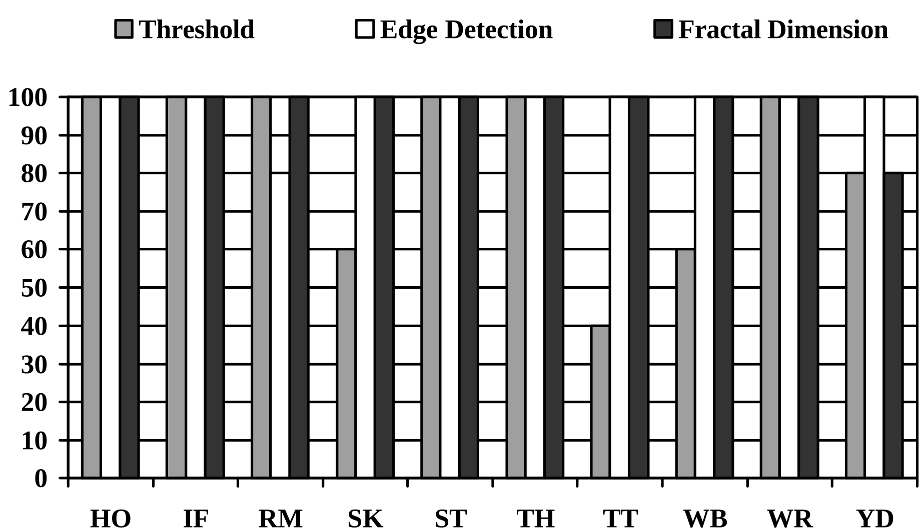

Figure 8. Percentage of accuracy of identification on textiles without defects.

However, in a closer look to these figures, we can see that none produces 100% of correct identification alone in all cases. The matching degree depends on the selected method and type of fault. In these experiments we use previous inspected fabric (by expert human inspector). In the implementation, the Inspection Unit (figure 7) always combines FD with one segmentation technique resulting in an implementation with 100% of correct identification and 0% false alarm, for all defects.

5. IMPLEMENTATION DETAILS

In the following, we discuss the software implementation approach and highlight the important features of the program structure and development. Figure 10 shows the logic flow of the main process occurring in each Inspection Unit. The starting point is the initialisation of the analysis in a position x of the fabric. This position is measured in centimetres from the beginning of the roll in inspection. The process ends with the answer to the question "Is this sample of textile defective?".

If the answer is no a new x position will be considered and the process start again. If the answer is yes, depending of the setting, many things can occur but always a report of the important data related to the defect is stored. For some types and dimension of defects, this answer trigger a supervisor interaction, stop the machines or trigger the marker device (figure 7). If identification of defects was required, the positive answer start the identification process. But in 95% of the cases, the type of the fault is a secondary mater, theirs extension, grade and repetitive (how many times it occur in this x position and how distance was the previous faults) is the main issue.

The image analysis uses the approaches described in section 4. Default option is “the use of all in combination”, but it is possible choose only one of the segmentation techniques (figure 11). At this point each (CCD) camera acquires the input digital image and process it using the pre-selected methods. So it answer the main question (is there a fault?) for the sample of each camera. The combination of all cameras' results answers the question for each x position.

However, before this final decision, for some cameras, other turns of acquisition and processing will occur. This number of acquisition depends on the textile width and on the frames' size. That is, an synchronisation process is executed to ensure correct covering of all (x,y) fabric surface This synchroniser is important because: (1) for covering all fabric width, each camera moves with different velocity on the (y) direction orthogonal to the fabric movement (due its capture distance and lens); (2) the focus position of each camera is not exactly at the same position (due to physical and optical characteristics -figure 7), and (3) depending on time restriction and quality insurance (parameter of control on figure 11) more than one image frame can be acquired for each camera and combined before processing.

The matching process is based in a learning step, where is defined the standards and the acceptable variations used for each approach. These standards depend on the used technique, textile and focus distance. Usually, this study can be divided in three steps. First, the approach to be used is selected (edge detection, threshold or fractal dimension). Second, no defective textile images are processed; then the standard value for the method and textile is determined. Finally, some defective textile images are analysed and the variation value for a specific textile/focus and approach is evaluated. This pre-process or learning step is fundamental for correct automatic inspection.

The system is developed in C++. The hardware used was PC machines, CCD Hitachi Denshi camera and Data Translation frame grabber. It is important to note that this hardware is neither specific nor expensive. This allows automation with low cost and adaptable with the industry necessity. The ControlSetup option of the implementation (figure 11) defines the parameters that will control the automatic process. These parameters are: the approach to be used (Method), time between successive frame acquisitions (DefineTime) and number of frames to be acquired (NumberofFrames).

6. CONCLUSION

A significant number of works have mentioned the need of advances in automatic control quality of many types of industries [2,4,20-22]. The fact that the accuracy of the human visual inspection declines with dull work is obvious. In general, manufacturers agree that automated systems increase productivity and improve product quality. Although few automated visual inspection systems can be seen, studies justify the potential advantages of automated visual inspection.

This work presented an application of software engineering to visual fabric inspection. A multimedia system that uses digital images as the main aspect of a control system for textile industries was proposed. We presented a prototype of this system that is on test, as well as and its performance. The system layout is modular and can be accommodated to any fabric characteristics. Since it is hard to perform experiments in the industrial environment, we executed they within a subset of 100 previous inspected and classified fabrics. Human experts do these previous inspections. We do experimentation to distinguish between correct identification of non-defective fabrics (no false alarm - figure 8) and defective fabrics (fault detection - figure 9). Figures 8 and 9 show results of testes done with 10 types of common defects, using separately each patterns recognition techniques, obviously when combined the results are always 100% efficient.

We believe that the success of this work is an example of the great integration possibilities promoted by the software engineering. This quality control model will next be fully integrated with a complete QIS. The model can also be used in other industries where the quality control is based on surface analysis.

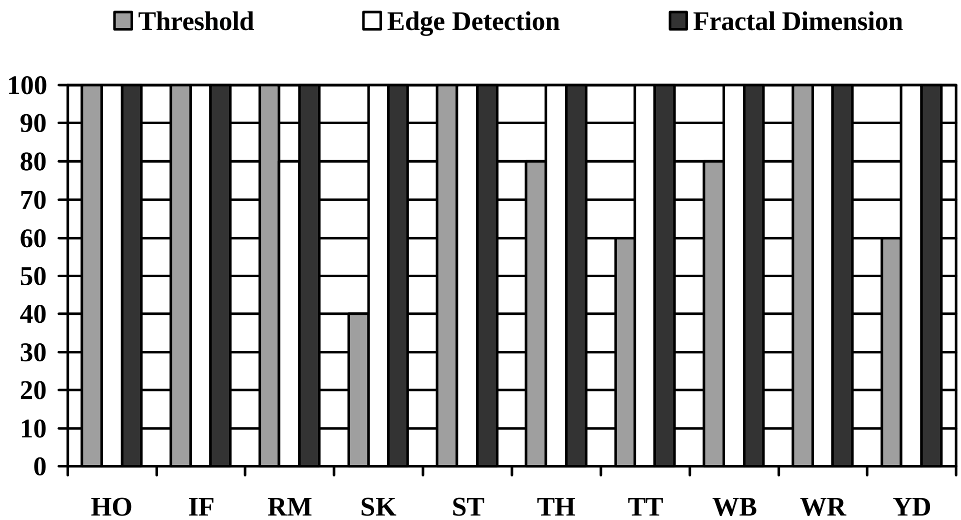

Figure 9. Percentage of correct identification of faults on defective textiles.

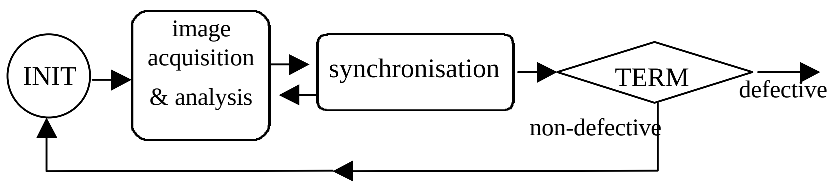

Figure 10. The main process in the Inspection Units.

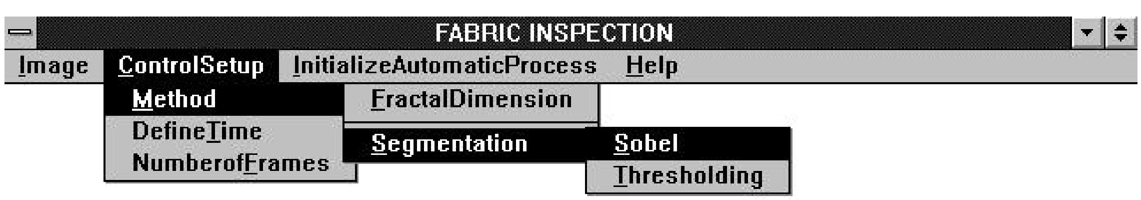

Figure 11. System screen.

7. CKNOWLEDGEMENTS

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