AN INTEGRATED SYSTEM FOR QUALITY INSPECTION OF TILES

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***Abstract* - The ceramic tiles manufacturing process has now been completely automated with the exception of the final stage of production concerned with visual inspection. In this paper we describe an integrated system developed for the detection of defects on colour ceramic tiles and for the colour grading of defect-free tiles. The results suggest that the performance is adequate to provide a basis for a viable commercial visual inspection system.**

1 INTRODUCTION

The ceramic tiles industrial sector has taken significant advantage of the advances in the world of automation in recent years. All production phases have been addressed through various technical innovations, with the exception of the final stage of the manufacturing process, namely the *product inspection*. This is still performed manually and is concerned with the sorting of tiles into distinct categories or the rejection of the tiles found with defects and pattern faults.

In this paper we describe the *integrated system* developed under the ASSIST project (Automatic System for Surface Inspection and Sorting of Tiles), for the detection of defects on colour tiles and for the colour grading of defect-free tiles. In Section 2 an overview of the sensors developed specifically for this project is presented. In Section 3 the algorithms developed for the detection of the defects will be described, while the colour grading framework is discussed in Section 4. In Section 5 the system integration is presented, and finally in Section 6 the performance evaluation of the system is discussed.

2 THE SYSTEM SENSORS

To meet the ASSIST demands, a multi-camera vision approach has been developed in order to cover many different kinds of defects. The acquisition system, which has been designed for the ASSIST project, is mainly made up of three CCD-based cameras.

A. Colour CCD image sensor

The first camera designed and developed for the project is a colour camera, TH7821C, based on a high resolution line array device sensor. This is a trilinear array with up to 3×8640 pixels, featuring very high performance in terms of linearity, dynamic range, and low noise response. It uses high quality on-chip colour filters to obtain full colour information from a single chip. The following electro-optical performance characteristics make this sensor the ideal device to satisfy the ASSIST demands.

- **Signal to noise ratio**: The TH7821C image sensor was especially designed to provide very high saturation output voltage (3V) in spite of its small pixel size ($7\mu m \times 7\mu m$).
- **Charge transfer efficiency**: The typical value of the total charge transfer efficiency is about 0.98 and the charge transfer inefficiency deduced for one CCD output register stage is equal to 5×10^{-6}. These results indicate a very good charge transfer for $6cm$ length CCD shift registers.
- **Lag**: The lag effect was measured for an average signal from $50mV$ to $600mV$ and the results obtained for this tricolour CCD image sensor show excellent transfer efficiency ($< 0.3\%$) as compared with a conventional linear CCD image sensor ($> 5\%$).
- **Responsivity**: A linear image sensor with photodiodes and 100% pixel aperture features high quantum efficiency providing a maximum sensitivity with an improved responsivity at $400nm$ (blue band).
- **Linearity**: Linearity is mainly dictated by the output amplifier characteristics. For a dynamic range of $20mV$ to $2500mV$ the linearity deviation is less than 2%. This value is better than 0.5% from $20mV$ to $500mV$ which fully satisfies the ASSIST needs.

B. Colour line-scan camera

The colour line-scan camera is used for the high precision colour grading of the tiles. It is fitted with the integrated, 3×8640 element-per-line, colour CCD image sensor described in Section 2. It provides three 8-bit digitised colour outputs one for each of the RGB channels. The circuitry within the camera comprises logic and driver controls of the CCD image sensor, the sensor itself, video preprocessing and processing blocks, the analog to digital converters and the line memories. An infra-red reject optical filter and a lens mounting adaptor are included in the enclosure.

To achieve fast scanning it includes a very high resolution trilinear architecture array sensor and functionalities for the remote control of the operational parameters such as gain and black level adjustments of each RGB video channel. These parameters can be tuned from the computer platform depending on the light conditions detected and the colour of the tiles. Since each colour has different sensitivity and responsivity characteristics, it is necessary to tune each colour in the camera for the maximum dynamic range of all colours for a given light source or coloured tile.

The trilinear CCD image sensor contains 3 coloured pixel arrays (red, green, and blue) which are implemented in parallel. Each line array is separated from the next by a space equal to 42 lines ($294\mu m$). This separation between RGB lines shows that at a given time, each pixel array does not capture the same image. A digital system mainly made up of FIFO memories and EPLDs to control read and write FIFO operations has been designed for the automatic restoration of the image geometry.

C. B/W cameras

There are two Black and White cameras used in the system and they are both fitted with linear CCD arrays. Three boards are currently used in these cameras: a sensor driver board, a timing generator board, and a digital video processing board. A major concern is the pairing effect which is caused by signal difference (gain and DC level misalignment) between odd and even CCD outputs. This produces a kind of fixed pattern noise at half the pixel frequency. In order to cancel this effect, the two CCD channels have been carefully matched from dark to white level so that the pairing effect is less than 1%.

In order to minimise transfer inefficiency and a dark signal component that increases with increasing temperature, the drivers and the trilinear colour CCD need to be thermally coupled to the camera front end. For each $8°C$ step, the dark current doubles, reducing the signal to noise ratio. High performance silicon grease ensures an efficient thermal exchange between the CCD, CCD drivers and the camera front end which is fitted with the lens mounting system.

3 TILE DEFECT DETECTION

The expected result of a defect detection module is the identification of defective regions (defect localisation) and the quantification of defect parameters (shape, extension, etc.) to be used for further classification purposes.

We now provide an overview of the most innovative approaches developed by the consortium for detecting different types of defects in tile images.

A. Inspection of the edges of the tile

The border area of a tile is a critical area for physical defects since it is the most fragile.

The problem was tackled in two ways; initially, by adopting appropriate sensing and lighting techniques to reduce as much as possible the acquisition problems (shading, reflections and non-uniform illumination), and subsequently by pre-processing the border area to produce a set of data compatible with the techniques used for the inner zone. This last operation was performed by using an algorithm made up of three steps:

1. Identification of the exterior border of the tile
2. Compensation of the luminance variation in the border area
3. Extension of the image by a pre-defined number of image lines (mirroring).

B. Crack detection in uniformly-coloured tiles

Cracks are linear structures contrasting with the rest of the tile. Our method [1] consists of two 1D convolutions, in the horizontal and vertical directions respectively with line detection filters [2]. Local maxima in the output indicate the possible presence of a line, and trigger the hypothesis that a line is present. The shape of the output signal around a local maximum is compared with the expected shape if a line were present in order to confirm or reject the hypothesis.

C. Spot defect detection in uniformly-coloured tiles

On light-coloured plain tiles, small, spot-like faults are of reasonably high contrast against the background. However, due to various sources of noise, e.g. non-uniform illumination, a simple threshold will not serve as an adequate solution to their detection. Thus, an adaptation of the line filter method from Section 3 was developed for spot-like defects [1]. The only difference is that the tile image is convolved with only one filter which is optimised for spot profiles. The spot peaks thus enhanced are extracted by thresholding.

D. Crack detection on textured tiles: A quick solution

Morphological techniques were used for the identification of cracks [3, 4]. In particular, we used the difference between a *Closing* and an *Opening* for the identification of thin structures. On the basis of these operations, a criterion called Anomaly Presence Degree (APD) has been proposed for the identification of the defective parts of the image. During the analysis phase the image is subdivided in blocks of dimension $L \times L$, and for each block the APD parameter is evaluated and compared with a threshold: if the threshold is exceeded, the block is classified as anomalous, otherwise it is considered regular.

E. Crack detection on textured tiles: A more sophisticated approach

We use the cojoint spatial and spatial frequency representation of the Wigner Distribution [1, 5] to enhance

pattern separability as the crack and texture patterns have disjoint support regions in the cojoint representation. According to this method, at each pixel position (x, y) we calculate the Fourier transform of a non-linear combination of pixel values within a window of size $N \times N$ centred at pixel (x, y).
The Wigner distribution is a real function and its components constitute the feature vector at each pixel position. The statistical distribution of these features is computed from the defect-free image during an off-line training phase. In the testing stage, the Mahalanobis distance of the feature vector of each pixel from this distribution is calculated. The values of this distance are used to form a residual map image. This image is subsequently processed by the optimal linear filter mentioned in Section 3 to detect the cracks.

F. Blob-detection: a quick approach

The image is subdivided into square blocks which are classified on the basis of their rank functions or morphological properties. The generalised rank function provides exactly the same information as the histogram but has the advantage of making possible the definition of an efficient difference measure that complies with the following three requirements: (i) to be zero if and only if the two histograms are exactly equal; (ii) to be proportional to the distortion caused by either the change in the spatial distribution of certain grey values, or change in the grey values themselves; (iii) to weight the point differences in relation to their differences from the mean value.
If a uniform texture is partitioned into sufficiently large blocks, each block is representative of the whole texture: the problem is then to define a prototype of the texture from the analysis of the block histograms. By using the rank distances, our strategy is to define as a prototype the rank function computed on the block, and when testing an unknown texture to evaluate the distance between the rank function of each block and the prototype [5, 6, 7].

G. Blob-detection: a more sophisticated approach

Using a perfect tile during the training stage, the various colour categories present in the defect-free tile can be identified with the aid of K-means clustering in RGB space. The number of these clusters is chosen to be high so that over-segmentation into chromatic classes is obtained, thus minimising (and eliminating) the under-segregation error. Next, these clusters are transformed into CIE-Luv uniform colour space for perceptual merging, i.e. merging of small clusters into super-clusters. Thus, the image is segregated into chromatic categories which are perceptually uniform [8].
The image can then be split into a stack of binary images one for each chromatic category. For each blob we compute as structural features its area, perimeter fractality, elongatedness, and some spatial information about the distribution of other blobs around it, and model the distribution of these attributes.
During testing, the image pixels are classified into the chromatic categories defined during the training stage using the nearest neighbor rule. Any unclassified pixels are rejected and considered as colour defects. The accepted pixels are used to form the stack of binary blob images again. The structural features of each resulting blob are then computed and any blob-like texture defects are identified by means of the Mahalanobis distance function using the structure statistics saved in the training phase.

H. Regular Pattern Fault Detection

To identify faults in regular patterns, a two stage approach is followed: the digitised image of the tile to be analysed is registered with a template (target pattern); then, the difference between actual and target patterns is calculated and the faults are identified. The analysis is performed in full colour, due to the possibility of errors in colour layer superposition.
Non-negligible shifts and rotations can happen among different layers of the same inspected tile (generated by successive applications of silk-screen colour drawings). Thus, a reliable registration of inspected tiles with the prototype (template) can only be obtained if the matching is performed for each layer separately. The registration algorithm developed takes into account two primary objectives: to maintain the distance between template and inspected pattern within one pixel accuracy and to minimise the computational requirements. The solution adopted consists of the use of a fast roto-translation procedure, that allows a fast optimisation of the angle and shift parameters.
The mean absolute difference between corresponding pixels was selected as a measure of correct pattern reproduction, because it showed the best trade-off between speed and reliability. Testing results showed that defects with total dimension as low as 3 pixels can be successfully detected by applying the proposed strategy.

4 COLOUR SHADE GRADING

The developed methodology allows the identification of colour grades that correspond to the threshold of human colour perception which are discriminated by human inspectors working at the peak of their performance. To achieve this, our methodology had to be able to measure colour differences at least one order of magnitude smaller than the various types of noise involved in the process of colour recording. For this purpose, the system uses an automatic scheme that can cope with spatial and temporal variability of illumination.
The spatial variation of the illumination manifests itself as a low frequency variation over the profile of the tile. Assuming for the moment that the inspected tile is of uniform colour, we fit the grey level function of the tile in a single colour band with a low order polynomial using the least squares error method. At each location then, the actual value of the grey level function is divided by the corresponding value of the fitted polynomial and multiplied with some reference value. This way, the low frequency variation due to variable

illumination is removed and all values are referred to the reference illumination value chosen. This process is repeated for all colour bands separately. To take care of the temporal variation of the illumination, we have to image each tile with the same reference surface, another tile which plays the role of a pallet. When the system is operational, the difference in the observed variation of grey values that can be attributed to the temporal illumination variation is removed with the help of the reference surface and only the difference that remains is recorded as genuine variation [9, 10].

After the above corrections take place, the tiles are graded by comparing their colour histograms with a reference histogram and using the correlation coefficient as a measure of similarity [11, 12].

5 SYSTEM INTEGRATION

The integrated vision system is schematically presented in Figure 1. The tiles are first inspected for bumps and depressions using a laminated light source at an angle for maximum sensitivity to surface imperfections. This means that each line across the tile receives more or less light of the same intensity. Next, the tile is inspected for other structural faults like cracks and holes, using diffuse lighting. Finally, the tile is inspected for colour defects and colour grading using the tri-linear colour scanner and again, diffuse lighting.

The system architecture (Figure 2) has been designed according to a modular approach. Two main functional modules have been identified: the Host Module and the Data Acquisition and Processing Module (DAPM).

The DAPM Module has been designed to control image grabbing, to process the image, to classify tiles and to drive the proper I/O modules for tile sorting. The Host Module is in charge of the interface with the human operator, output data collection and defect diagnosis. This module is split into a *Local Host Module* dedicated to provide I/O functionality (file access, screen and keyboard functions, etc.) to the image acquisition and processing sub-system and into a *Remote Host Module* providing the graphical man-machine interface and high-level data processing functionality (storing, statistics, and diagnosis).

The system has been realized using two machines, a "local" one placed near the sorting line and a "remote" one that controls operations and collects outputs. While a standard PC is used for the remote machine, both standard and special hardware are used for the local one. A VME cabinet has been chosen to host both the Local Host, a standard PC, and the DAPM module, implemented using both off-the-shelf and specially designed boards.

A multi-tasking operating system has been chosen both for the Local Host and for the Remote one: Microsoft Windows for Workgroup has the features needed for multiprocessing and LAN communication requirements.

An I/O Server daemon has been implemented into the Local Host in order to provide the DAPM module with I/O functionality. The Remote Host is made up of the following modules: Supervisor Module, Output Data Collector Module, Statistics Module, Diagnostic Module. The DAPM Module is based on a DSP network ; a quick parallel kernel was chosen in order to satisfy real-time requirements.

6 PERFORMANCE EVALUATION

The integrated demonstrator system was extensively evaluated on the factory floor, mainly with respect to defect detection. In particular, the quick methods used for defect detection were extensively tested with respect to two major kinds of tiles: uniformly coloured tiles and textured tiles.

Performance is quite like that of human operators in the case of uniformly coloured tiles, as Figure 3(a) shows. It must be noted that the main difference in the results between the prototype and human classifications is due to defects beyond the ASSIST specifications (i.e. smaller size faults than originally specified by the manufacturer), or due to minor problems (illumination or threshold settings) which were later on solved.

Textured tiles include a great variety of products, produced by a variety of technologies. The main kinds are flamed tiles, randomly textured tiles (i.e. dropped tiles), and pseudo-randomly textured tiles (i.e. marble like tiles). While flamed tiles (tiles with shadings caused by flame exposure) and dropped tiles (tiles coloured by drops, granite like) have been successfully tested, marble like tiles were beyond the limits of effectiveness of the quick approaches. More precisely, defects caused by problems in glazing by means of silk-screen rolls, proved very difficult to be detected. Figure 3(b) shows the comparison between automatic and human classification in the case of a marble-like textured product.

7 CONCLUSIONS

As a final evaluation, we can say that the quick methods developed are quite effective in defect detection in uniformly coloured tiles and in some kinds of textured tiles whereas they are less reliable in pseudo-random textures. On the other hand, the sophisticated methods described in Section 3 have no problem in identifying all defects in all types of tiles, but the present technology does not allow their real-time implementation. We believe, however, that in a few years time, the technology will have been sufficiently advanced to allow the incorporation of the sophisticated methods proposed in a real-time system.

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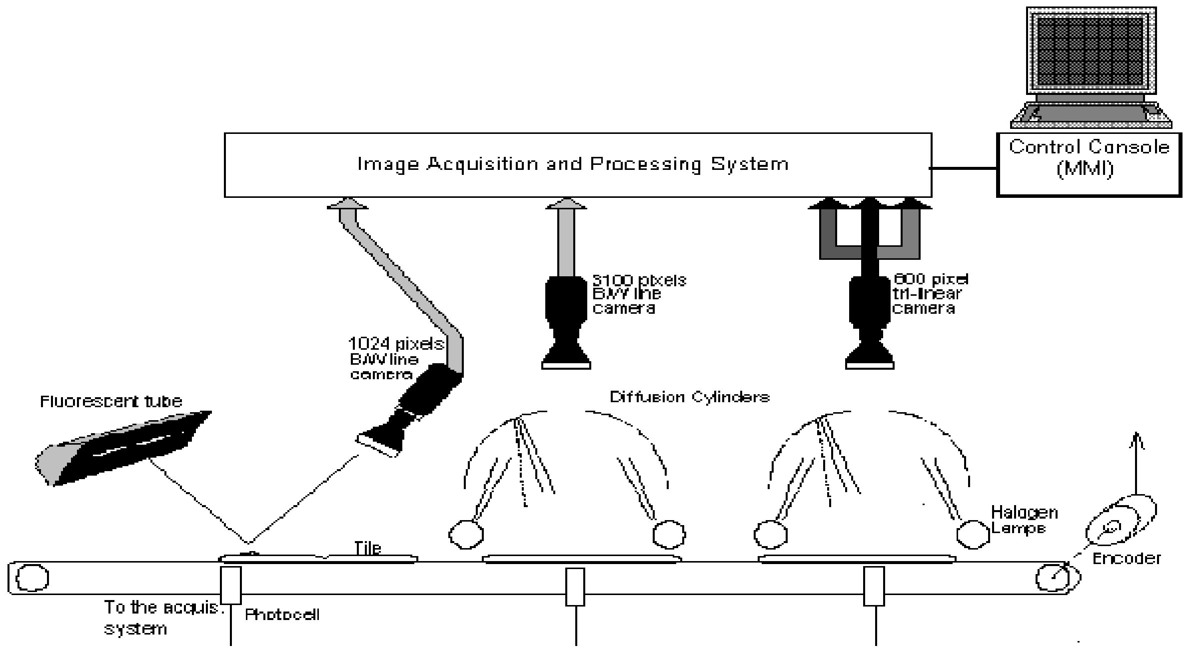


Figure 1: Overall ASSIST system structure

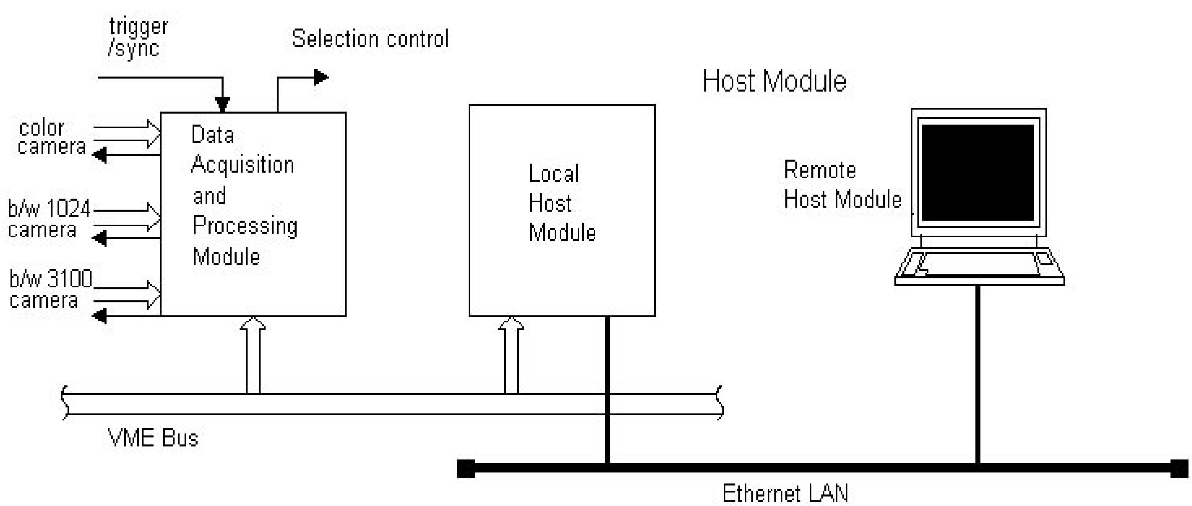
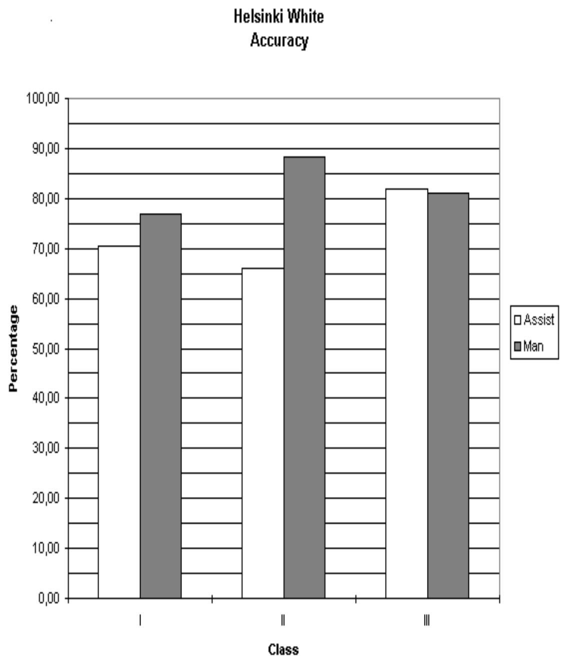
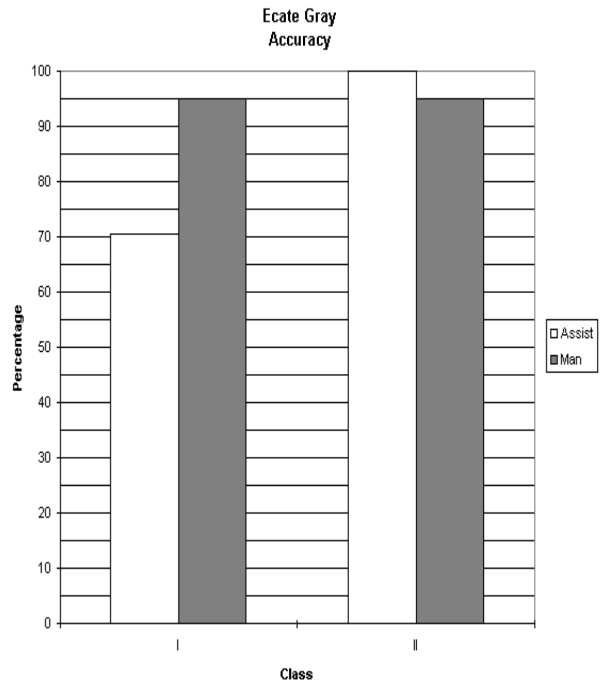


Figure 2: Overall ASSIST system architecture



(a)



(b)

Figure 3: ASSIST v. Human Accuracy in (a) plain white Helsinki tiles & (b) grey textured Ecate tiles

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