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Visual Inspection for Fired Ceramic Tile'S Surface Defects Using Wavelet Analysis

H. M. Elbehiery[1], A. A. Hefnawy[2] and M. T. Elewa[3]

Summary

This paper deals with the visual inspection of ceramic's tiles surfaces for the purpose of detecting flaws using a wavelet approach. Surface defects in the ceramic tiles are viewed as in-homogeneities in regularity and orientation fields. To improve the homogeneity of batches received by final users and to detect manufacturing defaults, most production lines for ceramic tiles must integrate a visual control stage before the packing operation. The goal of the inspection is not to give a statistical analysis of the production but to classify every tile into quality-constant batches. These tasks are often referred to as visual inspection; Visual inspection procedures have been implemented and tested on a number of tiles using synthetic and real defects. The results suggest that the performance is adequate to provide a basis for a viable commercial visual inspection system. Wavelet decompositions often provide very parsimonious image representations, and this feature has been exploited to devise powerful compression, Denoising and estimation methods. In our work we introduce a hierarchical wavelet- based framework for modeling patterns in digital images. This frame work takes advantage of the efficient image representations afforded by wavelets, while accounting for unknown pattern transformations.

keywords: Visual inspection, Ceramic tiles, Surface defects Wavelet decomposition.

Introduction

The ceramic tiles industrial sector is a relatively young industry which has taken significant advantage of the strong evolution 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. This is concerned with visual surface inspection in order to sort tiles into distinct categorizes or to reject those found with defects and patterns faults. The generally accepted manual method of tile inspection is labor intensive, slow and subjective. Automated sorting and packing lines have been in existence for a number of years, however, the complexity of inspecting tiles for damage and selecting them against the individually set quality criteria of a manufacturer has meant that, until recently, automated tile inspection has not been possible.[1]

Tiredness and lack of concentration are common problems, leading to errors in grading tiles. Gradual changes are difficult for human inspectors to detect and

[1]Zagazig University, Electronic Research Institute, hussam_elbehiery@hotmail.com
[2]Zagazig University, Electronic Research Institute, alaahouse@yahoo.com
[3]Zagazig University, Electronic Research Institute, tarek_elewa@yahoo.com

it is possible that slight and progressive changes will not be noticed at an early stage. Additionally, it is particularly difficult for the human eye to accurately sort tiles into shades, with changing light conditions in a factory. Human judgment is, as usual, influenced by expectations and prior knowledge. However this problem is not specific to structural defects. In many detection tasks for example, edge detection, there is a gradual transition from presence to absence. On the other hand, in "obvious" cases most naïve observers agree that the defect is there, even when they cannot identify the structure.

The defect detection operation induces that the entire surface of every tile must be imaged and analyzed. Therefore each tile needs to be imaged individually without any sampling operation. The image acquisition must be achieved directly on the line, in real time, and the image analysis algorithms must be fast enough to follow the production rate.[2] This paper is concerned with the problem of automatic inspection of ceramic tiles using computer vision. It must be noted that detection of defect in textured surfaces is an important area of automatic industrial inspection that has been largely overlooked by the recent wave of research in machine vision applications. So, this paper aims to create a system that is capable of classifying tiles effectively, objectively and repeatedly, with sufficient rapidness and low costs and the ability to adapt autonomously to changes in materials.

The techniques used range from Long crack, crack, blob, pin-hole and spot detectors algorithms for plain, and textures tiles. This therefore reduces the number of complaints tiles. The presented inspection procedures have been implemented and tested on a number of tiles using synthetic and real defects. Such a monitoring task is of course tedious, subjective and expensive but it is based on a long experience and can utilize the huge appreciation and recognition abilities of the human brain. The test criteria can be specified by those responsible for quality from the production and marketing divisions. The automated system accepts defect values which are acceptable to the Quality Management. One of its advantages; the automated system is flexible in regard to production changes and testing criteria and that is simple to operate and gives a good overview. By looking at the results we found it highly suitable for providing a rapid feedback in the production process, this relates especially to the sorting of dried tiles.[2]

Depending on the number of defects and their dimensions, the tiles are grouped into classes; Class I, Class II, Class III, and waste tiles. We use one of the most scientific foundations for computer vision which is Wavelet decomposition for the visual inspection system. In our work we introduce a hierarchical wavelet-based framework for modeling patterns in digital images. This frame work takes advantage of the efficient image representations offered by wavelets, while accounting for unknown pattern transformations, which we will see, its results in the next sections.[3]

Image capturing and acquisition

The main task of our work is to create new images that are more suitable for the purposes of visual perception object detection and target recognition can be used in the classifying or sorting process at the industry. Among the wide variety of available products for tiling, an important part present a glossy surface induced by polishing or glazing operations. Observing the surface under low angle lighting allows controlling the quality of the gloss. The ceramic tiles have been captured through the online camera held on the line production at the industry. Figure 1 shows a simplified view for the visual inspection system held on the line production. The image captured will convert to other kinds of images (Binary, and Gray scale) to be suitable for the various defect detection algorithms used for the different types of defects.[4]

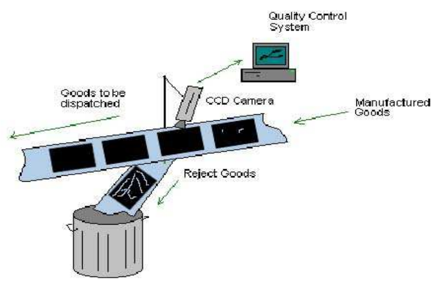

Figure 1: Simplified view of visual inspection system held on the production line

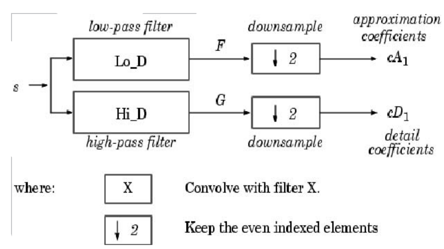

Figure 2: General algorithm for discrete wavelet transforms

Wavelet Processing

Wavelets are mathematical functions that cut up data into different frequency components, and then study each component with a resolution matched to its scale. They have advantages over traditional Fourier methods in analyzing physical situations where the signal contains discontinuities and sharp spikes.

The first in processing the discrete-time signals is analogous using the Fourier series (FS) where a continuous function is transformed into a discrete sequence of coefficients. The second is analogous to the Discrete Fourier Transform (DFT) where a discrete function is transformed into a discrete function. Indeed, the DFT is often used to calculate the fourier series coefficients, but care must be taken to avoid or minimize aliasing.[5]

It is possible to completely remove certain components of a signal while leaving others completely unchanged. The same can be done using wavelet transform to achieve wavelet based, wavelet domain signal processing, or filtering. Indeed, it is sometimes possible to remove or separate parts of a signal that overlap in both time and frequency using wavelets, sometimes impossible to do with conventional Fourier-based techniques.

The fundamental idea behind wavelets is to analyze according to scale. Indeed, some researchers in the wavelet field feel that, by using wavelets, one is adopting a whole new mindset or perspective in processing data.[6,7]

Wavelet algorithms process data at different scales or resolutions. If we look at a signal with a large "window," we would notice gross features. Similarly, if we look at a signal with a small "window," we would notice small features. The result in wavelet analysis is to see both the forest and the trees, so to speak. When we analyze our signal in time for its frequency content, unlike Fourier analysis, in which we analyze signals using sines and cosines, now we use wavelet functions.

The Continuous Wavelet Transform

The *continuous wavelet transform* (CWT) is defined as the sum over all time of the signal multiplied by scaled, shifted versions of the wavelet function ψ:

$$C(scale, position) = \int_{-\infty}^{\infty} f(t)\,\psi(scale, position, t)\,dt \tag{1}$$

The results of the CWT are many *wavelet coefficients* C, which are a function of scale and position. Multiplying each coefficient by the appropriately scaled and shifted wavelet yields the constituent wavelets of the original signal. If the signal is a function of a continuous variable and a transform that is a function of two continuous variables is desired. The continuous wavelet transform (CWT) can be defined by:

$$F(a,b) = \int f(t)\,\omega\left(\frac{t-a}{b}\right) dt \tag{2}$$

With an inverse transform of,

$$f(t) = \iint F(a,b)\,\omega\left(\frac{t-a}{b}\right) da\,db \tag{3}$$

Where $\omega(t)$ is the basic wavelet and a, $b \in R$ are real continuous variables.

Discrete Wavelet Transform Algorithms

Calculating wavelet coefficients at every possible scale is a fair amount of work, and it generates an awful lot of data. (What if we choose only a subset of scales and positions at which to make our calculations). It turns out, rather remarkably, that if we choose scales and positions based on powers of two, so called *dyadic* scales and positions, then our analysis will be much more efficient and just as accurate. We obtain such an analysis from the *discrete wavelet transform* (DWT).[4]

Given a signal s of length N, the DWT consists of $\log_2 N$ stages at most. Starting from s, the first step produces two sets of coefficients: approximation coefficients cA_1, and detail coefficients cD_1. These vectors are obtained by convolving s with the low-pass filter Lo_D for approximation, and with the high-pass filter Hi_D for detail, followed by dyadic decimation. More precisely, as shown in figure 2 the first step is:

The length of each filter is equal to $2N$. If n = length(s), the signals F and G, are of length n + $2N$ - 1, and then the coefficients cA_1 and cD_1 are of length.

$$floor\left(\frac{n-1}{2}\right)+N \tag{4}$$

The next step splits the approximation coefficients cA_1 in two parts using the same scheme, replacing s by cA_1 and producing cA_2 and cD_2, and so on. Therefore, the wavelet decomposition of the signal s analyzed at level j has the following structure: [cA_j, cD_j, ..., cD_1]. This structure contains for J = 3, the terminal nodes of the following tree as shown in figure 3.[6,10,11]

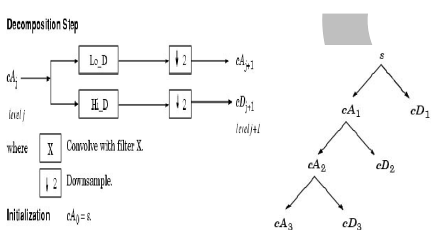

Figure 3: One-dimensional DWT Structure

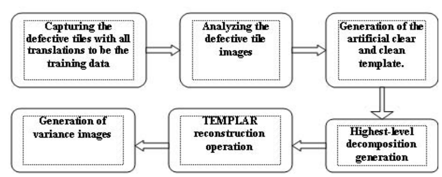

Figure 4: TEMPLAR algorithm block diagram

Fast Wavelet Transform (FWT)

In 1988, Mallat produced a fast wavelet decomposition and reconstruction algorithm. The Mallat algorithm for discrete wavelet transform is in fact a classical scheme in the signal processing community, known as a two-channel sub-band coder using conjugate quadrature filters or quadrature mirror filters (QMF). The decomposition algorithm starts with signal s, next calculates the coordinates of A_1 and D_1, and then those of A_2 and D_2, and so on. The reconstruction algorithm called the inverse discrete wavelet transform (IDWT), starts from the coordinates of A_J and D_J, next calculates the coordinates of A_{J-1}, and then using the coordinates of A_{J-1} and D_{J-1} calculates those of A_{J-2}, and so on.[9]

A Wavelet-based Approach to Pattern Analysis

Despite the success of wavelet decompositions in other areas of statistical signal and image processing, current wavelet-based image models are inadequate for modeling patterns in images, due to the presence of unknown transformations (e.g., translation, rotation, location of lighting source) inherent in most pattern observations.[11]

Wavelets are adjustable and adoptable. Because there is not just one wavelet, they can be designed to fit individual applications. They are ideal for adaptive systems that adjust themselves to suit the signal. The generation of wavelets and the calculation of the discrete wavelet transform are well matched to the digital computer.

In our work we introduce a hierarchical wavelet- based framework for modeling patterns in digital images. This frame work takes advantage of the efficient image representations afforded by wavelets, while accounting for unknown pattern transformations. Given a trained model, we can use this framework to synthesize pattern observations. If the model parameters are unknown, we can infer them from labeled training data using TMPLAR (Template Learning from Atomic Representations). TEMPLAR employs Minimum Description Length (MDL) complexity regularization to learn a template with a sparse representation in the wavelet domain.

Wavelet decompositions often provide very parsimonious image representations, and this feature has been exploited to devise powerful compression, denoising and estimation methods. The pattern interest undergoes an unknown or random transformation during data acquisition (e.g. variations in illumination, orientation, translation, and perspective). Modeling the wavelet of such transformed data leads to distorted components, or even components that model the transformations instead of the structure of the underlying object or pattern. The objective is to develop a wavelet based framework for modeling pattern observations that have undergone random transformations in the observation process.

We introduce an algorithm that combines the edge-detection property of wavelets with minimum description length (MDL) complexity- regularization to automatically learn a low dimensional pattern template from noisy, randomly transformed observations. The resulting template may then be applied to classification or pattern analysis. We work with a fixed wavelet basis, and allow the dimension of the template to vary.

When a pattern is observed in an image it can appear in any number of locations, orientations, scales , etc., in the image, depending on the spatial relationship between the image forming device and the pattern, further uncertainty in pattern observations can be caused by lighting sources, background clutter, observation noise, and deformations of the pattern itself (if the pattern is not rigid, like a human face).we model these uncertainties in pattern observations with a hierarchical frame work, based on the notion of deformable templates. Figure 4 shows the general block diagram for the TEMPLAR algorithm.

We apply TEMPLAR using Haar wavelet, Daubechies wavelet, Coiflets wavelet, Symlets wavelet, and Biorthogonal wavelet, and using transformations that cover translations of up to ± 32 pixels horizontally or vertically. The algorithm converges after five iterations for this particular realization of the training data. We also observe that the final template does not represent any of the clutter present in the training images. We illustrate template learning on real data. We see twelve observations of a randomly translated, noised, variable lighting, and rotated ceramic tile images. These $128 \times 128 = 16.381$ dimensional images were obtained with a digital camera. Finally TEMPLAR is an iterative, linear time algorithm that combines the edge detection property of wavelets with MDL complexity-regularization to learn a low dimensional template which is automatically inferred from the data. Once the template has been learned the resulting model can be used for pattern synthesis or pattern classification.[11,12]

Experimental work

The main task of our work is to create new images that are more suitable for the purposes of visual perception object detection and target recognition. Due to their time–frequency localization properties, discrete wavelet transforms have been proven appropriate starting points for the classification of the measured signals. They allow the extraction of richer problem-specific information from sensor signals than earlier methods for many practical applications. Defects are extracted from the background by thresholding the image and then classified according to size and shape parameters. Existing machines commonly detect the following defaults:

1. Chips (edges and corners)
2. Cracks
3. Scratches
4. Glaze faults
5. Holes and pitting
6. Lumps

The sensitivity of the imaging system is linked to the local roughness contrast induced by the defect; it has nothing to do with the color contrast. Because they rely on two independent physical properties of the material, color defects and surface defects inspection are complementary.[10] The new methods as TEMPLAR enables a large reduction of the wavelet transform data while retaining problem-specific information, which facilities an efficient pattern recognition process.

Due to desirable properties concerning approximation quality, redundancy, numerical stability, etc. The wavelet bases constructed by Haar, Daubechies became the foundation for the most popular techniques for signal analysis and representation in a wide range of applications. We applied five (5) kinds of wavelet decomposition types (Haar, Daubechies, coiflet, Biorthogonal, and Symlet) on two groups of tiles including different defects were studied (Crack defect, Long crack defect, and Blob defect).

In TEMPLAR, we begin with the generation of the artificial clear and clean template our experimental procedures concentrates on the measurements obtained from studying two different series of tiles having different defects as we mentioned previously. This is followed by applying our algorithm to each series of tiles. This explained in figure 5 showing the original clear and clean tile captured image in the factory. That is followed by; generating the artificial template from training data which contains randomly translated, noised and rotated tile images, with variable background and lighting conditions. Our algorithm will make use of this artificial template shown in figure 6 to produce at the final step in TEMPLAR the variance image including only the defect.

The same procedures were done for another series of tiles including different types of defects illustrated in figures 7 and 8.

In the second stage in TEMPLAR, we analyze the tile images which including the defects by the wavelet toolbox in Matlab to a maximum level for decomposition. The defective tiles images are shown in figures 9, and 10.

We choose the maximum level to be five levels. Also using five (5) kinds of wavelets (Haar, Daubechies, coiflet, Biorthogonal, and Symlet). The highest-level decomposition components in the five (5) kinds of wavelets used as the input to the next part of TEMPLAR.[8,12]. All of the results of this part are displayed in figures 11, and 12. The highest component images displayed is a sequence of templates means transformed into the spatial domain in the learning algorithm. So, the images are synthesized images not clear like the original images.

The third stage in TEMPLAR is the reconstruction operation, which carried out using wavelet transform toolbox in Matlab that gives us the Variance result as an image, which is a black & white or Gray scale image. It contains only the difference between the artificial template image (which can be considered the original template clear, and clean image tile) and the defect tile image. Crack defect variance images using Haar and Daubechies wavelets shown in figures 13, and 14. Long crack and Blob defect variance images using Haar and Daubechies wavelets shown in figures 15, and 16.

We could see a difference between the resultant variance images analyzed using Haar wavelet and Daubechies wavelet. This difference is because each type of

Figure 5: Original clear and clean tile captured image (first series)

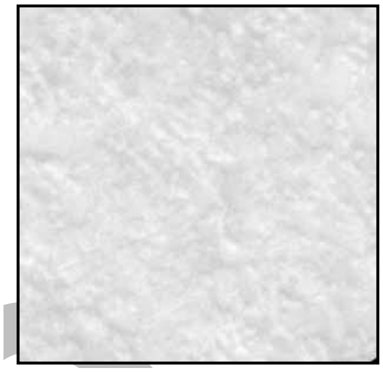

Figure 6: Artificial Template for tile image without the defect

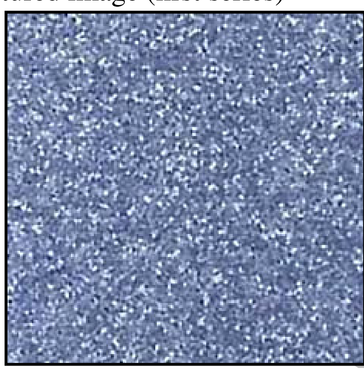

Figure 7: Original clear and clean tile captured image (second series)

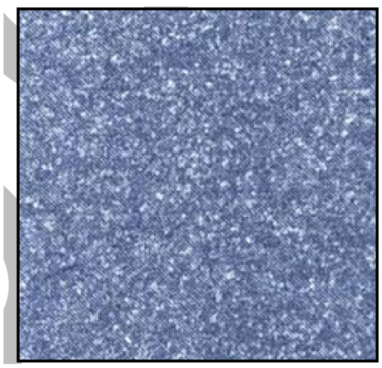

Figure 8: Artificial Template for tile image without the defect

Figure 9: The defective tile image for Crack defect

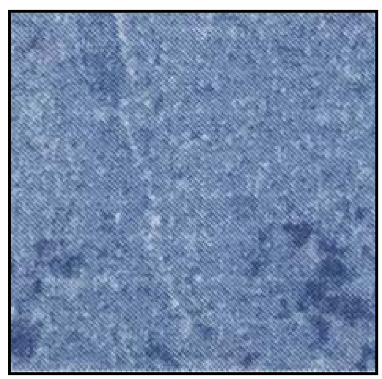

Figure 10: The defective tile image for Long crack & Blob defect

wavelets Haar or Daubechies even any other type of wavelets using different details in computations. Each type of wavelets working with the image's pixels in a

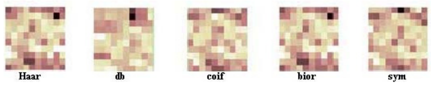

Figure 11: Reconstructed Highest components wavelet types decomposition for Crack defect tile image

Figure 12: Reconstructed Highest components wavelet types decomposition for Long Crack defect tile image

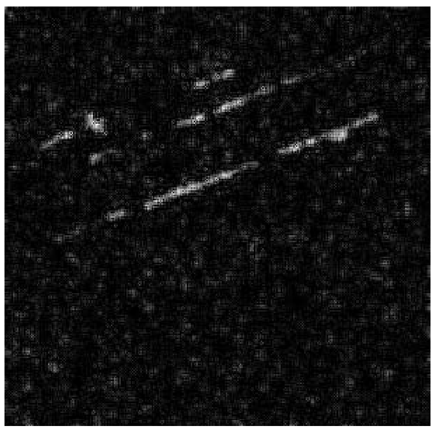

Figure 13: Variance for Haar Wavelet for Crack defect tile image

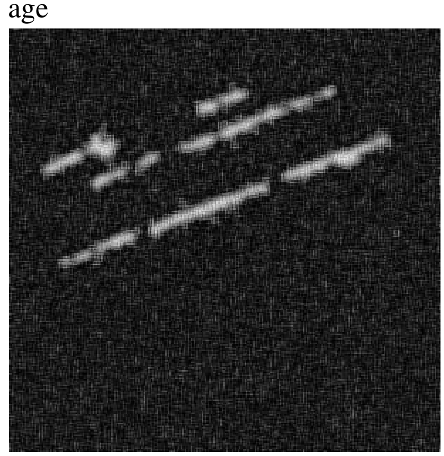

Figure 14: Variance for Daubechies Wavelet for Crack defect tile image

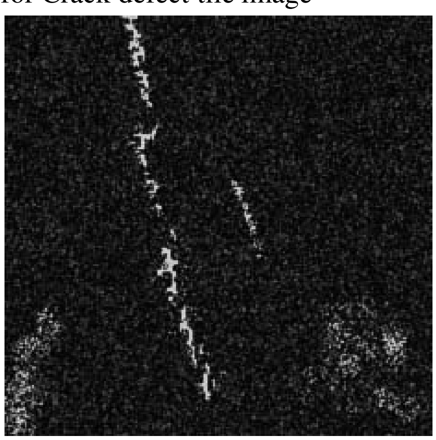

Figure 15: Variance for Haar Wavelet for Long Crack & Blob defect tile image

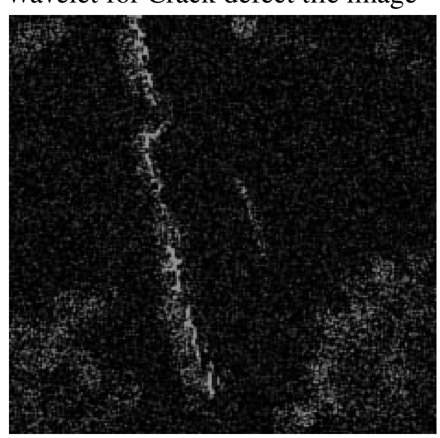

Figure 16: Variance for Daubechies Wavelet for Long Crack & Blob defect tile image

different way also number of pixels has been taken in each type of wavelet.

This affect when analyze the defective tile image with different types of wavelet. Generally, this difference is effective due to the accuracy degree needed in analysis. When we need high degree of accuracy we could use the Daubechies wavelet and when we need a lower degree of accuracy we could use Haar wavelet but that affect in the processing time when we work with more details. Working with more details takes more processing time than working with fewer details.

Conclusion

The result of the project is a prototype tone analyzer with some major simplifications compared to the solutions currently available on the market The essential advantage of an automated system compared with a manual sorting of dried tiles consists in the compliance with the testing criteria by a fast, continuous testing of the tile. By the use of the automated system, miss-sorting is kept at an extremely low level.

These results in lower indirect costs and means that the system can be moved when required. A lot of tiles were analyzed (many dozen per article for logistic reasons, whereas the operating conditions (speed of the line with all its irregularities, vibrations etc.) were similar to real conditions. Other typical conditions of ceramic factories (dust, high temperatures, etc) were taken into account during design.

Automated sorting systems would bring numerous benefits to the entire sector with major economic advantages. A fully automated sorting system would be able to guarantee product quality, increase plant efficiency and reduce fixed and periodic investments. Therefore a selection in homogeneous classes with similar characteristics is needed. The effects of unequal lighting and of the space sensitivity of the TV camera CCD are corrected analyzing a sample tile made of white Plexiglas whose image has been previously divided in 8x8 sectors. This number represents a compromise between spatial resolution distribution and computing time.

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