APPLYING TEXTURE ANALYSIS TO INDUSTRIAL INSPECTION

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Despite the obvious needs of applications, texture analysis is a rare method in automated visual inspection outside textile industry. Most textures in the real world are non-uniform, the inspection speed requirements extreme and very difficult to satisfy at a reasonable cost using textbook methods. Furthermore, the costs of retraining the systems tend to exceed any acceptable level. This paper gives a brief overview of the problem space of applying texture analysis for industrial inspection, presenting some solutions proposed and their prerequisites.

1 Introduction

There are many potential areas of application for texture analysis in industry [1-4], but only a limited number of examples of successful exploitation of texture in inspection exist. A major problem is that textures in the real world are often non-uniform, due to changes in orientation, scale or other visual appearance. In addition, the degree of computational complexity of many of the proposed texture measures is very high. Before committing effort into selecting, developing and using texture techniques in an application, it is necessary to thoroughly understand its requirements and characteristics.

Textured materials may have defects that should be detected and identified as in crack inspection of concrete or stone slabs, or the quality characteristics of the surface should be measured as in granulometry. In many applications both objectives must be pursued simultaneously, as is regularly the case with wood, steel and textile inspection. Because these and most natural and manufactured surfaces are textured, one would expect this characteristic to be reflected by the methodological solutions used in practical automatic visual inspection systems.

However, only a few examples of successful explicit exploitation of texture techniques in industrial inspection exist, while most systems, including many wood inspection devices, attempt to cancel out or disregard the presence of texture, trying to transform the problems solvable with other detection and analysis methods, e.g., as done by Dinstein *et al.* [5]. This is understandable against the high costs of texture inspection, and the fact that often the defects of interest are not textured, but embedded in it like cracks. Furthermore, as is the case with wood, the texture of the sound material may vary greatly, causing training problems for texture inspection algorithms.

The inspection of textured surfaces is regularly treated more as a classification and less as a segmentation task, simply because the focus is on measuring the characteristics of regions and comparing them to prior trained samples. Actual working texture based industrial inspection solutions are available mostly for homogeneous periodic textures, such as on wallpaper and fabric, where the patterns normally exhibit only minimal variation, making defect detection a two category classification problem. Natural textures are more or less random with large non-anomalous deviations, as anyone can testify by taking a look at a wood surface, resulting in the need to add features just to capture the range of normal variation, not to mention of the detection and identification of defects.

Defect detection may require continuous adaptation or adjustment of features and methods based on the background characteristics, possibly resulting in a complex multicategory classification task already at the first step of inspection. Solutions providing adaptability have been proposed, among others, by Dewaele *et al.* [6] and Chetverikov [7]. Proprietary adaptation schemes are regularly used in commercial inspection systems.

In most industrial applications inspection systems must process 10-40 Mpixels/s per camera, thus requiring dedicated hardware for at least part of the system, so the calculation of each new texture feature can be a significant expense that should be avoided. Therefore, the system developers try to select a few powerful straightforwardly implementable features and tune them precisely for the application problem. A prototypical solution depicted in Figure 1 uses a bank of filters or texture transforms characterising the texture and also defect primitives, each transform producing a feature image that is used in either pixel-by-pixel or window based classification of the original image data.

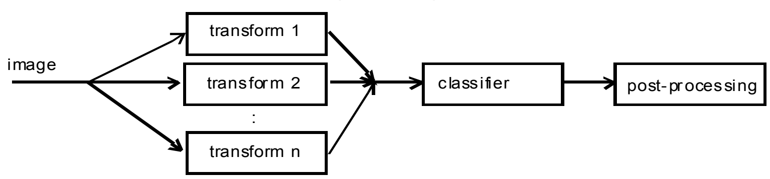


Figure 1. Typical methodological architecture of texture based inspection systems.

The dimensions of the filters used in applications have ranged up-to 63 x 63 for pixel classification [8], while most implementors rely on 3 x 3 Laws' masks [9] or other convolution filters in classification of partially overlapping or non-overlapping windows, e.g., based on means and variances of texture measures

The developments in feature distribution based classification [10,4] of texture will have a major simplifying impact on future systems, as the techniques have recently matured to the brink of real applicability. The improved efficiency in using the texture measures cuts the number of features needed in an application, enables classifying small regions, and potentially reduces training effort by relieving the dimensionality problem of classification. Nevertheless, many applications will always demand dedicated techniques for the detection of their vital defects.

2 Inspection System Training

Regardless of the feature analysis methodology, the effort needed for training an inspection system to detect and identify defects from sound background remains a key cost driver for system deployment and use. As texture inspection methods are notoriously fragile with respect to resolution, a minor change between the distance of the camera to the target may result in a retraining need. This need may also arise from normal variations between product batches.

Typically, training done in laboratory turns out to be useless after an inspection system has been installed on-line. Furthermore, on-line training performed by production personnel tends to concentrate on teaching in ‘near-misses’ and ‘near-hits’ rather than representative defects and background, so non-parametric classifiers should be favored.

Figure 2 shows two basic approaches to training defect detection: pixel-based training (2b) assumes that a human operator is able to correctly pinpoint pixels belonging to defects in the image and pixels that are from sound background. In region-based training (2c) the operator roughly labels regions that contain a defect or defects, but may also have a substantial portion of sound background, while the non-labeled regions are assumed sound.

We advocate the latter approach (2c), because it is less laborious, and because it is difficult for a human to precisely determine the boundaries of defects. It should be noticed that pixel based training disregards the transition region to defect, the characteristics of which may have high importance. For instance, the grain around a suspected defect in a lumber board helps in discriminating frequent stray bark particles from minor knots

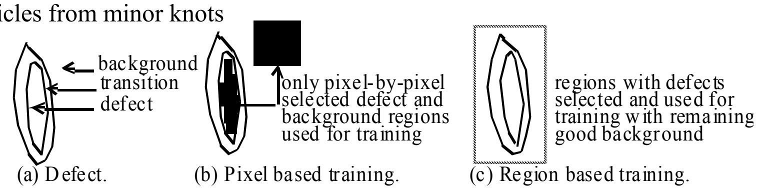


Figure 2. Alternatives for training defect detection methods.

As a practical case, it is worth considering lumber inspection in which the detection and classification of knots is essential. From Figure 3 that depicts a sound knot in a pine board we see the gradual transition from non-uniformly textured background. The great variations of the background coupled with the varying appearances of the defects clearly result in a very demanding training problem.

Figure 3. Typical sound leaf knot in a pine board.

3 Detection of Defects from Texture

The detection and segmentation of 'sufficiently' large defects in texture images can be performed reliably with pure texture measures both for periodic and random textures using proposed texture measures [11]. But because texture is a statistical concept, texture measures are good only for regions that have the minimum size that allows the definition of features [7].

Unfortunately, many defects are small local imperfections rather than 'real' texture defects such as knots with exactly the color of defectless background in wood. The detection of minor flaws from the background requires application specific knowledge. In addition, segmentation may be required for measuring the defects and determining their characteristics. Figure 4 presents a categorization of defects on textured surfaces.

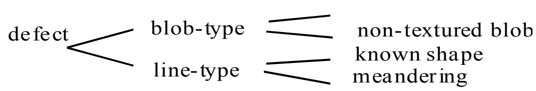


Figure 4. Categories of defects on textured surfaces.

3.1 Defect blob detection

The relative sizes of the minimum detectable defect patches for various features and textures can be roughly concluded from the boundaries in texture segmentation results given in literature: The lower the error, the smaller the defects that can be detected using that family of features. With a small patch size even most of the local texture imperfection can be detected, reducing, if not eliminating the need for application specific detection solutions for purposes such as the locating non-textured blobs from the background.

In practice, choosing the patch size for an application depends on the desired balance between false alarm and error escape rates. A smaller patch size increases the number of misdetections from normal variations, while using larger patches may contribute to detection failures. Normally all detections are subjected to further scrutiny, so in the end the patch size is defined by the general purpose computational resources available for detailed analysis.

The minimum patch size is smallest for periodic textures such as in textiles that must be inspected for both large and small weaving flaws that are generally multiplies of the mesh size. In textile inspection, Ade *et al.* [12] found that using an imaging resolution of three pixels per mesh width and averaged outputs of 3 x 3 to 5 x 5 pixel filters, derived via Karhunen-Loeve expansion of the spatial covariance matrix, the diameter of the minimum patch is around 15 pixels. The smallest detected defects in [12] appear to be around 10% of the patch area. Neubauer [13], using approximately the same imaging resolution, exploited three 5 x 5 FIR-filters and performed classification using histograms of features calculated from 10 x 10 pixel regions, achieving 1.6% false alarm and 9.3% escape rates.

The tests with LBP/C method for quasi-periodic textures performed by Ojala [14] with 16 x 16 pixel patch size and distribution classification detected 100% of the cases where more than about 25% of the block area did not belong to the same category. With natural textures the average detection threshold of other categories increased to around 35%.

3.2 Crack detection

It is evident that the inspection accuracy may significantly benefit from dedicated methods for detecting small defects. Crack or scratch detection is undoubtedly the most common defect for which specific techniques have been included in visual surface inspection systems.

The relative difficulty of detecting cracks depends on whether their shape and typical orientation is known a priori, whether they start from the edge of the object, and on whether the texture is periodic or random. A key problem is the typically very small transverse dimensions and poor contrast of cracks: the human visual system may easily detect them, but they may actually consist of ‘chains’ of nonadjacent single pixels in the image. In the worst case, the surface is randomly textured and the cracks may meander freely, starting and ending anywhere, leaving few application specific constraints that could be exploited.

The detection of cracks having a known shape is often straightforward applying Hough-transform or RANSAC to edge detected or high-pass filtered versions of the image. For instance, Gerhardt *et al.* [15] used Hough transform for detecting wrinkles in sandpaper in this manner.

With meandering cracks, the problem of discriminating them from other high frequency components in the image is very difficult. If the texture is periodic or quasi-periodic, texture measures characterizing the background may be powerful enough for detecting their presence. An alternative, a rather unusual simple method for defect detection from periodic patterns, based on a model of human preattentive visual detection of pattern anomalies, has been proposed by Brecher [16]. Detection is performed by comparing local and global first order density statistics of contrast or edge orientation.

Song *et al.* [17] have presented a trainable technique based on a pseudo-Wigner model for detecting cracks from periodic and random textures. The motivation behind selecting the technique is the better cojoint spatial and spatial frequency resolution offered by the Wigner distribution when compared to Gabor, difference-of-Gaussians and spectrogram approaches: this is an important factor due to the localness of cracks. The technique is trained with defectless images. During inspection it produces probabilistic distance images that are then postprocessed using rough assumptions on the shape of the cracks in the application.

4 Application Cases

Before committing effort into selecting, developing and using texture techniques in an application, it is necessary to thoroughly understand its requirements and characteristics. The developer should consider at least the following questions:

- Is the surface periodically, randomly, or only weakly textured? Strongly periodic textures can be efficiently characterized using linear filtering techniques that are also relatively cheap to implement with off-the-shelf hardware. For random textures LBP/C and gray level difference features with distribution based classification [10] are computationally attractive and rank among the very best. With weakly textured surfaces, plain gray-level and color distribution based classification may work very well [18].
- Are any of the properties of the defects known? In particular, are there any defects that cannot be discriminated from the background by their color or intensity? Due to their cost texture methods should usually be the last ones to be thrown in. They are generally much better in characterizing surfaces than in detecting anomalies. Thus, whenever feasible, application specific non-texture method solutions may be justified for detection, while texture measures may be powerful in eliminating false alarms and recognizing the defects.

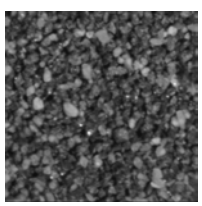
The following application cases, particle size determination, carpet wear assessment and leather inspection are demonstrations of analysis of random and quasi-periodic textures, and defect detection from random textures, respectively.

4.1 Case 1: determination of particle size distribution

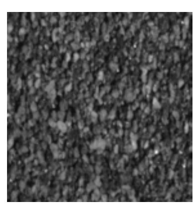
On-line measurement of the size distribution of granular materials, e.g., coke, minerals, pellets, etc., is a common problem in process industry, where knowledge of the mean particle size and shape of the distribution are used for control. The traditional particle size distribution measurement instruments, such as sieves, are suitable for off-line use in laboratory. The off-the-shelf machine vision systems developed for this purpose are based on blob analysis and require mechanical set-ups for separating the particles from each other. Separation is often necessary, because smaller particles may fall to the spaces between the bigger ones and are no longer visible, so the particle size distribution of the surface may not be representative. This happens if the relative size range as particle diameter is around 1.5 or larger.

Texture analysis has clear potential in granulometric applications. In principle, a measurement instrument could be trained with pictures of typical distributions, but the preparation of samples with known distributions is a laborious task, making this approach unattractive. Furthermore, the training problem is amplified by the need for frequent recalibrations, because the appearance of the material may change with time. The desired approach is to train the instrument by sieved fractions of the material, or to eliminate the need for training, as is the case with particle separation based measurements.

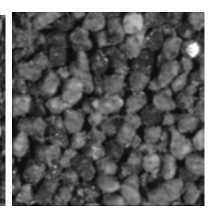
Rautio *et al.* [19] performed distribution measurement experiments using chrome concentrate that was sieved into 15 fractions, 37 to 500 μm, for use as training samples, and mixtures of three adjacent fractions were prepared for use as test samples. Various texture features, and distribution based and ordinary statistical classifiers were used in analysis. Figure 5 shows examples of the training material and mixtures, imaged at 7 x 7 μm resolution. The relative diameter range of particles in each mixture was 1.7 which results in only a minor "autosieving" phenomenon.



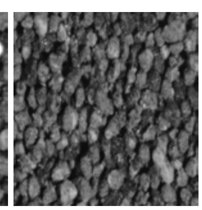
(a) 88-105 μm fraction



(b) 74-125 μm mixture



(c) 177-210μm fraction



(d) 149-250 μm mixture

Figure 5. Examples of sieved fractions and mixtures.

Gray level differences were found to be the best performing features with all classification schemes. Using the G metric and kNN classifier (k=3), the error of the leave-one-out test for training samples was 6%, when the gray level difference histograms with displacement 2 were used. The classification of mixture samples was performed by counting the classes of highest probability training samples, assuming that the relative counts represent the size distribution.

The measurement errors with test compositions were close to 50% for fractions below 125 µm, and around 22% for larger particle sizes. The overall error for the average size determination was 13%.

4.2 Case 2: carpet wear assessment

The assessment of appearance changes due to wear is a key factor in grading carpets. Typically, mechanical wear testers are used both during carpet development and production to produce samples that are then subjectively evaluated by panels of experts, but objective automated assessments are desired.

Siew *et al.* [20] performed a study to find image based measures that correlate with carpet wear. They considered and comparatively evaluated the power of statistics of spatial gray-level co-occurrence matrices, gray-level difference probability densities, gray level run-length matrices, and neighboring gray-level dependency matrices.

For experiments, four wool carpets with seemingly quasi-periodically textured appearance were selected and subjected to various durations of wear. Imaging was performed at 0.27 x 0.30 mm resolution, but at 0.54 x 0.60 mm for the coarsest texture. In the experiments the absolute percentage change in feature values with respect to the unworn control samples was computed.

It was found that while all the tested methods are promising for measuring carpet textures changes during wear, some of the features designed to measure specific characteristics work well only for certain textures. The neighboring gray-level dependency matrix based features had the best overall discrimination capabilities, followed by gray-level difference statistics, while the run-length and spatial co-occurrence methods had difficulties in assessing the wear of the finest, most randomly textured carpet.

4.3 Case 3: leather inspection

Leather hides were sorted based on their color, thickness, gray-level variations, texture and quality that is determined on the basis of the defects. For use in manufacturing shoes, belts, furniture and other leather goods, hides were selected on the basis of their characteristics and were cut into pieces of various shapes using moulds in a manner that the pieces have the desired quality, taking into account acceptable minor defects. The defects can be categorized as area faults that are local variations of gray-level or texture, line defects that are often scars or folds of skin, and point faults that are groups of spots, whose gray-levels differ from the background. The dimensions of the smallest defects that should detected are around 2 mm.

A methodology for inspecting leather hides has been investigated by Wambacq and his co-workers [21] who found that gray-level distributions for hides are symmetric even for the areas for defects, making plain histogram based detection schemes insufficient. They make a simplifying assumption that the gray values in the image are Gaussian distributed, and check whether the pixels in a 5 x 5 neighborhood are from the distribution determined for the good part of the hide using mean, variance and edginess tests. Because parts of the faults have the same characteristics as the defectless regions, the most deviating parts of the flaws are located first using stricter confidence intervals and requiring a certain number of detections in the 5 x 5 neighborhood to avoid overdetection. The reported difficulties with the methodology were mostly with very small spot and weak line faults.

5 Summary

Despite the progress in texture analysis methodology, the application of texture analysis to industrial problems is very rare. A major problem is that textures in the real world are often not uniform, due to changes in orientation, scale or other visual appearance. In addition, the degree of computational complexity of most texture measures is very high, and the methods are difficult to train properly. Recently introduced new texture measures and distribution based classification are a genuine step toward better applicability.

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