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Feature extraction and decision procedure for automated inspection of textured materials

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Abstract: This paper proposes a general system approach applicable to the automatic inspection of textured material. First, the input image is preprocessed in order to be independent of acquisition non-uniformities. A tone-to-texture transform is then performed by mapping the original grey level picture on a multivariate local feature sequence, which turns out to be normally distributed. More specifically, features derived with the help of the Karhunen–Loève decomposition of a small neighbourhood of each pixel are used. A decision as to conformity with a reference texture is arrived at by thresholding the Mahalanobis distance for every realization of the feature vector. It is shown that this approach is optimum under the Gaussian assumption in the sense that it has a minimum acceptance region for a fixed probability of false rejection.

Key words: Automated inspection, texture analysis, feature extraction, decision theory, Karhunen–Loève transform, eigenfilters.

1. Introduction

Image analysis techniques are being increasingly used to automate industrial inspection. Edge detection techniques have been largely employed for conformity testing and assembly inspection. Various examples such as shape control, printed circuit boards inspection have been reported in [2,3,4]. Surprisingly, the field of surface or material checking has received relatively little attention which means that this type of control still has to be carried out by inspection personnel. It seems reasonable to believe that this type of problem could be solved by means of a machine vision system using suitable image processing methods. The use of texture analysis techniques seems to be appropriate in accessing material surface quality [11] or detecting defects or local inhomogeneities [9].

This paper globally addresses the problem of defining in a very general way suitable features and a decision strategy applicable to the automatic inspection of textured materials for inhomogeneities. These can be due to defects such as scratches, impurities, cracks, bumps, tears, ruggedness, modification, overstretching, etc. It also proposes a set of

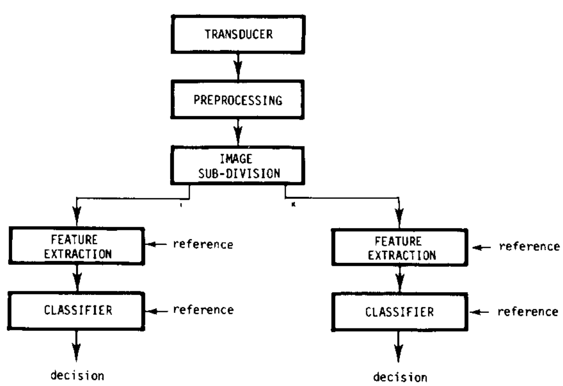

Fig. 1. Block diagram of a general texture inspection system.

features based on the Karhunen–Loève transform of a suitable neighbourhood of a pixel.

A general system approach for the detection of defects in textures has been suggested in a previous paper [9]. The block diagram of a complete texture inspection system is shown in Fig. 1 and can be sub-divided into different functional blocks. First, the textured surface is converted into a discrete bidimensional array of pixels with a limited number of grey levels. The digitized picture is then transformed in order to be better suited for further processing. For this purpose, an efficient algorithm that compensates for illumination changes and spatial non-uniformities of the sensor has been used. A set of sub-images that are treated separately is obtained by scanning the original image through a rectangular analysis frame. For every sub-image, a set of local statistical measures is computed and used for classification. The feature extraction process can be interpreted as a tone-to-texture transform that maps the original grey level picture onto a multivariate feature sequence. This point of view will be discussed in the next section. When complete knowledge of the different categories (normal and abnormal) is available in the form of some a priori probability density functions or large training sets of conforming and non-conforming texture samples, the final decision can be made by applying standard statistical classification schemes [7]. In this study, it was assumed that no representative abnormal training set would be available due to the fact that deviation from the reference texture may be infrequent and appear in an unpredictable way. Therefore, a decision procedure based on the reference class characterisation alone had to be designed. An optimum decision rule, in the sense that it has a minimum acceptance region for a fixed probability of false rejection, has been chosen rather than the usual heuristic solution based on the specification of a tolerance interval for each feature. The application of this formulation results in the definition of a reference dependent discrimination or test function summarising the information provided by a local feature vector. It can be used as a local measure of conformity (or homogeneity). The development presented in Section 3 is based on the assumption of a multivariate normal distribution for the local feature vector on a reference texture without defects. It has been verified experimentally that this condition is relatively well satisfied for a large family of features that can be expressed as the average of some particular function of pixels in a restricted neighbourhood.

2. Feature extraction

Texture is the term used to characterise the surface of a given object or phenomenon and is undoubtedly one of the main features used in image processing and pattern recognition. Texture must be regarded as a neighbourhood property of an image point. An image is said to have a uniform texture when it gives an almost homogeneous visual impression. The image of a single texture type can be defined as a picture in which the significant information (visual and semantic) is contained in any sub-image of sufficient size. A number of structural or statistical approaches to texture have been proposed but the problem of an efficient representation and description is by no means solved. Recent work by Haralick provides a comprehensive survey of most existing techniques [6].

In this study, a simplified characterisation of texture has been chosen. Feature extraction is performed by a hierarchical two-stage procedure. At the lower level the texture is analysed by means of certain local operators operating on a micro-window. They produce what might be termed 'primary' features measuring relations between pixels in a restricted neighbourhood. These primary features are then processed at a more global level by averaging over a macro-window. The features that result are used to characterize the texture sample, and form the input to the classifier. These quantities do not pretend to provide an exhaustive characterisation of texture, but they do implicitly capture certain local textural properties such as coarseness, directionality, regularity, etc.

2.1. *Tone-to-texture transform*

A discrete texture image defined on a $K \times L$ rectangular grid is denoted by

$$\{t_{k,l}\} \quad (k=1,2,\ldots,K;\ l=1,2,\ldots,L)$$

and is considered to be the realisation of a bidimensional stationary and ergodic stochastic process. The texture image is analysed through a rectangular $M \times N$ sliding window whose center is indexed by (k,l). For every position of the analysing frame (macro window), a set of q features with the following closed form is computed:

$$x_i(k,l) = \frac{1}{MN} \sum_{k'=-M/2}^{M/2} \sum_{l'=-N/2}^{N/2} y_i(k-k', l-l') \quad (1)$$

$(i=1,\ldots,q)$, where $y_i(k,l)$ is the result of a transform measuring some relations between pixels in a very close neighbourhood (micro window). In a very general form, this quantity can be expressed as

$$y_i(k,l) = F_i(N_{k,l})$$

with (2)

$$N_{k,l} = \{t_{i,j} \ (i = -\tfrac{1}{2}I + k, \ldots, \tfrac{1}{2}I + k; \\ j = -\tfrac{1}{2}J + l, \ldots, \tfrac{1}{2}J + l)\}$$

where $F_i(\cdot)$ is a given function of the elements of a micro window defined by the set $N_{k,l}$. This domain is chosen to be smaller than the analysing frame or averaging window. In many texture analyzing schemes the quantities $y_i(k,l)$ are defined on as few as two pixels. The local features $x_i(k,l)$ are unbiased local estimates of the theoretical mathematical expectations $E[y_i]$ over the previously defined macro window. It should be pointed out that most of the commonly used features in texture analysis satisfy the generic form (1). For example, some very popular features (mean, variance, correlation, average difference, contrast, homogeneity) usually extracted from the spatial grey level co-occurrence matrix proposed by Haralick in [5,6] can be computed by applying a specialized form of Eq. (1).

The local texture features measured in the $M \times N$ macro window centered on (k,l) can be arranged into a local feature vector

$$X_{k,l} = [x_1(k,l) \ x_2(k,l) \ \cdots \ x_q(k,l)]^{\mathrm{T}}. \quad (3)$$

The transformation of the original grey level picture $\{t_{k,l}\}$ into a multivariate local feature sequence $\{X_{k,l}\}$ is called a tone-to-texture transform. This procedure is illustrated in Fig. 2.

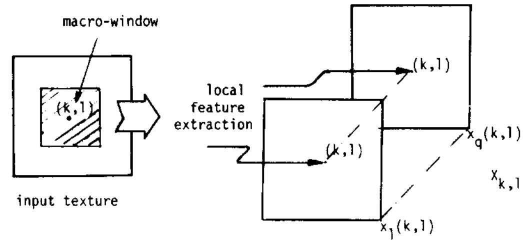

Fig. 2. Feature extraction procedure (tone-to-texture transform).

The use of a recursive algorithm [10] for the evaluation of the local feature vector can decrease computation time considerably. It is particularly suited for real time implementation.

In this study, a collection of energy measures at the output of a bank of so-called eigen-filters has been chosen as the set of features. These features are particularly interesting because the filters adjust automatically to the class of textures being treated. Obviously they are reference dependent. The method and its relation to other approaches is described more fully elsewhere [1]. The use of eigen-filters fits into the very general equation (2). In this case, the operator $F(\cdot)$ simply becomes the square of a weighted sum of the grey values of the pixels within a micro window (typically 3×3 pixels). In order to get the coefficients of the filters, one has to estimate the spatial covariance matrix associated with the random vector formed by the nine grey values of corresponding pixels. Scan-type numbering of the pixels will result in a center-symmetric, near-to-Toeplitz, covariance matrix. The eigen-vectors of this matrix can be used as 3×3 filter masks and provide the weights for $F_i(\cdot)$, $i=1,\ldots,9$. The estimated average power values over the $M \times N$ macro window at the output of these filters are chosen as the components of a feature vector $X_{k,l}$. This procedure is depicted in Fig. 3, which clearly shows that, in essence, the system is a filter bank. A similar system can be obtained by using fixed filters as, for example, those introduced by Laws [8]. However this last approach does not have the property of adapting automatically to a particular class of texture.

2.2. Distribution of the local feature vector

The derivation of an optimum decision rule is based on the knowledge of the multivariate pro-

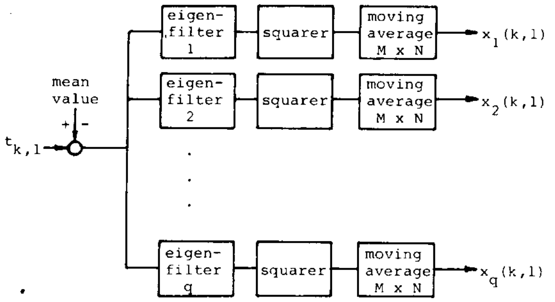

Fig. 3. Running evaluation of energy measures at the output of a bank of eigen-filters.

bability density function $p(X \mid \omega)$ of the local feature sequence for a reference texture without defect. It has been verified experimentally that this distribution can be fairly well approximated by a q-dimensional multivariate Gaussian distribution given by

$$p(X \mid \omega) = (2\pi)^{-q/2} |C|^{-1/2} \times \exp(-\tfrac{1}{2}(X-M)^{\mathrm{T}} C^{-1}(X-M))$$

where (4)

$$M = E\{X\} \quad \text{and} \quad C = E\{(X-M)(X-M)^{\mathrm{T}}\}.$$

3. Decision

As mentioned in the introduction, the abnormal distribution $p(X \mid \bar{\omega})$ is assumed to be unknown. In such a situation, the probability of false acceptance is not available and as a consequence the total probability of misclassification cannot be computed and used as a criterion for the performance of a given classifier. The only available quantity concerning the performance of such a system is the probability of false rejection. On the other hand, it is clear that the probability of false acceptance will depend on the volume of the acceptance region. Thus, it is reasonable to suppose that the best decision rule, for a fixed probability of false rejection, is the one that has the minimum acceptance region. According to such a requirement, the optimal decision rule is given by the following theorem.

Theorem. *For a fixed probability of false rejection, the optimal decision rule that minimises the acceptance region, is given as*

Decide ω

$$\text{if } X \in \mathcal{R}_a = \{X \in R^q, p(X \mid \omega) > T\} \tag{5}$$

else decide $\bar{\omega}$,

with T chosen in order to satisfy

$$P_{\mathrm{fr}} = 1 - \int_{\mathcal{R}_a} p(X \mid \omega)\,\mathrm{d}X. \tag{6}$$

Using (4), it can be shown that the condition

$$p(X \mid \omega) > T$$

is equivalent to

$$d(X) = (X-M)^{\mathrm{T}} C^{-1}(X-M) < T'$$

with (7)

$$T' = 2\log\{(2\pi)^{q/2} |C|^{1/2} T\}.$$

The quantity $d(X)$ is the Mahalanobis distance.

Let Φ be a $q \times q$ matrix consisting of the q eigenvectors of C,

$$\Phi = [\Phi_1 \ \Phi_2 \ \cdots \ \Phi_q], \tag{8}$$

and Λ a diagonal matrix constructed from their associated eigenvalues,

$$\Lambda = \begin{bmatrix} \lambda_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \lambda_q \end{bmatrix}. \tag{9}$$

By applying the linear transform $z = \Phi^{\mathrm{T}}(X-M)$, Eq. (7) can be rewritten as

$$d(X) = Z^{\mathrm{T}} \Lambda^{-1} Z = \sum_{i=1}^{q} z_i^2/\lambda_i \tag{10}$$

and one has the additional property that the components of the vector Z are mutually uncorrelated,

$$E\{ZZ^{\mathrm{T}}\} = \Lambda. \tag{11}$$

The feature vector Z is normally distributed. Because of the equivalence of uncorrelatedness and independence for Gaussian random variables, it follows that the z_i's are mutually independent.

4. Training procedure

Decision making will result from the application of Eq. (7). Therefore it is first necessary to determine the parameters of the distribution (mean and covariance matrix) and to select an appropriate threshold T'.

4.1. Parameter estimation

The distribution parameters will be estimated on a large sample of preprocessed reference texture without defects. Let $\{X_{k,l}\}$ be a $M_s \times N_s$ multivariate sequence of of local texture features measured on a large reference texture sample. The maximum likelihood estimates of the mean and covariance matrix are respectively given by

$$\hat{M} = \frac{1}{M_s N_s} \sum_{k=1}^{M_s} \sum_{l=1}^{N_s} X_{k,l}, \tag{12}$$

$$\hat{C} = \frac{1}{(M_s N_s - 1)} \sum_{k=1}^{M_s} \sum_{l=1}^{N_s} (X_{k,l} - \hat{M})(X_{k,l} - \hat{M})^{\mathrm{T}}. \tag{13}$$

4.2. Threshold selection

The value of the threshold T (or T') is fixed by the probability of false rejection. The multivariate integral (6) is not very convenient for the selection of this quantity. Therefore, one may do better by using the conditional probability density function associated to the one dimensional test variable $d(X)$. Applying Eq. (10), it is possible to show that $d(X)$ is chi-square distributed with q degrees of freedom. For a given probability of false rejection $(1-\alpha)$ the threshold T' will be chosen equal to the value χ_s^2 for which the χ^2 distribution yields

$$\operatorname{Prob}\{\chi^2 < \chi_s^2\} = \alpha = 1 - P_{\mathrm{fr}}. \tag{14}$$

The relation between the threshold and the probability of false rejection is shown in Fig. 4 in the case of a set of $q = 9$ features.

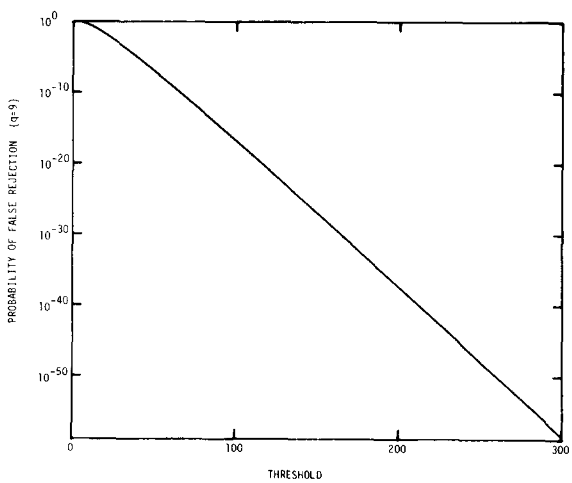

Fig. 4. Probability of false rejection as a function of the threshold ($q = 9$).

5. Experiments and results

Some examples of the application of the texture inspection system on real world texture data are reported below. A vidicon camera followed by an A/D converter were used to convert the texture samples into 256×256 picture arrays quantified into 256 grey levels. As one can see in the reproductions, the uniformity of the input data was rather poor because of faulty camera adjustment (shading effect). This effect was suppressed and a proper scaling (normalisation) of the data was obtained after preprocessing. The spatial covariance matrix associated with a 3×3 neighbourhood was computed on the reference texture and the nine resulting eigenvectors were used to form the masks of the corresponding eigen-filters. The set of nine energy measures was computed on a 32×32 sliding window on the preprocessed reference texture. These feature values were used to estimate the associated mean vector and covariance matrix. The Mahalanobis distance with respect to the reference texture was then computed on each texture for window positions with a 25% overlap. A zero order interpolation was used to generate a local Mahalanobis distance image, which is particularly well suited for interpretation. The texture defects are visualised as white peaks and can be easily detected by thresholding. The maximum values of the threshold that still guarantee correct detection of the defects in two different examples correspond to theoretical probabilities of false rejection of 10^{-50} and 10^{-35} respectively.

Additional experiments for other types of textures have also led to very encouraging results. Different sets of textural features have been used and, usually, have performed very well. For a good evaluation of the method further experiments need to be carried out on a large set of texture samples.

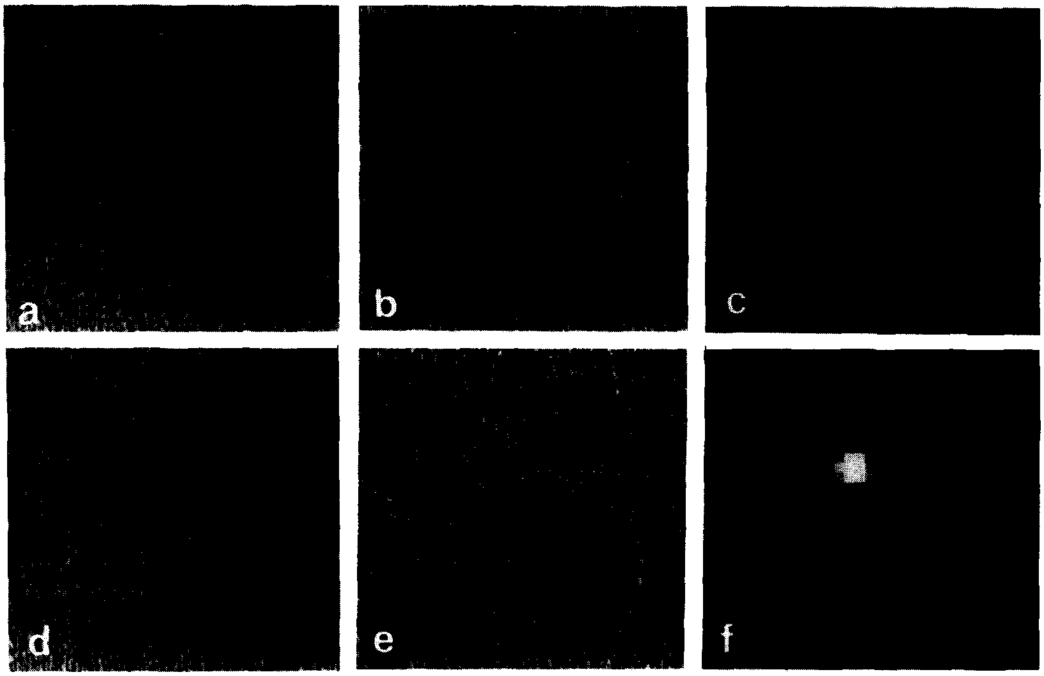

Fig. 5. First example of texture inspection; (a) input reference texture; (b) preprocessed reference texture; (c) local Mahalanobis distance for reference texture (scaling factor 1); (d) input texture with defect; (e) preprocessed texture with defect; (f) local Mahalanobis distance for texture with defect (scaling factor = 1, maximum value = 248).

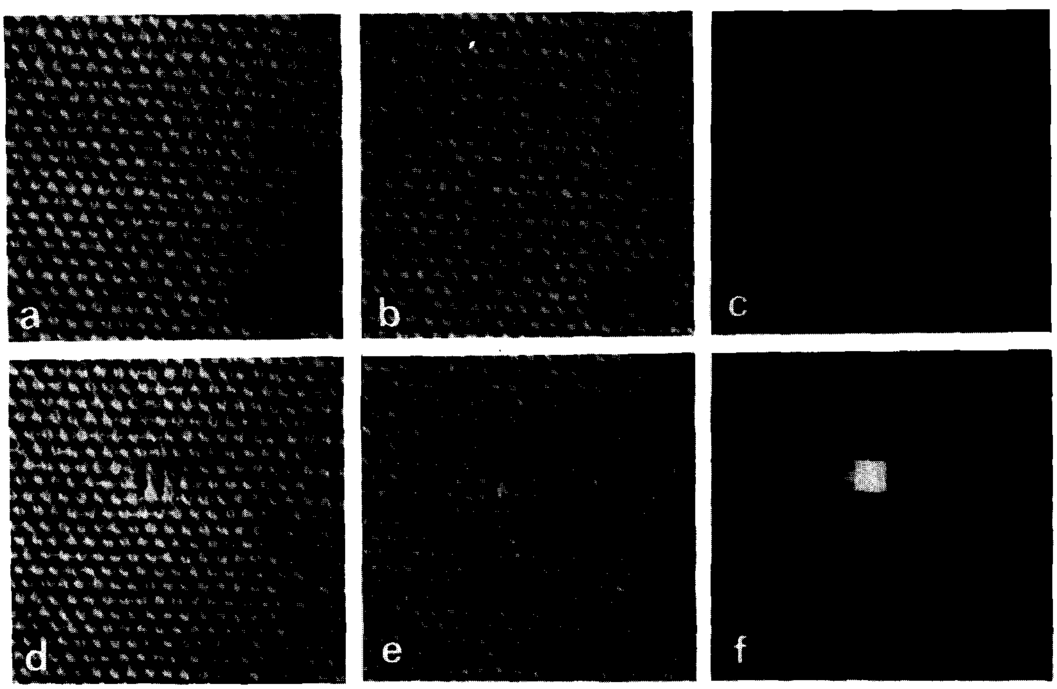

Fig. 6. Second example of texture inspection; (a) input reference texture; (b) preprocessed reference texture; (c) local Mahalanobis distance for reference texture (scaling factor 1.4); (d) input texture with defect; (e) preprocessed texture with defect; (f) local Mahalanobis distance for texture with defect (scaling factor = 1.4, maximum value = 175).

Nevertheless, it appears that this inspection system is sufficiently universal to be adapted to a variety of particular applications via the choice of an adequate set of features. For example, some relatively easy inspection tasks can be conducted by computing first order local features such as the mean, the variance, the skewness and kurtosis.

6. Conclusion

A flexible texture inspection system has been suggested. It is based on the evaluation of a sequence of local textural features. A relatively large class of textural features produced by a hierarchical two-stage procedure has been introduced. As an example, the energy measures at the output of a bank of eigen-filters have been considered. These filters are of particular interest because they adapt automatically to the class of texture to be treated. A decision procedure that is optimal in a well defined sense has been introduced. The resulting decision function, under the assumption of a Gaussian feature vector distribution, has been shown to be the local Mahalanobis distance.

This work is still preliminary but the results are very encouraging as shown in the examples, where an accurate detection of the defects was possible with an extremely low probability of false rejection. We are now pursuing efforts toward an objective evaluation of the method and comparing the performances of different sets of features for specific applications.

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