Improved Defect Detection in Manufacturing Using Novel Multidimensional Wavelet Feature Extraction Involving Vector Quantization and PCA Techniques.

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Abstract. This paper aims at investigating a novel solution to the problem of defect detection from images, that can find applications in the design of robust quality control systems for the production of furniture, textile, integrated circuits, etc. The suggested solution focuses on detecting defects from their wavelet transformation and vector quantization related properties of the associated wavelet coefficients. More specifically, a novel methodology is investigated for discriminating defects by applying a supervised neural classification technique, employing a Multilayer Perceptron (MLP) trained with the conjugate gradients algorithm, to innovative multidimensional wavelet based feature vectors. These vectors are extracted from the K-Level 2-D DWT (Discrete Wavelet Transform) transformed original image using Vector Quantization techniques and a Principal Component Analysis (PCA) applied to these wavelet domain quantization vectors. The results of the proposed methodology are illustrated in defective textile images where the defective areas are recognized with higher accuracy than the one obtained by applying two rival feature extraction methodologies. The first one of them uses all the wavelet coefficients derived from the k-Level 2-D DWT, while the second one uses only image intensities characteristics. Both rival methods involve the same classification stage as the proposed feature extraction approach. The promising results herein obtained outline the importance of judicious selection and processing of 2-D DWT wavelet coefficients for industrial pattern recognition applications

1 Introduction

Defect recognition from images is becoming increasingly significant in a variety of applications since quality control plays a prominent role in contemporary manufacturing of virtually every product. Despite the lot of interest, little work has been done in this field since this classification problem presents many difficulties. However, the resurgence of interest for neural network research has revealed the existence of powerful classifiers. In addition, the emergence of the 2-D wavelet transform [1],[2] as a popular tool in image processing offers the ability of robust feature extraction in images. Combinations of both techniques have been used with success in various applications [3]. Therefore, it is worth attempting to investigate whether they can jointly offer a viable solution to the defect recognition problem. To this end, we propose a novel methodology in detecting defective areas in images by examining the discrimination abilities of their K-level wavelet coefficients based features. Besides neural network classifiers and the K-Level 2-D wavelet transform, the tools utilized in such an analysis are vector quantization and Principal Component related analysis [4] of the vectors quantizing the K-Level wavelet domain of an image window.

The problem at hand can be clearly viewed as image segmentation one, where the image should be segmented in defective and non-defective areas only unlike its conventional consideration. Concerning the classical segmentation problem, that is dividing an image into homogeneous regions, the discovery of a generally effective scheme remains a challenge. To this end, many interesting techniques have been suggested so far including spatial frequency techniques [5] and relevant ones like texture clustering in the wavelet domain [5]. Most of these methodologies use very simple features like the energy of the wavelet channels [5] or the variance of the wavelet coefficients [6].

Our approach stems from this line of research related to the wavelet domain judicious processing. However, there is need for much more sophisticated wavelet feature extraction methods if one wants to solve the segmentation problem in its defect recognition incarnation, taking into account the high accuracy required. Following this reasoning we propose to incorporate in the research efforts multidimensional wavelet features, unlike the previously presented scalar feature extraction methodologies in the wavelet domain [6,5]. These multidimensional features, coming from the application of the K-Level 2-D DWT, are, in the sequel, processed using vector quantization and PCA methodology, which offer the accurate tools for describing transformed image characteristics and especially complex second order ones [4]. More specifically, PCA of the autocorrelation matrices analysis is well known to provide second order information about pixel intensities, while Vector Quantization algorithms provide the means for efficient vector space encoding. Two are the main stages of the suggested system. Namely, efficient multidimensional feature selection in the wavelet domain and neural network based classification. The viability of the concepts and methods employed in the proposed approach is illustrated in the experimental section of the paper, where it is shown that our methodology is very promising for use in the quality control field, by comparing its performance in defective areas classification accuracy with the one obtained by two rival feature extraction techniques.

2 Stage A: Efficient Multidimensional Feature Extraction in the K-Level Wavelet Domain

The problem of defect discrimination, aiming at segmenting the defective areas in images, is considered in the wavelet domain, since it has been demonstrated that discrete wavelet transform (DWT) can in general lead to better image modeling, as for instance to better encoding (wavelet image compression [7,8] is one of the best compression methodologies) and to better texture modeling [7]. Also, in this way, we can better exploit the known local information extraction properties of wavelet signal decomposition as well as the known features of wavelet de-noising procedures [9]. We use the popular 2-D discrete wavelet transform scheme ([1],[2] etc.) in order to obtain the wavelet analysis of the original image data containing defects. It is expected that the images considered in the wavelet domain should be smooth but due to the known time-frequency localization properties of the wavelet transform, the defective areas- whose statistics vary from the ones of the image background- should more or less clearly emerge from the background. We have experimented with the standard 2-D Wavelet transform using nearly all the well known wavelet bases like Haar, Daubechies, Coiflet, Symmlet etc. as well as with Meyer's and Kolaczyk's 2-D Wavelet transforms [2]. However, Daubechies and Haar wavelets have exhibited similar and the most accurate results and we employ them in the experimental section of the paper.

The proposed methodology involving multidimensional wavelet features obtained from the K-Level 2-D DWT, with application to defect detection, can be outlined in the following steps:

1) The N X N image is raster scanned by M X M sliding windows.
2) Each such window is transformed into the wavelet domain using the K-Level 2-D DWT. As a result, the wavelet coefficients organized in 3 * K + 1 channels (or bands) are obtained (see Figure 1).

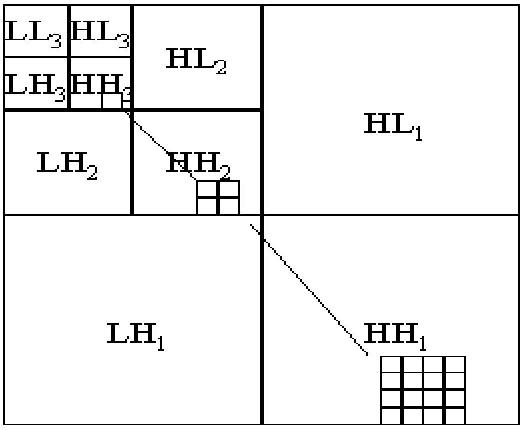

Fig. 1. Illustration of a sample of the corresponding wavelet coefficients sub-windows taking place in the formation of vectors Vi that span K-Level Wavelet domain. Three such windows are shown out of a total of 10 (one for each QMF channel).

3) Starting from the channel LL_K (the upper left window in Figure 1, which represents the Low Pass filtered image), the multidimensional vectors V_j are formed from the wavelet coefficients, having as components 3 * K +1 windows (each one associated with one channel) of $2^{(K- \text{ MAX\_ LEVEL\_INDICATED\_IN\_QMF})} * 2^{(K - \text{ MAX\_ LEVEL\_INDICATED\_IN\_QMF})}$ points. These points comprise a sub-window of wavelet coefficients belonging in the corresponding channel, and the position of this sub-window, as defined by its upper left point, is exactly the point in the QMF window under consideration associated with the LL_K channel point comprising the first component of vector V_i. For instance, concerning the three-level DWT of figure 1, each V_j is comprised of 10 main components, which are windows of wavelet coefficients. Each such window includes $2^{(3 - \text{ MAX\_ LEVEL\_INDICATED\_IN\_QMF})} * 2^{(3 - \text{ MAX\_ LEVEL\_INDICATED\_IN\_QMF})}$ of wavelet coefficients. For the LL_3 , HL_3 , LH_3 , HH_3 QMFs we have MAX_LEVEL_INDICATED_IN_QMF = 3 and, thus, 1 DWT coefficient is considered. For the HL_2 , HH_2, LH_2 QMFs we have MAX_ LEVEL_INDICATED_IN_QMF = 2 and, thus, 2 * 2 DWT coefficients are

considered. Finally, for the HL_1, HH_1, LH_1 QMFs we have MAX_ LEVEL_INDICATED_IN_QMF = 1 and, thus, 4 * 4 DWT coefficients are considered. Therefore, a total of 4 * 1 + 3 * 4 + 3 * 16 = 64 wavelet coefficients comprise each multidimensional wavelet vector V_j, in the case depicted in figure 1. The above mentioned sub-windows are illustrated in figure 1.

4) Obviously, the K-Level 2-D DWT space is spanned by the vectors V_i. In the sequel, the K-Level 2-D DWT domain is quantized using the vector quantization method of Kohonen Self Organizing Feature Map (SOFM) [4], which produces topology preserving codebook vectors [4]. These codebook vectors encode the topological space of the DWT domain by preserving input vectors probability distribution and are estimated as the associated with the SO map weight vectors [4]. Let's Cb1, Cb2,.... Cbn stand for these codebook vectors, where n<<r, if r is the multitude of Vi input vectors, that span K-Level 2-D DWT domain.
5) For each such Cbi we formulate its corresponding autocorrelation matrix $Cbi*Cbi^T$ and by applying the well known PCA techniques the associated ratio (λmin / λmax)i is calculated for the minimum and maximum eigenvalues of this autocorrelation matrix. Such a ratio plays a significant role in expressing the properties of these autocorrelation matrices and thus, to quantify the properties of the codebook vectors [4].
6) All the above calculated (λmin / λmax)i for every Cbi, form the input vectors for the neural classifiers of the subsequent stage B.

The practical aspects of the above proposed feature extraction approach, are next presented:

a) We have experimented with 256 x 256 images and we have found that M=32 is a good size for a sliding window raster scanning them and capable of locating defective areas (step 1).
b) A two-level 2-D DWT wavelet decomposition of these sliding windows associated images has been performed for each such window, resulting in seven main wavelet channels (step 2).
c) Step 3 above leads to vectors Vi having 4*1 + 3*4 = 16 wavelet coefficients as components. There are 64 (since LL_2 channel includes 8*8 coefficients) such vectors Vi that span the 2-Level wavelet domain. A total of 1024 wavelet coefficients comprise this domain, which is a large number of features to be employed in the classification stage of the proposed defect detection approach, since the curse of dimensionality obviously arises [4]. A judicious compression of this 64 vector space is therefore, required.
d) This is achieved through applying step 4 depicted above. To this end, a Kohonen SOM neural network involving 16 component (the wavelet coefficients) input vectors Vi as inputs and a 4 X 4 map of 16 output neurons compresses this vector space. The associated codebook vectors compressing the input space of 64 vectors are the 16 corresponding SOM weight vectors.
e) The autocorrelation matrices of these codebook vectors are of 16 X 16 dimensions. In step 5 above their 16 eigenvalues are calculated along with their min and max values. Therefore, for each Kohonen's SOM weight vector i the corresponding (λmin / λmax)i is estimated as indicated in step 5.

f) The input vectors of the neural based classification stage that follows, constructed by the suggested feature extraction technique, therefore, comprise 16 elements like (λmin / λmax)i, one for each codebook vector.

Thus, using the above in detail outlined feature extraction procedure, we have obtained 16 feature input vectors efficiently describing spatial distribution in the wavelet domain of each 32 x 32 sliding window raster scanning the images. These 16 features uniquely characterize such sliding windows and the corresponding feature vectors feed the neural classifier of the subsequent stage of the suggested methodology, next defined.

3 Stage B: Neural network based segmentation of defective areas

After obtaining the wavelet domain based characteristics of each M X M sliding window raster scanning the N X N image, involving the above defined methodology, we employ a supervised neural network architecture of the multilayer feedforward type (MLPs), trained with the conjugate gradients algorithm (Polak-Ribiere variation) [4], having as goal to decide whether such a sliding window covers a defective area or not. The inputs to the network are the 16 components of the feature vectors extracted from each such sliding window as previously defined. The best network architecture that has been tested in our experiments is the 16-8-8-1. The desired outputs during training are determined by the corresponding sliding window location. More specifically, if a sliding window belongs to a defective area the desired output of the network is one, otherwise, it is zero. We have defined, during MLP training phase, that a sliding window belongs to a defective area if the majority of the pixels in the 4 x 4 central window inside the original 32 X 32 corresponding sliding window belongs to the defect. The reasoning underlying this definition is that the decision about whether a window belongs to a defective area or not should come from a large neighborhood information, thus preserving the 2-D structure of the problem and not from information associated with only one pixel (e.g the central pixel). In addition and probably more significantly, by defining the two classes in such a way, we can obtain many more training patterns for the class corresponding to the defective area, since defects, normally, cover only a small area of the original image. It is important for the effective neural network classifier learning to have enough training patterns for each one of the two classes but, on the other hand, to preserve as much as possible the a priori probability distribution of the problem. We have experimentally found that a proportion of 1:3 for the training patterns belonging to defective and non-defective areas respectively is very good for achieving both goals.

4 Results and Discussion

The efficiency of our approach in recognizing defects in automated inspection images, based on utilizing wavelet domain information, is illustrated by applying it to the textile images shown in fig. 2,3,4 which contain various types of defective areas. Two other rival feature extraction methodologies are applied to these images too. The former of them uses all the 32 X 32 (=1024) wavelet coefficients obtained by the 2-D DWT transformation of each 32 X 32 sliding window without any further processing, while the latter uses the 32 X 32 (=1024) image intensities corresponding to the same sliding window. Therefore, the first feature extraction procedure used in this experimental study is the suggested novel one outlined in section II, which involves 16 components feature vectors. The second and the third feature extraction procedures as mentioned above, involve 1024 components feature vectors. The three images shown in figures 2,3,4 are of 256 x 256 dimensions and their associated 2-Level 2-D DWT are shown in figures 2, 3, and 4 respectively. The QMF channels shown in these figures have been obtained through applying the 2-D DWT with Daubechies wavelet bases to the original images. Obviously, the defective areas are preserved and enhanced in the corresponding wavelet domains and this explains the selection of the 2-D DWT as the baseline for the herein presented feature extraction methodology. There exist 50625 sliding windows of 32 x 32 size for each original image. The three rival feature extraction procedures used in this study are applied to every such sliding window, yielding the corresponding feature vectors. Therefore, for each image a set of 50625 training and test patterns is derived.

The neural networks corresponding to the classification stage (stage B) of the three defect detection systems under comparison are of the MLP type trained with the conjugate gradients algorithm (Polak-Ribiere variation). The best architectures found and compared are 16-8-8-1, 1024-64-32-1, 1024-64-32-1. For an image involved in the study, each MLP has been trained with its corresponding training set containing 1500 patterns extracted from the associated sliding windows as described above. On average (for the three images) 480 out of these 1500 patterns belong to the defective areas, while the rest belong to the class of non-defective areas. Each MLP has been tested on all 50625 patterns from which its training set comes from. The results obtained by involving our methodology are shown in fig. 5, 6 and 7 and clearly are very favorably compared, in terms of defect classification performance, to the two other feature extraction methodologies.

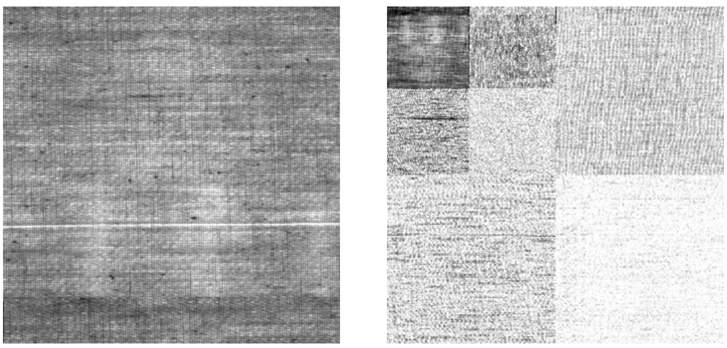

Fig. 2. First original textile image containing a defect (left) and the 2-Level 2-D Wavelet transformation of this image (right).

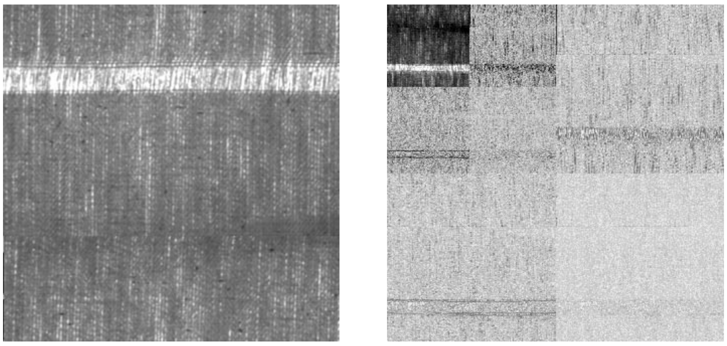

Fig. 3. Second original textile image (left) containing a defect and the 2-Level 2-D Wavelet transformation of this image (right).

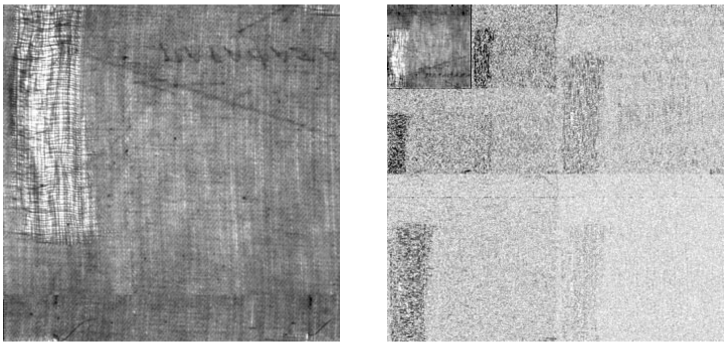

Fig. 4. Third original textile image (left) containing a defect and the 2-Level 2-D Wavelet transformation of this image (right).

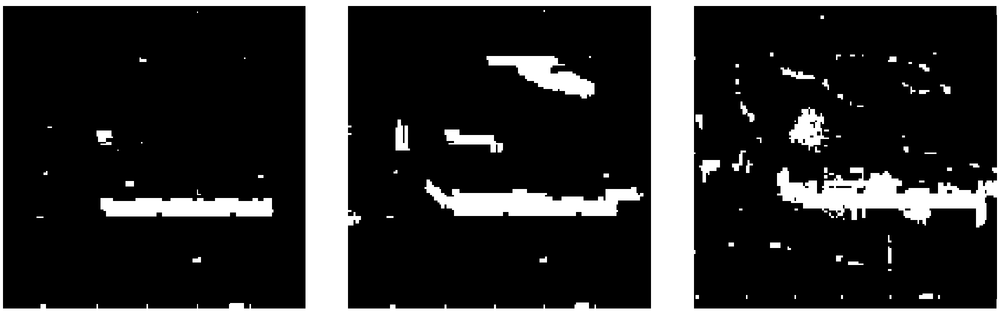

Fig. 5. Defect Detection results for the first textile image. From left to right the results obtained using the proposed feature extraction method, the 32 X 32 wavelet coefficients and the 32 X 32 pixel intensities as described in section 4.

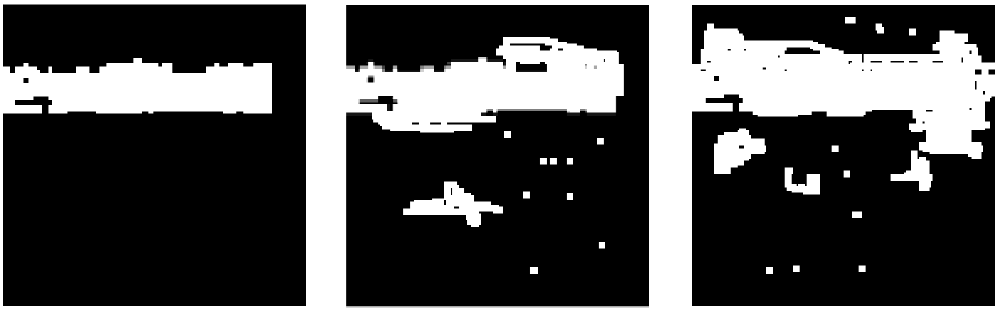

Fig. 6. Defect Detection results for the second textile image. From left to right the results obtained using the proposed feature extraction method, the 32 X 32 wavelet coefficients and the 32 X 32 pixel intensities as described in section 4.

Fig. 7. Defect Detection results for the third textile image. From left to right the results obtained using the proposed feature extraction method, the 32 X 32 wavelet coefficients and the 32 X 32 pixel intensities as described in section 4.

5 Conclusions

A novel methodology is developed for defect detection employing a new feature extraction approach applied to the k-Level wavelet domain and also, employing neural classifiers of the MLP type. This feature extraction approach considers multidimensional vectors of wavelet coefficients having as components suitably selected windows of these coefficients from their associated QMF channels. The K-Level wavelet domain is, therefore, composed as the space of all these vectors by using the suggested methodology. A vector quantization algorithm is subsequently applied to this new vector space and the associated codebook vectors are extracted. The vector quantization algorithm used is the Kohonen topology preservation map (SOM) and the resulting codebook vectors are the corresponding SOM weight vectors. A PCA analysis of the autocorrelation matrices associated with these codebook vectors provides the components of the feature vectors, which feed the supervised MLP architectures of the classification stage of the proposed defect detection system. The proposed defect detection system is favorably compared with one involving as feature vectors the image intensities and another one having as feature vectors the 2-D DWT wavelet coefficients only. Both rival systems use the same MLP based classification technique as the herein proposed system. The promising results herein obtained set the baseline for the future work of the authors, which is currently focused on building a real world defect detection system for the textile industry instead of the prototype investigated in this paper.

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