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Support Vector Machines for 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 using the Support Vector Machines (SVM) classification approach, 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 for manufacturing applications 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, namely SVM, 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 defect detection methodologies. The first one of them uses all the wavelet coefficients derived from the k-Level 2-D DWT and involves SVM again in the classification stage, while the second one uses again all the wavelet coefficients derived from the k-Level 2-D DWT but involves a Multilayer Perceptron (MLP) neural network in the classification stage. The promising results herein shown outline the importance of judicious selection and processing of 2-D DWT wavelet coefficients for industrial pattern recognition applications as well as the generalization performance benefits obtained by involving SVM neural networks instead of other ANN models.*

I. INTRODUCTION

A novel methodology is developed for defect detection employing the SVM approach along with a new feature extraction procedure applied to the k-Level wavelet domain. 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 SVM architectures of the classification stage of the proposed defect detection system. The proposed defect detection system is favorably compared with one system involving as feature vectors the set of all 2-D DWT wavelet coefficients and as the corresponding pattern classifier a SVM. In addition, it is favorably compared with another defect detection system involving as feature vectors the set of all 2-D DWT wavelet coefficients again and as the corresponding pattern classifier an MLP. 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.

The SVM approach is a relatively new ANN classification methodology and although there exist several research efforts concerning their applications to real world pattern recognition problems, there is lack of a systematic account with regards to the defect detection problem in manufacturing process. The first contribution of this paper lies exactly on investigating SVM defect detection performance and proving that it is better than the one obtained by applying MLP models as alternative in the classification stage of the suggested and outlined defect detection system. The second and major novelty and contribution of this work is the proposed feature extraction methodology, applied to the K-Level wavelet domain, which produces multidimensional wavelet vectors efficient for defect discrimination and demonstrates the significance of properly selecting and processing the wavelet domain coefficients in designing successful real world pattern recognition systems.

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 and by subsequently classifying them using SVM. Besides neural network classifiers of the SVM type 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. There are several reasons for involving SVM techniques instead of more traditional neural approaches.

More specifically, Support Vector Machines [4] are an attractive approach to data modeling through applying neural systems. They combine generalisation control with a technique to address the curse of dimensionality. The formulation results in a global quadratic optimisation problem with box constraints, which is readily solved by interior point methods. The kernel mapping provides a unifying framework for most of the commonly employed model architectures, enabling comparisons to be performed. In classification problems generalization control is obtained by maximising the margin, which corresponds to minimisation of the weight vector in a canonical framework. The solution is obtained as a set of support vectors that can be sparse. These lie on the boundary and as such summarise the information required to separate the data. The minimisation of the weight vector can be used as a criterion in regression problems, with a modified loss function [4]. Out of these properties, the most important reason to use SVM in the defect detection problem is actually the generalization control capability they offer and thus, the avoidance of overfitting. These properties seem to be very important concerning the required sensitivity and specificity to be exhibited by defect detection systems in manufacturing quality control. For instance minimization of false alarms is an absolute must, while on the other hand even the slightest defects should be detected if an automated real world quality control system is to be realized.

The problem of defect detection 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, 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 SVM 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 defect detection techniques.

II. 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)
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 $2^{(K- MAX_ LEVEL_INDICATED_IN_QMF)} * 2^{(K - MAX_ LEVEL_INDICATED_IN_QMF)}$ 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 $2^{(3 - MAX_ LEVEL_INDICATED_IN_QMF)} * 2^{(3 - MAX_ LEVEL_INDICATED_IN_QMF)}$ 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 SVM neural classifiers of the subsequent stage B.

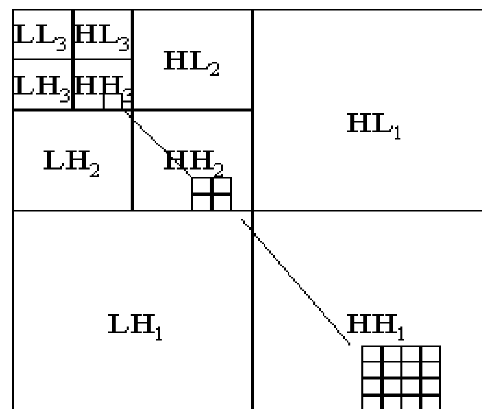

Figure 1. Illustration of a sample of the corresponding wavelet coefficients sub-windows taking place in the formation of vectors Vi that span K-Level Wavelet domain. Three such windows are shown out of a total of 10 (one for each QMF channel).

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 SVM neural classifiers of the subsequent stage of the suggested methodology, next defined.

III. STAGE B: SVM 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 SVM type with RBF (and polynomial) kernels and in parallel, as baseline for comparison we, also, consider Multilayer Feedforward models (MLP), trained with the conjugate gradients algorithm (Polak-Ribiere variation) [4]. The goal for both supervised training procedures is to decide whether such a sliding window covers a defective area or not. The inputs to the networks are the 16 (or 1024) components of the feature vectors extracted from each such sliding window as previously defined. 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 SVM/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.

IV. 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 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 and involves as defective area classifier a SVM, while the latter uses the 32 X 32 (=1024) wavelet coefficients again, corresponding to the same sliding window, and an MLP model instead. Therefore, the first defect detection procedure used in this experimental study is the suggested novel one outlined in section II, which involves 16 components feature vectors followed by a SVM pattern classifier. The second and the third procedures as mentioned above, involve 1024 components feature vectors and therefore, the curse of dimensionality might appear. 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 defect detection procedures used in this study are applied to every such sliding window, yielding the corresponding feature vectors along with their classifications. 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 first two defect detection systems under comparison are of the SVM type. Concerning the third such system an MLP network trained with the conjugate gradients algorithm (Polak-Ribiere variation) has been utilized. The best MLP architecture found and compared with the SVM is the 1024-64-32-1. For an image involved in the study, the SVM/MLP has been trained with its corresponding training set (obtained from the specific image) 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 SVM/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 defect detection methodologies.

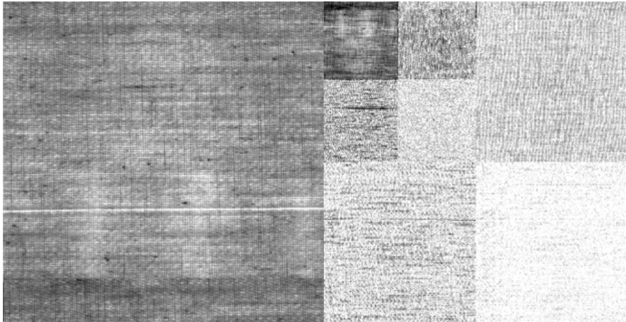

Figure 2. First original textile image containing a defect and the 2-Level 2-D Wavelet transformation of this image

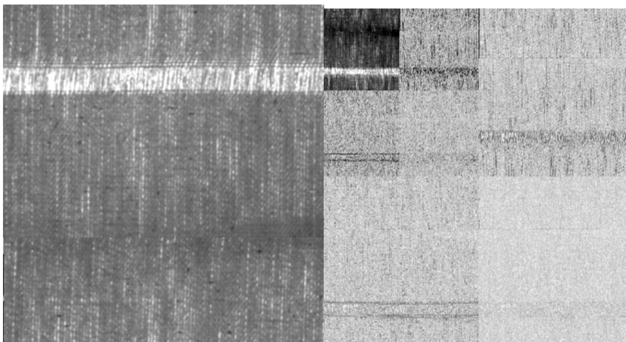

Figure 3. Second original textile image containing a defect and the 2-Level 2-D Wavelet transformation of this image

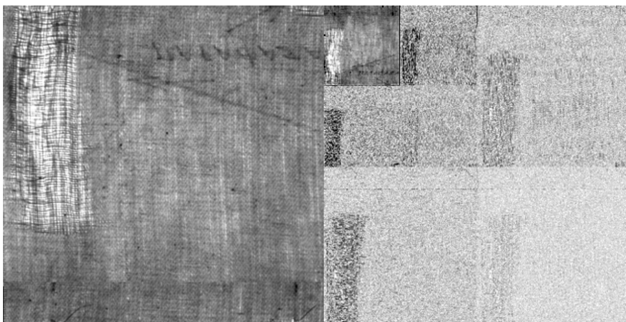

Figure 4. Third original textile image containing a defect and the 2-Level 2-D Wavelet transformation of this image

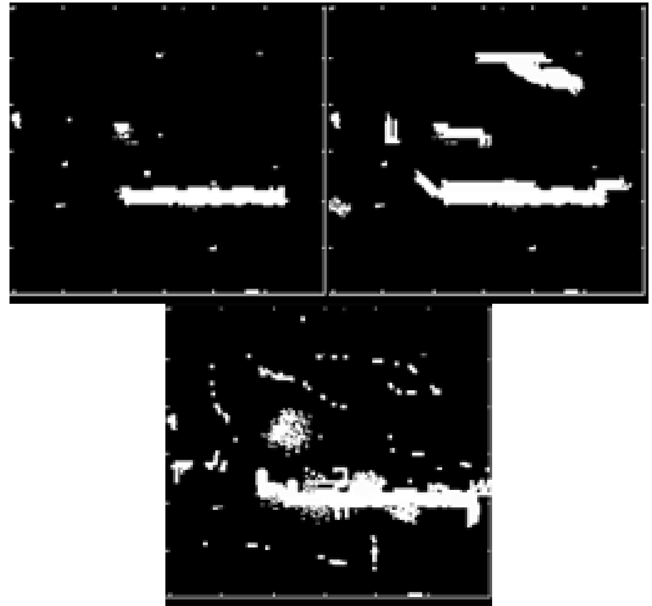

Figure 5. Defect Detection results for the first textile image. From left to right the results obtained using the proposed feature extraction method+ SVM, the 32 X 32 wavelet coeff. + SVM and the 32 X 32 wavelet coeff. + MLP, as described in section IV

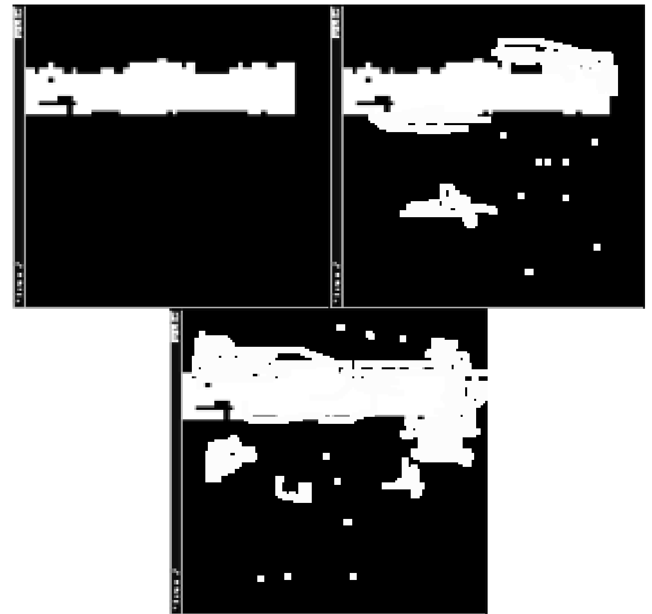

Figure 6. Defect Detection results for the second textile image. From left to right the results obtained using the proposed feature extraction method+ SVM, the 32 X 32 wavelet coeff. + SVM and the 32 X 32 wavelet coeff. + MLP, as described in section IV

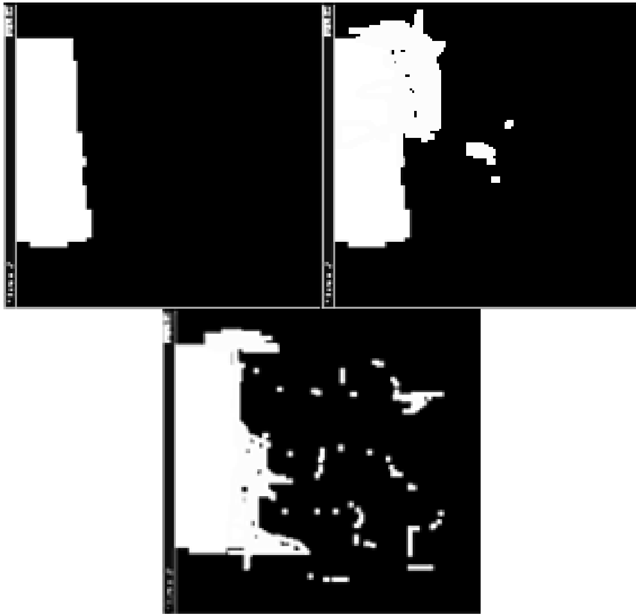

Figure 7. Defect Detection results for the third textile image. From left to right the results obtained using the proposed feature extraction method+ SVM, the 32 X 32 wavelet coeff. + SVM and the 32 X 32 wavelet coeff. + MLP, as described in section IV

V. CONCLUSIONS

A novel methodology is developed for defect detection employing the SVM approach along with a new feature extraction procedure applied to the k-Level wavelet domain. 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 SVM architectures of the classification stage of the proposed defect detection system. The proposed defect detection system is very favorably compared with one system involving as feature vectors all the 2-D DWT wavelet coefficients and as the corresponding pattern classifier a SVM. In addition, it is very favorably compared with another defect detection system involving as feature vectors the 2-D DWT wavelet coefficients again and as the corresponding pattern classifier an MLP. 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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