Multi Spectral Inter-Correlative Approach for Feature Selection in Pattern Recognition

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Abstract-*Feature representing is a prime requirement in the pattern recognition area, where features are represented in transformed domain to get finer resolution description of image representation. In the spectral oriented feature representation, wavelet based coding are more dominantly been used for its finer detail feature representiaon. The spectral feature representation based on wavelet transformation, are more informative, however the feature counts are of large count resulting in processing overhead. Towards improving the recognition efficiency, in this paper a new coding approach based on band correlation is presented, which minimizes the number of selective band coefficients, minimize the processing overhead.*

Keywords:*wavelet transformation, pattern recognition, inter-correlative coding, and feature selection approach.*

I. INTRODUCTION

Due to large volume of data information in a database, the memory consumption is observed to be very high. This limits the current system to be used for real time applications where speed of retrieval is mainly required. Hence an effective method should be developed to utilize the memory effectively by representing the image Data in a feature format revealing the most. The images are represented in various formats to represent in which shape, color, and textures are of prime importance. Where representing the data in more features format improves retrieval accuracy, more the representative coefficient the system takes that much time to process in retrieval. The texture information's reveals the content variation in the image and are mostly used feature. To retrieve texture features, wavelet transformations are mostly used due to their capability of representing the multi-resolution information. Wavelet-based coding provides substantial accuracy in representation by the hierarchical decomposition of image into resolution bands. Over the past few years, a variety of powerful and sophisticated wavelet-based schemes [3],[4] for image representation, have been developed and implemented..to have better represent ability of image the filters used in wavelet transforms should have the property of orthogonality, symmetry, short support and higher approximation order. Due to implementation constraints, these scalar wavelets do not satisfy all these properties simultaneously [5], [6]. A New class of wavelets called 'Multiwavelets' which possess more than one scaling filters [7] overcomes this problem. Thus Multiwavelets offer the possibility of superior performance and high degree of represent ability for imaging applications, compared with scalar wavelets. The Multiwavelet transform could achieve better level of performance than scalar wavelets with similar computational complexity.

In this paper, a new feature selecting approach is proposed to perform the pattern recognition. The proposed approach considers the inter correlative features of inputs samples to perform the recognition accurately. The inter correlative features increases the accuracy as well as reduces the time complexity. in this paper, a selective Multiwavelet coding was used to find the inter correlative features. The remaining paper is organized as follows: section II gives the details about the Multiwavelet coding. Section III gives the details about the proposed selective Multiwavelet coding. the experimental results are given in section IV and finally the section V concludes the paper.

II. MULTIWAVELET CODING

The wavelet transform is one of the signal transform technique, used commonly in image compression. An enhanced version of wavelet transform is multiwavelet transform. Multiwavelets and wavelets are almost similar but having some important differences. Wavelets have only two functions, wavelet function Ψ(t) and scaling function Φ(t), whereas multiwavelet have multi scaling and multi wavelet functions [8]. The scaling function set for multiwavelet coding can be written as $\Phi(t) = [\Phi_1(t),\Phi_2(t)\ldots, \Phi_r(t)]^T$, where Φ(t) is a multi-scaling function. Similarly, the multiwavelet function set for multiwavelet coding can be written as $\Psi(t) = [\Psi_1(t), \Psi_2(t)\ldots, \Psi_r(t)]^T$. in general 'r' can be a large value, but the study on Multiwavelets to present date is for r=2[9]. The two scale equation for multiwavelet can be defined as

$$\phi(t) = \sqrt{2}\sum_{k=-\infty}^{\infty} H_k \phi(2t-k) \quad (1)$$
$$\psi(t) = \sqrt{2}\sum_{k=-\infty}^{\infty} G_k \phi(2t-k) \quad (2)$$

Where, $\{H_k\}$ and $\{G_k\}$ are matrix filters, i.e., H_k and G_k are 'r x r' matrices for each integer k. The filter coefficients of these filters provide more degree of freedom compared with scalar wavelets [10]. Due to this extra degree of freedom, the extra useful properties such as orthogonality, symmetry and higher order approximation can be incorporated into the multiwavelet filters. For each and every multi filter bank the input and output is a vector [11]. The analysis (H and G multi filters) and synthesis (Ĥ and Ĝ multi-filters) is illustrated in figure.1 for a single level bi-orthogonal multi filter bank.

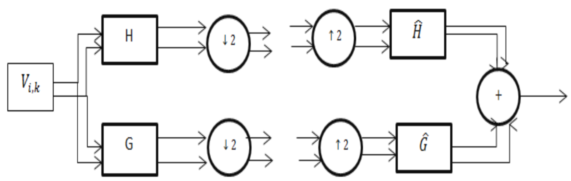

Figure1.One level Bi-orthogonalmulti-filter bank.

The basic properties of a Multiwavelet transform are illustrated as;

1. The inherent property, extra degree of freedom in Multiwavelets is the main property, can be used to reduce the limitations on the filter properties. For example, a scalar wavelet cannot possess both the extra properties such as symmetry and orthogonality. Orthogonality provides the easier design and implementation process while symmetry is necessary for symmetric filters for signal extension. Also, the scalar wavelets are directly linked with the vanishing moments and support length. i.e., to achieve higher order approximation, longer length filters are necessary at the expense of extending the wavelet's interval support. In general, shorter support is preferred to obtain the better localized approximation of the respective input function, but to achieve the higher coding gain, higher order approximation is desired. In addition to the limitations of traditional wavelets, Multiwavelets can possess the best of all the above mentioned properties simultaneously.

2.One necessary feature of any transform that is using in image compression is the amount of energy compaction obtained. A better and smaller number of scaling coefficients having most of the energy and larger number of sparse wavelet coefficients decomposition of a fair uniform input signal can be done by a filter that is having good energy compaction properties. This becomes significant during the quantization sine the number of bits required to represent the wavelet coefficients are less compared to scaling coefficients. To avoid the quantization noise as much as possible, by clustering the wavelet coefficient values about to zero with a little variance, the performance achieved should be better. So, Multiwavelets have the capacity to provide the better reconstructive quality at the same bit rate.

3. Multiwavelets, compared with scalar wavelets, can achieve better level of performance with same computational complexity. The organization and statistics of multiwavelet subbands should be different compared with scalar wavelets, because Multiwavelets produce two high pass bands and two low pass bands in each and every dimension. A scalar wavelet transform can decompose a 2-D image into four blocks for a single level of decomposition. These four blocks represents the subbands representing either high pass or low pass in both dimensions. Figure.2 (a) shows the single level of decomposition using scalar wavelets. The data obtained in subband 'LH' is obtained by high pass filtering the input along the rows and then low pass filtering along the columns. The Multiwavelets having two channels, so there will be two sets of wavelet coefficients and also two sets of scaling coefficients. Figure.2 (b) shows the subband decomposition using Multiwavelets. In the multiwavelet subbands, H and L labels have subscripts representing the channel to which the data belongs to. For example, L2H1 represents the data from the first channel high pass filter in the horizontal direction and the second channel low pass in the vertical direction.

LL	***LH***
HL	***HH***

L_1L_1	L_1L_2	L_1H_1	L_1H_2
L_2L_1	L_2L_2	L_2H_1	L_2H_2
H_1L_1	H_1L_2	H_1H_1	H_1H_2
H_2L_1	H_2L_2	H_2H_1	H_2H_2

(a) Scalar wavelets. (b) Multiwavelets.
Figure 2.single level subband decomposition of a 2-D image.

In the process of multi wavelet transform as the decompositions are made for each band isolately, the obtained coefficients are hence divided into further bands and processing over such 'n scale-bands' results in processing overhead. It could be observed that in multi-level band decomposition, the lower level bands are derived from the upper level subbands, hence the obtained information formulate a quad-band decomposition. Wherein each subband is represented into 4 lower bands. As these 4 bands are finer details of a detail sub band these bands reflects a similarity among these 4 bands. Hence to reduce the coefficients and to have the property of multi wavelet property a selective coding for band selection is proposed. The approach of selective coding for band selection is defined in following section.

III. SELECTIVE-MWVLT CODING

In various signal and image processing applications, refinement of a signal is made to achieve higher level of accuracy. In the process of band decomposition, it is observed that, finer details reveal more clear information's than the original processing signal. However as the band decomposition increases, the probability of redundancy among different bands increases. This redundancy of information increases the processing overhead, and intern makes the system slower. Hence it is required to have an adaptive band selection process for extracting the actual informative band from the processed bands. In the process of signal processing a adaptive band selection process for subband coding was made in [12]. However no such approach of band selection is observed in image coding. With reference to band selection process in this work the process of adaptive band selection is developed for multi wavelet coefficients. Considering the analysis and synthesis filter of the transformation as shown in figure 3, the generalized multiband decomposition can be shown as;

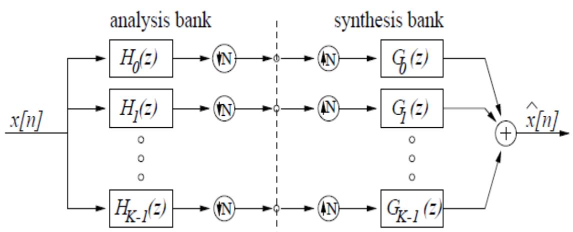

Figure.3. Analysis and synthesis branch of an n-channel filter bank [12]

In this process the analysis bank decomposes the image I into K subbands, each produced by a branch $H_z(k)$ of the analysis bank. After decimation and expansion by a factor N, the full band signal is reconstructed from the subbands in the synthesis bank by filtering with filters $G_k(z)$ followed by summation. The analysis filters $H_k(n)$ are derived from the real value of a lowpass FIR filter p[n] of even length L_p. For the estimation of signal using such filtration cost optimization approached is used where the subband are processed adaptively termed as subband adaptive filter (SAF) [12].The SAF operation is based on the LMS-type adaptive filter. The converged of such filter is based on the optimization of this LMS function, wherein weight functions are used to optimize the mean error. To converge the cost function faster in [13] a Normalized SAF (NSAF) is proposed. In this approach the convergence speed is increased by increasing the number of subband filters while maintaining the same level of steady-state error. However, it suffers from huge complexity when used in adapting an extremely long unknown system such as acoustic echo cancellation application. To overcome this problem in [14] a dynamic selection based NSAF (DS-NSAF) scheme is proposed. This approach sorts out a subset of the subband filters contributing to convergence performance and utilizes those in updating the adaptive filter weight. This approach dynamically selects the subband filters so as to fulfill the largest decrease of the successive mean square deviations (MSDs) at every iteration. This approach reduces the computational complexity of the conventional SAF with critical sampling while maintaining its selection performance. The operational approach for the conventional DS-SAF approach [13] is as outlined.In a SAF system the desired band d(n) that originates from an its lowering band is defined by,

$$d(n) = u(n)W^o + v(n) \quad (3)$$

where $w^0$is an unknown column vector to be identified with an adaptive filter, *v(i)* corresponds to a variance σ_v^2 for each band, and *u(n)* denotes a row input vector with length M defined as;

$$u(n) = [u(n)\, u(n-1) \;\ldots\; u(n-M+1)] \quad (4)$$

In the process of adaptive selection, the Normalized SAF (NSAF) [14] approach was proposed. A basic architecture for such coding is as shown in figure 4.

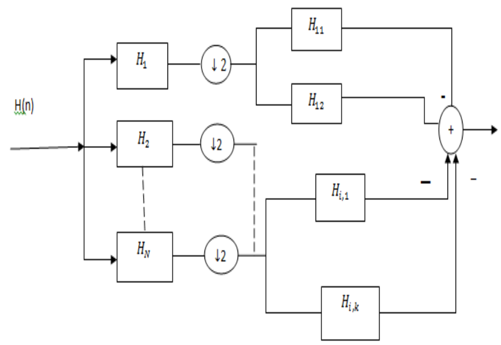

Figure 4. NSAF filter architecture [15]

In this approach the image sample is partitioned into N subbands by the analysis filters $H_0(z)$, … $H_{n-1}(z)$. The resulting subband signals are then critically decimated to a lower sampling rate relative to their demanded bandwidth. The original signal d(n) is decimated to k signals and the decimated filter output at each subband is defined as;

$$y_{i,D}(k) = u_i(k)w(k), \quad (5)$$

Where, $u_i(k)$ is a 1 x M row such that, $u_i(k) = [u_i(kN), u_i(kN-1), \ldots\ldots, u_i(kN-M+1)]$and $w(k) = [w_0(k),\ w_1(k), \ldots\ldots, w_{M-1}(k)]^T$ denotes the estimated weight value and the decimated band error is then defined by,

$$e_{i,D}(k) = d_{i,D}(k) - y_{i,D}(k) = d_{i,D}(k) - u_i(k)w(k \quad (6)$$

Where $d_{i,D}(k) = d_i(kN)$ is the reference information at each band. In the process of NSAF the weight optimization is defined as,

$$w(k+1) = w(k) + \mu \sum_{i=0}^{N-1} \frac{u_i^T(k)}{\|u_i(k)\|^2} e_{i,D}(k) \quad (7)$$

Where μ is the step size.

This weight is used to optimize the band selection process where in it takes a large computation to converge for the optimization. To overcome this issue in [13] a MSD based weight optimization is proposed. In this DS-NSAF approach the largest decrease of the MSDs between successive iterations is used.

Hence the weight error vector is then defined as, $\tilde{w}(k) = w^o - w(k)$. The weight optimization is then defined as,

$$\tilde{w}(k+1) = \tilde{w}(k) - \mu \sum_{i=0}^{N-1} \frac{u_i^T(k)}{\|u_i(k)\|^2} e_{i,D}(k) \qquad (8)$$

Using this weight vector and taking the expectation a MSD is computed which satisfies the absolute expectation as,

$$E\|\tilde{w}(k+1)\|^2 = E\|\tilde{w}(k)\|^2 + \mu^2 E\left[\sum_{i=0}^{N-1} \frac{e_{i,d}^2(k)}{\|u_i(k)\|^2}\right] - 2\mu E\left[\sum_{i=0}^{N-1} \frac{u_i(k)\tilde{w}(k)e_{i,D}(k)}{\|u_i(k)\|^2}\right] \triangleq \mathrm{E}\|\tilde{w}(k)\|^2 \qquad (9)$$

Where

$$\Delta = \mu \sum_{i=0}^{N-1} \left(2E\left[\frac{u_i(k)\tilde{w}(k)e_{i,D}(k)}{\|u_i(k)\|^2}\right] - \mu E\left[\frac{e_{i,d}^2(k)}{\|u_i(k)\|^2}\right]\right) \qquad (10)$$

Defines the difference of MSDs between two successive bands. With bands having minimum MSD is then chosen to have a selective band for processing rather to all decomposed bands. This band selection process reduces the processing coefficient with minimum deviation due to the selecting criterion of minimum MSD value. To this selected band then a modified encoding process is used to achieve higher level of compression as presented below.

V. EXPERIMENTAL RESULTS

The proposed system is tested for different test sample at different orientations, and it is observed to have classification rate in the range of 80-100%. Multiple instance of same class are recognized with 80% accuracy, because multiple instance of same class have close resemblance to each other. The accuracy of the developed system is defined by,

*Percentage of accuracy = (No. Of correctly recognized samples/Total No of samples in the test suite)*100.*(11)

Eight orientation features were used obtained from the gabor transformation of the wavelet sub bands and the results of the classification process obtained is as illustrated below.

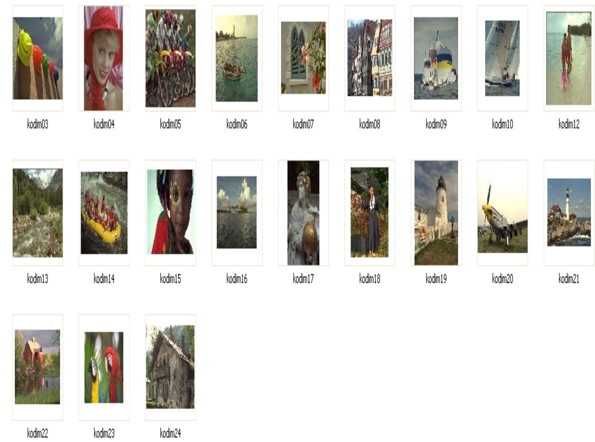

Figure 5:Test data set created using Kodak images

Figure 6: Given query sample

Retrived image

Figure 7: retrieved sample

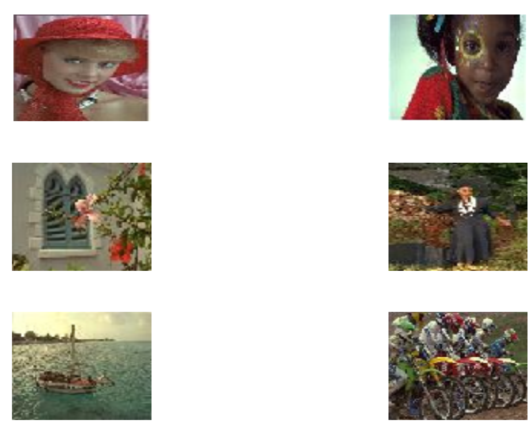

Figure 8: classified test sample


Figure 9: Test Query sample


Figure 10: Retrieved Sample

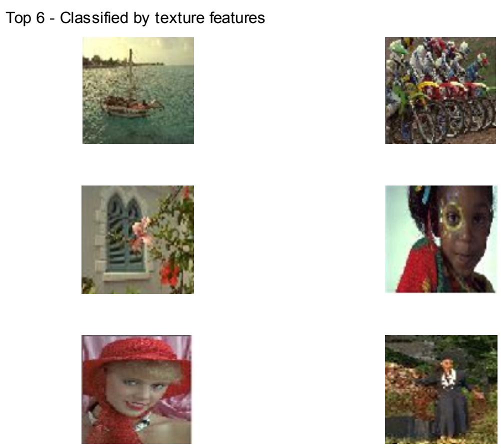

Figure 11: classified sample for the texture based recognition


Figure 12: Test query sample

Figure 13: retrieved image

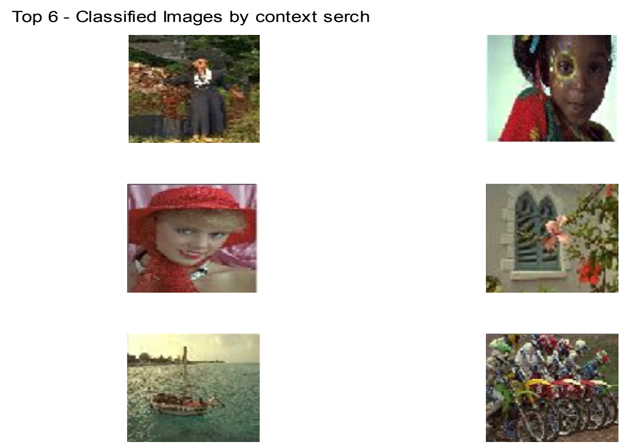

Figure 14: top classified images

The evaluation parameters are computed for the simulation defined by,

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (12)$$

Where,

TP = True positive (Correctly identified)
FP = False positive (Incorrectly identified)
TN = True negative (false, Correctly identified)
FN = False negative (false, incorrectly identified)

The Precision is computed as a ratio of TP to sum of TP and FP while recall is the ratio of TP to sum of TP and FN. The following expressions give precision and recall measurements

$$Recall = \frac{TP}{TP+FN} \quad (13)$$

$$Precision = \frac{TP}{TP+FP} \quad (14)$$

The observed performances are observed as;

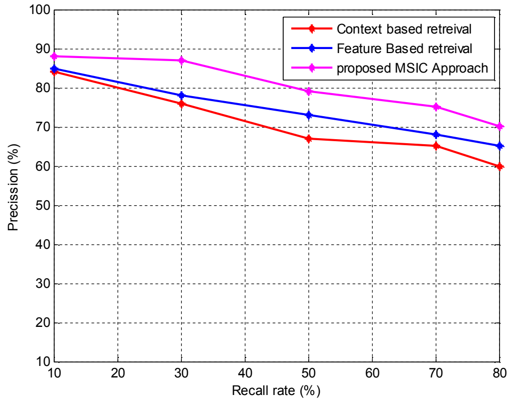

Figure 15 : observed precision for the developed system over variation in recall rate

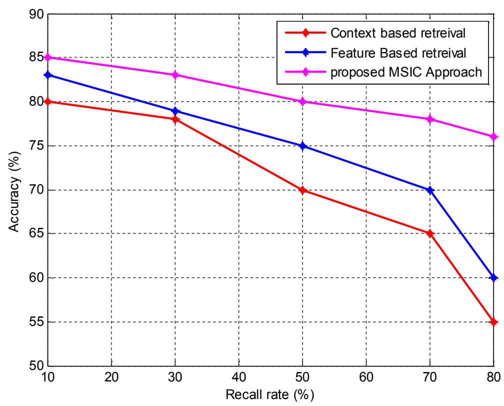

Figure 16: observed Accuracy for the developed system over variation in recall rate

VI. CONCLUSION

This paper presented a new coding approach to feature selection based on inter corrective property of band coefficient in spectral feature representation. A new inter band coding, results in finer feature selection, minimizing the redundant band coefficients. The significant coding of multi spectral band representation is utilized and coefficientsselection is made out to result in finer feature representation, resulting in improvement to performance accuracy. The observed metrics for the developed approach illustrates the significance of suggested featurerepresentation. This approach gives significance in more accurate feature representation with lower feature dimension representation and higher retrieval accuracy.

VII. REFERENCES

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