8 × 8 SMRT Based Texture Descriptors

B. Manju, V. L. Jaya, K. Meenakshy, and R. Gopikakumari

Abstract—In this paper texture features based on mapped real transform (MRT) is studied. Redundancy exists in MRT coefficients. Different algorithms have been proposed for removing the redundancy and placing the MRT coefficients. SMRT is a placement scheme based on sequency of the coefficients. The paper presents texture feature extraction based on SMRT placement algorithm. SMRT based texture feature extraction is found to be faster compared to UMRT based method.

Index Terms—Texture descriptors, MRT, feature extraction.

I. INTRODUCTION

Texture is an important property of image. Textural features are used to classify an image as belonging to one set of image class. The texture features used should have good discriminating power, for the classification algorithm to be effective. The challenging task in texture based image classification is therefore to identify textural features with high classification accuracy.

Literature review shows that many such feature sets have been used for texture based image classification. Texture analyses in the initial stages were based on the first order and second order statistics of texture images. Later, features derived from transform based methods were also used for classification.

Based on second order statistics, Haralick *et al.* [1] discussed Gray Level Cooccurrence Matrix (GLCM) and suggested a number of GLCM based features. Galloway [2] proposed five features for texture classification derived from Gray level runlength (GLRL) matrix.

Later many transform based methods for texture based image classification were proposed. Joan S. Weszka *et al.* [3] described a classification method with features obtained from fourier power spectrum. But the classification accuracy of the fourier power spectrum based features is less compared to statistical methods.

A new set of texture features were suggested by Tor Lonnestad [4] based on Haar Transform. Chang and Kuo [5] proposed a multiresolution approach for texture classification which uses tree structured wavelet transform. Van de Wouwer *et al.* [6] showed that texture can be characterized by the statistics of the wavelet detail coefficients. Mala and Sadasivam [7] used orthogonal wavelet transform to get the horizontal, vertical and diagonal details of an image. Statistical texture features were extracted from these details and used for image classification. A feature extraction

algorithm using wavelet decomposed image and its complementary image for texture classification is presented by Hiremath *et al.* [8].

R. C. Roy proposed [9] a new transform, MRT, for two dimensional signal representations. Anishkumar *et al.* [10] used MRT for image compression. Meenakshy presented in [11] texture classification based on 1-D and 2-D MRT. Both 1-D and 2-D MRT methods performed image classification better compared to GLRL and GLCM methods.

The present paper uses 2-D MRT for image classification. In Section II, mapped real transform (MRT) is explained. The UMRT and SMRT placement schemes are explained in subsections of Section II. Texture feature extraction based on the two placement schemes are explained in Section III. Simulation studies to compare the UMRT and SMRT texture descriptors are explained in Section IV. Results are discussed and concluded in Section V.

II. MAPPED REAL TRANSFORM

The complex multiplications in two Dimensional Discrete Fourier Transform (2-D DFT) computation was reduced by modifying it. This is done by projecting the data onto the $N/2$ twiddle factor axes, exploiting the periodicity and symmetry properties. By doing this the number of complex multiplications was reduced from N^2 to $N/2$ per coefficient. An integer to integer transform, MRT, that involves only real additions rather than complex multiplications, was developed from this modified DFT computation.

MRT coefficients, $Y_{k_1, k_2}^{(p)}$ for an image block, x_{n_1, n_2} , $0 \leq n_1, n_2 \leq N - 1$ is given as

$$Y_{k_1, k_2}^{(p)} = \sum_{\forall(n_1, n_2) | z=p} X_{n_1, n_2} - \sum_{\forall(n_1, n_2) | z=p+M} X_{n_1, n_2} \quad (1)$$

for, $0 \leq k_1, k_2 \leq N - 1$ and $0 \leq p \leq M - 1$,
where, $M = \frac{N}{2}$,

$$z = ((n_1 k_1 + n_2 k_2))_N.$$

In the expression k_1, k_2 are the frequency indices and p is the phase index.

From equation(1) we will get the $\frac{N^3}{2}$ MRT coefficients. As the total number of MRT coefficients is greater than the size of the image, it is difficult to use the transform. Methods were proposed to eliminate the redundancy in the MRT matrix and retain only the $N \times N$ unique MRT coefficients.

An algorithm to find all the MRT coefficients and to identify and place the unique MRT coefficients by removing redundancy was explained by R. C. Roy [12].

A. Unique Mapped Real Transform (UMRT)

Bhadran [13] proposed a new algorithm to identify and

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B. Manju and K. Meenakshy are with Government Engineering College, Thrissur, India (e-mail: manjudeepu@hotmail.com).

V. L. Jaya is with Cochin University of Science and Technology, Kochi, India.

R. Gopikakumari is with Division of Electronics, School of Engineering, Cochin University of Science and Technology, Kochi, India.

place the unique MRT coefficients, which is termed as UMRT algorithm. In the algorithm, a group of DFT coefficients, termed basic DFT coefficients were identified. For N a power of two, UMRT coefficients derived from the $(3N-2)$ basic DFT coefficients were placed in an $N \times N$ matrix. The algorithm places these coefficients where it actually duplicates. UMRT algorithm is faster than the earlier algorithm [12] as there is no need to find all the MRT coefficients.

This algorithm was modified in [14] which directly identifies and places the UMRT coefficients.

B. SMRT

A pictorial representation of MRT coefficients derived in terms of 2×2 data is given in [15]. In [16] visual patterns of UMRT coefficients were analyzed and found that they have a specific pattern. These patterns when reordered results in a new pattern. If the reordering is done according to the number of sign changes, it results in a new visual pattern. Based on this a new placement scheme is derived in [16] terms of sequencies along columns and rows. This new scheme is termed as Sequency based MRT, SMRT.

The (k_1, k_2, p) placement scheme of 8×8 UMRT and SMRT coefficients is shown in Table I and Table II.

TABLE I: (K_1, K_2, P) PLACEMENT OF 8×8 UMRT COEFFICIENTS

000	010	020	011	040	012	022	013
100	110	120	311	140	512	321	713
200	210	220	611	240	212	622	613
101	310	320	111	141	712	121	513
400	410	420	411	440	412	422	413
102	510	122	711	142	112	323	313
202	610	620	211	242	612	222	213
103	710	322	511	143	312	123	113

TABLE II: (K_1, K_2, P) PLACEMENT OF 8×8 SMRT COEFFICIENTS

000	010	011	012	013	020	022	040
100	110	310	510	710	120	320	140
101	111	311	511	711	121	321	141
102	112	312	512	712	122	322	142
103	113	313	513	713	123	323	143
200	210	211	212	213	220	620	240
202	610	611	612	613	222	622	242
400	410	411	412	413	420	422	440

III. TEXTURE DESCRIPTORS BASED ON MRT

The visual pattern of 8×8 MRT coefficients, $Y_{k_1, k_2}^{(p)}$, for different k_1, k_2, p values are shown in Fig. 1.

Texture is characterized by a given pixel and the pattern in a local area around the pixel. This can be perceived in images as homogeneous visual patterns representing the surface composition being imaged. Analysis of Fig. 1 clearly shows that each MRT coefficient computes gray level differences of pixel to some scale. This property of MRT coefficients can be used to represent texture. Based on the analysis, texture features are derived corresponding to each frequency from the absolute sum of the phase terms for individual blocks. Hence, 2-D MRT feature as in [17] is defined as,

$$f_{k_1, k_2} = \frac{\sum_{i=1}^{N_b} \sum_p |Y_{k_1, k_2}^{(p)}|}{N \times N} \quad (2)$$

where $N \times N$ - size of image and N_b - N_o . of blocks. In this

study block size chosen is 8×8 .

While mapping an 8×8 image matrix to SMRT or UMRT matrix there will be 22 different k_1, k_2 pairs which in general is equal to the number of basic DFT coefficients, $3N-2$. Each k_1, k_2 pair contribute to a texture feature resulting in 22 texture features as in Table III.

These features are effectively used in image classification in [17].

Fig. 1. Visual representation of 8×8 MRT coefficients for three different k_1, k_2, p values.

TABLE III: 2-D MRT FEATURES

$f(k_1, k_2)$	k_1	k_2	p
$f(0,0)$	0	0	0
$f(0,1)$	0	1	0,1,2,3
$f(1,0)$	1	0	0,1,2,3
$f(0,2)$	0	2	0,2
$f(2,0)$	2	0	0,2
$f(0,4)$	0	4	0
$f(4,0)$	4	0	0,1,2,3
$f(1,1)$	1	1	0,1,2,3
$f(3,1)$	3	1	0,1,2,3
$f(5,1)$	5	1	0,1,2,3
$f(7,1)$	7	1	0,1,2,3
$f(1,2)$	1	2	0,1,2,3
$f(2,1)$	2	1	0,1,2,3
$f(3,2)$	3	2	0,1,2,3
$f(6,1)$	6	1	0,1,2,3
$f(1,4)$	1	4	0,1,2,3
$f(4,1)$	4	1	0,1,2,3
$f(2,2)$	2	2	0,2
$f(6,2)$	6	2	0,2
$f(2,4)$	2	4	0,2
$f(4,2)$	4	2	0,2
$f(4,4)$	4	4	0

In [17], [18] UMRT algorithm was used for finding texture features and the features were termed as UMRT texture features. In the algorithm basic DFT coefficients were found out. They were placed in different (k_1, k_2, p) positions according to the algorithm. Placement details of UMRT coefficients are as shown in Table I.

For finding the texture features, MRT coefficients corresponding to particular (k_1, k_2) have to add for different p values. For doing this, positions of particular (k_1, k_2) for different p values have to be identified in UMRT placement scheme and added together to get a particular feature. This requires a good knowledge of the placement algorithm which is complicated.

In this paper, texture features are found out based on SMRT placement scheme. Analyzing the SMRT placement scheme given in Table II shows that particular (k_1, k_2) for different p values comes in a row or column. This clearly shows that texture features can be found out using row wise or column wise addition of SMRT elements. The algorithm used for placement is simple compared to UMRT placement scheme. Texture features found using this algorithm are termed as SMRT texture descriptors.

IV. SIMULATION RESULTS

To study the UMRT and SMRT texture features, experiments were performed on 12 images of size 512×512 from Brodatz album [19], given in Fig. 2. Simulation is performed using Intel core i5 machine with 4 GB RAM and clock speed 2.4 GHz on MATLAB 7.12 platform.

From each image, sub image of size 128×128 is extracted. The sub images are divided into blocks of 8×8 size. Texture features for each sub image is calculated as equation (2), based on both UMRT and SMRT methods. Calculation time for UMRT and SMRT texture feature extraction are found out. The results are tabulated in Table IV.

The result is verified by changing the sub image size to 256×256 and keeping the block size 8. The results are tabulated in Table V.

The table clearly shows that SMRT algorithm is almost six times faster than UMRT algorithm.

Fig. 2. Brodatz texture images D1, D2, D3, D4, D5, D6, D7, D8, D9, D10, D11, D12.

TABLE IV: COMPARISON TABLE OF UMRT AND SMRT TEXTURE FEATURE EXTRACTION TIME FOR 128×128 SUB IMAGE

Images	Time in Secs	
	UMRT	SMRT
D1	75.78	11.37
D2	74.95	11.32
D3	80.95	11.29
D4	74.75	11.47
D5	76.11	11.28
D6	75.14	11.34
D7	76.04	11.31
D8	74.29	11.34
D9	76.01	11.31
D10	74.04	11.35
D11	75.43	11.37
D12	73	11.33
Average Time	75.54	11.34

V. CONCLUSION

Feature extraction is an important task in texture based image analysis. The paper presents a fast algorithm to extract features which are used for image classification [17], [18].

The results in the tables makes clear that SMRT based texture feature extraction is much faster compared to UMRT based feature extraction. In SMRT based method it is only required to perform row wise or column wise addition. But in UMRT feature calculation, positions (k_1, k_2, p) of different coefficients has to identify and then add to get the texture features.

TABLE V: COMPARISON TABLE OF UMRT AND SMRT TEXTURE FEATURE EXTRACTION TIME FOR 256×256 SUB IMAGE

Images	Time in Secs	
	UMRT	SMRT
D1	76.39	11.32
D2	76.28	11.48
D3	76.2	11.28
D4	76.19	11.33
D5	75.86	11.33
D6	76.3	11.9
D7	75.85	11.35
D8	76.12	11.30
D9	76.2	11.28
D10	75.04	11.38
D11	74.8	11.39
D12	74.12	11.35
Average Time	75.78	11.39

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B. Manju received B.Tech. degree in the year 1996 from Mahatma Gandhi University, Kottayam, Kerala and M.Tech degree from Visvesvaraya Technological University, Belgaum in the year 2007. She is working at Government Engineering College, Thrissur, India from 1999 and currently she is pursuing her PhD degree as a part time scholar in the Cochin University of Science and Technology. Her fields of interest are image processing, embedded systems etc.

V. L. Jaya received B.Tech and M.Tech degrees from National Institute of Technology, Calicut in the years 1990 and 2000 respectively. She is working as an associate professor at College of Engineering, Kottarakara, IHRDE, Kerala and currently she is pursuing her PhD degree at CUSAT, Kochi. Her fields of interests are digital signal processing, image processing etc.

K. Meenakshy received B.Tech and M.Tech degrees from Kerala University in the years 1990 and 1995 respectively. She received her PhD degree from Cochin University of Science and Technology in the year 2010. She is working in Government Engineering College, Thrissur. Her fields of interest are biomedical applications, image processing etc.

R. Gopikakumari received B.Sc (Engg) degree from Kerala University and M.Tech and PhD degrees from Cochin University of Science and Technology in the year 1984, 1987 and 1999 respectively. She is working in Cochin University of Science and Technology from 1988 and currently she is a professor in Division of Electronics Engineering. Her fields of interest are digital signal processing, image processing, neural network etc.