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IMPROVED FINGERPRINT COMPRESSION TECHNIQUE WITH DECIMATED MULTI-WAVELET COEFFICIENTS FOR LOW BIT RATES

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Abstract
In this paper, a multi-wavelet transform with decimated frequency bands is proposed to be used in the Set Partitioning in Hierarchical Trees (SPIHT) algorithm to improve fingerprint image compression. Either shuffled or unshuffled multi-wavelets can be used for SPIHT algorithm. In both the cases, the quality of the compressed images at lower bit rates either remained the same or slightly improved compared to wavelets. To improve the performance at lower bit rates, a method which utilizes the decimated version of multi-wavelet for the initialization of lists in SPIHT algorithm is used. The multi-wavelet used for the proposed work is SA4 (Symmetric-Antisymmetric). The algorithm was tested and verified using NIST, Shivang Patel, NITGEN and other databases. An overall improvement in performance particularly at lower bit rates (0.01 to 0.09) compared to a multi-wavelet without decimation was obtained using this method. The improvement was 0.798dB, 0.857dB and 0.859dB for the images in NITGEN database for a multi-wavelet decimated by 2, 4 and 8 respectively. Similar performances were observed for other databases. It was further observed that the PSNR was highest when the multi-wavelet was decimated by a factor of 4.

Keywords:
Compression, Multi-Wavelet, Fingerprint Image, Decimation, Low Bit Rate

1. INTRODUCTION

Fingerprint recognition is one of the most commonly used biometric techniques for personal identification. Fingerprint images have been used in forensics, immigration, access control and law enforcement. Large volumes of fingerprint images have to be stored and transmitted over the biometric database network. This will require large storage space and transmission bandwidth. With the increase in the number of fingerprints, compression is essential for reduced storage space and faster data transfer. JPEG, SPIHT and JPEG 2000 are the different image compression algorithms based on DCT/wavelet. WSQ is a wavelet-based compression technique specifically designed for fingerprint images. For all these above-mentioned techniques, the quality of the reconstructed image degrades at lower bit rates. Wavelet filters do not possess the properties like orthogonality and symmetry simultaneously which are known to be important in achieving a good compression performance. Multi-wavelets can possess these properties simultaneously as it has more design options because of matrix filter coefficients [1].

According to theory, multi-wavelets should perform better due to the extra possibilities in the design of filter coefficients. Priya and Ananthi [2] verified the efficiency of various multi-wavelets on the compression of medical images. It was shown by them that the multi-wavelet Hardin Marasovich (HM) gave the best performance when compared to the other multi-wavelets on CT scan brain images. Feng et al. [3] proposed a Fractal Image Compression (FIC) algorithm based on multi-wavelet transform and the performance of compression was verified for natural images. It was shown that an improved compression performance can be achieved with increased coding speed compared to traditional FIC. Further, the computational complexity and coding time were still high compared to wavelet based progressive compression techniques. Jagadeesh and Nagabhooshanam [4] proposed a SPIHT compression algorithm based on multi-wavelet decomposition followed by spectral feature-based band selection. An improvement in the PSNR value was reported, compared to conventional approach for medical images using this technique. Sudhakar and Jayaraman [5] proposed fingerprint compression using SPIHT with a difference in scanning order of the multi-wavelet coefficients. No standard database was used for comparing the performance and particularly the performance at lower bit rates was not taken into account in their work. Ragupathy et al. [6] proposed an image compression technique using SPIHT with partial shuffling of the multi-wavelet coefficients with maximum number of decomposition levels. As the number of decomposition levels increased, the number of bits required to represent the transform coefficient increased leading to reduced coding efficiency [7].

With traditional techniques, the quality of the compressed fingerprint image becomes inadequate at lower bit rates. Emmanuel et al. [8] proposed fingerprint image compression using Coiflet wavelet and Lloyd-Max non-uniform quantization. An adequate quality fingerprint image was obtained by them at a compression ratio of 20:1 compared to 15:1 for the existing techniques. Shao et al. [9] and Shahanas and Selin [10] proposed fingerprint compression technique using sparse representation. A better image quality was achieved at lower bit rates and the algorithm exhibited higher complexity due to block processing in their work. It was reported that the multi-wavelets can reconstruct a better-quality image with lesser number of transform coefficients [11, 12] at lower bit rates. For improving the performance of fingerprint compression at lower bit rates, an unshuffled multi-wavelet with optimum prefilter coefficients for SPIHT algorithm was proposed in [13]. An improvement in PSNR was reported at lower bit rates compared to wavelets. It was shown that the reduction in number of nodes leads to an improvement in the performance at lower bit rates.

Usually a multi-wavelet with or without coefficient shuffling was used as a transform for multi-wavelet based SPIHT compression algorithms. From the literature, it is understood that the performance of compression at lower bit rates is not satisfactory in either case. In order to improve the performance at lower bit rates, a multi-wavelet with a decimated frequency band is proposed for the initialization of lists in SPIHT algorithm. Since decimation is performed in the lowest frequency band of the multi-wavelet transform, the number of nodes will be reduced during initialization. This reduction in the number of nodes will lead to an improvement in PSNR. An investigation into the proposed technique is carried out for various decimation factors and their corresponding performances. SA4 multi-wavelet is used for validating the proposed technique.

2. MULTI-WAVELET BASED SPIHT ALGORITHM

SPIHT algorithm [14] is a wavelet-based compression algorithm which can be extended to multi-wavelets since it is having a decomposition structure similar to that of a wavelet. In the case of wavelet-based algorithms, the wavelet coefficients are arranged in three lists: List of Insignificant Pixels (LIP), List of Insignificant Sets (LIS) and List of Significant Pixels (LSP). LIP and LIS are initialized with the coefficients in the lowest frequency subband of wavelet transform. Initially LSP is an empty set. An initial threshold value is set based on the highest magnitude of the wavelet coefficients. This threshold will be reduced in subsequent iterations. The coefficients in LIP are tested for significance first, followed by the coefficients in LIS. The significant coefficients are then moved into LSP. In LIP the individual pixels are tested for significance and the corresponding bits are transmitted. The significance of a group of pixels is represented by a single bit in LIS. When a set becomes significant, it will be split into subsets and the significance of subsets will be tested.

The Fig.1(a) shows the block diagram for general fingerprint image compression using multi-wavelet based SPIHT algorithm. Prefiltering is used to convert the input image into a vector form for applying the matrix valued decomposition filters in the multi-wavelet transform [15]. The prefiltered image is transformed using a multi-wavelet and then the compression algorithm SPIHT is applied to get the compressed bit stream. Inverse operations are performed to get the corresponding compressed image. Multi-wavelet based SPIHT algorithm, can have two variations based on the decomposition structure of the multi-wavelet transform i.e. either a shuffled or an unshuffled multi-wavelet transform can be applied to the SPIHT algorithm. In the case of shuffled transform [16], the multi-wavelet transform will be converted to a decomposition structure similar to that of wavelet decomposition. Compression can be further performed using the conventional wavelet based SPIHT algorithm. In the case of unshuffled multi-wavelet transform, compression can be performed with modifications in the initialization of lists in SPIHT algorithm [13]. In the proposed work, an unshuffled multi-wavelet combined with decimation has been used for SPIHT algorithm for further improving its performance. The Fig.1(b) shows the block diagram of the proposed technique for fingerprint image compression. Initially the input fingerprint image is prefiltered to make the input image suitable for applying the multi-wavelet transform. The resulting image is then transformed using multi-wavelet transform. The corresponding L_1L_1 band of the transformed image is downsampled by a factor of 2/ 4/ 8 and the SPIHT algorithm is applied to get the compressed bit stream.

For a typical input image size of 512×512 with an optimum level of decomposition of five [7], the L_1L_1 band of a low-low-pass (LL) submatrix (given by Eq.(1)) of the multi-wavelet transform is shown in Fig.2(a).

$$LL = \begin{bmatrix} L_1L_1 & L_1L_2 \\ L_2L_1 & L_2L_2 \end{bmatrix} \tag{1}$$

The decimated L_1L_1 band by factors of 2, 4 and 8 along both the horizontal and vertical directions are shown in Fig.2(b), Fig.2(c) and Fig.2(d) respectively. The Table.1 shows the maximum possible decimation factor for various decomposition levels for a typical image of size 512×512. The factor of decimation can go upto a maximum of 8 with an optimum level of decomposition of five. With decomposition levels smaller than the optimum level, the factor of decimation can be increased further.

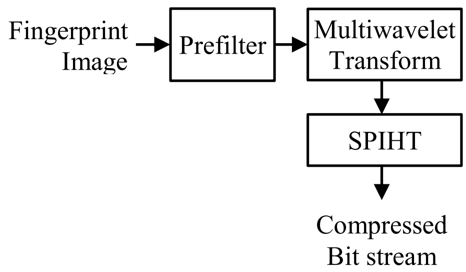

Fig.1(a). Block diagram for general fingerprint image compression

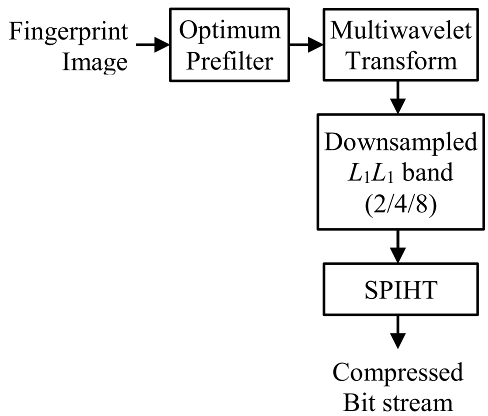

Fig.1(b). Block diagram for the proposed fingerprint image compression

In the case of decimation by N, the L_1L_1 band is divided into N^2 subbands. As N increases, the correlation of coefficients in the decimated band reduces. The LIP and LIS of SPIHT algorithm is initialized with this decimated band (shown by the shaded region in Fig.(2) instead of the whole L_1L_1 band of the unshuffled multi-wavelet transform. Coefficients in the remaining (N^2-1) bands are considered as descendants of the 1st band. If M represents the number of coefficients in the L_1L_1 band of the multi-wavelet transform, the number of nodes used for initialization of lists is reduced to M/N^2 using this method. The reduction in the number of nodes is directly proportional to the improvement in PSNR [13]. For a typical input image of size 512×512 with an optimum level of decomposition, the L_1L_1 band contains 64 coefficients and Table.2 shows the corresponding number of nodes used for the initialization of lists with various decimation factors. It can be seen from the Table.2 that there is a considerable reduction in the number of nodes used for initialization using decimation. The reduction in number of nodes leads to reduction in coefficients and sets in LIP and LIS which leads to reduced number of transmitted bits. At lower bit rates most of the transform coefficients will be insignificant because of the high threshold value. So, the sets in LIS will remain undivided and the number of insignificant bits transmitted can be reduced. As a result, more significant information can be included in the bitstream and the quality of the compressed image can be improved by using this method.

1	2	3	4	5	6	7	8
9	10	11	12	13	14	15	16
17	18	19	20	21	22	23	24
25	26	27	28	29	30	31	32
33	34	35	36	37	38	39	40
41	42	43	44	45	46	47	48
49	50	51	52	53	54	55	56
57	58	59	60	61	62	63	64

(a)

1	3	5	7	2	4	6	8
17	19	21	23	18	20	22	24
33	35	37	39	34	36	38	40
49	51	53	55	50	52	54	56
9	11	13	15	10	12	14	16
25	27	29	31	26	28	30	32
41	43	45	47	42	44	46	48
57	59	61	63	58	60	62	64

(b)

1	5	2	6	3	7	4	8
33	37	34	38	35	39	36	40
9	13	10	14	11	15	12	16
41	45	42	46	43	47	44	48
17	21	18	22	19	23	20	24
49	53	50	54	51	55	52	56
25	29	26	30	27	31	28	32
57	61	58	62	59	63	60	64

(c)

1	2	3	4	5	6	7	8
9	10	11	12	13	14	15	16
17	18	19	20	21	22	23	24
25	26	27	28	29	30	31	32
33	34	35	36	37	38	39	40
41	42	43	44	45	46	47	48
49	50	51	52	53	54	55	56
57	58	59	60	61	62	63	64

(d)

Fig.2(a). L_1L_1 band of multi-wavelet transform (b) Downsampling L_1L_1 band by a factor two (c) Downsampling L_1L_1 band by a factor four (d) Downsampling L_1L_1 band by a factor eight

Table.1. Maximum decimation factor for an input image of size 512×512 with various transform decomposition levels

Level of decomp.	Max. decimation factor
5 (optimum)	8
4	16
3	32
2	64
1	128

Table.2. Number of nodes used for initialization for a 512×512 image with optimum level of decomposition of 5

Decimation factor	No. of nodes for initialization
2	16
4	4
8	1

3. DATABASE

For validating the performance of compression, the fingerprint images from NIST Special database 4, Shivang Patel database, NITGEN database [17] and other databases are considered. National Institute of Standards and Technology (NIST) Special Database 4 contains fingerprint images in eight subgroups from figs_0 to figs_7. The subgroup figs_0 contains five hundred 8-bit gray scale fingerprint images of size 512×512. Shivang Patel database contains 168 fingerprint images of size 256×256. NITGEN database contains 200 fingerprint images of size 248×292 collected using NITGEN USB Fingkey Hamster (HFDU 01) fingerprint scanner. These fingerprint images are boundary extended and cropped to make the size as 256×256. Fingerprint verification competition (FVC) 2000dB1 and FVC 2002dB3 contain 80 fingerprint images of size 300×300 with a resolution of 500 dpi.

4. RESULTS AND DISCUSSION

The fingerprint images used for validation from various databases were prefiltered by an optimum prefilter [13] whose filter coefficients are given by Eq.(2) followed by the multi-wavelet transform. An optimum level of multi-wavelet transform decomposition is chosen for compression. For a 512×512 image the optimum level of decomposition [7] is 5 and for a 256×256 image the optimum level of decomposition is 4. The L_1L_1 band of SA4 multi-wavelet with optimum prefilter is downsampled by factors 2, 4, 8 and the compression algorithm SPIHT is applied. The optimum prefilter coefficients are given by Eq.(2).

$$PR = \begin{bmatrix} 0.9931 & 0.9980 \\ -0.7951 & 0.7961 \end{bmatrix} \tag{2}$$

For measuring the quality of compression, the metric Peak Signal to Noise Ratio (PSNR) given by Eq.(3) is used. Performance of the proposed compression technique is compared with compression achieved using multi-wavelet without decimation [13].

$$PSNR = 20\log_{10}\frac{255}{RMSE} \quad (3)$$

where, *RMSE* is the root mean square error between original and reconstructed image. The average PSNR is calculated for 200 fingerprint images in NIST database, 100 fingerprint images from Shivang Patel and NITGEN databases as shown in Table.3.

For multi-wavelet without decimation [13], the average PSNR is varying from 19.574dB to 37.141dB for bit rates 0.01 to 1 for the images in NIST database with optimum level decomposition as shown in Table.3a. For the multi-wavelet decimated by a factor 2, the average PSNR is varying from 20.249dB to 37.176dB. An average improvement in PSNR of 0.1817dB is observed compared to multi-wavelet without decimation. In the case of decimation by 4, the PSNR is varying from 20.365dB to 37.184dB. Using decimation by 8, PSNR is varying from 20.366dB to 37.185dB. The overall average improvement in PSNR obtained for the 200 images from bit rates 0.01 to 1 are 0.1817dB, 0.2218dB and 0.2223dB using multi-wavelet decimated by factors 2, 4 and 8 respectively compared to multi-wavelet without decimation. Similar results are obtained for Shivang Patel and NITGEN databases as shown in the tables 3a and 3b. An overall average improvement of 0.4658dB, 0.4970dB, 0.5020dB and 0.4914dB, 0.5282dB, 0.5300dB are obtained for multi-wavelet decimated by 2, 4 and 8 for the images in Shivang Patel and NITGEN databases respectively compared to the multi-wavelet without decimation [13]. The performance of compression is also verified for the images in FVC 2000dB1 and FVC 2002dB3 databases.

Table.3(a). Average PSNR indB for the images in NIST (512×512) databases

bpp	w/o dec. [13]	Dec. by 2	Dec. by 4	Dec. by 8
0.01	19.574	20.249	20.365	20.366
0.02	20.687	21.122	21.221	21.222
0.03	21.537	21.888	21.966	21.967
0.04	22.230	22.514	22.578	22.579
0.05	22.810	23.065	23.121	23.121
0.06	23.337	23.568	23.621	23.622
0.07	23.821	24.031	24.080	24.080
0.08	24.261	24.451	24.497	24.497
0.09	24.666	24.842	24.883	24.884
0.1	25.036	25.192	25.231	25.231
0.2	27.825	27.927	27.953	27.953
0.3	29.766	29.842	29.860	29.861
0.4	31.297	31.360	31.375	31.376
0.5	32.557	32.609	32.622	32.622
0.6	33.643	33.689	33.700	33.700
0.7	34.625	34.667	34.678	34.678
0.8	35.514	35.553	35.562	35.562
0.9	36.339	36.375	36.384	36.384
1	37.141	37.176	37.184	37.185

Table.3(b). Average PSNR indB for the images in Shivang Patel (256×256) databases

bpp	w/o dec. [13]	Dec. by 2	Dec. by 4	Dec. by 8
0.01	11.060	12.516	12.568	12.573
0.02	12.077	12.822	12.895	12.908
0.03	12.620	13.504	13.566	13.576
0.04	13.163	13.934	13.982	13.989
0.05	13.743	14.305	14.345	14.352
0.06	14.103	14.648	14.687	14.691
0.07	14.422	14.968	15.006	15.014
0.08	14.773	15.335	15.380	15.387
0.09	15.117	15.732	15.769	15.776
0.1	15.515	16.118	16.162	16.167
0.2	18.312	18.621	18.642	18.647
0.3	20.240	20.471	20.488	20.491
0.4	21.614	21.811	21.825	21.828
0.5	22.855	23.024	23.037	23.039
0.6	23.912	24.059	24.070	24.072
0.7	24.875	25.020	25.030	25.032
0.8	25.824	25.962	25.972	25.974
0.9	26.664	26.782	26.791	26.792
1	27.448	27.557	27.566	27.567

Table.3(c). Average PSNR indB for the images in NITGEN (256×256) databases

bpp	w/o dec. [13]	Dec. by 2	Dec. by 4	Dec. by 8
0.01	11.525	12.930	12.987	12.989
0.02	12.465	13.381	13.482	13.484
0.03	13.019	14.021	14.083	14.085
0.04	13.679	14.441	14.496	14.500
0.05	14.179	14.810	14.870	14.874
0.06	14.544	15.179	15.233	15.236
0.07	14.922	15.555	15.606	15.609
0.08	15.309	15.927	15.974	15.977
0.09	15.703	16.285	16.325	16.326
0.1	16.094	16.608	16.650	16.652
0.2	18.747	19.103	19.131	19.133
0.3	20.817	21.087	21.108	21.109
0.4	22.312	22.525	22.541	22.542
0.5	23.615	23.807	23.823	23.824
0.6	24.708	24.853	24.865	24.866
0.7	25.600	25.733	25.743	25.744
0.8	26.435	26.559	26.569	26.570
0.9	27.195	27.305	27.314	27.314
1	27.862	27.957	27.965	27.966

The performance of compression for the images in NIST and NITGEN databases at lower bit rates are shown in Fig.3(a) and

Fig.3(b). From the Fig.3, it can be seen that there is an improvement in PSNR for the proposed method compared to the performance of multi-wavelet without decimation at lower bit rates. The improvement in PSNR is due to the reduction in the number of nodes used for the initialization of lists in the SPIHT algorithm.

The Fig.4 shows the variation of normalized average PSNR with the increase in decimation factor for the images in NITGEN database at a bit rate of 0.01. As the decimation factor increases, the number of nodes used for initialization in the SPIHT algorithm decreases which leads to an improvement in the PSNR. From the graph it can be verified that there is a significant improvement in the PSNR for decimation by 2 compared to without decimation. Further it can be seen that there is no significant difference in performance between decimation by 4 and 8 which infers that decimation by 4 gives an optimum performance. The SPIHT algorithm is based on the similarity of coefficients in the spatial orientation tree. For decimation by 2 there exists some amount of similarity of coefficients in decimated bands. As the decimation factor increases, the correlation decreases and there is not much improvement in the PSNR for decimation by 8.

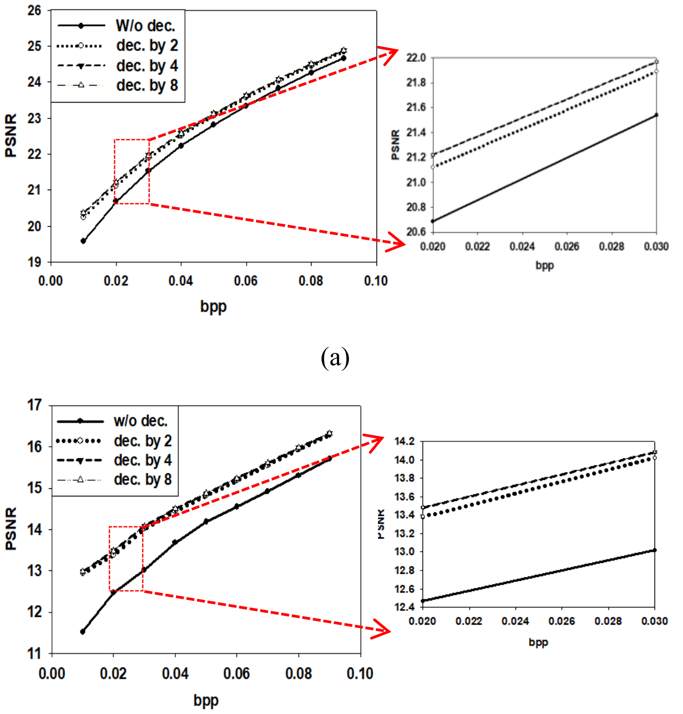

Fig.3. Average PSNR at lower bit rates with an inset showing the PSNR in between bit rates 0.02 and 0.03 for the images in (a) NIST database (b) NITGEN database

For the input images with sizes of 256×256, 512×512 and 1024×1024, the size of L_1L_1 band is 8×8 for optimum level of decomposition and the maximum possible decimation factor is 8 as discussed in section 2. For decimation by 8, each coefficient is considered as a band and only a single pixel is used for the initialization of lists in SPIHT algorithm. With optimum level of decomposition, the various decimation factors possible are 2, 4 and 8. For increasing the decimation factor further, the level of transform decomposition should be decreased from optimum level.

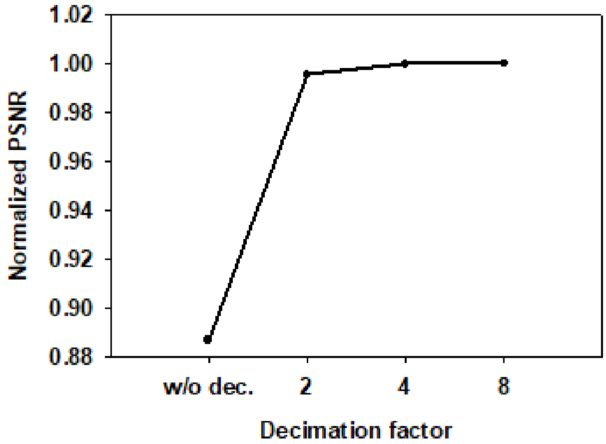

Fig.4. Comparison of normalized average PSNR versus decimation factor for the images in NITGEN database

5. CONCLUSIONS

In this paper multi-wavelet with decimated frequency band is used for fingerprint compression using SPIHT algorithm. The PSNR at lower bit rates is poor in conventional wavelet-based image compression algorithms. In order to improve the performance at lower bit rates, the lists in SPIHT algorithm are initialized with downsampled L_1L_1 band of multi-wavelet transform. So, the number of nodes during initialization of lists in SPIHT algorithm is reduced. As a result, an improved performance particularly at lower bit rates is obtained using this technique. The performance of compression is verified for the images in NIST, Shivang Patel, NITGEN and other databases. The overall average improvement obtained for multi-wavelet downsampled by factors 2, 4 and 8 are 0.798dB, 0.857dB and 0.859dB respectively for bit rates 0.01 to 0.09 compared to multi-wavelet without decimation for the images in NITGEN database.

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