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MULTIRESOLUTION COMPRESSION SCHEMES FOR MEDICAL IMAGE AND VOLUME DATA

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Abstract— **In this paper we propose a multiresolution compression scheme applied to image and volume data. It is intended for rapid browsing in graphical files, in which some regions of interest may exist; therefore the compression algorithms focus on incorporating quick full-reconstruction procedures, both in images and volumes. This scheme is based on vector quantization of the coefficients of a wavelet decomposition. The differences in the methods lie on how vectors in the multiresolution decompositions are selected for vector quantization. We have also developed a client-server application using this scheme, which allows images with increasing levels of detail to be represented in the client system, as they are received from the server and decoded. Numerical results show the performances of all the selections made.**
keywords– **vector quantization, wavelets, medical data compression, distributed application.**

I. Introduction

Graphical network applications involving health care are of major interest, especially on areas characterized by a great dispersion in population. However, such applications are particularly resource demanding; issues like fast information retrieval from medical databases, and rapid browsing in graphical files are compulsory, making compression schemes a necessary tool in the field of telemedicine.

In this paper we are mainly concerned with the build-up of an application that allows a physician to browse within graphical files (with both image and volume data) as interactively as possible. We are assuming that a physician is connected to a medical database by means of a slow speed network (for instance, a doctor in a rural area remotely inspecting medical records which are stored in a major hospital), so the purpose is to create a client-server application tuned to a compression scheme that allows progressive remote reconstruction of details in the image. Even though the methods presented and compared here are lossy (which is not acceptable for medical data [7]), a lossless scheme would be easily developed by transmitting the residual errors by well-known methods.

II. An image multiresolution compression scheme

In this section we will focus on compression schemes carried out in the wavelet domain [6]. This domain has been widely used in compression applications [1], [3], [4] due to the properties of wavelet basis, both in terms of energy compactation, and spatial and frequency localization.

Most of the previous works study the problems of the wavelet basis used for wavelet decomposition [11], [1], the determination of the centroid codebook [3], [2], [9], or the bit assignment during coding [1]. In our case, the main issue treated here is the vector selection procedure for multiresolution data compression. Therefore, regardless of the particular method used, the three common steps of the compression algorithms will be: multiresolution decomposition (MD)–using Daubechies-6 basis–, vector quantization (VQ) and scalar quantization (SQ) of the wavelet coefficients, and Huffman coding of the indices of the quantization levels; the differences in the algorithms will lie basically on how vectors are extracted from the MD to perform the VQ step. Every choice will be numerically studied.

A. Algorithm fundamentals

For both image and volume data we use a three-level decomposition as shown in figure 1 (the figure's caption contains also the nomenclature used in the paper). Levels of the MD are ordered according to Mallat's [6] convention, namely, lower resolution version on the left-bottom (and proximal) corner. With respect to quantization, we

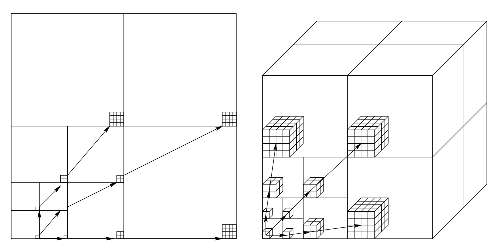

Fig. 1. A sketch of the MD. The lowest resolution image (LRI) is located left-bottom. Higher levels are referred to detail level-3 (DL3), intermediate as DL2 and lowest, DL1. a) 2D; b) 3D.

have used both SQ and VQ. As it is common practice (and it will be illustrated here) SQ is the best choice for the lowest resolution version of the image or volume. For the sake of efficiency, data are histogram-equalized prior to the quantization stage.

VQ has been applied for the coefficients in the rest of the hierarchy. As it is well-known, VQ requires a learning stage from data in order to place the centroids properly in vector space. We have used two learning algorithms: the classical *k-means* or *LBG* algorithm [5] (enhanced with an initialization procedure [2]) and a competitive learning scheme with a selection mechanism of the most-used centroids in every iteration [9]. We have obtained fairly close performance with both methods, so results will be solely reported using LBG.

In the three compression schemes that are analyzed in

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the paper, we have used medical images taken form the Visible Human project, both for training and for testing. The images (an example of which is shown in figure 2) are computed tomographies of the woman in the project.

B. Scheme 1: independent vectors in every channel

The first compression scheme extracts k-dimensional vectors independently in every channel of the MD. For comparison purposes we have studied the performance of the compression algorithm using SQ and VQ for the lowest-resolution image (denoted as cases (a) and (b) respectively in table I). Table I shows both the compression ratio (r),

	LBG				
	N_c	k	r:1	SNR	MSE
(a)	256	16	35.7:1	20.55	3209.6
	512	16	30.2:1	22.88	1877.9
	256	4	9.9:1	27.10	710.7
	512	4	8.5:1	29.02	456.6
(b)	256	16	47.0:1	14.95	14343.8
	512	16	39.0:1	19.16	4417.8
	256	4	10.5:1	25.37	1057.7
	512	4	9.0:1	26.63	790.2

TABLE I

N_c NUMBER OF CENTROIDS. k DIMENSION OF VECTORS.

signal to noise ratio (SNR) and the mean square error (MSE) for the combinations of two number N_c of centroids and two dimensions k of the vectors. It is obvious that more centroids with smaller vectors draw better SNR (and lower MSE) at the price of a lower r. The table shows also that a VQ vs. a SQ in the lowest resolution image does not seem worth-taking since, even though greater r are achieved, the quality of the images degrades severely. This can be seen in figures 2b) and 2c) as well. Table IIa) shows how the SNR of the reconstructed image grows as more levels in the hierarchical decompositions are added. It can be clearly seen that lower levels in the hierarchy have a greater weight in the overall image, since the change in MSE is faster. Higher levels in the hierarchy show a lower significance [6][8] and consequently the reduction in MSE is lower. This is illustrated in figures 2d)-g).

	r:1	SNR	MSE
LRI	142.4	16.53	8114
+DL3	91.4	19.13	4447
+DL2	35.0	22.61	1997
+DL1	9.9	27.10	710.7

a)

N_c	r:1	SNR	MSE
256	188.3	19.76	3844
512	156.1	21.11	2818

b)

TABLE II

C. Scheme 2: vectors selected across scales

The foregoing scheme makes use of the redundancy present in every level of the hierarchy, but it ignores the correlation that may exist across scales. It is therefore natural to consider an alternative to the former, by allowing vectors to be extracted across scales as shown in figure 1. Each vector will have dimension k=1+3(1x1)+3(2x2)+3(4x4).

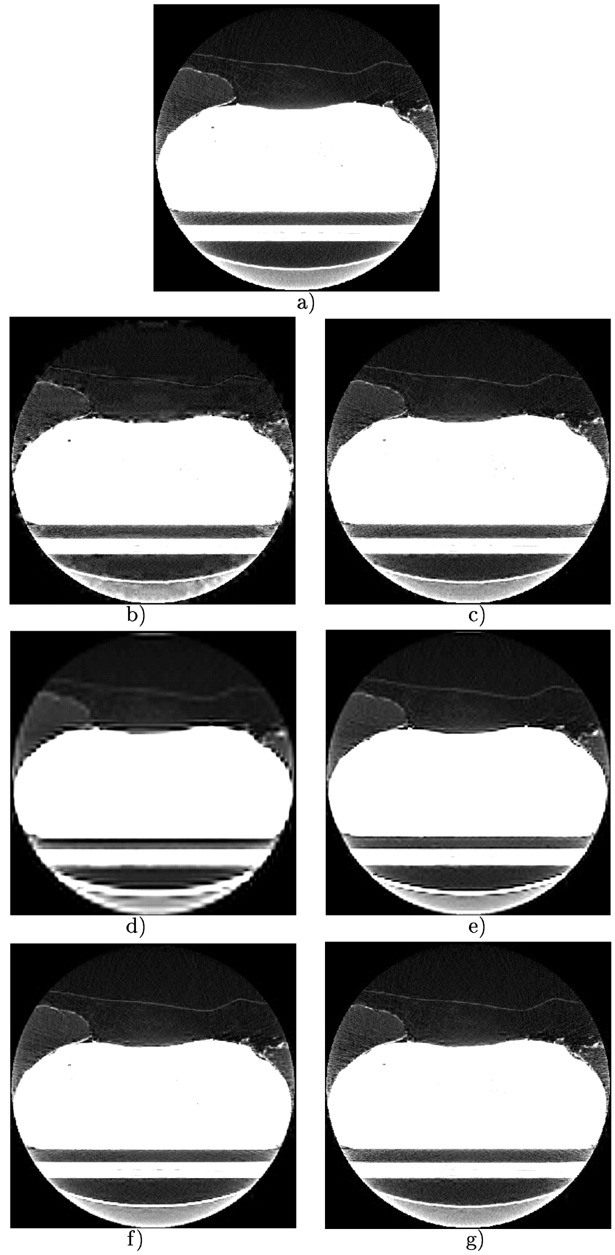


Fig. 2. a) Original image to be compressed with $N_c = 256$, $k = 4$. b) VQ of LRI. c) SQ of LRI. d) LRI. e) image d) + DL3. f) image d) + DL2. g) image d) + DL1.

Table IIb) shows the performance of the algorithm in the same terms as before, namely, r, SNR and MSE The table shows that this second technique obtains much higher compression ratios, though the quality in the reconstructed image is lower. However, things are somehow comparable. Recalling table IIa), one can see that when DL2 are included in the reconstruction, the compression ratio is about 35:1 and the SNR is about 22 dB. However, in this present scheme, a slightly lower SNR (about 20 dB, depending on N_c) is obtained at a much higher r.

The numerical results show that, even though this method is difficult to justify in terms of coefficient significance, the exploitation of the correlation across scales seems very efficient in terms of r. In addition, this method does not fulfill the requirement of multiresolution: even though locality can be used in the reconstruction, the reconstruction procedure needs to retrieve the full vector across scales (so it would be nonsense not to use it).

D. Scheme 3: a hybrid method

Our final coding scheme for (2D) images comes up naturally from the ideas so far exposed. We apply VQ to each resolution level separately, so as to have a real multiresolution coding scheme, but we will also exploit spatial redundancy by creating vectors out of pixels that come from the three details at each resolution level from the surroundings of every pixel in the lowest resolution image. Figure 3 illustrates this idea. With such a criterion, it is clear that we

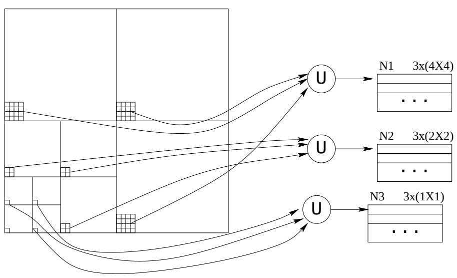


Fig. 3. Vector extraction for the hybrid method

are using low dimensional vectors for the lower resolution levels, and larger vectors in the higher levels. Therefore, this procedure also makes use of the concept of significance of the coefficients of the wavelet transform.

The performance of this algorithm is as indicated in table IIIa); this table should be compared with table IIa).

	r:1	SNR	MSE
LRI	126.7:1	16.55	8059.3
+ DL3	68.5:1	19.34	4240.5
+ DL2	48.0:1	22.29	2148.8
+ DL1	42.0:1	24.35	1338.9

a)

r:1	SNR
120:1	14.47
60:1	22.66
40:1	24.15
20:1	27.16
15:1	30.40
10:1	36.53

b)

TABLE III

As the table shows, this hybrid method has a much higher r than the the first method. Particularly meaningful are the last two rows of the tables; it is clear that the inclusion of the higher level details causes an important drop-off of the compression ratio in the first scheme, while the third scheme keeps up an important compression ratio at fairly constant values of the SNR.

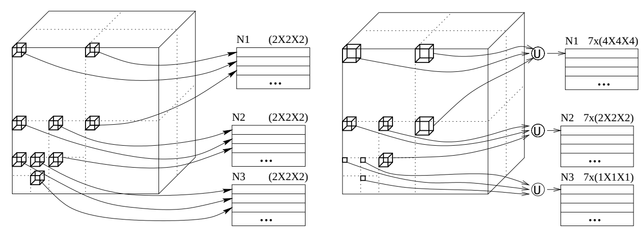
E. Comparison with JPEG

We have included a comparison of the above-mentioned compression schemes with the standard JPEG [10] in its lossy version. Table IIIb) shows the results for JPEG.

This table shows that the JPEG standard has a lower quality than our scheme 1 when compression ratios are high. However, for low compression ratios, the JPEG outperforms this scheme 1. As far as the hybrid scheme is concerned, no clear conclusions can be drawn: the two schemes seem to work fairly parallel in the range of compression ratios we have considered. We should then conclude that if large compression ratios are acceptable for rapid browsing, the first multiresolution scheme is the one to be used. However, if a higher quality is needed, either the JPEG or the hybrid scheme are to be chosen. If the application is oriented at working with (2D) images one would undoubtedly choose JPEG. However, if the application deals with volume data, the hybrid scheme can be immediately adapted to the 3D case, but this is not the case for JPEG (for instance, the quantization tables of the DCT coefficients have no straightforward counterpart in the 3D case).

III. A multiresolution strategy for volume data

In this section we generalize schemes 1 and 3 of the previous section to the case of volume data. Vectors are now extracted as shown in figure 4. For the case of using



a) b)

Fig. 4. Vector selection in 3D: a) scheme 1; b) hybrid method.

$N_c = 512$ centroids, the performances of the two methods are as shown in table IV. The table shows a similar

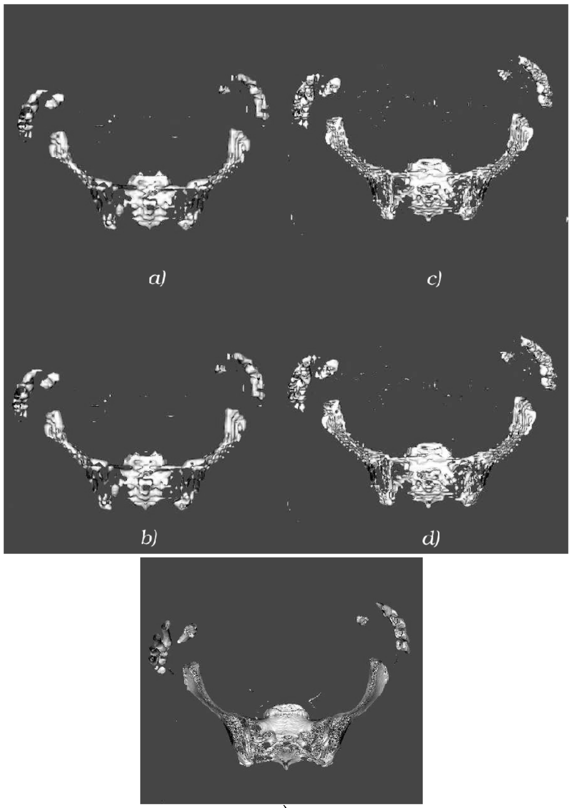
	Scheme 1		Scheme 3	
	r:1	SNR	r:1	SNR
LRI	1017.7:1	16.91	1017.6:1	16.97
+ DL3	644.6:1	18.91	630.0:1	18.80
+ DL2	139.1:1	21.48	469.4:1	20.42
+ DL1	17.7:1	24.14	356.9:1	21.0

TABLE IV

behavior as exposed in last section: for large compression ratios the scheme 1 has a higher quality, but an important drop-off in r shows up when DL2 and DL3 are included. However, for the hybrid scheme, adding up higher levels of detail increases quality, but at a much lower decrease in the compression capabilities. Therefore, we believe that this last compression technique is an interesting candidate for applications that deal with this type of data. Figure 5 shows an isosurface of a part of a human hip compressed by the hybrid method with three different levels of detail. The original volume data is shown at the bottom for comparison purposes.

IV. A client-Server Application for Multiresolution Image Retrieving

We have developed a distributed application to transmit medical images between a server and a number of clients; this platform will let us compare the multiresolution schemes (experiments have been done using scheme 1 though they should coincide with the other two methods) with other simpler approaches. The purpose is to find out



e)

Fig. 5. Rendered isosurface of a human hip $N_c = 512$, a) lowest resolution volume. b) volume a) + DL3. c) volume + DL2. d) volume a) + DL1. e) Isosurface from original image

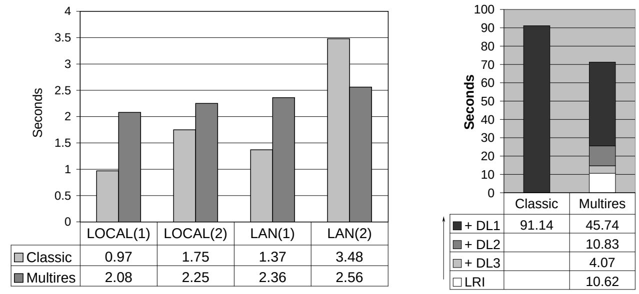
in which scenarios these higher-computational-cost-codecs are worth-taking.

The images in the server database are compressed off-line and stored in compressed format. A query from a client triggers a procedure in the server which progressively transmits each resolution level of the image or volume. The data are rendered once every resolution level has reached its destination, and the procedure is repeated until the whole resolution is rendered.

The tests have been carried out on Pentium II computers with Red Hat Linux 6.2, in the four following environments:
1. A client and a server in the same computer (LOCAL1).
2. Same as LOCAL1, but with more clients in the same Local Area Network (LOCAL2).
3. A client and a server in a Local Area Network (LAN1).
4. A server and several clients in the same LAN (LAN2).
5. A client and a server connected with a modem.

We have compared the multiresolution algorithm with the general purpose GNU-zip compression facility. Results are obtained by averaging 200 trials of every scenario above.

Results are shown in figure 6. Figure 6a) shows that in a LAN, where the transmission time is less important than the processing time, the classical scheme outperforms the other in almost all the cases. (results for our algorithm are the time after representing the data at their full resolution). In figure 6b), we show the time for each level of resolution. We can see in this case that the low bandwidth of the network makes our algorithm much faster (20 seconds) for the higher level of resolution. We can also see the advantage of the multiresolution for rapid browsing, since in only 10.83 s. the first version of the image can be represented, while the gzip procedure needs 91.14 s. to get anything rendered.



	LOCAL(1)	LOCAL(2)	LAN(1)	LAN(2)
Classic	0.97	1.75	1.37	3.48
Multires	2.08	2.25	2.36	2.56

a)

	Classic	Multires
+ DL1	91.14	45.74
+ DL2		10.83
+ DL3		4.07
LRI		10.62

b)

Fig. 6. Comparison between classical gzip and multiresolution compression: a) different LAN configurations; b) each level of detail with a 33 kbps modem.

V. Conclusions

We have analyzed several strategies for vector selection in both image and volume data for VQ in a multiresolution compression framework. The method denoted as *hybrid* has shown a performance fairly close to that of JPEG for images. This methods carries over easily to the case of volume data, so we believe this method is a candidate to be considered for applications in which volume data are involved, and large compressions are needed at a specified level of quality. We have also shown the advantages of a multiresolution compression scheme, which are highlighted in a low-bandwidth network.

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