# Cardiac MR Imaging Compression: Comparison Between Wavelet Based and JPEG Methods

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## Abstract

*High quality compression on cardiac MR images using wavelet based methods have been compared with standard JPEG. Since the last one is an unrestricted algorithm designed for true-color realistic images, its performance compressing gray-level images can be improved with alternate algorithms specifically designed for this purpose. In this work we present a method based on wavelet transforms and Huffman encoding; Daubechies and Lemarie-Battle wavelets have been used.*

*Different combinations of parameters and transforms have been compared against JPEG with 100, 85, and 75 quality factor. The results show that wavelet based compression performed better in quality and compression rate; differences among the several wavelet based methods implemented have also been found.*

## 1. Introduction

The high amount of images produced in a typical cardiac MR study creates a need for image compression methods that will reduce the massive storage capacity required as well as transmission times, without a degradation in the diagnostic contents. Compression techniques can be classified according to the difference between the original and the recovered image; lossy techniques recover representations similar to the original one and achieve high compression ratios, while lossless techniques are able to accurately recover the original image although lowering the compression efficiency. A further classification for the lossy techniques can be done according to the compression algorithms involved [1,2]: prediction-based, frequency-oriented or hybrid techniques. JPEG belongs to the last ones, and it has become a common widespread standard for color photographic images. JPEG has also a lossless coding mode, with a much lower compression performance.

Medical image compression requires higher quality and up today, no lossy method has been adopted by the health authorities as an accepted standard. This fact, together with the gray-scale nature of the radiographic images are the reason to promote new developments on this field. In our approach we have chosen wavelet based techniques mainly because of the good results obtained on previous experiences [3-9] pursuing a lossy compression method that can be widely accepted by the medical imaging specialists, mainly on MRI applications.

## 2. Methods

In this work we will compare the results obtained with a commercial JPEG software, therefore a compiled and optimized program, with our procedure based on wavelet theory. The last one was developed using Matlab$^{(TM)}$ command language, consequently less efficient in computation times.

JPEG compression technique consists in applying the discrete cosine transform (DCT) to blocks of 8x8 pixels of the original image, followed by a vector quantization and an entropy coding (Huffman or arithmetic). JPEG has a quality factor Q that allows the adjustment of the compressed image quality; there is a tradeoff between file size and final image quality. In this work we have used 75 (default), 85 and 100, although it is well known that with Q=100 image files are significantly larger than with Q=95, while the images are hardly differentiable.

The wavelet method proposed here has three stages:

1.- Discrete bidimensional wavelet transform [10,12], using an extended 2D version of the pyramidal algorithm described in [11], employing either Daubechies of different orders or Lemarie-Battle wavelets.

2.- Coefficient thresholding and quantization: the resulting coefficients from the wavelet transform are truncated with a threshold depending on the scale band, in order to remove the least significant coefficients on each band independently. For the quantification, two different approaches have been evaluated: an uniform quantification between the maximum and the minimum, and a quantification adjusted to the threshold; this last one proved to rise the efficiency of the following Huffman encoding. In our implementation two parameters are adjusted on each transformed band: the threshold below which the coefficients are eliminated, and the quantization step; their incidence on the final quality image have been studied separately.

3.- Coding: the codification is based on the Huffman method, modified to skip assigning any code to the large number of zero coefficients that result after the previous stage. To encode these removed zeros a bitmap of non–zero coefficients is used.

The evaluation has been done by analyzing several image quality factors: PSNR (peak signal to noise ratio) value between the original and the compressed-decompressed images, compression ratio in bits per pixel, maximum absolute difference and mean difference of gray levels, residual structures and subjective evaluation. All these figures have been calculated for a set of 90 images that includes, among other medical and non-medical gray-level images, sagital and axial cardiac MR images of healthy volunteers, acquired with a spin-echo protocol (TE=40 ms, TR adjusted to the heart rate, 400 ms aprox.), on a 1.5 tesla system.

## 3. Results

Considering the wavelet transform, time computation becomes longer as higher is the number of coefficients, as it was expected, but it is independent of the wavelet family. Limiting the scale depth of the transform doesn't influence significantly the computation time since the lowest scales are the most time consuming.

Table 1 presents quality measurements for several wavelet types.

| Type | Dau4 | Dau6 | Dau8 | Dau10 | Dau12 | LB1 | LB3 | LB5 |
|---|---|---|---|---|---|---|---|---|
| PSNR | 304.9 | 208.4 | 294.0 | 265.3 | 246.6 | 67.24 | 73.83 | 63.46 |
| Max.er | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.231 | 0.135 | 0.356 |

**Table 1:** PSNR and maximum error after direct and inverse transformation of an axial cardiac MR image using different wavelet families.

Threshold values and the number of quantization levels have also been evaluated for different transforms; the results are plotted on figures 1 and 2.

The following tables show the comparison between JPEG and wavelet based methods. The comparison with JPEG 75 is specially interesting as this is considered as the standard compression in many applications; JPEG 85 is also important because of its high quality compression. The wavelet based methods used in the comparison (hfm2 - hfm5) are all Daubechies order 3 (Dau6) with different thresholds (hfm2 has the lowest threshold and hfm5 the highest).

| method | jp100 | jp85 | jp75 | hfm2 | hfm3 | hfm4 | hfm5 |
|---|---|---|---|---|---|---|---|
| psnr | 43,58 | 40,10 | 38,82 | 44,74 | 42,47 | 40,38 | 38,87 |
| bpp | 4,05 | 1,33 | 0,99 | 2,34 | 1,42 | 1,03 | 0,85 |

**Table 2:** PSNR and compression rates of the different methods evaluated; averaged over the complete set of 90 images.

Table 2 shows the quality (expressed as PSNR) and the compression rates achieved with each method.

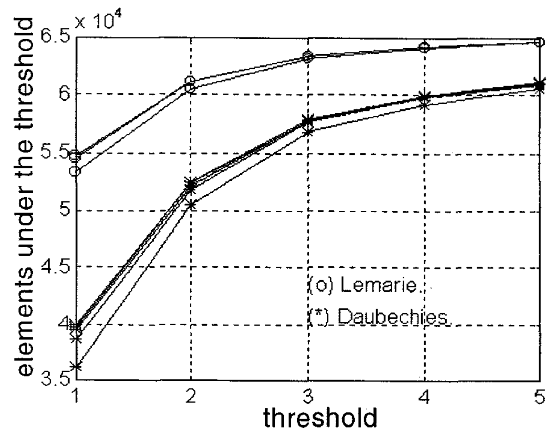


**Figure 1**: number of transform coefficients under the threshold as a function of the threshold.

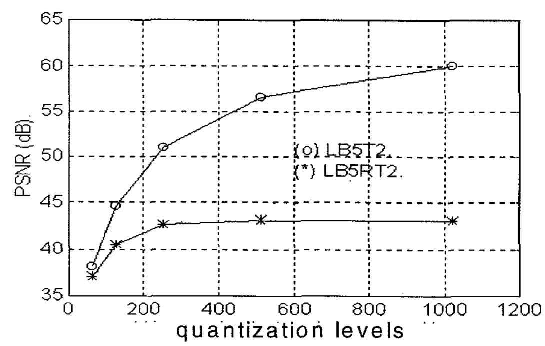


**Figure 2:** PSNR as a function of the quantization levels for the Lemarie-Battle transform: LB5RT2 is LB5T2 with half of the coefficients.

Table 3 compares execution times for JPEG with different quality factors and for wavelet based methods. It should be taken into account that JPEG is obtained with a compiled software while wavelet methods use a high level interpreted program.

| method | jp100 | jp85 | jp75 | hfm2 | hfm3 | hfm4 | hfm5 |
|---|---|---|---|---|---|---|---|
| comp. | 6,63 | 5,72 | 5,43 | 9,36 | 7,99 | 7,08 | 6,48 |
| desc. | 6,25 | 4,93 | 4,28 | 5,00 | 4,69 | 4,69 | 4,64 |

**Table 3:** execution time in seconds for image compression and the decompression on a 486 100 MHz CPU.

Table 4 and table 5 show the compression rate and quality measurements of the MR cardiac images shown on figures 3 and 4 respectively, evaluated for the most significant compression methods, namely JPEG 75 and 85, and hfm3 and hfm4.

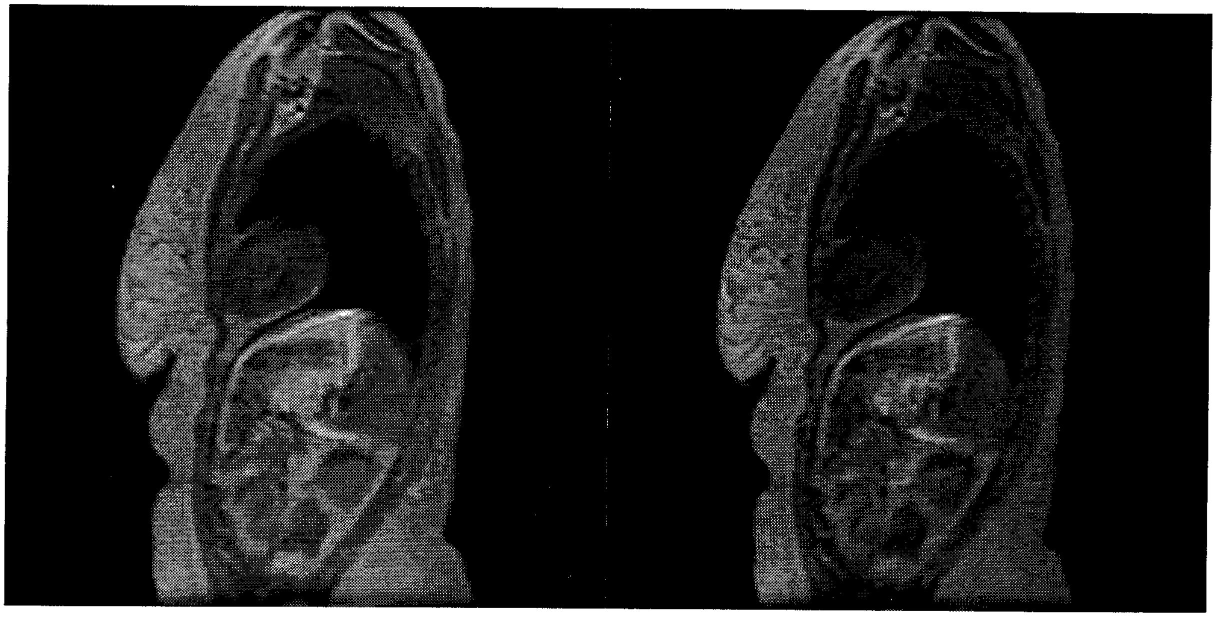

**Figure 3:** decompressed sagital cardiac MR images; on the left, using hfm3 compression method, on the right using JPEG with quality factor 85.

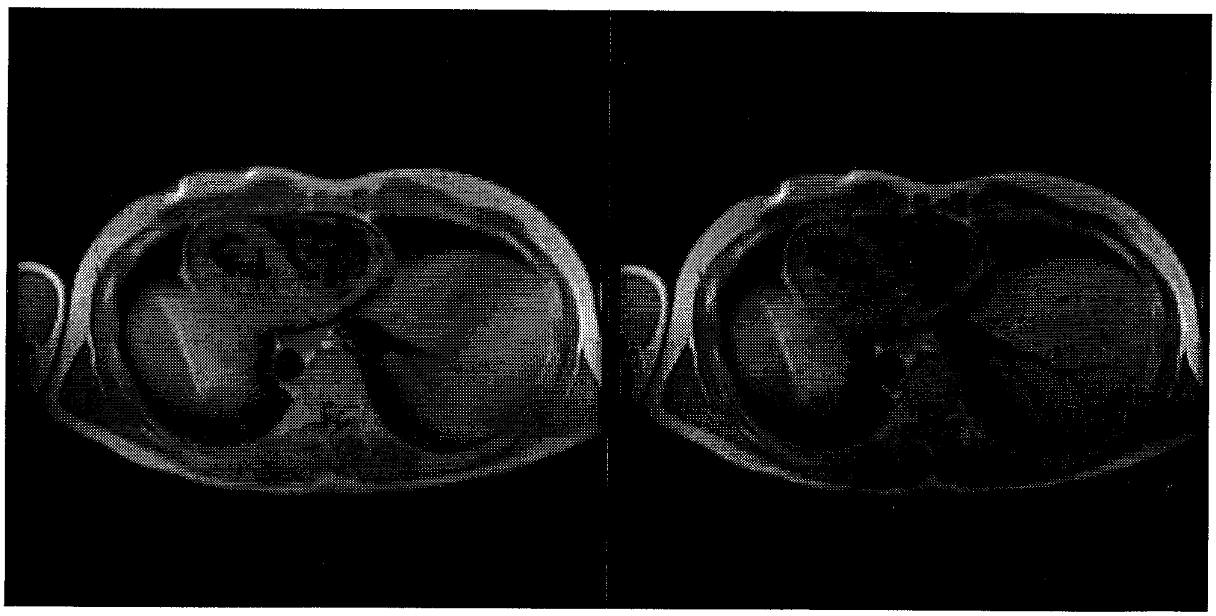

**Figure 4:** decompressed axial cardiac MR images; on the left, using hfm3 compression method, on the right using JPEG with quality factor 85.

| method | psnr(dB) | bpp | max(abs(error)) | mean(abs(error)) |
|---|---|---|---|---|
| hfm3 | 40,38 | 1,47 | 10 | 1,75 |
| jp85 | 40,18 | 1,43 | 15 | 1,92 |
| hfm4 | 38,80 | 1,06 | 14 | 2,20 |
| jp75 | 38,77 | 1,09 | 23 | 2,23 |

**Table 4:** compression rate and error quantification for different compressions of cardiac sagital MRI (figure 3).

| method | psnr (dB) | bpp | max(abs(error)) | mean(abs(error)) |
|---|---|---|---|---|
| hfm3 | 42,75 | 1,19 | 11 | 1,35 |
| jp85 | 41,12 | 1,19 | 13 | 1,76 |
| hfm4 | 40,72 | 0,87 | 14 | 1,69 |
| jp75 | 39,74 | 0,90 | 18 | 2,02 |

**Table 5:** compression and error quantification for the different compressions of cardiac axial MRI (figure 4).

## 4. Discussion and Conclusions

Among the wavelet based methods evaluated, Daubechies family provides higher image quality for cardiac MR images, as can be deduced from table 1; in our evaluation computation has also been faster for Daubechies than for Lemarie-Battle transforms. Comparing execution times of JPEG and Daubechies based technique on table 3, and considering that the wavelet compression procedure hasn't been compiled, it can be deduced that the proposed method will be faster than JPEG.

From table 2 it can be deduced that hfm4 is equivalent to JPEG with Q=85, and hfm5 is equivalent to JPEG with Q=75, when considering the complete data set of 90 images that includes non medical images. For the particular case of cardiac MR images, tables 4 and 5 show that hfm3 is equivalent to JPEG85, and hfm4 is equivalent to JPEG75. In both cases and for the test images, the proposed method based on wavelets performs slightly better both in compression rate and image quality, while computation times under the described circumstances do not differ significantly.

Analyzing the image difference between the original and the decompressed ones, JPEG images present some kind of structures correlated with the original images while the proposed method does not, what can be considered as a desired feature on medical image compression: non correlated structures on the image difference mean that losses on the compression/decompression procedure are mainly noise.

It can be concluded that methods based on wavelet transforms can provide higher compression and better image quality on gray level medical images; it should be reminded however that JPEG is a standard method for photorealistic true-color images, not optimized for our kind of images.

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