1 \textsuperscript{2} VERSUS L\textsuperscript{\infty} CRITERION
IN BIOMEDICAL IMAGE COMPRESSION (MAMMOGRAMS)

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ABSTRACT

Image compression using L\textsuperscript{\infty}-norm and confidence interval criteria was recently shown to have some advantages with respect to flexibility and accuracy. The improvements are due to a local control of the distortion, which allows some local knowledge on the original signal to be exploited. The coding scheme is flexible and can perform a large variety of coding qualities, including lossless compression. This quality is fixed a priori according to the use of the reconstructed image. This paper studies the advantages of the L\textsuperscript{\infty}-norm coding technique applied to medical imaging (mammography), compared to classical L\textsuperscript{2} norm techniques. The coding scheme is recalled and used to achieve different levels of compression: going progressively and accurately from lossless to near-lossless then lossy compression. Results of experiments conducted on several mammograms are presented. When compared to the classical m.e. based schemes, this approach is shown to give more flexibility and higher quality of the reconstructed mammograms (especially, microcalcifications).

1. INTRODUCTION

Nowadays, the digital techniques are used more and more often in various domains. As a result, a large volume of digital data is being generated. This large amount of data represents a significant cost in disk and communication resources. Therefore, compression is usually required in order to allow the manipulation (transmission and storage) of this digital data.

A multitude of different coding techniques has emerged due to the recent rising demand of activity in the field. All these techniques can be broadly categorized into two classes, namely, lossless (reversible) and lossy (irreversible).

In some applications, like satellite or medical imaging, every detail is pertinent. The reconstructed image after compression must have no visual artifacts. Therefore, a new intermediary class, called near-lossless coding techniques, has appeared and is increasingly investigated [1, 2].

In this paper, we use a high quality compression technique based on L\textsuperscript{\infty}-norm and confidence interval criteria. This method, detailed in [3], is described in section 2. By means a local control of the reconstruction errors, the same coding scheme is able to perform different levels of compression, going progressively from lossless to lossy. Section 3 shows some results obtained with mammograms. A comparison with the classical m.e.-criterion approach used in mammography coding is given in section 4.

2. COMPRESSION TECHNIQUE

The coding scheme is depicted in figure 1. It uses a linear pre-processing of the original signal (e.g. linear prediction, filter-banks, DCT, ...). Based on an L\textsuperscript{\infty}-norm criterion, the new coding technique introduced in [1] allows a local control of the distortions. It can be used in two approaches: one deterministic and the other statistical. In the deterministic approach, the idea consists of controlling the maximum error and constraining it to be less than a given threshold. This means that, for a given original signal x, the reconstructed one x̂ must satisfy:

\[ \| \Delta x \| \leq t \]

where \( \| \Delta x \| \) is the L\textsuperscript{\infty}-norm of the distortion \( \Delta x = x - x̂ \) and t is the given threshold. Notice that t is a function of the wanted degree of loss. For instance, if t equals half the original quantization step, we achieve lossless coding [3].

Used in the statistical context, this method is also able to offer more flexibility by allowing some errors to exceed the threshold. Typically, we reconstruct the image with a certain percentage p of distortion less than a given threshold t, i.e., within the confidence interval defined by t. In other words, we optimize the coding scheme under the statistical constraint:

\[ \text{prob}[\| \Delta x \| \leq t] = p\% \]  \hspace{1cm} (1)

When the percentage p decreases, we go progressively to more and more lossy compression. For example, we can reconstruct the image with, e.g., 99\% of pixels exactly equal to the original ones. This allows to take into account the measurement precision of the original pixel values, by reconstructing the image within the same confidence interval. Lossy compression can also be achieved by varying the threshold. Thus we can choose an image dependent threshold like, let say, 3\% of its computed dynamic range.

3. APPLICATION TO MAMMOGRAMS

In biomedical applications, there has been a growing interest in digital images. This yields to large files of data to handle, both for the purpose of archival and transmission. Therefore, the need of image data compression becomes more and more important in this field.
As an example of medical images, we considered mammograms. Digital mammography (used for the breast cancer detection) involves either the digitization of screen-film mammograms or the direct digital acquisition of x-rays. In both cases, the requirements for high resolution images with high dynamic range lead to large data sets, on the average about 40 Megabytes. In addition, screening digital mammography implies real time availability to the radiologist of a series of such images per patient for comparative study and accurate diagnosis. Several lossless and lossy compression methods have been investigated for medical imaging applications.

The choice of a coding algorithm for a given image depends on the considered kind of application and the use of the decoded image. For instance, a given radiography can be compressed with different degrees of accuracy if it is used for a diagnostic purpose or a chirurgical one. Besides, all medical images have to be coded without any loss, for archiving.

As seen in section 2, all these needs can be satisfied by the coding technique recalled above. Therefore, we used it in mammograms coding, where precision is required particularly on the microcalcifications' edges for diagnosis purpose.

As a first test of the method in this medical field, we used 15 mammograms digitized at a resolution of about 600 dpi (dots per inch). Sections of the images (512 x 512 x 8) containing the calcification cluster were used for compression. A first diagnosis of those images did not lead to any decision about the malignancy of the calcifications. Thus, they require high quality compression for an accurate examination of the microcalcification edges.

In the following, we will apply different levels of compression to digital mammograms and evaluate the quality of the lossy compressed image and the effect of the losses in the radiologist's diagnosis.

- **Lossless compression:**
  Using the deterministic approach with a threshold $t = .5$ (since the original images are initially coded on 8 bpp), we perform lossless coding. The compression ratio is on the average about 3. Which is very interesting seeing the initial size of such images.

- **Near-lossless context:**
  We can allow a small percentage of errors to exceed .5. Hence, we perform very near-lossless compression. Generally, the maximum error does not exceed 1, however the bit rates are considerably decreased (see figure 2).

- **More loss:**
  It is possible to use lossy techniques in medical imaging, provided that the diagnostic power is not lost or diminished.

For different thresholds $t$, we reconstruct the mammograms, as said above, with 99% of errors under the given threshold $t$. We choose $t$ as a percentage (from 1% to 7%) of the computed dynamic range of each image. The compression ratios are in this case between 10 and 30.

A questionnaire was formed for the qualitative visual analysis of the reconstructed images. The results are given as an appreciation mark rated on a scale of 0 (poor) to 6 (excellent). We did it for several images with various error thresholds. The results are summarized in figure 3.

We notice that the diagnosis is possible (appreciation mark $\geq 3$) until a threshold of at least 5% of the initial dynamic range. This corresponds to a compression ratio of more that 20, without any loss of the diagnosis quality.

4. **COMPARISON WITH M.S.E.-CRITERION COMPRESSED MAMMOGRAMS**

The coding scheme is the same with both $L^\infty$ and m.s.e. criteria. The only difference is the way how the quantizers are optimized. In the classical approach, the choice of the quantizers is based on the minimization of the $L^2$-norm of the reconstruction error, as explained in [4, 5], for example. However, this criterion is global and does not exploit "local" knowledge on the signal, such as the precision with which the pixel values of a biomedical image are obtained, or the number of bits on which the initial signal samples are encoded.

As seen above, the $L^\infty$-norm criterion allows a local control of the distortion. This offers the possibility to take advantage of the initial knowledge of the signal and to achieve lossless compression or practical lossless coding when the image is reconstructed within the initial confidence interval. In lossy context, it allows to fix the coding quality required by the application.

This is not possible to achieve with the same accuracy when we use the classical technique, which constrains the radiologists to use lossless compression. Hence, they don’t loose any detail, but they achieve less compression.

By controlling the distortion locally, the new technique allows more compression without any visible loss. To prove the efficiency of the $L^\infty$-criterion in visual lossy context, we also use $L^2$-criterion and compare the decoded images after a compression at the same bit rate with the two criteria. The results for 3 images, with respect to statistical and diagnostic criteria, are given in table 1. Moreover, we notice, in the visual context, that the $L^\infty$ reconstructed images are of higher diagnosis quality, especially on the edges of the microcalcifications. This is a very important advantage since the diagnosis is based on the precise shape of the microcalcifications.

5. **CONCLUSION**

The proposed method provides an additional criterion to the design of an optimal compression method for digital mammography. Based on an $L^\infty$-norm criterion, this technique offers a local control of the distortion. It allows several levels of compression going accurately and progressively from lossless to lossy coding. It performs high quality compression of the microcalcifications in mammography. At the same bit rate, $L^\infty$-criterion scheme outperforms the $L^2$ one. Particularly, the edges of the microcalcifications are better reconstructed. Those advantages make the considered technique well adapted to mammograms coding.
Figure 1. Nearlossless Coding Context. For several images, we plotted the bit rate (in bits per pixel, bpp) as a function of the allowed percentage of errors.

REFERENCES


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**Figure 2.** Compression Scheme. The quantization (Q) after a transform (T) is optimized in order to constrain the $L^\infty$-norm of the reconstruction error to be under a given threshold. $C$ denotes the coder.

![Diagram showing compression scheme](image)

**Figure 3.** Diagnostic Quality. For several images, we plotted the results of qualitative analysis as a function of the error threshold. (a) gives the appreciation on the whole reconstructed image; (b) on the background and (c) on the microcalcifications.

![Graphs showing diagnostic quality](image)

<table>
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<th>Image</th>
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<th>$E_{\text{max}}$</th>
<th>PSNR</th>
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<th>Diagnostic</th>
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<td>8</td>
<td>47.4</td>
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**Table 1.** Results with $L^2$ and $L^\infty$ criteria. We show statistical results: the maximum error, $E_{\text{max}}$, and the peak signal to noise ratio, PSNR (dB). We also give an appreciation about the visual quality in terms of detection of the calcifications and diagnosis.