Region-Based Wavelet Coding Methods for Digital Mammography

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Abstract—Spatial resolution and contrast sensitivity requirements for some types of medical image techniques, including mammography, delay the implementation of new digital technologies, namely CAD, PACS or telediagnosis. In order to reduce transmission time and storage cost, an efficient data compression scheme to reduce digital data without degradation of medical image quality is needed. In this study, we have applied two region-based compression methods to digital mammograms. In both methods, after segmenting the breast region, Region-Based Discrete Wavelet Transform (RBDWT) is applied followed by an Object-Based extension of the Set Partitioning In Hierarchical Trees (OB-SPIHT) coding algorithm in one method, and an Object-Based extension of the Set Partitioned Embedded block (OB-SPECK) coding algorithm in the other. We have compared these specific implementations against the original SPIHT on five digital mammograms compressed at rates ranging from 0.1 to 1.0 bpp. Distortion was evaluated for all images and compression rates by the Peak Signal-to-Noise Ratio (PSNR). For all images, OB-SPIHT and OB-SPECK performed substantially better than the traditional SPIHT, and a slight difference in performance was found between them. For digital mammography, region-based compression methods represent an improvement in compression efficiency.

Keywords—Lossy Image Compression, Region-Based Wavelet Transform, Object-Based Coding, Digital Mammography.

I. INTRODUCTION

As new and better methods of digital medical imaging are being developed, digital technology is closer to replace conventional screen-film imaging. The rapid progress in digital image processing has allowed filtering, enhancement or other types of digital image manipulation that may improve diagnostic interpretation, [1], [2]. Digital image format is required in Computer-Aided Diagnosis schemes (CAD) to assist the radiologist in the detection of radiological features that could point to different pathologies [3], [4]. Images in digital format constitute an obligatory requisite towards the implementation of both Picture Archiving and Communications Systems (PACS) and telediagnosis.

However, the usefulness of these new techniques mainly depends on two parameters of importance: the spatial and grey-level resolutions. They must provide a diagnostic accuracy in digital images equivalent to that of conventional films. Both, pixel size and pixel depth are factors that critically affect the visibility of small-low contrast objects or signals which often are relevant information for diagnosis [5]. Therefore, image recording systems for medical imaging must provide high spatial resolution and high contrast sensitivity.

Nevertheless, this requirement retards the implementation of digital technologies due to the increment in processing and transmission time, storage capacity and cost that good digital image quality implies. For instance, it has been shown that isolated clusters of microcalcifications are one of the most frequent radiological features of any neoplastic breast cancer. A careful search for the clustered microcalcifications that may herald an early-stage cancer should be done on all mammograms [6]. Microcalcifications frequently appear as small sized-low contrast radiopacities [7]. Because of this, a typical mammogram must be digitized at a resolution of about 4000 x 5000 pixels with 50 µm spot size and 12 bits, resulting in approximately 40Mb of digital data. Processing or transmission time of such digital images could be quite long. Also, archiving the amount of data generated in any screening mammography program becomes an expensive and difficult challenge.

It is clear that advances in technologies for transmission or storage are not sufficient to solve this problem. An efficient data compression scheme to reduce the digital data without degradation of the medical image quality for human and machine interpretation is needed. Several lossless (with exact reconstruction of the original image after compression) and lossy (some information is lost in the compression process) compression methods have been investigated for medical imaging applications [8]-[10]. However, lossless techniques provide only modest reduction in file size. To significantly affect transmission and storage costs, lossy compression methods are required, always taking into consideration that the loss must not be diagnostically significant for the specific clinical issue that could be addressed. Receiver Operating Characteristic (ROC) analysis on lossy compression showed that it is possible to use lossy techniques in medical image compression, provided that the diagnostic power is not lost or dismissed [11]-[13].

The growing interest in manipulating visual objects in digital images has led to new region-based (or contour-texture) coding techniques which describe the images in terms of arbitrary contours and textures (pixels inside the contour), coding them separately [14]. These new techniques can help to develop medical image compression methods that focus on those regions that are important for diagnostic purposes.

In this study, we have implemented two region-based
coding methods for digital mammography. In both methods a border detection technique segmented the mammogram into the tissue area and the radiological background. Then, as part of the texture coding method, a Region-Based Discrete Wavelet Transform (RBDWT) was applied to the tissue area decomposing the arbitrary region into wavelet subbands [15],[16]. In one of the methods implemented, an Object-Based extension of the Set Partitioning in Hierarchical Trees (OB-SPITH) algorithm [17] was used to encode the wavelet coefficients. For the second method, and Object-Based extension of the Set Partitioned Embedded block (OB-SPECK) coder was used [18]. SPIHT and SPECK are state of the art techniques for image compression performance. In both methods, a chain-code technique encoded the border of the breast region.

II. MATERIAL AND METHODS

A. Digital Images

Five single-view conventional mammograms containing clusters of microcalcifications and masses, all biopsy proven, were used in this study. The images had been collected over a period of time from the daily clinical case load in the Department of Radiology of the Hospital Xeral de Galicia, University of Santiago de Compostela (Spain). Mammograms were digitized with a commercially available LUMIS CAN 85 laser film digitizer Lumisys INC., resulting in images of 4096 x 5120 pixels at 12 bits.

B. Mammogram Segmentation

In a typical digitized mammogram much of the area in the image corresponds to background pixels rather than to tissue pixels. To optimize compression in digital mammograms it is important to code the least information about background as possible. Detection of the breast border allows to segment the image and only compress the breast region. The automatic method used for detecting the breast border was described in detail in [19]. Briefly, first a thresholding is applied to improve the performance of the detection method: two cut-off gray levels are used to threshold the image in order to eliminate artifacts and get an homogeneous background. Then, a smoothed version of the thresholded image is generated. Five reference points, \((x_1, y_1), (x_2, y_2), (x_3, y_3), (x_4, y_4),\) and \((x_5, y_5),\) are automatically selected dividing the breast into three regions.

Finally a tracking algorithm detects the border establishing that a point \((x_i, y_i)\) belongs to the breast border if the gray level value, \(f(x, y)\), of its nine previous pixels satisfy the condition:

\[
 f(x_{i-9}, y_{i-9}) < f(x_{i-8}, y_{i-8}) < \ldots < f(x_{i-3}, y_{i-3}) \leq f(x_{i-2}, y_{i-2}) \leq f(x_{i-1}, y_{i-1}) \leq f(x_i, y_i)
\]

The tracking process is applied along different directions depending on the breast region. In region I the algorithm searches the breast border from left to right; in region II from top to bottom; and finally in region III the border is searched from right to left. The detection algorithm was relaxed such that the breast border obtained was always outer to the real border.

Calculating the slope of the breast border in the reference points \((x_1, y_1)\) and \((x_2, y_2)\), the detected border was enlarged until it reached the edge of the digital image. Hence, the breast region where the relevant information for diagnosis is included was completely determined within a closed contour (Fig. 1).

A binary mask is constructed with the object shape information determined. This mask will be used in the Contour Coding and Region-Based Wavelet Transform processes.

![Fig. 1. Closed contour determined in the segmentation process. Reference points dividing the breast into three regions are also shown.](image)

C. Contour Coding

In region-based coding methods the object shape information has to be coded before the texture of the object.

Shape coding methods may be lossless or lossy methods. According to the coding technique, shape coding methods are classified into block-based or contour-based techniques. In the first, the binary image representing the object shape is encoded as in a conventional image coding method. In the latter, the information coding is performed along the object edge in the binary mask.

Among the contour-based techniques, a chain code [20] is one of the most frequently used methods for lossless coding of the object shape information. In this method, instead of encoding the absolute position of each contour point, the relative position between two consecutive points, called link, is encoded. Therefore, a initial starting point in the contour object and the necessary links following this point to describe the object shape are enough for reconstructing the object shape.

To improve the coding efficiency of the chain code method, a large number of schemes are proposed by imposing certain conditions on the contour or by exploiting the spatial characteristic of the contour [21]-[23].

In this implementation, a two-link chain coding method presented in [24] is applied for coding the breast border.

D. Region-Based Discrete Wavelet Transform

The Region-Based Discrete Wavelet Transform (RBDWT) we have used for coding the texture was proposed by Barnard in [15].

The binary mask obtained during the segmentation process will specify the region where the RBDWT will be applied. Consequently, the object shape in each of the wavelet
decomposition subbands must be obtained. The decomposition of the binary segmentation mask proceeds as follows:

The original binary segmentation mask is divided in blocks of 2x2 pixels. For each block, the upper-left pixel is put into the LL subband of the first decomposition level; the upper-right pixel in the LH subband; the lower-left is put into the HL subband; and finally, the lower-right pixel is put in the HH subband, splitting the binary mask into four subbands (Fig. 2). The decomposition of the binary mask continues on the LL subband until the required decomposition level.

![Fig. 2. Decomposition of the binary mask: (a) the original binary mask is divided in blocks of 2x2 pixels, (b) each pixel in the block corresponds to a subband, splitting the original mask into four subbands.](image)

Using separable wavelet filters, the 2D RBDWT is achieved applying 1D arbitrary length signal transform by rows and then by columns on the pixels inside the image object.

Efficient signal extensions let us decompose up to an arbitrary length for arbitrary length signals with perfect reconstruction property and without increasing the total number of samples, i.e. if the original signal has length N, the same number of wavelet coefficients will represent the signal after transformation [15].

Since neither all the signal segments inside the arbitrary shape start at an even-numbered row or column position nor at an odd-numbered row or column position, a proper subsampling strategy in the filter process has to be chosen in order to preserve the spatial correlation within the image object.

Therefore, depending on the parity of the segment length and the parity of the position at which the segment starts, there are four classes of signal segments which require different signal extension and subsampling.

These four classes are summarized below for the row lowpass synthesis filtering case:

1. The segment line starts at even-numbered column and its length is even: the filtering and subsampling take place as in the conventional wavelet transform. Even symmetry extension is used at the segment boundaries. The downsampling of the lowpass filtering keeps the even numbered coefficients in the segment line (remark that an even-numbered coefficient in the segment line -even local parity- not always corresponds to an even numbered coefficient in the column -even global parity-).

2. The segment line starts at an odd-numbered column and its length is even: the low pass filtering keeps the odd-numbered coefficients in the segment line (in fact, the coefficients located in even-numbered columns in the row). Even symmetry extension is applied to the boundaries of the segment.

3. The segment line starts at an even-numbered column and its length is odd: one pixel is added to the right-hand side of the segment such that the last highpass coefficient generated is zero. Even symmetry extension is used at the boundaries of the extended segment. Even-numbered coefficients in the segment line are kept in the lowpass filtering and downsampling. The known null highpass coefficient generated is not kept in the highpass downsampling. The lowpass band signal is, therefore, one coefficient longer than the highpass one, maintaining the same number of wavelet coefficients as pixels in the original segment line.

4. The segment line starts at an odd-numbered column and its length is odd: one pixel is added to the left-hand side of the segment line such that the first lowpass coefficient generated will be equal to the second lowpass coefficient. This segment extension preserves the statistics of the lowpass and highpass subbands. Even symmetry extension is applied to the boundaries of the extended segment. Odd-numbered coefficients in the segment line are kept in the lowpass filtering, but the known left-hand lowpass coefficient generated is not kept, so the total number of wavelet coefficients is equal to the number of pixels in the original segment line.

The filtering and downsampling is analogous for the column case.

A 5-level dyadic decomposition of the breast region inside the mammogram was obtained with the RBDWT method using 9-tap/7-tap biorthogonal filters [25].

E. Coding of the Wavelet Coefficients

SPIHT (Set Partitioning in Hierarchical Trees) and SPECK (Set Partitioned Embedded block) are both efficient wavelet-based codecs which represent the state of the art in image compression performance. The SPIHT image codec was developed by Said and Pearlman [17] and the SPECK codec by Islam and Pearlman [18]. The SPIHT technique is an improvement of the Embedded Zerotree Wavelets (EZW) algorithm developed by Shapiro [26].

Both algorithms are embedded techniques, i.e. the coding method produces an embedded bitstream which can be truncated at any point, equivalent to stopping the compression process at a desired rate, whereupon the image can be reconstructed. The wavelet coefficients with larger magnitude are those with a larger content of information. An embedded method transmits first those coefficients in order to achieve a reconstructed image with the minimum distortion for a given compression rate.

The SPIHT and SPECK algorithms order the wavelet coefficients according to its binary representation and transmit first an approximation of the most important coefficients providing a progressive in fidelity method based in a bitplane transmission where coefficients are progressively refined.
The partial ordering by magnitude of the transformed coefficients \( c(i, j) \) is due to sequential comparisons of coefficient magnitudes to a set of decreasing thresholds \( 2^{n-1}, 2^{n-2}, \ldots \) with the initial threshold \( 2^n \) satisfying the condition \( 2^n \leq |c(i, j)| < 2^{n+1}, \forall c(i, j) \).

Coefficients with magnitudes equal or larger than the considered threshold, \( 2^n \), are classified as significant, while others are classified as insignificant.

In order to reduce the number of comparisons, the sorting algorithms divide the set of pixels into partitioned subsets \( T_m \) and perform the magnitude test:

\[
\max_{(i, j) \in T_m} \{ c(i, j) \} \geq 2^n
\]

If the subset is insignificant, then all coefficients in \( T_m \) are insignificant, being unnecessary to sort the coefficients in the subset, otherwise a fixed rule is used to partition \( T_m \) into new subsets where the magnitude test is applied again.

The specific initial sets and partitioning rules are different for SPIHT and SPECK, the details of which are explained below.

E.1 The SPIHT Partitioning Algorithm

The set partitioning rules used by the SPIHT encoding method exploit the spatial self-similarity across subbands inherent in the wavelet decomposition of natural images [27].

The wavelet coefficients are considered to be organized into trees. In this tree-structure, called spatial-orientation tree, each node corresponds to a wavelet coefficient and its descendants are those of the same spatial orientation in the next subband level. In the initial set grouping, the highest level of the decomposition pyramid is divided into blocks of \( 2 \times 2 \) coefficients in which each coefficient, except for the upper left one, represents the root of a hierarchical tree: the upper-right coefficient is the root of the hierarchical tree in the LH subbands; the lower-left coefficient of the HL subbands; and the lower-right coefficient for the HH subbands (Fig. 3). If a coefficient is insignificant with respect to a given threshold, all its descendants are likely to be insignificant with respect to the same threshold.

Each time the algorithm finds a coefficient \( c(i, j) \) whose set of descendants is significant, the tree-based partitioning rule decomposes this set into the four direct descendants of \( c(i, j) \), called offspring, plus the subset formed by the rest of its descendants, called granddescendant. The magnitude test is then applied to the new five subsets. If the granddescendant subset of coefficient \( c(i, j) \) is determined as significant, the tree-based partitioning rule decomposes it into the four subsets of descendants of the offspring of \( c(i, j) \). This process continues until all significant coefficients with respect to the current threshold are identified.

E.2 The SPECK Partitioning Algorithm

The set partitioning rules used by the SPECK encoding method exploit the clustering of the energy in frequency and space in hierarchical structures of transformed images.

In this coding algorithm, the wavelet coefficients are considered to be organized in rectangular blocks of varying dimensions, called sets of type \( S \). There is another type of sets used, called sets of type \( I \), which are obtained by chopping off a small square region from the top left portion of a larger square region.

The algorithm initially groups the wavelet coefficients into two sets: set \( S \) which corresponds to the root of the pyramid decomposition, and set \( I \) which is everything left on the transformed image after taking out the root. SPECK starts testing the significance of set \( S \).

Each time a set \( S \) is found significant against a given threshold, a quadtree partitioning rule decomposes it into four subsets \( O(S) \), each one having one-fourth the size of the parent set \( S \) (defining the size of a set as the number of coefficients in the set) (Fig. 4). The significant test is applied recursively in these new sets of type \( S \). The quadtree partitioning rule provides a rapid zoom to high energy areas in the set \( S \) to code them first.

Once all sets \( S \) are processed the algorithm continues testing the set \( I \). If the set is found significant, an octave band partitioning rule splits it into four subsets: three sets of type \( S \) with equal size as the portion of the transformed image not belonging to the set \( I \), and a new set of type \( I \) (Fig. 4). The testing process continues recursively in the new four subsets until all significant coefficients are found for the current threshold. The octave band partitioning rule exploits the fact that energy is more likely to be concentrated at the top most levels of the pyramid structure of the wavelet decomposition.

It is important to remark that after the coding process finishes the significant test for the initial threshold, there are sets of type \( S \) of varying sizes. During the next significant tests, sets \( S \) are processed in increasing order of size.

E.3 Object-Based extension of SPIHT and SPECK

The binary mask obtained during the segmentation process provides the shape information needed for extending the conventional SPIHT and SPECK algorithms. With the
shape mask pyramid constructed as has been explained in section D, the nodes belonging to the breast region in each subband are known.

In these object-based extensions [24], before the coding process the nodes and child branches which are outside the image object are pruned. During the coding process, no information about nodes and branches outside the breast region is transmitted (Fig. 5 and Fig. 6).

![Figure 5](image-url)  
**Fig. 5.** Parent-child relations in the OB-SPIHT algorithm.

### III. Results

We evaluated the lossy compression performance obtained at different rates with the two proposed region-based wavelet coding methods on a set of five digital mammograms each with size of 4096 x 5120 pixels and resolution of 12 bits per pixel. The coding results were compared with those obtained applying the original SPIHT algorithm on the whole mammogram, by means of the Peak Signal-to-Noise Ratio (PSNR)

$$PSNR = 10 \log_{10} \left( \frac{4095^2}{MSE} \right) \text{ dB}$$

where 4095 is the peak amplitude and MSE is the mean squared-error between the original and the reconstructed image.

In order to compare region-based to full-image coding, the distortion measurements for the original SPIHT method were calculated for each image on the same breast region where the region-based coding methods were applied.

Tables 1-5 summarize the coding results obtained at rates ranging from 0.1 to 1.0 bpp. The bit rates were calculated from the actual size of the compressed file. Furthermore, using the fidelity progressive transmission capability of the three methods, the results for different bit rates in each image and method were obtained from a single encoded file.

For all images, the region-based coding methods, OB-SPIHT and OB-SPEC, performed substantially better than full-image SPIHT. A very slight difference on performance between OB-SPIHT and OB-SPEC was found.

In figure 7 and 8 comparative results between OB-SPIHT and OB-SPEC with normal SPIHT are shown for mammogram h60ci, which presents the lowest difference in performance between region-based and full-image methods. Yet, even with this image, a remarkable improvement on distortion measurements was found for the object-based techniques. On average, for h60ci, object-based techniques improve normal SPIHT by 0.995 dB at 0.2 bpp, and by 5.185 dB at 1.0 bpp, the highest rate tested. The PSNR obtained by normal SPIHT at 1.0 bpp was achieved approximately at 0.54 bpp by the object-based techniques.

Figure 9 and 10 plot the PSNR measurements for image h50cd, which is the case among the set of images tested showing the highest difference in performance between region-based methods and SPIHT. In fact, the distortion achieved at 1.0 bpp with the SPIHT method corresponds to a compression rate of 0.2 bpp with OB-SPIHT and OB-SPEC, making clear the improvement obtained with the object-based compression techniques. For all images, the climb of PSNR versus rate for full-image SPIHT is quite slow and even flat for some images in some ranges of rate, whereas this climb is, in average, an almost con-
constant 4 dB per 0.2 bpp for the object-based techniques. The full-image wavelet transform blends the black pixels of the background and the near white pixels of the object in the region embracing the boundary, making the resulting coefficients within the object region harder to encode efficiently.

### Table I

<table>
<thead>
<tr>
<th>Rate (bpp)</th>
<th>OB-SPIHT</th>
<th>OB-SPECK</th>
<th>SPIHT</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1</td>
<td>47.95</td>
<td>48.04</td>
<td>46.64</td>
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<tr>
<td>0.2</td>
<td>50.03</td>
<td>50.08</td>
<td>47.96</td>
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<tr>
<td>0.4</td>
<td>53.41</td>
<td>53.57</td>
<td>50.02</td>
</tr>
<tr>
<td>0.6</td>
<td>56.58</td>
<td>56.61</td>
<td>51.37</td>
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<tr>
<td>0.8</td>
<td>60.31</td>
<td>60.24</td>
<td>53.09</td>
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<tr>
<td>1.0</td>
<td>63.74</td>
<td>63.84</td>
<td>54.03</td>
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### Table II

<table>
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<th>OB-SPECK</th>
<th>SPIHT</th>
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</thead>
<tbody>
<tr>
<td>0.1</td>
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<td>48.03</td>
<td>46.15</td>
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<tr>
<td>0.2</td>
<td>50.30</td>
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<td>54.19</td>
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<td>57.78</td>
<td>57.88</td>
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<td>61.74</td>
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<td>1.0</td>
<td>66.02</td>
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### Table III

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<th>OB-SPECK</th>
<th>SPIHT</th>
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<tbody>
<tr>
<td>0.1</td>
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<td>45.99</td>
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<td>0.2</td>
<td>51.08</td>
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<tr>
<td>1.0</td>
<td>71.20</td>
<td>71.39</td>
<td>51.11</td>
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</tbody>
</table>

Reconstructed images obtained after compression at 0.4 bpp with the methods compared in this study are shown in figure 11. SPIHT compresses the whole image. OB-SPIHT and OB-SPECK compress only the breast region inside the mammogram improving in efficiency. The Regions Of Interest (ROIs) marked are magnified in figure 12. Although the reconstructed ROIs are at the same rate, more artifacts are visible in the SPIHT method.

### IV. Discussion and Conclusion

OB-SPIHT and OB-SPECK are object-based extensions of full-image SPIHT and SPECK compression algorithms, which represent the state of the art in image compression. Both object-based extensions preserve the features of the original methods, providing progressive transmission of images, gradually improving the image quality: a coarse signal approximation could be quickly provided and
progressively enhanced as more bits are transmitted. The encoding/decoding algorithms can even be let run until the reconstructed image is a nearly lossless representation of the original one. These features make these compression methods appropriate for telemedicine, allowing to transmit a first approximation of the original digitized mammogram and progressively increase the pixel accuracy until a radiologist could diagnose with the reconstructed image quality achieved.

The SPIHT coding algorithm has been applied successfully in lossy compression of medical images [12, 28]. Savcenko et al. evaluated the detection of subtle nodules and fibrosis in sixty compressed computed tomographies of the chest [12]. Images were compressed at 40:1 and 80:1 using SPIHT, and the performance of radiologists’ diagnosis was evaluated with an ROC method. They found that computed tomographies of the chest at 40:1 can be used for detecting pulmonary nodules and fibrosis without decreasing the diagnostic accuracy. Images at 80:1 did not show statistical significant difference in diagnostic accuracy, but decreasing detection ability was found.

Perlman et al. [28] designed a protocol to evaluate compressed digital mammograms. Fifty-seven mammograms were compressed in this study with SPIHT. They segmented the image, using a thresholding rule, into a rectangular subimage containing the breast and into a portion containing the background. The background was compressed at 0.07 bpp while the rectangular image containing the breast was compressed at 1.75, 0.4, and 0.15 bpp. In their study, they found no significant differences between analog and compressed images, even at the lowest bit rate, 0.15 bpp, representing an 80:1 compression ratio.

Lossy compression in digital mammography was also evaluated in [13] by Good et al. In their work sixty digital mammograms were compressed using a 12-bit version of the standard JPEG (Joint Photographic Experts Group). After identifying on each image the smallest rectangular area containing the breast and setting to a constant value the rest of the image, five compression ratios were applied to the whole image ranging from a mean compression ratio of 24:1 to 101:1. Compressed and non compressed images were evaluated by means of an ROC study to assess the

**Fig. 9.** Comparative evaluation of OB-SPIHT and SPIHT for mammogram 156cd.

**Fig. 10.** Comparative evaluation of OB-SPECK and SPIHT for mammogram 156cd.

**Fig. 11.** Reconstructed digital mammogram after compression at 0.4 bpp using; (a) SPIHT coding algorithm, (b) OB-SPIHT coding algorithm, and (c) OB-SPECK coding algorithm.
quality of each image for detecting masses and clusters of microcalcifications. They found that detection of masses is not affected by compression while at high levels of compression observer performance is degraded for detecting clusters of microcalcifications.

In our work, we have applied OB-SPIHT and OB-SPECK to digital mammography, coding only the breast region where the important information is included. For digital mammography, region-based methods represent an improvement in compression efficiency compared to full-image methods where the compressed file contains not only information about the breast region.

Motivated by the results obtained in this work, our next study will carry out the clinical evaluation of these region-based wavelet coding techniques in digital mammography.

REFERENCES


