DESIGN AND IMPLEMENTATION OF COMPRESSION ALGORITHM FOR MAMMOGRAMS WITHOUT VISIBLE LOSSES

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Abstract –In this paper the description and results of a mammogram compression algorithm are presented. This algorithm has no visible losses and works with wavelet transforms, thresholding, scalar quantization and lossless codification in order to obtain smaller files than the original; the resulting files allow reconstructing a similar image that amid the losses, does not affect the diagnosis.

The algorithm was tested with 330 mammograms and as result, the average compression rate was 16:1, the average PSNR 50dB and the average SSIM 0.96. In addition, the results were submitted to a clinical evaluation, which allowed making a statistic analysis. This analysis suggests that there is no alteration of the diagnosis when the compressed mammograms are used.

Keywords-component; Digital mammography, JPEG2000, lossy image compression, McNemar test, structural similarity (SSIM).

I. INTRODUCTION

With the development of new technologies in acquisition of medical images, new ways of non-invasive diagnostic have been achieved. These ways generate high resolution images that ease the medical labor. However, it has caused a new problem: bigger amount of data, which increase the hardware resource needed for the image processing. For this reason, new ways of compression are studied with the purpose to keep the main information and discard any data which are redundant.

From all the medical diagnostic images, there is a big interest in mammogram, since is a method for diagnosing cancer in early stage. With these X-ray images one can detect different types of injuries in the breast tissue that, depending on its characteristics, may suggest the presence of carcinoma. In addition it is an inexpensive test, so it has been implemented as a routine test which has reduced the mortality rate.

The mammograms are high resolution images, which mean that there is a lot of redundancy in its data; therefore the image file is quite large and hard to handle. Due to that, it is necessary to compress the images in order to remove the data that is not relevant to diagnostic. However, because mammograms are used for diagnostic and prevention, the process of compression should be done very careful.

Based on the previous ideas, the main objective of this paper is the proposal and implementation of a compression algorithm for mammogram images that do not influence the medical diagnostic, which one can call without visible losses [6]. In order to keep the medical reliability, several images quality measurements were chosen for comparing the original image versus the compressed image. Also a medical study to measure the effects of the compression was proposed, this method was based on contingency tables.

In the section II the proposed compression and decompression algorithm is described. Thereafter, in the sections III and IV the results and the proper analysis and conclusions are shown.

II. PROPOSED ALGORITHM

The mammograms are high resolution radiologic images. Because they are not periodic signals it is very useful to analyze them with wavelet transform, since it shows indirectly the frequency coefficients and the location in the image. Therefore is possible to identify the discontinuities of the images while its spectrum is observed, in order to obtain a representation without infinity frequencies that allow detecting the data which can be omitted. This is made through shifts and dilations of a scaling function and a mother wavelet.

The wavelet functions and scaling function are continuous signals of finite duration, then they belong to the $L^2(\mathbb{R})$ space, which is a separable Hilbert space [1, 2, 3]. This space has an orthonormal base. The scaling signals $\varphi(x)$ can be written as follows:

$$\varphi(x) = \sum_{b=-\infty}^{\infty} l(b)\varphi_{1,b} = \sum_{b=-\infty}^{\infty} l(b)\sqrt{2}\varphi(2^1x - b) \quad (1)$$

Where $l(b) =< \varphi, \varphi_{1,b} >$ is the inner product of the function with the base for a scaling factor equal to 1.This corresponds to coefficients of a low pass filter. Every value of b represents a shift in the scaling signal base.

Similarly, for the wavelet function $\psi(x)$ one can write:

$$\psi(x) = \sum_{b=-\infty}^{\infty} h(b)\sqrt{2}\psi(2x - b) \quad (2)$$

Where $h(b) =< \psi, \varphi_{1,b} >$ can be viewed as coefficients of a high pass filter.

In order to obtain a wavelet representation of a signal, the process is reduced to the design of a bank of filters that meet the analysis coefficients. For image reconstruction from wavelet coefficients, one can use the concept of quadrature mirror filters that allow a perfect reconstruction of the input function to the filter bank.

Since images are two-dimensional functions the process is a little different. First the wavelet transform is applied in an axis to get the approximation and details coefficients, then, for each, the wavelet transform component is calculated but in the other axis. Finally the four components are obtained and can be viewed as four images with one quarter of the original image size. As it is an energy finite transform, large number of coefficients has values close to zero, which facilitates quantification.

The images in the database DDSM [5] that were used have sizes that easily exceed four million square pixels with 16 or 12 bits per pixel, which means that although the wavelet transform can group the most significant pixels in an area, the direct encod-

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ing on the coefficients would be inefficient for the time and hardware demanded.

For this reason multiple wavelets were used. In this way it was possible to decompose the image in smaller sections which are more manageable computationally. Then, the proposed scheme of compression in the Fig. 1 is shown. In this scheme the different wavelet transforms are adapted according to the needs of each image. Also, with this scheme one can have more control over the quantization and thresholding processes, according to the information clustered in each component.

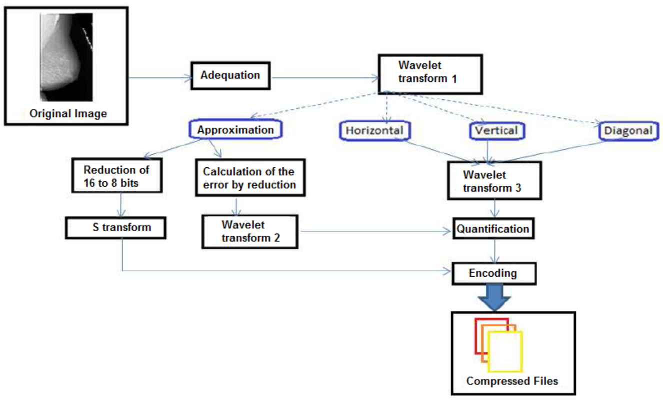

Figure 1. Mammogram compression scheme proposed. It has nine blocks which transform, quantize and code the image.

A. Image Adequation

Due to the different equipment used, dates and other factors, the images of the data base have diversity of visual characteristics, thus there is a need to standardize the display.

This step includes two settings: one for objects outside the breast and one for bright pixels that affect the visualization of the breast tissue. With a morphological opening operation the objects that are outside the contour of the breast are removed.
These objects may be caused by artifacts such as dust or label profile identification of the breast and have no effect on the diagnosis [4]. For the brightest pixels a correction by histogram is made.

B. Wavelet Transform

The first wavelet transformation is applied to the total image and as a result, four components are obtained. Yet, they are not subjected to the processes of quantization and coding since their dimensions and values are still too large.

After this first transform, a reduction of bits of the approximation component is done. Although it is established that mammography images should have as much information as possible by pixel, the visual capacity of the human eye is not enough to recognize 2^{16} different shades, so one can prescind from some bits.

Based on [6, 7] the most significant 8 bits per pixel are selected to create a new image. Nevertheless the 8 least significant bits are not discarded because they have information about the contour and contrast of the breast. To avoid losing data, the approximation component of original image of 16-bit is separated in two 8-bit images as follows: let I_{16} be the 16 bits image and let I_8 be the image conformed of the 8 most significant bits of I_{16}. If the bits of each pixel of I_8 are shifted 8 positions to left and those positions are filled with zeros, a 16-bit image $\widehat{I_{16}}$ is created. Then let I_{err} be the difference between I_{16} and $\widehat{I_{16}}$, ie:

$$I_{16} = \widehat{I_{16}} + I_{err} \qquad (3)$$

Then I_{err} is another image that can be represented with 8 bits, and as $\widehat{I_{16}}$ is obtained from I_8, therefore the image I_{16} can be built with two 8-bits images. With the reduction, the most significant information is concentrated in I_8, consequently lossless compression by means of S transform is used in order to encode all coefficients without quantification. Since I_{err} contains the least significant bits losses can be tolerated, thus a biorthogonal filter is used. Each of the components obtained by the wavelet decomposition is passed through three processes: thresholding, quantization and encoding.

Although the processes described before enable better handling of the information of the approximation component, when the first wavelet decomposition was done some components of details were generated. These components still have large size and number of coefficients; hence the final step is to apply a wavelet transform to each detail component of initial image (Horizontal, Vertical and Diagonal). For each one of the 12 components obtained, there is a stage of thresholding, of quantization and encoding, similarly to the process with I_{err}, but with different number of quantization levels.

C. Thresholding

The thresholding is done by removing the wavelet coefficients that do not affect the total energy significantly; the threshold is calculated as the product of wavelet coefficient with the largest magnitude per compression rate (in percentage). The compression ratio is determined by (4) where b is the minimum number of bits to represent the gray levels and H is the entropy of the image.

$$k = b/H \qquad (4)$$

The thresholding process for each wavelet component (Approximation, Horizontal, Vertical and Diagonal) is performed separately instead of calculating an overall compression ratio in order to get a minor error (mean square).

D. Quantization and Encoding

The wavelet transform on the images is a relation that goes from $\mathbb{N}$ to $\mathbb{R}$, which generates a wide range of values to be encoded, therefore it is necessary to quantize them.

In this case, a uniform quantizer was used, assuring that the error introduced is in the range $[-\frac{q}{2}, \frac{q}{2}]$, where q is the size of the quantization step. Consequently, it is possible to control the error and the amount of compression with the selection of quantization levels, allowing variations of q depending upon the importance of the data clustered in each component. It was further found that after a certain number, the inclusion of more quantization levels does not guarantee a significant improvement in image quality, but makes longer the encoding process. According to those statements different quantization levels were chosen for each wavelet component.

After the quantization process a coding stage is performed, to represent the quantized coefficients by means of a sequence of

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binary digits which is intended to obtain the compression with the minimum number of bits. The algorithm used is Huffman coding.

E. Decompressing

The decompressing process starts at decoding the files with a Huffman decoder. Then the inverse wavelet transform for I_{err}, I_8 and the components is obtained. Afterwards a 16 bit image is recovered combining I_{err} and I_8. Finally the recover image is obtained by an inverse wavelet transform from the components and the recovered 16 bit image. It is important to keep in mind that the recovered image is not equal to the initial image due to thresholding and quantization processes.

III. RESULTS

In this section the results obtained by compressing 300 images of fat tissue and 30 images of other densities are presented. The mammograms were taken from the database DDSM [5] and are 12 or 16 bits per pixel. Of the 330 selected images, 110 mammograms were classified as normal, 110 mammograms were diagnosed with malignant cancer and 110 with benign mammograms, with different types of findings to ensure that the algorithm was tested on a wide range of possibilities.

A. Quantitative Results

In all cases three measurements were taken: compression ratio (CR), peak signal to noise ratio (PSNR) and structure similarity index (SSIM)[19]. In addition to the 'normal - benign – malign' classification, the images were grouped in three classes: the mean of the overall images, the mean of the CC profiles and the mean of the MLO profiles. In the tables I, II, III and IV the mean values of the images of each category are shown.

For the normal sample, compression ratios in the range 10:1 and 29:1 were gotten and the PSNR varied between 52 and 70 dB. The average values shown in table I suggest that the compressed images exhibit high quality and there are not significant differences from their originals.

For the 16-bit malignant sample, compression ratios varied between 11:1 and 29:1 approximately, while the PSNR obtained varied between 51 and 69 dB. The average values for these mammograms can be found in table II. On average, the values suggest that the compressed images for this sample have high quality.

In contrast, for the sample of 12 bits the compression ratios varied between 10:1 and 16:1 approximately, while the PSNR obtained have a range from 35 to 45dB. The average values for this sample are shown in table III. These average values suggest that the compressed images for this sample have an average quality.

Finally, applying the compression algorithm to the benign sample, compression ratios varied between 10:1 and 18:1 while the PSNR varied between 39 and 45 dB. The average values for the benign sample can be found in table IV. These values suggest that the compress images for this exhibition have an average quality.

TABLE I. AVERAGE RESULTS FOR 16-BIT MAMMOGRAMS WITH NORMAL FINDINGS.

	CR	PSNR	SSIM
Average	16.072	57.492	0.966
CC Average	16.162	57.390	0.967
MLO Average	15.982	57.595	0.965

TABLE II. AVERAGE RESULTS FOR 16-BIT MAMMOGRAMS MALIGNANT FINDINGS.

	CR	PSNR	SSIM
Average	18.509	55.612	0.997
CC Average	18.854	57.759	0.997
MLO Average	18.163	57.171	0.997

TABLE III. AVERAGE RESULTS FOR 12-BIT MAMMOGRAMS WITH MALIGNANT FINDINGS.

	CR	PSNR	SSIM
Average	12.957	41.281	0.956
CC Average	13.002	41.325	0.956
MLO Average	12.912	41.236	0.956

TABLE IV. AVERAGE RESULTS FOR 12-BIT MAMMOGRAMS WITH BENIGN FINDINGS.

	CR	PSNR	SSIM
Average	15.182	43.456	0.965
CC Average	15.224	43.397	0.965
MLO Average	15.139	43.514	0.965

Regardless of the bit rate of digitization (16 or 12), the compression and decompression process takes approximately the same time, because regardless of the bits, the amount of coefficients to code is about the same due to the quantization process. However, both the values of image quality and compression rates show significant variation with respect to the amount of bits of digitization. This difference is obtained because in the images with 16 bits there are much more redundant data in 12-bit images.

It is important to notice that for all the compressed images the SSIM was not under 0.95, which means that although some images vary in contrast, they present good quality and do not differ in structure.

To illustrate the impact of the compression process some graphic examples are shown in Fig. 2 and Fig.3. In these figures, comparisons between the original mammograms, compressed and difference are displayed. In Fig.2 images of a mammogram with a malignant lesion are shown. In this case, the patient was found with a high suspicion for malignancy due to an apparent mass with irregular microlobulated margins. For this case, changes in contrast are not obvious; in fact, the ranges in which the error varies are small. As the zoom is increased, some pixelation effect in the compressed image can be seen, but the visibility of the injury is not affected. In Fig. 3 a mammography of patient with benign calcifications is displayed. A change in gray level in the bottom of the compressed image can be noticed, which reflects a change of contrast in the overall image. However, injuries are still evident despite the effect of pixelation appreciated when the zoom is increased.

By comparing the images displayed, one can see that the change between the compressed image and the original image is minimal: the contrast within the breast region is hardly affected and even expanding those areas with pixelated effect change is almost imperceptible.

In Fig. 4 the average measurements for different densities of are shown. Note that the SSIM value is multiplied by 10 in order to appreciate its variations. It is important to note that breast density has a strong impact on the rate of compression, those medium-density breasts have better compression ratios and better image quality. That is, the compression ratio is directly associated with the type of breast tissue. Those breasts that differ between tissues types are less prone to have lower compression ratio (fatty and dense) because they contain more low frequency components which are encoded lossless.

The results suggest that the algorithm exhibits a better compression rate for mammograms with benign or malignant findings. At the same time, mammograms without findings present a lower value on image quality. These aspects suggest a link between the compression rate and the presence of injured tissue.

It is also observed that regardless of the presence of lesions, the CC profiles have a better performance on the algorithm by reporting higher rates of compression due to the presence of pectoral muscle

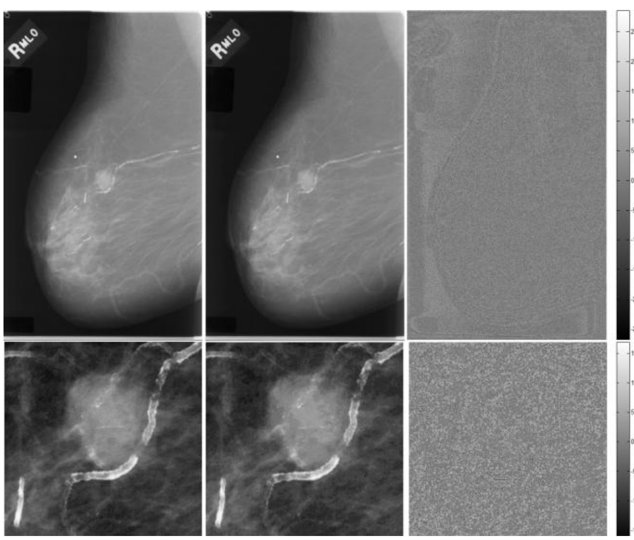

Figure 2. Comparison between original and compressed images for mammography with malignant lesion. Above: complete images. Bottom: Enlargement of the areas of injury. Left: Original image. Middle: Compressed image. Right: Difference between original and compressed image.

B. Qualitative Results

The diagnostic test is an important part of the research, since it allows establishing if the compression process has an impact in the management that is given to the patient. According to the discussion in [8] a test was done and several surveys were filled. The following data were analyzed according to each part of the survey.

The first question of the survey was intended to determine if the compression process has affected the overall perception of quality in the mammogram. It is important to mention that in the quality assessment some technical details, like the position of the breast, were omitted and only the perception of digitization was evaluated.

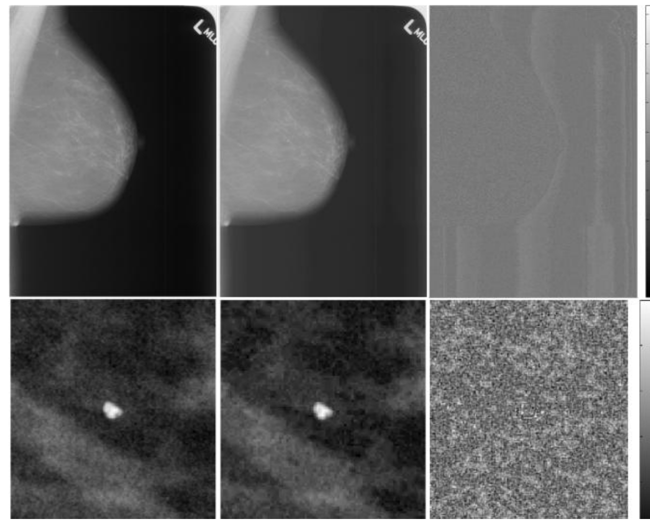

Figure 3. Comparison between original and compressed images for mammography with benign lesion. Above: complete images. Bottom: Enlargement of the areas of injury. Left: Original image. Middle: Compressed Image. Right: Difference between original and compressed image.

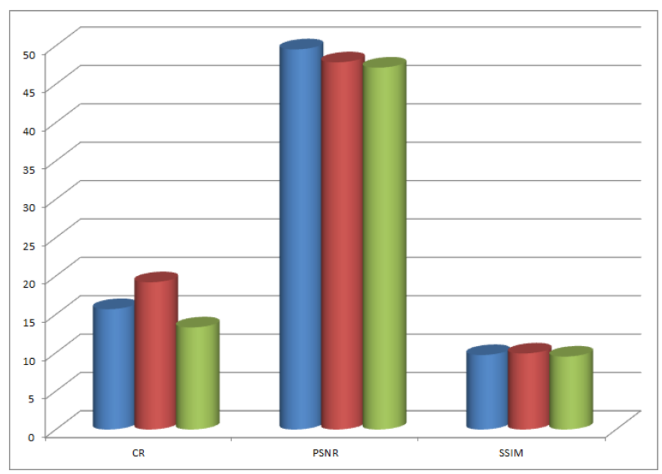

Figure 4. Average results for mammograms according to their densities. The mean of the compression rate, PSNR and SSIM are shown. In blue: average values obtained for mammograms two densities 1 and 2 (fat). In red: mean values obtained for the density 3 (fibroglandular). Green: average values for density 4 (dense).

From 40 mammograms tested, only 4 compressed images were classified with lower quality. This means that there was a quality change perceived in only 10% of the sample, while satisfying it in 90%. This change in the perception was perceived due to a change in brightness of the background: the compressed image had a lower rating.

The second question of the survey was intended to determine whether the compression process has affected the findings in the mammograms or not. The corresponding results are shown in table V. For the data presented in this table, the McNemar test with Yates correction was applied, resulting in $T_1 = 0.8$. In this case, the null hypothesis is "The compression does not induce significant changes in the present findings on mammograms". Since the value of rejection is 3.84 according to the χ^2 values, then the null hypothesis is accepted with 95% accuracy and it is declared that the differences found between mammograms are due to the intra – observer difference.

TABLE V. CONTINGENCY TABLE ANALYSIS FINDINGS BEFORE AND AFTER THE COMPRESSION PROCESS.

Compressed/Original	R	W	Total
R	21	4	25
W	1	14	15
Total	22	18	40

The third question of the survey was intended to determine if the algorithm had affected the position of the finding. The location of a lesion in the breast is given by quadrants. The profiles MLO divide the breast region in two quadrants: top and bottom, while the profiles CC divide the breast in the internal and external quadrants. According to the profile in which the finding was observed the location of the lesion is assigned.

In the CC profiles changes in the location were not observed, except for those lesions that were not detected in the compressed images and therefore are not included in this analysis, suggesting that the algorithm does not have great influence on the accuracy of the lesion position, once it has been detected.

In contrast, for the MLO profiles, a single change in the location of the injury was observed once it has been detected. This change is located in the lower quadrant of the original and was found in the upper quadrant of the compressed mammogram. It represents a 8.33% of the locations where lesions have been detected in both studies (original and compressed).However by looking in detail mammograms, the lesion is on the border of the quadrants, so the error in its location can be attributed to human error rather than the algorithm.

The final part of the survey is intended to give an appreciation of the management that should be given to the patient according to the findings. This operation is the most important part of the study because it is what ultimately allows making a diagnosis. The quality of life of a patient may depend on the management.

For patient management, four categories were defined, according to [8]. True Positive: It is stated that there is a real positive if both, original and compressed mammograms, were classified as F/U, both were classified as B/X or both were classified as C/B.

True Negative: It is stated that there is a real negative if both, original and compressed mammograms, were classified as RTS.

False Positive: It is stated that there is a false positive if the findings in the original mammogram were not found (RTS classification), but there were found findings in the compressed mammography (classification F/U, B/X or C/B). It is also stated as a false positive the case in which the original mammogram was classified as benign (F/U) and compressed mammogram was classified as malignant (C/B or B/X).

False Negative: It states that there is a false negative with respect to management if findings were found in the original mammography (classification F/ U, B/X or C/B), but no injuries were reported in the compressed mammography (RTS classification). It is also stated as a false negative the case in which the original mammogram was classified as malignant (C/B or B/X) and the compressed mammography has been classified as benign (F/U).

For the McNemar's test, the null hypothesis is “The compression algorithm does not introduce significant changes in diagnosis" meaning that the observed differences are due to chance. Computing the value for the test, one can get $T_1 = 0.25$. Also, one can know that the χ^2 distribution with one degree of freedom and accuracy of 95% is 3.84.

Since $T_1 < \chi^2$ the null hypothesis is accepted and declared with 95% certainty that the false positives and negatives observed in the management of the patient do not depend on the compression algorithm implemented.

TABLE VI. CONTINGENCY TABLE ANALYSIS OF PATIENT MANAGEMENT BEFORE AND AFTER THE COMPRESSION PROCESS.

MANAGEMENT			
Compressed/Original	R	W	Total
R	9	2	11
W	2	7	9
Total	11	9	20

As for the sensitivity and specificity, the data suggest that by using the compressed mammograms there is $81.\overline{81}\,\%$ certainty to classify them correctly, handling a sick patient when there is an injury. They also suggest that by using the compressed mammograms there is $77.\overline{7}\,\%$ of chances to classify the patient correctly, diagnosing a healthy patient when there is no injury.

C. Comparison with other Algorithms

Although it has been shown that the compression algorithm performs well, exhibiting a high compression rate while not affecting the diagnosis, it is important to compare with previous work and the standards of radiology. Although DICOM communications agency approves lossless JPEG and JPEG2000, some other works have been developed in parallel with the aim of offering a solution to the problem of data management in mammography. Then, it is important that the comparison is not made only with the standards, but such works.

Comparing the proposed algorithm with previous studies found in the state of art, it can be said that the compression rate is bigger than the results reported in the papers [7, 9, 10, 11, 12, 13]. Those works exhibit image loss and quality measures which are around 45 dB for the PSNR. In this case, the data suggest that the compression algorithm proposed here provides a better solution.

In contrast, the proposed algorithm does not excel the compression rates for the works [14, 15, 16, 17, 18], works in which losses are also presented. However, in terms of image quality the proposed algorithm presents a better image quality. As for the work proposed in [14, 18] medical evaluation is not presented, so despite having good measures of quality one cannot infer if there have been significant changes to the diagnosis.

To make the comparison with the general standards of radiology, a sample of the images were compressed with JPEG and JPEG2000 lossless since it has been proved earlier that the proposed algorithm does not have an impact on the diagnosis and therefore no induced losses are visible. For this case, normal, benign and malignant images were compressed. Only the compression rates are compared because the PSNR of the proposed algorithm is always lower than the one obtained with the standards. In table VII the comparison of compression rates for each algorithm is presented. According to the data, regardless of diagnosis, the proposed algorithm obtains a better compression ratio on these two standards, with a lower image quality. However it is recalled that the proposed algorithm has no visible losses and therefore they will not be apparent to the radiologist or for the diagnosis.

TABLE VII. COMPRESSION RATES ACHIEVED WITH THE PROPOSED ALGORITHM VS. RADIOLOGY STANDARDS

Compression Algorithm	CR
Proposed	16.58
JPEG Lossless	2.55
JPEG2000 (Lossless)	3.11

In conclusion, the proposed algorithm meets the stated objective by compressing images without altering the diagnosis. And even than in compression rate and image quality does not exceed the image quality imposed by sophisticated algorithms such as JPEG2000; it does exceed the compression rate and quality of other works. The advantages of this algorithm may not be denied, as well as its easy implementation, data manipulation and especially the introduction of losses despite they do not produce significant changes on the diagnosis, which added to the study of the implementation of compression algorithms without health consequences for patients.

IV. DISCUSSION

In this article an algorithm for mammogram image compression that does not introduce changes in diagnosis was proposed, developed and tested. The algorithm allows compressing the image in a rate of 16 times to 1 on average.

One great advantage in this work is the medical concept involved. Thanks to the evaluation of the compressed mammograms we found that not only the algorithm exhibit great PSNR and SSIM values, but that the differences found by the physician cannot be attributed to the algorithm. Also, it is worth to mention that along with the investigation several links were found between the compression process and some characteristics of the breast. Those are to say, the link between the breast density and the compression ratio achieved and the link between the presence of injured tissue and the compression ratio.

With the development of this work some aspects were found that suggest a deeper analysis and were not performed due to the current limitations and purposes, but deserve similar efforts. The first issue on which future research is focused is the type of transform to use. With the development of the ITI and other transforms based on wavelet and ridgelet, contourlet, bandelet, among others, one can find a transformation that works best for these images. The second aspect is the type of encoding. For the present work the impact of arithmetic and Huffman coding was tested, but this does not mean that one can make use of more sophisticated algorithms such as EZW or EBCOT. Finally, the third aspect is the sample of tests with the medical expert. For this case 40 mammograms were chosen and tested by a single physician. However, for future work one can attempt to expand the number of mammographic studies to be tested, and the number of diagnostic opinions about mammograms.

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