

# Mammogram Image Size Reduction Using 16-8 bit Conversion Technique

Ayman A. AbuBaker, Rami S.Qahwaji, Musbah J. Aqel, and Mohmmad H. Saleh

**Abstract**—Two algorithms are proposed to reduce the storage requirements for mammogram images. The input image goes through a shrinking process that converts the 16-bit images to 8-bits by using pixel-depth conversion algorithm followed by enhancement process. The performance of the algorithms is evaluated objectively and subjectively. A 50% reduction in size is obtained with no loss of significant data at the breast region.

**Keywords**—Breast cancer, Image processing, Image reduction, Mammograms, Image enhancement

## I. INTRODUCTION

EARLY detection is the best way to improve the breast cancer prognosis since the causes of the disease are still unknown. Breast cancer is the second most cancer diagnoses among women after skin cancer [20]. In addition, it accounts for the second most cancer deaths, second to only lung cancer [20]. Currently, three methods are used for breast cancer diagnosis: mammography, fine needle aspirate and surgical biopsy. Mammography has a reported malignant sensitivity which varies between 68% and 79% [15]. The second method depends on fine needle aspirate, which extracts fluid from a breast lump and inspects it under the microscope. This method has a reported sensitivity varying from 65% to 98% [15]. Surgical biopsy is more evasive and costly but it is the only test that can confirm malignancy. Efficient machine learning algorithms can enhance the performance of mammogram analysis and provide the robust and accurate performance of surgical biopsy without its evasiveness and cost.

Mammographic screening allows early detection of non-palpable, non-invasive and early invasive tumors. Hence, it can reduce the mortality from breast cancer by as much as 20%-30% [8]. There is an increasing need for automatic and

accurate detection of cancer cells. However, the low contrast between the breast cancer cells and normal cells makes the process of early detection harder.

Most of the work in mammography aims at detecting one or more of the three abnormal structures in mammograms [11]: microcalcifications [18], circumscribed masses [12], and speculated lesions [19]. Other methods depend on classifying the breast lesions as benign or malignant [2]. There are problems with manual analysis of mammographic images by radiologist as they tend to vary in their interpretations. In addition, the interpretation is a repetitive task that requires lot of attention to minute detail. Hence, it requires lot of staff time and effort, which results in slowing the diagnosis time. Thus, it is very important to apply intelligent detection and classification techniques that can help the radiologist do their job efficiently and fast.

Mammogram images are high-resolution and large size images that require specialized computing facilities to process them. Moreover, transmitting these images over computer networks can be difficult and may require image compression. Therefore, a reduction pre-processing stage is an important stage in most mammography-based systems. This stage is also important for computer graphics, multimedia and electronic publishing [9, 21].

This paper is organized as follows: A brief survey is introduced in Section 2. The database resources are explained in Section 3 while our algorithm is introduced in Section 4. The subjective evaluation is carried out in Section 5. The concluding remarks and suggestions for future work are introduced in Section 6.

## II. DIGITIZED MAMMOGRAPHY TECHNIQUES

There have been many advancements in image processing in the fields of image compression, enhancement, and feature extraction. However, the usefulness of these new techniques depends mainly on two important parameters, which are the spatial and grey-level resolutions [10]. They must provide a diagnostic accuracy in digital images equivalent to that of conventional films. Both pixel size and pixel depth critically affect the visibility of small–low contrast objects or signals, which may carry significant information for diagnosis [6]. Therefore, digital 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.

Manuscript received March 9, 2005.

Ayman A. AbuBaker, is PhD student at university of Bradford, School of Informatics, Richmond Road, Bradford, West Yorkshire, BD7 1DP, UK (Email: A.A.AbuBaker@Bradford.ac.uk)

Dr. Rami S. Qahwaji, is with EMIC, school of Informatics, university of Bradford, Richmond Road, Bradford, West Yorkshire, BD7 1DP, UK (Email: R.S.R.Qahwaji@Bradford.ac.uk).

Dr.Musbah J. Aqel, Assoc. Prof, post doctoral, university of Bradford, Richmond Road, Bradford, West Yorkshire, BD7 1DP, UK (Email: musbahaqel@yahoo.com).

Mohmmad H. Saleh is graduate student at the Electrical and Computer Eng. Dept, university of Applied Science University, Jordan. (Email: acol20@hotmail.com)

For instance, it has been shown that isolated clusters of microcalcifications are one of the most frequent radiological features of asymptomatic breast cancer. A careful search for the clustered microcalcifications that may herald an early-stage cancer should be carried out on all mammograms [3]. Microcalcifications frequently appear as small-size low-contrast radiopacities [16]. Due to this, a typical mammogram must be digitized at a resolution of approximately  $4000 \times 5000$  pixels with 50- $\mu\text{m}$  spot size and 12 or 16 bits, resulting in approximately 30 to 40Mb of digital data. The Processing or transmission times of such digital images could be quite long. Archiving the amount of data generated in any screening mammography program also 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 or reduction scheme to reduce the digital data without significant 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 [4, 5].

Recently, many techniques became to manipulate image sizes such as, linear interpolation, and cubic spline interpolation [1, 7, 13, 14,17]. Many reduction techniques are based on image interpolation which is followed by a re-sampling process. These techniques are simple to implement but they produce sub-optimal results [13].

The image interpolation has a central role in many applications [28][27]. An important application is changing the size of digital image according to the nature of the display device. The image interpolation is one of the key factors in image scaling processes. According to [29], three categories exist for image interpolation: static image interpolation [30][31], multi-frame image interpolation [32][33], and image sequence (video) interpolation.

One of the simplest techniques for image interpolation is the nearest neighbor pixel. In this approach, the intensity of every pixel in the resultant image is made similar to the intensity of its nearest corresponding pixel in the original image. This method is extremely simple to implement but tends to produce images with a clustered or blocky appearance. Bilinear interpolation is another interpolation technique that uses the weighted average value of the four neighboring pixels in the source image [28][34]. Another interesting interpolation that is used in this paper is the Bicubic interpolation. The cubic B-spline interpolation is a sophisticated technique that produces smoother edges compared to the bilinear interpolation [30]. In addition, it has a relatively good effectiveness combined with reduced complexity [34].

In order to optimize the reduction and minimize the loss of information, two image conversion algorithms are proposed in this paper. The first algorithm applies simple image conversion, while the second depends on an enhancement algorithm that can produce excellent results when compared with the input images.

### III. DATABASE RESOURCES

In this work, two conversion algorithms are applied to 64 mammogram cases that are obtained from the USF database. The USF (university of South Florida) database is a Digital Database for Screening Mammography (DDSM) and is widely used by the mammographic image analysis research community. This database is collected from different medicine university's schools and hospitals in the United States of America.

The primary purpose of this database is to facilitate sound research in the development of computer algorithms to aid in screening. Secondary purposes of the database may include the development of algorithms to aid in the diagnosis and the development of teaching or training aids. The database contains approximately 2500 case studies. Almost, all of these cases have the same specification ( $3000 \times 4500$  pixels with 16-bit pixel depth). This database is classified to four volumes to represent different types of diagnosis: *normal*, *cancer*, *benign*, and *benign without call back*. Normal cases are formed for patients with normal exam results that have had previous normal exams in the last four years. A normal screening exam is one in which no further "work-up" is required. Cancer cases are formed from screening exams in which at least one pathology proven cancer is found. Benign cases are formed from screening exams in which something suspicious is found, but it turned out not to be malignant (by pathology, ultrasound or some other means). The term benign without callback is used to identify benign cases in which no additional films or biopsy is done to make the benign finding. In this paper seven volumes of cancer and two volumes of normal cases are used. The cancer volumes are: *cancer\_01* (5 cases), *cancer\_05* (1 case), *cancer\_06* (2 cases), *cancer\_07* (2 cases), *cancer\_13* (1 case), *cancer\_14* (11 cases), and *cancer\_15* (10 cases). Whereas the normal volumes are: *normal\_07* (16 cases) and *normal\_09* (16 cases).

### IV. METHODOLOGY

The first step in most image processing systems is the preprocessing of the input image. In this work, the mammogram image is processed in order reduce the image size and highlight the suspicious regions (i.e., make them brighter) to make them easier to be detected by radiologists. The process is explained in the following sub-sections, which are designed to handle the USF database.

#### A. Image Shrinking Algorithm

This algorithm is proposed and used to eliminate unused gray levels in the original image. First, the gray level histogram of the entire digital mammogram is calculated for each mammogram and image shrinking was applied afterwards.

##### A.1. Image Shrinking Algorithm

As introduced in the above section, the main purpose of this algorithm is to find the maximum shrinking level on a digital

mammogram image. The following procedure describes the algorithm that performs the shrinking task.

1. The first step in this algorithm is to find the original histogram of the mammogram image.
2. The shrinking of the original histogram is carried out by testing the number of pixels in each gray level in order to eliminate the unused gray level by replacing it with the next gray level that is being used. As a result, the new histogram will use limited number of grey scales but their will be no gaps among them.
3. The output image is generated based on the new histogram.

#### A.2. Image Shrinking Algorithm

This algorithm was applied on 64 mammogram images using C+. The histograms in Fig. 1 show the output results for the original image shown in Fig 2.a.

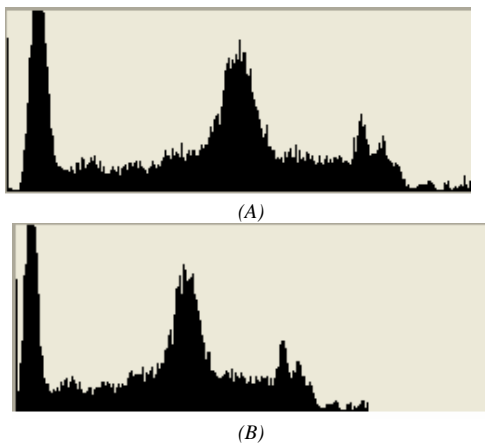
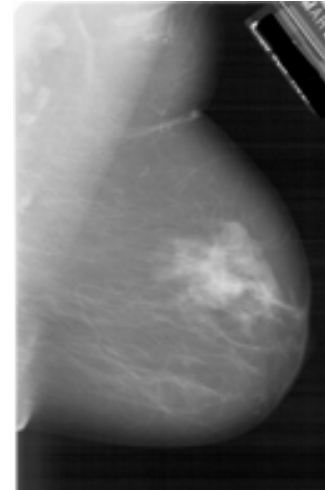
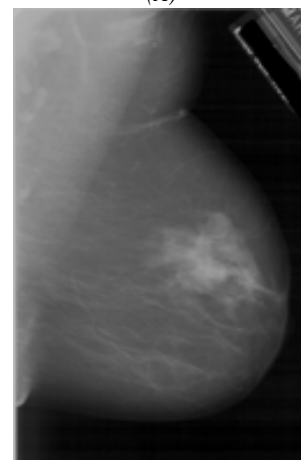


Fig. 1 Histogram manipulation in the shrinking process  
A) The Original Histogram for USF mammogram image The (A\_1900\_1.LEFT\_MLO.LJPEG.tif), B) the 16-bit shrinking Histogram of the mammogram image.

Comparing with the original histogram, the main concentrations of the pixels were in the left hand side of the histogram “i.e. dark side”. This made the output image appear darker compared to the original image. In the shrinking algorithm, no data loss occurs since none of the used grey levels is eliminated. So, we could argue that there has been no loss of the significant image data as shown in Fig2.



(A)



(B)

Fig. 2 Practical implementation of the Image shrinking process on (A\_1900\_1.LEFT\_MLO.LJPEG.tif), A) Original Mammogram image, B) 16-bit shrinking mammogram image

#### B. Pixel- Depth Conversion Algorithm

However, one of the techniques for the reduction of image sizes is to convert the pixel depth from 16 to 8 bits without any degradation of the medical data.

##### B.1. Algorithm Description

Our algorithm is divided to three steps:

- The first step is to obtain the histogram of the original image.
- The next step is to find the maximum shrinking level of the image. It is important to note that in most of the cases the 16 bits could be replaced by 9 bits. This result was obtained after the processing of 64 mammogram images. As explained in the previous algorithm, the output image from the shrinking algorithm has the same size as the original image.
- In order to reduce the image size, the depth of image pixels should be reduced from 16 to 8 bits. The conversion technique in this algorithm is performed by taking the first 8-bits of the shrunk histogram. After testing this method

using 64 cases from USF database, it is shown clearly that most of the important data is concentrated in the first 8-bits. The last bit (s) is usually in the background region. So, the loss of data at the breast region is minimal.

### B.2. Algorithm Implementation

After the implementation of this algorithm, the histogram shown in Fig 3.b is found to be similar to the one shown in Fig 1.b with the exception of the pixel depth. This is a good indication that the main features of the image did not change in the conversion process. Also, the peaks in the histogram remain similar to those of the original one, which means that the concentration for each level remained unchanged, with the exception of the pixel depth.

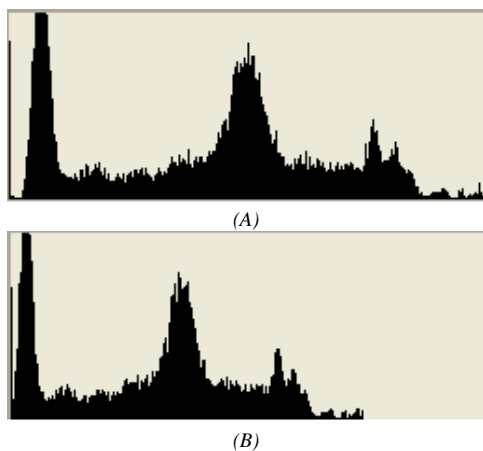
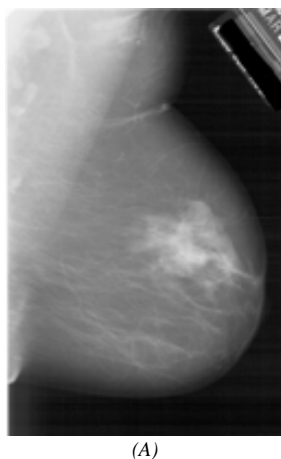
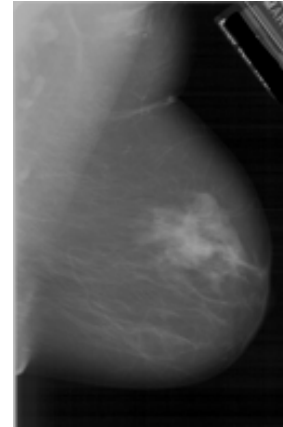


Fig. 3 Comparing the histograms for the 16 and 8 bit images  
A) the Histogram of the original USF mammogram image,  
B) the Histogram of the 8-bit mammogram image

The output image of this algorithm is shown in Fig. 4.B and it is similar to that shown in Fig 2.b.



(A)



(B)

Fig. 4 Pixel depth conversion images for USF database,  
A) Original Mammogram image, B) 8-bit mammogram image

### C. Enhanced Pixel Depth Conversion Algorithm

After the implementation of shrinking algorithm on the mammogram image and applying the pixel-depth conversion algorithm, the output results are close to each other but the problem that arises with both results is their brightness. So, to solve this problem, an enhanced pixel depth conversion algorithm is applied.

#### C.1. Algorithm Description

In any conversion process, the main problem is to find a suitable coefficient that can be suitable for all the pixel depths at the image. This coefficient should be efficient to convert the 16-bit pixel depth image to 8-bit. The aim of this algorithm is to find a suitable and efficient coefficient that can convert the image from 16 to 8 bits while maintaining the important medical details. The algorithm can be described as follows:

```

unsigned int max_level=max(Shrunk_Hist[]);
Long double divider=0.0;
While (true)
{
divider+=0.01
if (( max_level/divider)<=255)
break;
}
for (y=0;y<myimage_height;y++)
for ( x=0;x<myimage_width; x++)
{
myimage[y][x]= myimage[y][x]/divider}

```

The first step in the algorithm is to find the maximum level of used gray scale of the shrunk histogram. Usually, this number for a 16-bit mammogram image is less than 65536. So, the maximum level is determined for each image. Then, the maximum level is re-calculated to be in the range from 250 to 255 gray levels. However, the real challenge is to find the coefficient that would enable this. The divider coefficient can

be changed according to the maximum gray levels in the original image. On the other hand, data loss is not considered compared to the previous algorithm.

### C.2. Algorithm Implementation

This final algorithm is implemented on 64 mammogram images. As a result, the output histogram from this algorithm is approximately similar to the original histogram, taking the pixel depth into consideration. Fig.5 shows both, the original and the modified histogram.

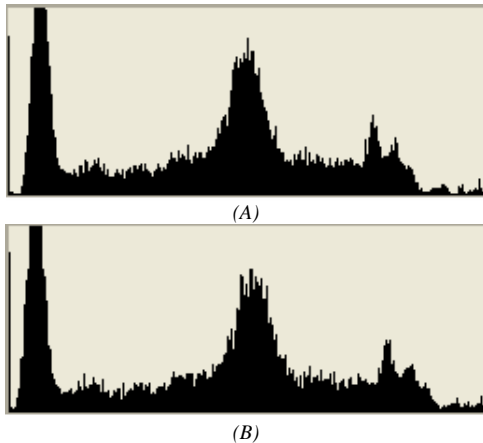
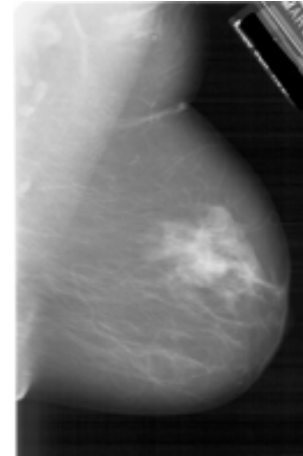
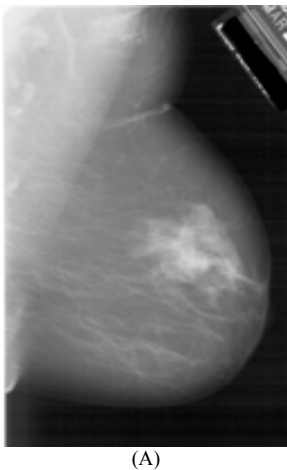


Fig.5. The 8- bit modified histogram A) the Original Histogram of the mammogram image, B) the 8-bit modified Histogram of the mammogram image.

The final results are shown in Fig.6. It is clear from this figure that the output result is approximately similar to the original one.



(B)  
Fig.6 Converting the (A\_1900\_1.LEFT\_MLO.LJPEG.tif) mammogram image to 8-bit image A) the Original Mammogram image, B) the Modified 8 bit mammogram image.

## V. EVALUATING THE PERFORMANCE OF THE ALGORITHMS

Objective and subjective evaluations are applied to the modified algorithm. The objective evaluation is implemented using the Amira visualization package to ensure that the connectivity and quality of pixels have not been affected by the algorithms. Also, the structural similarity (SSIM) index was used in order to test the image quality [25][26]. On the other hand, subjective evaluation is carried out using four radiologists from KHCC (King Hussein Cancer Center-Jordan).

### A. Objective Evaluation

For the reasons stated in [23], the Amira package [22] is used in this work to provide objective analysis for the performance of the enhanced pixel conversion algorithm. The Amira package is a series of tools that allow for interactive processing of 2D and 3D images [24]. It is a useful tool for comparing the quality of enhanced images. In a manner similar to Tomasz et. al.[23], the *isolines* visualization technique is used to connect the pixels with similar brightness in the image. In general, the *isolines* usually form a closed loop to help in identifying the region that has clusters of high or low pixel intensities [23][24].

The *isolines* visualization technique is used here to ensure that the quality of the compressed mammograms is not affected by the applied algorithms. Figure 7 shows a sample of the original mammograms and the modified ones. It is obvious that similar *isolines* are obtained for all cases, which indicate that the original connectivity of pixels is maintained and there is no loss of significant data in all cases.

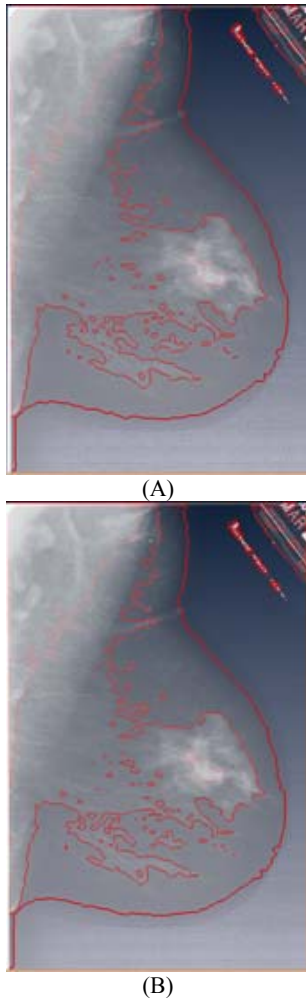


Fig.7 The Amira subjective comparison for (A\_1900\_1.LEFT\_MLO.LJPEG.tif), A) the Amira result of the original Mammogram image, b) the Amira result of the modified 8 bit mammogram image.

Another objective comparison is carried out using the SSIM index. The SSIM algorithm is based on measuring the differences in three categories which are luminance, contrast and structure [25][26]. The algorithm is downloaded and used to evaluate the modified images resulting from the enhanced pixel-depth conversion algorithm in order to test quality of these images. The average index for the whole mammogram cases is 92.6%. Table I, shows the results of the USF cases.

TABLE I  
THE SSIM INDEX FOR THE MAMMOGRAM CASES

No	Image name	SSIM	No	Image name	SSIM
1	A116	0.9861	33	D4500	0.9912
2	A1178	0.9805	34	D4501	0.9850
3	A1181	0.9798	35	D4502	0.9871
4	A1185	0.9887	36	D4503	0.9912
5	A1232	0.9885	37	D4506	0.9816
6	A1520	0.8403	38	D4508	0.8483
7	A1850	0.9880	39	D4509	0.9720
8	A1851	0.9821	40	D4510	0.8269
9	A1852	0.9796	41	D4512	0.9688
10	A1873	0.9739	42	D4515	0.9856

11	A1874	0.8552	43	D4519	0.9736
12	A1894	0.8954	44	D4520	0.9901
13	A1898	0.9784	45	D4524	0.9925
14	A1900	0.9885	46	D4525	0.9916
15	A1906	0.9859	47	D4526	0.9877
16	B3002	0.9665	48	D4528	0.9894
17	B3005	0.9569	49	B3600	0.8024
18	B3037	0.8738	50	B3601	0.9084
19	B3039	0.8873	51	B3602	0.8947
20	B3043	0.8558	52	B3603	0.8522
21	B3044	0.8607	53	B3604	0.9382
22	B3049	0.8840	54	B3605	0.8943
23	B3079	0.8964	55	B3606	0.9201
24	B3138	0.8813	56	B3610	0.9001
025	B3371	0.8555	57	B3611	0.8754
26	B3504	0.8573	58	B3612	0.8955
27	C0066	0.8936	59	B3613	0.9132
28	C0106	0.8942	60	B3614	0.9322
29	C0189	0.9178	61	B3617	0.9101
30	C0361	0.8647	62	B3618	0.8830
31	C0458	0.8776	63	B3622	0.8931
32	D4182	0.8520	64	B3626	0.9302

B. Subjective Evaluation

The radiologists were asked to evaluate the original and the resultant images. A questionnaire was designed to reflect their judgments. This questionnaire was designed to measure the degree of satisfaction that each radiologist has with the processed images. Four specialists were involved in evaluating the cases and filling the questionnaire for each case of the three algorithms.

For every radiologist, two cases were displayed, one of them is the original and the other one is the processed one. The radiologists were asked to make a comparison between the original and the processed images. The comparison is based on the characteristics of the benign and malignant regions in both images.

The results of the questionnaire were converted to the following table II that shows the percentage of satisfaction for each specialist.

TABLE II  
THE SATISFACTION PERCENTAGES OF IMAGE SIZE REDUCTION

	Shrinking Algorithm (%)	Pixel-Depth conversion (%)	Enhanced Pixel-Depth Conversion (%)
Specialist 1	72.222	76.66	80
Specialist 2	75.55	73.33	84.44
Specialist 3	67.77	76.6	83
Specialist 4	75.55	76	85
Total percentage	72.77	75.65	83.11

It is clearly shown that both algorithms (shrinking and pixel-depth conversion) provided similar satisfaction percentages. However, specialists were satisfied more with the enhanced 8-bits conversion algorithm. This result is acceptable, since most specialists found that the brightness and contrast were becoming low for the first two algorithms (shrinking and pixel-

depth conversion) and the last algorithm maintained the quality of the original images. It also managed to enhance the visual differences between the malignant or suspicious regions and helped the radiologists to take accounts of some regions that have not been noticed in the original images. This was the agreed upon by all the specialists.

## VI. CONCLUSION

In this paper, two algorithms for mammogram size reduction are proposed. These algorithms can successfully reduce the size of the mammogram images by 50%. For example, an image that has an original size of 21,217,280 bytes becomes 10,616,832 bytes with minimum processing time which is 12 seconds on 1.8GHz CPU processor and 512MRAM. The shrinking algorithm that is used as a pre-reduction process is developed and implemented. It maintained the original image features without any lose of significant data, but the image brightness was reduced compared to the original image. The pixel-depth conversion algorithm can convert the 16-bits images to 8-bits. This conversion also produces good results because the most important medical data are contained within the first 8-bits. Thus, the data loss in the breast region is minimal. The enhanced algorithm of pixel- depth conversion has produced excellent results, and the output image is similar to the original one in terms of quality, brightness and significant data. These results are approved by specialists at different Jordanian medical centers. Also, these results are tested using two subjective methods (Amira and SSIM index) and both of them indicate that there is no loss on the information at the breast region.

## ACKNOWLEDGMENT

We would like to express our deep thanks for Dr. William Maaieh, consultant of radiology at Al-Salt hospital, Dr. Ibrahim Shobash, consultant of radiology at Al-Basheer hospital, Dr. Essam Mansor and Dr. Munther Kandeel, consultants of radiology at King Hussein Cancer Center (KHCC) for their generous cooperation and evaluation of mammogram images.

## REFERENCES

- [1] A. Aldroubi, M. Unser, and M. Eden "Cardinal spline filters: Stability and convergence to the ideal sinc interpolation", *Signal processing*, Vol 28, pp. 127-138, 1992.
- [2] D. Brzakovic, X. M. Luo, and P. Brzakovic, "An Approach to Automated Detection of Tumors in Mammograms," *IEEE Transactions on Medical Imaging*, vol. 9, no. 3, pp. 233-241, 1990
- [3] D.B. Kopanes, "Breast Imaging" 2<sup>nd</sup> edition. Philadelphia, PA: Lippincott-Raven, 1998.
- [4] G. R. Kuduvalli and R. M. Rangayyan, "Performance analysis of reversible image compression techniques for high-resolution digital telerradiology," *IEEE Trans. Med. Imag.*, vol. 11, pp. 430-445, Sept. 1992.
- [5] G. S. Maitz, T. S. Chang, J. H. Sumkin, P. W. Wintz, C. M. Johns, M. Ganott, B. L. Holbert, C. M. Hakim, K. M. Harris, D. Gur, and J. M. Herron, "Preliminary clinical evaluation of high-resolution telemammography system," *Invest. Radiol.*, vol. 32, pp. 236-240, Apr. 1997.
- [6] H.-P. Chan, L.T. Niklason, D.M.Ikeda, K.L. Lam, and D. D. Adler. "Digitizing requirements in mammography: Effects on computer aided detection of micro-calcifications", *Med. Phys.*, Vol.21, pp.1203-1211, July 1994.
- [7] J. A. Parker, R. V. Kenyon, and D.E. Troxel, "Comparison of interpolating methods for image resampling", *IEEE Transaction Medical Images*. Vol. M1-2, pp 31-39,1983.
- [8] K. Coakley, F. Quintarelli, T. van Doorn, C. Hirst, "Classification of Equivocal Mammograms through Digital Analysis", *the breast*, vol. 3, pp. 222-226, 1994.
- [9] K. Wakabayashi "Evaluation of the effective information preservation method for binary image reduction", *System and computers in Japan*, 32(7), pp.1-11, 2001.
- [10] Monica Penedo, William Pearlman, Pablo Tahoces, Miguel Souto, and Juan Vidal "Region - Based Wavelet Coding Methods for Digital Mammography", *IEEE Trans. On Medical Imaging*, Vol:22, No:19, PP:1288-1295, Oct-2003.
- [11] M. Comer, S. Liu, and E. J. Delp, "Statistical Segmentation of Mammograms," *Proceedings of the 3rd International Workshop on Digital Mammography*, Chicago, pp. 475-478, 1996.
- [12] M. L. Giger, F.-F. Yin, K. Doi, C. E. Metz, R. A. Schmidt, and C. J. Vyborny, "Investigation of Methods for the Computerized Detection and Analysis of Mammographic Masses," *Proceedings of SPIE*, Washington, pp. 183-184, 1990.
- [13] M. Unser, A. Aldroubi, and M. Eden, "Enlargement or Reduction of Digital Images with Minimum Loss of Information", *IEEE transaction on image processing*, 4(3), pp.247-258, 1995.
- [14] M. Unser, A. Aldroubi, and E. Eden "Fast B-Spline transforms for continous image representation and interpolation" *IEEE Trans. Pattern Anal. Machine Intell.* Vol 13, pp. 277-285, 1991.
- [15] O.L. Mangasarian, "Breast cancer diagnosis and prognosis via linear programming", *Operations Research*, vol. 43, No. 4, pp. 570-577, 1995.
- [16] R.E. Bird, T.W Wallace, and B.C. Yankaskas, "Analysis of cancer missed at screening mammography" *Radiology*, Vol.184, pp. 613-617, Sept. 1992.
- [17] S. K. Park and R. A. Showengerdt, "Image reconstruction by parametric convolution" *Computer Vision Graphics, Image processing*, Vol 20, pp.258-272, 1983.
- [18] R. N. Strickland and H. I. Hahn, "Wavelet Transforms for Detecting Microcalcifications in Mammograms," *IEEE Transactions on Medical Imaging*, vol. 15, no. 2, pp. 218-229, 1996.
- [19] S. Liu and E. J. Delp, "multi-resolution Detection of Stellate Lesions in Mammograms", *Proceedings of the IEEE International Conference on Image Processing*, Santa Barbara, pp. 109-112, 1997.
- [20] S. Parker et al, "Cancer Statistics", *Cancer Journal for Clinicians*, vol. 47, pp. 5-27, 1997.
- [21] V. Rasche, R. Proksa, R. Sinkus, P. Bornet and H. Eggers, "Re-sampling of data between arbitrary grids using convolution interpolation", *IEEE transaction on medical imaging*, 18(5), pp.385-392, 1999.
- [22] Mercury computer system, Inc. "Amira 4.0" <http://www.tgs.com/>
- [23] Tomasz Arod'z, Marcin Kurdziel, Tadeusz Popiela, Erik O. D. Sevre, David A. Yuen, "A 3D Visualization System for Computer-Aided Mammogram Analysis", 2004.
- [24] Tomasz Arod'z, Marcin Kurdziel, Tadeusz J. Popiela, Erik O.D. Sevre, David A. Yuen, "Detection of clustered microcalcifications in small field digital mammography", 2006.
- [25] Zhou Wang, Alan Conrad Bovik, Hamid Rahim Sheikh, and Eero Simoncelli, "Image Quality Assessment: From Error Visibility to Structural Similarity", *IEEE Trnas on Image Processing*, Vol.13 , No. 4, pp. 600-612, 2004.
- [26] Zhou Wang, Alan Conrad Bovik, Hamid Rahim Sheikh, and Eero Simoncelli, Matlab source file, <http://www.cns.nyu.edu/~lcv/ssim/>.
- [27] J. A. Parker, R.V. Kenyon, and D.E. Troxel, "Comparison of interpolating methods for image resampling", *IEEE Trans Medical Imaging*, Vol.2, pp. 31-39, 1983.
- [28] W. K. Pratt, "Digital image processing", John Willey & sons inc, 1991.

- [29] Cheng-Soon Chuah, Jin-Jang Leou, An adaptive image interpolation algorithm for image/video processing, *Pattern Recognition* 34. pp: 2383-2393, 2001.
- [30] H.S. Hou, H.C. Andrews, "Cubic splines for image interpolation and digital altering", *IEEE Trans. Acoust. Speech Signal Process. ASSP-26* (6). PP: 508-517, 1978.
- [31] R.R. Schultz, R.L. Stevenson, A Bayesian approach to image expansion for improved definition, *IEEE Trans. Image Process.* 3 (3). PP: 233-242, 1994.
- [32] R.Y. Tsai, T.S. Huang, "Multiframe image restoration and registration", in: R.Y. Tsai, T.S. Huang (Eds.), *Advance in Computer Vision and Image Processing*, Vol. 1, JAI Press, Greenwich, CT, pp. 317-339, 1984.
- [33] A.J. Patti, M.I. Sezan, A.M. Tekalp, "High-resolution image reconstruction from a low-resolution image sequence in the presence of time-varying blur", *Proceedings of the IEEE International Conference on Image Processing*, Austin, TX, pp. 343-347, 1994.
- [34] R.G. Keys, "Cubic convolution interpolation for digital image processing", *IEEE Trans. Acoustics Speech and Signal Processing*, Vol.29, pp.1153-1160, 1981.

**Ayman A. AbuBaker** has obtained his B.Sc. in Mechatronics Engineering from Al-Balqa' Applied University- Jordan. He is currently doing his PhD research at school of informatics at the University of Bradford-UK in computer Engineering. He is interested in image processing and working currently at detection and recognition of cancer cells in mammogram images. Also he is interested in other related areas like neural networks, fuzzy logic and genetic algorithm.

**Rami S. Qahwaji** obtained his B.Sc. in Electrical Engineering, MSc. in control and computer Engineering and his PhD in computer Engineering from University of Bradford. His research area is included machine vision system design, image processing and pattern recognition.

**Musbah J. Aqel** he obtained his B.Sc. in electronics and communication Engineering and M.Sc. in computer Engineering from Aligarh Muslim University- India and his PhD from I.T, Banaras Hindu University- India in computer Engineering. He is currently associated professor of computer engineer, and chairman of Electrical and Computer Engineering Dept, Applied science university- Jordan. His research interest includes knowledge-base system design, image processing, and computer networks.

**Mohammad H. Saleh** he is a graduate student in computer engineering, Applied Science University- Jordan and recently is a research team member at the computer engineering department. His research is mainly in image processing, computer algorithms.