Journal of Computer Science 3 (2): 67-75, 2006
ISSN 1549-3636

Efficient Pre-processing of USF and MIAS Mammogram Images

[1]Ayman A. AbuBaker, [1]R.S.Qahwaji, [1]Musbah J. Aqel, [1]Hussam Al-Osta and [2]Mohmmad H. Saleh
[1]Department of Electronic Imaging and Media Communications, School of Informatics, Bradford University, Richmond Road, Bradford BD7 1DP, England, UK.
[2]Department of Electrical and Computer Engineering, Applied Science University, Jordan

Abstract: High quality mammogram images are high resolution and large size images. Processing these images require high computational capabilities. The transmission of these images over the net is sometimes critical especially if the diagnosis of remote radiologists is required. In this paper, a pre-processing technique for reducing the size and enhancing the quality of USF and MIAS mammogram images is introduced. The algorithm analyses the mammogram image to determine if 16-bit to 8-bit conversion process is required. Enhancement is applied later followed by a scaling process to reduce the mammogram size. The performances of the algorithms are evaluated objectively and subjectively. On average 87% reduction in size is obtained with no loss of data at the breast region.

Keywords: Breast cancer, image processing, image reduction, mammogram image

INTRODUCTION

Early detection is the best way to improve breast cancer prognosis since the causes of the disease are still unknown. Breast cancer is the second most prevalent cancer among women after skin cancer[1]. In addition, it accounts for most cancer deaths coming only second to lung cancer[1]. 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%[2]. Fine needle aspirate depends on extracting fluids from a breast lump and inspecting it under the microscope. This method has a reported sensitivity varying from 65 to 98%[2]. 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 an equivalent performance in terms of robustness and accuracy for 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 20-30%[3]. 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 increases the difficulty of early detection.

Most of the work in mammography aims at detecting one or more of the three abnormal structures in mammograms[4]: microcalcifications[5], circumscribed masses[6] and speculated lesions[7]. Other methods depend on classifying the breast lesions as benign or malignant[8]. There are problems with the subjective analysis of mammographic images by radiologist. Subjective analysis depends mainly of the experience of the human operator, but it is also affected by fatigue and other human-related factors. In addition, the interpretation is a repetitive task that requires lot of attention to minute details. Hence, it requires lot of staff time and effort, which results in slowing the diagnosis time. On the other hand, the objective analysis of mammograms, which is carried out by automated systems, provides consistent performance but its accuracy is usually lower. Due to the sensitivity of this problem, we believe that radiologists should be involved and computers should not replace them completely. However, computer systems can help them perform better by enhancing the quality of images, highlighting the suspicious regions and providing better analysis tools.

Most mammogram images are large size and high resolution images that require specialized computing facilities to enables efficient processing. To facilitate the transmission of these images over computer networks image compression techniques are usually applied. In this paper, we present a size reduction algorithm that can be implemented on most mammogram images as a pre-processing step to reduce their size without affecting their quality.

Digitized mammography techniques: There have been various advancements in digital image processing in the fields of filtering, enhancement, segmentation and others. However, the usefulness of the new techniques depends mainly on two important parameters: the spatial and grey-level resolutions[9]. An efficient algorithm should provide a diagnostic accuracy in digital images equivalent to that of conventional films. Pixel size and pixel depth are

Corresponding Author: Ayman AbuBaker, Department of Electrical and Computer Engineering, Applied Science University, Jordan

important factors that could critically affect the visibility of small-low contrast objects, which may carry significant information for diagnosis[10]. Therefore, digital image recording systems for medical purposes 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. For instance, it has been shown that isolated clusters of microcalcifications are one of the most frequent radiological features of asymptomatic breast cancer[10]. A careful search for the clustered microcalcifications that may herald an early-stage cancer should be carried out on all mammograms[11]. Microcalcifications frequently appear as small-size low-contrast radiopacities[12]. Due to this, a typical mammogram must be digitized at a resolution of approximately 4000× 5000 pixels with 50- m spot size and 12 or 16 bits, resulting in approximately 30 to 40Mb of digital data. Processing or transmission time 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[13]. 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 and lossy compression methods have been investigated for medical imaging applications[14,15].

So, image reduction is a very important stage in many image processing systems such as mammography, computer graphics, multimedia and electronic publishing[16,17]. Recently, many techniques became available to magnify or reduce images such as, linear interpolation and cubic spline interpolation[13,18, 19, 20, 21].

The image interpolation has a central role in many applications[22,23]. 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[24], three categories exist for image interpolation: static image interpolation[25,26], multi-frame image interpolation[27,28] 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 set 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 4 the neighboring pixels in the source image[22,29]. 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[29].

Other algorithms were developed to modify the interpolation process. Chun-Ho[30] proposed a new algorithm in image scaling which was called Winscale algorithm. The scaling (up/down) in this algorithm is based on using an area pixel model rather than point pixel model. As a result, the winscale algorithm had shown effective results for the images that need a good quality and low computational complexity. However, its performance is not very different from the bilinear interpolation technique[31]. Another adaptive algorithm was proposed by Cheng-Soon[24] to interpolate the low resolution (decimated) image frames. In this algorithm, two nonlinear filters are utilized to generate high-frequency components iteratively that were lost while implementing the low resolution procedure. Then the blocking artifacts-reducing scheme is adopted to improve the image quality.

Many reduction techniques are based on image interpolation that is followed by a re-sampling process. These techniques are simple to implement but they produce sub-optimal results[13]. Also, another technique was used in image reduction using the mean of each non-overlapping 8×8 pixel neighborhood[32].

Database resources: Most image processing systems applies a preprocessing stage as a first stage. The system we introduce here could aid radiologists by highlighting the suspicious regions in mammograms.

In this work, two image reduction algorithms are implemented and performed on 382 mammographic images from USF (university of South Florida) and MIAS databases (i.e., 64 from USF and the remaining from MIAS). The USF database is a Digital Database for Screening Mammography (DDSM) and it is publicly available. All its images are collected from different medical schools and hospitals across the USA. These images are available with the same specification (3000×4500 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).

Three hundred and twenty two additional mammogram images are taken from the MIAS database. The mammograms in this database are obtained from the medio-lateral oblique (MLO) view and are digitized to a spatial resolution of 0.05 mm pixel size with 8-bit density resolution. Four image sizes existed: small (4320 pixel ×1600 pixel), medium (4320 pixel ×2048 pixel), large (4320 pixel ×2600 pixel) and extra large (5200 pixel ×4000 pixel). Digitization was performed on a Joyce-Loeble scanning microdensitometer (SCANDIG-3) which had a linear response in the range 0.0 to 3.2 optical densities. The mammograms had been carefully selected from the United Kingdom National Breast Screening Program. The 322 digitized images represent 161 patients at the MIAS database. These images are carefully diagnosed and the position of the microcalcification for each image is recorded.

MATERIALS AND METHODS

The pre-processing stage is introduced in this section. The process is explained in Fig. 1 this stage is designed to handle different mammograms from different databases (i.e., USF and MIAS). The sub-sections describe the algorithms involved in this process.

Image shrinking procedure: The image shrinking algorithm is applied and used to eliminate the unused grey levels in the original 16-bit image. This is carried out by finding the histogram for the entire digital mammogram and then performing the shrinking process as explained below.

Image shrinking method

* Determine the histogram for the mammogram image.
* The unused grey levels are eliminated by replacing them with the next adjacent used grey level. As a result, the resulting histogram will have limited number of grey scales but their will be no gaps among them.
* The output image is generated based on the new histogram.

This algorithm is applied on 64 images taken from the USF database using C+. The histograms in Fig. 2 show the output results for the original image shown in Fig. 3a.

Comparing with the original histogram, the grey levels for the majority of pixels were located in the left hand side of the histogram (the dark side). This made the output image become rather "dark" compared to the original image. However, we could argue that there has been no loss of the original image data as shown in Fig. 3.

Applying this algorithm on the 8-bit MIAS mammograms would not result in significant reduction in the number of grey scales, as the maximum number of used grey scales is only 256.

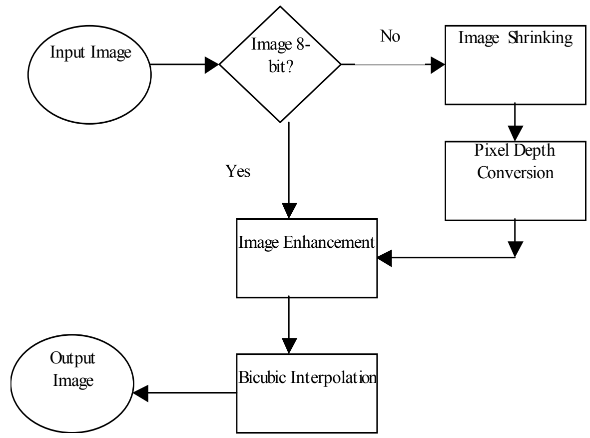
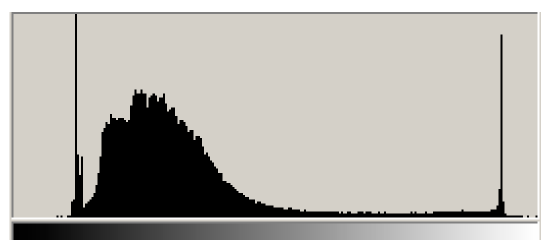
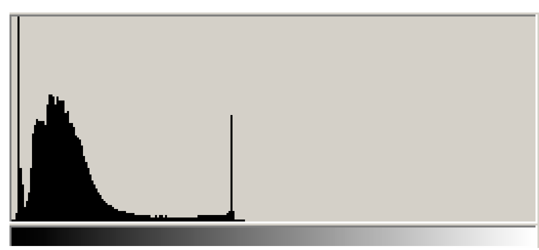


Fig. 1: Block diagram of image conversion process



(A) The Original Histogram for USF mammogram (A_1178_1.LEFT_CC.LJPEG.tif)



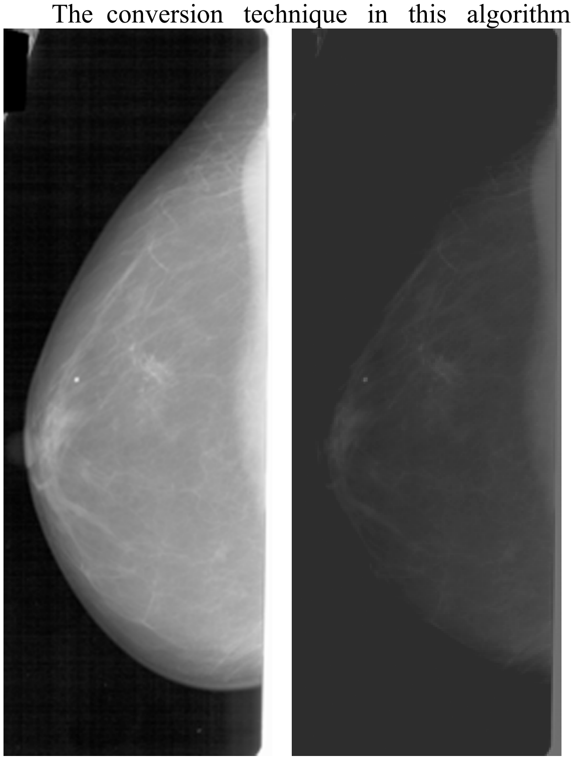
(B) Resultant histogram after applying the shrinking process

Fig. 2: Histogram manipulation in the shrinking process

Pixel- depth conversion algorithm: As illustrated earlier, the processing or transmission time of mammograms could be quite long. Thus, reducing the amount of data to be transmitted without the significant degradation of the medical image quality for human and machine interpretation is needed. However, one of the techniques for the reduction of image sizes is to convert the pixel depth from 16 to 8 bits without degrading the medical data. This algorithm has the ability to reduce the image to 50 or 60 percent of its original one. The algorithm is explained below.

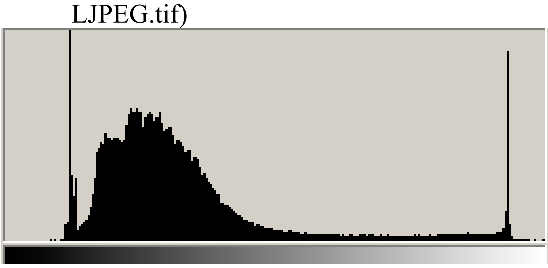
Algorithm description

* Extract the histogram for the original image.
* Find the maximum shrinking level for 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 the 64 USF mammogram images.
* 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 least significant 8-bits of the shrunk histogram. After testing this method on 64 cases, it was found that the most 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.

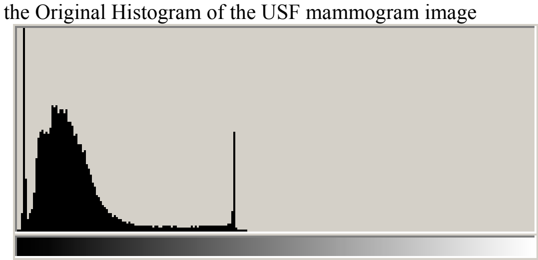


A) Original Mammogram image B) 16-bit shrinking mammogram image

Fig. 3: Practical implementation of the Image shrinking process on (A_1178_ 1.LEFT_CC. LJPEG.tif)

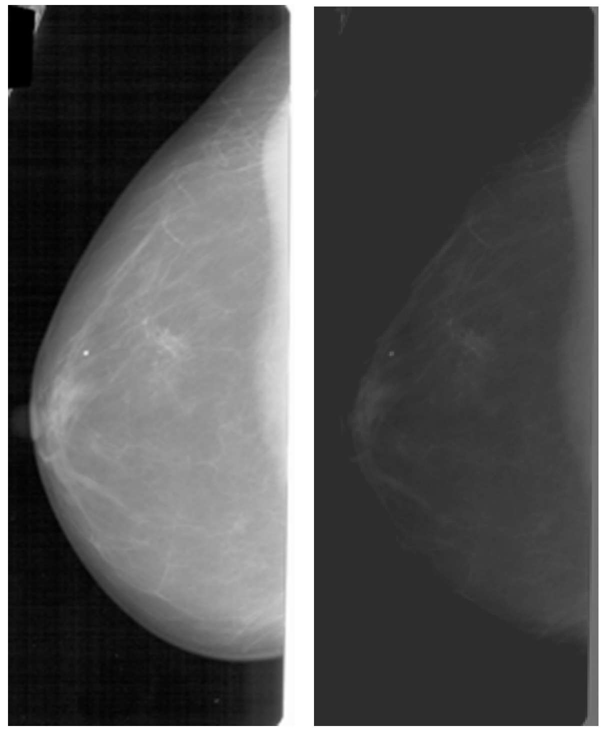


A) the Original Histogram of the USF mammogram image



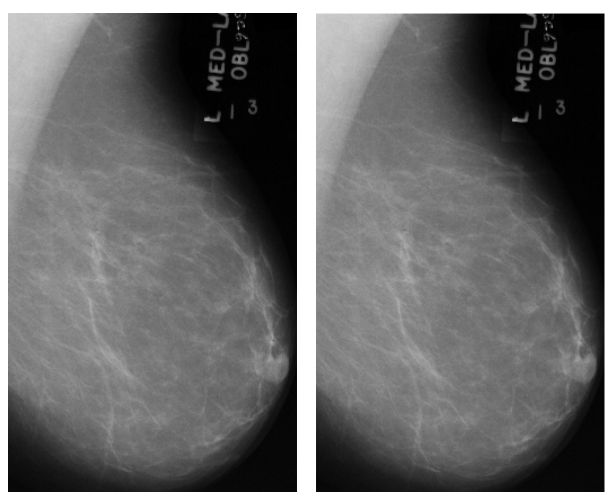
B) the 8-bit Histogram of the USF mammogram image

Fig. 4: Comparing the histograms for the 16 and 8 bit images



A) Original USF Mammogram image B) 8-bit USF mammogram image

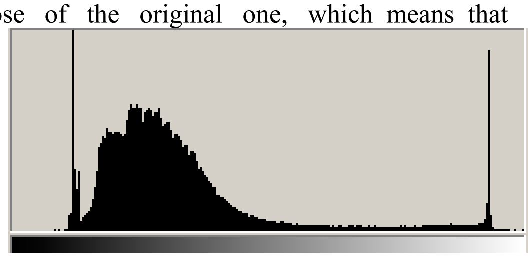
Fig. 5: Pixel depth conversion images for USF database



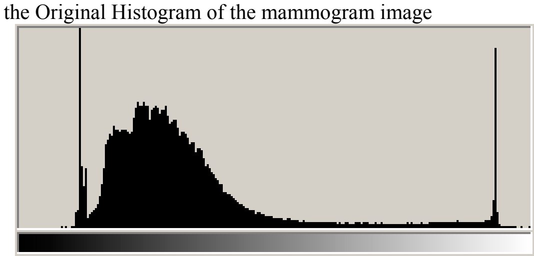
A) Original MIAS Mammogram image(mdb231ll) B) 8-bit MIAS mammogram image (mdb231ll)

Fig. 6: Pixel depth conversion images for MIAS database

Algorithm implementation: After the implementation of this algorithm on USF database, the histogram shown in Fig. 4b is found to be similar to the one shown in Fig. 2b with the exception of the pixel depth. This is a good indication that the main features of the image that did not change in the conversion process. Also, the peaks in the histogram remains similar to those of the original one, which means that the concentration for each level remains unchanged, with the exception of the pixel depth.



A) the Original Histogram of the mammogram image



B) the 8-bit modified Histogram of the mammogram image

Fig. 7: The 8- bit modified histogram

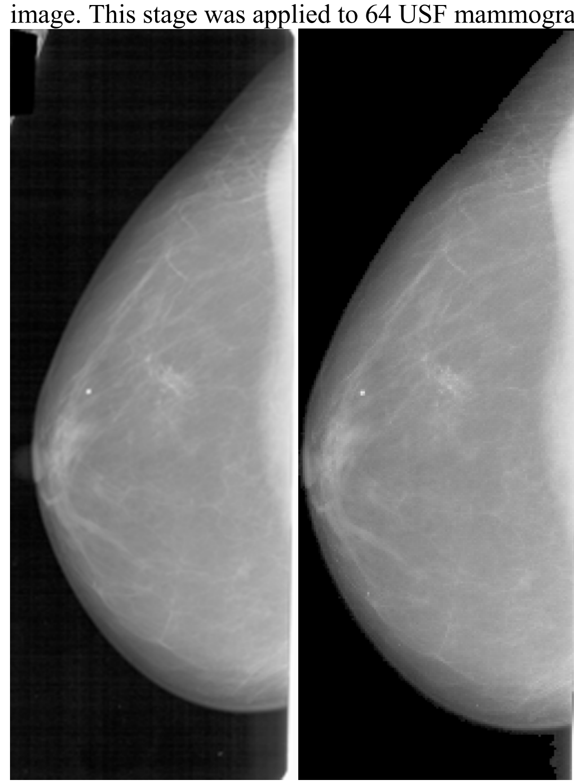
The output image of this algorithm is shown in Fig. 5b and it is similar to that shown in Fig. 3b. But in MIAS database, the resulted image did not change or enhance the original image since it is originally an 8-bit grey level as shown in Fig. 6.

Image enhancement: After the implementation of the shrinking algorithm on the 8-bit mammogram images and applying the pixel-depth conversion algorithm, an enhancement stage must be applied to ensure that no data loss occurs.

In any conversion process, the major challenge is to find a suitable coefficient that can perform well 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 with good resolution. The algorithm can be described as follows:

1. find the number of grey levels in the mammogram
2. define variable divider = 0
3. divider = divider+0.01
4. if ((number of grey levels / divider) ≤255) goto step 3
5. New mammogram is found by dividing the grey level value of every pixel in the input image by the value of divider

The first step in the algorithm is to find the maximum level of the grey scale. Usually, the number of maximum level of the 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 grey levels. However, the real challenge is to find the coefficient that would enable this. The divider is determined based on the characteristics of the input image. This stage was applied to 64 USF mammograms and in all cases the histogram of the resultant 8-bit image is very similar to the histogram of 16-bit input image, as shown in Fig. 7.



A) the Original USF Mammogram image   b) the Modified USF 8 bit image

Fig. 8: Converting the (A_1178_1.LEFT_ CC.LJPEG. tif) mammogram image to 8-bit image

The final results are shown in Fig. 8. It is clear from this figure that the output result is approximately similar to the original one.

Since the MIAS database is an 8-bit grey level, so the maximum grey level used in every mammogram will be 255 or less. Therefore, if the maximum grey level of the image is 255, then the divider will be equal to one and the resulted image will be similar to the original image. But if the number of grey scales is less than 255, this algorithm will work as a grey scale normalization algorithm. For example, if the maximum number of grey levels is 200, then level of an image is 200 grey levels, then the divider will equal to 0.79 and all image pixels will be modified according to this divider. As a result, this algorithm will act as an enhancement algorithm for the 8-bit grey level images as shown in Fig. 9.

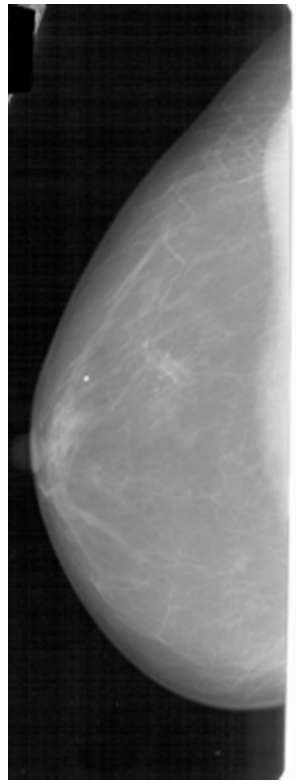
Image scaling: The capability to digitally interpolate the mammogram images to different sizes with same features and good quality is important for many applications. The mammogram images are high resolution images because they contain small features of interest that may be of significant importance for radiologists. Therefore, using bi-cubic interpolation will

A) the Original MIAS Mammogram image

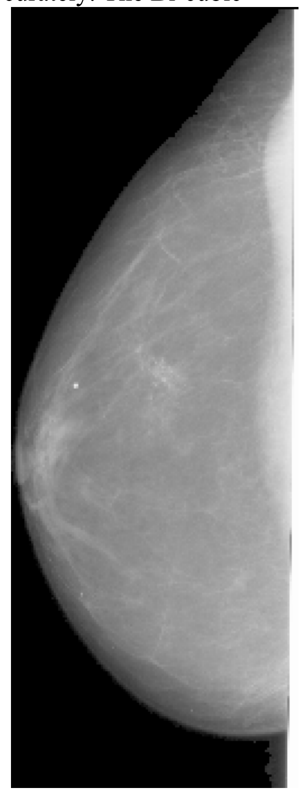
b) the Modified MIAS 8 bit image

Fig. 9: Converting the (mdb231l) mammogram image to 8-bit image

generate a new pixel which will represent the 6 neighboring pixels. This will facilitate in scaling down the mammogram images accurately. The Bi-cubic

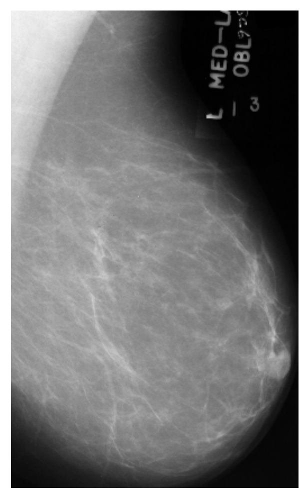


A) the Original USF Mammogram image



B) the Modified and scaled USF image

C) the Original MIAS Mammogram image



D) the Modified and scaled MIAS image

Fig. 10: The scaling process

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 and maintains good quality for scaled images[29]. Further information on image scaling using bicubic interpolation can be found in[25].

Scaling description: As illustrated earlier, mammogram images need to be scaled down to enable better transfer and processing. The bicubic interpolation technique is used to provide efficient reduction in the size of the mammogram without affecting its quality or regions of interest. The micro-calcification cluster is defined to be at least 3 micro-calcifications within a 1 cm^2 region of mammogram[33]. Therefore, the scaling ratio for the mammogram image should be suitable to keep the micro-calcification cluster clear and easily detected by radiologists. In most mammogram cases, the smallest micro-calcification cluster area has about 37 pixels in high resolution images. Therefore, the maximum scaling down ratio was set to 50% of the image height and 50% of the image width. This ratio will ensure that the microcalcification clusters can still be detected by radiologists.

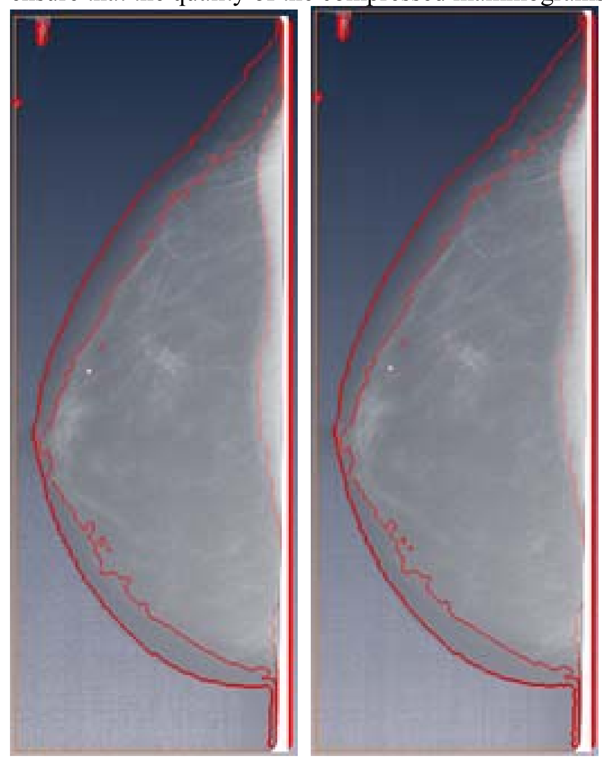
Scaling results: After the conversion technique was done accurately, the scaling procedure was carried out on the whole mammogram database. The Bi-cubic interpolation scaling technique was used in this method. So, the images that have a size 15,338,672 bytes become 1,925,120 bytes. So the scaling ratio is about 87% as shown in Fig. 10.

Evaluating the performance of the algorithms: Objective and subjective evaluations are applied to the algorithms. 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. On the other hand, the subjective evaluation is carried out using four radiologists from KHCC (King Hussein Cancer Center-Jordan).

Ten cases from the USF database were selected and processed using the three algorithms (Shrinking, 16-8 bit conversion and image enhancement). Eight of these had breast cancer and the remaining two were normal cases, as declared by the mammogram specialists. The samples were chosen carefully to handle the most popular breast types. Two mammogram radiologist from KHCC (King Hussein Cancer Center-Jordan) were involved in the choosing process.

Objective evaluation: For the reasons stated in[34], the amira package[35] is used in this work to provide objective analysis for the performance of the algorithms introduced here. Amira package is a series of tools that allow for interactive processing of 2D and 3D images[36]. It is a useful tool for comparing the quality of enhanced images. In a manner similar to[34] 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[34,36].

The isolines visualization technique is used here to ensure that the quality of the compressed mammograms



A) the Original Amira result of USF Mammogram image

B) the Modified resultes of Amira image

Fig.11: The Amira results

was not affected by the applied algorithms. Figure 11 shows a sample of the original mammograms and modified ones. It is obvious that similar isolines are obtained for all cases, which indicates that the original connectivity of pixels was maintained. There is no loss of significant data in all cases.

Subjective evaluation: The radiologists were asked to evaluate the original images and the resultant images and 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.

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 that shows the percentage of satisfaction for each specialist.

Almost similar satisfaction percentages were obtained for both shrinking and pixel-depth conversion algorithms. A higher satisfaction percentage was obtained for the image enhancement stage. This result is expected since most specialists found that brightness

Table 1: 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 for each algorithm	72.77	75.65	83.11

and contrast were low for the first two algorithms (shrinking and pixel-depth conversion), while the image enhancement provides an image with increased focus on the malignant or suspicious area. The radiologists reported that they were able to notice some features of interest in the enhanced images that they were not able to notice in the original images. This was agreed upon by all the specialists.

CONCLUSION

Two algorithms for reduction are proposed. The resulted algorithm could successfully reduce the mammogram images with 87% percent. For example, an image that has an original size 15,338,672 bytes became 1,925,120 bytes with minimum processing time which is 100 seconds. 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 important data, but the image brightness was less than the original. However, the pixel-depth conversion algorithm could convert the 16-bits to 8-bits. This conversion also produced good results as the most important data are concentrated in the first 8-bits. Thus, the data loss in the breast region was minimal. The enhanced algorithm of pixel- depth conversion has produced excellent results and the output image was similar to the original one with the same brightness and data. These results were approved by specialists at different Jordanian medical centers. On the other hand, the enhanced pixel depth conversion technique is also useful in enhancing the 8-bit grey level images such as the images in MIAS database.

ACKNOWLEDGMENTS

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) and Dr. Khalid Sharief, specialist Anesthesia at Al-Moasah hospital for their generous cooperation and a lot of evaluation of mammogrammy results they have carried so far.

REFERENCES

1. Parker, S. *et al.*, 1997. Cancer Statistics. Cancer J. for Clinicians, 47: 5-27.
2. Mangasarian, O.L., 1995. Breast cancer diagnosis and prognosis via linear programming. Oper. Res., 43: 570-577.
3. Coakley, K., F. Quintarelli, T. van Doorn and C. Hirst, 1994. Classification of equivocal mammograms through digital analysis. The Breast, 3: 222-226.
4. Comer, M., S. Liu and E.J. Delp, 1996. Statistical segmentation of mammograms. Proc. 3rd Intl. Workshop on Digital Mammography, Chicago, pp: 475-478.
5. Strickland, R.N. and H.I. Hahn, 1996. Wavelet Transforms for detecting microcalcifications in mammograms. IEEE Trans. Med. Imaging, 15: 218-229.
6. Giger, M.L., F.-F. Yin, K. Doi, C.E. Metz, R.A. Schmidt and C.J. Vyborny, 1990. Investigation of methods for the computerized detection and analysis of mammographic masses. Proc. SPIE, Washington, pp: 183-184.
7. Liu, S. and E.J. Delp, 1997. Ultiresolution detection of stellate lesions in mammograms. Proc. IEEE Intl. Conf. Image Processing, Santa Barbara, pp: 109-112.
8. Brzakovic, D., X.M. Luo and P. Brzakovic, 1990. An approach to automated detection of tumors in mammograms. IEEE Trans. Med. Imaging, 9: 233-241.
9. Penedo, M., W. Pearlman, P. Tahoces, M. Souto and J. Vidal, 2003. Region-based wavelet coding methods for digital mammography. IEEE Trans. on Med. Imaging, 22: 1288-1295.
10. Chan, H.-P., L.T. Niklason, D.M. Ikeda, K.L. Lam and D.D. Adler, 1994. Digitizing requirements in mammography: Effects on computer aided detection of micro-calcifications. Med. Phys., 21: 1203-1211.
11. Kopanes, D.B., 1998. Breast Imaging. 2nd Edn. Philadelphia, PA: Lippincott-Raven.

12. Bird, R.E., T.W Wallace and B.C. Yankaskas, 1992. Analysis of cancer missed at screening mammography. Radiology, 184: 613-617.
13. Unser, M., A. Aldroubi and M. Eden, 1995. Enlargement or reduction of digital images with minimum loss of information. IEEE Trans. Image Processing, 4: 247-258.
14. Kuduvalli, G.R. and R.M. Rangayyan, 1992. Performance analysis of reversible image compression techniques for high-resolution digital teleradiology. IEEE Trans. Med. Imag., 11: 430-445.
15. Maitz, G.S., 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, 1997. Preliminary clinical evaluation of high-resolution telemammography system. Invest. Radiol., 32: 236-240.
16. Wakabayashi, K., 2001. Evaluation of the effective information preservation method for binary image reduction. System and Computers in Japan, 32: 1-11.
17. Rasche, V., R. Proksa, R. Sinkus, P. Bornet and H. Eggers, 1999. Re-sampling of data between arbitrary grids using convolution interpolation. IEEE Trans. Med. Imag., 18: 385-392.
18. Aldroubi, A., M. Unser and M. Eden, 1992. Cardinal spline filters: Stability and convergence to the ideal sinc interpolation. Signal Process., 28: 127-138.
19. Paker, J.A., R.V. Kenyon and D.E. Troxel, 1983. Comparison of interpolating methods for image resampling. IEEE Trans. Med. Imag., M1-2: 31-39.
20. Unser, M., A. Aldroubi and E. Eden, 1991. Fast B-spline transforms for continous image representation and interpolation. IEEE Trans. Pattern Anal. Machine Intell., 13: 277-285.
21. Park, S.K. and R.A. Showengerdt, 1983. Image reconstruction by parametric convolution. Computer Vision Graphics, Image Processing, 20: 258-272.
22. Pratt, W.K., 1991. Digital Image Processing. Johm Willey & Sons Inc.
23. Parken, J.A., R.V. Kenyon and D.E. Troxel, 1983. Comparison of interpolating methods for image resampling. IEEE Trans. Med. Imag., 2: 31-39.
24. Chuah, C.-S. and J.-J. Leou, 2001. An adaptive image interpolation algorithm for image/video processing. Pattern Recognition, 34: 2383-2393.
25. Hou, H.S. and H.C. Andrews, 1978. Cubic splines for image interpolation and digital altering. IEEE Trans. Acoust. Speech Signal Process, ASSP-26: 508-517.
26. Schultz, R.R. and R.L. Stevenson, 1994. A Bayesian approach to image expansion for improved definition. IEEE Trans. Image Process., 3: 233-242.
27. Tsai, R.Y. and T.S. Huang, 1984. Multiframe Image Restoration and Registration. R.Y. Tsai, T.S. Huang (Eds.), Advance in Computer Vision and Image Processing, JAI Press, Greenwich, CT, 1: 317-339.
28. Patti, A.J., M.I. Sezan and A.M. Tekalp, 1994. High-resolution image reconstruction from a low-resolution image sequence in the presence of time-varying blur. Proc. IEEE Intl. Conf. Image Processing, Austin, TX, pp: 343-347.
29. Keys, R.G., 1981. Cubic convolution interpolation for digital image processing. IEEE Trans. Acoustics Speech and Signal Processing, 29: 1153-1160.
30. Kim, C.-H., S.-M. Seong, J.-A. Lee and L.-S. Kim, 2003. Winscale: An image-scaling algorithm using an area pixel model. IEEE Trans. Circuits and Systems for Video Technology, 13: 6.
31. Aho, E., J. Vanne, K. Kuusilinna and T.D. Hämäläinen, 2005. Comments on Winscale: An image-scaling algorithm using an area pixel model. IEEE Trans. Circuits and Systems for Video Technology, 15: 3.
32. Masek, M., 2004. Hierarchical segmentation of mammograms based on pixel intensity. Ph. D. Thesis. The University of Western Australia.
33. Sheshadri, H.S. and A. Kandaswamy, 2005. Computer aided diagnosis of digital mammogram. Inform. Technol. J., 4: 4.
34. Arod´z, T., M. Kurdziel, T. Popiela, E.O.D. Sevre and D.A. Yuen, 2004. A 3D visualization system for computer-aided mammogram analysis.
35. Mercury computer system, Inc. Amira 4.0. http://www.tgs.com/
36. Arod´z, T., M. Kurdziel, T.J. Popiela, E.O.D. Sevre and D.A. Yuen, 2006. Detection of clustered microcalcifications in small field digital mammography.