Original Article
Middle East Journal of Cancer; January 2020; 11(1): 80-90

Automated Analysis of Ultrasound Videos for Detection of Breast Lesions

Mohammad Mehdi Movahedi*,, Ali Zamani*, Hossein Parsaei*,***♦, Ali Tavakoli Golpaygani****, Mohammad Reza Haghighi Poya***

**Department of Medical Physics and Engineering, School of Medicine, Shiraz University of Medical Sciences, Shiraz, Iran*
***Ionizing and Non-ionizing Radiation Protection Research Center (INIRPRC), Shiraz University of Medical Sciences, Shiraz, Iran*
****Shiraz Neuroscience Research Center, Shiraz University of Medical Sciences, Shiraz, Iran*
*****Department of Biomedical Engineering, Standard Research Institute, Karaj, Iran*

Abstract

Background: Breast cancer is the second cause of death among women. Ultrasound (US) imaging is the most common technique for diagnosing breast cancer; however, detecting breast lesions in US images is a difficult task, mainly, because it provides low-quality images. Consequently, identifying lesions in US images is still a challenging task and an open problem in US image processing. This study aims to develop an automated system for the identification of lesions in US images

Method: We proposed an automatic method to assist radiologists in inspecting and analyzing US images in breast screening and diagnosing breast cancer. In contrast to previous research, this work focuses on fusing information extracted from different frames. The developed method consists of template matching, morphological features extraction, local binary patterns, fuzzy C-means clustering, region growing, and information fusion-based image segmentation technique. The performance of the system was evaluated using a database composed of 22 US videos where 10 breast US films were obtained from patients with breast lesions and 12 videos belonged to normal cases.

Results: The sensitivity, specificity, and accuracy of the system in detecting frames with breast lesions were 95.7%, 97.1%, and 97.1%, respectively. The algorithm reduced the vibration of the physician's hands' while probing by assessing every 10 frames regardless of the results of the prior frame; hence, lowering the possibility of missing a lesion during an examination.

Conclusion: The presented system outperforms several existing methods in correctly detecting breast lesions in a breast cancer screening test. Fusing information that exists in frames of a breast US film can help improve the identification of lesions (suspect regions) in a screening test.

Keywords: Automatic lesion detection, Breast lesion, Ultrasound imaging segmentation, Ultrasound video analysis

♦Corresponding Author:
Hossein Parsaei, PhD
Department of Medical Physics and Engineering, School of Medicine, Karim Khan Zand Blvd, Fars, Shiraz, Iran
P.O. Box: 7134845794
Tel/Fax: +98(71)32349332
Email: hparsaei@sums.ac.ir
hparsaee@gmail.com

Received: December 12, 2018; Accepted: September 02, 2019

Introduction

The second cause of death in women is breast cancer,[1-4] the early detection of which plays a major role in its treatment. Technologies that can contribute to these procedures have therefore attracted much scientific attention from the research community. Clinical examination, ultrasound (US) imaging, mammography, magnetic resonance imaging, and computed tomography are the common approaches to diagnose this disease.[5,6] Of these methods, mammography and US imaging are usually employed in cancer screening. Although mammography is considered as the "gold standard" for breast imaging,[7] US imaging is a highly common method as it is non-invasive, versatile, portable, and cost-effective and more importantly, does not make use of ionizing radiation. In addition, research has shown that using a combination of mammography and US can improve cancer detection more than mammography alone.[7,8] However, US imaging techniques provide low-quality images, mainly due to multiplicative speckle noise caused by the interference of reflected US wavefronts. Therefore, despite significant advancements in US imaging technology, inspecting and analyzing US images are still challenging tasks.

During the acquisition or inspection of breast image, the radiologist applies several processing techniques such as filtering, adjusting brightness levels, and zooming in/out of the image to improve its quality. For breast screening, identification of lesions (suspect regions) in the images is among the objectives of analyzing the provided breast images. Therefore, the operator's proficiency plays a substantial role in the final decision;[9,10] more specifically, environmental and personal factors can reduce the accuracy of the diagnosis.

Several methods have been developed for detecting lesions in US images.[5,11-21] Lefebvre et al.[22] used morphological and textural features to separate benign lesions from malignant ones in breast US images. Chen et al.[21] utilized bootstrap model to separate the regions of interest, further employing a decision tree model to classify benign and malignant lesions. Chen et al.[15] utilized morphological features and a multilayer feed-forward neural network to segment lesions. Karimi et al.[18] presented an automatic lesion detection algorithm using fuzzy logic and morphological and textural features. Madabhushi et al.[16] presented a fully automatic lesion detecting algorithm through the use of median, Butterworth, and average filters along with region growing segmentation technique. Further used in designing this system were intensity and texture information along with directional gradient and deformable shape-based model. Although fully automatic, the performance of the system is not clinically acceptable. Sehgal et al.[19] used multiple specifications such as margin sharpness and angular variation in different regions, both separately and together to accurately separate benign lesions from malignant ones. Shan et al.[17] used neural networks fed with two features from phase in maximum-energy orientation along with radial distance to segment a given US image. Afterwards, a combination of these two features was used with tissue and intensity in order to separate the lesion. The system proposed by Bocchi et al.[23] utilized neural networks, morphological features, and contouring methods to classify lesions detected using a semi-automated algorithm. The limitation of Bocchi's study is that the information derived in the previous frames is not employed in analyzing the next ones and each frame is segmented separately. Biwas et al.[24] analyzed tissue transfer and used the Markov method to detect abnormal regions. Making use of a database of 135 images, they reported an accuracy of 95.0%. The main disadvantage of the existing lesion detecting methods is that images of the breast are processed individually. In fact, in a breast screening exam, a video is acquired during imaging; hence, the fact that the information of the constituting frames could be fused in analyzing a frame or a selected image, a matter not considered by the majority of existing methods.

This study aims to develop an automated system to identify suspicious regions (lesions) in US images. The system considers all images in a

US video and makes use of the information pertaining to the previous frames in segmentation and analysis of a current frame.

Materials and Methods

The objective of this work was to derive an algorithm for analyzing US video and identifying abnormal regions in constituting frames. In fact, this system provide a summary of a given US video by identifying frames that may include breast lesion. In the developed method, each frame is analyzed and processed separately, but the characteristics of the regions detected in the previous frames are used in processing and analyzing the current frame. The structure of the presented methods and how they were evaluated using real data composed of 22 US videos are presented in detail.

The developed algorithm is composed of two main steps, namely a single frame segmentation and video analysis for breast lesion/abnormal region detection. Figure 1 illustrates the block diagram of the method proposed for analyzing and segmenting a single frame (US image). A given image is filtered using contra-harmonic filter[25] to remove (mainly speckle) noises. The local binary pattern[26] is then applied to the image to eliminate extra regions and segment tissues. Afterwards, morphological transformations are applied to remove small regions.[27] Subsequently, abnormal regions are separated from the studied frame, resulting in a distance image.[28] In the distance image, the regions that match the pattern of abnormal regions are identified and highlighted in the frame under analysis. Thereafter, key points for possible breast lesions/abnormal regions are determined. Finally, the main regions are detected by a seeded region growing method.[29-31] Details of each step are presented in the following subsections.

Preprocessing

The objective of the preprocessing step is to remove noises, mainly the speckle noise, from the image under analysis. Speckle noise reduction is necessary to accurately specify target regions in the image and maintain the anatomic information of the edges. In this work, a contra-harmonic mean filter[25] was employed for this purpose. Figure 2(b) exemplifies the effectiveness of the preprocessing step. As shown, preprocessing improves the discrimination between abnormal regions and the background in the images.

Table1. The performance of the developed US video analysis system

Sensitivity (%)	Specificity (%)	Accuracy(%)
95.7	97.1	97.1

Local binary pattern transformation

Local binary pattern (LBP) transformation[26] was applied to the image under study to highlight suspicious regions in the image. We used the LBP method because it is one of the best tissue analysis methods owing to its appropriate computational costs and robustness to uniform grey level

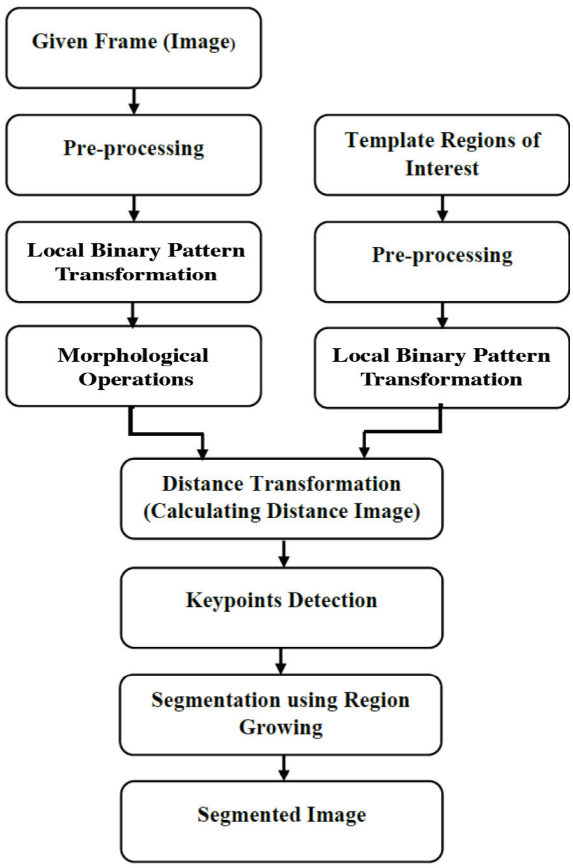


Figure1. Steps of segmenting an individual frame to detect lesion areas in the frame under analysis.

changes. The present work employed the first version of the LBP method proposed by Ojala et al.,[32] in which the brightness of each pixel is compared with its eight neighbors. If the intensity levels of any of these eight neighbors are greater than or equal to that of the center pixel's value, they are replaced by 1; otherwise, they are assigned a zero value. This gives an 8-digit binary number to each pixel which is usually converted to decimal, a process repeated for all pixels of the image under analysis. Figure 2(c) shows the results of LBP transformation on the image presented in figure 2 (b). As shown, this step highlights the region of interest (ROI).

Morphological operations

The output of LBP transformation contains several small regions that are in fact noises and do not represent ROI, (Figure 2 c). One solution for removing such regions is thresholding, where regions with an area smaller than a threshold are simply deleted. This method is simple and straightforward, yet requires a predefined threshold value and more importantly, may lead to the deletion of certain ROIs. In this work, we used morphological operations, dilation, and erosion specifically[27,33] in order to delete non-ROIs. First, the erosion operator is applied to the image, by which the areas detected via LBP shrink in size, resulting in the removal of small regions. Then, the dilation operator is applied, through which the areas of foreground pixels grow in size. Figure 2(d) shows the results of applying morphological operations on the images of figure 2(c). As shown, this step removes small regions and reduces the holes within ROIs.

Distance transformation

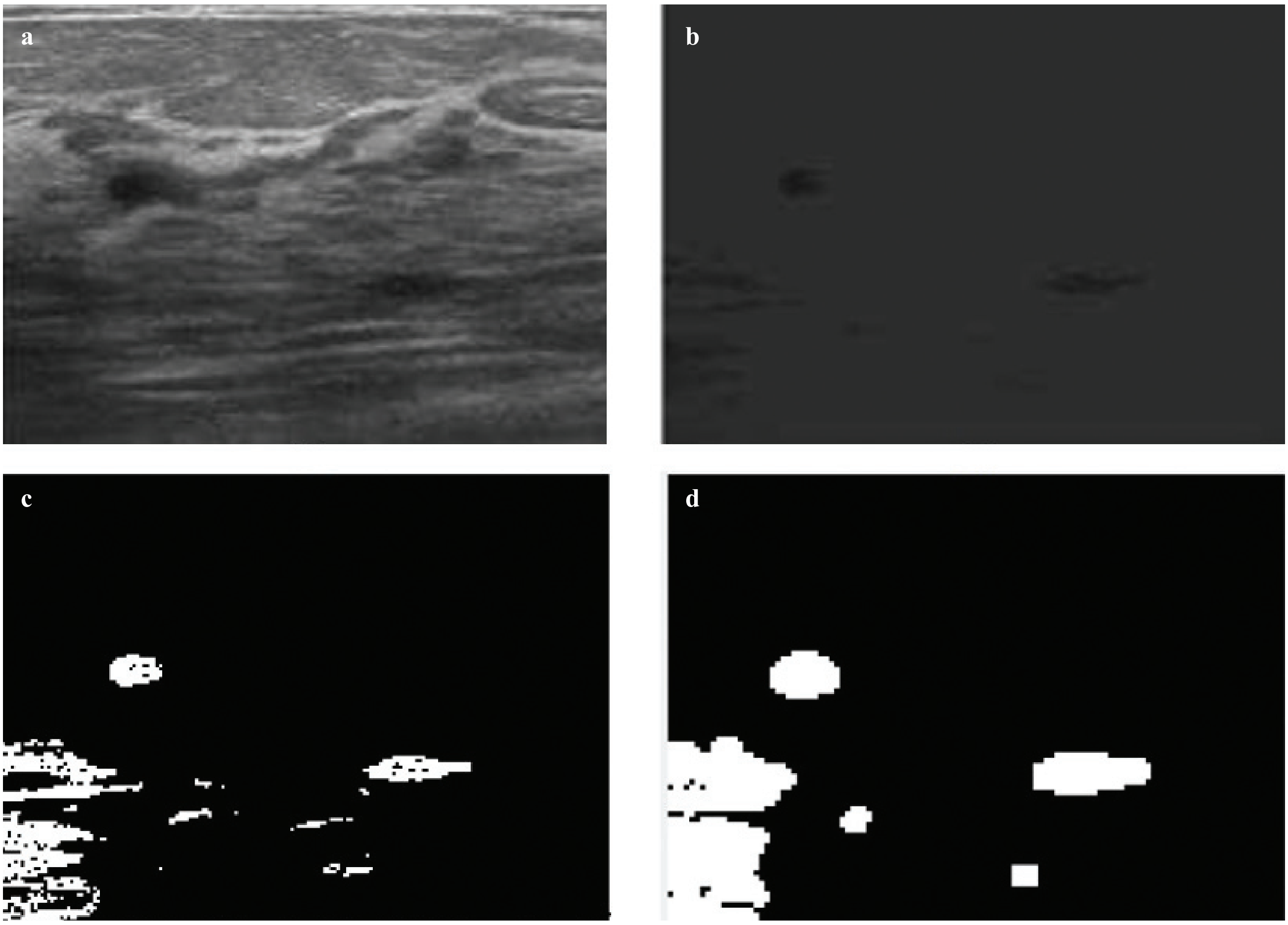


Figure 2. Illustration of the operation of the three stages: preprocessing, local binary pattern transformation and morphological operation, of the proposed algorithm. (a) Ultrasound image of breast; (b) preprocessed image; (c) processed using local binary pattern operator, (d) results of performing morphological operations (dilation and erosion) with the results of applying these three steps, probable abnormal regions were highlighted.

After applying noise reduction algorithms and LBP to a suspicious region pattern, two images are obtained, namely the processed image and the studied image. The dimensions of the first image (the output of suspicious region pattern) are always smaller than the second one (studied frame). Furthermore, in order to detect the region which is similar to lesion region pattern, the image from the LBP is moved and slipped on all parts of the studied frame (similar to filtering) and a differentiation process is performed between the studied frame and the pattern of the abnormal region. The output of this stage is an image derived from the obtained subtraction in each location. Pixels with the highest similarity receive the smallest values and those with the lowest similarity gain the highest value. The output of this stage is the input for distance image calculation. The distance from the minimum location is then calculated in the image belonging to the previous stage and the result is saved as a new image. It should be noted that in the new image, regions with the most similarity to lesions have the highest grey level intensity values and regions less similar to abnormal tissues have the lowest grey level intensity values in the image. Figure 3 depicts the output of the distance image calculation algorithm.

Key points detection

The objective of this step is to detect key points (interest regions) in the image under analysis. For this purpose, the edges of the potential regions in the distance image are primarily detected. Next, the points that lie within each region and have intensity values higher than a threshold are identified as potential key points. Finally, the number of these points is reduced using fuzzy c-means clustering algorithm. In fact, in this step, the centers of possible regions are identified. Figure 4 shows an example output of the keypoints detection step.

Segmentation using region growing

This step detects lesion areas in the frame under analysis. For this purpose, we used a seeded region growing image segmentation approach.[29-31] The points identified in the previous step are considered as the seed points.

Analysis of US video for breast lesions detection

Figure 5 shows the flowchart of the algorithm proposed for the analysis of US video to detect breast lesions. In the proposed algorithm, the studied film is firstly divided into its constituent frames. The first frame is then investigated using the single-frame analysis algorithm discussed in the above seven subsections. If the examined frame does not contain any abnormal regions, the algorithm moves to and analyzes the next frame, a procedure continued until a suspicious region is detected in a frame (e.g., i^{th} frame). After that, the next (i.e., $(i+1)^{th}$) frame is analyzed using the information of the abnormal region detected in the previous frame. If the area of the ROI detected in the $(i+1)^{th}$ frame is within *Tmin* and *Tmax*, defined by the radiologist, the detected region is considered as the main region. However,

(a) (b) (c)

Figure3. Illustration of the distance transformation stage of the developed algorithm. (a) an image processed using dilation and erosion operations; (b) results of performing LBP transformation, and (c) obtained distance image.

if it is out of *Tmin* and *Tmax*, the i^{th} frame is studied from the beginning using single frame analysis algorithm. To avoid missing any ROI due to its absence in the previous frames, for every 10 frames, the algorithm starts a new analysis where a new frame is assessed regardless of the results of the previous frames. The number of frames in each second is around 30, so 10 frames are captured in 0.33 seconds; therefore, this setting is effective in eliminating the effects of moving artifacts.

Experiment

The performance of the developed system was tested using a database composed of 22 US videos, in which 10 breast US films belonged to patients with breast lesions and 12 videos were of normal cases. Informed consent was obtained from all individual participants included in the study. Each film contained 100 to 125 breast images (frames) and was acquired using a Mindray DC-8 US machine (Mindray Medical International Ltd., Shenzhen, China). The probe was L14/6we/Breast. The breast scans were done in a private radiology clinic (Dr. Rasekhi and Dr. Reza Asad Sangabi radiology clinics) in Shiraz, Iran. All frames in the acquired films were examined by two radiologists and classified as breast lesions or normal cases (images without any abnormal regions). The label provided by the radiologists for each case was considered as "ground truth" and was used to assess the performance of the developed system. To reduce human errors, we considered the regions agreed upon by both radiologists. The breast images of patients with breast lesions contained at least one lesion. Three performance indices, namely sensitivity, specificity, and accuracy were considered for quantitative evaluation. These indices are given by:

$$\text{Accuracy}(\%)=(TP+TN)/(TP+FP+FN+TN)\times 100 \quad (1)$$
$$\text{Specificity}(\%)=(TN)/(TN+FP)\times 100 \quad (2)$$
$$\text{Sensitivity}(\%)=(TP)/(TP+FN)\times 100 \quad (3)$$

Where TP, TN, FP, and FN parameters are defined as follows:

TP: Number of frames with abnormal regions/ breast lesions that are correctly identified.
TN: Number of images with no abnormal regions (healthy cases) that are correctly identified as healthy, meaning no abnormal region is suggested in analyzing the breast US videos of these patients.
FP: Number of frames without breast lesions that are incorrectly classified as image with abnormal regions by the algorithm, at least one abnormal region in these images is detected by the algorithm.
FN: Number of frames with breast lesions or abnormal regions that are missed by the algorithm.

Results

The performance of the system in terms of the employed evaluation indices is shown in table 1. These results were obtained over 2700 frames in the database discussed above. As shown, overall, the system performed properly in detecting abnormal regions in the frames and correctly identifying frames with no abnormal regions. Compared to the values reported for several existing methods,[23] the accuracy and sensitivity of the proposed method are higher than those of the previous works; nevertheless, the dataset used in our work differs from that employed by Bocchi et al.[23]

Discussion

The main objective of this study was to present an automatic method for analyzing US video and

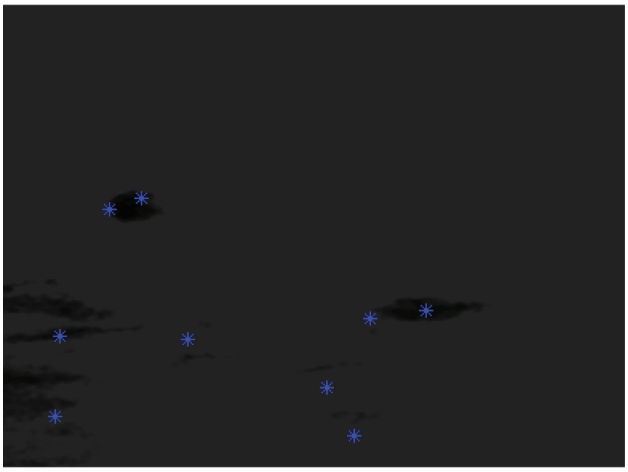


Figure 4. The detected keypoints for a given image. As shown for each region, at least one point representing the region was detected.

ultimately, detecting abnormal regions in each frame. The system somehow summarizes the video by identifying images that may include breast lesion and identify abnormal regions in these images. Such systems have been shown to be effective in analyzing medical data such as electrocardiogram signals.[34,35] The presented system does not classify the detected region as being a lesion or not. Rather, it assists physicians in the primary diagnosis of breast cancer, especially reducing the time required for analyzing and interpreting the whole images acquired during a screening test for breast cancer.

As shown in table 1, overall, the presented system performed well in detecting abnormal regions in each frame (Sensitivity >95%). Likewise, for the frames with no abnormal regions (healthy cases), the system performed well (Specificity>97%). Finally, the overall performance of the system in identifying the regions and categorizing the frames, presented as accuracy, is encouraging (Accuracy>97%). An example output of the system is shown in figure 6, where the system detected the abnormal region in the video correctly. Overall correctly, the obtained results show that the presented system can be used in summarizing a US film and detecting abnormal regions in a frame.

The main reason that the system performed properly in classifying frames and identifying abnormal regions in frames is that it fused the information related to the frames in making a

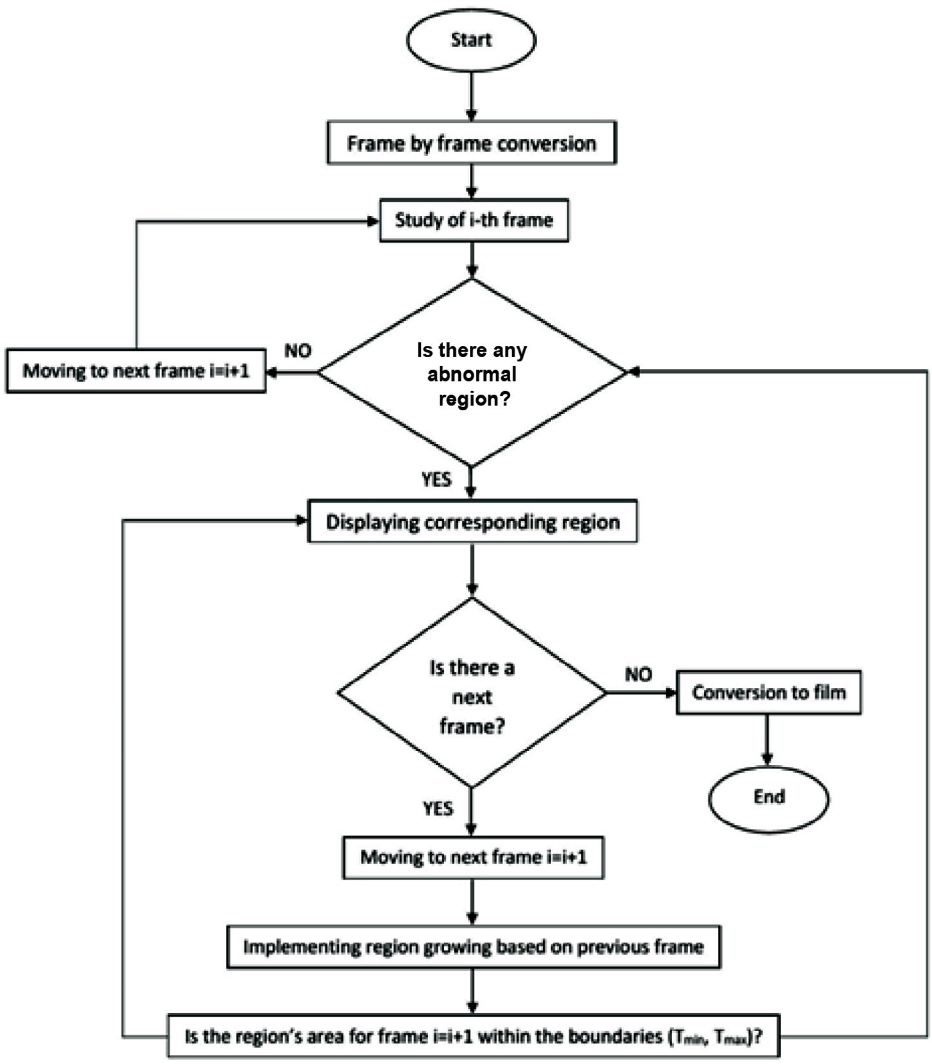
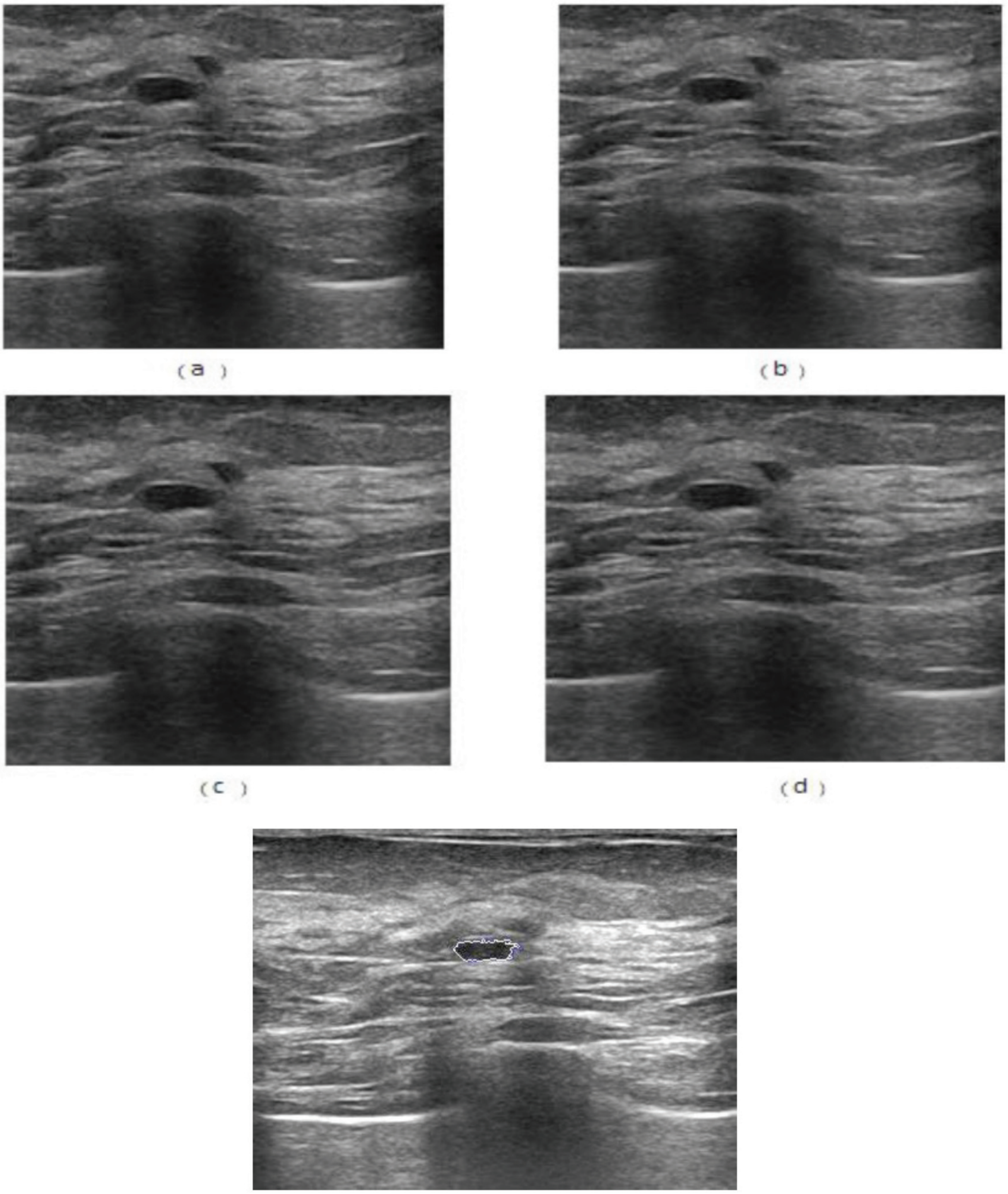


Figure 5. The flowchart related to the analysis of a given ultrasound video using the developed method is provided.

decision about the detected region in the frame. Fusing and considering the previous and next event information in analyzing current event have been shown to be effective in medical image analysis, particularly in MR image segmentation,[36] US image analysis, and classification of breast cancer[23] and editing and evaluating electromyographic signal decomposition results.[37-41] The presented algorithm does not judge a detected region based on its characteristics in a single frame, rather it considers the characteristics of the region in the previous frames. In this manner, the number of FPs is reduced significantly. In addition, every 10 frames is interpreted regardless



(e)

Figure 6. An example output of the segmentation results provided by the presented system. (a) to (d) four consequent frames of a US video, and (e) the segmentation result by the developed system.

of the results of the previous frame; hence, the low possibilty of missing an abnormal region. In this regard, FPs and FNs are significantly reduced, while TNs are increased. Consequently, the overall accuracy of the system is improved.

It should be noted that the performance of the system depends on several user-defined parameters such as the number of clusters in "keypoint detection" step, and *Tmin* and *Tmax* in determining an identified region. Increasing *Tmin* improves the specificity of the system, but reduces its sensitivity. In this work, the best values for these parameters were found experimentally using cross-validation technique.

Conclusion

Early detection of breast cancer plays a substantial role in its treatment. Owing to its several advantages over other imaging techniques, US imaging is the most common method for diagnosing breast cancer. However, it is difficult to analyze and detect breast lesions in US images because they have low-quality. Thus, the segmentation of US images to detect breast lesions is still a challenging task. In this paper, we presented an automated system for analyzing breast US videos and ultimately detecting abnormal regions. The system was developed using 22 US videos, including 10 breast US films from patients with breast lesions and 12 videos belonging to normal cases; the performance analysis revealed that with an accuracy of 97.1%, this system is able to precisely detect abnormal regions. The obtained results are promising and show that the proposed system can assist radiologists in the primary diagnosis of breast cancer, particularly by reducing the time required to analyze and interpret the images acquired during a screening test for breast cancer.

Acknowledgement

This paper has been extracted from parts of the MSc. thesis by Mohammad Reza Haghighi Poya, financially support by Shiraz University of Medical Sciences (Grant number: 94-01-01-9607). We would like to thank Dr. Rasekhi and Dr. Reza Asad Sangabi for sharing the US videos used in this research and assisting with the analysis of these videos.

Conflict of Interest

None declared.

References

1. Hirokawa K, Utsuyama M, Kikuchi Y, Kitagawa M. Scoring of immunological vigor: Trial assessment of immunological status as a whole for elderly people and cancer patients. In: Pawelec G, editor. Immunosenescence. Medical intelligence unit. New York Springer; 2007.p.15-23.
2. Chaudhary A, Singh SS. Lung cancer detection on CT images by using image processing. 2012 International Conference on Computing Sciences; phagwara, India: IEEE; 2012:142-6. doi:10.1109/ICCS.2012.43.
3. Ataollahi M, Sharifi J, Paknahad M, Paknahad A. Breast cancer and associated factors: a review. J Med Life. 2015;8(Spec Iss 4):6-11.
4. Sun YS, Zhao Z, Yang ZN, Xu F, Lu HJ, Zhu ZY, et al. Risk factors and preventions of breast cancer. Int J Biol Sci. 2017;13(11):1387-97. doi:10.7150/ijbs.21635.
5. Kamal R, Mansour S, ElMesidy D, Moussa K, Hussien A. Detection and diagnosis of breast lesions: Performance evaluation of digital breast tomosynthesis and magnetic resonance mammography. *Egypt J Radiol Nucl Med*. 2016;47(3):1159-72. doi:10.1016/j.ejrnm.2016.06.008.
6. Pardal RC, Abrantes AFL, Ribeiro LPV, Almeida RPP, Azevedo KB, Figueiredo TL, et al. Screening of breast lesions: a comparative study between mammography, B-mode ultrasonography, sonoelastography and histological results. *Radiol Bras*. 2013;46(4):214-20. doi:10.1590/S0100-39842013000400007
7. Sree SV, Ng EY, Acharya RU, Faust O. Breast imaging: A survey. *World J Clin Oncol*. 2011;2(4):171-8. doi:10.5306/wjco.v2.i4.171.
8. Berg WA, Blume JD, Cormack JB, Mandelson EB, Lehrer D, Böhm-vélez M, et al. Combined screening with ultrasound and mammography vs mammography alone in women at elevated risk of breast cancer. *JAMA*. 2008;299(18):2151-63. doi:10.1001/jama.299.18.2151.
9. Evans A, Trimboli RM, Athanasiou A, Balleyguier C, Baltzer PA, Bick U, et al. Breast ultrasound: recommendations for information to women and referring physicians by the European Society of Breast Imaging. *Insights Imaging*. 2018;9(4):449-61. doi:10.1007/s13244-018-0636-z.
10. Madjar H. Role of breast ultrasound for the detection

and differentiation of breast lesions. *Breast Care.* 2010;5(2):109-14. doi:10.1159/000297775.
11. Mohammadpoor M, Shoeibi A, Zare H, Shojaee H. A hierarchical classification method for breast tumor detection. *Iran J Med Phys.* 2016;13(4):261-8. doi:10.22038/ijmp.2016.8453.
12. Yap MH, Edirisinghe EA, Bez HE. A novel algorithm for initial lesion detection in ultrasound breast images. *J Appl Clin Med Phys*. 2008;9(4):181-99. doi:10.1120/jacmp.v9i4.2741.
13. Gu P, Lee W-M, Roubidoux MA, Yuan J, Wang X, Carson PL. Automated 3D ultrasound image segmentation to aid breast cancer image interpretation. *Ultrasonics.* 2016;65:51-8. doi:10.1016/j.ultras.2015.10.023.
14. Yap MH, Pons G, Marti J, Ganau S, Sentis M, Zwiggelaar R, et al. Automated breast ultrasound lesions detection using convolutional neural networks. *IEEE J Biomed Health Inform.* 2018;22(4):1218-26. doi: 10.1109/JBHI.2017. 2731873.
15. Chen CM, Chou YH, Han KC, Hung GS, Tiu CM, Chiou HJ, et al. Breast lesions on sonograms: computer-aided diagnosis with nearly setting-independent features and artificial neural networks. *Radiology.* 2003;226(2):504-14. doi:10.1148/radiol.2262011843.
16. Madabhushi A, Metaxas DN. Combining low-, high-level and empirical domain knowledge for automated segmentation of ultrasonic breast lesions. *IEEE Trans Med Imaging.* 2003;22(2):155-69. doi:10.1109/TMI.2002.808364.
17. Shan J, Cheng HD, Wang Y. Completely automated segmentation approach for breast ultrasound images using multiple-domain features. *Ultrasound Med Biol.* 2012;38(2):262-75. doi:10.1016/j.ultrasmedbio.2011.10.022.
18. Karimi B, Krzyżak A. Computer-aided system for automatic classification of suspicious lesions in breast ultrasound images. In: Rutkowski L, Korytkowski M, Scherer R, Tadeusiewicz R, Zadeh LA, Zurada JM, editors. 13th International Conference on Artificial Intelligence and Soft Computing (ICAISC); 2014 June 1-5; Zakopane, Poland: Springer, Cham. 2014.p.131-42.
19. Sehgal CM, Cary TW, Kangas SA, Weinstein SP, Schultz SM, Arger PH, et al. Computer-based margin analysis of breast sonography for differentiating malignant and benign masses. *J Ultrasound Med Off J Am Inst Ultrasound Med*. 2004;23(9):1201-9. doi:10.7863/jum.2004.23.9.1201.
20. Xian M, Zhang Y, Cheng HD. Fully automatic segmentation of breast ultrasound images based on breast characteristics in space and frequency domains. *Pattern Recognit.* 2015;48(2):485-97. doi:10.1016/j.patcog.2014.07.026
21. Chen DR, Kuo WJ, Chang RF, Moon WK, Lee CC. Use of the bootstrap technique with small training sets for computer-aided diagnosis in breast ultrasound. *Ultrasound Med Biol.* 2002;28(7):897-902.doi:10.1016/S0301-5629(02)00528-8.
22. Lefebvre F, Meunier M, Thibault F, Laugier P, Berger G. Computerized ultrasound B-scan characterization of breast nodules. *Ultrasound Med Biol.* 2000;26(9):1421-8. doi: 10.1016/S0301-5629(00)00302-1.
23. Bocchi L, Gritti F, Manfredi C, Giannotti E, Nori J. Semiautomated breast cancer classification from ultrasound video. 9th IEEE International Symposium on Biomedical Imaging (ISBI). 2012 May 2-5; Barcelona, Spain: IEEE; 2012, p.1112-5.
24. Biwas S, Zhao F, Li X, Mullick R, Vaidya V. Lesion detection in breast ultrasound images using tissue transition analysis. 22nd International Conference on Pattern Recognition. 2014 Aug 24-28;Stockholm, Sweden: IEEE; 2014, p.1185-88.
25. Dasgupta PB. Analytical comparison of noise reduction filters for image restoration using snr estimation. *Int J Comput Trends Technol.* 2014;17(3):121-4. doi:10.14445/22312803/IJCTT-V17P123.
26. Ahonen T, Hadid A, Pietikainen M. Face description with local binary patterns: application to face recognition. *IEEE Trans Pattern Anal Mach Intell.* 2006;28(12):2037-41. doi:10.1109/TPAMI.2006.244.
27. Sreedhar K, Panlal B. Enhancement of images using morphological transformation. *Int J Comput Sci Inf Technol*. 2012;4(1):33-50. doi:10.5121/ijcsit.2012.4103.
28. Dehghan E, Lee J, Fallavollita P, Kuo N, Deguet A, Le Y, et al. Ultrasound-fluoroscopy registration for prostate brachytherapy dosimetry. *Med Image Anal.* 2012;16(7):1347-58. doi:10.1016/j.media.2012.06.001.
29. Shih FY, Cheng S. Automatic seeded region growing for color image segmentation. *Image Vis Comput.* 2005;23(10):877-86. doi:10.1016/j.imavis.2005.05.015.
30. Cui W, Guan Z, Zhang Z. An improved region growing algorithm for image segmentation. 2008 International Conference on Computer Science and Software Engineering; 2008 Dec 12-14; Hubei, China: IEEE; 2008. p. 93-6.
31. Preetha MMSJ, Suresh LP, Bosco MJ. Image segmentation using seeded region growing. 2012 International Conference on Computing, Electronics and Electrical Technologies (ICCEET). 2012 March 21-22 ; Kumaracoil, India: IEEE; 2012. p. 576-83.
32. Ojala T, Pietikäinen M, Harwood D. A comparative study of texture measures with classification based on featured distributions. *Pattern Recognit.* 1996;29:51-9. doi:10.1016/0031-3203(95)00067-4.
33. Gonzalez RC, Woods RE. Digital image processing. 4th edition. New York, NY: Pearson; 2017.
34. Leinveber P, Halamek J, Jurak P. Ambulatory monitoring of myocardial ischemia in the 21st century-an opportunity for high frequency QRS analysis. *J*

Electrocardiol. 2016;49(6):902-6. doi:10.1016/j.jelectrocard.2016.07.034.

35. Homaeinezhad MR, Ghaffari A, Toosi HN, Tahmasebi M, Daevaeiha MM. Optimal delineation of ambulatory holter ECG events via false-alarm bounded segmentation of a wavelet-based principal components analyzed decision statistic. *Cardiovasc Eng Dordr Neth.* 2010;10(3):136-56. doi:10.1007/s10558-010-9103-2.
36. Amiri S, Movahedi MM, Kazemi K, Parsaei H. 3D cerebral MR image segmentation using multiple-classifier system. *Med Biol Eng Comput.* 2017;55(3):353-64. doi:10.1007/s11517-016-1483-z.
37. Parsaei H, Nezhad FJ, Stashuk DW, Hamilton-Wright A. Validation of motor unit potential trains using motor unit firing pattern information. 2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society. 2009 Sept 3-6; Minneapolis, MN, USA: IEEE; 2009. p. 974-7.
38. McGill K, Marateb H. Rigorous a posteriori assessment of accuracy in EMG decomposition. *IEEE Trans Neural Syst Rehabil Eng.* 2011;19(1):54-63. doi:10.1109/TNSRE.2010.2056390.
39. Parsaei H, Stashuk DW. A method for detecting and editing MUPTs contaminated by false classification errors during EMG signal decomposition. 2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society. 2011 Aug 30-Sept 3; Boston, MA, USA: IEEE, 2011. p. 4394-7.
40. Parsaei H, Nezhad FJ, Stashuk DW, Hamilton-Wright A. Validating motor unit firing patterns extracted by EMG signal decomposition. *Med Biol Eng Comput.* 2011;49(6):649-58. doi:10.1007/s11517-010-0703-1.
41. Parsaei H, Stashuk DW. SVM–based validation of motor unit potential trains extracted by emg signal decomposition. *IEEE Trans Biomed Eng.* 2012;59(1):183-91. doi:10.1109/TBME.2011.2169412.