

# Enhancement of Mammogram by Hyper-elastic Property of Non-rigid Images: a Histogram Modification Scheme

Jerald Prasath G<sup>1</sup>, Parimala Geetha K<sup>2</sup>, Mohanalin J<sup>3</sup>, Beena Mol M<sup>4</sup>, Prinza L<sup>5</sup>

<sup>1</sup>Computer Science and Engineering, Ponjesly College of Engineering, Nagercoil, India

<sup>2</sup>Electronics and Communication Engineering, Ponjesly College of Engineering, Nagercoil, India

<sup>3</sup>Electrical and Electronics Engineering, College of Engineering, Pathanapuram, Kerala, India

<sup>4</sup>Civil Engineering, LBS College of Engineering, Kasaragod, Kerala, India

<sup>5</sup>Electronics and Communication Engineering, TKR College of Engineering, Hyderabad, India

## ABSTRACT

Mammogram enhancement is of paramount importance for the successful detection of masses and micro calcifications. We propose a hyper elastic model based new histogram modification scheme that mimics the deformation property of the breast. Unlike state-of-the-art methods, the advantage of using such model is that the anatomical topology of masses and micro calcifications is preserved. Our approach is fully tested on the public available mini-MIAS database. The experimental results has earned higher average value of 7.57 in terms of effective measure of enhancement which clearly outperforms traditional techniques such as histogram equalization (1.13), contrast limited adaptive histogram equalization (6.37), brightness preserving bi-histogram equalization (2.34) and recursive mean separate histogram equalization(6.47). Most significantly, the visual inspection indicates that our method preserves the topological information of malignant breast structures without eliminating relevant image features.

## Keywords:

Mammogram; Enhancement; Hyper-elastic property; external force; internal force; Microcalcification; Mass.

## 1. INTRODUCTION

Breast cancer is the second leading cause of cancer death in women after lung cancer [1]. One out of eight women dies as a consequence of breast cancer and a new case is diagnosed every 19 seconds [2]. As a result, 1,3 million women are diagnosed of breast cancer worldwide on an annual basis [3].

In 2017, approximately more than 252,710 new cases appeared in US and approximately 40,610 women died [4]. From the data gathered in 2015 [5], around 54,900 new cases were diagnosed in UK per year, hence yielding an average of 150 cases in a day. In India, 144,937 new cases were diagnosed in the year of 2012 and the number of deaths was 70,218 [6]. The estimates predict that this number will increase to 1,797,900 by 2020. [7].

Early detection is essential to increase the survival rate and computer aided detection (CAD) plays a pivotal role. Mammogram is currently the most used image modality in CAD [8]. Enhancement of mammograms is of paramount importance for the successful detection of mass and micro calcifications. Traditional algorithms are based on histograms to improve the pixels of the region of interest [9,10]. Newer approaches aimed at enhancing the images [11-13] have been put forward with reasonable success. They consider the characteristics associated with mammograms before designing the enhancement methodology. Such image modality comprises the women breast, which is regarded as a soft tissue. [14] Proved that the images involving breast can be handled better, if the algorithm considers the property of the object involved. However they were concentrating on image registration techniques. Other works employed traditional techniques such as histogram equalization (HE) [9,10,15,16], contrast limited adaptive histogram equalization (CLAHE) [17,18], brightness preserving bi-histogram equalization (BBHE) [19, 21], minimum mean brightness error bi-histogram equalization(MMBEBHE)[20] and recursive mean separate histogram equalization (RMSHE)[21]. Some detailed surveys on the available methods for mammogram enhancement can be found elsewhere [1,15,17].

Moreover, hyper elastic works based on non-rigid image registration were previously published in [14,22,23]. Indeed, the first hyper elastic model was presented by [14] to match different mammogram acquisitions. This work was then extended in [22] using Poisson's equation. The method proposed by [23] established a polynomial hyper elastic technique based on the mixture of both breast fat and glandular

tissues. Authors in [24-27] discussed hyper elastic non-rigid deformation via finite elements on medical images such as magnetic resonance imaging.

The proposed approach established an algorithm that can enhance the mammogram by considering the property of the image. The idea involves generating an external force that separates the original mammogram from the HE mammogram. This force drives the original mammogram towards an equilibrium point, where a new modified histogram is established. Now this new modified mammogram will have its features enhanced by obeying with the hyper elastic nature of the body. The biggest advantage of this idea is, the features of the mammogram will be enhanced without exorbitantly enhancing the background features. To test the aforementioned method, we utilize 322 images of the mini-MIAS database. The performance obtained is calculated using the Image Quality Index (IQI), Structural Similarity (Ssim), Entropy (ENTR), Normalized Cross Correlation (NmCross) and effective measure of enhancement (EME).

This paper is organized as follows. Section 2 formulates the hyper-elastic deformation theory. Section 3 explains the proposed hyper elastic model based histogram modification scheme. Section 4 discusses the experimental results. Finally, Section 5 provides the conclusions and future perspectives.

## 2. HYPER ELASTIC DEFORMATION THEOREM

Objects are considered hyper-elastic bodies if the Hooke's law of elasticity is satisfied and the elastic potential ( $W$ ) is hold. The latter is defined as a scalar function of deformation tensors with a strain component ( $E$ ). The stress shall can be expressed as  $S_{xy} = \partial W / \partial E_{xy}$ , where  $S$  represents the stress tensor. Mammograms are isotropic elastic solids as the aforementioned law is accomplished. Therefore, the spatial difference between mammogram images or views is known as elastic deformation [14]. The shape of the mammogram histogram is modified by an external force  $d$ . The force opposed to this external force is the internal force  $d_i$  with a regularization parameter. The smooth transformation is achieved by expressing both forces in terms of a cost function  $C_f = d - d_i$ . This formulation is improved thanks to the regularization parameter, which allows the use of the direct motion equation. Hence, the equilibrium deformation equation can be expressed as  $\alpha \nabla^2 u(x) + (\beta + \alpha) \nabla(\nabla \cdot u(x)) = -d$ , where  $\alpha$  and  $\beta$  are constants and  $u(x)$  is the displacement field. The required deformation can be computed via the Finite difference method (FDM). Deriving finite difference approximations, the solution is calculated by Eq. (1,2).

$$2K_{10} * \frac{\partial^2 u_1}{\partial x_1^2} = -d_1 \quad (1)$$

$$2K_{10} * \frac{\partial^2 u_2}{\partial x_2^2} = -d_2 \quad (2)$$

$\partial^2 u_1 / \partial x_1^2$  is second order derivative of mammogram and  $\partial^2 u_2 / \partial x_2^2$  is second order derivative of mammogram.

The total force  $d = -(d_1 + d_2)$  is computed through the Poisson equation. According to its superposition property is Eq. 3 is obtained by

$$2K_{10} * \frac{\partial^2 u_1}{\partial x_1^2} + 2K_{10} * \frac{\partial^2 u_2}{\partial x_2^2} = -d \quad (3)$$

Finally, the above Eq. 3 derives as

$$\frac{\partial^2 u_1}{\partial x_1^2} + \frac{\partial^2 u_2}{\partial x_2^2} = \frac{-d}{2K_{10}} \quad (4)$$

These equations can be solved by the concepts of finite difference method (FDM). By solving this Partial differential equation (PDE), the histogram of the mammogram is modified (deformed) depending on the external and opposed internal forces. The enhanced mammogram is attained when the external force is almost nearby or equal to the opponent force.

## 3. HYPER ELASTIC DEFORMATION THEOREM

The HE algorithm forces the histogram of the mammogram to be raised unnaturally, which generates bleached images. The squared sum of the difference between the original and the HE mammograms is the external force that separates both images. The problem arises from the identification of a new histogram that provides the equilibrium. This balanced histogram will thus generate an enhanced mammogram without adding artificial pixels. Our novel idea takes advantage of the existent superposition property found in the Poisson's model.

The central, forward and backward finite differences are three different methods to solve the aforementioned PDE. The boundary conditions and the geometry of objects play a key role to decide which method is more convenient. In this work, we select the central difference procedure due to its highest accuracy and lower computational cost compared to the others. Fig. 1 shows the block diagram of the proposed approach. The HE mammogram  $h$  is obtained from the original input mammogram  $x$ . To solve the Poisson PDE, the force is calculated using the Euclidian distance.

The steps performed by our new enhancement algorithm are described as follows. Let  $x(i,j)$  be the input mammogram,  $h(i,j)$  the HE mammogram,  $m(i,j)$  the intermediate mammogram and  $r(i,j)$  the resulting enhanced mammogram. Note that  $d$  is the external force that modifies (deforms) the histogram.

1. The histogram of the input mammogram  $x(i,j)$  is constructed and considered as an elastic model.
2. The HE mammogram named  $h(i, j)$  is created by applying the HE algorithm to  $x(i,j)$ .
3. The difference between both mammograms is computed using the Euclidean distance (i.e.,  $d = (x(i,j) - h(i,j))$ ). This difference will act as the external deformable force  $d$  against the opposed internal force.

4. The computed force  $d$  is applied to the histogram of the input mammogram to deform it according to the elastic model.
5. The resulting deformed mammogram  $m(i,j)$  is set as the new input mammogram.
6. Repeat steps from 3 to 5 to get the minimum force  $d$  with respect to the HE mammogram.
7. The deformed mammogram is set as the new enhanced mammogram  $r(i,j)$ .

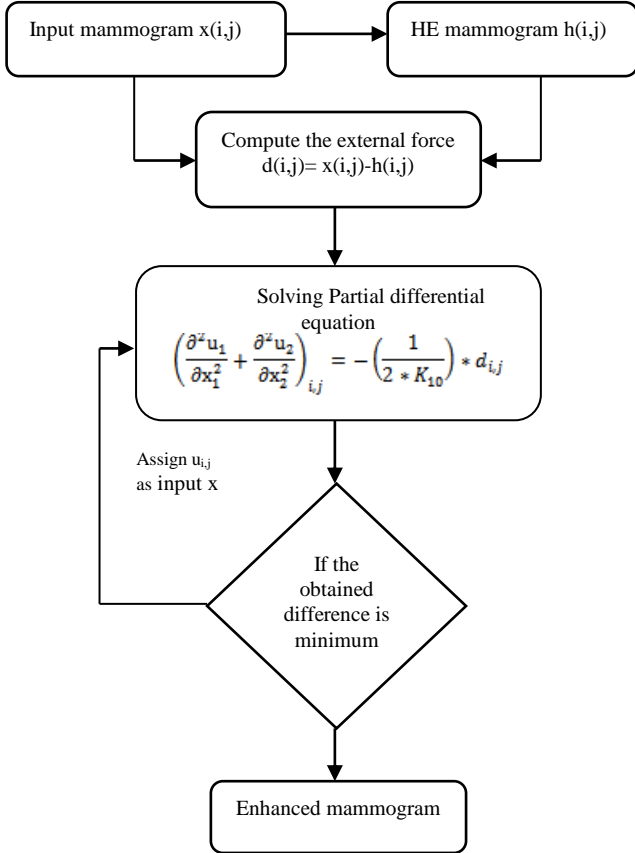


Figure 1. Block diagram of proposed approach

## 4. EXPERIMENTAL RESULTS AND DISCUSSION

### 4.1 Database

The used mini-MIAS database was created by the Mammogram Image Analysis Society (MIAS), a UK organization research. The dataset contains 322 mammograms (208 normal, 63 benign and 51 malignant cases), which were digitized through the Joyce-Loebl scanning micro densitometer (resolution = 50 micron pixel edge). All images were then reduced to 200 micron pixel edge and clipped to 1024 x 1024 pixels.

### 4.2 Performance Evaluation

There are no standard measures to evaluate the performance of the enhancement algorithms. In our case, the final performance is computed using statistical measures such as IQI [28], SSIM [29], NM\_CROSS, ENTR and EME [1]. The IQI evaluates the

luminance and contrast factors, and the loss of correlation. The combination of all these factors are calculated between the dynamic range of (-1, 1). The SSIM measures, the change in contrast and luminosity and also concentrate on the structure of the image. In addition, the ENTR measures the information content of the whole image. The final performance is also assessed in terms of EME [1], which quantitatively evaluates the enhancement quality. The EME can be employed by dividing the image into several blocks (see Eq. 5).

$$EME = \frac{1}{B_1 B_2} \sum_{n=1}^{B_2} \sum_{m=1}^{B_1} 20 \log \left( \frac{X_{max}(m,n)}{X_{min}(m,n)} \right) \quad (5)$$

where  $B_1$  and  $B_2$  are the number of horizontal and vertical blocks, respectively,  $x_{max}(m,n)$  corresponds to the maximum pixel values, and  $x_{min}(m,n)$  to the minimum pixel values.

### 4.3 Results

Results obtained through the proposed method are shown in Fig. (2-8). Fig. 2 and Fig. 3 present the enhanced mammogram using our algorithm. Moreover, Fig. 8 compares the proposed method with others state-of-the-art approaches such as HE, CLAHE, BBHE, MMBEBHE and RMSHE.

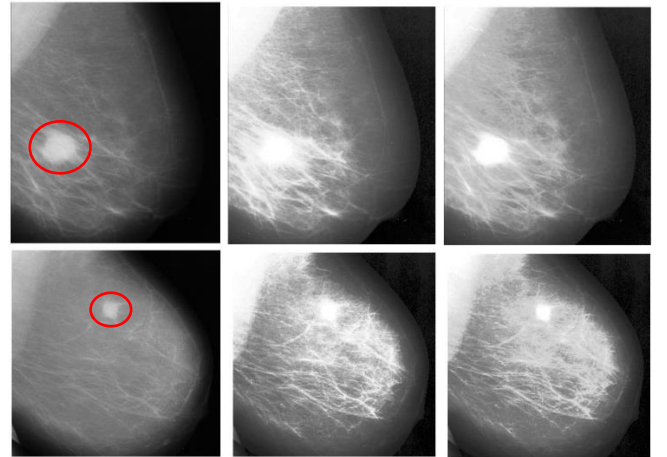
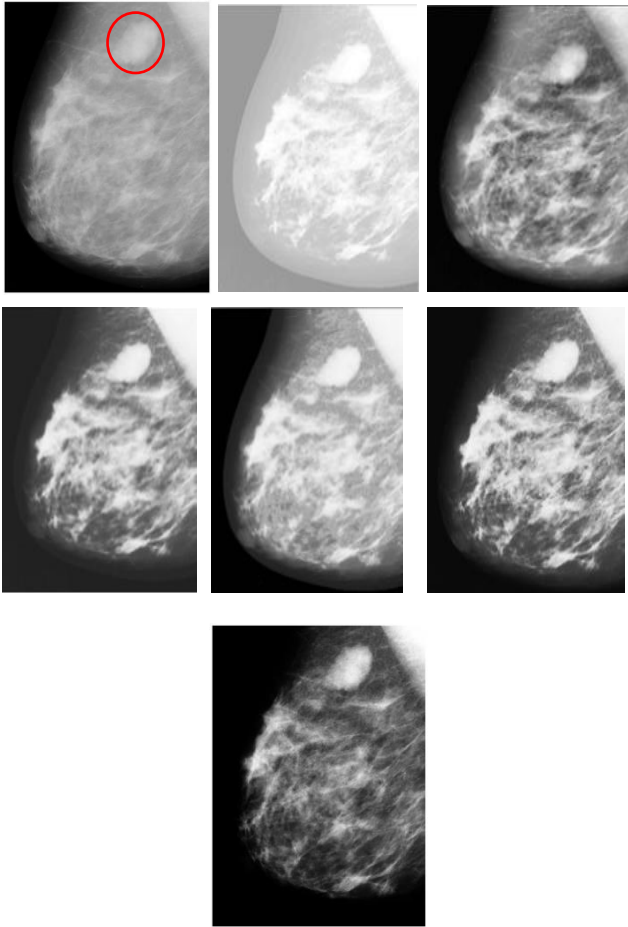


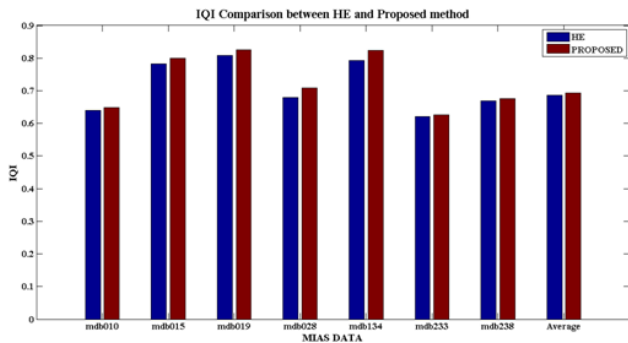
Figure 2. **Left)** Original mammogram with a mass (image mdb028and mdb134), **Middle)** Basic HE, and **Right)** proposed enhancement method

Table 1 lists several performance metrics (IQI, SSIM, NM\_CROSS and ENTR) for the basic HE algorithm and our new approach. For the average results shown in the last row of Table 1 the complete mini-MIAS dataset (322 images) has been considered. Our approach achieves a mean IQI of 0.6929 against the HE method for which this value is 0.6857. In terms of SSIM, the mean value resulting from the application of our method is 0.7188, whereas the HE holds a decreased value of 0.6637. The same applies to NM\_CROSS and ENTR final mean values. It is does clear that the proposed approach outperforms the traditional HE techniques. For more clear visual inspection, the performance metrics in terms of IQI, SSIM, NM\_CROSS and ENTR is compared for the basic HE

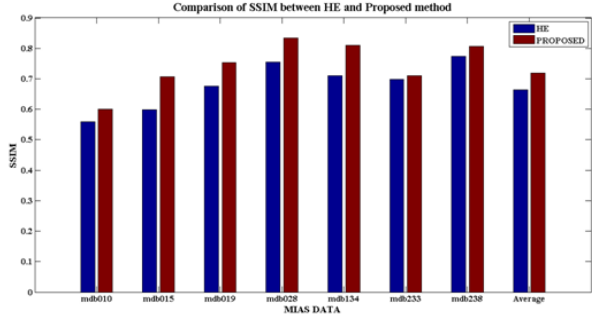
and our proposed algorithm in Fig. 4-7. Table 2 shows that our approach outperforms not only the basic HE but also other methods available in the literature [1] in terms of EME. Correspondingly, a bar plot is displayed in Fig. 8, again indicating that our approach is better.



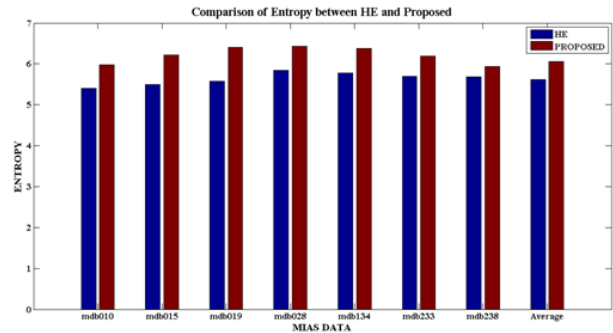
**Figure 3.** Mammogram mdb015 (from left to right and up to down): 1) original mammogram, 2) HE, 3) CLAHE, 4) BBHE, 5) MMBEBHE, 6) RMSHE and 7) our proposed enhancement method.



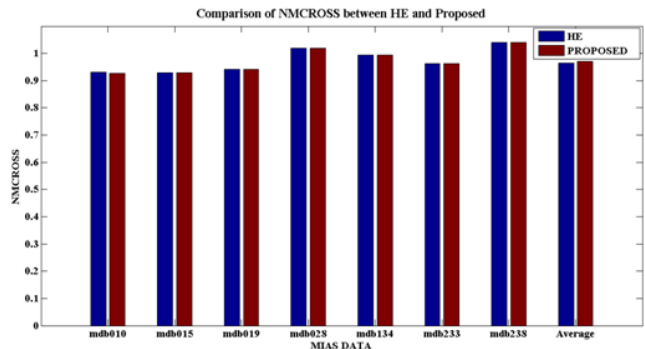
**Figure 4.** Comparison of the IQI performance measure between HE and proposed approach.



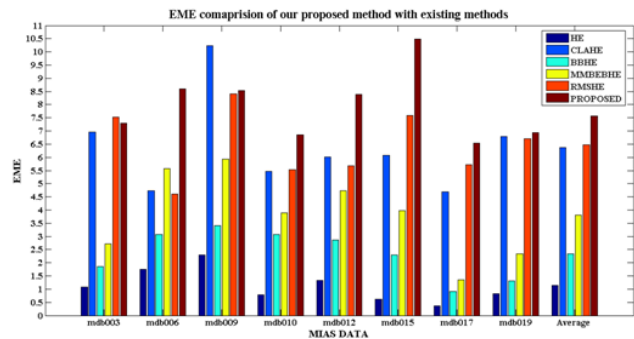
**Figure 5.** Comparison of the SSIM performance measure between HE and proposed approach.



**Figure 6.** Comparison of the NM\_CROSS performance measure between HE and proposed approach.



**Figure 7.** Comparison of the ENTR performance measure between HE and proposed approach.



**Figure 8.** EME comparison between proposed approach and different methods available in the literature.

**Table 1** Comparison of performance metrics between HE and our proposed method using the mini-MIAS database.

Image	Basic HE				Proposed Approach			
	IQI	SSIM	NM_CROSS	ENTR	IQI	SSIMIN	NM_CROSS	ENTR
<b>mdb010</b>	0.6402	0.5588	0.9300	5.4022	0.6479	0.5995	0.9268	5.9733
<b>mdb015</b>	0.7820	0.5988	0.9296	5.5014	0.7996	0.7074	0.9296	6.2130
<b>mdb019</b>	0.8077	0.6757	0.9422	5.5785	0.8260	0.7533	0.9422	6.4028
<b>mdb028</b>	0.6794	0.7552	1.0186	5.8402	0.7080	0.8342	1.0186	6.4332
<b>mdb134</b>	0.7923	0.7103	0.9939	5.7811	0.8238	0.8097	0.9939	6.3848
<b>mdb233</b>	0.6208	0.6981	0.9628	5.6960	0.6262	0.7102	0.9628	6.1937
<b>mdb238</b>	0.6693	0.7729	1.0397	5.6801	0.6752	0.8058	1.0406	5.9446
<b>Average</b>	<b>0.6857</b>	<b>0.6637</b>	<b>0.9636</b>	<b>5.6222</b>	<b>0.6929</b>	<b>0.7188</b>	<b>0.9715</b>	<b>6.0637</b>

**Table 2** .EME Comparison of performance metrics between HE,CLAHE, BBHE, MMBE BHE, RMSHE and proposed approach using the mini-MIAS database

Image	HE	CLAHE	BBHE	MMBEBHE	RMSHE	Proposed approach
<b>mdb003</b>	1.075	6.950	1.863	2.718	7.519	7.293
<b>mdb006</b>	1.758	4.730	3.077	5.579	4.616	8.587
<b>mdb009</b>	2.300	10.242	3.412	5.924	8.413	8.535
<b>mdb010</b>	0.797	5.469	3.068	3.889	5.528	6.852
<b>mdb012</b>	1.338	6.017	2.866	4.742	5.681	8.390
<b>mdb015</b>	0.622	6.084	2.293	3.983	7.595	10.487
<b>mdb017</b>	0.373	4.690	0.905	1.347	5.727	6.533
<b>mdb019</b>	0.834	6.792	1.305	2.343	6.697	6.948
<b>Average</b>	<b>1.137</b>	<b>6.372</b>	<b>2.349</b>	<b>3.816</b>	<b>6.472</b>	<b>7.578</b>

Unlike traditional methods, the proposed approach preserves the salient features of mammograms even in dense breasts. The IQI index reveals that the image quality obtained outperforms the state-of-the-art algorithms in terms of luminance, contrast and loss of correlation. The main advantage relies on the enhancement of the foreground features instead of the entire image (i.e., foreground and background features).

## 5. CONCLUSION

This work presents an oval mammogram enhancement approach based on a hyper elastic model that mimics the deformation property of the breast. The well-known mini-MIAS dataset is employed to test the feasibility of our method. The experimental results achieve an average rate of IQI = 0.693, SSIM = 0.719, NM\_CROSS = 0.972, ENTROPY = 6.064 and EME = 7.578. Therefore, our methodology clearly outperforms other existing state-of-the-art methods. We

conclude that in the medical image domain, it is advantageous to consider the properties of the anatomical structure involved in the image acquisition process. This improves quantitatively and qualitatively the quality of the final enhancement result. We will investigate other methods of solving the PDE in order to speed up and improve the performance of our approach. In addition, different segmentation tests using machine and deep learning techniques will be conducted on various public databases to validate whether the presented algorithm can be applied as an essential pre-processing step.

## REFERENCES

1. Akila, K., L. S. Jayashree and A. Vasuki, "Mammographic image enhancement using indirect contrast enhancement techniques—a comparative study," *Procedia Computer Science* 47,2015, pp.255-261.
2. Sun, Yi-Sheng, Zhao Zhao, Zhang-Nv Yang, Fang Xu, Hang-Jing Lu, Zhi-Yong Zhu, Wen Shi, Jianmin Jiang, Ping-Ping

- Yao, and Han-Ping Zhu, "Risk factors and preventions of breast cancer", *International journal of biological sciences* 13, no. 11, pp.1387, 2017.
3. Bartlett, John MS, and Wendy Parelukar, "Breast cancers are rare diseases—and must be treated as such", vol.11, 2017.
  4. Gong, Yue, Yi-Rong Liu, Peng Ji, Xin Hu, and Zhi-Ming Shao. "Impact of molecular subtypes on metastatic breast cancer patients: a SEER population-based study", *Scientific reports* vol.7, 45411, 2017.
  5. Gonda, Kohsuke, Minoru Miyashita, Hideo Higuchi, Hiroshi Tada, Tomonobu M. Watanabe, Mika Watanabe, Takanori Ishida, and Noriaki Ohuchi, "Predictive diagnosis of the risk of breast cancer recurrence after surgery by single-particle quantum dot imaging", *Scientific reports*, vol. 5, 14322, 2015.
  6. Jack, R. H., E. A. Davies, and H. Møller. "Breast cancer incidence, stage, treatment and survival in ethnic groups in South East England," *British journal of cancer* 100, no. 3, 2009, pp. 545.
  7. Lukong and Kiven Erique, "Understanding breast cancer—The long and winding road." *BBA clinical* 7, pp. 64-77, 2017.
  8. Muthuvel, Marimuthu, Balakumaran Thangaraju, and Gowrishankar Chinnasamy, "Microcalcification cluster detection using multiscale products based Hessian matrix via the Tsallis thresholding scheme," *Pattern Recognition Letters* vol. 94, pp.127-133, 2017.
  9. Lu, Li, Yicong Zhou, Karen Panetta, and Sos Aгаian, "Comparative study of histogram equalization algorithms for image enhancement," In *Mobile Multimedia/Image Processing, Security, and Applications*, vol. 7708, pp. 770811, 2010.
  10. Wang, Chao, and Zhongfu Ye, "Brightness preserving histogram equalization with maximum entropy: a variational perspective", *IEEE Transactions on Consumer Electronics* vol.51, no. 4, pp.1326-1334, 2005.
  11. Datta, Niladri Sekhar, Himadri Sekhar Dutta, and Koushik Majumder., "An effective contrast enhancement method for identification of microaneurysms at early stage," *IETE Journal of Research* vol.62, no. 5, pp. 571-580, 2016.
  12. Irmak, Emrah, and Ahmet H. Ertas, "A review of robust image enhancement algorithms and their applications," In *2016 IEEE Smart Energy Grid Engineering (SEGE)*, IEEE, 2016, pp. 371-375.
  13. Wang, Xuewen, and Lixia Chen, "An effective histogram modification scheme for image contrast enhancement," *Signal Processing: Image Communication*, vol.58, pp. 187-198, 2017.
  14. Mohanalin Raja Rathnam J, "Hyper-Elastic Image registration: An application to mammograms", Ph.D. Thesis, Dept. Elect. Eng., Indian Institute of Technology, Kanpur, 2009.
  15. Sundaram, M., K. Ramar, N. Arumugam, and G. Prabin, "Histogram based contrast enhancement for mammogram images" ,In *2011 International conference on signal processing, communication, computing and networking technologies*, IEEE, 2011, pp. 842-846.
  16. Wong, Chin Yeow, Shilong Liu, San Chi Liu, Md Arifur Rahman, Stephen Ching-Feng Lin, Guannan Jiang, Ngaiming Kwok, and Haiyan Shi, "Image contrast enhancement using histogram equalization with maximum intensity coverage", *Journal of Modern Optics* vol.63, no. 16, pp.1618-1629, 2016.
  17. Langarizadeh, M., R. Mahmud, A. R. Ramli, S. Napis, M. R. Beikzadeh, and W. E. Z. W. A. Rahman, "Improvement of digital mammogram images using histogram equalization, histogram stretching and median filter", *Journal of medical engineering & technology* vol.35, no. 2, pp.103-108, 2011.
  18. Aгаian, Sos S., Blair Silver, and Karen A. Panetta. "Transform coefficient histogram-based image enhancement algorithms using contrast entropy." *IEEE transactions on image processing* 16, no. 3, pp. 741-758, 2007.
  19. Tang, Jinshan, Eli Peli, and Scott Acton. "Image enhancement using a contrast measure in the compressed domain." *IEEE Signal Processing Letters* vol.10, no. 10, pp. 289-292, 2003.
  20. Tsai and Chun-Ming, "Adaptive local power-law transformation for color image enhancement", *Applied Mathematics & Information Sciences* 7, no. 5, pp.2019, 2013.
  21. Chen, Soong-Der, and Abd Rahman Ramli, "Contrast enhancement using recursive mean-separate histogram equalization for scalable brightness preservation," *IEEE Transactions on Consumer Electronics* 49, no. 4, pp.1301-1309, 2003.
  22. Kalra, Prem Kumar, and Nirmal Kumar, "Poisson's equation based image registration: an application for matching 2D mammograms", *Journal of Medical Imaging and Health Informatics* 4, no. 1, pp.49-57, 2014.
  23. Calvo-Gallego, Jose L., Javier Martínez-Reina, and Jaime Domínguez, "A polynomial hyperelastic model for the mixture of fat and glandular tissue in female breast", *International Journal for numerical methods in biomedical engineering* 31, no. 9, e02723, 2015.
  24. Chen, Li-Hua, Sun-Pui Ng, Winnie Yu, Jie Zhou, and KW Frances Wan, "A study of breast motion using non-linear dynamic FE analysis", *Ergonomics* 56, no. 5, pp. 868-878, 2013.
  25. Ribeiro, João, Hernâni Lopes, and Pedro Martins, "A hybrid method to characterise the mechanical behaviour of biological hyper-elastic tissues", *Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization* vol.5, no. 3, pp.157-164, 2017.
  26. Brock, K. K., M. B. Sharpe, L. A. Dawson, S. M. Kim, and D. A. Jaffray, "Accuracy of finite element model-based multi-organ deformable image registration," *Medical physics* 32, no. 6Part1, pp.1647-1659, 2005.
  27. Rohlfing, Torsten, Calvin R. Maurer, David A. Bluemke, and Michael A. Jacobs, "Volume-preserving nonrigid registration of MR breast images using free-form deformation with an incompressibility constraint," *IEEE transactions on medical imaging* 22, no. 6, pp.730-741, 2003.
  28. Wang, Zhou, and Alan C. Bovik, "A universal image quality index," *IEEE signal processing letters* 9, no. 3, pp.81-84, 2002.
  29. Wang, Zhou, Alan C. Bovik, Hamid R. Sheikh, and Eero P. Simoncelli, "Image quality assessment: from error visibility to structural similarity", *IEEE transactions on image processing* 13, no. 4, pp. 600-612, 2004.