A New Intelligent Telemedicine System based on Service-Oriented for Cancer Image Classification

Bassant M. El-bagoury, El-Sayed M. El-Horbaty, Abdel-Badeeh M.Salem

Faculty of Computer and Information Sciences, Ain Shams University, *Cairo, Egypt*

E-mail: bassantai@yahoo.com, shorbaty@cis.asu.edu.eg , abmsalem@yahoo.com,

Abstract

Micro-calcifications appearing as collection of white spots on mammograms show an early warning of breast cancer. Early detection is the key to improve breast cancer prognosis. This paper presents a new intelligent telemedicine framework that has been developed to improve the detection of primary masses and micro calcifications of the disease. Our main motivation is to provide remote services to radiologists and cancer patients. The proposed telemedicine framework is based on Service-oriented technology, where it uses in its application layer image compression by wavelet technique. Then image enhancement is applied on the image to prepare it for the segmentation. Finally, image segmentation is applied for the detection of the calcifications in the breast using Fuzzy C-Mean. The implementation of the system has shown a very good prototype result with integrated intelligent techniques and it has been tested with 326 mammogram breast cancer images with overall good results and this can serve as a real telemedicine platform for the cloud computing industry in the future.

Keywords - Telemedicine, Service-Oriented Architecture, Mammograms, Image Compression, Image Segmentation

1. Introduction

Telemedicine is a rapidly developing technology of clinical medicine, where medical information is transferred through interactive audiovisual media for the purpose of consulting [1]. Telemedicine can also be used to conduct examinations and remote medical procedures. Opportunities and developments of telemedicine discussed in states [2]. Also, Anna E.S. Klughammer [3] introduce improving breast cancer and cervical cancer screening in developing countries using telemedicine. Elvira M. Zilliacus et al. [4] introduce telegenetics of Tele-health cancer.

The term telemedicine encompasses an array of services:

- **<u>Specialist and primary care consultations</u>** may involve a patient “seeing” a health professional over a live
- **<u>Video connection or it may use diagnostic images and/or video</u>** along with patient data to a specialist for viewing later. This may be used for primary care or for specialist referrals. Recent surveys have shown a rapid increase in the number of specialty and subspecialty areas that have successfully used telemedicine. Major specialty areas actively using telemedicine include: dermatology, ophthalmology, mental health, cardiology and pathology. According to reports and studies, almost 60 different medical subspecialties have successfully used telemedicine.
- **<u>Imaging services such as radiology (Teleradiology)</u>** continues to make the greatest use of telemedicine with thousands of images “read” by remote providers. Digital images, sent to the specialist over broadband networks, are diagnosed with a report sent back. Radiology, pathology and cardiology are all using telemedicine to provide such services. It is estimated that over 400 hospitals in the United States alone outsource some of their medical imaging services . Radiological images include (X-rays, CT, MR, PET/CT, SPECT/CT, MG.. etc).
- **<u>Remote patient monitoring</u>** uses devices to remotely collect and send data to a monitoring station for interpretation. Such “home telehealth” applications might include using telemetry devices to capture a specific vital sign, such as blood glucose or heart ECG or a more

sophisticated device to capture a variety of indicators for homebound patients. Such services can be used to supplement the use of visiting nurses.

- **Remote medical education and consumer** information can include a number of activities including: continuing medical education credits for health professionals and special medical education seminars for targeted groups in remote locations; the use of call centres and Internet Web sites for consumers to obtain specialized health information and on-line discussion groups to provide peer-to-peer support.

In this paper, we focus on the third type of Telemedicine, which is Teleradiology. We propose an integrated teleradiology system, which is applied for breast cancer mammography images. This is because Breast cancer recent statistics shows that it is one of the major causes of death among women. Moreover, Mammography is the main test used for screening and early diagnosis, where the micro-calcifications appear in small clusters of few pixels with relatively high intensity compared with their neighboring pixels [5].. Also, S.Shaheb et el. [6] uses fuzzy logic for mammogram image segmentation.
In order to increase physicians' diagnostic performance, many researchers and companies introduce Service-Oriented Architecture (SOA) [7], which is a flexible paradigm for telemedicine phases development and computing.

In this paper, we introduce an integrated teleradiology system for breast cancer diagnosis. It is based on SOA and mammogram images compression, enhancement and fuzzy C-mean mammogram segmentation. The coming sections explain each module in details.

2. Brief Background and Related Work

Breast cancer image segmentation is the process of partitions an image to several small segments the main difficulties in image segmentation are, noise, bias field, partial volume effect (a voxel contributes in multiple tissue types). R.Ramani et al.[13] presents A Survey Of Current Image Segmentation Techniques For Detection Of Breast Cancer, where they discuss:

A.De-noising methods [Decreases the noise] In image pre-processing techniques ar necessary in order to find the orientation of the mammogram to remove the noise and to enhance the quality of the image[8].the pre-processing steps are very important in order to limit the search for abnormalities without undue influence from back ground of the mammograms. The main objective of this process is to improve the quality of the image to make it ready to further processing by removing the unrelated and surplus parts in the back ground of the mammograms [14].

1. Adaptive median filter: Adaptive median filter works on a rectangular region Pxy, it changes the size of Pxy during the filtering operation depending on certain conditions such as
Zmin = minimum pixel value in Pxy
Zmax = maximum pixel value in Pxy
Zmed = median pixel value in Pxy
Pmax = maximum allowed size of Pxy
Each output contains the median value in 3 by 3 neighborhoods around the corresponding pixel in the input images. The edges of the image however are replaced by zeros [15].adaptive median filter has been found to smooth the non repulsive noise from 2D signals without blurring edges and preserve image details. This is particularly suitable for enhancing mammograms images.

2. Mean filter
The mean filter replaces each pixel by the average value of the intensities in its neighborhood.It can localy reduce the variance and is easy to implement [16].

3. A markov random field method
In this method spatial correlation information is used to preserve fine details.in this method regularization of the noise estimation is performed. The updating of pixel value is done by iterated conditioned modes.

4. Wavelet methods: In frequency domain these method is used for de-noising and preserving the signal application of wavelet based methods on mammography 4. Wavelet methods In frequency domain these method is used for de-noising and preserving the signal application
of wavelet based methods on mammography image makes the wavelet and scaling coefficient biased.This problem can be solved by squaring mammograms images by non central chi-square distribution method.

5. Median filtering. A median filter is a non linear filter is efficient in removing salt and pepper noise median tends to preserve the sharpness of image edges while removing noise. The various of median filter are i) centre-weighted median filter ii) weighted median filter iii) max-median filter, the effect of increasing the size of the window in median filtering noise is removed effectively.

6. Max-Min filter

Maximum and minimum filter attribute to each pixel in an image a new value equal to the maximum or minimum value in a neighborhood around that pixel. The neighborhood stands for the shape of the filter, maximum and minimum filters have been used in contrast enhancement.

B. Image Segmentation Overview

The main objective of image segmentation is to extract various features of the images which can be merged or split in order to build objects of interest on which analysis and interpretation can be performed. Image segmentation refers to the process of partitioning an image into groups of pixels which are homogeneous with respect to some criterion. The result of segmentation is the splitting up of the image into connected areas. Thus segment is concerned with dividing an image into meaningful regions. The image segmentation techniques such as thresholding, region growing, statistics models, active control modes and clustering have been used for image segmentation because of the complex intensity distribution in medical images, thresholding becomes a difficult task and often fails [17].

1. Region growing segmentation

Region growing is an approach to image segmentation in which neighboring pixels are examined and added to a region class if no edges are detected. This process is iterated for each boundary pixel in the region. If adjacent regions are found, a region merging algorithms is used in which weak edges are dissolved and strong edges are left intact. The region growing starts with a seed which is selected in the centre of the tumor region. During the region growing phase, pixels in the neighbor of seed are added to region based on homogeneity criteria thereby resulting in a connected region.

2. K-Means clustering method. The k-means algorithms are an iterative technique that is used to partition an image into kcluster. In statistics and machine learning, k-means clustering is a method of cluster analysis which can to portions n observation into k cluster in which each observation belongs to the cluster with the nearest mean [20-21]. The basic algorithms is given below

- Pick k cluster centre's either randomly or based on some heuristic.
- Assign each pixel in the image to the cluster that minimum the distance between the pixels cluster centre.
- Re-compute the cluster centre's by averaging all of the pixels in the cluster. Repeat last two steps until convergences are attained. The most common algorithm uses an iterative refinement technique; due to this ambiguity it is often called the k-means algorithms.

The rest of this paper is organized as follows, In section 2, we present a brief background and related work. We propose our system architecture in section 3 and in section 4 the telemedicine system modules are presented. Results and discussion are given in section 5. Finally, conclusion and future work are given in section 6.

3. Proposed System Architecture

The proposed system is based on the basic SOA [7], which is shown in Fig.1 and it can be divided into three levels:-

- **Front-End layer:** which includes the Client interface and the network connection.
- **Application Layer:** that includes the images processing which consists of image compression, image decompression and image segmentation. Also that layer contains the feature extraction part as well as the CBR (Case-Based Reasoning) module.
- **Finally the Back-end layer** that contains the image database and the patients' database. The proposed system database consists of 326 mammogram images of different cases of breast cancer with different diagnosis. They were obtained from the MIAS (Mammographic Image Analysis Society) [8] database is used because it has complete information about abnormalities of each mammographic image like class of lesion, location, size. We have selected those images which included micro-calcifications.

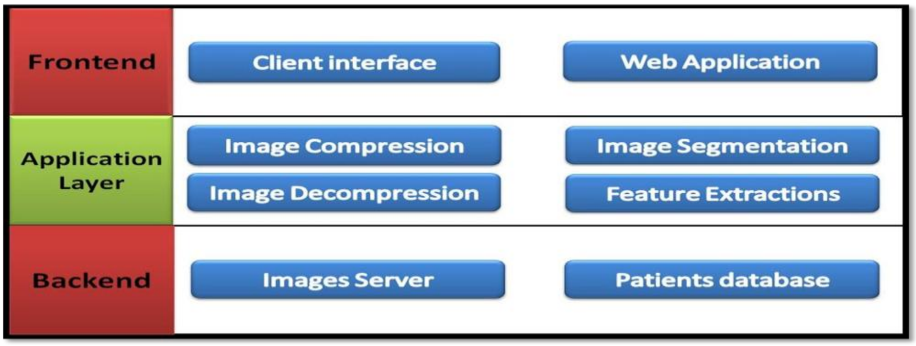

Fig1. Basic Service-Oriented Architecture (SOA)

SOA (Server Client Network) the move to service-oriented communication has changed software development. Whether done with SOAP (Simple Object Access Protocol) or in some other way, applications that interact through services have become the norm. For Windows developers, this change was made possible by Windows Communication Foundation (WCF). In our proposed work, WCF is implemented primarily as a set of classes on top of the. NET Framework's Common Language Runtime (CLR). This lets .Net developers build service-oriented applications in a familiar way. As shown in Fig 2. We use WCF service and configured it programmatically.

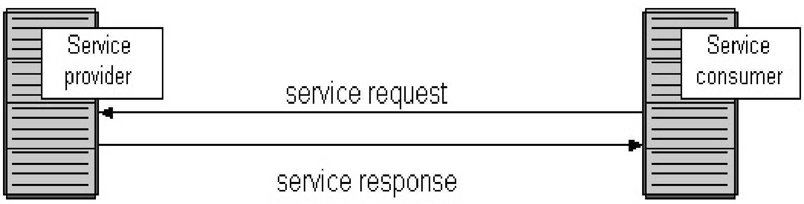

Fig 2. SOA Service Communication using WCF

SOA implementation based on WCF. In order to develop the telemedicine SOA framework, a server-client connection is established using **WCF** because it supports service-oriented cloud-computing development and also due to its interpolarity with applications that supports other technologies. Their main process connection is shown in Fig.3. As shown, WCF allows creating clients that access services. Both the client and the service can run in a pretty much any Windows process- WCF doesn't define a required host. Wherever they run, client and services can interact via SOAP. The whole system is implemented by WCF console connection, Microsoft ASP.net interface and matlab connection for coding. ***Creating a WCF service.*** Every WCF service has three primary components: A service class, implemented in C# as a CLR based language that implements one or more methods. A host process in which the service runs and one or more endpoints that allow clients to access the service. All communication with a WCF service happens via the service's endpoints. An endpoint includes an address (URLs) that identify a machine and a particular endpoint on that machine. It also includes a binding determining how this endpoint can be accessed. The binding determines what protocol combination can be used to access this endpoint along with other things, such as whether the communication is reliable and what security mechanisms can be used. Also, a contract name indicating which service contract this WCF service class exposes via this endpoint.

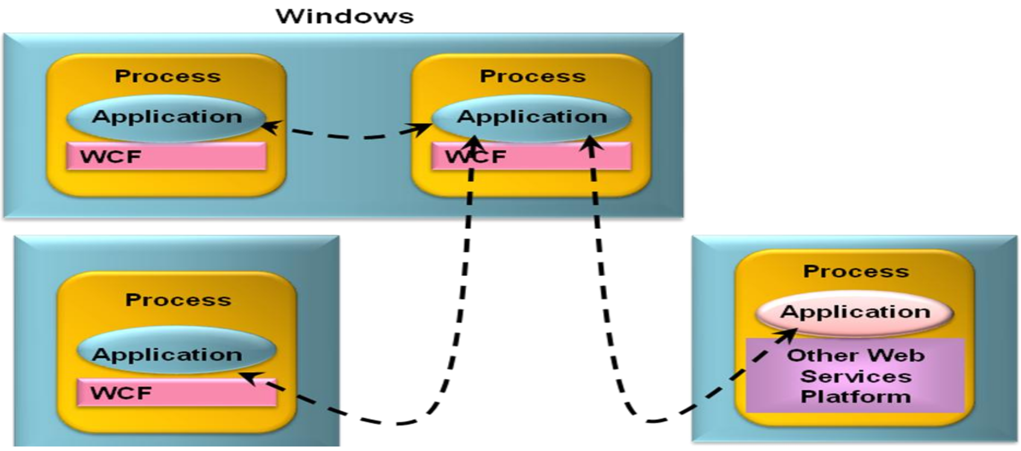

Fig 3. SOA implemented as WCF process and services

Creating a WCF client is even more straightforward. In the simplest approach, all that's required is to create a local stand-in for the service, called a proxy, that's connected to a particular endpoint on the target service, and then invoke the service's operations via the proxy.
Security aspects of WCF exposing services on a network, even an internal network, usually requires some kind of security. How can the service be certain of its client's identity? WCF provide the core security functions of authentication, message integrity, message confidentiality and authorization. All of these depend fundamentally in the notion of identity: who is this user ?. This can be done by directly invoking a WCF function. Therefore, establishing an identity is an essential part of using WCF security.

4. Telemedicine System Modules

In this section, we are going to describe the telemedical system components and mammogram algorithms in details, as shown in Figure 4. It consists of three main modules, Image compression, Image enhancement and Image Segmentation. This is send from the Client side to the radiologist side on the server.

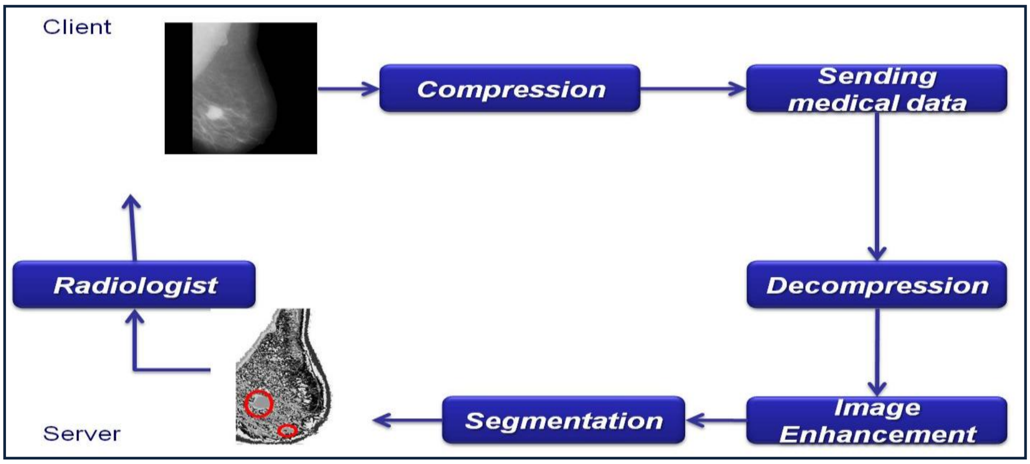

Fig 4. The Proposed Telemedicine System Modules

4.1 Image Compression

Mammogram images carry a lot of small features and details that are very important, they are also inherently voluminous so an efficient data compression techniques are essential for their archival and transmission. Image compression [9] is minimizing the size in bytes of a graphics file without degrading the quality of the image. We found that a common characteristic of most of images is that the neighboring pixels are correlated. Therefore most important task is to find less correlated representation of image. After surveying many algorithms for image compression, we have applied Discrete Wavelet Transform technique [9]. Fig 5 shows the block diagram of image compression sub-modules.

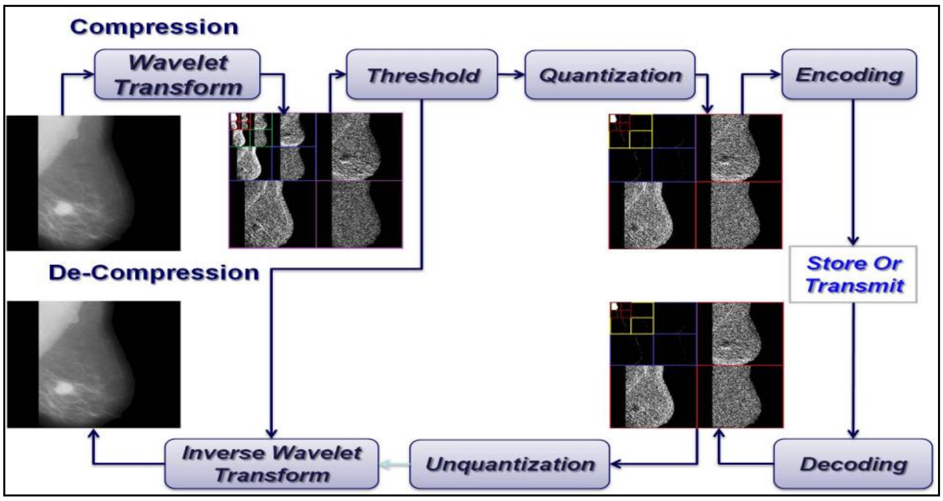

Fig 5. Block Diagram of Image Compression Using Wavelet Technique

Image compression using Discrete Wavelet Transform (DWT) has emerged as a popular technique for image coding applications; DWT has high decorrelation and energy compaction efficiency. One of the most important characteristics of DWT is multiresolution decomposition. An image decomposed by wavelet transform can be reconstructed with desired resolution. When first level 2D DWT is applied to an image, it forms four transform coefficients. The first letter corresponds to applying either low pass or high pas filter to rows and the second letter refers to filter applied to columns, as shown in Figure 6.

<table>
<tr><td>LL2</td><td>HL2</td><td rowspan="2">HL1</td></tr>
<tr><td>LH2</td><td>HH2</td></tr>
<tr><td colspan="2">LH1</td><td>HH1</td></tr>
</table>

Fig 6. Two level wavelet decomposition

A quantizer simply reduces the number of bits needed to store the transformed coefficients by reducing the precision of those values. Since this is a many to one mapping, it is a lossy process and is the main source of compression in an encoder. In uniform quantization, quantization is performed on each individual coefficient. Among the various coding algorithms, the Embedded Zero Tree Wavelet [EZW] coding and its improved version the SPIHT has been very successful [10]. EZW is a progressive image compression algorithm, i.e. at any moment, the quality if the displayed image is the best available for the number of bits received up to that moment. Compared with JPEC – the current standard for still image compression, the EZW and the SPIHT are more efficient and reduce the blocking artefact.

4.2 Image Enhancement and Region of Interest Segmentation

This section discusses image enhancement and Region of Interest (ROI) pre-processing segmentation algorithm [11] techniques. Figure 7 shows the main flowchart modules.

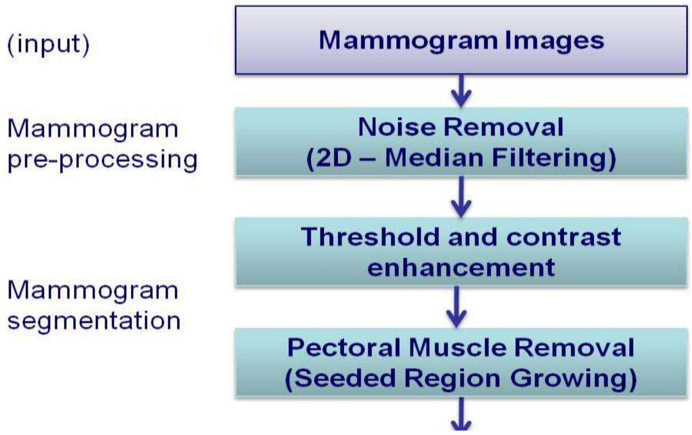

Fig 7. Image Enhancement and ROI segmentation flowchart

Image enhancement techniques [12] are used to emphasize and sharpen image features for display and analysis. General methods of mammographic image enhancement can be grouped into three classes: noise reduction, background removal, and contrast enhancement. Preprocessing steps include: a) noise removal, b) artifact suppression and background separation (Thresholding and Contrast Enhancement), c) pectoral muscle segmentation (Seeded Region Growing).
Digitization Noise Removal. The first step we apply is Median filter for noise removal. Digitization noises such as straight lines are filtered using a two-dimensional (2D) Median filtering approach in a 3-by-3 neighborhood connection. Each output pixel contains the median value in the 3-by-3 neighborhood around the corresponding pixel in the input images. The edges of the images however, are replaced by zeros (total absence or black color). Median filtering has been found to be very powerful in removing noise and isolated points from mammographic images without blurring edges. It is applied to remove the high frequency components in the mammogram image. The merit of using median filter is, it can remove the noise without disturbing the edges.

➢ **Median filters Algorithm:**

Step1: Read the image from left to right
Step 2: For each pixel get a 3X3 window with the pixel cantered in this window.
Step 3: Sort the values of the nine pixels that are in the window according to the gray level.
Step 4: Get the middle gray level value (median value) appearing in the sort
Step 5: Replace the pixel value with the new median value.
Step 6: Repeat the process over all pixels in image

Artifact Suppression and Background Separation. After applying the median filter algorithm, **Radiopaque** artifacts such as wedges and labels in mammograms images are removed using thresholding and morphological operations. Figure 8 shows a mammogram image with a Radiopaque artifact present. Through manual inspection of the all mammogram images acquired, a global threshold with a value T = 18 (normalized value, Tnorm = 0.0706) is found to be the most suitable threshold of transforming the grayscle images into binary[0,1] format.

After the grayscale mammorgram images are converted into binary, as shown in Figure 8. Morhological operations such as dilation, erosion, opening and closing are performed on the binary images.

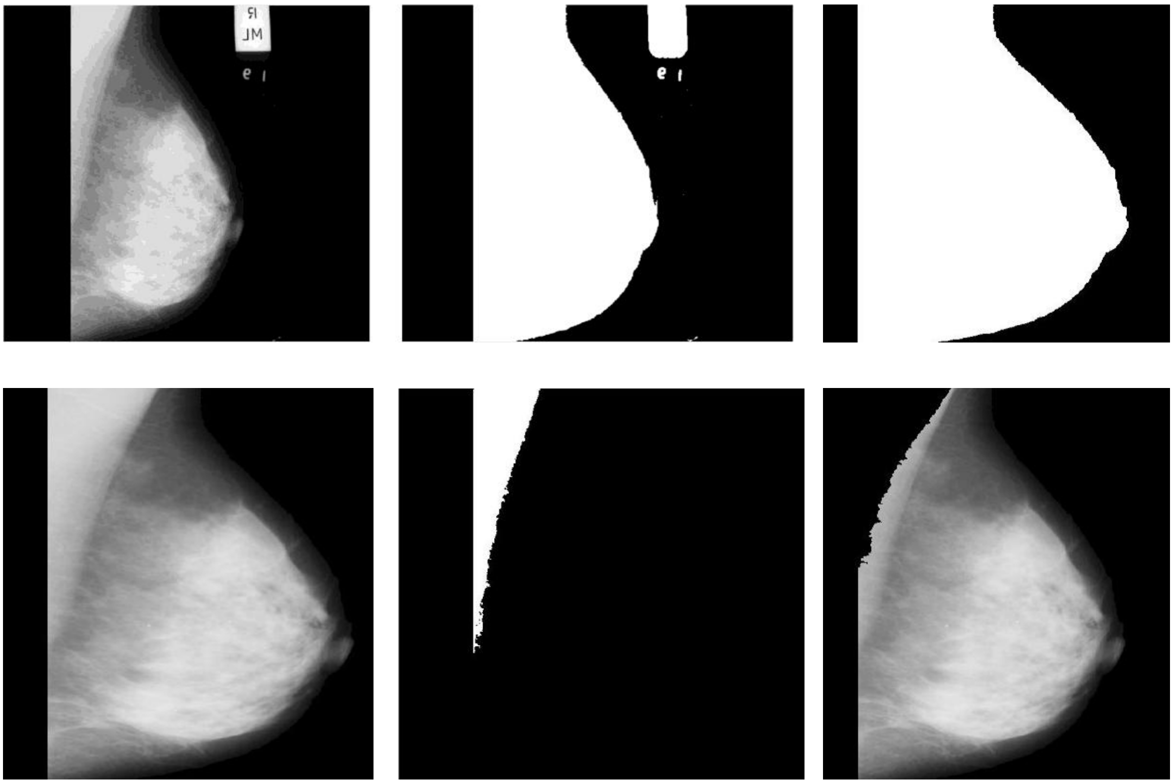

Fig 8. Results of Image Enhancement and Region of Interest Segmentation

➢ The algorithm of Suppression of Artifacts, lables and wedges:-

1. All objects present in the binary image in Figure 8(threshold using, T= 18) are labelled using the *bwlabel* function in MATLAB. The binary objects consist of the radiopaque artifacts and the breast profile region as indicated in Figure 8.
2. The 'Area' (actual number of pixels in the region) of all objects (regions) in Figure 8 is calculated using the *regionprops* function in MATLAB.
3. Next, a morphological operation to reduce distoration and remove isolated pixels (ndividual 1's surrounded by 0's) is applied to the binary images using the bwmorph function in MATLAB with parameter 'clean'.

4. Another morphological operation is applied the binary images to smoothen visible noise using the bwmorph function in MATLAB with the parameter ' majority'. This algorithm checks all pixels in a binary image and sets a pixel to 1 if five or more pixels in a binary image and sets a pixel to 1 if five or more pixels in its 3-by-3 neighbourhood are 1's, otherwise, it sets the pixel to 0.
5. The binary images are reoded using a flat, disk-shaped morphological structuring element (STREL) using the MATLAB *strel* and *imerode* functions. The radius of the STREL object used is R = 5.
6. Next, the binary images are dilated using the same STREL object in Step6. Morphological dilation is performed using the MATLAB *imdilation* function.
7. The holes in the binary images are filled using the *imfill* function in MATLAB with the parameter 'holes'. This algorithm fills all holes in the binary images, where a hole is defined as a set of background pixels that cannot be reached by filling in the background from the edge of the image.

8. The resulting binary image obtained from Step 8 is multiplied with the original mammogram image using the MATLAB *immultiply* function to form the final grayscale region growing (ROI) segmented image.

4.3 Fuzzy C-mean Algorithm Segmentation

Traditional clustering approaches generate partitions where each pattern belongs to one and only one cluster. The clusters in a hard partition are disjoints.

The Fuzzy C-means algorithm, also known as fuzzy ISODATA, is one of the most frequently used methods in pattern recognition. Fuzzy C-means **(FCM)** is a method of clustering which allows one piece of data to belong to two or more clusters [13]. It is based on the minimization of objective function to achieve a good classification. ***'J'*** is a squared error clustering criterion, and solutions of minimization are least squared error stationary point of 'J' in equation (1).

$$J = \sum_{j=1}^{C} \sum_{i=1}^{n} \left\| Z^{(j)} - V_j \right\| \qquad \textbf{\textit{Eq.(1)}}$$

Where, $\left\| Z^{(j)} - V_j \right\|$ is the chosen distance measure between every point $Z^{(j)}$, and the cluster , V_j. The value of this function is an indicator of the proximity of the n data points to their cluster prototypes.

The algorithm is composed of the following steps:

1. Select ***K*** points into the space represented by objects that are being clustered. These points represent initial group prototypes.
2. Assign each object to the group that has the closet prototype.
3. When all objects have been assigned, recalculate the positions of the ***K*** prototypes.
4. Repeat second and third steps until the values of the prototypes no longer change. The result is a separation of objects into groups, from which the metric to be minimized can be calculated.

Traditional clustering approaches generate partitions where each pattern belongs to one and only one, cluster. Hence, the clusters in a hard partition are disjoints. Fuzzy clustering extends this notion to associate each pattern to every cluster using a membership function **Theorem FCM.** if $D_{ikA_i} = \left\| Z^{(j)} - V_j \right\|$ > 0, for every I, k , m > 1 and ***Z*** contains at least ***C*** different patterns, then (U, V) Є $M_{fmc} \times R^{CxN}$ and J_{fmc}.

Following the previous equations of the FCM algorithm, given the data set ***Z*** , choose the number of cluster, $1 \le c \le N$, the weighting exponent **m** > 1, as well as the ending tolerance **δ** > 0. The solution can be reached following the next steps:

1. Provide an initial value to each prototype, $\mathbf{V_i}$, i = 1, …., C. These values are generally given in a random way.
2. Calculate the distance between the pattern $\mathbf{Z_k}$ and each prototype , $\mathbf{V_i}$ **.**
3. Calculate the membership degrees of the matrix, U = [μ_{iK}] , if $D_{ikA_i} > 0$.
4. Update the new values of the prototypes , $\mathbf{V_i}$.
5. Verify if the error is greater than **δ.** If this is true, go to the second step. Else, Stop.

5. Results and discussion

In this analysis, the first procedure is determining the seed regions. When dealing with mammograms, it is known that pixels of tumor regions tend to have maximum allowable digital value. Based on this information, morphological operators are used as Dilation and Erosion to detect the possible clusters which contain masses. Image features are then extracted to remove those clusters that belong to background and normal tissue as a first cut. Features used here include cluster area and eccentricity. The Fuzzy C-means clustering algorithm is used as a segmentation strategy to function as better classifier and aims to class data into separate groups according to their characteristics. Figure 8 shows the resulted image of clustering. As shown, after extracting the Region of Interest (ROI) and then applying the morphological operators, the Fuzzy C-Mean algorithm cluster the image and have successfully detected the breast cancer masses in mammograms.

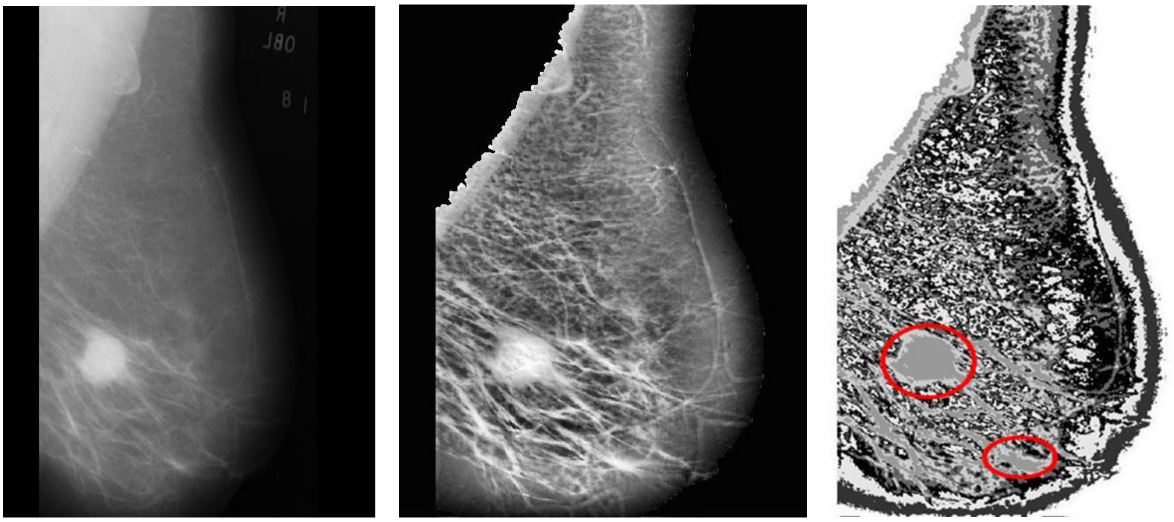

Figure 8. Mammogram images while applying steps of Fuzzy C-Mean algorithm steps. (a) Original image, (b) image with segmented ROI after applying the morphological operators, (c) The resulted image after clustering.

6. Conclusion and Future Work

This paper proposed a new architecture of Telemedicine that can be introduce as an intelligent SOA for cloud-computing technology. The whole system can be divided into: Service-oriented architecture, Server-Client network (WCF), image compression, image enhancement and image segmentation. SOA main advantage is abstraction. Services are autonomous, stateless and separate from the cross-cutting concerns of the implementation. Also, we have used the Server-client network (WCF) which is one of the best techniques in connecting a network since it unification of the original . NET Framework communication technologies and explicit support for service-oriented development. Another strength of our proposed telemedicine framework is that we apply a wavelet image compression algorithm to ease the transmission for the mammogram images through the network. Wavelet technique is used since it is one of the most efficient algorithms in image compression that compress the image with highest percentage of accuracy that might reach a lossless compression. Moreover, image enhancement was used to prepare the image for segmentation through the removing of noise and unwanted objects from the image other than the breast, also mathematical morphological operators used to clarify the details of the image through some operations. Finally, image segmentation is used to detect microclacifications in the breast using the Fuzzy C-Mean algorithm that depends on clustering the image for the detection of microcalcifications which has higher dentistry that the surrounding tissue.

In our future work, we may pursue different areas of the research. The areas of research that could be pursued include image compression, enhancement and segmentation and mobile computing. Mobile computing technology can help the user capture the image by the mobile camera and send it through the network to the server to be segmented and diagnosed.

7. References

1. Sandhya Pruthi, MD, Kevin J. Stange, MD, Gerald D. Malagrino Jr., Kashmira S. Chawla, BA, Nicholas F. LaRusso, MD, Judith S. Kaur, MD. **Successful Implementation of a**

Telemedicine-Based Counseling Program for High-Risk Patients With Breast Cancer. Mayo Clinic Proceedings, Volume 88, Issue 1 , Pages 68-73, January 2013.

2. Kjersti Engan, Thor Ole Gulsrud, Karl Fredrik Fretheim, Barbro Furebotten Iversen, Liv Eriksen, **A Computer Aided Detection (CAD) System for Microcalcifications in Mammograms – MammoScan μCaD.**, INTERNATIONAL JOURNAL OF BIOMEDICAL SCIENCES VOLUME 2 NUMBER 3, ISSN 1306-1216, 2007.
3. Anna E. Schmaus-Klughammer, **Improving Breast and Cervical Cancer Screening in Developing Countries Using Telemedicine**, Klughammer GmbH, Ulrichsbergerstrasse 17, Deggendorf 94469, Germany **http://www.medetel.lu/download/2013/parallel_sessions/abstract/day1/Improving_Breast.pdf**
4. Zilliacus EM, Meiser B, Lobb EA, Kirk J, Warwick L, Tucker K. **Women's experience of telehealth cancer genetic counseling**. http://www.ncbi.nlm.nih.gov/pubmed/20411313
5. Jawad Nagi, Sameem Abdul Kareem, Farrukh Nagi, Syed Khaleel Ahmed, **Automated Breast Profile Segmentation for ROI Detection Using Digital Mammograms**, 2010 IEEE EMBS Conference on Biomedical Engineering & Sciences (IECBES 2010), Kuala Lumpur, Malaysia, 30th November - 2nd December 2010.
6. S.Saheb Basha, DR.k.sayta Prasad; **AUTOMATIC DETECTION OF BREAST CANCER MASS IN MAMMOGRAMS USING MORPHOLOGICAL OPERATORS AND FUZZY C –MEANS CLUSTERING.** Journal of Theoretical and Applied Information Technology © 2005 - 2009 JATIT.
7. Edward Guillén, Jenny Ubaque, Leonardo Ramirez and Yaneth Cardenas. **Telemedicine Network Implementation with SOA Architecture: A Case Study**. Proceedings of the World Congress on Engineering and Computer Science 2012 Vol I. WCECS 2012, San Francisco, USA, September- October 2012.
8. S. Bouyahia, J. Mbainaibeye, N. Ellouze *Ecole Nationale d'Ingenieurs de Tunis, ENIT, BP37, Tunis le Belvédère 1002 Tunis, Tunisia,* **"Wavelet Based Microcalcifications Detection in Digitized Mammograms",** ICGST-GVIP Journal, ISSN 1687-398X, Volume (8), Issue (V), January 2009.
9. G. K. Kharate, "**Image Compression Using Wavelet Packet Tree**", ICGST-GVIP Journal, Volume (5), Issue (7), July 2011.
10. Janaki. R , and Dr.Tamilarasi.A , **"Still Image Compression by Combining EZW Encoding with Huffman Encoder"**, *International Journal of Computer Applications (0975 – 8887)Volume 13– No.7,* January 2011.
11. Jawad Nagi, Sameem Abdul Kareem, Farrukh Nagi, Syed Khaleel Ahmed**, "Automated Breast Profile Segmentation for ROI Detection Using Digital Mammograms",**2010 IEEE EMBS Conference on Biomedical Engineering & Sciences (IECBES 2010), Kuala Lumpur, Malaysia, 30th November - 2nd December 2010.
12. Kjersti Engan, Thor Ole Gulsrud, Karl Fredrik Fretheim, Barbro Furebotten Iversen, Liv Eriksen, **"A Computer Aided Detection (CAD) System for Microcalcifications in Mammograms – MammoScan μCaD"**, INTERNATIONAL JOURNAL OF BIOMEDICAL SCIENCES VOLUME 2 NUMBER 3, ISSN 1306-1216, 2007.
13. R.Ramani, Dr.S.Suthanthiravanitha, S.Valarmathy. **A Survey Of Current Image Segmentation Techniques For Detection Of Breast Cancer**. International Journal of Engineering Research and Applications (IJERA) ISSN: 2248-9622 www.ijera.com , Vol. 2, Issue 5, , pp.1124-1129, September- October 2012.
14. D. narvain ponraj,m.evangelin , jenifer,p.poongodi,j.samuvel manoharan.a survey on the pre-processing techniques of mammogram for the detection of breast cancer, journal of emerging trends in computing and information sciences.vol 2,no:12,December 2011.
15. Jwad nagi automated breast profile segmentation for ROI detection using digital mammogram IEEE EMBS confrerence on bio-medic al engineering and sciencesx, kuala lumpur, September- October 2012.
16. Junn shan wen ju,yanhui, guoa, ling zhang, h.d.cheng. automated breast cancer detection and classification using ultrasound images-a survey. Pattern recognition 43, 299-317, 2010.
17. Dr.samir kumar bandhyopathyway,tuhinutsab paul,segmentation of brian MRI images research in computer science and software engineering,volume 2,issue 3,march, issn;2277 128x, 2012.
18. T. Kanungo. D.M Mount ,N.Netanyahu,C.Piatko,R.Silverman and A.Y.wa.,An efficient k-means clustering algorithms,analysis and implementation proc.IEEE conference computer vision and pattern recognition pp.881-892, 2002.

19. Bhagwati charanpatel, Dr.G.R.sinha, an adaptive k-means cluster algorithms for breast image segmentation, international journal of computer applications(0975-8887),vol 10-n 4 ,nov-2010.