QUANTITATIVE EVALUATION OF AN AUTOMATED CONE-BASED BREAST ULTRASOUND SCANNER FOR MRI–3D US IMAGE FUSION

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ABSTRACT

Breast cancer is one of the most diagnosed types of cancer worldwide. Volumetric ultrasound breast imaging, combined with MRI can improve lesion detection rate, reduce examination time, and improve lesion diagnosis. However, to our knowledge, there are no 3D US breast imaging systems available that facilitate 3D US – MRI image fusion. In this paper, a novel Automated Cone-based Breast Ultrasound System (ACBUS) is introduced. The system facilitates volumetric ultrasound acquisition of the breast in a prone position without deforming it by the US transducer. Quality of ACBUS images for reconstructions at different voxel sizes (0.25 and 0.50 mm isotropic) was compared to quality of the Automated Breast Volumetric Scanner (ABVS) (Siemens Ultrasound, Issaquah, WA, USA) in terms of signal-to-noise ratio (SNR), contrast-to-noise ratio (CNR), and resolution using a custom made phantom. The ACBUS image data were registered to MRI image data utilizing surface matching and the registration accuracy was quantified using an internal marker. The technology was also evaluated in vivo. The phantom-based quantitative analysis demonstrated that ACBUS can deliver volumetric breast images with an image quality similar to the images delivered by a currently commercially available Siemens ABVS. We demonstrate on the phantom and in vivo that ACBUS enables adequate MRI-3D US fusion. To our conclusion, ACBUS might be a suitable candidate for a second-look breast US exam, patient follow-up, and US guided biopsy planning.

Keyword : - *Breast, phantom, image fusion, image quality, 3D US.*

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1. INTRODUCTION

Breast cancer is one of the most diagnosed type of cancer and the second cause of cancer death in the female population. Furthermore, one has to realize that 4% of invasive breast cancers is diagnosed in women under 40 years old. Several studies show that breast cancer in young women is more aggressive than in women over 40 years old. Many of these cancers occur in women at increased risk, who are annually screened. However, mammography has poor performance in this group since breast tissue is much denser than in older women. Consequently, other techniques, particularly contrast enhanced breast MRI,are recommended for adequate diagnosis of women at a high risk.

Breast examination includes most of the time an ultrasound (US) examination. It is a popular low-cost imaging modality for breast cancer detection due to its high usability and sensitivity. US is the most cost-effective tool for biopsy guidance and therapeutic monitoring. US is often used as a complementary screening tool, as well as a second-look imaging modality for otherwise detected abnormalities. The second-look 2D US examination has a high clinical value as an add-on to MRI. Several studies demonstrated that the sensitivity and specificity for tumor detection are improved by enabling the correlation between the lesions' appearances in US and MRI. It drives the decision on further patient management leading either to biopsy or follow-up avoiding over-diagnosis and, consequently, over treatment. However, 2D US imaging is limited by the field of view, operator-dependency, and low reproducibility that complicates patient follow-up. Furthermore, examination is required to be performed by a radiologist familiar with MRI to image the corresponding region.

Volumetric US imaging does not have the above mentioned shortcomings. It is increasingly being used in breast imaging. Compared to 2D Breast US, 3D Breast US depends less on the operator and also reduces examination time. It gives a better anatomic overview of the breast interior and facilitates quantitative volumetric lesion analysis. Furthermore, it substantially simplifies follow-up of patients with lesions, clearly visible in US. Therefore, a volumetric ultrasound breast imaging system that also enables MRI – 3D US image fusion will provide better breast diagnosis by reducing operator-dependency, improving robustness of the second-look US examination and follow-up. There are several ultrasound systems available that facilitate breast volumetric imaging. A 3D Breast US acquisition utilizing the ACUSON S2000 Automated Breast Volume Scanner (ABVS) (Siemens Ultrasound, Issaquah, WA,USA) is performed by translating a 2D ultrasound transducer over a breast while a woman is in the supine position. The 2D images are stacked to form a volume afterwards. A similar approach is used in the Invenia Automated Breast Ultrasound System (ABUS) that employs a concave ultrasound transducer array (Invenia ABUS, GE Healthcare, Sunnyvale, CA, USA). Shipley et al. described a system for volumetric imaging of the breast with women in prone-position using a conical container with a conventional linear 38 mm transducer array [20]. The cone's angle was 45◦ and the breast was deformed by the container during the scanning procedure. The Sofia system (Hitachi Medical Systems GmbH, Wiesbaden, Germany) uses an US transducer array also at a slight angle revolving around the prone breast, positioned in the semi-spherical cap, deforming the breast. The benefit of the Sofia system as well as the system described by Shipley is that women are scanned in prone position, which implies that the geometry of the breast more closely resembles that of the breast during MRI scanning than with the two systems that scan in the supine position. All above mentioned systems, however, perform breast scanning while the breast is in a highly deformed state, making the fusion between MRI and 3D US data challenging and requiring the use of sophisticated registration and fusion techniques. Such so-called deformable models have already been implemented to register MRI to X-ray mammograms, which are typically acquired while compressing the breast between two plates. Another study describes a registration method facilitating prone to supine breast registration. However, in both cases the boundary conditions such as the pressure between plates or the gravitational force are known. Unfortunately, the boundary conditions for current volumetric ultrasound devices are unknown, which makes the application of deformable models challenging. To our knowledge there are no studies published that report a successful registration between prone MRI and volumetric ultrasound breast images acquired with one of the above mentioned devices. An alternative ultrasound-based breast imaging modality is ultrasound computed tomography (USCT). USCT facilitates visualization of the speed of sound, ultrasound transmission coefficient, and attenuation of the breast tissue resulting in high sensitivity to detect lesions, comparable to MRI [24]. Several fully operational clinical and research prototypes that enable USCT have already been developed: USCT II described by Ruiter et al. in, a ring 3D ultrasound system from Liu et al., and a quantitative breast tissue tomography device from Wiskin et al. Furthermore, there are at least two commercially available USCT systems: the
SoftVue system (Delphinus Medical Technologies, Inc, Novi, MI, USA), and the QT Ultrasound system (QT Ultrasound LLC, Novato, CA, USA). For all above mentioned USCT systems, the patient is in prone position on the examination bed with the breast inside a cup filled with water as a coupling medium. To our knowledge, there is no study about USCT published that demonstrates successful MRI – 3D US image fusion. Besides, USCT is currently still a non-real time modality which impedes its usage in applications for therapeutic control or surgical navigation. In this paper, we describe and evaluate a novel Automated Cone-based Breast Ultrasound System (ACBUS) that acquires volumetric ultrasound data of the breast in a prone position with only minor deformation, thus facilitating MRI – 3D US fusion. The great benefit of this approach is that the breast position is similar to the MRI acquisition. The performance of the ACBUS in terms of image quality was evaluated quantitatively utilizing a custom-developed phantom and compared with the image quality obtained with a conventional S2000 ABVS. Finally, the technology was evaluated in vivo on a volunteer with a diagnosed cyst and a fibroadenoma.

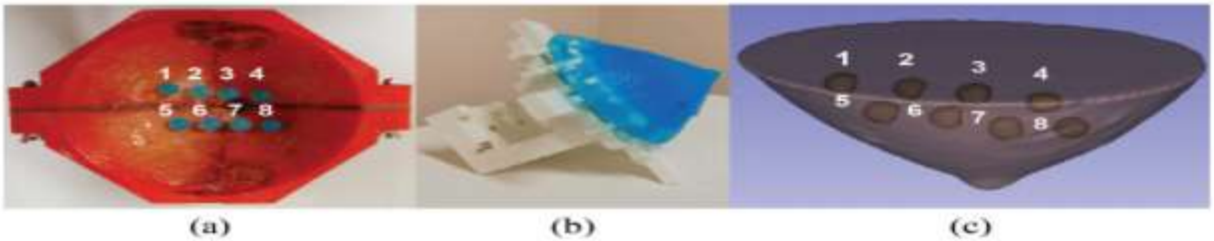

Fig. 1. Design of the QBP. (a) The lesions fixed inside the breast mold. (b) The manufactured QBP. (c) A rendered MRI image of the QBP.

2. RELATED WORKS

Siyabend Turgut et al., “Microarray Breast Cancer Data Classification Using Machine Learning Methods” : The paper uses microarray breast cancer data for classification of the patients using machine learning methods. In the first case, eight different machine learning algorithms are applied to the dataset and the results of classification were noted. Then in the second case, two different feature selection methods such as Recursive Feature Elimination (RFE) and Randomized Logistic Regression (RLR) were applied on the microarray breast cancer dataset and 50 features were chosen as stop criterion. Again, the same eight machine learning algorithms were applied on the modified dataset. The results of the classifications are compared with each other and with the results of the first case. The methods applied are SVM, KNN, MLP, Decision Trees, Random Forest, Logistic Regression, Ad boost and Gradient Boosting Machines. After applying the two different feature selection methods, SVM gave the best results. MLP is applied using different number of layers and neurons to examine the effect of the number of layers and neurons on the classification accuracy.

Varalatchoumy M et al., “Four Novel Approaches for Detection of Region of Interest in Mammograms - A Comparative Study” : The paper compares Four Novel approaches used for detection of Region of Interest in Mammographic images based on database and Real time images. In Approach I histogram equalization and dynamic thresholding techniques were used for preprocessing. Region of Interest (ROI) was partitioned from the preprocessed image by using particle swarm optimization and kmeans clustering methods. In Approach II preprocessing was done using various morphological operations like erosion followed by dilation. For the identification of ROI, a modified approach of watershed segmentation was used. Approach III uses histogram equalization for preprocessing and an advanced level set approach for performing segmentation. Approach IV, which is considered to be the most efficient approach that uses different morphological operations and contrast limited adaptive histogram equalization for image preprocessing. A very novel algorithm was developed for detection of Region of Interest. Approaches I and II were applicable for Mammographic Image Analysis Society (MIAS) database images alone. Approaches III and IV were applicable for MIAS and Real time hospital images. The various graphs presented in the comparative study, clearly depicts that the novel approach that used a novel algorithm for detection of ROI is proved to be the most efficient, accurate and highly reliable approach that can be used by radiologists to detect tumors in MRM images.

Ammu P K et al., “Review on Feature Selection Techniques of DNA Microarray Data” : This paper reviews few major feature selection techniques employed in microarray data and points out the merits and demerits of various approaches. Feature selection from DNA microarray data is one of the most important procedures in bioinformatics. Biogeography Based Optimization (BBO) is an optimization algorithm which works on the basis of migration of species between different habitats and the process of mutation. Particle Swarm Optimization (PSO) is an algorithm which works on the basis of movement of particles in a search space. Redundancy based feature selection approaches can be used to remove redundant genes from the selected genes as the resultant gene set can achieve a better representation of the target class. A two-stage hybrid filter wrapper method where, in the first stage a subset of the original feature set is obtained by applying information gain as the filtering criteria. In the second stage the genetic algorithm is applied to the set of filtered genes. Gene selection based on dependency of features where the features are classified as independent, half dependent and dependent features. Independent features are those features that doesn't depend on any other features. Half dependent features are more relevant in correlation with other features and dependent features are fully dependent on other features.

Bing Lan Li et al., "Integrating spatial fuzzy clustering with level set methods for automated medical image segmentation" : A new Fuzzy Level Set algorithm is proposed in this paper to facilitate automated medical image segmentation. It can directly evolve from the initial segmentation by spatial fuzzy clustering where centroid and the scope of each subclass are estimated adaptively in order to minimize a pre-defined cost function. The controlling parameters of Level Set evolution are also estimated from the results of fuzzy clustering. The level set methods utilize dynamic variational boundaries for image segmentation. The new Fuzzy Level Set algorithm automates the initialization and parameter configuration of the level set segmentation, using spatial fuzzy clustering. It employs a Fuzzy-C means (FCM) with spatial restrictions to determine the approximate contours of interest in a medical image. Moreover, the Fuzzy Level Set algorithm is enhanced with locally regularized evolution. Such improvements facilitate level set manipulation and lead to more robust segmentation. Performance evaluation of the proposed algorithm was carried on medical images from different modalities. The results confirm its effectiveness for image segmentation..

3. CONCLUSIONS

Breast Cancer represents one of the diseases that makes highest number of deaths every year. At present, only few accurate prognostic and predictive factors are used clinically for managing the patients with breast cancer. Here, by making use of Clustering with Level Set approach, high accuracy can be achieved in detection of effected cell shapes with exact marking on detected contours. The proposed system helps to enhance the performance of mammogram retrieval by selecting optimal features.

The Fuzzy-C-means (FCM) clustering has been used for Image segmentation. Each data point belongs to multiple clusters with varying degrees of membership, and it is based on the objective function. The segmented region is completely analyzed by using the Multi-level Discrete Wavelet Transform, Principal Component Analysis (PCA) along with Gray Level Cooccurrence Matrix (GLCM) features. Totally 13 features are extracted and their pixel values in the form of matrix is stored in database. After the features are extracted & completely trained the system classifies the image into Benign, Malignant and Normal using the KNN classifier technique which mainly depends on the shape of the cancer cells in the image.

By performing suitable morphological operations, system computes the suitable region properties such as Area, Euler number etc., and displays the boundary detected image along with the tumor area. These techniques improve accuracy in tracking the breast cancer cells. To assess the correctness in classifying data with respect to efficiency and effectiveness of each algorithm in terms of accuracy, precision, sensitivity, and specificity. Hence the design is to provide high accuracy and maximum efficiency in prediction and tracking of breast cancer. The combination of Multi-Level Wavelet Conversion strategy associated to PCA with 13 features extracted and then classified gives an average accuracy of nearly 92%.

As a future improvement, the system can add more features such as recommendation of medicines/treatments based on the severity of the patient. This prediction and recommendation system can help doctors to diagnose and cure the disease more efficiently.

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