

Multimodality imaging and state-of-art GPU technology in discriminating benign from malignant breast lesions on real time decision support system

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Abstract. The aim of this study was to design a pattern recognition system for assisting the diagnosis of breast lesions, using image information from Ultrasound (US) and Digital Mammography (DM) imaging modalities. State-of-art computer technology was employed based on commercial Graphics Processing Unit (GPU) cards and parallel programming. An experienced radiologist outlined breast lesions on both US and DM images from 59 patients employing a custom designed computer software application. Textural features were extracted from each lesion and were used to design the pattern recognition system. Several classifiers were tested for highest performance in discriminating benign from malignant lesions. Classifiers were also combined into ensemble schemes for further improvement of the system's classification accuracy. Following the pattern recognition system optimization, the final system was designed employing the Probabilistic Neural Network classifier (PNN) on the GPU card (GeForce 580GTX) using CUDA programming framework and C++ programming language. The use of such state-of-art technology renders the system capable of redesigning itself on site once additional verified US and DM data are collected. Mixture of US and DM features optimized performance with over 90% accuracy in correctly classifying the lesions.

1. Introduction

Breast cancer is the most frequent malignant tumour among women. Diagnostic mammography (DM) is the leading imaging protocol for screening of breast tumours [1]. Among the most important signs indicating the presence of malignant lesions in mammograms is the existence of masses, microcalcifications (mCs) and clusters of mCs [2]. However, in diagnostically difficult cases, such as in early stage cancer, the differentiation between normal and abnormal mammograms is not straightforward due to the complexity of the composition of breast tissues, which might lead to misinterpretations for up to 30% of the cases [3, 4]. Moreover, DM is among the projection radiological protocols with the highest dose profiles, although modern systems have reduced the dose profile. The above reasons have evoked attempts to propose different imaging modalities that would a/ replace and/or improve diagnostic mammography and b/ reduce overall dose. Such imaging modalities are the Magnetic Resonance Imaging (MRI) and the Ultrasonography (US) [5, 6]. MRI offers a competitive alternative to DM, however, the cost and the complexity of the exam is still one major



drawback. US, on the other hand, offers a non-ionizing alternative with low cost and complementary information to DM [7]. In this study we attempt to investigate the nature of this complementary information of US with respect to DM by means of pattern recognition system design for discriminating benign from malignant cancer cases.

2. Material and Methods

2.1. Material

Clinical material comprised 59 patients that underwent both DM and US examinations, which were conducted by the same experienced radiologist (N.D.). Twenty nine (29) cases were diagnosed as malignant whereas thirty (30) as benign. All patients were examined at the Department of Radiology of the Delta Digital diagnostic center, Athens, Greece.

2.2. Methods

An experienced radiologist outlined breast lesions on both US and DM images from 59 patients employing a custom designed computer software application (Figure 1). Textural features were extracted from each segmented lesion (Figure 2) and were used to design the pattern recognition system. These features comprised four (4) from the lesion's grey-tone histogram, twenty-six (26) from the lesion's co-occurrence matrix [8] and 10 from the lesion's run-length matrix [9]. Thus, eighty (80) features were computed for each case (patient), forty (40) from the segmented DM lesion and forty (40) from the segmented US lesion.

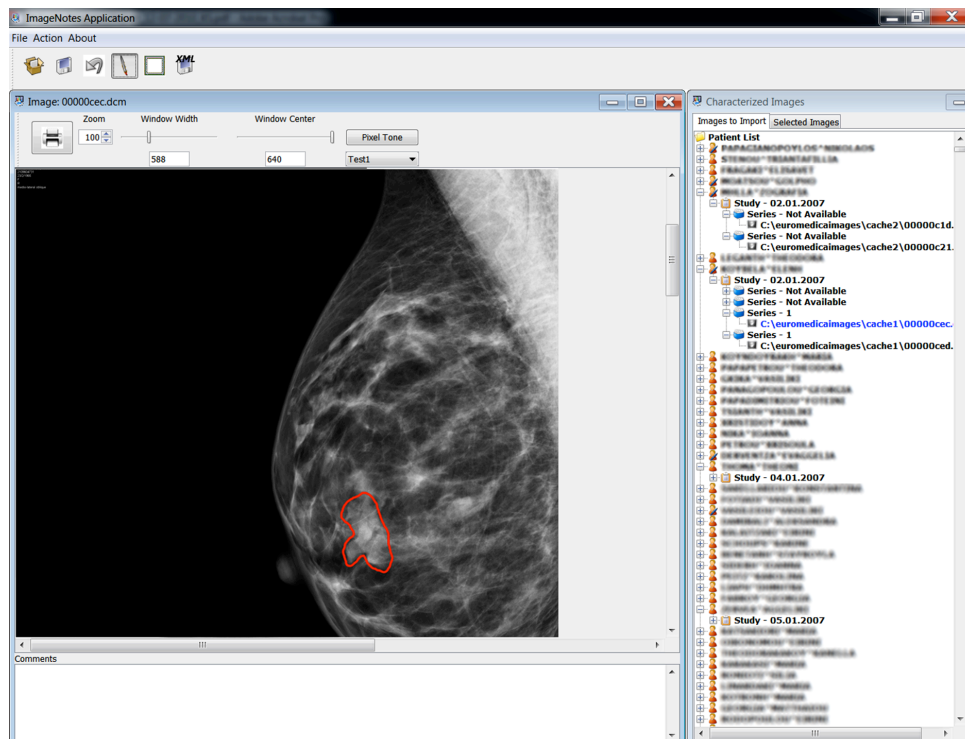


Figure 1. Custom designed software for breast lesion delineation

Three classifiers were tested (Support Vector Machines [10], k-Nearest Neighbor [11] and Probabilistic Neural Network [12]) for highest performance and were also combined into ensemble schemes for further improvement of system classification accuracy. The exhaustive search and the Leave One Out method [11] were used for system performance evaluation. That meant that for each

possible feature for the total of 80 features used, a different classifier should be designed and tested giving about 3 billion different architectures if one was to search for combinations up to 7 features (more feature combinations were not tested to avoid over-fitting [11]). In order to make this computational problem practical and feasible, when optimizing the system (selecting the best classifier configuration) the accuracy was not the only criterion. Another, equally important criterion was the complexity and simplicity of the classifier configuration scheme. The only classifier tested that combined both criteria (accuracy improvement and design simplicity) was the Probabilistic Neural Network classifier (PNN), which was then designed on the GPU card (GeForce 580GTX) using CUDA programming framework and C++ programming language [13].

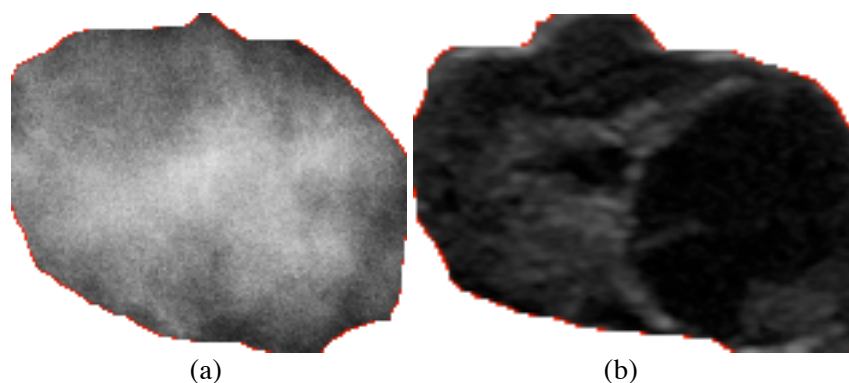


Figure 2. Segmented regions from a patient with benign lesion; (a) DM and (b) US images

To investigate whether the combination of features from both DM and US improves the overall accuracy of the system in distinguishing benign from malignant cases, the pattern recognition system was designed under three different scenarios: 1. using only DM features, 2. using only US features, 3. using both DM and US features.

3. Results and Discussion

Table 1 summarizes the results of the pattern recognition system for the three scenarios. Using only DM best accuracy (83%) was obtained with 8 features. Using only US best performance was 84.7% with 6 features. Using both DM and US overall accuracy was boosted to 93.2% with 7 features, 5 from the DM lesion and 2 from the US lesion. It has to be mentioned that there are no dependencies between the features of the two modalities since the physicians are treated separately. It was possible to examine so many combinations of features exhaustively only because the PNN classifier was applied on the GPU card. More specifically, it took about 2 hours on the 580GTX, in contrast to more than 24 hours required on the CPU, which in fact failed to complete after 24 hours when 7 features combinations were asked.

Table 1. Classification accuracies using the PNN classifier in discriminating benign from malignant breast tumours.

		DM	US	DM+US
Accuracies (%)	Benign	80.0	90.0	93.1
	Malignant	86.2	79.3	93.3
	Overall	83.1 (8 features)	84.7 (6 features)	93.2 (7 features)

The five DM features comprised the correlation^r, that is a measure of grey-level dependencies, the difference entropy^r, that is a measure of anisotropy in grey-level randomness, the short run emphasis^a, that indicates the existence of small structures within the lesion, the run percentage^a, that is related to

percentage of pixels that have the same grey-levels and the run percentage^r, where ^a and ^r stand for average and range over the four directions (0°, 45°, 90°, 135°). On the other hand, the two US features included the kurtosis and the run percentage^a. These results imply four main issues: a/ The texture of lesions in both DM and US images contain useful information regarding the malignancy of suspected tumours and may be used to discriminate benign from cancerous formations. b/ It is well known that morphology play a crucial role in the characterization of lesions, however, this study suggests that also the spatial homogeneity encoded by the textural features used, might be a strong, and perhaps complementary indicator for diagnosis. c/ The feature run percentage appears as important for both US and DM. This feature takes lower values for smooth textures, whereas its value increases for unsystematic distributions. Table 2 present the average feature values concerning benign and malignant for both modalities.

Table 2. The mean values and the standard deviation of the Run Percentage feature for different modalities.

Run Percentage/Modality	DM	US
Benign	0.48±0.06	0.22±0.10
Malignant	0.45±0.11	0.37±0.17

Thus, it may be speculated that benign tumours in DM present a coarser texture (many small runs, i.e. small homogeneous structures such as microcalcifications) as compared to malignant tumours, which are characterized by larger, smoother structures (large runs, i.e. masses). On the other hand, in US a different behaviour is observed regarding the values of the Run Percentage feature. Figure 2 visualizes such behaviour, since it is quite obvious that the benign lesion in the DM image is more homogeneous in terms of texture as compared to the benign lesion in the US image. Benign cases in US presented smaller values compared to malignant cases, indicating that the texture is coarser for malignant cases in US. d/ The combination of information from both DM and US boosts up the performance in discriminating the nature of the tumours, thus, it may be claimed that US gives complementary information to DM and should be further investigated not only as an additional protocol for screening of breast cancer, but as an essential prerequisite to DM that should be performed along with DM.

Acknowledgments

This research has been co-financed by the European Union (European Social Fund – ESF) and Greek national funds through the Operational Program "Education and Lifelong Learning" of the National Strategic Reference Framework (NSRF) - Research Funding Program: **ARCHIMEDES III**. Investing in knowledge society through the European Social Fund.

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