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Breast DCE-MRI Segmentation for Lesion Detection Using Grammatical Fireworks Algorithm

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1. Abstract

Breast DCE-MRI segmentation and lesion detection is a crucial image analysis task for cancer detection and tissue characterization. In this paper, a hard-clustering technique with Grammatical Fireworks algorithm (GFWA) is proposed to segment the breast MR images for lesion detection. GFWA is Swarm Programming (SP) method developed for automatic computer program generation in any arbitrary language. In this paper, GFWA is used to generate the cluster center for clustering the breast MR images. The segmentation process faces difficulties due to the presence of noise and intensity inhomogeneities in MR images. Therefore, at the outset, the MR images are denoised and intensity inhomogeneities are corrected in the preprocessing step. The preprocessed MR images are segmented using the proposed GFWA-based clustering technique. Finally, the lesions are extracted from the segmented images. The proposed method is applied to 10 DCE-MRI slices. The experimental results of the proposed method are compared with that of Grammatical Swarm (GS)-based clustering technique and K-means algorithm. Both quantitative and qualitative results demonstrate that the proposed method performs better than other methods.

2. Introduction

According to World Health Organization (WHO)'s report (WHO cancer prevention diagnosis screening breast cancer, https://www.who.int/cancer/prevention/diagnosisscreening/ breast-cancer/en/), it is estimated that 6,27,000 women in the world have died from breast cancer and it is approximately 15% of all types of cancer deaths among women in 2018. Breast cancer is the most common cancer in women in India and accounts for 14% of all cancers in women [1, 2]. Organized and opportunistic screening programs in the developed countries result in a significant decrease in mortality caused due to breast cancer [3]. Recently, dynamic contrast-enhanced magnetic resonance imaging (DCE-MRI) is widely used for breast cancer detection, diagnosis, and treatment planning or surgery. Several methods have been developed for lesion detection and its characterization in breast DCE-MRI in the recent past. [4] proposed a fuzzy c-means (FCM) clustering-based segmentation method for the detection of breast lesions in 3D DCE-MR images. FCM was applied to an enhanced region of interest (ROI) selected by a human operator manually. After clustering, binarization of the lesion membership map was done and lesions were finally selected followed by connected- omponent labeling [5]. developed a lesion segmentation and characterization methodology. First, Laplacian filter was used to enhance the lesions in ROI selected by a human operator manually. Then, extracted morphology and texture features from lesions were utilized for characterization in benign and alignant lesions using a Multilayer perceptron (MLP) [6]. developed a breast tumor analysis method using texture features and discrete wavelet transform (DWT). First, the active contour model was to segment the breast lesions in DCE-MRI. Texture features were extracted from segmented lesions and DWT was applied to the temporal texture features to extract the frequency characteristics from the lesion kinematics. Finally, the committee of support vector machines (SVM) for the classification. A Markov Random Field (MRF) model-based lesion segmentation in breast DCE-MRI was proposed in [7]. In this method, the first subtraction image was generated by subtracting a pre- contrasted image from 1st post-contrast image, and then ROI was selected from the subtraction image. The Iterative Conditional Mode (ICM) method was used to obtain the maximum a posteriori (MAP) estimate of the class membership of lesion and non-lesion [8]. proposed Improved Markov Random Field (IMRF) for lesion segmentation in breast DCE-MRI. The prior distributions of the class members were modeled as a ratio of conditional probability distributions of similar pixels and non-similar ones in a neighborhood. An adaptive moment preserving method was proposed by [9] (Wei et al., 2012) to segment the fibroglandular tissue in breast DCE-MRI. [10] (Chang et al., 2012) developed a computer-aided diagnosis (CAD) system for the characterization of breast mass lesions in benign and malignant breast tumors in DCE-MRI. [11] (Jayender et al., 2013) developed a statistical learning algorithm for tumor segmentation using Hidden Markov Models (HMMs) to auto-segment the angiogenesis corresponding to a tumor in breast DCE-MRI. [12] (Wang et al., 2013) proposed a hierarchical SVM-based segmentation method for breast DCE-MRI. 3D multi-parametric features from T1-weighted (T1-w), T2-weighted (T2-w), PD-w, and three-point Dixon water-only and fat-only MRIs were used as inputs to the SVM to classify the breast tissues into fatty, fibroglandular, lesion, and skin. [13] (Milenkovi´c et al., 2013) applied logistic regression, the least-square minimum-distance classifier (LSMD), and least-squares support vector machine (LS-SVM) classifiers on breast DCE-MRI for classification of malignant and benign breast lesions in the breast. [14] (McClymont et al., 2014) used mean-shift and graph-cuts algorithm for breast lesion segmentation in DCE-MRI. (Wang et al., 2014) used modifying FCM for clustering for breast tumor segmentation in DCE-MRI and further lesions are characterized using a pharmacokinetic model. A computer-aided detection auto probing (CADAP) system was developed by [15] (Sim et al., 2014) for lesion detection in breast DCE-MRI utilizing a spatial-based discrete Fourier transform and further characterized in benign, suspicious, or malignant.

As per the best knowledge of the authors, the hard or partitional clustering technique with metaheuristic algorithms is not used in the segmentation of breast DCE-MRI. This motivates to development a hard-clustering technique with Grammatical Fireworks algorithm(GFWA) [17] (Si, 2015a) to segment the breast MR images for lesion detection in this paper. GFWA is Swarm Programming (SP) method developed for automatic computer program generation in any arbitrary language. Here, GFWA is used to generate the cluster center for clustering the breast MR images.

3. Contribution of this Article

Now, contributions of this article may be summarized as follows:

1. A GFWA-based segmentation methodology for breast lesion detection in DCE-MRI is proposed. A hard-clustering technique with GFWA is proposed to segment the breast DCE-MRI.
2. GFWA is not used previously in the segmentation of breast DCE-MRI as well as in any kind of image segmentation. Hence, the application of GFWA in breast lesion detection is another novelty of this article.
3. Finally, a comparative study of the proposed method is made with Grammatical Swarm based clustering technique [16, 18] (Si et al., 2014, 2015b) and K-means algorithm [19] (MacQueen, 1967).

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