Total Variation based Edge Enhancement for Level Set Segmentation and Asymmetry Analysis in Breast Thermograms

Prabha S, Anandh K R, Sujatha C M and Ramakrishnan S

Abstract—**In this work, an attempt has been made to perform asymmetry analysis in breast thermograms using non-linear total variation diffusion filter and reaction diffusion based level set method. Breast images used in this study are obtained from online database of the project PROENG. Initially the images are subjected to total variation (TV) diffusion filter to generate the edge map. Reaction diffusion based level set method is employed to segment the breast tissues using TV edge map as stopping boundary function. Asymmetry analysis is performed on the segmented breast tissues using wavelet based structural texture features. The results show that nonlinear total variation based reaction diffusion level set method could efficiently segment the breast tissues. This method yields high correlation between the segmented output and the ground truth than the conventional level set. Structural texture features extracted from the wavelet coefficients are found to be significant in demarcating normal and abnormal tissues. Hence, it appears that the asymmetry analysis on segmented breast tissues extracted using total variation edge map can be used efficiently to identify the pathological conditions of breast thermograms.**

Keywords— Breast thermogram; Total variation; Reaction diffusion; asymmetry analysis.

I. INTRODUCTION

Breast cancer is the most frequently diagnosed cancer which accounts for 30% of all cancers in women. The survival rate of breast cancer patients can be improved by proper screening and early diagnosis of the disease. Thermal infrared imaging has great potential for early cancer detection and prognosis indication, used either independently or in conjunction with mammography [1]. It is a non invasive functional imaging method which records thermal patterns emitted by human skin in the form of images called thermograms.

It has been confirmed by many clinical studies that the temperature distribution of normal healthy people is almost symmetrical [1].

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However, this thermal symmetry is lost when the functional behaviour of a breast changes. The asymmetrical temperature distribution between left breast and right breast could be a strong indicator of abnormality [2]. Segmentation and feature extraction are essential to carry out asymmetry analysis in breast thermograms. Low contrast, low signal to noise ratio and absence of clear edges leads to segmentation as a challenging task in breast thermograms. The inframammary folds and unclear lower breast boundaries make segmentation more complex.

Level set (LS) methods have been widely used as effective image segmentation methods as they are capable of capturing dynamic interfaces and always produce sub-regions with continuous boundaries [3]. The idea behind the LS is to represent a contour as the zero level set of a higher dimensional function and to formulate its motion as the evolution of the level set function. Re-initialization is periodically employed during its evolution to restore the stability and shape of the LS. However, practise of re-initialization poses serious problems in the implementation leading to numerical errors [4]. To overcome the re-initialization problem, LS evolution is improved by adding reaction and diffusion terms in the diffusion rate equation. This diffusion term regularizes the LS function to be piecewise constant and the reaction term ensures stable level set evolution [4].

In conventional level set method, edge map, which is extracted using Gaussian diffusion, is used as edge stopping function. This edge map appears to be blurred, discontinuous with less sharpness. Total Variation based non linear filtering which could preserve sharper boundaries and reduce undesired smoothing of the edges can be adopted for edge map extraction [5,6]. In this study, image gradients are actually modeled by laplacian distribution [7].

In thermal images, asymmetry analysis is significant in the identification of abnormality. Segmentation of breast tissues without breast loss particularly in lower breast boundaries and infra mammary folds is essential in asymmetry analysis. The asymmetric abnormalities can be identified by comparing the features extracted from the breast regions. Several statistical and fractal features are found to be useful features in identification of pathological conditions of breast tissues [8-10]. However, it is observed that such textural features which are derived based on local properties are not very prominent in improving the sensitivity of breast cancer diagnosis [11]. Wavelet produces multiresolution representation of texture image and extracts variations at different scales [12]. Structural texture analysis that could effectively extract local and global properties of the image is found to be useful in characterizing asymmetry of MR and mammography breast images [13, 14].

In this work, infrared (IR) breast images are subjected to reaction diffusion based level set method to segment desired region of interest. The edge map extracted using total variation filter is used as stopping boundary in this level set. Wavelet based structural texture features are extracted to analyze the asymmetry between normal and abnormal tissues.

II. METHODOLOGY

A. Image Database

Breast thermal images for this study are obtained from online database of the project PROENG (http://visual.ic.uff.br/proeng). FLIR ThermaCam S45 camera was used to capture images at University Hospital of Federal University of Pernambuco. The acquisition procedure and protocol details have already been reported elsewhere [15]. Twenty images that have pathologies either in left or right region are considered. Asymmetry analysis is carried out for these images using total variation based reaction diffusion level set method and wavelets.

B. Reaction Diffusion based level set method

Active contour models [16] are dynamic curves or surfaces that are represented as $C(s,t) : [0,1] \times [0,\infty) \rightarrow R^2$, $s \in [0,1]$ and $t \in [0,\infty]$. The curve or surface under evolution is given by

$$\frac{\partial C(s,t)}{\partial t} = F\,N \quad (1)$$

where F is the parameter to influence motion of the contour and N is the inward normal vector to the curve C. The general form of rate equation can be written as

$$\frac{\partial \phi}{\partial t} = Reg(\phi) + F\delta(\phi) \quad (2)$$

where $Reg(\phi) = \alpha\, div[r(\phi)\nabla\phi]$, $r(\phi)$ can be any existing conventional diffusion rate equations, α is a small constant and F is the force term. Although many diffusion rate equations exists, they do not give stable solution in the level set equation and thereby leading to boundary leakage problems. A new level set evolution method is derived by adding diffusion term "$\varepsilon\Delta\phi$" in the level set evolution (LSE) equation to provide stable solutions [17]. The constructed reaction diffusion rate equation is given by

$$\frac{\partial \phi}{\partial t} = \varepsilon\Delta\phi - \frac{1}{\varepsilon}L(\phi),\ x \in \Omega \subset R^n \quad (3)$$

where ε is a small constant, reaction term $\varepsilon^{-1}L(\phi) = F\delta(\phi)$ and Δ is the Laplacian operator.

In the active contour model, the force term F in the equation $L(\phi) = -F\delta(\phi)$ is given by

$$F = div\left(\frac{g\nabla\phi}{|\nabla I_\sigma|}\right) + vg \quad (4)$$

where v is constant and g is an edge indicator function, which is given by

$$g = exp\left(-\frac{(|\nabla I_\sigma|)}{k}\right) \quad (5)$$

where I_σ is the image obtained after smoothing. Smoothing is performed by convolving the original image with the Gaussian kernel of standard deviation σ and k>0 is a contrast parameter. Edge indicator function is used as the stopping criterion for LSF near the edges. Since Gaussian edge map is discontinuous and blurred, it is proposed to use the edge map obtained using TV based diffusion filtering.

C. Total Variation based Nonlinear Filtering

Total variational non-linear filter is a partial differential equation based image de-noising technique that uses variational approach of energy functional minimization. The classical TV minimization process of Rudin Osher Fatemi formulation [5] is given by

$$E_{TV} = \int_\Omega \left(|\nabla I| + \frac{1}{2}\lambda(I - I_0)^2\right) dxdy \quad (6)$$

where I_0 is the noisy input image, I is the TV norm of the input image and λ is the scalar fidelity term. The ϕ formulation is used to generalize this function and is given by

$$E_\phi = \int_\Omega \left(\phi|\nabla I| + \frac{1}{2}\lambda(I - I_0)^2\right) dxdy \quad (7)$$

An approximation of TV is obtained by standard discretization of the Euler Lagrange equation which is given [6] by

$$-F = div\left(\phi'(.)\frac{\nabla I}{|\nabla I|}\right) + \lambda(I_0 - I) = 0 \quad (8)$$

The final de-noised image I_{TV} is obtained by solving the above equation using steepest decent method. The edge map g is obtained by taking image gradient of the denoised image.

D. Feature extraction

Structural texture features such as coarseness, contrast and directionality are extracted from wavelet transform coefficients of the segmented breast tissues.

Coarseness is the granularity measurement of texture. The differences between pairs of non-overlapping moving average (E) wavelet subband coefficients in the horizontal and vertical directions for each pixel are computed. The best neighborhood size that maximizes E in either direction is determined. The global coarseness is calculated by averaging best neighborhood size over the entire wavelet coefficient sub-bands.

The global contrast is defined as the mean of all the local contrast values.

The frequency distribution of orientation of local edges against their directional angle which is a measure of degree of directionality is computed.

III. RESULTS AND DISCUSSION

A typical gray scale breast thermogram is shown in Fig. 1(a and b). The presence of carcinoma condition exhibits asymmetry pattern in the left breast region and this region is bright due to increase in local temperature. The original images are subjected to segmentation using total variation based reaction diffusion based level set method. The edge map generated using Gaussian and TV filters are shown Fig.1(c and d) respectively. It is observed that edge map obtained using Gaussian filter has discontinuous, low contrast and weak boundaries. This edge map is characterized by the presence of numerous spurious edges in the inner breast regions. Also, poor edge pattern is observed in inframammary fold regions.

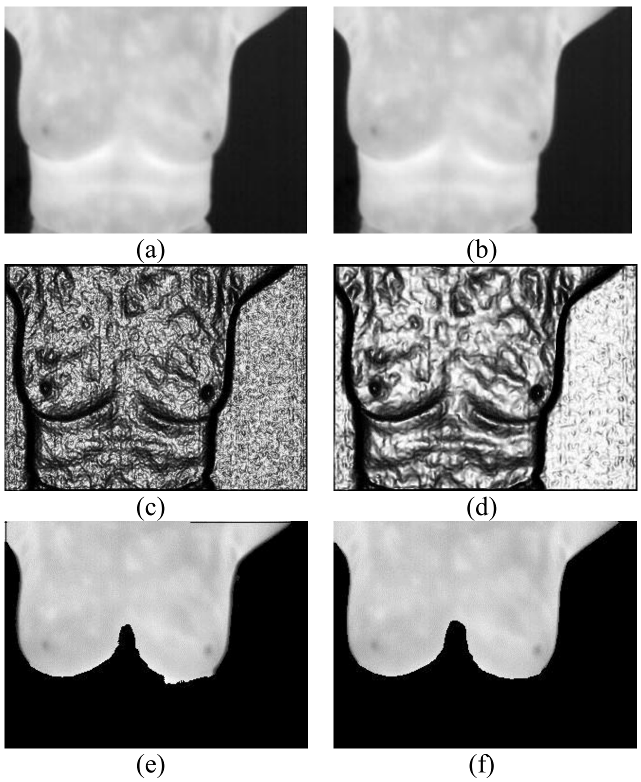

Fig.1 (a-b) Typical breast images, (c) Gaussian edge map, (d) TV edge map, (e) Segmented breast tissue using Gaussian edge map and (f) Segmented breast tissue using TV edge map

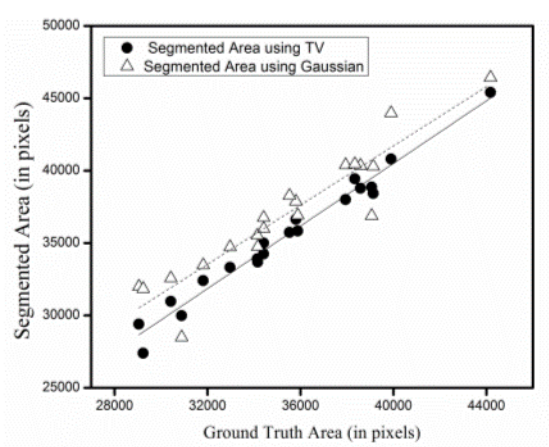

Fig. 2 Variation of segmented area with ground truth area

The optimal values of process parameters chosen for the edge map extraction using TV based non linear diffusion filtering are time step of 0.2, the gradient regularization parameter Ɛ of 1 and the fidelity term λ of zero to maintain regular smoothing over different regions.

This edge map is found to be distinct and has sharp boundaries. The map depicts more localized edges in the mid inframammary folds and lower breast regions. The absence of spurious edges illustrates that TV filter performs smoothing and also effectively enhance the edges. The edge map generated using Gaussian and TV filters are used as stopping boundary for the level set function to evolve towards the desired boundaries.

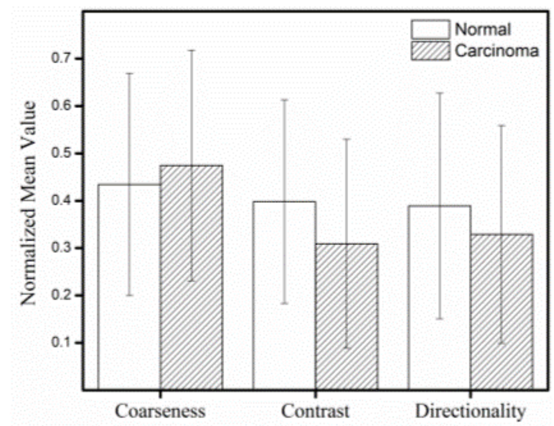

Fig.3. Normalized mean value of features for Gaussian based RD level set

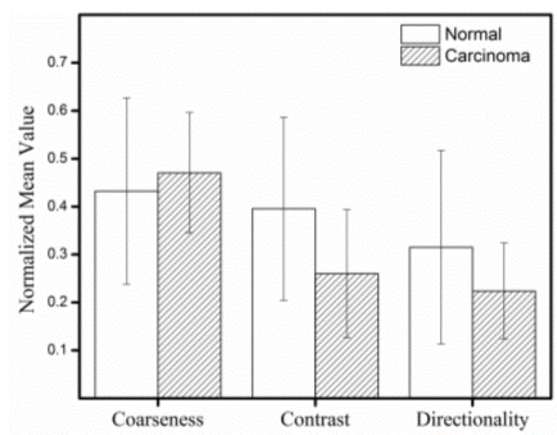

Fig.4. Normalized mean value of features for TV based RD level set

The initial contour of the level set function shrinks towards the breast tissues during the level set evolution. The value of α is fixed at 0.15 to move the contour towards the region of interest. The segmented breast tissues using Gaussian and TV edge maps are shown in Fig. 1(e and f). It is found that TV based level set could extract breast tissues with distinct and clear boundary.

The variations of area of segmented breast tissues extracted using total variation and Gaussian edge maps with that of the Ground truth image is plotted in Fig. 2. The segmented breast tissue extracted using Gaussian edge map is found to have weak boundary leakage. The segmented area of TV based level set is linear and high correlation (0.99) indicating the better performance of this segmentation method.

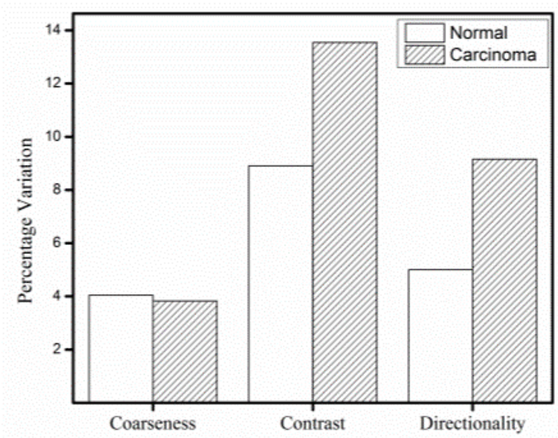

Fig.5. Variation (%) in feature values for Gaussian and TV based level set

Left and right regions are delineated using midpoint of inframammary folds. The normalized mean values and standard deviation of structural texture features such as coarseness, contrast and directionality extracted from the wavelet coefficients using Gaussian based RD level set are plotted in Fig. 3.

The values of contrast and directionality are found to be high for normal when compared to carcinoma subjects. This may due to loss of orientation of the thermal patterns associated with pathological conditions. The normalized mean values of structural features for TV based RD level set are shown in Fig.4. These features are found to be low for the carcinoma subjects indicating the high metabolic activity caused by the severe pathology. The contrast and directionality features are used to be significant in differentiating the abnormal breast tissues due to the presence of heterogeneous patterns.

The significance of asymmetry analyzed by evaluating the absolute difference between the features of segmented breast tissues extracted using total variation edge map and gaussian edge map is shown in Fig.5. The contrast and directionality feature have enhanced the value between normal and carcinoma by 4%.

IV. CONCLUSION

In this paper, reaction diffusion based level set method is employed to segment the breast tissues using TV edge map. The right and left breast tissues are separated on the segmented images for asymmetry analysis.

The obtained results are analyzed for normal and abnormal conditions. It is observed that TV edge map preserves clear edges in the mid inframammary folds and lower breast regions. The segmented area of TV based level set is linear and high correlation (0.99) indicating the better performance of this segmentation method. The values of structural texture features namely, contrast and directionality are found to be distinct for normal and carcinoma tissues. This study seems to be clinically useful for the mass screening of breast cancer detection and automated analysis such as content based image retrieval.

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