Mammographic Masses Segmentation Using Implicit Deformable Models: The LCV Model in Comparison with the Osher-Sethian Model

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***Abstract*—Breast cancer is one of the leading causes of cancer death among women. As such, the role of digital mammographic screening is to detect cancerous lesions, at an early stage, and to provide high accuracy in the analysis of the size, shape, and location of abnormalities. Segmentation is arguably one of the most important aspects of a computer aided detection system, particularly for masses. This paper attempt to introduce two level set segmentation models for mass detection on digitized mammograms. The first in an edge-based level set algorithm, proposed by Osher and Sethian. The second is a region-based level set algorithm called the local Shan-Vese model. A comparative study will be given, in which we will assess the performance of the second approach in terms of efficiency.**

***Index Terms*—breast segmentation, Level Set method, local chan-vese model, Osher and Sethian algorithm**

I. Introduction

A mammogram is an x-ray picture of the breast. It's considered as the most common method for early detection of breast cancer. The earliest sign of breast cancer is an abnormality detected on a mammogram. It can appear as an abnormal area of density mass, or calcification. Masses are space-occupying lesions, described by their shapes, margins, and denseness properties. Interpretation of mammograms can be difficult, because some breast cancers are hard to visualize, this is due to the nature of the beast, the location and the size of the abnormality. Furthermore, masses can have unclear borders, and can be obscured by glandular issues [1]. Accuracy of segmentation is crucial because many features extracted from segmented regions are used to discriminate benign and malignant lesions. Classical approaches to solve segmentation are divided in different categories: histogram thresholding [2], region-based methods [3], model-based methods (active contour, level set, Markov random field) [4], [5], clustering methods [6], [7]. In this paper, we introduce a robust and an efficient segmentation method from the geometric models family, for performing contour evolution to extract masses: the level set method, also called the implicit deformable model. The fundamental idea is to evolve the contour in such a way that it stops on the boundaries of the foreground region [8]. To perform the contour evolution, two types of forces are computed: the internal forces defined to keep the model smooth during the contour evolution process, and the external forces defined to move the contour toward the boundary of an object [9], [10].

In level set algorithms, we are interested to segment a single part from the whole image; this kind of methods is called image selective segmentation. Segmenting a single region aims to isolate a suspected abnormality in a mammogram, in order to extract relevant features (surface, perimeter, texture, variance, entropy…) used to classify breast masses. Among the level set models, we will focus on two models: the Osher and Sethian model [9] which is an edge-based level set model, and the local Chan-Vese model which is regarded as a region-based level set model. In Osher and Sethian model, the curve evolution is guided by the gradient of the image to stop the evolving curve on the boundary of the desired object. We will see that this solution suffers from several problems in detecting masses and curves may pass through the true boundaries. The Local Chan-Vese model [11] incorporates region-based information into the energy functional to stabilize the evolution to local variations. The functional energy is based on three terms: the global term, which includes global properties as the intensity average, the local term which incorporates local statistical information to improve the segmentation process, and the regularization term, used to ensure curve evolution stability. Experimental results show that this method is an efficient and accurate method to isolate and extract masses in mammograms, with weak boundaries, and intensity inhomogeneity, especially, when the abnormality presents physical characteristics similar to those of normal tissue, with blurred contour or hidden by superimposed or adjacent normal tissue, with an inhomogeneous density. This is clearly visible when the breast is dense. Dense breasts can make mammograms harder to interpret because both tumors and dense breast tissue appear white. The segmentation model we propose

Manuscript received May 21, 2014; revised November 28, 2014.

doi: 10.12720/joig.2.2.100-105

is efficient and well adapted to solve such problems. Also, in some screening mammograms presenting a dense breast tissue, a contrast enhancement based on the exponential distribution is applied

The outline of the paper is as follows: in section 2, a quick review of works proposed in the literature is presented. Section 3 describes the Osher and Sethian model (an edge-based contour method). In section 4, we introduce the Chan-Vese and local Chan-Vese models (region-based contour method) for image segmentation. In section 5, a comparison summary of the two models is presented. Section 6 describes experimental results. Finally, section 7 summarizes conclusion of the work.

II. Related Works

Segmentation of mass regions constitutes a difficult and important context of digital mammography screening. Consequently several works has been proposed to develop aided breast cancer detection systems. In their paper, Ying Cao *et al.* [12], proposed a novel segmentation algorithm based on adaptive region growing. They used a hybrid approach function considering both the likelihood and the edge gradients of segmented masses. These two components are adjusted by using the information entropy of the segmented image. The role of this hybrid assessment function is to choose the best mass contour between these two analysis functions. Bhattacharya and Das [6], used FCM clustering to segment regions. First, the radiologist specifies the suspicious location of the masses, then, FCM clustering technique is employed to accurately segment massed. The classification process is accomplished using an ANFIS classifier. Te Brake and Karssemeijer [4] presented a method based on discrete dynamic contour model, which is similar to snakes. The main idea is to define a set of vertices connected by edges (initial contour), which will evolve in response to two types of forces: internal and external. R. Belloti [13] has proposed an automatic computational technique for mass detection on mammograms, using an edge-based segmentation algorithm to separate suspicious regions. Martins *et al.* [14] showed a technique for mass detection based on growing neural Gas algorithm to segment breast regions, and used shape measures to detect suspicious masses. Leizheng *et al.* [15] proposed a technique based on the fractal dimension analysis to extract the suspicious region. They combined several techniques to determine the region of interest (DWT, multiresolution markov random field, dogs and rabbit algorithm…). H. P. Chan *et al.* [16] proposed a two-stage adaptive density-weighted contrast enhancement (DWCE) algorithm for tumor detection in mammograms. Their experiments were focused namely on masses and microcalcification.

III. The Osher and Sethian Segmentation Model

In the classical active contour models (edge-based approaches), the curve evolution depends on the gradient of the image $|\nabla_{\phi}|$, to locate the boundaries of the desired objects. It starts with a curve on the plane as the zero level set of a higher dimensional function [9], [17]. First, all pixels corresponding to the passage of the curve C are initialized to zero. The whole surface can be then, divided into an internal region (pixels inside the curve), and an external region (pixels outside the curve). In order to guarantee stability of the contour evolution, one needs to introduce gradient information, by the following formula:

$$\frac{\partial y}{\partial x} + F\left|\nabla_{\phi}\right| = 0 \tag{1}$$

where
$$F = (\pm 1 - \varepsilon K).\frac{1}{1+\left|\nabla(G_{\alpha}(x,y).U_0(x,y)\right|} \tag{2}$$

With ε a constant $\in [0,1]$, K corresponds to the local curvature at each point of the curve, $G_{\alpha}(x,y)$ is the Gaussian kernel with standard deviation α, $G_{\alpha}(x,y).U_0(x,y)$ is the convolution of the image with a Gaussian, and $\frac{1}{1+\left|\nabla(G_{\alpha}(x,y).U_0(x,y)\right|}$ is a decreasing function to slow down the evolution of the contour. The evolution equation involves curvature information, which makes this method widely used for cusps, corners, and automatic topological changes [18]. However, the curve evolution by the gradient, may hardly achieve the boundaries in practice. Alternatively to this solution, one can use a level set equation incorporating region-based information into evolution function such as the Chan-Vese model.

IV. Local Chan-Vese Segmentation Model

A. Chan-Vese Model

The Chan-Vese algorithm is the most representative and popular among region-based level set methods. It exhibits more interesting advantages compared to the previous model. It is based on local statistics to control the curve evolution, instead of the gradient which appears not efficient, particularly on low-contrast object. This model presents another advantage which occurs in its low sensitivity to the initialization of the curve. The basic idea of the CV model is the introduction of the 'fitting energy' functional, which has to be minimized during the segmentation process. One of the major drawbacks of this model is its inadaptability for segmenting images composed of inhomogeneous regions. The intensity inhomogeneous problems can appear particularly, because of image acquisition conditions, and are often not visible to the human eye. To address this problem, a variant of this model was proposed by [19], and known as the Local Chan-Vese model (LCV).

B. Local Chan-Vese Model

The LVC model is a based on global and statistical information to overcome the inhomogeneous intensity distribution, and thus, to drive the evolving curve towards the true boundaries. The functional energy is given by:

$$E^{LCV} = \alpha . E^G + \beta . E^L + E^R \quad (3)$$

E^G: is the global term, which includes global properties as the intensity average, it is given by the following equation:

$$E^G(c_1, c_2, \phi) = \int_\Omega |I_0(x,y) - c_1|^2 H(\phi(x,y))dxdy + \int_\Omega |I_0(x,y) - c_2|^2 (1 - H(\phi(x,y)))dxdy \quad (4)$$

The Heaviside function $H(\phi(x,y)$ indicates the set surrounded by the curve C.

E^L: is the local term. It incorporates local statistical information to improve the segmentation process. Each pixel is analyzed with respect to its neighborhood.

$$E^L(d_1, d_2, c) = \int_{inside(c)} |g_k . I_0(x,y) - I_0(x,y) - d_1|^2 dxdy + \int_{outside(c)} |g_k . I_0(x,y) - I_0(x,y) - d_2|^2 dxdy \quad (5)$$

where $g_k . I_0(x,y)$ is the convolution of the image with a filter of size k * k. d_1, d_2 are the intensity averages of $g_k . I_0(x,y) - I_0(x,y)$ inside and outside C, respectively.

E^R: is the regularization term, used to ensure curve evolution stability. The expression is formulated as a combination of two terms:

Curve *length regularizing term*: Given by the formula

$$L(\phi = 0) = \int_\Omega \delta(\phi(x,y) \,|\, \nabla(\phi(x,y))| \, dxdy \quad (6)$$

Penality *term*: introduced to the regularization term to eliminate the re-initialization step, and to define the signed distance function ϕ.

$$P(\phi) = \int_\Omega \tfrac{1}{2}(|\nabla(\phi(x,y))| - 1)^2 dxdy \quad (7)$$

Gradient Descent Flow

Recall that the goal of the segmentation is to minimize the energy functional for a given image by evolving level set function ϕ. The energy functional is formulated by considering the Heaviside function, and the Dirac Delta function as previously mentioned**,** used to determine pixels inside C, pixels outside C, and pixels on C. their approximations are given by:

$$H_\varepsilon(Z) = \frac{1}{2}\left|1 + \frac{2}{\pi}\arctan\left|\frac{z}{\varepsilon}\right|\right| \quad (8)$$

$$\delta_\varepsilon(z) = \frac{1}{\pi}\frac{\varepsilon}{\varepsilon^2 + z^2} \quad (9)$$

Now we can describe the overall energy functional as follows:

$$\begin{aligned} E^{LCV}(c_1, c_2, d_1, d_2, \phi) &= \int_\Omega (\alpha |I_0(x,y) - c_1|^2 + \\ &\beta |g_k I_0(x,y) - I_0(x,y) - d_1|^2 H_\varepsilon \phi(x,y))dxdy + \\ &\int_\Omega (\alpha |I_0(x,y) - c_2|^2 + \beta |g_k I_0(x,y) - I_0(x,y) - d_2|^2 . \\ &(1 - H_\varepsilon \phi(x,y))dxdy + (\mu \int_\Omega \delta(\phi(x,y)) |\nabla(\phi(x,y))| dxdy \\ &+ \int_\Omega \tfrac{1}{2}(|\nabla(\phi(x,y))| - 1)^2 dxdy \end{aligned} \quad (10)$$

The expressions of c_1, c_2, d_1, d_2 can be found in [19]. α and β take positive values as follows:

Image without intensity homogeneous $\rightarrow \alpha$ near or equal to β

Image with intensity homogeneous $\rightarrow \alpha$ <β

The gradient descent method is used to derive the level set function evolution that will minimize the energy function:

The numerical implementation of the level set function evolution, given previously, uses derivative approximations by a finite difference methods, the simplest scheme is of the form:

$$\begin{aligned} &\frac{\varphi_{ij}^{n+1} - \varphi_{ij}^n}{\nabla t} = \\ &\delta_\varepsilon(\varphi_{ij}^n)\left[-\alpha(I_{ij} - c_1(\varphi^n))^2 + \beta(g_k I_{ij} - I_{ij} - d_1(\varphi^n))^2 + \alpha(I_{ij} - c_2(\varphi^n))^2 + \beta(g_k I_{ij} - I_{ij} - d_2(\varphi^n))^2\right] \\ &+ \left[\mu \delta_\varepsilon(\varphi_{ij}^n)k + (\varphi_{i+1j}^n + \varphi_{i-1j}^n + \varphi_{ij+1}^n + \varphi_{ij-1}^n - 4\varphi_{ij}^n - k)\right] \end{aligned} \quad (11)$$

where δ_ε and K(curvature) are given previously.

V. Comparison

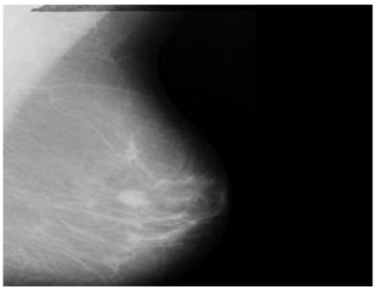
After this quick review on the Local Chan Vese (LCV) algorithm, and the classic Osher and Sethian algorithm, we can now, present a comparison summary according to the characteristics and parameters defined in each segmentation solution. As shown in Table I. Comparisons are based on: parameters used in the energy functional, image properties in terms of intensity, noise and texture, information used to stabilize the curve evolution, sensitivity to the location of initial contour, and the computation time needed in the re-initialization step. The adaptability and the robustness of the two models can be assessed and evaluated by executing several tests on different breast density levels with not only apparent masses, but also, masses hidden by superimposed or adjacent normal tissue.

TABLE I. Comparison Summary of the Two Models

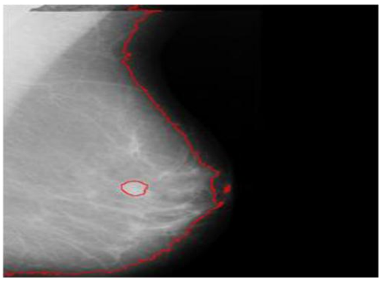
	LCV	Osher-Sethian
Method type	Region-based set level	Edge-based set level
Energy function	-Global term -Local term -Regularization term	Gradient
Image characteristics	-With intensity inhomogeneity -With weak boundaries -With noise -Textured images	With intensity homogeneity
Information type	-Global information -Local information	Global information
Sensitivity to the location of initial contour	Less sensitive	Very dependent
Time consuming re-initialization	Is avoided by the regularization term	Extremely important

VI. Experimental Results

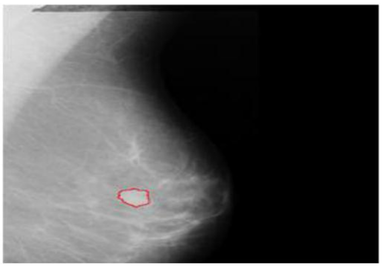
Our experiments were applied on images of mini-*MIAS* database (Mammogram Image Analysis Society database. (UK)) [20]. The database contains digitized films and is available on 2.3GB 8mm (Exabyte) tape. We choose different types of pictures presenting different kinds of abnormities. We take as a baseline for the LCV model, the following set of parameters: $\varepsilon=(1,1.5)$, the time-step $\Delta t = 0.1$ (we note that a large Δt can accelerate the evolution, but may lead to wrong location of the true boundaries). $\beta=1, \alpha=0.1$ for images with intensity inhomogeneous, and $\alpha=1$ for images without intensity inhomogeneous. It should be mentioned that in all our experiments, the initial forms (of circular shape) were placed on the mass to be segmented.



a) A circrumbed mass



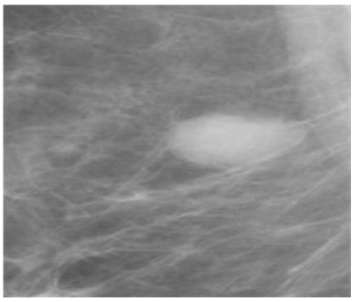
b) Final segmentation result using the Osher model



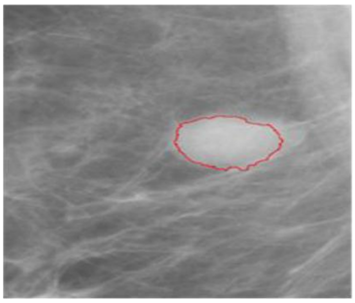
c) Final segmentation result using the LCV model

Figure 1. Circumscribed mass segmentation

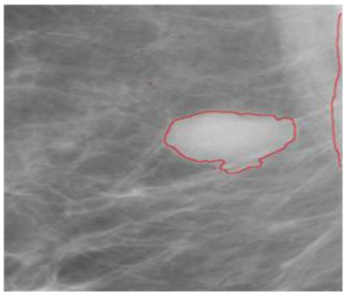
Fig. 1(a) presents a circumscribed mass (mdb 10). Fig. 1(c) shows that the LCV curve successfully approaches the true boundaries. The reason is due to the fact that this region is well defined and has visible contours. Approximatively, the same final contour is obtained using the Osher and Sethian model (Fig. 1(b)). Fig. 2 shows the segmentation results of another circumscribed mass (mdb 25). It can be seen that the Osher and Sethian model failed to segment the desired region, where the intensity decreases gradually from the left to the right (Fig. 2(b)), and the evolving curve stopped before reaching the boundary of the mass. However, we can see that the LCV model have succeeded in the segmentation task after short time and few iterations (Fig. 2(c)). It is important to highlight that the time required for segmentation using the LCV model, was significantly decreased comparing to the Osher and Sethian model, which can take few minutes.



a) A circumscribed mass



b) Final segmentation result using the Osher model

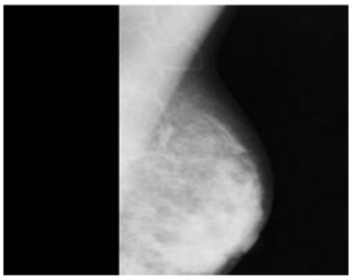


c) Final segmentation result using the LCV model

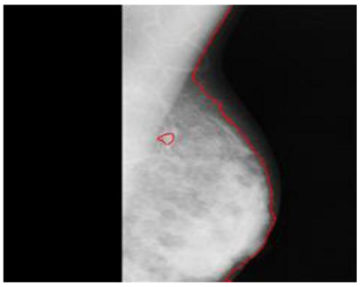
Figure 2. Circumscribed mass segmentation with intensity inhomogeneity

Fig. 3(a) (mdb 124), represents an architectural distortion on brast dense, hardly visible to the human eye. The LCV model shows to be successful in segmenting the region even without contrast enhancement. (Fig. 3(c)), in opposite to the Osher and Sethian curve, which stopped before reaching the lesion boundaries (Fig. 3(b)). A pre-processing step has been successfully applied on some screening mammograms, namely when the mammography presents a dense beast tissue. Dense breasts can make mammograms harder to interpret because both tumors and dense breast tissue appear white. Therefore, we applied a contrast enhancement based on the exponential distribution. This processing makes it possible to bring regions with high intensity of the dynamic range.

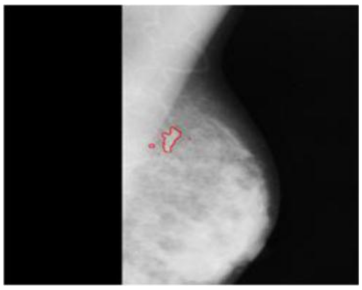
Fig. 4(a) presents a spiculated mass (mdb 178) difficult to distinguish from the surrounding parenchyma. The mass is difficult to be defined due to the great similarity between mass region and the neighboring structures. Fig. 4(b), shows the contrast enhancement result. In Fig. 4(d), we can see that the evolving curve of the LCV model quickly expand to surround the abnormality. However, the Osher and Sethian model provides false results because of only using the global information (Fig. 4(c)).



a) Architectural distortion abnormality(dense breast)

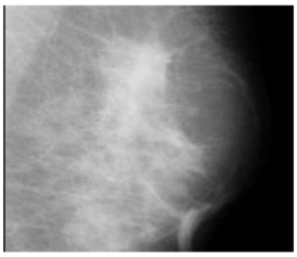


b) Final segmentation result using the Osher model

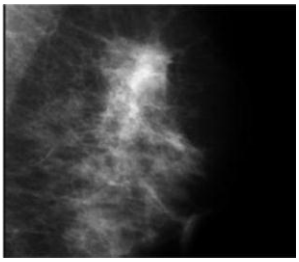


c) Final segmentation result using the LCV model

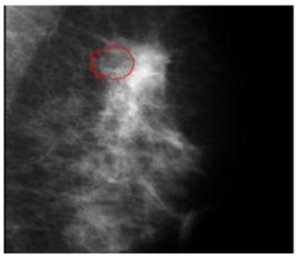
Figure 3. Segmentation result of an architectural distortion abnormality



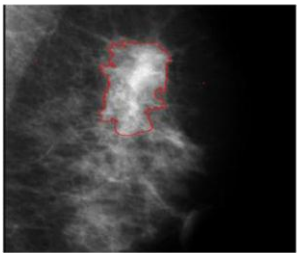
a) Spiculated mass



b) Contrast enhancement based on the exponential distribution



c) The Osher model failed to segment the mass and pass through the true boundary



d) Final segmentation result using the LCV model

Figure 4. Segmentation results of a spiculated mass

For the quantative segmentation performance evaluation, we consider the Area Overalop Measure (AOM), given by the following formula:

$$AOM = R_{manual} \cap R_{automatic} / R_{manual} \cup R_{automatic}$$

where: R_{manual} corresponds to the region of manual segmentation.

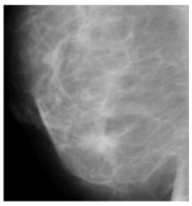
$R_{automatic}$ corresponds to the region of automatic segmentation.

Segmentation results of the previous set of mammograms are given in Table II. We can see that the AOM evaluation of the LCV algorithm shows better results than those of the Osher algorithm, and the final contour of the segmented masses are closer to the radiologist's outline. Furthermore, the final contour is obtained after few iterations in few seconds, in opposite to the Osher algorithm, where the iteration number is considerably greater.

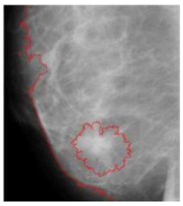
TABLE II. AOM SEGMENTATION EVALUATION OF THE TWO MODELS

mammogram	Manual segm-surface	AOM		Iteration number	
		LCV	Osher	LCV	Osher
Mdb 10 (Fig. 1)	538	0.85	0.75	110	300
Mdb 25 (Fig. 2)	3100	0.96	0.74	130	830
Mdb 124 (Fig. 3)	342	0.76	0.32	90	3220
Mdb 178 (Fig. 4)	3828	0.70	0.43	200	1500

Another case of a spiculated abnormality is shown in Fig. 5(a) (mdb 181).

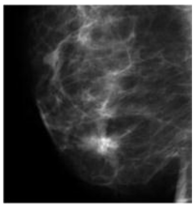


a) Architectural distortion

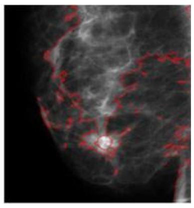


b) The Osher curve evolution pass through the true boundaries

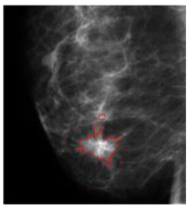
c) Segmentation result using the LCV model



d) Contrast enhancement based on the exponential distribution



e) The Osher curve evolution stopped on hight-frequency area



f) Segmentation result using the LCV model

Figure 5. Segmentation results of another spiculated mass abnormality

It can be seen from Fig. 5(b), which the small initial contour of the Osher and Sethian model, pass through the true boundaries. When the image is enhanced, the curve hardly grows, and stops on a hight-brightness area (Fig. 5(e)). Since the intensity information is incorporated into the LCV model, the evolving curve successfully approaches and surrounds the abnormality, after few iterations, and approximately, the same segmentation results are obtained before and after the contrast enhancement (Fig. 5(c) and Fig. 5(f)).

VII. CONCLUSION

In our work, we used two level set models for mammogram segmentation and mass extraction. The first is an edge-based level set algorithm proposed by Osher and Sethian, in which segmentation depends on the image gradient. The second is a region-based level set algorithm called the Local Chan Vese (LCV) model, in which the local image information is incorporated. The energy functional consists of three terms: global term local term, and regularization term. The comparative study demonstrated that the LCV model is an efficient and accurate method to isolate and extract masses in mammograms, and is better adapted to perform segmentation of regions with intensity inhomogeneity and with weak boundaries and noise. We note that the algorithm deals better performance in fatty breast. In some cases of dense breast, we applied a contrast enhancement based on the exponential distribution. Moreover, the time consuming re-initialization step (which is a necessary step in the classic Osher and Sethian model), can be avoided by incorporating penalty terms in the regularization term. The segmentation scheme of the model is less sensitive to noise and the curve evolution is considerably faster. Finally, to assess the robustness and the effectiveness of the LVC model for mammogram segmentation, we used several images from the MIAS database, namely images with intensity inhomogeneity, which exhibits weak boundaries. Our results for the LCV model has been compared with those obtained by using the traditional Osher and Sethian model, the LCV formulation provided better region segmentation and boundary detection results.

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