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Research Paper

LOCAL INTENSITY INFORMATION BASED IMPROVED LEVEL SET METHOD FOR IMAGE SEGMENTATION

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In real-world images, inhomogeneity in intensities usually occurs and this makes image segmentation a difficult task. In this paper, an attempt has been made to segment the images having different level of intensity variations. The major contribution of the proposed paper is to extract accurate local intensity information using the Gaussian kernel function. This kernel function is further used to define two spatially varying fitting functions which utilize the neighborhood intensity information of each centralized pixel and guided the motion of the contour towards the desired boundary of objects in the presence of inhomogeneity. Also, multi-resolution wavelet decomposition is incorporated in the proposed method to deal efficiently with noisy images. Further, an efficient level set method by preserving the distance function has also been implemented in this paper in order to perform the comparative analysis with the proposed method. The whole framework has been tested on 15 images obtained from standard Berkeley and Weizmann databases. The results confirmed that the proposed method outperforms efficient level set algorithm method by preserving the distance function in terms of Global consistency error, Probabilistic Rand Index and Variation of Information.

Keywords: Intensity inhomogeneity, Level set, Split-bregman, Segmentation, Wavelet

INTRODUCTION

Image segmentation is a primary and most important task in computer vision and image processing. Active contour models have been extensively applied to image segmentation (Kass *et al.*, 1988; Cohen and Cohen, 1991; Malladi and Sethian, 1995; and Chan and Vese, 2001). Active Contour Models have various advantages over basic image segmentation methods, such as Edge Detection, Thresholding, and Region Growing in the form of sub-pixel accuracy of object boundaries (Caselles *et al.*, 1997), easy formulation of the principle of energy

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minimization, allow using prior information such as shape and intensity distribution, for robust image segmentation (Chen *et al.*, 2002) and they provide smooth and closed contours as a result of segmentation. Most of existing Active Contour Models for image segmentation can be divided into two categories: region-based methods (Ronfard, 1994; Chan and Vese, 2001; and Tsai *et al.*, 2001) and edge-based methods (Malladi and Sethian, 1995; Chan and Vese, 2001; Li *et al.*, 2008; Yunyun *et al.*, 2010). Popularly, the region-based methods have more advantages than the edge-based methods. Intensity inhomogeneity has been a challenging difficulty for region-based methods. Piecewise Constant (PC) model, used in efficient level set method by preserving distance function, is typically based on the homogeneity of the image intensities, which is often difficult to maintain by real world images.

In this paper, the basic idea is to embed local intensity information by defining kernel function (Li *et al.*, 2007) as a Gaussian Kernel for inhomogeneous image segmentation. Then this neighborhood information is utilized for contour evolution to guide it over the desired region and boundary. As a result, the proposed algorithm can be used to segment images with intensity inhomogeneity efficiently. Wavelet is a tool for image processing and can suppress the noise in an image in the coarse scales (Fares *et al.*, 2011). Therefore, by utilizing multi-resolution wavelet transform for curve evolution; the proposed method seems to be robust for noisy images. At each level of decomposition, the image is split into high frequency and low frequency components; the low frequency components can be further decomposed until the desired resolution is reached (Chen *et al.*, 2005). When multiple levels of decomposition are applied, the process is referred to as multi-resolution decomposition.

METHODS

Efficient Level Set Method by Preserving Distance Function

The segmentation problem is defined as energy minimization problem (Virginia *et al.*, 2012) in terms of a level set function $\phi: \Omega \rightarrow R$, is defined in Equation (1) as follows:

$$\min_{\phi} \int_{\Omega} w_b(x)|\nabla H(\phi)| + w_r(x)H(\phi) \quad s.t\ |\nabla\phi| = 1 \qquad ...(1)$$

where Ω is the image domain, w_b is an edge detector function (Kichenassamy *et al.*, 1995; and Caselles *et al.*, 1997) and w_r is a region-term (Virginia *et al.*, 2012). The boundary term is formulated in Equation (2) as:

$$w_b = \frac{1}{1+\beta|\nabla(G_\sigma(x,y) * I(x,y)|} \qquad ...(2)$$

Here G_σ is Gaussian filtering used for smooth approximation. Detail level set of image segmentation is determined by the β. Generally it takes 30. Moreover, easy boundary detection is made possible with positive edge detector function. The region-based term (Virginia *et al.*, 2012) is defined in Equation (3) as:

$$w_r = -\lambda_1(I-c_1)^2 + \lambda_2(I-c_2)^2 \qquad ...(3)$$

Generally, λ_1, λ_2 and c_1, c_2 are global properties of the image contents both inside and outside the contour, respectively. Here c_1 and c_2 (Chan and Vese, 2001) is calculated in Equation (4) as:

$$\begin{cases} c_1(\phi) = \dfrac{\int_\Omega IH(\phi)d\Omega}{\int_\Omega H(\phi)d\Omega} \\ c_2(\phi) = \dfrac{\int_\Omega I(1-H(\phi))d\Omega}{\int_\Omega (1-H(\phi))d\Omega} \end{cases} \quad ...(4)$$

Further, with level set formulation, the contour evolution is performed using the Split-Bregman method and augmented Lagrangian. The main idea is to split the original problem, mentioned in Equation (1) into sub-optimization problems using Split-Bregman (Setzer, 2011), which is easy to solve and then combine them together using an Augmented Lagrangian as explained in Virginia *et al.* (2012). With the use of the Split-Bregman technique, minimization of energy functional is done in a more efficient way and also there is no need of regularization term (Yunyun *et al.*, 2010).

The main limitation of this method is due to the two optimal constants used as region term in Equation (3). This is also well-known as a Piecewise Constant model (PC).These constants are considered as averages of intensities in the entire regions outside (C) and inside (C), respectively. Obviously, such global fitting will not be accurate if the image intensities in either inside or outside the contour are not homogeneous. Therefore, it may fail to provide exact image segmentation with these constant approximations of inhomogeneous images.

PROPOSED METHOD

To overcome the above mentioned limitation of efficient level set method for preserving distance function algorithm, there is a need to reformulate the region term in Equation (3). Therefore in proposed method; the key idea is to embed the kernel function in energy functional. The new region term Virginia *et al.* (2012) introduced is defined in Equation (5) as:

$$W_r = -(\lambda_1 e_1 - \lambda_2 e_2) \quad ...(5)$$

where λ_1, λ_2 > 0 are fixed parameters and generally taken as $\lambda_1 = \lambda_2$. The (Li *et al.*, 2007) are given in Equation (6) as follows:

$$e_1(x) = \int_\Omega K_\sigma(y-x)\left|I(y) - f_1(x)\right|^2 dy \quad ...(6)$$

$$e_2(x) = \int_\Omega K_\sigma(y-x)\left|I(y) - f_2(x)\right|^2 dy \quad ...(7)$$

I: $\Omega \to R$ is an input image, K_σ is a Gaussian kernel discussed in (Li *et al.*, 2008) with standard deviation σ, which is flexible and chosen in Equation (8) as:

$$K_\sigma(x) = \frac{1}{\sigma^n (2\pi)^{n/2}} e^{-|x|^2/2\sigma^2} \quad ...(8)$$

The standard deviation σ of the kernel plays a key role and can be seen as a scale parameter that controls the region-scalability from small neighborhood of the whole image domain in practical applications and should be properly chosen (Li *et al.*, 2008). Here, $f_1(x)$ and $f_2(x)$ are two values that fit image intensities near the point x. These are calculated in Equation (9) as:

$$\begin{cases} f_1(x) = \dfrac{K_\sigma * [H_\varepsilon(\phi) I(x)]}{K_\sigma * H_\varepsilon(\phi)} \\ f_2(x) = \dfrac{K_\sigma * [H_\varepsilon(\phi) I(x)]}{K_\sigma * (1 - H_\varepsilon(\phi))} \end{cases} \quad ...(9)$$

The incorporation of two spatially varying fitting functions $f_1(x)$ and $f_2(x)$ (Li *et al.*, 2007) makes proposed method essentially different from piecewise constant models. In this method, x is taken as a local center point around which image intensities are considered due to the kernel function K with the above mentioned regional property that $K(x - y)$ takes higher values at the neighborhood point's y near the center point x, and it reduces to 0 as y go away from x (Yunyun *et al.*, 2010). Thus, the image intensities at the point's y close the point x have dominant influence on the values of $f_1(x)$ and $f_2(x)$. Therefore, able to deal with intensity inhomogeneity. In the above equations, the Heaviside function H is approximated by a smooth function $H_\varepsilon(x)$ (Li *et al.*, 2007) and is formalized in Equation (10) as follows:

$$H_\varepsilon(x) = \frac{1}{2}\left[1 + \frac{2}{\pi}\arctan\left(\frac{x}{\varepsilon}\right)\right] \quad ...(10)$$

The curve evolution is same as mentioned for efficient level set method preserving distance function. Thus due to the use of two fitting functions and localization feature of Kernel function, proposed method handles the intensity inhomogeneity. To deal with noise in images, multi-resolution decomposition is used in proposed method. The image is decomposed into levels of resolutions using wavelet transform (Chen *et al.*, 2005). The results of wavelet decomposition are approximation coefficients (A), horizontal details (H), vertical details (V) and diagonal details (D). Starting from coarsest image resolution, the level set algorithm is run on the coarsest approximation coefficient. At each current resolution, the converged curve of the current resolution is up-sampled to the finer resolution. Up-sampling is performed by a factor of 2. The algorithm continues until the curve is converged in the original resolution (Kother, 2012). Finally the curve is converged at the original image by utilizing the approximation coefficients information at each resolution.

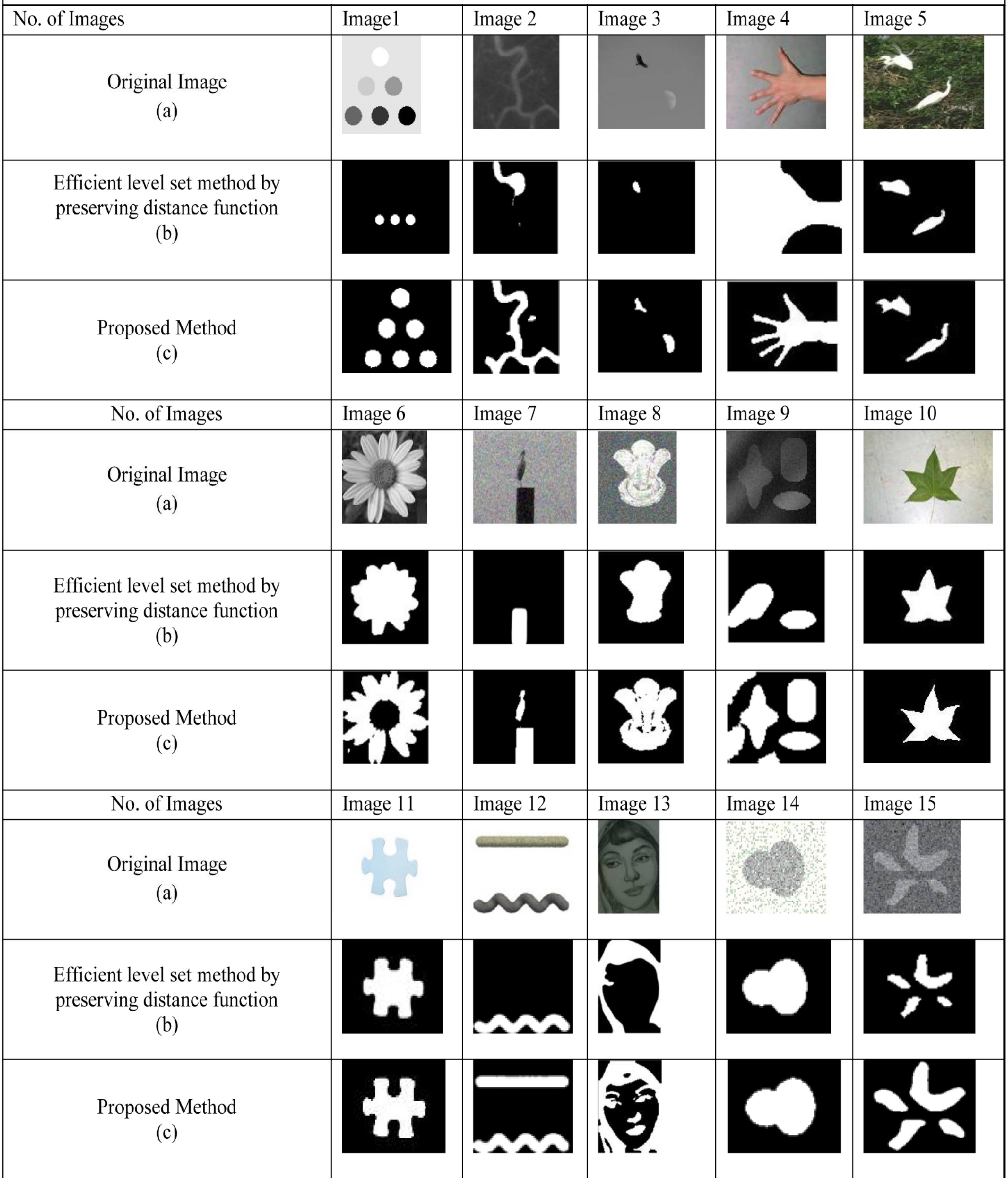
RESULTS AND DISCUSSION

The results are given in the form of comparative analysis between two segmentation methods, i.e., efficient level set method by preserving distance function and proposed method. These segmentation methods are applied to a set of different images obtained from standard Berkeley and Weizmann databases. Figure 1 shows visual analysis of results of Efficient level set method by preserving distance function and proposed method.

The segmentation results given in Figure 1 demonstrate that proposed method has promising and better performance than efficient level set method by preserving distance function for inhomogeneous images. Images 7, 8, 9, 14 and15 are the noisy images with Gaussian noise present in them are efficiently segmented by the proposed method. Haar wavelet is used for image decomposition due to its simplicity. For each image, a decomposition of three levels of resolutions is preformed.

Further for the objective evaluation of the results three different statistical parameters:

Figure 1: Visual Analysis of Results of Efficient Level Set Method by Preserving Distance Function and Proposed Method



Note: (a) Original images; (b) segmentation results obtained after implementing an Efficient level set method by preserving distance function; (c) segmentation results obtained after implementing proposed method.

(1) Global Consistency Error (GCE), (2) Probabilistic Rand Index (PRI), and (3) Variation Of Information (VOI) are used in this paper and these are defined as follows:

GLOBAL CONSISTENCY ERROR (GCE)

It quantifies the consistency between different granularities of image segmentations. It is used to compare the results of algorithms to a database of manually segmented images. It measures up to which one segmentation can be seen as a refinement of the other (Vapnik, 1998). Let *S* and *G* be the two segmentations. Consider the segments that contain xi in S and *G*0, for given pixel x_i. $C(S, x_i)$ and $C(G, x_i)$ are mentioned in the form of pixels. At point x_i, the Local Refinement Error (LRE) is given as:

$$LRE(S,G,x_i) = \frac{|C(S,x_i) \setminus C(G,x_i)|}{|C(S,x_i)|}$$

Global Consistency Error (GCE) pointed all local refinements (Fernando and Aurlio, 2006) in the same direction and is defined in Equation (11) as:

$$GCE(S,G) = \frac{1}{N}\min\left\{\sum LRE(S,G,x_i), \sum LRE(G,S,x_i)\right\} \quad ...(11)$$

The value of GCE should be minimum for efficient segmentation method.

PROBABILISTIC RAND INDEX (PRI)

Rand Index computes the pair wise label relationships to compare two partitions with different number of segments. PRI calculates the number of pairs of pixels having consistent labels between the computed segmentation and the human segmentations (Sujaritha and Annadurai, 2009), i.e., ground truth.

$\{S_1, S_2, ..., S_K\}$ is a set of manually segmented images corresponding to image $X = \{x_1, x_2, ..., x_i, ..., x_N\}$, where *N* is no. of pixels. Segmentation of a test image is denoted as S_{test} and PRI (Fernando and Aurlio, 2006) is given by Equation (12):

$$PR(S_{test}\{S_k\}) = \frac{1}{\frac{N}{2}}\sum_{i,j}[(l_i^{S_{test}} = l_j^{S_{test}})p_{ij} + I(l_i^{S_{test}} \neq l_j^{S_{test}})(1-p_{ij})] \quad ...(12)$$

This measure takes values in [0, 1] – 0 when *S* has no similarities and 1 when all segmentations are identical.

VARIATION OF INFORMATION (VOI)

It measures the amount of information that is lost or gained in changing from one clustering to another (Vapnik, 1998). It is nonnegative value and uses mutual information metric and entropy to estimate the distance between two clustering across the lattice of possible clustering. A random variable *X* represents the clusters $X_1, X_2, ..., X_k$ such that $p_i = |X_i|/n$ $i \varepsilon X$ and $n = \sum_i X_i$ the VOI between two clusters *X* and *Y* is defined (Fernando and Aurlio, 2006) to be in Equation (13) as:

$$VI(X,Y) := H(X) = H(Y) - 2I(X;Y) \quad ...(13)$$

where $H(X)$ is entropy of *X* and $I(X, Y)$ is mutual information between *X* and *Y*. The VOI should be minimum.

The results in the form of three statistical parameters which are calculated for the two mentioned segmentation methods are given in Table 1.

Table 1: Performance Comparison of Two Methods in Terms of Three Statistical Parameters, i.e., PRI, GCE and VOI

Images	Efficient Level Set Method by Preserving Distance Function			Proposed Method		
	PRI	GCE	VOI	PRI	GCE	VOI
Image 1	0.939	0.060	4.633	0.961	0.036	4.501
Image 2	0.457	0.243	2.520	0.846	0.157	2.192
Image 3	0.826	0.167	2.139	0.837	0.112	2.037
Image 4	0.832	0.332	1.750	0.846	0.302	1.641
Image 5	0.660	0.152	1.475	0.895	0.131	1.421
Image 6	0.733	0.329	4.841	0.763	0.300	4.619
Image 7	0.494	0.343	4.101	0.737	0.207	4.064
Image 8	0.896	0.068	2.537	0.905	0.059	2.329
Image 9	0.519	0.457	5.670	0.752	0.453	3.449
Image 10	0.678	0.177	1.833	0.838	0.137	1.701
Image 11	0.880	0.058	2.651	0.929	0.048	2.6083
Image 12	0.675	0.542	5.106	0.813	0.528	4.978
Image 13	0.649	0.641	3.919	0.810	0.502	2.229
Image 14	0.692	0.433	4.748	0.819	0.405	4.671
Image 15	0.677	0.060	2.588	0.938	0.052	1.844

Figure 2: Comparison of Results of Efficient Level Set Method by Preserving Distance Function and Proposed Method in Terms of Probabilistic Rand Index (PRI)

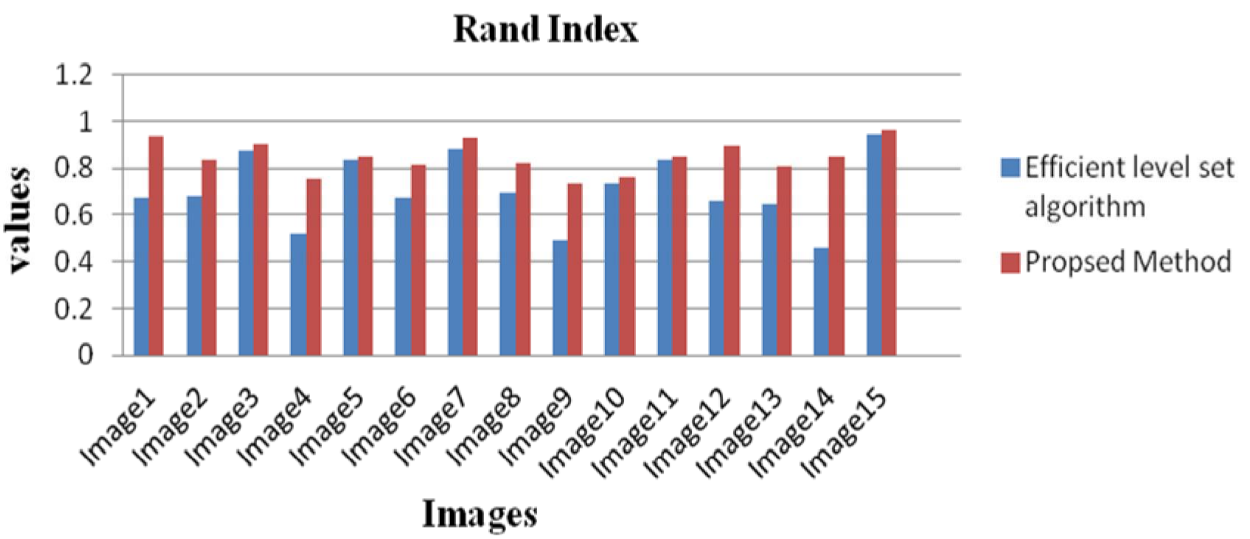


Figure 3: Comparison of Results of Efficient Level Set Method by Preserving Distance Function and Proposed Method in Terms of Global Consistency Error (GCE)

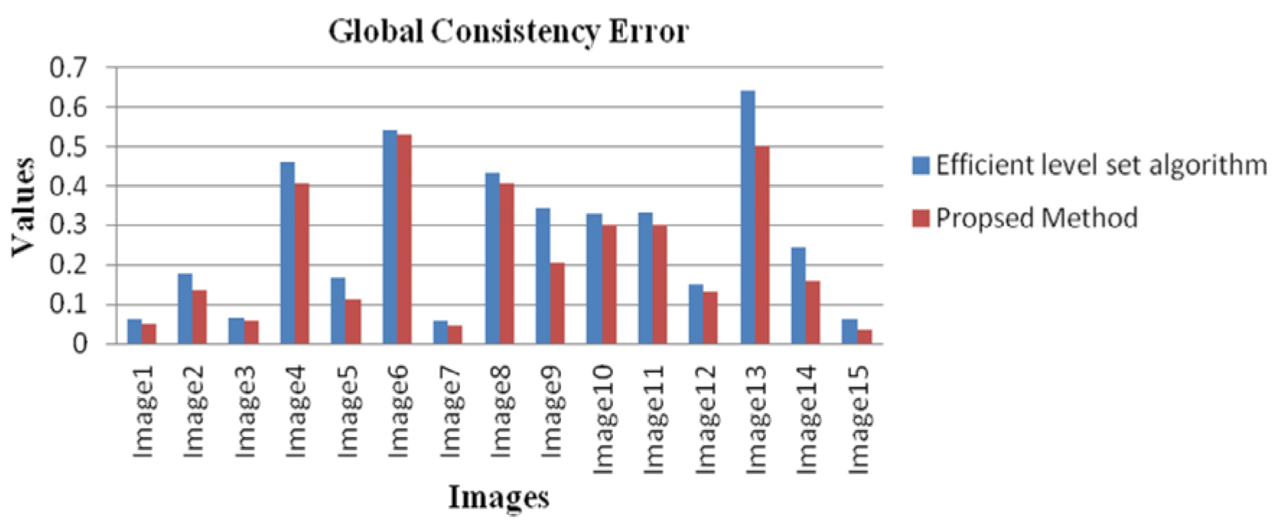
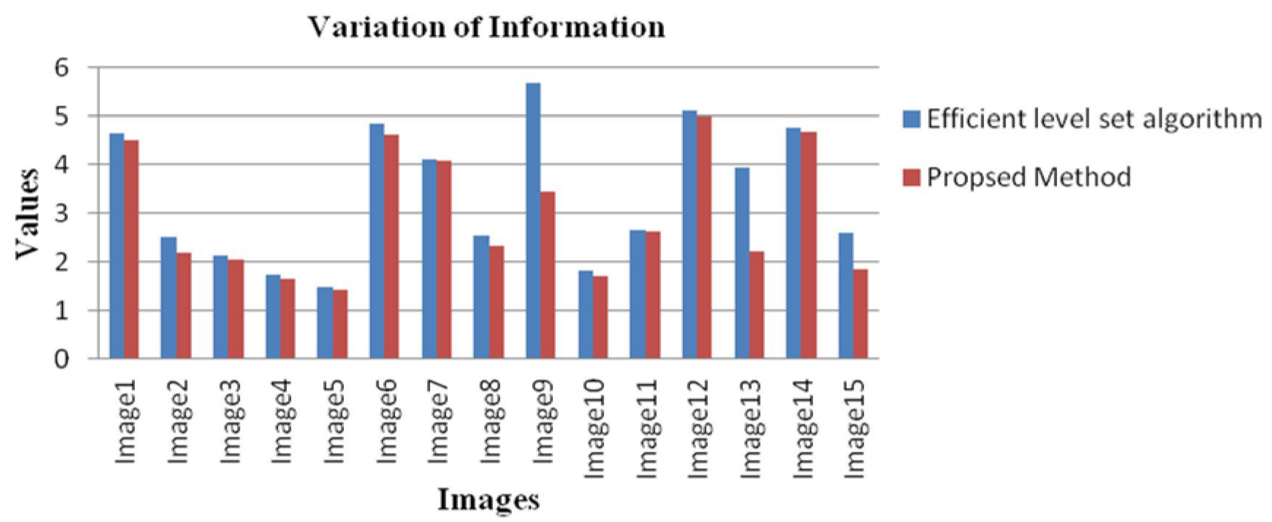


Figure 4: Comparison of Results of Efficient Level Set Method by Preserving Distance Function and Proposed Method in Terms of Variation Of Information (VOI)



After the evaluation of these results it is concluded that values of GCE and VOI obtained using the proposed method are less than the Efficient level set method by preserving distance function whereas the values obtained in terms of PRI are higher in the proposed method than other method.

The graphical representation of these results is also shown using Figures 2, 3 and 4 which clearly reflects the superiority of the proposed method over the Efficient level set method by preserving distance function.

CONCLUSION

In this paper, the proposed method inheriting its desirable ability to segment images with intensity inhomogeneity. The method efficiently and accurately utilizes the localized image information, which is further formulated in a level set framework. The use of wavelet decomposition allows the proposed method to handle noise in images. Comparison with efficient level set method by preserving distance function demonstrates the advantages of the proposed method. Moreover, images with weak boundaries and structures like vessels shows promising and superior results with required parameter values than the results calculated for efficient level set method by preserving distance function.

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