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Hybridized Level Set Based Image Segmentation in UAV Images for Surveillance Applications

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ABSTRACT: Image segmentation is one of the most difficult, dynamic and challenging problems in the image processing domain. It denotes a process by which a raw input image is partitioned into non-overlapping regions such that each region is homogeneous and the union of two adjacent regions is heterogeneous. This paper proposes a novel level set based method for image segmentation, which is able to deal with intensity inhomogeneities in the segmentation for UAV captured images. Level set algorithm is often used for region-based homogeneous image segmentation. When noisy, inhomogeneous image segmentation is required, Level set algorithm should be modified such that it can be less sensitive to noise and inhomogeneity in an image. In that context, our proposed method for noisy images, by hybridizing level set algorithm with superseding, is proposed. Experiments show that our method is more robust to initialization, faster and more accurate than the well-known other image segmentation model.

KEYWORDS*:* level set algorithm, superseding technique, image segmentation, UAV images

1. INTRODUCTION

Image segmentation and region identification is a necessary first step in many real life imaging problems and other applications. In the literature, many techniques have been developed for image segmentation. Thresholding is a popular tool for image segmentation for its simplicity, especially in the fields where real time processing is needed. However, the problem gets more and more complex when trying to achieve segmentation with greater detail by employing multilevel thresholding. Usually it is not simple to determine exact locations of distinct valleys in a multimodal histogram of an image, that can segment the image efficiently and hence the problem of multilevel thresholding is regarded as an important area of research interest among the research communities worldwide. Segmentation is the key and the first step to automatic target recognition, which will directly affect the accuracy of the following work. As a result, the division methods and its precision degree are essential. Infrared heat wave image is different from the visible light images. It reflects the distribution of the object surface temperature and latent characteristics of material form. We exploit the similarity of superseding and Level Set algorithms to present a unified segmentation routine combining their advantages.

Automatic detection and tracking of interesting targets from a sequence of images obtained from a reconnaissance platform is an interesting area of research for defense related application. The video images are obtained from an unmanned aerial vehicle (UAV) with on-board guidance and navigation system. The aircraft carries a multispectral camera which acquires images of the territory and sends the information to a ground control station (GCS) in real time. During flight, the pilot in the ground control station may identify a region of interest as a target. This identification can be click and target type or an intelligent perception type. The target which appears on a small window could be tracked by engaging track mode.

The related works in the area of image segmentation for high definition (SAR) images are described in section 2. The basics of level set algorithm and superseding algorithm is described in section 3. The hybrid approach which includes the advantages of both techniques is discussed in section 4. The implementation process is described in section 5. The results and discussions are made at section 6. We conclude the description of our work at section 7 and section 8 lists out the various reference journals and papers in support with realization of this article.

II. RELATED WORKS

Image segmentation and region identification is a necessary first step in many real life l imaging problems and other applications. Our approach is different than other stochastic level set-like algorithms, such as [7] and [8], which respectively utilize mean field theory and conditional random fields. Compared to level sets, our approach eases implementation by requiring no solution to PDEs or maintenance of a level set function and easily extends to multiregion segmentation without tracking multiple level set functions. In comparison to EM, our algorithm greatly enhances noise robustness by using a prior based on the geometry of the soft decision, thereby encouraging local classification similarity in a manner that extends the insight in [9].

SAR image classification/segmentation is a widely studied problem in the last two decades for automated SAR image analysis [1][2][3][4][5][6]. In radar polarimetry, different approaches have been developed to improve the classification accuracy. A widely accepted technique is the maximum likelihood classification based on the complex Wishart distribution (i.e., the Wishart classifier) [2] [6].

However, these methods, being pixel based, do not utilize the spatial information of the scene. It is beneficial to use a segmentation step to achieve improved classification performance, which is relatively easy for human experts but very challenging for automated systems. The variational level set formulation leads to effective segmentation algorithms [3][4][5]. But these methods are developed mainly on the intensity images and the original additive noise active contour models [4], which is not sufficient to describe the polarimetric SAR images with speckle noise. In [4], a multiphase level-sets model is proposed based on the Maximum-likelihood approximation and a complex Wishart/Gaussian distribution for polarimetric SAR image. However, the utilized boundary length for smooth segmentation boundaries is still gradient based, which is faint to present the edge information of SAR images and the selection of the parameters used to balance each component of the level set function is also crucial. Different parameters for different images results in methods lacking of flexibility and robustness.

Existing level set methods for image segmentation can be categorized into two major classes: *region-based models* [11], [14], [18], [19], [20], [22] and *edge-based models* [10], [12], [13], [15], [21]. Region-based models aim to identify each region of interest by using a certain region descriptor to guide the motion of the active contour. However, it is very difficult to define a region descriptor for images with intensity inhomogeneities. Most of region-based models [11], [17]–[19] are based on the assumption of intensity homogeneity. A typical example is *piecewise constant (PC) models* proposed in [11], [17]–[19]. In [20], [22], level set methods are proposed based on a general *piecewise smooth (PS)* formulation originally proposed by Mumford and Shah [16]. These methods do not assume homogeneity of image intensities, and therefore are able to segment images with intensity inhomogeneities. However, these methods are computationally too expensive and are quite sensitive to the initialization of the contour [14], which greatly limits their utilities. Edge-based models use edge information for image segmentation. These models do not assume homogeneity of image intensities, and thus can be applied to images with intensity inhomogeneities. However, this type of methods are in general quite sensitive to the initial conditions and often suffer from serious boundary leakage problems in images with weak object boundaries.

III. IMPLEMENTATION ALGORITHMS

3. a. Level set algorithm

Level set algorithm is often used for region-based homogeneous image segmentation. When noisy, inhomogeneous image segmentation is required, Level set algorithm should be modified such that it can be less sensitive to noise and inhomogeneity in an image. Level set method is a way to denote active contours. For a given image *i(x,y), we can create a level set* function *ø(x,y) to describe* the contour. The contour is defined as the zero level set of the function *ø*. By changing the *ø values, some regions that are originally* negative will turn into positive, and vice versa. Therefore, the contour will change according to the update of the level set function

C = {(x, y)} |ø(x, y) =0} …….(1)

Ø (x, y)>0 inside the contour
Ø (x, y) =0 contour
Ø (x, y) <0 outside the contour

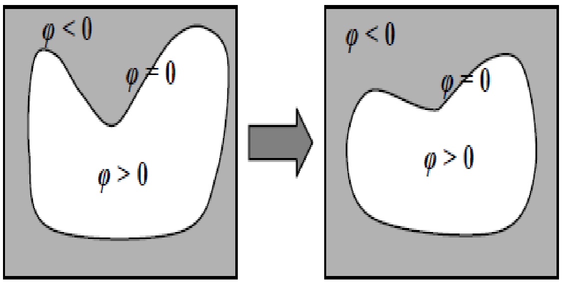

Fig 1. Level set algorithm

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3. b. Superseding algorithm

Noise is the major constrain in any UAV based imaging application. Segmentation of noisy images is the vital criteria and it depends upon the robustness of algorithm. Here superseding algorithm can perform that function. In an image, a pixel is described by a probability density function (pdf). As in noisy image a clear boundary cannot be defined, a pixel is selected in random called as index, then comes the Nearest Neighbor (NN) approach where a group of uncertain pixels is taken and the probability of closeness to the index is calculated and among the group which has greater probability to closeness will be considered as winner and the contour is drawn based on the calculation. Now the winning pixel is index and the process is continued, thereby contour is developed. There occurs a case if two pixels have same probability. In such cases superseding nearest neighbor core (SNN) is done, where the pixels are grouped in such a manner that no two pixels will have same probability. Even though the algorithm can be used for noisy images its computation time and number of iteration depends upon the type of images.

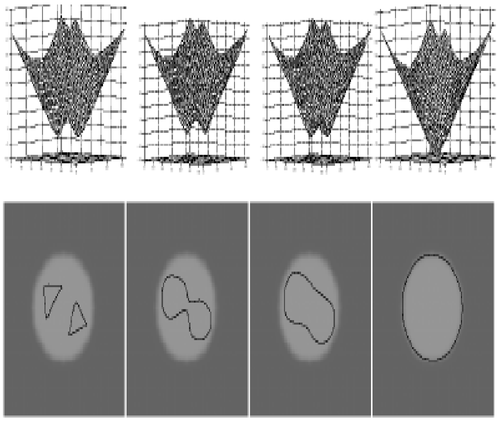

Fig 2. Superseding technique

IV. HYBRID SEGMENTATION

In this paper we hybridize level set algorithm and superseding algorithm to achieve effective results. By this hybridization we obtain Natural representation of regions and edges, Smooth and closed boundary is good for shape analysis and recognition applications and east to handle topological changes. By this segmentation technique Various image information can be integrated into a unified framework like Edge, intensity, color, statistical property, shape, Solid theoretical foundation and feasible tools, PDE, differential geometry, calculus of variation, Optimizing methods, numerical solution

V. IMPLEMENTATION

The implementation of the hybridization algorithm is done in MATLAB. The sample images are taken from various applications like surveillance, tracking and contour detection. The input images are RGB scaled and they are converted into grey scale. The level set function ø is defined. The contour is defined by the level set function. The position of the point in a contour is defined. By repeating this process a complete contour is obtained. This involves level set technique and since it is alone not sufficient to produce exact contour based on the accuracy the image is further subjected superseding. Here a source pixel is assumed for the initial image i(t) and the corresponding neighboring pixels are calculated. Based on the similarity of the neighboring pixels the contour is shifted to the boundary of the 8 neighboring pixels and the level set function is further defined. The process is repeated till the exact contour is got from the given image. The iterations may vary due to the complexity of the image.

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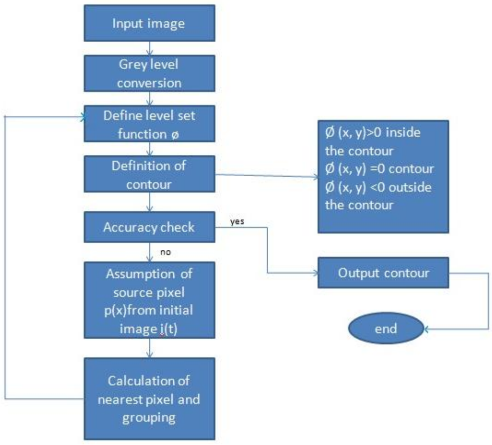

Fig 3.Flow chart for hybridization

VI. RESULTS AND DISCUSSION

The following results are obtained for the sample images when subjected to hybrid segmentation. The data is obtained from different fields obtain varied results for multiple applications.

Fig 4. Input image of the house

Fig 5. Output image of the house

Fig 6.Input image of a tanker (reconnaissance)

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Fig 7. Output image of a tanker (reconnaissance)

Fig 8. Input image of a city (aerial surveillance)

Fig 9. Intermediate result of image of a city (aerial surveillance)

Fig 10. Output image of a city (aerial surveillance)

Fig 11. Input image of a street (surveillance)

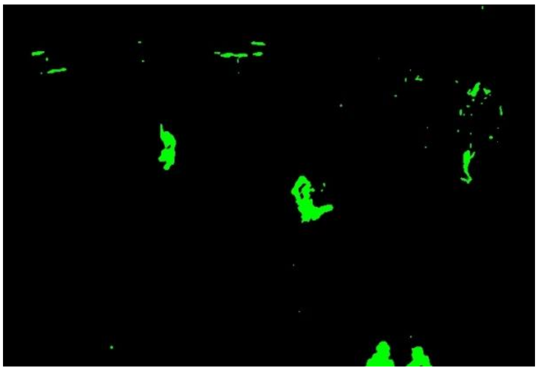

Fig 12. Output image of a street (surveillance)

VII. CONCLUSION

In this paper we hybridize level set algorithm and superseding algorithm to achieve effective results. By our technique we are able to deal with intensity inhomogeneity in the segmentation for UAV captured images. By this segmentation technique Various image information can be integrated into a unified framework like Edge, intensity, color, statistical property, shape, Solid theoretical foundation and feasible tools, PDE, differential geometry, calculus of variation, Optimizing methods, numerical solution. Moreover our method is more robust to initialization, faster and more accurate than the well-known other image segmentation model.

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