Comparison of different active contour models-based image segmentation techniques for metal alloy particle analysis in material science applications

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Abstract: Material particle analysis is one of the difficult tasks in material science engineering. To understand the particle characteristics, size and shape of the particle are important features for measurement. Image processing techniques predominantly segmentation technique provides effective analysis of particle. This paper presents an improved adaptive level set method; modified from traditional level set method (LSM) with respect to the parameters; adaptive directional speed and stopping force based on weighted probability, which further improves the algorithm accuracy for particle image segmentation and parameters measurement. Also, the proposed methodology is compared with the traditional LSM and Chanvese method both subjectively and objectively. In this paper, different microscopic images of metal alloy particles from material science research laboratory are tested on each segmentation method to effectively achieve parameters such as area, number, roundness, and so on. Experimental results show that the proposed method provides average accuracy of 87% with respect to dice coefficient.

Keywords: active contours; image processing; level set segmentation; metal alloy particle; particle counting; size analysis.


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1 Introduction

Material science is one of the most important engineering disciplines, which is concerned with the structure, behaviour and properties of materials used in today’s modern technology. Structural materials such as metals, alloys, ceramics and composite materials are some of the major elements used in our daily lives. Material science and engineering also plays a critically important role in computer industry from microprocessors to semiconductor memories in developing new materials for manufacturing at smaller dimensions. Almost every material we are aware of are found inside the earth. Metals (copper, iron, aluminium, zinc) are one of the major naturally occurring elements with which these materials are made. Though useful, metals can hardly be used directly in their natural form in many applications due to their softness or purity. Metals combined with other substances to make them stronger, lighter or better are called “metal alloys”. To understand the properties of these metal alloy materials as well as to have a better control over the quality of the material, the study of the different characteristics of particles inside these materials is necessary. Therefore, understanding the characteristics of particles has gain tremendous importance in material science industries. A particle can be defined as a discrete sub portion of substance, which has an interface with the surrounding environment. Particle characteristics can be analysed using different methods such as sieve analysis, sedimentation technique and laser light scattering analysis technique, and so on (Sarkhawas, Bang and Dandawate, 2015). But these methods have certain disadvantages such as the scope of quantitative information conveyed is relatively small and size range is defined within only two sieve sizes in sieve analysis; in case of sedimentation technique, the results are very sensitive to the sample preparation and the laser light scattering method is relatively time-consuming method.
comparison to these methods, researchers adopted optical microscopy and image analysis techniques to overcome these disadvantages (Sarkhawas, Bang and Dandawate, 2015). With the rapid development in technology, image processing technique is being considered as one of the standard parameter measurement techniques (Karakus et al., 2008).

Particle image analysis method is a high resolution direct technique for characterizing particles. Shape and size of a particle are two important parameters in particle analysis to define a particle in terms of its area, perimeter, roundness, and so on. This paper represents a complete particle image analysis technique, which consists of acquisition of a noise-free particle image and choosing a suitable and effective segmentation technique to achieve different particle parameter measurement for understanding the properties of a metal alloy material sample used in material science research laboratory.

2 Related works

A critical and most important part in particle analysis is segmentation of particles. Segmentation is defined as partition of an image into its sub-regions. The aim of segmenting an image is to achieve a better representation of the image for further analysis. Neither a single segmentation method can be considered as best for all type of images nor is a single image perfectly segmented using all segmentation methods. Before proceeding to implementation section, a brief summary of literature survey is presented in this section.

Different authors have adopted different segmentation techniques for shape and size analysis of particles based on their application environment and stability in the process. Young and Yi (2010) presented cereal grain size measurement based on 2D Otsu segmentation algorithm. Otsu is a global thresholding technique. The maximum between-cluster variance method (Otsu) is suitable for cereal images due to bimodal characteristics. This algorithm uses pixel and its spatial neighbourhood relevant information and shows potential accuracy towards reducing grain size measurement errors. An improved Otsu optimisation algorithm is presented by (XueYu and Binghui, 2010) for mineral particles based on the distance transformation and optimisation algorithm of seeds points. Distance transformation algorithm is used to ensure segmentation of touching particles and avoid over segmentation issue. This paper gives a development direction to particle detection technology by utilising image processing techniques instead of time-consuming measurement and lengthy testing steps of manual screening methods. (Young and Yi, 2010; XueYu and Binghui, 2010) above deals with 2D Otsu method, which has a disadvantage of histogram of an image as bimodal (i.e., two classes) and it is sensitive to the size of the particles. Huang and Zhou (2010) presented a segmentation method based on watershed algorithm for core particles.

Watershed algorithm is a region-based segmentation method. A landscape is partitioned into regions by dams called as watershed lines. The watershed transform is applied on the image gradients instead of the original image itself. The connected areas of core particles are well segmented using watershed method but in some areas over segmentation occur. Results show that watershed algorithm definition by immersion gives good performance both in speed and effectiveness for core particle image segmentation. Amankwah and Aldrich (2010) and Yuncai and Hui (2012) introduced an improved watershed algorithm using adaptive thresholding and shape markers
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respectively to overcome the over-segmentation problem. Adaptive thresholding divides the image into sub-images and uses different threshold to segment different regions (Amankwah and Aldrich, 2010). Marking operation and region merging are used to avoid over segmentation (Yuncai and Hui, 2012).

Active contour models (ACMs) are also the popular and effective segmentation techniques being adapted by most of the researchers (Chan and Vese, 2001; Virginia and Dominique, 2011). ACM, also called “Snake Model” as described by (Michael et al., 1988) is an energy minimisation technique with some external constraint forces and image forces to pull it towards the edges of an object. The classical approach (Balci and Burak, n.d.) had some difficulties such as the need to handle the topological changes, lack of parameterisation. To overcome these drawbacks (Chan and Vese, 2001) proposed an ACM based on level set method (LSM) and Mumford-Shah function for images of different shape objects. Here, a curve is evolved based on the image constraints in order to detect the objects and evolution is stopped at the desired boundary related to a particular segmentation stage of the image rather than based on the gradient of the image. Earliest LSM is setup by Osher and Sethian (1988).

LSM is an implicit ACM. A zero level set contour is used to represent the complex level set function. LSM has advantage of not needing parameterisation of objects and all computations are performed on a fixed Cartesian grid, because of which they are widely used for segmentation (Chunming et al., 2011).

But traditional LSM requires continuous re-initialisation of level set function to remain as a signed distance function during curve evolution (Li et al., 2005). Li et al. (2005) introduced a variational level set formulation to overcome the lengthy re-initialisation procedure, but it possesses a disadvantage of sensitivity to the curve’s initial position. Most of the LSMs uses image gradient based stopping force to represent the boundaries (Osher and Sethian, 1988; Li et al., 2005). Bin et al. (2014) presented a probability based stopping force, instead of an image gradient-based stopping force. The algorithm is tested on artificial images, medical images and BSD-300 image dataset and experimental results show that proposed method performs competitively compared with traditional LSM. Dandawate and Kinlekar (2013) proposes level set and modified Chan Vese algorithm (CV) for detecting rivers and coastlines over water bodies for satellite images. In this paper, CV method is modified with respect to contour smoothing parameters and results show that algorithm accuracy is improved for rive and coastline detection and computation time required for segmentation is also effectively reduced.

The study of literature survey shows that selecting a particular segmentation technique is a difficult task. Most of the segmentation techniques are either subjective or application dependent. Depending upon the application area and the type of images (rock, cereal grain, mineral, medical MRI, etc.), a suitable segmentation technique is chosen. Some authors adopted 2D Otsu segmentation algorithm for non-touching grains, others selected watershed algorithm for rock particles due to the similar landscape nature of the rock particles. This paper illustrates implementation of LSM-based segmentation with modification of certain parameters to improve the algorithm accuracy. Unlike earlier LSMs, which are applied to medical MRI images or images containing different shapes object, in this paper experiment is performed on different particle (specifically metal alloy) images from material science laboratory as they are more prone to noise and have boundaries as major element for particles counting.

Further, the authors present a comparison of the proposed improved adaptive level set method (ALSM) with the traditional LSM and Chanvese method: a geometric ACM,
both subjectively and objectively. For subjective comparison, parameters such as particle count, total number of iterations and computational time are used whereas for objective analysis, dice coefficient method is used. After segmenting the particles, different particle parameters are measured such as shape (roundness, aspect ratio, etc.), size (area, perimeter and centroid) and total number of particles. Experimental results show that the proposed improved ALSM gives effective segmentation accuracy for metal alloy particle parameters measurement and overcomes the drawback of sensitivity to weak boundaries.

The rest of the paper is organised as follows: Section 3 describes the design implementation for particle analysis using different active contour method-based segmentation techniques and then introduces the improved adaptive level set methodology used in this paper to improve the accuracy of analysis. Section 4 shows some experimental results tested on metal alloy particle images. Section 5 illustrates the comparative parameters applied on different segmentation techniques and finally Section 6 concludes the paper followed by references used.

3 Designs and implementation

In this paper, the authors performed a series of image processing techniques including different ACMs based image segmentation techniques to achieve the desired particle parameters measurement. Figure 1 shows the block diagram used for the analysis.

Figure 1  Block diagram

First, the image is acquired from optical microscope. After pre-processing of the input material sample image, segmentation is performed using different ACMs-based segmentation techniques which are explained in later part of this section. After segmentation, the image is free from noise and unwanted small particles which can now be used to calculate different particle parameters and total number of particles in an image as the next analysis step.

3.1 Image acquisition and pre-processing

The aim is to first acquire the particle image from optical microscope. The sample is a metal alloy material obtained from material science research laboratory. First, the metal alloy sample is kept under the optical microscope. A camera is fitted over the eye piece tube of microscope to capture the sample images. The video cable of camera is given to
USB TV Box, the USB output of which is then finally connected to the laptop where the material sample recording can be seen through TV Home media software.

Various regions of sample images are captured at 40X magnification factor and stored in the laptop. Around 100 sample images are captured and used for further analysis stages. Initially, the images captured were blurred and too noisy due to corrosion over the sample. Therefore, the authors had to prepare the steel alloy sample again first by manually polishing the sample over different polishing papers (400, 600 and 1000) and then performing the machine polish for the final finishing of sample.

Though the acquired images are less noisy than the previous captured images it still needs to be pre-processed as it contains some void spaces and small unwanted particles. The principle objective of pre-processing is to provide more suitable image than the original image for a specific segmentation algorithm.

In this paper, contrast enhancement (adaptive histogram equalisation) is applied to the original image and then median filtering is performed to remove noise and preserve some edges.

3.2 Image segmentation

Segmentation is defined as partition of an image into its sub-regions. The aim of segmenting an image is to achieve a better representation of the image for further analysis. The main factor in our acquired particle image is boundary, detection of true boundaries and neglecting the false boundaries to count the total number of particles in an image. ACMs are useful for this purpose as it deals with the evolution of curve around the object (particle) where the curve is driven by two forces.

The internal forces, defined within the curve, are used to keep the evolution of curve smooth whereas the external forces are used to stop the curve at the boundary using certain image parameter (Airouche, Bentabet and Zelmet, 2009).

In this paper, three ACMs-based segmentation techniques are presented. First, traditional LSM is applied on the acquired particle images, second, Chanvese: active contours without edges method which is piecewise ACM is used to improve the curve evolution and finally our proposed improved ALSM is applied to achieve better results. Note that the authors are comparing different ACMs only with respect to our metal alloy particle images used in material science applications. The comparison of segmentation methods may differ depending upon the application area and the type of images used for the analysis.

3.2.1 Level set method

The LSM was first introduced by Osher and Sethian. It is a numerical method for propagating interfaces. The basic aim is to evolve a curve perpendicular to itself at a defined speed. The level set function $\phi$ is defined (Airouche, Bentabet and Zelmet, 2009) as shown in Eq. (1):

$$\phi(x, y) = \pm d((x, y), C)$$  (1)
where \( d((x, y), C) \) is the distance from point \((x, y)\) to the contour \(C\), the sign is for the point to be inside or outside \(C\). Evolution of this closed curve \(C\) is implicitly given in terms of zero level set as shown in Eq. (2):

\[
C = \{(x, y) | \phi(x, y) = 0\}
\]

This function \( \phi \) is evolved using partial differential equation (PDE). The evolution equation of the level set function is given by Airouche, Bentabet and Zelmet (2009) in Eq. (3) as follows:

\[
\frac{\partial \phi(x, y)}{\partial t} = F|\nabla \phi|
\]

where \( F \) is the speed controlling the movement of the contour.

### 3.2.2 Chanvese active contour method

While many segmentation methods are dependent in some way on edge detection, “Active Contours without edges” by Chan and Vese (2001) ignore edges completely. Here, the boundary is represented implicitly with a level set function to easily handle topological changes in an image.

The fitting term for the closed curve \(C\) is given by:

\[
F_i(C) + F_2(C) = \int_{\text{inside } C} |u_0(x, y) − c_1|^2 \, dx\,dy + \int_{\text{outside } C} |u_0(x, y) − c_2|^2 \, dx\,dy
\]

In Eq. (4), \(u_0\) is the object with \(C_0\) as boundary. The fitting term is minimised only in the case when the curve is on the boundary of the object as shown in Figure 2. This fitting term is minimised by introducing the energy function \(F(c_1, c_2, C)\) defined by (Chan and Vese, 2001):

\[
F(c_1, c_2, C) = \mu \text{length}(C) + v \text{Area}\{\text{inside}(C)\}
\]

\[
+ \lambda_1 \int_{\text{inside } C} |u_0(x, y) − c_1|^2 \, dx\,dy + \lambda_2 \int_{\text{outside } C} |u_0(x, y) − c_2|^2 \, dx\,dy
\]

\(\mu, v, \lambda_1\) and \(\lambda_2\) in Eq. (5) are fixed parameters.

### 3.2.3 Improved ALSM

The proposed method improves the accuracy of LSM to effectively segment the metal alloy particle image by modifying certain parameters of energy function. It is necessary to keep the level set function \(\phi\) as shown in Eq. (3) as a signed distance function, which requires re-initialisation in every few steps by solving PDE in the process.

Li et al. (2005) presented a solution to overcome this problem by adding a penalty term in the energy function as follows:

\[
E_{\varphi}(\phi) = \mu \int \frac{1}{2}(\nabla \phi - 1)^2 \, dx\,dy + \lambda \int g \delta(\phi) \nabla \phi \, dx\,dy + v \int g H(−\phi) \, dx\,dy
\]

(6)
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First term on RHS of Eq. (6) is the penalty term; second term is the weighted length of the curve and the last term is area under the zero level set; \( \mu, \nu, \lambda \) are the weights controlling the associated energy terms and \( \alpha \) is edge-based stopping function.

Figure 2  Fitting term possible cases

Although this penalty term eliminates the need of re-initialisation lengthy procedure, there are two drawbacks that still exists in the LSM as

1. the initial position of curve is dependent on the sign of parameter \( \nu \) in the energy function
2. stopping force is image gradient based which makes it sensitive to noise.

To overcome these drawbacks, the authors added two terms in the energy function as:

1. Probability weighted stopping force: the edge based stopping function in Eq. (6) is given by:

\[
g = \frac{1}{1 + |\nabla G_\sigma \ast I|} \tag{7}
\]

In Eq. (7), \( G_\sigma \) is a Gaussian function with the standard deviation \( \sigma \); \( I \) is the image to be segmented; \( g \) is a positively decreasing stopping function. The boundaries are nothing but the change in the classes of pixels. Image gradient-based stopping force has disadvantage of considering the changes in the grey value as boundary, which could lead us to false detection of particles. Therefore, based on Wang et al. (2014), Sarkhawas, Bang and Dandawate (2015), the authors have combined both local and global features of image to design a stopping force as:
In Eq. (8), $\nabla G^* \ast I$ represents Gaussian smoothing. Thus, $g$ takes small value where the pixel values are neither the object nor background. This stopping force based on weighted probability prevents the edges away from the objects and enhances those around the objects.

2) Adaptive directional function based speed: the constant velocity parameter $v$ in Eq. (6) is basically used to increase the speed of the evolution curve and it represents the area term in the energy function. Variation in its value either misses out the weak boundaries or reduces the speed. Considering these two cases value must be chosen. Therefore, to maintain this variation throughout the evolution, an adaptive directional function (Adf) (Sarkhawas, Bang and Dandawate, 2015) is added in the velocity as:

$$v(x, y) = \frac{1}{1 + \exp(-\zeta \text{Adf}(x, y))}$$

(9)

where $m$ and $\zeta$ are the constants controlling the amplitude and degree of velocity. The values in Eq. (9) are selected as $m = 14$, $\zeta = 3$ in the experiment;

$\text{Adf}(x, y)$ is Adaptive directional speed function which is selected as:

$$\text{Adf}(x, y) = P(\Omega_1 \mid I(x, y)) - T$$

(10)

where $P(\Omega_1 \mid I(x, y))$ is the Posterior Probability given by the Bayesian rule and the authors have assumed that image domain is $\Omega = \Omega_1 + \Omega_2$, also $\Omega_1$ and $\Omega_2$ defines the object and background. Considering the deviations of the object and background in the equation, adds an advantage to the expansion and shrinking of the curve evolution. Also, this adaptive directional speed avoids the boundary leakage at the weak boundaries in the particle image. Thus, both the functions $v(x, y)$ and $g$ are integrated in Eq. (6) to form the energy function of our model, which can be easily solved by partial difference equations.

3.3 Particle parameters measurement

Detection of size and shape of the particles are important to gain information about the particle.

3.3.1 Size analysis

Particle size is one of the most important parameters in material science and technology. Apart from spherical particles where size is defined in terms of its diameter, for all other shapes, particle size is defined by equivalent spherical diameter concept. The most
common measurement used for size analysis of irregular particles is Ferret diameter of particles. Ferret diameter is defined as the distance between the two parallel tangents of a particle. It is considered as a projection of three-dimensional (3D) objects on a 2D plane in microscopic analysis. Figure 3 shows the definitions of ferret diameter in horizontal and vertical directions.

**Figure 3** Ferret diameters (min and max) definition (see online version for colours)

### 3.3.2 Shape analysis

One of the complex geometric characteristics of a particle is its shape, which involves not only the form and habit of the particle but also features like convexity and surface roughness (Pabst and Gregorova, 2007).

Some of the most widely used shape parameters determined as combination of size measurements are (Karakus et al., 2008):

\[
\text{Form factor} = \frac{4\pi \times \text{Area}}{\text{(Perimeter)}^2} \quad (11)
\]

\[
\text{Aspect Ratio} = \frac{\text{Minimum Ferret}}{\text{Maximum Ferret}} \quad (12)
\]

\[
\text{Roundness} = \frac{4 \times \text{Area}}{\pi (\text{Maximum Diameter})^2} \quad (13)
\]
Compactness = \frac{\sqrt{4 \times \text{Area}}}{\text{(Maximum Diameter)}}

(14)

Shape parameters are dimensionless quantities, which are often normalised in the range \([0, 1]\). Typically value 1 represents the ideal shape. These are calculated from measured quantities like perimeter, area, length, and so on. Aspect ratio of a particle is defined as the ratio between its width and height. Roundness defines the sharpness of the edges and corners of a particle. Form factor has a unity value for a perfect sphere or circle and decreases in value with increase in irregularity of a particle (Ghosh, 2011).

3.3.3 Counting

Object counting in an image is one of the major challenges in image processing. After the segmentation of particles, based on the connected components information and centroid of each particle, the total number metal alloy particles in an image is calculated.

3.3.4 Particle size distribution

PSD is a histogram graph of particles in different size ranges. It is obtained by counting the particles in different sizes in a microscopic image (Colloidal Dynamics Ltd, 1999). In this paper, PSD based on the ferret diameter is plotted.

4 Experimentation and results

The complete experiment is implemented by MATLAB 2013a on Intel Core2Duo processor with Windows 7 64 (bit) operating system. The experiment is performed on 100 different images of steel metal alloy. These images are captured from samples present in the material science research laboratory. The sample is kept under optical microscope with 40X magnification factor. A camera placed above the eye piece tube of microscope records the sample video, which is observed in TV Home Media software through PC/Laptop. Images of different region of the samples are captured and stored in PC/Laptop. Collectively, 100 images are captured and each segmentation method is tested on all the images. Each sample image has different number of particles.

Figures 4, 5, 6 and 7 illustrate four such particle images (a) with the segmentation results of; (b) traditional LSM, (c) Chanvese method and (d) the proposed improved ALSM, respectively. From these figures, it is found that the boundaries in the segmented images of improved ALSM are sharper and effectively better than the traditional LSM and CV method to count the total number of particles. Particle size distribution (PSD) graph for Image 1, based on the ferret diameter for the improved ALSM is shown in Figure 8, which represents the number of particles present in different size ranges. For Image 1, maximum number of particle is present in 40–45 micronmeter range.
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Figure 4  (a) Input image 1, (b) LSM output after 100 iterations, (c) CV output after 1000 iterations and (d) Adaptive LSM output after 80 iterations

Figure 5  (a) Input image 2, (b) LSM output after 100 iterations, (c) CV output after 1000 iterations and (d) Adaptive LSM output after 80 iterations
Figure 6  (a) Input image 3, (b) LSM output after 100 iterations, (c) CV output after 1000 iterations and (d) Adaptive LSM output after 80 iterations

Figure 7  (a) Input image 4, (b) LSM output after 100 iterations, (c) CV output after 1000 iterations and (d) Adaptive LSM output after 80 iterations
Particle size parameters such as area, length, width, centroid, and so on calculated for all particles in the images and values for the first five particles of Image 1 are shown in Table 1 for the proposed ALSM. Also, some of the shape parameters such as aspect ratio, roundness, form factor, compactness, and so on are calculated as shown in Table 2. These shape parameters are obtained using size parameters such as perimeter, area, ferret diameter, and so on.

Table 1  
Size analysis of particles

<table>
<thead>
<tr>
<th>Particle number</th>
<th>Area</th>
<th>Centroid (Max. value)</th>
<th>Length</th>
<th>Width</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1035</td>
<td>21.18</td>
<td>1</td>
<td>18</td>
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<tr>
<td>2</td>
<td>27</td>
<td>9.33</td>
<td>51</td>
<td>3</td>
</tr>
<tr>
<td>3</td>
<td>620</td>
<td>20.07</td>
<td>57</td>
<td>4</td>
</tr>
<tr>
<td>4</td>
<td>235</td>
<td>12.80</td>
<td>107</td>
<td>19</td>
</tr>
<tr>
<td>5</td>
<td>30</td>
<td>8.63</td>
<td>149</td>
<td>13</td>
</tr>
</tbody>
</table>

Table 2  
Shape parameters

<table>
<thead>
<tr>
<th>Particle number</th>
<th>Form factor</th>
<th>Aspect ratio</th>
<th>Roundness</th>
<th>Compactness</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.61</td>
<td>18</td>
<td>0.52</td>
<td>0.72</td>
</tr>
<tr>
<td>2</td>
<td>0.99</td>
<td>0.05</td>
<td>0.53</td>
<td>0.72</td>
</tr>
<tr>
<td>3</td>
<td>0.51</td>
<td>0.07</td>
<td>0.47</td>
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<td>4</td>
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<td>0.34</td>
<td>0.58</td>
</tr>
<tr>
<td>5</td>
<td>0.36</td>
<td>0.08</td>
<td>0.12</td>
<td>0.34</td>
</tr>
</tbody>
</table>
5 Comparative parameters

Many segmentation methods have been developed but most of them are application specific or depends upon the type of images used for segmentation. Therefore, comparison of different segmentation methods is still a difficult task. In this paper, the authors have compared the different ACMs-based segmentation methods specifically for metal alloy particle images only. Figure 9 shows the ground truth reference images, i.e., manually segmented images of four input images.

Figure 9  Ground truth reference images

5.1 Dice coefficient

Dice coefficient is a parameter used to measure the extent of spatial overlap between two binary images. Its value ranges from 0 (no overlap) to 1 (perfect similarity) (Babalola et al., 2008). Mathematically it is given (Dandawate and Kinlekar, 2013) as:

\[ D = \frac{2(A \cap B)}{A + B} \]  

where A and B are ground truth image and the test image.

Dice coefficient values for some images using each segmentation method are shown in Tables 3, 4 and 5 respectively along with the average dice coefficient.

5.2 Computation time

It is the time taken by each algorithm to perform the image segmentation. For LSM, CV and ALSM computation time is recorded for each image under analysis.

Tables 3, 4 and 5 shows the comparative parameters for each segmentation method respectively. From these tables, it can be seen that the average time required for ALSM is 10.5 which is less than LSM and CV methods. CV algorithm requires nearly 1000 iteration steps and average time of 230 seconds per image due to its complex computation to initialise the contour. Also, it shows that ALSM has a higher score of
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Dice coefficient (average 0.87) as compared to traditional LSM (average 0.43) and CV (average 0.74) methods which indicates that measure of similarity between ground truth image and the segmented image of ALSM is high. Figure 10 highlights accuracy based on iteration steps required by each method to segment an image.

Table 3  Comparative parameters for level set method (LSM)

<table>
<thead>
<tr>
<th>LSM</th>
<th>Time (sec)</th>
<th>Iterations</th>
<th>Dice coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image 1</td>
<td>15</td>
<td>100</td>
<td>0.55</td>
</tr>
<tr>
<td>Image 2</td>
<td>20</td>
<td>140</td>
<td>0.43</td>
</tr>
<tr>
<td>Image 3</td>
<td>15</td>
<td>80</td>
<td>0.44</td>
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<tr>
<td>Image 4</td>
<td>15</td>
<td>100</td>
<td>0.35</td>
</tr>
<tr>
<td>Image 5</td>
<td>15</td>
<td>120</td>
<td>0.24</td>
</tr>
<tr>
<td>Image 6</td>
<td>15</td>
<td>100</td>
<td>0.67</td>
</tr>
<tr>
<td>Image 7</td>
<td>20</td>
<td>140</td>
<td>0.56</td>
</tr>
<tr>
<td>Image 8</td>
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</tr>
<tr>
<td>Average</td>
<td>16.25</td>
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<td>0.43</td>
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</tbody>
</table>

Table 4  Comparative parameters for Chan Vese method (CV)

<table>
<thead>
<tr>
<th>CV</th>
<th>Time (sec)</th>
<th>Iterations</th>
<th>Dice coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image 1</td>
<td>240</td>
<td>800</td>
<td>0.77</td>
</tr>
<tr>
<td>Image 2</td>
<td>240</td>
<td>800</td>
<td>0.80</td>
</tr>
<tr>
<td>Image 3</td>
<td>300</td>
<td>1000</td>
<td>0.75</td>
</tr>
<tr>
<td>Image 4</td>
<td>180</td>
<td>400</td>
<td>0.55</td>
</tr>
<tr>
<td>Image 5</td>
<td>180</td>
<td>400</td>
<td>0.68</td>
</tr>
<tr>
<td>Image 6</td>
<td>200</td>
<td>800</td>
<td>0.88</td>
</tr>
<tr>
<td>Image 7</td>
<td>200</td>
<td>800</td>
<td>0.82</td>
</tr>
<tr>
<td>Image 8</td>
<td>300</td>
<td>1000</td>
<td>0.73</td>
</tr>
<tr>
<td>Average</td>
<td>230</td>
<td>-</td>
<td>0.74</td>
</tr>
</tbody>
</table>

Table 5  Comparative parameters for adaptive level set method

<table>
<thead>
<tr>
<th>ALSM</th>
<th>Time (sec)</th>
<th>Iterations</th>
<th>Dice coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image 1</td>
<td>10</td>
<td>80</td>
<td>0.93</td>
</tr>
<tr>
<td>Image 2</td>
<td>12</td>
<td>100</td>
<td>0.87</td>
</tr>
<tr>
<td>Image 3</td>
<td>10</td>
<td>80</td>
<td>0.92</td>
</tr>
<tr>
<td>Image 4</td>
<td>10</td>
<td>80</td>
<td>0.93</td>
</tr>
<tr>
<td>Image 5</td>
<td>10</td>
<td>80</td>
<td>0.89</td>
</tr>
<tr>
<td>Image 6</td>
<td>10</td>
<td>80</td>
<td>0.75</td>
</tr>
<tr>
<td>Image 7</td>
<td>12</td>
<td>100</td>
<td>0.82</td>
</tr>
<tr>
<td>Image 8</td>
<td>10</td>
<td>80</td>
<td>0.88</td>
</tr>
<tr>
<td>Average</td>
<td>10.5</td>
<td>-</td>
<td>0.87</td>
</tr>
</tbody>
</table>
Also, Figure 11 shows the counting accuracy of each method which indicates that the number of particles is calculated more accurately in case of ALSM then secondly by CV method and finally with least accuracy by traditional LSM. For example, the total number of particles in Image 1 by the proposed ALSM method is 36 whereas in ground truth image is 41. Therefore, accuracy for Image 1 is 86.11% whereas the accuracy decreases in case of LSM and CV methods.

Figure 11 Accuracy based on counting of particles (see online version for colours)

6 Conclusions and discussion

In this paper, particle analysis (size and shape analysis) is performed on 100 different material science particle images and results are compared using different ACMs, i.e., traditional LSM, Chanvese active contour method and proposed improved ALSM based segmentation technique. Experimental results show that the accuracy of proposed
Different active contour models-based image segmentation techniques

methodology is more efficient than the traditional LSM and Chanvese method as the dice coefficient scores high value and the computation time required is less. Also, the iterations required for segmentation is less in case of both LSM and ALSM whereas for Chanvese method it is more. With the proposed ALSM, uniformity of level set function is maintained and tedious re-initialisation procedure is prevented which gives efficient and satisfactory results for metal alloy particle segmentation and analysis. Moreover, the number of particles counted is more accurate in case of ALSM.

The proposed segmentation method which includes adaptive directional speed and stopping force based on weighted probability overcomes the disadvantages of boundary leakage and sensitivity to noise and curve’s initial position present in the traditional LSMs. The experimental results also show that the size and shape parameters are accurately calculated using improved adaptive level set algorithm which is required to understand the characteristics of the metal alloy material particle images being used in material science research laboratory.

References


