

## Research Article

# An Image Segmentation by BFV and TLBO

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This paper presents the establishing of a biconvex fuzzy variational (BFV) method with teaching learning based optimization (TLBO) for geometric image segmentation (GIS). Firstly, a biconvex object function is adopted to process GIS. Then, TLBO is introduced to maximally optimize the length penalty item (LPI), which will be changed under teaching and learner phase of TLBO, making the LPI closer to the target boundary. Afterward, the LPI can be adjusted based on fitness function, namely, the evaluation standards of image quality. Finally, the LP is combined item with the numerical order to get better results. Different GIS strategies are compared with various fitness functions in terms of accuracy. Simulations show that the presented method is more effective in this area.

## 1. Introduction

Image segmentation is very important in image processing. It is also an important research direction of computer vision technology and has been highly appreciated by people for many years. On the one hand, it is the foundation of target expression and has an important influence on the measurement of characteristics; on the other hand, because of the image segmentation and expression of segmentation, feature extraction and target parameter measurement based on segmentation will convert the original image into more abstract and more compact form, making it possible for higher level of image analysis and understanding. There are many methods in the field of image segmentation such as thresholding [1], edge detection of image [2], clustering for image [3, 4], regional active contour [5], and specific mathematical theory tools [6]. Some new segmentation methods were also proposed such as anterior cruciate ligament [7], improved firefly algorithm [8], and fuzzy  $c$ -means clustering for image detection [9]. They are relatively simple image segmentation methods and most widely used, but there are still various deficiencies. The active contour model without edges named CV model is one of the most successful models in image segmentation. However, CV model also has drawbacks: (1) converging to local optima [10], (2) being sensitive to selection of parameters [11], and (3) computational inefficiency [12]. In order to overcome these drawbacks, a novel BFV image

can be proposed [13], but the BFV method is only suitable for some special images and the LPI is randomly initialized; there is no universality. The paper proposes an efficient biconvex fuzzy method with TLBO for image segmentation. The TLBO approaches [14–16] used to maximally optimize the LPI will be changed under teaching phase and learner phase to get better results. Rao [17, 18] presented the Jaya algorithm in this area for optimization of the problem.

The article is organized as follows. Section 2 describes the CV model and the BFV model. Section 3 describes the TLBO strategy. Section 4 presents GIS algorithm based on BFV by TLBO. In Section 5, experimental results of the proposed model are given. Section 6 depicts the conclusion of this paper.

## 2. CV Model and the BFV Model

Chan and Vese [11] simplified the Mumford-Shah model, and they presented a novel active contour model based on region, namely, the CV model [19–21]. The model assumes that the image is divided into two types of target and background. The energy function is defined as follows:

$$E(C) = \mu L(C) + \nu A(C) + \lambda_1 \int_{i(C)} |I(x, y) - C_1|^2 dx + \lambda_2 \int_{o(C)} |I(x, y) - C_2|^2 dy, \quad (1)$$

where  $E$ ,  $I(x, y)$ , and  $C$  are the energy of image, original image, and contour of the original image, respectively.  $i(C)$  and  $o(C)$  show the region, which are inside and outside the contour. The latter two items are fitted to detect the target region and background region.  $L(C)$  indicates the length of the contour.  $A(C)$  shows the area inside the contour.  $C_1$  indicates the average gray inside the contour and  $C_2$  shows the average gray outside the contour. Also,  $\mu, \nu, \lambda_1$ , and  $\lambda_2$  are all nonnegative numbers, where  $\lambda_1$  and  $\lambda_2$  are weights for the LPI and the fitting item, respectively. To minimize the energy function and achieve the best effect, fuzzy energy functional is used as follows:

$$E = \lambda_1 \int_{\Omega} \mu^m (I - C_1)^2 dx + \lambda_2 \int_{\Omega} (1 - \mu)^m (I - C_2)^2 dy. \quad (2)$$

In formula (2),  $\mu$  and  $m$  are the membership function and a constant positive integer, respectively. In this paper,  $\lambda_1 = \lambda_2 = 1$ . The first-order partial derivatives in formula (2) are calculated with respect to  $C_1$  and  $C_2$ , and then they are set to be zero.  $C_1$  and  $C_2$  are as follows:

$$C_1 = \frac{\int_{\Omega} \mu^m I dx}{\int_{\Omega} \mu^m dx}, \quad (3)$$

$$C_2 = \frac{\int_{\Omega} (1 - \mu)^m I dx}{\int_{\Omega} (1 - \mu)^m dx}.$$

Another shortcoming of the CV model is that the LPI restricts the choice of the initial value for level set function. Also, the selection of initial level set function depends on  $\mu$ , so the proposed method is using TLBO to optimize the length item. Calculating the Gateaux derivative to energy functional according to formula (1) and derivative function on variables  $\delta$ , the level set function is expressed as  $\phi$ , which shows the initial surface of the contour. It should be noted that the zero level set is the contour. The evolution process is to get the derivative of the function  $\phi$  on variable  $t$ , as shown in the following:

$$\frac{\partial \phi}{\partial t} = \delta(\phi) \left[ \mu \operatorname{div} \left( \frac{\nabla \phi}{|\nabla \phi|} \right) - \nu - \lambda_1 (1 - C_1)^2 + \lambda_2 (1 - C_2)^2 \right]. \quad (4)$$

In formula (4),  $\operatorname{div}$ ,  $\delta(\phi)$ , and  $\nabla$  are divergence operator, approximating solution of Dirac function, and gradient operator, respectively.

In the experiment,  $\nu = 0$  and  $\lambda_1 = \lambda_2 = 1$ . In the same way, the evolution function for level set of formula (1) is

$$\frac{\partial \mu}{\partial t} = m \left( -\lambda_1 \mu^{m-1} (I - C_1)^2 + \lambda_2 (1 - \mu)^{m-1} (I - C_2)^2 \right). \quad (5)$$

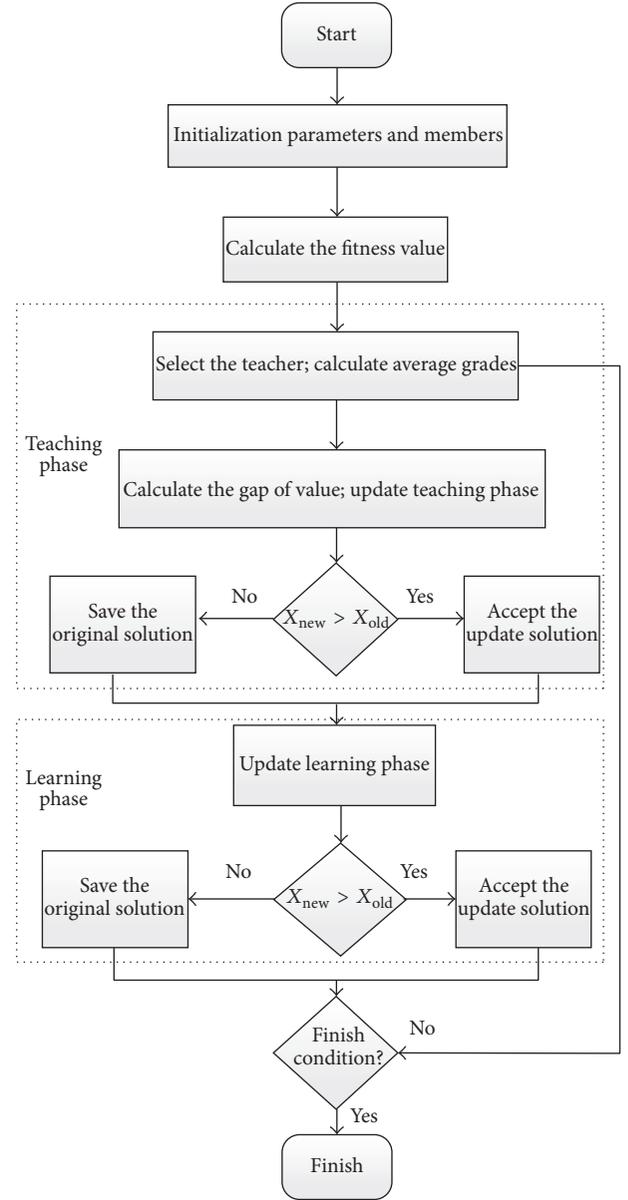


FIGURE 1: Algorithm of TLBO.

In this paper, standard Von Neumann analysis is applied for studying the time stability [22]. The following formula is used for calculation:

$$\mu_n = \mu_{n+1} + \Delta t g(p(|\nabla I|, s), s) \Delta \mu_{n+1/2},$$

$$p(|\nabla I|, s) = \varepsilon(s - s_0) |\nabla I| + (1 - \varepsilon(s - s_0)) |G * \nabla I|,$$

$$\varepsilon(s) = \frac{1}{1 + e^{-s}}, \quad (6)$$

$$g_{\max} = \max \{g(p(|\nabla I|))\},$$

where  $s$ ,  $G$ , and  $*$  are the SNR of test image, Gaussian kernel, and operation of convolution, respectively.

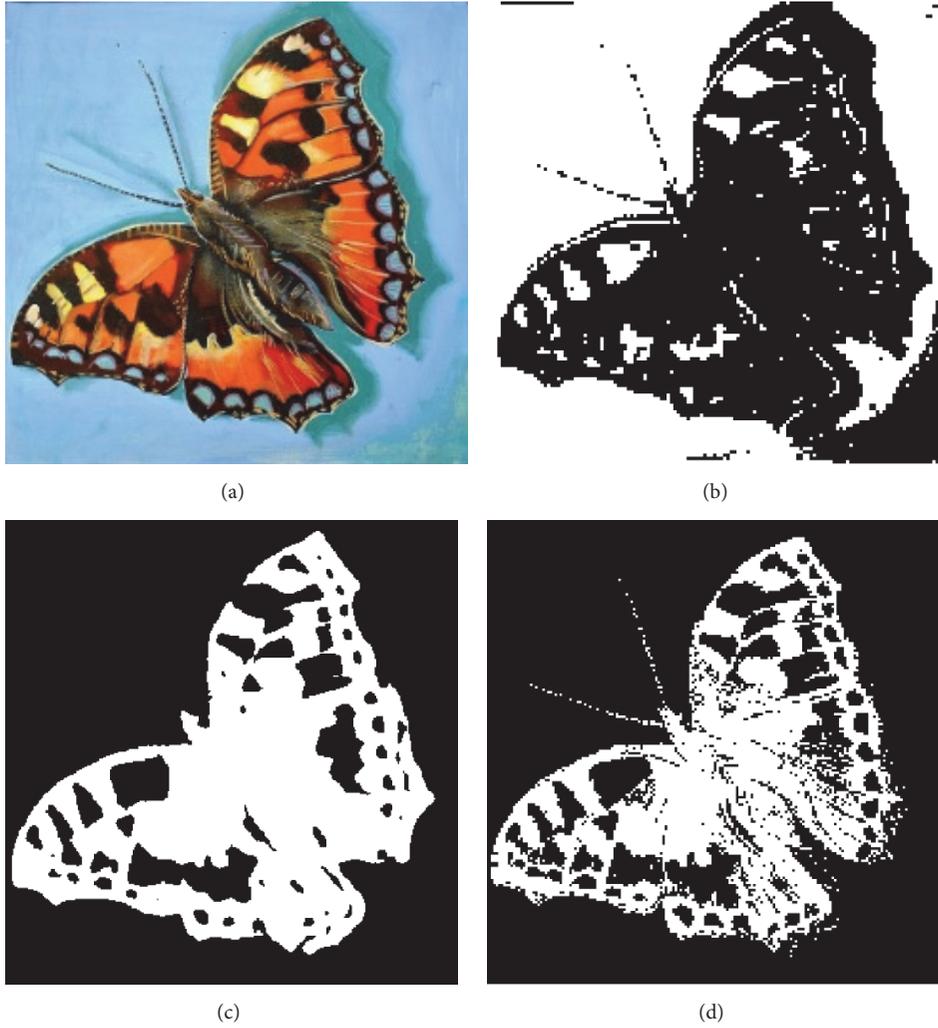


FIGURE 2: (a) Primary image. (b) CV segmentation. (c) BFV segmentation. (d) TLBO-BFV segmentation.

### 3. TLBO

The TLBO put forward by Rao et al. [14–16] is a novel heuristic algorithm. The model can be described that it randomly generated a series of solutions in the constraints space. These solutions can be regarded as a group of “students,” and one of the best is recognized as a “teacher.” The teacher imparts knowledge and answers students’ questions. Students enrich their knowledge from the teacher. This is the first process of TLBO algorithm [19], called the teaching phase. The learning phase, which is the second process, can be described as communicating with others and exchanging experience to promote each other. After a period of time, the students’ knowledge is higher and higher; that is to say, it is more and more tending to the optimal solution in the constraint space. The whole process is shown in Figure 1. The optimal model is as follows:

$$\begin{aligned} & \min \quad f(X) \text{ or } \max f(X) \\ & \text{Subject to} \quad X \in S \end{aligned}$$

$$\begin{aligned} g_i(X) &\leq 0, \\ (i &= 1, 2, \dots, m), \end{aligned} \tag{7}$$

where  $f(X)$  is optimized objective function, searching any point  $X^j = (x_1, x_2, \dots, x_d)$ ,  $j = 1, 2, \dots, S_p$ ,  $S_p$  is the number of species, and  $d$  are dimensions of  $X$ . Continuous variables  $S = \{X \mid x_q^L \leq x_q \leq x_q^U, q = 1, 2, \dots, d\}$ , and  $x_q^L$  and  $x_q^U$  are lower and upper bound of each dimension weight of  $X$ , respectively. Discrete variable  $x_q \in S = \{X_1, X_2, \dots, X_p\}$ , and  $p$  is a number of discrete set. In the TLBO algorithm, the relations of class, students, and teacher are as follows:

Class: set  $\{X^j, j = 1, 2, \dots, S_p\}$ .

Students: set  $X^j = (x_1, x_2, \dots, x_d)$ , where  $d$  is the subject of teaching.

Teacher: the best fitness value  $f(X)$  of set  $\{X^j, j = 1, 2, \dots, S_p\}$ .



FIGURE 3: (a) Primary image. (b) CV segmentation. (c) BFV segmentation. (d) TLBO-BFV segmentation.

The class matrix is defined as follows:

$$\left( \begin{array}{c|c} f(X^1) & X^1 \\ f(X^2) & X^2 \\ \vdots & \vdots \\ f(X^{S_p}) & X^{S_p} \end{array} \right) = \left( \begin{array}{cccc} x_1^1 & x_2^1 & \cdots & x_d^1 \\ x_1^2 & x_2^2 & \cdots & x_d^2 \\ \vdots & \vdots & \cdots & \vdots \\ x_1^{S_p} & x_2^{S_p} & \cdots & x_d^{S_p} \end{array} \right) \quad (8)$$

$$X_{\text{teacher}} = \min f(X^j),$$

$$j = 1, 2, \dots, S_p.$$

The marks distribution curve of the class is a normal distribution, as in formulation (6); in spite of having certain deviation with the actual, it still be helpful for analysis. The definition above can be described as

$$f(X) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}. \quad (9)$$

In formula (9),  $\sigma$ ,  $x$ , and  $\mu$  are the variance, the value in certain range, and the mean value, respectively.

**3.1. Teaching and Learner Phase.** In the beginning of teaching phase, students' values are relatively scattered and the average grades are  $S_A$ ; at the same time, the teacher' is  $T_A$ . After a period of teaching, students' results gradually concentrate distribution, and the average grade is increasing to  $S_B$ , and the teacher is also updated to  $T_B$ . Students learn knowledge from the teacher through the difference between the average of teacher and the student in the teaching phase. In short, the solution is updated with formula (9). If the new solution is better than the existing one, replace the existing solution with the new one.

$$\text{Difference\_Mean}_{\text{new},i} = r_i (M_{\text{new},i} - T_F M_i), \quad (10)$$

where  $r_i$  is a random number,  $r_i \in [0, 1]$ , and  $T_F$  is a teaching factor which decides how the mean value is to be changed. Because  $T_F$  is either 1 or 2, it can be presented as follows:

$$T_F = \text{round} [1 + \text{rand}(0, 2)]. \quad (11)$$

Solutions of the problem are updated based on the following strategy. At first, the value of objective function is obtained. If the new solution is better than the existing one, replace it



FIGURE 4: (a) Primary image. (b) CV segmentation. (c) BFV segmentation. (d) TLBO-BFV segmentation.

with the new one:

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ii ← random (pop_rize) (ii ≠ i)
if  $X_i$  is better than  $X_{ii}$  then
 $X_{i,new} = X_i + r \cdot (X_i - X_{ii})$ 
else
 $X_{i,new} = X_i + r \cdot (X_{ii} - X_i)$ 
end if
evaluate ( $X_{i,new}$ )
if  $X_{i,new}$  is better than  $X_i$ , then
 $X_i \leftarrow X_{i,new}$ 
end if

```

Figure 1 show the flowchart of TLBO algorithm.

#### 4. GIS Strategy Based on BFV with TLBO

In this paper, the fitness function applies Jaccard Similarity (JS) [23] value and standard deviation (Std) as the quantitative indexes to evaluate the results. The JS value is explained as

$$JS(S_1, S_2) = \frac{|S_1 \cap S_2|}{|S_1 \cup S_2|}. \quad (12)$$

In (12),  $S_2$  and  $S_1$  are the ground truth data and the segmentation results, respectively. The Std is defined as

$$Std = 100 \times \frac{1}{\left( \frac{1}{(n-1)} \sum_{i=1}^n (x_i - \bar{x})^2 \right)^{1/2}}, \quad (13)$$

where  $\bar{x}$  and  $x_i$  are the mean of image pixels and the value of image pixels, respectively. From the discussion above, it is not necessary to record experimental results each time. We can take a reaction part to  $T$  with step  $\Delta t$  ( $T = n\Delta t$ , where  $n$  is a positive integer). In summary, the flowchart of

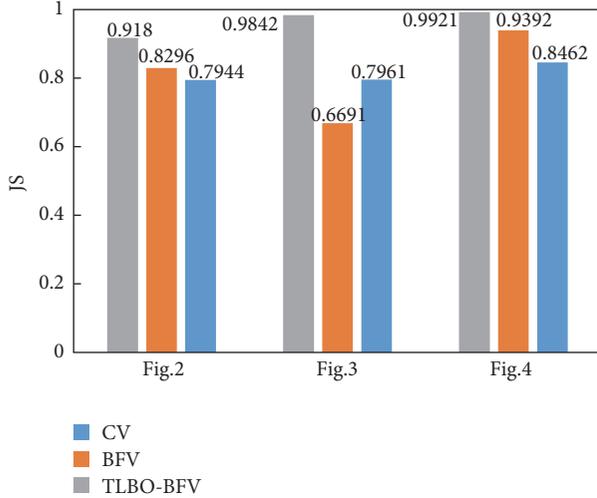


FIGURE 5: JS of methods.

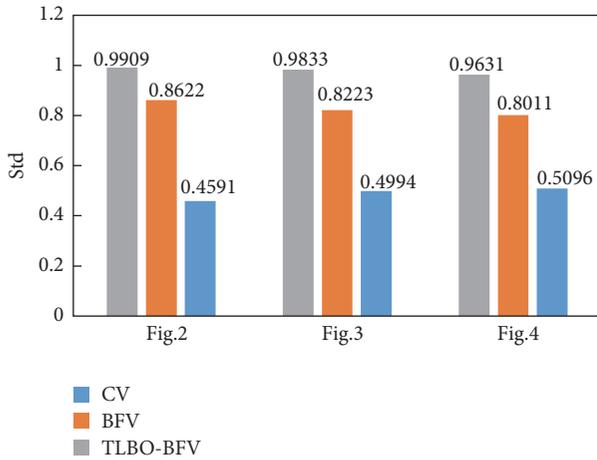


FIGURE 6: Standard deviation of methods.

the proposed algorithm (TLBO-BFV) can be summed up as in the following steps:

- (1) Set  $n = 0$ . It uses the TLBO method to optimize  $u$  and calculate  $g$  using formula (6).
- (2) Calculate  $C_1$  and  $C_2$  using formula (3).
- (3) Set  $t = 0$ . Compute  $\mu^{n+1/2}$  using formula (5). If  $t + \Delta t \leq T$ , then set  $t = t + \Delta t$  and  $\mu_n = \mu_{n+1/2}$  and it goes to step (2); otherwise, it continues.
- (4) It computes  $\mu_{n+1}$  using formula (6).
- (5) If  $\mu_{n+1}$  satisfy termination condition, it stops; otherwise, set  $n = n + 1$  and it returns to step (2).

## 5. Simulation

The CV model and BFV segmentation method are selected to compare with TLBO-BFV method. In the experiments, the same iteration number is set.

Tables 1, 2, and 3 demonstrate the results of Figures 2, 3, and 4, respectively.

TABLE 1: Results of Figure 2.

Model	Std	JS
CV	0.4591	0.7944
BFV	0.8622	0.8296
TLBO-BFV	0.9909	0.918

TABLE 2: Results of Figure 3.

Model	Std	JS
CV	0.4944	0.7961
BFV	0.8233	0.6691
TLBO-BFV	0.9833	0.9842

TABLE 3: Results of Figure 4.

Model	Std	JS
CV	0.5096	0.8462
BFV	0.8011	0.9392
TLBO-BFV	0.9631	0.9921

Figures 2, 3, and 4 show the value of JS and Std of the three methods.

Figures 5 and 6 demonstrate the JS and Std of the three methods, respectively.

## 6. Conclusion

This paper presents a new image segmentation method, named TLBO-BFV. The TLBO approach is used to maximally optimize the LPI, so as to improve the accuracy of segmentation. Simulations indicate that the proposed method improves the robustness and the recognition rate and the algorithm has advantages in stability and effectiveness.

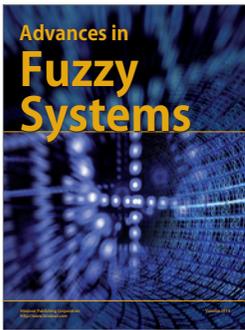
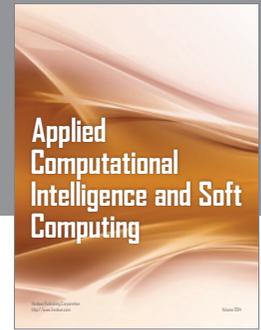
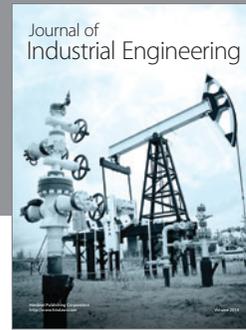
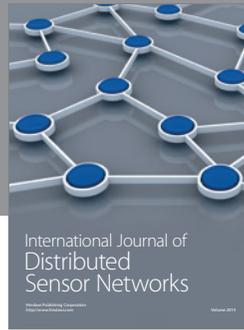
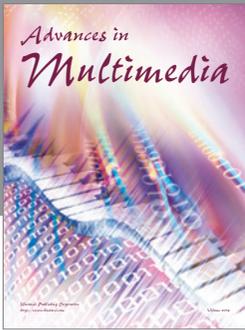
## Competing Interests

The author declares that they have no competing interests.

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