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ENERGY MINIMIZATION IN IMAGE SEGMENTATION USING SHUFFLED FROG LEAPING ALGORITHM

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Abstract. *In this paper we study an efficient energy optimization framework in image segmentation. First, the image segmentation is modelled as a labelling problem, and local gradient based image features are studied. Second, consider the global constraint on image contour, a high order energy function is proposed for joint optimization of the local edge based energy and the global shape based energy. Various optimization algorithms are studied, including Markov random fields, shuffled frog leaping algorithm, and active contour model. Third, in order to improve the computational efficiency, a fast implementation of the energy minimization is provided. Experimental results show that the proposed energy minimization framework is effective and it is robust to local extreme and poor initialization.*
Keywords: Image segmentation, Shuffled frog leaping algorithm, Energy minimization

1. **Introduction.** Image segmentation is one of the fundamental problems in computer vision. It is the foundation of many image processing applications. The existing segmentation algorithms can be studied from the view of energy optimization. Naturally, the characters of different optimization algorithms are key to the success of image segmentation.

Many optimization techniques [1, 2, 3] have been introduced to the image processing, such as Markov random fields (MRFs) [4], and dynamic programming [5]. Chen et al. [6], studied MRF in image segmentation. In their work, both likelihood information and prior knowledge were taken into account. Yang et al. [7], studied an efficient MRF based image segmentation algorithm. In their work, a fast and robust level set was adopted, and the computational efficiency was verified on radar images, medical images, and natural images. Peng et al. [8], proposed an image segmentation algorithm based on dynamic region merging. Image segmentation was performed by iteratively merging of the regions according to a statistical test.

When designing an effective optimization algorithm, there are many factors to be considered. Among them, the ability of jumping out of local extremes and the robustness towards poor initial states are especially important for image segmentation. In the segmentation process, it is very important to push the model out of a local extreme point. This will ensure a large searching area around the possible positions of the desired image contour. The dependencies on starting points should be as small as possible. Some of the previous segmentation algorithms are dependent on the manual input of correct initial position. For instance, the snake algorithm [9, 10] relies on a good initial position to ensure the global optimal to be found. A rough boundary is needed before snake algorithm can iteratively adjust the points to minimize the energy function towards the ground-truth image contour.

In this paper, we try to solve the local extreme problem and the initialization problem in image segmentation by a meta heuristic algorithm. We adopt the shuffled frog leaping algorithm and genetic algorithm to solve the optimization problem. The individuals in the population are computed based on the candidates of image contour, and the optimization target function, also known as the energy function, is determined by both the local image features and the global shape of the contour.

The rest of the paper is organized as follows. Section 2 provides detailed description of the local and global model. Section 3 provides the optimization method. Section 4 gives the experimental results. Finally, conclusions are given in Section 5.

2. **Efficient Local and Global Interactive Contour Model.** When we study the detailed structure of an image contour we can see that it can be defined as a set of nodes and edges:

$$\mathcal{G} = \{\boldsymbol{n}_i; \boldsymbol{e}_{i,j} | \forall i, j \in \phi; i < j\} \tag{1}$$

where $\mathcal{G}$ denotes a graph, $\boldsymbol{n}$ and $\boldsymbol{e}$ are the node and edge, i and j are the indexes of nodes, and ϕ is the set of node indexes.

The nodes can be either labelled as a member of the contour or the background. Therefore, the image segmentation problem can be modelled as a labelling problem. We can apply Markov random fields based method to search the optimal labelling configuration.

A labelling problem can be formulated as a mapping from a site set to a label set: $\mathcal{S} \to \mathcal{L}$ where $\mathcal{L}$ is the label set, and $\mathcal{S}$ is the site set. In our case, the nodes in the image graph are the labels and the image pixels are the sites.

The MRFs based approach relies on the initialization, in which good candidates must be provided. Finding good candidates is often difficult in fully automated image segmentation. In this paper, we study an alternative approach to the MRFs based method. We use meta heuristic searching strategy to optimize the energy function and the optimization will converge to a desired image contour.

2.1. **Local features.** Local image features provide key information for the detection of edges and points of interest. In our paper, we use image gradient magnitude as the local features. The gradient feature is defined as:

$$f(n_{i,j}) = 0.25 \times \sum_{k=1}^{4} g_k \tag{2}$$

where i and j are the index of coordinates, g_k can be computed according to Equation (3) to Equation (6), and k is the index of gradient direction.

$$g_1 = \sum_{k=-1}^{0} |I(i, j+k+1) - I(i, j+k)| \tag{3}$$

$$g_2 = \sum_{k=-1}^{0} |I(i+k, j) - I(i+k+1, j)| \tag{4}$$

$$g_3 = \sum_{k=-1}^{0} |I(i+k+1, j+k+1) - I(i+k, j+k)| \tag{5}$$

$$g_4 = \sum_{k=-1}^{0} |I(i+k, j-k) - I(i+k+1, j-k-1)| \tag{6}$$

where I is the intensity of the gray scale, and k is the index of adjacent node.

This feature can serve as a punishment component in the energy function for any misplacement of contours in evenly distributed areas in an image.

2.2. **Global constraint.** The major difference between edge detection and image segmentation is that the later takes the shape of an object into consideration. Image segmentation serves as an preprocessing step for many object recognition applications. The segmented image contours usually satisfy certain shape constraints. A simple rule of the shape constraint is the smoothing requirement, which punishes any sharp turns on the contour. More comprehensive rules can be made based on the prior knowledge of the target object. In this paper, we use a generalized shape model to learn the global constraints. The coordinates (x, y) of the node $\boldsymbol{n}$ in the image are represented as a shape vector, as shown in Equation (7).

$$\mathbf{s} = [x_1, y_1, x_2, y_2, \ldots, x_N, y_N] \tag{7}$$

where N is the total number of nodes on the contour.

A set of training images are required to achieve the mean shape $\boldsymbol{\mu}$ and the covariance matrix $\boldsymbol{\Sigma}$. The Gaussian mixture model, as defined in Equation (8), is adopted for the shape model and Expectation-Maximization algorithm is used for parameter estimation.

$$p(\boldsymbol{s}) = \sum_{q=1}^{Q} w_i b_q(\boldsymbol{s}) \tag{8}$$

where q is the index of Gaussian member, and Q is the total number of Gaussian members. b_q is the Gaussian distribution with mean $\boldsymbol{\mu}_q$ and variance matrix $\boldsymbol{\Sigma}_q$, as shown in Equation (9). Weight w_i satisfies $\sum_{q=1}^{Q} w_i = 1$.

$$b_q = \mathcal{N}\left(\boldsymbol{\mu}_q, \boldsymbol{\Sigma}_q\right). \tag{9}$$

2.3. **Definition of energy function.** In our image segmentation model, the energy is defined in such a way that closer feature and shape lead to lower energy. When the visual features around a certain point on the segmented contour are similar to that of the corresponding point on the ground-truth contour, the energy related to that point should be small. When a segmented shape is close to the ground-truth image contour, its energy should also be small. Furthermore, the energy function ought to have as few local minimums as possible in order to simplify the searching [11].

The definition of energy function consists of two parts, the image gradient magnitude based energy and the GMM shape model based energy.

$$E(\mathcal{G}) = \sum_{i=1}^{N} a_i F\left(\boldsymbol{n}_i\right) + \sum_{j=1}^{M} b_j L\left(\boldsymbol{s}_j\right) \tag{10}$$

where $\mathcal{G}$ stands for the graph model of image contour, N is the total number of nodes, i is the index of node, $\boldsymbol{n}_i$ stands for the ith node on the contour, F is the gradient based feature energy component, j is the index of sub-shape, M is the total number of sub-shapes $\boldsymbol{s}_j$ defined on the contour $\mathcal{G}$, and L stands for the GMM likelihood based energy component. a_i and b_j are the weights of each energy component.

2.4. **Fast implementation.** In order to improve the computational efficiency, a fast version of segmentation algorithm is proposed in this section. In the second part of the energy formula, instead of using a complete shape model, we select an incomplete and sparse set of nodes from the original contour.

We explore two principles in the sparse selection of nodes. The first principle is that a subset of nodes are selected by equal distance. The second principle is that more nodes should be selected around the large curvature position of the contour. The later one usually outperforms the first one in segmentation accuracy. With a reduced subset of nodes, the original GMM shape model can be projected onto a lower dimensional GMM model by marginal probabilities.

3. **Meta Heuristic Optimization.** The interactive contour model is based on the energy minimization, which guarantees the desired positions to be found by certain searching strategy.

In this section, we combine the powerful shuffled frog leaping algorithm with the proposed image segmentation model. SFLA is a memetic heuristic that has been originally developed by Eusuff et al. [12] for combinational optimization problems. It consists of a set of interactive virtual population of frogs, and the algorithm can perform simultaneous local search and global exploration. In this paper, we combine the meta heuristic searching with the contour model and enable the local and global interactive searching.

In the initial stage for the virtual frog population, each individual frog is computed based on a possible contour in the image. The initial positions can be randomly selected, and the convergence of the optimization algorithm is not dependent on the initial positions.

During the iterative optimization, the worst frog that related to the maximum energy of an image contour is updated by a prefixed searching step.

When the value of the energy function is lower than a certain threshold or the maximum allowed iteration number is met, the final optimal virtual frog is given as the segmentation result.

Algorithm 1 Image Contour Optimization Based on SFLA.

Require: Local features $f(n_{i,j})$, mean vector $\boldsymbol{\mu}$ and covariance matrix $\boldsymbol{\Sigma}$ of the global shape $\boldsymbol{s}$.
Ensure: Optimized image contour $\mathcal{G}_{opt}$.

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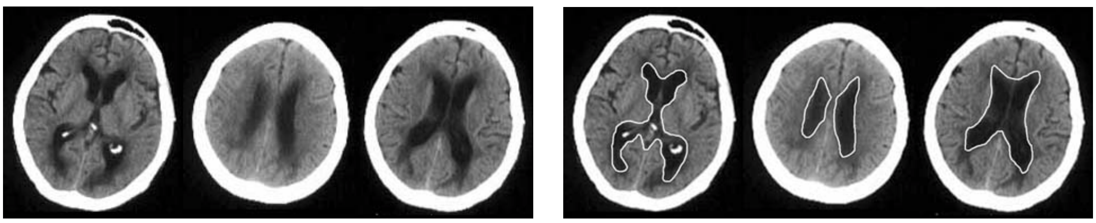
Initialize the virtual frogs: r_i = n_{i,j} ∈ G_i, where n_{i,j} is randomly generated around μ.
Set the maximum iteration number Q.
for all q = 1, ··· , Q do
    Calculate the fitness function f^q = E(G_i).
    Search the global optimal frog r_q^{opt}.
    Update the worst individual frog r_{q+1}^{worst} = r_q^{worst} + step × r_q^{opt}, where step is set to 0.5 empirically.
    Update the local features f(n_{i,j}) = f(r_q)
    Calculate the updated fitness function f^{q+1}.
    Terminate when the stopping criteria is met: f^{q+1} < θ, where θ is the energy threshold. θ is empirically set to 0.03.
end for
```

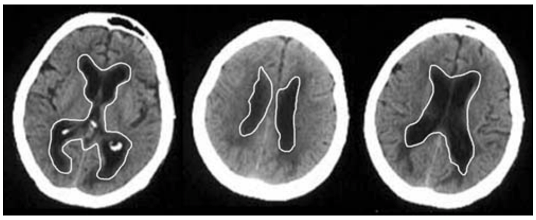
4. **Experimental Result.** In order to verify the performance of our image segmentation method, we investigate the brain image segmentation problem in this experiment. Examples of brain images from Leukoencephalopathy are depicted in Figure 1. The proposed algorithm is applied to the segmentation of key brain areas in the image.



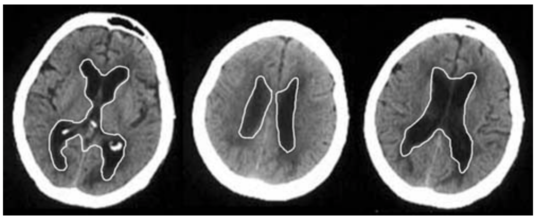
(a) Original image (b) Ground-truth segmentation

FIGURE 1. Examples of brain images from Leukoencephalopathy

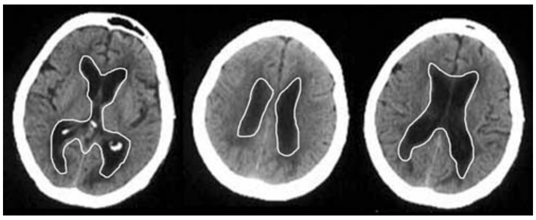
In our experiment, we compare the proposed segmentation algorithm with MRFs based segmentation method. In MRFs based method, a few candidate contours are generated from local image features by arbitrary selection. In our segmentation algorithm, the SFLA is used for optimization. In order to show the effectiveness of SFLA, we adopt the genetic algorithm (GA) as an alternative optimization tool. Hence, we have three image segmentation methods at hand, the MRFs based method (Algorithm I), the proposed efficient local and global interactive contour model from Section 2 combined with SFLA (Algorithm II), and the same proposed contour model combined with GA (Algorithm III). The corresponding segmentation results are demonstrated in Figure 2.



(a) Algorithm I



(b) Algorithm II



(c) Algorithm III

FIGURE 2. Segmentation results based on different algorithms

One of the drawbacks in the existing segmentation algorithms is the dependency on the initial contour positions. In our experiment, we choose different initial contours for the tested algorithms. One initial contour is close to the ground-truth position and the other two contours are farther away from the ground-truth. We denote these initial positions as initialization I (closest one), initialization II (middle one), and initialization III (farthest one).

We tested the three different image segmentation algorithms on 200 locally collected medical brain images, and the accuracies are shown in Table 1. We can see that, the initialization does not affect the proposed algorithm, while it affects the traditional MRFs based method. Algorithm II gives the best final results and proves the effectiveness of our energy optimization framework in image segmentation.

TABLE 1. Comparisons of image segmentation accuracies using various algorithms

Segmentation Accuracy	Initialization I	Initialization II	Initialization III
Algorithm I	83.8%	80.3%	76.4%
Algorithm II	93.4%	93.4%	92.1%
Algorithm III	90.2%	90.0%	89.2%

The computational efficiency is investigated using both the fast version of the proposed algorithm based a sparse contour and the original version. The computational speed is improved significantly when image pixel size grows, as shown in Figure 3.

5. **Conclusions.** In this paper we investigated the energy minimization problem in image segmentation. The local features and the global constraints are considered in a joint energy function. MRFs, GA, and SFLA are compared in this paper, and the optimization

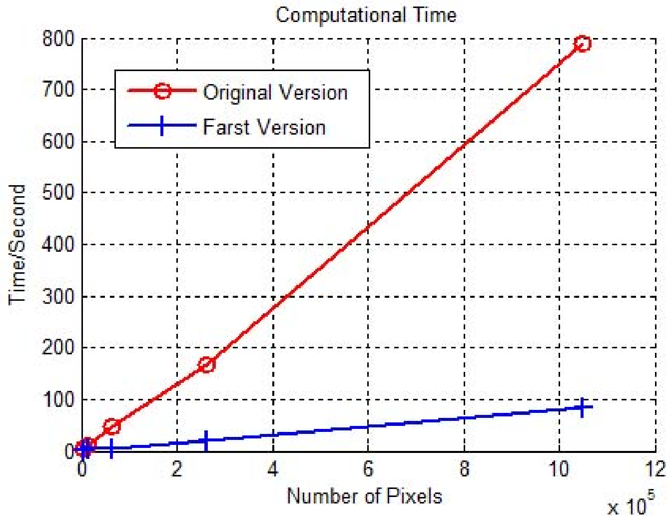


FIGURE 3. Improved computational efficiency using a sparse contour

results are successful. SFLA based image segmentation algorithm has an advantage of escaping local extremes and it is not sensitive to the initial positions. In future work, we will further explore the segmentation problem under various noise conditions, such as illumination change and low resolution.

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