ICIC Express Letters
Part B: Applications
Volume **9**, Number **1**, January **2018**

ICIC International ©2018 ISSN 2185-2766
pp. **69–76**

SUPERPIXEL SEGMENTATION ALGORITHM OF MRI IMAGES BASED ON STD_SLIC

Qi Qi[1,2], Xuanjing Shen[1,2], Haipeng Chen[1,2,*] and Xiaoxu Li[1,2]

[1]Key Laboratory of Symbolic Computation and Knowledge Engineering of Ministry of Education
[2]College of Computer Science and Technology
Jilin University
No. 2699, Qianjin Ave., Changchun 130012, P. R. China
qiqi15@mails.jlu.edu.cn; *Corresponding author: chenhp@jlu.edu.cn

Received July 2017; accepted September 2017

Abstract. *In this work, an improved SLIC (simple linear iterative clustering) superpixel segmentation algorithm for MRI images, std_SLIC, is proposed to deal with the effects of intensity inhomogeneity and boundary blurring exists in MRI images. Firstly, the original image was reconstructed by the three-dimensional histogram reconstruction model and enhanced by the γ correction; then, the image was segmented by std_SLIC superpixel segmentation algorithm, and the algorithm used a new cluster center updating rule which only used the pixels whose gray difference with present center is less than the standard deviation of the image to calculate the new center. Finally, undersegmentation error and boundary match were used to evaluate the efficiency of the algorithm. The experimental result shows that the proposed algorithm can improve the segmental effect at the fuzzy boundary, meanwhile, reduce the misclassification rate of pixels and improve the accuracy of segmentation, and the segmentation result is superior to the traditional SLIC superpixel segmentation.*

Keywords: Superpixel segmentation, std_SLIC, Three-dimensional histogram reconstruction, Image enhancement

1. **Introduction.** As the basis of various medical image applications, medical image segmentation technology shows important clinical value in the field of medical research and practice such as computer aided diagnosis (CAD), imaging guided surgery (IGS) and operative radiation therapy (ORT). Magnetic resonance imaging (MRI) has been widely used in medical imaging because it is good at soft tissue imaging. However, MRI has a long scanning time, and there exist intensity inhomogeneity and boundary blurring due to the limitation of imaging mechanism which has a great impact on accurate extraction of the target area and affects clinical diagnosis and treatment, so improving the accuracy of MRI image segmentation has attracted many scholars' attention [1,2].

With the development of imaging technology, traditional pixel-based segmentation method does not fully consider the spatial relationship between pixels, and has low calculation efficiency, so the segment result is difficult to meet the demand. Ren and Malik [3] proposed the superpixel to solve this problem [4,5]. Superpixel assembles pixels with similar characteristics, which is helpful to express the local and structural features of the image, and the number of superpixels is much smaller than the number of pixels, which improves the efficiency of subsequent operation. Therefore, superpixel segmentation as a preprocessing operation has become an important part of image segmentation in many fields [6-8]. However, for medical images, widely used superpixel segmentation methods such as normalized cuts [9], quick shift [10], and TurboPixels [11], are either complicated or time-consuming, which do not meet the requirements for accuracy and timeliness of medical image segmentation SLIC proposed in [12] can form regular superpixels simply and fast, which are suitable for medical image segmentation. In order to obtain more accurate medical image superpixels, an improved SLIC is proposed in this paper.

The rest of this paper is structured as follows. Section 2 describes the improved std_SLIC superpixel segmentation algorithm for MRI images; in Section 3, experimental results and analysis are presented; finally, conclusions are drawn in Section 4.

2. **std_SLIC Superpixel Segmentation.** As the preprocessing of medical image segmentation, the accuracy of superpixel segment result is highly required because the result will affect the subsequent processing of the image and affect the clinical application. In order to improve the accuracy of medical superpixel segmentation and overcome the problems existing in medical images, we proposed the std_SLIC superpixel segmentation algorithm.

2.1. **Segmentation scheme.** In the std_SLIC superpixel segmentation algorithm firstly, three-dimensional histogram reconstruction model and γ correction are used to reconstruct and enhance gray medical images, and then std_SLIC is used for superpixel segmentation. Experiments show that this algorithm can achieve better superpixel segmentation results. Figure 1 shows the framework of the algorithm.

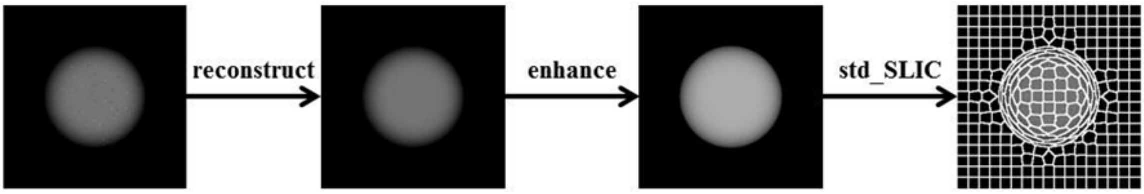

FIGURE 1. The framework of the proposed algorithm

2.2. **Three-dimensional histogram reconstruction.** Because of the long scanning time of MRI, the movement of sports organs and the patients during the imaging process makes intensity inhomogeneity exist in images, which affect the clinical diagnosis and treatment, so reconstructing intensity distribution of medical images is necessary.

In this paper, the three-dimensional histogram reconstruction model proposed in [13] is used to reconstruct the image. This model uses a three-dimensional histogram to represent the image; the three axes represent the gray value $f(x, y)$ of the pixel, the mean $g(x, y)$ and the median $h(x, y)$ in 3×3 neighborhood, respectively. For an intensity homogeneity image, the triplet $(f(x, y), g(x, y), h(x, y))$ should be distributed along the diagonal of the three-dimensional histogram (see Figure 2). For intensity inhomogeneity image, as shown

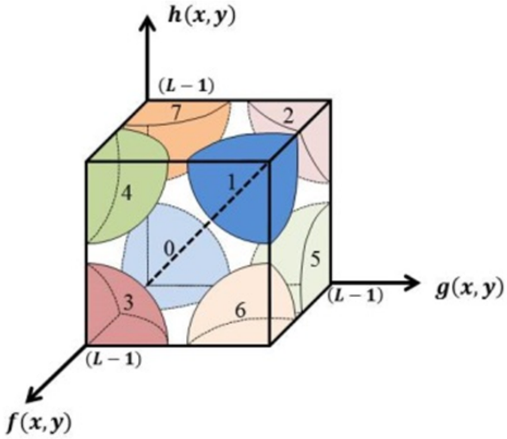

FIGURE 2. Three-dimensional rebuilding model

in Figure 2, the reconstruction model divides the three-dimensional histogram into eight regions:

(1) Region 0 and Region 1: The points in these two regions are normal distribution; there is no need to correct.

(2) Region 2 and Region 3: For points in these two regions, the gray value is corrected by the mean of the mean value and the median value:

$$f^* = (g + h)/2 \tag{1}$$

(3) Region 4 and Region 5: For points in these two regions, the mean value is corrected by the mean of the gray value and the median value:

$$g^* = (f + h)/2 \tag{2}$$

(4) Region 6 and Region 7: For points in these two regions, the gray value and the mean value are corrected by the median value:

$$f^* = g^* = h^* \tag{3}$$

In the reconstructed three-dimensional histogram, the pixels are distributed near the diagonal, and the medical image after reconstruction can be obtained by (4).

$$f(x, y) = (f^* + g^* + h^*)/3 \tag{4}$$

2.3. **γ correction.** Due to the limitation of the imaging mechanism, the target tissue in the MRI image will be dark, especially at the edge. The low contrast will affect the accuracy of image segmentation, so it is necessary to perform the enhancement processing before superpixel segmentation to highlight the edge of the target area. In this paper, we use the γ correction proposed in [14] to enhance the image.

Figure 3 shows the γ exponential equation where the range of the variable is $[0, 1]$, and γ is set to be 0.4, 0.5, 0.6, 0.8, 1.0.

The enhancement formula for MRI images in the experiment is:

$$D'(x, y) = 255 \left(\frac{D(x, y)}{255} \right)^{\gamma} \tag{5}$$

where $D(x, y)$ is the original image, and $D'(x, y)$ is the enhanced image.

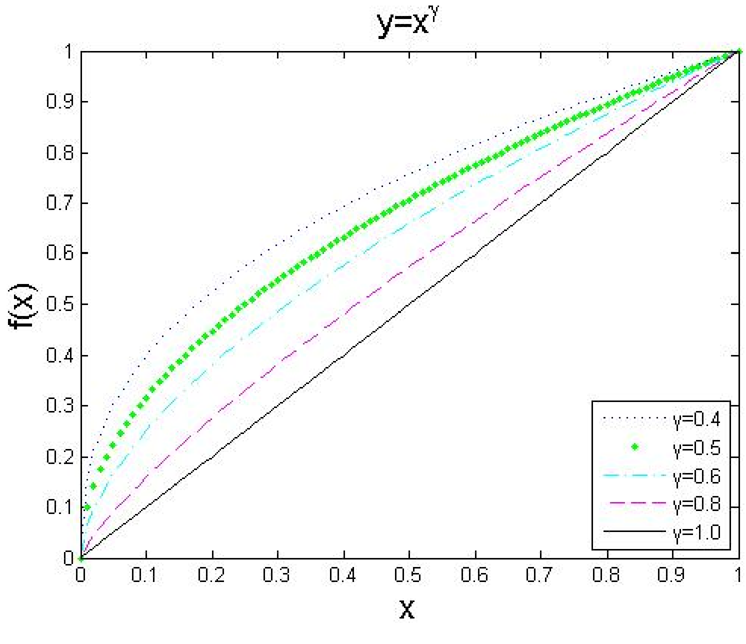

FIGURE 3. γ curve

It can be seen from Figure 3 and (5) that the γ correction has a large response output to the smaller input value, whereas the response output for the larger input value is very small [14]. Therefore, selecting the appropriate γ value will result in a significant enhancement of the target area.

2.4. **std_SLIC superpixel segmentation.** SLIC (simple linear iterative clustering) superpixel segmentation algorithm is an improved k-means clustering algorithm that reduces the search range to efficiently form superpixels [15]. Compared with other superpixel segmentation algorithms, the SLIC algorithm is simple, its computation time is fast and the computational complexity is low, and these advantages make the performance of image segmentation improved. So, SLIC superpixel segmentation algorithm is suitable for medical images.

SLIC clusters the pixels according to the color similarity and spatial distance. For gray images, SLIC superpixel segmentation is as follows.

Step 1. Initialize K clustering centers C_k by sampling pixels at regular grid steps $S = \sqrt{N/K}$, where N is the number of pixels in the image and K is the desired number of approximately equally sized superpixels set by oneself. Set label $l(i) = -1$ and distance $d(i) = \infty$ for each pixel i.

Step 2. For each pixel i in a $2S \times 2S$ region around C_k, use (6), (7), (8) to calculate the distance D between C_k and i:

$$d_c = \sqrt{\left(l_{C_k} - l_i\right)^2} \tag{6}$$

$$d_s = \sqrt{\left(x_{C_k} - x_i\right)^2 + \left(y_{C_k} - y_i\right)^2} \tag{7}$$

$$D = \sqrt{\left(\frac{d_c}{N_c}\right)^2 + \left(\frac{d_s}{N_s}\right)^2} \tag{8}$$

where d_c is the gray distance and l_i, l_{C_k} are the intensity of i and C_k, d_s is the spatial distance between C_k and i, N_c is the maximum gray distance and the value is 255, N_s is the maximum space within the class distance, $N_s = S = \sqrt{N/K}$. If $D < d(i)$, then set $d(i) = D$, $l(i) = k$.

Step 3. Update the cluster center. SLIC uses the following formula to calculate the new cluster center:

$$CO_j = \frac{1}{N_j} \sum_{j \in G_j} CO_i \tag{9}$$

$$S_j = \frac{1}{N_j} \sum_{i \in G_j} S_i \tag{10}$$

where G_j represents pixels set center on C_j, and N_j is the number of pixels in G_j. CO_j, S_j are the pixel color mean and distance mean of G_j, respectively.

Step 2 and Step 3 are iteratively executed until the preset number of iterations is reached. In general, 10 iterations are enough.

SLIC is an iterative clustering process. [16] pointed out that in the SLIC process of color images, there will be some pixels misclassified after the first iteration. Because all the pixels within the class will be used to update new cluster centers, after several iterations, the error will be amplified and affect the final superpixel segmentation results. In this paper, only the pixels whose intensity is close to the original clustering center are used to update the clustering center. (9) and (10) in the original SLIC algorithm are changed into Equations (11)-(14) in the std_SLIC algorithm:

$$C_j = \frac{1}{N_j} \sum_{i \in \Omega_j} \begin{bmatrix} C_i \\ S_i \end{bmatrix} \tag{11}$$

$$CO_j = \frac{1}{N_j} \sum_{j \in \Omega_j} CO_i \tag{12}$$

$$S_j = \frac{1}{N_j} \sum_{i \in \Omega_j} S_i \tag{13}$$

$$\Omega_j = (|l_j - l_i| < std) \cap G_j \tag{14}$$

where std is the standard deviation of the image gray scale calculated by (15):

$$std = \left(\frac{1}{n-1} \sum_{i=1}^{n} \left(l_i - \bar{l} \right)^2 \right)^{\frac{1}{2}} \tag{15}$$

where l_i represents the intensity of point i, $\bar{l}$ is the mean intensity of the image.

3. **Experimental Results and Analysis.** This experiment was implemented in MATLAB on a 3.40GHz quad core CPU running Windows XP with 2 GB RAM. Experiments were carried out on multiple MRI brain images and the segment results were compared with traditional SLIC and reconstructed enhanced SLIC. The images were taken from http://www.med.harvard.edu/aanlib/home.html.

Figure 4 shows the experimental results of MRI images. In Figure 4, after reconstruction and enhancement, most of the unrecognized target area parts whose intensities are close to the background are segmented, and the result of the segmentation is more accurate. Because of the complexity of medical image, the superpixels in the segment results are cluttered, and it is difficult to see the superiority of the algorithm. Therefore, undersegmentation error and boundary match are used to evaluate the experimental results [17].

(1) Undersegmentation Error

Undersegmentation error [11] is used to measure the "overflow" parts of the superpixels that have overlap with groundtruth. Assuming the superpixel segmentation algorithm divides the image into $s_1, s_2, \ldots, s_n$ superpixels, undersegmentation error is defined as the proportion of the outside parts to the entire target area, expressed as Formula (16):

$$UE = \frac{\left[\sum_{\{s_i | s_i \cap g \neq \phi\}} s_i \right] - g}{g} \tag{16}$$

The groundtruth target area g is used to normalize the value of "overflow". The value of UE is between $[0, 1]$. The smaller the UE value is, the more accurate the segment is.

Table 1 shows the contrast of UE values between the images in Figure 4.

Table 1. UE comparison of three algorithms

	SLIC	reconstructed enhanced SLIC	std_SLIC
(a)	0.5422	0.4068	**0.3791**
(b)	0.6239	0.5691	**0.4843**
(c)	0.6334	0.6239	**0.5190**
(d)	0.4121	0.3763	**0.3314**
(e)	0.3328	0.2545	**0.2306**
(f)	0.2621	0.2189	**0.1851**
(g)	0.3564	0.2465	**0.2210**
(h)	0.3199	0.2284	**0.2115**
(i)	0.2841	0.2568	**0.2141**
(j)	0.3324	0.2717	**0.2229**
(k)	0.4971	0.4258	**0.3911**

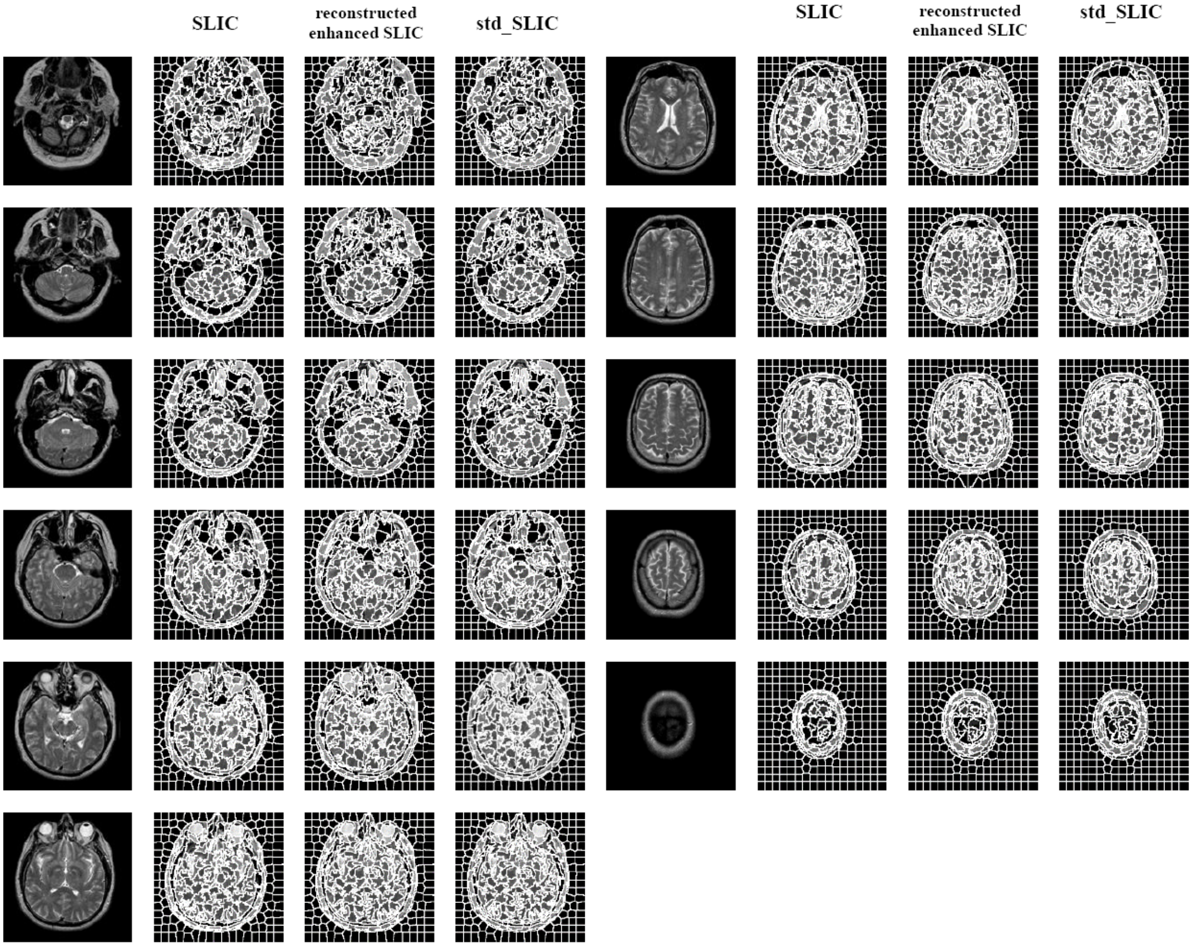

FIGURE 4. Experimental results of three methods

It can be seen from Table 1 that after reconstruction and enhancement, the image segment error was significantly reduced. After using std_SLIC algorithm, the intensity of the pixel in the superpixel is more consistent, and the edge of the superpixel is more affixed because the clustering center is updated with the pixels whose gray differences with present center are less than the standard deviation of the image. The "overflow" part is smaller, and the segment results are more ideal for medical images.

(2) Boundary Match

Boundary match is used to measure the boundary overlap ratio of the superpixel and groundtruth of the target area; it can be expressed as follows:

$$BM = \frac{SP(img) \cap GT(img)}{SP(img)} \tag{17}$$

where $SP(img)$ is the boundary of superpixels, and $GT(img)$ is the target region boundary marked in the groundtruth. The range of BM is $[0, 1]$. The larger the value of BM is, the more accurate the segmentation result is.

Table 2 shows the contrast of BM values between the images in Figure 4 in different methods.

It can be seen from Table 2 that after reconstruction, enhancement and std_SLIC, the BM values of segmentation results were significantly increased compared with traditional SLIC. It means that after the proposed algorithm, the edge of the superpixel has more overlaps part with target area in groundtruth because of the new update strategy of std_SLIC, which reduces the possibility of misclassification and increase the accuracy of

Table 2. BM comparisons of three algorithms

	SLIC	reconstructed enhanced SLIC	std_SLIC
(a)	0.5783	0.6333	**0.6471**
(b)	0.5741	0.6412	**0.6568**
(c)	0.6571	0.6898	**0.7051**
(d)	0.6367	0.6969	**0.7196**
(e)	0.6667	0.7014	**0.7163**
(f)	0.7158	0.7349	**0.7430**
(g)	0.6934	0.7075	**0.7415**
(h)	0.7018	0.7224	**0.7439**
(i)	0.7216	0.7376	**0.7568**
(j)	0.7230	0.7168	**0.7589**
(k)	0.6889	0.6732	**0.6999**

superpixel segmentation, and the accurate segment boundary makes the segment results more helpful for clinical diagnosis and treatment.

4. **Conclusions.** To overcome intensity inhomogeneity and boundary blurring in MRI images and misclassification exists in traditional SLIC, this paper presents a superpixel segmentation algorithm of MRI images based on std_SLIC. Firstly, the three-dimensional histogram reconstruction model is used to eliminate the phenomenon of intensity inhomogeneity, and then enhances the image in γ correction; secondly, for the timeliness and accuracy requirements, the std_SLIC algorithm that limits the intensity of pixels used to update clustering center is applied to improving the clustering center update process for MRI images superpixel segmentation. Undersegmentation error and boundary match are used to measure the segmentation result. The experimental results show that the proposed algorithm has more accurate segmentation result, and the superpixel preprocessing result for the subsequent processing and application of the medical image is of great help. In future work we aim to further improve the accuracy of SLIC superpixel segmentation and incorporate more image features like texture into SLIC.

Acknowledgment. This work is supported by National Natural Science Foundation of China (No. 61672259), the National Youth Science Foundation of China (No. 61602203), and the Natural Science Foundation of Jilin Province (No. 20150101055JC)

REFERENCES

[1] G. Jiang, W. Qin, S. Zhou et al., State-of-the-art in medical image segmentation, *Chinese Journal of Computers*, vol.38, no.6, pp.1222-1242, 2015.

[2] Q. Luo, W. Qin, J. Gu et al., Progress of the segmentation methods of magnetic resonance image and its application, *International Journal of Biomedical Engineering*, vol.36, no.3, pp.165-171, 2013.

[3] X. Ren and J. Malik, Learning a classification model for segmentation, *IEEE International Conference on Computer Vision*, vol.1, p.10, 2003.

[4] X. Song, L. Zhou, Z. Li et al., Review on superpixel methods in image segmentation, *Journal of Image and Graphics*, vol.20, no.5, pp.599-608, 2015.

[5] C. Wang, J. Chen and W. Li, Review on superpixel segmentation algorithms, *Application Research of Computers*, vol.31, no.1, pp.6-12, 2014.

[6] H. Zou, X. Qin, S. Zhou et al., A likelihood-based SLIC superpixel algorithm for SAR images using generalized gamma distribution, *Sensors*, vol.16, no.7, pp.1107-1122, 2016.

[7] H. Chung, G. Lu, Z. Tian et al., Superpixel-based spectral classification for the detection of head and neck cancer with hyperspectral imaging, *Proc. of SPIE – The International Society for Optical Engineering*, 2016.

[8] Z. Tian, L. Liu, Z. Zhang et al., Superpixel-based segmentation for 3D prostate MR images, *IEEE Trans. Medical Imaging*, vol.35, no.3, pp.791-801, 2015.
[9] J. Shi and J. Malik, Normalized cuts and image segmentation, *IEEE Trans. Pattern Analysis & Machine Intelligence*, vol.22, no.8, pp.888-905, 2000.
[10] A. Vedaldi and S. Soatto, Quick shift and kernel methods for mode seeking, *European Conference on Computer Vision*, pp.705-718, 2008.
[11] A. Levinshtein, A. Stere, K. N. Kutulakos et al., TurboPixels: Fast superpixels using geometric flows, *IEEE Trans. Pattern Analysis & Machine Intelligence*, vol.31, no.12, pp.2290-2297, 2009.
[12] A. Radhakrishna, A. Shaji, K. Smith et al., Slic superpixels, *Technical Report 149300, EPFL*, 2010.
[13] J. Long, X. Shen and H. Chen, Interactive document images thresholding segmentation algorithm based on image regions, *Journal of Computer Research and Development*, vol.49, no.7, pp.1420-1431, 2012.
[14] J. Long, X. Shen, H. Zang et al., An adaptive thresholding algorithm by background estimation in Gaussian scale space, *Acta Automatica Sinica*, vol.40, no.8, pp.1773-1782, 2014.
[15] R. Achanta, A. Shaji, K. Smith et al., SLIC superpixels compared to state-of-the-art superpixel methods, *IEEE Trans. Pattern Analysis & Machine Intelligence*, vol.34, no.11, pp.2274-2282, 2012.
[16] K. S. Kim, D. Zhang, M. C. Kang et al., Improved simple linear iterative clustering superpixels, *IEEE the 17th International Symposium on Consumer Electronics*, pp.259-260, 2013.
[17] A. Schick, M. Fischer and R. Stiefelhagen, Measuring and evaluating the compactness of superpixels, *The 21st International Conference on Pattern Recognition*, pp.930-934, 2012.