IET Image Processing

Research Article

Super-pixel image segmentation algorithm based on adaptive equalisation feature parameters

ISSN 1751-9659
Received on 29th March 2020
Revised 17th October 2020
Accepted on 6th November 2020
E-First on 24th February 2021
doi: 10.1049/iet-ipr.2020.0475
www.ietdl.org

Shifei Ding[1,2], Lijuan Wang[1,3] ✉, Lin Cong[1,2]

[1]School of Computer Science and Technology, China University of Mining and Technology, Xuzhou 221116, People's Republic of China

[2]Mine Digitization Engineering Research Center of Ministry of Education of the People's Republic of China, Xuzhou 221116, People's Republic of China

[3]School of Information and Electrical Engineering, Xu Zhou College of Industrial Technology, Xuzhou 221400, People's Republic of China

✉ *E-mail: donglittle@126.com*

Abstract: Image segmentation is a key step in the process of image data processing. The quality of image segmentation will directly affect the accuracy of image cognitive understanding. The purpose of image segmentation is to divide the image into regions with specific semantics. For the simple linear iterative clustering (SLIC) algorithm, the feature equalisation parameters need to be set manually during image segmentation, which results in the lack of segmentation effects and slow processing time. By introducing the theory of intermediary mathematics, an improved adaptive SLIC super-pixel algorithm is proposed, which can adaptive generate characteristic equalisation parameters according to the specific situation of the image, thereby simplifying the operation steps and improving the image segmentation effect. After experimental verification and analysis, compared with the original SLIC algorithm and several other super-pixel contrast algorithms, the algorithm in this study can effectively shorten the processing time and achieve a better segmentation effect.

1 Introduction

Image segmentation technology is one of the key technologies in the field of image analysis. These regions reflect the prominent expression information of the image [1]. With the development of image segmentation technology, a spectral clustering algorithm is more and more widely used in its field. The traditional spectral clustering image segmentation algorithm is based on the pixels of the image to be segmented as the basic processing unit [2–5]. However, with the continuous development and progress of image technology, the resolution of the image is getting higher and higher, so it needs to be segmented. The size of the image is getting larger and larger, but the traditional spectral clustering algorithm is not very effective in large-scale image segmentation, especially in the application of colour image processing, video image segmentation and other limitations are more obvious [6]. As a key step in image processing technology, image segmentation provides the underlying support for subsequent image recognition and analysis, which means that the quality of the output results of image segmentation directly determines the accuracy of subsequent analysis and cognitive results. Therefore, segmenting the coloured image effectively to extract the effective information in the image is an important issue in the field of image segmentation.

Super-pixel algorithm is a kind of algorithm that divides an image into several sub-regions which are local, consistent and can preserve the local structural features of the image. In image segmentation, a large number of pixels in the target image are gathered into multiple super-pixel regions to achieve pre segmentation, which can greatly reduce the total processing time of image segmentation. The super-pixel algorithm transforms the image segmentation problem into two steps. The first step is the clustering problem between similar pixels. The pixels with similar colour space positions are divided into a 'super-pixel' region [7]. The second step is to regard the 'super-pixel' region obtained in the first step as the pixel unit of general image segmentation processing. Super-pixel regions are segmented by corresponding segmentation algorithms, i.e. super-pixel regions are classified and merged to produce effective image segmentation [8]. By generating accurate super-pixel block segmentation in limited time, it will be conducive to subsequent feature extraction and target recognition, while effectively avoiding the low computational efficiency of general segmentation algorithm in the process of processing. Compared with the traditional method of image processing based on pixels, the advantages of super-pixels are mainly reflected in the extraction of local features and the expression of image structure information, as well as the reduction of the size of processing objects and the computational complexity of subsequent processing [9, 10].

In the field of scientific theoretical research, the theorems, definitions, or inferences proposed by experts and scholars are mostly deterministic, which means that some theoretical concepts are often unclear. However, in real life, everywhere phenomenon can be seen everywhere [11, 12]. For example, when we describe a painting that is not good-looking, good-looking, and very good-looking, there is no certain measure to define different evaluations; for example when we praise a researcher for his serious research attitude, there is no certainty The criteria to measure the so-called degree of seriousness. Therefore, this state or concept that cannot use certain concepts and cognition to describe the degree of things is called a fuzzy state or a fuzzy concept [13]. Such a similar situation is not uncommon in our lives, and for common vague phenomena, the use of ordinary deterministic definitions of reasoning can no longer solve the corresponding problems that arise. Therefore, we want to find a research method that can be used to quantitatively measure this phenomenon, and the emergence of intermediate mathematics can be used to describe the fuzzy concept and fuzzy state of things.

Simple linear iterative clustering (SLIC) algorithm is a gradient-based super-pixel segmentation algorithm, which proposed by Achantan *et al.* [14]. It uses the similarity between colour and distance to segment the image. The colour of the image is used to replace the super-pixel region, and the distance feature of a larger order of magnitude is used to replace the distance feature. In the similarity measurement of image segmentation, colour feature information and coordinate distance feature information are used, and there are equalisation parameters to balance the two functional information. The traditional SLIC super-pixel algorithm, when preprocessing the image, will determine the clustering centre by iteration, and the compactness between different regions needs to be set manually, and the corresponding segmentation effect is

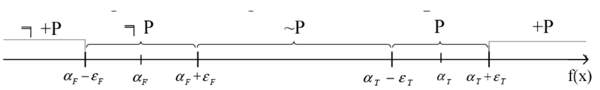


Fig. 1 *Numeric area division*

different under different parameters [15]. In this case, the operator often needs to spend a lot of time to adjust the value of the equalisation feature parameters to achieve a satisfactory segmentation effect. In addition, the segmentation effect and processing time of pictures under different values are also different. Therefore, in order to simplify the processing flow, compress the processing time and improve the effectiveness of image segmentation, users often use fixed equalisation parameters to calculate. However, in real life, the distribution of image colour information or the differences between colours are often different in different scenes. In this case, the fixed weight will lead to the unsatisfactory segmentation effect. In order to solve the shortcomings of traditional SLIC algorithm for obtaining equalisation parameters, this paper proposes an adaptive parameter SLIC (ASLIC) algorithm based on the idea of intermediary mathematics. According to the size and feature information of specific target image, this algorithm can adaptively generate better equalisation parameters for a specific image, so as to save time and improve the segmentation effect.

The rest of the paper is organised as follows: Section 2 of this paper describes the related theoretical knowledge and processing flow of super-pixel algorithm and intermediary degree measurement are described, including the comparative analysis of several classic super-pixel algorithms which are widely accepted at present and the related algorithm steps. In Section 3, aiming at the shortcomings of the super-pixel algorithm, a super-pixel algorithm based on the idea of intermediary mathematics is proposed, and the principle and implementation steps of the algorithm are introduced. In Section 4, the algorithm is validated by analysing and comparing the related data. Section 5 summarises a series of work done in this paper and clarifies the next research direction.

2 Related works

2.1 Colour space conversion of colour images

For colour image-oriented clustering segmentation algorithms, setting an appropriate colour space for colour images is an important basis for describing image feature information and accurately segmenting images. Generally speaking, the colour space is divided into RGB, HSV, and CIE. The RGB colour space is a colour space whose colour components have a highly linear relationship. The differences between the colour features corresponding to the colour information in the RGB colour space cannot be directly measured and calculated by Euclidean distance, and the distribution characteristics of the colours themselves are often ignored [16]. Therefore, when colour images are segmented using the RGB colour space, the effect is often significantly different from the image area obtained by the human eye. The CIELAB colour space [17] was developed by the International Illumination Commission and has a universally adopted colour model for international standards. The CIELAB colour space can describe any colour that exists in nature. Compared with the RGB colour space, the design of the CIELAB colour space is closer to the colours in the actual scene seen by the human eye. The CIELAB space can be derived from the RGB colour space according to the non-linear correlation transformation, where L represents the brightness of the image, A is the colour transformation from red to green in the image, and B is the transformation from blue to yellow in the image. Among them, the interval of A and B colour values is −128 to 127, and the interval capacity of brightness L is 0–100. By combining these three colour components with different numerical values, it is possible to describe a certain colour arbitrarily existing in nature.

$$\begin{cases} X = 0.4124R + 0.4125G + 0.4126B \\ Y = 0.2127R + 0.7152G + 0.0722B \\ Z = 0.0193R + 0.1192G + 0.9502B \end{cases} \tag{1}$$

After the image in the CIEXYZ colour space is obtained, it can be transformed into an image in CIELAB space according to the corresponding rules

$$\begin{cases} L = 116f(Y/Y_n) - 16 \\ A = 500[f(X/X_n) - f(Y/Y_n)] \\ B = 200[f(Y/Y_n) - f(Z/Z_n)] \end{cases} \tag{2}$$

$$f\begin{pmatrix} X_n \\ Y_n \\ Z_n \end{pmatrix} = g\begin{pmatrix} X/0.9504565 \\ Y/1 \\ Z/1.0888 \end{pmatrix} \tag{3}$$

$$g(t) = \begin{cases} t^{1/3} & t > \left(\dfrac{6}{29}\right)^3 \\ \dfrac{1}{3}\left(\dfrac{29}{6}\right)^2 t + \dfrac{4}{29} & \text{otherwise} \end{cases} \tag{4}$$

When the colour space is converted, the RGB colour space is first transformed into CIEXYZ space, as in formula (1), and then the components in the *XYZ* space are converted into CIELAB space according to formulae (2)–(4) can convert the colour components R, G, and B in the original RGB space in the colour image into L, A, and B components.

2.2 Selection of equilibrium parameters based on the measurement of the intermediate mathematical degree

Intermediate logic calculation system (the semantics describing things are defined by three values, namely positive value T, negative value F and intermediate value M. A complete intermediate logic calculation system can use the set $\{T, M, F\}$ to describe things. Intermediate value refers to the semantic value between positive and negative, which is used to describe the uncertain fuzzy state of things [18]. Combined with these States, for the general numerical range describing the degree of things, we can use the division of numerical region in the Fig. 1.

In one-dimensional space, the Euclidean distance d is usually used to calculate the distance between two individuals, i.e. similarity. By introducing the concept of hyper state, the one-dimensional numerical region can be roughly divided into $\neg^{+} P$, $\neg\ P$, $\sim P$, P, ^{+}P numerical region, where α_T is the ε_T truth standard of the predicate P; Accordingly, in the range of the value range represented as false value, α_F is the ε_F standard degree of $\neg\ P$, that is to say, the range of P true value can be simply described as $[\alpha_T - \varepsilon_T, \alpha_T + \varepsilon_T]$, while the range of $\neg$ false value is $[\alpha_F - \varepsilon_F, \alpha_F + \varepsilon_F]$. That is to say, the relationship between α_T and α_F determines the true false relationship of a predicate. By calculating the corresponding distance ratio function P (or $\neg\ P$) relative to the truth value $h_T(y)$ (or the false value $h_F(y)$), we can get the specific truth degree of things in their respective numerical regions.

Considering the universality and universality of the distribution of things, in general, if we do not involve the superstate in an event, we generally do not include the numerical region of the superstate. In other words, in the general application background, we only use P, $\sim P$, $\neg\ P$ to measure the degree value of things. Relative to the P distance ratio function of the predicate $h_T(y)$, the corresponding calculation formula can be obtained

$$h_T(y) = \begin{cases} \dfrac{-\mathrm{d}(y, \alpha_F - \varepsilon_F)}{\mathrm{d}(\alpha_T - \varepsilon_T, \alpha_F - \varepsilon_F)} & y < \alpha_F - \varepsilon_F \\ 0 & \alpha_F - \varepsilon_F < y < \alpha_F + \varepsilon_F \\ \dfrac{\mathrm{d}(y, \alpha_F + \varepsilon_F)}{\mathrm{d}(\alpha_T - \varepsilon_T, \alpha_F + \varepsilon_F)} & \alpha_F + \varepsilon_F < y < \alpha_T + \varepsilon_T \\ 1 & \alpha_T - \varepsilon_T < y < \alpha_T + \varepsilon_T \\ \dfrac{\mathrm{d}(y, \alpha_T + \varepsilon_T)}{\mathrm{d}(\alpha_T - \varepsilon_T, \alpha_T + \varepsilon_T)} & y > \alpha_T + \varepsilon_T \end{cases} \tag{5}$$

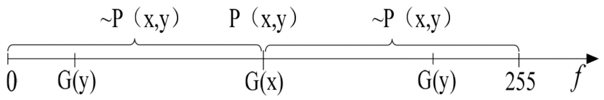


Fig. 2 *Similarity measure of grey information between pixels*

By analogy, for the predicate $\neg P$, according to similar calculation, the distance ratio formula can be obtained:

$$h_F(y) = \begin{cases} \dfrac{-\mathrm{d}(y, \alpha_T + \varepsilon_T)}{\mathrm{d}(\alpha_T + \varepsilon_T, \alpha_F + \varepsilon_F)} & y > \alpha_T + \varepsilon_T \\ 0 & \alpha_T - \varepsilon_T < y < \alpha_T + \varepsilon_T \\ \dfrac{\mathrm{d}(y, \alpha_T - \varepsilon_T)}{\mathrm{d}(\alpha_T - \varepsilon_T, \alpha_F + \varepsilon_F)} & \alpha_F + \varepsilon_F < y < \alpha_T - \varepsilon_T \\ 1 & \alpha_F - \varepsilon_F < y < \alpha_F + \varepsilon_F \\ \dfrac{\mathrm{d}(y, \alpha_F - \varepsilon_F)}{\mathrm{d}(\alpha_F - \varepsilon_F, \alpha_F + \varepsilon_F)} & y < \alpha_T - \varepsilon_T \end{cases} \quad (6)$$

3 Improved SLIC algorithm with adaptive equalisation parameters

The super-pixel algorithm is used in the field of image segmentation when it is available. At present, super-pixel algorithms can be divided into two broad categories: graph-based algorithm and gradient-based algorithm. The former is to transform the image segmentation problem into the problem of how to minimise the energy function. The algorithm considers the pixels in the image as the vertices of the graph. By calculating the corresponding weights between the vertices of the graph, select a variety of segmentation criteria to divide the graph, thus forming a super-pixel region. The basic idea of the gradient-based algorithm is based on the original pixel clustering, using the gradient method iterative computing to correct the clustering results until the convergence conditions are met, thus forming a number of super-pixel regions.

SLIC algorithm is a super-pixel calculation method based on the advantages of Turbopixel algorithm which has a simple process and high processing quality. The super-pixel algorithm performs feature extraction on the basis of 5D space (3D LAB colour space and 2D *XY* coordinate space) [19] and combines the colour information and spatial position information of the super-pixel area according to the distance metrics.

The processing steps of the SLIC algorithm are as follows:

(1) *Initialise cluster centre:* the user can set the number of super-pixels in advance according to the actual segmentation requirements of the original image, and then distribute the centre of mass randomly and evenly for all the number of pixel points in the whole image, i.e. allocate the corresponding cluster centres. The area of each super-pixel area block is $S \times S$, where $S = \mathrm{sqrt}(N/K)$.

(2) *Update cluster centre:* update in the neighbourhood of the cluster centre point (generally $n = 3$), i.e. redetermine the generation of a new round of cluster centre. The determination criterion of the cluster centre is generally to calculate the gradient value of pixel points in the region, and select the point with the minimum gradient value as the cluster centre point. The purpose of this step is to prevent the final clustering centre point from being on the edge of the larger gradient value and to avoid affecting the processing effect of the subsequent process.

(3) *Matching label:* the category label of the matching area of all pixel points in the neighbourhood around all existing clustering centre points. Considering the convergence speed of the algorithm in the specific operation process, the SLIC algorithm controls its search range to $2S \times 2S$.

(4) *Setting of similarity measure and distance measurement:* in this paper, distance measurement can be divided into the colour distance and space distance. For every pixel found in the process of operation, the SLIC algorithm will analyse and judge the distance between the pixel and its cluster centre in turn. The distance is calculated as follows:

$$d_{lab} = \sqrt{(l_k - l_i)^2 + (a_k - a_i)^2 + (b_k - b_i)^2} \quad (7)$$

$$d_{xy} = \sqrt{(x_k - x_i)^2 + (y_k - y_i)^2} \quad (8)$$

$$D_s = \sqrt{d_{lab}^2 + \lambda^2 d_{xy}{}^2} \quad (9)$$

Among them, d_{lab} represents the distance of colour related colour features between pixels, and d_{xy} represents the distance of coordinate space, among which $\lambda = m/S$ can be used to coordinate the compactness between colour features and coordinate space distance features. The larger the λ value is, the higher the compactness of super-pixel blocks formed after image processing, and the more regular the corresponding shape. In general, the specific size of λ value is determined by m, and the value range in the process of processing is between 1 and 40. Therefore, m is the feature equalisation parameter of equalisation colour feature space information and coordinate space information. D_s describes the comprehensive similarity degree of pixels in the *XY* spatial coordinate system and in CIELAB colour space. The larger the D_s, the more similar the two pixels described.

(5) *Iterative calculation is used to optimise the algorithm.* In theory, in the operation of the algorithm, the above process will continue to carry out iterative calculation until the error convergence.

SLIC super-pixel algorithm is used to preprocess the original image, so that the processing target can be transferred from pixel level to super-pixel level. Through this kind of preprocessing operation, the operation speed of the algorithm can be effectively improved, with less computation. Compared with other methods, the SLIC super-pixel method can process super large pictures and data with high performance.

In the theory of mediation logic system, the level of mediation truth can also be used to calculate the similarity between image pixels. For example, in an image, the number of all pixel points is n. for any two pixel points x and y, we can describe the similarity of image grey information according to the data area shown in the Fig. 2 [20–26].

Fig. 2 describes that in the measurement category of mediation degree, when the grey information between any two pixels in the same image is calculated, it can be divided into corresponding numerical regions, so as to calculate the similarity between the two according to the threshold value of pixel specific attribute.

$$G(x, y) = \begin{cases} \dfrac{d(G_y, -1)}{d(G_x, -1)} & 0 \le G_y < G_x \\ 1 & G_y = G_x \\ \dfrac{d(G_y, 256)}{d(G_x, 256)} & 255 \ge G_y > G_x \end{cases} \quad (10)$$

Formula (10) is a calculation method of grey level information of two pixel points in intermediate mathematics. Grey level information applies to the 2D grey level image, while the related attributes of pixel points in the 3D colour image can be grey level, brightness, colour, texture, coordinate distance and much other related information. Different algorithms often use different features to calculate similarity. Therefore, by using the extended formula (10), we can obtain the numerical region formed by other attributes of pixels of a colour image, and calculate the similarity of other attributes of pixels.

Given an image, any two pixels in the image have unique $L(x, y)$, $A(x, y)$, $B(x, y)$, $D(x, y)$, which are used to identify the relevant feature information of colour and coordinate space distance. Among them, $L(x, y)$ represents the brightness information between pixels, $A(x, y)$ identifies the red and green colour value information of the two, while $B(x, y)$ describes the yellow and blue colour value information, in addition, $D(x, y)$ represents the coordinate Euclidean distance of pixels. For any two pixel points x, y in the image, suppose we regard pixel points as x contrast pixel points and pixel points y as test points. Therefore, the

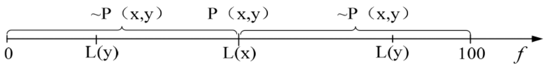


Fig. 3 *Similarity measure of brightness information between pixels*

Table 1 Description of ASLIC algorithm

Algorithm 1: ASLIC
Input: original image, number of super-pixels *K*
Output: Equalisation weights *ms*, *K* pre-processed super-pixel regions
1) $CIELAB \leftarrow RGB$
2) $m \leftarrow m(i,j) \leftarrow \sqrt{x(i,j)^2 + y(i,j)^2} / \sqrt{L(i,j)^2 + A(i,j)^2 + B(i,j)^2}$
3) $m_i \leftarrow (m_{i\max} + m_{i\min})/2$initial equalization weight of a certain super-pixel block *i*
4) Take the m_i divided set into two subsets, that is, if $m_{ij} < m_i$, then $m_{ij} \in ms$; if $m_{ij} > m_i$, then $m_{ij} \in mb$
5) $mm \leftarrow (\overline{ms} + \overline{mb})/2$update the equilibrium weight
6) $while((m_i - mm) <= allow)$, return$m_i$, $else\, m_i \leftarrow mm$, turn to (4)
7) Calculate *m* of other super-pixels according to (2)–(6)
8) $ms \leftarrow \sum_{i=1}^{N} m_i/K$the final weights of all super-pixel blocks
9) SLIC algorithm processing to generate segmentation results.

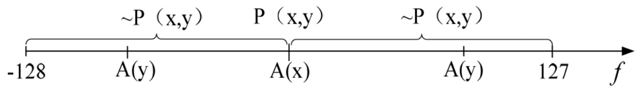


Fig. 4 *Similarity measure of red and green values information between pixels*

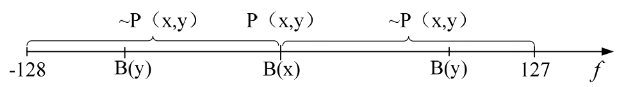


Fig. 5 *Similarity measure of yellow and blue values information between pixels*

brightness value of pixel y may be any value distributed in the range of 0–100, and the red–green colour value and yellow–blue colour value of y may also be any value in the range of − 128 to 127.

Set predicate p to describe the similarity relationship between y to be tested and x to be tested. According to the theory of intermediary mathematics, we can use $\sim P(x, y)$ to describe the relationship between similarity and dissimilarity. L_x and L_y are the brightness values of the contrast point x and the test point y respectively. Using the correlation shown above, the numerical region can be divided according to the brightness relationship between two pixels in an image.

It can be seen from Fig. 3 that when $y < x$, y is on the left side of the numerical region, and when $y > x$, y is on the right side of the numerical region. Therefore, according to the correlation formula of calculating pixel grey similarity in intermediary mathematics, the similarity of pixel brightness value can be extended.

$$L(x,y) = \begin{cases} \dfrac{|L_y + 1|}{|L_x + 1|} & 0 \le L_y < L_x \\ 1 & L_y = L_x \\ \dfrac{|L_y - 101|}{|L_x - 101|} & 100 \ge L_y > L_x \end{cases} \tag{11}$$

By analogy, Figs. 4 and 5 show that the similarity of colour feature information between pixels can be described by calculating the red–green value and the yellow–blue value between pixels.

$$A(x,y) = \begin{cases} \dfrac{|A_y + 129|}{|A_x + 129|} & -128 \le A_y < A_x \\ 1 & A_y = A_x \\ \dfrac{|A_y - 128|}{|A_x - 128|} & 127 \ge A_y > A_x \end{cases} \tag{12}$$

$$B(x,y) = \begin{cases} \dfrac{|B_y + 129|}{|B_x + 129|} & -128 \le B_y < B_x \\ 1 & B_y = B_x \\ \dfrac{|B_y - 128|}{|B_x - 128|} & 127 \ge B_y > B_x \end{cases} \tag{13}$$

By analogy, the similarity of colour feature information between pixels can be described by calculating the red–green value and the yellow–blue value between pixels. In formulae (11)–(13), $L(x, y)$, $A(x, y)$, $B(x, y)$, respectively, reflect the similarity degree of brightness information, red–green colour information and yellow–blue colour information of pixel points. When $L(x, y)$, $A(x, y)$, $B(x, y)$ values are all 1, it means that the similarity degree of two pixel points is exactly the same; when $L(x, y)$, $A(x, y)$, $B(x, y)$ values are smaller or larger, it means that the similarity degree between two pixel points is smaller; when $L(x, y)$, $A(x, y)$, $B(x, y)$ values are smaller or larger, it means that the similarity degree between two pixel points is smaller; when $L(x, y)$, $A(x, y)$, $B(x, y)$ values are when the value is 0 or close to infinity, the similarity between two pixels is almost the same.

Combining formulas (11)–(13) with the Euclidean distance formula of coordinate feature, we can get the distance similarity function of colour feature information and coordinate distance feature between any pixel point j and its clustering centre i in the test image, i.e. the equilibrium ratio function between colour feature and coordinate distance feature

$$m(i,j) = \frac{\sqrt{x(i,j)^2 + y(i,j)^2}}{\sqrt{L(i,j)^2 + A(i,j)^2 + B(i,j)^2}} \tag{14}$$

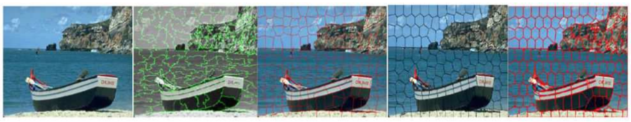
The lower half of formula (14) is the Euclidean distance of the pixel coordinates, and $L(i, j)$, $A(i, j)$, and $B(i, j)$ are the similarity of the pixel colour information calculated by formulas (11)–(13), respectively. According to formula (14), the calculation method of the parameters between the colour feature and the coordinate distance feature in the equalised image can be determined, i.e. the equalisation ratio function. By obtaining the equalisation ratio function, we can know the equalisation weight between a pixel in any super-pixel region and the centre pixel in the region. An iterative calculation can obtain the equalisation weight of a super-pixel region. By analogy, we can calculate the balance weight between the colour feature and the coordinate distance feature of the image to be tested. Table 1 describes the adaptive SLIC, namely ASLIC algorithm.

4 Experiment and analysis

In order to compare the difference between the SLIC algorithm and the improved ASLIC algorithm when processing images, we selected several representative images from the Berkeley Image Library (BSD500) for testing to verify the subjective visual effect of the algorithm and the effectiveness of the improved algorithm In addition, since the SLIC algorithm is proposed by absorbing the advantages of the Turboxipel algorithm, we also choose the experimental results of the Turboxipel algorithm for comparison in the subjective visual segmentation.

In this paper, eight representative original images are selected from the BSD500 image library. The experimental results are shown in Fig. 6.

Figs. 6*a*–*d* show the original images from left to right, the ERS algorithm segmentation results, the Turbopixel algorithm segmentation results, the traditional SLIC algorithm segmentation result and the ASLIC algorithm segmentation result, where the number of super-pixel blocks is set to K. Turbopixel algorithm is a typical level set image segmentation algorithm. The number can be manually controlled by the operator, but the disadvantage is that the tightness is uncontrollable and the operation speed is very slow. The ERS algorithm is dedicated to generating super-pixel blocks with strong boundary following. From the experimental comparison in Fig. 6, it can be seen that the Turbopixel algorithm can generate a controllable number of super-pixel regions compared to the SLIC and ASLIC algorithms. It is fuzzy, and it will appear similar to breakpoints. Compared with SLIC and ASLIC algorithms, ERS algorithm can generate denser super-pixel blocks, and the edges follow better, but the shape scale is large and the generated isolation The points are more serious. SLIC uses an equalisation parameter with a prior value of 10. In the image processing effect, although it can also generate super-pixel regions that are tighter and have more uniform boundaries, the differences between super-pixel blocks for image feature information and the extraction is weak, and it is difficult to divide the target boundary of the image more accurately. For example, the SLIC algorithm in Fig. 6*a* can roughly divide the target of the image, while the ASLIC algorithm can more accurately correct the rock in the upper right of the image and hull boundary segmentation. Compared with the ERS algorithm, ASLIC can basically avoid the generation of too small areas and isolated points; the target objects of Fig. 6*b* are wine bottles, wine glass tables, and lobsters. The ERS, Turbopixel, SLIC, and ASLIC algorithms can generate more dense and uniform super-pixel regions, but compared to ASLIC, they can distinguish more target foregrounds from backgrounds. In the process of Fig. 6*c*, the background and foreground colour of the image are significantly different. The ASLIC algorithm is significantly better than the Turbopixel and SLIC algorithms in terms of the outline of the human body and the approximate shape of the puppy. In the result of Fig. 6*d*, ASLIC has clearer segmentation than the Turbopixel and SLIC algorithms on the boundaries of castle buildings in the image. Therefore, in subjective visual evaluation, we generally tend to choose an algorithm that performs better and is stable overall, and considers its segmentation effect to be superior. In addition, the ASLIC algorithm still performs well in terms of the tightness, uniformity, and the presence of small regions and outliers in the generation of super-pixel regions. A super-pixel algorithm with a close fit and good edge division results can provide a better guarantee for the subsequent image segmentation processing. In summary, from the perspective of subjective visual evaluation of the image segmentation effect, the ASLIC algorithm has relatively excellent performance compared to the ERS algorithm, Turbopixel algorithm, and traditional SLIC algorithm.



a

b

c

d

Fig. 6 *Super-pixel algorithm image segmentation results*
(a) The original image, the result of ERS algorithm, ***(b)*** Turbopixel Algorithm, ***(c)*** SLIC algorithm, ***(d)*** ASLIC algorithm

Table 2 is a comparison of the values of the adaptive equalisation parameters and the running time calculated by the ASLIC algorithm during the processing of the experimental images. As can be seen from Table 2, compared to the Turbopixel algorithm, the ASLIC algorithm has a very obvious advantage in processing time, and compared to the SLIC algorithm, the ASLIC algorithm has also been streamlined to a certain extent. This is because the calculation time of image segmentation under different equalisation parameters will be different. Therefore, from the calculation time of Table 2, compared with Turbopixel and traditional SLIC algorithms, the calculation efficiency of ASLIC algorithm is relatively high.

In the super-pixel algorithm system, different algorithms have different performances when processing images. In order to choose a proper type of super-pixel algorithm to segment the image, we need to perform some typical super-pixels. Algorithms are compared and evaluated. The evaluation indicators selected in this paper are the generally accepted standards for super-pixel algorithms in the academic world, which include edge recall, ASA, normalised area variance, under-error segmentation rate, and five more popular indicators of block roundness in the super-pixel region. For the original image after processing, the degree of fit between the edges between the segmented areas and the edges of the actual image can be evaluated using the edge recall rate, ASA, and under-segmented segmentation rate. After processing, the degree of the close connection between the area blocks formed by the image can be described by selecting the circularity and the normalised area variance. This paper selects 30 typical natural images from the Berkeley Image Library (BSD500) for segmentation and processing. In order to perform a unified quantitative comparison of different algorithms, the number of super-pixel blocks in the test image is set to 50, 100, 150 to 600, and Figs. 7–11 show the segmentation processing effects of several typical super-pixel algorithms on five mainstream evaluation standards, respectively.

The edge recall rate reflects the proportion of edge pixels that account for all true-value edge pixels during segmentation. The larger the value, the higher the proportion of the true results in the segmentation results; the under-error segmentation rate describes the probability of errors in the segmentation results, which can be understood as the ‘deviation rate’. The lower the value, the better the performance of the part represented by the algorithm; area variance and circularity are used to describe the overall appearance of the super-pixel area intuitively. An area variance is more biased towards the area difference between areas, and circularity is generally used to express the closeness of the area to the circle. When the variance is not large and the circularity is high, the super-pixel region block is generally considered to perform better in the compact and uniform distribution.

ASA is the optimal segmentation accuracy, i.e. the ratio of the correctly segmented pixels to the total segmentation result. The higher the ASA, the higher the image segmentation accuracy. So

Table 2 Comparison of experimental data

Image	Size	Number of super-pixels, K	Adaptive equalisation parameter	ERS processing time, s	Turbopixel processing time, s	SLIC processing time, s	ASLIC processing time, s
(a)	481*321	150	8.7463	3.6249	7.2817	2.2904	2.8537
(b)	481*321	150	12.7541	3.6012	6.1199	1.6105	2.2635
(c)	481*321	150	7.8283	3.7367	5.8694	2.2531	2.5399
(d)	321*481	150	9.4553	3.7104	6.6949	2.2803	2.7976

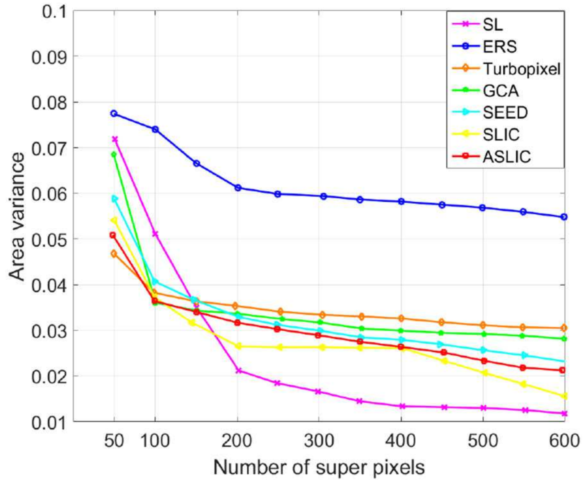


Fig. 7 *Comparison of area variance of super-pixel algorithm*

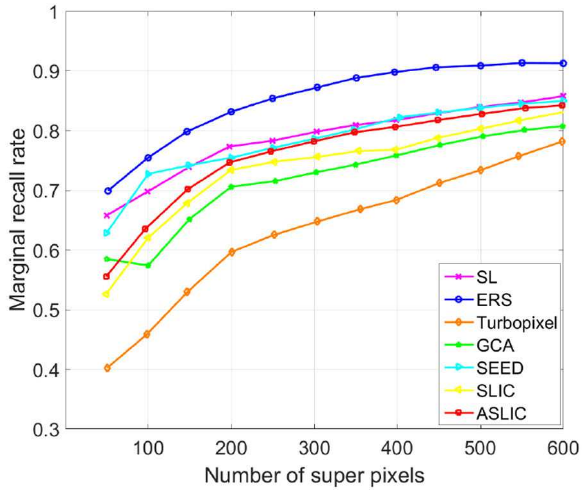


Fig. 8 *Comparison of edge recall rate of super-pixel algorithm*

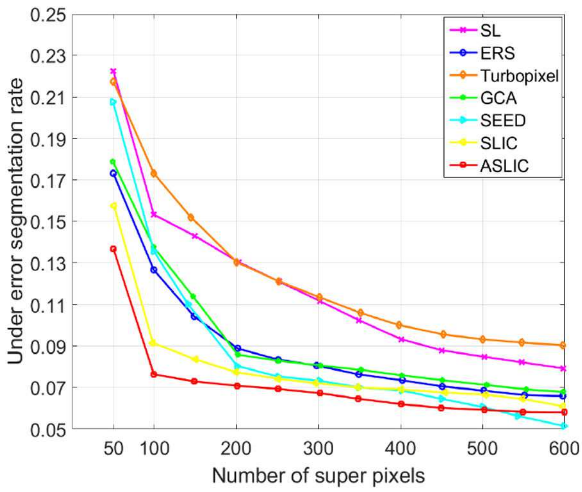


Fig. 9 *Comparison of under-error segmentation rates of super-pixel algorithms*

far, there is no algorithm, and the above indicators have achieved far better results than other algorithms. Generally speaking, we will choose an algorithm with better overall performance to consider it to achieve excellent segmentation performance.

It is not difficult to obtain from the quantitative comparison from Figs. 7–11. When the SEEDS, ERS, SLIC, and ASLIC algorithms perform image processing, there is a good the degree of fit, especially in terms of poor error segmentation rate and accuracy rate, the realisation of ASLIC is particularly prominent. In addition, for an area variance, ASLIC can generate super-pixel

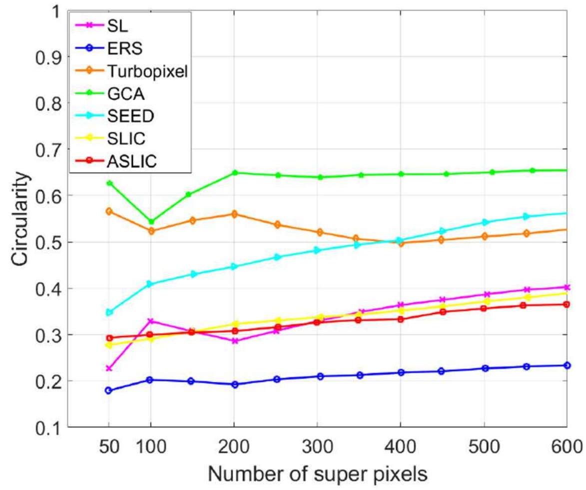


Fig. 10 *Roundness comparison of super-pixel algorithm*

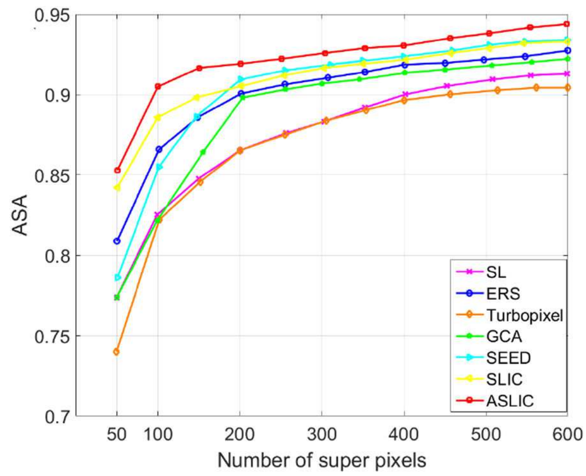


Fig. 11 *Comparison of accuracy of super-pixel algorithms*

regions that are not significantly different at different levels. In terms of circularity and boundary recall rate, although ASLIC is not the best performer, its overall performance is relatively moderate, and the performance of the algorithm is relatively stable. For other algorithms, ERS performs well in segmentation accuracy and boundary recall, but it has more obvious room for improvement in terms of running capital and area variance. The overall performance of the SL and SEED algorithms is relatively moderate; the performance of the Turbopixel and GCA algorithms on the edge of image segmentation is somewhat inferior, but Turbopixel can better generate super-pixel regions with the uniform area; GCA performs well on the degree of the close connection between pixel blocks and the circularity of region blocks.

In summary, the performance of ASLIC and SLIC is stronger than that of other comparison algorithms. Compared with the SLIC algorithm, ASLIC also has a certain improvement in performance. Also, for the algorithms compared above, Table 3 lists the controllability of their parameter performance and the time complexity of the algorithms.

It can be concluded from Table 3 that the algorithms in the table can control the number of super-pixel blocks; In terms of tightness controllability, ASLIC, SLIC, and ERS can control the tightness between super-pixel region blocks to achieve the best segmentation of the image. In addition, the time complexity is also an important index that affects the performance of the algorithm. From Table 3, it is known that in terms of time complexity, the time complexity of SLIC, SEEDS, Turbopixel, GCA, and ASLIC is relatively low.

Therefore, after comprehensive evaluation of the subjective segmentation effect and objective quantitative analysis above, ASLIC is not only in the intuitive visual effects of image segmentation and the shape of super-pixel blocks, but also in the

Table 3 Algorithm controllability comparison

Algorithm	Quantity controllability	Tightness controllability	Time complexity
SL	✓	✗	$O\left(N^{1.5}\lg N\right)$
SLIC	✓	✓	$O(N)$
SEEDS	✓	✗	$O(N)$
Turbopixel	✓	✗	$O(N)$
ERS	✓	✓	$O\left(N^2\lg N\right)$
GCA	✓	✗	$O(N)$
ASLIC	✓	✓	$O(N)$

accuracy of edges and the time complexity and running time of the algorithm. Has a better performance.

5 Conclusion

Aiming at the uncertainty of the equilibrium parameters between colour features and coordinate position features in the traditional super-pixel SLIC algorithm, this chapter proposes a super-pixel image pre-segmentation algorithm based on the mediation math degree measure. By using mediation math and mediation logic calculus Based on the system's related ideas and theoretical basis, a feature ratio formula for calculating the equilibrium parameters in the super-pixel SLIC algorithm is proposed. The goal is to qualitatively calculate the corresponding characteristic equilibrium parameters for a certain sample data, thereby obtaining relatively good results. Image pre-splitting effect. Compared with the traditional super-pixel SLIC algorithm and other comparison algorithms, the performance of this algorithm has been greatly improved. Although the running time of this method is still waiting, compared with the traditional super-pixel SLIC algorithm and other comparison algorithms, the algorithm has achieved outstanding performance. Although this method still needs to improve the running time. This performance improvement is mainly reflected in the improvement and standardisation of the algorithm operation process and the stability of the algorithm processing performance.

6 Acknowledgments

This work was supported by the National Natural Science Foundations of China (nos. 61672522 and 61976216).

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