mDBSCAN: Real Time Superpixel Segmentation by DBSCAN Clustering based on Boundary Term

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Abstract: mDBSCAN is an improved version of DBSCAN (Density Based Spatial Clustering of Applications with Noise) superpixel segmentation. Unlike DBSCAN algorithm, the proposed algorithm has an automatic threshold based on the colour and gradient information. The proposed algorithm performs under different colour space such as RGB, Lab and grey images using a novel distance measurement. The experimental results demonstrate that the proposed algorithm outperforms the state of the art algorithms in terms of boundary adherence and segmentation accuracy with low computational cost (30 frames/s).

1 INTRODUCTION

In these days, superpixels have a great interest in the field of computer vision and image processing. They have been widely applied in image segmentation (Saito et al., 2017) (Lei, 2017) (Zhang et al., 2018), 3D reconstruction (Concha and Civera, 2014) (Kucas and Margarita, 2017), scene flow (Vogel et al., 2013) and object tracking (Chan et al., 2015). A superpixel is a set of pixels that share the same features, for example, color information, texture features, and others. Superpixel algorithms are performed as a pre-processing step in many computer vision applications in order to reduce the computational time of subsequent processing without affecting the performance of the entire system. Therefore, fast computation superpixel algorithms that provide high boundary adherence and segmentation accuracy are preferred.

Many superpixel algorithms have been introduced such as Simple Linear Iterative Clustering (SLIC) (Achanta et al., 2012), Entropy Rate Superpixel Segmentation (ERS) (Liu et al., 2011)), Superpixels Extracted via Energy-Driven Sampling (SEEDS) (Van et al., 2012), and DBSCAN (Shen et al., 2016).

Different approaches have been followed to generate superpixels, for example, SLIC deals with superpixels as an iterative clustering problem. On the other hand, SEEDS considers the superpixels as an energy maximization problem, which achieved a good boundary adherence. Our approach deals with superpixels as a non-iterative clustering problem. Moreover, it presents precisely the boundary adherence by defining a novel simple distance measurement that considers the boundary information as well as the color and spatial information between the superpixel and its neighbors.

All of the approaches are aiming to fulfill the requirements of superpixels by having regular, compact and connected superpixels with high boundary adherence and low computational complexity.

Fig. 1 shows the superpixel results of the modified DBSCAN algorithm (mDBSCAN) that have compact and regular shapes, which precisely represent the image boundaries as described in section 4.5.

Recently, DBSCAN clustering algorithm (Martin et al., 1996) has been used to generate the superpixels. DBSCAN superpixel algorithm achieved the state of the art algorithms at a substantially smaller computation cost even for complex images. However, the DBSCAN algorithm suffers from few limitations such as it needs to be trained in order to select the values that describe the relation between the color and spatial information and to select the suitable threshold value for the distance measurement. Furthermore, it works only with RGB images. Thus, it deals with color and spatial information, which do not perfectly describe the boundary information.

Therefore, in this paper, we present a modified version of the DBSCAN algorithm to overcome its limitations as described above. The proposed algorithm is used with introducing a novel distance

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measurement that enforces the connectivity and regularity of the superpixels, which can handle gray images as well as color images independently from the color space. In addition, instead of training the algorithm, our approach uses an automatic threshold value based on color and edge information. The proposed algorithm performs a local clustering of pixels in 6D space for color images defined by three color information values, one for contour information and two values for spatial information and 4D space for grey images defined by one color information value, one for contour information and two values for spatial information. mDBSCAN with low losing meaningful image edges and low computation cost, will be utilized as pre-processing step for optical flow computation and moving objects tracking in a moving platform.

The proposed algorithm has been tested on the Berkeley segmentation benchmark . The results show that the proposed approach outperforms the state of the art in terms of boundary recall, under segmentation error and explained variation.

The main contributions of this paper are:

- Real time DBSCAN clustering with an automatic parameter for distance measurement .
- Novel distance measurement that works independently from the color space such as RGB, Lab and gray images and at the same time improves the segmentation quality and boundary adherence.

Figure 1: Image segmentation using mDBSCAN algorithm. The number of superpixels are 250, 500 and 1000, respectively.

2 RELATED WORK

In this section, we briefly revisit the DBSCAN algorithm (Shen et al., 2016) and other important superpixel algorithms. The superpixel algorithms are divided into two categories: graph based algorithms and clustering based algorithms.

2.1 Graph based Algorithms

Graph based approaches describe the image as undirected graph consisting of vertex set and edge weights. The vertex set represents the pixels in the image where the edge weights define the similarities between the neighboring pixels.

Recently, Liu et al. have proposed a graph based algorithm .The entropy rate superpixel algorithm (ERS) deals with superpixels as a maximization problem. The superpixels are generated by maximizing the entropy rate of a random walk. According to the superpixel benchmark (Stutz et al., 2016), ERS algorithm is one of the top performance superpixel algorithms. It has three input parameters; the balancing term, kernel bandwidth and the number of superpixel. The main shortcoming of ERS algorithm is the computation cost. As results, it needs around 2.5 seconds to generate the superpixels for one image which not suitable for real time applications.

2.2 Clustering based Algorithms

One of the clustering based approaches is SLIC algorithm. In SLIC algorithm (Achanta et al., 2012), the superpixels are generated based on a gradient ascent principle. Firstly, initial seeds are defined using a regular grid. After that, an iterative process is performed to obtain better segmentation performance. During each iteration, the seeds are refined from the previous iteration based on the gradient information. Because of its simplicity, low computation cost and good boundary adherence, SLIC becomes the most famous superpixel algorithm. However, it has a few disadvantages. It uses an iterative process, which increases the computation cost. Moreover, SLIC needs a post-processing step to enforce the connectivity (Stutz et al., 2016) (Achanta and Süsstrunk, 2017).

On the other hand, SEEDS algorithm (Van et al., 2012) generates the superpixels by optimizing an energy function. Each superpixel is defined as a region with color and shape boundary information. Using a simple hill climbing optimization, superpixels are refined by updating the boundaries of the superpixels. Although the SEEDS algorithm has a high performance in terms of boundary adherence and computation cost, six parameters have to be defined (Liu et al., 2011).

2.3 DBSCAN Clustering Algorithm

DBSCAN clustering algorithm (Shen et al., 2016) is a clustering based approach for image superpixels segmentation by applying the density based spatial clustering of applications with noise (DBSCAN) algorithm. DBSCAN performs a two-steps framework using RGB color information and spatial information. The first step is the clustering step. In this step, the initial superpixels are generated based on the color information of two adjacent pixels (n, m) using a geometric condition such that the maximum number of pixels in each superpixel does not exceed a certain value as given in (2). Subsequently, the initial superpixels are merged to form the final superpixels through a distance measurement of both color and spatial information of the superpixels seeds as described in (3). DBSCAN has only one parameter – the number of required superpixels. The authors of the DBSCAN algorithm show that their algorithm outperforms the state of the art and achieves the real time capability.

$$d_s^{m,n} = \sqrt{(R_m - R_n)^2 + (G_m - G_n)^2 + (B_m - B_n)^2} \quad (1)$$

$$D_1 = \alpha_1 d_s^{i,j} + \alpha_2 d_s^{i,Seed} \quad (2)$$

φ ,α_1, α_2 and φ are constant values

$$D^{seed\ i,seed\ j} = d_s^{i,j} + \alpha_3 \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \quad (3)$$

Despite it has a good performance, DBSCAN suffers from certain shortcomings. It needs to be trained in order to select suitable parameters from (2) and (3). The output number of superpixel per image varies from the required number of superpixel. Lastly, it works only under RGB images.

3 mDBSCAN ALGORITHM

Like DBSCAN, the pixels are classified into three categories as seed, root and unlabeled sets. The top left pixel is assigned as the first seed and root. For each pixel in the root set, four or eight neighboring pixels are found, then the distance between the unlabeled pixel and both the seed pixel and root pixel is calculated. If the unlabeled pixel satisfies the distance measurement, it assigns the same label as the seed pixel and considers as the next root. The process is repeated until the termination condition such as the searching area is satisfied. In this section, the proposed algorithm will be described.

3.1 Contour Map

Representation of the objects boundaries in an image is an essential property of the superpixel algorithm, as they will be used as a pre-processing step for objects segmentation and tracking. Therefore, the contour map is introduced in the proposed algorithm. Given an image I, the contour map is computed based on the vector filed method with Sobel filter (Shinohara et al., 1993). Firstly, the derivatives of an image are determined, and then the maximum eigenvalues of the Jacobian matrix J as described in (4) is computed. The gradient value of a pixel x is computed based on a w x w sized window around it. In this paper, w has a value of three. The advantage of this method that no threshold value is required and it works under all types of color spaces. Fig. (2) shows the contour map of an input image.

$$J_I = \begin{bmatrix} \partial_x R & \partial_x G & \partial_x B \\ \partial_y R & \partial_y G & \partial_y B \end{bmatrix} \quad (4)$$

Figure 2: The contour map using the vector filed method.

3.2 Novel Distance Measurement

As explained before, the relation between an unlabeled pixel and its seed and root is described by a distance of color, gradient and spatial information. The distance combines three terms i.e., normalized spatial information, gradient information, and weighted color information.

$$D_s = w_{sp} \times (1 + \|G_i - G_k\|) \times \left(d_{colour}^{i,k} + d_{colour}^{j,k} \times \frac{d_{xy}^{j,k}}{S} \right) \quad (5)$$

$$d_{colour}^{m,n} = \sqrt{\sum_{k=1}^{colour\ channels} (I_k\,(m) - I_k\,(n))^2} \quad (6)$$

$$d_{xy}^{m,n} = \sqrt{(x_m - x_n)^2 + (y_m - y_n)^2} \quad (7)$$

$$w_{sp} = 0.5 \times \left(1 + \frac{d_{xy}^{i,k}}{S} \right) \quad (8)$$

Where i, j, k, and G are the seed, root, unlabeled pixel and the pixel gradient value from the contour map, respectively. The w_{sp} is the weight of the spatial information between the seed and unlabelled pixel. Assuming a square shape of a superpixel, each superpixel should contain N/K pixels where N is the total number of pixels in an image and K is the number of required superpixels. The size of superpixel should be control, therefore, the searching region is restricted to an area of S x S around the seed where S is set to be $\sqrt{\frac{N}{K}}$.The w_{sp} is introduced as another geometric constraint to control the shape of the superpixel and produce compact, regular shapes. As given in (5), the distance measurement does not have any external parameters; therefore, it does not need to be trained like DBSCAN algorithm [18].

3.3 Effective Threshold Value

The main principle of DBSCAN clustering is to compare the computed distance value with a certain threshold. DBSCAN algorithm chooses manually the threshold value, which adapts the value to have a good performance. However, choosing manual values provides scope for error especially when the algorithm is used for real applications. This is an important parameter where any change of its value will affect the output of the algorithm. The proposed algorithm introduces an automatic threshold to compute the suitable threshold value for an input image I. The threshold E is defined as:

$$E = \min\{\max(I_i) - \min(I_i)\} \times C \times N \times \sigma_{gradient} \quad \forall\, i \in [i, \ldots, C] \tag{9}$$

Where C is the number of color channels in image I. N describes the number of neighbors around the pixel (it has two values 4 or 8 neighbors). $\sigma_{gradient}$ is the standard deviation of the contour map of the image as described in section 3.1.

3.4 Superpixel Segmentation Algorithm

The mDBSACN consists of two steps similar to DBSCAN algorithm; clustering step and noise removal step. In the clustering step, the seeds are selected in a certain order of column-by-column (from top to bottom and from left to right). As mentioned before, the top left pixel assigns the first seed and root. For a seed and a root, the four or eight neighboring pixels are obtained, then only the pixels that fulfill the distance measurement are selected. This step is repeated for each new combination of a seed and a root until the searching region condition is satisfied.

The second step is a noise removal step. Due to the sensitivity of distance measurement and the noise in an image, small noisy pixels are generated. DBSCAN algorithm deals with noisy pixels indirectly as it generates small superpixels in the first step and then margining them to form the final superpixels. However, using this approach will affect the number of required superpixels as discussed in section 4.5. In the mDBSCAN, all noisy pixels are stored in a queue set. This queue set consists of a small group of pixels that may not belong to the final superpixel but locate on the searching region S x S, which will be labeled as the final superpixel. In addition, if the small group of pixels lies on the boundary between different superpixels, these pixels will be considered as noisy pixels and will be assigned a label according to the shortest distance between these pixels and the surrounding superpixels. All noisy pixels in the queue set will be either root pixels or unlabeled pixels.

Algorithm 1: Superpixel clustering step.

Inputs: Image I, contour map C, regular step S.
Output: Noisy superpixel L.
for each unlabeled pixel p in image I **do**
set pixel p as a seed i;
find 4 or 8 neighboring pixels N_{set} around seed i;
for each pixel k in N_{set} **do**
compute the distance $D_s(i,k)$;
if $D^k_s(i,k) < E$ **then**
set $k \in R_{set}$;
set $k \in L(k)$;
endif
endfor
for each pixel k in R_{set} **do**
if the number of pixels in $L(k) < S^2$ **then**
find 4 neighboring pixels N_{set} around root j;
for each pixel m in N_{set} **do**
compute the distance $D_s(i,j,m)$;
if $D_s(i,j,m) < E$ **then**
set $m \in L(k)$ & set $m \in R_{set}$;
else
set $m \in Noise_{set;}$
endif
endfor
endif
endfor
endfor

Algorithm 2: Noise removal step.

Inputs: Superpixels L(P) and noisy superpixels $Noise_{set}$
Output: Final superpixel L_f.
for each pixel n_s in $Noise_{set}$ **do**
find the 8 neighboring superpixels N_{sup} in L;
for each superpixel Q in N_{sup} **do**
compute the distance $D_s(n_s,Q)$;
endfor
find the minimum distance D_s;
assign $L(n_s)=L(\min(D_s))$;
endfor

4 EXPERIMENTAL RESULTS

In this section, the proposed algorithm is compared with four well-known and high performance state of the art algorithms, Superpixels Extracted via Energy-Driven Sampling (SEEDS), Entropy Rate Superpixel Segmentation (ERS), Simple Linear Iterative Clustering (SLIC) and DBSCAN clustering algorithm using the available online implementation source codes. SEEDS and ERS are considered the state of the art with regarding performance and SLIC is considered the state of the in terms of computation cost. All the methods are evaluated on the Berkeley Segmentation Dataset 500 (BSD500). This dataset consists of 500 images with human-labelled ground truth segmentation. The parameters of the methods SEEDS, ERS, SLIC, and DBSCAN are selected according to their suggestion parameters in their papers.

The results are demonstrated using qualitative (visual) and quantitative comparison based on all 500 images in the BSD500 dataset, whereas DBSCAN algorithm was evaluated based only on the testing datasets as it needs to be trained. The qualitative comparison is based on boundary adherence, compactness and regularity of the superpixels as shown in fig 5. Fig. 3 shows the results of the mDBSCAN based on different color space. For the quantitative comparison as shown in fig. 4, undersegmentation error (UE), boundary recall (Rec), achievable segmentation accuracy (ASA) and compactness factor (CO) are used based on the 500 images in the Berkeley Segmentation Dataset.

4.1 Undersegmentation Error (UE)

The perfect case when each superpixel overlaps with only one object. However, sometimes the superpixel lies on different objects that produce a segmentation error. The undersegmentation error measures the overlap error between the superpixel (S) and the ground truth (G) by counting the pixels lie outside the ground truth objects, and then divided it by the total number of image pixels (N). The undersegmentation error is computed using Nuebart and Protzel formulae (Vogel et al., 2013). The lower UE value indicates better performance.

$$\mathrm{UE}(G,S) = \frac{1}{N}\sum_{G_i}\sum_{S_k \cap G_{i \neq \emptyset}} \min\{|S_k \cap G_i|, |S_k - G_i|\} \tag{10}$$

4.2 Boundary Recall (Rec)

The boundary recall assesses the performance and quality of boundary adherence. The boundary recall (Rec) (Martin et al., 2004) measures the percentage of the ground truth boundaries (G) that covered within three pixels of a superpixel boundary (S). The boundary recall is defined as:

$$\mathrm{Rec}(G,S) = \frac{T_p(G,S)}{T_p(G,S) + F_N(G,S)} \tag{11}$$

Where TP (G, S) and FN (G, S) are the number of true positive boundary pixels and the number of false negative boundary pixels, respectively. A higher value is better.

4.3 Achievable Segmentation Accuracy (ASA)

The achievable segmentation accuracy computes the highest achievable segmentation accuracy by using superpixels as units. ASA is computed as the fraction of the number of labeled pixels that correctly overlap with the ground truth objects to the total number of image pixels (Liu et al., 2011).

$$\mathrm{ASA}(G,S) = \frac{1}{N}\sum_{S_k}\max_{G_i}\{|S_k \cap G_i|\} \tag{12}$$

4.4 Compactness (CO)

The compactness is the fraction of the area of each superpixel S to the area of a circle that has the same perimeter of this superpixel. A higher value is better. Schick et al. have proposed a formula to compute the compactness as follow

$$\mathrm{CO}(S) = \frac{1}{N}\sum_{S_k}\frac{4\pi A(S_k)}{A_{circle}(P(S_k))} \tag{13}$$

4.5 Discussion of Results

A high performance superpixel algorithm is the algorithm, which has a low undersegmentation error with high boundary recall. Therefore, undersegmentation error (UE), boundary recall (Rec), achievable segmentation accuracy (ASA) and the compactness factor (CO) are used to evaluate the quality of the superpixel algorithms. Fig. 4 shows the results of UE, Rec, ASA, and CO. With respect to UE, good performance algorithm should have low UE. UE is computed as the average value of the minimum UE value of each image in the dataset. As shown in fig. 4a, the modified DBSCAN with lab color space outperforms the other algorithms, whereas the other color spaces of modified DBSCAN lie more closely together. The reason for that is the introduction of the contour information in the distance measurement, which makes the edges of the superpixels overlap consistently with the image object boundaries. For Rec, as shown in fig. 4c, the modified DBSCAN with lab color space achieves almost the same performance of the SEEDS algorithm. However, the modified DBSCAN performs better than SEEDS algorithm in term of ASA. The modified DBSCAN has better results than DBSCAN algorithm, as DBSCAN algorithm generates superpixels using pre-trained thresholds without the contour information, which reduce the performance of the algorithm especially in weak image boundaries as shown in fig. 5. Regarding the compact shapes, SLIC algorithm has the most compact and regular shapes as shown in fig. 4d. However, the modified DBSCAN still generates compact and regular shapes of superpixels for different color spaces as shown in fig. 3 and fig. 5, because of the restricted searching area as described in section 2.2.

Another important factor for evaluating the performance of the superpixel algorithms is the computational cost. We perform all experiments on a desktop PC with 32 GB RAM and 2.7GHz Intel Core i7. According to Table 1, the computational complexity of ERS algorithm is O(nN2logN), this indicates that it will spend time in generating superpixels. SLIC algorithm has a computational complexity of O(N), however, it iterates many times to obtain good segmentation performance and boundary adherence.

Though the complexity of DBSCAN algorithm is O(N), it deals with noisy pixels as small superpixels and needs pre-trained threshold values. Our algorithm does not need pre-trained threshold values without an iterative process or merging step. According to the computational time, the proposed algorithm achieves the speed of 30fps. Thus, it is obvious that the proposed algorithm has the real time performance. Fig. 6 shows the computational time with regarding to the different number of superpixels.

5 CONCLUSION

An improved real time version of DBSCAN superpixel algorithm is introduced. Our mDBSCAN produces regular shapes of superpixels with high boundaries adherence in 30 fps with a novel distance measurement. In addition, an automatic threshold is introduced instead of using pre trained threshold values. The mDBSCAN algorithm generates superpixels independently of the colour space. In future work, the proposed algorithm will be extended to video content for tracking objects and optical flow determination.

Figure 3: Superpixel segmentation results of the mDBSCAN based on different color spaces. From top to bottom, the results are obtained by using gray values, RGB color space and lab color space.

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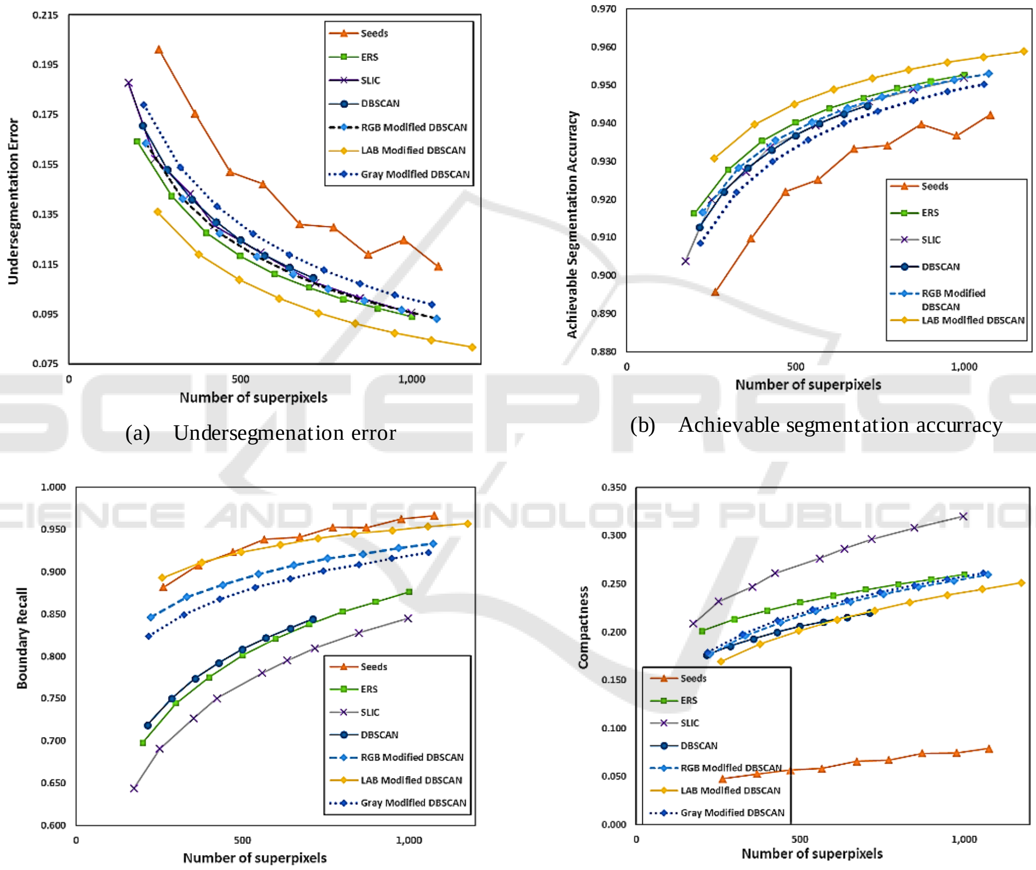
Table 1: The performance results of superpixel algorithms. The number of superpixel is roughly 400.

	SEEDS[10]	ERS[9]	SLIC[11]	DBSCAN[18]	mDBSCAN
Boundaries adherence					
Undersegmentation error(UE)	0.152	0.128	0.143	0.132	0.109
Boundary recall (Rec)	0.923	0.775	0.727	0.792	0.923
Achievable segmentation accuracy (ASA)	0.922	0.935	0.927	0.933	0.945
Computational speed					
Computational complexity	O(N)	O($nN^2\log N$)	O(N)	O(N)	O(N)
Average time per image(seconds)	0.0506	0.8916	0.0882	0.03	0.033



(a) Undersegmentation error

(b) Achievable segmentation accurracy

(c) Boundary recall

(d) Compactness factor

Figure 4: Quantitative comparison of superpixel segmentation results based on BSD500 dataset. In contrast, undersegmentation error (lower is better), boundary recall (higher is better) and achievable segmentation accuracy (higher is better) present the overview of the performance.

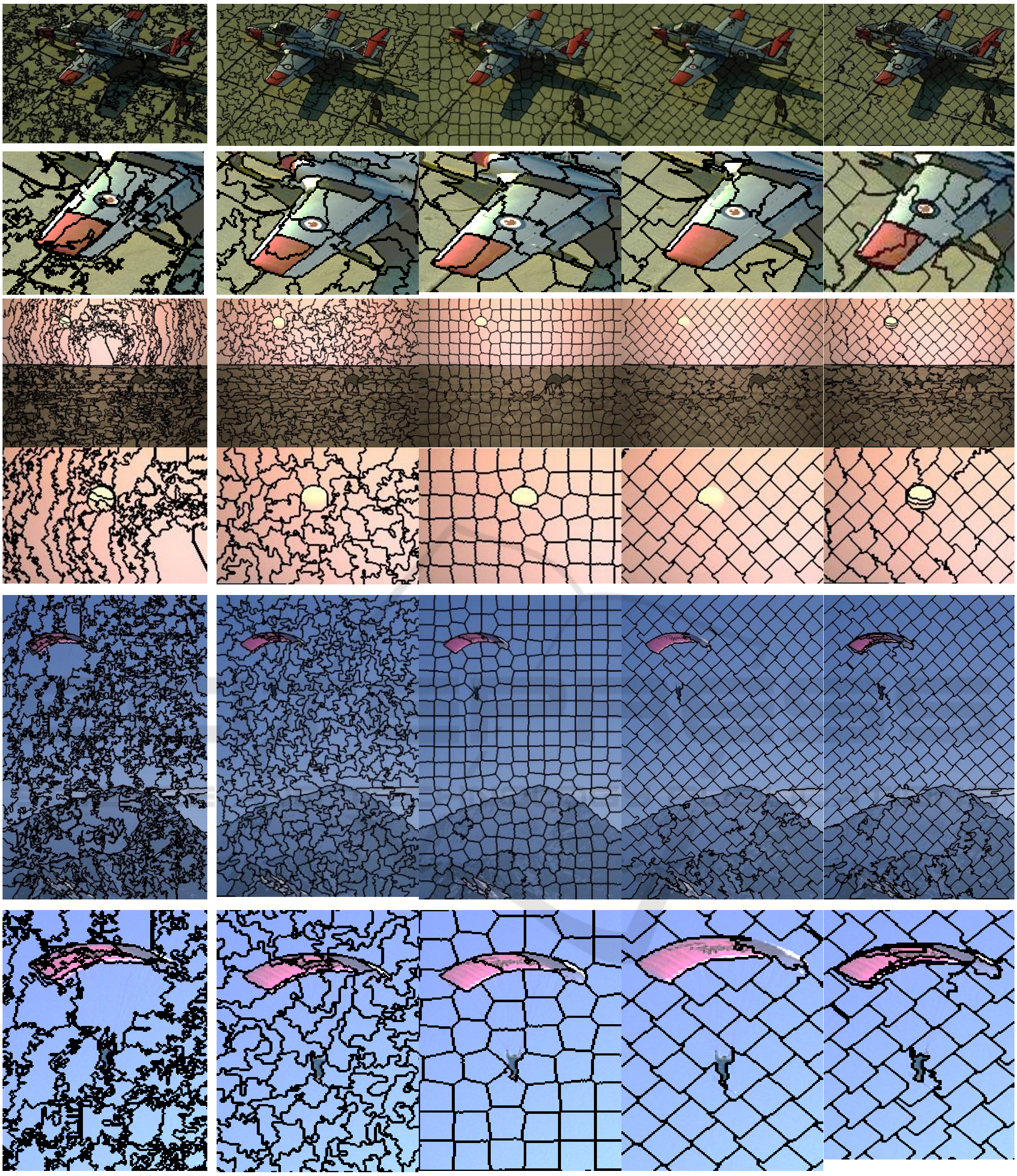


Figure 5: Visual comparison of superpixel segmentation results. The average number of superpixels is roughly 300.

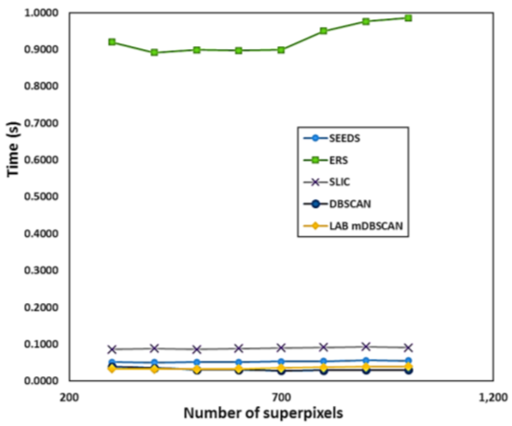


Figure 6: Computational time comparison of state of the art superpixel algorithms (SEEDS, ERS, SLIC, DBSCAN and mDBSCAN).

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