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# Detection Of Airport Runways In Optical Satellite Images Using Machine Learning

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***Abstract***— Automatic airport extraction in remote sensing images (RSIs) has been widely applied in military and civil applications. An efficient airport extraction framework for RSIs is constructed in this letter. In the first step, we put forward a two-way complementary saliency analysis (CSA) scheme that combines vision-oriented saliency and knowledge-oriented saliency for the airport position estimation. In the second step, we construct a saliency-oriented active contour model (SOACM) for airport contour tracking, where a saliency orientation term is incorporated into the level-set-based energy functions. Under the guidance of saliency feature representations obtained by CSA, the SOACM can acquire well-defined and highly precise object contours. Experimental results demonstrate that the proposed extraction framework shows good adaptability in remote sensing scenes, and uniformly achieves high detection rate and low false alarm rate. Compared with three state-of-the-art algorithms, our proposal can not only estimate the location of airport targets, but also extract detailed information of the airport contours.

***Index Terms***—Active contour model (ACM), airport extraction, object detection, remote sensing, saliency analysis

## INTRODUCTION

With the remote sensing technology highly developed, automatically recognizing the airport targets in remote sensing images (RSIs) has become one of the most important but challenging computer vision problems. In reality, it is applied to airport navigation, military reconnaissance, and many other practical applications. To the best of our knowledge, previous studies on this issue can be divided into two categories: unsupervised works that are based on airport feature modeling and works that introduce the supervised learning mechanism into the detection problem. The first scheme basically puts emphasis on the artificially designed representations of the airport geometrical characteristics, and the regions of interest (ROIs) can be recognized in terms of line segment detection [1], or saliency features that combine texture information [2], [3]. Since the first class uses primary properties of the airports, it can achieve fast detection with relatively good recognition results discriminative feature representations for the airport targets are difficult to predict and artificially construct, this method can be sensitive to complex background noises and the existence of irrelevant linear objects. On the contrary, in the second class, the supervision mechanism and machine learning are incorporated into the detection framework. In most cases, this method identifies the targets by means of an appropriate feature classifier, such as support vector machine (SVM) [4], and Adaboost algorithm [5]. In [6], the airport is described by a set of scale invariant feature transform keypoints and then selected from candidate regions by SVM.

In recent years, a lot of studies have been conducted from the perspective of image saliency analysis [7], where a variety of saliency cues are employed to take the place of traditional airport feature descriptions. In [8], the top-down and bottom up saliency maps are combined to separate the candidate regions. Then, the airport ROI is determined with a pretrained SVM. Besides, the deep learning theory also receives more and more attention in image processing applications. For example, in [9] and [10], the convolutional neural network (CNN) is utilized to extract high-level features and hierarchical representations of the objects. With a well-designed learning network and training set, the CNN-based method uniformly presents highly robust detection results. In general, supervised detection algorithms achieve better recognition rate than do unsupervised methods. But it needs a large quantity of image samples that are precisely marked by the researchers, which makes it task-dependent and causes low model reusability. The process of pattern matching and sample training can be quite time consuming, and largely determines the quality of the whole detection framework. In an image, the salient areas will catch human being's visual attention with low-level properties such as luminance, color, and contrast distribution. This vision-oriented saliency (VOS) indiscriminately extracts the eye-catching areas. For another, an observer can distinguish the airport targets by inherent prior cognition. This knowledge-oriented saliency (KOS) selectively focuses on the regions that contain more line segments, but fails to separate the airport runways from other disturbing linear objects such as the residential areas, long rivers, and highway.

Inspired by the two types of visual saliency mechanisms, this letter presents a complementary saliency analysis (CSA) model. The VOS connects contrast distribution with spatial relation of image sub regions. The KOS considers the airport target as a cluster of organized lines and generates a quality weighted line density map. To gain the information of airport contours, we incorporate fusion saliency representations into the framework of traditional active contour model (ACM), and formulate an innovative saliency-oriented ACM (SOACM)

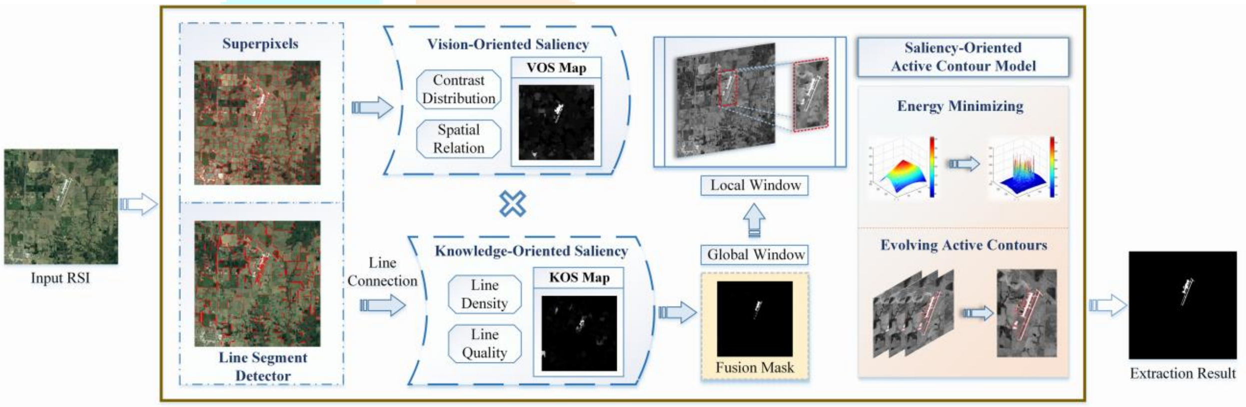


Fig. 1. Flowchart of the proposed airport extraction method.

In our implementation, a saliency orientation term (SOT) is added to the level-set-based energy functions, so that the object contour keeps evolving in the right direction and converges faster to the airport runways. In conclusion, the contributions of this letter mainly lie in the following two aspects.

1) We put forward a CSA scheme that can accurately estimate the spatial location of the airport in remote sensing scenes.

2) We present an innovative SOACM for airport contour tracking. Compared with existing ACMs, the proposed SOACM significantly improves the evolving speed and succeeds in extracting airport contours that highly conform to the actual objects.

## II. MODEL CONSTRUCTION

The proposed detection framework starts by segmenting the input RSI into a series of superpixels. In the first step, the VOS generates a bottom-up saliency map in terms of the interactions of interior contrast and spatial location among the superpixels. In the second step, the KOS detects the line segments and draws a top-down saliency map in terms of line density distribution. Finally, the proposed SOACM exploits the saliency feature representations to guide the process of energy minimizing, and acquires the airport contours within a small localized operating window. The flowchart of our method is shown in Fig. 1.

### A. Superpixel Segmentation

Superpixel segmentation usually acts as a preprocessing step to reduce the complexity of subsequent image processing tasks. It decomposes the image into homogeneous subregions with well-preserved boundaries, aiming to simplify the image details and highlight structural information. In this letter, an efficient algorithm, simple linear iterative clustering (SLIC) [11], is introduced to acquire superpixels from RSIs. The SLIC method can generate regular and compact

superpixels, with adjustable number of clusters. Compared with pixel-wise saliency models, the superpixel-based scheme can present more concise image information and is more robust to remote sensing noises. Mathematical morphological filter is a useful tool for image noise suppression. Since superpixel segmentation is typically used for natural image processing, the quality of segmentation can be degraded in complex RSIs with large quantity of colors and uneven luminance distribution. To solve this, we utilize a morphology closing operator, where the image area will

be first dilated and then be eroded, to strengthen the line segments of airport runways and remove small, isolated image fragments.

### B. Complementary Saliency Analysis (CSA)

Human vision systems extract salient objects from complex background without effort. However, automatically detecting the salient region from images is still a challenging problem. In this section, we construct a two-way CSA model that is operated on superpixels. In the VOS layer, low-level saliency cues of contrast distribution and spatial relation are taken into account to acquire visually prominent candidate regions. In the KOS layer, we describe the airport target in terms of

regional line density and length quality. The VOS and KOS are designed to be complementary, inter-reinforced, and highlight the airport ROI from different and independent aspects. Note that in this letter, saliency is used particularly to guide the curve evolution of ACM and enhance the quality of airport contour tracking, not to directly extract the airport targets. Therefore, it would be acceptable if the CSA fails to acquire the complete ROI, as long as the fusion saliency mask does fall on part of the actual airport fields. And this enables us to impose stricter target matching criteria. Generally, the fusion saliency is given by

$$\mathrm{Sal}(r_k) = \mathrm{VOS}(r_k) \cdot \mathrm{KOS}(r_k) \quad (1)$$

where $\mathrm{VOS}(r_k)$ and $\mathrm{KOS}(r_k)$ mean the vision and knowledge

layer saliency of the superpixel $r_k$ .

*C. VOS With Low-Level Saliency Cues*

The VOS layer implements the assumption that the salient region distinguishes itself by higher contrast with other parts of the image. We also notice that the distance between two regions can largely determine to what extent one makes contrast with another. Thus, we naturally obtain the following statements.

1) Higher contrast is indicative of higher saliency.
2) Contributions that contrast make to saliency declines as the distance between two regions increases.

### CONCLUSION

This letter focuses on airport extraction in RSIs. A two-way CSA model is proposed to estimate airport ROI by combining low-level VOS and high-level KOS cues. Based on the fusion saliency map, we present a novel SOACM to acquire the airport contours. Considering that conventional ACMs are less reliable in RSIs with faint contrast and ill-defined boundaries. We proposed the method of airport detection has higher accuracy. We can find that the recognition ability of this method for non-airport images is much higher than that for airport images, which is due to the complexity of the regional environment of the airport.

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