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Recognize Aircraft a Using Template Matching In High Resolution Satellite Images

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ABSTRACT: Automatic aircraft recognition in high-resolution satellite images has many important applications. Due to the diversity and complexity of fore-/background, recognition using pixel-based methods usually does not perform well. In this letter, we propose a new method integrating the high-level information of a shape prior, which is considered as a coarse-to-fine process. In the coarse stage, the pose of an aircraft is roughly estimated by a single template matching with a defined score criterion. In the fine stage, we derive a parametric shape model by applying principal component analysis and kernel density function, which have good effects on both dimension reduction and sample space description; then, a new variational formulation combining region information and a shape prior is proposed to segment the object using a level set method. Finally, the parameters of the segmentation result are directly applied to verify aircraft type with two k-nearest neighbor steps. Experiments on Quick Bird images demonstrate the robustness and accuracy of the proposed method.

KEYWORDS: Aircraft recognition, image segmentation, level set method, shape prior, template matching.

I.INTRODUCTION

AIRCRAFT recognition is an important issue of target recognition in satellite images and has many important applications in practice such as airfield dynamic surveillance. As the resolution of satellite images gets higher, more abundant color, texture, and spatial information are provided..Such information offers good opportunity to recognize aircraft that has a very complex structure. However, automatic aircraft recognition is not a simple problem. Besides the complex structure, different aircraft differ in size, shape, and color, and even for one kind of aircraft, the texture and intensity are usually dissimilar in different scenarios. Moreover, recognition often suffers from various disturbances such as clutter, different contrasts, and intensity in homogeneity. Thus, the robustness and resistance to disturbance are highly required for the method. We illustrate some typical satellite aircraft images in Fig. 1 to show the difficulties.

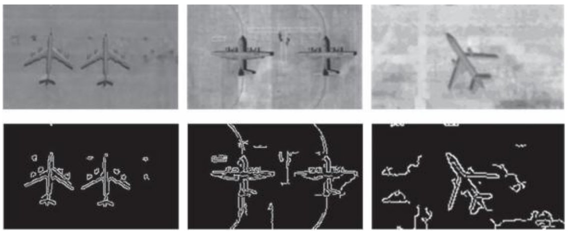

Fig: Aircraft images and canny edge detection with Thresholds 60 and 150

II. OVERVIEW

A. COARSE STAGE: POSE ESTIMATION

Pose estimation is essential in aircraft recognition and is usually done after segmentation in conventional methods [6], [8]. In our method, shape is integrated in the segmentation with a parametric model, so the refined pose information is contained while segmenting, and will be obtained when the segmentation is accomplished. On the other hand, the integrated shape model needs an initial pose. Due to the special complex structure of aircraft, segmentation with a

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random pose initialization easily runs into local minimum. Thus, in this stage, we roughly estimate the pose information, which coarsely addresses the problem of translation, rotation, and scaling. Considering the common cross structure of aircraft, we adopt the method of coarse template matching with the average shape of test aircraft

A. Pre-processing

Template matching is usually edge based or region based. In our method, edge information is used. As mentioned before, edge extraction often suffers from image blurring and poor contrast. However, the edges obtained still preserve structure information for aircraft to some extent. In addition, aircraft is usually on parking aprons, most of which are often flat and smooth, so edges are mostly produced by the contrast between object and background. On the contrary, color feature is not steady. Intensity in homogeneity on aircraft often occurs due to illumination, and sometimes, the intensities of pixels on aircraft look even the same as background.

B. Pose Estimation

Aircraft have the common feature of cross structure. To roughly estimate the pose of an aircraft, this common structure can be adopted. In our pose estimation, the average binary shape template of test aircraft is used to match the pre-processed gradient image coarsely on translation r, rotation θ, and scaling s with the following defined score criterion:

$$\text{Score}(r, \theta, s) = \sum \frac{I(x)}{(D(x, T(r, \theta, s)) + 1)} * s\xi$$

where $I(x)$ denotes the value of the preprocessed image, $T(r, \theta, s)$ represents the template with translation, rotation, and scaling ,and $D(x, T(r, \theta, s))$, is the distance from pixel x to template which can be obtained by distance transformation. ξ is a constant, and $s\xi$ is a scaling regular term of Score.

III. FINE STAGE: SEGMENTATION AND RECOGNITION

In the fine stage, shapes of aircraft are globally modelled with a parametric representation and kernel density estimation. This model is then integrated into the popular energy-based level set method which is convenient to combine various priors.

Curve evolution is driven by the image region-based energy and simultaneously regulated by the shape model. The last obtained coefficients of shape model are directly used in the recognition.

1.Shape Modelling
2. Shape-Based segmentation
3.Aircraft Recognition

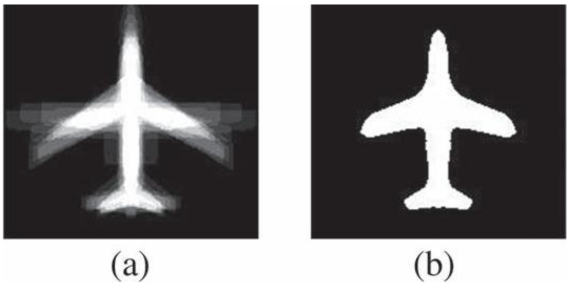

Fig: Shape modelling
(a)shape alignment
(b)Average shape template

III. RELATED WORK

In our experiments, due to the lack of standard data sets of high-resolution satellite images for aircraft recognition, 300 gray images, 30 per type, including ten kinds of airplanes, are collected from Quick Bird with the resolution of 0.61 m to evaluate the proposed method. Templates of these aircraft are shown in Fig. 4. The engines of most of the

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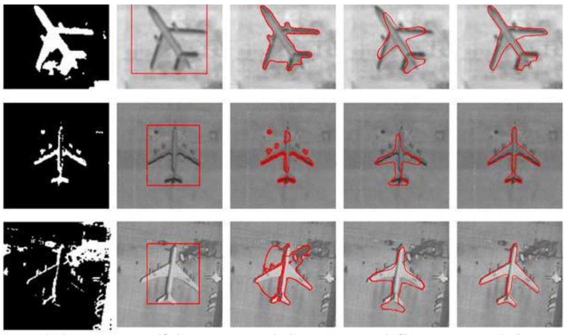
aircraft are removed since they are small structures and have little common features. Table I lists the sizes of these airplanes, which are obtained from the internet, to illustrate the scale differences. In our shape modelling, first, we align all the templates with the region correlation method in [10]. Then, PCA is done for the SDF representations. We take four Eigen shapes to parametrically represent the shape of the aircraft, and the average reconstruction accuracy is 96.31%.

A. Pose Estimation

In the pose estimation, since the center of aircraft is usually located near to the middle of the image in practice, we restrict our search region for translation r in (1) just around the middle, which is a 50 × 50 square considering the resolution of image
and the sizes of samples. The steps of translation r, rotation θ, and scaling s are set to 5 pixels, 15◦, and 0.2, respectively. The length and width of
template that we used are 48 and 46 m, respectively, and 48 and 46 m,respectively and the scaling s ranges from 0.6 to 1.4.



(a) (b) (c) (d) (e)

Fig. 6. Pose estimation. (a) Test image. (b) Sobel image. (c) Threshold with otsu's method

B. Shape-Based Segmentation

We apply the proposed energy function to segmentation. The parameters are chosen empirically. The scale τ of Gaussian kernel is set to three. The ε in Heaviside function is set to five.
We set α = 1× 104 in (6). The step-size parameters of W in (16) are set to 2.0, 1.2, 0.8, and 0.6, respectively, and those of a, b, h, and θ are set to 3 × 10−4, 3 × 10−4, 1 × 10−8, and 2 × 10−8, respectively. We fix the number of iteration to 200 to stop the minimization process. Fig. 7 shows some examples of contour evolution. We can see that, with the integration of the shape prior, the contours of segmentation always look regular and good results are obtained at last. In segmentation, to illustrate the effect of our pose estimation, we compare our method with the segmentation using a random initialization. Fig. 8 shows some comparisons. It can be seen that segmentation using a random initialization easily runs into a local minimum, while with our pose estimation, this
problem can be better avoided. We also compare our method with Otsu's method and RSF that is the first energy term in (6) without shape prior.

DISADVANTAGES

1. Detection of object is optimal for all lighting conditions of an image.
2. Lack of representing shape of object regions.
3. Low recognition accuracy.

IV. PROPOSED SYSTEM

- A coarse-to-fine aircraft recognition method.
- The similarity and difference of shapes for aircraft are explored in the coarse and fine stages, respectively.

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- A single template with a defined score is adopted to estimate the pose roughly in the coarse stage. In the fine stage, template matching and kernel density function are used to model shapes to get good effects on dimension reduction and sample space description.
- A new energy function is proposed to embed the shape model to segmentation. In addition, the obtained size and template matching coefficients are used directly to recognition

ADVANTAGES

1. It provides better accuracy of segmenting objects
2. Correlation is useful to detect desired object with help of templates rather than Euclidean distance.
3. Flexibility and better compatible approaches in recognition

CONCLUSION

A coarse-to-fine aircraft recognition method for similarity and difference of shapes for aircraft are explored in the coarse and fine stages, respectively. A single template with a defined score is adopted to estimate the pose roughly in the coarse stage. In the fine stage, PCA and kernel density function are used to model shapes to get good effects on dimension reduction and sample space description. A new energy function is proposed to embed the shape model to segmentation. In addition, the obtained size and PCA coefficients are used directly to recognition. Experiments show that our proposed method is robust with respect to various disturbances.

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