

Novel Aircraft Type Recognition with Learning Capabilities in Satellite Images

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Abstract

The collection of satellite images is not constrained by time and can be captured day and night. It is unlike the images captured by aircrafts which are heavily constrained by weather conditions and environmental factors to secure useful images. Recently, satellite images have been widely applied in many fields, such as resource mining, pollution monitoring, etc. In this paper, we plan to apply it to the military to analyze different types of aircrafts for security purpose. In our system, image processing techniques are first employed to perform the image preprocessing tasks, such as image quality enhancement, noise removal, rotation, scaling, and translation adjustment. Then, distinguishable features are extracted from aircrafts for recognition. Last, a multi-level recognition scheme is adopted for recognizing the types of aircrafts by incorporating suitable weight into each recognition level. Experimental results reveal the feasibility and validity of the proposed approach in recognizing aircrafts in satellite images.

1. Introduction

Satellite images can be captured without any constraints by time, weather, country boundary, and other environmental factors. Thus, surveillance through satellite images is a very important application for military needs. The analyzed target can be bridge, airports, roads, streets, buildings, and so on. One particular feature of these human-build targets is "line structure". Therefore, in the literatures [1]-[4], there have been many different detection schemes proposed for detecting line structures. For examples, Nevatia and Babu [1] proposed a line edge detector to detect all line-like structures. Gruen and Li [2] used wavelet transform to sharpen road boundaries. However, since the objects in satellite images are very small, all the above methods focus only on detecting objects and don't further recognize them. Although there have been many methods [5]-[7] proposed for object recognition, when satellite images are handled, all these methods fail to correctly recognize the objects in satellite images since they are very small and polluted by different dazzle paints, shadows, and other noise.

In this paper, we propose a novel recognition

system for recognizing various aircrafts in satellite images by a hierarchical boosting algorithm. Since each aircraft has different orientations, sizes, textures, and even dazzle paints, some preprocessing techniques like image quality enhancement, noise removal, automatic Binarization, rotation, scaling, and translation adjustments are first employed to perform. Thus, all above variations to a minimum can be reduced before recognition. For the orientation adjustment, the common method to estimate object orientation is through a moment analysis [8]. However, the moment-based method will fail to work when aircrafts have longer wings, shadows, fragments, and other noise. Therefore, in this paper, we propose a symmetry based method for the rotation adjustment. Since an aircraft even polluted by noise still maintains its symmetry, the symmetry-based method can perform more robustly and accurately than the moment-based method. Then, distinguishable features derived from the characteristics exhibited by aircrafts are extracted for aircraft recognition. Four features are used and derived, respectively, from wavelet transform, Zernike moment, distance transform, and the bitmap itself. Different features have different capacities to discriminate aircrafts. In order to integrate these features together, a novel learning scheme is then proposed to determine suitable weights from training samples for capturing the characteristics of aircrafts. Based on these two ingredients, i.e. weights and features, all input aircrafts can be recognized very accurately. From experimental results, the proposed method indeed achieves great improvements in terms of accuracy, robustness, and effectiveness in recognizing aircrafts in satellite images.

2. Processing

This paper proposes a novel system to recognize aircrafts on satellite images for military surveillance. The proposed system can be divided into three modules, i.e., preprocessing, feature extraction, and recognition. In what follows, details of the preprocessing module are first described.

2.1 Binarization and Noise Removing

In this paper, a "minimum within-group variance" dynamic thresholding method [8] is applied to binarize each input region. After binarization, a conventional labeling technique is then applied to locate each

connected component from the binarized aircraft image (as Fig. 1). If the size of a component is less than a threshold, it will be filtered out.

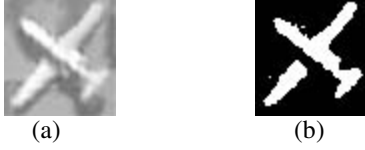


Fig. 1: Result after inarization.

2.2 Orientation Estimation and Rotation Normalization with Symmetry

In practice, each aircraft in satellite images will have different orientations when it parks in an airport. In order to make the task of recognition more easily, its orientation should be corrected in advance. In this paper, a symmetry-based method is proposed for this orientation normalization.

Let $\Omega(R)$ be the symmetry measure of an aircraft R and R^θ be the rotated version of R with an angle θ . If θ_{axis} is the direction of the body axis of R , it should satisfy:

$$\theta_{axis} = \arg \max_{0^\circ \leq \theta < 180^\circ} \Omega(R^\theta). \quad (1)$$

To solve Eq.(1), the first thing is to define the symmetry measure $\Omega(R)$. Let $x_R(j)$ be denoted as the average value of the x coordinates of pixels in the j th horizontal line of R and w_R be the width of R .

Then, $x_R(j)$ can be calculated as follows:

$$x_R(j) = \frac{1}{H_R(j)} \sum_{0 \leq i < w_R} i \times R(i, j), \quad (2)$$

where $H_R(j) = \sum_{0 \leq i < w_R} R(i, j)$.

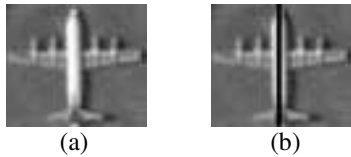


Fig. 2: Aircraft with a northern direction.

As shown in Fig. 2, the black line in (b) is the average x coordinates of all horizontal lines of (a). Clearly, if R is toward the northern direction, the black line is the body axis of R and all the values $\{x_R(j)\}$ should be similar. Thus, the variance of $\{x_R(j)\}$ is small and can be a good index to measure the symmetry of R . Let $\sigma_x(R)$ be the variance of the set $\{x_R(j)\}_{0 \leq j < h_R}$. Then, Eq.(1) can be rewritten as:

$$\theta_{axis} = \arg \min_{0^\circ \leq \theta < 180^\circ} \sigma_x(R^\theta). \quad (3)$$

In what follows is our symmetry-based rotation estimation algorithm.

Symmetry-based Orientation Estimation Algorithm:

- S1: Let $s = 20$ and $\Theta = \{\theta \mid \theta = 0, \dots, 180/s\}$.
- S2: For each θ in Θ , calculate the symmetry measure $\sigma_x(R^\theta)$.
- S3: Sort all angle θ in an ascending order according to the value of $\sigma_x(R^\theta)$. Let $\Phi = \text{NULL}$;
- S4: If $s = 1$, choose the θ with the smallest $\sigma_x(R^\theta)$ as the solution θ_{axis} and go to S8 for ending. Otherwise, collect the top N angles θ with smaller $\sigma_x(R^\theta)$ from Θ to the set Φ as possible candidates, where $N = \lfloor |\Theta|/4 \rfloor$ and $|\Theta|$ is the number of elements in Θ .
- S5: Half the quantization step, i.e., $s = s/2$;
- S6: For each ϕ in Φ , generate two candidates $\beta + s$ and $\beta - s$ to the new set Φ' .
- S7: $\Theta = \Phi \cup \Phi'$. Go to Step 2.
- S8: Stop and record the θ_{axis} as the desired solution.

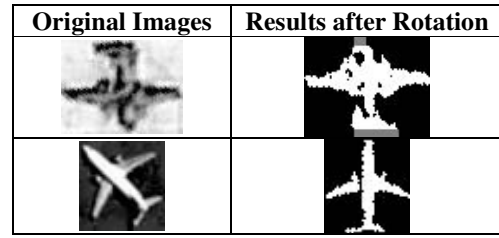


Fig. 3: Result of aircrafts after orientation estimation and adjustments.

3. Feature Extraction

This paper uses four features to describe the characteristics of aircrafts including binary map, contours, moments, and wavelet coefficients.

3.1 Binary map

Assume Map_Q and Map_F are the binary maps of Q and F , respectively, where Q is a query aircraft and F another aircraft in database. The distance between Map_Q and Map_F can be defined as:

$$d_{Map}(Q, F) = \sum_{0 \leq i < w_F} \sum_{0 \leq j < h_F} |Map_Q(i, j) - Map_F(i, j)|, \quad (4)$$

where w_F and h_F are the width and height of F .

3.2 Contours

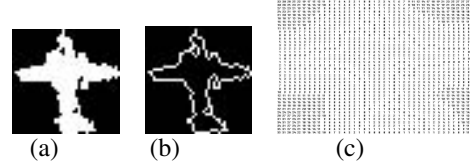


Fig. 4: Result of distance transform. (a) Original Image. (b) Boundaries of (a). (c) Distance transform of (b).

Contour is a good feature to describe the shape of an aircraft R and can be captured by converting R to a

distance map. Assume $B_F(x, y)$ is a binary boundary image of an aircraft F . Then, the distance transform of a pixel p in $B_F(x, y)$ is defined as:

$$DT_{B_F}(p) = \min_{B_F(q)=1} d(p, q), \quad (5)$$

where $d(p, q)$ is the Euclidian distance between two pixels p and q . In order to enhance the strength of distance changes, Eq.(5) is further modified as:

$$\overline{DT}_{B_F}(p) = \min_{B_F(q)=1} d(p, q) \times \exp(\kappa d(p, q)), \quad (6)$$

where $\kappa=0.1$. Fig. 4 shows the result of the distance transform of Fig. 4(b). Then, given an unknown query aircraft $Q(x, y)$, the dissimilarity of distance maps between Q and F is defined as:

$$d_c(Q, F) = \frac{1}{|B_F|} \sum_{r \in B_F} |\overline{DT}_{B_Q}(r) - \overline{DT}_{B_F}(r)|, \quad (7)$$

where $|B_F|$ is the image size of $|B_F|$.

3.3 Zernike Moments

Zernike moments provide size, translation, and rotation invariant properties for shape descriptions. The two dimensional Zernike moment with p order and q repetition of an image $f(x, y)$ is defined as:

$$A_{pq} = \frac{n+1}{\pi} \sum_{x^2+y^2 \leq 1} f(x, y) V_{pq}^*(x, y), \quad (8)$$

where $V_{pq}^*(x, y)$ is the conjugate complex of $V_{pq}(x, y)$, a Zernike basis polynomials with p order and q repetition. Let $ZM_{pq} = \|A_{pq}\| / \|A_{00}\|$. In addition, assume that $ZM_{pq}(Q)$ and $ZM_{pq}(F)$ represent the Zernike moments of a query aircraft Q and a aircraft F in the database, respectively. Then, the distance of Zernike moments of Q and F can be defined as:

$$d_{ZM}(Q, F) = \sum_{\substack{0 < p \leq 9, |q| \leq p, p-|q| \text{ is even}}} |ZM_{pq}(Q) - ZM_{pq}(F)|. \quad (9)$$

3.4 Wavelet Coefficients

Wavelet transform (WT) uses two kinds of filters to decompose a signal into different resolutions. After decomposing, each wavelet coefficient can be classified into four different bands, i.e., LL, LH, HL, and HH. Then, we label a pixel p as 1, 2, 2, and 4 if p locates in the LL, LH, HL, HH bands, respectively. Then, the distance of wavelet coefficients between a query aircraft Q and a aircraft F can be defined by:

$$d_w(Q, F) = \sum_p l(p) |Coeff_F^w(p) - Coeff_Q^w(p)|, \quad (10)$$

where $Coeff_Q^w(p)$ and $Coeff_F^w(p)$ are the WT coefficients of Q and F , respectively, and $l(p)$ is the band labeling of p .

4. Feature Integration and Comparisons

In what follows, a novel learning algorithm is proposed to learn proper weights from data for integrating above four features together.

4.1 Recognition with One Single Feature

Let $d(Q, F)$ be the distance of one specific feature between a query aircraft Q and an aircraft F in the database. For all aircrafts F_j , we can sort them in an ascendant order based on the $d(Q, F_j)$. Assume L is the set of the top K sorted results in the list. Then, each element F_j in L is assigned to a score by the rule:

$$Score_Q(F_j) = 1 - j/L. \quad (11)$$

Assume there are K categories of aircrafts in the database, where a specific class C_k has N_{C_k} samples. Then, the similarity between the Q and C_k is defined:

$$S(Q, C_k) = \frac{1}{N_{C_k}} \sum_{F_j \in C_k} Score_Q(F_j). \quad (12)$$

Based on Eq.(12), the proposed system classifies the Q into class l when

$$\forall k \neq l, S(Q, C_l) \geq S(Q, C_k). \quad (13)$$

4.2 Recognition with Multiple Features

Let $S_i(Q, C_k)$ be a similarity between Q and a category C_k if the i th feature is used. The integrated similarity between Q and C_k can be then represented:

$$S_{\text{integration}}(Q, C_k) = \sum_{i=0}^{N_f-1} w_i S_i(Q, C_k), \quad (14)$$

where w_i is a weight for balancing the contribution of $S_i(Q, C_k)$. Here, N_f is the number of features. Then, when multiple features are used, the proposed system classifies the Q into class l if

$$S_{\text{integration}}(Q, C_l) \geq S_{\text{integration}}(Q, C_k) \text{ for } \forall k \neq l. \quad (15)$$

In what follows, we will propose a novel learning algorithm to learn the w_i based on a boosting concept. Assume U is the set of total training samples, where U^k is a subset of U whose elements are in the category C_k . Then, given a sample u_j^k in U^k , the learning algorithm will increase the i th weight w_i if it lets one instance in C^k have the best ranking. After training all the samples several times, the weights $\{w_i\}$ will gradually converge.

Weight Learning Algorithm

Input: MaxIterations = 10;

S1: Set all $\{w_i\}_{i=0, \dots, N_f-1}$ to be $1/N_f$ and $t=0$;

S2: For each sample u_j in U ,

2.1 k = the category which the u_j belongs to.

2.2 For $i=0$ to N_f-1

2.2.1 Sort all categories C_n in decendant order according to the value of $S_i(u_j, C_n)$;

2.3 $l = \arg \min_{0 \leq i < N_f} Id(i)$, where $Id(i)$ is the sorted

index of the k th categories for the i th feature.

2.4 $w_i = w_i + \Delta w$, where $\Delta w = 0.01$.

2.5 $w_i = w_i / \bar{w}$ and $\sum_{i=0}^{N_f-1} w_i$ for $i=1, \dots, N_f-1$.

S3:
$$\varepsilon = \frac{1}{N_f} \sum_{i=0}^{N_f-1} (w_i - \bar{w}_i)^2.$$

S4: If $\varepsilon = 0$ or $t < \text{MaxIterations}$, increase t by 1 and go to Step 2. Otherwise, the desired set of weights $\{w_i\}_{i=0, \dots, N_f-1}$ is obtained.

5. Experimental Results

In order to analyze the performance of our proposed approach, a test database containing 218 aircrafts, which come from 12 categories, is used. In addition, a training database containing 70 aircrafts is adopted to train proper weights for feature integration. Table 1 shows parts of aircraft types used for recognition.

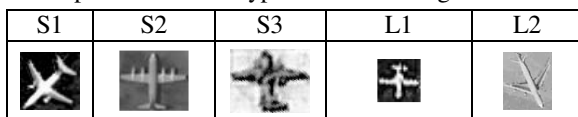


Table 1: Types of aircrafts built in the database.

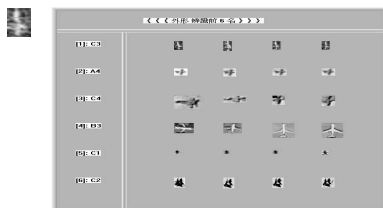


Fig.5: Recognition result when an "S3" image is input and the bitmap feature is used.

Features Rate	Bitmap	Dist Table	Z. M.	Wavelet	Integration
Accuracy (%)	68.57	72.86	77.14	77.01	97.14

Table 2: Types of aircrafts built in database.

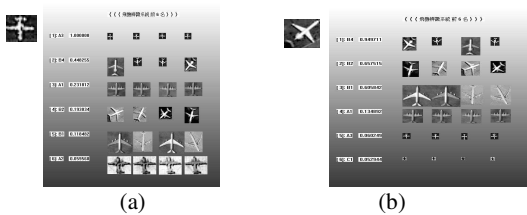


Fig.6: Recognition results when all features are used. (a) Recognition result of the "S3" aircraft. (b) Recognition result of the "L4" image.

Fig. 5 shows the result when the "S3" aircraft is queried and the bitmap feature is used. Fig. 6 shows the recognition results when multiple features are used. (a) is the result of an "S3" aircraft and (b) the result of a "L4" one. Table 2 lists the average accuracies of recognition when different features are used. The

average accuracy of the integration scheme is shown in the 6th column of Table 2. The recognition accuracy of the learning scheme is high and up to 97.14%. According to the above experimental results, the superiority of the proposed method can be verified.

6. Conclusions

In this paper, we have presented a hierarchical recognition method to recognize the types of aircrafts from satellite images. The contributions of this paper can be summarized as follows:

- A symmetry-based method was proposed to estimate the axis direction of an aircraft for rotation adjustment.
- A multi-level recognition scheme was proposed to recognize the types of aircrafts by incorporating suitable weights into each recognition level. The integration has been proved very usefully in capturing the characteristics of aircrafts.

Acknowledges

This work was supported in part by Economic Council and National Science Council of Taiwan under Grants NSC92-2213 -E-150-049 and 93-EC-17-A-02-S1-032.

References

- R. Nevatia and K. R. Babu, "Linear Feature Extraction and Description," *Computer Graphics and Image Processing*, vol. 13, pp. 257-269, 1980.
- A. Gruen and H. Li, "Semi-Automatic Road Extraction by Dynamic Programming," *International Archives of Photogrammetry and Remote Sensing*, vol. 30, part 3/1, pp. 324-332, 1994.
- Donald Geman and Bruno Jedynek, "An Active Testing Model for Tracking Roads in Satellite Images," *IEEE Transactions on PAMI*, vol. 18, no. 1, pp.1-14, January 1996.
- M. Pesaresi and J.A. Benediktsson, "A New Approach for the Morphological Segmentation of High-Resolution Satellite Imagery," *IEEE Transactions on Geosciences and Remote Sensing*, vol. 39, no. 2, pp.309-320, Feb. 2001.
- S. C. Tien and T. L. Chia, "Using cross-ratios to model curve data for aircraft recognition", *Pattern Recognition Letter*, no. 12, pp. 2047-2060, 2003.
- R. Alferez and Y.F. Wang, "Geometric and Illumination Invariants for Object Recognition," *IEEE Transactions on PAMI*, vol. 21, no. 6, pp. 505-536, June 1999.
- Greenberg and J. Guterman, "Neural-network classifiers for automatic real-world aerial image recognition," *Applied Optics*, vol. 35, no. 23, pp. 4598-4608, Aug. 1996.
- M. Sonka, V. Hlavac, and R. Boyle, *Image Processing, Analysis and Machine Vision*, London, U. K.: Chapman & Hall, 1993.