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STATIONARY AIRCRAFT DETECTION FROM SATELLITE IMAGES

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Abstract: *Satellite image analysis is an important research area in the field of image processing. Detection and recognition of regions and objects from satellite images find many useful civil applications such as detection of buildings, roads, bridges and other man-made objects as well as land plant classification. On the other hand, the detection of stationary aircrafts in airports can be strategically important in military applications. In this study, a learning-based system that detects stationary aircrafts in satellite images obtained from Google Earth is developed. The features that emphasize the geometric structure of an aircraft are determined using 2D Gabor filter. The aircraft detection is performed using Support Vector Machines (SVM) classification method. The SVM is a supervised learning method that analyzes data and recognizes patterns for classification The SVM takes a set of input data (a vector consists of Gabor filter output of images) and predicts the one of two classes (aircraft or non-aircraft). The performance of the system is demonstrated using satellite images collected from airports in Europe and United States.*
Keywords: *Aircraft detection, satellite image analysis, support vector machines, Gabor filter.***.**

1. Introduction

The Detection and recognition of objects from satellite images is one of the important research areas in the field. Satellite image analysis can be useful in many applications such as water and climate observation, land cover classification and energy exploration. Especially, the detection of stationary aircrafts can be strategically important in military applications. This type of information provides more robust and successful decision mechanism in dynamically changing military operations. Detection of aircrafts from satellite images using image processing algorithms highly depends on learning the geometrical structure of aircrafts. Making this structure more evident plays important role for the detection of these aircrafts from satellite images.

In airports, there may be many disturbing objects near aircrafts. It is important to perform preprocessing steps to suppress such noises and make clearer the features of aircrafts for successful detection. In the literature different aircraft detection and recognition researches have been conducted. In [1], detecting aircrafts with a low resolution infrared sensor is presented. A hierarchical classification algorithm to accurately recognize aircraft in satellite images is proposed in [2]. A system for aircraft recognition under real-world conditions that is based on the use of a hierarchical database of object models is also presented in [3]. A self-adaptive cluster segmentation method for the problem of automatically detecting the aircraft location from complex aerial images is also presented in [4].

The objective of this study is to develop a learning-based system that detects stationary aircrafts in satellite images obtained from Google Earth® [5]. Google Earth is a virtual globe, map and geographical information program that maps the Earth by the superimposition of images obtained from satellite imagery. The features that emphasize the geometric structure of an aircraft are determined using Gabor filter [6]. A set of Gabor filters with different frequencies and orientations is useful for extracting useful image features from an image. Frequency and orientation representations of Gabor filters are similar to representations of the human visual system, and they are widely used in many preprocessing steps of image processing systems that include texture representation and discrimination. In the spatial domain, a 2D Gabor filter is a Gaussian kernel function modulated by a sinusoidal plane wave.

In this study, a learning-based aircraft detection system is developed using 2D Gabor features obtained from satellite images. The detection is performed by using Support Vector Machines (SVM) classification method [7]. The SVM is a supervised learning method that analyzes data and recognizes patterns for classification. The SVM is used in many applications including optical character recognition [8], data mining [9], face recognition [10], facial expression analysis [11] and biomedical [12]. The SVM takes a set of input data (a vector consists of Gabor filter output of images) and predicts the one of two classes

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(aircraft or non-aircraft in this study) that the input data fall on. The SVM is a non-probabilistic binary linear classifier.

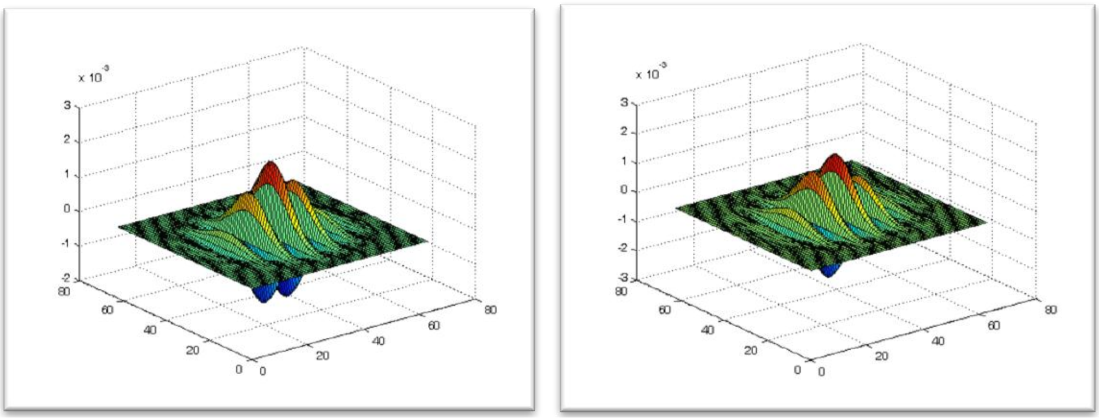


Figure 1. Real (left) and imaginary (right) part of the complex Gabor function.

An SVM training algorithm builds a mathematical model from a set of training examples (aircraft images collected from airports using Google Earth program) each marked as belonging to one of two categories. These examples are represented as points in a space so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on.

The paper is organized as follows. In section 2, a brief description of Gabor filter for feature extraction, the SVM method for building mathematical model and classification of the data are presented. The results are also presented in Section 2. Finally, the conclusion is given in section 3.

2. The Proposed System

The details of the proposed system are given in the following sections.

2.1. Gabor Filter

Gabor filter is used for feature extraction and object detection in many image processing and computer vision applications [12-14]. Two dimensional complex Gabor function in the spatial domain can be defined as:

$$g(x,y)=\frac{1}{2\sigma_x\sigma_y}\exp\left[-\frac{1}{2}\left(\frac{\tilde{x}^2}{\sigma_x^2}+\frac{\tilde{y}^2}{\sigma_y^2}\right)\right]\exp\left[j2\pi f\,\tilde{x}\right]$$
$$\tilde{x}=x\cos\theta+y\sin\theta$$
$$\tilde{y}=-x\sin\theta+y\cos\theta \tag{1}$$

where σ_x and σ_y are the standard deviations of the Gaussian envelope along the x and y axis respectively. $\theta\left(\theta\in[0,\pi)\right)$ is the orientation of the Gabor filter and f is the frequency of the sinusoidal wave. The real and imaginary parts of complex Gabor function in the spatial domain are shown in Figure 1.

In order to capture features with different orientations and frequencies, a filter bank consisting of different Gabor filters can be employed. In this study, a Gabor filter bank system is used with four orientations at 0, 45, 90 and 135 degrees and one frequency.

The filtering is performed by convolution of the input image $I(x,y)$ and the Gabor filter $G_n(x,y)$ for each orientation;

$$R_n(x,y)=I(x,y)*G_n(x,y) \tag{2}$$

where $*$ represents the two dimensional convolution. The feature vector was obtained from the magnitude response of the filter outputs. Each of the convolution results $R_n(x,y)$ is a complex function and is composed of a real part $\Re\{R_n(x,y)\}$, and an imaginary part $\Im\{R_n(x,y)\}$. The magnitude of feature vector then can be defined as follows:

$$\|R_n(x,y)\|=\sqrt{\Re^2\{R_n(x,y)\}+\Im^2\{R_n(x,y)\}} \tag{3}$$

Figure 2 shows the real parts of Gabor filter with four orientations (0, 45, 90 and 135 degrees) and three frequencies. Each of the input aircraft images with 40x40 pixels is convolved with Gabor filters for four different orientations and one frequency value, resulting total 40x40x4 = 6400 features (attributes) are obtained. The resulting images are shown in Results section.

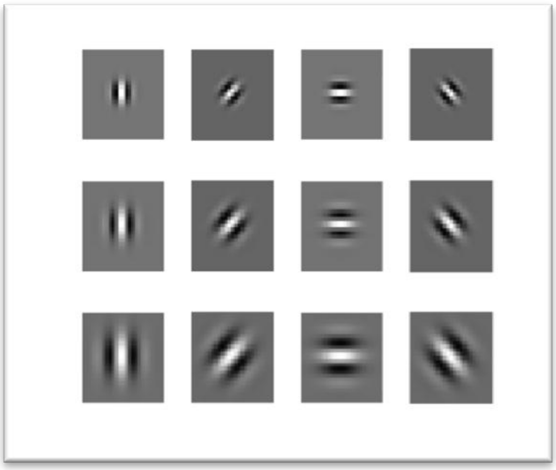


Figure 2. Gabor the real parts of Gabor filter with four orientations (0, 45, 90 and 135 degrees) and three frequencies.

2.2. Support Vector Machines (SVM)

The SVM is a supervised learning method that analyzes data and recognizes patterns for classification. The SVM takes a set of input data (a vector consists of Gabor filter output of images) and predicts the one of two classes (aircraft or non-aircraft in this study). An SVM training algorithm builds a mathematical model from a set of training examples (aircraft images collected from airports using Google Earth program) each marked as belonging to one of two categories as follows:

$$S = \{(x_1, y_1), \dots (x_l, y_l)\}, (x_i, y_i) \in X \times \{-1, +1\} and\ i = 1,2, \dots l \quad (4)$$

where (x_l , y_l) is the labeled input data, X is the multi-dimensional feature space (R^d), and {-1,+1} are the labels representing aircraft or non-aircraft classes. The purpose of the SVM algorithm is to learn a classifier function that maps the data into two classes such that $f: X \rightarrow \{-1, +1\}$.The output of the classifier depends on the sign of a linear function:

$$f(x) = sign(< w, x > + b) \quad (5)$$

A pair of $(w, x) \in X \times R$ defines a hyper plane in the form of:

$$H_{w,b} = \{x \in X: < w, x > + b = 0\} \quad (6)$$

This hyper plane divides X into two half space representing two classes. If the training set is linearly separable (the aircraft and non-aircraft images are on the each side of the hyper plane), the SVM algorithm finds the hyper plane with maximum margin (γ) between classes as shown in Figure 3.[11]

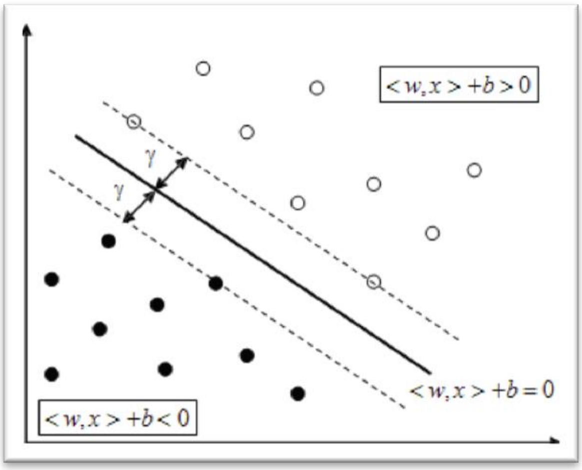


Figure 3. The SVM algorithm finds the hyper plane with max. margin that separates the two class of data.

2.3. The Proposed System and Results

The objective of the study is to develop a learning-based classification system that detects stationary aircrafts on the ground from satellite images obtained using Google Earth program. The overview of the system is shown in Figure 4. The detailed description of the system is given in the following sections.

2.4. Collecting Aircraft Data for Training

In order to build a mathematical model for aircraft images using SVM, many training examples are needed. Google Earth program is used to collect training images. It is a map and geographical information program that maps the Earth by the superimposition of images obtained from satellite imagery.

The images are taken from the well-known airports in Europe and the United States. A total of 120 aircraft images were collected from the same altitude. A number of examples are shown in Figure 5. A total of 450 non-aircraft images are also collected from airports in order to model the non-aircraft class. All images are sampled down to 40x40 pixels in order to keep the number of features lower providing less time and memory requirements.

2.5. Feature Extraction

A set of Gabor filters with different frequencies and orientations is useful for extracting useful image features from an image. Frequency and orientation representations of Gabor filters are similar to representations of the human visual system, and they are widely used in many preprocessing steps of image processing systems that include texture representation and discrimination. In the spatial domain, a 2D Gabor filter is a Gaussian kernel function modulated by a sinusoidal plane wave.

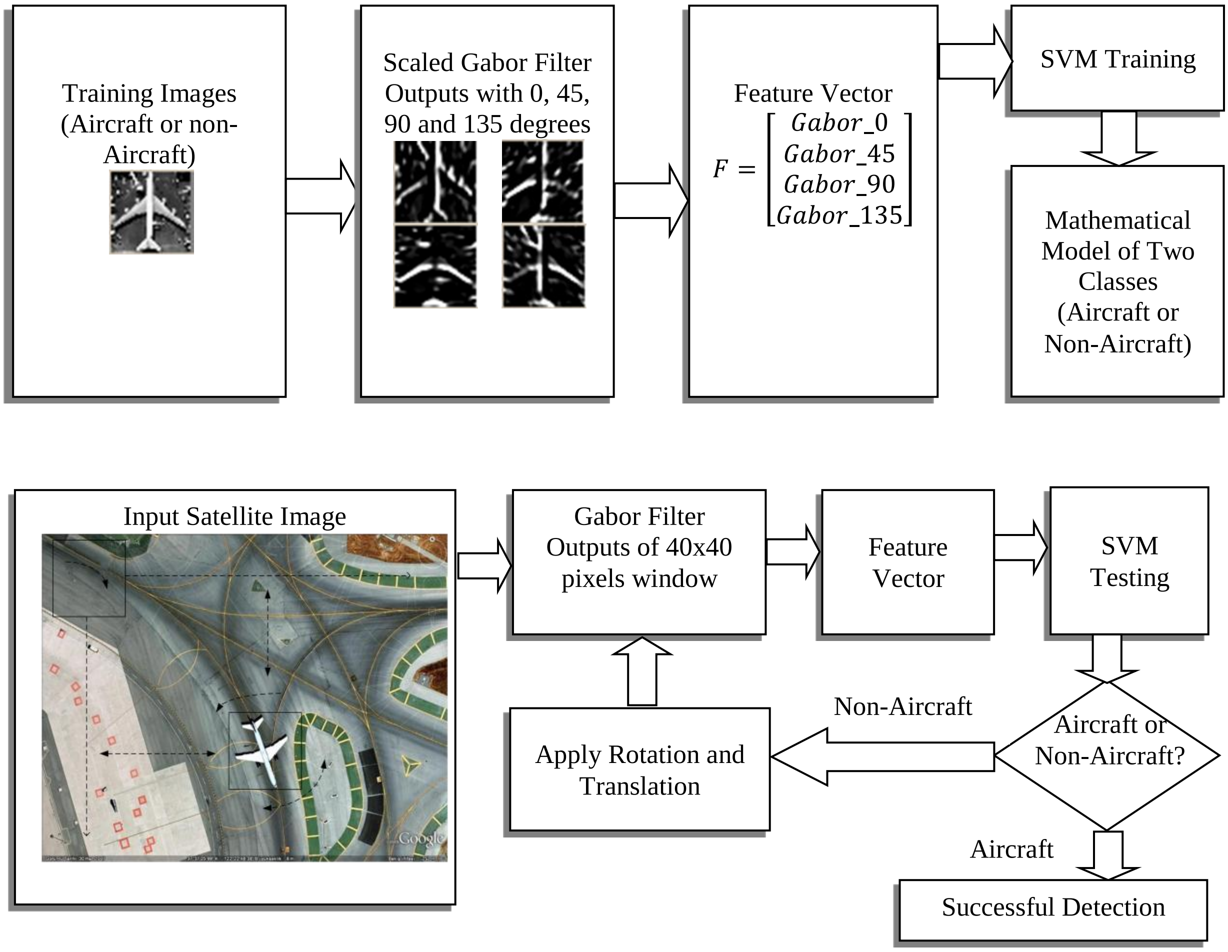


Figure 4. The overview of the proposed system.

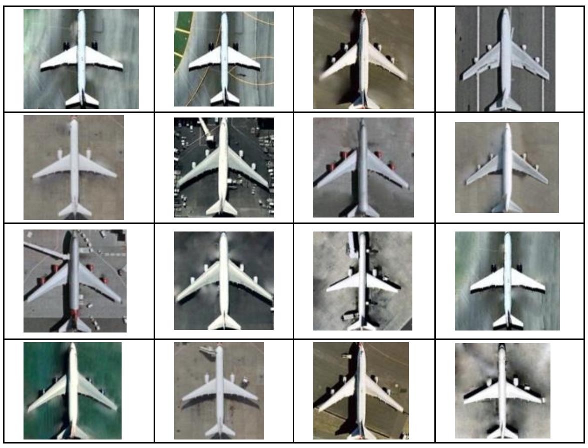


Figure 5. Examples of training images.

In this study, the features that emphasize the geometric structure of an aircraft are determined using Gabor filter [6]. A learning-based aircraft detection system is developed using 2D Gabor features obtained from satellite images. An example of 40x40 pixel aircraft image, 2D Gabor filter outputs in four orientations (0, 45, 90 and 135 degrees) are given in Figure 6.

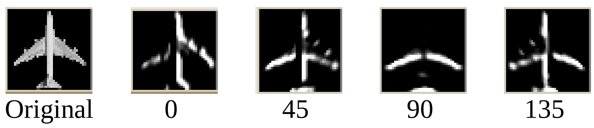


Figure 6. An aircraft image and 2D Gabor filter outputs in four orientations (0, 45, 90, and 135 degrees).

The feature vector for SVM training and testing is given:

$$F = \begin{bmatrix} Gabor\ 0 \\ Gabor\ 45 \\ Gabor\ 90 \\ Gabor\ 135 \end{bmatrix} \tag{7}$$

where Gabor 0, 45, 90 and 135 are the Gabor filter outputs in four orientations. These values are then scaled in the range of [-1, 1] for better classification performance. The scaling of data into smaller range provides many advantages. The main advantage is to avoid attributes in greater numeric ranges dominate those in smaller numeric ranges. Another advantage is to avoid numerical difficulties in calculations since kernel values usually depend on the inner products of feature vectors.

2.6. Training, Classification and Results

The training process takes images of known class (aircraft or non-aircraft) for feature extraction and then apply the SVM algorithm for mathematical modeling of input data. After training, given an input image that may contain an aircraft image, the following procedure applies:

- Take a 40x40 pixels window of image data from top left of the input image.
- Apply Gabor filter in four orientations to the data, and form the feature vector.
- Scale the feature vector data in the range of [-1, 1] for better classification performance.
- Test the data whether it belongs to"aircraft" class or "non-aircraft" class using SVM.
- If it is not an "aircraft" class, apply a rotation transformation to the data and perform the previous step until it finds a match or rotation reaches to 360 degrees.
- Apply a translation to the window in horizontal direction to get a new window of data and apply the same procedure from the beginning to the new window of data.
- Apply a translation in the horizontal and vertical directions so that all the pixels in the input image are scanned. Apply the all procedure all the window of data.

The results of the procedure are given in Figure 7.

2.7. Performance Evaluation

In order to evaluate the system performance quantitatively, the following metrics are defined [15] for characterizing detection rate (DR) and false alarm rate (FAR). These rates are based on the following measurements:

- TP (True positive) : The number of correctly detected aircrafts in the data set.
- FP (False positive) : The number of incorrectly detected (i.e., detected in different location) aircrafts in the data set.
- FN (False Negative) : The number of not detected aircrafts in the data set.

Using the values of TP, FP and FN, the detection rate (DR) and false alarm rate (FAR) can be defined as follows:

$$DR = \frac{TP}{TP + FN} \qquad FAR = \frac{FP}{TP+FP} \tag{8}$$

The performance of the system using these rates are given in Table 1.

Table 1. Performance of the system.

Number of Images in Data Set	58
True Positive Detections (TP)	49
False Positive Detections (FP)	4
False Negative Detections (FN)	5
Detection Rate (DR)	0.91 (91 %)
False Alarm Rate (FAR)	0.075 (7.5 %)

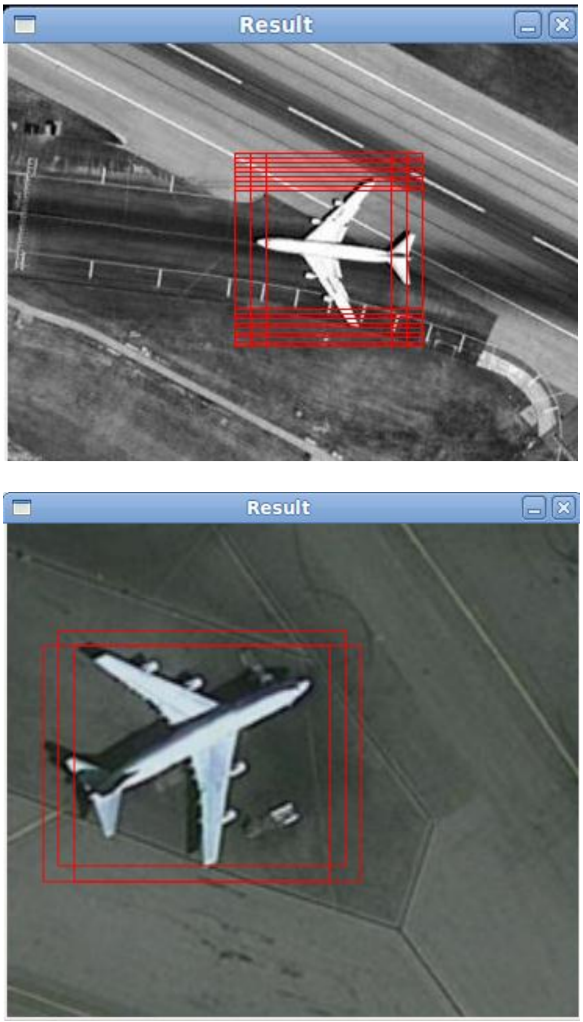
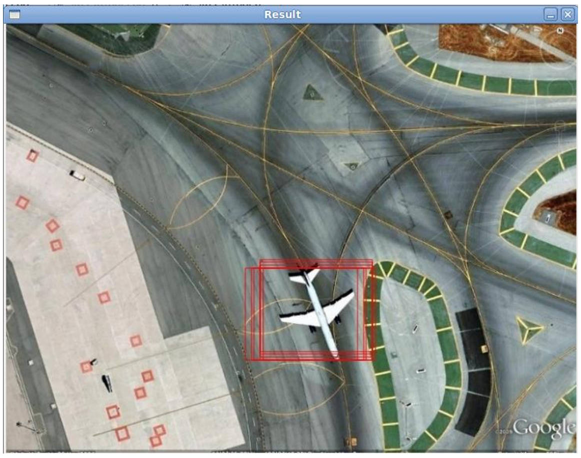


Figure 7. Aircraft detection results. Red boxes show the detected aircrafts in that region.



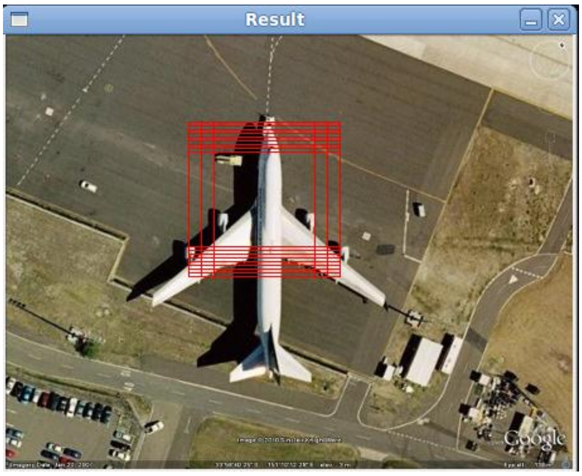


Figure 7 (cont.). Aircraft detection results. Red boxes show the detected aircrafts in that region.

3. Conclusions

In this study, a learning-based system that detects stationary aircrafts in satellite images obtained from Google Earth is developed. The features that emphasize the geometric structure of an aircraft are determined using 2D Gabor filter. The detection is performed by using Support Vector Machines (SVM) classification method. An SVM training algorithm builds a mathematical model from a set of training examples (aircraft images collected from airports using Google Earth program) each marked as belonging to one of two categories aircraft or non-aircraft. The detection performance of the system is demonstrated using images taken from well-known airports in Europe and the United States. The system is useful for localization of aircrafts around the globe for civil and strategic military purposes.

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