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Aircraft recognition using modular extreme learning machine

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ABSTRACT

In this paper, a novel recognition scheme is proposed for identifying the aircrafts of different types based on multiple modular neural network classifiers. Three moment invariants including Hu moments, Zernike moments and Wavelet moments are extracted from the characteristics exhibited by aircrafts and used as the input variables of each modular neural network respectively. Each modular neural network consists of multiple single-hidden layer feedforward networks which are trained using the extreme learning machine and different clustering data subsets. A clustering and selection method is used to get the classification rate of each modular neural network and then based on their weighted sum the final classification output is obtained. The proposed recognition scheme is finally evaluated by recognizing six different types of aircraft models and the simulation results show the superiority of the proposed method compared with the single ELM classifier and other classification algorithms.

1. Introduction

Traditionally, an aircraft was recognized with the use of manual binoculars on the basis of their engine sound and shapes [1]. But the complex backgrounds where an aircraft flies limit the effectiveness of the manual techniques. A lot of research studies has been motivated by the need for automatically identifying aircraft types in air traffic control, as well as in military applications [2–5]. The general goal of automatic aircraft recognition is to analyze the images of a given scene and to identify the potential targets from the given scene. In the automatic aircraft recognition, the silhouette and boundary of an aircraft has been widely exploited by extracting certain features representing the image. The utilization of good features plays a key role in the aircraft recognition. The features should be independent of the object's position and orientation and should contain enough information to uniquely recognize one object from another. But in reality, the geometric distortion of the aircraft including shift, scale and rotation is often met and thus the image patterns have to be able to be extracted regardless of its geometric distortion.

Moments and functions of moments have been utilized as pattern features in the aircraft recognition. Such features capture global or local information about the image and do not require closed boundaries as boundary-based methods such as Fourier descriptors. Hu has derived a set of moment functions with the desired property of invariance under image translation and rotation, which have been applied by many researchers in automatic aircraft identification [2,3]. In [4], Wavelet moment has been used for feature extraction of the aircraft in the infrared image where the global and local features are extracted by using different scaling and shifting factors. The experiment results show that the recognition efficiency with Wavelet-moment invariants is better than that with Hu-moment. Although Hu moment and Wavelet moment are effective in the aircraft recognition, their individual discrimination abilities are limited. In [5], the different shape characteristics of an aircraft are extracted using the four methods including binary map, contours, Zernike moments, and Wavelet coefficients. For recognition, these different features are integrated together into a large feature vector by assigning a set of proper weights on features. Experimental results have shown that the recognition results with integrated features are better than those using the individual features extracted from one of the above four methods. Although the integrated features show the superior performance, they require a large amount of computation and storage capability due to the high dimensionality of the integrated feature vector.

After the features are extracted, they are input to a designed classifier to decide a label for the underlying image. In [6], on the basis of the Hu-moment features, two distinct classifiers including a Bayes decision rule and a distance-weighted *k*-nearest-neighbor rule are used in classification experiments. The nearest-neighbor distance algorithm is utilized for classifying the aircraft with the multiple features in [5]. Although the Bayes decision method is characterized by a well-defined sense of optimality, it requires

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a priori information concerning the statistics of the observation. The nearest neighbor algorithm only considers partial measurement information. Neural networks can learn to classify from labeled training data without requiring the knowledge of statistical models and thus are attractive alternative in the aircraft recognition. In [7], the multiple-layer feedforward neural networks are used for the radar target classification and the results indicate that neural networks can achieve similar performance compared with decision-theoretic classification techniques which require either nearest neighbor prototypes or complete statistical models. A three-layer neural network is also presented to recognize the aircraft types in [8]. In the two methods, the learning abilities of neural networks are guaranteed based on the back-propagation algorithm that is widely used in many neural-network applications. However the back-propagation method faces some trivial issues such as learning parameters (learning epochs, learning rate, etc.), stopping criteria, and/or local minima.

Recently, a new fast neural learning algorithm referred to as Extreme Learning Machine (ELM) with any hidden nodes has been developed for Single-Hidden Layer Feedforward Networks (SLFNs) in [9,10]. In ELM, the hidden nodes need not be adjusted during training. All the parameters of hidden nodes could randomly be generated according to any given continuous probability distribution without any prior knowledge of the target function. The output weights of the network are analytically determined using simple generalized inverse operation of the hidden layer output matrices. The ELM algorithm not only possesses better computational efficiency in terms of the learning speed and generalization capability compared with the back-propagation algorithm but also avoids the difficulties faced by the back-propagation method [10,11]. ELM has been successfully applied in many real world applications [12–16].

The primary objective of the present investigation is to study the use of ELM for the aircraft recognition. In the paper a hierarchial modular ELM recognition scheme is proposed for recognizing the aircraft types. In order to improve the accuracy of aircraft recognition, three features derived from Hu moment, Wavelet moment and Zernike moment respectively are used in the proposed scheme. Different from [5], the three individual features need not be combined together to form a feature vector and are used to perform a module recognition task. In each module, the task is further decomposed by dividing the training dataset into several independent subsets using the clustering method. Then ELM is used to learn each subset and classify the aircraft types. The classification result of each module is first obtained according to a clustering and decision decision method and then the final classification result is achieved based on the weighted sum of each module's classification rate for the unknown patterns where the classification rate of each module got in the validation process is used as the weight factor. The proposed scheme is evaluated on a group of six aircraft models of different types and the simulation results verify its superior performance in terms of recognition accuracy, computation speed and robustness in recognizing aircrafts.

This paper is organized as follows. Section 2 reviews the feature extraction methods together with the feature selection process. In Section 3, the design procedure of the proposed recognition scheme is introduced together with the ELM algorithm and modular ELM classifier. Section 4 shows the simulation results from the recognition of six different types of aircrafts. Section 5 presents the conclusions from this study.

2. Feature extraction

Moments can describe the geometrical features of different objects and thus have been widely used in pattern recognition applications. In the paper, three features from Hu moments [17], Zernike moments [17] and Wavelet moments [18] are extracted to represent different characteristics of aircrafts so that a high recognition accuracy can be obtained based on the integration of their discrimination abilities. The following will give a simple description about each moment method.

2.1. Hu moment

For a 2D image with the density distribution function $f(x,y)$, the geometric moment of $(p+q)$ order is defined as

$$m_{pq} = \iint x^p y^q f(x,y)\, dx\, dy \tag{1}$$

where p, q are non-negative integers, $x^p y^q$ is a standard power basis, $f(x,y)$ is the gray value of the image at x and y location.

Invariance to translation can be achieved simply by shifting the polynomial basis into the object centroid. When the centroid of the image is (x_c, y_c), the central geometric moment is defined as

$$\mu_{pq} = \iint (x-x_c)^p (y-y_c)^q f(x,y)\, dx\, dy \tag{2}$$

where $x_c = m_{10}/m_{00}$ and $y_c = m_{01}/m_{00}$ are the gravity center of the image. m_{00} is an area of the object for binary images. m_{10} and m_{01} are one-order geometric moments. It is noted that $\mu_{10} = \mu_{01} = 0$ and $\mu_{00} = m_{00}$ always hold.

Scaling invariance is obtained by proper normalization of each moment. Since low-order moments are more stable to noise and easier to calculate, the moment is normalized most often by a proper power of μ_{00}, which is given by

$$\nu_{pq} = \frac{\mu_{pq}}{\mu_{00}^{w}} \tag{3}$$

where ν_{pq} is the normalized central geometric moment, $w = (p+q)/2+1$.

Hu has derived a set of seven moments invariant to translation, scale change and rotation using the low-order, second- and third-order normalized central moments. They are given as

$$\begin{aligned}
\phi_1 &= \nu_{20} + \nu_{02}\\
\phi_2 &= (\nu_{20}-\nu_{02})^2 + 4\nu_{11}^2\\
\phi_3 &= (\nu_{30}-3\nu_{12})^2 + (3\nu_{21}-\nu_{03})^2\\
\phi_4 &= (\nu_{30}+\nu_{12})^2 + (\nu_{21}+\nu_{03})^2\\
\phi_5 &= (\nu_{30}-3\nu_{12})(\nu_{30}+\nu_{12})((\nu_{30}+\nu_{12})^2 - 3(\nu_{21}+\nu_{03})^2)\\
&\quad + (3\nu_{21}-\nu_{03})(\nu_{21}+\nu_{03})(3(\nu_{30}+\nu_{12})^2 - (\nu_{21}+\nu_{03})^2)\\
\phi_6 &= (\nu_{20}-\nu_{02})((\nu_{30}+\nu_{12})^2 - (\nu_{21}+\nu_{03})^2) + 4\nu_{11}(\nu_{30}+\nu_{12})(\nu_{21}+\nu_{03})\\
\phi_7 &= (3\nu_{12}-\nu_{03})(\nu_{30}+\nu_{12})((\nu_{30}+\nu_{12})^2 - 3(\nu_{21}+\nu_{03})^2)\\
&\quad - (\nu_{30}-3\nu_{21})(\nu_{21}+\nu_{03})(3(\nu_{30}+\nu_{12})^2 - (\nu_{21}+\nu_{03})^2)
\end{aligned} \tag{4}$$

where ν_{20} and ν_{02} are the second-order normalized central moments. ν_{30}, ν_{03}, ν_{21} and ν_{12} are the third-order normalized central moments.

2.2. Zernike moment

Zernike moment is one of the orthogonal moments and constructed based on the Zernike polynomials orthogonal on a unit circle. A Zernike basis polynomial with p order and q repetition is given by

$$V_{pq}(x,y) = R_{pq}(r) e^{jp\theta} \tag{5}$$

where p is a non-negative integer, $|q| \le p$ and $p-|q|$ is even. (r,θ) are the polar coordinates of Cartesian coordinates satisfying $r = \sqrt{x^2+y^2}$ and $\theta = \arctan(y/x)$. $e^{jp\theta}$ is an angular part of the