A Survey on the Various UAV Landing Sign Detection Techniques

Prakruthi S. T.[1] Anjali Muralidharan[2] Dhanalakshmi B.[3] Aman Kumar Dubey[4]
[1]Assistant Professor [2,3,4]Student
[1,2,3,4]Department of Information Science Engineering
[1,2,3,4]New Horizon College of Engineering, India

Abstract— Image recognition is a vital task within the field of computer vision. Image recognition refers to process of detection of images and classifies them into one of the predefined categories. Various techniques have been developed for image recognition. In this survey we describe some recognition techniques such as Support Vector Machine(SVM), Harris Corner Detection, Global Positioning system(GPS),Deformable part Modules(DPM),Convolution Neural Network (CNN).

Key words: Support Vector Machine (SVM), Harris Corner Detection, Global Positioning system (GPS), Deformable part Modules (DPM), Convolution Neural Network (CNN), Landing Sign Detection

I. INTRODUCTION

With the rapid development of UAV technology, one of the greatest challenges is the detection of landing signs. One of the primary hindrance to the allowance of UAV journeys over populated area is the lack of sophisticated automated detect drone landing sites. The advent of computers with higher capacity, the availability of low-priced and better quality cameras has led to an interest in Image recognition algorithms.

A simple Classification includes image acquisition (acquiring images for image processing), image pre-processing, feature extraction, and finally generating the desired result. A classifier is considered more optimal if they can predict image accurately.

In supervised classification, known pixels are grouped and given the appropriate class labels are given. This process is being coined as training. These trained pixels are used to classify other images.

In unsupervised classification pixels are grouped according to their properties. This process is coined as clustering and groups are known as clusters. A user gets to decide how many number of clusters he wants.

Efficient algorithms have been implemented using various image processing techniques such as Convolutional Neural Network (CNN), Random forest, Support Vector Machine, k-Nearest Neighbor .The advantages and disadvantages of each of these methods have been specified.

II. RELATED WORK

A. Support Vector Machine (SVM)

SVM-based intrusion detection algorithms have been widely used to identify an intrusion quickly and accurately. SVM, one of the machine learning technologies, is a new algorithm based on statistical learning theory that has shown higher performance than the traditional learning methods in solving the classification problem of pattern recognition and speech recognition. The Support Vector Machine (SVM) provides a robust, accurate and effective technique for pattern recognition and classification. Although the SVM is essentially a binary classifier, it can be adopted to handle multi-class classification tasks. For shape classification, we use linear SVMs. Compared with other classification algorithms. SVM can better solve the problems of small samples, nonlinearity and high dimensionality. However, with the advent of the era of big data, SVM encounters the problem of long training and testing times, high error rates and low true positive rates, which limit the use of SVM in network intrusion detection. Therefore, SVM feature selection, feature weighting and SVM parameter setting are critical to improved detection performance, and several researchers proposed SVM-based IDS [1].Although SVM based IDS can improve IDS performance in terms of detection rate and learning speed compared with traditional algorithms (such as neural networks), room for improvement still exists. However, the training and testing time of the algorithm is relatively long. M. A new fitness function was proposed that includes the classification accuracy, the number of features and the number of support vectors, but it required a long time to train the SVM.

The procedure of SVM training for moving object classification is summarized as follows.

1) Step 1: Train the classifier using the training samples with type I block size and compute the boosting HOG features.
2) Step 2: with the obtained features, train the SVM classifier with all the samples. Test the trained SVM on the same training samples. Find all the false positive and false negative samples.
3) Step 3: Use the false positive samples and false negative samples to train the ad boost classifiers with type II blocks as in step 1).
4) Step 4: Train the ad boost classifier with type III blocks similar as in step 1).
5) Step 5: Combine the obtained ad boost classifiers to build the feature vector and train the final linear SVM classifier to classify images.

B. Disadvantages

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The Support Vector Machine (SVM) provides a robust, accurate and effective technique for pattern recognition and classification. Although the SVM is essentially a binary classifier, it can be adopted to handle multi-class classification tasks. The conventional way to extent the SVM to multi-class scenarios is to decompose an m-class problem into a series of two class problems, for which either the one-vs-one (OVO) or one-vsall (OVA) approaches are used.

The solution of binary classification problems using SVMs is well developed. Multi-class problems (such as object recognition and image classification [5]) have typically been solved by combining independently produced binary classifier

C. Harris Corner Detection

Harris Corner Detector is a corner detection operator that is commonly used in computer vision algorithms to extract corners and infer features of an image. It was first introduced by Chris Harris and Mike Stephens in 1988 upon the improvement of Moravec's corner detector[6].Compared to the previous one, Harris' corner detector takes the differential of the corner score into account with reference to direction directly, instead of using shifting patches for every 45 degree angles, and has been proved to be more accurate in distinguishing between edges and corners[7]. Since then, it has been improved and adopted in many algorithms to preprocess images for subsequent applications.

Harris corner detector has been a widely used feature point detector. It is based on the local automatic cross-correlation function of the signal. The basic principle is that the image window w (which is usually a rectangular area) is required to move the small displacement (x, y) to any direction. The gray variable is defined as:

$$E_{x,y} = \sum W_{u,v} [I_{x+u,y+v}]$$
$$= \sum W_{u,v} [xX+yY+O(x2, y2)] = Ax^2 + 2Cxy + By^2 = (x, y)M(x, y)^T \quad (1)$$

where X and Y is a first-order gray gradient and can be got from the image convolution,

$$X = \frac{\partial I}{\partial x} = I(-1,0,1) \quad (2)$$

$$Y = \frac{\partial I}{\partial x} = I(-1,0,1)^T \quad (3)$$

Gauss smoothing is used to smooth the image window, to improve the anti-noise ability. The selected Gauss window is:

$w_{u,v} = \exp[-(u^2+v^2)/2\sigma^2]$ (4)

Defining,

$$A = X^2,\ B = Y^2,\ C = (XY) \quad (5)$$

M is a matrix and is defined as: $M = \begin{matrix} A & C \\ B & D \end{matrix}$ In (1), E represents the local autocorrelation function, and M represents the shape of the autocorrelation function at the origin. Supposed λ1 and λ2 to be the two characteristic values of M, λ1, λ2 and partial autocorrelation function of the principal curvature are proportional to M. They constitute rotation invariant numbers to M. λ1 and λ2 are regarded as rotation invariant descriptors. The values of λ1 and λ2 can be used to determine the size of the flat area, corner and edge. There are three cases:

- The values of λ1 and λ2 are very small, which indicates that the local auto correlation function is relatively flat, and the gray scale of the image window area is approximately constant;
- The value of λ1 and the value of λ2 differ greatly. One is large, the other is small. This means the local automatic cross-correlation function is ridge-like distribution. Local transfer in horizontal direction will cause small changes in E whereas a big change in the vertical direction means here is the edge;
- The values of λ1 and λ2 are both large, then the local auto correlation function is sharp and the local transfer in any direction will lead to obvious increase, which means here is a corner.

Using Harris detection principle, the feature point is the maximum value of the Harris corner points in the local area, and can be defined as the formula:

$$R = Det(M) - k \bullet Tr2(M) \quad (6)$$

where Tr(M) represents the trace of the matrix M and can be defined as (7), Det(M) represents the value of the determinant of M and can be defined as (8), the value of k is set to 0.04

$$Tr(M) = \lambda1 + \lambda2 = A + B \quad (7)$$

$$Det(M) = \lambda1 \bullet \lambda2 = AB - C2 \quad (8)$$

Corner response function can be defined as:

$$R = AB - C^2 - k^2 (A+B)^2$$

In order to keep the gray value of the matched image Unchanged, an improved Harris corner detection algorithm is proposed in this article, which is the scale invariant detector with scale adaptability. The difference between the scale invariant detector and Harris detector is that the former has the scale adaptation to the second order moment matrix, achieving detecting Harris corners in the 2D image and scale space simultaneously. This means rough structural information of the image can be obtained on a large scale, resulting in a large number of corner points whereas detail feature information of the image can be got on a small scale, realizing precise positions of corners.

The disadvantage of this detector is it is not invariant to large scale change.

D. Deformable Part Models

Our system often represents objects using mixtures of deformable part models. These models are trained using a discriminative method that only requires bounding boxes for the objects in an image. Using these models we implemented a detection system that is both highly efficient and accurate, processing an image in about 2 seconds and achieving recognition rates that are significantly better than previous systems.

DPMs are discriminative sliding-window classifiers, which predicts a score related to presence or absence of the object for each and every possible positions and scales of image. The scores are then computed by taking the totality of the inner products between the model's filters and the matching sub-windows of the image, inserting each filter at an "optimal" image location. The strength of DPMs exist in in their ability to characterize an exponential number of patterns by leasing the part filters float around their reference location, and in judging the optimal part conformation at every possible root position professionally using a generalized distance transform [9].

Many new works build upon the original DPM attempt to advance either its detection performance or its

computational complexity. As an example of a work belonging to the first category, [11] enhances the HOG features usually used with LBP ones, in order to be sensitive to not only edges but also patterns, resulting in 10% gain in average relative accuracy. In order to simplify the original star-based part model, [12] represents objects by a mixture of hierarchical tree models organized on a 2D grid, where the nodes represent object parts, and solves the non-convex optimization problem using the Concave Convex Computational Procedure (CCCP) [10]. Arguing that the most important component of DPMs is the mixture one, [13] proposes to improve their initialization by switching from aspect-ratio to appearance clustering, and reports that a mixture of monolithic models clustered by appearance can compete with DPMs.

Standard DPMs comprise a root and several parts, all detected independently by a linear filter, and organized in a hierarchical structure.

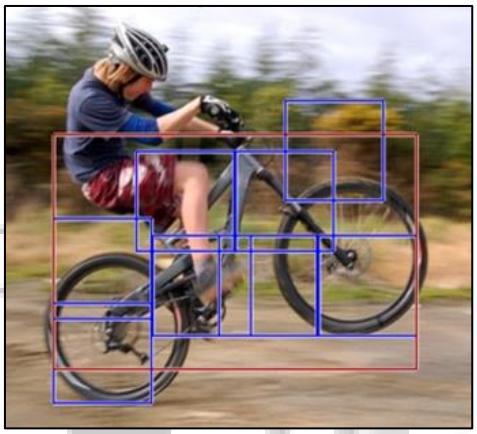

Fig. 1: Deformable Part Model

E. Global Positioning System

GPS (Global Positioning System) is a navigation system based on a group of 24 satellites developed by U.S. Department of defence. Every satellite sends data to the receiver in the form of signals, having some information about satellite and orbital information. GPS (Global Positioning System) receivers are widely used as the radars for navigation and control of (UAVs). A GPS receiver can provide position, velocity, and time information and its results are highly precise with limited errors, not dependent on time. GPS receivers could be in danger to external environments, they are widely used due to their simple and appropriate usage and low cost with high accuracy. GPS keeps being more efficient. Satellite navigations such as GALILEO and GLONASS are under development. Thus accuracy, integrity, availability and continuity of satellite navigations systems will be more enhanced or upgraded [14].

III. THE SATELLITES

Practically all satellite navigation now customs the Global Positioning System (GPS). The system uses a constellation of satellites diffusing radio frequencies, 1227.60 mHz and 1575.42 mHz. The initial model of the system was provided for eighteen satellites, with three satellites in each of six orbits. Presently, there are four satellites in each orbit. In the basic plan, the six orbits are evenly spaced every 600 around the Earth, in planes that are inclined at 550 from the Equator. Orbits are circular, at a rather high altitude of 20,200 kilometers above the surface of the Earth.

A. Receivers

Current GPS receivers are electronic prodigies. They are hand-held, usually run on small batteries, weigh as little as nine ounces, and can cost less than $150. We can turn on a receiver at any point on or above the surface of the Earth and, within a few minutes, see a display showing our latitude, longitude, and altitude. The indicated surface position is usually accurate to within 100 meters, and the altitude is usually in error by no more than 160 meters.

How does a small radio receiver listen to a group of satellites, and then compute our position, with great accuracy? Now this is one of the most frequently asked question related to GPS receiver. We start by noting exactly what sort of information is received from the satellites. Each satellite sends signals, on both of its frequencies, giving (1) its position and (2) the exact times at which the signals were transmitted. The receiver receives time signals from the satellites, and it uses them to maintain its own clock. When a signal comes in from a satellite, the receiver records the difference, At, in the time at which the signal was transmitted and the time at which it was received. If the Earth had no atmosphere, the receiver could use the speed, c, of radio waves in a vacuum to compute our distance d = c At from the known position of the satellite. This information would suffice to show that we are located at some point on a huge sphere of radius d, centered at the point from which the satellite transmitted. However, the layer of gasses surrounding the Earth slows down radio waves and, therefore, distorts the measurement of distance. Receivers can partially correct for this by allowing for the effect of mean atmospheric density and thickness. Information from several satellites is combined to give the coordinates-latitude, longitude, and altitude-of our position in any selected reference system.

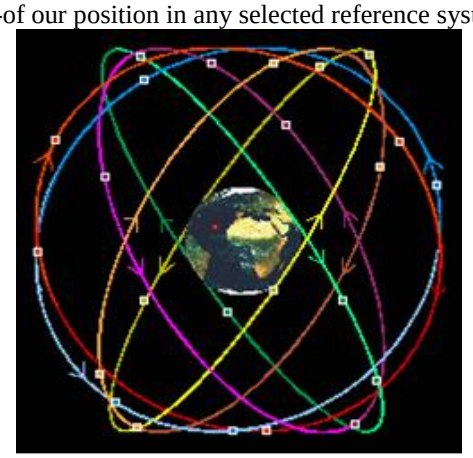

Fig. 2: The System of Satellites

B. Convolutional Neural Network

In recent years deep learning has become a subject undergoing intense study in in recognition and object classification domain. Convolution neural network (CNN) [7] is a classic network structure of deep learning. It mainly consists of two parts: the convolution layer and the convergence layer.

Convolution is a mathematical operation that's used in single processing to filter signals, find patterns in signals etc. In a convolutional layer, all neurons apply convolution operation to the inputs; hence they are called convolutional neurons. The most important parameter in a convolutional neuron is the filter size.

Convergence layer is the characteristic of figure analysis. It adopts drop sampling operation and filters out the characteristics of the local figure. This layer includes pooling layer, reLU layer and fully connected layer.

Convolutional neural network (CNN) [8] puts the feature extraction process integration into the multilayer perceptron through restructuring and the same surface weight sharing. At any given level, each neuron input is from the previous level and combined with this level of weight. In other words, the current layer is a result of a front layer convolution with a pair of convolution kernels. CNN [8] can use as many layers as required, and each layer can have any number of features desired. A simple CNN is shown in figure 1.

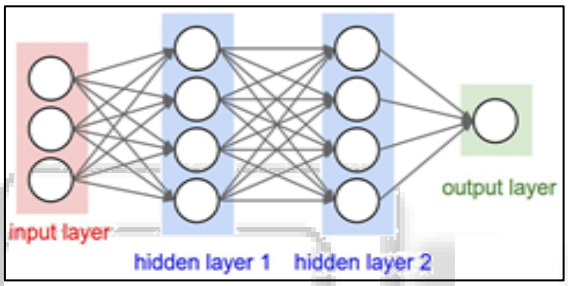

Fig. 3: Convolutional Neural Network (CNN)

IV. CONCLUSION

In this paper various kinds of algorithms have been used for Image recognition. Any classification technique uses the following procedure: image acquisition, segmentation, training the required model for classification and finally obtaining the desired output. They include Convolution neural networks for high performance and efficiency, Harris Corner detection for visual navigation variable screening and Support Vector Machine (SVM) are the other techniques used for image recognition. The above listed are some of the well-known techniques .however there are many more methods which can be implemented based on the requirements.

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