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(Research Article)

Autonomous UAV forced landing site prediction using machine learning

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Abstract

Unmanned aerial vehicles, or UAVs, are being used in an increasing range of applications, including surveillance, search and rescue, and environmental tracking. However, unanticipated engine issues, engine failures, and breakdown of the flying surface may necessitate forced landings, putting the UAV and its surroundings in danger. If there are any obstacles in the way of the UAV's ability to land safely, such as buildings or trees, it must be able to return to its emergency landing place. Thus, in these emergency scenarios, automated technology that can identify safe landing places rapidly. This paper presents an innovative approach that adds feature extraction, including HOG, HSV, LBP, and SFIT. GMM, SVM and kernels that use machine learning techniques to instinctively select the proper UAV-forced landing places. Through the use of machine learning and feature extraction techniques, we raised our accuracy by 40% over the baseline. The proposed system integrates data from several sources, including topography maps, satellite images, and board sensors. The machine learning algorithms predict possible landing sites. Annotated datasets with factors including topographic height, land cover type, slope, and proximity to obstacles are used to train these algorithms. especially artificial neural networks, or ANNs.

Keywords: Machine Learning; Detecting Safe Zone; Automated Landing; Gaussian Mixture Model; Support Vector Model.

1. Introduction

Unmanned Aerial Vehicles (UAVs), commonly known as drones, are aircraft that fly without a human pilot aboard. They are essentially pre-programmed automobiles. The UAV has a variety of uses, including military use, environmental disaster relief. They come in a variety of sizes and designs, and are outfitted with sensors and GPS. UAVs have grown in popularity across sectors for jobs such as aerial photography, surveillance, agriculture, and search and rescue, since they are less expensive, more versatile, and often safer than manned aircraft.

Although UAVs seldom make emergency landings, sometimes a hardware or software problem forces the UAV to try a forced landing. However, reliable UAV-forced landing technologies do not yet exist. The uneven visual quality makes it hard to identify a safe landing. However, because of the possible risks to the property and the people, UAVs are now prohibited from entering civilian airspace.

In this paper, we present 1) machine learning to the issue of automatically choosing a safe landing location. 2) We use the mixing feature to enhance the performance overall.

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2. Literature survey

The author has previously expounded upon the characteristics and forced landing side detection of the UAV. Classifying the image data can be achieved by applying an image feature to the images captured by the UAV. The evaluation of automated road detection algorithms utilizing massive aerial image datasets is detailed in [2]. This research assesses the efficacy and constraints of different approaches in quantifying roads from aerial imagery, therefore offering valuable insights into their practical implementations, including urban planning and navigation. The author of [3] described how the system enables unmanned aerial vehicles (UAVs) to identify suitable emergency landing sites autonomously. The inclusion of machine vision in the system enables automated decision-making capabilities during emergency situations, thereby enhancing UAV safety. By optimizing response times, the risks associated with manual intervention are effectively mitigated. The incorporation of machine vision technology provides enhanced precision and dependability in the identification of appropriate landing locations across a wide range of environmental circumstances. This innovation signifies a substantial progression in unmanned aerial vehicle (UAV) operations, specifically in guaranteeing secure emergency protocols.

The authors of [4] present a methodology for the automated identification of roads within high-resolution aerial imagery. A model is trained using machine learning methodologies, specifically convolutional neural networks (CNNs), in order to identify road patterns in aerial images. The methodology seeks to optimize the efficacy of road detection operations, a critical component in a multitude of applications including urban planning and navigation systems. By utilizing CNNs, the system acquires the ability to accurately detect roads, even in the presence of varied illumination conditions and complex backgrounds. This study makes a valuable contribution to the field of automated image analysis by enabling the more efficient application of aerial imagery in the context of road-related activities. The author introduces the foundational notion of support vector machines (SVMs), an influential algorithm for supervised learning, in [5]. SVMs seek to identify the hyperplane that maximizes the margin between classes in order to effectively partition the dataset. While this method is especially effective for binary classification tasks, it is also amenable to multiclass problems. The mathematical foundations of SVMs are explicated by the authors, who highlight the significance of the kernel and margin functions in attaining resilient classification. SVMs are extensively employed across diverse domains owing to their robustness against overfitting and capability to process high-dimensional data. The contributions of Cortes and Vatnik to the comprehension and implementation of SVMs are significant solidifying their place as seminal figures in the domain of machine learning.

2.1. Aerial image classification system

First, the system finds the pictures that the camera took. Now, the edges of each pixel separate the pictures into fragile square layers. The binary picture that is made has "safe" regions colored white and "unsafe" regions in black. After that, these parts are labelled as "safe" or "unsafe" based on the features they have. Finally, because a safe landing site needs to be bigger than a certain size, the blob cleaning process will get rid of any "safe" blobs that are smaller than a starting point of *minimal-width× minimal-height*. For analyzing the *minimal-width* and *minimal-height* values, we have to consider the length and width of the UAV for analyzing the area correct for the landing site.

2.2. Feature extraction

Three things are looked at in the pictures taken by the UAV: color, image processing, and texture. These are looked at by the following features:

Masked-HSV feature, in computer vision and image processing, a method. It entails converting an RGB colour space to an HSV (Hue, Saturation, Value) colour system and then using a mask to exclude certain colour ranges from the picture. This is often used to jobs like colour-based analysis, segmentation, and object recognition.

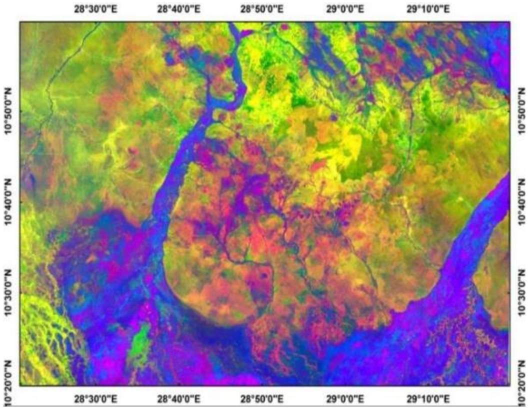

Figure 1 Example of the masked-HSV feature

Histogram of Oriented Gradients (HOG) Feature, Object detection and identification are both accomplished via the usage of this method in computer vision. Calculating the distribution of gradient orientations over the various portions of a picture is how it does its operation. The intensity and direction of the image's edges are represented by these gradients. Division of the picture into smaller parts is a necessary step in the process. The key shape and texture information is captured by this feature descriptor, which does so by first computing the gradient orientations inside each tiny area and then generating a histogram of these orientations. For tasks such as pedestrian identification, face recognition, and object tracking, machine learning algorithms, such as support vector machines (SVMs), often make use of this descriptor feature.

Local Binary Pattern (LBP) feature is a texture descriptor that is used in the field of computer vision and image analysis. It does this by comparing the intensity of a center pixel to that of its nearby pixels, which allows it to describe the local patterns of texture. A binary pattern is produced by the LBP operator, which assigns a label to each pixel in an image by thresholding the intensity value of the pixel in question against the intensity values of the pixels that surround it. After that, the binary patterns are transformed into decimal values, which results in the creation of a histogram of patterns for a specific local area across the picture. LBP is beneficial for applications such as texture classification, face recognition, and texture segmentation since the histogram that is produced as a result depicts the texture properties of the picture.

Scale-Invariant Feature Transform (SIFT)feature, is an approach to computer vision that is commonly used for the purpose of extracting distinguishing characteristics from pictures. Performs its function by locating essential spots in a picture that are unaffected by changes in size, rotation, or lighting. The first step in the process is for the algorithm to locate important places, also known as interest sites, by locating areas of the picture where the gradient magnitude is elevated. After that, these essential spots are developed further by removing those that have a poor contrast or are situated on the margins. The SIFT algorithm computes a value called a descriptor at each key point. This descriptor is a vector representation of the local picture patch that surrounds the key point. The construction of descriptors is based on brightness histograms in the picture patch, which makes them resistant to changes in size and orientation. There is also a technique for scale-space extrema detection that is included into SIFT. The system allow SIFT to identify critical locations at many scales.

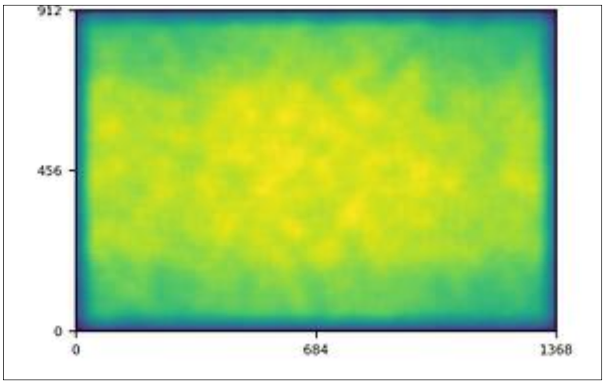

Figure 2 Example of the SIFT feature

2.3. Classification of data

The main role of machine learning in this is to classify the images. So, the perfect classifier is chosen.

Gaussian Mixture model: A sufficient number of categories are created for the data by the GMM. This is able to process data of any shape or form. Speaker identification and object detection are the primary applications of GMM. With a high degree of classification confidence, the image will be categorized by the GMM in our system. This is extremely beneficial for classification as the classifiers are trained using trail-based data sets. We compute the mean value of the output from the chosen subset of classified data in order to merge the features and the set of data.

Support Vector model: The model is a supervised algorithm. The data is thus divided into two distinct divisions. By calculating the optimal distance between the two data sets, classification is achieved. In our system, dual categorization is conducted by separating the two classes. Aside from this, other methods of enhancing efficacy in order to implement non-linear classifications, various kernels are implemented. SVM models exhibit a higher level of sophistication in comparison to alternative machine learning models. And for improved results, certain changes should be made for the parameters in require.

3. Methodology

The experimental configuration for the model is depicted in the block diagram presented in Figure 3. The images transmitted to the system by the UAV make up the system's input. The features created by the module are presently augmenting the images. This functionality enables the modules to analyze the images in order to extract the essential features required for the machine learning and its modules to categorize them into data groups and perform binary classification. The landing is executed by the landing confirm module in order with its analysis of the output. The assessment metrics calculate the accuracy and comprehensiveness of the landing execution executed by the system.

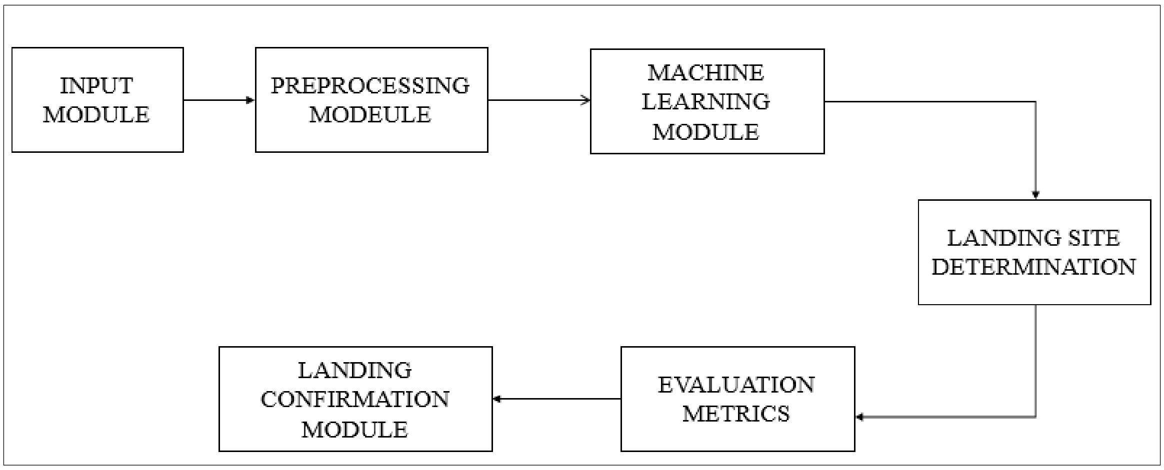

Figure 3 Block diagram

The model experimental setup is the block diagram shown in Figure 3, block diagram. The input of the system is the images fed by the UAV to the system. Now the images are enhanced by the features used by the module. This feature helps the modules to examine the images to convert them into the necessary features that helps the machine learning and its module for classifying them into data groups and convert the data to perform binary classification. The landing confirmation module analyze the output and perform the landing based on the output. The evaluation metrics compute the correctness and completeness of the landing performance made by the system.

3.1. Experimental Setup

We made use of the data sets that were provided by [1] and [2]. It is possible that these pictures depict either urban, rural, or woodland settings. In the beginning, there ought to be between 400 and 500 photos for certain. In terms of zoom, the three resolutions that have been stated are about 17, 18, and 20. There are three, one, and 0.7 pixels per meter in terms of resolution respectively. The landing location must to be able to handle the precise size of the unmanned aerial vehicle (UAV), taking into consideration the size of the UAV. Consequently, the minimum landing size is a minimum width of forty pixels and a minimum height of one hundred pixels, which corresponds to a landing site that is twenty meters by fifty meters for zoom level 18, or sixty meters by two hundred and twenty meters for zoom level 17.

It is necessary to separate 500 photographs into five categories, each of which is of identical size, for each zoom level. There are now four classes that are being used for the training, and the remaining one class is being utilized for the testing stage. During the training step, photos from all zoom levels are used in order to accomplish the goal of building classifiers that are sensitive to degrees of magnification. Imagery from all possible zoom ranges is employed throughout the testing phase. For the purpose of evaluating the classifier's performance at a number of different resolutions, we separately execute a number of different zoom levels. Binary values, which are denoted by the letters '0' and '1', are what we acquire as the outcomes. The number '0' denotes the "unsafe" region for landing, whereas the number '1' denotes the "safe" portion of the landing spot as shown in figure 4. In order to determine whether or not the findings are accurate and comprehensive, we assess them.

Figure 4 Example for converting the safe zone in white and unsafe zone in black.

3.2. Performance Analysis

After computing the safe area, the correctness and completeness is analysed for knowing the actual correctness of the results.

$$\text{Comp} = \frac{Scrt}{SA} = \frac{Scrt}{Scrt + Sfu}$$

We calculate the system's completeness to assess its accuracy in finding the "safe" area. Cp denotes completeness, Scrt represents the accurately identified safe area, and SA represents the safe area.

$$\text{Cor} = \frac{Sdu}{Sua} = \frac{Scds}{Sdu + Sfs}$$

The accuracy of the system in identifying the "unsafe" region is determined by computing its correctness. In this context, the symbols Cr denotes accuracy, Sdu signifies accurate detection of a hazardous area, and Sua signifies the hazardous area itself.

The assessment of the effectiveness of secure landing site detection is determined by the combined influence of veracity and completeness in the detection process. The criterion for excellence is the

$$\text{Q} = \frac{Scrt}{Scrt + Sfs + Sfu}$$

4. Result and Discussion

The aerial images in this section provide the contextual information regarding a forced landing. A total of 5,760 outcomes were assessed, taking into consideration the twelve classifier configurations, three image processing and texture features (HSV, HOG, LBP, and SIFT), and three magnification resolutions:

- The components are classified equally by GMM.
- The SVM algorithm employs a linear kernel.
- The SVM kernel is RBF-based.
- SVM implements a kernel of polynomials in the sequence 1, 3, 5, 7, 9, 20.

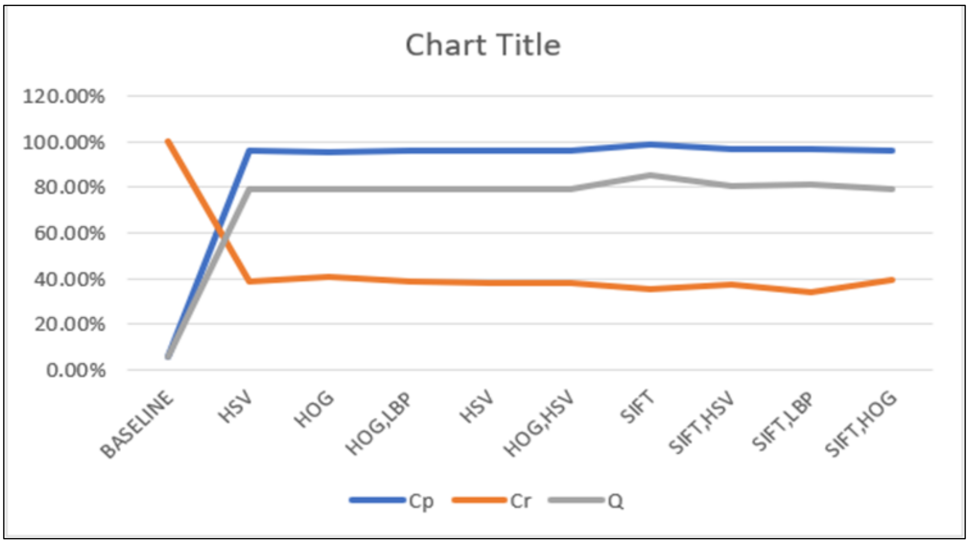

Figure 5 Comparison between HSV, HOG, LBP and SIFT

Upon the conclusion of the outcome, it automatically calculates the accuracy, comprehensiveness, and excellence of the acquired results. The polynomial Support Vector Machine (SVM) has superior performance and possesses a wider range of parameters. SVM and GMM systems have a greater number of polynomials compared to RBF or linear SVM due to the use of distinct components for classifications. Based on the data, it is evident that the GMM model does not have a significant impact on the system. Based on the graph shown above (Figure 5), it can be seen that the feature extraction technique known as Histogram of Oriented Gradients (HOG) offers a greater amount of information pertaining to both texture and shape. The SIFT method offers more precision compared to the HOG method. The performance of LBP was subpar as a result of its characteristics being high-dimensional. Compile the results.

Table 1 Evaluation results on quality, correctness and completeness score.

FEATURE	**C_P**	**C_r**	**Q**
BASELINE	5.60%	99.90%	5.60%
HSV	96.10%	38.80%	79.20%
HOG	95.70%	40.60%	79.20%
HOG, LBP	96.10%	38.60%	79.20%
HSV	96.20%	38.10%	79.20%
HOG, HSV	96.20%	38.10%	79.20%
SIFT	98.60%	35.33%	85.60%
SIFT, HSV	96.67%	37.33%	80.60%
SIFT, LBP	97.06%	34.05%	81.03%
SIFT, HOG	96.10%	39.65%	79.40%

Table 1 presents a comparison of the quality, accuracy, and comprehensiveness of the characteristics.

- The component exhibits a much superior level of quality.

- The selected settings provide a high level of accuracy. (Accuracy up to 100%).
- The level of completeness has risen by 8.5%, resulting in an enhanced ability to forecast the landing location.
- While the SVM polynomial algorithm yields the most optimal outcomes, both the SVM and RBF algorithms provide high-quality results when implemented with more advanced settings.
- This method performs more effectively when used with high-resolution images.

5. Conclusion

The technology being suggested is an autonomous UAV-based landing site prediction. The machine learning used in this context is quite advantageous for discerning the form, characteristics, and texture of the photographs. The Higher Order Cumulants (HOC), Histogram of Oriented Gradients (HOG), Local Binary Patterns (LBP), and Scale-Invariant Feature Transform (SIFT) techniques used in that context improve the quality and resolution of the picture. The findings demonstrate that the SVM system, using a polynomial kernel and a combination of features, is superior in its ability to classify aerial photos based on the detected images. The aerial picture dataset demonstrates a significant improvement of 40.38% in the overall quality score. The findings demonstrate a higher level of consistency in performance when the resolution is altered. The next work will include implementing the classification method described in the paper, which may be enhanced by including new techniques for feature extraction.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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