Vision-Based Site Selection for Emergency Landing of UAVs

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Abstract. In this paper, a new method is proposed for finding the suitable forced landing sites for UAVs. This approach does not have any limitations of the previous few researches done in this area. For finding the suitable landing sites, we first segment the aerial images based on classification using both color and texture features. Classification is performed based on k-nearest neighbor algorithm by incorporation of Gabor filters in HSV color space. Then, a geometric test is carried out for finding appropriately sized and shaped landing sites. Output images highlight the selected safe landing locations. Experimental results show the effectiveness of the proposed method.

Keywords: Aerial image segmentation, Feature extraction, Surface type classification, k-nearest neighbor (KNN), Unmanned Arial Vehicles (UAVs).

1 Introduction

Nowadays, applications of machine vision can be found in every aspect of life [10-20]. Using the unmanned systems in the war is not new, but what will be new in the future is how such systems are used in the civilian space. Unmanned Aerial Vehicles (UAVs) are going to be used in the civil and commercial applications extensively, and are receiving noticeable attention by industry and research community. For performing majority of civilian tasks, Unmanned Aerial Vehicles are restricted to flying only in distinct spaces, which are commonly not above populated areas [1]. Current UAV technologies have not an acceptable level of safety, especially when an engine failure happens and so an emergency or forced landing in the civil areas is required.

Piloted aircraft in the same situation have a pilot on board who is able to do a complex decision making process for choosing a suitable landing site. If UAVs fly usually in civilian airspace, then an important unresolved problem is finding a safe landing location for a forced landing which must be dealt with [2].

The main purpose of this paper is designing a system for choosing autonomously the “safe” landing sites for a UAV by using machine vision and image processing

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techniques. A “safe” landing site is a place which has three properties including (i) Does not cause any injury to a person; (ii) Does not damage the environment; (iii) Minimize damage to the UAV [2]. These three properties are listed in order of priority. It means minimizing damage to the UAV itself has the lowest priority. For example a UAV forced landing system should choose a lake instead of a busy road for landing. The criteria of landing site selection for UAVs are based on the criteria that a human pilot considers in a forced landing scenario. These include:

- Size
- Shape
- Slope
- Surface
- Surroundings
- S(c)ivilisation

These factors are known as the six S’ and many of them are still important for selecting a landing site in a UAV forced landing situation. To date, there are very few publications on landing site selection for UAVs forced landing based on image processing and machine vision techniques [3, 4]. One of the best researches has tackled the specific problem of a UAV forced landing, has been done by Fitzgerald [2]. In [2] based on the “size”, “shape”, “surface” and “slope” criteria, for finding the safe landing sites these steps were proposed: (1) Segmenting the image, (2) Finding sites with suitable **size** and **shape**, (3) Classifying the **surface** type, (4) Estimating the slope.

In spite of testing different methods, Fitzgerald didn’t get acceptable segmentation results. He proposed a simple method for extracting regions from aerial images which have similar texture and also are free of obstacles. But he used some assumptions in his method which are not valid under every condition. For instance, he used the edge detection measure in his algorithm for objects identification in the image based on the assumption that distinct edges situate between boundaries of objects. This assumption is valid only under the condition that the contrast between objects or regions in the image is enough and that the spatial resolution is high sufficient. Another drawback is that he used the intensity measure to eliminate some of the manmade objects in the image which usually are the white building or roof tops, as these areas are most likely to reflect the sun. But on more cloudy days or at soon or late times of the day, it is possible that some objects do not be detected. In this paper, by considering the “size”, “shape” and “surface” criteria for landing site selection.

The remainder of the paper is organized as follows. Section 2 describes the segmentation step including the feature extraction and the k-nearest neighbor (KNN) classification. Then, section 3 explains the method of finding suitably sized and shaped landing areas. After that, section 4 represents the final results of landing site selection. Finally, conclusions are given in section 5.

2 Image Segmentation Based on Surface Type Classification

Image segmentation is one of the most difficult problems in image processing and computer vision which has a lot of useful applications. A segmentation algorithm is performed to semantically divide the image into some regions, or objects, to be used by the next processing steps for interpretation. The segmentation of different land cover regions in aerial images is known as a complicated problem. The natural scene typically has many regions including grass, water, tree, building, etc. It is really a challenging task to separate these regions correctly [5]. Some of the segmentation methods in the literature work well, but they have different parameters which need manual accurate tuning for every image to reach the optimal segmentation performance and this is not suitable for the purpose of automatic (unsupervised) segmentation. In this paper, we use a method for partitioning aerial images into different regions based on pixel level classification.

2.1 Feature Extraction

The features that we tested for aerial image segmentation include (1) Color features and (2) Texture features. We consider the features of RGB, HSV and LAB color spaces for the segmentation task. The analysis of texture is an important step for aerial image segmentation. However, many existing texture segmentation methods are orientation dependent and therefore cannot correctly classify textures after rotation [5]. In this research, we use the orientation independent textures. So the algorithms are independent from the direction that UAV approaches to the area.

Gray Level Co-occurrence Matrix

Gray Level Co-occurrence Matrix (GLCM) features are based on statistical properties of the GLCM. The GLCM is a matrix of relative frequencies which describe how often two gray level pixels appear in a specific distance and at a certain orientation in an image area.

The features of normalized GLCM at each pixel are computed in a $w \times w$ window with that pixel in the center. For deriving rotation invariant features, 4 orientations (0˚, 45˚, 90˚, and 135˚) are considered. For the distance measure, one of the values of 1, 2 and 3 and for number of quantization levels, one of the values of 8 and 16 are used after comparison. Selecting the suitable size of window is also important. The features we consider to extract from GLCM are: “contrast, homogeneity and energy” or just “contrast and homogeneity”. Also we test different combination of Haar like features. Assume we extract contrast and homogeneity features in 4 orientations and 1 given distance in every window. As a result, the feature vector length will be 8.

Wavelet Transform

Manthalkar et al. in [6] introduced a method for extracting rotation and scale invariant texture features different type of wavelet filters. Cao et al in [5] used this method for extracting features of aerial images and got the good results. In this method, a multi-level wavelet decomposition of a small area of the image is computed. Then, by calculating the energy of each decomposed image, the rotation invariant features for a pixel are derived. If the decomposed image is $x(m, n)$, where $1 \le m \le M$ and $1 \le n \le N$, and i denotes the decomposition level, the energy features are:

$$en_i = \frac{1}{MN} \sum_{m=1}^{M} \left(\sum_{n=1}^{N} |x(m,n)| \right) \tag{1}$$

$$en_{istd} = \frac{1}{MN} \sqrt{\sum_{m=1}^{M} \left(\sum_{n=1}^{N} (|x(m,n)| - en_i)^2 \right)} \tag{2}$$

To get rotation invariant features, the energy features in LH and HL channels in each level of decomposition are grouped. The feature vector is a vector of mean and standard deviation of all HL and LH channel in the proposed decomposition. This feature vector is given as Eq. 3 and 4.

$$EN_i = 0.5 \times [en_{iHL} + en_{iLH}] \tag{3}$$

$$EN_{istd} = 0.5 \times [en_{istdHL} + en_{istdLH}] \tag{4}$$

In this paper, 3-level wavelet decomposition is used and in every decomposition level, both mean and standard deviation features is derived. So the feature vector length will be 6 ([EN_1, EN_{1std}, EN_2, EN_{2std}, EN_3, EN_{3std}]) and we use it to characterize each class. Note that all the features are normalized from 0 to 255. To this end, every elements of feature vector for all pixels is mapped to 0-255 range individually and independently of other elements. Therefore, maximum and minimum of each element should be calculated through the image and then using ($\frac{value\ of\ every\ element - \min\ (value)}{\max(value) - \min\ (value)} \times 255$) formula and considering the fix part of answer, normalized value of desired element will be derived.

To choose the wavelet filter in [6], one Daubechies wavelet (Db4) and three Biorthogonal wavelet (Bior5.5, Bior4.4, and Bior3.3) have been tested and compared. The best result has been gain by Db4 and Bior4.4. In this paper different type of Orthogonal and Biorthogonal wavelet filters including Daubechies, Coiflets, Symlets, Discrete Meyer, Biorthogonal and Reverse Biorthogonal for choosing the best one are used. For defining the window size, different amounts are tested and the results are compared.

Local Binary Patterns

One of simple methods to prepare high accurate texture features of an image is Local Binary pattern (LBP). We compute the normalized histogram of LBP features at each pixel in a $w \times w$ window with that pixel in the center. The uniform rotation-invariant LBP ($LBP_{P,R}^{riu_2}$) is computed by selecting (P, R) parameters, once as (8, 1) and at the second time as (16, 2) which result the feature vector length of 10 and 18, respectively. Selecting the suitable size for the window is also important. We also test Local Binary Pattern (normalized) Histogram Fourier Features. In this case, considering (8, 1) and (16, 2) as (P, R) parameters, respectively result the feature vector length of 38 and 138.

Gabor Filters

Gabor features can be used to infer texture of an image region. There are a large number of publications which show that Gabor features can successfully discriminate between textures [2]. Chang et al. [7] claimed that Gabor filters are the best textural features out of the methods considered. A Gabor filter is a linear and local filter that is defined by a certain orientation and spatial frequency. It acts as a band-pass filter with optimal joint localization properties in both the spatial domain and the frequency domain [8]. Gabor filters are popular because the human vision system uses similar banks of directional band-pass filters with similar frequency and orientation representations [9].

We convolve the gray-scale image with two-dimensional 3×3 Gabor filters with various orientations (rotations) and frequencies (scales). Considering different orientations cause independency of image rotation. The output is a set of Gabor filtered images (one for each filter) that retain spatial information and can therefore be used for segmentation purposes.

2.2 Classification

There are different regions including water, grass, tree, road and building in aerial images; but in different places, the color of waters is different; also the shape of trees and their color are different and are affected by season changing; also buildings have different shapes, some of them have flat roofs and others sloped ones. Such issues affect surface type classification and make the problem more complicated.

There are different methods for image classification with a number of advantages and disadvantages. However, good results are usually obtained by careful selection of features and appropriate training practices [2]. In all of the classification methods, the features of test samples are extracted and compared with features of training data set. Then one of the output classes is assigned to each of the test samples. In pattern recognition, the kNN algorithm is a method for classifying objects based on closest training examples in the feature space. In this method, an object is assigned to the most common class amongst its *k* nearest neighbors. The neighbors are taken from a set of objects for which the correct classification is known. This can be thought of as the training set for the algorithm.

The classification process in kNN method like other classifiers has two steps of training phase and classification phase. The training phase of the algorithm consists only of storing the feature vectors and class labels of the training samples. In the classification phase, *k* is a user-defined constant, and an unlabeled vector is classified by assigning the label which is most frequent among the *k* training samples nearest to that query point.

Choice of the classification classes is an important component of classifier designing. The classes must include the different surface types that may be encountered by the classifier. The classifier would have to be able to distinguish between these classes correctly, so that the UAV is able to land on the appropriate target. These classes are (1) Grass, (2) Tree, (3) Water, (4) Road, and (5) Building.

Appropriate training data are also important to the operation of any classifier. We trained our kNN classifier on 150 sample images for each of the classes of grass, tree, water, road and building. For assessing the performance of the kNN classifier (trained on 150 sample images), 280 test images were manually selected and categorized. These images were then used as inputs to the kNN classifier. The best kNN classification results are obtained by considering one of the values of 1, 2, 3 or 4 for parameter k and L1 norm (Sum of absolute differences) or L2 norm (Euclidean distance, Sum of square differences) as the distance metric (the distance from the test point to each of its k nearest neighbors). We consider parameter k equal to 3 and use L2 norm as distance metric in our tests.

For any classification problem, a suitable set of features must be chosen. Good features are ones that allow discrimination between the output classification classes [2]. The best results of classification are obtained by combination of HSV color feature and Gabor texture feature. So for extracting the features of test samples or the features of training data set, we consider the given color image in HSV color space and separate it into three H, S, and V channels. Then we filter each channel of the image with Gabor filters in different orientations and frequencies. The mean of filtered images is calculated in every channel. The result is 3 images for 3 channels, that by calculating the average of each of them, we obtain 3 values finally. These 3 values will be used as feature vectors related to the considered image. This classifier performed extremely well on the test sample set, achieving a classification accuracy of 97%.

2.3 Image Segmentation Based on Classification

Our proposed method for image segmentation consists of identifying the objects present in an aerial image given a set of known patterns. In aerial images, the image contains several regions of different patterns and we label each pixel with one of the given classes based on specified features. Evidently, the labeling process subsumes image segmentation but besides segmenting the image to different regions, it assigns each region to one of the objects patterns.

We perform a per-pixel classification task and define the class for each pixel. For this purpose, we consider a window around each pixel and classify the area inside it using k-nearest neighbors algorithm (kNN). Then we assign the label of classification result to the central pixel of window. After computing all pixels in the image we obtain a segmented image which surface type of each segment is also defined.

3 Finding Sites with Suitable Size and Shape

In the previous step, aerial images have been segmented into a number of homogenous areas and simultaneously the surface type of each area has been defined by classification. In the final stage, a geometric test for finding appropriately sized and shaped landing sites should be performed. All areas that are too small or the incorrect geometric shape would be rejected, leaving only areas large enough for a UAV landing.

The algorithm in this phase involves the use of a mask, which is circular in shape and also is scalable. We have chosen circular shape for some reasons including possibility of approaching to the candidate landing site from different directions, wings of UAV and minimizing the processing time.

Size of the mask is determined by the pixel resolution calculation and is dependent on the category of UAV (small, medium or large) and the current height above ground. For example, a small UAV may have a landing site requirement of 15×60 meters, as opposed to a larger UAV requiring a landing site of 30×200 meters. Fig. 1 shows some example of these masks with different dimensions.

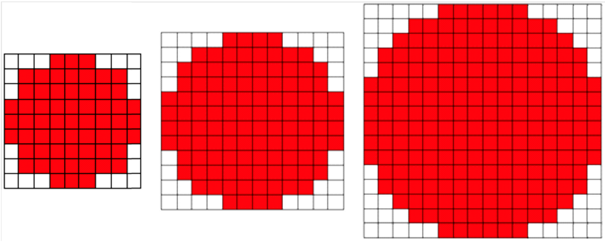


Fig. 1. Mask definitions of Landing Site matrix

For geometric test, we choose an arbitrary landing mask size (12×12 pixels). Note that the value of landing mask dimension depends on the height from which the image is taken. So when the height above ground decreases, bigger value for the mask dimension should be considered. However, as the differences between the heights of our test images are not very large, we use the same value for all of them.

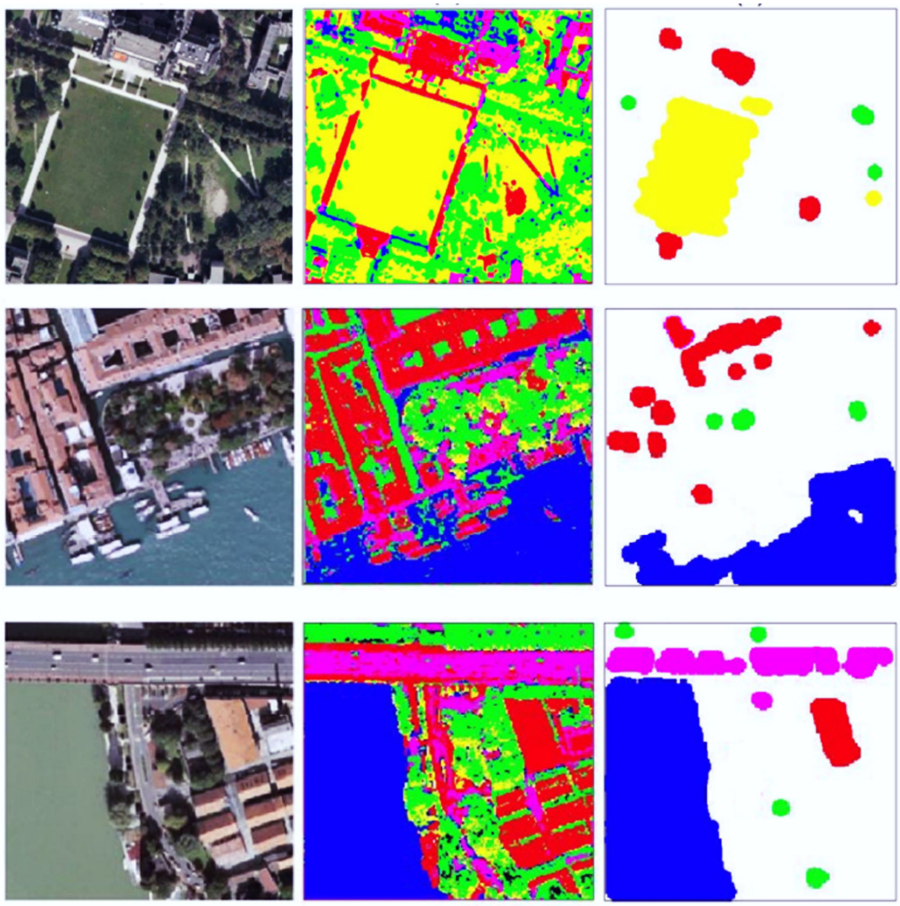
The mask moves over the output image from the previous steps and is compared with the proper segments of the image. If the mask can be fitted in an area, that area would be a candidate for landing of UAV.

4 Experimental Results

Fig. 2 shows the final results of landing site selection. In this figure, firstly aerial images are segmented; then by a geometric test, areas with suitable size and shape are located. White color areas in the final results (output of the geometric test) are the areas which are not suitable for landing because of non-suitable size and shape. Other areas are candidate landing sites and are shown with a special color based on their surface type (water with blue color, grass with yellow color, tree with green color, building with red color and road with pink color).

Based on the assumption that landing on the natural objects has a lower chance of injury to people, natural areas are more suitable for landing than man-made areas. So the priority for landing is in the order of:

(1) Grass
(2) Water
(3) Tree
(4) Building
(5) Road



(a) (b) (c)

Fig. 2. Experimental results of landing site selection: (a) Original image, (b) Segmentation result, (c) Final result

5 Conclusion

In this paper, we proposed a process for landing site selection for UAVs forced landing which has not any limited assumption of the previous work. We segmented and determined the proper areas for forced landing of UAVs. A method based on k-nearest neighbor (kNN) classification was used for segmentation considering both color and texture features of the areas. We evaluated the classification performance over a variety of 'color' and 'texture' features and combination of them and found the most appropriate ones. Experimental results indicated that the best performance is obtained by using Gabor filters in HSV color space. The segmentation method produces consistent results and also it is easy to implement and able to segment aerial images automatically without any supervision i.e. without a priori knowledge of image content. After segmenting the image into a number of regions, in the final step, the algorithm locates areas of a given size and shape suitable for a UAV forced landing.

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