Multi-Information based Safe Area Step Selection Algorithm for UAV'S Emergency Forced Landing

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***Abstract*—In order to solve the problem of forced landing in emergency for Unmanned Aerial Vehicles (UAVs), a multi-information based algorithm for selecting forced landing area by step is proposed. In order to extract the slowly varying edges and weak edges in an aerial image, this algorithm adopted improved edge detection method to detect landing area without obstacles. To select the detected safe areas which are suitable for landing in terms of size and shape, four masks with adequate coverage were designed. The elevation data of the areas were acquired to analyze its terrain. By extracting features of color and texture based on Gray Level Co-Occurrence Matrix (GLCM), fast classification and recognition of landing areas was carried out based on Support Vector Machine (SVM) classifier. Simulation results show that the algorithm, comparing with Bayesian classifier, presents a more fast and accurate classification and selection of the landing areas, fulfilling the demand of forced landing for UAVs in emergency.**

***Index Terms*—forced landing, improved edge detection, gray level co-occurrence matrix, support vector machine**

I. INTRODUCTION

It's apparent that Unmanned Aerial Vehicle (UAV) will become increasingly prevalent in both military and civilian scenarios in the future. One goal of a UAV is to fully integrate into the civilian airspace, especially to fly over populated areas [1-2]. The number of UAV has been on the rise since the 21th century came, however some severe hidden danger lies behind the promising development of UAVs. For example, an American MQ-9 reaper UAV lost control when performed mission in the north mountainous area of Afghanistan. American military had nothing to do but send a combat aircraft to shoot it down in case of it flying into the territorial airspace of Tajikistan or China. As can been seen, UAVs may inevitably confront emergencies during the flight, such as engine failure, interruption of data link from the ground and other unexpected accidents, so forced landing measures are urgent to be adopted. Given that the approaches for forced landing like parachute and other flight termination systems can cause injury and damage to human [3], gliding approach which minimizes the damage was adopted. In addition, UAV should be able to autonomously find a safe area suitable to land. GPS signal so subject to be interrupted and controlled by other nations that it can't provide a good solution. But vision navigation has strong autonomy and anti-interference performance, is very suitable to autonomous landing for UAV [1-3].

Fewer study about forced landing in emergency situations for UAVs was presented in domestic. Although some researches were investigated abroad like references [3-4], they used artificial Neural Network to solve classification problems. Since artificial Neural Network requires large amounts of training data and needs much time [5], it can't satisfy the fast demand of forced landing for a UAV in emergency. A more effective method than other conventional nonparametric classifiers in terms of classification accuracy and stability to parameter setting is the support vector machine (SVM), which is a supervised learning technique from the field of machine learning applicable in classification. SVM has been successfully used in a number of applications [6-7].

Texture features are recognized as special hints in images and are widely used in many applications for image classification currently. Lots of research results have shown that texture features have a great contribution to improve the quality of classification. The gray level co-occurrence matrix (GLCM) has been better used for image texture measurements since it was first proposed. It has been used very successfully as feature texture in classification [7].

Therefore, a new multi-information based algorithm for selecting forced landing area by step was presented, adding the control from ground data link for validity verification, in order to achieve UAVs' forced landing fast and accurately.

Manuscript received May 5, 2012. This work was supported by The Program for New Century Talents in University.

doi:10.4304/jsw.8.4.995-1002

II. ALGORITHM OVERVIEW

Before designing the algorithm, what kind of area should be selected should be known. The safe landing area is one that won't cause any injury to human, minimizes property damage and tries to save the UAV itself [3]. The area's type, size, shape, slope and surroundings should be considered.

This paper proposed a multi-information based algorithm for selecting forced landing area by step in emergency. It was consisted of four parts with different information of the input aerial images as follows: in order to select a safe landing area for UAV, firstly, it detected no-obstacle areas with the same texture by adopting a kind of improved edge detection method, which can detect the weak edges and slowly changing edges effectively; secondly, it selected appropriate areas in terms of size and shape from the detected areas without obstacles, in which four masks were devised to fast achieve the area selection; thirdly, whether the selected areas are flat to land by gliding approach, elevation data was acquired to analyze the terrain of the areas and gave the solution, what's more, this step recognized the water body from selected areas; finally, in case that forced landing affects traffic or causes injury to human beings, the surface features of the selected areas need to be classified and recognized, by extracting features of color moment according to HSV models and texture features according to Gray Level Co-Occurrence Matrix (GLCM), one-versus-one classification of Support Vector Machine (SVM) was used to achieve the aim with accurate and fast result. If the image doesn't match the condition in some step, the algorithm returned to next frame to select over. After the current frame of image was processed, the algorithm returned to the processing of next frame in case of finding no suitable area to land or landing is unsuccessful.

The overall algorithm flow chart is shown in Figure 1.

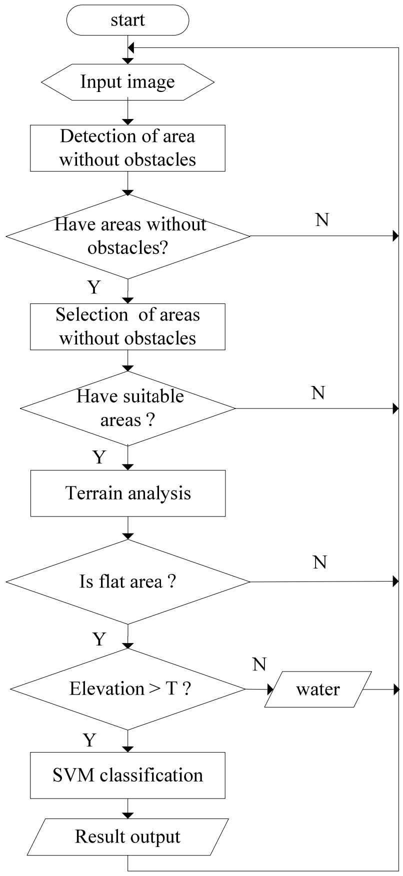


Figure 1. The overall algorithm flow chart

III. ALGORITHM PRINCIPLE

A. Detection of Landing Area wihout Obstacles

A safe landing area of a same type without obstacles should be detected before forced landing for a UAV. As the edges between different areas and different objects are obvious and are assumed to be obstacles, edge detection approach was adopted to divide areas into two kinds---areas with and without obstacles. Traditional Canny operator used Gauss function to smooth and filter images, which was widely used so far and turned out a better result. But when it smoothed the image, edges were filtered as high frequency part, causing some edges into slowly changing edges that could be lost in the non-maximum value suppression [8-9]. Meanwhile lots of edges with low intensity were filtered too, causing the lost of slight edges in the detection result [10]. In purpose of solving the aforementioned problem, a way similar to wavelet transformation was adopted to filter the image and calculate the gradient amplitude and direction to better protect useful high frequency information.

The algorithm firstly use two-dimensional Gaussian function $G(x, y)$ and its' first derivative $G(x, y)'$ respectively to convolute with original image $f(x, y)$ in the stage of smoothing and filtering the image [11]. In actual calculation, two-dimensional Gaussian function $G(x, y)$ should be discretized and represented as $G(i, j)$:

$$P(i, j) = G(i, j) * f(i, j) \tag{1}$$

$$Q(i, j) = G^{'}(i, j) * f(i, j) \tag{2}$$

Then calculate the gradient from the convolution result, and extract two single-dimensional gradient vectors in x and y direction respectively.

$$\begin{bmatrix} P_x(i, j) \\ P_y(i, j) \end{bmatrix} = \begin{bmatrix} \partial P / \partial x \\ \partial P / \partial y \end{bmatrix} \tag{3}$$

$$\begin{bmatrix} Q_x(i, j) \\ Q_y(i, j) \end{bmatrix} = \begin{bmatrix} \partial Q / \partial x \\ \partial Q / \partial y \end{bmatrix} \tag{4}$$

Then the gradient direction $\theta(i, j)$ and gradient amplitude $M(i, j)$ in point (i, j) were acquired:

$$\theta(i, j) = \arctan(\frac{P_x(i, j)}{P_y(i, j)}) \tag{5}$$

$$M(i, j) = [Q_y \cdot \sin(\theta(i, j)) + Q_x \cdot \cos(\theta(i, j))] \tag{6}$$

In the traditional Canny algorithm, it calculated gradient direction by x and y direction of gradient amplitude directly, causing a certain deviation between calculated direction angle and the real one [11]. The algorithm in this paper firstly calculates the gradient direction $\theta(i, j)$ in point (i, j) and then calculates the gradient amplitude $M(i, j)$, which can avoid the effect of aforementioned deviation on the detection result and improve the detection accuracy.

The algorithm then adopted rectangular structure element of 2×2 size and used eroding operation in morphology to expand the edge. Thus, objects in the image can be seen clearly on one hand, on the other hand safe boundary between landing area and the obstacle was set.

B. Selection of Landing Area without Obstacles

The size of landing area is dependent on the type and flight height of UAV. A small UAV requires landing area of 15×60 meters, while a large one requires 30×200 meters [3]. The flight height can be obtained from altimeter. To determine its size on the image, the pixel ground resolution should be known. Assuming that the height is 1300 meters, the image is 550×450 pixels and that camera viewing angle is 35.0×26.1degrees (horizontal ×vertical). The calculation of pixel ground resolution was shown in Figure 2. The selected landing area has the minimum size of 90 × 24.

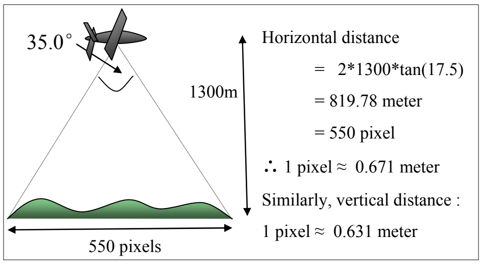


Figure 2. Pixel ground resolution calculation.

As landing area is rectangular, four kinds of masks with suitable size and shape were devised as shown in Figure 3. These masks are scalable and can rotate in a number of orientations. Additionally, as this scanning process is very processor intensive, the use of only four masks keeps the processing time to a minimum [3].

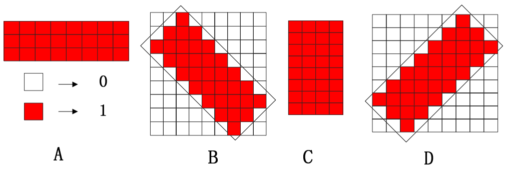


Figure 3. Four masks of area selection

These masks are each respectively moved over the binary image after edge detected. The image area which the masks pass over is scanned to determine whether or not the area contains edges. If no edges are found, then the area is marked as a candidate landing location.

To perform this scanning check, each mask is represented by a matrix with "1", representing that it is part of the mask and "0" indicating that it is not part of the mask. For example, mask B, contains both "0" and "1" elements – the elements that are labeled as "1" are members of the mask.

Each mask matrix is moved over the edged image, and at each location, mask elements containing a "1" are tested against the pixel below for an edge (a "1" in the binary image). If an edge is detected, then the mask is moved on, otherwise the additional pixel in the area are tested. If all pixels under the mask "1" elements are equal to "0", then the area is marked as a candidate landing area.

C. Terrain Analysis

As the image is shown plane, whether the selected landing area is flat or uneven can't be distinguished only by image information. The algorithm acquired elevation data to analyze the terrain of selected areas. Elevation information is a dataset of plane coordinates (X, Y) and elevation Z within a certain range [12-14], which mainly describes the space distribution of the general configuration of the earth's surface. The elevation data is illustrated as shown in Figure 4. According to the longitude and latitude of an area, elevation data can be obtained by Shuttle Radar Topography Mission (SRTM). If the elevation data in some area vary little, that is, the deviation of these data is smaller than a threshold value, then the area is judged as flat; otherwise it is judged as uneven. If the elevation data in some area is almost 0 which is lower than a threshold value T, then the area is judged as water body. Thus it avoids the misclassification of water and grass because of their similarity in features and greatly improves the accuracy of classification.

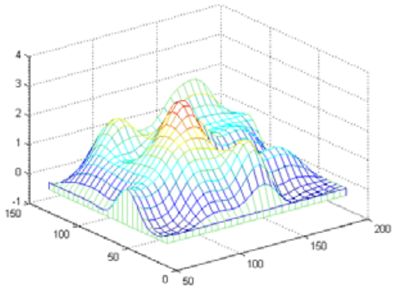


Figure 4. The terrain elevation

D. Extraction of Color and Texture Features

Whether the candidate safe landing area is suitable to land for UAV, the surface features of the selected areas need to be classified and recognized in case of affecting traffic or causing injury to human beings. By extracting features of color moment according to HSV models and texture features according to GLCM, the algorithm adopted one-versus-one classification of SVM to achieve an accurate and fast classification of surface features.

For any classification problem, a suitable set of features must be chosen. This paper extracts effective features of color and texture. In the following, the extracting approaches were given.

The method of extracting color features is: change the image from RGB color space into HSV color space, then, calculate the color moment from HSV model. The theory of color moment [15] is that any color distribution in the image can be represented by its moment. As the information of color distribution mainly lies in the low dimension moments, and in order to shorten the dimension of feature samples, only one-dimension and two-dimension moment of H, S, and V are need to be calculated respectively, which are enough to express the color information. Then the color moment of an image only requires six components: three kinds of color component, two low-dimension moment of each color component, consisting of a six-dimension color feature vector. The calculation formulas are as follows:

$$E_i = \frac{1}{N}\sum_{j=1}^{N} p_{ij} \tag{7}$$

$$\sigma_i = \left[\frac{1}{N}\sum_{j=1}^{N}(p_{ij} - E_i)^2\right]^{1/2} \tag{8}$$

Where N represents the total number of pixels in the image, p_{ij} is the i th color component of the j th pixel. One-dimension moment represents the average of each color component and two-dimension moment represents the variance of each color component.

Then the color feature vector is normalized according to the formula (9):

$$y = \frac{x - MinValue}{MaxValue - MinValue} \tag{9}$$

Where x, y are the values before and after normalization, $MaxValue$ and $MinValue$ are the maximum and minimum of features.

Texture features were extracted based on gray level co-occurrence Matrix (GLCM) [16]. GLCM reflects the synthetic information of image gray in direction, neighbor interval and varying amplitude. It starts from the pixel whose gray is i (whose position is (x, y)), and counts the occurring number $p(i, j, d, \theta)$ of the pixel whose gray is j and the distance with the pixel i is d. The math formula is:

$$\begin{aligned} &p(i,j,d,\theta) = \\ &\{(x,y),(x+D_x, y+D_y) \mid f(x,y)=i, f(x+D_x, y+D_y)=j\} \end{aligned} \tag{10}$$

Where $x, y = 0,1,\cdots,N-1$ is the pixel coordinate in the image; $x, y = 0,1,\cdots,L-1$ is the gray level; D_x, D_y is the position offset; d is the step generating the GLCM; θ is the generating direction, with the four directions of 0°, 45°, 90°, 135°, thus generating GLCMs of different directions. In order to make the features immune to the effect from the region, the GLCM was normalized:

$$\hat{p}(i, j) = \frac{p(i, j)}{\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} p(i, j)} \tag{11}$$

In order to describe the texture with GLCM more intuitively, this algorithm adopted some feature extraction parameters which are widely used to reflect the matrix to extract the features of an image, including energy ASM, entropy ENT, contrast CON, inverse difference matrix IDM [17], calculating formulas are as follows:

$$ASM = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} p(i, j, d, \theta) \tag{12}$$

$$ENT = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} p(i, j, d, \theta)\log(\, p(i, j, d, \theta)\,) \tag{13}$$

$$CON = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1}(i-j)^2\, p(i, j, d, \theta) \tag{14}$$

$$IDM = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1}\frac{p(i, j, d, \theta)}{[1+(i-j)^2]} \tag{15}$$

These four features have no relation with each other, thus they can effectively describe the texture features of optical or remote sensing images, convenient to calculate and with better ability to distinguish. As the gray levels of the original image to be processed are very large, the algorithm compressed it to 9 levels in terms of the calculating time and the separability of texture. Given the rotation invariability of the parameters, the step length was set 1, and the texture feature vector of sixteen-dimension was acquired by calculating the four features of four directions.

Combining the color moments and texture features, we got the extracted features of 22-dimension of a sample image.

E. Surface Features Classification

The SVM [18] was introduced by Vapnik in the late 1960's on the foundation of statistical learning theory. There are two kinds –linear and non-linear SVM. It can be considered that SVM creates a line or a hyper-plane between two sets of data for classification. If input data x fall one side of the hyper-plane, i.e. $w^T \cdot x + b \geq +1$, they are labeled as +1, representing the class $y_i = +1$, if they fall on the other side, $w^T \cdot x + b \leq -1$, then the input data are labeled as –1, representing the class $y_i = -1$ [19]. where w is the hyper plane which is not computed directly. To guarantee each learning sample is correctly classified, constraint conditions are added. The Lagrangian multiplier $A = (\alpha_1, \alpha_2, \cdots \alpha_{N_s})^T$, where N_s is the number of support vector (SV), for each SV s_i is used for training and to compute the classification label directly:

$$f(x) = \mathrm{sgn}(\sum_{i=1}^{N_s} a_i y_i s_i + b) \tag{16}$$

where x is the input data to be classified and sign $(\cdot)$ is a sign function that outputs either +1 or –1 depending on the sign of the computed value inside the parentheses.

The set of parameters for the SVM training model would be the set of Lagrangian multipliers, i.e. $A = (\alpha_1, \alpha_2, \cdots \alpha_{N_s})^T$.

For problems that have a non-linear decision hyper plane, a non-linear mapping function $\Phi(x): R^n \to H$ is used to transform the original input space R^n into a new higher-dimensional Euclidean input space H , in which the optimum hyper plane is found using quadratic programming method [20].

The mapping function $\Phi(x)$ is actually not used to map inputs directly. It's a function that computes the dot product in the higher-dimensional space, called a kernel function $K(s_i, x) = \phi(s_i) \cdot \phi(x)$, is used both in training and in classification, i.e.

$$f(x) = \mathrm{sgn}(\sum_{i=1}^{N_s} a_i y_i K(s_i, x) + b) \tag{17}$$

This distinguishing function is the so-called SVM. The data of training sample are mapped into higher-dimension space, avoiding the calculation of non-linear function in solving the optimum problem and calculating the decision function. The requirement of only the calculation of a kernel function avoids the disaster of dimension of feature space.

The SVM structure is shown as follows:

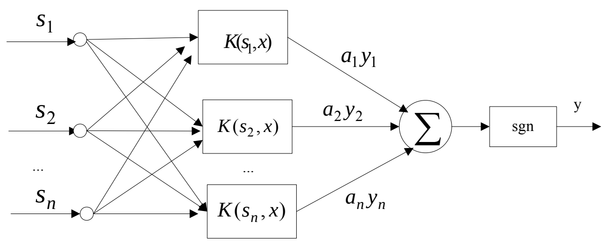


Figure 5. SVM structure

SVM theory is proposed for solving the problem of binary classification. There are many approaches proposed to extend the binary SVM to multi-class problems. The common scheme is that collecting two-classifications SVM into a multi-class SVM to deal with the problem of multi classes.

Two strategies to build multi-class classifiers based on binary SVM are as follows (example for K-class problems):

1) one-versus-one (1-v-1)

One-versus-one classification [19] is to decompose a multi-class problem to multi two-class problems, each time to select training samples from only two classes, then to construct a hype plane between any possible pair of classes. For k-class problems, $k(k-1)/2$ binary SVM classifiers need to be constructed in all. When classifying an unknown sample, voting method was used. That is: each classifier judged the two classes and vote for the corresponding class, the class with highest votes was the sample belongs to. These binary SVMs compose a parallel array.

2) one-versus-rest (1-v-r)

The theory of one-versus-rest method [19] is that to distinguish one class from the remaining training samples by constructing any possible k binary SVM classifiers, then to combine all the binary SVM by some strategy in the aim of solving multi-class problems. For example, the i th SVM classifier is trained with all the examples in the i th class with negative (–1) labels and all remaining examples with positive (+1) labels. The i th SVM classifier constructs a separating hyper plane between class i and the other $k-1$ classes (1-v-r strategy). These binary SVMs compose a serial array.

Currently, these two strategies are respectively used at parallel classification levels and serial classification levels. As one-versus-rest classifier needs to deal with all the data of samples, consuming much time, one-versus-one method is adopted in this paper which improves the speed of classification a lot.

The SVM classifiers can be trained in advance and are embedded into the equipment of UAV, which can save a great deal of time, improving the efficiency of landing area selection in emergency.

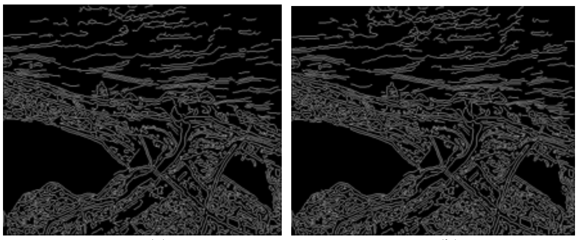
IV. THE RESULT AND ANALYSIS

The hardware environment used for verification in the experiment is SUMSUNG computer and the software is Matlab 7.11.

A. The Comparison of Detection Algorithm

The example aerial image collected is shown in Figure 6, as we can see, the suitable landing area and landing direction in the image is as shown in A which is a flat grass field. By comparing it with the result in the experiment, we can validate the accuracy of the algorithm. The detection result using traditional Canny edge detection and improved edge detection in this paper is shown as Figure 7 (a) and (b). Comparing the two figures, we can acquire the information: the edges between objects are detected and the areas without obstacles are clearly divided in both figures, in addition, the improved edge detection algorithm greatly improve the ability to detect the slowly changing edges and weak edges, with the result of more edges detected apparently than that in Figure 7 (b). Figure 8 shows the result after edge expanding using eroding operation for Figure 7 (b), which sets a certain safe boundary for candidate landing areas.

Figure 6. Original image



(a) (b)

Figure 7. (a) Image after Canny edge detection, (b) Image after improved edge detection

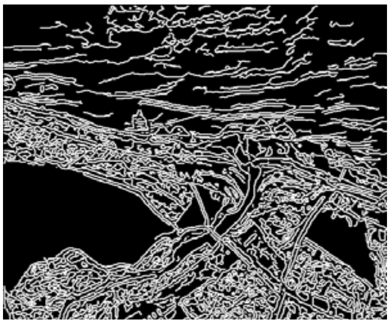


Figure 8. Edge expanding result for Figure 7 (b)

B. The Result of Area Selection

The result of area selection using four masks in Figure 3 is shown in Figure 9 with candidate landing areas marked as A-D with red line around. As can be seen, the algorithm's output yielded large safe areas to land in with no obstacles. The selected areas in the original image are shown in Figure 10, from which we can see that majority of these areas were large grass fields and large water bodies. Meanwhile, these four masks make the scanning process very intensive and keep the processing time to a minimum.

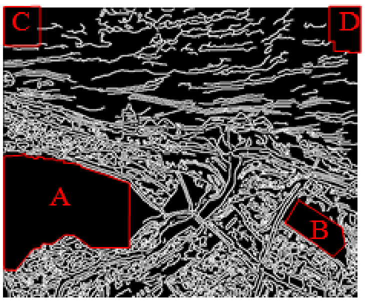


Figure 9. Candidate landing area

Figure 10. Landing area in the original image

C. The Result of Terrain Analysis

According to the current longitude and latitude of UAV when in emergency, the SRTM data of the position can be acquired by loading from the website of International Science Data Service Platform. Given the SRTM data, by drawing contour lines in the Global Mapper software, we can get the KML file, then, it is transformed into database file by KML2ContourMDB software. The elevation data of the area is within the database file. Assuming the known elevation data of the world wide are loaded into the computer of UAV, the elevation information of candidate landing areas can be looked up in the table of database.

Part of the elevation data of the aforementioned A-D areas are shown in table I.

TABLE I.

ELEVATION DATA OF THE SELECTED AREAS

number	Longitude (E)	Latitude (N)	Elevation (m)
1	122.0013	30.0145	0
2	121.5929	30.0153	0
……	……	……	……
43	122.0596	30.1435	2
44	122.1246	30.1277	2
45	122.1256	30.0476	2
……	……	……	……

According to the elevation data in the table I, the terrain of selected areas marked with A-D were analyzed. The elevation of the A and B areas has little variance, we can judge that they are flat in terrain. The elevation of C and D area are near 0 and lower than a threshold value of 0.2 and they are judged to be water bodies.

D. The Comparison of SVM and Bayesian Classifier

After the above three phases of the algorithm, the ground features of candidate landing areas can be classified into three kinds of grass, road and land. According to the reference [17, 20], the RBF kernel function of SVM was chosen, which has relative better learning ability. And the optimum parameters with better classification result were $C = 64, \gamma = 8$.

200 images of grass, water and road respectively were collected with 3/5 to be training samples and 2/5 to be testing samples. The extracted color moments and texture features were inputted into SVM classifiers, by training and testing, we can get the result of classification. The comparing result that was measured by classification efficiency and accuracy between SVM and Bayesian is shown in table II. The classification efficiency represents the average time consumed in classification of each image. And the accuracy represents the ratio of correctly classified images to the total images. As can be seen from table II, the algorithm that uses SVM to perform classification by non-leaner decision function can achieve satisfying result without need of large numbers of samples. Compared with Bayesian classifier [21-22], SVM classifier achieves a great improvement in the efficiency and accuracy of classification. It's apparently to make the conclusion that the algorithm presented in

this paper can achieve a fast and accurate landing area selection in emergency for an UAV.

Base on the SVM classification method, the identification result of candidate landing areas are truly and fast achieved: The areas marked A and B are classified as flat grass field that are suitable to land in for UAV.

TABLE II.
CLASSIFICATION RESULT.

Testing samples	Efficiency (s/frame)		Accuracy (%)	
	Bayesian	SVM	Bayesian	SVM
grass	2.35	2.21	91.24	91.67
road	2.18	2.06	91.45	92. 13
land	2.26	2.13	91.16	92.04

V. CONCLUSION

It's clear that UAVs will become increasingly prevalent in both military and civilian scenarios in the future. One goal of a UAV to fully integrate into the civilian airspace, especially to fly over populated areas is expected to be achieved. The key problem hindering it is about the selection of an appropriate safe forced landing area in the case of emergency. The algorithm presented in this research is proved to provide a safe landing area for the accident failure.

The algorithm synthesized multi-information of an image to select by step the best forced landing area for UAV in emergency, and turned out a good result in each phase. The algorithm using SVM to perform classification by non-leaner decision function in the final stage achieves a satisfying result without need of large numbers of samples and acquires a great improvement in the efficiency and accuracy of classification and identification of suitable landing areas compared with Bayesian classifier. The algorithm will have a promising and wide aspect.

ACKNOWLEDGMENT

This work was supported by Program for New Century Talents in University. The authors wish to thank the Program.

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