IDENTIFICATION OF UAV SAFE LANDING ZONES BY GLCM TEXTURAL FEATURES

Mr.B.RAJMOHAN[1],S.NARMADHA[2]
Assistant professor,PG Student
Dept.Of.IT, Adhiparasakthi Engineering College, Melmaruvathur.

ABSTRACT-An Unmanned aerial vehicle (UAV) is used in military and civilian application such as research and rescue and environment monitoring. The objective of placing this in a safer zone leads many requirements on the design work. The vision-based method has the advantages of large detection range and high scalability compared to other methods but difficult in many cases therefore most reliable techniques are required for finding safer zone for landing. In the existing system, Terrain classification is based on edge extracted object comparison with pre-defined library values & GLCM based textual description for detecting Safe Landing Zones .The proposed work of this project is to extract local binary pattern (LBP) representing the texture content of ground objects and the classified feature which differentiate smooth and non-smooth regions, and then Grey-Level Co-occurrence Matrix texture measurements have been the workhorse of image texture since it has good computation efficiency. Through texture based terrain classification is performed with morphological operation for detecting smoothen regions for safe landing.

Keywords—UAV,SLZ,LBP,Terrain classification

I. INTRODUCTION

An unmanned Aerial vehicle (UAVs) is used in many applications such as civilian (policing), military (fighting) and non-military applications (pipelines surveillance). An unmanned Aerial vehicle is an aircraft without a human pilot and it is controlled either autonomously by an onboard computers or the remote control of a pilot on the ground or another vehicle. The UAV may take off and lands itself. It is of two types: autonomous and remotely piloted. Autonomous UAVs can fly under the control of a software program that controls the aircraft flight. Remotely piloted UAVs can control in real time by human operator from point to point. It is of three fundamental elements: aerial, ground control Station and crew. A key advantage provided by UAVs is the removal of humans from situations which may be classified as dull, dangerous or dirty such as power line inspection, aerial surveillance and monitoring of atmospheric pollution. The development of UAVs began in the early 1900s and the technology in its early stages was used by the military during the World War I and expanded by World War II.

UAVs have two main advantages for terrain classification: Firstly, UAVs operates under strict power constraints therefore they are unlikely to observe an entire operational area. Observations such as terrain classification from neighboring UAVs global interpretation of the operational area can be constructed which can enhance tasks such as SLZ detection. Secondly, the accuracy of terrain classification of an area is to be influenced by altitude of capture in addition to sensor type. Due to constraints imposed by payload capacity and available power it is likely that in an operational deployment each swarm member will only have a single sensing device.

Spectral, textural and contextual are the three fundamental pattern elements used in human interpretation of images features. Spectral features describe the average tonal variation in visible/infrared spectrum. Texture is used to give information about the spatial arrangement of color or intensities in an image or selected region of an image. Contextual features give information derived from blocks of pictorial data surrounding the area being analyzed. Textural features have several parameters such as energy, entropy, contrast, homogeneity, variance, sum average, correlation, maximum correlation coefficient, sum entropy, sum variance, difference in variance, difference entropy

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information measures of correlation and angular secondary moment.

Texture analyses are usually categorized into structural, model-based, statistical and transform. Structural approaches characterize texture by well defined primitives (micro texture) and a hierarchy of spatial arrangements (macro texture) of those primitives. Statistical approaches do not attempt to understand explicitly the hierarchical structure of the texture. Model based texture analysis using fractal and stochastic models attempt to interpret an image texture generate image model and stochastic model. Transform methods such as Fourier and wavelet transforms represent an image in a space whose co-ordinate system has an interpretation that is closely related to the characteristics of a texture.

II. RELATED WORK

There are two main types of SLZ detection algorithms within the literature namely, semi-autonomous and fully autonomous. Semiautonomous approaches rely on a human operator delineating a general suitable landing area after which the UAV detects a specific landing site. Alternatively fully autonomous approaches rely solely on SLZ detection algorithms on-board a UAV.

Stephen Cameron[9] placed the existing approaches lies in the creation and control of swarms of UAVs that are individually autonomous (i.e. not under the direct real-time control of a human) but that collaboratively self-organize: to sense the environment in the most efficient way possible; to respond to node failures; and to report their findings to a base station on the ground.

When considering data fusion within the context of terrain classification from aerial imagery two popular techniques include Dempster-Shafer and probability theory. The success of these techniques within this domain is in part due to their suitability for modelling uncertainty of Membership within a well-defined class of objects[4]. The main advantages of using Dempster-Shafer theory is the ease with which ignorance, and therefore imprecision, in sensor readings can be quantified.

Mitch Bryson was described in[6] reconstruction phase integrates all of the sensor information using a statistically optimal non-linear least squares bundle adjustment algorithm to estimate vehicle poses simultaneously to a highly-detailed point feature map of the terrain. The classification phase uses feature descriptors based on the color and texture properties of vegetation observed in the vision data, and uses the terrain information to build a geo-referenced map of different types of vegetation.

P.T.Eendabak A.W.M. van Eekeren was proposed in [8] able to detect the objects in the presence of camera movement and motion parallex. Using the detected objects, the safe landing zone is identified.

Srikanth Saripalli was described in [11] results from flight trials in the field which demonstrate that our detection, recognition and control algorithms are accurate and repeatable.

Fazekas and Chetverikov compared normal flow features and regularized complete flow features in dynamic texture classification [10].They concluded that normal flow contains information on both dynamics and shape.

David G. Lowe was proposed in [3] recognition proceeds by matching individual features to a database of features from known objects using a fast nearest-neighbor algorithm, followed by a Hough transform to identify clusters belonging to a single object, and finally performing verification through least-squares solution for consistent pose parameter.

Cox et al. proposed in [12] minimize the expectation of human casualty, external property damage, Maximise the chance of survival for the aircraft and its payload

In this paper, Local binary pattern (LBP) based GLCM texture features are used to increase the level of textual description about image structure. Along with textual data, shape, color features will be extracted from input images to increase the accuracy level of terrain classification.

III. METHODOLOGY

IDENTIFICATION OF SAFE LANDING ZONES

The identification of safe landing zones (SLZs) is based on Edge detection, Texture description, morphological operation, classification. the block diagram is shown in fig(1)

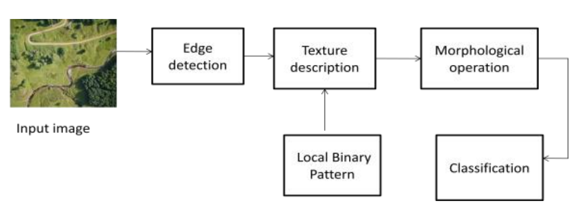

Fig.1. Block diagram

IV.EDGE DETECTION

Edge detection is the most common approach used for detecting sharp intensities or meaningful transitions in an image. Different types of

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edge detectors are available in image segmentation. Among these, canny edge detection operator is the most popular and efficient edge detection technique. It was formulated with three main objectives: optimal detection with no spurious responses; good localization with minimal distance between detected and true edge position; single response to eliminate multiple responses to a single edge. The first requirement aims to reduce the response to noise. This can be effected by optimal smoothing; the second criterion aims for accuracy: edges are to be detected, in the right place. This can be achieved by a process of non-maximum suppression. This result in thinning: the output of non-maximum suppression is thin lines of edge points, in the right place. The third constraint concerns location of a single edge point in response to a change in brightness. The canny edge detector algorithm has four steps .they are smoothening, compute gradients, non-maxima suppression, double thresholding. Due to the fundamental role of edge detection within the SLZ identification algorithm it is desirable that detected edges correspond, as accurately as possible to region boundaries. The input and output image is shown in the fig 2 & 3

fig.2.input image

fig.3.edge detection

V.LBP BASED TEXTURE DESCRIPTORS

The aim of this work is to find the best way for describing a given texture using a local binary pattern(LBP) based approach. Texture descriptors are the description of the visual features of the contents in images and used for detecting safe landing zones. Local binary pattern (LBP) is extracted for representing the texture content of ground objects, which is a well-classified feature to distinguish between smooth and non-smooth regions and then Gray-Level Co-occurrence Matrix texture measurements have been the workhorse of image texture since it has good computation efficiency.

A statistical method of examining texture that considers the spatial relationship of pixels is the gray-level co-occurrence matrix (GLCM), also known as the gray-level spatial dependence matrix. The GLCM functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures from this matrix. The number of gray levels in the image determines the size of the GLCM. The gray-level co-occurrence matrix can reveal certain properties about the spatial distribution of the gray levels in the texture image.

The basic idea behind LBP is that an image is composed of micropatterns.LBP is the first-order circular derivative of patterns that is generated by concatenating the binary gradient directions. A histogram of these micropatterns contains information about the distribution of edges and other local features in an image. The conventional LBP operator extracts information that is invariant to local grayscale variations in the image. It is computed at each pixel location, considering the values of a small circular neighborhood (with radius R pixels) around the value of a central pixel qc.

Formally, the LBP operator is defined by eqn(1)

$$\mathrm{LBP(P,R)} = \sum_{P=0}^{P=1} s(qp-qc)\, 2^{P} \qquad (1)$$

where P is the number of pixels in the neighborhood, R is the radius, and s(x) = 1 if x P 0, otherwise 0. The histogram of these binary numbers is then used to describe the texture of the image. Two types of patterns are distinguished: uniform patterns, which have at most two transitions from 0 to 1, and non uniform patterns. A simple method for selecting a set of uniform patterns is to choose the rotation invariant bins. Results show that the proposed system achieves more accurate by using the GLCM textural features.

Gray level Co-occurrence matrices capture properties of a texture, but they are not directly useful for further analysis, such as comparing two textures. Instead, numeric features are computed from the co-occurrence matrix that can be used to represent the texture more compactly. The following are standard features derivable from a normalized co-occurence matrix. Energy associated with an image that is a measure of textural uniformity of an image is defined by eqn (2)

$$\text{Energy} = \sum_i \sum_j P\mathrm{d}(i,j) \qquad (2)$$

The image texture contrast measures the amount of local pixels intensity variation within an image is defined by eqn (3)

$$\text{Contrast} = \sum_i \sum_j (i-j)^2 \mathrm{Pd(i,j)} \qquad (3)$$

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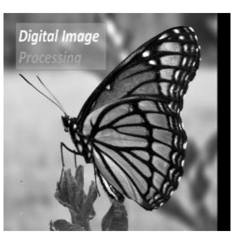
Correlation calculates the linear dependency of the gray level values in the co-occurrence matrix. It shows how the reference pixel is related to its neighbor is defined by eqn (4)

$$\text{Correlation}=\left\{\sum_i \sum_j (i,j)Pd(i,j)\right\} - \mu x \mu y / \sigma x \sigma y \quad (4)$$

Where μx,μy and σx, σy are means and standard deviations respectively of P(i,j).

VI. MORPHOLOGICAL OPERATION

Erosion and dilation are the fundamental operators of morphology operation**.** The morphological process of dilation increases the width of the detected edges. The objective of identifying potentially suitable SLZs, dilation has two main purposes. Firstly, from a safety prospective, assuming detected edges correspond to region or object boundaries the process of dilation enables a safety buffer to be placed around such boundaries. This safety buffer allows for a margin of error when performing the actual landing. Furthermore, the process of dilation closes small gaps in region boundaries helping to ensure consistency between detected and real world boundaries. Secondly, an important component of potential SLZ detection is the identification of areas of sufficient size to contain the UAV.



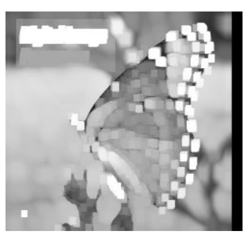


Fig.4. input image *Fig.5.dilation output*

VII. CLASSIFICATION

KNN is the most efficient for classifying the smoothen region for safe landing of UAV.*k*-nearest neighbor algorithm is a method for classifying objects based on closest training examples in the feature space. *k*-nearest neighbor algorithm is among the simplest of all machine learning algorithms. Training process for this algorithm only consists of storing feature vectors and labels of the training images. In the classification process, the unlabelled query point is simply assigned to the label of its *k* nearest neighbors. Typically the object is classified based on the labels of its *k* nearest neighbors by majority vote. If *k*=1, the object is simply classified as the class of the object nearest to it. When there are only two classes, *k* must be an odd integer. However, there can still be ties when *k* is an odd integer when performing multiclass classification. K-Nearest Neighbor or K-NN algorithm has been used in many applications in areas such as data mining, statistical pattern recognition, image processing. Successful applications include recognition of handwriting, satellite image and EKG pattern. The main advantages by using this classifier is that Analytically tractable, simple implementation, Uses local information, which can yield highly adaptive behavior, Lends itself very easily to parallel implementations.

VIII.CONCLUSION

The main focus of this paper is on analyzing the texture of region thereby smoothen region can be identified. Various Smoothen region can be analyzed based on the combination of feature vector set of contrast, correlation, energy and homogeneity. From the experimental results discussed above, we infer that the MLBP classification can serve as an effective tool in identifying smoothen region for safe landing. The future work will be based on developing algorithms to identify smoothen region, to improve the overall efficiency.The performance of ordinary LBP operator is limited. MLBP performed the best among several classical methods for texture classification. Compared with traditionally LBP, Multi-scale LBP could get more accurate results.

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Engineering, University of Padua Via Gradenigo, 6/B, 35131 Padova, Italy

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