TERRAIN CLASSIFICATION FOR TRAVERSABILITY ANALYSIS FOR AUTONOMOUS ROBOT NAVIGATION IN UNKNOWN NATURAL TERRAIN

* PRIYANKA MATHUR
Department of Electronics and Communication Engineering
Ansal Institute of Technology, Gurgaon, India
Email: mathur.priyanka10@gmail.com

KK SOUNDRA PANDIAN

Department of Electronics and Communication Engineering
Indian Institute of Information Technology, Design & Manufacturing ,Jabalpur,India
Email:kpandian@iiitdmj.ac.in

Abstract

Autonomous robot navigation in unknown natural terrain is the key requirement of a robotic system such as a rover as the natural terrain is unpredictable. For safe and robust navigation a robot must possess onboard intelligence to perceive the terrain ahead so that it can avoid hazardous areas by discriminating the navigable regions for traversal thereby optimizing its speed and increasing its efficiency. This is accomplished by real-time assessment and classification of terrain for traversability analysis. In this paper terrain classification system is developed for its traversability analysis for the robot operating in natural unknown terrain. The proposed method classifies the unknown terrain describing its suitability for navigation by extracting the textural features from visual imagery of terrain data. Clustering technique is employed to classify the features derived from statistical and transform based texture analysis. And further we have presented a fast and optimum algorithm for path planning of robot on the assessed navigable terrain. Images from NASA's Mars exploration rover and those obtained from real time natural terrain have been tested to validate the proposed approach.

Keywords: Autonomous robot navigation, real-time assessment, terrain classification, traversability analysis, path planning

1. INTRODUCTION

In today's high tech world, autonomous robots are becoming increasingly useful in various applications such as in department of defense for battlefield reconnaissance, surveillance military operations. Autonomy is a key enabling technology for both NASA and ISRO for future robotic space exploration missions in the areas such as navigation path planning by traversability assessment, local obstacle avoidance, and detection of changes in terrain and object recognition. An important functionality of an autonomous robotic system, such as a spacecraft or a rover, is real-time assessment and quantification of terrain safety for landing or navigation. In NASA's space exploration missions, the autonomous rover approaching a planetary surface will need to make a real-time safety assessment of potential landing terrain using on-board sensors, and select the safest acceptable site for touchdown. Many of these applications require the robot to navigate through various types of unknown natural environments which is intricate and unpredictable. An autonomous planetary rover operating on a rough natural terrain will also need to constantly evaluate the quality of the terrain segments available for traversal, and choose the most traversable path. This can be accomplished by classifying the terrain for traversability assessment so that it can optimize its speed or avoid potentially hazardous areas and select suitable paths without jeopardizing its safety and mission. When the terrain is rough and deformable it is possible for the rover to lose the mobility and get trapped in the terrain. There were several incidents that caused NASA's robotic mission Opportunity to become immobilized for several weeks as exemplified in April 29,2005 and on may 30 2006 opportunity became trapped in loose drift material (NASA/JPL).This loss of mobility may cause mission failure and must be avoided. To avoid these situations it is important to assess terrain traversability. Without considering terrain physical properties which can strongly influence rover's mobility, safe motion planning and control is difficult to achieve .A method to deal with this information will help in planning safe paths and controlling rover motion.

The purpose of this paper is to develop a terrain classification algorithm is proposed based on extracting textural features from terrain image obtained by using vision sensors. Our method identifies the terrain prior to traversing so that unsuitable terrains and obstacles could be avoided. This will enables the robot to sense its underline terrain similar to how humans determine the terrain on which they are driving.

Our approach uses the texture information derived from statistical and transform based analysis of the terrain regions. Salient features of terrain such as energy, entropy and contrast are extracted from co-occurrence matrix computed out of the sub bands of wavelet packet decomposed region of the terrain. These features form a complete feature vector which is classified by using k means clustering Furthermore; we have developed an optimum and shortest path planning algorithm for mobile robot in natural terrain similar to Mars surface terrains.

The rest of the paper is organized as follows. A review of the related research work in the area of terrain classification is given in section 2.Section 3.describes the proposed methodology for terrain classification for traversability assessment. It explains the feature extraction methods and discusses the classifier used. The details of the proposed path planning algorithm for the robot in navigable terrain are elucidated in section 4.Section 5.presents the experimental results of our traversability assessment of terrain and path planning algorithm and finally section 6.deals with the conclusion and possible extension for the future work.

2. PROLOUGE ASSESSMENT

Terrain classification methods provide semantic descriptions of the physical nature of a given terrain region. These descriptions can be associated with nominal numerical physical parameters, or nominal traversability estimates, to improve traversability prediction accuracy. Numerous researchers have proposed terrain classification methods based on features derived from remote sensor data such as color, image texture, and range (i.e. surface geometry) and vibration derived from different sensors such as laser range finder, ultrasonic range finder, vision sensor, tactile sensors Terrain traversability based on terrain classification and path planning of terrain-adaptive robots have been addressed by a number of researchers. Howard and Seraji [1] introduced the Fuzzy Traversability Index Algorithm, which used visual intensity levels to determine the terrain characteristics such as the roughness, slope, and discontinuity. Another classification method by Vandapel [2] avoids the effects of variability in light intensity by the use of statistical properties of 3D ladar sensor data to detect the surrounding terrains This method applied off-line statistical analysis techniques to ladar sensor data to segment a scene into three classes: vegetation, terrain rocks, and thin wires or tree branches. Machine learning methods were employed by D.F.Wolf [3] using 2 D laser range finders. Range information also known as geometric information, generates point clouds which are classified into navigable and not navigable area using hidden markov models (HMM). J.Soenneker et al. [4] used local point statistics features extracted from 3-D point cloud generated by ladar scans and enabled Naïve Bayes Decision Tree to learn to distinguish between different classes of terrain. In [5] Manduchi used a combination of color camera images and ladar data to detect and classify obstacles, with the detection done via ladar and classification using camera. A.Birk et al. [6] processed the range data obtained from Laser Range Finder by a Hough transform with three dimensional parameter spaces for representing planes and classified the terrain by Decision tree. However such methods cannot easily detect non-geometric hazards or terrain classes that are not characterized by variations in geometry. . Shirkhodaie et al. [8] used visual terrain modeling using soft classifiers like rule based and neural networks. Olson et al. [9] used visual stereo imaging fusion technique and demonstrated a reliable method for high fidelity terrain mapping and robot world perception modeling.

Another line of research for terrain classification is to use the interaction between the terrain and the locomotion system for classification purposes as Iagnemma et al. [10] classified terrain based on analysis of vibrations arising from robot wheel –terrain interaction. However, treating the vehicle as a particle results in poor performance at certain speeds and on certain terrains, especially when the vibration amplitudes are low. Edmond M. DuPont · Carl A. Moore [11] presents a method that characterizes the terrain by the measured frequency response of the vehicle vibrations. It assumes that the vehicle vibrations are correlated to the terrain type and the terrain signature is given by the magnitude frequency responses of the vibration sensors. An offline set of frequency response data previously recorded from each terrain type is statistically compared to the online measured frequency response data using a probabilistic neural network (PNN); a match between the two sets is used to estimate the current terrain. Color based classification [12] has yielded accurate results in natural terrain. Kelly et al. [13] utilized multispectral imaging, different color spaces and their distribution statistics is used by Dima et al.[14] because many major terrain types possess distinct color signatures.

Texture analysis can also be efficiently utilized in the area of terrain classification. Dong Min et.al[15] used co-occurrence features with linear discriminate classifier and clustering algorithm based on artificial neural network for terrain classification especially for shadow, grass and road class. Texture classification itself is an image processing technique which is basically employees ed in computer vision applications, industrial automation and in content based image retrieval. Mathur P. et.al used textural gray level co-occurrence features with crisp rule based classifier to classify the terrain into several regions of navigable and not navigable area [16]

3. METHODOLOGY

3.1 *System Overview*

Classification of terrain consists of two stages .Initially identifying and extracting the features that could be used for achieving maximum classification accuracy and then classifying the data using classifiers We have used textural analysis on the visual imagery terrain data. Texture is a measure of the local spatial variation in image intensity .It can be characterized by different approaches such as statistical means; model based or transforms based texture analysis. Statistical method is based on various joint probabilities of gray values. Gray Level Co-occurrence Matrices (GLCM) estimates the second order statistics by counting the frequencies for all the pairs of gray values and all displacements in the input image. The major texture attribute such as energy, entropy and contrast are derived from co-occurrence matrix. Model based methods include fitting of model like Markov random field, autoregressive, fractal and others. The estimated model parameters are used to segment and classify textures. Transform based approach analyses texture in various transform domains usually implemented through various filter banks such as Gabor filter and wavelet decomposition etc.

The proposed terrain classification method consists of initially dividing the terrain image into finite number of sub frames where each frame represents a small portion of the actual terrain called the sub terrainian region. Texture features are then extracted from each sub image which is fed to the classifier that classifies/renders the given sub frame into either navigable or not navigable region

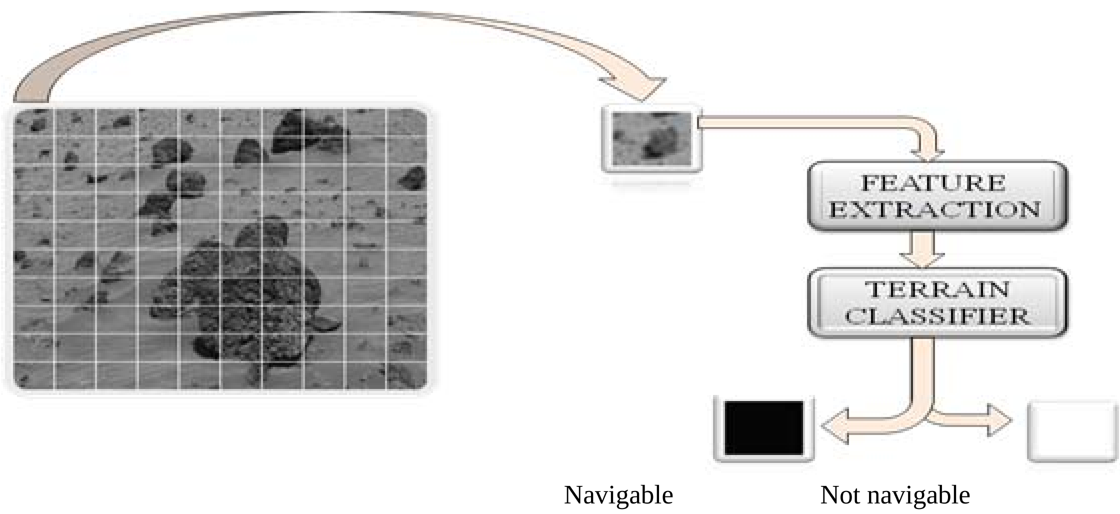


Fig. 1. Design flow of terrain classification

The proposed feature extraction method utilizes the statistical and transform based analysis of the various sub-terrainian regions. The feature vector is composed of texture attributes such as energy, entropy and contrast, derived from co-occurrence matrix computed out of the sub bands of wavelet packet decomposition. The features thus obtained are fed to the classifier which uses semi supervised k means clustering algorithm to classify the given sub terrain image into navigable and not navigable class. After the classification terrain assessment is done for planning the navigation strategy of autonomous robot. The architecture of our terrain classification is given in fig.2.

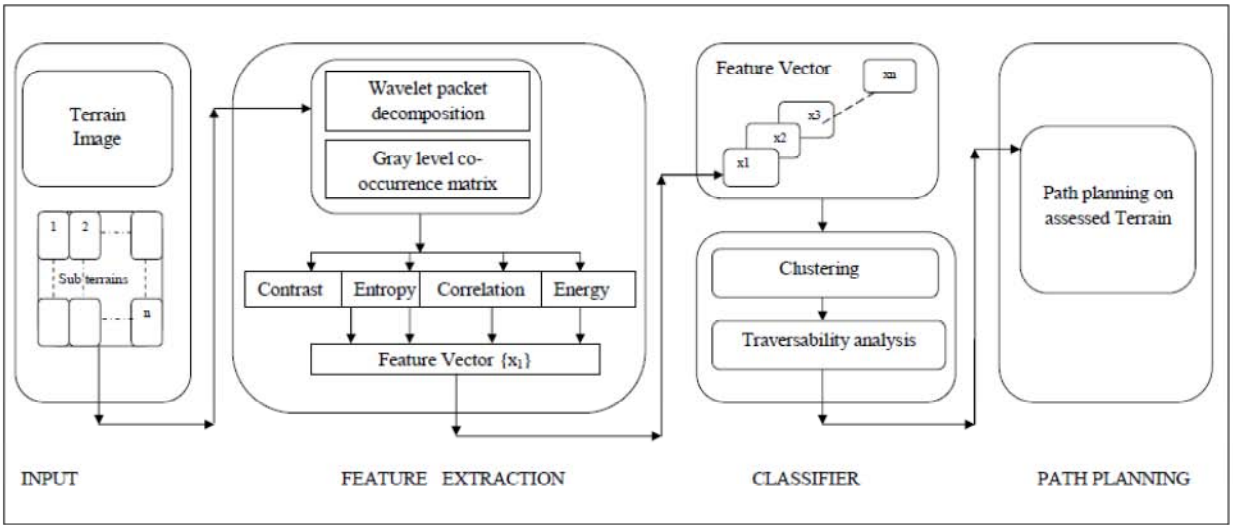


Fig.2. System Architecture of terrain classification

3.2 *Feature Extraction*

Our approach to obtain feature vector is to apply wavelet packet decomposition on each sub terrain image and the co-occurrence matrix is calculated out of the sub bands of decomposed images. Several texture measures are directly computed from the grey level co-occurrence matrix such as contrast, entropy, variance and energy.

3.3 *Grey Level Co-Occurrence Matrix*

Gray Level Co-occurrence Matrices (GLCM) estimates the second order statistics by counting the frequencies for all the pairs of gray values and all displacements in the input image. An image is a matrix of pixel intensities, I (i,j) We can define co-occurrence of image matrix as Pd (i,j)such as every entry in co-occurrence matrix, Pd(i,j), is difference in intensity between a pair of image pixels(i and j), that are distance d pixels apart in original image in a given direction. Energy associated with an image that is a measure of textural uniformity of an image is defined by equation (1)

$$Energy = \sum_{i}\sum_{j} P_d^{\,2}(i,j) \tag{1}$$

Furthermore, Image Entropy is a measure of disorder of an image Entropy is inversely proportional to Energy and is defined by equation (2)

$$Entropy = -\sum_{i}\sum_{j} P_d(i,j)\log P_d(i,j) \tag{2}$$

The image texture contrast measures the amount of local pixels intensity variation within an image

$$Contrast = \sum_{i}\sum_{j} (i-j)^2 P_d(i,j) \tag{3}$$

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.

$$Correlation = \{\sum_i \sum_j (i,j) P_d(i,j)\} - \mu_x \mu_y \ / \sigma_x \sigma_y \quad (4)$$

Where $\mu_{x,} \mu_y$ *and* σ_x, σ_y are means and standard deviations respectively of P(i,j)

We compute these features for all the sub terrain regions which serve as feature vector for the classifier and forms first feature set (FS1). In addition two more feature database is created by using wavelet statistical features which contains energy values of leaf nodes of the wavelet packet decomposed image at level 3 forming feature set 2 (FS 2) and other obtained by directly calculating co-occurrence features from the original sub image forming feature set 3 (FS 3).

Classification is done using all the three different feature databases. It is found that the success rate is improved much in our approach by combining wavelet statistical and co-occurrence matrix features of decomposed images

3.4 *The Wavelet Packet Decomposition*

For many signals, the low-frequency part contains the most important part. In such cases, one must pay attention in the bands of high energy, instead of looking with fine frequency bandwidths at low-frequency bands of low energy. This leads to the adoption of wavelet packets .Discrete wavelet packet transform consists of Wavelet packet decomposition (WPD) sometimes known as just wavelet packets. It is a wavelet transform where the signal is passed through more filters than the discrete wavelet transform (DWT).

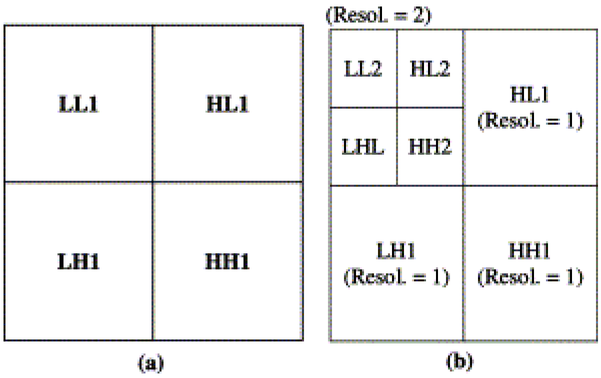


Fig.3. Image decomposition (a) One-level (b) two level.

In DWT The image is actually decomposed i.e., divided into four sub-bands and critically sub-sampled by applying DWT as shown in Fig. These sub-bands labeled LH1, HL1 and HH1 represent the finest scale wavelet coefficientsi.e., detail images while the sub-band LL1 corresponds to coarse level coefficients i.e., approximation image.

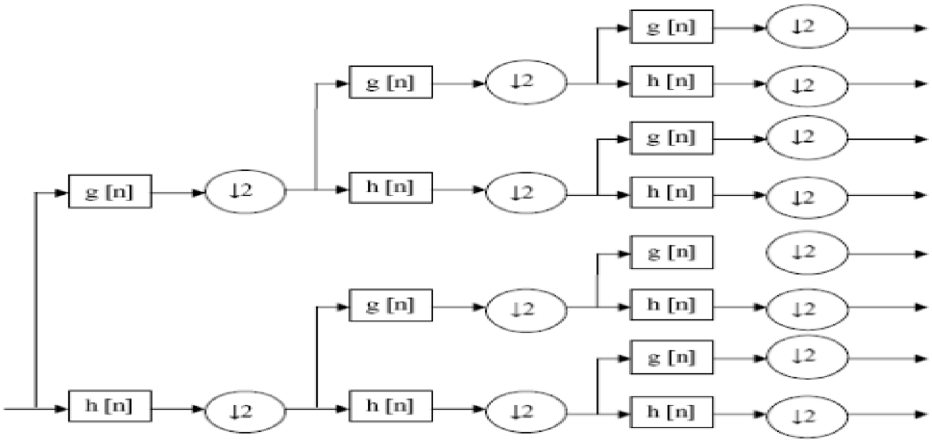


Fig.4. Wavelet Packet decomposition tree

The standard 2D discrete wavelet packet transform (DWPT) is a generalization of 2D discrete wavelet transform (DWT) that offers a richer range of possibilities for image analysis. In 2D-DWT analysis, an image is split into an approximation and three detail images. The approximation image is then itself split into a second-level approximation and detail images, and the process is recursively repeated. So, there are (n + 1) possible ways to decompose or encode the image for an n-level decomposition. In 2D-DWPT analysis, the three details images as well as the approximation image can also be split. So, there are 4^n different ways to encode the image, which provide a better tool for image analysis.

3.5 *Terrain Classifier (K means Clustering)*

A cluster is a collection of objects which are similar between them and are dissimilar to the objects belonging to other clusters. Clustering of numerical data forms the basis of various classification and system modeling algorithms. The purpose of clustering is to identify natural groupings of data from a large data set to produce a concise representation of a system's behavior. Clustering algorithms are not only used to organize and categorize data, but are helpful in data compression and model construction. In statistics and machine learning, the k-means algorithm is clustering algorithm to partition n objects into k clusters, where k < n. This technique is based on randomly choosing *k* initial cluster centers, or means. These initial cluster centers are updated in such a way that after a number of cycles they represent the clusters in the data as much as possible. The k-means algorithm starts with k- cluster centers or centriodes. Cluster centriodes can be initialized to random values or can be derived from a priori information. Each data point then assigned to the closest cluster (i.e. closest centriodes). Finally, the centriodes are recalculated according to the associated data. This process is repeated until convergence. Data vectors within a cluster have small Euclidean distances from one another, and are associated with one centriodes vector, which represents the "midpoint" of that cluster. The centriodes vector is the mean of the data vectors that belong to the corresponding cluster.

1. The algorithm starts out with initializing *Ci* this is achieved by randomly Selecting *C* points from among all the data points.

2. Determine the membership matrix U, where the element *uij* is 1 if the *j*th data point x*j* belongs to the group 1 and 0 otherwise.

3. Compute the cost function by the equation given below. Stop if the value of cost function is below a certain threshold value.

$$J = \sum_{i=1}^{c} J_1 \ = \sum_{i=1}^{c}\left(\sum_{k,X_k \in c_i} ||X_k - C_i \ ||^2\right) \tag{5}$$

4. Assign each data point to the cluster closest centroide

5. Update the clusters center centers Ci by re calculating the clusters centriodes as mean of all data points within the each cluster and determine the new U matrix.

4. PATH PLANNING ON ASSESSED TERRAIN

Once the terrain is classified into clusters, each region is assessed as either navigable (black) or not navigable (white). Thus unknown natural terrain is now divided into various regions of two classes depending on its traversability. We have proposed a grid based path planning algorithm as our terrain is divided into various sub-terranian regions. Path planning algorithm developed for the classified terrain obtains optimally shortest path for the robot. A four connected flood fill algorithm is developed in order to start at the goal and assign the lowest value- zero (0) to that cell of the grid. The not navigable regions are assigned the highest values-infinity (∞). All the four connected cells, starting from the goal, are filled with the values just one more than its smallest neighbor till the obstacle is met; source or end of the grid is reached. After filling the grid the path is planned starting from source cell and following the values downhill to the goal .Moreover it optimizes the path by incorporating diagonal movement also. For example the path is 5(source)-3-2-1-0(goal) as shown in fig. 5.

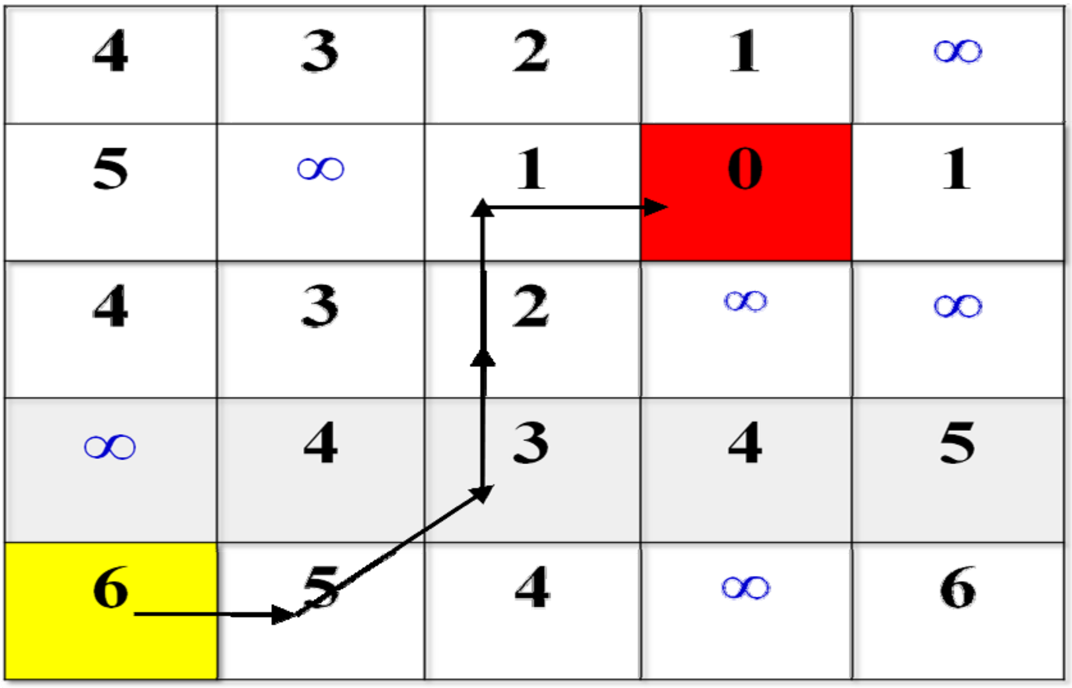


Fig.5. Path planning algorithm from source (yellow) to goal (red)

The algorithm determines the most suitable way point towards the goal in the navigable region that minimizes the number of traveling cells thereby giving the shortest path.

5. RESULTS AND PERFORMANCE EVALUATION

The performance of the terrain classifiers for traversability analysis was on two different terrain image databases. The first set was compiled from NASA's Mars Exploration Rover mission. High resolution panoramic camera images selected from MARS Analysts Notebook database to verify the algorithm performance on MARS surface scenes. The second set of images was collected through digital camera from real time natural terrain.

Initially we divide the terrain image into finite number of sub frames. Each frame represents a small portion of the actual terrain called the sub terrain region. The images were of the size 320X 320 .We chose a sub window frames of size 32 X 32 for terrain sampling. For Mars surface scenes, primary terrain types that are believed to possess distinct traversability characteristics are: rocky terrain composed of outcrop or large rocks; sandy terrain, composed of loose drift material and smooth mixed terrain .Examples of these terrains are shown in Fig.6

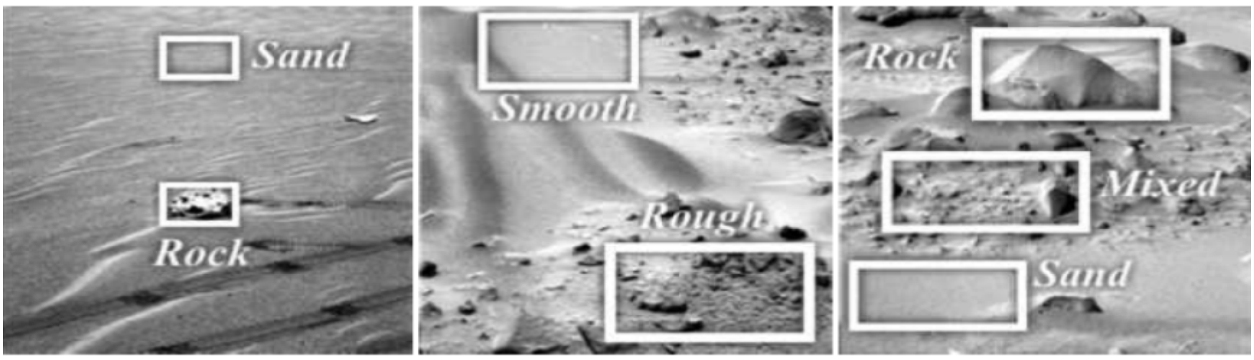
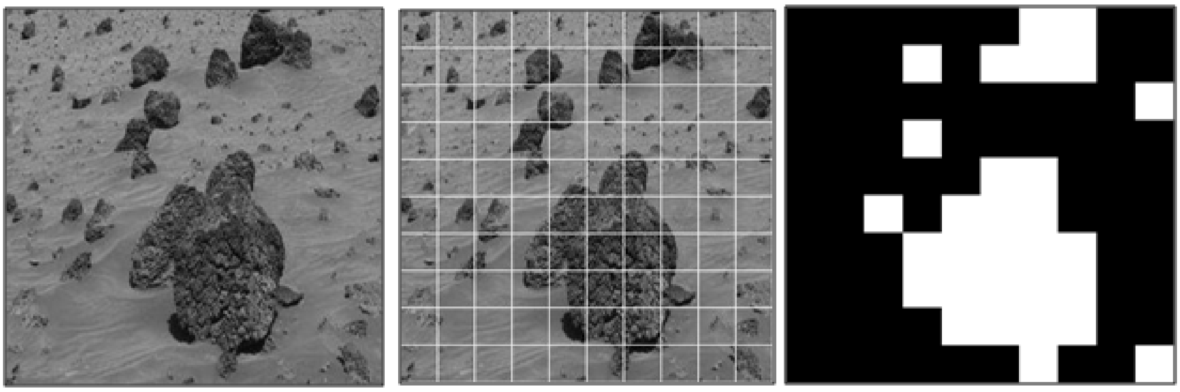


Fig.6. Class Distinction of Mars terrain

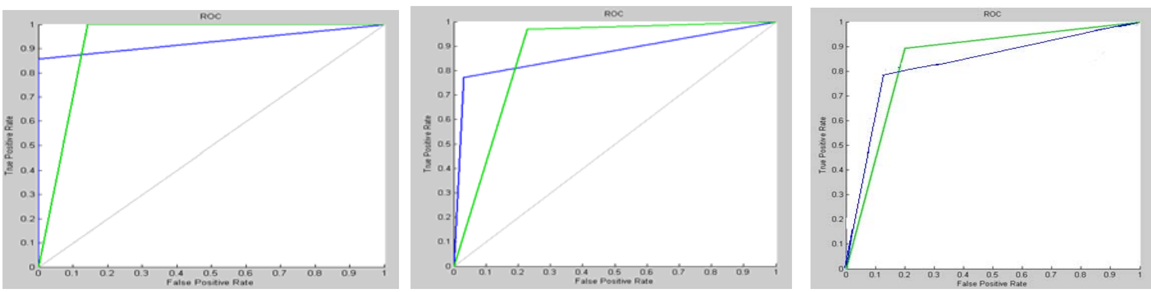
We have used two more feature sets for comparison of our approach .First feature vector consists of attributes calculated from gray level co –occurrence matrix directly computed from terrain sub image. Second feature set contains energy values of the leaf nodes of wavelet packet decomposed image. Fig. 7 shows the classification result of the terrain image 1 (TI 1) using features of first feature set (FS1)



(a) (b) (c)

Fig. 7. (a) Terrain Image 1 (b) Sampled Terrain (c) Classified Terrain

The performance of a classifier can be measured by classification accuracies and speed. Accuracy is evaluated using Receiver Operating Characteristics (ROC) curve and the confusion matrix .It summarizes how well the classifier has performed for that problem at different thresholds. It allows us to show graphically the trade off of each classifier between its true positive rate (the number of correct positive cases divided by the total number of positive cases) and its false positive rate (the number of incorrect positive cases divided by the total number of negative cases) by the total number of positive cases) and its false positive rate (the number of incorrect positive cases divided by the total number of negative cases). Here horizontal axis indicates the percentage of false positives and the vertical axis indicates the percentage of true positives. The point (0,1) is the perfect classifier as it classifies all positive cases and negative cases correctly. It is (0,1) because the false positive rate is 0 (none), and the true positive rate is 1 (all). The point (0,0) represents a classifier that predicts all cases to be negative, while the point (1,1) corresponds to a classifier that predicts every case to be positive. Point (1,0) is the classifier that is incorrect for all classifications. Thus, higher the curve is towards the left higher is the correct classification rate as vertical axis shows true positive value, its higher percentage corresponds to higher correct classification and horizontal axis showing false positive value should have minimum value therefore it should have lower percentage for less number of misclassified regions. ROC curve should lie as close to left for FPR to be nearly close to zero and TPR to be nearly close to maximum 100%.Fig. 8(a) shows the ROC curves for terrain image 1. Here,green curve is the roc for navigable classes and blue curve is roc of not navigable class.As the curve in fig. 8 (a) is highly towards the left as compared to the curve in fig. 8 (b) and 8c), it indicates that the classified output performed better using FS 1 as the true positive rate is more and false positive rate is low. In fig. 8(b) and 8(c) curve lies away from the vertical axis showing more false positive rate as compred to fig. 8 (a). Thus the classification accuracy uaing our feature set performed better Blue curve line indicates the correct positive rate for not navigable regions and dotted green curve indicates correct classification rate for navigable regions.



(a) (b) (c)

Fig.8. ROC (a) (FS 1) (b) FS 2 (c) FS 3

A confusion matrix lists the values of known cover types of the reference data in the columns and of the classified data in the rows The main diagonal of the matrix lists the correctly classified pixels One basic accuracy measure is the overall accuracy, which is calculated by dividing the correctly classified pixels (sum of the values in the main diagonal of confusion matrix) by the total number of pixels checked. It is known as correct classification rate.

$$Correct\ Classification = \frac{\text{sum of the values in the main diagonal of confusion matrix}}{\text{sum of the all values in the confusion matrix}} \quad (6)$$

Confusion matrix of image (TI 1) is shown in fig. 9. It can be deduced from the table that correct classifIcation rate (classification accuracy) of the terrain classifier is 95% for this image as 95 sub terrainian regions which are navigable are correctly classified.

		Ground truth	
		Navigable	Not Navigable
Classified data	Navigable	30	5
	Not Navigable	0	65

Fig.9. Confusion matrix (FS 1)

Confusion matrix using feature set 2 is shown in fig. 10 .It can be deduced from the matrix that the corect classification rate is 79%.Thus the correct rate using our feature set (FS 1) performed better than the other two feature sets.

		Ground truth	
		Navigable	Not Navigable
Classified data	Navigable	15	20
	Not Navigable	1	64

Fig.10 Confusion matrix (FS 2)

Fig. 11 shows the confusion matrix using feature set 3 on same image (TI 2) indicating that the correct classifiaction rate is 85%

		Ground truth	
		Navigable	Not Navigable
Classified data	Navigable	28	7
	Not Navigable	7	58

Fig.11. Confusion matrix (FS 3)

The result obtained by using our approach gives an accuracy of 96 % as compared to feature set 1 which gives 93 % correct classification and feature set 2 giving only 94 % accuracy for the test image. Results on real time image captured from IIITDM campus also shows that our approach performs better than rest of the two feature sets.

Table I. shows the classification accuracies of the classifier for 1100 sub terrain regions of 11 martial terrain images NASA’s mars exploration rover [15]. WPD is feature set obtained by wavelet packet decomposition and GLCM is the feature set obtained by gray level co- occurrence matrix. Table II.represents correct classification rate for 900 image regions of 9 terrain image obtained from real time IIITDM campus. Each image has hundred sub terrain regions which are classified as either navigable or not navigable. Results of classifier on 20 terrain images is shown having a total of 2000 sub terrain regions which are classified for traversability analysis.

Table 1. Correct classification (%) for Mar's terrain images

Terrain Image (100 sub regions in each image)	GLCM +WPD feature set (FS1)	GLCM feature set (FS2)	WPD feature set (FS3)
1	88	86	96
2	95	79	85
3	94	92	93
4	97	96	96
5	96	96	96
6	95	95	93
7	97	89	90
8	92	94	92
9	97	95	93
10	97	91	96
11	95	87	85
Number of image regions correctly classified (1100 subterranean regions)	1043	904	1004

Table II. Correct classification (%) for real time terrain images of IIITDM campus

Terrain Image (100 sub regions in each image)	GLCM +WPD feature set (FS1)	GLCM feature set (FS2)	WPD feature set (FS3)
11	93	92	92
12	85	89	80
13	88	87	76
14	95	86	84
15	94	88	90
16	94	92	93
17	82	85	82
18	82	91	78
19	87	85	85
Number of image regions correctly classified (900 subterranean regions)	800	795	760

Fig.12. is the graph for correct classification rate for each of 20 images.

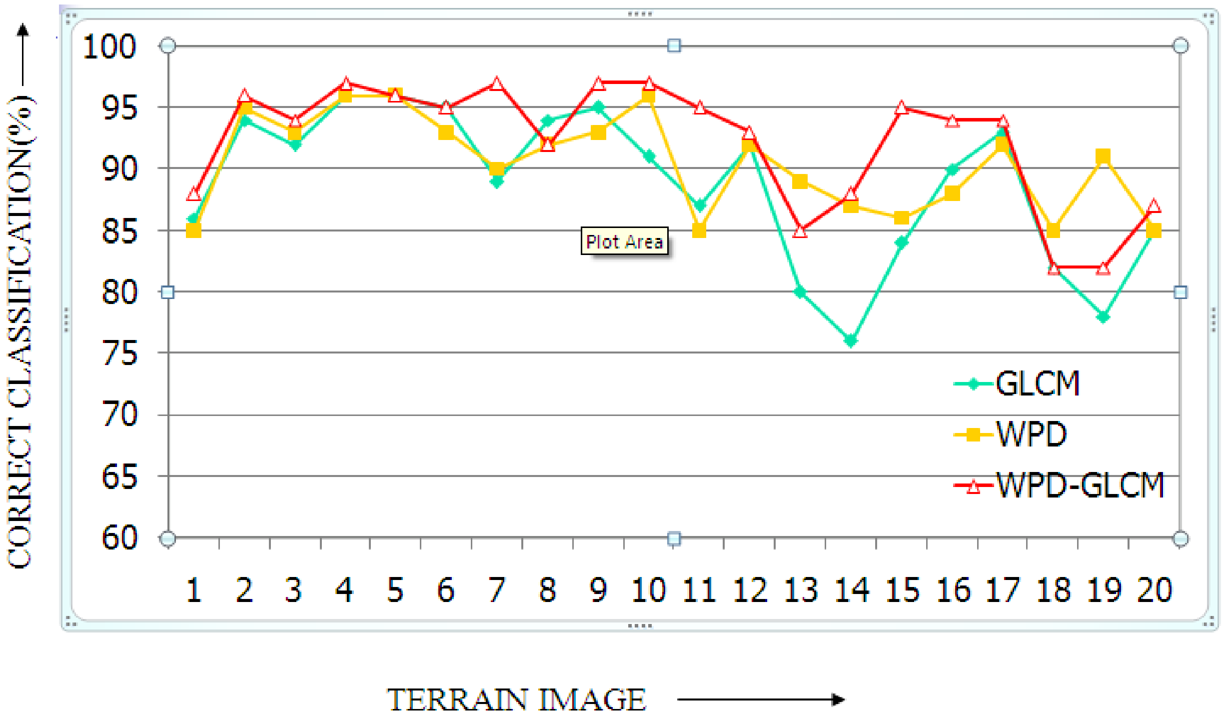


Fig.12. Graph showing correct classification rate

Mean success rate of the classifier using two feature sets is shown in fig. 13 for different image databases.

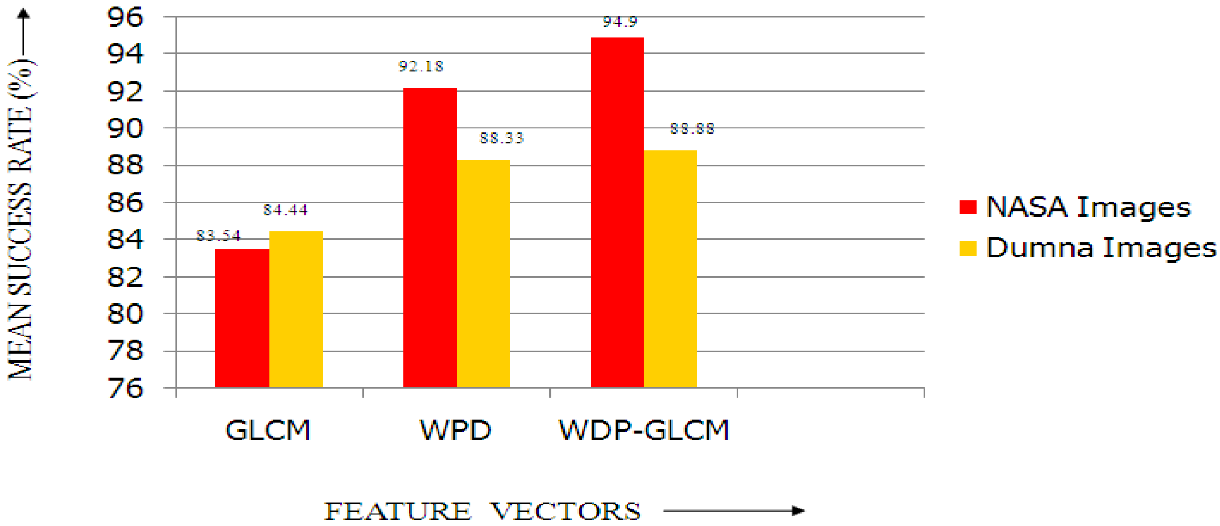


Fig.13. Graph of mean success rate

6. CONCLUSION AND FUTURE ASPECTS

In this paper classification of the unknown terrain describing its suitability for navigation by extracting the textural features from visual imagery of terrain data is described .In the first part of this work, a feature extraction algorithm has been presented to extract textural features of each sub terrain region, from the combination of co-occurrence features derived from the wavelet packet decomposed image and statistical features obtained from the coefficients of the decomposed. The feature vectors thus formed are then used for clustering to classify the terrain image into navigable and not navigable classes. In the second part a grid based path planning algorithm is proposed as our terrain is divided into various sub-terrainian regions. The proposed algorithm is both fast and shortest in generating free path in classified sampled terrain

In future, this line of inquiry can be continued to develop improved terrain classifier that will able to differentiate more than two classes (navigable or not navigable) and should identify sandy, rocky and muddy terrain in the not navigable region. Also, addition feature could be used to improve the classification accuracy. Further, the effects of employing different wavelets and alternative classifier architecture (such as support vector machines) to yield better classification accuracies on the terrain classification will also be investigated.

Another promising avenue would be to the hardware implementation of this intelligence on a real time robotic platform equipped with high precision vision sensors.

Acknowledgments

This work was supported by Indian Institute of Information Technology ,Design and Manufacturing Jabalpur MP India

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