Traversability Assessment of Terrain for Autonomous Robot Navigation

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***Abstract* - Autonomous robot navigation with the capability to perceive the surrounding environment of the robot enhances the efficiency and safety of the robot. A technique for terrain classification for traversability assessment of mobile robot navigating in natural terrain by extracting the textural features from visual sensing of terrain data using co-occurrence matrix is presented in this paper. The algorithm uses crisp rule based (CRB) classifier to detect the navigable terrain thereby planning the optimum path for the robot.**

Index Terms - ***Terrain classification, Traversability assessment, Autonomous robot, Co-occurrence matrix, Path planning Navigation (PPN)***

I. INTRODUCTION

Autonomous navigation in natural unknown terrain is an emerging technology as natural terrain is unpredictable and intricate. For safe autonomous operation, a robot should possess onboard intelligence and capability to perceive the terrain ahead so that it can optimize its speed; avoid hazardous areas by discriminating the negotiable regions for traversal. Embedding terrain knowledge in autonomous robot requires traversable assessment of the terrain. Terrain classification to detect derivable ground for robot provides adaptability to control by optimizing its speed and planning strategies to avoid hazardous areas thereby improving its efficiency and safety.

This paper presents terrain classification using visual sensing of the terrain data. We have used statistical texture analysis technique to compute the salient feature of the terrain for classification. Furthermore, we have developed an optimum and shortest path planning algorithm for mobile robot in natural terrain similar to Mars surface terrains.

Terrain classification is fundamentally employed in Department of Defense for military surveillance, target tracking applications and in particular in NASA and ISRO for robotic planetary space explorations in the areas such as navigation path planning by traversability assessment, local obstacle avoidance, and detection of changes in terrain and object recognition.

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Lack of terrain knowledge suspends reliable navigation and traversal to the goal successfully as exemplified by the NASA's Mars exploration rover in 2006 which became entrenched in loose drift material and remained stationary for several weeks [3].

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 system overview and our approach In Section 4, path planning based on classified terrain is described. Section 5 presents our results and finally section 6.deals with conclusion and our future work.

II. PROLOGUE ASSESSMENT

Terrain classification for derivable path for robot has been addressed by many researchers based upon the features like range, color, image texture and vibration derived from different sensors such as laser range finder, ultrasonic range finder, vision sensor, tactile sensors. Ayanna Howard et al. [1] used fuzzy logic framework to develop terrain based navigation system coupled with obstacle avoidance and goal based navigation strategy. Olson et al. [2] proposed a method based on visual terrain mapping for Mars rovers. Using a visual stereo imaging fusion technique, they have demonstrated a reliable method for high fidelity terrain mapping and robot world perception modeling. Iagnemma et al. [3] classified terrain based on analysis of vibrations arising from robot wheel –terrain interaction. Vandapel et al. [4] categorized ladar data points as either clutter, linear or surface using range feature. 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. Shirkhodaie et al. [6] used visual terrain modeling using soft classifiers like rule based and neural networks. Machine learning methods were employed by D.F. Wolf [7] using 2 D laser range finders. Range information generates point clouds which are classified into navigable and not navigable area using hidden markov models (HMM)

Color based classification [5] has yielded accurate results in natural terrain. Kelly et al. [8] utilized multispectral imaging, different color spaces and their distribution statistics is used by Dima et al.[9] because many major terrain types possess distinct color signatures. A.Birk et al. [10] 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. J.Soenneker et al. [11] used local point statistics features extracted from 3-D point cloud generated by ladar scans and enabled Naïve

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Bayes Decision Tree to learn to distinguish between different classes of terrain.

III. MOTIVATION AND APPROACH

A. System Overview

Terrain classification method extracts the relevant features which should be easily computed, robust, insensitive to various distortions and variations in the sensor data. Our features are based on imaging surface texture analysis (STA).

Texture is a measure of the local spatial variation in image intensity. The attributes of texture include contrast, variance, energy, and entropy. Terrain classifiers provide semantic descriptions of the physical nature of a given terrain region. The texture quantitative statistics enable CRB classifier to distinguish navigable region .Once trained, the developed classifier module can be used to classify terrain image in real time. After the classification terrain assessment is done for planning the navigation strategy of autonomous robot

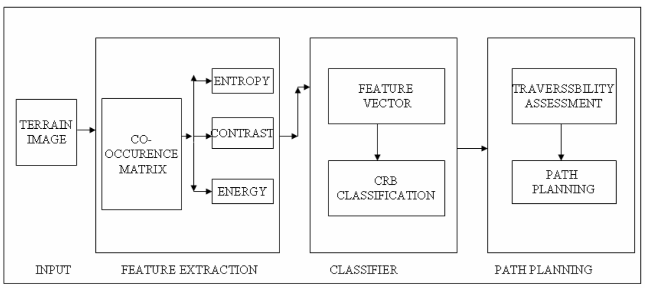

Figure 1.Architecture of the terrain classification system

B. Feature Extraction

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 [2]. Image texture features as shown in figure 2, Howard et al [1] are extracted from the statistical means on each region using second order gray level co-occurrence matrix. Several texture measures are directly computed from the grey level co-occurrence matrix such as contrast, entropy, variance and energy. An image is a matrix of pixel intensities, I (i,j) We can define co-occurrence of image matrix as P_d(i,,j)such as every entry in co-occurrence matrix, P_d(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)

$$Energy = \sum_i \sum_j P_d^{\,2}(i,j) \qquad (1)$$

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

$$Entropy = -\sum_i \sum_j P_d(i,j) \log P_d(i,j) \qquad (2)$$

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

$$Contrast = \sum_i \sum_j (i-j)^2 P_d(i,j) \qquad (3)$$

We compute these features for all the sub terrain regions which serve as feature vector to train the classifier. In order to minimize the computation requirement, we chose the contrast and entropy as main attributes to obtain reliable statistical assessment of terrain surface textures.

C. CRB Classifier

CRB classifier is knowledge based model which has set of predefined thresholds for classification of different terrain like rocks, sand and smooth terrain. These thresholds were determined by examining several such terrains. Training is done on images of Mars surface terrain image for: navigable and not navigable regions. Using this classified traversable image path planning is performed to navigate the robot from start to goal location in specified safe area.

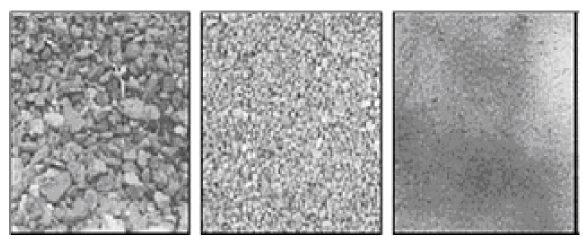

Figure 2.Examples of terrain textures.

IV. PATH PLANNING ON ASSESSED TRAVERSABLE TERRAIN

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 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. For example the path is 5(source)-4-3-2-1-0(goal) as shown in figure 4.

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

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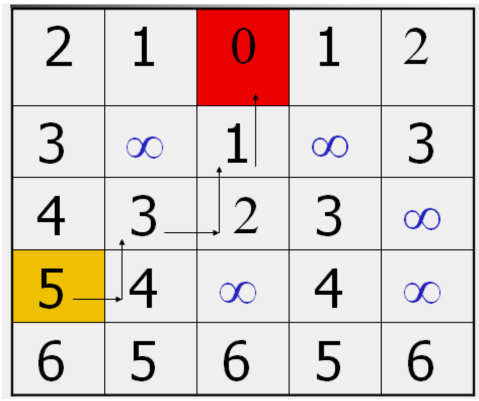


Figure 3.Grid based path planning from source (yellow) to goal (red)

V. RESULTS

Our terrain traversability assessment method was tested on images obtained from NASA's Mars exploration rover mission [15].The images were of the size 512 x 512 .We chose a sub window frames of size 25 x 50 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 Figure 4. Halatci.et al. [16]

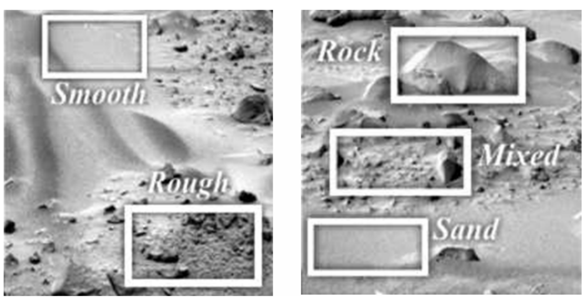
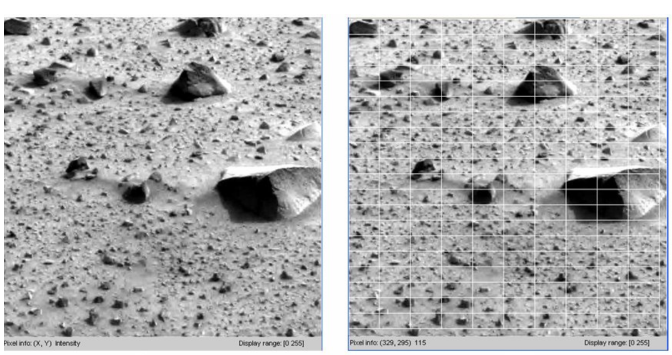
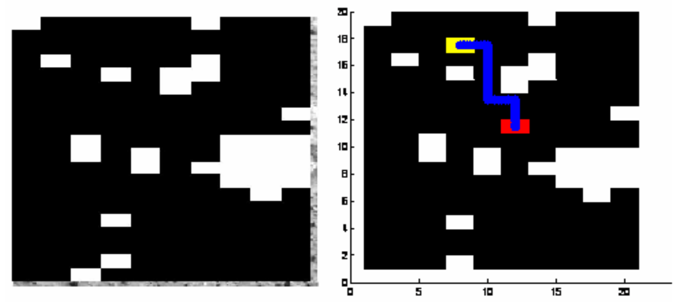


Figure 4.Class distinction of Mars terrain

Figure 5 shows the result analysis of the martial terrain. As shown in figure 5b terrain image is divided into sub terrain frames. Classified terrain is shown in figure 5c where white color corresponds to not navigable region and black indicates the traversable region. Figure 5d path planning is shown as developed by the MATLAB code where yellow cell indicates the source and red indicates the goal positions. The path followed is shortest grid based path for the robot



(a) (b)



(c) (d)

Figure 5. (a) A Martial Terrain (b) Sampled Terrain
(c) Classified Terrain (d) Generated Free Path

VI. CONCLUSION AND FUTURE WORK

Mobile robots adaptability in the natural terrain is the fundamental requirement for safe autonomous navigation. This paper has presented terrain traversability analysis using terrain classification. The method employs visual imagery technique for the detection of terrain textural features. A crisp rule based Classifier is developed to distinguish derivable ground. For path planning we have used a flood filling algorithm that is both fast and shortest in generating free path in classified sampled terrain. The Classifier and path planning is developed using MATLAB

Future work would mainly focus on expanding the classifier to be able to differentiate more than two classes (navigable or non navigable) and should identify sandy and muddy terrain in addition to rocky and smooth terrain. Also, additional features such as homogeneity, correlation and angular central moment (ASM) could be used to improve the classification accuracy. Size of the sub terrain frames can be altered for better precision of assessable terrain.

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