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Object Scanning based Road Obstacles Detection using Weighted Sum Method

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Abstract : This study presents a image processing vehicle detection and tracking algorithm for smart vehicle vision system. The algorithm applies in two stages of vehicle detection. At first stage, we generally find all the edges which is there in the camera window but considering of over segmentation concept so that not to leave any vehicle behind even if that vehicle is very much similar in intensity with the background and even of low intensity too. At the second stage, we apply Weighted Sum Method along with the intensity and texture consideration to merge internal edges with in the AOI (Area of Interest) so that we will get vehicles segmented in the current image. Then we will count vehicles using block wise counting analysis.

Keywords: Road Obstacle Detection, K-Means Color Clustering, Threshold based Segmentation and Weighted Sum Method

I. Road Obstacle Detection

Road Detection is the major task of autonomous vehicle guidance. The autonomous vehicle guidance has been a hot research area in the past 20 years. Among the complex and challenging tasks that have received the most attention and road following which is composed of road detection and obstacle detection is the most important one. Recently, due to the low cost of camera and well-developed algorithm in computer-vision, visual guidance for autonomous vehicle has been highlighted research field which focuses on machine vision techniques that detect particular features in images of the road ahead of the vehicle and determine the desired vehicle position with respect to the road boundary based on these features [1].

The obstacle detection algorithm developed here simplifies the task of detection. Further certain justifiable assumptions are made to speed up the system of detection. These assumptions make the system amenable to real time and real world situations. In this section first describe the assumptions and then the system requirements and finally the detection algorithm [1].

Assumptions of Obstacle Detection

The basic assumptions that underlie the Obstacle detection algorithm:

- Obstacles can be defined as objects protruding sufficiently high from the ground or crevices sufficiently deep in the surface. For the system described here, obstacles are restricted to objects that are at least k feet above the ground-plane and the system is not designed to detect crevices.
- ***Flat Ground:*** It is assumed that the ground can be locally represented by a plane. The assumption is justifiable on the basis that the area where a big vehicle can be safely driven is more or less locally flat.
- ***Object boundaries form good features:*** Obstacles are assumed to be visually distinguishable from the background in the intensity image since local intensity discontinuities form the basis for matching across stereo image pairs.
- ***Epipolarity:*** Image coordinating is a two dimensional pursuit that can be diminished to a one dimensional inquiry if limitations forced by epi-polar geometry natural in a situated picture pair are met. The identification calculation misuses the epi-extremity imperative by utilizing cams with indistinguishable central lengths that are adjusted up to a scan line.
- ***Identical camera/Digitizers:*** Identical cameras and digitizers are assumed to simplify the task of finding correspondences and processing intensity images. A difference in focal lengths of the stereo camera lenses introduces 2D an affine transform and obtaining correspondences becomes more complicated results. There are some differences in the dynamic response of the sensors to incident light and scaling or offset of the input signal by the digitizers requires costly and time consuming intensity normalization [6].

II. Techniques Used

There are some vital techniques used for Road Obstacle Detection that is discussed below in detail:-

a) ***K-Means Color Clustering*** K-Means clustering is a method of vector quantization and originally from signal processing that is popular for cluster analysis in data mining. K-Means clustering aims to partition *n* observations into *k* clusters in which each observation belongs to the cluster with the nearest mean serving as a prototype of the cluster. This results in a partitioning of the data space into Voronoi cells.

The K-means algorithm is an iterative technique that is used to partition an image into *K* clusters. The basic algorithm is

- Pick *K* cluster centers, either randomly or based on some heuristic
- Assign each pixel in the image to the cluster that minimizes the distance between the pixel and the cluster center
- Re-compute the cluster centers by averaging all of the pixels in the cluster
- Repeat steps 2 and 3 until convergence is attained

Description of K-Means: Given a set of observations ($\mathbf{x}_1$, $\mathbf{x}_2$, …, $\mathbf{x}_n$), where each observation is a d-dimensional real vector, k-means clustering aims to partition the n observations into k ($\leq n$) sets $\mathbf{S} = \{S_1, S_2, …, S_k\}$ so as to minimize the within-cluster sum of squares (WCSS). As it were, its goal is to discover:

$$\underset{\mathbf{S}}{\arg\min} \sum_{i=1}^{k} \sum_{\mathbf{x} \in S_i} \|\mathbf{x} - \boldsymbol{\mu}_i\|^2$$

Where $\boldsymbol{\mu}_i$ is the mean of points in S_i. The two key features of k-means which make it effective are regularly viewed as its greatest drawbacks:

- Euclidean distance is utilized as a metric and variance is utilized as a measure of cluster disseminate.
- The number of clusters k is an input parameter: an improper decision of k may yield poor results. That is the reason when performing k-means, it is critical to run indicative checks for deciding the quantity of clusters in the information set.

b) Segmentation

The image segmentation is a situated of segments that collectively cover the whole image or an arrangement of forms removed from the image. Each of the pixels in an area is comparative concerning some trademark or figured property, for example, shading, power, or composition. Nearby areas are altogether diverse regarding the same characteristic(s). At the point when connected to a stack of images, average in medical imaging the resulting contours after image segmentation can be utilized to create 3D reproductions with the assistance of interpolation algorithms like marching cubes. The following are the five general ways to segmentation:-

- ***Threshold based segmentation:*** Histogram thresholding and cutting strategies are utilized to portion the picture. They may be connected specifically to a picture, however can likewise be joined with pre and post-preparing procedures.
- ***Edge based segmentation:*** With this procedure detected edges in an image are expected to represent object boundaries and used to identify these objects.
- ***Region based segmentation:*** Where an edge based procedure may attempt to discover the object boundaries and after that find the object itself by filling them in a region based method takes the inverse methodology by starting in the middle of an object and afterward "growing" outward until it meets the object boundaries.
- ***Clustering techniques:*** Although clustering is some of the time utilized as an equivalent word for (agglomerative) segmentation procedures, they utilize it here to denote methods that are principally utilized as a part of exploratory data analysis of high-dimensional measurement designs. In this context clustering techniques attempt to gathering together designs that are similar in some sense. This objective is fundamentally the same to what they are endeavoring to do when they fragment an image and surely some clustering procedures can promptly be sought image segmentation.
- ***Matching:*** When individuals recognize what an item they wish to identify in an image looks like they can utilize this learning to find the object in an image. This way to deal with segmentation is called matching [14].

c) Weighted Sum Method for Standard Deviation

Standard Deviation is a measure of scattering in measurements. It gives a thought of how the individual information in an information set is scattered from the mean. Standard deviation is characterized as the square foundation of the mean of the squares of the deviations of every last one of estimations of an arrangement taken from the math mean. It is otherwise called the root mean square deviation. The image utilized for standard deviation is σ [1].

This instrument performs a weighted summation on multiple input images. This instrument can be utilized to consolidate multiple factors with differing levels of weight or relative significance. For example how about we say's that you wish to make another variable that joins the impact of local slope gradient and elevation and the wetness index and that the relative importance or weighting of these three factors is 0.5, 0.2, and 0.3 respectively. If a particular grid cell has slope = 6.4 and elevation = 200 and wetness index = 5.2 then the Weighted Sum will evaluate the output value as:

$$S = 6.4 \times 0.5 + 200 \times 0.2 + 5.2 \times 0.3 = 44.76$$

- ***Purpose of Standard Deviation***

The purpose of acquiring the standard deviation is to measure the standard distance from the mean.

- ***Calculate Standard Deviation***

To locate the standard deviation first locate the arithmetic mean of the qualities. After that discover the deviation of everything from the mean. Discover the squares of the deviations and include them. At that point divide the sum by the quantity of things in the arrangement and take the square root. To compute standard deviation they take after specific steps.

- ***Steps to Calculate the Standard Deviation:-***

Step 1: Calculate the arithmetic mean.
Step 2: Find the deviation of everything from the mean.
Step 3: Square these deviations and include them.
Step 4: We get ∑ (x−x¯) 2.
Step 5: Divide this sum by the aggregate number of things.
Step 6: Take the square root of the consequence of step 5. This will give the standard deviation.

III. Methodology

In this thesis work, a new method is proposed for better results. The proposed work is based on the Weighted Sum Method. The work flow can be described with the following flow chart:-

a) Start: In this step, the original image is uploading to start a process.

b) ***Depth Map:*** Depth map is the second main step of proposed work. The difference between two images is called depth map.

c) ***Extracting Road with Geometrical Calculations:*** This step is used to extract the road or tracks or end row with geometrical calculations by using some following points:-

- Variation in Colors
- Make a logical image by using logical operators
- Background Subtraction
- Apply morphological operations on logical image
- Elementary Multiplication of original image and logical image with morphological operations
- Separate RGB components to make a histogram with results

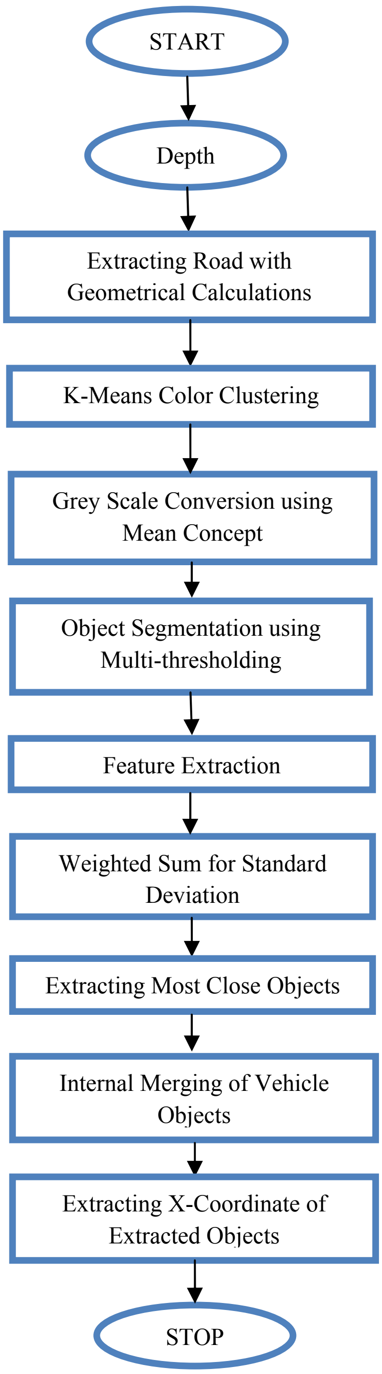

Figure 1: Flowchart of Proposed Work

d) ***K-Means Color Clustering:*** K-Means clustering is a method of vector quantization and originally from signal processing that is popular for cluster analysis in data mining. K-Means clustering aims to partition *n* observations into *k* clusters in which each observation belongs to the cluster with the nearest mean serving as a prototype of the cluster. This results in a partitioning of the data space into Voronoi cells.

e) ***Grayscale Conversion using Mean Concept:*** In this step, the image is converted into grayscale by using mean value of RGB components and also apply mean value on the output of previous step to make the bunches of colors.

f) ***Object Segmentation using Multi-thresholding:*** This step describes that the object is divided into small parts or segments i.e. segmentation using multi-thresholding to get the intensity values of each part of object. Following is the pseudo code of Multi-thresholding:-

$I_t = 0;$
$for\ i = 1\ to\ i = n$
$if\ Hist\ i > 0$
$I_1 = F_H\ (I_i\ ,\ 20);$
$I_2 = \mathrm{SOBEL}\ (I_1);$
$I_T = I_T\ (OR)\ I_2\ ;$
end if
end

where i denotes the number of frequencies present in the image.
F_H is the high pass filter with threshold 20 and SOBEL is the filter for edge detection.
I_T is the output logical image having all objects.

g) ***Feature Extraction:*** The next main step is Feature Extraction. In this step, some features are extracted that are area, position of row, position of column, mean of RGB components.

h) ***Weighted Sum for Standard Deviation:*** In this step, the standard deviation is to measure the standard distance from the mean by using weighted sum method. The pseudo code of weighted sum method is:-

$for\ j = 1\ to\ j = n$
$R_i = (A_i.W_i) + (M_{ri}.W_2) + \left(M_{gi}.W_3\right) + (M_{bi}.W_4)$
$if\ R_i < th$
$j\ \Sigma\ Ex.out\ ;$
$end\ if$
End for

Where R_i , M_{ri} , M_{gi} and M_{bi} are the respective features for i^{th} object (Area, Mean r, Mean g, Mean b)
R is the rank for i^{th} object.
Th is the rank threshold.
Ex-out is the output matrix having excepted object id's.

i) ***Extracting Most Close Objects:*** This step is used to extract the most close vehicle objects that has more frequency by using morphological operations and elementary multiplication.

j) ***Internal Merging of Vehicle Objects:*** The internal merging of vehicle objects step is used to show the selected area of obstacle.
k) ***Extracting x-coordinate of Extracted Objects:*** Extracting x-coordinate of extracted objects is the last main step of proposed work which is used to determine the x-coordinate of extracted objects.

IV. RESULTS

The following figures show the results of proposed work:

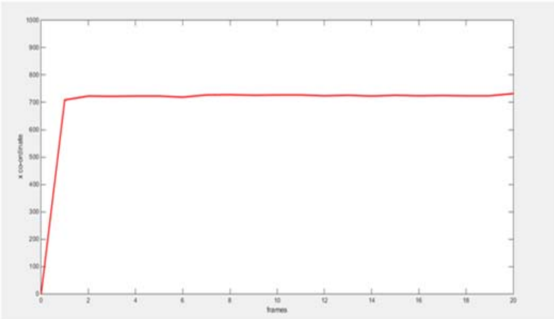

Figure 2: Proposed Results

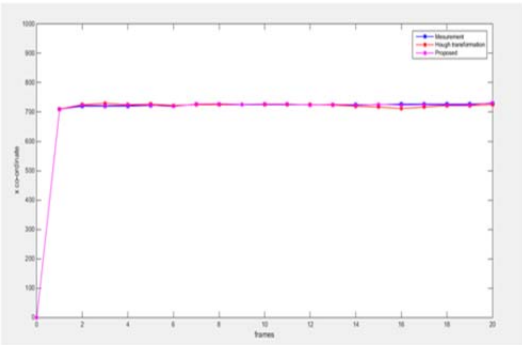

Figure 3: Compare the results with previous results

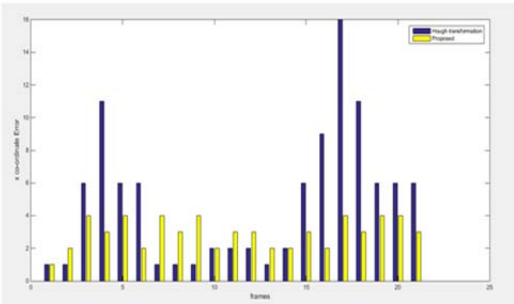

Figure 4: Compare the Error rate of proposed work and previous work

V. CONCLUSION

In this thesis it have developed an algorithm that detects and tracks road obstacles and this algorithm is proposed to detect and to track road obstacles using scanned objects which are obtained from cameras installed at a moving vehicle. The proposed obstacle detection algorithm can be used for the development of driver assistance system and autonomous vehicle systems. Firstly the road obstacle detection process will be carried out to segment the road by using a slope of the geometry road to extract road disparities. Secondly the obstacle detection process used to retrieve all objects found it in the road. Then the weighted sum method is used for tracking these objects. The obtained results are better and satisfactory. It can further apply new formulas or algorithm for the enhancement of accuracy in detection of characters and reducing time for execution. The proposed algorithm can be implemented on different tools.

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