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INDOOR NAVIGATION OF AUTONOMOUS PATH TRACKING ROBOT USING VISION BASED PIECEWISE LINEAR APPROACH

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***Abstract*-Autonomous path tracking robot without any knowledge about the environment must muddle through the obstacle. The onboard sensing technique uses sensor to detect obstacle. The vision based technology progress with camera to become aware of obstacle. On comparing the above two approach, the latest one provides detailed information about the environment which is not obtained by using sensor. There are some drawbacks in onboard sensing technology like selection of sensor based on color and lightning condition which can be overcome by the proposed method. The proposed method depends on vision based technology which is capable of providing detailed description about the environment to avoid obstacles. The piecewise linear contrast stretching is used for image segmentation. The map less navigation where the robot is not trained to any environment behaves like a human when the robot detects an obstacle from the captured image. Once the obstacle is detected the robot takes another possible path for the further safe navigation.**

Index Terms – Obstacle, Onboard Sensing, Piecewise Linear

I.INTRODUCTION

The field of robotics creates interest among researchers across various fields in the recent past. The idea of employing a robot to perform a specific task instead of a human has been emerging. Robotics involves computational intelligence which is embedded into physical machines. Such robotic systems can carry out tasks that are unachievable by conventional machines or even by humans working with conventional tools.

The goal is to develop autonomous robots to explore their environment and also to navigate in their workspace intelligently. To achieve this, the recent advances in the field of computer vision are utilized. The research in these areas has advanced to certain level that is not only possible to make robust and accurate but also efficiently learn their models. This leads to an increase in their application to solve robotic problems. Specifically, the techniques developed in these fields provide opportunity to perform better and thus they are utilized to enhance the image-based navigation in household task. The current trend in robot navigation is to try and use vision instead of more sensors. The systems employ either camerasor Omni directional vision sensors for viewing the environment. Much attention is being devoted to solve theproblems implied by using visual information for navigating through the environment [2].One of the main obstacles that have hindered the penetration of mobile robots is the unavailability of powerful, versatile and cheap sensing.

Vision technology is potentially a clear winner as far as the ratio of information provided versus cost is considered. Cameras are sold at a price less than laser and sonar scanners. Vision potentially offers more portable and cost effective solutions that has resulted in significantly reduced price and increased performance. Moreover it can provide information unavailable to other sensors: for instance, it provides information of a scene for understanding of its visual appearance [10].

Vision-based robot navigation has now become a primary goal in the area of robotics and computer vision. Progress has been made in the last two decades on two separate fronts: indoor and outdoor robot navigation [3]. The progresses made in above two areas are noteworthy. For example, earlier it is impossible for an autonomous indoor mobile robot to make its path in a messy areabut it is not a great challenge at current scenario [11][12]. Unstructured and dynamic environments pose a crucial challenge to many real-world applications. With non-vision sensors, it is impossible to predict and model every possibility. As a result the parameters of the robot system were earlier tuned in order to work properly in the new environment. However with the emergence of cameras, such environments can be tackled more efficiently.

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II. OBJECT DETECTION METHOD

Visual servoing system is divide into position-based visual servoing system (PBVS) and image-based visual servoingsystem(IBVS). Xiao-Jing Shen, Jun-Min Pan(2003) explains about the two servoingmethod[4][6]. PBVS needs to estimate the pose of target in 3D space and IBVS often control the feature in 2D image plane. The performances of both systems depend on the selection of the state vector. So, it is important to select a desirable state vector to design a visual servoing system.

The generalized Hough transform for object detection technique is used by Carter *et al* (2004) where they describes a robust algorithm for random object tracking in a sequence of image [5][13]. The dynamic Hough transform has been extended to detect a random shape that undergoes affine motion. There is no need of any information to be provided in prior, an efficient implementation can be achieved with course to fine dynamic programming and pruning. This method is robust under noise because of its evidence based nature. Hough transform is also used for industrial application where robot motion planning in done, (2006) it also includes the Hough transform where the path planning is done in a two-dimensional configuration whereas mobile robot and obstacles are designed by 3D geometrical views. The computation of the translational distance of penetration is made use full for obstacle avoidance.Hough transform has also been used for automatic generation of geometric models.Static obstacles are avoided with single-camera vision and dynamic obstacles are detected with sensors. The sensor used here is to detect moving obstacle using ultrasonic sensor [1]. This is to find the integration of camera and sensor in the vision-based process for mobile robots that is able to simultaneously navigate and avoid static obstacles using camera images. Obstacle avoidance capability is limited to the detection and avoidance of stationary obstacles. This results in the limitations of the hardware available to the robot. Even though dynamic obstacles must still be detected using sensors.

III. PROPOSED METHOD

Vision-based navigation has been mostly analyzed as a localization problem in the literature. Most robot is provided with a set of images obtained during a training stage to describe its environment. Localization is then performed by comparing the current image with the set of images. However, there has been no single method developed until now that addresses the issues of exploration, mapping, localization, planning, servoing and learning in a single comprehensive framework. Localization allows the robot to autonomously learn and navigate in a wide variety of unknown environments extending their capabilities and applications. The ability to automatically learn from the image build a dynamic map while autonomously exploring an unknown environment opens the door for robotic systems to be widely deployed. Several industrial applications can benefit from this framework.

Image preprocessing using the Piecewise Linear Contrast Stretching Function is introduced. An input color lane image is converted into a grayscale image. Gray values are normalized to the range (0, 1). The PLCSF is used to improve the contrast level of the input image, particularly the ROI. All normalized gray values are then converted into new output gray values.The input video with obstacle undergoes segmentation for the enhancement of the video by using piecewise linear contrast stretch that makes easier for the obstacle detection using blob analysis. Video is allowed to process frame by frame.

A grayscale image in which the value of each pixel is considered as a sample where each pixel value consist of information about the intensity. Images of these kindremains as black and white which also includes the shades of gray, varying from black to white. With black as a least intensity and white as a greatest intensity.Grayscale images are distinct from one bit black and white images.

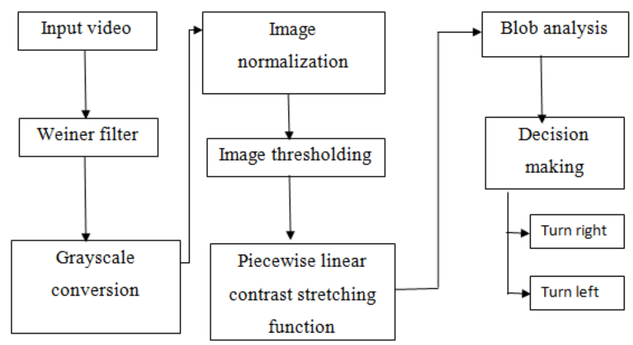

Fig. 1. Block diagram

Grayscale images have many shades of gray in between. Grayscale images are used for measuring the intensity value at each pixel. But also they can be synthesized from a full color image.The storage method is 8-bit storage. The 8 bit storage. For 8 bit gray scale image it consist of 256 gray level and the intensity of each pixel can vary from 0 to 255, with 0 as black and 255 as white.

Wiener filter is employed for the inverse filtering method i.e., once the image is blurred by a illustrious low pass filter, it's potential to recover the image by inverse filtering or generalized inverse filtering. However, inverse filtering is extremely sensitive to additive noise. The approach of reducing one degradation at a time permits to develop a restoration formula for every degradation and easily mix them. The Wiener filtering executes an optimum exchange between inverse filtering and noise smoothing. Normally used storage methodology is 1-bit storage that's being employed here for the standardization of

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obtained gray scale image. There are 2 grey levels, with zero being black and one being white is noted as image standardization to(0,1). As binary pictures are simple to control, it's reborn into binary format.

From a grayscale image, Thresholding are often want to produce binary pictures. Image thresholding may be a straightforward, however effective, approach of partitioning a picture into a foreground and background. This image analysis technique may be a kind of image segmentation that isolates objects by changing grayscale pictures into binary pictures that is best in pictures with high levels of distinction [9]. The best thresholding ways replace every component in a picture with a black component if the image intensity Ii,j is a smaller amount than some fastened constant T (that is, Ii,j< T), or a white component if the image intensity is larger than that constant.

Contrast enhancement increases the dynamic range of intensities in low-contrast images.The basic properties of contrast stretching are contrast stretching transformation function must be single-valued and monotonically increasing, preserve the order of grey levels, the greater the slope the higher the contrast (spread) at that range, binarisation (thresholding) is a special case of contrast stretching shown in figure 2. That obtain binary image by setting to zero all intensities below a threshold and to maximum value all other intensities[8].

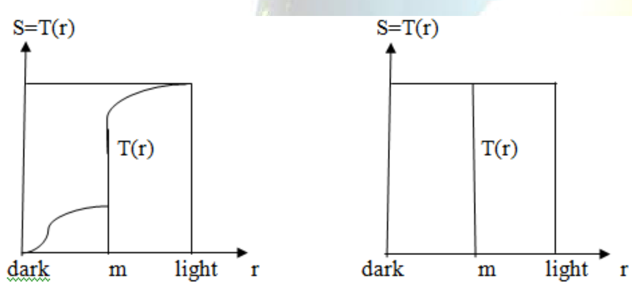

Fig. 2. Gray-level transformation functions for contrast stretching and binarisation

The enforced piecewise linear contrast stretch operation target grayscale pictures, with bit depth of eight bits per element, wherever the minimum and most element values are 0 and 255. The essential transformation is shown figure where the horizontal axis represents the input value and also the vertical axis represents the output value. As seen, there are 3 line segments want to rework associated with the input pixel value in order to ensure the output pixel. Explicit otherwise, the transformation from the input pixel value to the output pixel value is via the piecewise linear transformation is shown within the figure.

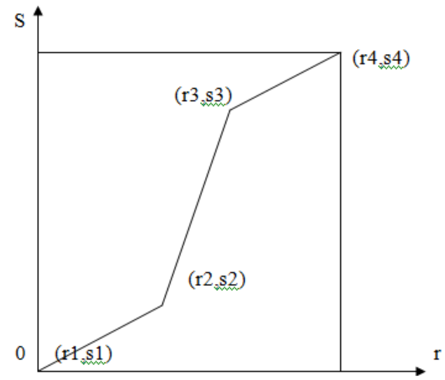

Fig. 3. Piecewise linear approximation of contrast stretching

The parameters specifying the contrast stretch mapping are the four values r2, s2, r3, s3, which determine the position of the intermediate straight line segment. Modifying any of these four values modifies the contrast stretch transformation. The values of r1, s1, r4, s4 are fixed.

III. RESULT AND DISCUSSION

As video is given as an input the software used here is the MATLAB R2013a. The extension of the input video should also be indicated in the program. The output video is displayed in the movie player of the MATLAB. The input video given is displayed in movie player of MATLAB which is shown in figure 4.

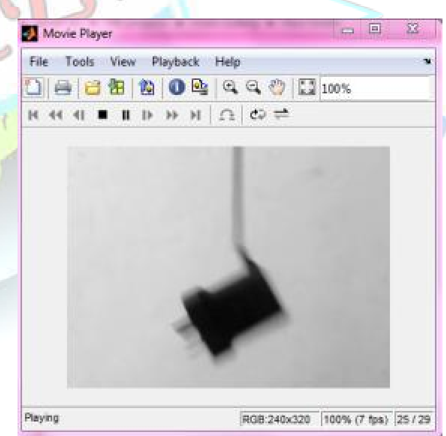

Fig. 4. Input video

The reason for gray scale conversion is , only with the gray scale video the piecewise linear contrast stretch is applicable. Once the video is converted to gray scale, the gray scale image level ranges from 0 to 255 it is then processed to get normalize image. For normalized image the level is 0 and 1 either black or white shown in figure 5.

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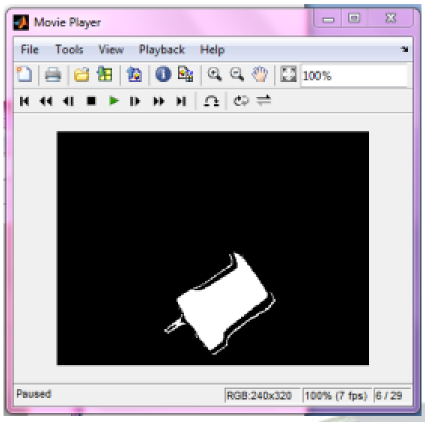

Fig. 5. Normalized video

After the video is get normalized by frame by frames then the next step involves the contrast stretching. This approach enhances the image quality.

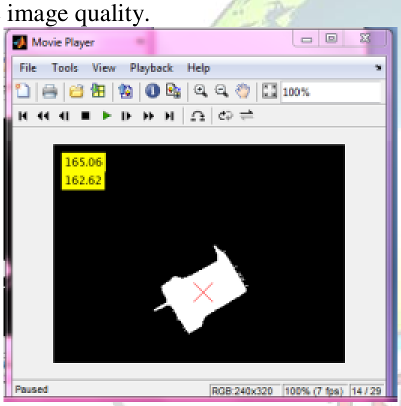

Fig. 6. Enhanced video with centroid

The bright pixel becomes brighter and the dark pixel gets darker. When the contrast of the image is enhanced the centroid calculation becomes easier. The next step involves the marking of centroid after the contrast stretching shown in figure 6.

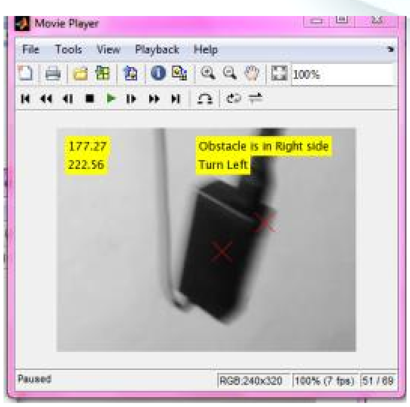

Fig. 7. Alert message for left turn

Based on the command for safe turn the robot changes its direction. Thus the Image segmentation with piecewise linear contrast stretch is done for obstacle detection and blob analysis is made to determine the direction for safe navigation.

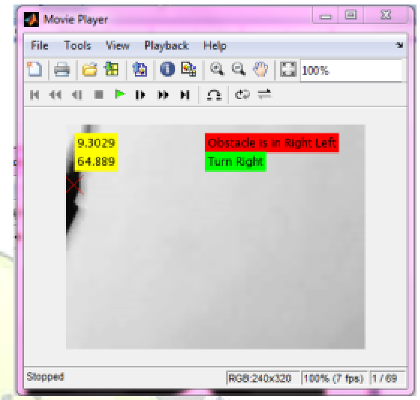

Fig. 8. Alert message for right turn

IV. CONCLUSION AND FURURE WORK

The aim is to find an obstacle and avoid the obstacle. The experimental results prove that the planned algorithmic rule is appropriate for period systems. A necessary warning message is issued once the measure exceeds limit. From the results it is concluded that the given methodology used for obstacle (object) detection is for each static and dynamic obstacles. With the utilization of the methodology we will simply sight the obstacle and notice the trail that may be used for several application like image tagging, mobile path designing, indoor navigation with numerous application, etc. Future work includes the implementation of hardware.

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