AI based steering of Robot with Zero Collision by Using Image Segmentation

J.Jasper Gnana Chandran[1], Tharani Vimal[2]
Professor& Head[1], Department of Electrical and Electronics Engineering[1]
Associate Professor[2], Department of Information Technology[2]
St.Peter's College of Engineering and Technology[1,2],Chennai,Tamilnadu
jasper_fx@yahoo.co.uk[1],tharanimadhan@yahoo.com[2]

Abstract

The robot in the working environment should be provided with good vision for detection and avoidance of the obstacle present in the path. The proposed method called Pixel Based Image Segmenter (PBAS) is an image segmentation technique that follows a nonparametric background modeling paradigm which segment and extract the details about the obstacles from the static background. In the PBAS, the background update is based on a learning parameter and the foreground decision depends on a decision threshold. The Fire Bird V robot is used here to implement the proposed approach i.e. the PBAS segmentation algorithm. The camera mounted on the robot senses the obstacles present in the vicinity. The video sequence is transmitted to the PC in which the segmentation process is carried out. The segmentation algorithm is applied on the image frames of the video sequence for segmenting the dynamic foreground from the static background. The decision making is performed over time to choose an alternative path for avoiding the obstacle. Thus the proposed method can effectively segment the image frames for detecting the obstacles in the vicinity of robot and the decision making can be carried and finally it makes the direction better for avoiding the obstacles by providing the details about the unknown surface.

Keywords: Pixel Based Image Segmenter, Fire Bird Robot, Segmentation Process, Decision Thershold

1.INTRODUCTION

The robot varies widely with researchers, engineers, and robot manufacturers. However, robot is accepted and used in many industries in its working environment. Robots are expected to have higher mobility and dexterity than the traditional machine tools. They must have the ability to work in a large reachable range, to access crowded places, handle a variety of work pieces, and perform complex and flexible tasks. The origin of industrial robots is in two preceding technologies: numerical control for machine tools, and remote manipulation which generate control actions based on stored data and performs a task at a distance respectively. It is used in environments where human workers cannot access easily or safely, e.g. for handling radio-active materials, some deep sea and space applications. Here operator's motion is transformed into electrical signals, which are then transmitted to the mechanical arm to cause the same motion as the one that the human operator performs.

The research [10], [12] in the area of robot navigation involved only the single features such as edge/texture to detect objects which suffers from poor accuracy while detecting objects, since it employs single feature. As reported in [10], edge detection based path planning using SOBEL operator assumes the edges formed in the images are due to straight lines and further assumes that the images are symmetric which will be a serious drawback of this technique. Further that has been experimented in a closed room environment, which does not provide the accurate results in external scenario.

The authors in [12] have segmented the images into road and non-road type classification using Gaussian mixture model (GMM), those parameters are trained by selecting a set of images with large variation in the greyscale values of the road. While training the GMM parameter the Gaussian distribution with least overlapping between road and non-road regions is considered. Once the GMM parameter is trained, these parameters are not automatically updated and thus human intervention in choosing the Gaussian distribution parameters to segment the image which is a major drawback in this algorithm.

To detect the motion of objects in a old film sequences [14] uses adaptive Gaussian mixture models. In this, the author has accounted for changes in the background by updating the GMM parameters throughout the video sequence. The learning rate is the reciprocal of the current frame number. The drawback of this method is for larger duration video sequences and the time required to learn changes in the background is high.

The recent research in [09] used the image segmentation along with edge features to navigate the robot autonomously over a homogeneous surface without any collisions during its motion. They used a monocular camera to sense obstacles which are present in the vicinity of the robot. The edges are identified with the help of a threshold which is dynamically computed. The adaptive GMM of the captured image segments the image into 2. They are

1. Floor information
2. Non-floor information

During the navigation, the GMM parameters are trained. After completion of the training period, the algorithm used both edge information and GMM classified output to navigate the robot without collisions. Since the designed algorithm employed more features compared to the similar works carried out in the past, the motion control of the robot becomes dynamic and robust.

Based on the fuzzy ART neural architecture [11], an autonomous mobile robot is operated on an unknown environment. The sensor network embedded on robot [07] computes the direction within the network using the value iteration. The communication is achieved through the Zigbee protocol [08], [13], which signifies the position of the mobile robot. They utilized the vision sensor for the purpose of landmark recognition. The Zigbee with mobile robot has enhanced the robot’s perception ability and the control over its environment.

The digital image processing techniques can be utilized for extracting the most important information from the environment to solve the problem of mobile robotic platform. The localization and mapping structures integrated the probabilistic approach and the navigation process together. The location and the shape of the object in each frame are required for tracking purposes.

2.PROPOSED METHOD

PBAS mechanism is meant for static object detection and is rooted on consecutive frame differencing. This technique provide license to pick out the halted foreground objects (e.g. a car at the traffic) from false detections (shadow, as ghosts) using edge similarity.

Pixel-Based Adaptive Segmenter (PBAS) treat the values as adaptive state variables, and not as parameters. The PBAS follows a non-parametric paradigm, thus it can dynamically change over time for each pixel separately. The array of recently observed background values models each and every pixel Xi. This method consists of many components which are illustrated as a state machine. The decision block is based on the current image and a background model B(xi) and it decides for or against foreground. According to the pixel threshold R(xi), the decision is made in our model. In order to allow for gradual background changes, the background model has to be updated over time. This update depends on pixel learning parameter T(xi). Now, the crucial aim of our PBAS approach is that both of the pixel thresholds dynamically change based on an estimate of the background dynamics.

This proposed approach let the improvement in the performance of the method for sequences with the stopped objects. In the PBAS segmentation, the system should have the ability for processing 50 frames with a resolution of 720 × 576 pixels per second. This is the reason why the immobility of each connected component is determined, as well as the object edges are compared with those present in the current frame. Both parameters provide feedback for the PBAS module and it differentiates the stopped objects from ghosts.

The Pixel Based Image Segmenter (PBAS) is an image segmentation technique that treads on the heels of a nonparametric background modeling paradigm which segment and extricate individual detail about the obstacles from the fixed background. In the PBAS, as said above, the background update ground on learning parameter and the foreground decision pivot on decision threshold

2.1Operation of proposed method

The proposed method consists in the total of 6 updates and settings. They are included as follows,

2.1.1. Decision Making

The decision making involves two parameters. Namely, distance threshold and minimum number. This decision process takes the input image and compares it in some manner with the background model.

1. The distance threshold $R(xi)$ is defined for each pixel one by one and it can change dynamically(constant changes); and
2. The minimum number #*min* is a fixed global parameter.

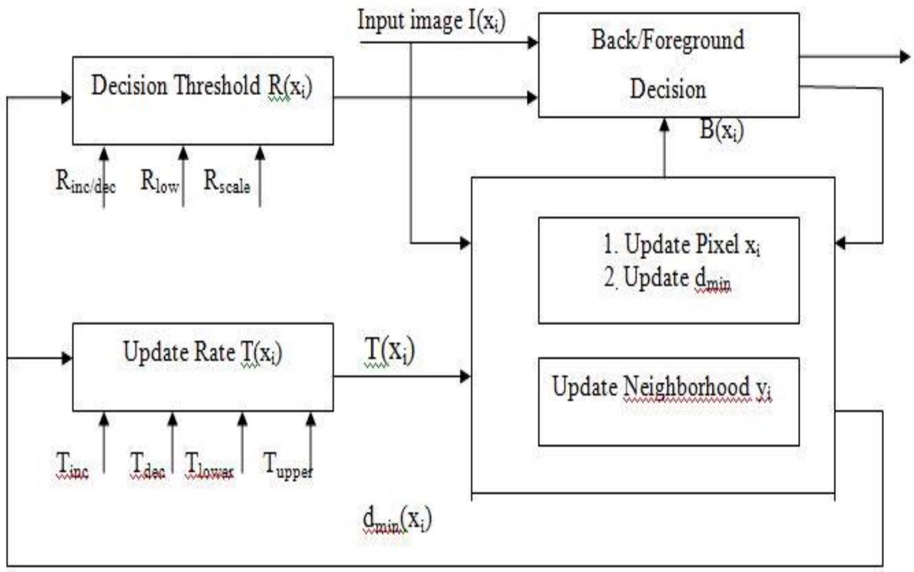

Fig. 1. Pixel Based Adaptive Segmenter

2.1.2 Update of Background Model

Depending on the update parameter $T(xi)$, every foreground object will be ”eaten-up”(dominate) from the outside after a certain time. Updating the background model is extremely important in order to account for the background changes, such as lighting changes, shadows and moving background objects such as trees. This means that certain foreground pixels at the boundary will gradually be considered into the background model. The advantage of this variable is that erroneous foreground objects will quickly vanish.

2.1.3 Update of Learning Rate

Depending on the learning parameter T(xi), every object in the image will be merged into the background. To make the problem less, there is a need to introduce a (second) dynamic controller for background model T(xi), such that when the pixel is background, the probability of background learning gradually gets increased and when the pixel is foreground, the probability of background learning slowly decreased.

2.1.4 Implementation Details

The input image $I(xi)$ is a three channel color image practically. In the PBAS approach, each channel is treated independently and its algorithms are all implemented in three parallel threads. And finally, all the three segmentations are ORed in a bit wise manner to generate the final segmentation $F(x_i)$ results.

2.1.5 Parameter Settings

The tunable parameters have to be adjusted for optimal system performance.

1. *N* is the number of components of the background model. At N = 35, the performance gets saturated.
2. #min is the number of components that should be closer than *R*(*xi*) for setting the pixel as background. An optimum is found at #min = 2.
3. $R_{inc/dec}$ is the rate at which the controller regulates the decision threshold *R*(*xi*). For lower regulation, camera jitter and dynamic background seems to perform optimally. $R_{inc/dec} = 0.05$.
4. R_{lower} is the lower bound of the decision threshold. Setting it too low leads to ghosts and false positives, too high will lead to misses. $R_{lower} = 18$.
5. R_{scale} is the scaling factor in the controller for the decision threshold. It controls the equilibrium value, such that low values lead to low precision, while high values lead to low recall. Rscale = 5.
6. T_{dec} is the rate at which T(xi) is decreased, if xi is the background. (i.e the rate at which the probability of background update is increased). $T_{dec} = 0.05$.
7. T_{inc} is the rate at which T(xi) is increased, where xi is foreground (i.e the rate at which the probability of background update is decreased). Because a priori, foreground is less likely than background, a lower adaptation for foreground is beneficial. $T_{inc} = 1$.
8. T_{lower} is the lower bound of T(xi). Quite constant in the tested range. In case of intermittent objects and camera jitter, there is a slight decrease for high values. $T_{lower} = 2$.
9. T_{upper} is the upper bound that should not be chosen too low. Values higher than 200 lead to good results. Therefore minimum update probability of 1/200 is required. $T_{upper} = 200$.

2.1.6. Post-Processing With Median Filter

As the PBAS method is a pixel based method, it makes the segmentation decision independently for each pixel. The resulting output can be from spatial smoothing, which is done using simple median filtering.

3.Evaluation

Our method performs best for the categories baseline, shadow and thermal. The result of the PBAS is compared to several state of the art methods. It can be seen that at the chosen optimal operating point, PBAS greatly outperforms.

Table 1: result of the PBAS is compared to several state of the art methods

SCENARIOS	RECALL	SPECIFICITY	FPR	FNR	PBC	F1	PRECISION
Baseline	0.9594	0.9970	0.0030	0.0021	0.4858	0.9242	0.8941
Camera Jitter	0.7373	0.9838	0.0162	0.0100	2.4882	0.7220	0.7586
Dynamic Background	0.6955	0.9989	0.0011	0.0045	0.5394	0.6829	0.8326
Intermittent Object Motion	0.6700	0.9751	0.0249	0.0222	4.2871	0.5745	0.7045
Shadow	0.9133	0.9904	0.0096	0.0039	1.2753	0.8597	0.8143
Thermal	0.7283	0.9934	0.0066	0.0104	1.5398	0.7556	0.8922
Overall PBAS	0.7840	0.9898	0.0102	0.0088	1.7693	0.7532	0.8160

4. Outlook and Conclusion

We have presented a highly efficient background modeling method. The basic idea behind this method is to use two controllers with feedback loops for both the decision threshold and the learning parameter. Tuning the resulting parameters leads to outperform the state of the art.

5. Result and Discussion

The software programming is done to segment the images and to perform decision making. Here we utilized the MATLAB software to do so. Any video files of extension .avi, .mp4 is given as the input to the PBAS segmentation coding. The Fig.2 shows the input video file.

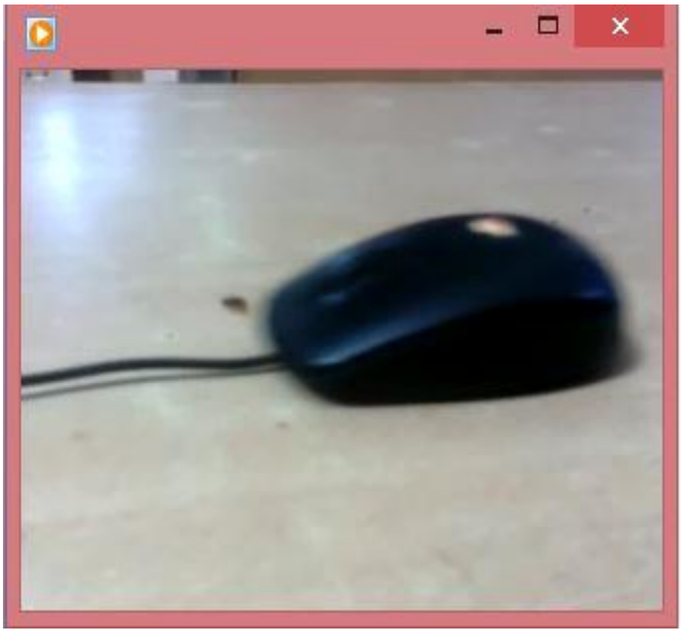

Fig. 2 Input Video File

The PBAS segmentation is performed for the given input file (Fig.2). The PBAS Segmentation segments the region of interest, that is, it segments the objects and edges by them knowing through the highest threshold value. After the pre-processing and segmentation process, the image will be shown as the gray scale or binary images. The Fig.3 shows the PBAS segmentation.

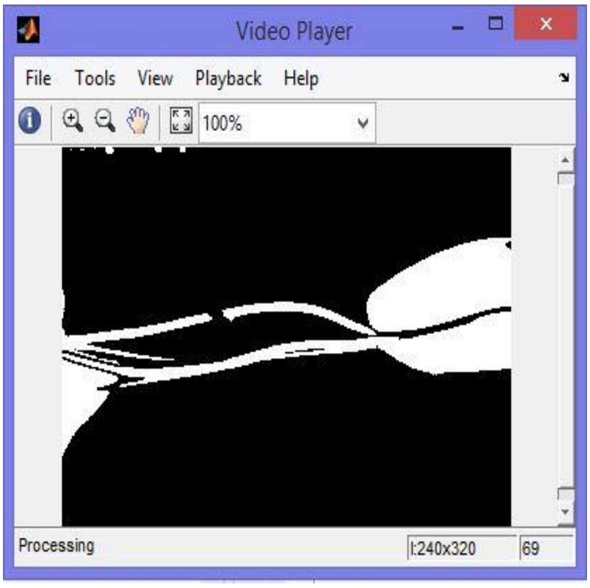

Fig. 3 PBAS Segmentation

The decision making follows the segmentation process. Here the RGB image of the object will be produced with the direction indication. The RGB is shown at the output for the human perception and for easy understanding. The decision making is performed and the object is detected as in Fig.4.

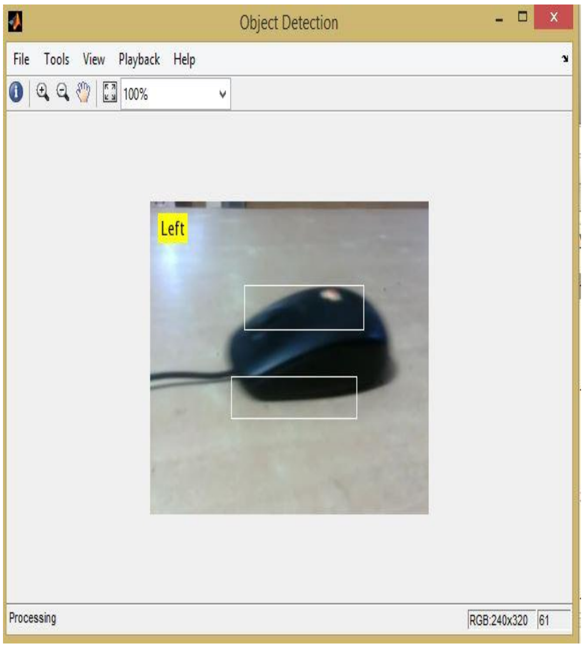

Fig. 4 Object Detection

6. Conclusion & Future Work

The vision of robot plays a vital role in its working environment. As the sensor based robot could not provide the detailed information about the vicinity, we have gone through the segmentation which gives the full details about its surrounding for navigation without any collision. The proposed method called Pixel Based Adaptive Segmenter (PBAS) is an image segmentation technique that follows a nonparametric background modeling paradigm which segment and extract the details about the obstacles from the static Background. In the PBAS, the background is updated based on a learning parameter and the foreground decision depends on a decision threshold. And the segmentation is followed by the decision making to direct the robot by avoiding the obstacles.

Further in future, the proposed PBAS segmentation algorithm is to be implemented on the Fire bird V robot which captures the video by using the camera mounted on it and sends the video to PC via the Zigbee module.

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