The Development of the Obstacle Detection Monocular TV System in Virtual Environment for a Mobile Robot

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***Abstract*—The article discusses the developed algorithm of the obstacle detection with using monocular TV system. The essence of the algorithm is video analysis from TV camera. System detects pixels of each frame, which has different color from the underlying surface. The article deals with the image processing of one frame. The algorithm of color models accumulation describes the underlying surface. Virtual environment shows mobile robot model.**

I. INTRODUCTION

Recently there has been increasing use of high growth of mobile robots in life. Statistics show very popular robots used in house conditions [1].

The obstacle detection is an important task for mobile robots. Most of the robots rely of sensors which measures the distance to obstacles. Nowadays the most popular: ultrasonic sensors; laser range finders; radars; stereoscopic vision; methods based on optical flow; methods based on the depth of focus [2]. Since these sensors measure distance between the robot and an obstacle. They can be used for obstacle detection and obstacle avoidance. But none of these sensors is perfect. Ultrasonic sensors are cheap, but they have small angular resolution and there is the problem of mirror effect. Laser range finders and radars provide higher resolution, but they are more complex and expensive.

For the proper functioning of the method based on the depth of focus the textured surface is required.

Methods of stereoscopic vision and optical flow require large computational cost [3]. In addition to their individual disadvantages, all these methods are bad for detecting small and flat objects lying on the ground.

Reliable detection of such obstacles requires high precision measurements and consequently accurate calibration system. Also, these methods are unable to distinguish differences between different types of surfaces. This mainly concerns the outdoor robots where these methods cannot distinguish pavement from the surrounding grass surface in most cases.

Despite the fact that the measuring distance sensors are bad for detecting small objects and different types of underlying surface, they generally can be found with using of the color information [4].

For example, in their work Fazl-Ersi and Tsotsos propose to use the method of stereo processing of images. Using this method the similar pixels in appearance are combined to a single cluster. Special points are introduced on the left and right images and then for each pair of matched points, its symmetric transfer distance from the ground homography is computed [5].

In the article [6] for obstacle detection authors use laser range with monocular video system. They use the laser data whenever it is available to train image classifiers that are consequently used for traversability estimation during navigation.

In the article [7] authors iteratively estimate the ground plane based on the detected flow. From the floor features, they then train visual classifiers to label the traversable area in successive camera images.

Viet and Marshall in the article [8] propose the use of histograms for the separation of obstacles and the floor. Their robot has two the sonar for improvement.

The described method in this paper is opposed to methods outlined in that it uses the accumulation of color information, thereby allowing the robot to adapt to changing light conditions.

The purpose of the work is the development of computer vision algorithm for obstacle detection by color attributes of underlying surface, which operational in changing external conditions using a single TV camera.

II. THE OBSTACLE DETECTION ALGORITHM

Fig. 1 shows the proposed system. The essence of the algorithm is the system detects pixels of each frame, which has different color from the underlying surface.

The algorithm works in real time under different conditions and provides the output high-resolution image. The system is also easily trained [9].

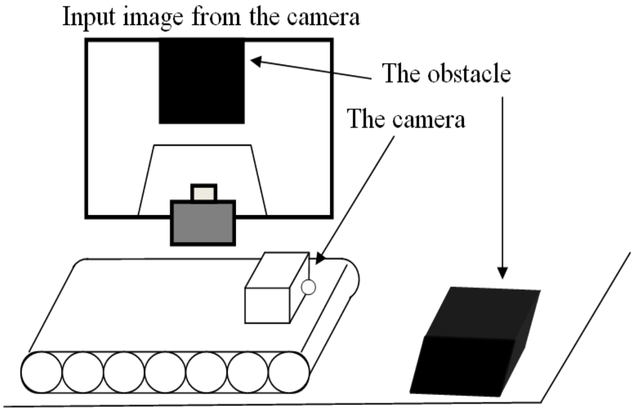

Fig.1.The proposed system

A. The conceptual description of the algorithm

The obstacle detection system is based on solely on the appearance of the single pixels. The system classifies the pixel as an obstacle if it differs in appearance from the ground.

The method is based on three suppositions that are reasonable for different internal and external conditions:

1) Obstacles differ from the ground by their appearance.
2) The ground is relatively flat.
3) There are no overhanging obstacles.

The first supposition lets us distinguish obstacles from the ground and the second and the third ones let us to estimate the distance between the detected obstacles and the camera.

The pixels classification representing an obstacle or the ground can be based on a number of local visual attributes, such as intensity, color, texture and boundary. It is important that the selected attributes provide information that is enough to system reliably operating in different environments. Selected attributes should also require little computational resources that the algorithm can run in real time and the removal equipment is not required.

The less computing resources required by the system the greater the number of frames processed per second and the faster the mobile robot can move safely.

The best way to meet these requirements is using color information as a basic feature. A color provides more information than the intensity. Compared with texture, colors are more localized properties and can be calculated much faster.

Systems that rely solely on the information on the boundaries may only be used in environments with untextured floor as environments Shaky and Polly [10]. Also such system worse distinguish shadows from obstacles compared to systems based on color information.

For many applications it is important to estimate the distance from the camera to a pixel representing an obstacle.

Monocular vision is a common approach to assessing the distance lies in the assumption that the ground is relatively flat and there are no hanging obstacles. If these two assumptions are correct then the distance is a monotonically increasing function of the height of pixels in the image [11].

Estimated distance to the base of any obstacle is correct but the higher the barrier rises above the earth the more overrated the distance. The easiest way to solve this problem is to use only obstacles pixels that lie below in each column of the image.

A more complex approach consists of groups of obstacles pixels and search the shortest distance to the entire group [12].

B. The technical implementation of the obstacle detection algorithm

Fig. 2 shows the block-scheme of processing of one frame.

To start work we need to receive an incoming image (block 1): it can be video sequence or just a static image.

The next step is image filtration (block 2). Filter is a usual scheme of decimation and interpolation (lower pass filter implementation, odd information removal, signal enhancing by blank readings and interpolation using lower pass filter) [13]. The usage of this filter is conditioned by the fact that after its implementation the areas similar in color will be supremely homogeneous and it is essential for the clustering tasks.

The filtered image is converted to the HSV color system (block 3). The way this conversion influences the algorithm considered in [14].

For the analysis of the underlying surface with no obstacles in the image the trapezoid is drawn (block 4).

The trapezoid area is divided into 3 clusters (block 5) using the K-means algorithm [15]. On the basis of each cluster we create a taught model (on its basis the system will be taught for the following environment exploration; block 6). This model will include:

1) a number of trapezoid pixels that got into the given cluster;
2) the percentage of the pixels of the cluster in relation to the total number of pixels;
3) cluster covariance matrix;
4) the mean value of the pixels of the cluster by corresponding color components.

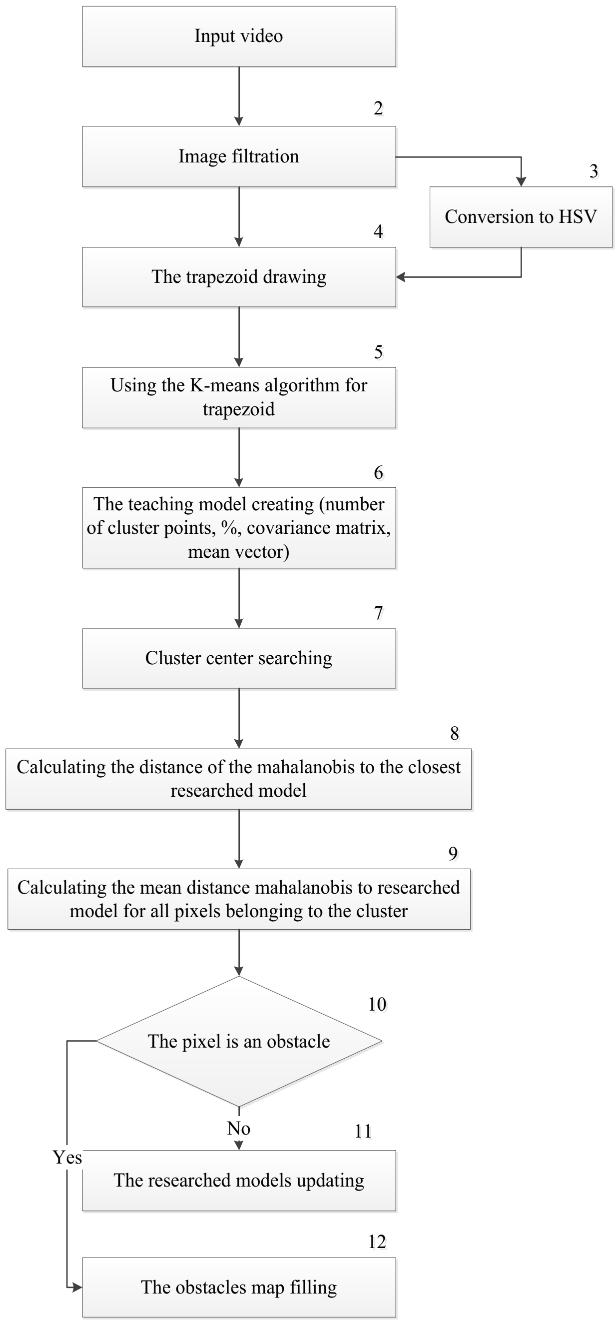

Fig. 2.Block-scheme of the processing of one frame of video

For all image pixels we calculate the mahalanobis distance d to the closest researched model (block 8; researched model is a color model of the underlying surface that has been accumulated during several frames) by the formula:

$$d(\vec{x},\vec{y}) = \sqrt{(\vec{x}-\vec{y})^T S^{-1}(\vec{x}-\vec{y})}, \quad (1)$$

where $\vec{x}$ – compare pixel coordinates in the color space, $\vec{y}$ – meant cluster pixel coordinates in the color space, S – covariance matrix of the cluster.

For each cluster of the trapezoid we calculate the mean mahalanobis distance d' for all pixels belonging to the cluster (block 9).

Then the pixels forming obstacles are marked. If the following condition is fulfilled the pixel is considered underlying surface otherwise is an obstacle:

$$d - d' < \tau, \quad (2)$$

Then the researched models are renewed using teaching models. Fig. 3 shows the renewing algorithm.

In the renewing algorithm first of all there is a removal of all old models (those that there are more than 30 frames).

Then the algorithm moves all the teaching models and compares with the researched models. If the models are similar they are combined and “weight” of the model is increased else the system replaces one of the older models.

Models use the coefficient S for models comparison, calculated as follows:

$$M_D = M_T - M_R,$$
$$C_D = C_T - C_R, \quad (3)$$
$$S = M_D^T C_D^{-1} M_D$$

where M_T – mean vector for the teaching model;
M_L – mean vector for the researched model;
C_T – covariance matrix for the teaching model;
C_L – covariance matrix for the researched model.

The system recalculate parameters of the current model (the researched model) when the current model is updated.

$$M_{NR} = \frac{M_T N_T + M_R N_R}{N_T + N_R},$$
$$C_{NR} = \frac{C_T N_T + C_R N_R}{N_T + N_R}, \quad (4)$$

$$N_{NR} = N_T + N_R$$

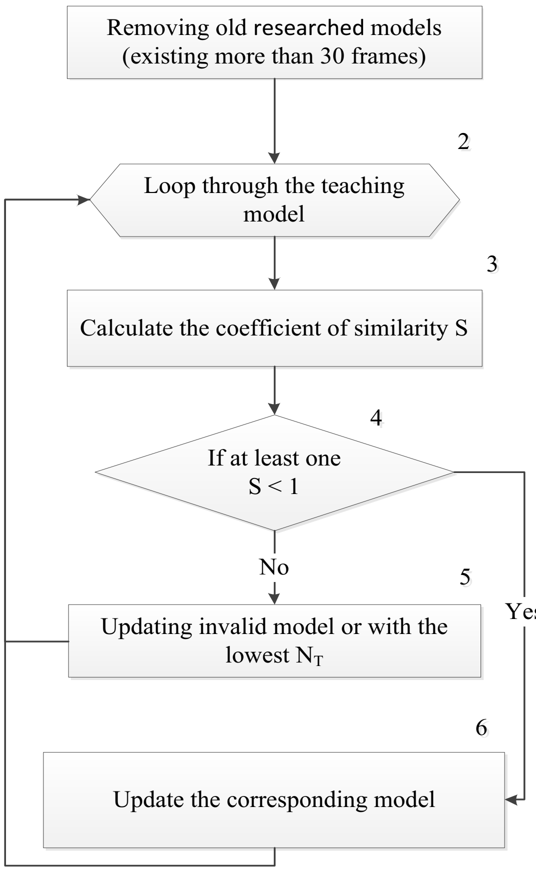

Fig. 3.The renewing algorithm

where N_T – the number of the teaching model pixels;

N_R – the number of the researched model pixels;

M_{NR} – a new mean vector;

C_{NR} – a new covariance matrix;

N_{NR} – a new number of points.

The research of the algorithm presented in the article [16].

III. THE VIRTUAL ENVIRONMENT

The main purpose of the created virtual environment is research of computer vision algorithms without using of hardware. It is possible to implement and to test such algorithms.

Basic structural part of the project is a mobile robotic platform (hereinafter MRP). For its effective functioning requires not only computer vision algorithms, but also behavioral strategies that increase the autonomy of the robot and reduce the burden on the operator giving him the opportunity to solve other problems in addition to manual control of the mobile robotic platform. Modeling behavior strategies MRP is another task that successfully solved in the virtual environment. Realized behavior strategy (model) of the MRP passing the test will be used by real robot (Fig. 4).

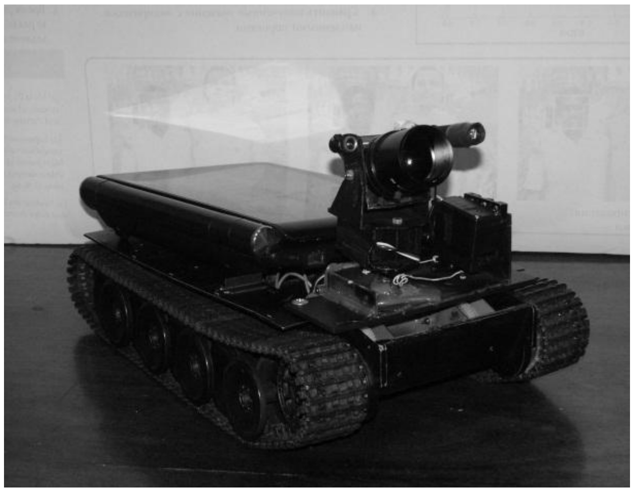

Fig. 4.Appearance of mobile robotic platform

A. Mobile robotic platform model in a virtual environment

The MRP is a mobile tracked base with autonomous power supply and set-board computer, a digital video camera, as well as wireless transmission of video and telemetry data.

At this stage in specialized virtual environment implemented virtual three-dimensional model of the MRP as a tank on the tower of which installed a video camera that produces pictures in the visible range (Fig. 5).

Fig. 5.The image from the camera in the virtual environment

"Tank" is a conventional name. In fact the barrel of the tank is identified with the optical axis of the camera, so it is not drawn in the virtual environment. Currently image obtained from the camera is the only one available source of environment data for the virtual model of MRP. The processing of these data should allow MRP to change its speed and direction of motion.

Control signals for the motion of real MRP are two numbers from the output of a control chip, operation of which is modeled in the virtual environment. The module of numbers defines the power of left and right engines. The sign indicates the direction of rotation (forward or backward). In addition digital video camera installed on the MRP is equipped with servo drives to rotate in two planes. They perform a camera rotation with constant angular velocity. The control signal for them is the value of the rotation angles. Thus any command of operator and any MRP decision taken on the basis of data of the processing computer vision system is implemented as a combination of numbers. This numbed are engine power and rotation angles of the camera.

In the virtual environment, motion control for MRP model is performed by means of operations (see. Fig. 6):

1) Move (x) - moving to x conventional units along the axis O'X 'object
2) Turn (S) - turn on S degrees around the axis O'Y'

Also similar to the rotation of the real MRP computer vision system camera in the virtual environment has the ability to rotate "tower" of platform with a constant angular velocity (Fig. 7).

Fig. 8 shows the correspondence between the control commands of real MRP and its virtual model.

$$x = \frac{\Delta x_{left} + \Delta x_{right}}{2}$$
$$S = \frac{\Delta x_{right} - \Delta x_{left}}{D} \quad (5)$$

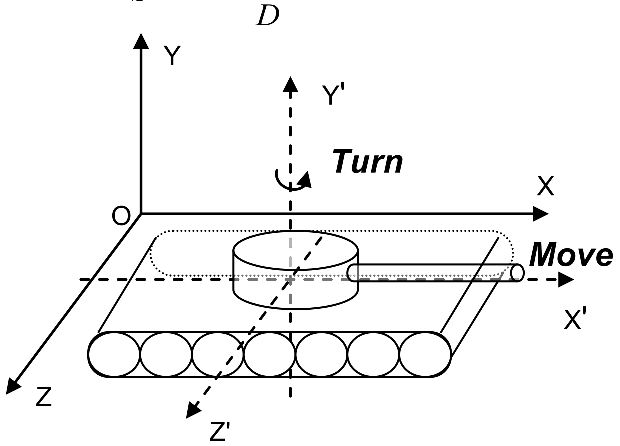

Fig. 6.The movement patterns of the MRP in the virtual environment: XYZ - world coordinate system, X'Y'Z' – coordinate system of MRP

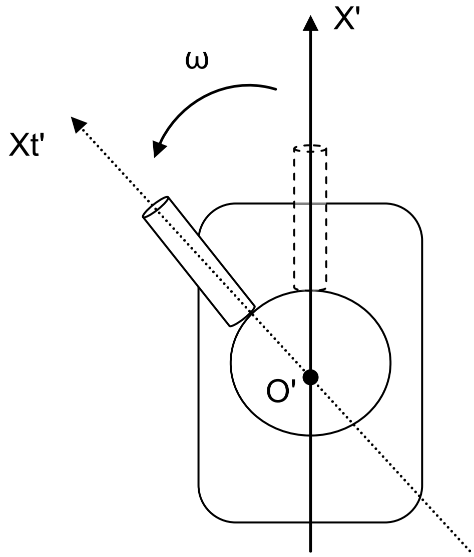

Fig. 7.Rotating tower platform. There is ability to rotate the camera in a horizontal plane (O'Xt'- optical axis of the camera) in the virtual model by analogy with the real MRP

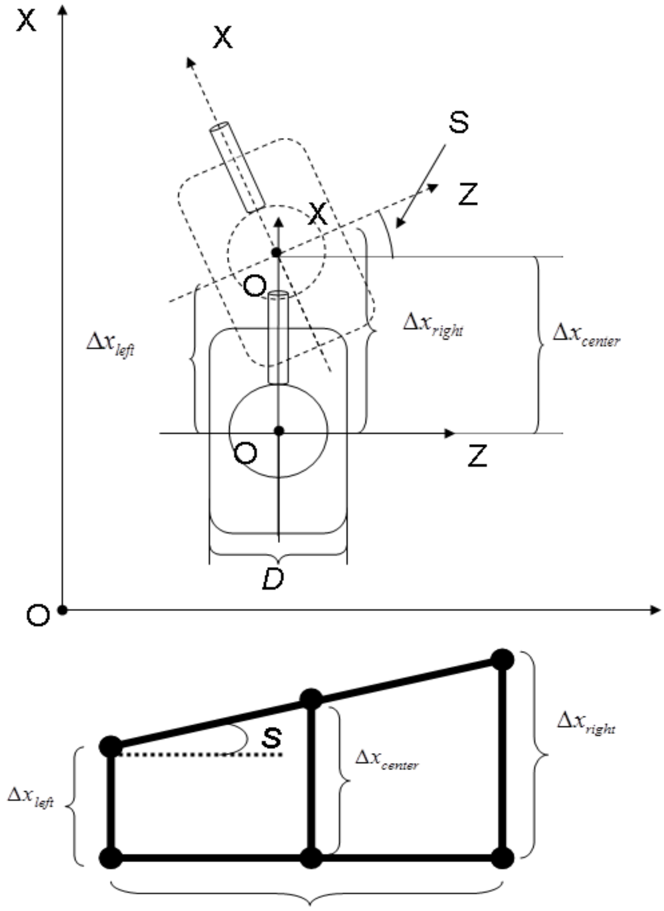

Fig. 8.The connection between the real and virtual MRP commands MRP: an example of changing the position MRP (top); geometric constructions (bottom)

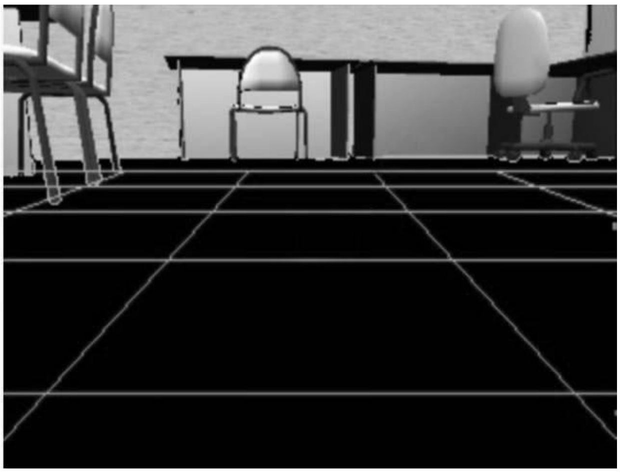

Fig. 9.The superimposing of a bottoming surface model

B. Obstacle avoidance algorithm

At the output of the algorithm is an image in which the black labeled obstacles. Then this image is superimposed a grid representing horizontal surface (Fig.9). The grid is drawn on the basis of knowing of camera position.

Then each square of the grid are analyzed for getting into the pixels obstacles. If there are a lot of pixels that represent obstacles, this square is considered as prohibited area. The result is a map of the area. Navigator is implemented in the virtual environment for the navigation platform in the space. With the help of this navigator it is possible to pave the way for the MRP. Route of the platform and vector along which the movement should be performed are calculated using the wave algorithm on the basis of endpoint knowledge and obstacles location. Fig. 10 shows example of map. Thus, even if some of the table's pixels would have been highlighted as an obstacle, they would still not considered as interest because only pixels falling within the plane model are interested.

6				
X	5			X
X	3	4		X
X	1	2		X
X	X	0	X	X

Fig. 10.Formation of obstacles map. X - area representing obstacles. Numerals indicate stages of movement MRP

IV. CONCLUSION

This paper presents an algorithm for determining the bottoming surface on the basis of the color image analysis. It should be noted that this algorithm can be applied to aircraft tasks which must separate sky from the rest in the image. The algorithm can operate in real-time using only one camera in modern computers. Color models are used for clustering pixels. Color models information can both maintain and update when moving mobile robotic platform and be given initially. It is also possible to combine these methods that can improve solution of the problem of free movement in a given room.

Implemented virtual environment allows debugging of computer vision algorithms without a real platform. The research of the algorithm in the virtual environment has shown that the algorithm works well with inhomogeneous surface in the changing light conditions. Implemented obstacles avoidance algorithm tested in the virtual environment and prepared for introduction in the real mobile robotic platform.

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