Color-Image Classification using MRFs for an Outdoor Mobile Robot

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ABSTRACT

In this paper, we suggest to use color-image classification (in several phases) using Markov Random Fields (MRFs) in order to understand natural images from outdoor environment's scenes for a mobile robot. We skip preprocessing phase having same results and better performance. In segmentation phase, we implement a color segmentation method considering I_3 color space measure average in little image's cells obtained from a single split step. In classification phase, a MRF was used to identify regions as one of three selected classes; here, we consider at the same time the intrinsic color features of the image and the neighborhood system between image's cells. Finally, we use region growing and contextual information to correct misclassification errors. We have implemented and tested those phases with several images taken at our campus' gardens. We include some results in off-line processing mode and in on-line execution mode on an outdoor mobile robot. The vision system has been used for reactive exploration in an outdoor environment.

Keywords: Color image classification, color space, Markov Random Fields, mobile robot and outdoor environment.

1. INTRODUCTION

Computer vision is widely used as a perception subsystem of an outdoor mobile robot, the robot needs to understand and recognize what it sees in order to perform navigation tasks in outdoor environments. Mostly, three phases of a recognition system are: preprocessing, segmentation and classification. Preprocessing helps to filtering the original captured image. Image segmentation refers to the partition of an image into a set of disjoint regions that cover it; each region should be uniform and homogeneous with respect to some features, such as color, texture, dimension, etc. Classification allows us to recognize each object or region as being of one particular type or class.

The work developed in this paper is the first step of a sensor-based outdoor mobile robot navigation project. This will be a part of the autonomous vision-based navigation system that will combine vision with other sensors. Here, we focus on natural images from the unstructured scenes taken in outdoor environments in our institution. Some preprocessing methods were tested (color reducing, smoothing, and blurring), but they take significant amount of time and no better results were obtained; therefore, we skip the preprocessing phase and we segment the original image. We decide to use color segmentation; during this, we perform a first split of the image in homogeneous size regions that we call cells and we select the color space measure to use. After that, we perform the image classification using a probabilistic method called Markov Random Fields (MRFs). We have defined three significant classes: 'grass', 'shrub or trees' and 'sky'. Misclassification errors were corrected using a region adjacency graph (RAG) to identify invalid adjacency regions based on contextual information.

This paper is structured as follows: section 2 briefly reviews related work, section 3 describes our methodology, section 4 describes how to use the visual information to explore the environment, section 5 shows some experimental results, and finally in section 6, conclusions and future work are discussed.

2. RELATED WORK

Image understanding in natural environment scenes is a difficult task because the great variety and complexity of images, therefore, there no exist a universal technique for segmentation and classification. Color regions segmentation and probabilistic classification have been widely used to understand natural scenes in outdoor environments. In [1], they segment with hue color feature and perform Bayesian classification, but they use four qualitative constraints (shape, dimensions, position and orientation) instead of one that we use (position) for misclassification errors. In [2], they are using material and illumination information in color images and perform Bayesian classification. [3] and [4] segment using the three HSI (hue, saturation, intensity) color features and a fuzzy region growing algorithm, but they need to do a previous smoothing in RGB (red, green, blue) format. [5] works with texture information from histograms of RGB and intensity, and they use a k-means method for classification. Neither of them works with the same color segmentation feature and with the same classification method that we used.

Some other works use MRFs for classification. For example, in [6], they apply MRFs, but for indoor environments' scenes. Others have joint segmentation and interpretation techniques for natural outdoor images using MRFs, like in [7, 8, 9]. But, these three works don't use color information, only gray level. We used Modestino's MRF approach in [7] for classification, but Modestino et. al. only tested with some synthetic images and simple aerial real images. Dugad and Desai (in [8]) use HMM (Hidden Markov Models) for constructing the MRFs cliques functions, and also only tested with aerial images. In [9], they use too much features: average gray level, area, perimeter, compactness, variance, contrast, etc.

All previous related works do not present processing times. Other domain of works includes the color image understanding in outdoor environments for mobile robot navigation tasks [10, 11, 12, 13, 14, 15]. In [10], they work with an image resolution of 64 x 64 pixels performing three segmentation methods (considering edges, RGB and HSI) that later are fused in one;

this is for obstacle detection and obstacle avoidance, but they have problems with shadows and reflexes.

Our current system is most closely related to Murrieta-Cid et al. [13, 14, 15] using the I_1 I_2 I_3 color space; from that space they use I_2 and I_3 color measures for performing the color segmentation instead of one that we use (I_3). They perform Bayesian classification considering more features (mean, variance, energy, entropy, contrast, homogeneity) than we are considering (mean and variance for a MRF classification). Finally, we also add contextual information for correcting misclassification errors.

3. GENERAL APPROACH

In Fig. 1, a diagram representing all phases of our approach is shown. At top, there are all phases that allow us to understand the image. At bottom, we show the acquisition of previous knowledge phase.

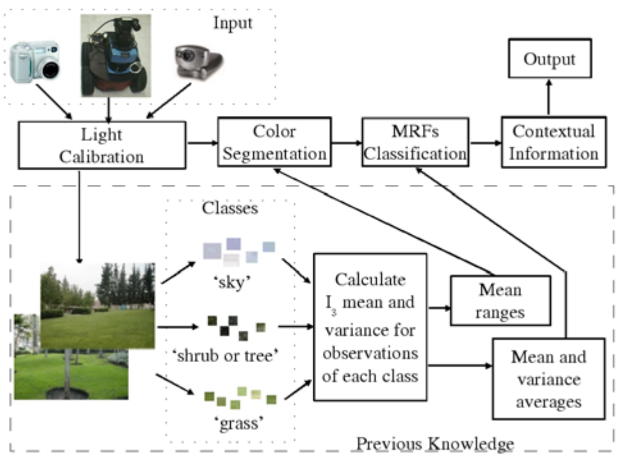

Fig. 1. Diagram of our approach. At the top, from left to right, there are the image capture, calibration, segmentation, MRF classification, region growing and contextual information phases. At the bottom, there is the acquisition of previous knowledge.

Our processing phases that are mentioned here, will be explained in detail at following subsections:

1) Capturing. A natural environment scene image is taken from a video source.
2) Light Calibration. The camera's parameters are modified in order to automatically adjust the light.
3) Segmentation. Color segmentation is based on an average measure. Image is split into a regular grid with a homogeneous size cells.
4) Classification. Supervised classification according to color features (mean and variance) and neighborhood system between cells.
5) Region growing. All adjacency cells belonging to the same class are joined in regions. A RAG represents the neighborhood system between regions.
6) Contextual information. Misclassification regions are corrected based on contextual information. For example, a region 'grass' can not exist in the middle of a region 'sky'.
7) Acquisition of previous knowledge used for supervised classification.

Capturing
Outdoor scene images can be taken in two modes. First mode is off-line processing, using one of three following video sources: a Coolpix 775 digital camera (from Nikon), a webCam Plus (from Creative Labs), a mounted camera on a robot. Second mode is on-line processing, capturing images on-line directly from a mounted camera system on an outdoor mobile robot (All terrain Pioneer 3-AT from ActivMedia, see Fig. 2) with a computer on-board (Pentium III, 850MHz). The images are obtained from the left camera of the stereo system.

Fig. 2. Pioneer 3-AT outdoor mobile robot.

All images that are captured in RGB format have 256 colors either in PPM or JPEG format. We are working with two different image resolutions: 160x120 and 320x240 pixels. Initially, we did some preprocessing tests like reducing to 16 the colors number, smoothing with MRF and Gaussian blurring, but our results were not improved and processing times were too high. Therefore, image captured (either in off-line or on-line modes) is directly processed by segmentation phase skipping preprocessing.

Light Calibration
Off-line images have little light changes, however, in on-line processing each image from the video, taken in real time, has too much variations in illumination; even two consecutive captured images have different light conditions. This generates problems in segmentation and classification phases obtaining wrong results.

If the environment has moderate changes in illumination, we perform an off-line calibration, either modifying several camera's parameters (exposure, contrast, gain and brightness) or adjusting previous knowledge ranges. In worst cases, we use an automatic light calibration method developed to adjust light conditions of captured images modifying camera's parameters in order to maintain a red range value in upper right corner section of image where a red flag is located.

Color segmentation
A color image is described by the distribution of three-color components R, G and B, and attributes calculated transforming R, G and B to different color spaces. Two color spaces were tested in order to perform color segmentation: HSI (Hue, Saturation and Intensity) and I_1 I_2 I_3 color features derived from transformation of RGB defined by Ohta in [16], Tan et al. in [17] and mainly used in our domain by Murrieta et al. in [13, 14, 15]. They show that I_1 I_2 I_3 color space is better than HSI and others color spaces because are statistically uncorrelated

color features independent of intensity changes, especially in outdoor environments where the light conditions are not controlled. This color space is defined as follows:

$$I_1 = \frac{R+G+B}{3} \quad I_2 = (R-B) \quad I_3 = \frac{2G-R-B}{2} \qquad (1)$$

Murrieta et al. consider I_2 and I_3 for segmentation and classification features. Eliminating I_2, we are not loosing too much information and can be obtained similar results only using the I_3 component in the MRF classification features.

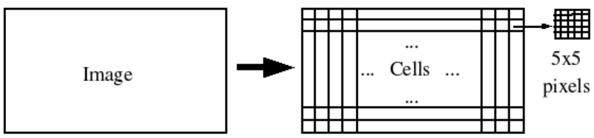

Fig. 3. Regular cells grid.

The image is divided into a grid of regular cells (5 x 5 pixels), as is shown in Fig. 3. Each pixel is transformed from RGB to the I_3 component, and the average of I_3 is calculated for each cell. Reducing image resolution by considering cells and using only the I_3 component, we can obtain faster processing times useful for future mobile robot navigation tasks. Each cell is provisionally labeled according to the range identified in previous knowledge in which the average lies either for 'grass', 'shrub or trees' or 'sky', these labels are the inputs for potential functions in the first MRF iteration. After this, there could exist regions that do not belong to any class (labeled as 'unknown' cells).

MRF Classification

MRF is used to identify cells considering at the same time the intrinsic color features of image and the neighborhood system between image cells in a supervised classification.

MRF model [7] is expressed considering the spatial relationship between related variables and can be defined on a graph with a neighborhood system and random variables. A MRF is a set of random variables.

Let **G**={**R**,**E**} be a graph, where **R**={R_1, ..., R_N} is the set of nodes and **E** is the set of edges. The neighborhood system is defined by **n**={$n(R_1)$, ... , $n(R_N)$}, where $n(R_i)$, $i=1, 2, \ldots, N$ is the set of nodes in **R** that are neighbors of *Ri*.

Let **I**={I_1, ..., I_N} be a family of random variables defined on **R**, called a *random field*, where I_i is the random variable associated with R_i. **I** is a MRF on **G**, if and only if:

1) P[**I**] > 0 for all realizations of **I**.
2) P[$Ii \mid Ij$, all $Rj \neq Ri$)] = P[$Ii \mid Ij$, $Rj \in n(Ri)$]

Where P[**I**] and P[$Ii|Ij$] are the joint and conditional probability distribution functions (pdf).

An important feature of MRFs is that their general function form of the pdf can be expressed as a Gibbs distribution defined in cliques of **G**:

$$P(I_i) = Z^{-1} \exp[-U(I_i)] \qquad (2)$$

$$U(I_i) = \sum_{\forall cliques} V(I_i) \qquad (3)$$

$$Z = \sum_{\forall labels} \exp[-U(I_i)] \qquad (4)$$

Where: $U(I_i)$ is the Gibbs energy function, Z is the normalization factor, and $V(I_i)$ are the potential functions of cliques.

In this paper, each image cell is considered as a random variable I_i represented by a graph node (see Fig. 4). The variable can take three possible values, each value representing a class. The random field **I** is the set of all variables I_i in the graph. We consider a first order neighborhood system; this means that each node has four neighbors as is shown in Fig. 5.

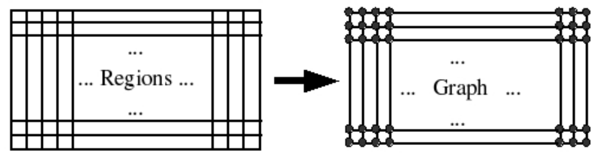

Fig. 4. Graph representing the MRF corresponding to the regions.

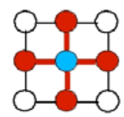

Fig. 5. First order neighborhood system.

We use two potential functions from [7]: *Vo* and *Vc* in order to consider color features and neighborhood respectively for each node. For each cell, all possible labels are tested to find the label that minimizes energy *U* and maximizes the probability of that cell belonging to that label. The label that maximizes the probability is the label assigned to that cell. This process will eliminate the 'unknown' cells and will integrate some isolated cells in the middle of cells with a different label.

The *Vo* function considers the color features and is defined as follows:

$$Vo = \frac{1}{2}\log 2\pi S_d^{\,2} + \frac{(I_a - I_d)^2}{2S_d^{\,2}} \qquad (5)$$

Where:
I_d is the mean value of the I_3 component for the class *d*. This value was computed in the previous knowledge phase.
S_d^2 is the variance of the I_3 component for the class ***d***. This value was computed in the previous knowledge phase.
I_a is the I_3 average value for the cell that is being analyzed.

The *Vc* function is defined as the sum of integers *k* representing the validity rules considering the spatial relationships between regions. For each node, we test two types of rules: first type considers pairs of cells (as valid or not valid pairs), and the second type considers a one central cell surrounded by four neighbors of the same class (if the central cell class is different from the neighbors class then is a not valid combination). First types of rules are showed in table 1 and the others in table 2.

Cells pair	Validity	*k*
tree and grass	Yes	0
tree and sky	Yes	0
grass and sky	No	1

Table 1. First type of rules for the relations between two cell regions with different classes, J represents the value to sum.

Central cell class	4-neighbors class	*J*
Tree	grass	4
Tree	sky	4
Grass	sky	4
Grass	tree	4
Sky	tree	4
Sky	grass	4

Table 2. Second type of rules for not valid relations between a central region with its four neighbors, J represents the value to sum.

Finally the energy function *U* is calculated as follows:

$$U = Vo + \lambda Vc \qquad \textbf{(6)}$$

Where λ represents a weight that controls the contribution between *Vo* and *Vc* functions in the energy value. In this case, weight λ=4 was assigned considering the possibility that a cell or region may be closer to the label *x* according the function *Vo*, but its relationships with neighbors determine that it is not a valid label *x*, so the label must be changed by another label *y* according to a "high" value of the potential *Vc*. That value was determined by trial and error through examining interpretation results.

Region Growing

All adjacency cells, belonging to the same class, must be joined in a single region. For this, we use the region growing algorithm. This algorithm begins on first cell (the most left-top cell), and considering an adjacency-4 neighborhood, recursively cells having the same class are added to a region until no more adjacency cells with same class are found. If another cell belonging to a different class is found, a new region is started from this cell.

When all cells in the image belong to some region, a RAG is constructed indicating the relationship between regions. In this phase, not only the regions in image are considered as nodes in the graph, but also the limits ('top', 'bottom', 'left', 'right') of the image are considered as well, we call these: special location nodes. This is particularly useful in order to apply the contextual information.

In right side of Fig. 6 we show an example of RAG built from the MRF represented in the left side of the figure. Each node is labeled with a number representing the class: '0' for 'shrub or tree', '1' for 'grass' and '2' for 'sky'. Special location nodes are denoted by: 'top' with '^', 'bottom' with '_', 'left' with '<' and 'right' with '>'.

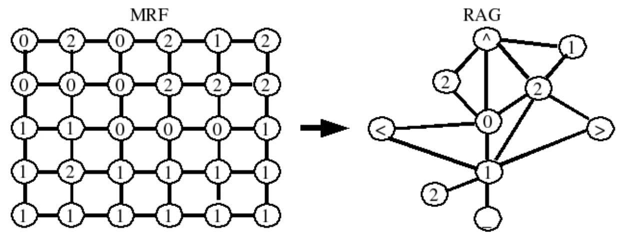

Fig. 6. An example of a MRF graph and the corresponding RAG.

Contextual Information

In classification phase, may exist several regions that are mislabeled because of shadows or reflexes. Classification phase cannot avoid this problem because is performed using only cells, without considering a set of cells. Using the RAG, we can determine, for example, if a region labeled as 'sky' is located at the bottom of the image or surrounded of 'grass', therefore we have a misclassification error.

In order to identify and correct those errors, considering that the images will be taken from a small height mobile robot, some rules have been defined to represent not valid region configurations in contextual information.

For nodes with one neighbor:

- 'sky' with only one neighbor 'grass' is changed for 'grass'.
- 'sky' with only one neighbor 'shrub or tree' is changed for 'shrub or tree'.
- 'grass' with only one neighbor 'sky' is changed for 'sky'.
- 'grass' with only one neighbor 'shrub or tree' is changed for 'shrub or tree'.
- 'shrub or tree' with only one neighbor 'sky' is changed for 'sky'.

For nodes with two neighbors (having one special location node):

- 'sky' with a neighbor 'grass' and a second neighbor 'left', 'right' or 'bottom' is changed for 'grass'.
- 'sky' with a neighbor 'shrub or tree' and a second neighbor 'left', 'right' or 'bottom' is changed for 'shrub or tree'.
- 'grass' with a neighbor 'sky' and a second neighbor 'left', 'right', 'bottom' or 'top' is changed for 'sky'.
- 'grass' with a neighbor 'shrub or tree' and a second neighbor 'top', 'left' or 'right' is changed for 'shrub or tree'.
- 'shrub or tree' with a neighbor 'grass' and a second neighbor 'bottom' is changed for 'grass'.

In the RAG in Fig. 6, for the node labeled with '2' in the left down corner, the rule 'sky' with only one neighbor 'grass' is changed for 'grass' is applied. Therefore the node is labeled as '1' and fused with the neighbor. In the same graph, the node labeled with '1' in right top corner, the rule 'grass' with a neighbor 'shrub or tree' and a second neighbor 'top', 'left' or 'right' is changed for 'shrub or tree' is applied and the label is changed to '2'. The final RAG after applying these rules is shown in Fig. 7.

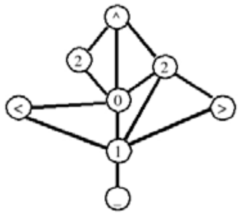

Fig. 7. An example of a RAG after applying the contextual information phase.

Acquisition of previous knowledge

We compute off-line the acquisition of the previous knowledge based on several little observations of each type of class from several different images. Every observation is converted to the I_1, I_2, I_3 space. We calculate the mean and the variance of I_3 for every observation in order to obtain the range of valid values for each class. With this, we have also calculated the average mean value I_d and the average variance S_d^2 for each class that will be used for the MRF classification.

4. VISION BASED EXPLORATION

We propose to use one camera as the only sensor to process information that allows the robot to recognize traversable and non-traversable areas in order to navigate reactively. The vision system, described in the previous section, is the input for the exploration of unknown natural environments with a non holonomic mobile robot (Pionneer 3-AT).

At this moment, the robot's reactive system only has two layers. The first one is for obstacle avoidance, the second one for exploring through areas without any obstacle.

Monocular vision allowed us to identify the 'shrub or tree' and 'sky' regions as non-traversable areas and the 'grass' regions as traversable areas. We are working only with traversable areas located at the bottom of the image ('grass' region with a neighbour 'bottom' on the RAG). From the set of traversable areas, the largest one is selected according to the minimal area, in order to make sure that at any time there will be enough free space in front of the robot.

The robot performs the obstacle avoidance layer only if there is not a minimal traversable area; this means that at the base of the image most of the areas are non-traversable because there are obstacles that must be avoided. Then, the robot rotates a predefined angle to the right.

In the second layer, robot navigation performs a predefined Bezier curve towards the largest traversable area. The curve is defined according to the non holonomic restrictions of the robot. The details for the exploration algorithm can be found in [18].

5. EXPERIMENTAL RESULTS

Our system was implemented in C/C++ using two open source libraries only for open, save and display images (OpenCV 0.95 from Intel [19] and XVision 2 of Greg Hager [20]). System was tested in off-line processing mode at 160x120 resolution with several images taken in natural environment areas at our campus (eight of them are showed in this section as results). In the following images light green represents the label 'grass', dark green represents 'shrub or tree' and blue represents 'sky', see Fig. 8.

"grass" "shrub or tree" "sky"

Fig. 8 Corresponding colors for each class

In Fig. 9 there is an example where auto calibration was made with a red flag because the illumination had too many changes in several parts of the images.

Fig. 9. On-line auto calibration example

Figs. 10-17 have three-image sequences: first one is the original image, second image is the result of MRF classification, and last image is the final result after correct misclassification errors with contextual information. Fig. 10 is one of the best-classified images, the classes are well defined at simple view, and there are not visible shadows or reflexes; because of this, from classification phase were obtained good results.

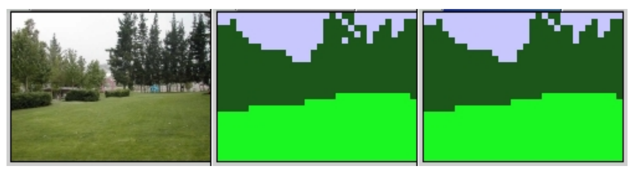

Fig. 10. Results for test image 1

All images were taken between 10 and 15 hours at our campus gardens during a period of two months (late spring), so there are different sizes of grass. Most of shadows on grass have been successfully classified in the MRF phase like in Figs. 11, 12 and 13. However, we had some problems with shadows and reflexes on 'shrub or tree', but this misclassification errors were corrected using contextual information as can be observed in Figs. 11, 12, 13, 14 and 15. But, our application is not perfect, because some little regions are still mislabeled in final image (for example: little left region on Fig. 11 and little down right region on Fig. 14).

Our application is able to work with different levels of green for classifying 'shrub or tree' including the trunk. In some images (for example Fig. 16 and 17), even the ground surrounded the base of the trunk is classified as 'shrub or tree'. This is useful because the mobile robot navigate reactively only through 'grass'.

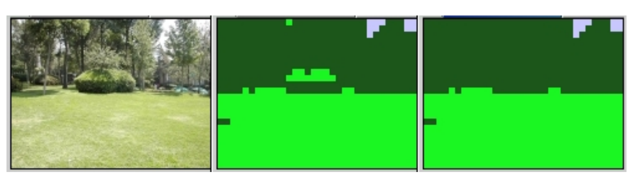

Fig. 11. Results for test image 2

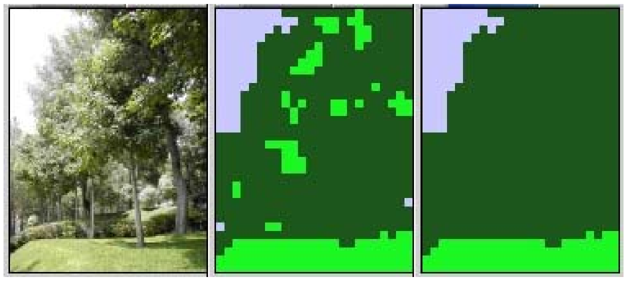

Fig. 12. Results for test image 3

Fig. 13. Results for test image 4

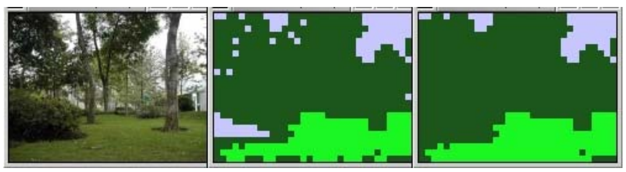

Fig. 14. Results for test image 5

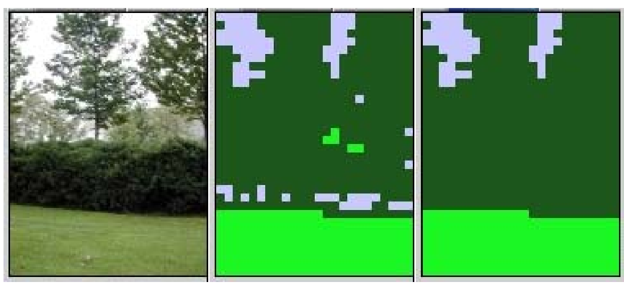

Fig. 15. Results for test image 6

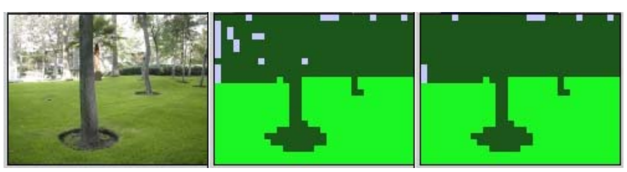

Fig. 16. Results for test image 7

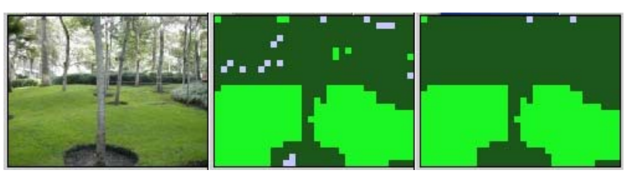

Fig. 17. Results for test image 8

Without considering display time, in average processing times results in milliseconds for each phase on a Laptop Pentium Celeron 500 Mhz with Linux RedHat 7.2 were initially: 51.9 ms for segmentation, 4.5 ms for classification, 12.6 ms for region growing, and 7.3 ms for contextual information (total time: 76.3 ms). We can see that the maximum time is spent during segmentation phase, this happens because segmentation is the only phase that works with pixels directly; the rest of the phases work on cells or regions.

Also, our system was tested on the Pioneer 3-AT mobile robot in on-line processing mode. After perform code optimization, we diminish the total time to 11 ms for all monocular vision processing. In Figs. 18-23 there are some images taken from a video result (original videos are in [21] and were taken in fall) at a 320x240 resolution. First of each pair is the original image and second one is our result image in seconds 5.5, 15 and 23 from video (total video duration 25.5 seconds). The video was taken in the same area like the image in Fig. 10. During this video and other video tests, we teleoperate robot movements and the camera. This robot has an onboard computer Pentium III 850 Mhz with Linux RedHat 7.3. Our processing times results in frames per second (fps), with the code optimization, were: 8fps at 320x240 and 30fps at 160x120. With these times, we have real-time processing allowing to spent more time during the navigation phase.

Fig. 18. Image taken at 5.5 seconds

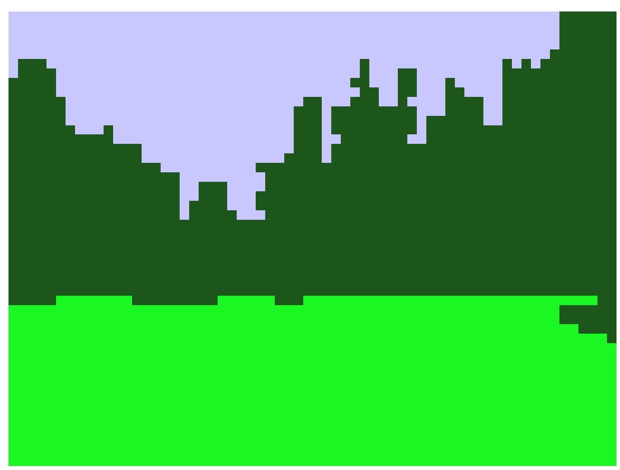

Fig. 19. Result image at 5.5 seconds

Several tests of robot exploration (between 8 to 15 meters) were performed at our campus gardens. Four images sequence of one exploration test is presented in Fig. 24. A sequence of two captured and processed images during the same exploration is shown in Fig. 25. During first and second images (in Fig. 24) the robot is performing a Bezier curve to the right to avoid obstacles to the left. In the last image, the robot enters to the reactive layer rotating to the right to avoid all the obstacles in front of it. The blue cable behind the robot in Fig. 24 is only for monitoring issues. In all exploration tests, class 'shrub or tree' is used to define non-traversable areas.

Fig. 20. Image taken at 15 seconds

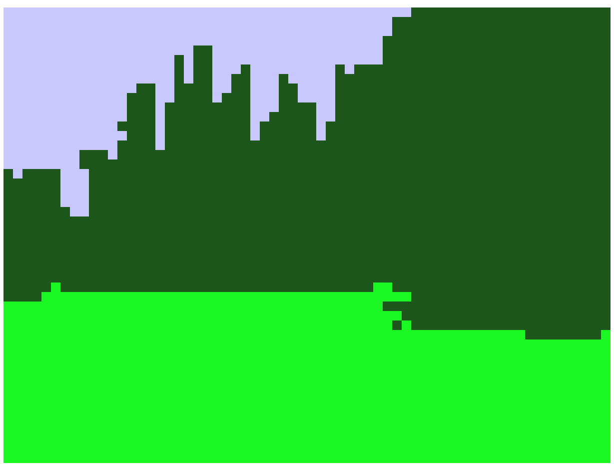

Fig. 21. Result image at 15 seconds

Fig. 22. Image taken at 23 seconds

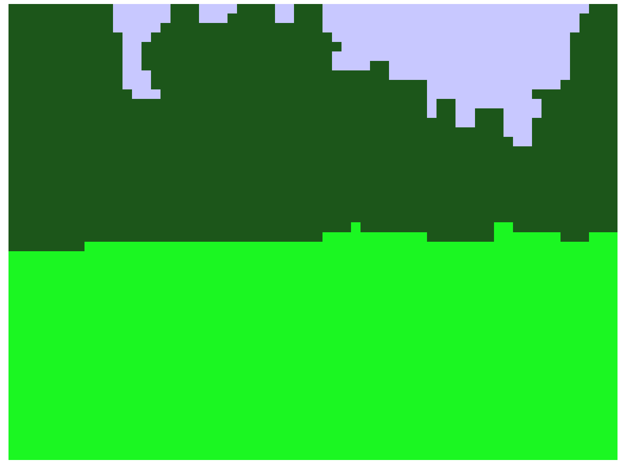

Fig. 23. Result image at 23 seconds

Fig. 24. Robot navigation sequence

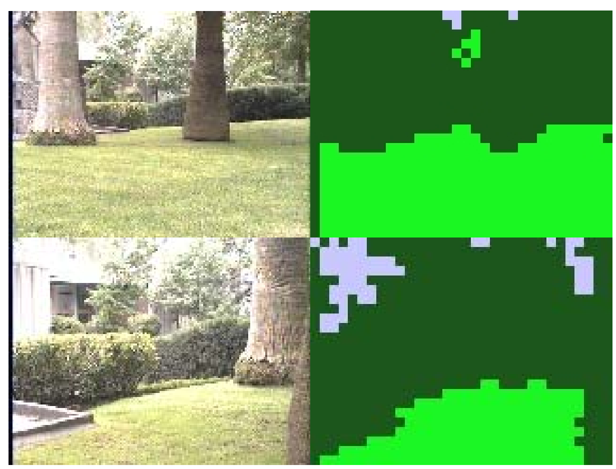

Fig. 25. On-line capture sequence during navigation

6. CONCLUSIONS AND FUTURE WORK

In this paper, is presented a system that segment and classify natural environment scenes. We use only I_3 measure from I_1 I_2 I_3 color space for performing the segmentation and MRF in classification phase. After classification, some problems were observed because shadows and reflexes in images, resulting in misclassified regions, this was corrected with the use of a RAG after using region growing algorithm from cells allowing to incorporate contextual information to identify mislabeled regions and successfully correct the labels. Our system can work with different illumination depending on a range of hours of day, with different levels of green and with different sizes of grass. We test off-line and on-line processing on a real mobile robot obtaining fast performance in most of results.

Some images tested in the afternoon had a lot of problems because the low illumination. We will still taking more images in different seasons of the year to test our system approach.

We also have used the vision system for performing an exploration in outdoors environments with a non holonomic robot.

As future work, we are working on images having structured (buildings) and unstructured (natural) parts mixed on images in outdoor environments. Also, uncertainty in control and sensing will be considered for planning.

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