Color Active Contours for Tracking Roads in Natural Environments

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Abstract. Scene interpretation and feature tracking in natural environments are very complex perceptual functions. Complexity lies on several factors, for example: the lack of control on illumination conditions and the presence of different textures in the environment. This paper presents a real-time method to track roads in natural environments. The scene is previously characterized and classified in different regions by a combined ICA and color segmentation method (not described in this paper). This method is not so fast to track desired features in real time. The region tracking is executed on color active contours. New color potential fields are proposed: a) one to attract active contours depending on the selected region color, and b) the second one to repulse active contours when it is inside the region. Two potential fields are defined from the results of the initial characterization process and are updated by the same process at a given constant frequency, to avoid errors mainly due to global changes in illumination conditions or to local changes on the characteristics of the selected region. This approach has been evaluated on image sequences, acquired in natural environments.

1 Introduction

In natural environments, objects can be characterized by their color or texture. It compensates the lack of structure in order to extract, localize and recognize objects. However, segmentation and real-time tracking of objects or features in such environments are very hard and complex tasks. The complexity lies on several factors like, lack of control in illumination conditions, not structured images, and a great scene variability, making difficult the region interpretation and classification.

This work concerns the navigation of autonomous vehicles in agricultural environments. The principal task is to detect and track roads in real-time, in order to guide an autonomous machine, for example to go from a farm to a given field.

The task of road extraction and tracking in an image sequence acquired on natural environments can be considered as the segmentation and tracking of a deformable object that grows or shrinks in the image with unpredicted directions. This task could be solved by the active contour method (*snakes*) proposed by Kass et al. [1]. An active contour is a deformable curve, which is deformed by internal and external forces, to fit desired features along an image sequence. The main problems of active contours

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are well known: a) they need to be initialized close to the object to be tracked in order to get a good convergence, and b) they could be trapped by objects in their neighborhood with higher gradient zones.

This paper presents a tracking method for roads in natural environments; roads are previously characterized by an ICA and color segmentation algorithm [2]. Classification results allow (1) to initialize an active contour on a region boundary and (2) to define two external potentials in the image. The active contour is attracted by the first potential towards a selected color gradients; the second potential works as a repulsive field, when the active contour is over the selected region. The definitions of these new potential fields add robustness to active contour fitting in such complex environments. Color gradients for snake segmentation or tracking have been studied in different papers. However, more of them restrict the complexity to track matte or saturated colors as in [3].

The paper structure is as follows. Section 2 describes the classic approach of active contour methods. Section 3 develops the new potential fields required for real-time tracking and defined from the region characterization process. In section 4, our approach is compared with others works. Section 5 describes results obtained on several image sequences acquired in natural environments, and finally section 6 gives our conclusions.

2 Active Contours

Snakes or active contours have been extensively used for object segmentation and tracking. This method is based on the minimization of an energy function (equation 1) along a continuous curve subject to internal and external forces. These forces are defined by the desired curve and image properties, respectively.

The total energy for an active contour $\mathbf{v}$ described with a parametric representation $\mathbf{v} = (x(s), y(s))$ can be written as:

$$E_{tot}(\mathbf{v}) = \int E_{\text{int}}(\mathbf{v}(s)) + E_{ext}(\mathbf{v}(s))\, ds \tag{1}$$

where subscripts on E represent the internal and external energy terms.

Internal energy is commonly defined by:

$$E_{\text{int}}(\mathbf{v}) = \int_0^1 \omega_1(s)\mathbf{v}_s^2 + \omega_2(s)\mathbf{v}_{ss}^2\, ds \tag{2}$$

where subscripts on $\mathbf{v}$ denote differentiation, ω_1(s) and ω_2(s) are weights given to the elasticity and the smoothness energy terms.

In order to reduce complexity, the control points that define the deformable curve can be restricted to move to preferential directions (i.e. perpendicular lines to the curve). However, if there is no a priori knowledge about the possible curve shapes or about the directions of future deformations (as in our case), the contour could not fit with the boundary of the desired region, here the road region. Some problems can be solved, as in [4], where the contour is considered as an electric conductor that is charged by a constant electric charge Q. This charge generates a new repulsive force that distributes the control points along a curve according to its curvature [5].

Taking into account this new repulsive force, the internal energy (equation 2) can be written as:

$$E_{\text{int}}(\mathbf{v}) = \int \omega_1(s)\mathbf{v}_s^2 + \omega_2(s)\mathbf{v}_{ss}^2 + k\frac{\sigma^2}{\mathbf{v}_s^2}\,ds \tag{3}$$

where k is a constant coefficient, and σ is the electrical charge density. Once the electric charge is given $k\sigma^2$ can be see as a constant coefficient.

Classic active contours move to the desired characteristics under the influence of external energy currently defined as:

$$E_{ext}(\mathbf{v}) = \int_0^1 P(\mathbf{v}(s))ds \tag{4}$$

where commonly $P(\mathbf{v}(s))$ is the image gradient intensity.

Due to the intrinsic complexity of natural environments, the image gradient provides many contours. In addition, the lack of control on illumination conditions could create very poor gradients. These gradient difficulties could perturb the fitting of active contour to the desired characteristics. Such problems could be solved adding information to the image gradient, as multi-spectral images, in order to focalize the tracking to the desired color combination, as it will be develop ed in the next section.

3 Color Active Contours

Some works have been proposed to deal with multi-spectral information in order to get invariant color snakes. In [3], Gevers and al have analyzed the following color features derived from *RGB*: a) Intensity $I=(R+G+B)/3$, b) normalized colors, $r = \frac{R}{R+G+B}$, $g = \frac{G}{R+G+B}$, $b = \frac{B}{R+G+B}$, and c) Hue, $H = \arctan\left(\frac{\sqrt{3}(G-B)}{(R-G)+(R-B)}\right)$.

They define different color gradients for these spaces showing that Hue gradient and the normalized color gradients are the best in order to get color invariance. However, they only have studied matte and shiny objects, under controlled illumination conditions.

In [6], Ivins and al have defined an active region model. They replace the external energy of the active contour by a region force, defined as multi-spectral goodness function. Considering that tracking needs to be made in real time, they choose to use normalized colors. However, they also use controlled illumination conditions as well as a matte color.

Our main problem is that in natural environments it is quite difficult to have regions with a matte color or a plain texture. So it is not easy, to find a good region attribute, to characterize it. A suitable color space must be found in order to easily filter a specific region by its color characteristics in real time. This information should be incorporated in a region color gradient, in order to avoid noise from other features or objects. However, as we can see in figure 1, neither intensity gradient, nor color gradients tested in different color spaces are enough to guarantee good stability and convergence on the desired features, here the road boundary.

Moreover, in complex environments, any of these color spaces are enough robust to characterize regions features. So for tracking initialization, a region will be charac-

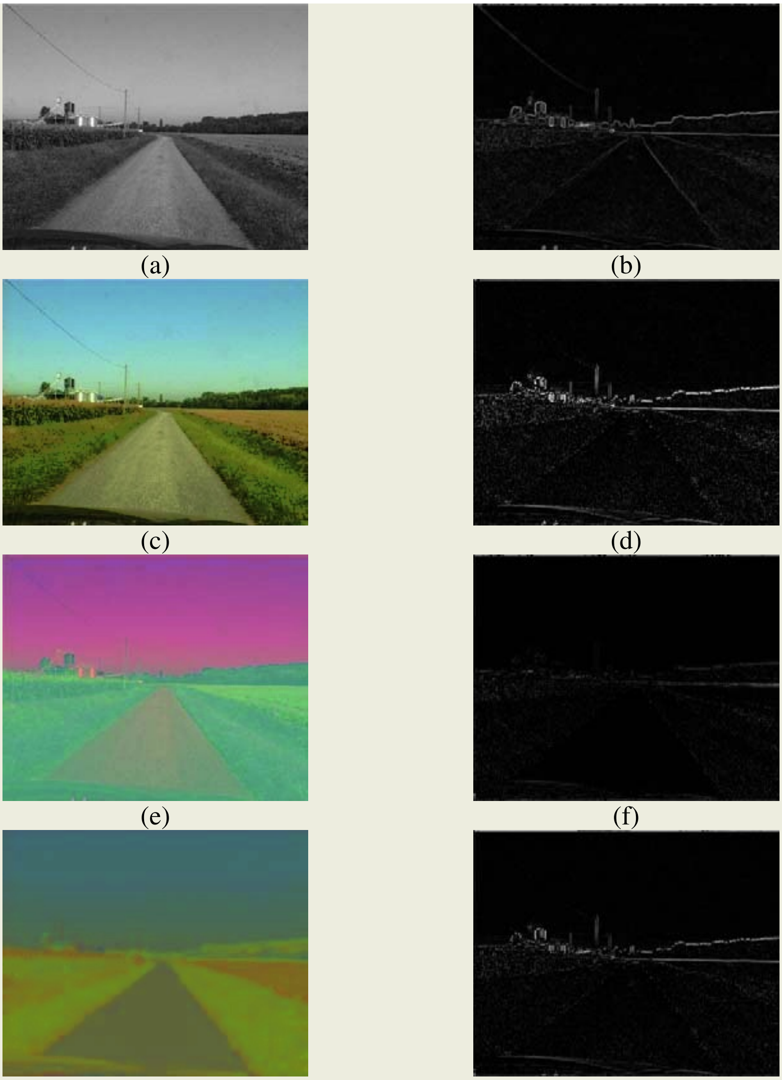


Fig. 1. Image features and gradients. In a), c), e) and g) are shown, Intensity, *RGB*, Ohta, and normalized color spaces respectively, and b), d), f), and h) are single or multi-spectral gradients of left images.

terized by the method described in [2], which will be also used on line to adapt the region attributes in order to avoid error accumulation. In [2] it is proposed to add extra features based on texture operators in order to get a good region characterization. This method uses Ohta color space, in the first step of the segmentation process; so, region characteristics in this space have been calculated previously and can be incorporated easily, in the tracking process. However, this color space is not the optimum to characterize the region, as we will see on next section.

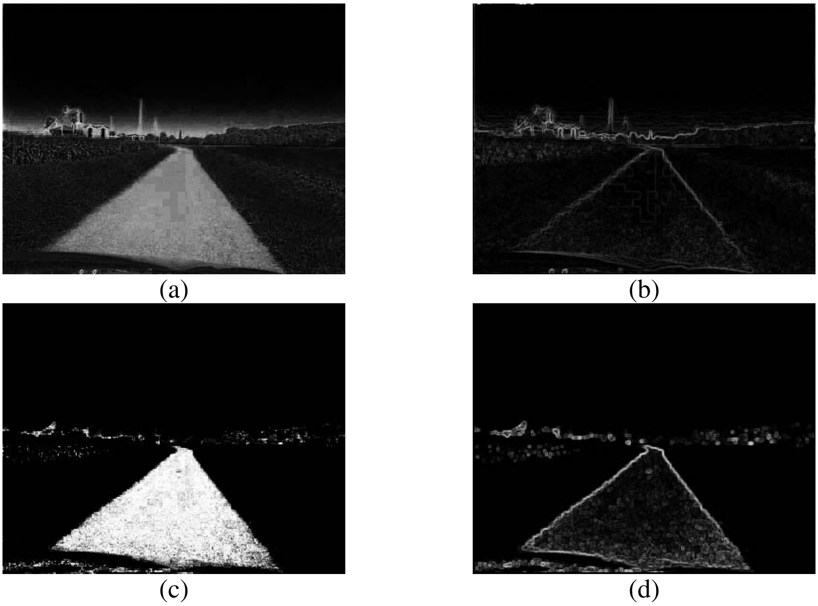


Fig. 2. Region characterization for different color spaces and gradient images. a) and b) respectively are region detection and gradient for Ohta color space and, c) and d) for normalized color space.

3.1 Color and Region Potentials

To track the desired region in real-time, it is important to characterize it by a reduced set of color features in some color space. This information will be introduced on external potentials. It is very important to compute external potentials easily, in order to get the required real-time performance. These potentials are defined from the results of the previous region classification, to get the color mean and variance on the selected region, using different color spaces. As we can see in figure 2, the selected region is very well characterized on both, Ohta and normalized color spaces. The specific textures of a natural environment make the region characterization more difficult on other spaces as HSV. The strongest image potential from gradient images is the one resulting from normalized color space (fig. 2d), because texture is almost erased on this color space.

In order to incorporate previous color space characterization, two external potentials are defined: a) one to attract active contour to desired characterized features and b) the second to make a repulsive force when the active contour is inside the region.

Then external energy will be described as:

$$E_{ext}(\mathbf{v}) = \int P_G(\mathbf{v}(s))ds + \int P_R(\mathbf{v}(s))ds \tag{5}$$

where subscripts on P denotes, the *gradient* potential field G which generates attractive forces (figure 2d), and the *region* potential field R, which generates repulsive forces (figure 2c).

As we have described on previous sections, the region classification method is used at a constant frequency, in order to correct errors, and to reinitialize the active contour adapting the number of control points, depending on the size of the tracked surface. Consequently, variations of the mean and variance due to illumination changes can be incorporated.

Our implementation for specific region potentials could be seen as a combination of a multi-spectral band pass filter, and a color gradient function.

4 Discussion

Recently, it has been proposed similar methods to deal with active contours in color images. In [7] is proposed to use the HSV color space: the external potential field given by the image gradient, is replaced by a statistical pressure term. However, initially, they suppose that HSV color space is enough to characterize regions, which is not always true. As we can see in their examples, where two adjacent blocks are fused, nonetheless they have different textures. Moreover, the pressure term is redundant, because when the active contour is not on the statistical region, the attractive force made by the statistical term could be replaced by doubling the weight of tension term on internal forces.

In [8], Seo and al have proposed an adaptive color snake model, adding a new energy term to the original active contour model. This term acts in an opposite way depending if the snake is inside or outside the region. The region is defined by its color distribution on normalized color space. However, the use of normalized color space is not justified, and they left the external potential field without any change. As we can see in figure 1, color gradient computed on different color spaces does not assure that active contour will evolve to the desired features. Moreover, the color value manually assigned to the tracked region is adapted, only by some scale factors without knowing how this color changes with respect to the environment.

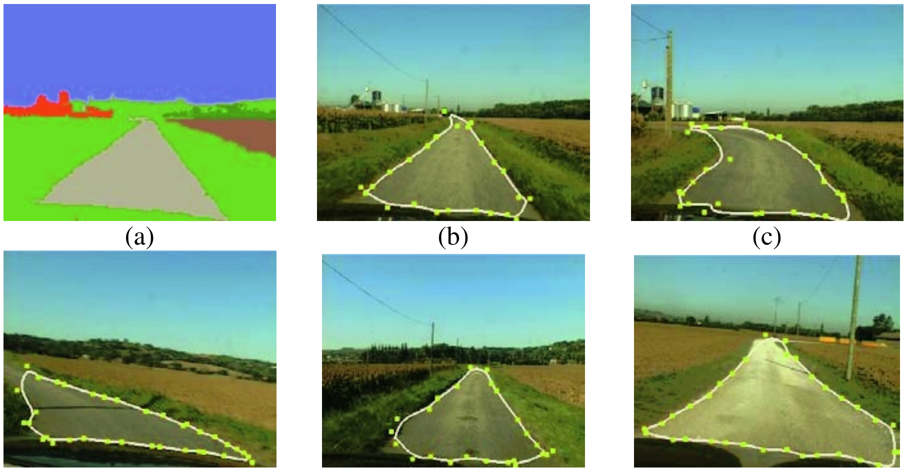
As we have described, our method initializes active contours and makes color adaptation automatically using previous region classification results. It is important to note that the chosen color space is the best adapted to our conditions; for different conditions or for a different task, it could be different.

5 Results

Our approach has been evaluated on several image sequences acquired on natural environments. The region characterization and classification have been automatically processed by the method described in [2]. The contour of the region to be tracked has been sampled at a given frequency (approximately each 20 pixels) to initialize our active contour. The same region is used to find the mean and variance color using a normalized color space as described above. This first process takes about 80 ms on a Sun Blade 100.

The tracking method uses this information to attract active contour to the desired object boundary. The method processes an average of 14 images per second (on the same computer); the performance depends strongly on the number of control points, but not from the results of the image region gradient. The minimization problem is solved by a dynamic programming method proposed by Amini et al. [9] and it is accelerated applying it with a multi-scale neighborhood.

The process runs in double loop, in order to reinitialize active contours, with a different number of control points and different regions features, depending on the region size and on illumination conditions.



(a) (b) (c) (d) (e) (f)

Fig. 3. Tracking results: a) segmented image use for the initialization and characterization, and from b) to f) results from the tracking sequence (Because color is important in this work, color images can be see on http://www.uv.mx/anmarin/CIARP04.html).

The first image in figure 3 shows the characterization and classification process; the central grey zone, classified as a road, defines the region to be tracked; its boundary is used to initialize an active contour. The next five images show different tracking steps on the same sequence; as we can see, the method works in spite of some changes in the road color, caused principally by illumination variations.

6 Conclusion

This paper has proposed two new external potential fields for use in real time tracking on natural environments These new external potentials combine region and contour features to attract active contours on specific zones along an image sequence. The features are defined by an initialization process, consisting in a region segmentation and classification function described in [2]. Different color gradients have been tested using different color spaces, on which individual pixels could be easily expressed. Nevertheless, as is show in this paper they do not contain enough information to assure active contour convergence on the selected region. The statistical region segmentation has been made for Ohta color space, as well as, for normalized color space. Despite the characteristics for Ohta color space have been calculated in classification process, they shows that are not enough to assure convergence. Normalized color regions features are calculated for the desired region using a previous classification process.

Normalized color space is better suitable for region description because it erase the texture, in the selected region. Tracking has been achieved at a very good frame frequency; the tracker is updated on line by the classification process to deal with convergence errors or illumination changes.

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