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Application of the Watershed Method and the Topological Gradient Approach in the Detection of Vehicles on Highways

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Abstract

The main goal of this work is to present a mathematical method for the detection of vehicles on highways. To achieve this goal, we propose an approach based on a coupled method between the watershed transformation and the topological gradient. The HSI (Hue, Saturation, and Intensity) color space is adapted in our method. Different propositions to treat the given problem are presented in this work and a survey of some approaches based on both the topological gradient and a watershed technic is presented. We end this paper by some numerical tests.

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Keywords: Color vision, image processing, topological asymptotic expansion, topological gradient, vehicles detection, watershed technic

1 Introduction

The road vehicle detection represents one of the most promising applications of computer vision. This application has received particular attention over last years due to its importance either for safety reasons or traffic control. Various approaches are proposed in the literature for the study of road and vehicles detection. Most of them are based on the detection of the road border and lane markers existing only on highways and not generally on any country road. Our objective through this work is to apply a segmentation method which permits to detect vehicles and then to control the traffic for any kind of road. To achieve this goal, we propose the use of the watershed technic which is well known to be an excellent tool for the segmentation process. In fact, the segmentation process consists to construct a symbolic representation of the image: the image is described as homogeneous areas according to one or several a priori attributes and the watershed approach allows to detect these homogeneous regions. However, some drawbacks in applying this method are noted. These drawbacks are related to the over-segmentation phenomenon. To overcome this inconvenience, a multitude of papers have been proposed in literature. In [4], the authors have proposed a coupled algorithm for image segmentation using the topological gradient approach [6] and the watershed transformation [8] and the numerical results of segmentation obtained were very promising. However, these results cannot be generalized to the problem of vehicles detection. In fact, various numerical tests have been made and all of them have shown a non significant traffic control result and prove once again that segmentation results depend of the objects we want to detect and the kind of applications we want to explore. To perform the application of the topological gradient approach combined to the watershed technic, to image segmentation, we propose in this paper to segment our image using a classification process based on a restoration one. The restoration and classification processes are applied using the topological gradient approach. The main advantage of the topological gradient approach is to give more weight to the main edges, since it provides a more global analysis of the image than the Euclidean gradient or the morphological gradient, and so, the results are less sensitive to noise. On the other part, the segmentation process uses a watershed algorithm which has the interesting property to give closed contours.

The structure of this work is the following. Section 2 is devoted to the the grey level image segmentation process. First, we review the topological gradient approach for edge detection. Then, we propose a watershed algorithm based on the topological gradient method, and present some numerical results applied to road and vehicles detection. Section 3 is devoted to the segmentation problem applied to color images. First, we propose a generalization of the first algorithm to color images by decomposing the image with respect to the three channels. Second, we propose a segmentation process based on a classification one. Third, we present a numerical comparison of different color gradients in order to study and perform the segmentation results. We illustrate these methods by some numerical tests and comment both their advantages and inconveniences. We end this paper with some concluding remarks.

2 Gray level image segmentation by topological gradient approach and a watershed technic

2.1 An introduction to topological gradient method

In this section, we recall the principle of the topological asymptotic expansion [6, 1], and how we use it for image restoration process.

Let Ω be an open bounded domain of $\mathbb{R}^2$ and $j(\Omega) = J(u_\Omega)$ be a cost function to be minimized, where u_Ω is the solution to a given PDE problem defined in Ω. The mathematical formulation of the initial problem defined on a safe domain can be expressed as: for a given function v in $L^2(\Omega)$, we have to find $u \in H^1(\Omega)$ such that

$$\begin{cases} -div\,(c\nabla u) + u = v & \text{in} \quad \Omega, \\ \partial_n u = 0 & \text{on} \quad \partial\Omega, \end{cases} \tag{1}$$

where n denotes the outward unit normal to $\partial\Omega$ and c is a positive constant.

For a small $\rho \geq 0$, let now $\Omega_\rho = \Omega \backslash \sigma_\rho$ be the perturbed domain by the insertion of a crack $\sigma_\rho = x_0 + \rho\sigma(n)$, where $x_0 \in \Omega$, $\sigma(n)$ is a straight crack, and n a unit vector normal to the crack. The topological sensitivity theory provides an asymptotic expansion of j when ρ tends to zero. It takes the general form

$$j(\Omega_\rho) - j(\Omega) = f(\rho)G(x_0, n) + \circ(f(\rho)), \tag{2}$$

where $f(\rho)$ is an explicit positive function going to zero with ρ and $G(x_0, n)$ is called the topological gradient at point x_0.

For a given function v in $L^2(\Omega)$, we consider the following problem: find $u_\rho \in H^1(\Omega_\rho)$ such that

$$\begin{cases} -div\,(c\nabla u_\rho) + u_\rho = v & \text{in} \quad \Omega_\rho, \\ \partial_n u_\rho = 0 & \text{on} \quad \partial\Omega_\rho. \end{cases} \tag{3}$$

The basic idea is as follows. If we insert a crack in a flat part of the image, nothing happens. But, if we insert a crack along an edge (strong gradient), the potential energy decreases. Then, edge detection is equivalent to look for a sub-domain of Ω where the energy is small. So our goal is to minimize the energy norm outside edges

$$j(\rho) = J(u_\rho) = \int_{\Omega_\rho} \|\nabla u_\rho\|^2, \tag{4}$$

by considering v_0, the solution to the adjoint problem

$$\begin{cases} -div(c\nabla v_0) + v_0 = -\partial_u J(u) & \text{in} \quad \Omega, \\ \partial_n v_0 = 0 & \text{on} \quad \partial\Omega. \end{cases} \tag{5}$$

We obtain in the case of a crack $\sigma_\rho(n)$ with a boundary condition $\partial_n u = 0$, the following topological asymptotic expansion

$$j(\rho) - j(0) = \rho^2 G(x_0, n) + \circ(\rho^2), \tag{6}$$

with

$$\begin{aligned} G(x_0, n) = -\pi c(\nabla u_0(x_0).n)(\nabla v_0(x_0).n) \\ -\pi|\nabla u_0(x_0).n|^2. \end{aligned}$$

The topological gradient could be written as

$$G(x, n) =< M(x)n, n >, \tag{7}$$

where $M(x)$ is the symmetric matrix defined by

$$\begin{aligned} M(x) = -\pi c \frac{\nabla u_0(x)\nabla v_0(x)^T + \nabla v_0(x)\nabla u_0(x)^T}{2} \\ -\pi \nabla u_0(x)\nabla u_0(x)^T. \end{aligned}$$

For a given x, $G(x, n)$ takes its minimal value when n is the eigenvector associated to the lowest eigenvalue λ_{min} of M. This value will be considered as the topological gradient associated to the optimal orientation of the crack $\sigma_\rho(n)$. We note that from a numerical point of view, cracks are simulated by a small value of c. It is more convenient for numerical implementation. The restoration algorithm consists in inserting small values of c (cracks) in regions where the topological gradient is smaller than a given threshold $\alpha < 0$. These regions are the edges of the image. The algorithm is as follows.

Topological gradient algorithm

- Initialization : $c = c_0$.
- Calculation of u_0 and v_0 the solutions of the direct (3) and adjoint (5) problems.
- Computation of the 2×2 matrix M and its lowest eigenvalue λ_{min} at each point of the domain Ω.
- Set

$$c_1 = \begin{cases} \varepsilon \quad if \quad x \in \Omega, \quad \lambda_{min} < \alpha < 0, \quad \varepsilon > 0 \\ c_0 \quad elsewhere. \end{cases} \tag{8}$$

- Compute u_1, the solution of problem (1) with $c = c_1$.

We refer the reader to [5], for some theoretical and numerical comparisons with conventional restoration methods.

2.2 An overview of the watershed approach

Let I be a gray level image defined by a given function $f : \Omega \rightarrow \mathbb{R}$, where $f(x)$ quantifies the level grey intensity at the pixel x. The watershed technic suppose that this image I is viewed as a topographic surface having some minima. By supposing that this topographic surface is immersed in water, and that the water will go through the holes progressively during this immersion process, catchment basins representing the set of all pixels leading to the same local minimum will be constructed. These catchment basins represent the connected components leading to the segmentation process. The different lines dividing these catchment basins defines the watershed.

Several algorithms have been proposed for the computation of watersheds and the most commonly used are based on an immersion process analogy. Let us express this immersion process according to [8]: we consider l_{min} and l_{max} the smallest and the largest values taken by u. Let $T_l = \{x \in \Omega, u(x) \leq l\}$ be the threshold set of u at level l. We define a recursion with the gray level h increasing from l_{min} to l_{max}, in which the basins associated with the minimum of u are successively expanded. We consider X_l the union of the set of basins computed at level l. A connected component of the threshold set T_{l+1} at level $l+1$ can be either a new minimum, or an extension of a basin in X_l. Finally, by denoting by min_l the union of all regional minima at level l, we obtain the following recursion which defines the watershed by immersion

$$\begin{cases} X_{l_{min}} = T_{l_{min}}, \\ \forall l \in [l_{min}, l_{max} - 1], X_{l+1} = min_{l+1} \cup IZ_{T_{l+1}}(X_l), \end{cases}$$

with $IZ_{T_{l+1}} = \bigcup_{i=1}^{k} iz_{T_{l+1}}(X_{l_i})$, where k is the number of minima of I, and $iz_{T_{l+1}}(X_{l_i})$ is defined by

$$iz_\Omega(Y_i) = \{z \in \Omega, \forall k \neq i, d_\Omega(z, Y_i) \leq d_\Omega(z, Y_k)\}. \tag{9}$$

The set of the catchment basins of a gray level image I is equal to the set $X_{l_{max}}$. At the end of this process, the watershed of the image I is the complement of $X_{l_{max}}$ in Ω.

2.3 Numerical results

It is well known that the main problem of the watershed method is that the images we consider are often noisy, which implies that we have a lot of local minima and this leads to an over-segmentation. In [4], a new method for decreasing the over-segmentation of standard watershed based techniques is proposed. The algorithm proposed combines the topological gradient tool with the watershed technic. In fact, as the topological gradient has the interesting property to give more weight to the main edges, it provides a more global analysis of the image than the Euclidean gradient or the morphological gradient. This globally analysis affect positively segmentation results and the over-segmentation will be considerably attenuated. This was our first motivation. In Figure 1, we illustrate this motivation by some numerical tests. As our application concerns traffic control and road detection, so we consider a real 494×351 image representing a highway in France token from the data base of Google. In order to apply our first algorithm, we begin by transforming this color initial image to a grey level one given in Figure 1. As we mention it previously, both morphological and classical gradients have locally behaviors in comparison to the topological gradient which proceeds globally on the image studied. The three gradients are given in Figure 1.

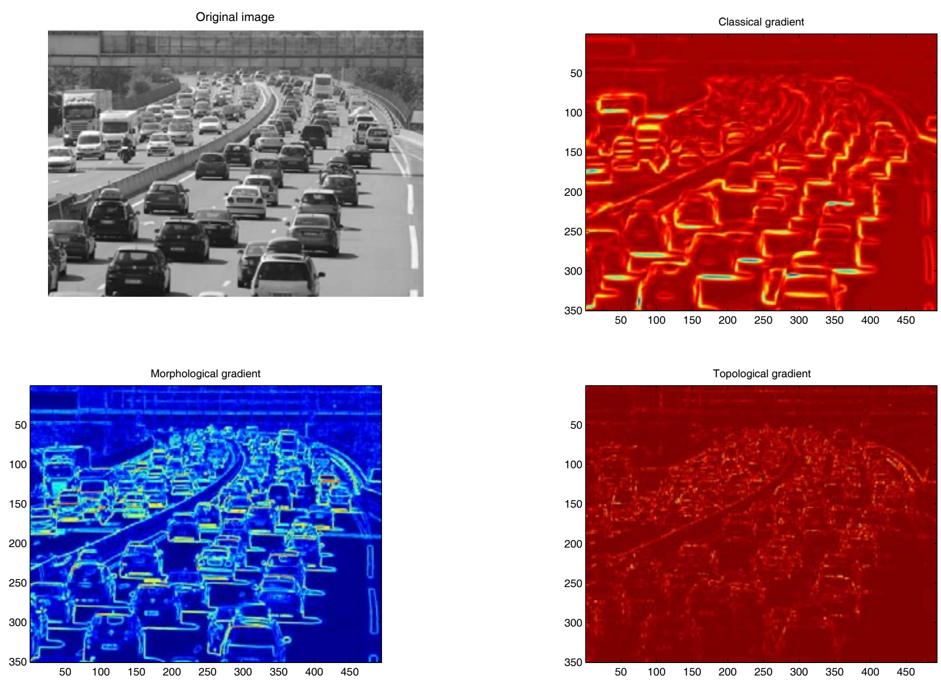

Figure 1: Representation of the different gradients of the image

In order to illustrate the effect of the advantage of the topological gradient on image segmentation, we present in Figure 2 some numerical tests concerning the segmentation process on road detection and traffic control. The image at top left in Figure 2 represents the segmentation result using the watershed technic without any pre-treatment. It easy to conclude that the over-segmentation obtained make the result non acceptable. In the literature, some approaches have been proposed to attenuate this over-segmentation usually seen with watersheds. In fact, one can uses sequential alternating filters which have the property to denoise the image and then to eliminate unwanted contours in the segmentation process. One can combine the watershed technic with others approaches as wavelet tools, Fourier analysis, marker technic and so on. Our method is based on the topological gradient tool which will participate considerably to attenuate this over-segmentation. The numerical results are shown in Figure 2 from top right to down right. Let us mention here that the homogeneous regions detected using the watershed technic are equal to 9241 homogeneous regions while our approach based on both topological gradient and watershed technic detects only 1405 homogeneous regions. Moreover, the first segmentation shown at top right in Figure 2 is obtained with $c = 1$, but we can attenuate the number of identified regions in the segmentation process by choosing larger values of the coefficient c. In fact, the number of homogeneous regions depends of what we want to segment and what we want to obtain at the end of the segmentation process: if one would obtain a maximum of details then it suffices to take $c = 1$, otherwise, one should consider larger values of c which gives a considerable attenuation of the segmented regions as we can see it over the images segmented given in Figure 2. We can clearly observe an attenuation of the segmented regions such that the main edges of the two images are conserved. These results are obtained by varying the coefficient c which takes successively the values $1, 50$ and 100 and gives respectively $1405, 715$ and 283 regions.

3 The method proposed for color image segmentation.

Let Ω be the given open bounded domain of $\mathbb{R}^2$ and u be a given color image, defined as a vectorial function

$$u : x = (x_1, x_2) \in \Omega \subset \mathbb{R}^2 \longmapsto u(x) = (u^1(x), u^2(x), u^3(x)) \in \mathbb{R}^3, \qquad (10)$$

where u^k is the value of the pixel $x = (x_1, x_2)$ in each color subspace. In image processing, color has been represented or modeled in various ways [7]. Let us consider in this work the HSI space, in which images are represented at each pixel $x = (x_1, x_2)$, by the vector value $u(x)$ giving the hue, the saturation and the intensity of u. Each monochromatic component u^k is called one channel.

The first method proposed consists in decomposing the image with respect to the channels H, S and I as we can see it in Figure 3.

As each channel represents a grey level image, then our idea is to apply the previous algorithm for each component. The goal of this decomposition is to compare the different homogeneous regions detected in the three cases.

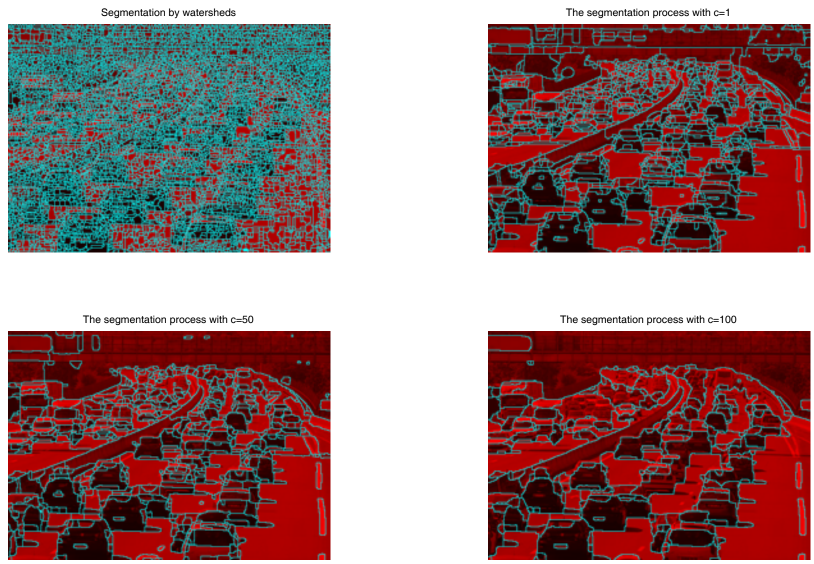

Figure 2: Segmentation results of a traffic road real image using our new approach based on the topological gradient coupled with the watershed technic using different values of c from 1 to 100.

In order to better visualize the difference between the three components and their influence in edge detection, we present in Figure 4, the edges of each component. The numerical results obtained using the watershed algorithm applied to each gradient with respect to each channel, are represented in Figure 5. It is comprehensive that the intensity channel gives an over-segmentation in comparison with the hue and the saturation channels. In fact, the intensity is the most sensitive component and the saturation is the less sensitive one, with respect to noise, texture and other blurring effects. We note here that the numerical tests give 812 regions detected using the intensity component and 314 regions using the hue component, while there is just 159 regions with the saturation component.

Inspired by the work of Beucher [3], we propose in the following, to use a marker criterion for selecting objects to be segmented in the image considered. In [3] the authors have considered both influence zones and minima of the filtered image as markers. We have tested this idea for our road and vehicles detection application but unfortunately, the numerical results were not conclusive. An alternative idea is to choose a marker based on a color selection. We propose to begin by classifying our image before applying a watershed technic. This classification is made using a topological gradient algorithm. The numerical tests shown this approach are represented in Figure 6. The watershed is

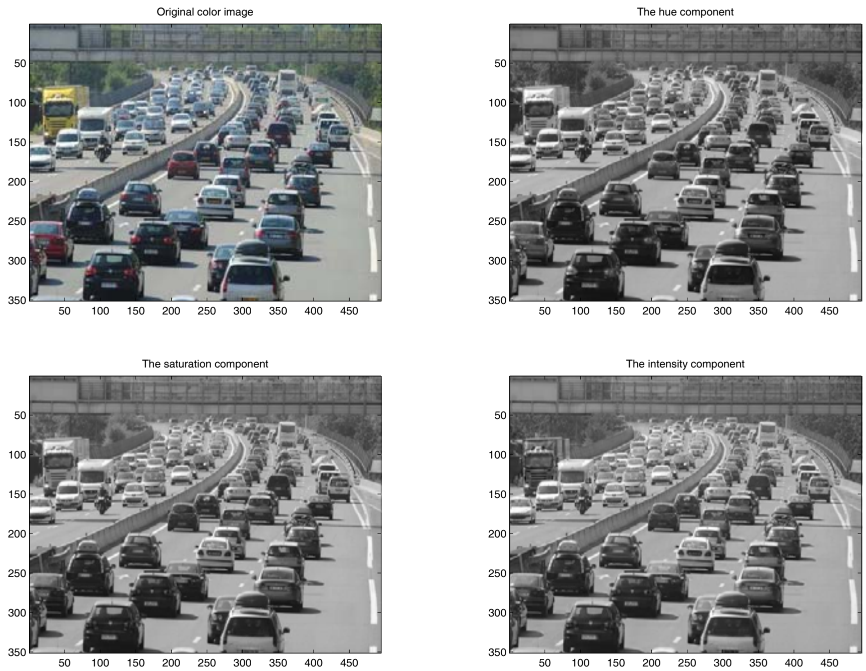

Figure 3: Representation of the three channels: the hue one, the saturation one and the intensity one.

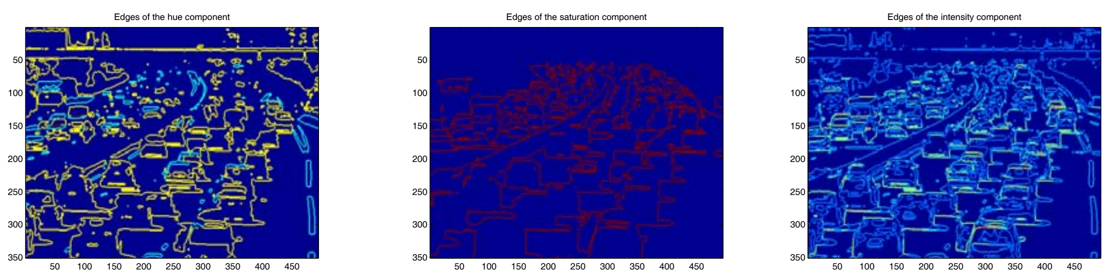

Figure 4: Representation of the edges of the three channels.

used in a second step on the classified image. Let us note here that by applying a classification process in a first step, we reduce significantly the number of regions to be treated. These regions are represented by the different colors in our example. In fact, by studying the histogram of the three components H, S and I, and by setting 6 classes for the first component, 4 for the second and 5 for the third one, we obtain $5 \times 4 \times 5 = 120$ different colors to be treated, instead of $256^3 = 1.7 \times 10^7$. This selection contributes considerably in the segmentation process using the watershed algorithm, as we can see it in

Figure 5: Representation of watersheds applied to the three gradients. From left to right: the watershed associated to the gradient of the hue channel, the watershed associated to the gradient of the saturation channel and the watershed of the gradient of the intensity channel.

Figure 6. These classification results in addition to a theoretical study of the influence of color components will be used in a future work for the extraction of information on images detected by radars in highways and country roads.

In order to ameliorate these results by giving more attention to color components, it is more convenient to treat directly the color images by considering different forms of color gradients. In the future, we propose a study of these gradients in order to perform our numerical tests for road detection and traffic control. The idea is to apply a watershed on the color gradient and to avoid the over-segmentation associated to the watershed algorithm. This part is under study and will be developed in a future work.

4 Conclusion

We have proposed in this paper a generalization of the topological gradient method associated to watershed algorithm for the problem of road detection and traffic control. Moreover, we have proposed a numerical comparison between different manners to treat the problem of road and vehicles detection. The numerical results obtained illustrate that our method can easily and efficiently be adapted to such problems. In order to ameliorate these results, we propose in a the future to work on other alternatives and methods. More precisely, in [2] one of the authors has proposed to use the Di Zenzo gradient for a better detection of the edges in the process of color restoration. In order to identify the local variations of the image, Di Zenzo [9] defines a multi-spectral tensor associated to the image vector field. The largest eigenvalue of the tensor will correspond to the norm of the gradient called the Di Zenzo gradient. The method of topological gradient has been extended to color images by coupling it to the Di Zenzo approach. One can use this extension coupled with the watershed technic for a segmentation process. In fact, we will propose to restore

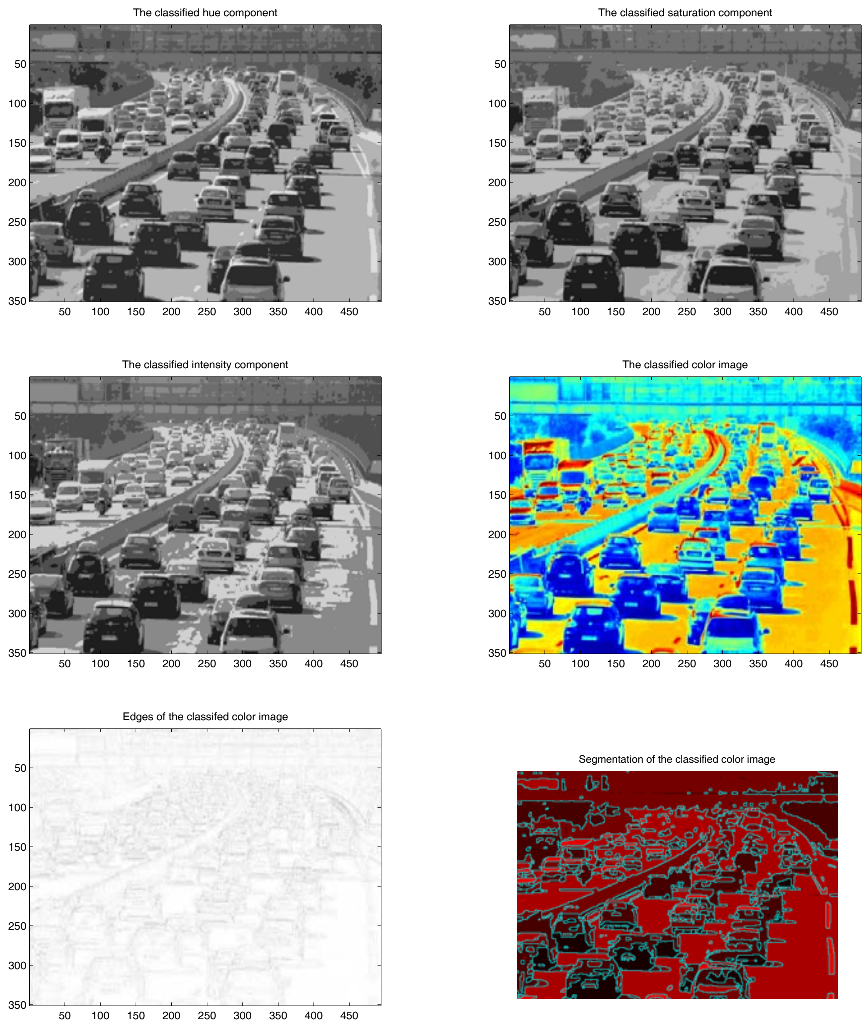

Figure 6: Classification and segmentation results.

the color image directly using the color topological gradient method based on the Di Zenzo gradient, and then to apply the watershed algorithm generalized to color images. In a first step, the topological gradient is constructed using the Di Zenzo gradient. In the second step, the color topological gradient replaces the color morphological gradient generally used with the watershed algorithm.

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