Level set and Watershed for image segmentation

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***Abstract*—level set and watershed transform has interesting properties that make it useful for many different image segmentation applications: it is simple and intuitive, can be parallelized, and always produces a complete division of the image. However, when applied to image noisy. We present an improvement to the watershed transform that enables the introduction of prior information in its calculation. We propose in this paper a combine the watershed transform and level set to image segmentation. We have applied this algorithm segmented different type of image, to evaluate this methods a validation of the results is provided, demonstrating the strength of the algorithm for image with noise.**

Keywords—segmentation, level set and watershed, evaluate.

I. INTRODUCTION (HEADING 1)

The active contours method (deformable models) which is a particular technique of segmentation, its main advantage is to provide a constituent contour in a chain of points. Segmentation of images using deformable models is reduced to minimizing a two-term energy function (internal and external). The internal energy models our prior knowledge in terms of the regularity of the solution sought.

The external energy depends on the image data and serves to attract the deformable model to the desired characteristics, such as the boundaries of the object of interest. Segmentation is a major challenge in image analysis, referring to the task of detecting boundaries of objects of interest in an image. Several approaches have been proposed and many of them belong to one of the following categories: energy-driven segmentation and watershed-based.

The classical way to solve the minimization problem is to solve the corresponding Euler-Lagrange equation. For instance, relatively early, Mumford and Shah [10] introduced a celebrated segmentation model by minimizing an energy functional that penalizes smoothness within regions and the length of their discontinuity contours. Recently, Various modifications of Chan-Vese model, related to different aspects of the image analysis, have been proposed, such as adaptive segmentation of vector images [1, 2] knowledge-based segmentation [3]. Watershed is normally implemented by region growing based on a set of markers to avoid severe over segmentation[9].The watershed segmentation has proven to be a powerful and fast technique for both contour detection and region-based segmentation. In principal, watershed segmentation depends on ridges to perform a proper segmentation, a property which is often fulfilled in contour detection where the boundaries of the objects are expressed as ridges. Niu et al. [4] reported an improved watershed algorithm to segment the cotton leaf area. Peng et al. [5] presented an improved Chan–Vese (C-V) model for detecting the boundary in given leaf images by combining local statistical information with global information.

The purpose of this document is to design the ChanVese algorithm using the active contour principle to determine the outline of an object in an image. The work presented in this document is organized in two stages:

The first step is a generalization on image processing, it presents the definition of some fundamental concepts such as digitization, codification of a digital image, luminance, contrast, contour, region, texture, etc.

In the second part, we present a state of the art concerning the different methods of image segmentation, it approaches the field of application of the image segmentation, one finds there the definition of an image segmentation, the definition of the active contours and the energies at stake. These methods drive one or more initial curve(s), based on gradient and/or region information in the image, to the boundaries of objects in that image. The basic idea of variational methods is to minimize energy. This functional generally depends on the features of the image.

However, the active contour methods based on level-set framework have some limitations. First, these methods are usually implemented by solving the partial differential equations (PDEs) and thus computational efficiency sharply decline because of numerical stability constraints.

The success of watershed segmentation relies on a situation where the desired boundaries are ridges. Unfortunately, the standard watershed framework has a very limited flexibility on optimization parameters.

The rest of this paper is organized as follows. Section 2 describes the materials and mechanism of the proposed method. Section 3 presents the experimental results. A discussion and future work is given in Section 4. Finally, the conclusion is provided in Section 5.

II. METHODS

II.1 ALGORITHME CHAN-VESE:

We have an image on which we will evolve a curve C. We define c1 and c2 the inner and outer mean of the curve. Let's take a simple example: either our image, uo the intensity of a pixel in the image, C the curve that will allow us to detect the object. Our image contains an object and a background. The curve cuts the image into 2 regions whose intensity is one pixel the values uo¹ and uo²; then we have uo = uo¹ inside the curve and uo = uo² outside. This is the principle of the Mumford-Shah function used for segmentation [9].

This gives us an energetic image in a sum of the outer energy and the inner energy of the curve.

$$\mathrm{F}_1(\mathrm{C}) + \mathrm{F}_2(\mathrm{C}) = \int_{\mathrm{inside(c)}} |\mathrm{u}_0 - \mathrm{c}_1|^2 \mathrm{dxdy} + \int_{\mathrm{outside(c)}} |\mathrm{u}_0 - \mathrm{c}_2|^2 \mathrm{dxdy} \qquad (1)$$

With C a variable curve

We can say that we are on the edges of the object when

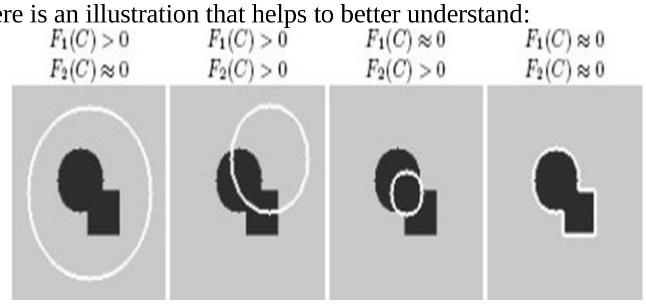
$$inf_C\{F_1(C) + F_2(C)\} \approx 0 \approx F_1(C) + F_2(C)$$

$$inf_C\{F_1(C) + F_2(C)\} \approx 0 \approx F_1(C) + F_2(C) \qquad (2)$$

Indeed, if the curve is inside the object: $F1 \approx 0$, $F2 > 0$ Si elle is outside: $F1 > 0$, $F2 \approx 0$

If she is on the edge : $F1 \approx 0$, $F2 \approx 0$

Here is an illustration that helps to better understand:



An energy F is thus obtained as a function of C, c1 and c2 such that:

$$\mathrm{F}(\mathrm{C}, c_1, c_2) = \mu.length(C) + v.area(insideC) + \int_{\mathrm{inside(c)}} |\mathrm{u}_0 - \mathrm{c}_1|^2 \mathrm{dxdy} + \lambda_2 \int_{\mathrm{outside(c)}} |\mathrm{u}_0 - \mathrm{c}_2|^2 \mathrm{dxdy}$$

$$\mathrm{F}(\mathrm{C}, c_1, c_2) = \mu.length(C) + v.area(insideC) + \int_{\mathrm{inside(c)}} |\mathrm{u}_0 - \mathrm{c}_1|^2 \mathrm{dxdy} + \lambda_2 \int_{\mathrm{outside(c)}} |\mathrm{u}_0 - \mathrm{c}_2|^2 \mathrm{dxdy} \qquad (3)$$

with μ, λ1, λ2 which are positive parameters.

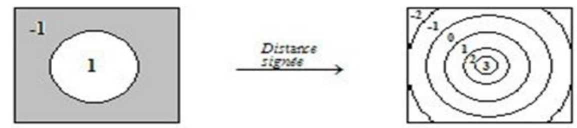
We will take for our applications v = 0; length (c) is a smoothing parameter of the curve.

We will then use the method of LevelSet to evolve the curve C [2] [3]. This method propagates a curve that is represented by when is equal to O.

For this, we create a new image 8 of the same size as the image I that we want to treat. In this image, we have the curve C for = 0, we are inside the curve for> 0, and outside for <0.

We then initialize 8 independently of I.

We then calculate the signed distance [3], that is to say starting from an image whose value is -1 outside and + 1 inside and we try to have a value that tends towards 0 at the edge, which increases inwards and decreases outward.



The signed distance is given by the following

equation:

For the continuous case:

$$\frac{d\varphi}{dt} = \Delta t.signe(\varphi)(1 - \nabla\varphi)$$

Pour le cas en discret :

$$\varphi_{n+1}(i,j) = \varphi_n(i,j) + \Delta t(signe(\varphi)(1 - |\nabla\varphi|) \qquad (1)$$

avec

$$|\nabla\varphi| = \sqrt{(0.5^2[(\varphi(i+1,j) - \varphi(i-1,j))^2 + (\varphi(i,j+1) - \varphi(i,j-1))^2} \qquad (4)$$

Returning to image I, we have a new function [2]

$$F(\emptyset, c_1 c_2) = \mu.length\{\emptyset = 0\} + v.area\{\emptyset \geq 0\} + \lambda_1 \int_{inside(c)} |u_0 - c_1|^2 dxdy + \lambda_2 \int_{outside(c)} |u_0 - c_2|^2 dxdy \qquad (5)$$

We then define the Heaviside H function:

$$H(x) = \begin{cases} 1, & if\ x \geq 0 \\ 0, & if\ x < 0 \end{cases} \qquad (6)$$

The Dirac function is defined by:

$$\delta(x) = \frac{d}{dx} H(x) \qquad (7)$$

The terms of energy F are expressed as follows:

$$\begin{cases} length\{\emptyset = 0\} = \int_{\Omega} |\nabla H(\emptyset)| = \int_{\Omega} \delta(x)|\nabla\emptyset| \\ area\{\emptyset \geq 0\} = \int_{\Omega} H(\emptyset)dxdy \end{cases} \qquad (8)$$

et :

$$\begin{cases} \int_{\emptyset \geq 0} |u_0 - c_1|^2 dxdy = \int_{\Omega} |u_0 - c_1|^2 H(\emptyset) dxdy \\ \int_{\emptyset < 0} |u_0 - c_2|^2 dxdy = \int_{\Omega} |u_0 - c_2|^2 (1 - H(\emptyset)) dxdy \end{cases} \qquad (9)$$

The expression of energy can then be written in the following form:

$$F(\emptyset, c_1, c_2) = \mu \int_\Omega \delta(\emptyset)|\nabla_\emptyset| + v \int_\Omega H(\emptyset)dxdy + \lambda_1 \int_\Omega |u_0 - c_1|^2 H(\emptyset)dxdy + \lambda_2 \int_\Omega |u_0 - c_2|^2 (1 - H(\emptyset))dxdy \quad (10)$$

By keeping fixed, and minimizing the energy F according to c1 and c2, we can easily express these constants c1 and c2 as a function of.

$$c_1(\emptyset) = \frac{\int_\Omega u_0 H(\emptyset)dxdy}{\int_\Omega H(\emptyset(x.y))dxdy}$$
$$c_2(\emptyset) = \frac{\int_\Omega u_0(1 - H(\emptyset))dxdy}{\int_\Omega (1 - H(\emptyset(x.y)))dxdy} \quad (11)$$

Keeping then c1 and c2 fixed, we minimize the energy according to obtain the Euler-Lagrange equation for:

$$\frac{\partial \emptyset}{\partial t} = \left[\mu div\left(\frac{\nabla\emptyset}{|\nabla\emptyset|}\right) - \lambda_1(u_0 - c_1)^2 + \lambda_2(u_0 - c_2)^2\right] \quad (12)$$

Where div $((\nabla\emptyset) / |\nabla\emptyset|)$ is the curvature that keeps a smooth curve. In discrete, the equation of evolution is of the form:

$$\varphi_{n+1} - \varphi_n = \nabla t[k - \lambda_+(I(x,y) - \mu_1)^2] \quad (13)$$

whit:

$$K = \frac{(\varphi_{xx}\varphi_y^2 - 2\varphi_y\varphi_x\varphi_{xy} + \varphi_{yy}\varphi_x^2}{(\varphi_x + \varphi_y)^{3/2}} \quad (14)$$

and:

$$\lambda_+(I(x,y) - \mu_1)^2 + \lambda_-(I(x,y) - \mu_2)^2 \quad (15)$$

is the speed of evolution.

For multi spectral images, the principle remains the same; it is enough to consider these images as several monospectral images. We then obtain for averages

$$C_i^+ = \frac{\int_\Omega u_{0.i(x,y)} H(\emptyset(x,y))dxdy}{\int_\Omega H(\emptyset(x.y))dxdy}$$
$$C_i^- = \frac{\int_\Omega u_{0.i(x,y)}(1 - H(\emptyset(x,y)))dxdy}{\int_\Omega H(\emptyset(x.y))dxdy} \quad (16)$$

and we get for the evolution of:

$$\frac{\partial\emptyset}{\partial t} = \left[\mu div\left(\frac{\nabla\emptyset}{|\nabla\emptyset|}\right) - \frac{1}{N}\sum_{i=1}^{N}\lambda_i^+(u_{0.i} - C_i^+)^2 + \frac{1}{N}\sum_{i=1}^{N}\lambda_i^-(u_{0.i} - C_i^-)^2\right] \quad (17)$$

This approach is very interesting, we have been able to test our model for different images and the results are satisfactory, whether it is a spectral mono or multi spectral image.

Let's look at the results we have obtained with this method and explain where some of the problems are occurring.

II.2 Segmentation by Watershed Algorithm

Watershed is one of the most powerful segmentation techniques of mathematical morphology. Although it is usually considered a segmentation approach by growing regions.

The Watershed breaks down an image in the region that represents the zones of influence of local minimum intensities. In analogy with the topography, if the image is considered an elevation map, each region of the watershed is a distinct watershed, separated from the adjacent basins by peaks of higher intensity. For this reason, applying Watershed to a gradient image is an effective way to separate objects by their outlines.

II.2.1. Description:

The watershed refers to a geographic boundary that divides a Landsoire into one or more watersheds. Indeed, the waters flow in different directions, on each side of this line [12].

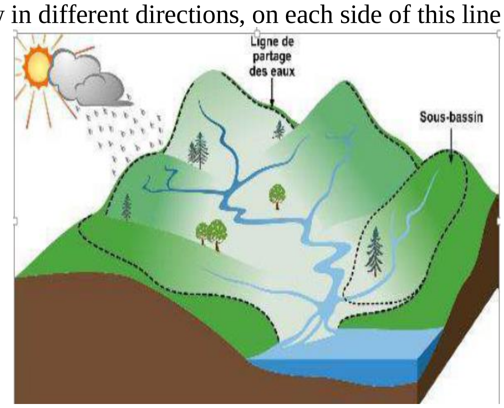


Fig.1 : watershed.

We then obtain a topology similar to those illustrated in the figure (Fig..1): peaks, basins, separating lines

3.1.2 OPERATION:

The watershed uses the description of the images in geographical terms. An image can indeed be perceived as a relief if we associate the gray level of each point to an altitude. It is then possible to define the watershed as the ridge forming the boundary between two watersheds.

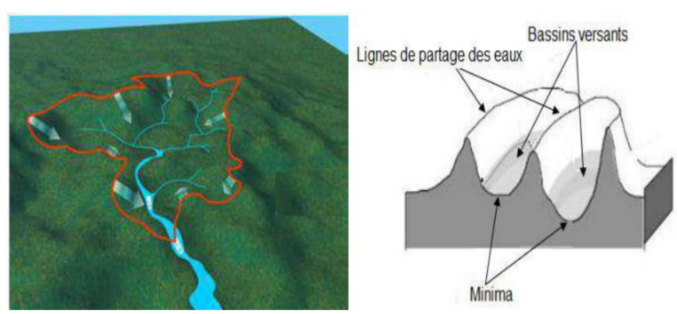


Fig.2 : Description Watershed.

We define the following notions :

Minimum: point from which it is impossible to reach a height point without having to climb.

Basin Versant: zone associated with a minimum such that a drop of water falling at a point of this zone finally descends to the minimum.

Zone of influence of a basin: set of points that are closer than any other basin.

The operation is as follows:

The watershed makes it possible to segment an image taking into account the topology of the relief of its gray levels. If we consider the gray levels of the image as the altitudes of a landscape, the watershed is formed by ridges scattering two watersheds. The principle is illustrated by the following figure:

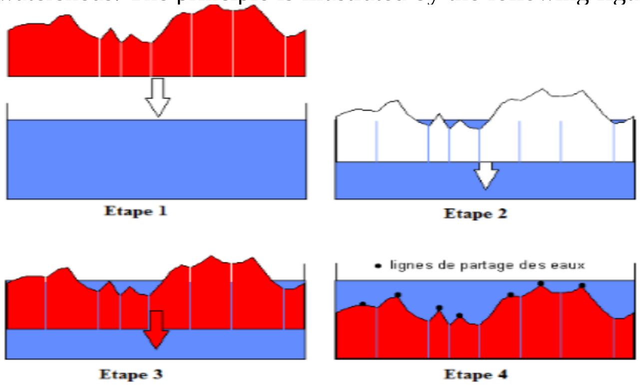


Fig.3 : Watershed with

The relief is flooded by water penetrating from below (step 1). Watersheds

Begin to join, forming the first ridge lines (step 2). The water continues to rise, forming new ridge lines (steps 3 and 4) .The points where two disjoint basins meet form the LPE and thus determine the lines along which gray levels vary rapidly (Frontiers of Regions) .

The advantage of the watershed for segmentation is that it provides regions delimited by closed outlines forming a partition of the image. Another advantage is that this technique does not require a long computation time in comparison with other segmentation methods.

The watershed is the segmentation tool par excellence in mathematical morphology. This approach was introduced by Beucher and Lantuejoul (Beucher and Lantuejoul, 1979), it has been widely studied and obtained encouraging results in image segmentation.

3.2. *Segmentation d'image par le Gradient*

3.2.1. Description :

The gradient, in one pixel of an image I, is a vector characterized by its amplitude and its direction. Amplitude is directly related to the amount of local variation in levels of gray. The direction of the gradient is orthogonal to the boundary at the point considered. The simplest method for estimating a gradient is therefore to make a one-dimensional variation calculation, i.e. by having chosen a given direction. We then have the following schema:

$$Gd(x, y) = (I * Wd)(x, y) \tag{18}$$

Where Wd is the derivation operator in the d direction and the convolution product.

$$G_d(x,y) = \sum_{i=-m}^{m} \sum_{j=-n}^{n} I(x+i, y+i)\, w_d(i,j) \tag{19}$$

In this discrete version, the size of this operator is given by the pair (m, n). Except in special cases, we always consider m = n. Since the gradient is a vector, the most classical approach to estimate the gradient consists in choosing two privileged directions (naturally those associated with the mesh, i.e. row and column) on which the gradient is projected. The gradient of the image I is the vector ∇I (x, y) defined by:

$$\nabla I(x,y) = \left(\frac{\partial I(x,y)}{\partial x}, \frac{\partial I(x,y)}{\partial y}\right) \tag{20}$$

The module || ∇I (x, y) || reflects the intensity of the gradient in each pixel and θ the direction of the strongest gradient in each pixel.

III. *Methods of Calculating Gradient Levels of Gray:*

The gray scale gradient calculation is performed by conventional contour detection operators in monochromatic images. In an image, a contour corresponds to a local variation of intensity presenting a maximum or a minimum. The edge pixels belong to regions with different average intensities.

The detection of outlines in gray scale images is based on a local convolution of the image by a given 2D filter. Convolution involves sequentially scanning the image through a window and applying the filter to the pixels to estimate significant transitions in the image. The gray scale gradient operators are then distinguished by the smoothing filter used. Filters can be "simple" or "more complex". In our approach of choosing the best invariant / gradient pair, we tested six "simple" operators and two "complex" operators that we define in the following sections.

3.2.3. Filtre de detection de contours:

Historically, this filter has been used regularly in image processing.

The filter that we detail in this section is the first derivative of the image. Their application on an image amounts to calculating the gradient operator at each pixel. It is based on the discrete approximations of first-order derivatives given by equations (17) and (18)

$$\frac{\partial I(x,y)}{\partial x} = \Delta x * I(x,y) = I(x+1,y) - I(x,y)$$
$$\frac{\partial I(x,y)}{\partial y} = \Delta y * I(x,y) = I(x,y+1) - I(x,y) \tag{21}$$

where I (x, y) is the value of the pixel (x, y) of image I. The symbols * correspond respectively to the convolutions in the horizontal and vertical directions.

The result of this operator is an amplitude image of the gradient. The amplitude value of the gradient at a point (x, y) reflects the gray level variation observed in image I at this point. The higher this value, the greater the variation. The amplitude is obtained by the maximum of the derivative in x and y. The calculation of the derivative is done by convolution of the image with a mask [-1 0 1] in all directions. The amplitude value selected is the one that is maximum.

2 . MEASURING QUALITY:

The objective of this part is the study and definition of evaluation criteria to quantify the quality of image segmentation results. There are a multitude of segmentation methods whose effectiveness remains difficult to evaluate. It seems important to be able to measure the quality of the images. However, this is a difficult problem for which there is no ideal solution, especially when there is no reference image.

We are going in this part to define some basic metrics.

EAM(ERROR AVERAGE MEAN):

The MSE (Mean Squared Error) and the Mean Absolute Error (MSE) measure the quality of reconstructed images compared to the original image. The idea is to calculate a value reflecting quality. The larger this value, the more the image is degraded (different from the original image).

Let I1 be the original image and let I2 be the image whose quality we want to measure. m and n, being the coordinates of the pixels.L'EAM est pour équation:

$$EAM = \frac{\sum_{M.N}[I_1(m,n)-I_2(m,n)]}{M*N} \quad (22)$$

$$EAM = \frac{\sum_{M.N}[I_1(m,n)-I_2(m,n)]^2}{M*N} \quad (23)$$

These distortion measures are not assimilated to human perception. Indeed, it is sufficient that the reconstructed image is the original image shifted by one pixel so that this measurement is large while the two images are globally identical.

PSNR:

Or f is the image whose MSE is to be measured, the mean squared error in relation to the original image. Peak Signal to Noise Ratio (PSNR) is a more common measure of quality.

$$PSNR = 10 * \log_{10}(\frac{R^2}{MSE}) \quad (24)$$

Ou

$$PSNR = 20 * \log_{10}(\frac{\text{valeur maximale}}{\sqrt{EQM}}) \quad (4.4)$$

In the case of an image coded on 8 bits, the maximum value is 255. Also, the previous formula becomes

$$PSNR = 20 * \log_{10}(\frac{255}{\sqrt{EQM}})$$

$$= PSNR = 10 * \log_{10}(\frac{255^2}{EQM})\ 10 * \log_{10}(\frac{255^2}{EQM}) \quad (5)$$

IV. RESULTATS AND DISCUSSIONS

In this paper we have presented the different methods of segmentation by active contours. The evaluation of different methods of segmentation is given by the values of the criteria. Much work on evaluation has been proposed in [50], seeking to quantify the quality or readability of the image.

We propose to use as criteria: EAM (average absolute error), EQM (mean square error), and PSNR (Peak Signal to Noise Ratio). We present in the values of the validation criteria for all the proposed methods.

This will be followed by an interpretation of the results, in order to be able to compare the segmentation methods used. First, define the evaluation criteria; mean squared error (MSE), mean absolute error (EAM), and signal-to-noise ratio (PSNR). In this part of the results, we will present the tests and results of the work provided. These are mainly, comparisons between the proposed segmentation method of ChanVese and other segmentation models: "Water Sharing Lines and Gradient".

a) First 1 for segmentation

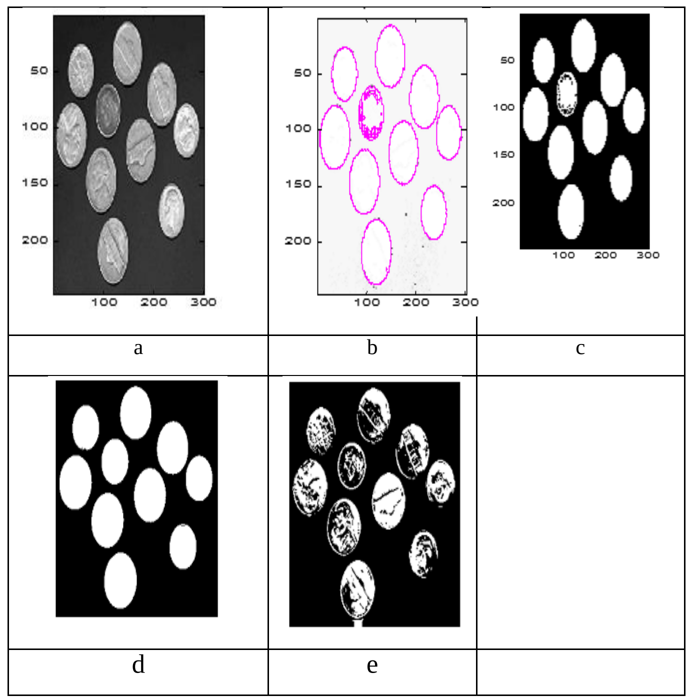


Figure 4.1 a) Original Image b) Chan Vessel Outline c) Image Segmentation Chan Vese d) Segmentation with Gradient e) Segmentation with LPE

Tableau 4.1- Segmentation quality measurement

Méthods and creteria	EAM	EQM	PSNR
Chan-Vese	0.9863	280.4995	23.6515
Watershed"	102.7776	1.3652e+04	6.7789
Gradient	102.7776	1.3652e+04	6.7789

b) second 1 for segmentationstreet:

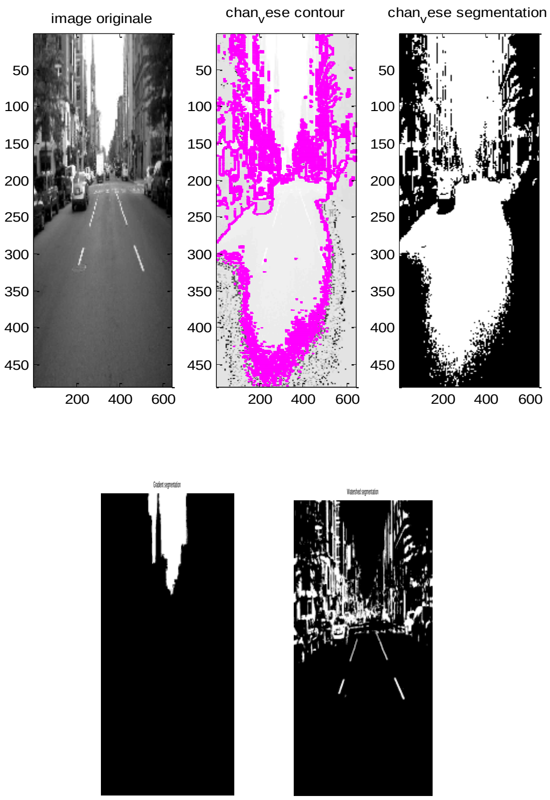


Figure 4.2 a) Original Image b) Chan Vessel Outline c) Image Segmentation Chan Vese d) Segmentation with Gradient e) Segmentation with LPE

The results obtained for the previous figures from the segmentation evaluation criteria are presented in the following table:

Tableau 4.2- Segmentation quality measurement

Méthods and creteria	EAM	EQM	PSNR
Chan-Vese	0.3815	1.7778e+03	15.6320
Watershed	101.5283	1.3439e+04	6.8472
Gradient	101.5283	1.3439e+04	6.8472

c) thurd 1 for segmentation

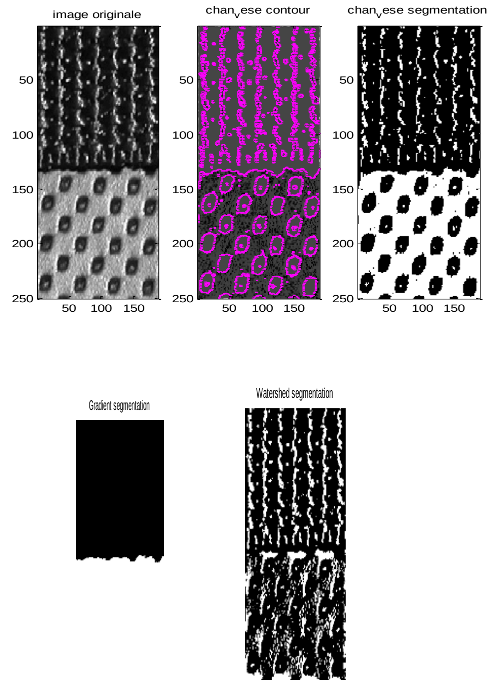


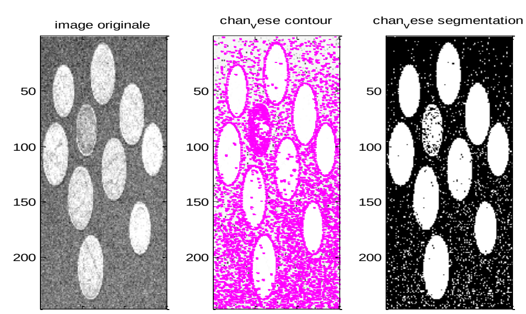
Figure 4.3 a) Original Image b) Chan Vessel Outline, c) Image Segmentation Chan Vese, d) Segmentation with Gradient, and e) Segmentation with LPE

The results obtained for the preceding figures from the segmentation evaluation criteria are presented in the following table:

Tableau 4.3- Segmentation quality measurement.

Méthods and creteria	**EAM**	**EQM**	**PSNR**
Chan-Vese	0.1494	843.9429	18.8677
Waterhed	89.1052	1.2550e+04	7.1443
Gradient	88.8536	1.2495e+04	7.1634

d) segmentation image noisy with 'gaussian' :



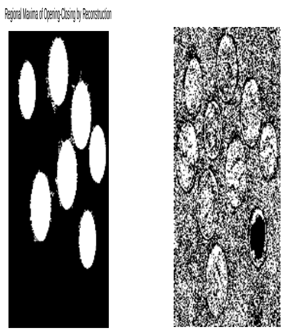


Figure 4.4 a) Original Image b) Chan Vessel Outline c) Image Segmentation Chan Vese d) Segmentation with Gradient e) Segmentation with LPE

The results obtained for the preceding figures from the segmentation evaluation criteria are presented in the following table:

***Tableau 4.4**- Mesure de qualité de segmentation*

Méthods and creteria	**EAM**	**EQM**	**PSNR**
Chan-Vese	0.0225	740.6712	19.4345
Watershed	102.4597	1.3610e+04	6.7922
Gradient	151.4199	2.6218e+04	3.9449

The results obtained for the preceding figures from the segmentation evaluation criteria are presented in the following table: In this work, we presented the design of an algorithm variant to apply it to the image segmentation problem. Segmentation is the most important step in an image processing system because it is the step that isolates the different entities that make up an image and this has a strong influence on interpretation and analysis.

There is no general solution to the problem of segmentation, but rather a set of mathematical and algorithmic tools, which can be combined together to solve specific problems. The present work has mainly shown us the variety of existing segmentation methods as well as their application in the field of image processing. We have tested this method of segmentation by applying the Chan-Vese algorithm, and we make a comparison between the proposed algorithm and other existing algorithms by validity criteria that we will use previously.

The test results obtained clearly demonstrate the effectiveness of this image segmentation algorithm with respect to other algorithms in the field of image segmentation. We have exposed in the first chapter a generality on image processing. In the second chapter, we presented the different methods of image segmentation, we are interested in the method of Chan-Vese, then we will give and explain other models of segmentation "Lines of Water and Gradient Sharing" which we use them for comparison the results for scalar images in gray level.

In this article, we will present the tests and results of the work provided. These are mainly, comparisons between the proposed Chan-Vese segmentation method and some other segmentation models: "Water Sharing Lines and Gradient". To make an objective comparison of the different methods proposed, we propose to use as criteria: EAM (average absolute error), EQM (mean square error), and PSNR (Peak Signal to Noise Ratio). We present in tables the values of the validation criteria for all the proposed methods. We introduced the Chan-Vese algorithm for image segmentation and showed that it is effective on a wide variety of images. It is particularly useful in cases where algorithm-based edge segmentation will not suffice, as it relies on global properties (gray scale intensities, contour lines, regions) rather than local properties such as gradients. This means that it can elegantly deal with noisy images, fuzzy images and images whose foreground region has a complicated topology (multiple holes, disconnected regions, etc.).

Although all the test images in this article have taken less than a minute to segment, the movie Chan-Vese algorithm is excessively slow for some applications. Depending on the type and size of the image and the number of iterations required, segmentation can take several seconds, which is too slow to follow typical video framerates. A literature review reveals that the predominant uses of this method have been the analysis of medical images, especially for segmentation problems where a diagnostically relevant feature, such as a lesion or tumor, appears as a dark or clear spot.

Finally, we mention that this algorithm represents an exciting trend in the "modernization" of image processing and analysis. Mathematical topics and methodologies that have traditionally used little in image processing, such as partial differential equations and computations, have found over the last decade a multitude of applications. From segmentation to imaging inpainting and denoising problems and beyond, such methods will undoubtedly play an important role in future research in image analysis.

V. CONCLUSION

In this paper, we have proposed and implemented a new image segmentation algorithm based on the Chan-Vese active contour model. The discrete gray level-set method is employed in our numerical implementation. This algorithm works in two steps, smoothing the noisy image by using the heat equation filter method and then using the new discrete gray level-set method to segment the region of the original image.

The evaluation indices and the comparison of the results obtained by the three methods showed that the Chan-Vese method is very interesting and better than the two other methods given the results of the evaluation criteria (MSE, EAM, PSNR). Our results are relatively satisfactory for all cases of Chan-Vese model. In the second part of the results we show that our model allows to detect the contour of a highly noisy object and consequently the contour of an image which is not well defined by its gradient. despite the fact that noise is present in the images, the geometric forms are reconstituted, without filtering the noise. The results of segmentations by "LPE" and "Gradint" as shown in the figures are very sensitive to noise, may notice that the CV method appears to be the most efficient in this case compared to the other two methods. The CV method gives excellent results, but for highly noisy images, contour detection is always more delicate. However, we are confident that this approach remains better than the other two approaches.

We had positive results with the Chan-Vese model that we implemented on monospectral images (gray level).

The CV model also shows that it is well qualified when applied to images with non-gradient boundaries. The Chan-Vese approach gives excellent results, but for highly noisy images, contour detection is always more delicate. However, we are confident that this approach remains better than the approach that uses other segmentation methods . But like all methods of optimizations, the two proposed methods, hybrid and non-hybrid, have registered some disadvantages during execution like: The number of parameters, which is relatively large, the results depend directly on the optimization of these parameters.

The time calculate is sometimes high estimated at a few minutes due to the number of iterations applied, the more the number of iterations increases the more the execution time increases.

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