Journal of Engineering Science and Technology
Vol. 16, No. 4 (2021) 3119 – 3135

PARALLEL OBJECT TRACKING IN IMAGE SEQUENCES BASED ON K-MEANS AND AN IMPROVED GRADIENT VECTOR FLOW

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Abstract

Object tracking present an essential challenge in computer vision and image processing. In this paper, we focus on tracking objects in medical image sequences. The proposed approach defines three agents. The first Agent decomposes the images into multiple resolutions using *Gaussian pyramid* algorithm. The second one detects the object in parallel at the superior levels of pyramids. The detection is done by K-means clustering combined with Generic Gradient Vector Flow and Normally Biased Gradient Vector Flow models. The initial contour of the improved GVF Snake (IGVF-SNAKE) is the k-means edges. To reduce the convergence time, a subdivision occurs; the initial contour becomes independent sub-contours that converge simultaneously. The last Agent projects the IGVF-SNAKE points found in low-resolution to high-resolution images. Extensive experiments are provided to evaluate our method, showing significant improvements on both noise sensitivity and tracking time. This combined approach gives accurate result for especially concave object tracking.

Keywords: Gradient vector flow, K-means clustering, Medical image, Multi-resolution, Object tracking, Parallel execution.

1. Introduction

Object segmentation and tracking in image sequences have a great importance in different fields related to computer vision, such as: surveillance, medical reasoning and others. Object tracking is a process that determines the positions of moving objects in image sequences. Its aim is to follow objects that move or evolve over time while preserving the identity of each object. Several techniques can be applied to ensure these operations [1-3].

In the medical field, many applications require the detection of moving objects and their tracking in the environment. Object tracking in medical images sequence still a sensitive problem when it comes to obtain precise results while respecting different possible movements and scenes.

For the development of a robust tracking algorithm, we have two constraints; the first one is the tracking quality and the second one is the time aspect expressed via the algorithm's speed and complexity.

A considerable research has been tackled in non-rigid object tracking during the last few years in the context of deformable models. Tirandaz and Azadi [4] presented object tracking system using Gradient Vector Flow (GVF) active contours, and a technique of optical flow. The latter is less sensitive to background structure that is why it needs less time to process the image, while the GVF have a good precision for image segmentation. Sultan et al. [5] proposed an integration of optical flow in an open-ended active contour framework for the segmentation and the track of the Anterior Mitral Leaflet in echocardiographic image. This promotes solutions with contours next to high leaflet displacements.

Sun et al. [6] proposed a new algorithm for hand tracking with particle filter and skin colour adaptive gradient vector flow model. It aims at the implementation of hand tracking in an accurate and quick way in complex background. Their approach was applied to the extraction of deep concave region of hand contour. Cuenca et al. [7] treated the problem of circle tracking across an image sequence, a new energy for active contour model was proposed. In each frame the centre and radius of the circle was optimized in search of a local minima of such energy. Wang et al. [8] presented a behaviour tracking algorithm based on linear discriminant analysis which is combined with the gradient vector flow. First the GVF is calculated through the reference coordinate system, parameters of the appropriate curve are set, the behaviour's position is determined. Once the discreteness is calculated the behaviour's detection is done.

However, the use of deformable models for tracking object is a challenging task. It's becomes even more complex when image sequences present noise at the time of acquisition, and when the object changes appearance (size and shape) frequently. The use of the classical deformable models, make the object detection with complex concavities difficult, and consume lots of tracking time when having a large number of images in one single sequence.

In this paper, to satisfy the first tracking constraint (tracking quality), we are interested to Gradient Vector Flow snakes' models due to their efficiency to segment and track non-rigid objects. And to have a Fast object tracking, the satisfaction of the second tracking constraint, we define three agents running in parallel. The first Agent uses an analysis of multiresolution to reduce active contours sensitivity from the noises and to get fast convergence of the Snake. Then, parallel object localization is done by the second Agent using hybrid model that combines: K-means, Generic Gradient Vector Flow, and Normally Biased Gradient Vector Flow models. The last, project the sub-contours detected in low-resolution to the high-resolution images.

The remainder of the paper proceeds as follows. Section 2 gives a brief review of the literature, focusing on active contour models. Our multiresolution representation technique is given, in section 3. The K-means algorithm is defined in section 4. The next section explains in details Gradient Vector Flow snake and its improvements models. We provide the principles of the developed approach in Section 6. Section 7 shows the results of proposed approach for tracking several sequences. The last section finalizes the research paper and give some suggestions for further future work.

2. Related Work

This section, briefly cover some important techniques that improve the classical active contour.

The concept of active contours was introduced by Kass et al. [9]. This method is widely used in many recent image analysis applications, including edge detection and segmentation [10-12]. The traditional snakes have many disadvantages. First it is difficult to handle a boundary concavity that is why much research has been conducted to find improved models.

Xu and Prince [13] developed an external force for active contour called GVF: gradient vector flows. To spread the gradient’s edge map, which is taken from the images, vector diffusion equation was added. Then they presented two coefficients that have the ability to vary in the image. As result they gained an external force named GGVF: Generic gradient vector flow. Ning et al. [14] proposed external force field which is a normal gradient vector flow (NGVF); this force abandons the tangent diffusion which makes the protection of the weak edge difficult for the NGVF model. Wang et al. [15] introduced NBGVF: normally biased gradient vector flow, which represents external force field that retains in a complete way the tangent diffusion, with having the ability to adapt a normal diffusion for the image structure. Zhang et al. [16] combined GGVF and NBGVF; they have adopted a new setting type of coefficients that takes a convex function form to ameliorate the capacity of preserving weak edges from smoothing noises. Mengmeng et al. [17] developed a novel improved model using GVF-snake. The main idea is to add a dynamic balloon and tangential forces to reinforce the GVF force.

The second disadvantage of the classical active contours is that the snakes are extremely sensitive to noise and to the initial contour which must be close to the object. To solve these problems, Zhao et al. [18] combined K-means with GVF snake.

Thirdly, the traditional active contours need considerable processing time. This point remains a challenge for the original snake and its improved models. Fekir and Benamrane [19] introduced multi-agent system using NetLogo platform for parametric snake model. Rossantl et al. [20] presented parallel double snakes which progress simultaneously to minimize an energy functional that attracts the contours at high image gradients. Sajan and Kumar [21] provided a high-level overview of OpenMP, it has an effective and easy implementation in adapting parallelism to sequential GVF-Snake method using instruction, data and loop level parallelism.

3. Multiresolution

The goal of Multiresolution methods is to get a global view of image through the examination of it, at different resolution levels. There are many types of multi-resolution image decomposition as: Gaussian pyramids, Laplacian pyramids and wavelets [22].

Gaussian pyramid is a multiresolution image representation obtained through a recursive reduction, i.e., low-pass filtering and decimation of the image data set. Compared with other pyramid algorithms, GP (Gaussian pyramid) has a good visual effect and less computation. In GP layers, all the levels can be obtained iteratively by the below equation.

$$G_0(x,y) = I(x,y)$$

$$G_l(x,y) = \sum_{m=-2}^{2} \sum_{n=-2}^{2} W(m,n) G_{l-1}\,(2x+m, 2y+n) \quad (1)$$

where W is a 5×5 Gaussian kernel.

The original image represents the low level (0) that is the pyramid's base. For the upper layers, the data of level 1 are the result of filtering the data of the level (1-1). Thus, the image is decimated by a factor 2 in all spatial components (see Fig. 1). This means, if the image at level (1) has dimensions N×N, the resulting image at level (1+1) will have dimensions N/2 × N/2.

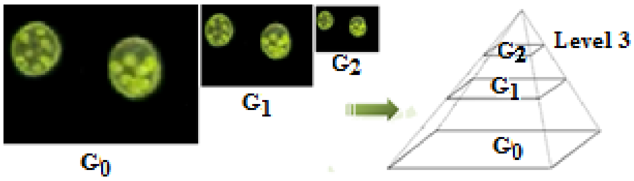


Fig. 1.Three-level pyramid (G_0, G_1 and G_2).

The Gaussian kernel W is formulated from a vector w of size 5, such as:

$W(m, n) = w(m).\ w(n)$

$m = -2, \ldots, 2 \qquad n = -2, \ldots, 2$

Some constraints imposed on w, express the Gaussian kernel from a single parameter a, where:

$1/4 \leq w(0) = a \leq 1/2$

$w(1)= w(-1)=1/4 \qquad w(2)= w(-2)=1/4 - a/2$

4. K-means cluster

Much research has been conducted in the area of image segmentation, which is defined as the classification of an image into various groups with the use of clustering; K-Means is one of the most popular clustering algorithms [23].

K-Means clustering is unsupervised, non-deterministic, and iterative method. It is used to segment the interest area from the background. The aim is to get some groups based on certain kind of data similarity; the number of groups is represented by K.

K-Means minimize the sum of squared distances between all points and the cluster centre by the following equation:

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n} \left\| x_i^{(j)} - c_j \right\|^2 \tag{2}$$

First, the k-centres are calculated and, then every point is taken to the cluster that has the nearest centre from the respective data point. When the grouping is completed the new centre of each cluster is calculated for the second time, based on these centres, a new Euclidean distance is calculated between each centre and each data point. Finally, it assigns the points in the cluster which have minimum Euclidean distance.

5. GVF-Snake Models

An active contour or a snake [9] can be an open or a closed elastic curve (*C*), which is deformed from an initial position, around the desired object and it is then attracted towards the object by minimizing the energy function *E*(*C*) subject to certain constraints (see Fig. 2).

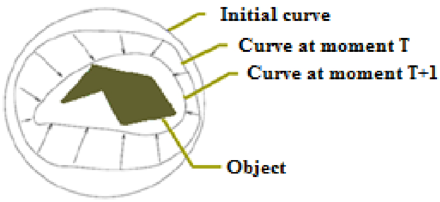


Fig. 2. Principle of active contours.

The energy functional *E*(*C*) generally contains two terms:

$$E(C) = E_{int} + E_{ext} \tag{3}$$

where E_{int} represents the internal energy of the snake, it serves to impose a piecewise smoothness of the snake; it is calculated by two forces: the continuity and the Curvature force [20]. Equation (4) represents this energy.

$$E_{int} = aE_{continuity} + bE_{curvature} \tag{4}$$

where *a* and *b* are weighting parameters representing the degree of the smoothness ($a \geq 0$) and rigidity ($b \geq 0$) of the contour, which are used to give more (or less) influence on each energy.

- Continuity Force: makes the Snake points more equidistant. When $a = 0$, the curve can have discontinuities.
- Curvature Force: prevent the snake from containing isolated points and therefore incoherent points for the regular form. When $b = 0$, the curve can take a strong convexity.

The second term of Eq. (3); E_{ext} denotes the external energy that pushes the snake toward the image objects which are generally edges, and subjective boundaries. Generally, the external energy is a gradient function of the image intensities. Thus, the snake will place itself in parts of the image with high gradient values.

5.1. Gradient vector flow

In classical active contours [9], the initial contour of snake must be close to the true boundary of the object, since the external force has small capture range [24].

Several researchers proposed solutions to enhance the capture range of external force, the most popular solution is, the Gradient Vector Flow (GVF) and its generalization [13], and the NBGVF [15] model.

The external force GVF is a field ($U(x, y)$, $V(x, y)$) obtained by a diffusion of the gradient vectors of an edge map (f_x, f_y). The GVF is constructed by the minimization of the following energy functional (Eq. (5)):

$$E(U, V)= \frac{1}{2}\iint (\mu(U_x^2 + U_y^2 + V_x^2 + V_y^2) + \left(f_x^2 + f_y^2\right)[(U - f_x)^2 + \left(V - f_y\right)^2])dxdy \quad (5)$$

where, μ is a positive parameter that governs the trade-off between the first term and the second term in the integrand. Using the calculus of variation, the external force can be found by solving the Euler equations:

$$\mu\nabla^2 V - \left(f_x^2 + f_y^2\right)\left(V - f_y\right) = 0 \quad (6)$$

$$\mu\nabla^2 V - \left(f_x^2 + f_y^2\right)(U - f_x) = 0 \quad (7)$$

where, ∇^2 is the Laplace operator. Resolving Eqs. (6) and (7) for (U, V), result an external force field (GVF) for the active contour.

5.2. GGVF model

Xu and Prince [13] proposed a Generic Gradient vector flow as external force, to treat the problem of the hard convergence of GVF Snakes towards the long concave shape and the dilemma of the robustness to noise. The evolution equation of GGVF field is the Eq. (8) which can be obtained using Eqs. (9) and (10).

$$V_{t-ggvf}(x,y,t) = g(|\nabla f|)\nabla^2 V(x,y,t) - h(|\nabla f|)[V(x,y,t) - \nabla f] \quad (8)$$

$$g(|\nabla f|) = e^{-|\nabla f|/K} \quad (9)$$

$$h(|\nabla f|) = 1 - e^{-|\nabla f|/K} \quad (10)$$

where, $g(|\nabla f|)$ Eq. (9) and $h(|\nabla f|)$ Eq. (10) represent smooth and data coefficients. K determines the weight of the smooth and the data terms.

5.3. NBGVF model

Ning et al. [14] proposed an improved external force field for active contour model, called NGVF. Based on analysing the diffusion process of the GVF and three interpolation functions, it is found that the generation of GVF contains diffusions in two orthogonal directions along the edge of image, one is the tangent direction and the other is the normal direction. Moreover, the diffusion in the normal direction plays the key role on the diffusion of GVF, while the diffusion in the tangent direction has little effect.

Wang et al. [15] introduced an external force which is normally biased gradient vector flow, that conserves tangent diffusion and adapt a normal diffusion for image structure. NBGVF solve the problem of weak edge protection.

5.4. Improved GVF Model

Zhang et al. [16] combined between GGVF and NBGVF. The developed version is defined as a vector field which is obtained by the following energy functional (Eq. (11)):

$$E(V) = \int\int g(x,y)(gs(x,y)V_{NN} + hs\,(x,y)V_{TT})\,dxdy + h\,(x,y)(V - \nabla f)\,dxdy \tag{11}$$

$$hs\,(f) = \begin{cases} 1 & (|e| \geq \tau) \\ -\frac{f^3}{8\tau^3} + \frac{5f}{8\tau} + \frac{1}{2} & (0 < |e| < \tau) \\ 0 & (|e| = 0) \end{cases} \tag{12}$$

$$gs(f) = 1 - hs\,(f) \tag{13}$$

Equation (11) can be resolved using the Eqs. (9), (10), (12), and (13). V_{NN} and V_{TT} represent the second-order derivative along the tangent and normal directions.

6. Proposed Approach

The goal of the presented method is to have a robust tracking of one single object in a sequence of images. The proposed method is a cooperative approach between three Agents running in parallel (see Fig. 3).

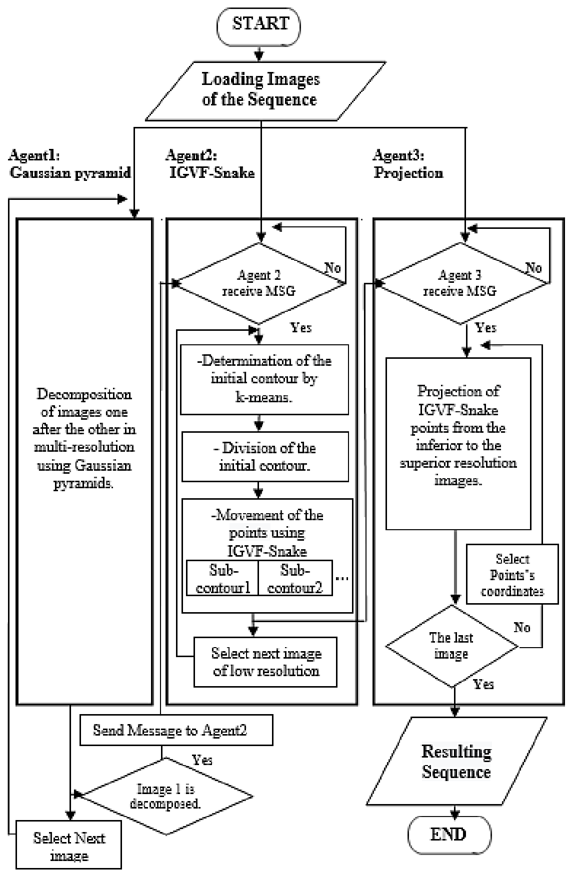


Fig. 3. The flowchart of the proposed approach.

6.1. Agent1: Gaussian pyramid

The first agent breaks down the images of the sequence one after the other in multiresolution. Gaussian pyramid is the method of our multiresolution decomposition. In this research, we have pyramids of three levels at most. The number of pyramids is equal to the number of images in the sequence.

Gaussian pyramid Algorithm:

```
Begin
Level = 0
Gaussian -image [Level] =original- image
While (Level<n) do
    Begin
    Gaussian -image [level+1] =REDUCE (Gaussian -image [Level])
    Level=Level+1
    end
End
```

For each pixel of coordinates (i, j), the REDUCE procedure uses Eq. (1) of Section 3 above.

When the first agent finishes the decomposition into multiresolution of the first image of the sequence, it sends a message to the second agent (Agent2: IGVF-Snake) so that it starts the detection of the object.

6.2. Agent2: IGVF-snake

The second Agent detects the object in the high levels of pyramids built by the first Agent.

6.2.1. Initial contour

In the developed method, K-Means algorithm gives initial segmentation for low-resolution images.

K-Means Algorithm:

1: Select the number of clusters K,
2: Initialize the K-cluster centres randomly,
3: Attribute each data point to the nearest centre,
4: Calculate and set the new centre of each cluster.
5: Reattribute each data point to the new nearest centre. If any reassignment occurs, go back to step 4.

After that, morphological reconstruction is applied to the output of the K-means algorithm for correct segmentation; Reconstruction is a morphological transformation that involves a structuring element B, and two images. One image (F) is a marker which contains the starting point of the transformation, and the second (G), the mask, which defines the transformation. The morphological reconstruction by dilation of G from F, is $R_G^D(F)$ with $F \subseteq G$. This reconstruction is defined by the following iterative procedure.

The result becomes the initial contour for IGVF method.

Morphological reconstruction Algorithm:

1: **Begin**

2: Create the structuring element: B

3: **Repeat**:

$$D_G^{(K+1)}(F) = (FB) \cap G$$

Until $D_G^{(K+1)}(F) = D_G^{(K)}(F)$

4: $R_G^D(F) = D_G^{(K+1)}$

5: **End**

6.2.2. The initial contour division

When initial contour is set, it will be divided into two sub-contours. The sub-contours number can be extended to four or eight. The division procedure is defined by the following steps.

Division Algorithm:

1: Create four points *A*, *B*, C and *D* to form a rectangle that surrounds the initial contour.

2: Split the rectangular into two, four or eight sub-rectangles when (*A*-*C*), (*B*-*D*), (*e*-*g*) and (*f*-*h*) points are connected (see Fig. 4).

3: Insert pattern points above and under the drawn line that have equivalent distance between them.

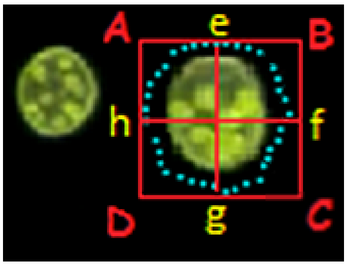


Fig. 4. The initial contour division into four sub-contours.

In our approach, each sub-contour is affected to one thread that runs in parallel to attain the object boundary.

6.2.3. IGVF evolution

When the division of the initial contour is completed, the sub-contours start to converge simultaneously using IGVF-Snake method [16], that combines GGVF (Generic Gradient Vector Flow) and NBGVF (Normally Biased Gradient Vector Flow) models. The active contour convergence is fast in images of low- resolution, because of the detail's elimination. The energy functional used is as follow:

$$E(C)=\sum_{i=1}^{N}(a\,E.continuity(pi) + b\,E.curvature(pi) + c\,E.IGVF(pi) \qquad (14)$$

where, *Pi: i*=1...*N* are snake points, and *a*, *b*, *c* represents attached coefficients to each energy.

Through the minimization of Eq. (11), the external force is obtained. The Euler Lagrange equation of the energy functional is written as follow:

$$g(gs.VNN + hs.VTT) + h.(V - \nabla f) = 0 \tag{15}$$

In order to obtain the vector field in Eq. (15), the parameter *t* was introduced to construct the following partial differential equation.

$$\frac{\partial V}{\partial t} = g.(gs.VNN + hs.VTT) + h.(V - \nabla f) \tag{16}$$

$$\begin{cases} V_{NN} = \frac{1}{|\nabla V|^2}(V_x^2 V_{yy} + V_y^2 V_{xx} - 2V_x V_y V_{xy}) \\ V_{TT} = \frac{1}{|\nabla V|^2}(V_x^2 V_{yy} + V_y^2 V_{xx} + 2V_x V_y V_{xy}) \end{cases} \tag{17}$$

In the last equation Eq. (17), $V_x V_y$ is the first-order partial derivative with respect to *x* or *y*, $V_{xx} V_{yy}$ is the second-order partial derivative with respect to *x* or *y*, and V_{xy} is the result achieved by computing the partial derivative with respect to *x* and to*y*. Equation (16) can be resolved by the following partial differential equations:

$$\begin{cases} \mu_t = g\,.(gs.\mu_{NN} + hs.\mu_{TT}) + h.(\mu - f_x) \\ v_t = g\,.(gs.v_{NN} + hs.v_{TT}) + h.(v - f_y) \end{cases} \tag{18}$$

where $\mu = \frac{\partial V}{\partial x}$, $v = \frac{\partial V}{\partial y}$, $f_x = \frac{\partial f}{\partial x}$ *and* $f_y = \frac{\partial f}{\partial y}$.

The equation of evolution that concerns this external force is:

$$V_t(x,y,t) = g(|\nabla f|)\big(gs(f)\,V_{NN}(x,y,t) + hs(f)V_{TT}(x,y,t)\big) - h(|\nabla f|)[V(x,y,t) - \nabla f] \tag{19}$$

6.2.4. Minimizing the energy functional of the Snake

To solve the problem of minimizing the energy function *E*(*C*) of Eq. (14), we focus on “Fast Greedy algorithm” which is an improvement of Greedy algorithm [25]. For every Snake point and for (3×3) neighbourhood the "Fast Greedy algorithm» steps are summarized as follow:

Fast Greedy Algorithm:

1: Compute the *E*(*c*) energy of the four cardinal neighbours and the Snake point itself (see Fig. 5(b)).

2: The energies calculated in 1, should be normalized.

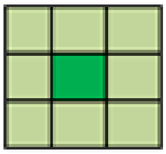
3: If one of cardinal neighbours have inferior or equivalent energy to the one of Snake point, it is not a must to diagnose the diagonal neighbours then move to step 6.

4: Compute the energy *E*(*c*) for diagonal neighbours (see Fig. 5(c)).

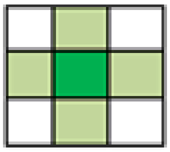
5: The energies calculated in 4, have to be normalized.

6: Displace Snake point to neighbour which has a minimal energy.

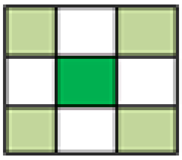
To stop the snake evolution, stopping criterion is presented by the percentage of points that does not move for a number of iterations. If this condition is not verified, the Snake continue to deform until reaching a certain number of iterations.



(a) (3×3) Neighbourhood.



(b) Cardinal neighbours.



(c) Diagonal neighbours.

Fig. 5. Neighbourhood.

After detecting the object in the first image, Agent IGVF-Snake proceeds to the second image which is at the top of the second pyramid. And so on, until the object is detected in all tops of the pyramids. Agent IGVF-Snake sends a message to the third agent (Agent projection), when the object is detected in each low-resolution image. This message contains the coordinates of IGVF-Snake points found at superiors' levels of pyramids that will be used by the Agent Projection.

6.3. Agent3: Projection

Once the sub-contours finish their evolution, Agent3 moves IGVF-Snake points from the lower to the higher resolution images.

To visualize IGVF-Snake points in level "*i*" on level "*i*-1" of the image, we precede the algorithm below:

IGVF-Snake points Projection Algorithm:

```
Begin
For each IGVF-snake point at level " i" do
Compute the position of the point "p" on level"i-1"
    For each point in the neighbourhood of  " p" do
            Calculate energies
     end  for
    For each point in the neighbourhood of  " p" do
            Normalize
     end  for
Minimize to get the IGVF-Snake point on the level"i-1"
Display the new IGVF-snake point on the level " i-1"  of the   image
end  for
End
```

The final result of object tracking is all the converged sub-contours at levels 0 of pyramids.

7. Experimental Results

In this section, we present some results in order to validate our proposed approach. We have used different type of images sequences: synthetic, echocardiographic and biological sequences. Our simulation environment is Java programming language.

In all the tests, each lower-resolution level is obtained by using filters (5 × 5) and the Gaussian kernel parameter value was fixed at 0.66.

For IGVF-Snake object detection in the superior levels of pyramids, we have used a neighbourhood (3×3) and our stopping criterion is 80% of IGVF-Snake points that maintain the same position between two iterations.

Table 1 presents the parameters that we used for all experiments.

Table 1. IGVF-Snakes parameters.

	Synthetic Sequence (Concave shape)	Biological sequence (Microbe)	Echocardiography sequence
Number of points	60	80	20
Continuity: *a*	0.6	1	0.6
Curvature: *b*	0.1	0.13	0.14
IGVF: *c*	0.8	1	1
IGVF {*k*, *τ*}	{1, 0.5}	{1, 0.2}	{1, 0.5}

Since we have a large number of images in a sequence, we will select and present the results of only two images from the sequence.

Figure 6 shows pyramids of three levels. The multiresolution decomposition use (512×512) resolution for the original images, level 1 contains images of (256×256) resolution and the superior level (level 2) has the resolution of (128×128).

The initial contours obtained by K-means algorithm are divided into two sub-contours (see Fig. 7) and they converge simultaneously by IGVF-Snake.

We have noticed that the detection of object contour was successful in all the image sequences. The final segmentation that combines k-means and IGVF-Snake demonstrated that IGVF have a vast capture range and have the ability to displace in boundary concavities.

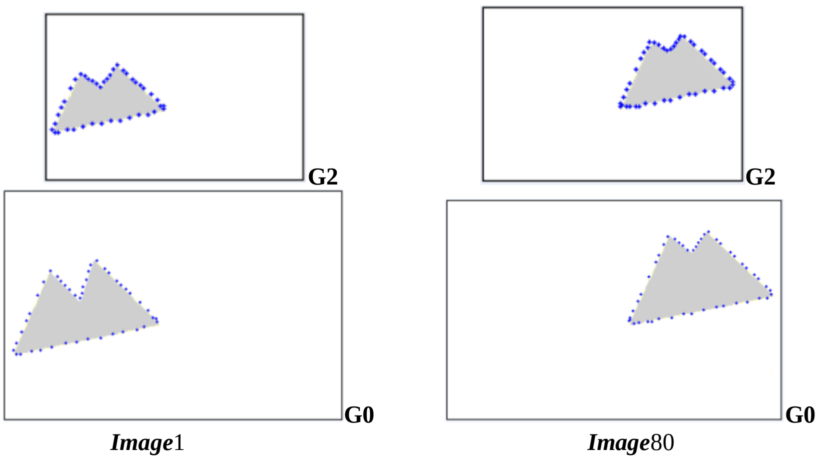
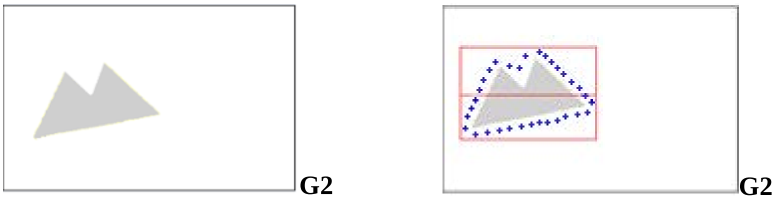


Fig. 6. Result of the synthetic sequence (Concave shape).



(a) The tenth synthetic image on level 2 (Top) of the pyramid.

(b) Initial contour using K means algorithm which is divided into two sub-contours.

Fig. 7. Result of dividing the initial contour of the synthetic image (Concave shape).

Figure 8 presents pyramids of biological sequence "microbe". The object contour was fully detected in all sequence levels, despite the presence of noise in their images. This is due to multiresolution decomposition based on low-pass filters, and to the K-means clustering.

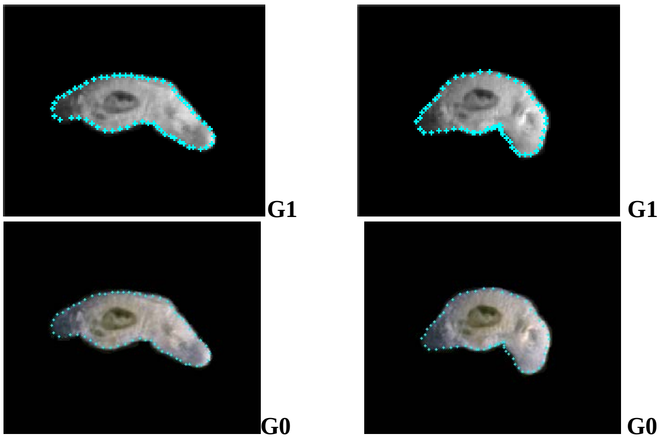


***Image*1** ***Image*60**

Fig. 8. Result of Biological sequence (Microbe).

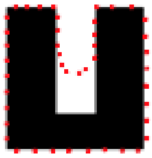
The developed approach is compared with the traditional GVF-Snake that uses manual initialization (circle) instead of the K-means algorithm. The result shows that when we have a long concave shape the proposed approach has a large capture range and it is capable to move to boundary concavities see (see Fig. 9). The IGVF-snake is more robust to noises (see Fig. 10).

A temporal comparison is made between:

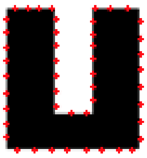
- Sequential IGVF-Snake method with manual initializations (circle) that neither use the Agents model, nor divide the initial contour to sub-contours.
- The proposed approach with the use of watershed algorithm [26] instead of K-means algorithm.
- The proposed approach.

Table 2 summarizes this comparison:

(a) Original image.

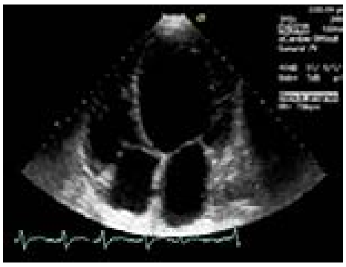


(b) Classical GVF-snake that uses manual initialization.

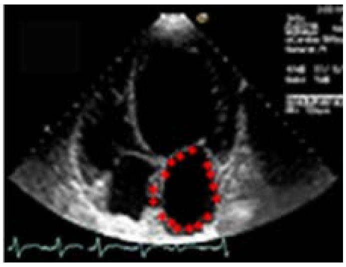


(c) Proposed method.

Fig. 9. Comparative results of object detection for U-Shape (Level 0).



(a) Original image.



(b) Classical GVF-snake that uses manual initialization.

(c) Proposed method.

Fig. 10. Comparative results of object detection for echocardiographic image (Level 0).

Table 2. Detection time improvements (in second).

	Sequential approach	Watershed Algorithm [26]	Proposed Approach
Synthetic sequence (Concave shape)	410.986	284.842	212.793
Biological sequence (Microbe)	389.510	222.431	91.764
Echocardiography sequence	202.150	132.881	62.561

The processing time improvements obtained are due to the simultaneous convergence of sub-contours, and to the K-means algorithm which give us an initial contour closer to the object to be detected.

Another temporal comparison was performed for the biological sequence. In this comparison we vary the number of sub-contours (Threads), as can be seen in Table 3:

Table 3. Improvements time for biological sequence (in seconds).

	Proposed Approach (Greedy)	Proposed Approach (Fast Greedy)
Two sub-contours	164.142	91.764
Four sub-contours	126.551	86.164
Eight sub-contours	112.911	82.465

The Fast Greedy algorithm optimizes the window of neighborhood compared to the Greedy algorithms, which signify the obtained time improvements.

Being given the nature of treatments performed, we believe that these gains are important and may possibly be improved.

8. Conclusion and Perspectives

In this paper, a parallel approach for robust object tracking has been proposed. Our parallel processing system has three agents, the first performs multi-resolution decomposition for all the images of the sequence, and the second detects the object in the high levels of the pyramids by the combination of K-means algorithm with improved GVF (Gradient Vector Flow). By the division of the initial contour, we can obtain two, four or eight sub-contours which converge in parallel. The third Agent performs the projection of the IGVF-snake points from the low-resolution images to the high one. The results show that our developed approach is able to converge in concavities with an interesting processing time and a less sensitivity to noise. However, in our model the precision of object detection is controlled by the fixation of IGVF-Snake parameters, they have to be adjusted for each new type of image sequence using manual tests based on essays, this process takes time.

Our next work is to compare the proposed detection and tracking system with related works cited in section 1 and 2, also implementing an approach for the automatic determination of the IGVF-Snake parameters, and lastly, we will test our approach using a Grid computing.

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