Analysis of strengths and weaknesses of Gradient Vector Flow snake.

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I. Introduction

Image processing is a technique which is used to extract information from images by applying different techniques to it. Different techniques used for the separation or segregation of information from the image. Active contour is one of the active model in segmentation techniques, which makes use of the energy constraints and forces in the image for segmentation of the object boundary or curvature from the image. This technique is used in various image processing applications, specially in medical image processing, while other applications are motion tracking and stereo tracking. In this paper we are testing two different active contour models, the Standard Vector field(SVF) and the Gradient Vector Flow (GVF) by fitting the active contours or snakes to locate object boundaries. The models are evaluated on different images throughout the paper with different values of parameters, which are explained as below:

a) Alpha(α): It controls the tension of the snake by adding more weight in the energy function to the first derivative of the contour variable at each point. Therefore, it represents the elasticity of the control points in the active contour [1]. Higher value of the α will let the control points go further away from each other in order to follow the shape of the object boundary.

b) Beta(β): It controls the rigidity of the snake by adding more weight in the energy function to the second derivative of the contour variable at each point. Therefore, it represents the smoothness of the contour formed using the control points. Higher value of the beta will make smoother contour line which is formed by control points.

c) Gamma(γ): It provides the value of step size in each iteration. So higher gamma value will lead to faster convergence to the shape of the object boundary, but it could also lead to suboptimal solution sometimes.

d) Kappa(κ): It is external force weight acting on the active contour. Higher value of κ will force the contour points to align themselves more to the shape of the object boundary. Noise can greatly affect the active contour shape for higher value of κ. Very high value of κ could lead to distorted contour as well. Whereas smaller value of κ will lead to suboptimal active contour plot.

e) Dmin: Minimum resolution of the snake.

f) Dmax: Maximum resolution of the snake.

g) Iteration: Number of iteration of the active contour algorithm with given fixed parameters value.

h) Sigma(σ): Sigma value controls the blurring of the gradient magnitude square. When contour lines are far away from the gradient, then to simulate the shifting of the active contour lines, we blur the gradient. Blurring will cause creation of a force field or potential field, which will cause the contour lines to shrink. Hence, σ value increase the range, but the boundary localization will become less accurate. Therefore, at higher value moving in the concavity of the object boundary decreases.

i) Mu(μ): Mu adds a regularization parameter governing the trade-off between the sum of the squares of the partial derivatives of the vector fields and the gradient of an edge map. Its value is set in accordance to the noise present in the image. We choose higher value of Mu for higher level of noise in the image.

II. Exercises

Exercise 1

In this first exercise, we explored the main parameters used in active contour with both classical and GVF snake models. The image manipulated is a binary image of 'U' shape with a boundary concavity on the top, which makes it ideal to test active model and exploring the influence of each parameter in the snake contour due to the shape and binary format. Three preprocessing techniques were used in the preprocessing phase. Firstly, convolution of the image with a kernel to obtain the gradient image. The resultant image has each pixel representing the gradient of the previous image pixel. For the first exercise, we did not apply this pre-processing step.

Secondly, the convolution using Gaussian function kernel was applied to obtain blurring or smoothing of the image. The main goal of this step is either to reduce noise or to produce a less pixelated image, or both. However, for U shaped object, the smoothing process could be more useful for the SVF model than GVF model due to the lack of external forces as shown in Figure 1, last image). Hence, increasing σ increases the edge range of the object shape. On the other hand, the boundary localization will become less accurate and the concavities could overlap. An initial contour remote of the object boundaries in the SVF model could cause that the snake doesn't deform due to the lack of forces, whereas the smoothing step process could assist via increasing the influence of the force field.

Finally, the normalization of the image. It is the process of changing the range of the pixel values(Fig.2. Therefore, the convergence of the snake at the boundaries is faster and fewer iterations were needed.

The next experiments were run with a selected value of σ = 1, a value that increase the force field for the SVF model without losing the concavity boundaries of the image object. No gradient convolutional kernel was used and the initialization of the active contour was done based on human knowledge, i.e. selecting a radius which locates the snake near to the desire contour. As mentioned before, in the SVF model, it is important that the initial contour is within the influence of the potential force field of the image else the contour will not be deformed towards the object boundary. The radius of the initial rounded contour selected in the experiment is of 0.68. Different values of α, β and κ were selected to evaluate the deformation of the contour. A fixed step size is used, and 500 iteration were ran.

Model was run with the above-mentioned parameters and α values were taken as [0.5, 1, 5]. Since smaller values of alpha represent less weight being applied to the tension of the energy equation, it is easier to stretch where the distances between point are bigger. While larger values depict higher weight, so active contour lines were not able to adapt to the concavities or outgoing edges. α value equal to 0.05 is selected as a suitable option for achieving good concavity of the object, since this would allow contour to stretch as per requirement. Despite selection of optimal value of α, the SVF model could not adapt the contour of the object at the shape concavity due to the forces in the concavity are horizontal and opposite so canceling out its effect, and not forcing the contour to go inside the moving boundary concavity as shown in the Figure 2.

β controls the weight of the rigidity of the snake in the energy equation (second derivative of the contour). So increase in the value will make the active contour more prompt to not getting deformed and adapt to the concavity of the object shape. Therefore, for this experiment, we are using a low value of β.

Exercise 2

Classical snake model and GVF snake model were run on "room" example with various parameters settings and initialization steps which are discussed as follows:

- Initialization - Active contour was initialized as in the Figure 3a to study its effect on classical and GVF snake model. It is seen that classical potential forces were too weak to overpower the snake's internal forces, so snake's contour instead of moving outwards towards the edge of the object, it shrank to a point at the centre of the image as shown in Figure 3b. Whereas, in GVF model, active contour takes the shape of the object boundary as shown in Figure 3b.

  Another way of initialization is explored, as seen in the Figure 4a. For classical model, snakes stops at a very undesirable configuration since all the point of contact between contour and object gradient boundary is normal and the rest of the snake that lies outside the capture range of the other parts of the boundary as shown in Figure 4b. Whereas, GVF model gives better results as shown in Figure 4c.
- Alpha(α) With proper initialization of the active contour, classical as well as GVF model gives correct shape of the room in the image at default value of alpha. But when the value of α is raised to a very high value (α = 5) then the active contour stops moving into boundary concavities. GVF model has a slight better result than classical model at high values of alpha.
- Beta(β) Beta parameter is related to the smoothness of the active contour, Both classical and GVF model gives good results with default value of beta. At a given value of beta GVF model gives slightly smoother snake contours at the edges as compared to classical model. Hence, classical model gives better results in detecting object boundary with sharp corners.
- Kappa(κ) It is the external force weight acting on the active contour. Classical model and GVF model gives similar results with realistic value of kappa. But at higher kappa value classical model gives distorted active contour while GVF model is similar active contour as the shape of the object boundary with reduced size.
- Mu(μ) Classical model does not have regularization feature while with GVF, its value is relevant for noise prone image of the object. So for the "room" example, which is noise free, we kept is as the default value.

  Other parameters don't have significant impact on both the models, so they are kept constant while doing the experiment. So after all the experiments conducted on both classical and GVF snake model, firstly we could conclude that initialization is a major step for achieving correct output of the classical snake model whereas, for GVF snake model it is not relevant. Secondly, for achieving good boundary concavities, we need realistic value of alpha. Thirdly, kappa has a role to play in achieving good result when object edges have boundary close to each other but for room example since the opposite boundaries were far so good results were obtained for both classical and GVF approach. Finally, other variables did not play a major role in room example image since the image was noise free and edges of the object were in simple geometry.

Exercise 3

Both models were run with the chest resonance example image and parameter values were fine-tuned in order to obtain the best result ergo best fit to the contour of the chest. For both models, a high value of σ was selected to reduce the impact of noise of the image (for example, noise generated due to veins). Better results were obtained with the GVF

Fig. 1: First image is the original image. In the second and third image the traditional distance forces of the SVF model are display without and with a smooth kernel apply. In the last image the GFV the image with the distance potential forces. In all the images a initial active contour of the same size is display to give perspective.

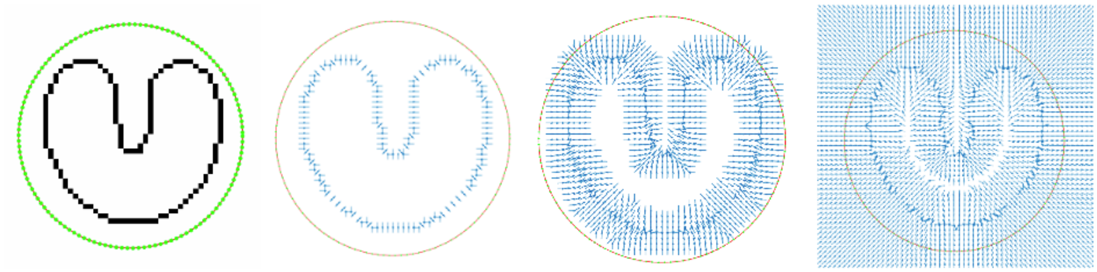
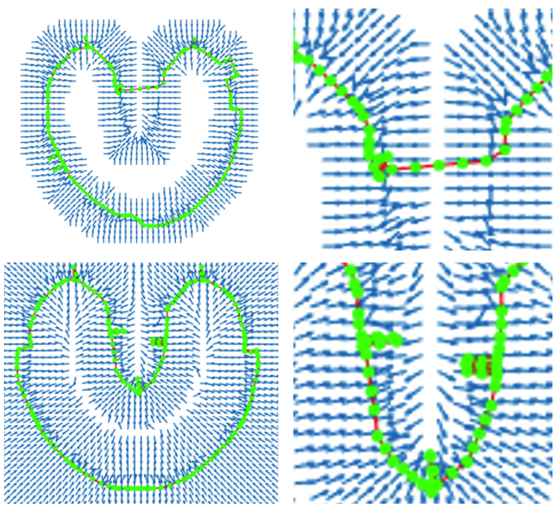
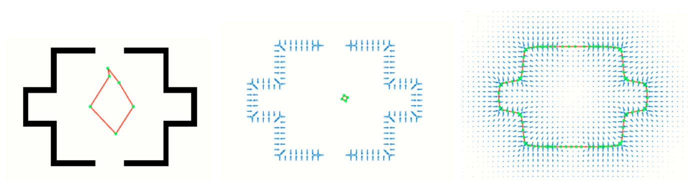


Fig. 2: In the two upper images are shown the final contour of the SVF model, where the contour can reach the boundary of the concavity due to the horizontal field (second upper image). In the lower images the higher convergence of the GFV model in the concavity is display.



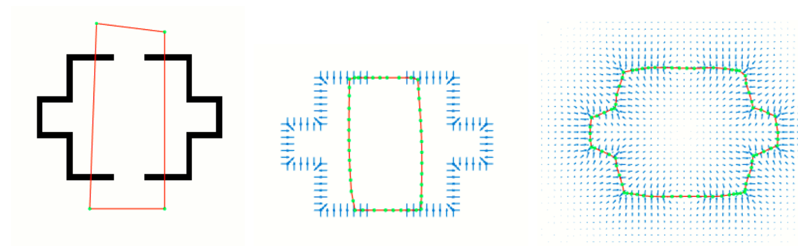


(a) Initial curve inside object edges

(b) Classical snake

(c) GVF snake

Fig. 3: Initialization of curve inside object edge in classical and GVF snake model.

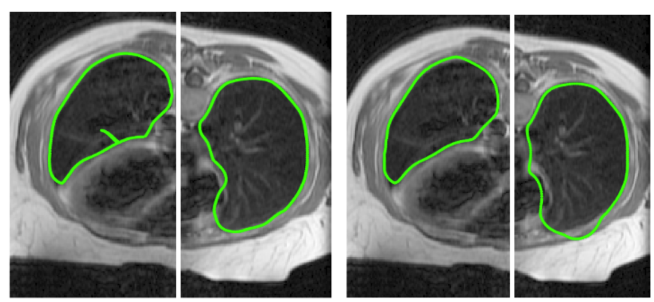


(a) Initialization of curve partially covering object edge

(b) Classical snake

(c) GVF snake

Fig. 4: Initialization of curve partially covering object and running classical and GVF model on it.



(a) Classical snake

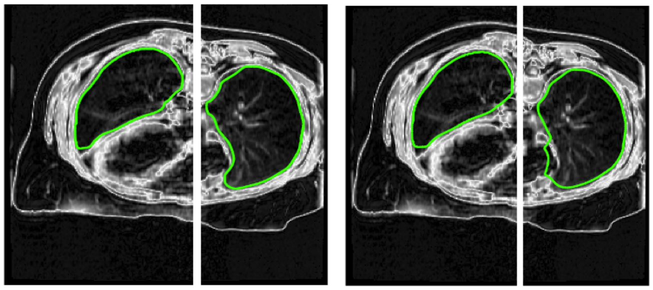
(b) GVF snake

Fig. 5: Best convergence of active contour both models of the new.png image left and right lungs.

model, as we can see in the Figure 5. For the SVF model, we choose low value of α so it could adapt to the lung shape and higher value of β to prevent fluctuation due to noise in the image. In the GVF model, low values of all parameters were selected as optimal. Standard vector field converged into a better solution by looking at the right lungs snakes from both model. Since both models had poor convergence on the right lung, so we considered that for the performance evaluation.

Exercise 4

With a similar image to the previous section but with higher contrast, the model try to find the boundaries of two lungs (Figure 6). The initialization of the active contour has been done based on human knowledge. Classical and GVF snake models are used with fine-tuned parameters. A high value of σ was used to reduce the noise of veins inside the lungs. In addition, high values of α could counter low level details and focus on global contour that were found during the experiments. Therefore, higher values of α and β were selected in order to counter the noise caused by veins in the lung by discouraging stretching and bending of the snake. Although both model had convergence problem at the boundaries of the right lung, an optimal result was found with the classical snake. The boundary convergence obtained with a high contrast image was higher, as seen in right lung, where in the previous section we obtained a poor convergence.

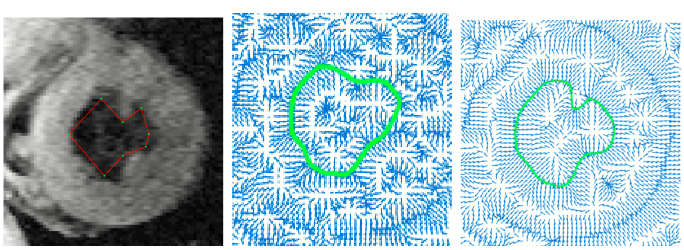


(a) Classical snake (b) GVF snake

Fig. 6: Best convergence of both models with the new.pgm image.

Exercise 5

Figure 7a shows a heart ultrasound image with the initial contour plot drawn in red. We could observe that image captured has a lot of noise content in it. So when the experiment was run with 0 as σ value than snake fits itself with object gradient as well as the noise in the data, and we don't get the true boundary of the object as depicted in Figure 7b. But with increase in the value of σ, true shape of the object boundary is achieved as shown is Figure 7c. With default value of alpha and beta, the shape of contour is crude, so α, and β values were altered to give better smoothening to the curve. Increasing the external force value distorts the curve at object boundaries, so it's better to have them at default position. Different configuration of initial curve of contour lines were also experimented, and the results obtained were mostly similar, hence GVF final active contour for detecting the object boundary is not dependent on the initiation curve inside object edges. Similar experiments were conducted with classical snake model as well, but results obtained were far from true active contour(object boundary).



(a) Initial curve inside heart ultrasound image (b) Sigma = 0 (c) Sigma = 2.5

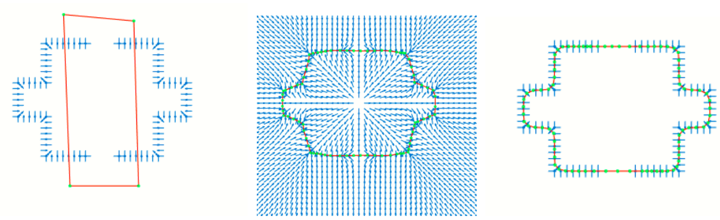
Fig. 7: Initialization of curve inside object edge in classical and GVF snake model.

Exercise 6

Snake based segmentation works well for detecting objects in an image, even through the image might have worse signal-to-noise ratio. It also works well for complex geometry like heart ultrasound imaging. But there are few limitations of the process. Few of them are: a lot of parameters needs to be decided like threshold value, and in flat regions noise will affect the outcome and convergence is relatively slow. Another shortcoming is that sometimes we get suboptimal solution through greedy algorithm. Optimal solution could be achieved through dynamic programming, but that would lead to high order of time complexity.

While using classical model, moving into boundary concavities is one of the problem other than proper initialization requirement in accordance to the object of the image requirement. While GVF works fairly well in general, but with complex object edge detection like heart ultrasound, it requires good initialization of the contour. A simple large circle outside the object boundary used for initialization would never lead to the realization of the complex geometry.

In the Figure 8a, we have partially covered the room example image with the initialized curve. With the classical model approach snake contour stops at a very undesirable configuration while with the GVF we could better detect the boundary of the object but sharp corners of the room example as in Figure 8b are a bit rounded. So to overcome the correct initialization problem as required by classical model by iteratively running the GVF model initially till the snake contour reaches the vicinity of the object boundary, then run the classical model to obtain the sharp corners similar to the object boundary as shown in Figure 8c. Therefore, through adapting the above procedure, we could overcome the initialization problem of the classical model as well as get sharp corners of the object boundary by running the classical model on the resultant of the GVF model snake.



(a) Initialization of curve partially covering object edge (b) GVF snake (c) Classical model on the top of GVF model

Fig. 8: Simulation of Classical model on the top of GVF model to obtain sharp corner contours.

III. Author's contribution

The experiments themselves were often performed during lab time and thus the time spent on this is approximately equal. For the report, we wrote our "own" sections of the first part of the practical individually. The other parts were all written together.

References

[1] G. Zhu, S. Zhang, Q. Zeng, and C. Wang, "Gradient vector flow active contours with prior directional information," *Pattern Recognition Letters*, vol. 31, pp. 845–856, 07 2010.