Flow Visualization Using Texture Fields

*K. S. Om, *D. H. Lee, J. W. Kim†, J. H. Kim†, H. C. Kim†, B. G. Min†

*Dept. of Biomedical Engineering, College of Engineering, Seoul National University
†Dept. of Biomedical Engineering, College of Medicine, Seoul National University

ABSTRACT

A new flow visualization image processing technique was studied. Our approach is based on texture fields and has higher performance than similar methods. We tested our method to flow visualization of Total Artificial Heart.

Introduction

Flow visualization has been intensively studied for many engineers and scientists to understand fluid mechanics [1]. There have been much researches about that, and they have each intrinsic merits and shortcomings. Methods for acquiring flow pattern depends on the image source heavily. It can be said that there are largely three classes of image sources and methods for handling those. First method is to get multi-frame images and to find motion matching between them [2]. Second is to get two frames and to analyze by optical flow estimation technique [3], and the last is to handle only one image which has streak-like patterns. Our methods belong to the last one, and they are the extended version of Rao and Schunck' studies [4].

Oriented Texture Fields

Local intensity contrast and orientation angle are the two important intrinsic properties for identifying a flow pattern and edge detection [1][5]. Oriented texture can be computed by using these two properties, and uni-directional points have similar contrast and orientation angle (coherence).

Our methods consist of three steps:

Step 1. compute the gradient and orientation angle (gradient and angle map)

Step 2. find the coherence. (coherence map)

Step 3. find the last local orientation (local orientation map).

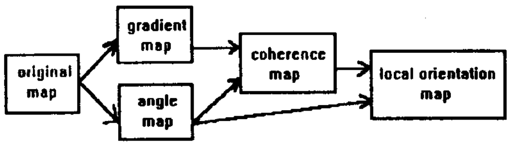


Fig. 1. The overall structure of our approach.

The first step (gradient and angle map) :

Kass and Witkin use a laplacian-of-Gaussian operator as the oriented filter [6], and Rao and Schunck use a gradient of Gaussian which is proposed by Canny and well-known as Canny operator [7]. The reason of selecting Canny operator as a gradient operator in Rao's studies is that the gradient of Gaussian involves one less differentiation, and will have better performance in the presence of noise.

Lyvers and Mitchell have investigated the contrast and orientation estimation performance of several edge operators which have been proposed in the literature [8][9], and they concluded the performance of the facet model IDD (Integrated Directional Derivative) [10] and the moment-based operators [11] are approximately equal and are the best. Especially they found the Canny operator to be significantly less accurate for orientation estimation than the moment and IDD operators. So we adopted the IDD operators not Canny ones.

After the x and y direction gradient G_{mn}^{x}, G_{mn}^{y}

which are located at $x = m$, $y = n$ was acquired by gradient operator, the magnitude of gradient G_{mn} and direction or angle θ_{mn} can be related to intensity derivative by

$$\theta_{mn} = \tan^{-1}\frac{G_{mn}^{\ y}}{G_{mn}^{\ x}} \quad (1)$$

$$G_{mn} = M \times (\,|G_{mn}^{\ x}| + |G_{mn}^{\ y}|\,) \quad (2)$$

Here, we considered positive M, because there is possibilities that low contrast points even if they have higher coherence may exist.

The second step (coherence map) :

The uni-directional properties (coherence) can be calculated by [4]

$$\rho_{mn} = K\frac{\sum_{(i,j)\in W}|G_{ij}\cos(\theta_{mn} - \theta_{ij})|}{\sum_{(i,j)\in W} G_{ij}} \quad (3)$$

where W is a window of prescribed size around the point (m,n), and we set K 'gradient-1'. As the conventional gray level is 256, so the K is 255. Rao uses 'G_{mn}' as a K for placing more weight on regions that have higher visual contrast, but we think this has fallacy - there exist low contrast points even if it has flow-pattern. So considering this, our K is even more reasonable and ρ ranges from '0' to 'gray level - 1' depending on coherence.

The third step (local orientation map) :

The estimate of the dominant orientation θ is an $N \times N$ neighborhood of the image is [4]

$$\theta = \frac{1}{2}\tan^{-1}\left(\frac{\sum_{m=1}^{m=N}\sum_{m=1}^{m=N}\rho_{mn}^2\sin(2\theta_{mn})}{\sum_{m=1}^{m=N}\sum_{m=1}^{m=N}\rho_{mn}^2\cos(2\theta_{mn})}\right) + \frac{\pi}{2} \quad (4)$$

, since the gradient vector is perpendicular to the edge direction the term of $\pi/2$ is added. Here we use ρ_{mn} than G_{mn}. Rao's research uses G_{mn} but coherence is more important than gradient in flow-like texture image. This is also another difference point compared with others.

thresholds :

We considered three thresholds for the more promising performance.

T_coh : threshold for magnitude of coherence,
T_gra : threshold for magnitude of gradient,
T_ori : threshold for pixel % in $N \times N$ window of local orientation map [%].

We set $\rho_{mn} = 0$ if $\rho_{mn} < T\_coh$ or $\rho_{mn} < T\_gra$. And we displayed no dominant orientation direction if the number of ρ_{mn} in $N \times N$ window is smaller than $N \times N \times T\_ori$.

Experiments

We applied our method to the flow of TAH (Total Artificial heart). In order to obtain streak-like picture in the artificial ventricle, we developed a transparent pump system (TPS) with one ventricle and a simple circulatory system. Polystyrene particles (IRA 904, Amberite ion exchange rein, Rehm & Hass Co., Philadelphia, PA), less than 100 μm were suspended in the testing fluid as scatters and planar He-Ne laser light source illuminated the artificial ventricle located in the center of TPS through a cylindrical lens. The testing fluid was a blood analogue fluid consisting of 36.7 vol. % glycerine and distilled water. The picture was captured by use of a photo camera, and the photo image is converted to digital image by CCD camera.

The acquired image has 480 × 480 spatial resolution and 256 gray levels and we adopted 5 × 5 IDD mask.

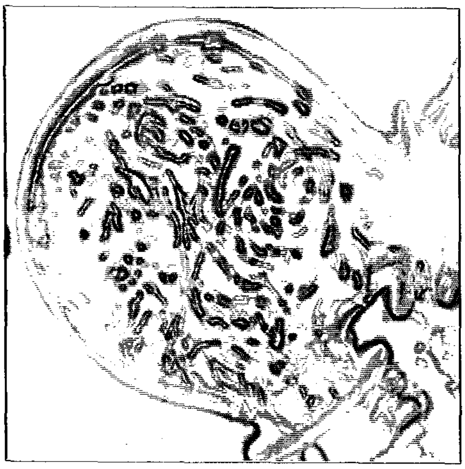
The parameters are as follows.
{ M, W, N } = { 3, 5, 16 }.
And the thresholds are as follows.
{ *T_coh*, *T_gra*, *T_ori* } = { 20, 20, 15 [%] }

For the visual effect, all image are converted to negative ones. The result images are in Fig 2. They show good results and we can see that the turbulent flow also can be well described.

Conclusions

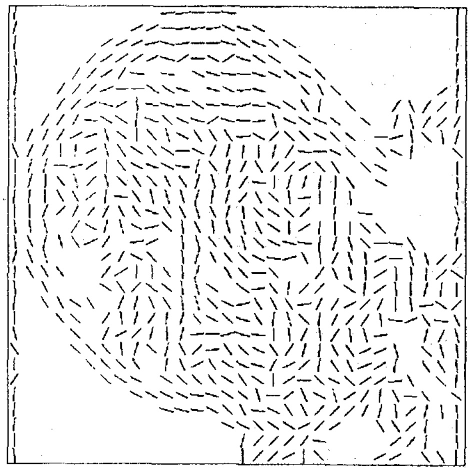
In this paper, we proposed a new method for flow visualization using texture fields. Our method requires only one-frame image and does not require heavy and expensive equipments. Also, proposed methods have higher performance than Rao's as stated in section II, and we considered three thresholds for the enhancement of performance. Our research results have possibilities of application to other oriented pattern images widely such as a finger print images, wood knot images, and so on.

(a)



(b)

(c)



(d)

Fig 2. The tested results images.
(a) Original map,
(b) gradient map,
(c) coherence map,
(d) local orientation map.

REFERENCES

[1] C. F. Shu and R. C. Jain, "Direct Estimation and Error Analysis for Oriented Patterns," *CVGIP: Graphical Models and Image Processing*, vol. 58, pp. 383-398, Nov. 1993.

[2] D. H. Lee, S. W. Lee, H. An and B. G. Min, "PIV System for the Flow Pattern Analysis of Artificial Organs ; Applied to the In Vitro Test of Artificial Heart Valves," *J. of KOSOMBE*, vol. 15, pp. 489-487, 1994.

[3] J. D. Kim, "An Optical Flow Estimation Method by Kalman Filtering and Improved Temporal Gradient Estimation," *Ph. D dissertation at KAIST*. 1989.

[4] A. R. Rao and B. G. Schunck, "Computing Oriented Texture Fields," *CVGIP: Graphical Models and Image Processing*, vol. 53, pp. 157-185, March, 1991.

[5] A. K. Jain, *Fundamentals of Digital Image Processing*, Prentice-Hall, Inc. 1989.

[6] M. Kass and A. Witkin, "Analyzing oriented patterns," *Comput. Vision Graphics Image Process*, vol. 37, pp. 62-385, 1987.

[7] J. F. Canny, "A Computational Approach to

Edge Detection," *IEEE Trans. Pattern Anal. Mach. Intelligence,* vol. PAMI-8, pp. 679-698, Nov. 1986.

[8] E. P. Lyvers and O. R. Mitchell, "Precision Edge Contrast and Orientation Estimation," *IEEE Trans. Pattern Anal. Mach. Intelligence,* vol. PAMI-10, pp. 927-937, Nov. 1988

[9] E. R. Davies, *Machine Vision,* Academic Press, 1990.

[10] O. Zuniga and R. M. Haralick, "Integrated Directional Derivative Gradient Operators, " *IEEE Trans. Systems, Man, and Cybernetics,* vol. SMC-17, pp. 508-517, 1987.

[11] A. P. Reeves, M. L. Akey, O. R. Mitchell, "A Moment-based Two-dimensional Edge Operator," *Proc. IEEE Comput. Soc. Symp. Comput. vision and Pattern Recogn.* pp. 19-23, June, 1983.