論文 89-26-7-16

An Enhanced Optical Flow Calculation Using Scalar Edges

(스칼라 경계선을 이용한 개선된 Optical Flow 계산)

尹 相 雲,* 趙 奭 濟,* 河 永 浩*

(Sang Oon Yoon, Seok Je Cho and Yeong Ho Ha)

要 約

Optical flow는 물체의 속도 결정과 추적 뿐만 아니라 영상분할과 물체의 3차원 정보로서도 중요하다. 순차적인 영상으로부터 optical flow를 계산하기 위하여 경사법 알고리듬이 많이 사용된다. 본 논문에서는 경사법의 문제점인 영상전체에 대한 속도벡터의 평활화 현상을 국부적으로 한정시키기 위하여 스칼라 경계선을 이용하는 새로운 주위평균 계산방법을 제시하였으며, optical flow의 분산의 역치로 가중된 평균을 이용하여 이동경계 주위와 폐색영역에서 발생되는 속도오차를 감소시켰다.

Abstract

Optical flow is important not only for determining velocity and trajectory of the object but also for image segmentation and 3D information. The gradient-based method is mostly used to compute optical flow from image sequences, but it accompanies smoothing effect of velocity vectors. In this paper, an enhanced algorithm for computing optical flow using scalar edge to restrict smoothing effect. Weighted average depending on the scalar edges and local variance of velocities is also applied to reduce errors both around motion boundary and in the occlusion region.

I. Introduction

Optical flow is the field of two-dimensional velocities projected on the image plane by the three-dimensional velocities of the corresponding points of an object[1].

Optical flow is mostly used not only for determining velocity and trajectory of the object but also for image segmentation. Also, it provides information about three-dimensional structure and depth of the object. The methods to compute optical flow are classified into two major approaches, which are feature-based and gradient-based method[1]-[3].

The feature-based method is to find and track prominent features by matching process from frame to frame and hence can estimate velocities of prominent points accurately. However, only a sparsely set of points as features can be obtained, so that the velocity vectors of the points are not dense. Therefore it is not easy to use the velocity

*正會員, 慶北大學校 電子工學科

(Dept. of Elec. Eng., Kyungpook Nat'l Univ.)

接受日字：1988年 12月 30日

vectors for image segmentation. For extracting depth information, we should take interpolation on the velocity vectors.

The gradient-based method uses both spatial and temporal gradients under the assumption that the image function is differentiable. This method as a non-matching process can compute velocity vectors of all points in the image plane and need not interpolation. This approach is more useful for image segmentation and three-dimensional depth extraction than the feature-based methods [4].

There are some problems in the gradient-based method; (1) Since the global smoothness constraint is used, the discontinuity of the velocity vector field around motion boundary becomes dull. (2) At the neighbor point around motion boundary, the image value of the object with different motion is included in the 3x3 window for calculating spatial or temporal gradients of the point. Thus the velocity vector of the point is errorneous because both gradients are affected by the other motion region. (3) There are some occlusion regions around motion boundary of moving object. In these regions there are not any corresponding points between the first frame and the second frame [3].

To overcome those problems, we propose an enhanced gradient-based method using scalar edge and weighted average to estimate relatively accurate optical flow. The proposed method limits smoothness constraint within the region segmented by the scalar edges and uses both weighted average depending on the scalar edges and the inverse of the local variance of velocities to reduce error by occlusion region. The method described in this paper allows that objects may translate and rotate in the 3-D world and may occlude one another. We assume that objects are rigid and their motion is smooth.

Ⅱ. Local Average Computation Using Scalar Edge

The gradient-based method relies on the optical flow constraint equation which relates optical velocities to spatial and temporal changes in the image:

$$G_x u + G_y v + G_t = 0 \qquad (1)$$

where u and v are x and y components of velocity vector at a point in the image space. G_x and G_y are the spatial gradients of image intensity to each direction. G_t is the temporal gradient between the first and the second frame. The main assumption for the validity of Eq. (1) is that the brightness of a point on the surface of an object in space does not change with time and temproral and spatial gradients moves within the range of linearity

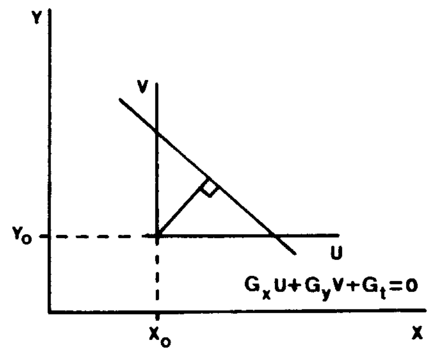


Fig.1. Constraint line.

Eq. (1) provides only a constraint on the value of the velocity vector at each point in the image space and it cannot have unique solution. Thus an additional assumption is needed to get unique velocity vector. In motion problem, velocity vectors vary across the image, but they are almost constant in the local image. Thus we can assume that velocity vectors at neighbor points vary smoothly. This is the smoothness constraint of the optical flow field. The measure of the departure from smoothness of the velocity vector field is given by

$$E_1^2 = |\nabla u|^2 + |\nabla v|^2 \qquad (2)$$

where ∇ is gradient operator. Due to the noises and quatization errors in the image, some errors arise in Eq. (1). These errors can be described by

$$E_2^2 = \{G_x u + G_y v + G_t\}^2 \qquad (3)$$

and then total error E can be represented by

$$E=\iint \{a^2 E_1^2+E_2^2\}\,dx\,dy \qquad (4)$$

where a^2 is the Lagrange multiplier The minimization is to be accomplished to find proper values of optical flow velocity, (u,v). From Eq.(4) using the calculus of variations, we obtain

$$a^2\nabla^2 u-G_x^2 u-G_xG_y v-G_xG_t=0$$
$$a^2\nabla^2 v-G_xG_y u-G_y^2 v-G_yG_t=0 \qquad (5)$$

where ∇^2 is Laplacian operator. These equations include the first-and the second-order partial derivatives in the image data and the velocity vector field. These derivatives of scalar or vector field are determined by their values in the immediate neighborhood of the point. Thus the discrete solution from Eq.(5) can be obtained by local computation. The approximation of Laplacian of u and v takes the following form.

$$\nabla^2 u=k(\bar{u}-u)$$
$$\nabla^2 v=k(\bar{v}-v) \qquad (6)$$

where $\bar{u}$ and $\bar{v}$ are the local averages of velocities except itself at a point in the image space, and k is a proportionality factor. Let k=1 in Eq.(6), then the optimized solution of Eq.(4) is given as follow.

$$u=\bar{u}-\frac{G_x(G_x\bar{u}+G_y\bar{v}+G_t)}{a^2+G_x^2+G_y^2}$$
$$v=\bar{v}-\frac{G_y(G_x\bar{u}+G_y\bar{v}+G_t)}{a^2+G_x^2+G_y^2} \qquad (7)$$

The gradient-based method uses the global smoothness constraint to compute optical flow. Hence this constraint leads to the smoothing effect of optical flow, which provides error around motion boundary and makes it difficult to detect motion boundary from velocity vector field. The smoothing effect occurs in the process for calculating local average, $(\bar{u}, \bar{v})$. Now we may use scalar edges to exclude the influence from velocity vectors of the other object if we assume that scalar edges are generated by jump boundary of an object.

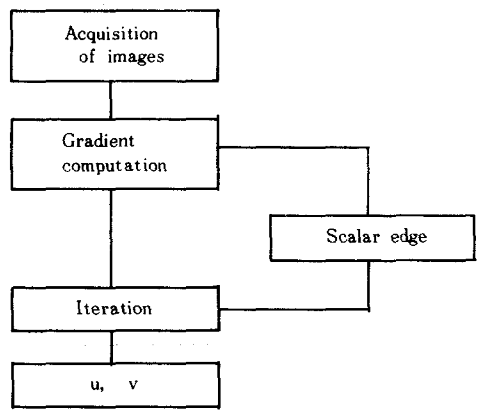


Fig.2. Algorithm using the scalar edges.

If the reference frame in computing optical flow is the first, the scalar edges of the first frame of the image sequence are used to estimate velocity vector field. The scalar edge function is defined by

$$E(x,y)=\begin{cases}0 & : \text{edge}\\ 1 & : \text{otherwise}\end{cases} \qquad (8)$$

and the scalar edge is extracted by non-maxima suppression method after gradient operation. The proposed algorithm is shown in Fig.2. It is possible to maintain distinct motion boundary if we use scalar edge to restrict smoothness constraint in a region. Fig. 3 and Fig. 4 show the average window function that the local average

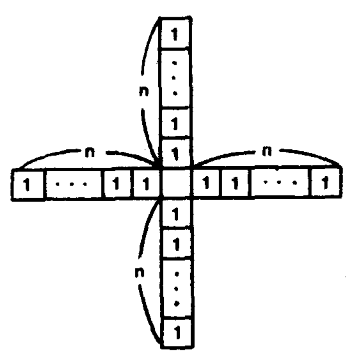


Fig.3. Window for computing local average in the region with no scalar edge.

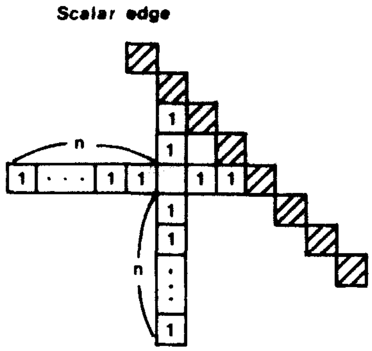


Fig.4. A deformed window on and over the scalar edge.

isn't affected by velocities of the different motion region on and over the scalar edges. Fig. 3 represents local averaging by window when no scalar edge in the region and Fig. 4 shows the window deformed by eliminating its part of reaching at the other region on and over the scalar edge. This window is considered to reduce the averaging effect from different motion region in the iteration steps.

The enhanced local average using scalar edge is formulated by Eq.(9) through Eq. (11)

$$\begin{aligned} E'(x-i, y) &= \bigcap_{k=1}^{i} E(x-k, y) \\ E'(x+i, y) &= \bigcap_{k=1}^{i} E(x+k, y) \\ E'(x, y-i) &= \bigcap_{k=1}^{i} E(x, y-k) \\ E'(x, y+i) &= \bigcap_{k=1}^{i} E(x, y+k) \end{aligned} \qquad (9)$$

where E'(x+i,y), E'(x,y-i) , E'(x-i,y) and E'(x,y+i) are edge functions of the i-th point to each direction of 0°, 90°, 180° and 270° from a reference point. If the i-th point from the reference point lies on scalar edge, E' on and over the edge will become zero. The local sum of the products of velocity vector by E' is described by

$$\begin{aligned} N_u(x, y) = \sum_{i=1}^{n} \{ & E'(x-i, y)\ u(x-i, y) \\ & + E'(x+i, y)\ u(x+i, y) \\ & + E'(x, y-i)\ u(x, y-i) \\ & + E'(x, y+i)\ u(x, y+i) \} \end{aligned} \qquad (10)$$

$$\begin{aligned} N_v(x, y) = \sum_{i=1}^{n} \{ & E'(x-i, y)\ v(x-i, y) \\ & + E'(x+i, y)\ v(x+i, y) \\ & + E'(x, y-i)\ v(x, y-i) \\ & + E'(x, y+i)\ v(x, y+i) \} \end{aligned}$$

where n is the size of the window for local average as shown in Fig.3 and Fig.4. If n is large, smoothing effect will increase but optical flow will be less affected by local feature of image. For small window, smoothing effect and execution time will be reduced. N_u (x,y) and N_v (x,y) aren't affected by the velocity vectors in the other motion region where E' is zero. The sum of weights is represented by

$$\begin{aligned} D(x, y) = \sum_{i=1}^{n} \{ & E'(x-i, y) + E'(x+i, y) \\ & + E'(x, y-i) + E'(x, y+i) \} \end{aligned} \qquad (11)$$

Finally we can obtain the local average of velocityes given in Eq. (12).

$$\begin{aligned} \bar{u} &= \frac{N_u(x, y)}{(x, y)D} \\ \bar{v} &= \frac{N_v(x, y)}{D(x, y)} \end{aligned} \qquad (12)$$

Thus through these steps, the local averages of velocitis the region segmented by scalar edge aren't affected by the velocity vectors in the other motion region because the scalar edge behaves blocking the smoothing effect.

III. Weighted Average

In the conventional method there are basically two fundamental problems. One is that the spatial and the temporal gradients at the neighbor points of motion boundary are affected by the image value in the different motion region because of using 3x3 or 5x5 window as a partial derivative operator as shown in Fig. 5, the points, p_1 and p_2, are neighborhood of motion boundary and the shaded region in the window is different motion part from the points. Thus the velocity vectors at the neighbor point of motion boundary are erroneous. The other is that some occluded region causes unreliable optical flow because no matching point exists between two frames. In Fig.

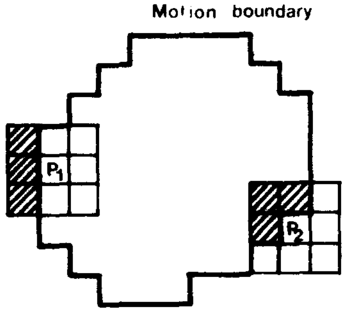


Fig.5. Affection of 3x3 window for calculation of spatial and temporal gradient around motion boundary.

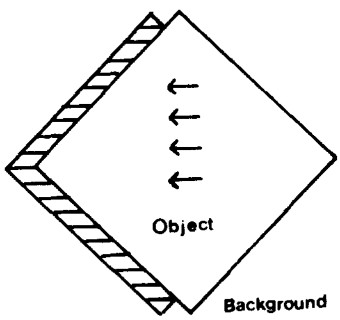


Fig.6. Over lapped region.

6, shaded region represents the one overlapped by the one in the second frame when it moves to the arrow direction.

To overcome these conventional problems we may adopt the concept of weighted local average of velocity vectors to correct errors in the occluded region and around motion boundary after iterative solution is obtained. The local variance of velocity vectors in the unreliable region is relatively larger than that of the other region. Therefore the proper weight is the inverse of the local variance of velocities. The weights are determined by Eq. (13)

$$\begin{aligned}
W_u(x-i, y) &= E'(x-i, y)/\sigma_u^2(x-i, y)\\
W_u(x+i, y) &= E'(x+i, y)/\sigma_u^2(x+i, y)\\
W_u(x, y-i) &= E'(x, y-i)/\sigma_u^2(x, y-i)\\
W_u(x, y+i) &= E'(x, y+i)/\sigma_u^2(x, y+i)\\
W_v(x-i, y) &= E'(x-i, y)/\sigma_v^2(x-i, y)\\
W_v(x+i, y) &= E'(x+i, y)/\sigma_v^2(x+i, y)\\
W_v(x, y-i) &= E'(x, y-i)/\sigma_v^2(x, y-i)\\
W_v(x, y+i) &= E'(x, y+i)/\sigma_v^2(x, y+i)
\end{aligned} \qquad (13)$$

where σ_u^2 and σ_v^2 are the local variances of disparity vectors with respect to u and v. In practice, they are computed in the 3x3 neighborhood. The weighted average can be defined by

$$u_w = \frac{N_{wu}(x, y)}{D_{wu}(x, y)}$$

$$v_w = \frac{N_{wv}(x, y)}{D_{wv}(x, y)} \qquad (14)$$

where the numerators and denominators are given by Eq. (15) and (16) respectively.

$$\begin{aligned}
N_{wu}(x, y) = \sum_{i=1}^{n} \{&W_u(x-i, y)\ u(x-i, y)\\
&+W_u(x+i, y)\ u(x+i, y)\\
&+W_u(x, y-i)\ u(x, y-i)\\
&+W_u(x, y+i)\ u(x, y+i)\}
\end{aligned}$$

$$\begin{aligned}
N_{wv}(x, y) = \sum_{i=1}^{n} \{&W_v(x-i, y)\ v(x-i, y)\\
&+W_v(x+i, y)\ v(x+i, y)\\
&+W_v(x, y-i)\ v(x, y-i)\\
&+W_v(x, y+i)\ v(x, y+i)\}
\end{aligned} \qquad (15)$$

$$\begin{aligned}
D_{wu}(x, y) = \sum_{i=1}^{n} \{&W_u(x-i, y)+W_u(x+i, y)\\
&+W_u(x, y-i)+W_u(x, y+i)\}
\end{aligned}$$

$$\begin{aligned}
D_{wv}(x, y) = \sum_{i=1}^{n} \{&W_v(x-i, y)+W_v(x+i, y)\\
&+W_v(x, y-i)+W_v(x, y+i)\}
\end{aligned} \qquad (16)$$

IV. Initial Value of Optical flow and Partial Derivative Operator

Whether to determine proper initial value of velocity relates to the execution time. In this paper, we regard the nearest point on the constraint line from the origin as the initial value,

(u_0, v_0), of each velocity vector. This is used as the initial estimate for computing new vector, (u,v). The initial value is given by

$$u_0 = \frac{-G_x\,G_t}{G_x^2+G_y^2}$$

$$v_0 = \frac{-G_y\,G_t}{G_x^2+G_y^2} \qquad (17)$$

Eq. (5) for obtaining velocity vectors is used in the case of continuous image funtion, but the real image are discrete. Therefore the first-order difference operator to compute spatial and temporal gradients is necessary The first-order difference operators to each direction are then given by

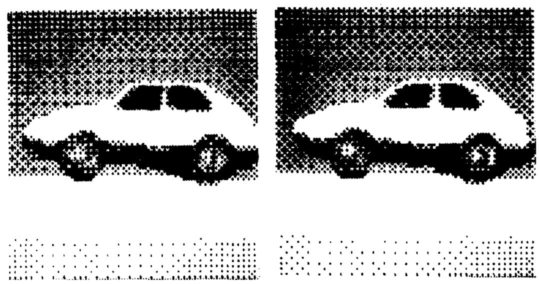
$$\frac{\delta}{\delta x} = \frac{1}{2}[-1\ 0\ 1] * \frac{1}{4}[1\ 2\ 1]^T = \frac{1}{8}\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$$

$$\frac{\delta}{\delta y} = \frac{1}{4}[1\ 2\ 1] * \frac{1}{2}[-1\ 0\ 1]^T = \frac{1}{8}\begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \qquad (18)$$

These operators are chosen to combine a first central difference in the direction of the partial derivative and smoothing in the perpendicular direction. These operators can be regarded as Sobel edge detection operator except scale factor of 1*6 and have a good characteristic to immunize noise. They, however, generate erroneous velocity vectors around motion boundary in the optical flow. But this problem can be overcome by adopting weighted average as suggested in the previous section.

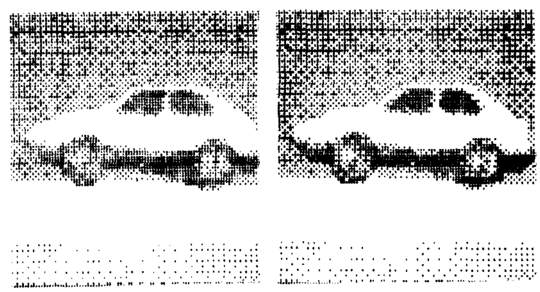
V. Simulation and Discussion

Two synthetic sequential images as shown in Fig. 7 and Fig. 8 are used and the size of each image is 100x100. Fig.7 shows the noise-free image sequence, and Fig.8 shows the noisy image sequence with the white Gaussian noise of standard deviation of 10. The object (car) in the images is considered to move one pixel to the left



(a) The first frame　(b) The second frame

Fig.7. Noise-free image sequence.

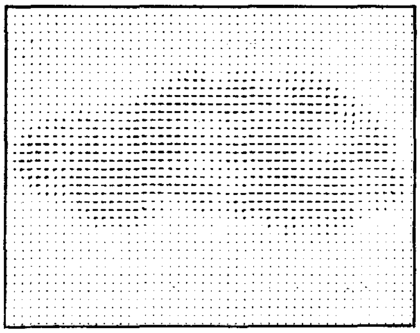


(a) The first frame　(b) The second frame

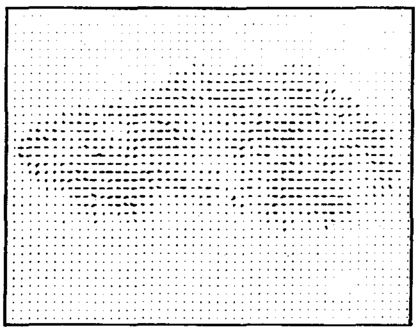
Fig.8. Noisy image sequence.

In Fig.9, the results by the conventional method show smoothing effect around moton boundary between the object and the background, as mentioned in section III.

In the proposed algorithm, the scalar edges were extracted from the first frame by non-maxima suppression and the edge images are as shown in Fig.10, and then the results of optical flow obtained by the proposed algorithm are shown in Fig. 11. It is shown that smoothing effect around motion boundary is significantly reduced and velocity vectors around the motion boundary are clearly divided into an object and background. In Table 1, the statistics of the

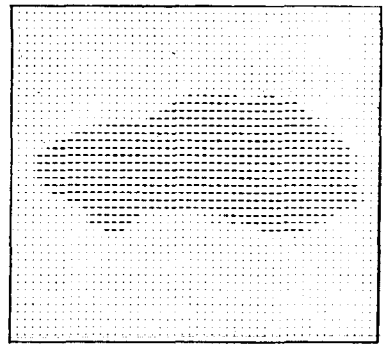


(a) Optical flow of noise-free images

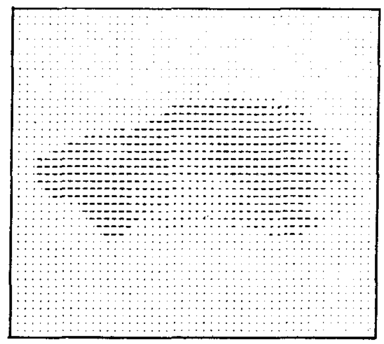


(b) Optical flow of noisy images

Fig.9. Results of the conventional method.

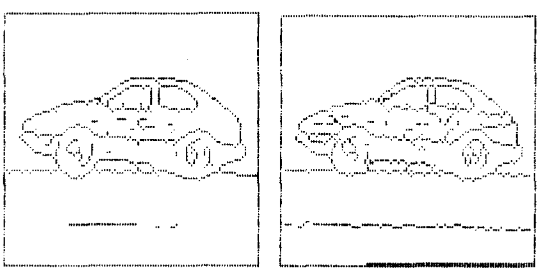


(a) Optical flow noise-free images



(b) Optical flow of noisy images

Fig.11. Results of the proposed method.



(a) Edge of noise-free image (b) Edge of noisy image

Fig.10. Edge of the first frame of each image sequence.

disparity vectors of the object by the proposed algorithm are compared to those of the conventional method. Table 1 shows that the disparity

Table 1. Velocity statistics of the object region from the noise-free image sequence and the noisy image sequence.

Velocity components	Conventional method		Proposed method	
Characteristics	U	V	U	V
Average	−0.773	0 0.012	−0.999	0.000
Standard deviation	0.201	0 0.091	0.004	0.001
Maximum	0.449	0 0.587	0.000	0.033
Minimum	−1.089	−0.449	−1.009	−0.020

(a) noise-free image sequence

Velocity Components	Conventional method		Proposed method	
Characteristics	U	V	U	V
Average	−0.646	0.012	−0.760	0.010
Standard deviation	0.288	0.184	0.192	0.045
Maximum	0.305	0.839	0.000	0.256
Minimum	−1.785	−0.891	−1.075	−0.174

(b) noisy image sequeuce

vector fields by the proposed method are better than those of the conventional method.

IV. Conclusion

Applying the conventional gradient-based method to real image sequences generates erroneous optical flows around motion boundary and in the occlusion region. To overcome this problem, an enhanced gradient-based method using scalar edges has been developed for computing optical flow. It consists of two parts; (1) compute the optical flow using both scalar edges and the proposed local average operator, (2) correct the velocity of each point using the weighted average.

The results of the proposed algorithm show that smoothing effect around motion boundary is significantly reduced and optical flow at motion boundary is clearly divided into the object and background. And the noise immunity is better than that of the conventional method.

But it is not easy to perfectly detect scalar edge on jump boundary of an object in the real image. Therefore scalar edge detection method for jump boundary should go on being discussed.

The velocity vectors computed in this paper is not the actual velocity of 3-D scene but the apparent velocity in the image plane. By use of "structure from motion" theorem, it might be possible to recover 3-D shape and motion.

References

[1] Berthold K.P. Horn and Brian G. Schunck, "Determining optical flow," *Artificial Intelligence*, vol. 17, pp. 185-203, 1981.

[2] S.T. Barnard and W.B. Tomson, "Disparity analysis of images," *IEEE Trans PAMI-2*, pp. 333-340. July 1980.

[3] William B. Thompson and Kathleen M. Mutch, "Dynamic occulusion analysis in optical flow field," *IEEE Trans. PAMI*, vol. 7, no. 4, pp. 374-383, July 1985.

[4] A. Scheuing and H. Niemann, "Computing depth from stereo images by using optical flow," *Pattern Recognition Letters*, vol. 35, pp. 20-46, 1986.

[5] Frank Glazer, "Hierarchical gradient-based motion detection," *Proceedings: Image Understanding Workshop*, pp. 733-748, Feb. 1987.

[6] Berthold K.P. Horn, Robot Vision, The MIT Press, 1986.

[7] Ballard and Brown, Computer Vision, Prentice-Hall, Englewood Cliffs, 1982.

[8] Masahiko Yachida, "Determining velocity maps by spatio-temporal neighbors from image seguences," *CVGIP.*, vol. 21, pp. 262-279, 1983. *

著 者 紹 介

尹 相 雲(正會員)
1960年 6月 19日生. 1986年 경북대학교 전자공학과 졸업. 1989年 경북대학교 전자공학과 대학원졸업 공학석사학위 취득. 1989年～현재 국방과학연구소 연구원

趙 爽 濟 (正會員) 第26卷 第4號 參照
현재 경북대학교 전자공학과 박사과정 재학

●

河 永 浩 (正會員) 第25卷 第10號 參照
현재 경북대학교 전자공학과 조교수