TRANSPARENT-MOTION ANALYSIS

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Abstract

A fundamental assumption made in formulating optical flow algorithms is that motion at any point in an image can be represented as a single pattern component undergoing a simple translation: even complex motion will 'look like' uniform displacement when viewed through a sufficiently small window. This assumption fails for a number of situations that commonly occur in real world images. For example, transparent surfaces moving past one another yield multiple motion components at a point.

We propose an alternative formulation of the local motion assumption in which there may be two distinct patterns undergoing different motions within a given local analysis region. We then present an algorithm for the analysis of transparent motion.

1 Models for Local Motion

Motion estimation is based, ultimately, on an assumed model relating motion to observed image intensities. The traditional model used in optical flow computation postulates a single pattern moving uniformly within any local analysis region [7, 9, 4]. We introduce a new model that postulates two such components.

Let $I(x,y,t)$ be the observed gray scale image at time t. Let R be the analysis region in which we wish to estimate motion. The traditional model used in optical flow analysis [8, 1, 6] assumes that within the region R, $I(x,y,t)$ may be represented as a pattern $P(x,y)$ moving with velocity $\mathbf{p} = (p_x, p_y)$.

$$I(x,y,0) = P(x,y) \qquad \text{and} \qquad I(x,y,t) = P(x - tp_x, y - tp_y) = P^{t\mathbf{p}} \tag{1}$$

where $P^{t\mathbf{p}}$ denotes the pattern P transformed by the motion $t\mathbf{p}$.

We introduce an alternative model for local motion. Within the analysis region the image is assumed to be a combination of two distinct image patterns, P and Q, having independent motions of $\mathbf{p}$ and $\mathbf{q}$:

$$I(x,y,0) = P(x,y) \oplus Q(x,y) \qquad \text{and} \qquad I(x,y,t) = P^{t\mathbf{p}} \oplus Q^{t\mathbf{q}}. \tag{2}$$

Here the $\oplus$ symbol represents an operator such as addition or multiplications to combine the two patterns.

2 Estimating Multiple Motion

We now consider the analysis of motion described by the multiple component model. Alternative approaches have been proposed that simultaneously estimate multiple component motion without segmentation. Examples include the use of Hough transform techniques and cross correlation [4, 5]. However, these are computationally complex, and do not provide precise results.

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A key observation for the present approach is that if one of the motion components and the combination rule $\oplus$ are known, it is possible to compute the other motion using a single component motion algorithm without making any assumptions about the nature of the patterns P_i. In what follows we will assume that the combination operation is addition.

Suppose, for the moment, that motion $\mathbf{p}$ is known, so that only motion $\mathbf{q}$ must be determined. The pattern component P moving at velocity $\mathbf{p}$ can be removed from the image sequence by shifting each image frame by $\mathbf{p}$ and subtracting it from the following frame. The resulting sequence will contain only patterns moving with velocity $\mathbf{q}$.

Let D_1 and D_2 be the first two frames of this difference sequence. From Equation (2):

$$\begin{aligned} D_1 &\equiv I(x,y,2) - I^{\mathbf{p}}(x,y,1) = (P^{2\mathbf{p}} + Q^{2\mathbf{q}}) - (P^{2\mathbf{p}} + Q^{\mathbf{q}+\mathbf{p}}) \\ &= Q^{2\mathbf{q}} - Q^{\mathbf{q}+\mathbf{p}} = (Q^{\mathbf{q}} - Q^{\mathbf{p}})^{\mathbf{q}} \end{aligned} \quad (3)$$

$$\begin{aligned} D_2 &\equiv I(x,y,3) - I^{\mathbf{p}}(x,y,2) = (P^{3\mathbf{p}} + Q^{3\mathbf{q}}) - (P^{3\mathbf{p}} + Q^{2\mathbf{q}+\mathbf{p}}) \\ &= Q^{3\mathbf{q}} - Q^{2\mathbf{q}+\mathbf{p}} = (Q^{\mathbf{q}} - Q^{\mathbf{p}})^{2\mathbf{q}} \end{aligned}$$

The sequence $\{D_n\}$ now consists of a new, fixed, pattern $Q^{\mathbf{q}} - Q^{\mathbf{p}}$ moving with a single motion $\mathbf{q}$, that is: $D_n = (Q^{\mathbf{q}} - Q^{\mathbf{p}})^{n\mathbf{q}}$. Thus the motion $\mathbf{q}$ can be computed from the two difference images D_1 and D_2 using a single motion estimation technique.

In an analogous fashion the motion $\mathbf{p}$ can be recovered when $\mathbf{q}$ is known. The observed images $I(x,y,t)$ are shifted by $\mathbf{q}$, and a new difference sequence is formed:

$$D_n = I(x,y,n+1) - I^{\mathbf{q}}(x,y,n).$$

This sequence is the pattern $P^{\mathbf{p}} - P^{\mathbf{q}}$ moving with velocity $\mathbf{p}$: $D_n = (P^{\mathbf{p}} - P^{\mathbf{q}})^{n\mathbf{p}}$, so $\mathbf{p}$ too can now be recovered using a single motion estimation.

In practice, of course, neither motions $\mathbf{p}$ or $\mathbf{q}$ are known a priori. Still it is possible to recover both motions precisely if we start with even a crude estimate of either. Multiple component motion analysis can therefore be formulated as a two (or n) component iterative refinement procedure. Let $\mathbf{p}_n$ and $\mathbf{q}_n$ be the estimates of motion after the n^{th} cycle. Estimates alternate between p and q, so if p is obtained on even numbered cycles, $\mathbf{q}$ is obtained on odd cycles. Steps of the procedure are:

1. Set an initial estimate for the motion $\mathbf{p}_0$ of pattern P.
2. Form the difference images D_1 and D_2 as in Equation (3) using the latest estimate of $\mathbf{p}_n$.
3. Apply a single motion estimator to D_1 and D_2 to obtain an estimate of $\mathbf{q}_{n+1}$.
4. Form new difference images D_1 and D_2 using the estimate $\mathbf{q}_{n+1}$.
5. Apply the single motion estimator to the new sequence D_1 and D_2 to obtain an update $\mathbf{p}_{n+2}$.
6. Repeat starting at Step 2.

In the cases that we have tried convergence of this process is fast: with artificially generated image sequences, the correct transformations are recovered to within roughly 1% after three to five cycles regardless of the initial guess of $\mathbf{p}_0$.

3 Examples of Multiple Motion Analysis

We have tested the transparent motion algorithm with several examples. In all examples, the analysis region R is taken to be the entire image.

a. b. c.

Figure 1: Transparent motion. A viewer face is reflected in a picture, with images taken from a moving camera.

a) One frame from the sequence.

b) Subtracting two consecutive frames after compensating for **p**, the motion of the picture.

c) Subtracting two consecutive frames after compensating for **q**, the motion of the reflected face.

Example 1: Transparent Motion

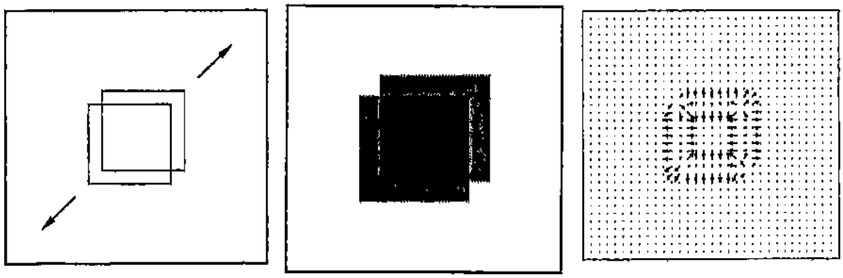
An example involving additive transparency is shown in Figure 1. In this case a sequence was captured with a moving video camera showing a face reflected in the glass covering a print of Escher's "Three Worlds". A single frame from this sequence is shown in Figure 1a. As the camera moved, the image reflected in the glass and the image in the print moved differently. These two motions were computed from this sequence and used to produce the compensated difference images shown in Figure 1b and Figure 1c. In Figure 1b the reflected image (barely visible in Figure 1a) is revealed showing that the other component was accurately registered. In Figure 1c, the reflected image has been nulled.

Example 2: Multiple Aperture Effect

An example involving both transparency and multiple aperture effects is shown in Figure 2. The image sequence in this case consists of the sum of two squares moving diagonally in opposite directions. In this case, the actual motions were $(2.0, 2.0)$ and $(-2.0, -2.0)$. The estimated velocities after 2 iterations were accurate to machine precision. For comparison, an optical flow computation was also made on this sequence using a previously described 'warp motion' technique [2]. The resulting flow field is shown in the lower right. Note that only at the corners of the square do the estimated velocities correspond to the actual motions. Attempts to resolve this complex flow field into correct estimates of the motions would be complicated by the presence of the two differently moving objects.

4 Concluding Remarks

A method has been presented for detecting multiple components of motion within an image region. This technique is based on a two component model of local image motion, which is a generalization of the single component model implicit in standard optical flow computation. The technique does not require segmentation to obtain precise motion estimates. Instead, it relies on an iterative process in which each estimate of one component of the motion is used to improve the accuracy of the other. This allows the motions to be estimated accurately without explicitly knowing their corresponding



a. b. c.

Figure 2: Multiple motions with aperture effects.

a) Input configuration.
b) One frame from sequence. The multiple motion analysis technique accurately extracts both motions.
c) Optical flow field computed from two frames of the sequence. Note aperture effects.

pattern components. This work has been extended to additional cases of multiple motion as near occluding edges [3].

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