MOTION SEGMENTATION IN SEQUENTIAL IMAGES BASED ON THE DIFFERENTIAL OPTICAL FLOW

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Abstract: This work deals with motion detection from image sequences. An algorithm to estimate the optical flow using differential techniques is presented. Noise effects affecting motion detection were taken into account and provisions to minimize it were implemented. The algorithm was developed within the Matlab environment using mex-files to speed up calculations and it was applied to surveillance and urban traffic images. For the considered cases, the results were quite satisfactory.

1 INTRODUCTION

Image motion segmentation is often coupled with motion detection, where each region corresponds to a particular motion model explaining the temporal changes in that image region (Boult and Brown, 1991).

Several works describe techniques to separate or extract the motion under certain hypothesis that assures its applicability. Among the image motion extracting methodologies, we are interested in those ones based upon optical flow. This technique has been studied for application in areas such as biomedicine, meteorology, visual inspection systems, process control and real time urban traffic monitoring (Branca et al., 1997) (Giachetti et al., 1998).

This work presents an approach to motion segmentation in sequential images. Using the optical flow concept, applying morphological transformations to binary images, as well as, spatial processing the image motion can be extracted. This procedure seems to be independent on motion rigidity, on acquisition conditions and on scene elements.

Initially the image segmentation for motion extraction is discussed (section 2). Section 3 deals with the optical flow concept and its determination using differential techniques, being the noise influence discussed. Section 4 describes the development and implementation of the motion segmentation algorithm. Finally, in section 5, results from the algorithm application to indoors and outdoors images are presented.

2 IMAGE SEGMENTATION

Image segmentation has an important role on image analysis and computer vision, finding the regions that are associated to the objects in a given image. The methodology is based upon low semantic content information, directly resulted from the neighborhood proximities especially restricted, so that it is widely classified as a low-level processing.

Segmentation algorithms are generally based on one of two basic principles: discontinuity and similarity (Gonzalez and Woods, 2000). In the first principle, the approach consists on image partitioning based on rough changes in brightness. The main interests here are the detection of isolated points, lines and edges. In the second principle, the main approaches are based on threshold levels and on growing, splitting and merging regions.

The choice of the segmentation technique depends on the characteristics of each problem (Hendee and Wells, 1997). For human beings it is easy to perceive the movement of an object in reference to a background. Trying to implement this procedure using computer-based artificial vision is a complex task. The proposed algorithm applies image-processing techniques and performs motion segmentation in an efficient way for the examples here considered. It shows to be independent of such factors as motion rigidity and object shape.

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3 OPTICAL FLOW

The optical flow approximates the image motion field by representing the apparent motion of the image brightness pattern on the image plane.

In determining the optical flow, two aspects must be taken into account. One is related to the accuracy level of data concerning motion direction and intensity. The other aspect encompasses certain properties related to the computational load required for optical flow determination under minimal conditions of accuracy. The compromise between these aspects depends on the situation and the expected results. The trade-offs between efficiency and accuracy in optical flow algorithms are discussed by (Liu et al., 1998).

The methods of determining the optical flow can be divided (Barron et al., 1994) in: a) differential techniques; b) region-based matching; c) energy-based methods; and d) phase-based techniques. Initially we considered the differential techniques. Among them, one has a particular interest; it uses spatiotemporal derivatives of the image brightness intensity (Horn and Schunck, 1981). The optical flow can be obtained from these variations. This technique assumes that the motion is intrinsically coupled to image brightness variations. It assumes as well that the scene illumination does not change; otherwise, the light changes will influence the motion detection.

3.1 Horn & Schunck Differential Method

According (Horn and Schunck, 1981) the optical flow cannot be calculated at a point in the image independently of neighboring points without introducing additional constraints. This happens because the velocity field at each image point has two components while the change in brightness at that point due to motion yields only one constraint. Before describing the method, certain conditions must be satisfied.

For convenience, it is assumed that the apparent velocity of brightness patterns can be directly identified with the movement of surfaces in the scene. This implies that, according the object surface that moves, it does not exist (or there is a little) brightness variation. This happens, for example, with objects of radial symmetry, low global contrast and high specular reflectance level. It is further assumed that the incident illumination is uniform across the surface.

Denoting $I(x,y,t)$ as the image brightness at time t of the image point (x,y). During motion, it is assumed that the brightness of a particular point is constant, that means

$$\frac{dI\,(x,y,t)}{dt} = 0 \tag{1}$$

Expanding and rewriting the equation 1

$$I_x u + I_y v + I_t = 0 \tag{2}$$

where: I_x, I_y and I_t represent partial derivatives of brightness in x, y and t respectively; u and v are the $x-$ and $y-$velocity components.

Considering that, the brightness pattern can move smoothly and independently of the rest of the scene, there is a possibility to recover velocity information.

The partial derivatives of image brightness are estimated from the discrete set of image brightness measurements. To avoid problems caused by zero values for the derivatives in the spatiotemporal directions, the point of interest is located at the center of a cube formed by eight measurements as shown in figure 1 (Horn and Schunck, 1981).

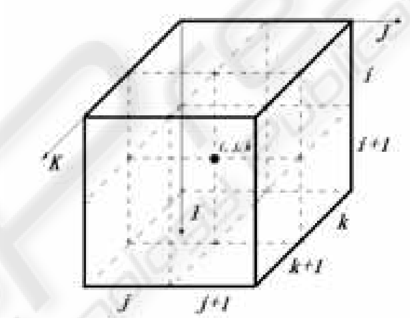


Figure 1: Estimating image partial derivates

Each of the partial derivatives is estimated as the average of the four first differences taken over adjacent measurements

$$\begin{aligned}
I_x \approx \tfrac{1}{4}\{&I_{i,j+1,k} - I_{i,j,k} + I_{i+1,j+1,k} - I_{i+1,j,k} + \\
&I_{i,j+1,k+1} - I_{i,j,k+1} + I_{i+1,j+1,k+1} - I_{i+1,j,k+1}\} \\
I_y \approx \tfrac{1}{4}\{&I_{i+1,j,k} - I_{i,j,k} + I_{i+1,j+1,k} - I_{i,j+1,k} + \\
&I_{i+1,j,k+1} - I_{i,j,k+1} + I_{i+1,j+1,k+1} - I_{i,j+1,k+1}\} \\
I_t \approx \tfrac{1}{4}\{&I_{i,j,k+1} - I_{i,j,k} + I_{i+1,j,k+1} - I_{i+1,j,k} + \\
&I_{i,j+1,k+1} - I_{i,j+1,k} + I_{i+1,j+1,k+1} - I_{i+1,j+1,k}\}
\end{aligned} \tag{3}$$

The additional constraint for the velocity calculation results from the assumption of smoothness of the velocity field. The solution to the optical flow problem consists therefore in: a) minimize equation 4; and b) minimize the smoothness measurement of the velocity field. Equation (5) is a measure of the departure from smoothness in the velocity field. For minimization two errors are defined

$$\xi_b = I_x u + I_y v + I_t \tag{4}$$

and

$$\xi_c^2 = \left(\frac{\partial u}{\partial x}\right)^2 + \left(\frac{\partial u}{\partial y}\right)^2 + \left(\frac{\partial v}{\partial x}\right)^2 + \left(\frac{\partial y}{\partial x}\right)^2 \quad (5)$$

The total error to be minimized will be

$$\xi^2 = \iint \left(\alpha^2 \xi_c^2 + \xi_b^2\right) dxdy \quad (6)$$

A weighting factor α^2 is introduced to associate the error magnitude with quantization errors and noise.

Using the Gauss-Seidel iterative method (Hildebrand, 1974) to minimize equation (6) one obtains u and v velocity components. The estimated values for u_{k+1} and v_{k+1} are obtained from

$$u^{k+1} = \overline{u}^k - \frac{I_x\left[I_x\overline{u}^k + I_y v^k + I_t\right]}{\left(\alpha^2 + I_x^2 + I_y^2\right)} \quad (7)$$

$$v^{k+1} = \overline{v}^k - \frac{I_y\left[I_x\overline{u}^k + I_y v^k + I_t\right]}{\left(\alpha^2 + I_x^2 + I_y^2\right)} \quad (8)$$

In equation (8) $\overline{u}^k$ and $\overline{u}^k$ are the average velocities estimated from the Laplacian of the brightness pattern in iteration k, in which the neighboring pixels values are weighted with the mask shown in figure 2.

$1/12$	$1/6$	$1/12$
$1/6$	-1	$1/6$
$1/12$	$1/6$	$1/12$

Figure 2: Laplacian estimation mask

Figure 3 shows the image sequence from: a) surveillance video camera; b) urban traffic monitoring camera; and c) robot soccer game (synthetic images). Figure 4 shows the calculated optical flow, sketched as directional arrows, for the examples in Figure 3.

3.2 Influence of the α weighting factor

In equations (7) and (8), the weighting factor α^2 represents a threshold effect upon the obtained velocity field. By varying this weighting factor, the sensitivity level of the motion to undesirable data can be adjusted. This effect was applied in the implementation of the algorithm for motion segmentation. Figure 5 shows the influence of the weighting factor in motion segmentation.

4 MOTION SEGMENTATION ALGORITHM

Most of the image segmentation methods demand a previous knowledge of the model in order to produce reasonable results. The algorithm here presented uses information that is not dependent on the kind of motion. Initially the time and space information are decoupled. After this, the problem consists on segmenting the components of the obtained motion map.

4.1 Algorithm Overview

The algorithm consists of three fundamental sections, as shown in figure 6. The first section of the algorithm is the extraction of a map that contains information related to the scene motion intensity.

The motion map is obtained adjusting the α weighting factor during the optical flow calculation. This adjustment affects the accuracy and intensity levels of the resulting map.

The second section of the algorithm consists of a sequence of post-processing techniques to analyze the obtained map as an image by itself.

The procedures in the post-processing step (Figure 7) are applied sequentially:

a) Noise filtering - for eliminating noises from the motion map computation. A Wiener low-pass adaptive filter was applied. It uses stochastic information related to the pixel neighborhood, yielding then satisfactory results (Gonzalez and Woods, 2000).

b) Binarization - for image binarization an optimum threshold is obtained from the motion map histogram; and

c) Morphological filtering - to obtain the contour of the segmented element. The structure element used is adjusted according the size of the object to be segmented.

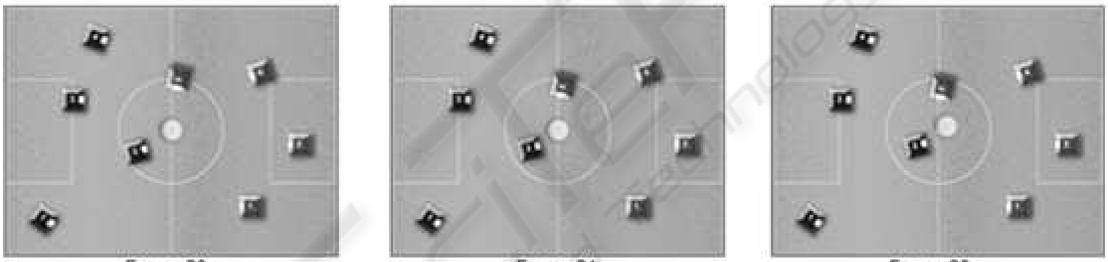
The third section of the algorithm implements the interpretation of the obtained segmentation. It extracts the contour of the region that moved in the image.

5 RESULTS

The motion segmentation algorithm was applied to the surveillance, urban traffic and robot soccer scenes and the results in figures 8, 9 and 10 respectively. All the sequences were obtained by using a fixed camera, with 320 x 240 pixels of spatial resolution and with a 1 frame/sec sample image rate.

(a)

(b)



(c)

Figure 3: Applications: (a) Surveillance camera sequence; (b) Urban traffic sequence; (c) Robot soccer game (synthetic) sequence.

The algorithm was developed within the Matlab environment. To speed up data processing, sub-routines in C language for critical procedures were written and incorporated as mex-files (a Matlab feature).

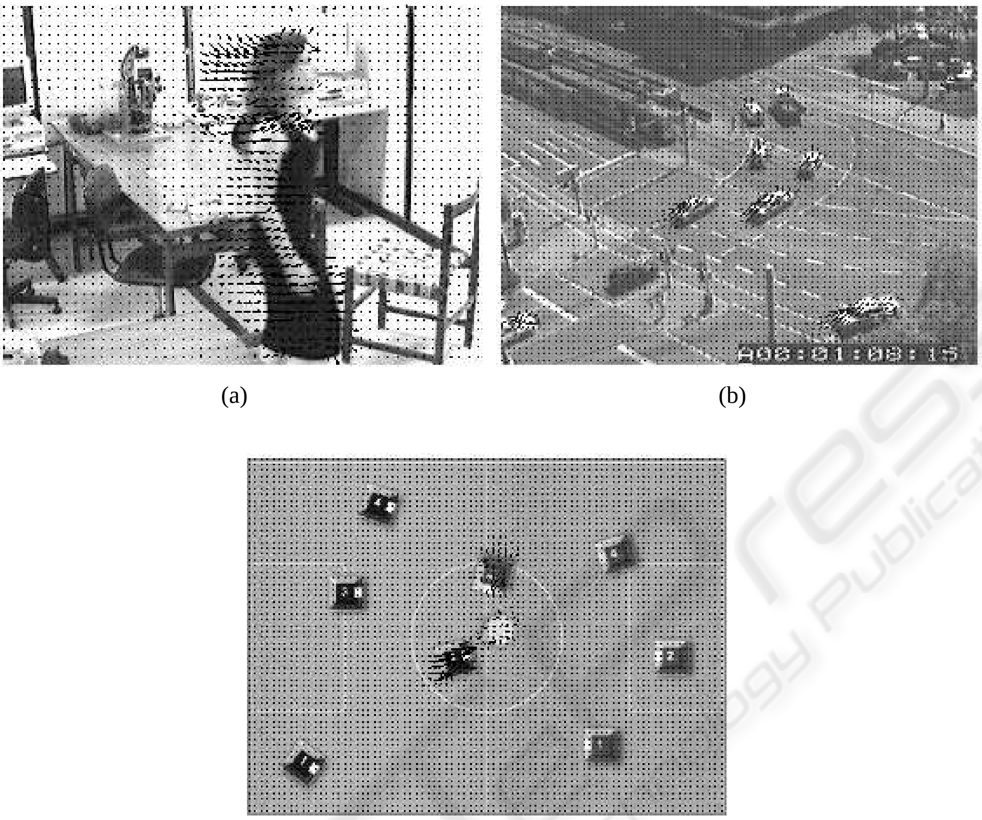
Case 1: Surveillance Camera - Figure 8 illustrates the motion of a single person through an environment surrounded by many objects. Moreover, there are some regions with a high degree of ambiguities. The influence of ambiguities is higher on the other methods of determining the optical flow than the ones that use differential techniques (Barron et al., 1994).

Case 2: Urban Traffic Monitoring - Figure 9 shows many objects moving along different directions. There are then situations with shape change (perspective), occlusions and ambiguities.

Case 3: Robot Soccer Game - Figure 10 shows the robot players performing translation and rotation movements to implement a soccer game. For synthetic images, the algorithm performs more efficiently due the reduced noise and quantization interference over the motion segmentation.

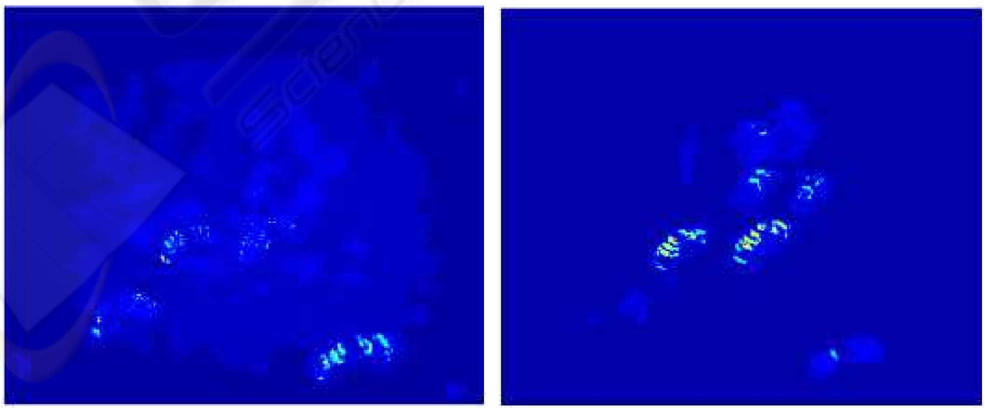
For the cases studied, the algorithm segmented the objects and the moving objects were tracked successfully. For the cases studied, the values of a factor and of the structuring element were adjusted for the best results. The adjusted values are shown in table 1.

The errors shown in table 1 were calculated from a comparison of the moving object area to the area of the region bounded by the algorithm.



(a) (b) (c)

Figure 4: Optical flows using Horn & Schunck method for the cases in Fig. 3. (a) Surveillance camera sequence; (b) Urban traffic sequence; and (c) Robot soccer game sequence.



(a) (b)

Figure 5: Variation of α factor for the urban traffic sequence, (a) α = 10; (b) α = 100

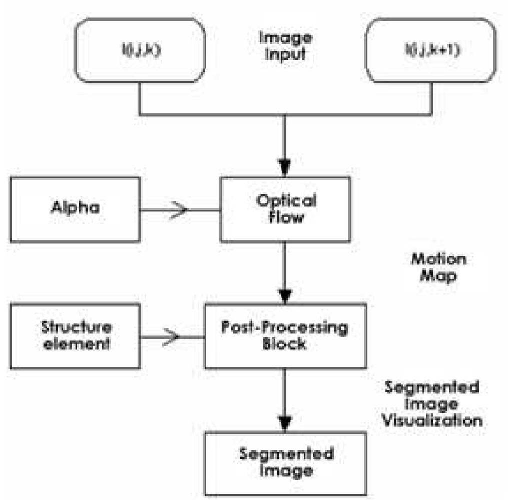


Figure 6: Algorithm main loop

Table 1: Setup Algorithm Parameters

Sequence	α	Structuring Element Size	Error Estimative
Surveillance Camera	1	18	$\sim 10.5\%$
Urban Traffic	75	7	$\sim 8.3\%$
Robot Soccer	10	12	$\sim 5.1\%$

6 CONCLUSIONS

This works presents an algorithm for segmenting image motion by determining an optical flow calculated through differential methods. The determination of the optical flow allows varying a weighting factor, which allows adjusting the sensitivity level of the motion to undesirable data.

Within the post-processing stage of the algorithm, a morphological filtering step allows adjusting the structuring element according to a given situation. As shown in the results, the limit region motion was successfully tracked, with acceptable errors. The algorithm does not use parametrical methods; it needs not pre-calibration or additional image improvements, showing then some robustness to motion complexity.

An upgrade to the algorithm would be the inclusion of the feature of an auto-adjustable structuring element that uses information from the motion map. Further work would be the conception of a hybrid image-tracking algorithm to estimate moving regions by differential methods and their tracking using region-based matching techniques. This approach could reduce the computational effort and processing time demanded by these matching techniques, which search

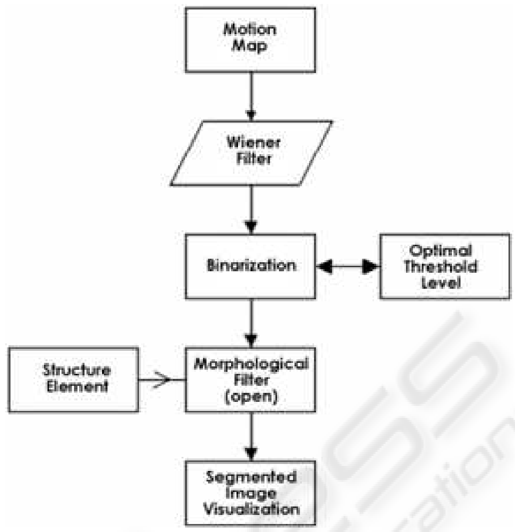


Figure 7: Description post-processing step

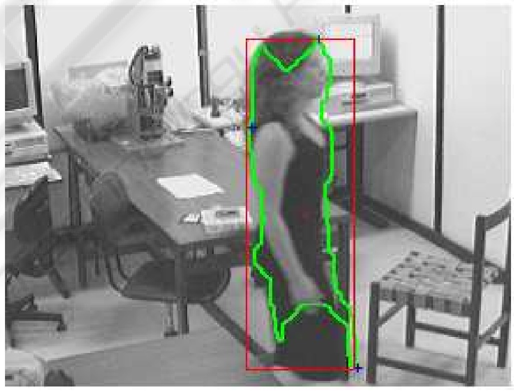


Figure 8: Surveillance sequence segmented

throughout the whole image. Performing the segmentation previously, the search is restricted only to those regions of interest.

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Figure 9: Urban Traffic sequence segmented

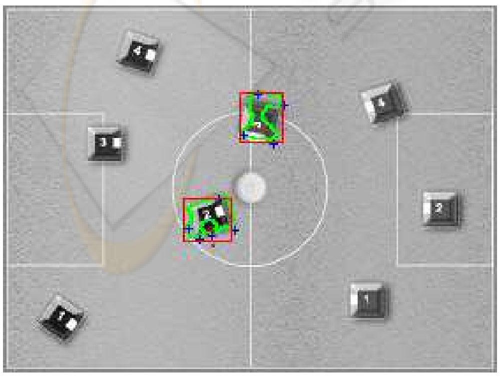

Figure 10: Robot soccer sequence segmented