Efficient Object Tracking Algorithm using Image Segmentation and Pattern Matching

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1. Introduction

The moving object tracking in video pictures has attracted a great deal of interest in computer vision. For object recognition, navigation systems and surveillance systems, object tracking is an indispensable first-step.

The conventional approach to object tracking is based on the difference between the current image and the background image. However, algorithms based on the difference image cannot simultaneously detect still objects. Furthermore, they cannot be applied to the case of a moving camera. Algorithms including the camera motion information have been proposed previously, but, they still contain problems in separating the information from the background.

In this paper, we propose a novel algorithm for object tracking in video pictures. Our algorithm is based on image segmentation and pattern matching. With the image segmentation algorithm, we can extract all objects in images. The proposed algorithm for tracking uses pattern matching between successive frames. As a consequence, the algorithm can simultaneously track multiple moving and still objects in video pictures and can even be applied in the case of a moving camera.

2. Proposed Concept for Moving Object Tracking

An accurate image segmentation algorithm is necessary for our object tracking algorithm. A candidate for such an algorithm has been proposed in Ref. [2]. The image segmentation algorithm allows digital VLSI implementation and has already been verified by designed and fabricated image segmentation testchip [3].

Using image segmentation results, we extract the following eight features of segmented objects:
1) Area: By counting the number of pixels included in segment \(i\) of the \(t\)-th frame, we calculate the area of the object \(a_i(t)\).
2) Width and Height: We extract the positions of the pixel \(P_{\text{max}}, P_{\text{min}}\), \(P_{\text{max}}, P_{\text{min}}\), and \(P_{\text{min}}\) and then calculate the width \(w_i(t)\) and \(h_i(t)\) as follows (see Fig. 1)
\[
w_i(t) = \frac{X_{\text{max},t} - X_{\text{min},t}}{2}, \quad h_i(t) = \frac{Y_{\text{max},t} - Y_{\text{min},t}}{2}.
\]
3) Positions: We define the positions of each object \((x_i(t), y_i(t))\) in the frame as
\[
x_i(t) = \frac{X_{\text{max},t} + X_{\text{min},t}}{2}, \quad y_i(t) = \frac{Y_{\text{max},t} + Y_{\text{min},t}}{2}.
\]
4) Color: Using the image data at \(P_{\text{max}}, P_{\text{max}}, P_{\text{max}}, P_{\text{min}}\), and \(P_{\text{min}}\), we define the color features of each object for the \(R(\text{Red})\) component
\[
R_i(t) = \frac{R(P_{\text{max}}) + R(P_{\text{min}}) + R(P_{\text{max}}) + R(P_{\text{min}})}{4}
\]
and vice versa.

We now go into details of our algorithm. The proposed algorithm for object tracking exploits pattern matching with the features above. We make use of the minimum distance search between \((t,i)\) and all objects in the preceding frame \((t-1,j)\) (the notation \((t,i)\) stands for the object \(i\) in the \(t\)-th frame). The object \((t,i)\) is identified with the object in the \((t-1)-t\) frame which has the minimum distance from \((t,i)\). Repeating this matching procedure for all segments in the current frame, we can identify all objects one by one and can keep track of the objects between frames.

A few comments on refinements of the proposed algorithm are in order.
1) In calculation of the distance between \((t,i)\) and \((t-1,j)\) in position space, it is more appropriate to take account of motion determination and use estimated positions \(x_i(t-1)\) and \(y_j(t-1)\) instead of raw positions \(x_i(t-1)\) and \(y_j(t-1)\) (see Fig. 2). These replacement are available and used from the third frame onwards.
2) We have not specified the distance measure used for matching yet. In the simulation experiments we could confirm that besides the Euclidean distance the simpler Manhattan distance is already sufficient for object tracking purposes.
3) In order to treat all object features with equal weight, it is necessary to normalize the features. One possible way is dividing them by their maximum values. Dividing by \(2^n\) where the integer \(n\) is determined for each feature so that approximately equal weights result, is another possibility. The later has the advantage that the division can be realized by a shifting operation in a hardware realization.

3. Simulations

This section presents simulated results of the object tracking algorithm. In Fig. 3, a sequence of four sample frames with QVGA size can be seen. Note that we explicitly show object indices in the pictures. The extracted features of the objects in frames are listed in Table I. In this table, we have normalized the area feature by division with \(2^n\) and the other features by division with \(2^n\). Furthermore, the decimal parts of the numbers have been omitted.

The tracking quality is evaluated with the Euclidean and the Manhattan distances. In Tables II and III, distances between successive frames are listed. One can see that all objects correctly match with their counterparts in preceding frame no matter whether the Euclidean distance is used or the Manhattan distance is. These results of simulation experiments verify the proposed algorithm’s efficiency.

We have also confirmed that the algorithm works very well for more complicated video pictures including rotating objects and occlusion of objects. Furthermore, if mistracking occurred at some frame by reason of occlusion, newly appearing or disappearing objects, the proposed algorithm could recover correct tracking after a couple of frames. This stability characteristic of the algorithm results from the fact that the object matching is performed in feature space between all objects in successive frames.

4. Conclusions

We have proposed an object tracking algorithm for video pictures, based on image segmentation and pattern matching of the segmented objects between frames in a simple feature space. Simulation results for a frame sequence with moving balls verify the suitability of the algorithm for reliable moving object tracking.

The relative simplicity of this tracking algorithm promises that an FPGA implementation is possible and already sufficient for real-time applications with a few moving objects. As noted earlier, it is sufficient for the tracking to use the simple Manhat-
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Acknowledgment

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TABLE I: Extracted features of the objects.
The symbol \((t, i)\) denotes the object \(i\) in the \(t\)-th frame. In order to treat all features with equal weight, we have normalized area by division with 2^3 and the other features by division with 2^4. Furthermore, the decimal parts of the numbers have been omitted.

<table>
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<tr>
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<th>(a)</th>
<th>(w)</th>
<th>(h)</th>
<th>(x)</th>
<th>(y)</th>
<th>(w_0)</th>
<th>(h_0)</th>
<th>(G)</th>
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Fig. 2: Estimation of the positions in the next frame. Here, \((t, i)\) denotes the object \(i\) in the \(t\)-th frame and \(v_{(t-1),j}\) and \(m_{(t-1),j}\) denote the motion vector of \(x\)- and \(y\)-directions of the object \(j\). These estimations are available from the third frame onwards and included in pattern matching.

Fig. 3: Sample video pictures "5 moving balls", including a collision between the balls. We have explicitly shown object indices in the pictures.

TABLE II: The Euclidean distances between successive frames. Distances shown in red correspond to the minimum distances. Obviously, all objects in the current frame match with their counterparts in the preceding frame.

<table>
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<th>object</th>
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<th>((1,3))</th>
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</table>

TABLE III: The Manhattan distances between successive frames. Distances shown in red correspond to the minimum distances.

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References

Object tracking in video pictures is of great interest in
a) Computer Vision
b) Navigation Systems
c) Surveillance Systems

Conventional approaches, based on the image difference, contain problems in
• multiple objects tracking
• simultaneous tracking of still and moving objects
• the case of a moving camera

Proposed novel approach to object tracking, based on
1) image segmentation,
2) pattern matching,
realizes an efficient, simple, and stable tracking of multiple objects

Outline

Feature Extraction for Segments

1. Extraction of area, width, height, positions (x and y), and RGB color data for segment i in the t-th frame

\[
a_{i} = \text{number of pixels}
\]

\[
b_{i} = \frac{G_{i}(P_{i}(x, y)) + G_{i}(P_{i}(x, y)) + G_{i}(P_{i}(x, y))}{4}
\]

\[
x_{i} = \frac{X_{i} + X_{i} + X_{i} + X_{i}}{4}
\]

\[
y_{i} = \frac{Y_{i} + Y_{i} + Y_{i} + Y_{i}}{4}
\]

2. Pattern matching (minimum distance search in the 8-dimensional feature space)

\[
D(t, i) = \text{distance between (x, y) and (x', y')}
\]

\[
D_{i}(t, i) = \min_{j \neq i} D(t, i; t-1, j)
\]

3. Estimation of the positions of the segment i in the t-th frame

4. Repeating the matching procedure [from 1. to 3.] for all segments

Feature Calculation and Object Tracking

Calculation of area, width, height, and RGB color data

Motion determination estimation of the positions in the next frame

Pattern Matching
minimum distance search in the feature space
between objects in the successive frames

Distance measure used for tracking

Euclidean distance: \( D_{e}(x, y) = \sqrt{(x-x')^2 + (y-y')^2} \)

Manhattan distance: \( D_{m}(x, y) = |x-x'| + |y-y'| \)

Position data used for the pattern matching

\( (x, y) \):
object i in the t-th frame

\( (x', y') \):
minimum distance search in feature space

\( (x, y) \):
Estimated positions of segment j in the t-th frame

\( (x, y) \):
Motion vector of object j in the (t-1)-th frame

Simulation Experiments

QVGA sample video pictures including a collision between balls
(object indices are explicitly shown in the pictures)

Image segmentation results for the 1st frame

Conclusions

- New object tracking algorithm, based on
  image segmentation and pattern matching is proposed.
- The use of the simple Manhattan distance is sufficient for
  the pattern matching (minimum distance searches)
- All objects correctly match with their counterparts
- Both distance measures are effective
- The use of Manhattan distance is sufficient for tracking

The characteristics of the algorithm

The algorithm works well for pictures including
1) multiple moving and still objects
2) occlusion of objects
3) rotating objects
4) non-rigid objects

If mistracking occurs at some frame (e.g. by reason of occlusion),
the algorithm can recover correct tracking after a couple of frames

Conclusions

VLSI implementation of the proposed algorithm

VLSI implementation is possible by using the previously developed architectures for
• an image segmentation cell-network,
• a fully parallel associative memory for high-speed
minimum Manhattan distance search,
Both architectures have been already realized as VLSI circuits

Image segmentation VLSI based on cell-network
(T. Morimoto et al., Ext. Abs. SSDM, pp. 138-139, 2004)
• efficient segmentation of gray scale and color images
• real-time processing
(processing time) \( \approx 200\mu s \) for QVGA image

Fully parallel associative memory with high-speed Minimum Manhattan Distance search