

A Novel Approach to Track High-Speed Skater

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Abstract

Color-based tracking is a very popular technique for object tracking. However, under varying environmental conditions in video sequences, the existing tracking methods tend to be unreliable for tracking high speed objects. It is possible under such a complex environment that the targets may disappear totally or partially due to occlusion. To over this problem, a novel approach of multiple-color model is proposed in this paper. Different colors extracted from the skater's head and body are tracked with Kalman filter, respectively. A confidence measure representing the reliability of each color tracking result is presented to guide possible re-detection for continuous tracking. Experimental results show that the proposed approach is very efficient and effective in tracking high-speed skater in real short track sequences.

Keywords: Multiple color tracking; Kalman filter; Occlusion; High-speed object tracking.

1. Introduction

The most common method to track objects is to detect them using background subtraction of an established correspondence frame by frame [1], [2]. Despite its popularity, it can only be applied to imagery acquired by "stationary camera". An alternative approach to background subtraction is using simple geometric models to transform the object from frame to frame. In [3], Comaniciu et al. use the mean-shift approach to compute the translation of a circular region. The object appearance is modeled by weighed histograms.

Tracking of the complete object can be achieved by employing the active contours, which were introduced by Kass et al [4]. In [5], Nonrigid object motion can be modeled in terms of combining optical flow with active contours, Mansouri uses a probabilistic form of the brightness constraints, where the color is defined by a Gaussian distribution. Optical flow derived from the brightness constraint is computed. However, the brightness constraint requires very small variation in the intensities and it is not suitable for images with high dynamic intensity ranges.

Tracking with multiple cue fusion becomes more and more popular. In [6], an autobinomial Gibbs Markov random field is used for modeling the texture and a 2D Gaussian distribution is used for modeling the color. This allows a probabilistic fusion of the texture and color cues. Similarly, in [7], visual features (color, texture) and the object shape are considered. Color and texture models are generated for the object and the background regions. A shape prior is used for recovering occluded object parts during the occlusion.

The goal of our study is to track high-speed nonrigid skater under a complex environment, where background drastically changes and successive occlusion often occurs and the colors of similar clothing are very close, etc. Many above methods using ideal model or some constraint are not suitable.

In this paper, a novel approach for tracking high-speed skater is proposed. Color features are firstly extracted from skater's head and body. Then, Kalman filter is utilized to estimate the search region and to evaluate each color, respectively. Afterwards, these evaluations are integrated to determine which part of the object needs to re-detect. The detection result is regarded as the initial data of tracking module. To enhance the robustness of tracking, a confidence measure representing the reliability of each color tracking result is presented to guide possible re-detection for continuous tracking. Moreover, the lost tolerance of object is introduced in order to avoid stopping tracking exceptionally due to totally occlusion. The approach is robust and can perform real-time skater detection and tracking.

2. Proposed Approach

2.1. Framework of Our Algorithm

The flow chart of the proposed algorithm shown in Figure 1 consists of three major processing modules:

- Object detection based on colors.
- Kalman filter prediction.
- Object re-detection determined by confidence measure.

2.2. Color Space Selection

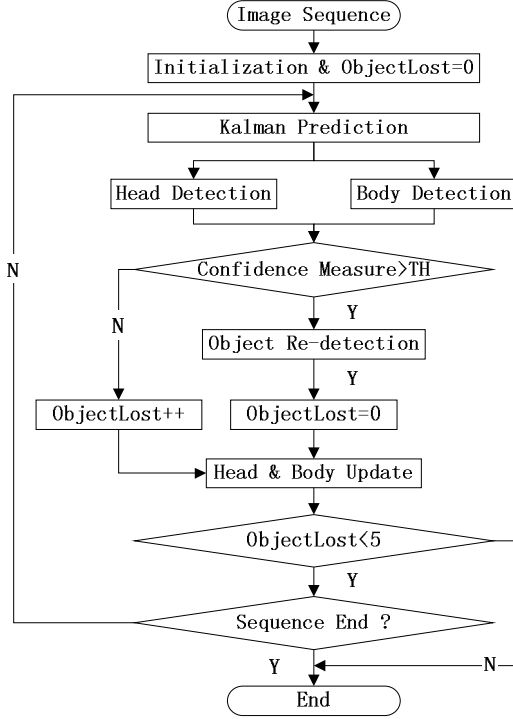


Fig. 1: Flow chart of the proposed algorithm

An important aspect of any color-based tracking system is to choose a color space that is relatively invariant to minor illuminant change. The two most popular color spaces robust to minor illuminant changes are HSV and normalized RGB. [8],[9] proved that normalized RGB color model is more sensitive to lighting changes since the saturation influenced by lighting is not separated out of that model. Hence the best color space is HSV which has been applied to many color tracking problems [9],[10]. HSV space separates out hue and saturation from intensity, and we create color models by 2D histograms from the hue and saturation channel in HSV space.

2.3. Kalman filter prediction

The Kalman filter is one of the most popular estimation techniques in motion prediction because it provides an optimal method for linear dynamic systems with white Gaussian noise. In general, the Kalman filter describes a system with a system state model and a measurement model as in Eqs. (1) and (2):

$$S_{k+1} = A g S_k + w_{k+1} \quad (1)$$

$$M_{k+1} = H g S_{k+1} + v_{k+1} \quad (2)$$

The system state S_{k+1} at the (k+1)th time frame is linearly associated with the state at the kth time frame, and there is also a linear relationship between the

measurement M_{k+1} and the system state S_{k+1} . The random variables w_{k+1} and v_{k+1} represent the state and measurement noise, respectively. A is the state transition matrix that relates the state at frame k to the state at frame $k+1$, and H is called the observation matrix that relates the state to the measurement. In our case, the system state S consists of the following components:

$$S = \begin{bmatrix} x: & x\text{-coordinate of Center} \\ y: & y\text{-coordinate of Center} \\ v_x: & \text{horizontal velocity of Center} \\ v_y: & \text{vertical velocity of Center} \\ w: & \text{width of bounding box} \\ h: & \text{height of bounding box} \\ s: & \text{area of Target} \end{bmatrix} \quad (3)$$

the state transition matrix A , the observation matrix H and the measurement M are given by:

$$A = \begin{bmatrix} 1 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad (4)$$

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad (5)$$

$$M = [x', y', v_x', v_y', s]^T \quad (6)$$

2.4. Object Confidence Measure

It is frequently the case in our tracking problem that an actual measurement on a target is not reliable due to occlusion and complex environment. When an actual measurement is heavily corrupted, the measurement error accumulates through the feedback cycle and the reliable estimation can not be obtained, which results in tracking failure. Therefore, we should get an optimal detection result as possible as we can. A confidence measure (CM) representing the reliability of each color tracking result is given by the following formula:

$$CM = \begin{cases} -1 & P(H_k^s) = 0 \wedge P(B_k^s) = 0 \\ 0 & P(H_k^s) = 0 \wedge P(B_k^s) = 1 \\ 1 & P(H_k^s) = 1 \wedge P(B_k^s) = 0 \\ 0.5 + a \cdot P(\text{error}) & P(H_k^s) = 1 \wedge P(B_k^s) = 1 \end{cases} \quad (7)$$

$$P(H_k^s) = \begin{cases} 0 & H_k^s = 0 \\ 1 & H_k^s > 0 \end{cases} \quad (8)$$

$$P(B_k^s) = \begin{cases} 0 & B_k^s = 0 \\ 1 & B_k^s > 0 \end{cases} \quad (9)$$

$$P(\text{error}) = b \cdot P(H_k^v, H_{k-1}^v) + (b-1) \cdot P(B_k^v, B_{k-1}^v) \quad (10)$$

$$P(H_k^v, H_{k-1}^v) = \begin{cases} 0 & |H_k^v - H_{k-1}^v| > Th \\ 1 & |H_k^v - H_{k-1}^v| \leq Th \end{cases} \quad (11)$$

$$P(B_k^v, B_{k-1}^v) = \begin{cases} 0 & |B_k^v - B_{k-1}^v| > Th \\ 1 & |B_k^v - B_{k-1}^v| \leq Th \end{cases} \quad (12)$$

where H_k^s and B_k^s represent the detected area of head and body at k^{th} time frame, respectively. H_k^v and B_k^v represent the velocity of head and body at k^{th} time frame, respectively. a and b are weighted factors, Th is a prior threshold of velocity. Consequently, the unreliable part determined by CM will be re-detected by the reliable part according to the correlation of initial model.

3. Experimental Results

In short track skating, the skaters are very close and compete with others furiously and overtaking is allowed all the time. As a result, occlusion happens frequently and successively, which is a real challenge to the robustness of tracking system. The experiments demonstrate that the performance of the proposed approach is very good.

In Figure 2, the competitor skating through the curve is exactly tracked despite successive occlusion and size variation. Figure 3 shows good tracking result under a complex environment, where the color of advertisement baffle-board is similar with that of skater's clothing (body).

The experiment results also demonstrate the robustness of our method. Once one of multiple color features is tracked exactly (or not corrupt) even none of them is tracked within limit frames, our tracking system can still work continuously. The unreliable color feature determined by confidence measure (CM) is re-detected according to the correlation of the initial

model, which improves the tracking accuracy in every frame to avoid accumulated error.

Our approach saves more computational time than that in [6]. The program has been implemented by using Visual C++ on a PIV 3.0GHz machine and it takes only 28ms to process averagely on a true color image with 720×576 resolution and can achieve real-time processing.

4. Conclusions

A novel approach for tracking high-speed skater is proposed. Color features are firstly extracted from skater's head and body. The combination of them is efficient and effective for tracking skater under a complex environment or successive occlusion. A confidence measure representing the reliability of each color tracking result is presented to guide possible re-detection for continuous tracking. Moreover, the lost tolerance of object is introduced in order to avoid stopping tracking exceptionally due to totally occlusion. The approach is robust and can achieve real-time skater detection and tracking.

It will fail under some special conditions such as all color features lose successively or the light is too dark so as to the color feature in HSV space is unstable and not exactly detected due to nonremovable singularity [11]. It will be investigated in the future.

5. Acknowledgements

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6. References

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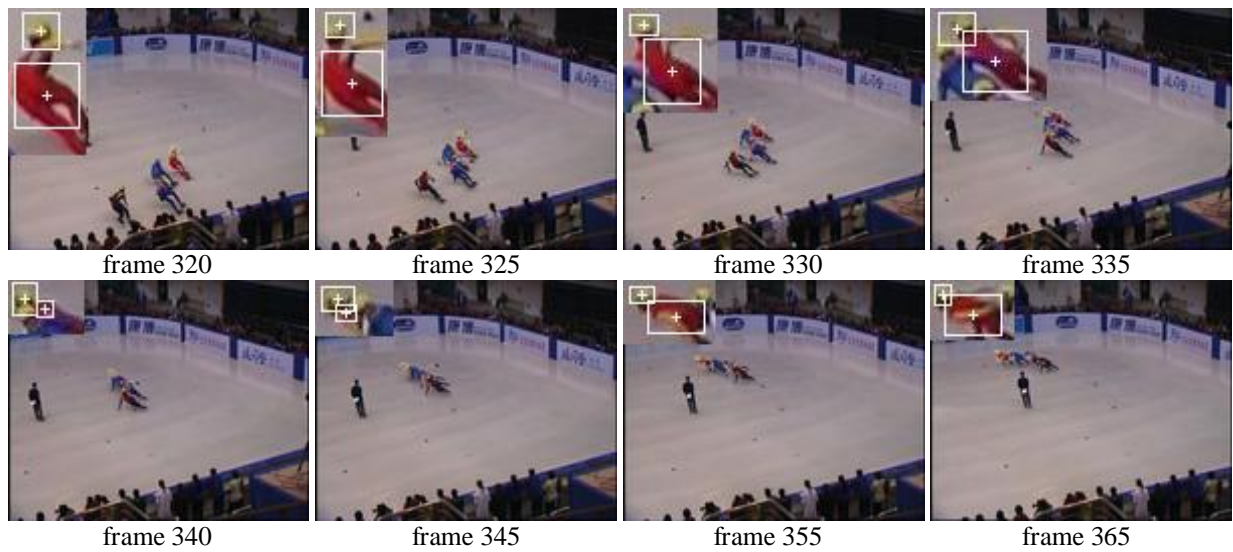


Fig. 2: Tracking results of successive occlusion

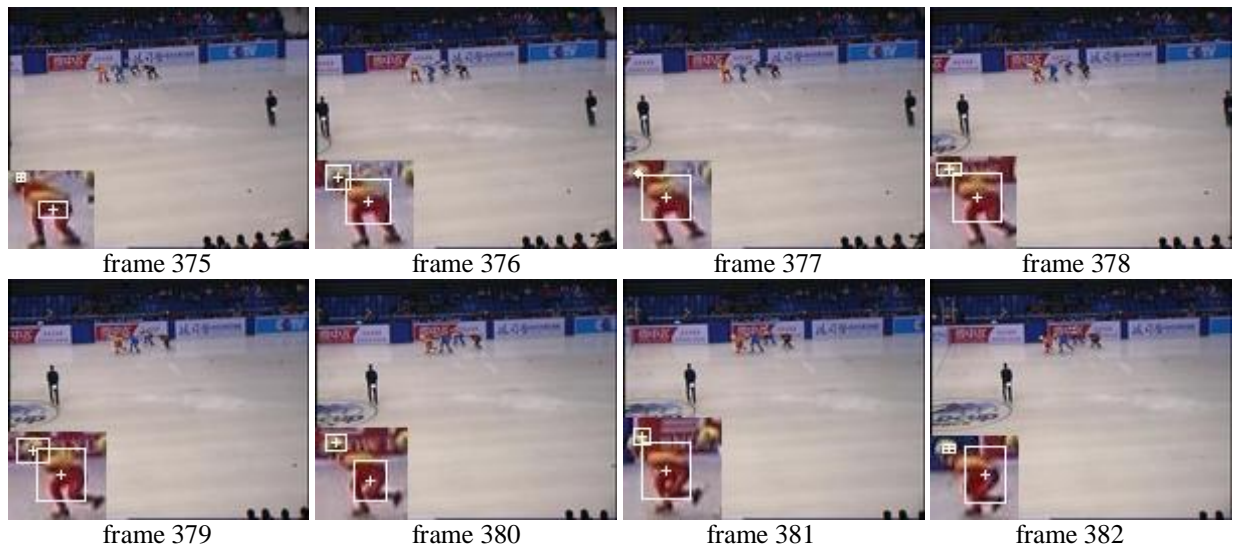


Fig. 3: Tracking results under a complex environment