A Novel Tracking Features Selection Method Based on Genetic Algorithm

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Abstract

In this paper a novel tracking feature selection method is presented. Assuming the features that best discriminate between object and background are also best for tracking the object. A two-class variance ratio is employed to measure the discriminability. Genetic algorithm is used to optimize the different features combination to generate the best tracking feature. To demonstrate our proposed method, selected feature are combined with Kernel-based tracking method. Experimental results show that the proposed method can robustly tracking moving object in low discriminately background scenario.

Keywords: Tracking Feature Selection; Discriminative Tracking Features; Genetic Algorithm; Kernel-Based Tracking

1. Introduction

Visual tracking is a common task in computer vision and play key roles in many scientific and engineering fields. Various applications ranging from video surveillance, human computer interaction, traffic monitoring to video analysis and understanding, all require the ability to track objects in a complex scene [1, 2, 3, 4]. Many powerful algorithms for target tracking have yielded two decades of vision research. Frame difference and adaptive background subtraction combined with simple data association techniques can effectively track in real-time for stationary cameras target tracking [5,6]. Optical flow methods using the pattern of apparent motion of objects, surfaces and edges in a visual scene caused by the relative motion between the camera and scene. These methods can achieve the target tracking in the stationary cameras scene and the mobile cameras scene [7,8]. Modern appearance-based methods using the likelihood between the tracked target appearance describe model and the reference target appearance describe model can achieve the target tracking without prior knowledge of scene structure or camera motion. Modern appearance-based methods include the use of flexible template models [9,10] and kernel-based methods that track nonrigid objects used color histograms [11,12,13]. Particle filter and Kalman filter are using to achieve more robust tracking of maneuvering objects by introducing statistical models of object and

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camera motion [14,15].

Our review of that variety of tracking methods' tracking performance and our own experimental results indicate that, tracking success or failure depends primarily on how distinguishable an object is from its backgrounds. If the object is very distinctive, even a simple tracker can achieve a good performance. If the object has low-contrast or is camouflaged, robust tracking can only obtained by imposing prior knowledge about scene structure or expected motion. Most tracking applications are conducted using a fixed set of features, based on priori information. In a complex scenario, object and surrounding background change during tracking. Sometimes object has low-contrast or is camouflaged with background. In those conditions using a fixed set of features always result to tracking fail. Online tracking features adaptively selection methods are introduced to solve these problems [16,17,18,19]. Collins et al.[16] proposed to online select discriminative tracking features from linear combination of RGB values. The two-class variance ratio is used to rank each feature by how well it separates the sample distributions of object and background. Top N features that have the greatest discrimination are selected to embed in a mean-shift tracking system. However this approach, using exhaustion method to find the top N features from 49 candidate feature sets. It's high time consume for real time tracking. Dawei Liang et al. [17] extend the work of Collins et al. by introducing adaptive feature selection and scale adaptation. A new feature selection method based on Bayes error rate is proposed. From a feature set, the most discriminative features are selected after ranking these features based on their Bayes error rates. But it still is using exhaustion method to find the most discriminative features. Wang and Yagi [18] selecting reliable feature from color and shape-texture cues according to their descriptive ability. But, using color and shape-texture cues are based on prior information it's hard extend to other scenario.

A key issue addressed in this work is a novel tracking feature selection method using genetic algorithm. Tracking features selection problem is taken as a local discrimination problem with two classes: object and background. Many works have point the features that best discriminate between object and background are also best for tracking performance [18]. To avoid exhaustion research in candidate feature sets solve the time consuming problem, genetic algorithm is employed.

2. Tracking Feature Selection Criterion

Feature selection is a technique for select a subset of \(d\) features from a total of \(D\) features, where usually \(d<<D\) based on a given optimization criterion and search strategy. This technique can improve classification performance and reduce computing time by discarding irrelevant or redundant features.

Feature selection criterion function is a quantitative measurement used to compare one feature subset against another. The feature selected for tracking only needs to be clearly separable from its surroundings. It can take as a discrimination problem. For discrimination problems, the criterion involves evaluation of the discriminating power of the selected feature subset. There several approach to evaluate the discriminative power of a feature, such as augmented variance ratio (AVR), information gain and mutual information [16]. AVR is the ratio of the between-class variance of the feature to the within-class variance of feature, compare with other method it has the advantage of less computation. In this work AVR is employed for tracking feature selection.

In this paper, the target is represented by a rectangular set of pixels covering the target, while the
background is represented by a larger surrounding ring of pixels. Given a feature \( f \), let \( H_{fg}(i) \) be a histogram of target and \( H_{bg}(i) \) be a histogram for the background. The empirical discrete probability distribution \( p(i) \) for the object and \( q(i) \) for the background can be calculated as

\[
p(i) = \frac{H_{fg}(i)}{n_{fg}} \quad \text{and} \quad q(i) = \frac{H_{bg}(i)}{n_{bg}},
\]

where \( n_{fg} \) is the pixel number of the target region and \( n_{bg} \) the pixel number of the background. The weight histograms represent the features only. It does not reflect the descriptive ability of the features directly. A log-likelihood ratio image is employed to solve this problem. The likelihood ratio nonlinear log likelihood ratio maps feature values associated with the target to positive values and those associated with the background to negative values. The likelihood ratio of a feature is given by

\[
L(i) = \max(-1, \log\left(\frac{\max(p(i), \varepsilon)}{\max(q(i), \varepsilon)}\right))
\]

where \( \varepsilon \) is a very small number (set in 0.001 in this work), that prevents dividing by zero or taking the log of zero. Likelihood ratio images are the foundation for evaluating the discriminative ability of the features in the candidate features set.

In the practice, the whole weighted images weighted by log likelihood are not needed to be calculated for the computational complexity. The corresponding variance is employed to measure the separately between target and background classes. Based on the equality \( \text{var}(x) = E[x^2] - (E[x])^2 \), the variance of the log likelihood is computed as

\[
\text{Var}(L : p) = E[L(i)^2] - (E[L(i)])^2.
\]

3. Tracking Feature Selection Based on Genetic Algorithm.

Genetic Algorithms is a stochastic algorithm that mimics natural evolution. It has wildly using in the feature selection field [19, 20]. In a Genetic Algorithm a population of individuals representing possible space solutions is maintained through several generations. Each individual is evaluated in each generation based on its fitness with respect to the considered function to minimize or maximize. The selection, crossover and mutation of the fittest ones produce new individuals. Through the generations, the population is led to the space of the better solutions in the given domain.

3.1. Chromosome Encoding

Representation is a key issue in the work of GAs because problem representation is the bridge baleen GA and specific application. In principle, a wide range of features could be taken as tracking feature set, including color, texture, shape and motion. Each potential feature set typically has dozens of tunable parameters, the potential features that could be used for tracking is enormous. In this work, target
appearance is represented using histograms of color filter bank responses applied to R, G and B pixel values within local image windows. Histogram-based representation is relatively insensitive to variations in target appearance due to viewpoint, occlusion, and non-rigidity. In this paper only color features are considered, but the proposed approach can be extended easily to other cues represented as histograms of feature values. The set of seed candidate features is composed of linear combinations of camera R, G, B pixel values. Specifically, in this work, the following set of feature candidates is chosen:

\[ F_i \equiv \{ m_1R + m_2G + m_3B \} \]  

(3)

The coefficient \( m_\ast \) is an integer value between -3 and 3. The total number of potential feature combination would be 73.

A potential feature candidate could be formed by linear combination with different pre-assigned numbers. Thus a potential feature is encoded as a sequence of number as Fig.1. Every potential feature turning parameter is code by three bits binary number. The number with drop shadow is feature turning parameter's flag number. '0' means positive value and '1' means negative value. Then the next two bits binary numbers are the weights of every feature in the feature set. The example shows feature candidate \( F_1 \) can denoted as \( F_1 = -2R + G - 3B \)

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<tr>
<th>R</th>
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Fig.1 An Example of Chromosome

3.2. Parameters Setting

There are several important parameters need set in GA population size, crossover probability and mutation probability. Population size sets how many chromosomes are in population. If there are too few chromosomes, GA has a few possibilities to perform crossover and mutation. There are only a small part of search space is explored. On the other hand, if there are too many chromosomes, GA slows down. Crossover probability sets how often will be crossover performed. Crossover is made in hope that new chromosome will have good parts of old chromosomes and maybe the new chromosome will be better. However it is good to leave some part of population survive to next generation. Mutation probability sets how often will be parts of chromosome mutated. Mutation is design to prevent falling GA into local extreme.

The efficiency of a GA is greatly dependent on its tuning parameters. However, there still not have a standard parameters setting method. In this work, the GA parameters are set by experience. To get the best efficiency of the GA, population size is set as 20, crossover probability is set as 0.9 and mutation probability is set as 0.001.
4. Kernel-based Tracking

Mean shift recently gained more attention due to its low computational complexity and robustness to appearance change, however, the basic mean shift tracking algorithm assumes that the target representation is discriminative enough against the background. This assumption is not always true, especially when tracking is carried out in a dynamic background [12, 21]. An online, adaptive features fusion mechanism is embedded in the kernel-based mean shift algorithm for effective tracking. Due to the continuous nature of video, the distribution of target and background features in the current frame should remain similar to the previous frame and the fused feature model should still be valid. The initial position of the target is given by $y_0$ which is determined in the previous frame. The target model is $P = p_{1:t=1...m}$, $\sum_{t=1}^{m} P_t = 1$, and the candidate target model is $P(y_0) = p_{1:t=1...m}$, $\sum_{t=1}^{m} P_t = 1$ where $P_t$ is the fused feature model.

The Epanechikou profile [11, 12] is employed in this paper. The target's shift form $y_0$ in the current frame is computed as

$$y_1 = \frac{\sum_{i=1}^{m} X_i \omega_i g\left(\frac{y_0 - x_i}{h}\right)}{\sum_{i=1}^{m} \omega_i g\left(\frac{y_0 - x_i}{h}\right)}$$

(4)

where $g(x) = -k'(x)$, $k(x)$ is Epanechikou profile, $h$ is bandwidth and $\omega_i$ can compute as

$$\omega_i = \sum_{t=1}^{m} \sqrt{\frac{P}{P(y_0)} \delta[b(x_i) - t]}$$

(5)

And the tracker assigns a new position of the target by using

$$y_1 = \frac{1}{2}(y_0 + y_1)$$

(6)

If $\|y_0 - y_1\|$, the iteration computation stops and $y_1$ is taken as the position of the target in the current frame. Otherwise let $y_0 = y_1$, then using Eq. (4) get the shift vector and do position assignment using Eq. (6).

5. Experiments and Results

To illustrate the efficiency of the proposed approach for low discriminately background, a moving vehicle sequence is employed. The sequence has 1000 frames of 480×640 pixels. The moving vehicle is taken as tracking target initialized with a hand-draw rectangle of size 71×28, and the background rectangle size is 92×42. The experiment was done using Pentium core 1.8G, Win XP, Matlab 7.0, the GA parameters set as section 3.2. Take 30 iterative steps as genetic algorithm ending criterion.
Fig. 2 is the initial frame of the first tracking sequence, while the vehicle on the bottom of this frame is taken as tracking object. The inside black rectangle is taken as tracking object area; the outside black rectangle is taken as tracking object background. The background width is 1.3. Using proposed tracking feature selection; the best tracking feature is R-3G-3B. Fig. 3 shows the pseudo-color image of best tracking feature. Know from Fig. 3, the best discriminative feature the tracking object has a good discriminative with the background. It’s good to separate the tracking object from background.

Fig. 4 shows the discriminability between tracking object and background using proposed tracking feature selection algorithm. While Fig. 5 shows the discriminability between tracking object and background using exhaustive method. Compare the two figures, we can know, in 30 steps iteration the proposed approach is converging to the best discriminability. The best discriminability value is 0.5501 which equal with the discriminability value using exhaustive method. Meanwhile, using the proposed approach the computational complexity can reduce 90% compare to exhaustive method. Fig. 6 shows the tracking results using the selected feature. As contrast the tracking results using RGB color feature are shown as a Fig. 7. In Fig. 6 shows even in a very low discriminately background scene, the proposed approach have good performance for object tracking. However, the traditional mean shift tracking method lost it tracking object from 250th frame, because there have a similar object beside the tracking object. The traditional mean shift tracking method lacks an appropriate tracking feature selection mechanism. It’s hard
to distinguish the tracking object from the similar background objects, and tracking a wrong object.

Fig. 6 Tracking Results using Proposed Approach
6. Conclusion and Discussion

In this work, a novel tracking feature selection method is proposed. Object tracking problem is taken as a local discrimination problem with two classes: object and background. The feature has best discriminately between object and background is taken as the best tracking feature. To avoid exhaustion research in candidate feature sets, genetic algorithm is employed to chosen tracking feature. Experiments show the proposed tracking feature selection method is efficiency and it can obvious improve the performance of object tracking.

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References


