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Adaboost Classification-Based Object Tracking Method for Sequence Images

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Abstract. An object tracking framework based on adaboost and Mean-Shift for image sequence was proposed in the manuscript. The object rectangle and scene rectangle in the initial image of the sequence were drawn and then, labeled the pixel data in the two rectangles with 1 and 0. Trained the adaboost classifier by the pixel data and the corresponding labels. The obtained classifier was improved to be a 5 class classifier and employed to classify the data in the same scene region of next image. The confidence map including 5 values was got. The Mean-Shift algorithm is performed in the confidence map area to get the final object position. The rectangles of object and background were moved to the new position. The object rectangle was zoomed by 5 percent to adapt the object scale changing. The process including drawing rectangle, training, classification, orientation and zooming would be repeated until the end of the image sequence. The experiments result showed that the proposed algorithm is efficient for nonrigid object orientation in the dynamic scene.

Introduction

The object tracking of sequence images is a process that recognizing the interested object and analyzing the characters of it. The cases of object tracking can be classified according to three standards. The first is that the scene of the sequence images is static or dynamic. The second is that there is single object or there are multi-objects in the images. The third is that the object is rigidity or nonrigid. Some factors will affect object orientation and tracking including noise disturbing, complexity of motion curve, nonrigid objects, obstruction, requirement for real time and so on. The nonrigid object tracking in the dynamic scene is the aim of the paper. The solving method of this problem was already discussed in some literatures such as the algorithm based on Bayesion and template. The method based on template requires exact prior information in the first image and the quality of the following image should be perfect [1]. The method based on Bayesion theory is also called sequence particle filter algorithm. The predominance of the method is the adaptability to nonrigid object and dynamic scene, but the shortcoming is that it is complexity and not adapted to real-time tracking [2,3,4].

The paper proposes an object orientation algorithm based on adaboost classification for nonrigid object tracking in the dynamic scene. In the initial image of the sequence, the rectangle surrounds the object should be chosen to get the pixel data and the rectangle of scene surrounds the object rectangle should also be chosen to get the scene pixel data. The object pixel data would be labeled as 1 and the scene pixel data will be labeled as 0. The object pixel data, scene pixel data and the corresponding labels are employed as the training data of the adaboost classifier which was obtained after the training procedure. This classifier was used to classify the data of the pixels in the same range of the next image in the sequence. After the improvement, the adaboost classifier would label the pixel data as 0, 0.25, 0.5, 0.75, 1 and these data constructed the confidence map. According to these labels, the object location would be calculated by Mean-shift. Then, move the rectangles of object and background to the new position. Zooms the object rectangle by 10 percent to adapt the object scale changing. The process including drawing rectangle, training, classification, orientation and zooming would be repeated until the end of the orientation or tracking.

Adaboost Classifier for Image Data

Adaboost is an iterative algorithm. The samples' weights should be calculated according to the correctness of the rates of classification. The final strong classifier is obtained by construct the weak classifiers after the train. In the adaboost algorithm, every sample is combined with a weight value which denotes the probability of the sample being selected into the train set [5]. The probability of being chosen of the sample will increase if the classification result was wrong. So the adaboost classifier will focus on the samples that are difficult to classify [6].

In the first iterative step, the weights of all the samples are equal. For the iterative step t, the samples should be chosen according to the corresponding weights to train the classifier. The classification result will be employed to increase the weights being classified incorrectly and decrease the weights being classified correctly [7]. Then, the samples with new weights will be used to train the next classifier. The whole process can be expressed as following.

In the train sample sets $S=\{X,Y\}$, $X=\{x_1,x_2,\ldots,x_N\}$ is the sample set and $Y=\{y_1,y_2,\ldots,y_N\}$ is the label set whose value is 1 or 0.

Step 1. Initialize the sample weights: $w_{t,i}=\frac{1}{N}$, $i=1,2,...,N$ and t is the number of iterative step;

Step 2. For $t=1,2,\ldots,T$ (T is the time of the train or the number of the classifier):

a) Weights standardization: $w_{t,i}=\frac{w_{t,i}}{\sum_{j=1}^{N} w_{t,i}}$;

b) Train weak learner $h_t(X)$ classifier using $S=\{X,Y\}$ according to the weight set $W_t=\{w_{t,i}\}$;

c) Calculate the classification error: $e_t=\sum_i w_{t,i}\left|h_t(x_i)-y_i\right|$. If $e_t<0.5$,let the weak classifier weight $\alpha_t=\frac{1}{2}\ln[(1-e_t)/e_t]$, if not, delete this weak classifier and stop the iterative algorithm.

d) Update weight set: $W_{t+1}=\left\{w_{t+1,i}=w_{t,i}\left[e_t/(1-e_t)\right]^{1-\eta_i}\right\},\eta_i=\begin{cases}0 & \text{if } x_i \text{ was classified corectly}\\ 1 & \text{otherwise}\end{cases}$;

Step 3. The final strong classifier is

$$H(X)=\begin{cases}1 & \sum_{t=1}^{T}\alpha_t h_t(X)\geq\frac{1}{2}\sum_{t=1}^{T}\alpha_t\\ 0 & \text{otherwise}\end{cases}. \tag{1}$$

The generic form of weak classifier is $h(x_i)=\begin{cases}1 & p_i*y_i<p_i*\theta_i\\ 0 & \text{otherwise}\end{cases}$, in which θ_i is the threshold and p_i is the sign parameter which value is ±1 [8].

According to the theory above, the adaboost is a binary strong classifier. But some information is missed in the process. After the classification, the label set of image data is including two values, 1 and 0. Not only noise but also image information is removed. The paper proposes a new strong classifier form based on adaboost to solve this problem. The formula (1) is changed as following.
Let

$$F_1=\sum_{t=1}^{T}\alpha_t h_t(X). \tag{2}$$

And

$$F_2 = \frac{1}{2}\sum_{t=1}^{T}\alpha_t \ . \tag{3}$$

The weak classifier output $h_t(X) \le 1$, so $0 \le F_1 = \sum_{t=1}^{T}\alpha_t h_t(X) \le 2F_2 = \sum_{t=1}^{T}\alpha_t$. The new strong classifier is

$$H(X) = round(4 * \frac{F_1}{2F_2}) = round(\frac{2F_1}{F_2}). \tag{4}$$

The value range of $H(X)$ is $\{0,1,2,3,4\}$ including 5 values. The Fig.1 showed the difference of classified image data using formula (1) and (4). The classification result including the label 0 and 1 using formula (1) is shown in the left of Fig.1. The classification result including the label 0, 1, 2, 3 and 4 using formula (4) is shown in the right of Fig.1.

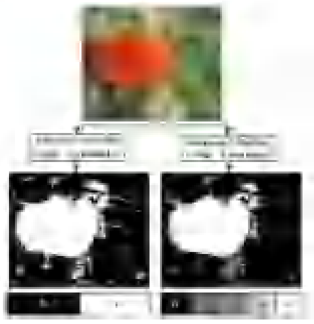


Fig.1 The difference of classified image data using formula (1) and (4).

Mean-Shift

Mean-Shift, which means the vector point to the mean of the data, is proposed by Fukunaga. In the d dimension space, there is a data set $Z = \{z_i\}_{i=1,2,\cdots,n}$ with a probability density. A kernel function including multi-parameter should be employed if we want to estimate the probability density function. The kernel is expressed as $K(z)$, for $z \ge 0$,

$$K(z) = ck(\|z\|^2) \ . \tag{5}$$

in which, $k(z)$ is the profile function of $K(z)$ and c is the unitary parameter. The Mean-Shift vector at the point z can be calculated as

$$M_k(z) = \frac{\sum_{i=1}^{n} z_i k\left(\left\|\frac{z - z_i}{h}\right\|\right)}{\sum_{i=1}^{n} k\left(\left\|\frac{z - z_i}{h}\right\|\right)} - z \ . \tag{6}$$

The parameter h is the width of the kernel [9].

Assume that $\{y_j\}_{j=1,2,\ldots}$ is the location sequence of the kernel. If the current kernel center is y_j, the next center can be expressed as

$$y_{j+1} = \frac{\sum_{i=1}^{n} z_i k\left(\left\|\frac{z - z_i}{h}\right\|\right)}{\sum_{i=1}^{n} k\left(\left\|\frac{z - z_i}{h}\right\|\right)} \qquad j = 1,2,\ldots . \tag{7}$$

So, the next shift vector can be calculated iteratively [10].

$$M_k(y_j) = y_{j-1} - y_j . \tag{8}$$

The Mean-Shift algorithm can be described as the following process.

1) Chose the initial searching window whose width is *h*;
2) Chose the initial position of the window;
3) Calculate the Mean-Shift vector and then, change the window position;
4) Repeat the step 3) until constringency.

Orientation Method Framework

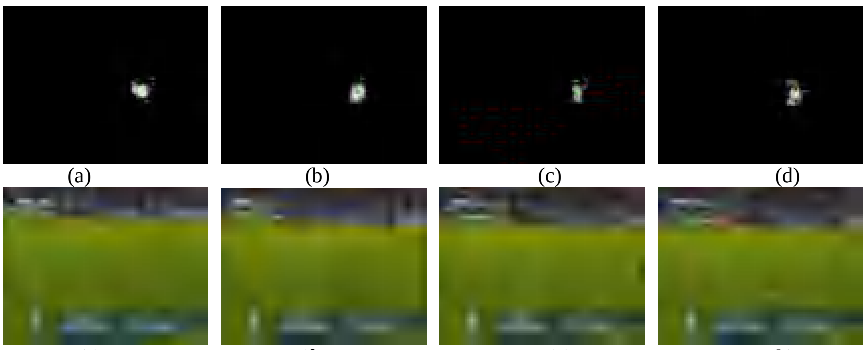
The orientation method framework proposed in this paper follows the steps as

1. Chose the initial object rectangle and the scene rectangle;
2. Train the adaboost classifier using the object and scene data in the corresponding rectangle;
3. Classify the pixel data at the same position in the next image of the sequence and get the confidence map including 5 values 0,1,2,3 and 4.
4. Employs the Mean-Shift algorithm to orientate the object;
5. Zoom the object rectangle with 10 percent, compare it with the prevenient object rectangle data to ascertain the optimized object scale. This method can adapt the scale changing of the object;
6. Repeat this process from Step 2 until the end of the image sequence.

The calculation of the confidence map is shown in Fig.2.In the paper, we want the rectangle dimension being unitary. So, the rectangles are segmented by $M \times N$ grid(M and N are integer and in the paper, $M = N = 10$). Then we get $M \times N$ data set for one rectangle. The comparability of two rectangles is calculated by comparing the two $M \times N$ data sets.

Fig.2 The procedure of the confidence map calculation

Experiment



(a) (b) (c) (d)

(e) (f) (g) (h)

Fig.3 Sequence image tracking result (a) Confidence map of the 1st image; (b) Confidence map of the 10th image; (c)Confidence map of the 20th image; (d) Confidence map of the30th image; (e)

Tracking result of the 1st image; (f) Tracking result of the 10th image; (g) Tracking result of the 20th image; (h) Tracking result of the 30th image.

The results showed that the object rectangle should include more real object pixel data so that to get the more reasonable classification results. The scene pixel data in the object rectangle will lead the miss classification.

The Fig.3 showed the tracking result of an image sequence of the football game video. The results showed that the method proposed in this paper could adapt the changing of the object scale. The object in the image sequence zoomed with the image sequence number.

Conclusions

The paper proposes an algorithm for the nonrigid object tracking in the dynamic scene based on the Adaboost classifier and the Mean-Shift. The rectangles of object and scene are chosen and the pixel data is employed to train the Adaboost classifier which could label the pixel data by 0, 1, 2, 3 and 4 after the improvement. The obtained classifier is used to classify the pixel data in the same region of the next image. After the classification, the confidence map is gotten and the Mean-Shift algorithm is used to find the object position. To adapt the scale changing, the object rectangle is zoomed and compared with the prevenient object rectangle. The experiment result showed that the tracking method was efficient for nonrigid object tracking in the dynamic scene.

References

[1] Kim C, Hwang J N. Fast and automatic video object segmentation and tracking for content based application[J]. IEEE Trans. on Circuits and Syst. Video Technol. 2002, 12(2): 122-128.

[2] B. Bascle and R. Deriche. Region Tracking through Image Sequences[C]. Proc. Fifth Int'l Conf. Computer Vision, pp. 302-307, 1995.

[3] Weiming Hu, Tieniu Tan. A Survey on Visual Surveillance of Object Motion and Behaviors[J]. IEEE Transactions On Systems, Man, and Cybernetics-Part C: Applications And Reviews, vol. 34, no. 3, August 2004.

[4] Collins R. T, Liu Yanxi, Leordeanu M. Online Selection of Discriminative Tracking Features[J]. IEEE Trans on Pattern Analysis and Machine Intelligence, 2005, 27 (10): 1631-1643.

[5] Viola P, Jones M. Rapid object detection using a boosted cascade of simple features[J]. Computer Vision and Pattern Recognition 2001. FlR 2001. Proceedings of the 2001 IEEE Computer Society Conference on. Volume 1. 8-14 Dec. 2001: 1-511, 1-518.

[6] Ravindran S and Anderson D. Boosting as a dimensionality reduction tool for audio classification[J]. Proceedings of IEEE International Symposium on Circuits and Systems, Vancouver, 2004: III-465-8.

[7] B. C. Kuo, and D. A. Landgrebe. Nonparametric Weighted Feature Extraction for Classification[J]. IEEE Transactions on Geoscience and Remote Sensing, Vol. 42, No. 5, pp.1096-1105, May, 2004.

[8] E. Bauer, and R. Kohavi. An empirical comparison of voting classification algorithms: Bagging, boosting, and variants[J]. Machine Learning, Vol. 36, No. 1, pp.105-139, 1999.

[9] Comaniciu, D. and P. Meer, Mean Shift: Robust application toward feature space analysis[J]. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2002. 24(5): 603-619.

[10] Yang C, Duraiswami R, Davis L. Efficient spatial-feature tracking via the mean-shift and a new similarity measure[C]. IEEE Conference on Computer Vision and Pattern Recognition, San Diego, CA, 2005: 351-357.

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DOI References

[3] Weiming Hu, Tieniu Tan. A Survey on Visual Surveillance of Object Motion and Behaviors[J]. EEE Transactions On Systems, Man, and Cybernetics-Part C: Applications And Reviews, vol. 4, no. 3, August 2004.
doi:10.1109/TSMCC.2004.829274
[8] E. Bauer, and R. Kohavi. An empirical comparison of voting classification algorithms: Bagging, oosting, and variants[J].Machine Learning, Vol. 36, No. 1, pp.105-139, 1999.
doi:10.1023/A:1007515423169
[9] Comaniciu, D. and P. Meer, Mean Shift: Robust application toward feature space analysis[J]. EEE Transactions on Pattern Analysis and Machine Intelligence, 2002. 24(5): 603-619.
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