Efficient Fast Object-Tracking Scheme Based on Motion-vector-located Pattern Match

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***Abstract*—In the process of object tracking, the major problem is how to mark the tracking box of the object. Moreover, multi-objects tracking is also difficult. This paper proposed and efficient fast object-tracking scheme based on motion-vector-located pattern match, which adopts motion vector of Mpeg2 to mark the moving targets in static video in order to mark and locate the targets automatically and quickly. Then, extract multi-dimensional characteristics from the initial targets taken by motion vector and make the model. Then accurately identifies the particles of larger weight and combines with inertia factor of velocity through matching the original data and the observations of particle filter. The matching of the characteristics of the new particle and the original one is more accurate and faster because of adopting the method of pattern classifying. The experiments show that the algorithm had good tracking performance and strong robustness.**

***Index Terms*—object tracking, motion vector location, particle filter, Pattern Match**

I. INTRODUCTION

In the process of object tracking, how to locate, recognize and track the target is a difficult problem to solve. Knowledge of pattern recognition is introduced into the process of precise tracking of object, and makes object identifying more detailed, thus provides a reliable guarantee for more accurate capture of dynamic object, so locating the object in the image center of computer is the key step. In the process, usually dynamic monitoring is needed to detect the video in static background and the method of motion vector is mainly used in moving objects detection of static background. The process is as follows [1]: firstly, create a motion model, then get information of object point in the plane position of image, velocity and acceleration from motion model, and then use Kalman Filter to predict the related information about object position, velocity and acceleration of next frame based on this information, so as to achieve the purpose of tracking. Karlman Filter has Gaussian, linear required constraints to motion features [2]. Although Extended-Kalman Filter has improved the Kalman Filter, but it has also increased the complexity of motion model. In order to better track the moving objects, this article uses Particle Filter to track athletes, and make feature extraction model to objects' tracking box of calibrated from motion vector represented by each particle. In this way, it can track the objects more accurately.

When comparing the tracking boxes, a mare accurate way of calculation is needed to determine whether the tracking box is more similar with the previous one of larger weight. We use a more accrue way to describe the tracking box, and use pattern recognition method to determine whether the tracking box is similar to the previous. Experiments show that the results are better than general histogram. Kalman Filter [3] is described by a series of recursive mathematical formula. They provide an efficient and computable method to estimate the state of process, and have minimum errors [4]. Kalman Filter is widely used and powerful: it can estimate signal's past and current status, and even the future state, even it does not know exact nature of model. The idea of Particle Filter is based on Monte Carlo method, which is uses a set of particles to represent probability, and can be used in any form of space model's state [7].

The main idea is expresses their particle distribution through extracting particle of random state from posterior probability; it is an important method of Sequential Importance Sampling [8]. In short, Particle filter uses current information of known to predict probability of what will happen. The sample here refers to particles, when numbers of sample $N \to \infty$, it can approach any form's distribution of probability density. The advantage of particle filter technology in non-linear, non-Gaussian systems determines its wide range of applications. The correlation of time and space in successive video frames provides possibility for video compression. The compression is that visual macro of next frame and last frame with the range of allowable error malpractices only uses a macro block of last frame and motion vector of current frame to represent, thus we reduce waste space to re-storage similar macro block [9]. In video tracking process, we can use motion vectors to express motion information of tracking object in the video. The motion information can bring contribution to our tracking [10, 11, 12].

This paper adds speed information which was not used in the past, and when speed information is put into the state transition matrix as a factor, and it can describe motion objects more accurately. The method is able to predict relative position of dynamic objects, and provides a reliable guarantee for accurate tracking moving object. There are more advantages than before, such as reducing blind time of searching and reducing complexity accordingly.

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II. PROPOSED SCHEME

A. Improved Filter Design

A classic example of Kalman Filter is that it can predict coordinates and direction of objects from a limited observation sequence of objects' location including noise (possibly have deviation)[5].And measured information of motion objects often has noise at all times. Kalman Filter uses dynamic information of the object, tries to remove the noise, and gets a good estimate about objects' location. This estimate may be the filter of current objects' position, possibly the estimate of the prediction, and possibly it can be estimated of the past (interpolation or smoothing).

Kalman Filter is used to estimate state variables in discrete-time process $x \in R^n$. This process of discrete-time is described by following differential equation of discrete stochastic:

$$x_k = Ax_{k-1} + Bu_{k-1} + w_{k-1}, \tag{1}$$

Defined observation variables $z \in R^n$, get measurement equation:

$$z_k = Hx_k + v_k. \tag{2}$$

Random signals w_k and v_k denote the process noise and observation noise. Assume them as white noise of independent and normally distribute:

$$p(w) \sim N(0, Q) \tag{3}$$

$$p(v) \sim N(0, R) \tag{4}$$

In actual system, process noise covariance Q and observation noise covariance matrix R may change with each iterative calculation, but here we assume that they are constant.

When control function of u_{k-1} or process noise w_{k-1} is zero, gain matrix A of n*n in differential (1) will be linear map state of time k-1 to state of current time k. In practice the A may change over time, but it is assumed constant. Matrix B of n*l denote optional control input's gain of $u \in R^l$. Matrix H of m*n in the measurement (2) said state variable x_k gain to measured variables z_k . In practice the H may change over time, but it is assumed constant.

Particle filter usually defines two models, one is model of system state, the other is model of observation, and assume that model is consistent with process of first-order Markov. We can get probability of state transition from model of system state. We can get posterior probability of prediction under the given information from model of observation. The implementation of particle filters is four steps:

1. Sampling stage of initialize particle; sampling the importance in accordance with density distribution P (x_0) of initial probability of objectives.

2. Predicting stage of particle state; p (x | x-1) usually made model based on mechanics of object, if it is case of non-linear and non-Gaussian, then use random process of meeting certain random distribution to predict, and you can also get model of next step by tracking state through model of second-order autoregressive.

3. Evaluating stage of particle weight; it plays a key role of object tracking, the size of weights shows that whether different particles are close to status characteristics of tracking objects. The objects' features of selection include color-based, profile, model, region, etc., through an effective sample size:

$$N = \frac{1}{\sum_{i=1}^{n} \omega_i} \tag{5}$$

Then set T_h is a degradation threshold, if T_h <N, shows a serious degradation of particle and needs to re-sampling particle. In this process, it is possible to discard particle whose weight is small but it has valuable in tracking process.

4. Re-sampling stage of particle; it is a solution for particles whose weight become smaller and smaller under a real-time processing, usually discards particles of smaller weight relatively, and retains particles of larger weight, and decomposes those particles with large weight relatively.

In sampling process, the goal is to find particles with larger weight that is to find the most similar tracking box with the previous.

Now method of correlation tracking is more focused on using Particle Filter and Kalman Filter, Kalman's assumptions are more than Particle Filter, so Particle Filter is more extensive use. But recent studies, Kalman Filter using in tracking would be a better classical algorithm. A lot of people's study will be extended to three-dimensional image. Images are captured by two cameras simultaneously. Although information of objects we get have increased, increase computational complexity in the process.

The main problem of Particle Filter is which need a large number of samples to get a good approximation density of posterior probability in system. The more complex of environment, the more number of samples required by posterior probability distribution, the more complexity of algorithm. Therefore, the focus of algorithm is to effectively reduce number of samples through sampling strategy. In addition, stage of re-sampling will cause loss of effectiveness and diversity of sample, and will result necessitous phenomenon in sample. The focus of study is how to maintain effectiveness and diversity of particles to overcome necessitous phenomenon.

B. Fast Object-Tracking Scheme

Usually we just get histogram of tracking box, but after we considered, only calculating tracking box of histogram cannot response detail information of overall object.

MPEG defines three types of image frame in his own stream.

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Frame I is frame of encode whole image, which is the largest amount of data frames, including all images, so that it can achieve entrance frame of random access;

Frame P is obtained from previous frame, previous frame of frame P can be frame I, and also can be frame P, the frame P can be reference frame of next frame too. Since frame P only store error signal of current frame and reference frame, thus frame P has been greatly compressed;

Frame B encode referring its previous frame and next frame, its compression ratio is the largest, which also makes frame B can not be used for reference frames of other frame.

In MPEG standard, image frame of three types is also very flexible organization; specific implementation will depend on provisions' parameters of applicatio. Two important techniques of using by MPEG are motion compensation and spatial redundancy reduction. Motion compensation is obtained frame P or frame B through reference frame. The first step to achieve motion compensation is decomposed whole image into small block of 16×6, and comparing with piece of image with the same location of its reference frame. If two images are same, so ignore, only save the difference. This greatly reduces amount of data to be saved.

Reducing space redundancy with using motion vector is further reducing amount of data by describing difference between small images. By using a known method of Discrete Cosine Transform (DCT), we further divide small block image into matrix of 8×8, and record changing trajectory with time of color and brightness.

1 About the type of motion vector:

In MPEG-2, choice of motion vector is from image blocks of different sizes, there are two types' motion vectors to predicted frame (P-type or B-type): motion vector of frame and motion vector of field.

When image of frame adopt motion vector, each motion vector includes horizontal and vertical directions respectively, the two components are $V_{x16\times16}$ and $V_{y16\times16}$, which corresponds to an image area of 16×16.When used motion vector of field , each macro block corresponds to two motion vectors of field, a motion vector ($V_{x16\ 8top}$,$V_{y16\times8top}$) of field corresponds to the top field of image area of 16×8, and the other motion vector ($V_{x16\times8down}$,$V_{y16\times8down}$) corresponds to the end field of image area of 16×8.

Motion vector ($V_{x16\times8up}$,$V_{y16\times8up}$) of prediction mode in field map of 16×8 corresponds to the top of image field 16×8 within image area, ($V_{x16\times8low}$,$V_{y16\times8low}$) corresponds to the bottom of image area 16×8. Standard of MPEG-2 uses diversity of motion estimation, which makes species diversity of motion vector, so in process of extracting motion vectors, one hand need to determine each macro block's choice of motion vectors in image according type of image (I, P, B), so that motion vector extracted are as possible as closing to previous frame of image displayed based on information of movement. And the other hand need to determine combined approach of each macro based on type of prediction motion vector, scientific combining movement information of each macro block into a motion vector of previous frame display.

2 Initial extractions

Overall, select original motion vector according type of image: frame I do not need other frames' information of reference, directly extract zero value in extracting. For frames P, extract the forward motion vector; for frames B, only use the forward motion information. Here is forecast of MPEG-2 type, it explains initial extraction method in accordance with classification of different types of prediction, and motion vector of initial extraction is expressed as (V_{tmp_x},$Vtmp_y$).

1)In frame prediction mode of frame map, each motion vector corresponds to an image area of 16×16. Previous motion vector ($V_{x16\times16f}$,$V_{y16\times16f}$)extracted from corresponding image area are as initial motion vectors of extraction.

$$Vt_{mp_x}=V_{x16\times16f},\ V_{tmp_y}=V_{y16\times16f} \tag{6}$$

2)In field prediction mode of frame map, target is transformed motion vector into a previous motion vector, so top field predict the top field, bottom field to the bottom field of prediction:

$$V_{tmp_x}=(V_{x16\times8top}+V_{x16\times8down})/2 \tag{7}$$

$$V_{tmp_y}=(V_{y16\times8top}+V_{y16\times8down})/2 \tag{8}$$

In which, top of subscript is top pixels field of 16×8, down is bottom pixels field of 16×8. When top field predicates the top field and bottom field:

$$V_{tmp_x}=(V_{x16\times8top}+V_{x16\times8down})/2 \tag{9}$$

$$V_{tmp_y}=(V_{y16\times8top}+V_{y16\times8down}+1)/2 \tag{10}$$

When bottom field predicates the top field and bottom field:

$$V_{tmp_x}=(V_{x16\times8top}+V_{x16\times8down})/2 \tag{11}$$

$$V_{tmp_y}=(V_{y16\times8top}+V_{y16\times8down}-1)/2 \tag{12}$$

3) Field prediction mode of field mapping; initial extraction method is similar with the first method: only use motion vector of pervious prediction of macro block; original motion vector are motion vectors of initial extraction.

4) In prediction mode of field map in 16×8, for frames P, each macro block corresponds to two motion vectors ($V_{x16\times8up}$,$V_{y16\times8up}$) and ($V_{x16\times8low}$,$V_{y16\times8low}$); For frames B, each macro block corresponds to maximum of four motion vectors, where only obtains pervious motion vectors.

Initial extraction of motion vector in field map of 16×8 prediction mode:

On the horizontal component,

$$V_{tmp_x}=(V_{x16\times8up}+V_{x16\times8low})/2 \tag{13}$$

On the vertical component, if two parts are based on the same reference field,

$$V_{tmp_y}=(V_{y16\times8up}+V_{y16\times8low})/2 \tag{14}$$

If our parts are based on different field, vertical component of directly extracting and referring closer image are as the result of initial extraction.

5) Prediction for double-base: motion vectors of preliminary extraction of P-type field map: the short distance field-based display vector is initial vector

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extracted from macro block in the two groups. The first choices of opposite parity field are based on the *[vector] [r] [0] [0:1]*:

$$V_{tmp_x} = [vector]\ [r]\ [0]\ [0] \quad (15)$$

$$V_{tmp_y} = [vector]\ [r]\ [0]\ [1] \quad (16)$$

For the second choice based on the same parity field get motion vector *[vector] [0] [0] [0:1]*:

$$V_{tmp_x} = [vector]\ [0]\ [0]\ [0] \quad (17)$$

$$V_{tmp_y} = [vector]\ [0]\ [0]\ [1] \quad (18)$$

Particle filters represent posterior probability distribution of random variable using some random samples or particles of system, and create particle filter in turn. The mathematical model of posterior probability of Bayesian with tracking is:

$$p(x_{0:t} \mid y_{1:t}) = p(x_{0:t-1} \mid y_{1:t-1}) \frac{\int_{x_t} p(y_t \mid x_t) p(x_t \mid x_{t-1}) d x_t}{p(y_t \mid y_{1:t-1})} \quad (19)$$

In which, X is state vector of state model in the system; Y is observation vector in the observation model. In order to simplify tracking, we usually only study the following recursive and iterative model of Bayesian:

$$p(x_t \mid y_{1:t}) = \propto p(y_t \mid x_t) \int_{x_{t-1}} p(x_t \mid x_{t-1}) p(x_{t-1} \mid y_{1:t-1}) dx_{t-1} \quad (20)$$

Formula of Bayesian is that we calculated posterior probability of system state through all known information, including two states of prediction and update, and assume that tracking state of object meet process of first-order Markov.

C. Motion-vector-located Pattern Match

This article is to study the tracking problem of moving object (player) in the movement. Methods of feature selection based color improve robustness of tracking. We use similar model of HSV color values. In the actual feature extraction, the color mode h0 of reference moving object is changing. According to the changed model of reference color, and further tracking and referring to difference of color model, and then calculating likelihood.

We set I_t is the image at time t, tracking rectangular box is R_t, h ( ) is a normalized function of color histogram. D is correlation coefficient matrix, in which h (R_0) obtained through the start frame of training. The following is observation equation of likelihood:

$$p(y_t \mid x_t) \propto e^{-\lambda D^2 [h(R_0), h(R_t)]} \quad (21)$$

This is a particles' function of importance.

Next, we establish color model for moving object. Let h (R_0) is normalized color for the first frame of feature extraction, and so on h (R_1) , h (R_2) , h (R_3), etc. Then let Δs is absolute difference of histogram from rectangle box of tracking in different background, $\Delta s_1 = |h(R_0) - h(R_1)|$,in which

$$\Delta S = \Delta S_2 \cap \Delta S_2 \cap \ldots \cap \Delta S_{n-1} \cap \Delta S_n \quad (22)$$

We set color object model with motion is m, set current background model of changing is b, function of learning and extraction is L ();L(h(R_1)) said that we keep learning and extracting moving object of tracking box and current background model from track rectangle of second frame. L_m (h (R_1)) is color model of moving object. Now, what we want to compare becomes the following equation,

$$p(y_t \mid x_t) \propto e^{-\lambda D^2 [l_m(h(R_{0:t-1})), l_m(h(R_t))]} \quad (23)$$

This comparison can increase tracking accuracy of moving object.

The model of state transition used in this paper is model of first-order autoregressive:

$$X_t = AX_t + B_0 w \quad (24)$$

After getting actual observations value of z, in order to obtain posterior probability of state, we need to establish observation equations, and to find observations probability of z. Set H is matrix of observation, V is matrix of measurement noise, then equation of measurement is:

$$y_t = H \cdot x_{t-1} + V \quad (25)$$

Here x and y are coordinates of location, s is factor of scaling, t is constant of time. Matrix is designed as follows:

$$X^T = \begin{bmatrix} x \\ v_x \\ y \\ v_y \\ s \\ v_s \\ d \end{bmatrix}, \quad A = \begin{bmatrix} 1,t,0,0,0,0,0 \\ 0,1,0,0,0,0,0 \\ 0,0,1,t,0,0,0 \\ 0,0,0,1,0,0,0 \\ 0,0,0,0,1,t,0 \\ 0,0,0,0,0,1,0 \\ 0,0,0,0,0,0,1 \end{bmatrix},$$

$$H^T = \begin{bmatrix} 1,0,0,0,0,0,0 \\ 0,0,1,0,0,0,0 \\ 0,0,0,0,1,0,0 \end{bmatrix} \quad (26)$$

Get coordinates of location, need to analyze characteristics of tracking box. Block the track box, extract an even number of features (such as 8, 16, 24, etc.), calculate each block. Use average value to represent the block.

$$M_1 = mean(block_1) \quad (27)$$

That is obtained the following matrix: $K = R^{4\times4}$ or $K = R^{6\times4}$, in which, $R \in [0, 255]$. The matrix is:

$$K = \begin{bmatrix} M_1 & M_2 & M_3 & M_4 \\ M_5 & M_6 & M_7 & M_8 \\ M_9 & M_{10} & M_{11} & M_{12} \\ M_{13} & M_{14} & M_{15} & M_{16} \end{bmatrix} \quad (28)$$

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We make current coordinates of particle corresponding to coordinates of original background stored, and take the same tracking box.

$$K' = \begin{bmatrix} M_1' & M_2' & M_3' & M_4' \\ M_5' & M_6' & M_7' & M_8' \\ M_9' & M_{10}' & M_{11}' & M_{12}' \\ M_{13}' & M_{14}' & M_{15}' & M_{16}' \end{bmatrix} \quad (29)$$

Then compare similar between A and A' :

$$a \in K, a' \in K', if \mid a - a' \mid > d, a = a : M = M,$$
$$else \mid a - a' \mid = d, a = 0 : M = 0.$$

We get new matrix of tracking B. Then, use B to compare with tracking box of the greatest weight for similarity. That is, computing

$$same(B, B') = l. \quad (30)$$

When $| l | < 5, | d | < 7$, the experiment results are better.

Problem of covering is a very difficult problem for tracking field, there are many scientific articles to study and resolve this situation [12]. However, the effect is general. We think when object is moving at a certain time, from common sense, possibility of sudden changing direction is usually not great. And sudden changing speed is not justified in terms of common sense. So, in this paper, we introduce the key factors of speed to remove the main impact of block, which is an innovation of the article.

In order to get credibility of particles, we analyze moving objects during process of particle filter tracking. Firstly, we analyze tracking of single object. We find that through observation, when athletes move accelerating, the probability toward a fixed direction will be increased. When athletes suddenly slow down, it is likely to change the direction of movement. Through the conclusions, we establish velocity equation for moving object of tracking

$$V = F(x) \quad (31)$$

The equation of location and zoom level of object points with motion

$$Z = f(x, y, s) \quad (32)$$

In which, (x, y) is location of tracking object, s is zoom level of tracking object's size, Z is the current speed.

$$\frac{\partial f}{\partial l} = \ell im_{\rho -> 0} \frac{f(x + \Delta x, y + \Delta y, s + \Delta s) - f(x, y, s)}{\sqrt{(\Delta x)^2 + (\Delta y)^2 + (\Delta s)^2}} \quad (33)$$

The above equation is changing rate of velocity which tracking points of moving object are along with L direction, if value of $\frac{\partial f}{\partial l}$ are incremental changing from the minimum point to the maximum points in the curve of movement, that is accelerating movement. At this time, we add a MIF to ensure advantages of weight of original particles, so tracking object move towards original direction. This increases accuracy of tracking, which re-evaluating interference particles of heavily weighted increases accuracy of particles' state, and increases stability and anti-jamming capability of particle.

III. EXPERIMETAL RESULTS

The hardware and software of experimental platforms is P4 2.4G, 128M memory, Kodak digital camera.

In the first scenario, we observe numbers of motion vector in different MPEG2 frames, then determine using some frames to locate the target. Experimental data is shown in table 1.

TABLE 1.

THE SITUATION GETTING MOTION VECTORS IN THE PAPER

	Motion Vector(MV) in I frame	Motion Vector in P frame (8*8blocks)	Motion Vector in B frame (8*8blocks)
Between two I frames	No	96-112 MVs in 15 P frames	predicted
Between I and P frame	No	12-15 MVs in one P frame	predicted
Among P,B and P frame	No	About 20-30 MVs	predicted

The result shows that frame P has more sports vector in variety situations. So we will use the frame P as a locating target.

TABLE 2.

BLOCK OF TRACKING BOX AND LOSS OF PARTICLES

Number of blocks	Number of particles	Loss (missing)
None	10	Yes
24	10	No
30	100	No

In the second scenario, we analyze tracking box of blocking and none blocking. We look tracking block (8*8) pixels as the basic unit of block, table 1 is the experimental results of none blocks, 24 blocks and 30 blocks. Experimental data are shown in table 2.

The conclusion of experiments 2 is that, there are lost tracking in the case of none blocking. And if blocks, there are none lost tracking in the case of 24 blocks and 30 blocks.

We do experiment in the case of none blocks and blocks of 24*24, 16*16, 8*8, the accuracy of particle weight are shown in figure 1.

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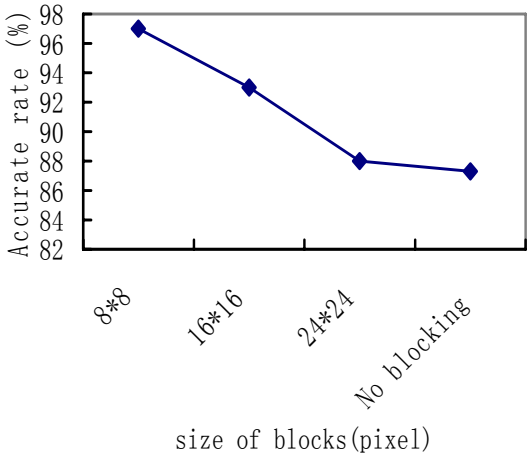


Figure1. Accurate rate of Particle weight after blocking

When none blocks, we can see the accuracy of particle weight is 88.1%. When block is unit pixels of 8*8, the accuracy of particle weight is 96.7%. So the smaller blocks can describe more internal details in tracking box, and can improve the match accuracy of prediction in the tracking box.

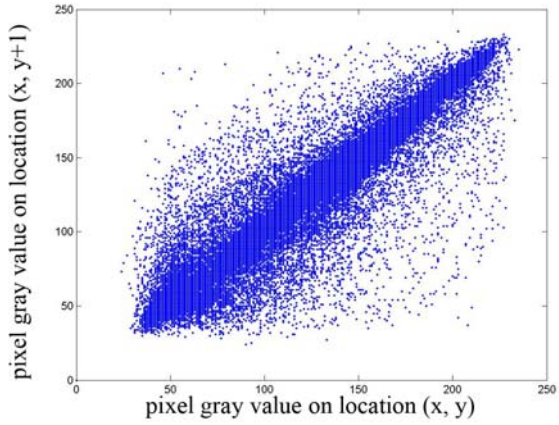


Fig. 2. Correlations in plain image and cipher image.

Figure 2 shows the correlations of two horizontally adjacent pixels in the plain image and the cipher image: the correlation coefficients are 0.9683 and 0.0367. Similar results for diagonal and vertical directions are obtained and shown in Table III. We increase factor of speed on the basis of experiment 3, the results are shown in figure 2. We can see that the accuracy of particle weight is improved after increasing speed factor of velocity. Figure 3 is the final results of this algorithm. We use of motion vectors, speed factor and block in tracking box.

TABLE 3. CORRELATION COEFFICIENTS OF TWO ADJACENT PIXELS IN TWO IMAGES

	Plain image	Cipher image
Horizontal	0.9683	0.0367
Vertical	0.9404	0.0298
Diagonal	0.9130	0.0342

Fig. 3 and Fig. 4 illustrate average annotation precision and average annotation coverage of all the Flickr photos we have downloaded. In this experiment, the final annotations include three top ranked initial tags which located in the first three positions, and the other positions in final annotations are made up of expanding tags.

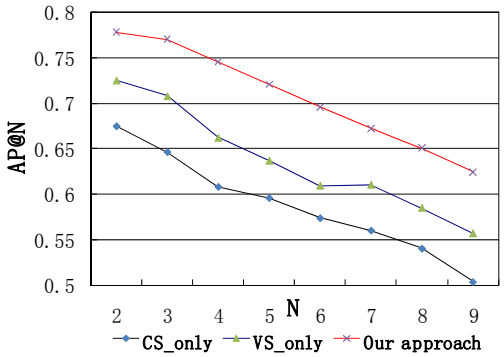


Figure 3. AP@N performance under different settings.

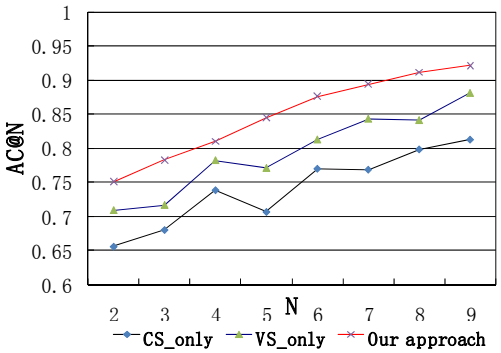


Figure 4. AC@N performance under different settings.

From the experimental results shown in Fig. 3 and Fig. 4, several conclusions can be drawn: 1) Adopting the two-level tag similarity measuring method could enhance the overall annotation performance in both AP@N and AC@N. 2) After tag ranking and expanding process, more relevant annotations are located in top positions.

The UW image set, which contains 1019 images from the University of Washington D.C. was used to conduct the experiments. A number of experiments were conducted on the image set by taking Fig. 14 as the sample. The experiments can be summarized as follows in terms of the feature sets used.

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1) MPEG-2 Homogeneous Texture Descriptor (HTD) only.

2) MPEG-2 Color Layout Descriptor (CLD) only.

3) Combination of two MPEG-2 features and set W_{HTD} and W_{CLD} as 1 in (13) and calculate the distance.

4) Combination of two MPEG-2 features and using the MARS as an optimization method.

5) Combination of two MPEG-2 features and using the PGA as an optimization method.

The retrieval result set by using before-mentioned feature sets shown as Fig. 5 and Fig. 6.



Figure 5. The result by the proposed scheme



Figure 6. The retrieval result by CLD

We can see from the algorithm analysis and experiment, on the one hand, in the process of tracking goal, partition method to goal's box can make the basic particle filters constantly to find more accurate iterative position, namely, the particles of larger weight concentrated in position of tracking box where we expect, and it descript the actual characteristics of tracking target and approach the real target. On the other hand, the goal has speed in the mobile process. We increase factors of speed in the algorithm and prediction of target position is more scientific and accurate in the target tracking process. So we don't have too much influence by background color and get the wrong results of tracking, but also solve the problem of covering object.

The experimental results show that the factors of partition of the target box and speed can greatly reduce probability of wrong and lost, and the smaller partition can bring the greater accuracy of tracking target, but it can lead to speed down, how to balance the contradictions of accuracy and speed is concreting application occasions and it is our next research.

IV. CONCLUSIONS

In order to track object efficiently, this paper proposed and efficient fast object-tracking scheme based on motion-vector-located pattern match, which adopts motion vector of Mpeg2 to mark the moving targets in static video in order to mark and locate the targets automatically and quickly. Then, extract multi-dimensional characteristics from the initial targets taken by motion vector and make the model. Then accurately identifies the particles of larger weight and combines with inertia factor of velocity through matching the original data and the observations of particle filter. The matching of the characteristics of the new particle and the original one is more accurate and faster because of adopting the method of pattern classifying. The experiments show that the algorithm had good tracking performance and strong robustness.

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