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A Highly Efficient Real-Time Tracking Method in Augmented Reality System

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Abstract: *A highly efficient real-time tracking algorithm is very important for augmented reality implementation by computer vision mode. The mean-shift (MS) algorithm is widely used in object tracking for augmented reality system because of its not only speed but also highly efficient and real-time features. The traditional MS algorithm only use color feature as one of the important cues in image sequences. Even though the MS tracking algorithm cannot very suitable for complex environments, such as the background with object's similar color, sudden light changes, occlusion types and so on. The proposed algorithm use a convex kernel function in association with the motion information to improve the MS tracking algorithm for the purpose to solve the above problems. Using these new features fusion, a robust mean-shift tracking algorithm is proposed. Experimental work show the proposed mean-shift algorithm has an optimum performance in robust and real-time object tracking for the augmented reality system.*

Keywords: *Augmented Reality; Virtual Reality; Object Tracking; MS algorithm*;

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I. Introduction

Today pilots are trained in many different types of simulators. Some of these simulators are used to certify pilots, while others are used simply for training. Both types of simulators are used for pilot practice, skill building, and research. Simulator research can evaluate events that pilots typically do not face to improve pilot safety [1].Training facilities display on a computer the primary flight instruments. Traditional pilots training are expensive use physical device with big size shows in Fig.1(a).A small number of flying cockpit with virtual reality shows in Fig.1(b).We put forward the complete solution based on computer vision shows in Fig.1(c).

(a)Physical Device (b)VR Interaction (c)Computer Vision Interaction

Figure.1. Interaction Mode

There are some tracking algorithms suitable for augmented reality system. The first one is a probability approach, under the Bayesian framework. Particle filter, Monte Carlo tracking, Kalman filter and its derivatives are now belonged to this category [2-3]. And the MS tracking algorithm is speed and simply for deal with fast tasks. But one of the well-known tools in color feature extraction is to use mean shift (MS) tracking algorithm. The traditional MS algorithm only use color feature as one of the important cues in image sequences. Although the MS tracking algorithm can not be well applied to complex environments, such as the color of the object in the background, the color of the object is suddenly bright, and the occlusion type is changed. The proposed algorithm use a convex kernel function in association with the motion information to improve the MS tracking algorithm for the purpose to solve the above problems. With these new different features fusion, a robust mean-shift tracking algorithms are derived. The proposed algorithm combined the MS kernel function by using both color feature and motion information, simultaneously, in comparison with single color feature, noises and also mistake areas can be avoided. With these new different features fusion, a robust mean-shift tracking algorithms are derived. Experimental work shows the proposed mean-shift algorithm has an optimum performance in robust and real-time object tracking for the augmented reality system.

II. Mean Shift Algorithm Analysis

2.1 Basic MS algorithm theories

Given a set of n points in the d-dimensional space R^d , as $\{x_i\} i = 1 \cdots n,$ at first. The multivariate kernel density estimate with kernel function $K(x)$, and band width (window radius) h, is shown as：

$$\hat{f}(x) = \frac{1}{nh^d} \sum_{i=1}^{n} k\left(\frac{x - x_i}{h} \right) \tag{1}$$

The Profile of a kernel k ,as a function $k : [0, \infty] \to R$,such that $K(x) = k(\|x\|^2)$ can be defined，
Another used the profile of a kernel function is the multivariate normal kernel, given by,

$$\hat{f}_{h,k}(x) = \frac{1}{nh^d} \sum_{i=1}^{n} k\left(\left\| \frac{x - x_i}{h} \right\|^2 \right) \tag{2}$$

Now, by employing the profile notation, the density of the estimator can be rewritten as：

$$\hat{\nabla} f_{h,k}(x) \equiv \nabla \hat{f}_{h,k}(x) = \frac{2}{nh^{d+2}} \sum_{i=1}^{n} (x - x_i) k' \left(\left\| \frac{x - x_i}{h} \right\|^2 \right) \tag{3}$$

the derivative of the kernel profile $k(x)$ exists for all $[0, \infty)$, except for a finite set of points, then denoting the following function $g(x) = -k'(x)$. A kernel $g(x)$ can be considerable as $G(x) = Cg(\|x\|^2)$ ， in which C is a normalization constant and can be assumed to be a positive number. density estimate at x, calculated with the G

$$\hat{f}_G(x) = \frac{C}{nh^d} \sum_{i=1}^{n} g\left(\left\| \frac{x - x_i}{h} \right\|^2 \right) \tag{4}$$

Now, (2) could be shown using (3) and (4) as

$$\hat{\nabla} f_{h,k}(x) = \hat{f}_{h,G}(x) \frac{2/C}{h^2} M_{h,G}(x) \tag{5}$$

$$M_{h,G}(x) = \frac{\sum_{i=1}^{n} x_i g\left(\left\| \frac{x - x_i}{h} \right\|^2 \right)}{\sum_{i=1}^{n} g\left(\left\| \frac{x - x_i}{h} \right\|^2 \right)} - x \tag{6}$$

In such a case, (6) proves that the MS vector is yielded with the kernel G , as an estimate of the normalized density gradient obtained with kernel k. The MS vector always points in the direction of maximum in the density. This is a more general formulation of the property, which is first remarked by Fukunaga [5].

$$M_{h,G}(x) = \frac{1}{2} h^2 C \frac{\hat{\nabla} f_{h,k}(x)}{\hat{f}_{h,G}(x)} \tag{7}$$

The amount of above is the weight mean-shift vector to computed with kernel G . However, the center of the initial position of the is x . The density estimates, computed with kernel $k(x)$, in the points (7), are $g(x)$ it is needed to prove kernel a theorem in accordance with the results. In this way, if the kernel K has convex and monotonically decreasing profile, the sequences $m_{h,G}(x)$ and $G(x)$ converge is monotonically increasing. So Mean shift vector is always pointing in the direction of maximum to the density increases. Repeat the following two steps: the commonly described Mean-shift process, (1) calculating the mean shift vector; (2) using an improved kernel. This is a single connection, which is a “local average” for most mobile areas. The average shift vector is parallel to the local gradient estimation, and it refers to the “point” to estimate the density.

The relationship is also very straightforward, "local average" towards most moving area. Mean shift vector and parallel to the local gradient estimation, it refers to the "point" to estimate the density, density of model is the "point".
Here x is the value of the unit n dimensional Euclidean space [4], finite aggregate $S \subset X$, Define the characteristic function

$$K(x)=\begin{cases}1, & \|x\| \le \lambda \\ 0, & \|x\| > \lambda\end{cases} \tag{8}$$

And then

$$m(x)=\frac{\sum_{s\in S} K(s-x)s}{\sum_{s\in S} K(s-x)}, x \in X \tag{9}$$

For collection S sampling average at x. $\forall s \in S$ until the convergence of iterative calculation $s \leftarrow m(s)$, this method is called the Mean shift algorithm.

1.2 Tracking by original MS algorithm

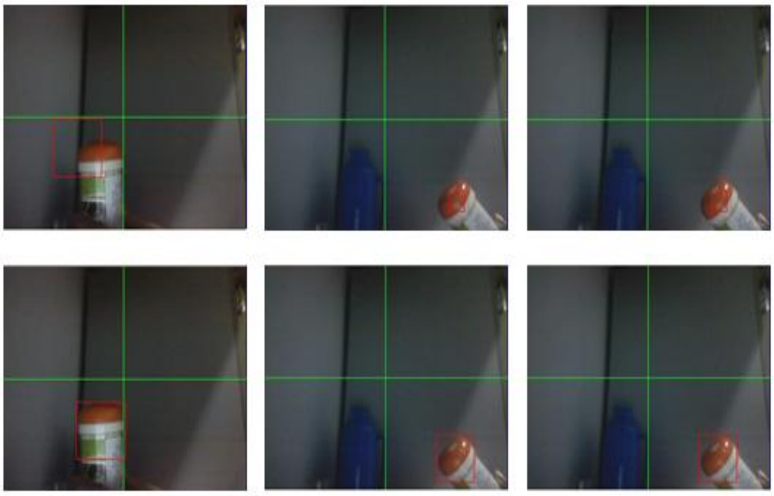

Figure.2. MS algorithm tracking result

Row1 utilize parameter bandpass image(k=[1，2]) and Row2 utilize parameter bandpass image (k=[2，4]).The poor of original MS tracking by single color feature is obviously, it cannot suitable for complex environment, such as sudden light change. Therefore, in the next section we propose a improved MS tracking algorithm use motion information to resist the disadvantages use single color feature.

III. The Proposed MS Tracking Algorithm

3.1 A convex kernel function histogram model

The desired object in the MS tracking algorithm is firstly chosen by n operator for M class Gray scale, in order to show it, as a rectangle. The inside pixels' locations of the rectangles are here presented as $\{x_i\} i=1\cdots n,$. The selected area is considered as the object model [6-7], where its color histogram could be calculated by

$$s=\phi\sum_{i=1}^{n} k\left(\left\|\frac{y-x_i}{h}\right\|^2\right)\delta[T(x_i)-t], t=1,\cdots,m \tag{10}$$

In this case, $T(x_i)$ is at the position of the X pixel and the normalized color associated number $(1,\cdots,m)$. Here, ϕ is a normalization constant that gives [8]. Because s as the histogram component value t is the number m of components $(m<M)$ of the pixel quantitative value x_i, as the width of the kernel k function window, the image coordinates are normalized by restricting the weighted histogram of kernel function, so that the core radius is 1. In fact, a color distribution indicates that the weight is determined by the kernel function k, which

is closer to the core value .

Therefore, by assuming $\sum_{t=1}^{m} s = 1$; $\{s\} t = 1 \cdots m$, the maximum likeness between both the object and the candidate models could be acquired.

Bhattacharyya coefficient：

$$\hat{\rho}(y) = \rho[\hat{p}(\hat{y}, s)] = \sum_{u=1}^{m} \sqrt{\hat{p}_u(\hat{y}), s_u} \tag{11}$$

3.2 Using the motion information

However, it should be pointed out that a single feature may not introduce the desired object. In the color based MS tracking algorithm, color features are easily extracted and include some color, like background areas, which will disperse tracking. After that, this is considered a color model of the background. In order to achieve a suitable mask, the difference between the rectangles around the object in the first frame and the rectangle is also surrounded by the object in the next frame. The process is now shown as

$$Locate_n(x_i) = \begin{cases} 1 & x_i \in f \\ 0 & x_i \in b \end{cases} \tag{12}$$

The parameters f and b represent the foreground and the background. It is used on the whole image by increasing the function. Therefore, the whole hole filling and the resulting mask will be ready for the kernel of the MS tracking algorithm. In order to use the obtained binary mask in the MS tracking algorithm, it must be multiplied by an improved kernel function. A new kernel is obtained, which is regarded as the weight of the probability of the object existence. Therefore, only the luminance region is checked when the object model and the candidate model are calculated. Therefore, in this study, it is more important to obtain the binary mask in the case of motion information extraction, and combine the results with (10). In this process, (11) - (12) is fully implemented, and the increase of the kernel power used in the target model and candidate model will be loaded.

3.3 The flow step of proposed algorithm

The color based MS tracking algorithm is easy to extract using a single color feature, while the background is similar to the object and distracts. The change of light was less than that of light. However, the feature of motion is the obvious feature of tracking the object. In the MS tracking, proposed algorithm combination color feature with motion feature in the MS tracking. By using $Locate_n$ as the binary mask, the new kernel function for object model is just given as

$$Locate_n(\|x_i^*\|^2) = Locate(\|x_i^*\|^2) \times Locate_n(x_i) \tag{13}$$

The algorithm as the following steps: (1) calculate coefficient represent color model initialization; (2) maximum Bhattacharyya coefficient between both objects and corresponding candidate models;(3) a convex kernel function in association with the motion information is used in MS tracking algorithm.

IV. Result and Discussion

There show tracking results of poor illumination sequence are illustrated in Fig. 3. The first row shows the phenomenon of the traditional mean shift tracker. The fact that the background's color is approximate to that of the color object, which tracking results is worst. In the second row, utilize the SIFT features correctly of the color object. Thus, the proposed mean shift tracker can be achieved better features for probability distribution computation. At last, the third row show that the proposed tracker has good performance than the classical mean shift.

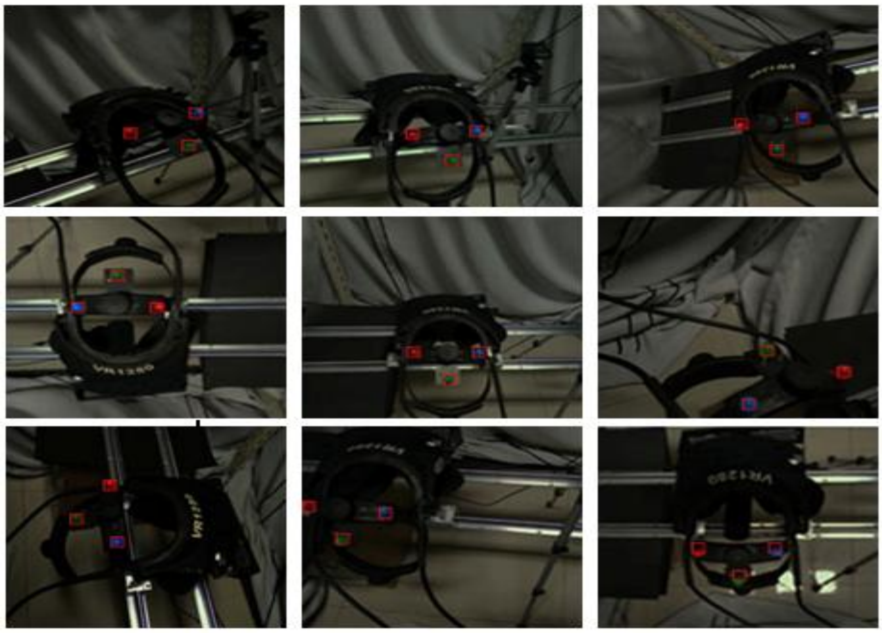

Figure. 3. Example 1: tracking results comparison of the classical mean shift (first row), SIFT feature correspondence method (row 2) and proposed tracking method (row 3).

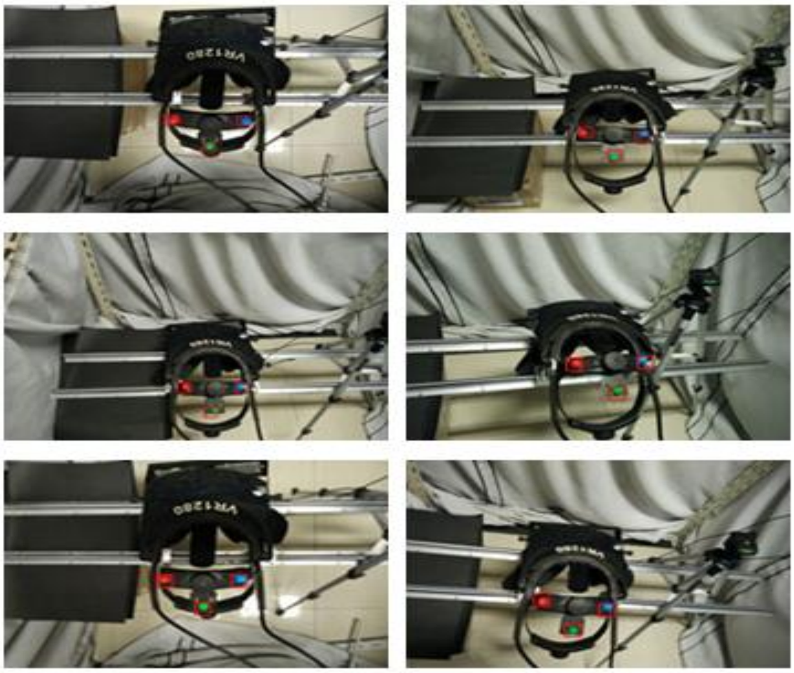

Figure. 4. Example 2: tracking results comparison of the classical mean shift (first row), SIFT feature correspondence method (row 2) and proposed tracking method (row 3).

Fig. 4 shows some tracking results of performance comparison of traditional approaches and modified methods in normal illumination sequence. It is difficulty to achieved the better results by the reflect light situation of the color object. In this particular example, this reflect light situation rapidly changed of the color object move during the tracking. This led to fast blanking of the feature points. Thereby, the traditional tracking results of mean shift, shown on rows1 and the method utilize sift tracking results shown on rows 2. At last, the proposed SIFT-mean shift algorithm allowed the subject to be better tracked results shown on row 3.

Fig. 5 shows three tracking results that cut out in video frames interval be 20 frames. The results show that the traditional method tracking results is achieved small offset error. The method utilizes SIFT method fails to maintain the tracking window, tracking size is being arbitrary scale to detect the object. At last, the proposed

SIFT-mean shift algorithm allowed the subject to be better tracked results shown on row 3. Comparably, the proposed MS algorithm can be achieved the object accurately and tracking results remain stable throughout.

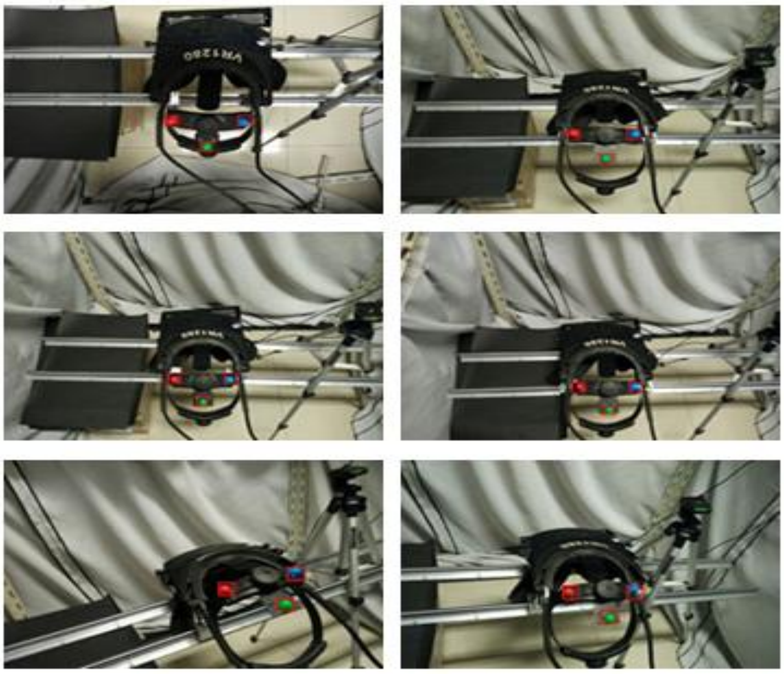

Figure. 5. Performance comparison of classical mean shift (first row), utilize SIFT feature method (row 2) and the proposed tracking method (row 3).

Table.1 show the ability of the proposed MS tracking algorithm is better than the traditional MS tracking algorithm is poor in the complex environment.

Table. 1 Comparison the tracking results of various methods

Exampless	Frames	Standard ms method	Sift feature method	The proposed method
Sequence 1	50	89.125	91.241	93.567
Sequence 2	25	87.457	90.124	97.524
Sequence 3	50	82.2351	86.254	96.241
Sequence 4	25	79.358	78.698	95.214

V. conclusion

In this paper, we have presented a real-time tracking method based on MS algorithm with a histogram equalization model combination motion feature. In the proposed method, the probability of finding the object location in line with this tracking algorithm of image features represents the object appearance. Furthermore, the location of target was transformed from the enlarged image to the original. In addition, the Bhattacharyya coefficients between the two objects and the corresponding candidate models are maximized. We use the convex kernel function related to the motion information. It can reduce the traditional MS algorithm and dealing with complex environment, there is not enough advantage in terms of background color, sudden change of light and occlusion type. The proposed MS tracking algorithm is more suitable for multi-target tracking for augmented reality system.

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