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Real Time Object Tracking using Different Mean Shift Techniques–a Review

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Abstract— The many different mean shift techniques for object tracking in real time are discussed in this paper. The mean shift is a non-parametric feature space analysis technique. It is a method for finding local maxima of a density function from given discrete data samples.There are several approaches that use the mean shift techniques for locating target objects. These techniques are taken from the literature dating back to the earliest methods. It is shown that at least 07 distinct methods have been introduced in the literature, with many variations on implementation. This paper should serve as a convenient reference for future work in real time object tracking.

Index Terms— Mean shift, CAMshift, ABCshift, Path assigned mean shift , SOAMST and Fuzzy clustering mean shift

I. INTRODUCTION

Object tracking refers to method to track an object (or multiple objects) over a sequence of images. Tracking of visual objects can be done either by forward-tracking or by back-tracking. Mean shift analysis is a possible forward-tracking technique because it estimates the positions of the regions in the current frame from the previous frame. Mean-shift tracking is a technique for following an object of interest as it moves through a video sequence. It is a gradient ascent approach that models the image region to be tracked by its color histogram. The mean shift is a non-parametric feature space analysis technique. The mean shift is a method for finding local maxima of a density function from given discrete data samples.It works with a search window that is positioned over a section of the distribution. The mean shift technique is an application independent tool .It is suitable for real data analysis because it does not assume any prior shape (e.g. elliptical) on data clusters. Therefore, there are numerous approaches employing the mean shift algorithm in object tracking. A large number of papers exist on mean shift tracking techniques. This paper provides a single reference of the great majority of papers and techniques presented on mean shift technique. We compiled over 10 years' papers pertaining to different Mean shift methods published up to the date of submission of this manuscript. Papers referencing mean shift methods from previous papers without any modification or improvement have been omitted. It is possible that one or more papers were unintentionally omitted. We apologize if an important method or improvement was left out. This manuscript steps through a wide variety of methods with a brief discussion and categorization of each. We have avoided discussing slight modifications of existing methods as distinct methods.

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1.1 Related Work

There are numerous methods employing the mean shift algorithm on object tracking. Cominiciu et al [1] proposed tracking of non-rigid objects from a moving camera using Mean Shift method. Further, a general nonparametric technique was proposed for the analysis of a complex multimodal feature space and to delineate arbitrarily shaped clusters in it. The basic computational module of the technique is the mean shift [2]. Histogram-based target representation was improved by spatially masking the object to be tracked (spatially smoothness achieved in similarity function) with an isotropic kernel [3]. Bradski [4] proposed an improved version of Mean Shift, CAMShift (Continously Adaptive Mean Shift) Method. In this method the mean shift algorithm is modified to deal with dynamically changing color probability distributions derived from video frame sequences. Allan et al [5] extended the method of Bradski [4] by a default implementation to allow tracking in an arbitrary number and type of feature spaces. Stolkin et al [6] described a new color based tracking algorithm, ABCshift (the Adaptive Background CAMSHIFT) tracker. Pooransingh et al [7] proposed a new method for color image segmentation derived from the mean shift theorem. When applied to color image segmentation tasks, the path assigned mean shift algorithm performed faster than existing fast mean shift methods. Ming-Yi Ju [8] proposed a fuzzy color histogram generated by a self-constructing fuzzy cluster to reduce the interference from lighting changes for the mean shift tracking algorithm. The number of color bins generated by the proposed fuzzy cluster varies according to the target image. J. Ning [9] proposed scale and orientation adaptive mean shift tracking (SOAMST) algorithm to enable estimation of the scale and orientation changes of the target under the mean shift tracking framework.

Previous surveys and the number of conferences, and research papers on object tracking show that it is a highly researched area. Fig. 1 shows the frequency of publications in the area of object tracking published between 2002 and 2011.

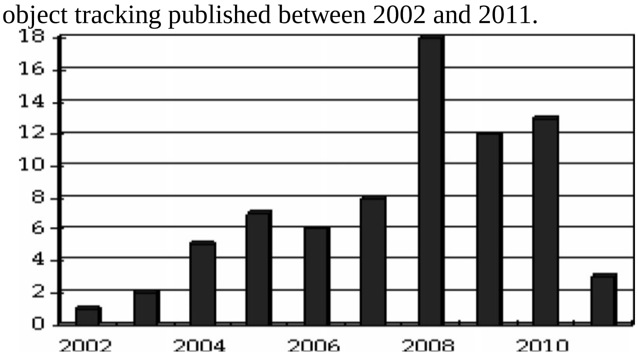

Figure 1: Frequency of publications in the area of object tracking between 2002 and 2011 as reviewed in this review. Note the rising trend in research interest in the area

The rest of the paper is organized as follows: Section 2 describes various approaches of mean shift for object tracking. In Section 3 the results and discussion finally, conclusions are summarized.

II. VARIOUS MEAN SHIFT TECHNIQUES

2.1 CAMshift [4-5]

It is Continuously Adaptive Mean Shift Tracking. It is based on an adaptation of Mean Shift that, given a probability density image, finds the mean (mode) of the distribution by iterating in the direction of maximum increase in probability density.Unlike Mean Shift that uses Static Distributions, it uses continuously adaptive probability distributions (that is, distributions that may be recomputed for each frame). It is one of the simplest methods and supplies reliable and robust results, if the colors in the background differ significantly from those in the target object.

1. Set the region of interest (ROI) of the probability distribution image to the entire image.
2. Select an initial location of the Mean Shift search window. The selected location is the target distribution to be tracked.
3. Calculate a color probability distribution of the region centered at the Mean Shift search window.
4. Iterate Mean Shift algorithm to find the centroid of the probability image. Store the zeroth moment (distribution area) and centroid location.
5. For the following frame, center the search window at the mean location found in Step 4 and set the window size to a function of the zeroth moment. Go to Step 3.

2.2 ABCshift [6]

It is acronym for Adaptive Background CAMshift Tracking. CAMSHIFT was designed for close range tracking from a stationary camera and failed when color of tracked object resembled its background. ABCshift achieves robustness against camera motion and other scene changes by continuously relearning its background model at every frame. It tracks efficiently even when the object shares common color with the background. Therefore, it enables robustness in difficult scenes where the tracked object moves past backgrounds with which it shares significant colors.

1. Identify an object region in the first image and train the object model, P(C|O).
2. Center the search window on the estimated object centroid and resize it to have an area r times greater than the estimated object size.
3. Learn the color distribution, P(C), by building a histogram of the colors of all pixels within the search window.
4. Use Bayes' law, equation (1), to assign object probabilities, P(O|C), to every pixel in the search window, creating a 2D distribution of object location.
5. Estimate the new object position as the centroid of this distribution and estimate the new object size (in pixels) as the sum of all pixel probabilities within the search window.
6. Repeat steps 2-6 until the object position estimate converges.
7. Return to step 2 for the next image frame .

2.3 PAMshift [7]

It is short for Path Assigned Mean shift tracking. It is a fast tracking method. In PAMS assignment, all points along the path towards the mode point are assigned to that final mode value. Points already assigned modes are eliminated from the mean shift process and are not traversed in the future. Since large swathes of feature space vectors are now assigned in one iteration step, the complete mean shift process converges much faster.

1. Select a point site (p, q) at random in the image.
2. Extract the colour values vector of the pixel at that point $I_{U,V}(p,q)$.
3. Find the j neighbourhood vector, $I_{(U,V)j}(t)$, within the colour bandwidth, hc.
4. Compute the Center of Mass, CoM_c in the colour domain.
5. Translate by the mean shift vector, $m_c(U, V)$.
6. Repeat 3 and 5 till convergence to stationary mode vector,$I(_{Um,Vm})$. Assign the final mode vector,$I_{(Um,Vm)}$, to the entire mean shift path, $U^{t=i}_{t=0} I_{(U,V)j}(t)$, where i is the number of iterations to convergence.

2.4 Fuzzy Clustering Mean Shift [8]

Color information has been extensively used for characterizing an object in the application of computer vision. However the conventional approaches use fixed number of color bins to quantize the RGB color space for generating the color histogram as the tracked features. Such approaches may result in unfeasible classification and are sensitive to noisy interference such as lighting changes and quantization errors. In order to properly classify the color information, a sequential version of self-constructing fuzzy cluster is generated from the training data set, i.e. the target image, based on similarity tests. During the training phase, one data pattern is considered in each time. The similarity between the input pattern and the existing fuzzy clusters is calculated to decide whether to combine the considered pattern into the most similar existing cluster or to create a new cluster for the pattern. Once a new cluster is created, the corresponding membership function should be initialized. On the contrary, when the considered pattern is combined into the most similar existing cluster, the corresponding membership function of that cluster should be updated according to the statistical mean and deviation of the data points included in the cluster. After all the training patters are considered as above, we finally obtain a set of fuzzy clusters and corresponding membership functions.

2.5 SOAMST [9]

It is a scale and orientation adaptive mean shift tracking. SOAMST algorithm employs the weight image derived from the target model and the target candidate model in the target candidate region to estimate the target scale and orientation. Such a weight image can be regarded as the density distribution function of the object in the target candidate region, and the weight value of each pixel represents the possibility that it belongs to the target. Using this density distribution function, we can compute the moment features and then estimate effectively the width, height and orientation of the object based on the zeroth-order moment,

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The second-order center moment and the Bhattacharyya coefficient between target model and target candidate model.

1. Initialisation: Calculate the target model $\hat{q}$ and initialise the position y_0 of the target candidate model in the previous frame.
2. Initialise the iteration number k $\leftarrow$0.
3. Calculate the target candidate model $\hat{p}(y_0)$ in the current frame.
4. Calculate the weight vector $\{w\}_{i=1\ldots n}$.
5. Calculate the new position y_1 of the candidate target model.
6. Let $d \leftarrow \| y_1 - y_0 \|$, $y_0 \leftarrow y_1$. Set the error threshold ε (default 0.1) and the maximum iteration number N (default 15)

a. If ($d< \varepsilon$ or $k\geq N$) Stop and go to step 7

b. Otherwise $k\leftarrow k+1$ and go to step 3

7. Estimate the width, height and orientation of the candidate target model using covariance matrix.
8. Estimate the initial target model for the next frame.

III. RESULT AND DISCUSSION

In this section, the results of applying the mean shift methods on various test sequences are shown.

Figure 2 shows the result of CAMShift method on a test sequence of an orange ball. In this example, the color of the object being tracked, that is orange ball, has similarity with its background. In such case, the CAMShift algorithm fails to track the object, rather it keeps on adapting its window to include the background. It works well only when the object significantly differs from its background in color. Similar situation is shown in Figure 3, where the tracking window saturates itself to background and tracking fails. Figure 4 shows the result of applying ABCShift method where the object color is similar to its background. As shown this method tracks the object well. Thus, the shortcoming of CAMShift is overcome by ABCShift method.

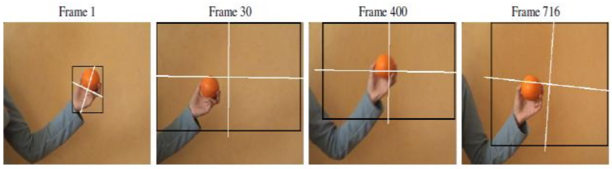

Figure 2. CAMshift at frame1,frame 30,frame 400,frame 716 [10]

Figure 3. Person tracking with CAMshift from a moving camera in outdoors environment [6]

Figure 4.ABCshift successfully tracks throughout the sequence and is not disturbed by red regions of background [6]

The result of fast mean shift method PAMS is shown in Figure 5. It improves the complexity inherent in traditional mean shift method. It is efficiently applied to color segmentation problems as shown. It performs 1.5 to 5 times faster than other existing fast methods when applied to segmentation tasks.

Figure 6 shows the result of Fuzzy Mean Shift method. As mean shift method suffers from quantization error, it is unable to efficiently track the object. This shortcoming is overcome by Fuzzy Mean shift Method as clear from the example shown. In addition to this, this also reduces the complexity associated with the mean shift method.

Figure5(a) Original (b) PAMS (c)Mean shift Image [7]

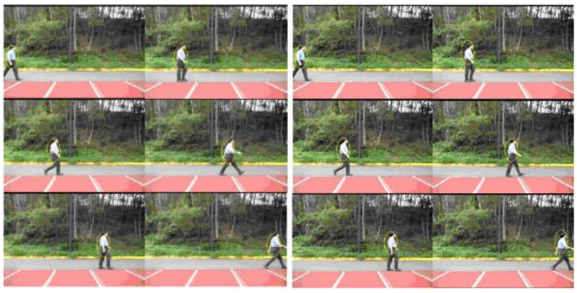

Figure 6 [8](a) Mean shift (b)Fuzzy clustering mean shift

a

b

Figure 7: (a) Traditional Mean Shift Method; (b) SOAMS Method [9]

Figure 7 shows the result of Scale and Orientation adaptive mean shift method for tracking hand of a person, which undergoes changes in orientation and scale both. As clear from Figure 7(a) traditional mean shift method is unable to adapt to changes in orientation and scale and thus fails to track the object efficiently. This has been improved by SOAMS technique that tracks scale and orientation changes of the object, as is clear from Figure 7(b).

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IV. RESEARCH PAPERS' REVIEW

Table 1 summarises the works of mean shift object tracking techniques. It identifies the advantages and shortcomings of a particular method, along with the improvements proposed for each of those methods. Any improvements, if possible in future, are also summarised in the table.

Table 1:Pros, Cons and Improvements

Paper	Pros and Cons	Improvements Proposed/ Possible
1.Real-time Tracking of Non-rigid Objects using Mean Shift *By: Dorin Comaniciu, Peter Meer*[1]	1.Superior Tracking Performance with low computational Complexity 2.Direct projection into new frame produces large bias in estimated location, i.e., target scale variant	Further improvement proposed in [2] and [3]
2.Mean Shift: A Robust Approach towards Feature Space Analysis *By: Dorin Comaniciu, Peter Meer*[2]	1. The presence of a significant feature when pooled together provides an excellent tolerance to noise levels. 2. Features with lesser support in the feature space may not be detected in spite of being salient for the task to be executed.	The disadvantage of missing a salient feature can be largely avoided by either augmenting the feature space with additional (spatial) parameters from the input domain, or by robust post/pre processing of the input domain guided by the results of the feature space analysis. These improvements have been proposed by Comaniciu in [3] and by many other authors.
3.Kernel Based Object Tracking *By: Dorin Comaniciu, Peter Meer*[3]	1. Coped well with camera motion, partial occlusions, clutter and target scale variations 2. Sophisticated motion filter required , if occlusions present	The traditional mean shift process is limited by the fixed kernel bandwidth. It was overcome by CAMshift [4]
4.Computer Vision Face Tracking For Use in a Perceptual User Interface *By: Bradski*[4]	1. CAMSHIFT handles noise well without the need for extra filtering or adaptive smoothing. 2. Since CAMSHIFT relies on color distributions alone, errors in color (colored lighting, dim illumination, too much illumination) will cause errors in tracking	This work was extended for multiple quantized feature spaces in [5].
5.Object Tracking Using Camshift Algorithm And Multiple Quantized Feature Spaces *By:John G. Allen, Richard Y. D. Xu, Jesse S. Jin*[5]	1. CAMSHIFT fails with camera motion, since it relies on a static background model which is unable to adequately represent changing scenery. 2. CAMSHIFT tracker also fails to detect target when target shares color pixels with its background.	These problems were addressed by ABCshift algorithm proposed by [6]. Scale and orientation adaptive tracking has been further improved by Ning et al [9].

6.Efficient Visual Servoing With The ABCshift Tracking Algorithm *By: Rustam Stolkin, Ionut Florescu, Morgan Baron, Colin Harrier and Boris Kocherov*[6]	Robustness against camera motion and similar color pixels of object and background	Future work concentrates in both developing further the algorithm as well as modifying the platform and the mechanical issues involved.
7.The Path Assigned Mean Shift Algorithm: A New Fast Mean Shift Implementation For Color Image Segmentation [7]	1. Fast mean-shift method 2. Improper selection of bandwidth and kernel	Future work will focus on the proper selection of bandwidth and kernel to minimize the mislabeling rate.
8. Shift Tracking Using Fuzzy Color Histogram *By: Ming-Yi Ju, Chen-Sen Ouyang, Hao-Shiu Chang* [8]	1. Robust and reliable 2. Less mean shift iterations required than the conventional algorithm for tracking a moving object.	This paper proposed the method only for RGB model. It can be further extended to other color models and texture as well.
9.Scale And Orientation Adaptive Mean Shift Tracking *By: J. Ning, L. Zhang, D. Zhang, C. Wu*[9]	1. Adaptive to object's scale and orientation changes 2. Restricted to only ellipse and rectangular model	Future work will focus on how to detect and use the true shape of the target, instead of an ellipse or a rectangle model, for a more robust tracking.

V.CONCLUSION AND COMMENTS FOR FURTHER RESEARCH

Several Mean shift techniques taken from the literature are discussed and analyzed herein, with their pros and cons. The traditional mean shift process limited by the fixed kernel bandwidth has been improved by the CAMshift algorithm.

Camshift algorithm for object tracking does reasonably well when the object significantly differs in color from its background. ABCshift tracking overcomes the shortcomings of CAMshift tracking. It tracks an object efficiently despite the camera motion and resemblance of object color with the background.

To improve computational complexity of standard mean shift algorithm, fast mean shift methods have been proposed. These include PAMS and Parallel Mean Shift Method. Recent work on object tracking has included texture in the feature space, instead of only color. Fuzzy color clustering for tracking has also been proposed to overcome the effects of quantization inherent in fixed bin histogram. The concluding discussion and table should serve as a useful guide in choosing the right Mean shift method for object tracking.

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