

Adaptive Mean-Shift Kalman Tracking of Laparoscopic Instruments

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Abstract—Laparoscopic surgery becomes increasingly popular due to high benefits to both surgeon and patients. In this paper, we propose the adaptive mean-shift Kalman tracking algorithm based on the mean-shift algorithm and the Kalman filter for tracking a laparoscopic instrument in laparoscopic surgery. An iterative update of the target candidate in the mean-shift process can improve the tracking performance over a typical mean-shift algorithm. In addition, the Kalman filter is employed to enhance the chance of tracking accuracy, especially when the object disappears from the scene. In this study, we tested the tracking performance of our proposed algorithm by using the different situations from simulated videos. Our experimental results show that the proposed algorithm can locate the target object correctly even when the size and the shape of the target have been changed. In the difficult situation when the target is hiding behind an obstacle, this algorithm can still track the target object correctly after it becomes apparent. Therefore, this proposed algorithm can be used for locating the tip of the laparoscopic instrument in real laparoscopic surgery.

Index Terms—Mean-shift algorithm, kalman filter, object tracking, laparoscopic surgery.

I. INTRODUCTION

The development of surgery is moving toward minimization or elimination of incision, which is known as minimally invasive surgery (MIS) [1]. Patients can receive many benefits from MIS. For example, blood loss can be reduced small incision results in reducing pain and shortens recovery time; and exposure of internal organs to possible external contaminants decreases the risk of infections. Laparoscopic surgery, a type of MIS, is performed with several laparoscopic instruments and a laparoscope which is a telescopic rod lens system connecting to a CCD camera. A fiber optic cable system is used to connect a light source to illuminate an operative field, which is viewed through a laparoscope to display a 2D image. The position of the laparoscope is always changed according to the instruction of the primary surgeon. In addition, the surgeon requires a lot of skills to operate the laparoscopic instrument.

Many researchers have proposed different methods to track the laparoscopic instrument. Omote *et al.* [2] presented

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the color tracking algorithm to control a robotic laparoscope instead of using human; however, this method cannot track many types of instruments. Casals *et al.* [3] introduced feature tracking algorithm based on shape information of a surgical instrument; however, it works only with a specific surgical instrument. Lee *et al.* [4] proposed a color and shape tracking algorithm by using the contour of the surgical instrument. This algorithm worked well in the normal situation, but not when the instrument is blocked by some obstacles. Wei *et al.* [5] presented a simple algorithm for tracking target features. However, this algorithm is based on the artificial color marks attached to a surgical instrument, but there are many disadvantages, such as sterilization of the mark on the surgical instrument and its convenience in the real practice.

Because of some limitations in previous methods, in this paper, we propose a new object tracking algorithm to track the laparoscopic instrument called the adaptive mean-shift Kalman algorithm [6], which is based on the mean-shift algorithm [7] and the Kalman filter [8]. In this algorithm, the size of the target candidate can be adjusted during tracking processes to increase the chance of tracking. We simulated videos with different scenarios to test the performance of our proposed algorithm. Furthermore, the proposed algorithm is intended to use for controlling our new laparoscopic-holder assistant robot [9-10] and tracking the tip of its instruments in laparoscopic surgery.

II. OBJECT TRACKING SYSTEM

Object tracking is usually divided into two parts: *Target Representation and Localization*, and *Filtering and Data Association* [11]. The *Target Representation and Localization* part is the main process for locating and tracking a target object. It consists of three different techniques: point tracking, silhouette tracking, and kernel tracking. In this study, we will focus on kernel tracking, specifically the Mean-Shift algorithm, to locate the target object. The mean-shift algorithm can locate both rigid and non-rigid objects, as well as varying-size objects. *Filtering and Data Association* is a supplementary process utilizing the result of the target representation and localization process to improve object tracking capability to overcome some difficult tasks, such as a situation when the object is blocked by some obstacles. Examples of filtering algorithms are Kalman Filters and Particle Filters. In this part, the Kalman filter is the suitable estimation state of one target object, which is our main focus.

A. Mean-Shift Algorithm

A Mean-Shift algorithm [7] is an iterative process to locate the target object by maximizing the similarity function. The

similarity function will be compared between the target model, \hat{q} , and the target candidate, $\hat{p}(y)$. The target model and the target candidate are represented by a small elliptical or rectangular area in the frame. Then pixel values in the region of interest (ROI) are used for calculating the target model and target candidate histograms. The main algorithm consists of five steps when computing each frame of video sequences. The result of processing in the current frame is the target object which is the target model in the mean-shift algorithm. The five steps are performed as described below.

Step1: In the first frame, we need to initialize the target model, $\{\hat{q}_u\}_{u=1\dots m}$, to be its distribution and y_0 to be the center location of the target model in the current frame. The target model can be computed by the following equation:

$$\hat{q}_u = C \sum_{b(x_i)=u} k(\|x_i\|^2) \quad (1)$$

where x_i is the normalized pixel value at the i th pixel of the target model area, $b(x_i)$ is a color value at pixel x_i which depends on the m -bin histogram, C is a normalization factor, which can be set as a constant, $k(x)$ is a kernel function, such as a Normal kernel as follows:

$$k_N(x) = C * \exp\left[-\frac{1}{2}\|x\|^2\right] \quad (2)$$

Then we need to initialize the new center location of the target in the current frame at the previous center location y_0 and compute the distribution of the target candidate at y_0 :

$$\hat{p}(y_0) = \{\hat{p}_u(y_0)\}_{u=1\dots m} \quad (3)$$

$$\hat{p}_u(y_0) = C_h \sum_{b(x_i)=u} k\left[\left\|\frac{y_0 - x_i'}{h}\right\|^2\right] \quad (4)$$

where x_i' is the normalized pixel value in the target candidate which is defined to have the center at y_0 in the current frame, h is the bandwidth of the candidate area, and C_h is a normalization factor, which can be set as a constant.

To compare between the target model and the target candidate, the similarity function, $\rho(\hat{p}(y), \hat{q})$, is based on the Bhattacharyya Coefficient as follows:

$$\begin{aligned} BC1 = \rho(\hat{p}(y_0), \hat{q}_u) &= \sum_{u=1}^m \sqrt{\hat{p}_u(y_0)\hat{q}_u} \\ &= \sum_{u=1}^m \hat{p}_u(y_0) \sqrt{\frac{\hat{q}_u}{\hat{p}_u(y_0)}} \end{aligned} \quad (5)$$

Step2: Derive the weights $\{w_i\}_{i=1\dots n_h}$, as follows:

$$w_i = \sum_{u=1}^m \sqrt{\frac{\hat{q}_u}{\hat{p}_u(y_0)}} ; i = 1 \dots n_h \quad (6)$$

Step3: The mean shift vector computes the new location y_1 , by calculating the minimum distance between the target model and the target candidate. The current position y_0 will be moved to the new location y_1 . Therefore, the new location of the target candidate can be derived as follows:

$$y_1 = \frac{\sum_{i=1}^{n_h} x_i' w_i g\left(\left\|\frac{y_0 - x_i'}{h}\right\|^2\right)}{\sum_{i=1}^{n_h} w_i g\left(\left\|\frac{y_0 - x_i'}{h}\right\|^2\right)} \quad (7)$$

where $g(x) = -k(x)$

After updating the new center target location at y_1 , the distribution of target candidate at y_1 is computed as follows:

$$\hat{p}(y_1) = \{\hat{p}_u(y_1)\}_{u=1\dots m} \quad (8)$$

Then the second Bhattacharyya coefficient or the similarity function between the target model and the target candidate of the new location is evaluated.

$$BC2 = \rho(\hat{p}(y_1), \hat{q}_u) = \sum_{u=1}^m \sqrt{\hat{p}_u(y_1)\hat{q}_u} \quad (9)$$

Step4: This process will iterate until $BC2 > BC1$; however, if $BC2 < BC1$, then the new center target y_1 will be updated as follows:

$$\begin{aligned} \text{While} & \quad \{BC1 < BC2\} \\ \text{Do} & \quad \left\{y_1 = \frac{1}{2}(y_0 + y_1)\right\} \end{aligned}$$

Step5: This process will check the condition to terminate the algorithm based on the predicted threshold value ϵ . The threshold value is defined to be the minimum distance between the target model and the target candidate. The condition of this step will be computed as follows:

$$\text{If} \quad (\|y_1 - y_0\| < \epsilon)$$

Stop the process

Else

Set $y_0 = y_1$

Go to step 1

B. The Kalman Filter Algorithm

The Kalman filter [8] is based on a set of mathematical equations which implements a predictor-corrector step to estimate the result. This filter is a tool for estimating the states of a linear system. The Kalman filter is a recursive process which is separated into two steps consisting of prediction and correction steps. The prediction step defines the time update equations and the correction step defines the measurement equations. The goal of the Kalman filter is to determine a posteriori state estimate \hat{x}_k .

The time update equations, responsible for projecting in time, consist of the current state and the priori estimate error covariance for the next time step as follows:

1) Project the priori state, \hat{x}_{k+1}^- , in the next time, $k+1$, as follows:

$$\hat{x}_{k+1}^- = A\hat{x}_k + Bu_k + w_k \quad (10)$$

where A is an $n \times n$ state transition matrix, \hat{x}_k is the $n \times 1$ state matrix in the previous time (frame) step, n is number of estimate values, B is an $n \times l$ optional control transition matrix, l is the number of the control values, u_k is a k -time optional

control input which is an $l \times l$ matrix, and w_k is the process noise which is an $n \times l$ matrix or a constant.

2) Project the priori estimation error covariance, P_{k+1}^- , in the next time, $k+1$, as follows:

$$P_{k+1}^- = AP_k A^T + Q \quad (11)$$

where $Q = [w_k w_k^T]$ is the process noise covariance which is an $n \times n$ matrix, and P_k is the posteriori estimate error covariance.

The measurement equations use the actual measurement z_k to update the state object consisting three processes as follows:

1) Compute the Kalman gain, K as follows:

$$K = P_k^- H^T (H P_k^- H^T + R)^{-1} \quad (12)$$

where K is called the ‘‘Kalman gain’’ which is an $n \times m$ matrix, P_k^- is a priori estimate error covariance, H is an $m \times n$ measurement transition matrix, $R = [v_k v_k^T]$ is an $n \times n$ measurement noise covariance matrix.

2) Update estimate state as follows:

$$\hat{x}_k = \hat{x}_k^- + K(z_k - H\hat{x}_k^-) \quad (13)$$

where \hat{x}_k^- is an $n \times 1$ priori state estimate matrix, z_k is an $m \times 1$ actual measurement matrix, which can be written as follows:

$$z_k = Hx_k + v_k \quad (13)$$

where v_k in the measurement noise which is an $m \times 1$ matrix or a constant, x_k is the result of the Target Representation and Localization part which is an $m \times 1$ matrix.

3) Update the posteriori estimation error covariance, P_k in the current time k , as follows:

$$P_k = (I - KH)P_k^- \quad (15)$$

III. ADAPTIVE MEAN-SHIFT KALMAN TRACKING

In this research, we propose the adaptive mean-shift Kalman tracking based on the mean-shift algorithm combined with the Kalman filter to track the object of interest object. Unlike the traditional mean-shift algorithm the proposed mean-shift algorithm can vary different ROI sizes of the target candidate. The overall process of adaptive mean-shift Kalman tracking summarized in Fig. 1 as described below.

1) Initial Step: Selection of target model

In the first frame, the user selects the target model which is the predefined ROI. From the target model, we will compute the initial state of the Kalman filter.

2) First Step: Mean-Shift algorithm process

In the next frame, the algorithm defines the target candidate which is at the same center location as the target model. However, the size of the target candidate is larger than the size of the target model which is the size of the region, h . The target model and the target candidate will be computed to get the second Bhattacharyya coefficient ($BC2$) in the mean-shift algorithm.

3) Second Step: Similarity comparison from the mean-shift algorithm

First, we will define the first similarity threshold value ($CT1$) to determine the tracking criteria. This value will be compared with $BC2$. If $BC2$ is more than $CT1$, then we will update the Kalman filter by using the result of the mean-shift algorithm in the first step. Thus, the target result in this case will be acquired from the mean-shift algorithm, and the next sequence frame can be proceeded. However, if $BC2$ is less than $CT1$, then go to the third step.

4) Third Step: Estimation of the Kalman filter

In this step, the estimate state of the Kalman filter will feed back to the adaptive mean-shift algorithm. If the tracking result is not in the predefined similarity threshold value, the algorithm will increase the target candidate up to twice the size of the current ROI. In addition, this target candidate will define the new location from the current state of the Kalman filter. Hence, the third Bhattacharyya coefficient ($BC3$) is computed.

5) Fourth Step: Similarity comparison between the Kalman filter and the adaptive mean-shift algorithm

We compare the second similarity threshold value ($CT2$) with the $BC3$ from the third step. If $BC3$ is greater than $CT2$, then we will use the result from the adaptive mean-shift algorithm. If $BC3$ is smaller than $CT2$, then we will use the estimate state of the Kalman filter, increase the target candidate ROI and go back to the third step. This process is repeated until the maximum target candidate size is met. Otherwise, the target result will be acquired from the adaptive mean-shift algorithm, and the next sequence frame can be followed.

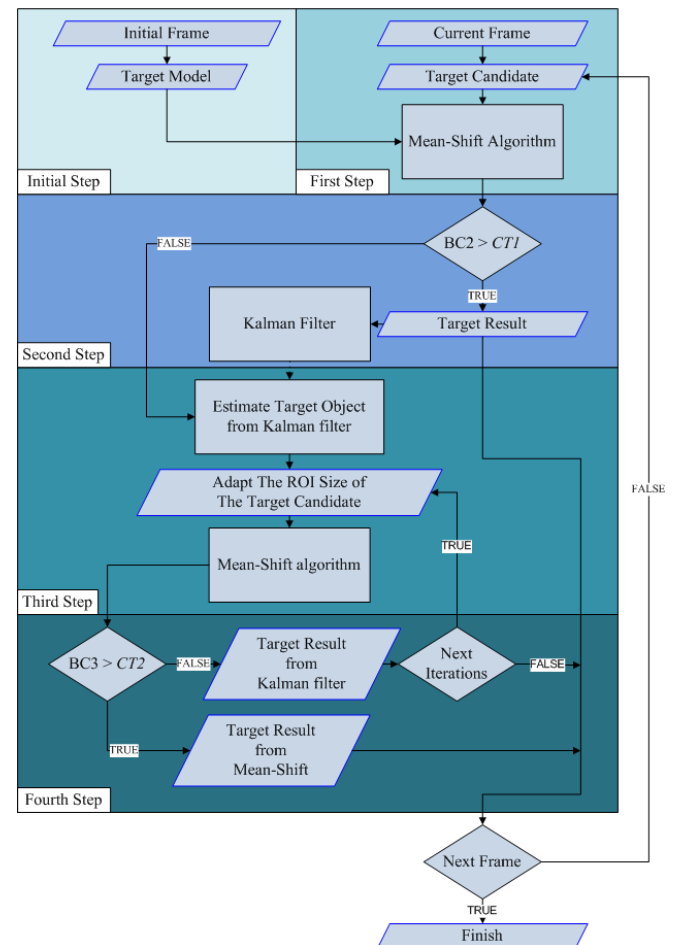


Fig. 1. The overall process of the adaptive mean-shift kalman tracking.

IV. EXPERIMENTAL RESULTS

We tested the performance of our proposed algorithm by simulating videos for different situations. From the simulated videos in Fig. 2, the red background represents the color of the internal body in laparoscopic surgery. The yellow ball represents an obstacle. The tip of the real laparoscopic instrument represents the target object, which is shown in the white rectangle. The green rectangle in the tracking process is the result of the tracking algorithm. In the first frame, we need to initialize the target model for the proposed algorithm as shown in Fig. 2.



Fig. 2. The target model with an initial value in the white rectangle.

1) Simulated Experiment #1: Move the target model in front of the obstacle

The goal of this experiment is to track the target object when moving the target in front of the obstacle. This experiment was computed on a video with 129 frames covering about 14 seconds. Thus, the average of frame rate is 9.2frames per second. Fig. 3 shows fifteen sample frames at different times. The proposed algorithm can track the target object with correct locations.

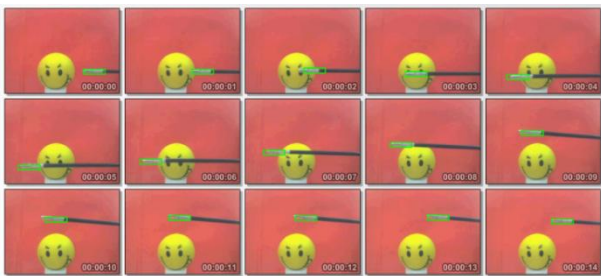


Fig. 3. Sample results in simulated experiment #1.

2) Simulated Experiment #2: Change the shape of the target model and move in front of the obstacle

The goal of this experiment is to track the target object when changing the shape of the target and moving the target in front of the obstacle. Here, the tip of the grasper was opening and closing. This experiment was computed on a video with 196 frames covering about 20 seconds. Thus, the average of frame rate is 9.8 frames per second. Fig. 4 shows fifteen sample frames at different times. The results show that the algorithm provides correct tracking.

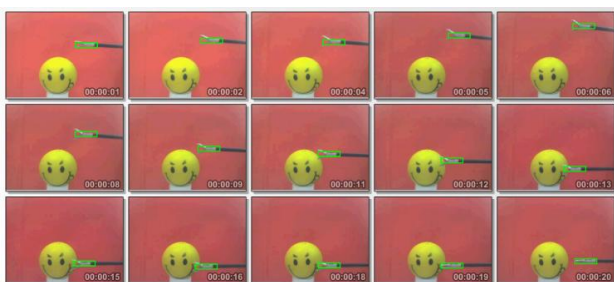


Fig. 4. Sample results in simulated experiment #2.

3) Simulated Experiment #3: Resize the shape of the target

The goal of this experiment is to track the target object when changing the size of the target. This experiment was computed on a video with 100 frames covering about 12 seconds. The tracking results in some frames are shown in Fig. 5. Again, the proposed algorithm can track the target object in all frames.



Fig. 5. Sample results in simulated experiment #3.

4) Simulated Experiment #4: Resize and change the shape of the target

The goal of this experiment is to track the target object when changing the size as well as the shape of the target. This experiment was computed on a video with 240 frames covering about 25 seconds. The tracking results in some frames are shown in Fig. 6. The proposed algorithm can successfully track the target object.



Fig. 6. Sample results in simulated experiment #4.

5) Simulated Experiment #5: Move behind the obstacle

The goal of this experiment is to track the target object when the object moves behind the obstacle. This experiment was computed on a video with 140 frames covering about 14 seconds. Some tracking results are shown in Fig. 7. From 4-12 seconds, the whole target object was hiding behind the obstacle. After that, the target appeared in the scene again and the tracking process can track the target correctly. This is due to the estimation process in the Kalman filter to improve tracking performance. Without the Kalman filter, we were not able to track the target object correctly after it disappeared from the scene.

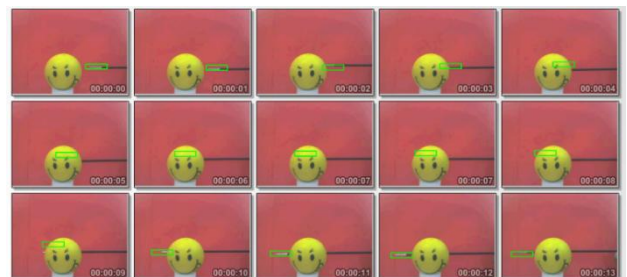


Fig. 7. Sample results in simulated experiment #5.

V. CONCLUSION

In this paper, we have proposed the adaptive mean-shift Kalman tracking algorithm based on the mean-shift algorithm combined with the Kalman filter for tracking the tip of the laparoscopic instrument. The ROI size of the target candidate at each frame can be adjusted to increase the chance of tracking. The experimental results of all simulated situations show that the proposed algorithm can locate the target object correctly even when the size and the shape of the target have been changed. In addition, when the target is hiding behind some obstacles, this algorithm can still track the target object once it appears. Thus, this proposed algorithm will be suitable for locating the tip of the laparoscopic instruments well as guiding the path of our conceptual robot in real laparoscopic surgery.

REFERENCES

[1] R. H. Taylor, J. Funda, L. Joskowicz, A. D. Kalvin, S. H. Gomory, A. P. Guezic, and L. M. G. Brown, "An overview of computer-integrated surgery at the IBM Thomas J. Watson Research Center," *IBM J. Research and Development*, vol. 40, pp. 163-183, 1996.

[2] K. Omote, H. Feussner, A. Ungeheuer, K. Arbter, and A. Guo-Qing Wei, "Self-guided robotic camera control for laparoscopic surgery compared with human camera control," *The American Journal of Surgery*, vol. 177, pp. 21-24, 1999.

[3] A. Casals, J. Amat, and E. Laporte, "Automatic guidance of an assistant robot in laparoscopic surgery," *International Conf. on Robotics and Automation*, vol. 1, pp. 895-900, 1996.

[4] C. Lee, Y. F. Wang, Uecker, and Y. Wang, "Image analysis for automated tracking in robot-assisted endoscopic surgery," *Proceedings of the 12th IAPR International Conference*, vol. 1, pp. 88-92, 1994.

[5] A. Guo-Qing Wei and G. Hirzinger, "Real-time visual servoing for laparoscopic surgery. Controlling robot motion with color image segmentation," *IEEE Engineering in Medicine and Biology*, vol. 16, pp. 40-45, 1997.

[6] V. Sa-Ing, S. S. Thongvigitmanee, C. Wilasrusmee, and J. Suthakorn, "Adaptive Mean-Shift Kalman Tracking for Laparoscopic Surgery," *the 4th IEEE International Conference on Computer Science and Information Technology (IEEE ICCSIT 2011)*, June 10-12, 2011, pp. 204-208.

[7] D. Comaniciu and P. Meer, "Mean shift: A robust approach toward feature space analysis," *IEEE Transactions on Pattern Analysis and Machine Intelligence* vol. 25, pp. 603 – 619, 2002.

[8] C. Masreliez and R. Martin, "Robust bayesian estimation for the linear model and robustifying the Kalman filter," *IEEE Transactions on Automatic Control*, vol. 22, pp. 361 – 371, 2003.

[9] V. Sa-Ing, S. Sotthivirat, C. Wilasrusmee, and J. Suthakorn, "Design of A New Laparoscopic-Holder Assistant Robot," *The 3rd International Symposium on Biomedical Engineering (ISBME 2008)*, Bangkok, Thailand, pp. 278 – 281, 2008

[10] V. Sa-Ing, S. S. Thongvigitmanee, C. Wilasrusmee, and J. Suthakorn, "A New Laparoscopic-Holder Assisting Robot and Workplace Analysis," *The 7th Asian Conference on Computer-Aided Surgery (ACCAS 2001)*, Bangkok, Thailand, 2011.

[11] A. Yilmaz, O. Javed, and M. Shah, "Object Tracking: A Survey," *ACM Computing Surveys*, vol. 38, pp. 1 - 45, 2006.



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