Aggregate of Mean Shift and Kalman Filter: An Option for Automatic Object Tracking in Digital Videos

KF5042 Intelligent Systems Assignment 2

ABSTRACT

One of the oldest uses of Artificial Intelligence or Machine Learning is the tracking of objects with vision sensors such as cameras and infrared surveillance equipment, etc. While many of these algorithms are not in fact new, they are still being heavily developed upon. Some of the latest examples of this development iteration is the aggregate of Mean Shift (MS) and Kalman Filters (KF), which are two of the most promising algorithms that are heavily used in object tracking today. This paper will review each of these algorithms and their aggregate, showing why the new algorithm is such a beneficial addition to the field of Computer Vision.

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1. INTRODUCTION

Object Tracking is not a new technology, compared to self-driving cars, intelligent assistants and data analytic algorithms. While the uses of Object Tracking are not immediately apparent, they are in fact one of the most promising aspects of the possibilities of machine learning. The benefit of being able to identify and track number plates of criminals as an aid in law enforcement or assisting in human computer interaction via gestures or body tracking for the disabled cannot be understated.

2. Mean Shift, Kalman Filters and their Aggregate

2a. Mean Shift

The first algorithm to be studied is the basic form of the Mean Shift (MS) algorithm. This algorithm is very powerful in certain situations, allowing users to track objects in real time (D. Comaniciu, V. Ramesh and P. Meer. 2000). Using a histogram, naïve estimator and kernel estimator, Mean Shift (MS) allows an estimation of the relative density of the object (Silverman, B.W., 1986).

Tracking algorithms like these can face many problems when tracking a target, such as occlusion of the target, changes in scale and sudden differences in illumination (Chris, T. Karamchandani, S.H. Biradar T.B. 2000). Most forms of Mean Shift (MS) often leave the target frame on the occluding object rather than following the target itself. Illumination is also stated as a difficulty for the Mean Shift (MS) algorithm, as the basic form of the algorithm places too much weight on the background of the target, so when the background is illuminated suddenly or experiences a lack of illumination, the target may be lost.

2b. Kalman Filter

The Kalman Filter was theorised in 1960 by Rudolf Emil Kálmán, (Kalman, R. E. (1960) and is a statistical point tracking algorithm (Jatoth, R.K. Shubhra, S. Ali, E. 2013) that consists of two phases, prediction and correction, as shown in figure 1. These phases are iterated throughout the tracking, and can be quite efficient at predicting movement based on the previous position of the target (P. R. Gunjal et al. 2008). The State Prediction variable of the Kalman Filter determines the past, present, and possible future states of the object. This is used for prediction of where the target is moving, and is used and constantly updated in order to best describe the object using a single variable (P. R. Gunjal et al. 2008). This allows it to be particularly effective at tracking after occlusion.

Kalman Filters are not a perfect algorithm, however, as they are not accurate at predicting the initial location of the target. This is why many version of the Kalman Filter have an initial precursor search using a different algorithm such as Mean Shift in order to start the tracking accurately.

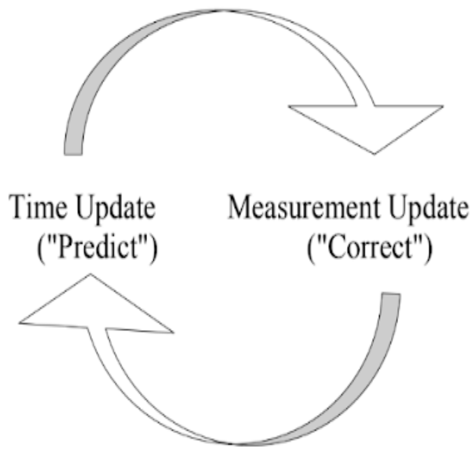

FIGURE 1: Kalman Filter Update Cycle (P. R. Gunjal et al. (2008).)

2c. Mean Shift (MS) - Corrected Background Weighted Histogram (CBWH) - Adjusted Kalman Filter with Adapted F, Q and R (AKFQR) as (MS-CBWH-AKFQR)

The last algorithm to be reviewed is a combination of the previous two, proposed by the researchers at the National Institute of Technology in Tamil Nadu (Agarwal, V.K. Naidu, VPS. Sivakumaran, N 2016). The algorithm they have proposed comprises primarily of a Kalman Filter (KF) and Mean Shift (MS) aggregate, automatically adapting the System Matrix (F), Process Error Covariance Matrix (Q) and the Measurement of the Noise Covariance Matrix (R) of the Kalman Filter (AKFQR). The Mean Shift algorithm uses a Corrected Background Weighted Histogram (CBWH) for its capability in removing scaling, rotation and partial occlusion problems, which is useful when the target moves behind solid objects or is accelerating towards the sensor. This combination of algorithms is used to eliminate the drawbacks of Mean Shift (MS), (Chris, T. Karamchandani, S.H. Biradar T.B. 2015) which are primarily a failure to track objects through noisy environments and sudden changes in speed and scale, among others. (Agarwal, V.K. Naidu, VPS. Sivakumaran, N 2016)

This algorithm aggregate (MS-CBWH-AKFQR) works by using the Adapted Kalman Filter (AKF) to predict the initial position of the target, then the Mean Shift (MS) algorithm uses that observation to calculate the distance in update equations of the Adapted Kalman Filter (AKF). As this process is iterated and continued, the F, Q and R values for the Kalman Filter are adapted according to the Bhattacharyya Coefficient. In this case, the Bhattacharyya Coefficient measures the overlap between the previous iterations in order to calculate the velocity and trajectory of the target by adapting F, Q and R accordingly. Comparing this with pre-set values for F, Q and R, the Adapted values are more precise and efficient with a higher Bhattacharyya Coefficient. This is evidenced in figure **2,** showing a table from the study performed by the researchers at the National Institute of Technology in India, stating a difference of 0.035 between the Mean Shift algorithm and the MS-CBWH-AKFQR algorithm in mean Bhattacharyya Coefficient. (Agarwal, V.K. Naidu, VPS. Sivakumaran, N 2016)

Tracking Algorithms	Bhattacharya Coefficient
	Mean±Std.
MS	0.1827±0.1565
MS-CBWH	0.1892±0.1549
MS-CBWH-K	0.2137±0.1617
MS-CBWH-AKF	0.2034±0.1546
MS-CBWH-AKQR	0.2117±0.1573
MS-CBWH-AKFQR	0.2177±0.1476

FIGURE 2: Bhattacharyya Coefficient between MS and MS-CBWH-AKFQR (Agarwal, V.K. Naidu, VPS. Sivakumaran, N 2016)

This new algorithm is not always the best option due to processing time, however. In the same research study, the MS-CBWH-AKFQR algorithm can sometimes take longer than less complex algorithms, shown in figure 3. The increase in processing time may be attributed to overworking the algorithm, or the algorithm is running more processes than it needs to run to efficiently track the target (D. Comaniciu, V. Ramesh and P. Meer. 2003). Considering that the increase in processor time comparatively is seen on a simpler tracking objective, it can be theorised that the MS-CBWH-AKFQR algorithms should be implemented when more complex tracking is likely to occur. On the other hand, when the target is far more likely to somewhat follow a set pattern, the simple models may in fact be a more efficient substitute, as they can take up less processing time and resources.

Tracking Algorithms	Execution time (sec)
	Mean±Std.
MS	0.002404±0.001968
MS-CBWH	0.002489±0.02481
MS-CBWH-K	0.003371±0.002588
MS-CBWH-AKF	0.003144±0.00249
MS-CBWH-AKQR	0.002875±0.002729
MS-CBWH-AKFQR	0.002761±0.002573

FIGURE 3: Execution Time between MS and MS-CBWH-AKFQR **(**Agarwal, V.K. Naidu, VPS. Sivakumaran, N 2016)

3 CONCLUSION

Mean Shift (MS) and Kalman Filters (KF) can be used to track objects through noisy environments, however, they have their limitations. These limitations often include difficulties in tracking targets through occlusion or large changes in scaling as targets accelerate towards the tracking sensor. Combining these two algorithms, with slight modifications to their process and automating some of their values allows a much more efficient and powerful system, including benefits to performance in most situations and a higher accuracy through occlusion. This aggregate is not perfect all of the time, however, as for more simple tracking situations, the higher complexity of the MS-CBWH-AKFQR algorithm is a detriment to processing resource usage. This method therefore should only be used in situations where high accuracy and complex movements are more likely to occur.

If the future of this algorithm were considered, certain improvements could be implemented such as using an extended or unscented Kalman Filter (KF). One of the long term goals of the algorithm would be to allow multiple objects to be tracked at once with the same accuracy.

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