PERFORMANCE OF REFERENCE BLOCK UPDATING TECHNIQUES WHEN TRACKING WITH THE BLOCK MATCHING ALGORITHM

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ABSTRACT

An important problem when using the Block Matching Algorithm to track objects is how to update the reference block to take account of the changing target appearance. This paper investigates and reports on the accuracy and stability of a variety of update strategies and on the robustness of these strategies to image noise. These strategies are applicable where an object is being tracked using the Block Matching Algorithm over an extended period of time or where the object appearance is changing over time.

1. INTRODUCTION

The Block Matching Algorithm (BMA) is a correlation-based approach to motion estimation [1] and tracking [2], where the motion of a block of pixels, called the Reference Block, is estimated by looking for the most similar block in subsequent frames. An important issue when using the Block Matching Algorithm is the update strategy for the reference block, since the apperance of an object will usually be changing over time. Peacock *et al* [3] propose a number of strategies for updating the reference block and report that the performance of the Adaptive BMA is very dependent on the choice of update strategy. This paper presents an empirical investigation of the effect parameter choice has on the stability and accuracy for the Kalman and FIR filter update strategies. In the remainder of section 1 the two update strategies are introduced. Section 2 reports on the performance of the update strategies over a range of parameter values and section 3 reports on the performance under increasing levels of image noise.

1.1. Kalman Filter Update Strategy

The use of a Kalman filter, applied to the reference block, is reported as the most robust strategy by Peacock *et al* [3] and it incurs relatively small overhead, given the optimisations reported. However, to acheive optimal performance the Kalman filter parameters must be fixed on initialisation and remain constant throughout operation. Therefore, it is necessary to identify suitable parameter values *a priori*.

The two noise parameters present in the Kalman filter are the Dynamic Model Noise Covariance matrix (Q_n) and the Observation Noise Covariance matrix (R_n) [4]. The Dynamic Model Noise gives the magnitude of the random-velocity component of the target; while the Observation Noise gives the accuracy of the measurements for the target. It is assumed that there is no inter-dependency in the errors between the pixels in the reference block, therefore, the covariance noise matrices simplify to:

$$Q_n = qI_n \quad (1)$$

$$R_n = rI_n \quad (2)$$

where q and r are scalar values. The Block Matching Algorithm assumes the reference block is constant, so the state transtion matrix in the Kalman filter is the identity matrix. The constant noise parameters allow the Kalman gain to be precalculated [5] from the values of q and r. Therefore, a simplified reference update equation, which is actually a normalised IIR filter, can be used for the Kalman filter update strategy:

$$R_t = R_{t-1} + K(M_{t-1} - R_{t-1}) \quad (3)$$

1.2. FIR Filter Update Strategy

The FIR filter also produced robust estimates but, in the general case, is computationally more expensive. However, the FIR filter in the update strategy given in Peacock *et al* [3] sets all the filter coefficients to be the same. In this case it is possible to reduce the computational complexity from linear in terms of filter order to a constant computational cost. The resulting equation is:

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$$R_t = K\left(M_t + R_{t-1} - K^d M_{t-d}\right) \quad (4)$$

where K is the filter coefficient, M is the best-match block from the image sequence and O is the order of the filter. The output must then be normalised for the given filter coefficient. This optimisation makes comparison with the Kalman filter update strategy more favourable than originally reported and for this reason the FIR update strategy is also investigated in this paper.

1.3. Test Data

Four data sets are used for testing: two sequences from a car park security camera, a sequence taken from one car following another and a sequence showing a cyclist riding around a car park. The two sequences from the car park securty camera have a fixed camera showing a pedestrian walking across the car park (A) and a car moving behind a fence (B). The car following sequence has both the camera and target car in motion, resulting in a lot of small quick movements due to uneven roads. The cyclist sequence has a fixed camera with smooth motion by the cyclist, but the reference block undergoes significant change as the cyclist turns in the scene.

The data sets provide considerable variation in content, including zoom, change of perspective and partial occlusion. The focus of this paper is on the reference update strategy and other problems, such as missing or unintelligible frames, are dealt with in the literature [6, 7]. For each data set, a point on the target object was chosen and its position at 5 frame intervals manually tracked over the sequences. These measurements are used as a ground truth to enable comparison of the update strategies. The accuracy of the manual measurements is ± 2 pixels. Figure 1 shows the first image from the four data sets, with the position of the 8×8 block used for tracking.

For reference, Figure 2 shows the performance of the Block Matching Algorithm on the four test data sets when no form of reference block updating is used. In this case, a single unaltered reference block is used throughout the sequence.

2. PARAMETER CHOICE

The fundamental trade-off in the filter design is the speed at which it should react versus the stability of output. If the filter takes too strong account of the most recent result, or does not take account of enough previous results, then it may react too quickly to a few erroneous results, leading to inaccurate output from the filter. Similarly, a slowly reacting filter may fail to respond fast enough to a fundamental change in input, again leading to inaccurate output from the filter.

Fig. 1. The first image from the four test data sets showing the block being tracked (clockwise from top left: CarParkA, CarParkB, Cyclist and CarFollowing).

	No. of Frames	Block Size	BMA Mean Error
CarParkA	70	8×8	10.5 (35.7)
CarParkB	105	8×8	3.9 (8.4)
CarFollow	240	8×8	8.1 (161.0)
Cyclist	100	8×8	1.4 (1.5)

Fig. 2. Results for the Block Matching Algorithm with no form of reference block updating showing mean error (pixels), with error variance in brackets, for the position estimates.

It is important to remember that the Kalman filter is being applied to the pixels in the reference block and not the position of the reference block. Therefore, the velocity in the Kalman filter is the speed of pixel intensity change in the reference block, which makes it difficult to directly map the Dynamic Model Noise (Q_n) and the Observation Noise (R_n) to real-world values. It is important when determining suitable values for the two parameters to work out their relative magnitude.

Observation Noise gives the accuracy of the measurements for the target. This can be seen to map closely to the level of image noise present. However, the effect of the Observation Noise implies a continuing effect on the velocity. Image noise has only an immediate effect on the single frame and does not continue to affect the next frame. In the majority of cases, there will be little permanant random-velocity in the reference block and so the magnitude of Observation Noise is initially set very low.

Dynamic Model Noise (pixels)	Observation Noise (pixels)				
	0.001	0.01	0.1	1	10
0.05	*1.6 (1.1)*	3.3 (4.0)	20.2 (259.3)	LOST	LOST
0.5	9.1 (16.4)	*1.6 (1.1)*	3.3 (4.0)	20.2 (259.3)	LOST
5	9.6 (21.6)	10.0 (21.0)	*1.6 (1.1)*	3.3 (4.0)	20.2 (259.3)
50	10.8 (31.6)	10.8 (30.8)	18.1 (157.4)	*1.6 (1.3)*	3.3 (4.0)
500	9.9 (39.9)	10.0 (39.0)	10.9 (31.0)	18.2 (149.4)	*1.9 (1.3)*

Fig. 3. Results for Kalman filter update strategy on the CarParkB data set showing the mean error (pixels), with error variance in brackets, for the position estimates. LOST indicates that the track was lost.

Filter Order	Filter Coefficient				
	0.75	0.8	0.85	0.9	0.95
4	2.3 (1.3)	4.8 (9.5)	4.8 (9.5)	4.0 (5.1)	13.4 (183.8)
5	2.0 (1.2)	4.4 (6.0)	13.7 (210.0)	2.2 (1.6)	2.7 (2.2)
6	2.1 (1.2)	2.1 (1.3)	2.1 (1.3)	2.2 (1.3)	2.2 (1.3)
7	2.1 (1.4)	2.0 (1.2)	2.3 (1.2)	1.8 (1.3)	*1.8 (1.3)*
8	5.5 (11.9)	2.1 (1.4)	2.0 (1.4)	*1.7 (1.3)*	*1.9 (1.4)*
10	LOST	2.0 (1.6)	*1.8 (1.6)*	*1.8 (1.6)*	*2.0 (1.6)*

Fig. 4. Results for FIR filter update strategy on the CarParkB data set showing the mean error (pixels), with error variance in brackets, for the position estimates.

The Dynamic Model Noise gives the magnitude of the random-velocity component of the target. The Kalman model used assumes a constant state for the reference block ($S_n = I_n$), however, the reference block will change slowly over time. When viewing any data set it can be seen that a reference block changes significantly and unpredicatably over time. This means that the reference block estimates provided by the Kalman filter will always have a significant degree of inaccuracy. Therefore, the Dynamic Model Noise should be considerably higher than the Observation Noise. The range over which Observation Noise was tested is 0.001 to 10 pixels and the range over which Dynamic Model Noise was tested is 0.05 to 500 pixels.

The results in Figure 3 are representative of all the data sets and show that there is a series of values (shown in italics) for Q and R that provide the most accurate estimates. The Kalman gain (K) is a combination of these two and by keeping their relative magnitudes the same the Kalman gain remains the same, which in this case was 0.132. Although it may be possible to identify optimal values for a specific data set that vary slightly from those shown in Figure 3 this results provide an excellent starting point for any implementation of the Kalman filter update strategy.

The parameters for the FIR filter are the filter coefficient (K) and the order of the filter (O). The higher the filter cofficient the longer a result will have a significant effect on the output of the filter, therefore the deeper the filter can be. A suitable range of FIR filter orders would be 4 to 8 and this suggests that the range of filter coefficients should be 0.75 to 0.95. The results for the FIR over these ranges on sequence CarParkB are shown in Figure 4.

It can be seen from the results in Figure 3 that the filter is relatively stable, with only two giving significant estimation errors and one combination losing the object being tracked (O=10 K=0.75). In the case of the tracked object being lost, the filter reacted too quickly to the changing reference block as the car moved behid the fence. Furthermore, it is clear that a higher filter coefficient, which weights the filter over more results, combined with a order of 7 or more gives the best overall performance. These results where repeated across the other data sets, with the best combination across all data sets being O=8, K=0.9.

In comparison to the Kalman filter, the FIR filter shows slightly less accurate results on all the image sequences but it has a slower degradation in accuracy than the Kalman filter under the parameter ranges tested.

3. PERFORMANCE UNDER IMAGE NOISE

The accuracy reported for both update strategies is very good but the four data sets have low levels of image noise present. However, in many real world applications the levels of image noise will be considerably higher and it is important that the reference update strategies continue to provide increased accuracy. Therefore, the performance of the two update strategies under artificial white gaussian-distributed additive noise on the four image sequences was investigated. The range of noise added is intended to cover a wide range of conditions in which BMA may have to operate, although noise reduction techniques would normally be applied to data with high levels of noise ($\sigma > 15$) prior to block matching.

Figure 5 shows the accuracy of the Kalman filter and FIR filter update strategies applied to the four data sets. Data sets CarParkA, CarParkB and Cyclist contain significant changes in target appearance over the image sequence but do not contain occlusion of the target; both strategies show graceful degradation in accuracy as the level of image noise increases.

The Kalman filter and FIR filter on CarParkB show a noticeable drop in accuracy, where they lose the target entirely. In this test sequence, the critical part of the sequence is when the target being tracked moves behind the wire fence, causing partial occlusion. Without image noise both strategies allow the target to be tracked accurately at this point. However, the inclusion of significant image noise causes serious problems, in paticular for the Kalman filter. The problem with the Kalman filter is that the noise parameters heavily weight reference block changes to Dynamic Model Noise, thereby embedding the image noise

		Standard Deviation (σ) for Artificial Image Noise				
	Filter	None	1	5	15	30
CarParkA	None	3.9 (8.4)	4.0 (8.6)	LOST	LOST	LOST
	FIR	1.7 (1.0)	1.7 (1.0)	2.0 (1.9)	1.3 (0.8)	LOST
	Kalman	1.2 (0.4)	1.7 (0.9)	2.5 (4.3)	6.2 (63.4)	LOST
CarParkB	None	10.5 (35.7)	7.7 (31.7)	5.1 (22.0)	LOST	LOST
	FIR	2.1 (1.4)	2.1 (1.4)	2.1 (1.4)	LOST	LOST
	Kalman	1.6 (1.1)	LOST	LOST	LOST	LOST
CarFollow	None	8.1 (161.0)	8.1 (161.0)	8.2 (162.0)	8.4 (227.0)	LOST
	FIR	3.0 (1.1)	3.0 (1.1)	3.2 (1.9)	17.4 (918.4)	LOST
	Kalman	2.5 (0.6)	2.5 (0.6)	1.8 (0.7)	2.6 (13.6)	LOST
Cyclist	None	1.4 (1.5)	1.4 (1.5)	1.4 (1.5)	7.5 (138.0)	3.1 (15.6)
	FIR	1.4 (0.5)	1.4 (0.5)	1.2 (0.3)	1.1 (0.4)	4.0 (3.6)
	Kalman	1.1 (0.3)	1.1 (0.3)	1.1 (0.3)	1.4 (0.6)	2.1 (1.1)

Fig. 5. Results for the Kalman and FIR filter under varying levels of artificial image showing the mean error (pixels), with error variance in brackets, for the position estimates.

into the reference block. Figure 6 shows that by reducing the importance of the Dynamic Model Noise, the accuracy under high image noise may, in some cases, be increased. However, the accuracy under low image noise is slightly reduced and the advantages are highly sequence dependant. Figure 6 also gives an estimate of the image noise variance [8]. This estimate may provide a useful measure for determining the relative magnitudes of the two noise measures in the Kalman filter. For the FIR filter, the only applicable solution is to increase the order of the filter. However, the level of accuracy in the number representation used by the computer places an upper limit on the order (about 12 deep for IEEE single-precision floating point).

4. CONCLUSIONS

The optimised FIR filter update strategy that has been proposed, which has a small constant computational cost, has been demonstrated as stable and accurate under a variety of test data sets. The Kalman filter has similarly been demonstrated as accurate but not quite as stable. The FIR and Kalman update techniques both report accuracy greater than ± 2 pixels when properly applied. Given that the ground truth accuracy for the test data sets is ± 2 pixels it is not possible to directly compare the two techniques in terms of accuracy.

The Kalman filter update strategy proved highly accurate, but also highly dependent on parameters choice and on the level of image noise. The use of image noise variance estimation may provide a possible way of determining the parameter values for the Kalman filter. However, the FIR filter update strategy performed very well under increasing levels of image noise and would probably be preferable in situations with higher levels of image noise. The general conclusion for both filter update strategies is that they can help increase the accuracy of the Block Matching Algorithm

	Kalman	Standard Deviation (σ) for Artificial Image Noise				
	q	None	1	5	15	30
CarParkA	5	1.2 (0.4)	1.7 (0.9)	2.5 (4.3)	6.2 (63.4)	LOST
	3	2.0 (1.5)	2.0 (1.5)	6.3 (126.3)	LOST	LOST
CarParkB	5	1.6 (1.1)	LOST	LOST	LOST	LOST
	3	1.6 (1.1)	2.3 (1.3)	2.5 (1.4)	LOST	LOST
CarFollow	5	2.5 (0.6)	2.5 (0.6)	1.8 (0.7)	2.6 (13.6)	LOST
	3	2. (0.61)	2.7 (0.7)	2.7 (0.9)	2.9 (5.3)	LOST
Cyclist	5	1.1 (0.3)	1.1 (0.3)	1.1 (0.3)	1.4 (0.6)	2.1 (1.1)
	3	1.3 (0.4)	1.3 (0.4)	1.4 (0.4)	0.9 (0.4)	2.3 (0.7)
Estimation of Image Noise Var		0.1	0.2	0.3	0.9	1.9

Fig. 6. Results for the Kalman filter under varying levels of artificial image showing the mean error (pixels), with error variance in brackets, for the position estimates.

with a low computational cost, or low hardware cost, under significant image noise.

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