Object Tracking Using Moderate Derivative Gain Kalman Filter

Arjun Nelikanti, G. Venkata Rami Reddy, and G. Karuna

Abstract Object tracking in a video sequence is becoming challenging and important research area, and it becomes more complex when there are multiple objects. Many researchers have proposed several algorithms for detection and tracking in various videos including sports. In this paper, Kalman gain is calculated using moderate derivative of Grunwald–Letnikov function, and the modified Kalman filter is used to track the object in video sequence. The performance of the proposed method is analyzed by root mean square error (RMSE) metric and also compared with other methods. The results demonstrate that the proposed algorithm showing improvement by up to 12%.

Keywords Object tracking · Kalman filter · Grunwald–Letnikov · Fractional derivative and RMSE

1 Introduction

In Kalman filter, series of calculations are made at time intervals. It is an algorithm where state variables are estimated with noise and other inaccuracies for given parameters. Since 1968, constant gain has been analyzed in Kalman filter; an algorithm is proposed which determined piecewise-constant feedback gains for a linear system over a finite interval [1]. Kalman filter proposed with constant gain [2–5] for target tracking in both standalone and data fusion mode. Kalman filter with adaptive gain [6–8] was proposed based on minimization of variance to help in improving performance with constant gain. For evaluating the filter performance, the difference of actual and estimated state variables are calculated. There are few cases where the

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filter does not converge on innovation process. There are many adaptive versions of filter proposed by researches to improve the performance of Kalman filter.

Kalman filter is a state estimator with two stages, i.e., predict and update. In tracking an object, the filter can give more weight for the measurements to predict close values by having high gain. The filter can follow measurement closely with model having optimal gain and also smoothening noisy signals resulting low responsiveness. The Kalman filter gain can perform well in few cases when the gain can be tuned for desired results. The extended Kalman filter (EKF) will have high convergence rate if the difference between estimated state and actual state is low [9]. The EKF diverges if the error is large; the solution for controlling this divergence is by inserting a feedback loop at the calculation of gain. Fractional calculus is gaining more importance in many research areas for different applications related to material science, electrical, computer networking and mathematical formulations of mechanics [10]. This is also applicable in image processing which showed good accuracy results for some systems [11]. The objectives for this work are:

- Track the object accurately even under different occlusion conditions
- Normalize the Kalman gain to handle abrupt changes of the object in video sequence.

To address these above objectives, in this paper, we have tried to integrate Kalman filter and fractional calculus concepts for tracking an object in a video sequence under different foreground situations.

1.1 Motivation

In numerous sports, exceptionally competitive expert associations have developed, where technically flawlessness has gotten fundamental for competitors to stay aware of their opponents. Cricket has consistently been quite possibly the most mainstream sports in numerous nations in Asia. Because of its wide range of components, it is in fact exceptionally testing, and the need of analyzing these events became important to do in efficient way.

The rest of the paper is organized as follows: Sect. 2 provides overview of related work done in same area. Section 3 discussed proposed work, Sect. 4 provides details of experiment and results obtained, and Sect. 4 presents conclusions of the work done.

2 Literature Review

Kalman proposed Kalman filter in 1965 [12]. It has attracted many researches due to its capabilities and scope of applications. Various versions of Kalman filter were proposed based on an important parameter, i.e., Kalman gain.

In [2], Cook and Dawson proposed a version of Kalman gain computed using integral equation which showed good results. There were also different equations used to compute the Kalman gain matrix, for example, Chandrasekhar equation proposed in [13].

Kalman filter also handles occlusion and the adjustments made to occlusion rate designed adaptive Kalman filter discussed in [14]. Chung et al. [7] proposed a concept of adaptive control for calculating Kalman gain without taking initial state estimation and process noise. In [15], adaptive high gain EKF is proposed for navigation system where the gain is increased by changing the innovation. Xu et al. [16] proposed an adaptive iterated extended Kalman filter to increase the performance by statistics estimator for noise in iteration of Kalman filter.

In [17], geo-location of mobile terminals was predicted using digital fractional integration (DFI). The trajectories of these mobile terminals are predicted in two indoor scenarios with noisy environment, namely spiral and sinusoidal trajectories. Autocorrelation of paths obtained showed good results for proposed method.

In [18] an algorithm for tracking bearings only passive maneuvering target is proposed. A modified function of Galkowski-Islam was used to propose the algorithm. The proposed algorithm predicts the target with chi-square in sliding window format; while tracking the maneuvering, the noise is increased. The process noise is decreased after tracking is completed. Using adaptive fating, EKF and adaptive UKF was proposed in [19] to decrease the noisy effect.

In [20], an adaptation process was proposed where the desired Kalman gain was achieved by choosing appropriate window length of sample and latency time. The gain was modified to normalize the prediction error autocorrelation. P. Li et al. proposed a new tracker based on UKF, and it employs a nonlinear model for measurement. The results showed better estimation of the state of system having same order as EKF [21]. Van Der Merwe [22] had extended EKF different algorithms based on derivative-less sampling of Gaussian statistics to the category of algorithms called as Sigma-Point Kalman Filters. Using this, the results obtained were better when compared with the results of EKF.

In [23], using UKF, an aerodynamic model is designed which uses six auxiliary states for computation with less intense, and the results are compared with EKF. Adelina Ioana Ilieş et al. [24] proposed a system to find the state of charge in a battery and the performance is compared using UKF and EKF.

In tracking of an object in different situations, the state of object can show abrupt changes. For these scenarios, Kalman can diverge while tracking, so optimization of high gain could provide better results. By introducing derivate gain feedback loop at Kalman gain, the divergence can be reduced where the loop can normalize the sudden variations and increases the gain. This loop does not diverge as it uses moderate derivation. This process is explained in the following section III.

3 Proposed Method

This section provides the proposed modifications in Kalman and also some concepts described which are useful for the discussions here. The below Eq. 1 is the nth order derivative of function 'f' in terms of x:

$$f^{(n)}(x) = \frac{d^n f}{dx^n} = \lim_{h\to 0} \frac{1}{h^n} \sum_{r=0}^{n} (-1)^r \binom{n}{r} f(x - rh) \tag{1}$$

Accordingly, fractional derivative of the Grunwald–Letnikov[10] for single variable function 'f' can be defined as in below Eq. 2:

$$D^{\alpha}_{G-L} f(x) = \lim_{h\to 0} \frac{1}{h^{\alpha}} \sum_{r=0}^{[\frac{x-a}{h}]} (-1)^r \binom{\alpha}{r} f(x - rh) \tag{2}$$

where
$\binom{\alpha}{r} = \frac{\Gamma(\alpha+1)}{\Gamma(r+1)\Gamma(\alpha-r+1)}$,
and Γ is gamma function.

Fig. 1 shows the block diagram of Kalman filter with a change at Kalman gain 'K,' where a loop f(KG) is fed back to the Kalman gain block.

The color intensity of image at point (x, y) can be defined in terms of a 2D function using two spatial coordinates x and y as $f(x, y)$. In the field of image processing, the Grunwald–Letnikov derivative [25] in 2D in the x-direction can be defined as follows:

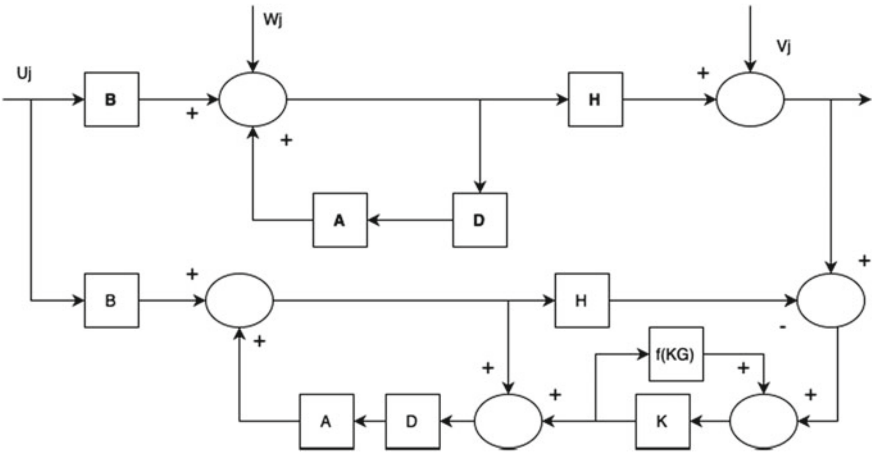


Fig. 1 Kalman filter block diagram

$$D^{\alpha}_{G-L} f_x(x, y) = f(x, y) - \alpha f(x-1, y) + \frac{\alpha(\alpha-1)}{2} f(x-2, y) \tag{3}$$

The derivation of function f in y direction can be expressed using *G–L* derivative. Hence, fractional derivative of *G–L* can be defined by Eq. 4:

$${}_m D^{\alpha}_{G-L} f(x, y) = \sqrt{({}_m D^{\alpha}_{G-L} f_x(x, y))^2 + ({}_m D^{\alpha}_{G-L} f_y(x, y))^2} \tag{4}$$

We express a modification of *G–L* derivative in both the directions as follows, the function M is the minimized of function f can be defined as Eq. 5:

$$M(x, y) = \frac{1}{s^n} \min\{f(x, y), f(x-1, y), f(x-2, y)\} \tag{5}$$

We obtain the below Y value shown in Eq. 6 and X value shown in Eq. 7 both from Eq. 5

$$Y(x, y) = M(x, y)\left(\frac{s - X(x, y)}{s}\right) \tag{6}$$

$$X(x, y) = \left| f(x, y) - \alpha f(x-1, y) + \frac{\alpha(\alpha-1)}{2} f(x-2, y) \right| \tag{7}$$

Using Eq. 7, we define the modified *G–L* in X direction given in Eq. 8

$${}_m D^{\alpha}_{G-L} f_x(x, y) = \frac{f(x, y) - \alpha f(x-1, y) + \frac{\alpha(\alpha-1)}{2} f(x-2, y)}{Y(x, y) + 1} \tag{8}$$

Kalman gain is modified using the Eq. (8)

$$KG_{\text{new}} = KG_g + \Delta^{\alpha} KG_{GL}, \tag{9}$$

where α is moderate fractional order Eq. (8), and $\Delta^{\alpha} KG_{GL}$ is modified fractional derivative of previous Kalman gain.

Equation 9 is the new moderate derivative Kalman gain. The modified Kalman gain KG_{new} having the terms, KG_g is previous Kalman gain, and $\Delta^{\alpha} KG_{GL}$ is calculation of mean fractional difference of previous Kalman gains.

Uj is input, *Wj* is noise and *Vj* is output noise at instant *K*, *D* is delay element, *A*, *H* and *B* is transition, measurement and control input matrix, respectively.

4 Results and Discussions

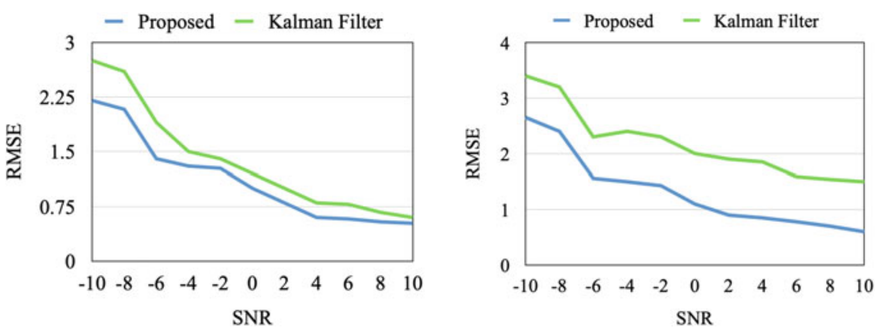
The proposed work performance validation is evaluated with both 1D and 2D data. 1D dataset includes square and sinusoidal waveforms. 2D dataset includes videos taken from online benchmark datasets [26] as well as data captured indoor and outdoor using two cameras, Canon Power Shot A4000 IS and second camera is SonyDSC-T70 with a standard tripod. We have implemented the proposed method and executed on the PC that has Intel(R) CoreTM i5 CPU and 6144 MB memory running MATLAB R2018a.

While applying Kalman filter for object tracking, various types of noise may corrupt the data. Measurement and process noises are the main noise which can be seen in Kalman filter. For evaluation of proposed method, measurement noise which is added at acquisition like sensor noise is added to signal with varying SNR. This signal to noise ratio ranging [−10, 10 dB], the noise added is to simulate the Gaussian noise with various values of variance and 0 mean. In Fig. 2a, b is shown the results of RMSE for square and sinusoidal noisy inputs, respectively. Equation 10 is used to calculate the RMSE values, and the results shows the proposed work has the lower values than Kalman filter.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} e_i^2} \tag{10}$$

Detection of the object is done using background subtraction. The masked object is tracked using the proposed method, a rectangular blue box in Figs. 3 and 4 shows the object being tracked in the frame. The proposed method is evaluated on the TB50 David3 and walking benchmark datasets shown in Fig. 3 and also on the secondary dataset captured indoor and outdoor where the object is a ball as shown in Fig. 4.

In Fig. 3a, b is the dataset of David3 and c, d is walking dataset from TB-50 sequences available online. The object is person in the sequences, and the person is tracked using the proposed method and the results are compared.



a) noisy square b) noisy sinusoidal

Fig. 2 Depict RMSE values for 1D inputs

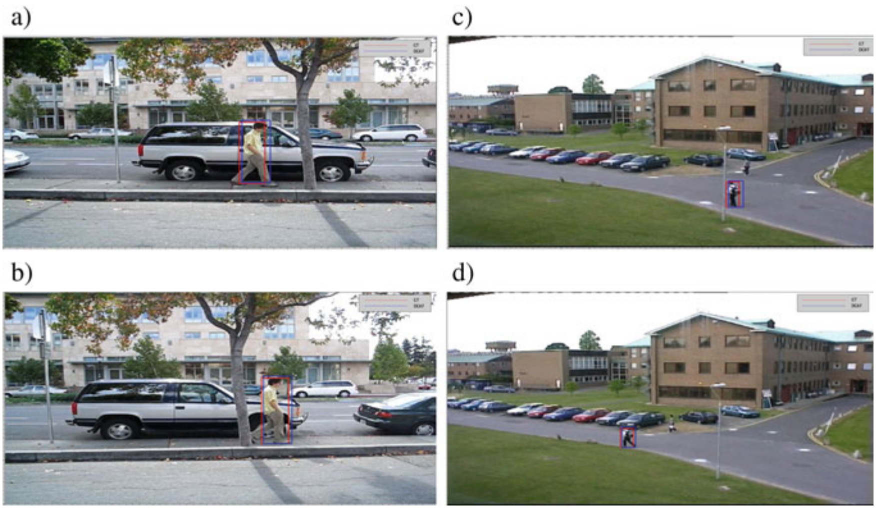

a)
b)
c)
d)

Fig. 3 **a**, **b** David3 and **c**, **d** walking from TB-50 dataset

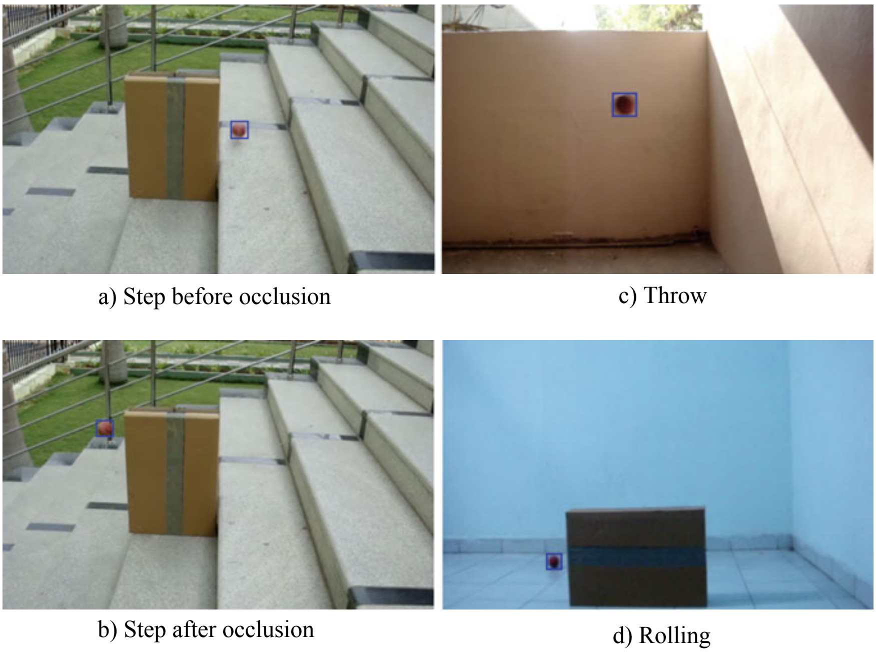

a) Step before occlusion
c) Throw
b) Step after occlusion
d) Rolling

Fig. 4 Outdoor ball thrown dataset

In Fig. 4a, b and d, the ball undergoes occlusion in different situations, and the ball is successfully detected and tracked before and after the complete occlusion. The performance of the proposed method is evaluated using RMSE for both the datasets.

4.1 Limitations

The proposed work is evaluated on few benchmark datasets of the object tracking where the size of object is large. To track the smaller object in a video sequence is the actual challenge.

5 Conclusion and Future Work

For tracking object, a novel method is proposed in this paper which uses moderate derivative gain Kalman filter. This modified gain is used as feedback to Kalman which is obtained by fractional derivation using modified G–L function of previous Kalman gain. For evaluation of proposed method derivative gain Kalman filter, RMSE metric is used which has shown better capability and improved by up to 12%. The results shown in this paper on 1D data on different waveforms, on benchmark data and also on secondary captured data indicate the proposed approach exhibits good improvements on comparison with Kalman filter. In the future, the proposed method can be evaluated on different dataset containing smaller objects which undergoes occlusion.

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