Target Image-Centroid Tracking and Fusion with UD Square-Root Information Filtering Algorithm

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Abstract: In this paper a new algorithm for image centroid tracking is proposed. It combines the merits of the factorised UD filtering (UDF) and square root information filtering (SRIF) algorithms for tracking as well as image-centroid fusion. Certain parametric studies and the performance metrics are evaluated for this centroid tracking-cum-fusion algorithm by utilizing synthetic images and implementation in MATLAB.

Index Terms : Image-centroid tracking algorithm (ICTA), UD filter(UDF), Square Root Information Filter (SRIF), percentage fit error(PFE), Root mean square Position error (RMSPE),Root mean square velocity error (RMSVE)

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1 INTRODUCTION

The target-image tracking is very important aspect of locating moving objects in real-time using some online and appropriate filtering algorithm. Any such filtering algorithm would utilize each image-frame that arrives at the processing centre and updates the location of the moving object. This process has two basic aspects: i) detection of the moving object/target in each image frame, and ii) tracking-cum-filtering of the detected object in each sequential image frame. In many such situations the acquired images would often be cluttered and noisy. This aspect might be due to the fact that the distance to the target from the sensing centres is relatively very large and weaken the signal which accentuate the noise relatively. The tracking problem involves processing of measurements obtained from the sensors, for a target of interest and producing at each time-step, an estimate of the target's current states. These states can be position, velocity and even acceleration. The uncertainties present, are modelled as additive random noise in the measurements and the corresponding uncertainties in the target states. Hence, the detection and tracking of moving object is a reasonably difficult problem in forward-looking infrared (FLIR) image sequences. The factors like low signal-to-noise (SNR) ratio in the acquired image/s, low contrast, presence of background clutter and false alarms and partial occlusion of the target image. This necessitates the use of efficient, accurate, and numerically stable filtering algorithms for image-centroid tracking and image fusion.

Different aspects on the target-image tracking are: correlation trackers for structured targets [1], image-centroid tracking using the conventional least square (LS) linear method for weld pool application [2], image-template matching application [3], square root algorithms for estimation of certain classes of large scale interconnected systems [4],[5], and cooperative tracking approach using the square root sigma point information filter. For the foregoing application areas the use of efficient and numerically stable centroid tracking algorithms is very limited. Several studies on square root type factorization filtering algorithms for state estimation and target tracking have been carried out, so far there has been no concrete evaluative study for the problem of image-centroid tracking [6],[7].

In this paper a new algorithm based on UDF and SRIF is proposed for centroid tracking-cum-fusion. Certain parametric study and performance results of image-centroid tracking and fusion using are presented. This new image-centroid tracking-cum-fusion algorithm has several merits and eliminates some demerits of the CTUDF and CTSRIF algorithms.

2 TARGET IMAGE-CENTROID TRACKING

Particle segmentation is used to identify the target (object of interest) from the background. Target detection in the received image sequences is done in two steps.

i)Grey level image is converted into binary image using lower and upper threshold limits of the target. Thresholds are identified using histogram of acquired images by the sensors.

ii)The detected pixels are grouped into clusters with nearest neighbour technique.

The centroid of a cluster (in the normalized way) can be determined using non-convolution method as

$$(x_c, y_c) = \frac{1}{\sum_{i=1}^{n}\sum_{j=1}^{m} Iij}\left[\sum_{i=1}^{n}\sum_{j=1}^{m} iI(i,j), \sum_{i=1}^{n}\sum_{j=1}^{m} jI(i,j)\right] \qquad (1)$$

In (1), Iij or I(i,j) is the intensity of the pixel with co-ordinates (i,j) and n, m are the dimensions of the cluster. The 'regionprops' function in MATLAB can be used to find this centroid of the target image.

Image tracking system needs target-image-centroid tracking algorithm with lower computational cost in filtering, efficient data association schemes, numerically accurate and stable algorithms. Square-root type algorithm is more suitable for such requirements. In a Centroid Tracking Algorithms (CTA), the determination of a moving object's position and velocity from a noisy time series of images captured by image sensors constitutes a statistical estimation problem, often represented as a linear problem. A suitable state space model for centroid representation is given by

$$x(k+1) = \phi x(k) + Gw(k) \tag{2}$$

$$z(k+1) = Hx(k) + \mathrm{v(k)} \tag{3}$$

In (2), and (3), x is a state vector that contains the image-centroid coordinates of a target, z is the vector of observables (image-centroid measurements), and w(.), and v(.) are process and measurement noises with zero means and covariance matrices Q, and Rm respectively; often these noise processes are assumed to be white and Gaussian, and their statistics are assumed known and given, as also other matrices in (2), and (3) are known.

3. UDF-SRIF ALGORITHM FOR CENTROID TRACKING

To reduce the effect of finite word length computing KF filter is implemented in a factorized form. Factorization implicitly preserves the symmetry and ensures the non-negativity of the covariance matrix P [8]. Such requirement would be very useful for real time implementation for the centroid tracking algorithm. One such widely used form of the algorithm is the UD filter (Kalman factorization filter). Here 'U' and 'D' are matrix factors of the covariance matrix P of the KF, where U is a unit upper triangular matrix (with 1's on diagonal elements) and D is a diagonal matrix. The major advantage from UD filter comes from the fact that the square-root type algorithm which processes square roots of the covariance matrices essentially use half the word length normally required by the conventional KFs. Information filtering (IF) is the more direct way of dealing with the target tracking and multi sensor data fusion problems than the conventional covariance based KF. However, the IF is more sensitive to computer round-off and quantization errors, like the KF. This would degrade the tracking performance of the filter. This is crucial if the algorithm is used for target tracking in a real time-online environment. The square root information filter (SRIF) offers a solution to this problem of numerical accuracy and stability of the filtering algorithm[9].

Thus, by capturing the merits of UDF [7] and SRIF algorithms[9][10], a new filtering algorithm UDSRIF using the time propagation part of the UD filter and the measurement update part of the SRIF filter is proposed and implemented. It can be used for image filtering of 1D image strings, converted from a 2D image and for fusing of image-centroids, of any number, at measurement level. All initial values of P, F, G, Q, H, Rm are similar to that taken in the above filter implementations and P, F are n x n matrices. H and Rm are individually composite matrices. Rm is the covariance matrix of the measurement noise. Since, these values are known, steps for designing this new filter are as follows:

Step 0: Initial part with initial conditions

$$P(0) = \{x_f(0) - \hat{x}_f(0)\}\{x_f(0) - \hat{x}_f(0)\}^T \tag{4}$$

Now, take only diagonal elements of P(0) and assign to the

D=diag{P}; U=eye(n,n) (5)

Thus, the initial UD factors of P(0) are known; P(0)→ UDUT, approximately, since we have neglected the off-diagonal elements of P(0). Now, we need initial R(0) matrix as the square root of the information matrix, and it is given as

$$R(0)=U^{-T}D^{-1/2} \tag{6}$$

For simplicity $R_f(0)$ is denoted as R, x_f^(0) is denoted as x(0), y_f^(0) as y(0) in the following.

Then, we get

y(0)=R(0)*x(0) (7)

Thus, at this stage R, and y as required for the time propagation of the state estimate are available.

Step 1: Time propagation part of CTUDSRIF filter

The time propagated information state is obtained as

yf(new)=R*F*inv(R)*y_f(previous) (8)

In (8), use R from (6), and y from (7) for the start; then, in the next cycle these will be available from the output of the measurement/data part.

Then, form the following matrices using the values from (2), and known F, G, and Q:

V=[F*U G]; Dc=diag[D,Q] (9)

This means that the previous U, D factors are to be augmented with the new information i.e. by using F, G and Q. Then, call the time propagation part (UDTP) of the normal UD filter with the inputs as in (6). Next, obtain the R matrix needed in the measurement/data update part of SRIF by using the updated U, D factors obtained by the time propagation of (9):

$$R=U^{-T}D^{-1/2} \qquad (10)$$

In this R matrix, the effects of F, G and Q are included by virtue of (9). Hence, matrix R is time propagated factor. So, at this stage we have R from (10), and y from (8), i.e. the information pair for us to go to SRIF measurement/data update part.

Step 2: Measurement/data update part of the CTUDSRIF filter

Since, now, R, y are available from the output of the time propagation part[10], form the composite matrix

$$T(k)\begin{bmatrix}\tilde{R}(k-1) & \tilde{\hat{y}}\ (k-1)\\ H & z(k)\end{bmatrix}=\begin{bmatrix}\hat{R}(k) & \hat{y}\,(k)\\ 0 & e(k)\end{bmatrix} \qquad (11)$$

From (11), we get the estimated $\hat{R}$ and $\hat{y}$ .Since, now updated y is available, the Kalman gain is not needed. These $\hat{R}$ and $\hat{y}$ are used in equation (8). At this stage, since we need x (for each time step), we can use

$$\hat{x} = inv(\hat{R})\ \hat{y} \qquad (12)$$

The U, D factors required in Step 1, in (10) are obtained as follows:

i. covariance matrix P is formulated as

$$P = inv(R^2) \quad ; \qquad (13)$$

ii.With P as in (13), call the following subroutine, assuming P as (n x n) matrix:

```
for j=n:2;
D(j)=P(j,j); a=1./D(j);
for k=1:j-1;
b=P(k,j); U(k,j)=a*b;
for i=1:k;
P(i,k)=P(i,k)-b*U(i,j);                  (14)
end
end
j=j-1;
end
D(1)=P(1,1);
```

Since, now the new U, D factors are available from (14), substitute in Step 1, and repeat the cycle.

The merits of the proposed filtering algorithm, UDSRIF are:

In the time propagation part, it does not need inversion of the state transition matrix as required in the SRIF.

It does not need specification of the information state yw, related to the process noise, as is required in the case of SRIF, because it uses the square root of the information matrix formed from the time propagated U-D factors of the composite matrix.

In the measurement/data update part, it does not need the computation of the Kalman gain, since, now it uses the measurement/data update part of the SRIF, and hence, it is the gain free filter; the main reason is that the information state yf is now directly available from the orthogonal transformation, and the covariance state if required can be easily computed.

It is the hybrid algorithm based on the U-D factors and SRIF, a combination of the covariance and the information filter (SRIF).

It retains the merits of the two filters: a) UD filter, and b) SRIF; and the new algorithm eliminates some demerits of both the filters.

4. TARGET IMAGE FUSION USING UDSRIF ALGORITHM

A system with two sensors H1 and H2, their measurements can be fused at data level. The least square solution is obtained by applying the method of orthogonal transformation. This method of solving is likely to be less susceptible to computer round off errors. This process results in the state estimate of the two sensor data fused.

$$T(k)\begin{bmatrix}\tilde{R}_f(k-1) & \tilde{y}_f(k-1)\\ H_1(k) & z_1(k)\\ H_2(k) & z_2(k)\end{bmatrix}=\begin{bmatrix}\hat{R}_f(k) & \hat{y}_f(k)\\ 0 & e(k)\end{bmatrix};\ k=1,..., \qquad (15)$$

Here $\hat{y}$ f is the information state. The updated Rf and yf (fused only). Since, now yf is available, we do not need the Kalman gain. These Rf and yf are used in equation (8). At this stage, since we need xf (for each time step), we can use

$$xf = inv(Rf)\ yf \qquad (16)$$

5. EVALUATION OF THE ALGORITHMS

A set of 50 synthetic images that represents target environment is considered for the evaluation of the above new algorithm. For centroid computation formula (1) is used in MATLAB. Each image frame is of the dimension 64 x 64 with the target size fixed with a dimension of 9 x 9.The image constitute an object and its surrounding along with noise that is uniformly distributed. This noise is assumed to be Gaussian with zero mean and covariance σ2. Intensity of the grey level image vary in the range 0 to 255. Target intensity value and its background have a certain mean and variance. Target image intensity has a mean and std (100, 10) while Target background intensity has a mean and STD (50, 50) (can be varied based on the study; TGBSTD). The measured centroid of the given synthetic image are determined. The other input parameters for the tracking algorithm are:

Measurement model/matrix: H = [1 0 0 0; 0 0 1 0];

State transition matrix, ‘phi’: [1 T 0 0; 0 1 0 0; 0 0 1 T; 0 0 0 1];
Measurement noise variance: Rm=0.5 (could be varied based on the study);
Process noise coefficient matrix: G = [$T^2/2$ 0; T 0; 0 $T^2/2$; 0 T];
Process noise co-variance: Q = 0.00001 (can be varied).
Track scan (sampling interval/period, T): 1 sec.
The initial states {x(0),y(0)}=(10,10), with constant initial velocity of 1 m/s in both the coordinates;
The performance metrics Percentage fit error (PFE) and Root mean Square Error with position (RMSPE) and velocity (RMSVE) are evaluated as follows:
PFE=Percentage Fit error

=|state or measurement error|*100/ |true signal| (17)

$$\text{RMSPE} = \sqrt{(\text{mean}(\text{xperr2} + \text{yperr2}))} \quad (18)$$

Similarly for the velocity state variable RMSVE is also calculated.

5.1 TARGET IMAGE CENTROID TRACKING USING CTUDSRIF

Table 1 gives the performance metrics for different target image noise STDs (TGNSTDs) for the filter. It is seen that there is not much of trend of the performance metrics with respect to the STDS. However, it was established earlier that CTUDSRIF performed somewhat better than CTKF in a similar centroid tracking task [9], and that the position and velocity state errors (time histories) were found to lie within their theoretical bounds as predicted by the CTUDF.

Table 1: Performance metrics of image-centroid tracking algorithm using CTUDSRIF

Parameter (*) Metrics (%fit errors)	TGNSTD		
	1	5	9
PFEx	0.2255	0.1961	0.1989
PFEy	0.7927	0.5986	0.4782
RMSPE	0.3158	0.2414	0.1985
RMSVE	0.0290	0.0315	0.0316

(*: Q=0.00001; TGBSTD=50)

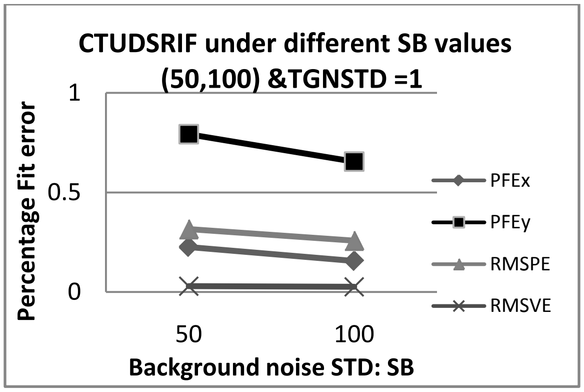

Figure 1 Tracking performance with UDSRIF with target noise std as 1 and background std of 50 &100

5.2 TARGET IMAGE CENTROID TRACKING AND FUSION USING CTUDSRIF

The satisfactory tracking performance has been established. Applying CTUDSRIF algorithm for image-centroid fusion by direct measurement level fusion, MLF is carried out. The target background is set at (mean=50, std=50, 100). Two images are considered with target image set as (mean=100, std=10), and with variation in the target noise standard deviation as 1 (image 1, CTUDSRIF1), and 5 (image 2, CTUDSRIF2); these images are considered two-at-a-time for centroid tracking-cum-fusion. The performance metrics are shown in Table 2. Two of such results are plotted in Figure 1.

Table 2 Performance metrics of image-centroid tracking-cum-fusion using CTUDSRIF

Filter	Target noise STD 1 & 5 (SB=50)				Target noise STD 1 & 5 (SB=100)			
	PFEx	PFEy	RMSPE	RMSVE	PFEx	PFEy	RMSPE	RMSVE
CTUDSRIF1 (std=1)	0.2255	0.7927	0.3158	0.0290	0.1554	0.6551	0.2580	0.0261
CTUDSRIF2 (std=5)	0.1961	0.5986	0.2414	0.0315	0.1596	0.4354	0.1777	0.0277
CTUDSRIFMLF	0.2226	0.6459	0.2616	0.0315	0.1644	0.5933	0.2357	0.0277

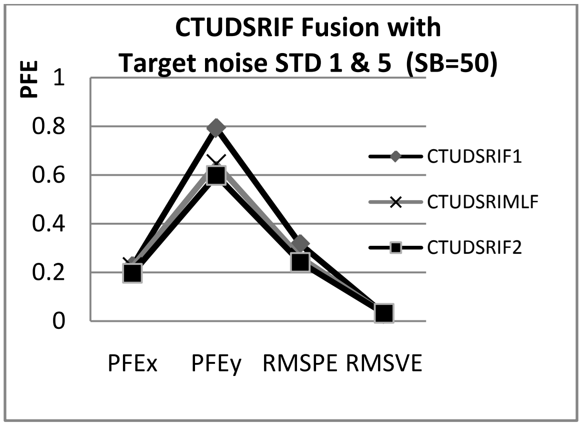

Figure 2 Fusion performance with CTUDSRIF with target noise std as 1 & 5 with Background std 50.

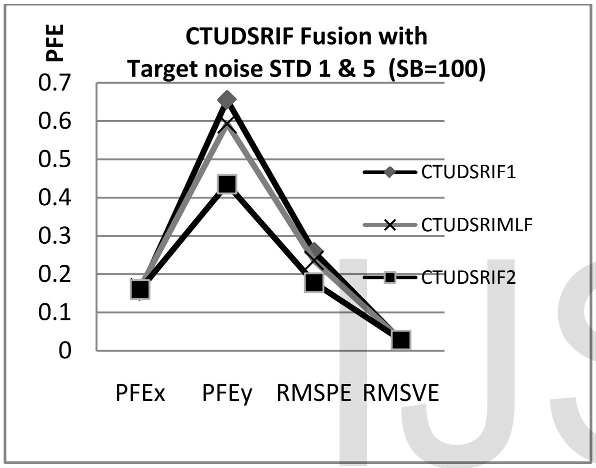

Figure 3 Fusion performance with CTUDSRIF with target noise std as 1 & 5 background noise std 100.

The target image fusion results with tgnstd 5 & 9 have been obtained for fusion of centroid of two images, using CTUDSRIF. The trends of these results were found to be similar to those in Table 2, Figure 1 ,Figure 2and Figure 3.

6.CONCLUSION

The image-centroid tracking and fusion using square root type filtering algorithms CTUDSRIF are proposed. The performance of this new filter is evaluated with synthetic images generated using MATLAB. Based on the performance metrics and plots, it has been found that this algorithm gives satisfactory performance in tracking and fusion. The performance of the square root type filtering algorithm CTUDSRIF has remained nearly robust despite there are certain, and small trends in the performance metrics with respect to target noise variance and background noise variance. The proposed new algorithm with several merits can be considered as a viable alternative for online-real time applications for variety of image/target tracking and multi-sensor data fusion tasks.

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