An Imaging Target Tracking Software for a Precision Guided Missile Application

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Abstract – *Detection and tracking are the critical problems of computer vision. It is essential pre-processing for other algorithms. In this paper, we present an efficient and robust detection and tracking algorithm which is based on morphological operation and dynamic filtering (HPDAF: Highest Probability Data Association Filter). In airborne IR imagery, objects are usually obscure and too small to recognize their shape. Therefore dynamic filtering approach can be the best solution for tracking. Several experimental results show that our proposed algorithm efficiently detects and tracks the object regardless of size and their shape consistency. Temporarily occluded targets can be handled track-termination and re-detect sequence of the proposed algorithm.*

Keywords: Detection, Tracking, Filter, HPDAF, IR imagery, Data association

1 Introduction

Image target detection and tracking have attracted many researchers to find more practical and effective solutions. One of the remarkable approach is proposed in [1]. Comaniciu *et al.* classified the problems into two major components, target representation and localization, filtering and data association. In [2], scale invariant feature transform (SIFT) is used to represent the target and subsequently used mean shift tracker. But SIFT descriptor contain too detailed description for maintaining scale invariant features to implement in real-time applications. Moreover, such kind of detector is based on region not point. That means their pixel-localization accuracy is relatively lower than point detectors. GPU based implementation [3] has been proposed for real-time applications. However, GPU is a graphic device dependent code. In other words, it is neither general nor cheap for practical use. The object appearance modeling is very vulnerable due to the low resolution and energy saturation in airborne IR imagery. From this point of view, a *track before detect* method is appropriate for our purpose. It is practical example of filtering and data association. Traditional kalman filter assumes that state transition and noise can be represented by gaussian distribution. To overcome this weakness, particle filtering has been extensively studied in wide field of computer vision. Particle filtering utilizes fundamentally a non-parametric filter and it gives a tractable solution to non-gaussian systems. However it heavily depends on proposal distribution and may lose historical information while taking resampling [4].

Some other researchers tried to find out alternative solutions to deal with non-gaussian systems. An example is the unscented kalman filter (UKF) [5]. Julier *et al.* introduced that extended kalman filter (EKF) is a just crude generalization and the UKF is accurate to second-order taylor expansion of the transition function. It uses the original non-linear state transition function to transform sampled *sigma point* with compared to the EKF which uses first-order of taylor expansion to approximate non-linear functions. The UKF also have a weakness due to numerical unstability to obtain matrix square root $\sqrt{P}$, while decomposing covariance matrix, if matrix P may not be positive-semi definite. In [6], singular value decomposition (SVD) is used to find out numerically stable solution.

In a real environment, target signal can often be attenuated due to the spurious clutter background. For this matter, data association plays an important role in cluttered environment. Data association approaches such as probabilistic data association(PDA), joint PDA(JPDA) [7], and multiple hypothesis tracking(MHT) [8] consider all possible events. Therefore, it causes heavy computational complexity especially for multiple-target tracking.

In this paper, we present the verification results of applying the algorithms to a guided missile application. We use the morphological operation to detect the target and the HPDAF to track it in airborne IR imagery. These algorithms are inspected in two points of view; 'How these are efficient?' and 'How these are robust?' The paper is organized as follows: Section 2 explain fast and efficient target detection algorithm we use. Then we discuss a novel filtering algorithm HPDAF in Section 3. Several experimental results are presented in Section 4. Finally, we conclude and discuss future works in Section 5.

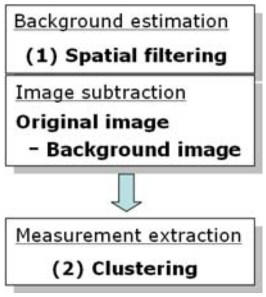


Figure 1: Block diagram of target detection

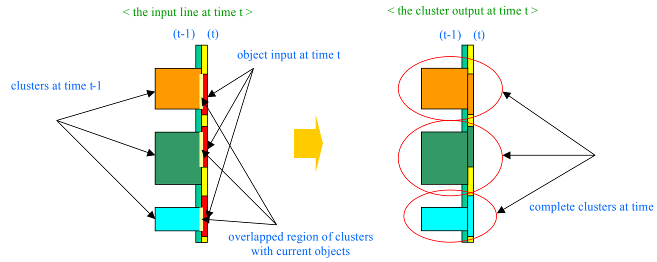


Figure 2: 1D line clustering algorithm

2 Target detection

Detecting a target in airborne IR imagery is challenging issue. In related works, Gabor filter [9] and target modeling [10] is used for detect the target. In this section, we describe the method that detects the target in airborne IR imagery even though it is very small (approximately two or three pixels at first).

Target detection can be classified into two parts [1]: (1) Spatial filtering that makes the target easily be discriminated and (2) Clustering that makes valuable information from filtered image to use as measurement inputs during dynamic filtering process, which will be discussed in detail in the next section.

Spatial filtering is essential pre-processing algorithm for discriminate the target in the image. Usually, IR imagery contains a lot of noise due to low signal-to-noise ratios(SNR) in cluttered environments. Efficient spatial filtering algorithm is required for detecting a real target. For this reason, we carefully examine several spatial filtering algorithms to choose adequate one from mean, median, morphological filters.

Clustering can be considered as a unsupervised learning problem and it deals with finding a structure in a collection of unlabeled data. In this paper, however, clustering extracts the measurement from pre-filtered images. If we already know the number of clusters and approximate center position of clusters, several clustering algorithms can be useful including K-means clustering algorithm [11]. 1D line clustering algorithm is good for our purpose because we assume that no prior knowledge is given. Detailed descriptions of algorithms are given in the next section.

2.1 Spatial filter

Mean or median filter can be considered as candidates for treating noisy images. However, they are appropriate for coping with high frequency noise not detecting salient objects in the images. Morphological filters (*i.e.* erosion, dilation, opening, closing and top-hat)[12] successfully discriminate the target from cluttered background in IR images. We adaptively apply these filters in accordance with the size of target while the camera is approaching to the target. Morphological filtering operation can be defined as follows:

$$(f \ominus b)(x,y) = \min f(x+x', y+y') | (x',y') \in D_b \quad (1)$$

$$(f \oplus b)(x,y) = \max f(x-x', y-y') | (x',y') \in D_b \quad (2)$$

where D_b is the region of kernel, $f(x,y)$ is pixel value at the image location of x and y. $\ominus$ and $\oplus$ is defined as operator, morphology erosion and dilation, respectively. The combination of these two operations also defined as follows:

$$A \circ B = (A \ominus B) \oplus B \quad (3)$$

$$A \bullet B = (A \oplus B) \ominus B \quad (4)$$

$$T_w(f) = f - f \circ B \quad (5)$$

Equation (3), (4), (5) are morphology open, closing and white top-hat, respectively.

2.2 Clustering algorithm

As we mentioned above, to make the valuable information (*i.e.* measurement inputs) clustering algorithm is crucial part of target detection. Not only is it important, but also have the most of computational burden. So, obviously, computation time of clustering is main criterion for real-time application. Our clustering method is carefully designed for real-time application. Let us assume that image data will be transferred to clustering module line by line. It should be calculated by line by line, so that embedded system hardware perform to the best of its ability. 1D line clustering algorithm can be implemented as shown in Fig. 2. It shows how the clustering algorithm works when a line data is injected.

3 Dynamic filtering: HPDAF(Highest Probability Data Association Filter)

Data association is essential for accurate target tracking in a cluttered environment. The simplest approach of existing data association is to select one validated measurement that is closest to the predicted measurement or has the strongest signal amplitude information around predicted measurement and the selected one is used as if it were from the target, what is called nearest neighbor (NN) or strongest neighbor (SN) data association. The nearest neighbor filter (NNF)[13] and the strongest neighbor filter (SNF)[14] are known for simplicity and easiness of implementation. However, tracking performance of each filter algorithm in a cluttered environment is incomplete because each filter may conclude unconditionally that the selected measurement is target-originated in spite of clutter. To overcome such defects, the probabilistic nearest neighbor filter (PNNF)[15], probabilistic strongest neighbor filter (PSNF)[16], PNNF with m validated measurements (PNNF-m)[17], and PSNF with m validated measurements (PSNF-m)[18] are proposed. Moreover, The PNNF-m and PSNF-m directly utilize the number of validated measurements so that they have reliable performance even for the case of unknown clutter density. The probabilistic data association filter (PDAF)[7] and the PDAF with amplitude information (PDAF-AI)[19] are known to have superior tracking performance at a cost of high computational complexity. The most probable data association (MPDA)[20] and highest probability data association (HPDA)[21] algorithm in this paper utilizes both distance and amplitude information as the PDA-AI algorithm, but MPDA and HPDA algorithms do not update information in all measurements as done in the PDA algorithm. Therefore, MPDA and HPDA algorithms could reduce computational complexity.

The validation gate used is the ellipsoid:

$$R_\gamma(k) = \{\nu_k; \nu_k^T S_k^{-1} \nu_k \leq \gamma\}, \tag{6}$$

where $\nu_k = z_k - \bar{z}_k$ is a zero-mean Gaussian residual with covariance of S_k for the true measurement z_k and the predicted measurement $\bar{z}_k$, and $\sqrt{\gamma}$ is called the gate size. The volume of the n-dimensional gate $R_\gamma(k)$ satisfies

$$V_G = C_n |S_k|^{\frac{1}{2}} \gamma^{\frac{n}{2}} \tag{7}$$

where the closed form for C_n is $\frac{\pi^{\frac{n}{2}}}{\Gamma(\frac{n}{2}+1)}$ such that c_1, c_2, c_3 are $2, \pi, \frac{4}{3}\pi$ etc. The validated measurements consist of n-dimensional location information z and signal amplitude information a. The following assumptions are used in this paper.

Assumption 1 The true target signal amplitude is the magnitude-square output of a matched filter, so that the signal is χ^2-distributed with probability density function (pdf)

$$f_1(a) = \frac{1}{1+\rho} e^{-\frac{a}{1+\rho}}, \tag{8}$$

where ρ is the expected signal-to-noise ratio. The clutter signal amplitude satisfies

$$f_0(a) = e^{-a}. \tag{9}$$

Assumption 2 The number of validated true measurements is denoted by m^T, and m^T is at most 1. Prior probability that $m^T = 1$ is $P(m^T = 1) = P_D P_G$ where P_D is the probability of target detection indicating that the target signal amplitude exceeds a threshold τ; and P_G is the probability that the target falls inside the validation gate. P_D satisfies $P_D = e^{-\frac{\tau}{1+\rho}}$ from A1), and the probability that the false measurement signal exceeds the threshold τ is $P_{fa} = e^{-\tau}$.

Assumption 3 The number of validated false measurements in the validation gate, denoted by m^F, is Poisson distributed with a spatial density λ such that

$$\mu_F(m) = P(m^F = m) = \frac{(\lambda V_G)^m}{m!} e^{-\lambda V_G}. \tag{10}$$

Assumption 4 The state prediction error $\bar{e}_k = x_k - \bar{x}_k$ for any given time k is a zero-mean Gaussian process with a covariance $\bar{P}_k$ such as $\bar{e}_k \sim N(\bar{e}_k; 0, \bar{P}_k)$.

Assumption 5 The validated false measurements at any time are i.i.d. uniformly distributed over the gate.

Assumption 6 The location and amplitude of a validated false measurement are independent of the true measurement at any time and other validated false measurements at any other time.

Assumption 7 Measurement amplitude of the target or clutter is independent of the location.

Assumption 8 The target is existing and can be detectable.

When tracking a target in a cluttered environment, a set of m measurements $z_k = \{z_k^1, z_k^2, ..., z_k^m\}$ may fall inside the validation gate at the kth time step. Existing probabilistic data association (PDA) is an all-neighbor association method that accounts for the probability that each measurement in the validation gate is target-originated. PDA utilizes a weighted average of all the measurements to update the track state. Nearest neighbor association selects a measurement which is located with the smallest normalized distance squared while strongest neighbor association selects a measurement with the strongest signal amplitude. Highest probability data association (HPDA) proposed in this paper selects a measurement with the highest probability that it is target-originated and uses it to update the target state so that it makes one-to-one assignments of measurement to track. The concept is similar to the probabilistic nearest neighbor filter (PNNF) and the probabilistic strongest neighbor filter (PSNF) which account for possibility that the selected measurement could be originated from clutter. The probability is evaluated individually for each measurement in consideration of the number of measurements. There are at most two events for each measurement $z_k^l, l = 1, 2, ..., m$ if $m > 0$,

$$M_T^l = \{z_k^l \text{ is target-originated}\}$$
$$M_F^l = \{z_k^l \text{ is not target-originated}\}.$$

The m measurements are lined up in the order of signal strength in such a way that the strongest measurement is z_k^1, the second strongest measurement is z_k^2, and so on. In HPDA for image target tracking, signal amplitude information a is not directly used. It is used only for ordering the measurements. We employed this scheme because it may provide robustness in tracking performance as the probabilistic distributions of signal in real and clutter environments may be different from Assumption 1. The probability density function (pdf) about the event that the number of validated measurements is m and the lth measurement of z_k is target-originated satisfies

$$P(M_T^l, m) = \begin{cases} P_D P_G \gamma(l) \bar{P}_A(m) \\ \mu_F(m-1), & 1 \le l \le m-1 \\ P_D P_G \frac{1}{m+(m-1)\rho} \\ \mu_F(m-1), & l = m \end{cases} \quad (11)$$

Similarly, the pdf of the event that the lth measurement among the m validated measurements is not target-originated becomes

$$P(M_F^l, m) = \begin{cases} (1 - P_D P_G)\mu_F(m) + \\ P_D P_G (1 - \gamma(l)\bar{P}_A(m)) \\ \mu_F(m-1) & , 1 \le l \le m-1 \\ (1 - P_D P_G)\mu_F(m) + \\ P_D P_G (1 - \frac{1}{m+(m-1)\rho}) \\ \mu_F(m-1) & , l = m \end{cases} \quad (12)$$

where $\bar{P}_A(m)$ is the probability that the validated target amplitude a is the strongest among the m validated measurements and $\bar{P}_A(m)$ satisfies

$$\bar{P}_A(m) = 1 + \sum_{i=1}^{m-1} (-1)^i C_i^{m-1} \frac{1}{(i+1) + i\rho} \quad (13)$$

and $\gamma(l)$ is the probability of the validated target order among the m validated measurements.

$$\gamma(l) = \begin{cases} 1 & , l = 1 \\ \dfrac{\prod_{j=1}^{l-1} \left[(j-1)(1+\rho) + 1\right]}{(l-1)!(1+\rho)^{l-1}} & , 2 \le l \le m-1 \end{cases} \quad (14)$$

The association probability is obtained as

$$\begin{aligned} \beta_k^l &= \frac{f(D^l, M_T^l, m_k)}{f(D^l, M_T^l, m_k) + f(D^l, M_F^l, m_k)} \\ &\quad , l = 1, 2, \ldots, m \\ &= \frac{\frac{N(D^l)}{P_G} P(M_T^l, m_k)}{\frac{N(D^l)}{P_G} P(M_T^l, m_k) + V_G^{-1} P(M_F^l, m_k)} \end{aligned} \quad (15)$$

The association probability β_k^l is obtained by the pdf about the D^l which is the normalized distance of lth measurement, the event that the lth measurement of z_k is target-originated and the number of validated measurements is m. The measurement with the highest probability β_k^s is selected as target-originated and the measurement z_k^s is used in the weight update step. β_k^s is evaluated as

$$\beta_k^s = \max\{\beta_k^l, l \in [1, m]\} \quad (16)$$

The HPDA algorithm is summarized as Table 1. The case of M_0 is that the measurement is not exist in validation gate

Table 1: HPDA algorithm

Prediction step

$$\bar{x}_k = \Phi_k \hat{x}_{k-1}$$
$$\bar{P}_k = \Phi_k \hat{P}_{k-1} \Phi_k^T + Q_k$$

Update step

(1) For the case of M_0

$$\hat{x}_k = \bar{x}$$
$$\hat{P}_k = \bar{P}_k^0 = \bar{P}_k + \frac{P_D P_G (1 - C_{\tau G})}{1 - P_D P_G} K_k S_k K_k^T$$

(2) For the case of $\bar{M}_0$

$$\begin{aligned} \hat{x}_k &= \bar{x} + \beta_k^s K_k \nu_k \\ \hat{P}_k &= (1 - \beta_k^s)\bar{P}_{k,M_F} + \beta_k^s (\bar{P}_k - K_k S_k K_k^T) \\ &\quad + \beta_k^s (1 - \beta_k^s) K_k \nu_k \nu_k^T K_k^T, \end{aligned}$$

where

$$\begin{aligned} \bar{P}_{k,M_F} &= \bar{P}_k - K_k S_k K_k^T + \alpha K_k S_k K_k^T \\ \nu_k &= z_k - H_k \bar{x}_k \end{aligned}$$

$$\alpha = \begin{cases} \frac{(1-P_D P_G C_{\tau g})\mu_F(m) + P_D P_G C_{\tau g}(1-\bar{P}_A)\mu_F(m-1)}{(1-P_D P_G)\mu_F(m) + P_D P_G (1-\bar{P}_A)\mu_F(m-1)} \\ , s = 1 \\ \frac{(1-P_D P_G C_{\tau g})\mu_F(m) + P_D P_G C_{\tau g}(1-\gamma(s,m))\mu_F(m-1)}{(1-P_D P_G)\mu_F(m) + P_D P_G (1-\gamma(s,m))\mu_F(m-1)} \\ , 2 \le s \le m-1 \\ \frac{(1-P_D P_G C_{\tau g})\mu_F(m) + P_D P_G C_{\tau g}(1-\frac{1}{m+(m-1)\rho})\mu_F(m-1)}{(1-P_D P_G)\mu_F(m) + P_D P_G (1-\frac{1}{m+(m-1)\rho})\mu_F(m-1)} \\ , s = m \end{cases}$$

$$\gamma(s, m) = \frac{\prod_{j=1}^{l-1} \left[(j-1)(1+\rho) + 1\right]}{(s-1)!(1+\rho)^{s-1}} \bar{P}_A(m)$$

and the case of $\bar{M}_0$ is that one or more measurements are exist in validation gate.

Track initiation along with data association is essential for automatic target detection and robust target tracking. Track initiation is bound up with data association. Existing track initiation method is Integrated Probabilistic Data Association (IPDA)[22] algorithm proposed by Darko Musicki. Track initiation method based on HPDA, like IPDA algorithm, shall model the track existence as a Markov process and examine two possible case about the track existence(track exists or does not exist).

$$H_k = \{\text{Target exists at scan k}\}$$
$$\bar{H}_k = \{\text{Target does not exist at scan k}\}$$
$$\prod = \begin{bmatrix} \prod_{11} & \prod_{12} \\ \prod_{21} & \prod_{22} \end{bmatrix} = \begin{bmatrix} P(H_k|H_{k-1}) & P(H_k|\bar{H}_{k-1}) \\ P(\bar{H}_k|H_{k-1}) & P(\bar{H}_k|\bar{H}_{k-1}) \end{bmatrix}$$

Which we will call Markov chain one, models the probability that the track exists at scan k as probability $P(H_k|Z_k)$ and the probability that the track does not exist at scan k as $1 - P(H_k|Z_k)$. This model is useful in the track initiation phase and prior probability of the track existence given by

$$\begin{aligned} P(H_k|Z_{k-1}) &= P(H_k|H_{k-1})P(H_{k-1}|Z_{k-1}) \\ &+ P(H_k|\bar{H}_{k-1})P(\bar{H}_{k-1}|Z_{k-1}) \\ &= P(H_k|H_{k-1})P(H_{k-1}|Z_{k-1}) \\ &+ P(H_k|\bar{H}_{k-1})[1 - P(H_{k-1}|Z_{k-1})] \end{aligned} \tag{17}$$

Posterior probability of the track existence by is obtained as

$$\begin{aligned} &P(H_k|Z_k, m_k) = P(H_k, M_T^l|Z_k, m_k) + P(H_k, M_F^l|Z_k, m_k) \\ &= \tilde{c}^{-1} \begin{bmatrix} f(z_k^l|M_T^l, m_k, H_k, Z_{k-1})P(M_T^l, m_k|H_k) \\ +f(z_k^l|M_F^l, m_k, H_k, Z_{k-1}P(M_F^l, m_k|H_k) \end{bmatrix} \\ &P(H_k|Z_{k-1}) \\ &= \tilde{c}^{-1} \begin{bmatrix} f(z_k^l|M_T^l, m_k, Z_{k-1})P(M_T^l, m_k) \\ +f(z_k^l|M_F^l, m_k, Z_{k-1}P(M_F^l, m_k) \end{bmatrix} P(H_k|Z_{k-1}) \end{aligned} \tag{18}$$

Finally, track existence probability which called track score is evaluated as

$$\begin{aligned} \mu_k &= \frac{(1-\delta_k)\bar{\mu}_k}{1-\delta_k\bar{\mu}_k} \\ \bar{\mu}_k &= P(H_k|Z_{k-1}) = \pi_{11}\mu_{k-1} + \pi_{12}(1-\mu_{k-1}), \end{aligned} \tag{19}$$

where

$$\begin{aligned} \delta_k &= \begin{cases} P_D P_G & , m = 0 \\ P_D P_G - \frac{m}{\lambda V_G} P_D P_G [1 - \bar{P}_A(l,m)] & \\ -\frac{m}{\lambda} P_D N(z_k^l) \bar{P}_A(l,m) & , m > 0 \end{cases} \\ \bar{P}_A(l,m) &= \begin{cases} \gamma(l)\bar{P}_A(m) & , 1 \leq l \leq m-1 \\ \frac{1}{m+(m+1)\rho} & , l = m \end{cases} \end{aligned} \tag{20}$$

The track management is attended by the track score in each track. The track with enough large track score is confirmed that the track is threatening target. On the other hands, the track with small track score is removed. The recursive formula of track initiation method is updated from scan to scan and the track score is used as a measure of track quality for track initiation, confirmation, and termination.

(a) (b)

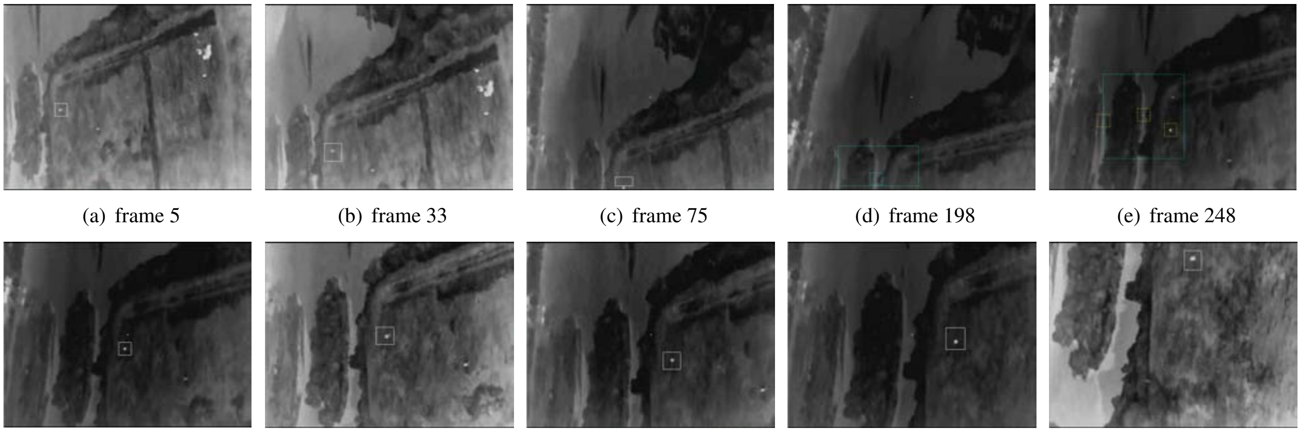
Figure 3: Two *ground test* sites. Distance to the target is about 1Km on (a) and 500m on (b).

4 Experimental results

At first, we examine our proposed algorithm on the top of the roof (9th floor). We called this type of preliminary experiment *ground test*. This type of test is composed of a *fixed camera* and a *moving target*. Fig. 3 shows taken image sequences from the observed place. We took several image sequence from the place.

Initial search area is manually designated as shown in Fig. 5, 6 which depicted as green rectangular region. Candidate target is chosen from the initial search area which was spatial filtered and clustered as described in section 2. The number of them is limited up to 10 by order of its intensity. Probability value β that is to be the target is calculated from them using eq. (15). Among them, most probable one is finally selected as a target to be tracked. White rectangle shows that continuous target tracking result. Size of the rectangle is corresponds to its covariance. The larger rectangle represent that its confidence is relatively lower than smaller one. Our proposed method successfully track the target that we want to. In Fig. 6, Although, the target is almost occluded by bushes at 1801st frame, HPDAF robustly track the target.

Secondly, airborne imagery is used for verify robustness of our algorithm. We called this type of experiment CFT(*captive flight test*). This type of test is composed of a *moving camera* and a *moving target*. Moreover, we cannot expect similar background clutter every time we try. This kind of severe experimental condition verifies effectiveness and robustness of our proposed algorithm. In Fig. 4, tracking result using airborne IR imagery is shown. After five frame sequences are passed from initial frame, the target is detected and tracked as shown in Fig. 4(a). Because an airborne camera agilely moves and changes its viewpoint, the target is apt to be out of FOV as shown in Fig. 4(d). In such a situation, we break the track as checking two conditions: (1)determinant of zero-mean Gaussian residual covariance value $\det S_k$ is larger than threshold and (2)validation gate value V_G is negative.



(a) frame 5 (b) frame 33 (c) frame 75 (d) frame 198 (e) frame 248

(f) frame 258 (g) frame 350 (h) frame 400 (i) frame 500 (j) frame 600

Figure 4: Frame 5, 33, 75, 198, 248, 258, 350, 400, 500 and 600 are shown. (a) The target is started to be tracked. (d) The target is completely disappeared in FOV. (e) Re-detection is in progress. (f) Tracking is started again.

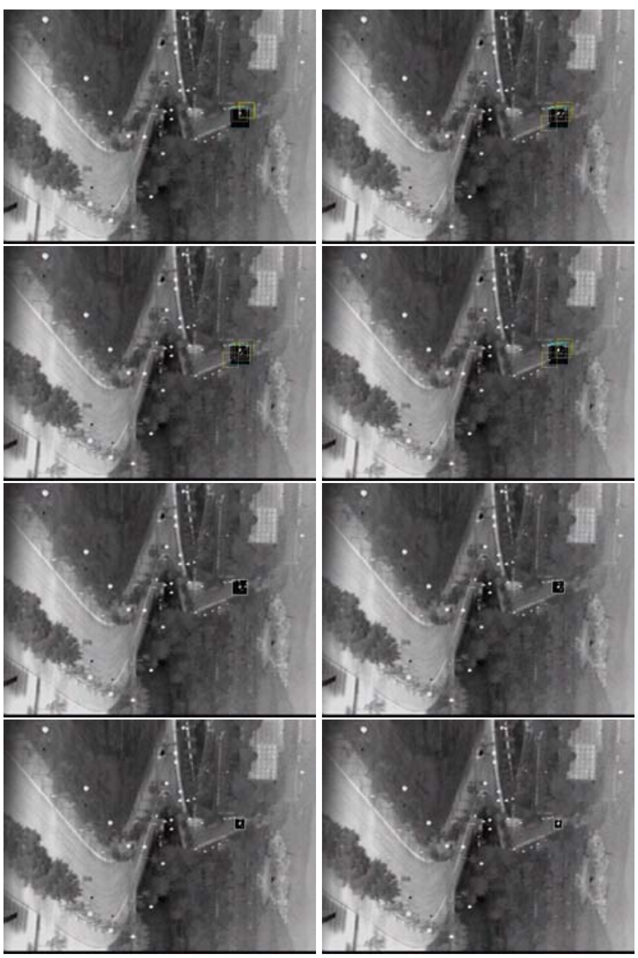


Figure 5: Green rectangle shows the initial search area. Yellow rectangles are candidate targets. White rectangle is selected one that have the highest probability after couple of frame sequences. 8 frame sequence is presented from inital frame.

5 Conclusion and future works

We have presented a practical target detection and tracking algorithm in airborne IR imagery using morphological operation and novel HPDAF. The experimental results show that our proposed algorithm can perform robustly in real-time. Also, our track-termination and re-detect method retrieve temporarily hidden or out of FOV target. In this work, we use HPDAF to find out the most probable target in cluttered environments. One limitation of this method is long-term period of hidden target cannot be retrieved. We will investigate shape representation algorithm coping with CCD imagery in one probabilistic framework.

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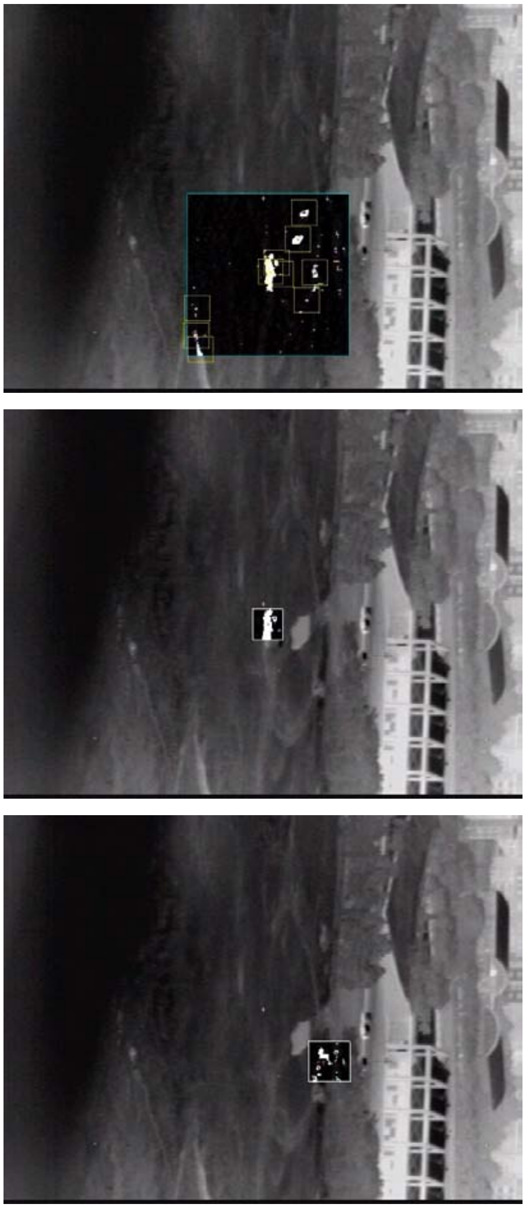

Figure 6: Frame 1, 301 and 1801 are shown.

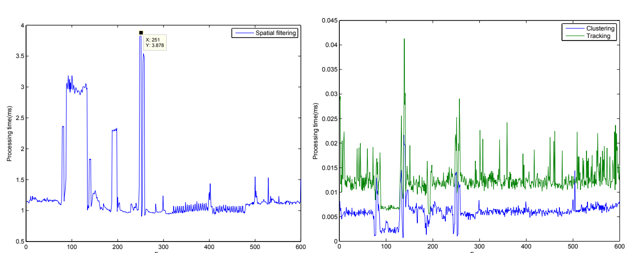

Figure 7: Processing time graph. This graph shows that our proposed system can be used under extremely critical real-time purpose. In worst case, total running time is below 5ms on commonly used PC. We can realize that peak frame coincides with re-detect time in fig. 4(e) and 4(f).

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