HIDDEN MARKOV MODEL PARAMETER ESTIMATION FOR MULTIPLE DIM TARGET DETECTION

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Abstract

This paper presents a modified hidden Markov model (HMM) filtering algorithm for detecting multiple dim targets in image sequence under low SNR condition. The proposed algorithm consists of three steps. As a first step, morphological filtering is applied for extracting features in pre-processing level. The second step is a hidden Markov model filter. To enhance a detecting performance of the filter, state transition probability matrix of HMM filter is updated to the re-defined parameter in each single recursive process. The estimation process uses potential target's local path from several continuous frames. The last third step is sub-window application. When a target is detected, the target is treated by sub-window to apply individual HMM filtering for detecting multiple targets. Based on numerical results, the proposed algorithm has slightly better detecting performance for multiple targets from a sequence of an image sensor under very low SNR($\simeq 2$) conditions

1 Introduction

In recent years, unmanned aerial vehicles (UAVs) have been rapidly developed for various missions such as surveillance, reconnaissance, armed attacks, transportations, and gathering terrain information, etc. To accomplish these complicate missions, some fundamental autonomous operations should be guaranteed such as awareness of obstacles, and sense and avoid other aircrafts. In order to introduce UAV system into public aerial zone, the aircraft should satisfy the requirements to aware existence of other near aerial vehicles. The passive image sensors have been interested for target detection and tracking as a result of development of computer vision science. The most significant advantage of the image sensor is that it can be easily implemented to aerial vehicles rather than other sensors. However, weather and daylight conditions influence critically measurements quality of the image sensor. Also the distance from the target is the most important factor. The target appears very small dim points when the target is far from the sensor.

Several track-before-detect algorithms have been developed for dim target detection which is gathering some information about a potential target over time before declaring target existence. The DP-based TBD algorithms [1]-[4] integrate the measurement data to calculate possible trajectories, consisting of possible target pixels which score function value exceeds a given threshold. Arnold et al. [3] and Zhang et al. [7] modified DP-based TBD algorithms to reduce computational load. On the other hand, TBD algorithms based on Hidden Markov Model are recently studied [8]-[10]. Lai et al. propose filter banks algorithms considering different movement direction of targets to modify HMM filter [8]. Davey et al. [10]

compared performance of several TBD algorithms including DP and HMM.

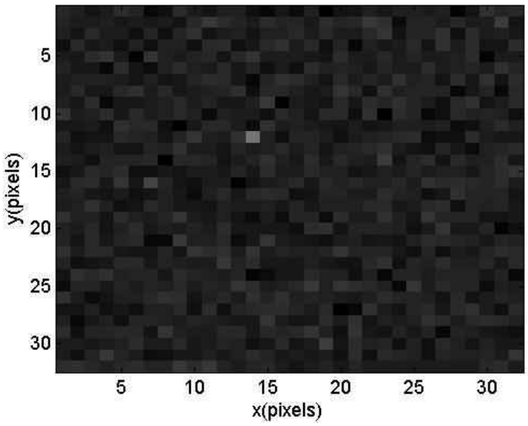
The standard HMM filter method is based on Lai's earlier study [8]. The aim of this paper is to consider different movement of multiple targets to state transition probability matrix of the filter. A proper local path of the potential targets is calculated by Viterbi based algorithm from several continuing frames. The local path is used to update part of the state transition probability matrix of the basic HMM filter for every each iteration.

Once a target is detected, the target is separated by sub-windows from the original image frame for multiple target detection to apply HMM filter independently. Several parallel HMM filters for each sub-window is used.

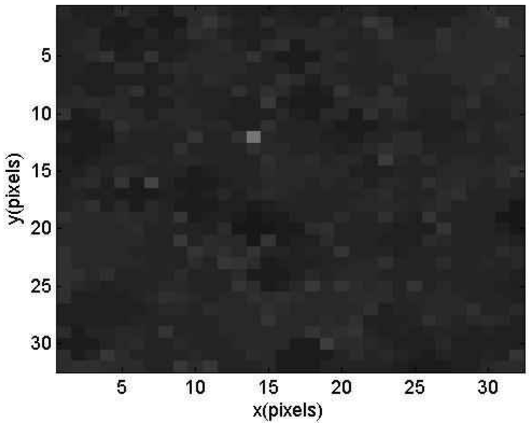
This paper is organized as follows. In section 2, the morphological filtering is presented as the pre-processing. In section 3, the basic HMM filtering methods and suggested parameter estimating algorithms for detecting a single target in image sequence are described. Section 4 illustrates how to consider multiple targets using sub-windows method. The numerical simulation and its performance assessment of the proposed algorithms are shown in section 5. The last section 6 will present the conclusions.

2 Morphological Filters

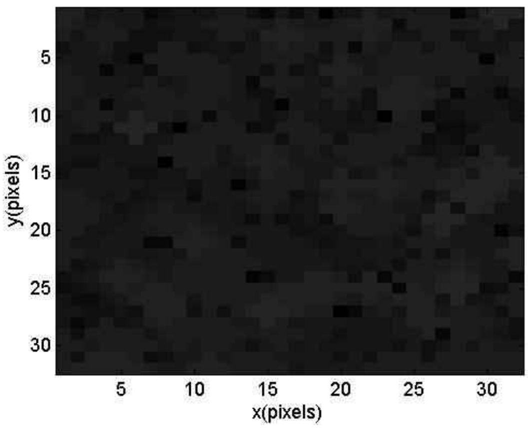
To extract feature and dim target in the cluttered image frames, the gray-scale morphological filtering are applied.



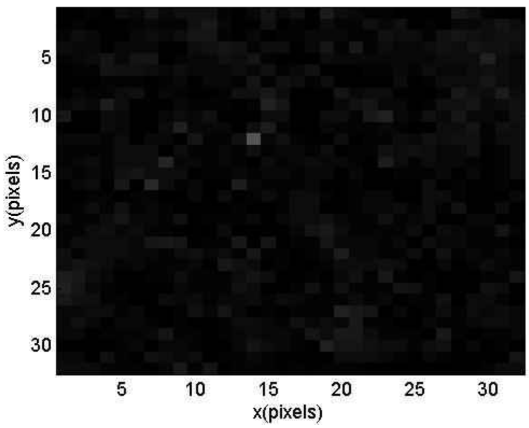
a) The original image



b) Close result



c) Open result



d) CMO filter result

Figure 1 Morphological filtering results

The morphological filters are consisted of combination of two basic operations: erosion and dilation.

The erosion and dilation operations for the given image frame, $I(x,y)$, are respectively defined as follows:

$$(I \ominus R)(x,y) = \min_{(x',y')\in R}\{I(x+x',y+y')\} \quad (0.1)$$

$$(I \oplus R)(x,y) = \max_{(x',y')\in R}\{I(x-x',y-y')\} \quad (0.2)$$

The erosion operation erodes the pixel in the region of interest, R, and the dilation operation enlarges the pixel in the region of interest, R.

The opening of image $I(x,y)$ by R is obtained by the erosion of I by R, followed by dilation of the resulting image by R

$$I \circ R = (I \ominus R) \oplus R \quad (0.3)$$

while the closing of image $I(x,y)$ by R is obtained by the dilation of I by R, followed by erosion of the resulting image by R.

$$I \bullet R = (I \oplus R) \ominus R \quad (0.4)$$

The opening operator tends to remove bright small peaks and disconnect two narrow bright regions. On the other hands, the closing operator tends to remove small dark holes and connect two bright regions. A close-minus-open (CMO) morphological filtering is employed to extract feature of given raw image frames. The CMO filter can be described as

$$CMO(I,R) = (I - (I \circ R)) - ((I \bullet R) - I) \quad (0.5)$$

The raw measurements frames are pre-processed by CMO filter, and the output of CMO filtering is used as a measurement data of HMM filter. The raw image frame and the results of morphological filter are shown in Figure 1.

3 Hidden Markov Model Filters

3.1 Standard Hidden Markov Model Filters

In this chapter, hidden Markov filtering method is described for detecting dim point target. The standard hidden Markov model filter is based on Lai's previous work [8]. The state vector of the hidden Markov model filter at discrete time k, $\mathbf{X}_k$, is defined a $N^2 \times 1$ column vector as follows:

$$\mathbf{X}_k = \{x_i \,|\, x_i = \Pr(\text{target exist in i-th pixel})\} \quad (1.1)$$

Each element of the state, x_i, represents probability of the target existence for corresponding pixel. Under hypothesis of the single target presenting at (p,q) pixel in the k-th image frame, the state vector can be described as follows:

$$\mathbf{X}_k = \mathbf{e}_{(q-1)N+p} \quad (1.2)$$

where $\mathbf{e}_i = [0,\cdots,0,1,0,\cdots,0]^T$ has zeros for every elements except the i-th element with 1.

The hidden Markov model filter consist of following three parameters; an initial probability matrix, $\mathbf{\Pi}$, a state transition probability matrix, $\mathbf{A}$, and a measurement probability matrix, $\mathbf{B}$. The initial probability matrix represents a priori state of at the first time

$$\mathbf{\Pi} = \{x_i \,|\, x_i = \Pr(\mathbf{X}_1 = \mathbf{e}_i)\} \quad \text{for } i = 1,\ldots,N^2 \quad (1.3)$$

The transition probability matrix $\mathbf{A}$ represents the dynamics of the target for a first order discrete time Markov chain, $N^2 \times N^2$ size of matrix $\mathbf{A}$ is given by

$$\mathbf{A} = \{A_{ij} \,|\, A_{ij} = \Pr(\mathbf{X}_{k+1} = \mathbf{e}_i \,|\, \mathbf{X}_k = \mathbf{e}_j)\} \quad (1.4)$$

which means that the probability of a target in j-th pixel moves to i-th pixel. For the standard hidden Markov model, we assume that the possible state transition is defined by eight adjacent transitions (moving to neighbor pixel) and one self-transition (holding position). Figure 2 illustrates the possible state transition.

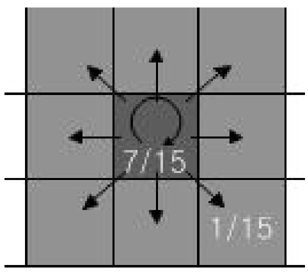


Figure 2 Possible state transition of basic HMM filter

The last parameter $\mathbf{B}$ describes the relationship between true target state, $\mathbf{X}_k$, and the measurement $\mathbf{Z}_k$, $N^2 \times N^2$ dimension of matrix $\mathbf{B}$ is given by

$$\mathbf{B}(k) = \{B_{ij}(k)\}$$

$$B_{ij}(k) = \begin{cases} \Pr\left(\mathbf{Z}_k \middle| \mathbf{X}_k = \mathbf{e}_i\right) & \text{if } i = j \\ 0 & \text{otherwise} \end{cases} \quad (1.5)$$

To calculate exact value of the conditional probability, $\Pr\left(\mathbf{Z}_k \middle| \mathbf{X}_k = \mathbf{e}_i\right)$, is too intricate problem, so the probability will be assumed to be proportional to ratio of the intensity of corresponding pixel and total intensity summation of the given frame. Consequently, an approximated matrix can be described by

$$\widehat{B}_{ij}(k) = \begin{cases} \dfrac{z^i{}_k}{\sum_{i=1}^{N^2} z^i{}_k} & \text{if } i = j \\ 0 & \text{otherwise} \end{cases} \quad (1.6)$$

The standard hidden Markov model filtering equation for calculating conditional mean of the state is expressed as follows:

$$\mathbf{X}_{k+1} = \overline{N}_k \mathbf{B}(k) \mathbf{A} \mathbf{X}_k \quad (1.7)$$

where $\overline{N}_k$ is a normalization factor. The detection of a target is made by accumulated normalization factor which calculated during given period of T. The detection variable α_k is defined by

$$\alpha_k = \frac{1}{T} \log\left(\prod_{i=k-1}^{k-T} \frac{1}{\overline{N}_i} \right) \quad (1.8)$$

To calculate the variable, at least numbers of T frames are required, therefore the variable cannot be defined for beginning T frames. After T frames, a target existence is declared if the detection variable exceeds a certain threshold. Then, the target position, γ_k, can be obtained by

$$\gamma_k = \arg\max_i \left(\hat{X}^i_k \right) \quad (1.9)$$

3.2 HMM filters with Updating Parameters

The state transition matrix $\mathbf{A}$ is determined a constant matrix for the standard hidden Markov model filters. The matrix $\mathbf{A}$ is representing the target dynamics. However, actual target motion can be changed randomly. Then, the probability of state transition cannot represent the target motion. If a constant matrix $\mathbf{A}$ is incorrect, entire performance of the filter will be degraded. To enhance a performance of the filter, and to make robust to the unknown target motion, the matrix $\mathbf{A}$ will be updated using local path of potential target pixels. A local path is defined a set of pixels containing maximum probability among the surrounding region for several consecutive frames. A surrounding region $\mathbf{R}$ is 3×3 small mask with corresponding pixel in the center. A local path of a certain pixel can be expressed as

$$\mathbf{L}_p(k) = \left\{ l_i \middle| l_i = \arg\max_{X \in R} \left(\mathbf{X}_t \right) \right\} \quad (1.10)$$

$$\text{for } k - n < t \le k,\ i = 1, \ldots, n$$

The target movements are updated for every discrete time k by using calculated local path, $\mathbf{L}_p$. The Viterbi algorithms are employed with considering a movement of the potential targets as a state, and calculated local path as a measurement.

4 Multiple Target Detection

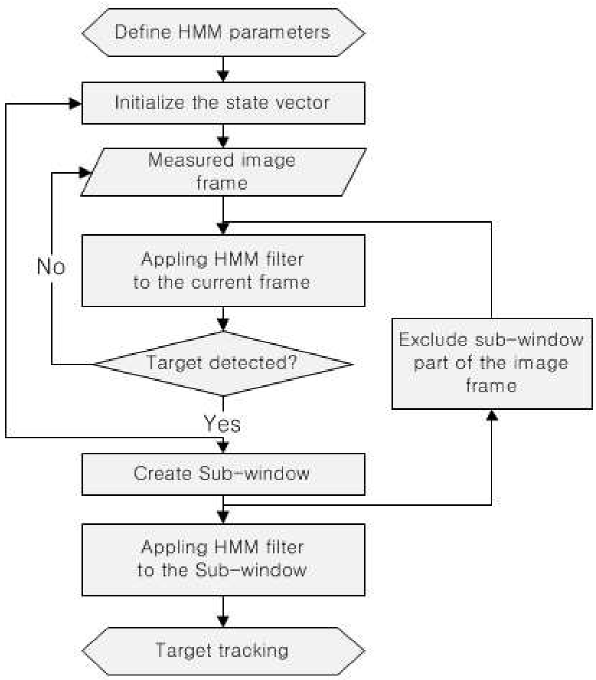


Figure 3 State flow diagram of sub-window algorithm

A modified hidden Markov model filtering method for multiple target detection is proposed using sub-window method. The standard hidden

Markov model filters can only detect a single target from the highest value of the probability state vector, $\mathbf{X}_k$. To detect multiple targets, we proposed a sub-window method. Once a target detected, the target will be treated by individual filter in small sub-window. When a target detected, m-by-m size of small region lying near target will be selected as a sub-window for the target tracking with another hidden Markov model filter simultaneously. Sub-window algorithm for multiple target detection is described as a state flow diagram at Figure. 3.

The algorithm is summarized as follows:

Step 1. Define the parameters of basic hidden Markov model filter; $\mathbf{\Pi}$, $\mathbf{A}$, $\mathbf{B}$

Step 2. Initialize the state vector for entire frame.

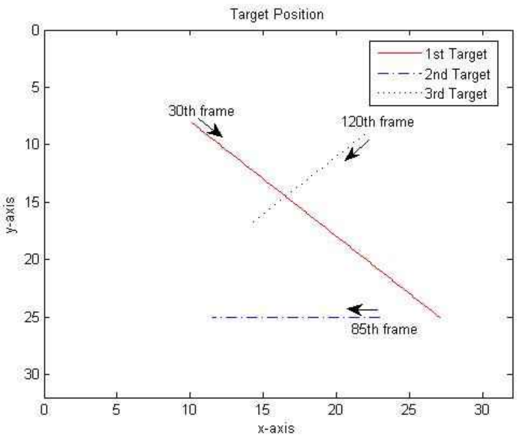
Step 3. Appling the standard hidden Markov model filter until a target has been detected.

Step 4. If a target is detected in step 3, create a small sub-window consisting of m-by-m pixels surrounding the target.

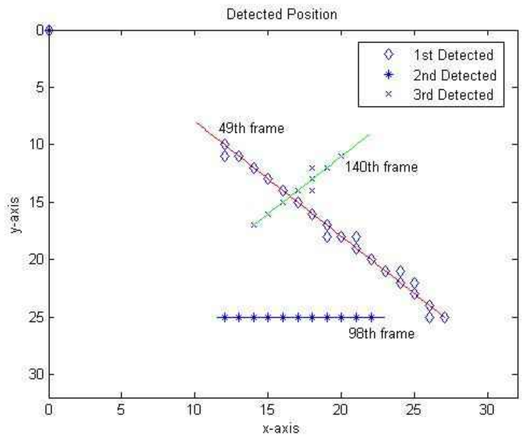
Step 5. Define the parameters of another hidden Markov model filter to apply new sub-windows; $\mathbf{\Pi}_{sub}$, $\mathbf{A}_{sub}$, $\mathbf{B}_{sub}$

Step 6. Hidden Markov model filter in sub-window is tracking the detected target until the target disappears.

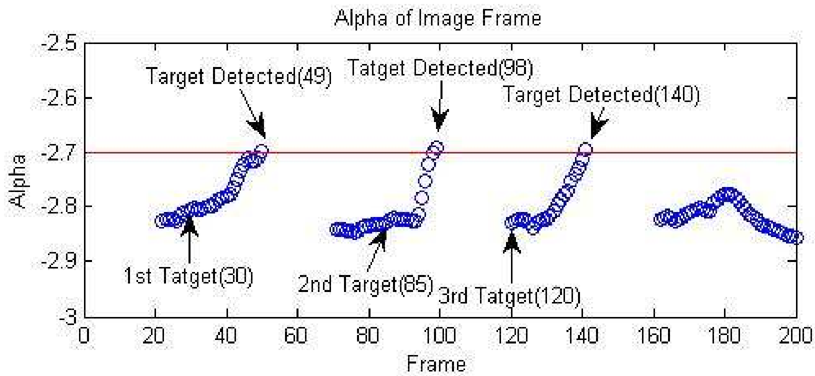
Step 7. Sub-window part is excluded for original measurement frame. Then, go back to step 2.



(a)



(b)



(c)

Figure 4 Simulation results with three moving targets : a) True target trajectory, b) Detected target trajectory, and c) History of detection variable α

Finally, each target is assigned by several own tracking filter and multiple targets can be tracked in same time.

5 Numerical Results

To make a simulation for hidden Markov model filter with sub-window method, the image sequences are made numerically. There are three moving targets in cluttered background. The size of the measurement frame is 32×32 and the minimum target speed is 0.1 pixel/frame. The measurement set consists of 200 frames.

For the given scenario, the first target appears at (10,8) pixel and moves right-down direction in 30th frame, the second target appears at (23,25) pixel and moves left direction in 85th frame, the last target appears at (23,10) pixel and moves left-down direction in 120th frame.

As shown in figure 4. The three targets are successfully detected and their trajectories are well tracked. In this simulation, we set the length of time T, 20, for detection variable, α .After 20 frames, the detection variable has certain values and increases during the target presenting until the value exceeds threshold value, -2.7. After declaring of the target detection, the variable α is initialized.

To compare the performance of standard hidden Markov model filter and modified filter with updating state transition matrix, the 50 frames including a single very low intensity ($SNR \cong 2$) target which appears at 20th frame. The target's moving direction is changing during the simulation.

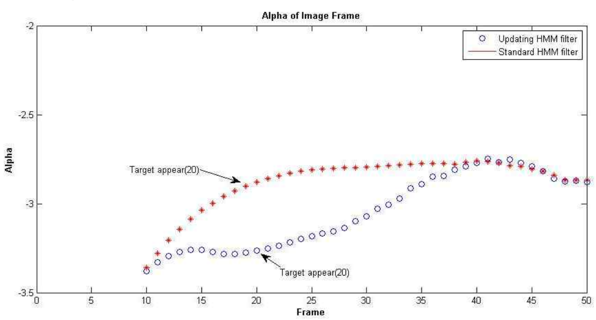


Figure 5 Comparison of standard HMM filter and modified HMM filter

The target such low SNR, the detection variable α of the modified HMM filter is changed more rapidly after the target appears in 20th frame, while standard HMM filter cannot classify the target existence. Therefore, we can detect the target by setting reasonable threshold of the detection variable even for very low SNR and direction changing target.

6 Conclusion

In this paper, our contribution to a hidden Markov model based TBD algorithms are twofold. First, the hidden Markov model filter with partially update state transition matrix is proposed for improving detection performance of motion changing target. The simulation results show slightly improved performance. Second, the sub-window algorithm application to the hidden Markov model filtering is formulated for multiple target detection. Based on basic HMM filter, sub-window algorithm successfully detects multiple targets. However, the proposed algorithm detects targets in consecutive order, so it cannot detect targets at once. The following work will cover this problem and the updating scheme will be applied for that multiple target detection algorithm.

Acknowledgment

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