TARGET TRACKING ALGORITHM IN INFRARED IMAGERY

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ABSTRACT

Target tracking plays a vital role in the development of battlefield surveillance, airspace surveillance and Border Patrolling. The use of infrared imagery in target tracking prevents from a wide range of attacks in border security, sea shore security. Infrared imagery is an effective method to cluster heat generating targets and it can penetrate fog, haze, dust, smoke, snow, rain and extreme darkness operate at day and night. Infrared imagery is one of the major and efficient defensive medium in surveillance and monitoring activity. In this paper, an introduction of target tracking algorithms in infrared imagery is discussed and two detection algorithms with tracking algorithm are implemented and analyzed on single and multiple target dataset. This will open the new area for the researcher in the research field of security.

1. INTRODUCTION

1.1. Target Tracking

Target tracking has been an intensive research area since the early 1960s, driven primarily by aerospace applications such as radar, sonar, guidance, navigation, and air traffic control. It has also found applications in biological systems, econometrics, robotics and sensor networks. Target is generally described as any area of interest such as persons, mammals, birds, air vehicles, land vehicles, water vehicles, and buildings. Tracking is the process of locating a moving object over time using a camera. The objective of video tracking is to associate target objects in consecutive video frames. To perform video tracking an algorithm analyzes sequential video frames and outputs the movement of targets between the frames so we say that Target Tracking can be defined as the problem of estimating the trajectory of an object or target in the image plane as it moves around a scene. There are number of merits of Target Tracking such as

- Tracking is the key for monitoring motion parameters, such as location, velocity, orientation and acceleration, are obtained by targets.
- A target tracking is used for recognizing and understanding target behaviours, especially suffering from illumination, scale, pose variations and occlusion

In this target tracking, first step is infrared video acquisition then split this video into frames. Second step is to do pre-process theses frames means eliminate noise added during video acquisition or transmission. Background modeling or foreground detection in infrared video is used in third step. In this paper background modeling is used such as single frame differencing (SRF), Running Average (RA). In the fourth step, tracking is performed with Kalman filter and labeling based connected component. There are also some other methods in which tracking is performed before detection, called track before detect (TBD). Here, in this paper tracking is performed after detection of target. In the last step, the performance of tracking algorithm along with selected detection algorithm will be evaluated through performance metrics like sensitivity(s) measure, PPV, detection and tracking accuracy. Target tracking can be classified in two forms:

1.1.2. Single Target Tracking

A single target and single sensor scenario consists of a target whose state evolves through time and is only partially observed by a sensor at discrete intervals of time. The objective is to estimate the state of a target given a sequence of observations made by the sensor up to the current time step.

1.1.3. Multiple Target Tracking

In a multiple target tracking scenario, the number of targets changes over time as new targets may appear in the surveillance region due to spontaneous target birth. Moreover, existing targets may not survive to the next time interval and disappear from the scene. The duration for which a target exists in the surveillance region is unknown. At the sensor, not all targets present in its field of view generate measurements.

2. TYPES OF TRACKING ALOGRITHM

There are many types of algorithms which usually use in target tracking but in infrared, some other classification of tracking algorithm is used by researcher. Tracking can be done through target representation and localization or by the use of filtering and data association [1]. Target representation and localization is mostly a bottom –up process which has also to cope with change in the appearance of the target. There are some common target representations and localization algorithms such as blob tracking, kernel based tracking, contour tracking. Filtering and data association is mostly a top – down process dealing with the dynamics of the tracked object, learning of scene priors, and evaluation of different hypotheses.

Some filters for tracking are such as optimal Bayesian filter, linear filter (Kalman filter), non-linear filter (extended Kalman, unscented Kalman, Gaussian sum filter, particle filter) and techniques for data association are such as nearest neighbour standard filter, probabilistic data association filter, multiple hypothesis tracking, Random sets for multi-target tracking. According to A.Yilmaz et al [2] object tracking is classified into three parts such as point tracking, kernel tracking, silhouette tracking. Point tracking consists of MGE tracker, GOA tracker, Kalman filter, JPDAF, PMHT and kernel tracking consists of mean- shift, KLT, Eigntracking, SVM tracker and Silhouette Tracking consists of state space models, heuristic methods, Hough transform, and histogram.

3. COMPARATIVE ANALYSIS OF DIFFERENT DETECTION ALGORITHM WITH TRACKING ALGORITHM

In this section, two target detection algorithms such as Single Reference Frame (SRF) and Running Average (RA) along with Kalman filter (KF) is applied on Ohio State University (OSU) Infrared dataset.

3.1 Single Reference Frame (SRF)

The simplest method is the frame difference method for the reason that it has great detection speed, can be implemented on hardware easily and has been used widely. While detecting moving object by frame difference method, the reference image can be a single first frame containing no moving objects in the difference image, the unchanged part is eliminated while the changed part remains [4]. This change is caused by movement or noise, so it calls for a binary process upon the difference image to distinguish the moving objects and noise. Furthermore, connected component labeling is also needed to acquire the smallest rectangle containing the moving objects [5]. The noise is assumed as Gaussian white noise in calculating the threshold of the binary process. According to the theory of statistics, there is hardly any pixel which has dispersion more than 3 times standard deviation. Thus the threshold is calculated as following:

$$T = u \pm 3\sigma$$

While u is the mean of the difference image, σ is the standard deviation of the difference image.

3.2 Running Average (RA)

Many background models have the problem of high computational complexity except the running average background model. The running average background costs low computational complexity[4][6]. Running average background model dynamically update the background image to adapt to the scene changing by using the weighed sum of the current image and background image. The updating formula is:

$$B(t+1) = (1-\alpha)B(t) + \alpha\, F(t)$$

Where α is the updating rate, B (t) is the background image at the time t, F (t) is the current image at time t.

The updating rate α represents the speed of new changes in the scene updated to the background frame. However, α cannot be too large because it may cause artificial "tails" to be formed behind the moving objects. Because the running average background just needs to compute the weighted sum of two images, so it has low computational complexity and space complexity. Dynamically updating the background makes this model can adapt to very complex scene[5].

Motion detection is started by computing a pixel based absolute difference between each incoming frame F(t) and an adaptive background frame B(t). The pixels are assumed to contain motion if the absolution difference exceeds a predefined threshold level. As a result, a binary image is formed where active pixels are labeled with "1" and non-active ones with "0". It is necessary to update the background image frequently in order to guarantee reliable motion detection [6]. The basic idea in background adaptation is to integrate the new incoming information into the current background image using the following equation [4-6].

3.3 Kalman Filter

The Kalman filter is a recursive estimator. This means that only the estimated state from the previous time step and the current measurement are needed to compute the estimate for the current state [8]. In what follows, the notation $\mathbf{X}_{n|m}$ represents the estimate of at time n given observations up to, and including at time m. The Kalman filter can be written as a single equation; however it is most often conceptualized as two distinct phases: "Predict" and "Update". The predict phase uses the state estimate from the previous timestep to produce an estimate of the state at the current timestep. This predicted state estimate is also known as the *a priori* state estimate because, although it is an estimate of the state at the current timestep, it does not include observation information from the current timestep. In the update phase, the current *a priori* prediction is combined with current observation information to refine the state estimate. This improved estimate is termed the *a posteriori* state estimate [8].

- *Predict:*
  Predicted (*a priori*) state estimate
  $\mathbf{X}_{k|k-1} = \mathbf{F}_k\ \mathbf{x}_{k-1|k-1} + \mathbf{B}_k \mathbf{u}_k$
  Predicted (*a priori*) estimate covariance
  $\mathbf{P}_{k|k-1} = \mathbf{F}_k\ \mathbf{P}_{k|k-1} \mathbf{F}_k^T + \mathbf{Q}_k$
- *Update:*
  Innovation or measurement residual
  $\mathbf{y}_k = \mathbf{z}_k - \mathbf{H}_k\ \mathbf{x}_{k-1|k-1}$
  Innovation (*or residual*) covariance
  $\mathbf{S}_k = \mathbf{H}_k\ \mathbf{P}_{k|k-1}\ \mathbf{H}_k^T + \mathbf{R}_k$
  Optimal Kalman gain
  $\mathbf{K}_k = \mathbf{P}_{k|k-1}\ \mathbf{H}_k^T\ \mathbf{S}_k^{-1}$
  Updated (*a posteriori*) state estimate
  $\mathbf{X}_{k|k} = \mathbf{X}_{k|k-1} + \mathbf{K}_k\ \mathbf{y}_k$
  Updated (*a posteriori*) estimate covariance
  $\mathbf{P}_{k|k} = (\mathbf{I} - \mathbf{K}_k\ \mathbf{H}_k)\ \mathbf{P}_{k|k-1}$

Where for each time step k, $\mathbf{F}_k$ the state-transition model, $\mathbf{H}_k$ the observation model, $\boldsymbol{Q}_k$ the covariance of the process noise, $\mathbf{R}_k$ the covariance of the observation noise, $\boldsymbol{B}_k$ the control-input model, $\boldsymbol{u}_k$ control vector, $\mathbf{z}_k$ an observation (or measurement) of the true state $\boldsymbol{x}_k$, $\mathbf{K}_k$: Kalman gain

3.5 Analysis of Algortihm with OTCBVS Datasets

In this paper, three different infrared dataset with multiple targets are used to analyze the detection and tracking accuracy from IEEE OTCBVS WS Series Bench, Roland Miezianko, Terravic Research Infrared Database. The first thermal data set, Two objects enter the FOV from opposite directions and walk toward each other. They stop in the center of the FOV for a while, then turn around and return to their previous positions. In second thermal Dataset, Two objects walk from right to left and briefly stop in the center of the FOV. First objects starts to walk left while second object is stationary. Later, the second object also begins to walk left. And last third thermal Dataset, Two objects enter the FOV from opposite directions. They walk towards each other and stop in the center of the FOV. Finally, they walk together to the right of the FOV. In which sensor details are Raytheon L-3, Thermal-Eye 2000AS, Format of images = 8-bit grayscale JPEG, image size = 320 x 240 pixels. All the experimented results on these infrared images are shown in Figure1 with Data1 (Frame no: 203, 256, 375), Data2 (Frame no: 65, 300,485), Data3 (Frame no: 130, 390, 601). In multiple target frames (Dataset1, Dataset2, and Dataset3), green and blue rectangles represents the current estimation and red rectangle are moving around the target that predict the next stage. For analyzing and predicting the tracking accuracy rate, TAR, TTAR, PPV, FAR are measured. Result analysis of target detection and tracking are shown in Table I and Table II. To Track the target with single frame differencing with Kalman filter is not well suitable in infrared imaging. Due to high susceptibility for slight change in atmospheric condition, it is suitable for normal visible images but it cannot track varying intensity object of infrared image sequences. Running average with Kalman is more suitable to track those objects in an environment where there may be slight changes in background or there may be changes in size of the objects but it is not fitted for non-uniform object in infrared imagery. It is also suited for normal visible image or colour image sequences. In this paper, we have implemented the algorithm on benchmark data set of Ohio state university infrared image sequence and done some performance test like f- measure for sensitivity and target accuracy rate and target tracking accuracy rate are calculated that are shown in different graph. With the help of this statistical data we can analyze the tracking accuracy of the multiple targets with SRF with Kalman and RA with Kalman. It also analyzes detection of multiple targets in SRF and RA with graph as shown in Figure2.

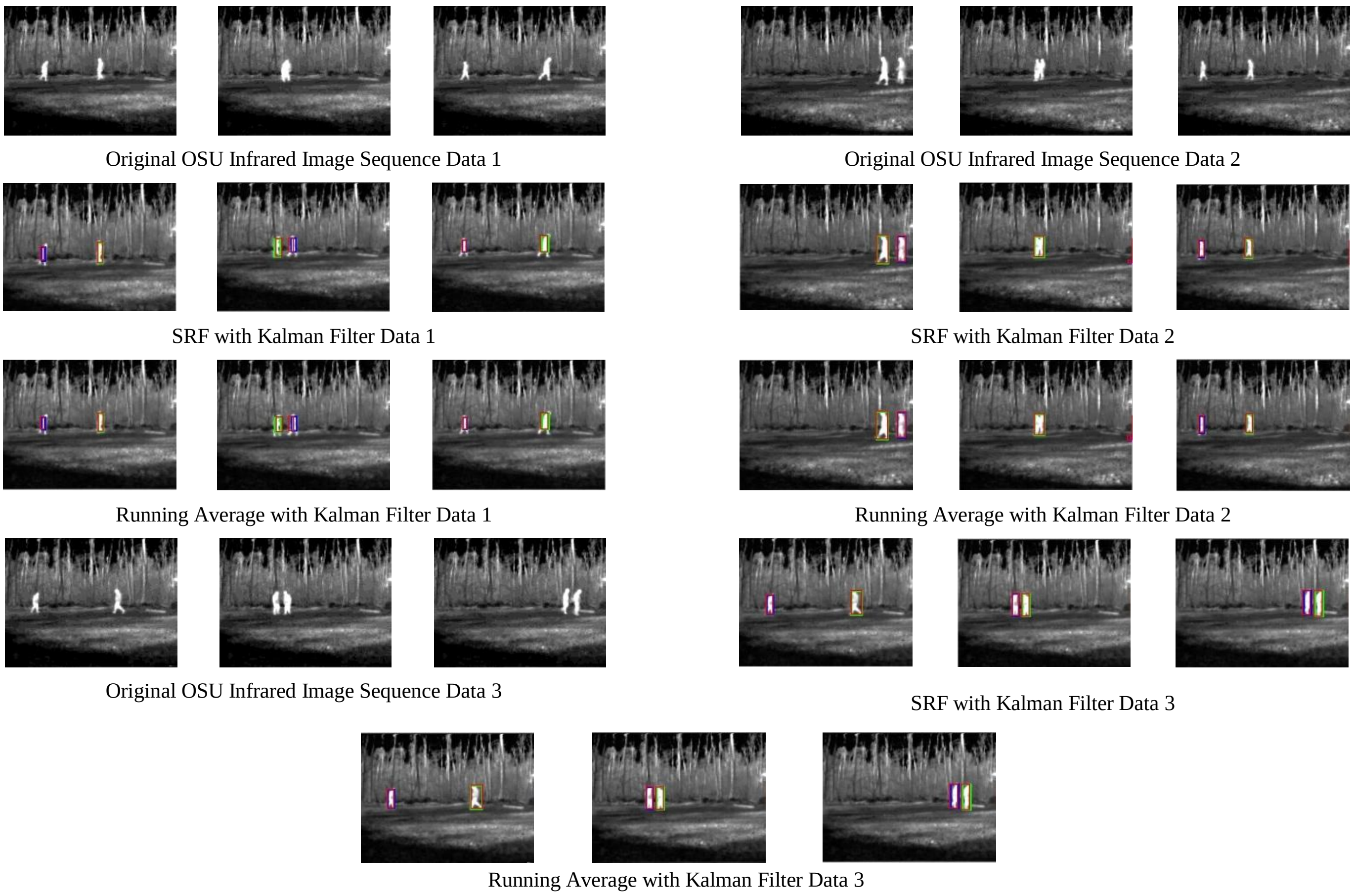


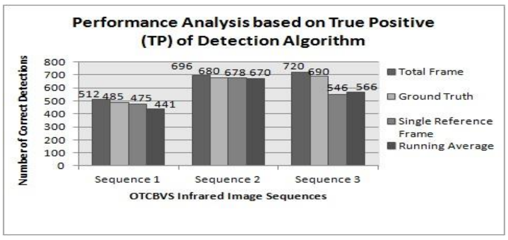
Figure 1: Result of OSU Infrared Image Sequence on SRF and RA with Kalman Filter

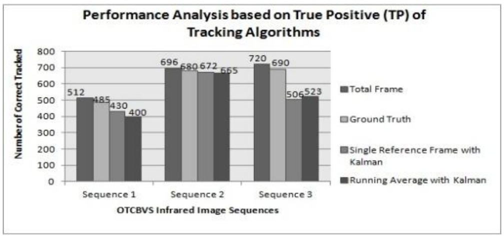
Table I: Result Analysis of Target Detection

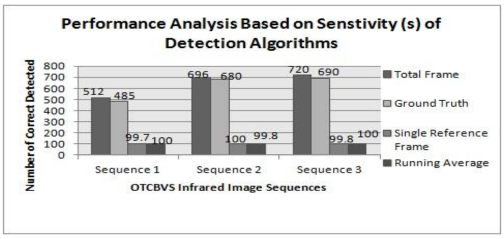
S No	Sequence	GT	Single Reference Frame							(Moving)Running Average						
			TP	FP	FN	S	PPV	FAR	TAR	TP	FP	FN	S	PPV	FAR	TDAR
1	Multiple Person Cross each other	485	475	23	1	0.997	0.953	0.047	0.974	441	1	0	1	0.997	0.003	0.998
2	Multiple Person comes from the same Direction	680	678	2	0	1	0.997	0.003	0.998	670	5	1	0.998	0.992	0.008	0.994
3	Multiple Person comes from different direction and move in same direction	690	546	1	1	0.998	0.998	0.002	0.998	566	1	0	1	0.998	0.002	0.998

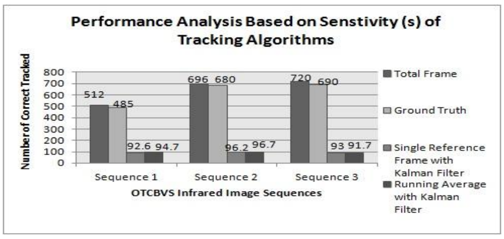
Table II: Result Analysis of Target Tracking

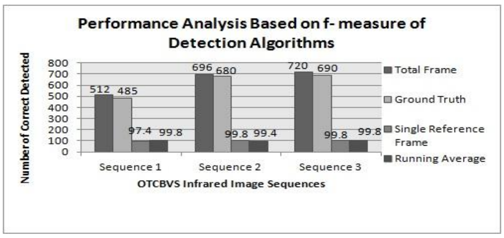
S No	Sequence	GT	Single Reference Frame With Kalman								(Moving)Running Average With Kalman							
			TP	FP	FN	S	PPV	FAR	TAR	TTAR	TP	FP	FN	S	PPV	FAR	TAR	TTAR
1	Multiple Person Cross each other	485	430	20	34	0.926	0.955	0.045	0.940	0.888	400	1	22	0.947	0.997	0.003	0.971	0.952
2	Multiple Person comes from the same Direction	680	672	1	26	0.962	0.998	0.002	0.979	0.960	665	4	22	0.967	0.994	0.006	0.980	0.961
3	Multiple Person comes from different direction and move in same direction	690	506	1	38	0.930	0.998	0.002	0.962	0.943	523	2	47	0.917	0.996	0.004	0.954	0.928

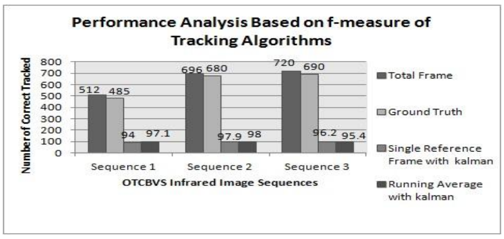












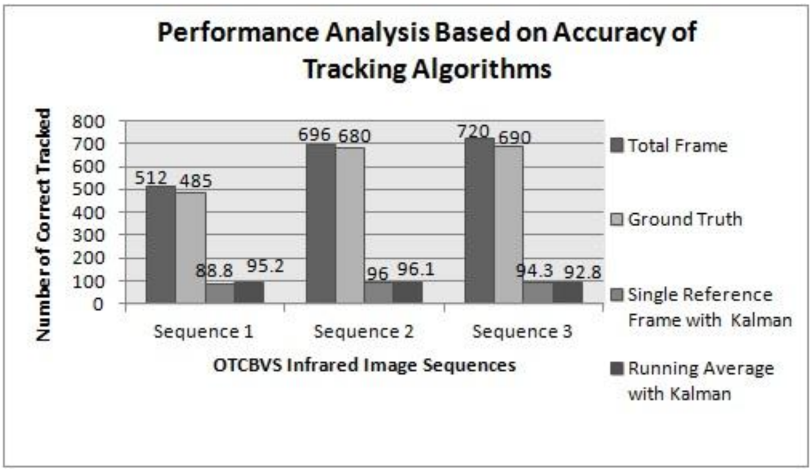


Figure 2. Performance Parameters Analysis of target tracking with Kalman Filter

4. CONCLUSION

In this paper, we presented a brief review of different approaches of multiple targets tracking in infrared imaging. We all know that intruder detection and tracking system are essential parts of security in every field such as border security, sea shore security, traffic monitoring and robotics based rescue operations. There are many obstacles such as noise, directional view, pose, illumination that affects the overall performance of the tracking. Experimental results of SRF and RA with Kalman Filter on OSU dataset with multiple targets are analyzed and computed.

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