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Research Survey

Visual Target Detection and Tracking Based on Kalman Filter

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Abstract

In this study, in order to prevent collision and target tracking in autonomous aircraft, Kalman filter with appropriate solutions for target detection and tracking problems are presented. For the Kalman filter application, the motion-based tracking method that facilitates the tracking of multiple objects has been used. A background subtraction algorithm was used for the detection of moving objects while corrective actions were applied to the foreground mask to eliminate noise, and the connected pixel groups correspond to moving objects were identified. The used image represents an image taken by a hovering drone. Although the tracked multiple targets disappeared behind the obstacle, the estimated location was determined by means of Kalman filter. Thanks to the fine tuning of the program codes, a successful follow-up has been achieved. The program has continued to follow the moving shadow as a part of the target.

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Kalman Filtresine Dayalı Görsel Hedef Tespiti ve Takibi

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Öz

Bu çalışmada, otonom uçaklarda çarpışmayı ve hedef takibini önlemek amacıyla, Kalman filtresine dayalı hedef tespit ve takip problemlerine uygun çözümler sunulmuştur. Kalman Filtre uygulaması için birden fazla nesnenin takibini kolaylaştıran hareket tabanlı izleme yöntemi kullanılmıştır. Hareketli nesnelerin algılanması için bir arka plan çıkarma algoritması kullanılırken, gürültüyü ortadan kaldırmak için ön plan maskesine düzeltici eylemler uygulanmış ve hareketli nesnelere karşılık gelen bağlı piksel grupları belirlenmiştir. Kullanılan görüntü, havada asılı duran bir drone tarafından çekilen bir görüntüyü temsil etmektedir. Takip edilen birden fazla hedef, engelin arkasında kaybolsa bile, Kalman Filtresi sayesinde tahmini lokasyon belirlenmiştir. Program kodlarının ince ayarı sayesinde başarılı bir takip sağlanmıştır. Program, hedefin bir parçası olarak hareket eden gölgeyi takip etmeye devam etmiştir.

1. INTRODUCTION

Both real-time and offline approaches are used for target tracking problem. In real-time object tracking, some uncertainties occur differ from offline approaches. These uncertainties are occurred in the displayed environment, scale change during zooming in and out, target mismatch or false overlap, distortion, motion blur, rapid dynamic movement, going out of view, mixing with the background, and low resolution. It is seen that it is very difficult to develop an algorithm that can solve all the problems. Therefore, in the area to be used, it is more appropriate to identify certain sub-problems that may occur as a result of the determined method and to develop approaches to these problems. For example, while a method gives good results against light changes, it cannot track the interaction of the target with other objects in the environment.

UAV are encountered in many areas today. Defense and security are the most common ones in these areas. With the increase in the use of UAV, these systems are seen as an important force multiplier in the defense industry for countries. They can perform tasks by eliminating the loss of trained personnel, especially in military operation environments where there is a high flight risk. Pilots are one of the costliest personnel groups to train in all armies of the world. Training a pilot costs enormous. For this reason, the loss of trained personnel together with the loss of the aircraft means loss of financial and capability for the armies. Armies prompted to use unmanned aerial vehicles systems due to the low cost of casualties. Many times, in the history, they played a great role in the delay of enemy air defense elements and in the use of bait as the main attack elements to pass the line of fire. Another area where unmanned systems are used for defense and security needs is aerial reconnaissance, surveillance, and intelligence activities. There may be problems in target detection and tracking using UAV.

There are some new studies about target detection and tracking problems. As a result of the development of deep learning in the last twenty years, it has been used in many algorithms.

Lao et al. presented a visual detection and tracking method which estimates smooth target position for various applications on micro aerial vehicles. Their proposed method consists of two items. These are a detector and a correlation filter. Here, the detector first detects a target and initializes the tracker. The estimated target position from the tracker will be updated by the detector. Their proposed method is able to realize real-time detection and tracking with 30 frames per second on their system [1].

Hossain and Lee introduced a target tracking approach for moving objects. Their algorithm for tracking moving objects was based on the extension of simple online and real-time tracking. They developed by integrating a deep learning-based association metric approach with online and real-time tracking which uses a hypothesis tracking methodology with Kalman filtering and a deep learning-based association metric. They show the effectiveness of the proposed their algorithms by real-time experiments with a small multi-rotor drone [2].

Duan et al. proposed a robust cooperative target detection method by contrast sensitivity mechanism of eagle’s eye to extract the cooperative target. They simulated the contrast sensitivity mechanism based on the attenuation effect of contrast sensitivity function of an eagle to suppress the texture edges [3].

Wang et al. proposed an edge-based target detection algorithm using Competitive Bird Swarm Algorithm for UAVs in formation flight. Their method based on structured forest was adopted to obtain discriminating edges in aerial images. They adopted in the proposed their algorithm to build an attraction pattern for image edges to attract the edge template [4].

Lusk and Beard demonstrated a visual multiple target tracker running in real-time onboard a descending multirotor. The situation awareness of autonomous vehicles was increased with a robust target tracking solution. They claim that more processing time is available for tracking improvements and higher-level tasks such as path planning and control [5].

Kim and Park proposed an extended Kalman filter that mirrors characteristic of radar sensors. They analyzed this characteristic of the radar, then designed the Kalman filter with a certain function to express distance characteristics. They improved the accuracy of position estimation by detecting the sensor errors according to distance. They claim experimental results showed that this method produced accurate distance estimations. [6].

Farahi and Yazdi proposed a recent probabilistic learnable follower for online environments. Their method is capable of giving more correct prediction when more observations are available. The observations were dedicated to the filter by detecting the most probable track of the graph. The most significant benefit of using this graph is to process obstruction. Also, it can follow a goal with anomalous attitude that is suitable for several applications [7].

Wang et al. presented an adaptive Kalman filter. Their proposed method has comparable stability with and advanced integrity over the open loop tracking. They claim proposed algorithm improved performance of tracking [8].

Khalkhali et al. studied utilizing online situation estimation inside Kalman filter. They used a certain graph as online modeling of the history of the vehicle motions to improve the estimation [9].

It is seen that Kalman filter has different applications regarding target tracking problems [10-13].

The aim of this study is to present the approach used in visual target tracking problem using Kalman filter with deep learning. The used image represents an image taken by a hovering drone. Although the tracked target disappeared behind the obstacle, the estimated location was determined by means of Kalman filter. Thanks to the fine tuning of the program codes, a successful follow-up has been achieved. The program has continued to follow the moving shadow as a part of the target. In the second part of the study is target tracking and here, Kalman filter algorithms are explained; in the third part, the application details of visual target detection and tracking based on Kalman filter are given.

2. TARGET TRACKING

The Kalman filter is an effective filter and predicts the state of a linear dynamic system from measurements. It is called recursive to calculate the current state estimate; only once requires first state-space estimation and valid measurement data [14, 15].

Kalman filters are particularly helpful in navigation problems with Gaussian noise [16-20]. In a control theory, the Kalman filter is an algorithm that produces an effective prediction to predict the state of the process to terminate noise. This filter is very good in several ways; supports previous, current, and next situation predictions. This can still be done, although the actual system model is unknown. Kalman filter is also called optimal stochastic estimator.

Kalman filter is a method of predicting state variables of a separate linear stochastic dynamical system that minimizes the prediction error covariance [21]. Kalman filter is a technical approach to estimate the function of parameters in time series estimation. The advantage of the KF method is that it can predict a situation based on minimum data. The minimal data in question are measurement data from the measuring device. It is a method that combines Kalman filter models and measurements. Measurement data are used to correct the estimate results. For this reason, the estimate results approach real conditions every time.

Kalman Gain holds an important place in Kalman filter mathematical operations. Estimation and measurement error values are used to calculate the gain. The instant estimate is then calculated. In this process, the previous predicted value and measured value are used. Then the error value in the new estimate is calculated. Defect definition is sometimes used as uncertainty in the literature.

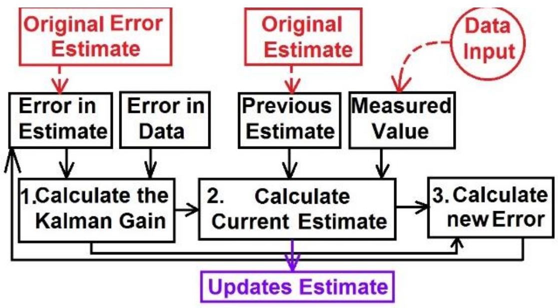


Figure 1. Kalman filter flow chart.

Figure 2 shows the model of the Kalman filter. As can be seen, the Kalman filter continuously performs its prediction and update processes in a loop. The Kalman filter is initiated by initial state estimation, initial covariance matrix, determination of process and measurement errors. The next step after their determination is the first state estimation and estimation of covariance matrices.

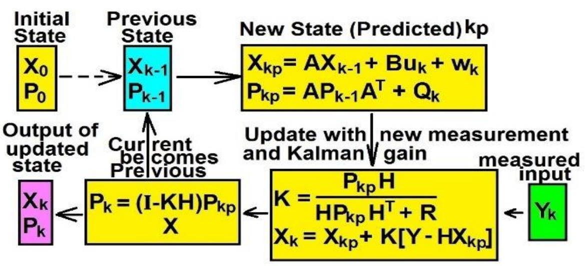


Figure 2. Basic Kalman filter.

In the first round of the cycle, initial values and estimated values are calculated. However, for the next steps, state estimation and covariance matrix produced as output during a round run of the filter are used. After the preliminary estimation processes, the measurement estimates are calculated using the first state estimation. Measurement residual is found by taking the difference between measurement and measurement estimates. The residual covariance measurement matrix is obtained using the measurement noise covariance, the initial covariance matrices. The Kalman gain mentioned earlier is calculated with the first covariance matrix, measurement matrix and residual covariance matrices in the multidimensional model. As the last stage, there is the correction process and the final estimation stage. Here, the preliminary state estimation and covariance are verified using the measurement residue and the measurement matrix. As a result, the final state estimation and covariance matrix are calculated. As the filter is run each turn, the output is used in the next cycle.

In practice, the gain is adjusted to obtain a minimum variance state error estimation. Measurement and modeling noise effects are added to the system. Kalman filter has an iterative calculation structure. Different sensor models can be included in the basic KF algorithm because the process and observations can be clearly defined. These advantages ensure that Kalman filter is used widely.

Equations showing the formulas include the observer dynamic model and the error statistical model. The model used is computationally successful but not perfect. Uncertainties arise due to unpredictable and errors during measurements [22]. Parameter uncertainty, target maneuver, process noise, and numerical bottlenecks are examples of model flaws. The convergence of the model accuracy to the measurement noise indicates that the Kalman filter performance is good and suitable for the applied system. If there is an opposite conflict, the situation and predictions diverge. This shows that the error between the actual and predicted values could not be filtered.

Kalman filter consists of three main stages. Calculation of the state variables of a dynamic system at the time of $t < t_i$ condition by using the previous properties of the system is called the prediction stage. If the state variables of a dynamic system at time t at any time t are calculated with the measurements at time t with the condition $t = t_i$, this phase is called the filter phase (update). If the state variables of a dynamic system at time t at any time t are calculated together with the measurements up to the time t> ti, this phase is called the smoothing phase. The filter is limited to the first two stages in the implementation of instant applications. Because the softening phase can only be applied after all measurements are made [23].

Kalman filter equation consists of two parts. These are dynamic model and measurement model respectively.

$$x_k = x_{k-1} + Bu_k + w_{k-1} \tag{1}$$

$$z_k = Hx_k + v_k \tag{2}$$

In these formulas, $x \in R_n$ is the state vector of the system in discrete time, and $z \in R_m$ is the observation matrix of the state vector. w_k and v_k represent system and measurement distortions. Measurement distortions are independent random variables suitable for Gaussian distribution.

$$p(w) \approx N(0, Q) \tag{3}$$

$$p(v) \approx n(0, R) \tag{4}$$

Q is the system noise covariance matrix and R is the measurement noise covariance matrix. In the real case, these values change with every measurement. However, it is taken as fixed for convenience in matrix calculations. Matrix A is n×n size and it is the transition matrix that connects the state in step k to step k. Matrix B is an n×1 size control matrix. $u \in RI$ is the control vector. The control vector may not be available in all systems. It is decided whether it will be used or not according to the structure of the system to be measured. H is the m×n-dimensional observation matrix of the system.

$\hat{x}_k \in R^m$, k is defined as the premise estimate in k steps. Here, k is the filtered state vector obtained using the measurement value z_k, in k steps. If this equation is arranged in the proper format, the following equation is reached.

$$\hat{x}_k = \hat{x}_k^{-} + K(z - H\hat{x}_k^{-}) \tag{5}$$

$(z - H\hat{x}_k^{-})$ can be represented as $\tilde{z}$. This predicted measurement expresses the degree of difference between $H\hat{x}_k^{-}$ and the actual measurement, z_k. If the value is zero, the predicted value and the actual measured value are the same. The K coefficient is the matrix gain coefficient of the optimal filter of size n×m.

$$K_k = P_k^{-} H^T (HP_k^{-} H^T + R)^{-1} \tag{6}$$

Here, as the measurement noise covariance, R, decreases, Kalman gain increases. As R approaches zero, the value of K approaches H^{-1}. On the other hand, as the preliminary prediction error covariance P_k^{-} approaches zero, the gain K will also approach zero. In other words, as the measurement error covariance, R, approaches zero, the reliability of the real measurement value z_k increases, the reliability of the estimated measurement value decreases. Otherwise, as the preliminary prediction error covariance, P_k^{-} approaches zero, its reliability in the real measurement value z_k decreases, and the reliability of the predicted measurement value increases.

The prediction error covariance, P_k^{-} is shown as:

$$P_k^{-} = A P_{k-1} A^T + Q \tag{7}$$

Kalman filter can be examined in two groups due to its structure. The first is shown as "time update" and the other as "measurement update". Moving the state and error covariance estimates used in obtaining the preliminary estimation for the next step one step further is called advancing the step. In the correction of the measurement, the new measurement value and the preliminary estimation value and the filtered state vector are calculated. The first one makes a prediction about the measurement; the other one corrects this prediction and brings it closer to the actual measurement.

To express the operation of the Kalman filter, the measurement error covariance, R and system error covariance, Q, must be present before system startup. When the system starts, initial values are determined for the moment t_0 or the first measurements are calculated. Then, according to the initial values, the state vector and first premise estimation for t_1 is made; the error covariance of measure estimation is found. At time t_1, the Kalman gain is calculated from the error covariance of the preliminary estimate. Using the measurement at time t_1, the filtered state vector with Kalman gain and preliminary estimation is reached [24]. The system continues to work in this way until the last step.

The basic Kalman filter is limited by a linear assumption as examined. However, more complex systems are generally nonlinear. Different methods have been developed for this.

Nonlinear state-observation functions are linearized by means of the Taylor series expansion using Extended Kalman Filter (EKF). Although this method offers good solutions in many applications, the acceptance that it will linearize may not occur due to instability and the filter may diverge. The partial derivatives of nonlinear functions need to be taken. Q matrix process noise is used as a solution to this problem. This process stabilizes the EKF but brings an extra uncertainty [25]. An average stay gain is produced with measured covariance estimates.

Linear processes do not usually exist in the real world. So, they need to be linearized in some way before they can be predicted. The function f is used to calculate the situation estimated with the previous estimate. The measurement estimated with the function h is calculated from the estimated situation. In EKF, the Jacobian matrix is calculated around the estimated state of functions f and h because it cannot be directly applied to the covariance f and h. The purpose of the process is to find the curve of the model function centered on the state. This matrix contains all partial derivatives of a vector [26-28].

Linearization is done through the average of the filter. It is calculated based on the current state estimates of the filter along the mean of the partial derivatives in the EKF. Stability and convergence are imprecise in the EKF. These problems are tried to be reduced by using different methods.

Linear Kalman filter and EKF have almost the same structure. Only the measurement matrix differs in terms of linearization operations and state transition matrix. In the nonlinear Kalman filter, mean and covariance should be updated using process and measurement models. Calculation of mean and covariance from this transformation shows that Kalman update equations are applicable [29].

In this study, a Kalman filter is used to estimate the position, velocity, and acceleration of a maneuvering target. Kalman filter is used together with deep learning. Convolutional Neural Networks are used as deep learning.

3. IMPLEMENTATION

To use deep learning is the one way of the solutions. In this method based on Convolutional Neural Networks.

Convolutional Neural Networks are a class of biologically inspired neural networks which solve (8) by passing X through a series of convolutional filters and simple non-linearities. They have shown remarkable results in a wide variety of machine learning problems.

A Convolutional Neural Network has a hierarchical architecture. It starts from the input signal x, each subsequent layer x_j is computed as:

$$x_j = \rho W_j x_{j-1} \tag{8}$$

Here, W_j is a linear operator and ρ indicates the non-linearity and it is a point-wise non-linearity. and W_j is a convolution, and ρ is a rectifier max(x, 0) or sigmoid *1/1+exp(−x)* in generally. It is easier to accept of the operator W_j as a stack of convolutional filters. So, the layers are filter maps and each layer can be written as a sum of convolutions of the previous layer.

$$x_j(u, k_j) = \rho \left(\sum_k \left(x_{j-1}(.,k) * W_{j,k_j}(.,k) \right)(u) \right) \tag{9}$$

Here $*$ is the discrete convolution operator:

$$(f * g)(x) = \sum_{u=-\infty}^{\infty} f(u) g(x-u) \tag{10}$$

The optimization problem defined by a CNN is highly non-convex and the weights W_j are learned by stochastic gradient descent, using the backpropagation algorithm to compute gradients.

The flowchart of moving object detection tracking is seen Figure 3.

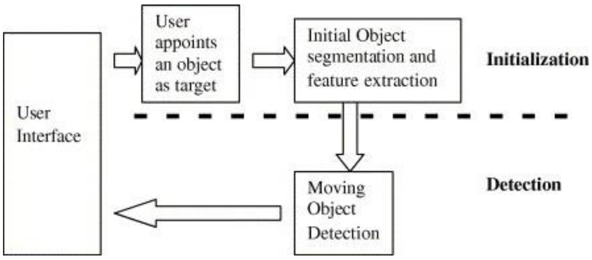


Figure 3. The flowchart of moving object detection tracking.

Collective tracking of the intended target or targets is the certain of this activity. In case the target detected with Kalman filter, one of the target tracking methods, comes out of the sight, following up by estimation is carried out by calculating the target's motion parameters. Deep learning method is slow to calculate this change in image data in a short time. In order to get output from each frame of the image data at the frequency determined in the video, the artificial neural network must be launched. As a result of the literature search and studies, motion-based object tracking in target tracking with Kalman filter provides convenience for Kalman calculations.

Detection of moving objects and tracking are used in many artificial vision applications. If we divide motion-based object tracking into sections; the first is the detection of moving objects, the second is the correlation of perceptions.

A background subtraction algorithm is used for the detection of moving objects. Corrective actions are applied to the foreground mask to eliminate noise. Then, the connected pixel groups that are corresponded to moving objects are determined.

Many different data sets can be modeled using the Gaussian distribution. In the literature, the Gaussian distribution is also referred to as the normal distribution and roughly resembles the bell curve. Gaussian mixture model is the model that explains the data set as a mixture of k-pieces Gaussian distribution under the assumption of normality. It assumes that the aggregators of the instances given are k-pieces Gaussian distributions. This is the optimization of the Gaussian parameters of the instances to maximize the density function to the mixture problem. It is an algorithm that uses more than one distribution instead of modeling the data set assuming that it is produced from a single distribution. Gaussian mixing model is an unchecked clustering algorithm based on Gaussian distribution. It gives the probability of relation to the samples and clusters in the data set in the probability-based approach. It makes clustering not circular but elliptical unlike other clustering algorithms.

The algorithm involves two steps:

Step 1: Compute the cost of assigning every detection to each track using the distance method of the vision.KalmanFilterSystem object. The cost takes into account the Euclidean distance between the predicted centroid of the track and the centroid of the detection. It also includes the confidence of the prediction, which is maintained by the Kalman filter. The results are stored in an MxN matrix, where M is the number of tracks, and N is the number of detections.

Step 2: Solve the assignment problem represented by the cost matrix using the assignDetectionsToTracks function. The function takes the cost matrix and the cost of not assigning any detections to a track.

The first code used for this purpose is vision.ForegroundDetector function. It compares a color or grayscale video frame to the background model to establish. Then it calculates a foreground mask. The 'NumGaussians' used in this function is the number of Gaussian modes in the model specified as a positive integer. The MimimumBackgroundRatio property is the threshold for determining the background model, specified as a numerical scalar. This property is set to represent the minimum probability of pixels to be considered as background values. If this value is too small, multimodal backgrounds cannot be processed.

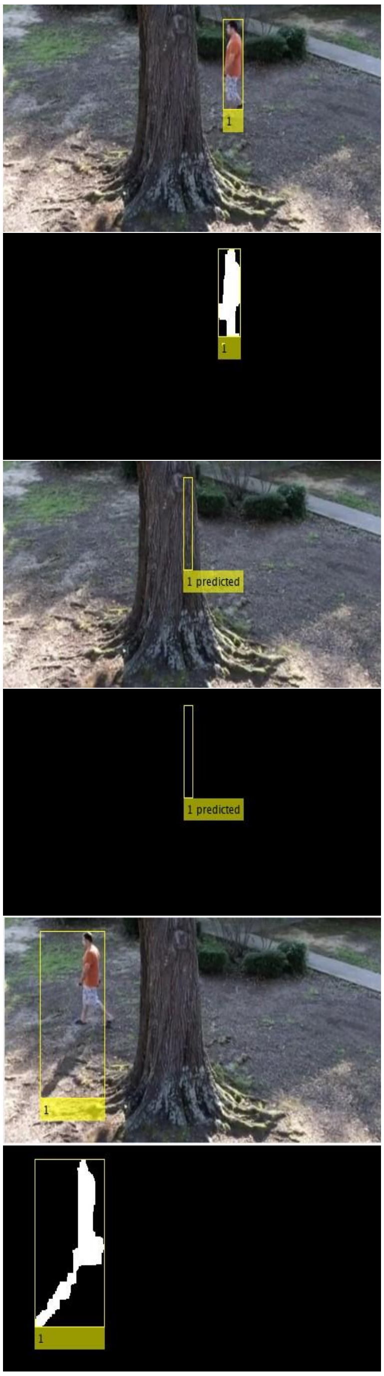
The Block Analysis block calculates statistics of the labeled regions in a binary view.

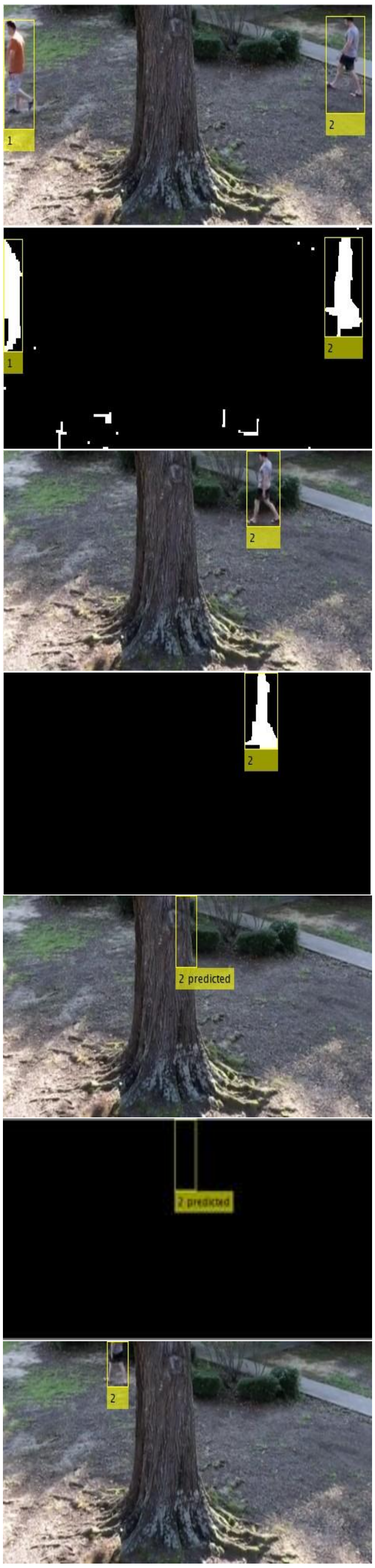
Object’s detection function is available in 'detectObjects' code block. This function returns the centers of gravity and bounding boxes of detected objects. Afterwards, the noisy pixels are removed with the morphological processes performed on the resulting binary mask and the holes in the remaining spots are filled.

Imopen and imclose commands are used on the working frame to detect the objects. These codes perform morphological opening or closing on a grayscale or binary image mask. Another function, imfill fills the holes in the input binary image. The 'holes' used in the code are a series of background pixels.

ConfigureKalmanFilter function is used to follow the targets in the image with Kalman filter. Thanks to this feature, MATLAB provides the opportunity to carry out projected tracking without making very detailed calculations for Kalman filter. The first feature, MotionModel, is the motion pattern specified as "Constant Speed" or "Constant Acceleration". The selected motion pattern is valid for all dimensions. The InitialLocation property is the initial position of the object specified as a numeric vector.

The intended tracking algorithm was created by making necessary changes and fine tuning in the codes used in this study. The image represents an image taken from a hovering drone. Although the tracked multiple targets disappear from the view behind the obstacle, thanks to the Kalman filter, the estimated location was determined. Thanks to the fine tuning of the program codes, a successful tracking has been achieved. As can be seen from the outputs of the program (Figure 4), the program continued to follow the moving shadow as a part of the target. Since a certain proportion of foreground inferences are combined, tracking is not performed against small movements in the image.





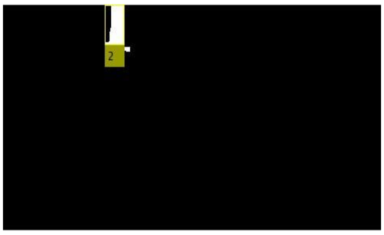


Figure 4. Prediction, detection and tracking of human by means of our algorithm.

The used image represents an image taken by a hovering drone. Although the tracked multiple targets disappeared behind the obstacle, the estimated location was determined thanks to the Kalman filter. Thanks to the fine tuning of the program codes, a successful follow-up has been achieved. As can be seen from the outputs of the program, the program continued to follow the moving shadow as a part of the target. Since a certain ratio of foreground inferences were combined, tracking was not performed against small movements in the image. In short, although the method used does not give good results in moving images, it is possible to get successful results if used by fixed drones suspended in the air. Future work will include parallax compensation and trajectory optimization for ground target avoidance during landing.

4. CONCLUSION

In this study, both Kalman filter and deep learning are used to detect and track for targets. Here, Kalman filter is used to estimate the position, velocity, and acceleration of a maneuvering target. Convolutional Neural Networks are used as deep learning. The motion-based tracking method that facilitates the tracking of multiple objects has been used. For the detection of moving objects, a background subtraction algorithm based on Gaussian mixing models was used while corrective actions were applied to the foreground mask to remove noise and drop analysis has identified connected pixel groups that are corresponded to moving objects. The required changes and fine adjustments were made with the codes used in the study, and the desired tracking algorithm was created in the image.

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