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Automatic Missile Tracking System using Mean-Shift Algorithm

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A B S T R A C T

The use of visual sensing to acquire and track targets has the potential to significantly reduce cost in comparison to active sensors. This project is to design and construct automatic missile detection and destroying system. The system is designed to detect the target (missile) moving in multiple directions. The destroying system moves automatically in the direction of missile and fires it upon fixing the target. This system consists of a vision-based object tracking system that continuously monitors the target. Upon detecting the target, it sends the target's location to a Central Control System. The Central Control System takes the action of moving the firing mechanism in the direction of target missile. Upon fixing the direction, it sends the control command to firing system to attack the target. We interface with the missile tracker via USB, and implement a second vision system based on gradient detection to provide pose feedback for the tracker unit. The system is consistently able to intercept targets, within the parameters of our testing.

Introduction

The missiles and rockets have been used in numerous military missions over the years. They were used as both attacking and defensive instruments against munitions, airplanes, structures, automobiles, and a wide range of additional valuable targets in the battlefield. In July 2014, Hamas launched a mortar attack on Israel's adjacent towns [1], [2]. In reaction, the Israel Defence Force (IDF) constructed its Iron Dome air missile defense system to defend against missiles hitting populated regions [3].

Missile identification and monitoring, using either passive or active detectors installed on a UAV, is critical for effective defense against missiles. Active detectors, such as radar, use a transmitter in order to bounce radio waves off the object being monitored and an antenna that records the signal that is reflected by the target. However, the adversary's anti-radar detectors are capable of identifying such sensors that are active. In response, an opponent can determine the tracking system's location and activate counterattack against it.

A UAV that uses sensors that are passive, such as a thermal-imaging camera or a color-imaging camera, has the benefit of tracking and identifying the intended target without warning the adversary. The passive sensor doesn't send information to the target; rather, it uses video imagery from its camera to identify the object being tracked. Consequently, the UAV's susceptibility to countermeasures during missions is substantially decreased.

In an effort to monitor and identify the missile silently using the UAV's active sensor, the object being targeted must have an individual mark in the captured footage. The UAV can identify an adversary's missile by processing infrared images from the thermo-imaging sensor, which collects the thermal gradient of the environment within its area of view. The thermal-imaging sensor is going to identify the heat profile of the missile's propulsion engine, which emits elevated temperatures gases to produce the thrust necessary for flight. However, in order to produce an excessive temperature gradient between the missile's propulsion motor and the surrounding environment, the thermal-imaging sensor must be cooled prior to each operation. This lengthens the installation period for the UAV's passive sensor, and the cooling mechanism adds to the UAV's total weight.

In contrast, the UAV may utilize a color-imaging camera to identify and follow the adversary's missile. Because the color-imaging camera records images of every object in its area of viewpoint, the UAV must distinguish its target from other elements of the environment before detecting its launch and tracking its trajectory. However, the passive sensor requires no extra equipment to function and offers a very short period for setup.

This thesis investigates the challenge of analyzing a missile launching video captured by a color-imaging camera on a program for simulation in order to identify and monitor the missile's path. The simulation program cannot process the initial missile launch videos taken from the quadcopter because they are not stabilized. As a result, further missile launch videos, captured from a stabilized station on ground level, were recorded during the May 21 missile launching experiment in the Mojave Desert in California. These missile launching videos are subsequently utilized to create the simulation system and assess its performance. Once the computer program detects a missile launch and tracks the path it takes, it is able to determine the missile's speeds and location.

This data can be transmitted to an attacking UAV, allowing a countermeasure to be launched. Because the software used for simulation lacks the ability to analyze missile release videos captured from an unsteady platform, it is unable to be deployed on a surveillance UAV to detect missile launches and track path in actual time. If the simulation application can be improved by stabilizing the video before any video processing, it could be used to detect missile launches and track their trajectory in real time from a surveillance UAV. The following section discusses present methods to addressing this problem, and the last part presents an extensive structure of the works.

The main significances of this work are as follows:

-Design a vision-based missile trackers with the consideration of the target-surrounding context at the time of filter training stage.

- Develop an inexpensive object identification module that integrates depth image-based object detection with real missile object, the location, and orientation details to enhance environmental awareness and guidance.

-An adaptable ground segment method has been suggested that makes use of an adaptable threshold calculation algorithm as well as ground level continuity between frames that are adjacent.

-Present a direction search method to guide missile attacking system to the target object.

-Build a new missile tracking dataset and performed comprehensive experimental on this dataset

Related Works

The goal of a missile monitoring mechanism is to defend allies from local dangers within their area, address particular safety issues, and increase credibility in dealing with specific challenges. The primary objective of the project is to develop and implement a missile surveillance system for use in military. Modern missile defense systems may set up decoys and manoeuvre to avoid in the middle interception. To successfully cope with these sophisticated dangers, algorithms must be able to track throughout movements and handle with one objective breaking into various separate objects when decoys are used. This study focuses on the feasibility of using the interacting multiple model (IMM) [3] and joint probability data association (JPDA) [4] monitoring filters for a ballistic missile detection. In particular, the capacity to precisely forecast missile status during maneuvering and target split operations will be investigated.

There are various artificial intelligence techniques for detecting and tracking an object in photos or videos. The background removal, Scale-Invariant Feature Transform (SIFT), and Speeded-Up Robust Feature (SURF) detection, as well as Kalman filtering, are commonly used techniques for identifying objects. These techniques are frequently employed on video recordings of athletes in sports events to help trainers identify ways to enhance their player's performance.

In detection of motion and monitoring, it is constantly desirable to retain the movement of the thing of interest in the image after applying the background removal technique to subsequent frames. However, as the recording device moves during filming, it will impact the environment around it. The surrounding area will appear as interference in the picture after performing the background subtraction method. As a result, the video image must be stabilized prior to applying background subtraction in order to reduce the noise caused by neighboring movement and allow the simulation application to detect movement of objects more easily. Lucas and Kanade described a method for identifying features in two photos that might be used as anchors for stabilization of video footage [4]. Szeliski demonstrated a method [5] for automatically registering video frames into 2D and partial 3D scene models. This method identifies common features in successive images and stitches them together to create a video mosaic.

After stabilizing the video picture, the intended object in the frame might have been recognized using descriptor of the object's distinguishing features. This could be accomplished using the SIFT [6] and SURF methods [7]. Rublee et al. proposed an alternative method to SIFT and SURF that enhances the accuracy and effectiveness of feature detection [8].

Once the object was recognized in the video picture, its movement might have been calculated by comparing its location in subsequent frames of video. Patel employed successive frame distinguishing and pixel variation to monitor, identify, and verify an object that moves in a video sequence [9]. Fleet and Weiss described several mathematical models for determining object motion [10].

Proposed Methodology

This part includes an in-depth explanation of our proposed technique. The system we suggest includes camera calibration, a motion model, feature integrating, missile object tracking, continuous missile dimension calculation, and missile monitoring across successive frames of video.

Camera Calibration

A digital camera is an electronic gadget that transforms 3D world images into 2D images. A camera plays a crucial part in acquiring three-dimensional pictures and preserving them as images with two dimensions. Understanding the mathematical concepts behind it is absolutely fascinating. The lens of the camera can be represented using the following equation.

$$x=PX \tag{1}$$

Here x denotes 2-D image point, P denotes camera matrix and X denotes 3-D world point.

$$\underbrace{\begin{bmatrix} X \\ Y \\ Z \end{bmatrix}}_{\substack{\text{homogeneous} \\ \text{image} \\ 3\times 1}} = \underbrace{\begin{bmatrix} p_1 & p_2 & p_3 & p_4 \\ p_5 & p_6 & p_7 & p_8 \\ p_9 & p_{10} & p_{11} & p_{12} \end{bmatrix}}_{\substack{\text{Camera} \\ \text{matrix} \\ 3\times 4}} \underbrace{\begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}}_{\substack{\text{homogeneous} \\ \text{world point} \\ 4\times 1}}$$

Figure-1: vector representation of $x=PX$ [1]

In most cases, this entails recovering two types of parameters. Intrinsic or Internal Parameters:

It allows mapping between pixel coordinates and camera coordinates in the image frame. E.g. optical center, focal length, and radial distortion coefficients of the lens. Extrinsic or External Parameters: It describes the orientation and location of the camera. This refers to the rotation and translation of the camera with respect to some world coordinate system.

Intrinsic camera parameters calibration was not considered for this application, however it was necessary to calibrate the position and orientation of the camera relative to the position of the missile launcher. Automation of this process was briefly considered however was decided to be beyond the scope of the project. It proved sufficient to measure the location of the image centre and align the vertical axis of the image plane with the line at zero elevation and azimuth of the missile launcher. Applying the standard camera model:

$$p = R(P+t) \tag{1}$$

where p is the point on the image plane, R is the rotation matrix, P is the point in the world frame and t is the translation vector. The rotation matrix is the identity matrix as there is no rotation. The translation vector is defined as

$$t=[X_{cam} \;\; Y_{cam} \;\; 0] \tag{2}$$

Motion Model

All tables should be numbered with Arabic numerals. Every table should have a caption. Headings should be placed above tables, left justified. Only horizontal lines should be used within a table, to distinguish the column headings from the body of the table, and immediately above and below the table. Tables must be embedded into the text and not supplied separately. Below is an example which the authors may find useful. In this study, the model under consideration is constant velocity model. The trajectory state x_k is equal to

$$x_k = [x, y, \dot{x}, \dot{y}] \tag{3}$$

where x and y are position coordinates and $\dot{x}$ and $\dot{y}$ are velocities in both x and y coordinates, respectively. Target trajectory state propagates as

$$x_k = Fx_{k-1} + w_k \tag{4}$$

where F is state transition matrix, and x_k is zero mean white Gaussian noise with covariance Q.

$$F = \begin{bmatrix} I_2 & TI_2 \\ 0_2 & I_2 \end{bmatrix} \tag{5}$$

$$Q = \begin{bmatrix} 0.25T^4 I_2 & 0.5T^3 I_2 \\ 0.5T^3 I_2 & T^2 I_2 \end{bmatrix} \tag{6}$$

where 0_2 is the second order zero matrix and I_2 is second order identity matrix. T is the sample time. The object measurement model is

$$y_k = Hx_k + v_k \tag{7}$$

where H is measurement matrix and v_k is white Gaussian measurement noise.

$$H = [I_2, \; , 0_2] \tag{8}$$

Missile Detection and Tracking

Fukunaga et al. [11] first introduced the mean-shift algorithm in 1975. It shifts the mean vector and estimates the gradient function. Cheng et al. [12] extend mean-shift algorithm and used in computer vision application in 1995. Comaniciu et al. [13] first used this method in visual object tracking problem. This algorithm provided the fast search strategy and estimated the similarity between the image data and target model. It moves within the search window to find the target by using the climbing method of the same gradient channel. It finishes the object tracking when it covers the local extremum. Mean-shift algorithm works as an iterative fashion. The general mean-shift vector is computed by using equation (9) as:

$$M_v = \frac{1}{k}\sum_{y_j \in S_k}(y_j - y)$$
$$S_v(y) = \left\{z : (z - y_j)^T (z - y_j) < v^2\right\} \tag{9}$$

where S_k represent the d-dimensional sphere with the bandwidth v, y_j represent the sample point and y represent the chosen point in S_u, and u denoted the total number of points in S_k. The equation (2.6) is calculated by using the kernel function $K()$.

$$\hat{f}_{v,k}(y) = \frac{b_{k,d}}{nv^d}\sum_{j=1}^{n} k\left(\frac{y - y_i{}^2}{v}\right) \tag{10}$$

By using the derivation of the equation (2.6), we obtained the mean-shift formula as:

$$\nabla\hat{f}_{v,k}(y) = \frac{2b_{k,d}}{nv^{d+2}}\sum_{j=1}^{n}(y - y_i)k\left(\left\|\frac{y - y_i{}^2}{v}\right\|\right) \tag{11}$$

The transformation of the equation (2.6) to equation (2.7) is obtained by applying $l(y) = -k'(y)$ and Gaussian kernel as:

$$\nabla\hat{f}_{v,k}(y) = \hat{f}_{v,L}(y).\frac{2b_{k,d}}{nv^{d+2}}m_{v,L}(y) \tag{12}$$

where the mean-shift $m(y)$ presented as:

$$m_{v,L}(y) = \frac{\sum_{j=1}^{n} y_i l\left(\left\|\frac{y - y_i{}^2}{v}\right\|\right)}{\sum_{j=1}^{n} l\left(\left\|\frac{y - y_i{}^2}{v}\right\|\right)} - y \tag{13}$$

The sample mean-shift vector is calculated by taking $m_{v,L}(y) = 0$ as below:

$$y = \frac{\sum_{j=1}^{n} y_i l\left(\left\|\frac{y - y_i{}^2}{v}\right\|\right)}{\sum_{j=1}^{n} l\left(\left\|\frac{y - y_i{}^2}{v}\right\|\right)} \tag{14}$$

The mean-shift algorithm used Bhattacharyya coefficient to compute the similarity between the potential region and target feature models as like:

$$D(f, g) = \sum_{j=1}^{m}\sqrt{\sum f_j . \sum g_j} \tag{15}$$

where f, g represents two histograms and m represents each histogram color numbers.

The conventional mean-shift method cannot properly track the non-rigid object due to the lacking spatial distribution information, to minimize this problem we used the target shape and color feature and they showed that their tracker run in real time to tracked the non-rigid object.

Results and Discussion

To evaluate the experimental data analysis, we used missile object data image whose resolution is 640 × 480 and the depth map capture rate is 30 frames per second. The sensing range is 0.8 to 4.0 m. We ran our algorithm in MATLAB 2017b with a 64-bit Windows environment. The hardware environment included a PC with Intel Core i7 CPU and 8 GB RAM.

We also employ three evaluation measures that are precision, recall and F-measure to evaluate the performance of object detection results. These measures are defined as follows:

$$\mathrm{Pr}\,ecision(p) = \frac{TP}{TP+FP} \tag{16}$$

$$\mathrm{Re}\,call(R) = \frac{TP}{TP+FN} \tag{17}$$

$$F = 2\,\frac{\mathrm{Pr}\,ecision * \mathrm{Re}\,call}{\mathrm{Pr}\,ecision + \mathrm{Re}\,call} \tag{18}$$

Table 1. The success rate and the failure rate for missile detection of our proposed method.

Total images	**Success Rate (%)**	**Failure Rate (%)**
Video-1(786)	83.48%	16.52%
Video-2(1036)	79.75%	20.25%
Overall	81.61%	18.39%

Conclusion

In this research, we have discussed several challenging issues that are involved in the real-life environments for the missile detection and tracking. We investigated that it is very important to consider these factors to enhance the overall missile tracking performance. We have been seen that our missile object tracking approaches are able to tackle these problems with the extra benefits over the holistic approach. Most of the traditional real life application based missile tracking system used simple tracking models to increase their runtime requirement that is very important in real life object tracking applications. To increase the tracking speed, they reduced the complexity of the model. This model complexity reduction leads tracking failure problems. The suggested Matlab computer program detected a missile launching and tracked its trajectory within the movie's field of view. However it only achieved an actual positive tracker accuracy of 81.61 percent, the simulated program's missile location updating rate was adequate for an attack system to detect it reliably. This implies that for a missile release video at 65 images per second, the modeling program might offer approximately 14 missile location upgrades per second.

On the other hand, the simulation application cannot handle any missile release images that have not been stabilized, nor can it identify a missile launching with a small dust plume. In its present form, the simulation application is unable to analyze the CUAV's footage of surveillance in order to provide targeted data for an attacking UAV to capture it reliably. However, if the camera footage can be stabilized before being analyzed by the modeling program, it may be mounted on an observation UAV to identify a missile launching risk and offer targeted details to an attacking UAV, allowing it to intercept the missile with greater reliability.

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