YOLOv5-based Passive Missile Detection using simulated Solar Blind Ultraviolet Signatures

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Abstract—Civilian and military aircraft face significant threats from passive missiles, such as short-range or within-visual-range air-to-air missiles (SRAAMS or WVRAAMS) and man-portable air defense systems (MANPADS), which do not emit radio frequencies (RF) and thus evade detection by an aircraft’s Radar Warning Receiver (RWR). In this paper, we present a deep learning-based passive missile detection algorithm utilizing simulated Solar Blind Ultraviolet (SBUV) signatures of missiles, which offer inherent advantages over infrared (IR) signatures. The proposed algorithm employs the YOLOv5 (you only look once) framework of Convolutional Neural Networks (CNNs) and moving object tracking to detect and classify the simulated passive missile UV signatures from a sequence of images. Data synthesis techniques, using 3D missile and aircraft combat scenario simulations in the SBUV spectrum, are applied to overcome the challenge of limited training data. Our findings demonstrate that the proposed algorithm effectively detects the simulated passive missile UV signatures, de-cluttering them from the background and classifying detected missiles as threatening or approaching threats. Consequently, this deep learning-based approach provides a promising approach for improving the detection and direction assessment of passive missile threats, ultimately enhancing aircraft safety and security.

Index Terms—Artificial Intelligence (AI), Convolutional Neural Networks (CNNs), Passive detection, Radar warning receivers (RWRs), Solar Blind Ultraviolet (SBUV), YOLOv5.

I. INTRODUCTION

COMBAT aircraft and aircraft operating in other hostile and sensitive zones are always at risk of a missile attack. Since the 1960s, passive heat-seeking missiles have been responsible for seventy percent of all enemy-inflicted aircraft damage [1], [2]. Although radar-guided Surface-to-Air Missile (SAM) systems are notable for their extended engagement ranges, faster response times, and superior accuracy, passive missile attacks continue to demonstrate noteworthy effectiveness [3]–[5]. The suitability of this methodology is significantly contingent upon the specific circumstances in which it is implemented. A comprehensive discourse regarding this topic will probably give rise to contemplations concerning classified information.

Due to the threat posed by man-portable passive infrared homing SAMs, passive missile warning systems have been developed to sound an alarm as soon as a missile engages an aircraft [6]. Once a missile is fired at the aircraft, the missile approach warning system (MAWS) detects the threat and displays a warning on display within a short time (on the order of a few milliseconds), referred to as detection time. Once a target is identified, its location and approach direction is determined. When it is determined that the detected platform is not clutter but rather an approaching threat, an alert is triggered for the pilot [7], [8].

In the development history of missile warning technology, infrared (IR) and radar have dominated the field of warning for almost 30 years. However, radars detect targets using active transmission which makes it prone to detection [9]. In the past, major work to develop passive missile detection systems has been by utilizing IR sensor imagery [10], [11], dual-band infrared sensors imagery [12] and multi-spectral imagery [8], [13]. These advancements are progressively establishing IR missile warning systems as the preferred option, thereby displacing ultraviolet (UV) missile warning systems from their traditional role. However, compared with IR warning technology, UV warning technology and specifically Solar Blind Ultraviolet (SBUV) band located between 240 and 290 nanometers still has many advantages such as low false alarm rate, refrigeration independence, small volume and light weight [14]–[17]. Background clutter is the biggest challenge faced by IR-based missile detection systems, especially operating close to ground surfaces, as the IR clutter from the surface of the earth is the highest and poses a serious challenge to missile identification systems [14]–[16]. However, it is critical to acknowledge that the SBUV band experiences a significant reduction in background clutter. This reduction can be primarily attributed to the lack of solar radiation at the surface of the Earth within this particular spectral range. The threat from MANPADS is also generally higher at low altitudes. Therefore, a detection system that can perform better at lower altitudes is considered appropriate for developing a detection system against MANPADS. Considering this requirement, SBUV sensor-based detectors appear to be a better alternative. A comparative analysis of the mentioned spectrums of detection is depicted in Table I.

Efficient and accurate detection of missile signature in real-time and predicting its future motion are key requirements of any missile warning system. Traditionally, engineered approaches based on statistical models are used to predict future motion. Most commonly used approach for predicting the future position of a detected object is based on propagating its state over time based on the kinematic model and assumption of the underlying physical system. The state estimate includes position, speed, acceleration and heading information and
TABLE I: Comparison of Various Missile Detection Techniques [14]–[16]

<table>
<thead>
<tr>
<th>Type</th>
<th>Advantages</th>
<th>Disadvantages</th>
</tr>
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<tbody>
<tr>
<td>Radar</td>
<td>Low detection range</td>
<td>Prone to detection</td>
</tr>
<tr>
<td>IR</td>
<td>Long detection range</td>
<td>High false alarm rate</td>
</tr>
<tr>
<td>UV</td>
<td>Low false alarms</td>
<td>Atmospheric attenuation</td>
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<tr>
<td>SBUV</td>
<td>Extremely low false alarms</td>
<td>High cost</td>
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techniques such as Kalman filter (KF) [18] are utilized to estimate position in the future. This approach is appropriate for short-term predictions, but for longer horizons and large fields of view, as in the case of this study, where a total of 4 MAWS sensors are supposed to provide 360-degree azimuth and 180 degrees elevation coverage to the aircraft, the performance of the KF model degrades as it ignores wide scale surroundings [19], [20]. In [21], passive missile distance estimates were conducted using the target’s surface area. Extended Kalman Filter (EKF) has been used to estimate the image-derived area parameter of the threat plume. This investigation was primarily concerned with range estimation rather than detection precision. In this study, several aspects were overlooked when predicting the engagement scenario, including the change in viewing angle between the guided missile and the sensor and atmospheric impacts on the region of motor flame during the engagement. Our proposed methodology accounts for these facets of engagement angles. Another technique for solving such problems is learning approaches using classical machine learning. Using Hidden Markov Model is one example that uses Bayesian networks for state prediction [22]. But in Bayesian methods, computations are expensive and are not feasible for real-time tasks [23]. In [8], passive missile detection has been accomplished via multi-spectral imagery and the Hidden Markov Model, an analytical model in which the system being studied is viewed as a Markov process with unobserved states. Due to the use of IR and UV spectrum, the suggested system has a good detection range. However, the number of false alarms is high because the detector employs maximum intensity across all spectral bands and makes no assumptions about what it is seeking, compromising the overall dependability and reliability of the detector system.

Furthermore, in [24], a Dynamic Bayesian network-based prediction model is proposed in which the target state is updated by using the statistics encoded in a navigation map of the scene. Scenario-specific motion patterns of targets like bicyclists and pedestrians are hand-crafted to capture context information and applied to new scenes manually, resulting in sub-optimal performance under crowded environments. Gaussian process regression may be utilized to address motion trajectory prediction. It can measure uncertainty in position, but it has limitations while modeling complex environments with multiple objects.

Another method for moving object detection (MOD) is by applying conventional image processing techniques such as foreground and background separation. Robust Principal Component Analysis (RPCA) has been extensively utilized to solve such challenges. In [25], a virtual missile model and motion model estimation is proposed for passive missile detection utilizing foreground and background separation information and applied to new scenes manually, resulting in sub-optimal performance due to the delay in processing time as well as miss detection [26].

With the advancements in computer vision and deep learning, detecting fast-moving objects in real-time has become feasible with promising outcomes [27]–[29]. Some studies have used convolutional neural networks (CNNs) to analyze video data and identify objects of interest like motion prediction of road users for self-driving vehicles [19], [30], [31], human trajectory prediction in crowded areas [32], [33]. Some researchers have used recurrent neural networks (RNNs) to predict the future trajectory of similar objects [34]. However, deep learning has not been explored to its full potential in the domain of missile detection and trajectory prediction which is a highly dynamic environment and objects of interest are moving at speeds faster than Mach 2. Predicting the trajectory especially when the objects are moving at speeds above Mach 2 is even more complex because the high speeds make it difficult for sensors as well as detection algorithms to accurately track the objects, and there may be issues with motion blur, noise, and other factors that can affect the accuracy of the data. In [16], a multi-band SBUV early warning system investigation was conducted for ballistic missiles. The design of a geostationary orbit space-based ultraviolet early warning system is also simulated.

After conducting a thorough literature review, it was found that there is a pressing need to create a detection algorithm and development methodology that can accurately detect fast-moving objects travelling at speeds above Mach 2 while minimizing the occurrence of false alarms. These two key performance indicators are essential for any MAWS since the pilot’s confidence in the system relies on them. In addition, aircraft have a limited quantity of countermeasures. Deploying countermeasures against false alarms can be dangerous, as it can deplete the limited number of countermeasures available on board the aircraft. This can leave the aircraft vulnerable to threats that may emerge later in the mission. Additionally, deploying countermeasures unnecessarily can alert the enemy to the presence of the aircraft, potentially making it easier for them to track and target. Therefore, it is critical that MAWS evaluate alarms effectively and only deploy countermeasures when under attack. This requires a high degree of accuracy and precision of the deployed detection system.

In this paper, we propose to develop a MAWS using deep learning techniques to detect the signatures of SRAAMs, WVRAAMS and Man-Portable Air Defense Systems (MANPADS) through simulated SBUV data. The proposed detects incoming threats by employing an efficient CNN architecture to detect and predict the future position of the threat accurately. The availability of training data is a big challenge for deep learning models in this domain as no current open-source data sets contain training information encompassing missile signatures in the specified frequency range. In the proposed research, we seek to address the lack of training data in the SBUV spectrum by synthesizing data using 3D simulations.
A. Assumptions

We work under the presumption that threats are identified through the utilization of a high-resolution imaging system that offers an extensive field of view concurrently. This situation poses a counterintuitive problem in that while it is essential to cover a 90-degree field with a limited number of pixels, it is also critical to acquire a comprehensive image of the threat. In the simulated imagery, background noise is entirely disregarded. Although the sensor is designed to be solar-blind, there remains the possibility of residual photons reaching the detector. Additionally, sensor noise is not accounted for in these simulations. This influences the edges of the objects and might affect the detection algorithms which need to separate objects from the background. The signal of a missile plume is assumed to be constant over the flight which might not be necessarily the case over the flight, because the motor thrust may vary over the flight. A ring plume is not the only way a missile approaching the aircraft could be seen. Most missiles do not aim at the aircraft target directly but fly towards the predicted interception point because this yields the shortest distance to the target and minimizes manoeuvring for the missile. So missile plumes observed under small angles may still be threats.

B. Data Synthesis

The method for detecting missile plumes is based on the YOLOv5 framework, which necessitates massive training data for supervised learning. There are a variety of publicly accessible data sets used to train a CNN detector. However, the unique dataset necessary for this investigation is unavailable. For the preparation of optimum training data, an SBVU sensor is required to capture photos of missile plumes when they are fired at aircraft in diverse combat circumstances. Due to the lack of such leverage, a dedicated 3D rendering software is utilized to construct simulations of the desired scenarios in the SBVU spectrum. Based on the literature survey, different possibilities of aircraft engagement by MANPADS, SRAAMS and WVRAAMS are analysed for this study, and a total of 10 combat scenarios of aircraft and MANPAD engagement, and 10 scenarios of SRAAMS and WVRAAMS engagement scenarios were simulated. By training the system on multiple scenarios, the proposed system is prepared to detect and respond to real-world missile threats. All possible firing angles in 360-degree azimuth have been covered in simulations. Firing speeds and firing distance have been defined separately in each simulation with the help of a literature study. For MANPADS firing speed of 1,900 to 2,400 kilometers per hour and firing distance is 5 to 6 kilometers [40], for SRAAMS speed is defined as 3,700 kilometers per hour and is fired from a distance of 20 to 40 kilometers and for WVRAAMS speed of firing is 4,800 kilometers per hour and is fired from 50 kilometers [41] in the simulations. It's worth noting that these are rough estimates of speeds and ranges utilized in simulations and can vary significantly based on many factors.
including the specific models and conditions of the missiles and the target aircraft. After simulating a handful of SBUV videos of missile aircraft engagement, 2D images (frames) were extracted from the videos. Data augmentation techniques were utilized to extend the dataset. All the simulated data (20 videos and 6600 frames) can be divided into five significant engagement categories, elaborated further one by one.

1) Approaching Missile: In this category of engagement, the missile operator attempts to acquire the target aircraft visually, using the missile’s infrared seeker to lock onto the aircraft’s engine exhaust or other heat source. One MAWS sensor is positioned on the tail of the aircraft and it visualizes a growing ring of missile plume as it approaches the aircraft. Fig. 2 displays the SBUV image of an approaching missile where a smaller plume is evident in initial frames, yet a greater plume ring is observed in subsequent frames. To generalize the results, firing angles were also varied in the simulated videos along with variation in firing speeds and distances for MANPADS, SRAAMS and WVRAAMS as defined in the above paragraph. Generally, 4 to 6 MAWS sensors are used to provide complete 360-degree coverage to aircraft, which requires that the minimum field of view of each sensor is 90 to 60 degrees. Therefore, in our simulations, we varied the firing angle ± 45 degrees from the tail side of the aircraft to ensure a complete 90-degree visualization within the field of view of the sensor mounted on the tail of the aircraft.

In the simulations, it can be seen that the middle section of the plume is eluded by the missile body, which makes it look like a ring instead of a circle.

2) Receding Missile: In this category of scenario, a SRAAM missile is launched by the subject aircraft and the simulation extracts visual frames of a receding missile signature captured by the MAWS sensor mounted on the pylon of the aircraft. In another simulation, a WVRAAM missile is launched by a friendly jet flying parallel to our subject aircraft and the MAWS sensor mounted on a pylon visualizes the receding signature of the missile plume. In yet another simulation of this category of engagement, a formation flying is simulated and SRAAM is fired by a friendly jet in formation flying and visualized by MAWS sensor. In these simulations, the image of the missile plume shrinks in consecutive frames in terms of area, as shown in Fig. 3.

3) Aircraft flying over High Power Electric Transmission Lines: Fig. 4 depicts a situation in which an aircraft flying over high-voltage transmission wires is simulated. Corona discharge occurs on high power lines whose spectral emission band resembles a missile plume. It is invisible to the naked eye, but UV and SBUV sensors can detect it [42]. Hence, it poses a significant chance of false alarms for our application. Multiple simulations were rendered in which MANPAD is fired towards aircraft from a distance of 5km and there is corona discharge in the background. The MAWS sensor visualized the MANPAD signature along with the corona discharge. Similarly, in a few other simulations, the aircraft is flying above high power lines and is being targeted by SRAAMS and WVRAAMS. Again the MAWS sensor visualizes the coming missile as well as the corona discharge at the same time. This category of simulated scenarios helped develop a training image data set with corona as background clutter.

4) Formation Flying and Missile hitting the other jet flying parallel: Fig. 5 depicts the formation flying with the missile initially pursuing both planes, the subject aircraft with MAWS sensors and another aircraft flying in formation. In the initial frames of the simulated 3D modeling, the MAWS sensor/camera mounted on the aircraft’s tail is visualizing the coming missile. During the later half of the simulation, the missile abruptly alters its course to pursue the other aircraft rather than the target plane with MAWS. (old) This simulated scenario produces a training data set for the system to evaluate a situation in which it detects a missile initially that is not to be deemed as a potential threat. It will help the system to decide smartly not to waste its countermeasures for an unintended threat. The purpose of this simulation is to create a training data set for the system to evaluate situations where a missile is initially detected but is not deemed a potential threat. This will help the system to make smart decisions about when to deploy countermeasures and when to conserve them for more serious threats. The use of a simulated scenario allows for controlled testing and evaluation of the system’s capabilities without the risk of actual harm or damage.

5) Missile Chasing another aircraft flying in a different direction: In the scenario depicted in Fig. 6, the MAWS sensor
on the target aircraft identifies a passive missile being fired at an aircraft flying in a direction other than parallel. This simulation educates the system to recognize which incoming missiles pose a threat and which do not. Additionally, the simulation aids the system in rejecting clutter, as the subject aircraft’s tail plume and other jets’ tail plumes act as clutter. Once trained on such data, the system shall be able to distinguish between actual missile threats and other non-threatening objects or distractions. Using simulated scenarios such as this allows for the system to be trained in a controlled environment and exposed to various types of potential threats and clutter. This training is essential for the system to effectively detect and respond to missile threats in real-world situations.

C. Object Detection and Classification

Numerous deep CNN architectures exist for object detection, such as RCNNs, Fast RCNN, Faster RCNN, Mask RCNN, and AlexNet. In this study, we employed the YOLOv5 framework of CNN for the object detection component of the method due to its superior detection results and faster inference speed [43].

1) Model Architecture: The YOLOv5 model architecture employed to address the object detection and classification problem is depicted in Fig. 7. It comprises of 213 layers, 7,015,519 parameters and a computational complexity of 15.8 GFLOPs.

2) Training: The detection model was trained with a confidence threshold set to 0.25 and an intersection over union (IoU) threshold of 0.45. The training process utilized a dataset containing 6,500 images, each with dimensions of 1920 x 1080 pixels. The implementation of the model was carried out in Pytorch [44], and the training was performed on an Intel(R) Core(TM) i5-5300U CPU @ 2.30GHz equipped with two cores and four logical processors.

Supervised learning models necessitate ground truth data (labeled dataset) during training. In this research, we used Labelme (an open-source annotation tool) in the YOLOv5 model format to annotate the data. Object detection combines image classification and object localization. The image classification process requires assigning object classes to an image, which can involve one or more objects. In contrast, object localization needs to identify both the object class and the bounding box, i.e., the location where a class is detected in an image. This study defines three classifications based on shape and features shown in Fig. 8. The terminologies used for each class is explained here to highlight the difference between each of them.

- Ring plume (r-plume). It represents a plume of a missile heading directly toward an aircraft. It is the only class that is fed forward to the next sub-module, ‘Tracker,’ for further processing to find the direction of the threat.
Fig. 8: Three classes defined for data annotation

- **Plume.** Plume represents any missile or aircraft plume headed in any direction other than towards the subject aircraft. This class stays with the classifier as long as the missile signature is present within the system’s field of view and does not change into the class ‘r-plume.’ As soon as it changes into ‘r-plume,’ it is fed forward to the next sub-module ‘Tracker.’

- **Corona.** This represents electric discharge on high-power transmission lines. This class is the recognizable clutter and it is dropped by the Classifier module and is not sent for tracking.

**D. Object Tracking**

Prediction of the trajectory of fast-moving objects is a complex problem. We build this part of our system on the work described in [30], [31], which considered road users as an input to CNNs and predicted future trajectories. However, the speed of objects of interest in this study is above Mach 2 which is much more than any other objects like pedestrians, bicyclists, and cars for which future position prediction has been carried out in the mentioned previous works. The tracking technique in our work employs a Discriminating Correlation Filter with Channel and Spatial Reliability (DCF-CSR) on the 2D image frames. A spatial reliability map is used to tailor the filter support to the portion of the tracking frame’s specified region. This allows for the enlargement and localization of the targeted region and enhanced tracking of non-rectangular areas or objects. In order to minimize the processing workload on the MAWS processor and to optimize the performance in real-time, only one class of detection, ‘Ring Plume’, is segregated by the detection algorithm which depicts all those missiles which are heading directly towards the aircraft. Therefore, input to the tracking module is only one detected class ‘Ring Plume’ on which threat direction assessment and future trajectory analysis has been performed in this study as shown in Fig 9.

The area of the detected object is estimated from the bounding boxes drawn by the detection algorithm. The calculated area is stored in an array, and after every 10 frames, the comparative analysis is performed to estimate the direction of the threat. In YOLOv5 data annotation format, bounding boxes are saved with X center point, Y center point, width, and height. So the area calculation is performed by multiplying the width and height of the bounding box. As shown in Fig. 10, the detected target is evaluated as an approaching threat or receding missile based on the change in the cross-sectional area of the SBUV image. The calculated area information is stored and plotted graphically in real-time, where the gradient of the graph estimates the threat’s direction of motion. The threshold value for the number of frames (10 in this study) is selected, assuming that the frames per sec (FPS) of the SBUV sensor is 50. After processing through all three sub-systems, the system’s final output displays a bounding box on the detected object along with object class label, confidence level, area information and direction assessment as shown in Fig 9.

**III. RESULTS AND DISCUSSION**

The performance of the object detection model is evaluated using specific metrics extensively employed in computer vision and deep learning to assess algorithm performance.

1) **Loss Function:** A loss function measures the neural network’s performance based on training data. Networks are trained to minimize total “loss” between actual and predicted outputs. The model’s loss function is calculated using the Intersection over Union (IoU) value, which estimates the intersection of the ground truth bounding box and the predicted object’s bounding box. With an IoU threshold value of 0.8, loss percentages are computed. As the number of training cycles (Epochs) increases, the detection loss of the class, box, and object decreases, converging at 2% during training and 1% during validation after 100 training cycles as can be seen in Fig. 11.

2) **Precision and Recall:** Precision measures the accuracy of positive class predictions, while recall refers to the proportion of positive class predictions collected from all positive examples in the dataset. Fig. 12 shows the Precision and Recall values on top and mean average precision on the bottom. As the number of epochs (training cycles) depicted on the x-axis increases, the recall and precision percentage
values also increase, reaching as high as 85%. Similarly, the recall value approaches 95% with 100 training epochs. Fig. 13 depicts the overall precision curve $P_{\text{curve}}$ of the detection system against confidence levels (x-axis) and demonstrates that the precision of all three detection classes increases with increasing confidence level and reaches 100% at a confidence threshold of 0.8. The value of precision is lowest for class corona (90% at 0.8 confidence) because of less training data (200 frames), and it is highest (100% at 0.8 confidence level) for class Ring plume because of the peculiar shape and distinctive identity of this image type. Similarly, recall curve $R_{\text{curve}}$ has also been plotted and shown in Fig. 14.

3) Mean Average Precision: The mean average precision (mAP) value is calculated over recall values from 0 to 1. In this study, mAP is first calculated at the IoU threshold set at 0.5, it is calculated at different IoU thresholds starting from 0.5 to 0.95, increasing in step sizes of 0.05. mAP results are depicted in Fig. 12 on the bottom. When IoU is set to 0.5, then the value of mAP reaches to 95%, but when the IoU value is gradually increased from 0.5 to 0.95, the value of mAP becomes 70%.

4) F-Measure & Confusion Matrix: Precision and Recall are mutually contradictory quantities. A greater value of one diminishes the value of the other. For this reason, to evaluate the performance of a CNN model, the F-Measure / F-score is calculated considering it as the harmonic mean of precision and recall, giving the same weighting to both. F-Measure calculated in this study is shown in Fig. 15. It is 95% for all three classes at a confidence threshold of 0.5, which is a reasonably high F-measure.

Fig. 16 shows the confusion matrix plotted for the created system. It compares actual targets to those predicted by the
machine learning model. The optimal accuracy for a confusion matrix is 1, but in a real-time environment, this is impossible owing to false detection and false negatives (target miss).

The correct and incorrect prediction values for all three classes are represented in number count in Fig. 16. It can be seen that the class Plume is predicted with 99% accuracy, class Approaching Plume / Ring Plume is predicted with 98% accuracy; however, the third class, Corona, is predicted with 100% accuracy. Background objects which were neither a clutter of SBUV domain but were still detected by the model have a 32% chance of detection as Plume and 68% chance of detection as Corona (SBUV domain clutter). This result is very significant because it provides good data visualization. Therefore, we can say that if the detector module of the proposed system accepts a non-SBUV spectrum object and passes it on to the classifier module, then there are 32% chances of having False alarms in this system, depicting a non-missile object as a missile. This confusion matrix has provided insight into the errors made by the classifier and the types of errors made.

5) Inference Time: The proposed system has an inference time of 403.2 msec for processing any scenario video containing approximately 1669 2D frames each, which includes both detection as well as prediction of the future trajectory of a potential threat. This processing time meets the real-time requirement for the system, as in actual combat situations, the MAWS must be able to detect and process a threat quickly and relay the warning signal to the electronic warfare suite of the aircraft within a matter of seconds [45], [46].

6) Tracking results: The output of the tracking module is evaluated on random test data selected from the synthesized data set. Training and testing data were randomly selected initially with a 60 and 40 percent ratio, respectively. We experimented with providing different simulated videos to the detection system. These videos generalize the combat scenarios with all possibilities of firing angles, directions, speeds and firing ranges for MANPADS, SRAAMS and WVRAAMS that can be faced by any fighter or civilian aircraft in any real time environment. Multiple tests were run on the simulated data for future trajectory prediction. Out of these, Table II shows the results of five experiments run with the complete detection system pipeline, and Fig. 17 depicts the direction prediction performed by the tracking sub-system. Area of the bounding boxes of the detected object is calculated on the sequence of frames after every ten frames and based on this, future trajectory and direction assessment is performed. It is evident from Fig. 17 that the proposed system predicts the direction of the threat for all the test cases defined for the scope of this study. These test cases generalize the combat scenarios effectively and future trajectory prediction is carried out with detection accuracy and in less than a second timeframe.

IV. CONCLUSION

We have introduced a deep learning-based method that offers both detection and future position predictions for objects moving at a very fast speed generally above Mach 2. This proposed method offers advantages over conventional statistical, probabilistic and image processing-based detection and tracking methods which suffer from limited performance under highly dynamic, large field of view and highly cluttered environments. The proposed methodology demonstrates reduced false positive rates and high detection probability, ensuring greater confidence in the detection algorithm. The proposed detection system is based on the SBUV spectrum which has proved it is effective over IR or MWIR spectrum when confronting SRAAMS, WVRAAMS and man-portable air defense
systems (MANPADS), the primary threats aircraft face in modern warfare. The data synthesis technique employed in this study encompasses all aspects, angles of alignment, firing directions, firing ranges and possible 3D combat scenarios of engagement for SRAAMs, WVRAMs and MANPADS, surpassing the models presented in prior research. However, this study does not account for environmental parameters in the simulation. Future work can validate the presented approach using actual SBUV signatures obtained from commercially available SBUV sensors. In complex conflict zone scenarios, the existing algorithm can be extended to simultaneously develop tracking approaches for multiple targets and prioritize specific threats over others. The current work can be a foundation for future position, velocity, and range calculations research. While the current algorithm is designed for use on desktop computing systems, it is conceivable that a version optimized for edge devices could be developed for real-time implementation in the aircraft avionics suite.

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