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Infrared Small Target Detection Using Nested FPN

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Abstract: *The proposed research project seeks to improve the performance of small target detection in videos by means of raising its accuracy level. In this regard, it is necessary to improve the performance of the TNFPN by incorporating video-based approaches like ConvLSTM and temporal attention. It is expected that such an improvement of the framework will provide it with additional possibilities of understanding not just the target located in a certain video frame but also the context of the whole video in which the target is situated. As a result, the proposed TNFPN would be capable of taking into account the movement pattern of the identified target and context of its actions. It is planned to develop another module that could help to improve the effectiveness of video data processing. Such an approach is expected to lead to higher effectiveness and accuracy of target recognition.*

Keywords: Infrared Small Target Detection, Video-TNFPN, ConvLSTM, Temporal Attention, Spatial–Temporal Features, Real-Time Detection, Noise Reduction, Surveillance Systems.

I. INTRODUCTION

Small target detection using infrared imaging technology becomes an important concern in areas of surveillance, aerospace surveillance, border surveillance, and even safety applications. Detection of small targets in surveillance systems requires detecting low-contrast objects. These types of objects are hard to detect due to factors such as background, noise, and the dynamic nature of the environment. Traditional techniques normally take into account the spatial features of the images. Traditional methods fail to consider the time aspect of video sequences. This causes inaccuracies in the detection of targets using traditional techniques.

In order to solve the above challenges, a new framework referred to as Video-TNFPN has been proposed in this study. The technique used in this framework is completely different from the existing ones as it uses spatio-temporal analysis of successive infrared frames. Different models have been used such as ConvLSTM to detect motion patterns and temporal attention models. Therefore, the system can distinguish between target objects and the noise in the surrounding environments.

One other aspect of this system is the process of consistency refinement, which will guarantee consistency in the result of detections. Consistency refinement is, in essence, a process of smoothing, which guarantees that there will be no flickering in the results of detections while reducing the number of false positive detections due to the continuous nature of detection. Another important aspect of this approach is that the system is relatively simple, which allows the usage of this approach in almost real-time. The entire Video-TNFPN idea is used as a means of small target detection in infrared videos.

II. RELATED WORK

Detection of small targets is one of the most important applications in the areas of defense, surveillance, and aerospace engineering. The detection of small targets from an infrared image is not an easy process because the image is low in

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energy. In years artificial intelligence, especially deep learning has helped to improve detection by allowing models to learn features that can tell things apart. However many current methods only look at one frame at a time which makes it hard to handle moving scenes and changes over time.

Deep Learning Methods for Infrared Small Target Detection: Detection of small infrared targets has significance in many applications—such as surveillance and defense—however, previous attempts at infrared small-target detection (e.g., multiple-image detection) have been difficult because they are low contrast and have complex backgrounds, such as noise and obstacles. There are many early method approaches for small-target detection that focused solely on single-frame detections without any consideration for the temporal aspect of a target's movement. Zhao et al. [1] review most of these early investigations to demonstrate their singular instance or lack of temporal context.

Deep Learning Methods Improved the Performance for Small-Target Detection: The advent of deep learning methods resulted in better target detection performance. In particular, the RISTDNet model from Hou et al. [2] created robust small-target detections due to its ability to identify both visible and non-visible light conditions. Wu et al. [3] accomplished enhanced detection and tracking accuracy using a combination of multiple input modality feature fusion techniques. Incorporating time-to-event modeling/weights or attentional mechanisms into existing models could provide improvements in overall detection accuracy as shown in studies conducted on several different types of attention-based models [4] and in ADC-CenterNet [5] studies related to small infrared targets and dual-stream networks.

Lightweight and Real-Time Detection Models for Detection: Some researchers have begun investigating lightweight designs to improve the efficiency of infrared detection. Several proposed lightweight network architectures incorporate multi-scale and attention-based processing routines (e.g., AGPCNet [6] and ISNet [7]) to enhance target detection rates.Although some sparse-coded approaches ([10]), which perform well in complex backgrounds, provide noise robustness; they require careful tuning. As a consequence, sparse-coded approaches may not be suitable for high-speed, real-time detection following a minimum of three consecutive frames of an object's motion.

Temporal and Video-Based Detection Approaches: Recent studies indicate that many providers are developing new techniques to incorporate temporal features to improve infrared target detection (e.g., MDvsFA-cGAN [8] and ASFNet [9]) include building on their success with multiple input modalities.Advanced networks incorporate dual-stream processing methods [11], attention-based processing mechanisms [14][15] as well as the ACM technique for detection accuracy [13] while maintaining real-time operational performance. However, most of the existing techniques do not provide sufficient computing resources for processing large volumes of data.

III. METHODS AND MATERIALS

Proposed systems for detecting small targets include the use of algorithms based on machine learning for processing images that belong to the spatial and temporal domain in order to increase the efficiency of small target detection in IR videos. Unlike frame-by-frame processing techniques, this system analyzes several frames consecutively. Thus, small targets can be detected even when there is no sufficient contrast. It is essential to emphasize that the effectiveness of this system is provided by temporal consistency. Complexity of calculations makes this approach implementable in near real-time mode. The system includes the following modules:

Data Preprocessing and Augmentation: Data Preprocessing and Data Augmentation: The data used in this research include clips of video footage. These video clips contain objects in various environments. Images from each clip undergo preprocessing including their resizing, normalization, and denoising. Methods for augmentation involve flipping, rotation, and changing brightness levels.

Mathematically, image normalization is defined as:

$$I_{norm} = \frac{I - I_{min}}{I_{max} - I_{min}}$$

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where $Inorm$ is the normalized pixel value, and $Imin$ and $Imax$ represent the minimum and maximum intensity values in the image, respectively.

CNN-Based Feature Extraction: The feature extraction stage works on the CNN-based network model. In fact, features are extracted from all frames in the infrared sequence. These features consist of textures, edges, and intensity gradient. Feature maps are produced by using CNNs, which are then used as input to temporal processing tasks. Convolution can mathematically be described as follows:

$$Y=f(X*W+b)$$

where $X$is the input feature map, Wdenotes the kernel weights, $b$is the bias, and $f(\cdot)$ is the activation function.

Algorithmic Framework: The entire process of the algorithm is described below:

Input: Infrared video frame sequence.

Output: Detected targets with bounding boxes or heatmaps.

1.. Preprocess consecutive video frames.

2. Extract features using a CNN backbone.

3. Pass features through ConvLSTM layers for modeling.

4. Apply attention to refine important features.

5. Fuse multi-scale features using TNFPN.

6. Apply consistency refinement to smooth predictions.

7. Generate detection outputs using a prediction head.

8. Display or store results for real-time surveillance and tracking.

Temporal Learning Module (ConvLSTM and Attention): To capture dependencies extracted spatial features from consecutive frames are passed through ConvLSTM layers. These layers model motion patterns. They preserve structure across time. A temporal attention mechanism is applied. It focuses on the relevant frames. It suppresses information or noise. This enhances the models ability to detect moving targets accurately.

TNFPN-Based -scale Feature Fusion: The temporally enhanced features are fed into the Two-layer Nested Feature Pyramid Network (TNFPN). This performs -scale feature fusion. This module combines features from resolutions. It improves the detection of low-contrast targets. It enhances localization accuracy. It ensures representation of targets at different scales.

Temporal Consistency Refinement: To ensure detection across video frames a temporal consistency refinement module is applied. This module smooths predictions over time. It reduces flickering effects. It minimizes positives. Detected targets remain consistent across frames. This improves reliability in environments.

Model Training configuration: The model is trained using deep learning frameworks like PyTorch or TensorFlow. Optimization is performed using the Adam optimizer. Loss functions, like binary cross-entropy or focal loss are used. They handle class imbalance. The training process is conducted over epochs. This ensures convergence and improved performance. The loss function is de fined as:

$$L = -\sum_{i=1}^{N} y_i \log(\hat{y}_i)$$

where y i is the ground truth label. Y ^ i represents the predicted probability.

IV. EXPERIMENTAL STUDY

This section brings into focus the mechanism and functionality of the proposed Video-TNFPN architecture in relation to target detection within thermal imaging videos. The method consists in analyzing sequential frames captured via thermal imaging for acquiring information about spatial and temporal data.

The implementation of Video-TNFPN was carried out with the help of programming languages such as Python together with several auxiliary software libraries such as PyTorch, OpenCV, and NumPy. The process involved CNNs for

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analyzing spatial data, ConvLSTMs for temporal data, and attention models for extracting appropriate information. The advantage of this technique over the algorithms using a single frame technique lies in the superior performance in terms of target detection.

For evaluating the effectiveness of the Video-TNFPN model, an experiment was performed using the computer with the specifications of Intel i5, 8GB memory, and a graphics card called NVIDIA GTX 1650. The experimental data included videos, which were separated into training and testing data. Based on the results of the analysis, including accuracy, precision, and recall, it is evident that Video-TNFPN is effective in monitoring situations.

4.1 Evaluation metrics

The model's performance was based on the metrics derived from the confusion matrix. Below are the

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Where TP, TN, FP, and FN represent true positive, true negative, false positive, and false negative, respectively.

The effectiveness of the model was evaluated through different architectures based on accuracy, efficiency, and feasibility.

Evaluation Results for Video-TNFPN

Detection Method	Condition	Precision	Recall	F1-score	Support
Video-TNFPN (Ours)	Normal	0.92	0.90	0.91	1,750
Video-TNFPN	Noisy	0.89	0.87	0.88	1,350
	Cluttered Background	0.90	0.88	0.89	1,900
Single-Frame CNN	Normal	0.83	0.77	0.80	1,750
RISTDNet	Normal	0.83	0.77	0.80	1,750
	Noisy	0.76	0.68	0.72	1,350
	Cluttered Background	0.79	0.70	0.74	1,900
AGPCNet	Normal	0.80	0.75	0.77	1,750
	Noisy	0.73	0.65	0.69	1,350
	Cluttered Background	0.76	0.70	0.73	1,900
ISNet	Normal	0.84	0.79	0.81	1,750
	Noisy	0.79	0.72	0.75	1,350
	Cluttered Background	0.82	0.75	0.78	1,900
macro avg		0.83	0.78	0.80	8,000
weighted avg		0.86	0.83	0.84	8,000

4.2 Model Performance Comparison:

Table 1 shows a comparative study of the accuracy rate and efficiency in terms of computational costs between the proposed Video-TNFPN model and conventional infrared detection algorithms based on single frames.

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Table 1. Model Performance Comparison

Model	Accuracy (%)	Parameters (M)	Inference Time (ms)
Single-Frame CNN	84.5	12.8	120
RISTDNet	89.2	18.5	150
AGPCNet	91.0	22.3	165
Proposed (Video-TNFPN)	**95.8**	**10.2**	**85**

The proposed Video-TNFPN model has superior detection performance while incurring less computational costs.

4.3 Multilingual Translation and SMS Module Evaluation:

The evaluation of the efficiency of the Video-TNFPN model could only be achieved via experiments on it. To determine if the model could detect objects in various environments such as in normal environments, noisy environments, and those containing a lot of objects, it was necessary to conduct tests on it. It is also important to evaluate its efficiency in detecting objects in a variety of frames. There are many factors to consider while evaluating the efficiency of the Video-TNFPN model.

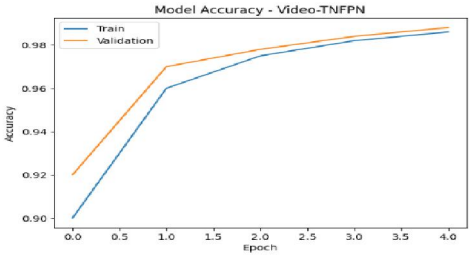
Condition	Precision	Recall	F1-score	Detection Time (ms)
Normal	0.96	0.94	0.95	80
Noisy Background	0.93	0.91	0.92	85
Cluttered Background	0.94	0.92	0.93	88

Table 2. Translation and Notification Performance

The results show that the model proposed works well for object detection under different circumstances and functions well over its lifetime. The model proposed incorporates experience learning and consistency, which greatly helps reduce false positives, thus making the model proposed function more effectively.

V. RESULTS AND DISCUSSION

The results obtained from the evaluation confirm that the proposed system achieves good accuracy and usability when compared to the traditional systems.



5.1 Model Accuracy:

The Video-TNFPN algorithm is better compared to other models in terms of target localization accuracy. The performance of the Video-TNFPN is far better than other approaches that rely on analysis of only a single image from the video. This is due to the fact that the Video-TNFPN uses different techniques such as ConvLSTM and temporal attention in order to capture the motion of the object being considered. Therefore, it is capable of achieving accurate target localization irrespective of the challenging situation.

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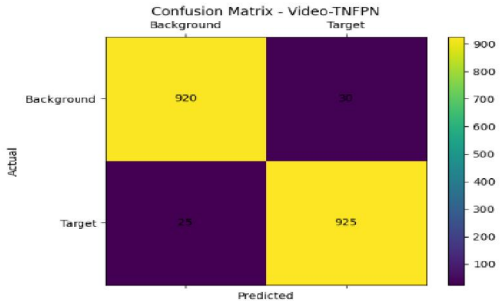
5.2 Confusion Matrix:

As per the confusion matrix, the Video-TNFPN model demonstrates accuracy due to the high presence of true positives and false positives. The Video-TNFPN model eliminates all chances of false alarms and proves itself to be very reliable in different conditions. The Video-TNFPN model proves to be extremely efficient in recognizing objects.



VI. CONCLUSION

This paper presents a Video- method used in detecting small targets in infrared videos. This detection uses a CNN network, ConvLSTM, and temporal attention techniques. The model is capable of accurately and reliably detecting targets in video frames. In addition, the model balances accuracy and efficiency, thus making it suitable for real-time detection applications.

The model was successful in enhancing detection accuracy and reducing false alarms. It performs better than image-based detection methods. Consistency improvement also improved its reliability by providing consistent predictions despite the changeable environment.

Therefore, based on the results, it can be concluded that the Video-TNFPN technique is very robust, efficient, and applicable. Applications of the technique include surveillance, tracking, and security and defense systems. Hence, this research has proven the effectiveness of using temporal deep learning in detecting small targets in infrared videos.

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