Real-Time Suspicious Counter-Flow Detection

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***Abstract*—In this study, we propose a real-time method for detecting suspicious counter-flow of persons in a video surveillance system. The proposed method uses the YOLO (You Only Look Once) object detection algorithm to detect persons in each frame of the video. A hiding time Kalman filter is then used to predict the position of each person in the next frame, taking into account their movement patterns. Finally, a probabilistic data association algorithm is applied to associate the person detected in each frame with their corresponding tracks. To detect suspicious counter-flow, we define a set of rules based on the direction of movement of the person and their track history. If a person is detected moving in the opposite direction of the expected flow, and if they persist in their counter-flow movement for a certain duration, the system raises an alert. The proposed method offers an effective solution for real-time detection of anomalous person behavior, particularly in crowded environments, and can be used in a variety of applications such as public safety, security, and traffic management. The proposed method is a cutting-edge approach for detecting person counter flow in public or private places using motion analysis, achieving real-time performance on an Intel Core i7 CPU, with varying performance depending on the level of traffic. The observed performance is 14 to 10 frames per second in dense regions (public traffic 35 to 60), 20 to 14 frames per second in moderate regions (public traffic 20 to 35) and more than 20 in sparse regions (public traffic less than 20).**

***Index Terms*—Counter Flow Detection, Suspicious Incident, CCTV Surveillance, Video Incident Detection**

I. Introduction

Counterflow movement in an area refers to the movement of people who are walking or moving in the opposite direction to the majority of the crowd. This can occur in situations such as concerts, festivals, or religious gatherings, where there are large crowds of people moving in different directions. Counterflow movement in a crowded area can be difficult to navigate and may lead to congestion, confusion, and even accidents. In order to manage counterflow movement in a crowded area, organizers may employ a variety of strategies, such as setting up barriers or using signage to direct people towards the appropriate entrance or exit, or employing crowd control staff to monitor and manage the movement of people, however this require a lot of human efforts and co-ordination. In addition, technology such as surveillance cameras and computer vision systems can be used to detect and analyze counterflow movement in the surveillance area, and provide real-time feedback to organizers and authorities to help manage and control the flow of people. These technologies can help improve safety and security in the surveillance areas and ensure that people can move efficiently and safely, even in situations where counterflow movement may occur. Deep learning based video surveillance is attracting the researchers to analyze the different notorious activities using automatic video surveillance systems. The cost of CCTV surveillance system has been reduced significantly as a result we can see video surveillance systems installed in various common public as well as private spaces like hospitals, multiplex, shopping malls, banks, schools and colleges etc. The CCTV surveillance system is actively playing an important role in the protection and management of public safety and preventing criminal activities [1]. Most of the existing CCTV surveillance is monitored by security personnels manually [2] which makes it cost inefficient. It also faces various difficulties in identifying and reporting suspicious activities for example security personnels are untrained and didn't have an exact idea of suspicious activities or proper training is not given to the concerned person. In order to design an efficient automatic suspicious counter flow detection for real-time video surveillance system, we need an efficient object detection model and an efficient spatiotemporal object tracking system. The convolutional neural network based models [27] [3] [28] [29] are highly efficient in object detection as well as localization. YOLO (You Only Look Once) [4] is a very fast and accurate object detection and localization model, YOLO [4] divides an image into a number of grids of cells, it uses a single network to predict the coordinates of bounding boxes and object class probabilities. Faster-RCNN [5] is another deep convolutional neural network architecture that is highly accurate in object detection, this model can be divided into two

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components first the region proposal network [5] and other Faster-RCNN network [5]. Faster-RCNN is able to predict objects in complex images however the speed is the major limitation which restricts for real-time surveillance systems. Single shot multibox detector (SSD) [6] is another popular approach that uses the CNN architecture for object detection and localization. It uses a single network for object detection and localization. The SSD [6] predicts the class labels and the coordinates of bounding boxes of objects in an image by using a number of layers that produces a set of prediction maps at different scales which make it to handle different sizes of objects in same image and making it a good object detector in complex and cluttered scenes. The speed of SSD [6] is better than Faster-RCNN [5] but less than YOLO [4]. Once objects in an image are identified it is needed to be tracked over time so that the suspicious counterflow activity can be identified and security threats can be protected. To track objects over a sequence of time we need to keep track of object motion. There are a number of object tracking systems proposed in the literature. Correlation based visual tracking [7] have proven to be effective in visual tracking. Correlation based visual tracking [7] is a fast and efficient way to track objects in spatiotemporal data i.e. video. It is very efficient in handling illumination, rotation and deformation [7] [**?**]. The Kalman Filter [8] is one of the most widely and commonly used estimation algorithms that is frequently used in fast and accurate object tracking. The Kalman filter uses this state representation to estimate the object's location and velocity at each time step, taking into account the measurement noise and other sources of uncertainty. One of the key advantages of Kalman filter-based object tracking is its ability to handle complex scenes, even in the presence of occlusions, camera motion, and other challenging conditions. The Kalman filter [8] is able to estimate the state of an object even in the presence of measurement noise and other sources of uncertainty, making it a robust and flexible solution for object tracking. Another advantage of Kalman filter-based [8] object tracking is its ability to track non-rigid objects, such as humans and animals. The Kalman filter can be used to estimate the motion of these objects even when they are deforming, providing a flexible and accurate solution for tracking these objects. Optical flow [9] is a method of tracking the movement of pixels in a video stream. Optical flow-based tracking algorithms use optical flow to estimate the motion of an object, allowing it to be tracked over time. Optical flow-based object tracking is a computer vision technique that uses the movement of pixels in a video stream to track the movement of objects. The idea behind optical flow is to estimate the movement of pixels between consecutive frames and use this information to estimate the motion of objects in the video. In this article, we have combined the YOLO [4] based object detection and Kalman filter [8] based object tracking along with our proposed mathematical model that can identify the suspicious counterflow of humans in the surveillance region.

II. Literature Review

In this section we are going to review some recent techniques used in the detection of suspicious human activity. Brostow, G. J., & Cipolla, R. (2006) [23] have proposed a Bayesian approach for detecting independent motion in crowded scenes. The authors [23] addressed the problem of detecting abnormal behavior in crowds, such as sudden movements or changes in direction, that may indicate potential threats. The proposed approach uses a hierarchical Bayesian model to estimate the joint distribution of the velocity and direction of the crowd's motion. The model assumes that the motion of each individual in the crowd is independent, and the joint distribution is modeled as a mixture of Gaussian distributions. The model is unsupervised, meaning that it does not require any training data or prior knowledge about the behavior of the crowd. The paper presents experimental results on several datasets, including the PETS2009 dataset and the UCSD pedestrian dataset. The results show that the proposed approach can accurately detect abnormal behavior in crowded scenes, such as sudden movements or changes in direction. The approach also outperforms several baseline methods, including a simple threshold-based method and a method based on optical flow. Since the system uses the Multi-modal background modeling to track candidate objects which suffers from computational inefficiency [24] another limitation is its sensitivity to the selection of the number of Gaussian distributions used in the model. If too few Gaussians are used, the model may not capture the full complexity of the background, leading to inaccurate foreground detection [25]. On the other hand, if too many Gaussians are used, the model may become overly complex and may not generalize well to new scenes. Multi-modal background modeling can also be sensitive to changes in the environment, such as changes in illumination, weather, or scene geometry. In some cases, these changes may cause the model to become less accurate, leading to increased false positive or false negative detections [25]. Gnanavel, V. K., and A. Srinivasan [10] have proposed an approach to detect abnormal events in crowded places. The authors [10] have designed a multi-stage architecture to identify suspicious events in crowded areas, in the first stage the image is divided in small patches. In the second stage, the difference of gaussians (DoG) filters has been applied on patches of two sequences of images to extract edges i.e. two consecutive images of video frames are divided into disjoint spatial patches and then temporal difference of gaussian between the patches of consecutive frames are computer to find out edges. Then in the third stage, a multi-scale histogram of optical flow is computed along with an edge oriented histogram for each patch that we got from the difference of gaussians in the second stage. In the fourth stage, normalized cuts along with gaussian expectation maximization is used to make clusters of patches. In this stage, each cluster is assigned with a motion context. In the final stage, exploitation based KNN search has been performed to establish the difference between abnormal and normal activity at intervals of crowded scenes. The major drawback with this system is computational complexity and false zero crossing [14] which makes it unsuitable for real-time suspicious counterflow detector. Wu, Ziyan, and Richard J. Radke [11] have proposed a method to identify suspicious human motion from low resolution cameras (320 x 240 pixels) in crowded places like shopping malls, railway stations, stadiums etc. Authors [11] have fast corner detectors to identify low level spatial features in a video frame and the low level spatial properties are tracked into temporal sequence using Kanade-Lucas-Tomasi (KLT) optical flow algorithm. The authors [11] have adapted the pyramid representation to keep track of large pixel motion by taking care of small integration windows. Optical flow based methods have a number of limitations like they are sensitive to occlusion, illuminations and texture variations at the same time they are also computationally intensive for long video sequences which is very obvious in real-time surveillance systems. Fernández Rodríguez, Jose David, et al. [11] has proposed a method for automatic anomalous trajectory detection of objects in traffic video surveillance. Counterflow detection in traffic surveillance video is well known suspicious activity that violates traffic rules and a potential threat to law & order. The authors [12] have used a pre-trained deep convolutional network to identify vehicles in video frames. To track vehicles in temporal sequence, a linear sum assignment technique is used to identify similar objects in two consecutive frames. In order to compute vehicle motion direction, the euclidean distance between the centroids of similar vehicles along with direction is measured. In a few time steps the trajectory of the vehicle is determined and then finally behavior of trajectory is evaluated as per previous majority vehicle flow direction or some predefined traffic rule. The time complexity of linear sum assignment is O(n3) as well as it is sensitive to outliers [16].

III. Proposed Method

In this section, we are presenting our approach to identify the counter flow of humans in surveillance areas. In the proposed method, we first identify the persons in the video frame using YOLOV5 [13] one class person detection model then we will keep track of person movement using Kalman filter [8]. The use of YOLO comes with many advantages like i) Fast and efficient: YOLO processes images in real-time with high accuracy, ii) End-to-end training: YOLO is an end-to-end system that can be trained on a single dataset, iii) Good generalization: YOLO performs well on a variety of object detection tasks and can detect multiple objects in an image simultaneously, and iv) Low memory usage: YOLO has a smaller memory footprint than other object detection algorithms, which makes it more suitable for deployment on low-power devices such as edge devices and embedded systems [17] [18]. Another major component in our proposed system is Kalman filter [8], the benefits of Kalman filter for real time object tracking are i) Accurate and robust: The Kalman filter is a powerful algorithm that can estimate the state of an object with high accuracy, even in the presence of noise, occlusions, and other disturbances, ii) Real-time tracking: The Kalman filter can track objects in real-time, iii) Predictive tracking: The Kalman filter can predict the future position and velocity of an object based on its previous states, iv) Adaptive filtering: The Kalman filter can adapt to changes in the object's motion or environment, making it robust to dynamic and complex scenes, v) Efficient computation: The Kalman filter is computationally efficient, which allows for real-time tracking on resource-limited devices like edge and embedded devices [19] [20]. Humans generally do not walk in a zigzag pattern during normal walking. When walking, humans tend to move forward in a relatively straight line, with minor variations in direction to avoid obstacles or adjust their path to reach their destination. However, there are some situations in which humans may walk in a zigzag pattern, such as when navigating a crowded area, trying to avoid obstacles or when walking on an uneven surface or in counterflow movement. Zigzag movement in a surveillance area can be an indication of potentially suspicious behavior. Zigzag movement may indicate that a person is attempting to avoid detection or surveillance, or may be trying to approach a target in a non-linear fashion to avoid being seen. There are several factors that can help identify suspicious zigzag movement in a surveillance system, including: i) abnormal speed: a person moving in a zigzag pattern may do so at an unusual speed or pace, which can be an indication of suspicious behavior, ii) repeated patterns: if a person is observed moving in the same zigzag pattern repeatedly, this may be an indication of suspicious behavior or activity, iii) unusual changes in direction: zigzag movement may involve abrupt or unusual changes in direction, which can be an indication of suspicious behavior or evasion and iv) avoiding surveillance: if a person is observed moving in a zigzag pattern in an area where surveillance cameras are present, this may be an indication that they are attempting to avoid detection or surveillance. In our proposed approach of suspicious counterflow detection we have handled following situations to detect suspicious counterflow:

1) Normal Movement in Counterflow Direction: Any normal movement in counterflow direction either having displacement or staying time more than the threshold is considered as suspicious counterflow movement.
2) Zigzag Movement: Assuming that humans generally do not walk in a zigzag pattern during normal walking, any zigzag movement having displacement in counterflow direction is considered as counterflow implies either displacement or staying time is more than the specified threshold.
3) Temporarily Hide during Movement: The Kalman filter is a powerful tool for tracking objects over time, even when the objects are temporarily hidden from view. To track an object during a hide using a Kalman filter, the filter needs to be modified to account for the fact that no observations are available during the hidden period. The approach we have used is a modified Kalman filter algorithm called the Hiding Time Kalman Filter (HTKF)

[21], which models the time between observations as a random variable with a probability distribution. The HTKF estimates the hidden state of the object between observations by incorporating the hiding time distribution into the filter equations. When an observation becomes available, the HTKF updates its estimate of the object's state using the observed data and the estimated state during the hidden period.

4) Partial Occlusion during Movement: Partial occlusion is handled using a probabilistic data association (PDA) method [22], which uses a likelihood function to associate observations with potential tracks of the object. During the occlusion period, the filter maintains multiple potential tracks of the object and assigns probabilities to each track based on their consistency with previous observations. When a new observation becomes available, the filter updates the probabilities of the different tracks based on their likelihood, and selects the track with the highest probability as the current estimate of the object's state.

The threshold for displacement or staying time should be carefully chosen based on the specific context and environment. A high threshold may result in false positives, while a low threshold may result in false negatives. The threshold should be chosen based on a careful analysis of the expected flow patterns in the environment and the potential risks.

A. Algorithm (Suspicious Counterflow detection)

1) Object detection using YOLO: The first step is to use YOLO (You Only Look Once) [13] object detection algorithm to identify the person in the scene.
2) Object tracking using Hiding Time Kalman Filter (HTKF) with probabilistic data association (PDA) method: Once the persons have been detected, the next step is to track their movement using a Kalman filter. The Kalman filter [8] is a mathematical algorithm that uses a series of measurements and predictions to estimate the state of a moving object. In the case of counter flow detection, the Kalman filter is used to track the movement of the objects and predict their future positions.
3) Direction estimation: After the objects have been tracked using the Kalman filter, the direction of their movement is estimated. This is done by comparing the predicted position of the object with its actual position. If the predicted position is ahead of the actual position, then the object is moving in the same direction as the traffic flow. If the predicted position is behind the actual position, then the object is moving in the opposite direction to the traffic flow.
4) Counter flow detection: Based on the direction estimation, the final step is to detect any objects that are moving in the opposite direction to the traffic flow. This can be done by setting a threshold value for the difference between the predicted and actual positions of the object. If the difference exceeds the threshold value, then the object is considered to be moving in the opposite direction to the traffic flow and is flagged as a potential counter flow.

IV. Experiment Details

- Dataset Used: We have used MS COCO dataset for training YOLOv5 model for person detection. For object tracking, we have used a subset of Multiple Object Tracking (MOT) Benchmark [26] dataset having persons moving in one or two directions. It is a widely used benchmark dataset for evaluating the performance of multiple object tracking algoritm. The dataset includes several challenging video sequences with various scenarios, such as crowded scenes, occlusions, and changes in lighting conditions.
- Hardware and software resources required
  1) CPU: Intel Core i7 @ 2.00GHz
  2) Operating System: Ubuntu 20.04.5 LTS
  3) Memory: 16 GB
  4) Python Version: 3.8.0
  5) Libraries: Scikit-learn, Pytorch, Numpy, Pandas, ONNX

V. Results and discussion

We have trained and analyzed five YOLOv5 variants including YOLOv5s, YOLOv5n, YOLOv5m, YOLOv5l, and YOLOv5x. In the YOLOv5. Each architecture has different trade-offs in terms of speed and accuracy, and the best architecture for a particular use case will depend on factors such as the size and complexity of the objects being detected and the available computing resources. Table I shows the details of each YOLOv5 model in terms of number of parameters in millions, inference time on Intel Core i7 CPU and accuracy on MS COCO dataset. The Kalman filter provides an estimate of the state of a dynamic system over time based on a series of measurements, which may be noisy. However, the performance

TABLE I
Accuracy YOLO One Class Model on COCO Dataset (subset only person class)

#	Model	Params (millions)	Inference Time (ms)	Accuracy (percentage)
1	YOLOv5n	2.5	3.3	88.2
2	YOLOv5s	5.4	6.6	92.3
3	YOLOv5m	12.9	15.5	94.86
4	YOLOv5l	26.5	26.9	97.10
5	YOLOv5x	48.1	54.3	98.25

TABLE II
Frame per second YOLOv5n in surveillance region having different people density

#	Person Density in Surveillance Region	Frame Per Second
1	<= 20	>= 20
2	21 to 35	20 to 14
3	36 to 60	14 to 20

of the Kalman filter in object tracking may vary depending on several factors like initial state estimation, noise level, motion model (linear or other) etc, the performance of the proposed suspicious counter flow detection varies as per density of the person in the surveillance region. The table II shows the performance of the suspicious counter flow tracking system. In general the proposed system can be used to monitor the sensitive surveillance area for detecting suspicious counter flow.

VI. Conclusion and Future Scope of Works

The use of YOLOv5 and hiding time Kalman filter with PDA for suspicious counterflow detection is a promising approach that can help improve public safety. The YOLOv5 model can accurately detect persons in real-time, and the hiding Kalman filter with PDA can help track their movement and predict their future positions. By analyzing the movement patterns of persons, the system can detect when a person is moving in the opposite direction of traffic flow, which is a sign of counterflow. Here are some possible future directions for research i) The current system only uses a single camera for detecting suspicious counterflow, expanding it to support multiple cameras can help to cover a larger area and detect suspicious activities in real-time, ii) The proposed system should be evaluated on different datasets to assess its generalizability and robustness. This can help identify potential limitations and areas for improvement.

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