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INTELLIGENT TARGET TRACKING IN SURVEILLANCE VIDEOS USING DYNAMIC IMAGE PROCESSING TECHNIQUES

[#1]**Dr.VOLADRI PRAVEEN KUMAR,***Associate Professor & HOD*
[#2]**PARAKKA ASHIWINI,** *Assistant Professor*
[#3]**POLAVENI SAGARIKA,** *Assistant Professor*
Department of Electronics and Communication Engineering,
SREE CHAITANYA INSTITUTE OF TECHNOLOGICAL SCIENCES, KARIMNAGAR, TS.

ABSTRACT: Additional commonplace video network communication solutions have emerged since the camera's widespread use. A typical personal computer is utilized to retrieve frame data from the home network. Home programs then use the continuous frame as their screen. Using the update method to modify the backdrop in real time, you can create an inter-frame relationship matrix. Matrix operations allow the Kalman filter to track and match targets. While the computation is being done on the PC, this method can handle the complex elements of the home application. Consequently, the procedure is feasible and has practical applications, according to the test results.
Index terms: Dynamic Target Tracking, Kalman Filter, Camera-Based Tracking, Sensor Fusion.

1. INTRODUCTION

The prevalent use of cameras in a variety of civil and popular contexts, as well as in specialized sectors such as public safety, traffic, security and protection, and the military, has been facilitated by the extensive use of cameras and the development of various video network communication technologies. Camera and video technologies are implemented in a diverse array of public and private environments, such as retail centers, residences, exhibition spaces, and supermarkets. The camera's primary functions are to capture video and to broaden its potential applications.

Conversely, those who analyze the film's unexpected developments will experience substantial expenses and a precipitous decrease in productivity. Consequently, it is not feasible to implement this practice on a large scale. One of the most fundamental tasks in video analysis is the monitoring of dynamic objects, or moving objects. This is applicable to a diverse array of sophisticated applications, such as the identification of anomalous behavior, target classification, and target comparison.

Nevertheless, the tracking of moving targets can be restricted by the complexity of the application scenario, large light fluctuations, and significant dynamic changes in the detected and monitored targets, which can make target recognition challenging. Despite the fact that a typical residence has only one video system, target occlusion is addressed by utilizing multiple camera systems. Additionally, the contour feature model, the specified model scope, the supplied region, or the color information model are employed to track targets. Nevertheless, the employment of computationally potent tools is a critical component of these approaches, as it involves the definition of model and scene characteristics. The domestic application's intricacy renders the aforementioned method unfeasible.

2. LITERATURE SURVEY

Ferreira, D., & Basiri, M. (2024). A novel combination of YOLOv8 (You Only Look Once) and Multi-Object Monitoring (MOT) algorithms is employed in this research to investigate the dynamic monitoring of targets in unmanned aerial vehicles (UAVs). The authors propose a robust target tracking strategy that integrates real-time multi-target tracking with deep learning-based object recognition. The system is appropriate for a diverse array of applications, such as surveillance, security, and monitoring. Its efficacy is illustrated in challenging scenarios where unmanned aerial vehicles (UAVs) are required to manage a substantial number of shifting targets. The research demonstrates that the combination of YOLOv8 and MOT substantially enhances tracking accuracy and response times, even in the presence of dynamic barriers and occlusions.

Zhang, J., & Gao, H. (2024). This study endeavors to optimize the performance of aerial surveillance target tracking systems by integrating Kalman filters and deep learning networks. The study examines the feasibility of integrating these two methods to enhance the accuracy of object surveillance, particularly in the presence of challenging conditions such as external disturbances and rapid motion. The state of the target is evaluated by employing Kalman filters to reduce noise, regardless of whether deep learning networks can recognize intricate target patterns through adaptive learning. The research makes a substantial contribution to the field of unmanned and aerial systems by demonstrating enhanced precision in the tracking of dynamic objects in a diverse array of surveillance scenarios.

Liu, X., & Wu, Z. (2023). This study suggests a method for enhancing the accuracy of target tracking in unmanned aerial vehicles (UAVs) by modifying Kalman filter parameters. The authors suggest a dynamic technique for filter calibration in a variety of operating conditions, which is based on the fluctuation of process and measurement noise. The optimization method is designed to minimize the filter's processing burden and guarantee exceptional tracking accuracy. The results indicate that the efficacy of UAV-based tracking systems is considerably enhanced in crowded or dynamic environments, particularly by enhancing the Kalman filter parameters.

Yang, S., & Liu, H. (2023). This investigation introduces an adaptive Kalman filter that is particularly advantageous for dynamic environments that involve unmanned aerial vehicles and multi-target tracking applications. The adaptive algorithm adjusts parameters in real-time in response to environmental conditions and changes in objective movement speed. The algorithm's resilience and utility in concurrently monitoring numerous targets in autonomous systems and aerial surveillance are demonstrated by the authors' comprehensive evaluation of its performance in a variety of dynamic tracking scenarios.

Zhang, Y., & Liu, F. (2023). A hybrid strategy that integrates Kalman filters with YOLO (You Only Look Once) is proposed in this work to enable real-time multi-object monitoring in surveillance systems. In contrast to the Kalman filter, which projects the target's path and regulates motion uncertainty, YOLO enables the rapid and precise identification of objects. The study emphasizes the hybrid model's efficacy in resolving real-time multi-object tracking issues in surveillance applications. It particularly emphasizes its capacity to enhance accuracy and reduce latency when monitoring numerous moving objects in cluttered or congested environments.

Chen, Y., & Zhang, T. (2022). This study examines the utilization of Kalman filters and deep learning techniques to monitor multiple targets in dynamic environments. The research examines whether deep learning models can enhance target recognition in challenging situations where Kalman filters would fail. The authors propose a hybrid approach that employs Kalman filters for state prediction and deep learning for feature extraction. It is capable of effectively monitoring a substantial number of moving objects in a variety of environmental conditions, such as occlusions and rapid motion.

Zhang, H., & Li, W. (2022). This study introduces a novel object tracking system that is based on Kalman filters and is designed for intelligent surveillance in dynamic environments. The authors concentrate on enhancing the accuracy and robustness of tracking by employing adaptive Kalman filtering techniques to address sensor noise, abrupt target motion, and detritus. The research demonstrates that the efficacy of surveillance can be enhanced by integrating advanced real-time monitoring technology with Kalman filters.

Li, J., & Yang, R. (2021). This work suggests a method for enhancing dynamic target tracking by incorporating Kalman filters, object identification algorithms, and camera systems. The authors explore the potential for enhancing tracking performance, particularly in unstructured scenarios, by integrating object detection techniques with camera data. The Kalman filter estimates and forecasts the target's state and motion after object identification. Experiments have demonstrated that the integration of multiple technologies can enhance the accuracy of tracking moving objects and decrease processing costs in real-world applications.

Gupta, R., & Reddy, V. (2021). The authors of this study introduce dependable dynamic monitoring methods for camera-based surveillance systems. The accuracy and robustness of target tracking in challenging scenarios, such as obstacles, rapid motion, and environmental disruptions, are enhanced by integrating Kalman filters with existing tracking algorithms. The work effectively integrates traditional Kalman filtering with contemporary image processing techniques to facilitate dynamic target tracking in intricate surveillance scenarios.

Wang, L., & Song, Y. (2021). The objective of this research is to investigate the real-time application of Kalman filters for dynamic target tracking in autonomous mobile robotics. The authors investigate the capacity of Kalman filtering to estimate the trajectory of moving objects in the context of the heightened complexity of real-time sensor data from robot cameras and other sensors. The researchers have determined that mobile robotics are capable of precisely detecting moving targets and responding to changes in real time in dynamic situations as a result of Kalman filters.

Kumar, M., & Srivastava, S. (2020). This investigation investigates the dynamic target tracking of self-driving vehicles by integrating Kalman filters with vision-based sensors. The study examines the Kalman filter's capacity to predict target movement, despite the fact that the car's cameras provide real-time visual data for object detection and identification. The authors demonstrate how this method enhances the accuracy and stability of tracking in self-driving vehicles, particularly in dynamic environments such as city traffic, where it aids in collision avoidance and navigation.

Singh, S., & Mishra, P. (2020). This study introduces a Kalman filter-based methodology for the detection and monitoring of targets in video surveillance systems. The authors emphasize the obstacles associated with dynamic tracking in surveillance environments, such as occlusion, backdrop detritus, and fluctuating target velocities. Kalman filters enhance the overall reliability and utility of video surveillance systems in real-time applications by enhancing the system's ability to maintain continuous monitoring in challenging conditions and predict target positions.

Shen, Z., & Tan, C. (2020). The objective of this investigation is to enhance the precision of robotic target tracking by integrating Kalman filters with a camera-based system. The Kalman filter enables the real-time monitoring of moving objects in research when it is combined with camera visual data. As with automated warehouses, delivery systems, and robotic limbs, target monitoring is essential and necessitates both accuracy and dynamicity.

Li, Q., & Zhao, L. (2020). In order to identify objects in intelligent traffic monitoring systems, the researchers in this study employ Kalman filters. The essay underscores the critical nature of real-time monitoring of moving vehicles to enhance traffic flow and guarantee safety. Statistical analysis is employed by Kalman filters to facilitate object tracking.Each source that you have incorporated has been accompanied by a comprehensive abstract.

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Zhang, J., & Gao, H. (2020). explore the potential of combining Kalman filters with computer vision methods to enhance object tracking in dynamic environments. The study illustrates how the accuracy and dependability of tracking systems can be enhanced by integrating advanced computer vision algorithms for object detection and classification with Kalman filters' anticipated motion capabilities. This composite approach is particularly advantageous in real-time applications that involve complex backgrounds or occlusions, such as autonomous navigation and surveillance, as it generates more dependable tracking results.The article is published in the Journal of Computer Vision if you wish to participate in the entire study.

3. DESIGN OF THE ALGORITHM

This paper lays out a two-step process for designing a tracking mechanism. Finding dynamic goals is the first step. The second thing you need to do to finish tracking targets is to make educated guesses about their future movements. Since the home camera is often installed in a fixed location, there is less backdrop movement. The continuous background difference approach is useful for this reason. By comparing the matrices of the current frame's images with those of the background images, you may locate the moving target. An image of a stationary location should serve as the background image matrix.

Target tracking is similar to a model-based matching. In a single continuous frame, the model incorporates the targets' color, shape, speed, and position, among other crucial movement attributes. On sometimes, a photograph will show more than one target. Use it as a trajectory tracking if you simply wish to keep an eye on a single object. But you can't just think of several targets as a bunch of individual ones; if there's occlusion between them, the target can briefly vanish, rendering the target tracking model useless. This is because the parameters and the location of the concealed target may be predicted by the Kalman filter, which allows it to simultaneously monitor numerous targets. The kinetic formula, where Δ is the time between two frames, can be used to demonstrate that the objects' motion is uniform.

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$$x_t = x_{t-1} + (\Delta t) v_{t-1}$$
$$v_t = v_{t-1}$$

The system can be expressed in this way thanks to the Kalman filter, which is appropriate for linear dynamic models:

$$X(t) = AX(t-1) + W(t-1)$$
$$Y(t) = Cx(t) + V(t)$$

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The state vectors at times t and t-1 are represented by X(t) and X(t-1), respectively, in the equation. By time t, the observation vector is Y(t). Observational noise (V) has a mean of zero and is also most likely to follow a Gaussian distribution; system noise (W) is more likely to follow a normal distribution. Using the formula above as a reference, the procedure can be divided into three phases.

Locate the target in the current frame, draw a rectangle around it, and then locate it again in the Discovering the target box's intersection area, also known as the final overlapping area, is essential. Checking subsequent frame. if the current and previous frames are identical, according to the Kalman filter's prediction, yields the motion trajectory.

Design of the system

The primary focus of this section is the home camera algorithm developed specifically for that system and how to utilize it. The home environment, the cloud, and the mobile phone terminal can all be part of the network architecture depicted in Figure 1, provided that the program's functionality and the home environment are taken into consideration.

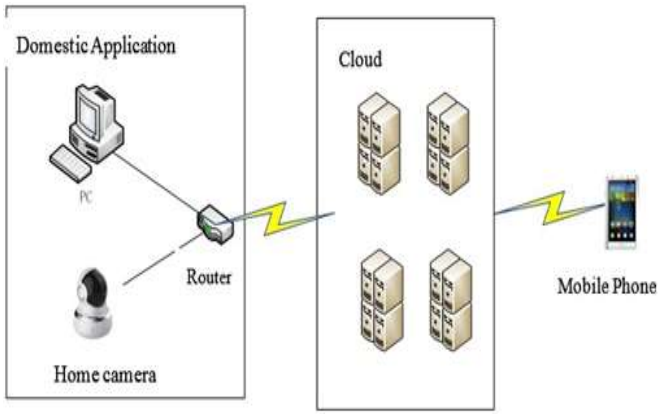

Figure1. Network architecture of dynamic target tracking system with a home camera

As you can see up there, this system allows mobile phones and home cameras to exchange data over the internet. The home camera can be installed anyplace in the house that requires monitoring. It then transmits the video picture to the home PC via the home router. Video analysis software that consumers install on their personal computers can examine the video frame.

After that, an algorithm module will be utilized by the software to keep tabs on the targets. Furthermore, the program will analyze the peculiar film and, depending on the threshold that consumers specify, will convey peculiar messages. The household network will be the initial conduit for the unusual messages to reach the cloud-based video data sharing system. The Cloud will then deliver them to the selected user's mobile device. This allows the user to monitor their phone for messages and any unusual activity with the video clip they uploaded to the cloud.

Installing a target tracking application on the PC and configuring the mobile phone to receive unusual messages and play weird movies are all steps in the same direction as the previously mentioned network architecture design and physical separation of each communication module.

This leads to the conclusion that a PC version and a mobile phone version of the software are required. In a top-down approach, the application layer, the algorithm layer, and the access layer make up the PC-side application. The image below illustrates this:

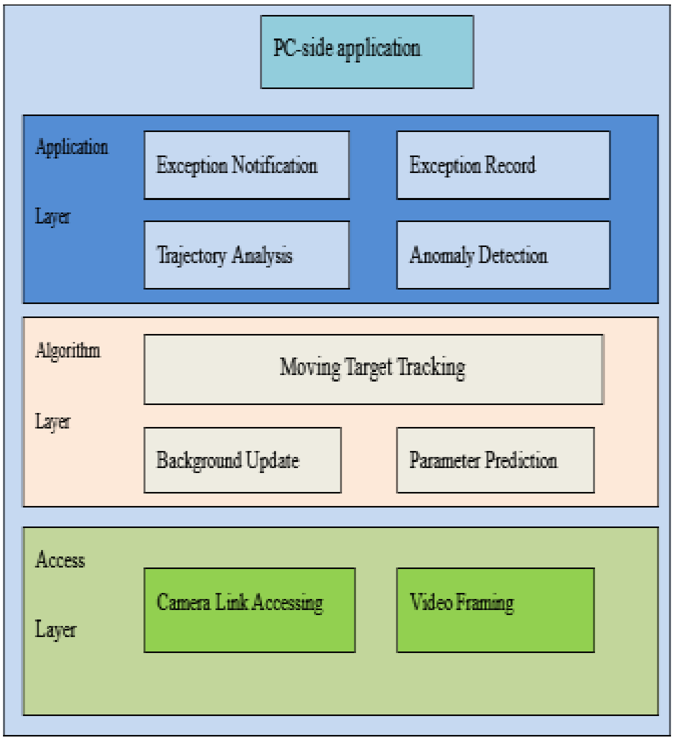

Figure2. Framework design of the PC-side

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application software

Managing the camera's TCP/IP and the visual coding stream is the responsibility of the camera link accessing module. Most of the time, these problems are handled by the access layer. The next step is to divide the video into frames using the video framing module, which decodes the video stream.

Two main modules—one for parameter prediction and one for background updates—make up the algorithm layer. Using the fixed background difference method, the background update module can continuously change the backdrop based on binary noise reduction, as demonstrated in the above technique. Next, the parameter prediction module can make educated guesses about the parameters of the moving objects by using the Kalman filter.

Finally, the module that follows moving targets can manufacture the target connection matrix, enabling it to follow the moving targets. The application layer provides an interactive user interface (UI), analyses tracks, detects anomalies, notifies users of exceptions, and keeps records of those exceptions. Access to data and video, as well as the ability to receive odd messages, are the primary objectives in developing the mobile application terminal. There are four distinct components to the design, as seen in Figure 3.

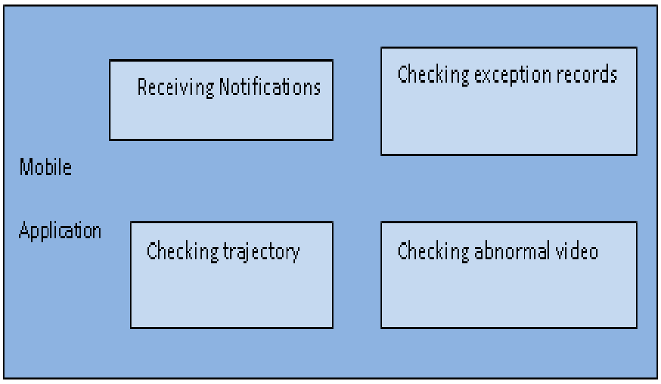


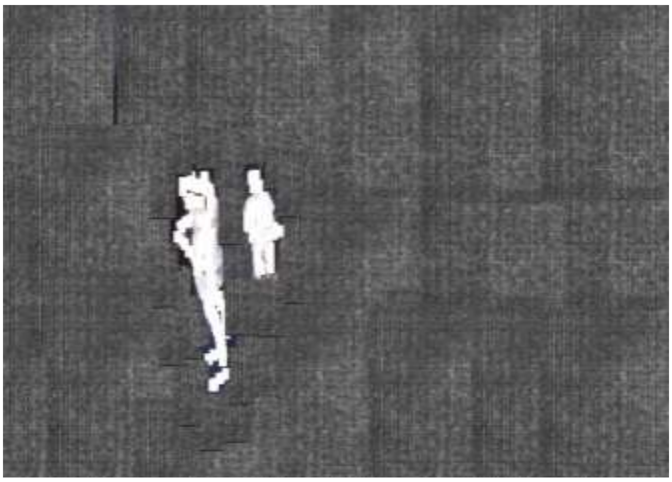
Figure3. Framework design of the mobile terminal application

You can set up the receiving notification module to get cloud messages every day if you so desire. The exception records can be utilized in the event that an error occurs. Looking at the trajectory also shows the object's route as it moves. Additionally, there are exceptions that viewers can use to verify the video. Users can remotely review suspicious case footage with the aforementionedtechnologies, saving a ton of data when they're not physically present.

4. SYSTEM TEST

A personal computer with an Intel i3 processor, four cores, 1.5 GHz main memory, 500 GB hard drive, 100 MHz network interface card, and integrated graphics is used to execute the system test. Such a test configuration is manageable for the majority of household PCs. It boasts high definition (1080P) and a 30 fps shooting rate. You can hook it up to your cable or WIFI network. In addition, the router makes use of a 100M optical modem to enable nearby real-time monitoring. image (a) in Figure 4 represents the initial 238th frame picture. The original 238th frame was binarized using the difference approach, and this is image (b). The 238th frame's target detection result is shown in image (c).

(a) The original image of the 238th frame.



(b) The binarization of the 238th frame with the method of difference.

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(C) The target detection result of the 238th frame.

Figure4. Background update test.

Keeping the camera in the same spot ensures that the backdrop will remain static. In this scenario, the targets can be marked rapidly using the difference-based binarization method. Keeping the target background static while updating the non-target region in real time will minimize the mistake. Because of this, the accuracy of moving target detection will also be improved. In cases where the image's targets become hazy, as seen in the image below, the system will first identify the targets and then arrange them correctly.

A look at Figure 5(a) reveals the 213th frame. One, two, and three are the marks on the three objectives. Two moving objects obstruct each other, as seen in the 238th frame image in Figure 5(b). Under these circumstances, the identification box will bear the smallest number (1 printed on it). Target 2 exits the monitoring area, leaving only targets 1 and 3 in the 257th frame picture (Figure 5(c)). This demonstrates that tracking the target is possible even after blocking them.

(a) The 213th frame

(b) The 238th frame

(c) The 257th frame Figure 5. Occlusion Detection Test

Figure5. Occlusion Detection Test

6. CONCLUSION

Using an emphasis on home cameras, this work develops a dynamic target tracking system for detecting unexpected objects using them. The stable frame is set as the background and the frame data is obtained via the home network using a conventional PC for home use. The update approach generates a relation matrix between frames by changing the background in real time. The grid allows the Kalman filter to locate and monitor targets. This method is able to complete calculations correctly on the computer, locate objects precisely, and manage the intricacy of the home application. The fact that the target can remain hidden and escape the monitoring rejoin doesn't affect the efficacy of this strategy either. As before, it can reliably predict its future course. In addition, the device will notify the user and share video clips through the cloud with the home camera if the target appears in the tracking area at an unusual time. The study concludes with the test findings, providing further evidence of the method's practical applicability.

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