Dean&Francis
ISSN 2959-6157

Application of Unmanned Aerial Vehicles (UAVs) in Traffic Flow Monitoring

Yiyang Zhao

Manchester Metropolitan Joint Institute, Hubei University, Wuhan, Hubei, 430062, China
E-mail: zhaoyiyang0616@qq.com

Abstract:
Unmanned aerial vehicles (UAVs) are increasingly applied in traffic flow monitoring due to their mobility, wide-area coverage, and cost-effectiveness. Compared with traditional fixed sensors, UAVs enable real-time, multi-dimensional traffic data collection and violation detection. This study reviews UAV-based traffic monitoring technologies, including vehicle detection algorithms (inter-frame difference, background difference, and template matching) and tracking methods (generative and discriminative approaches). Case studies from China, France, the UK, and the USA demonstrate practical applications in congestion management and traffic law enforcement. Key challenges such as environmental adaptability, endurance, and real-time algorithm performance are also discussed.

Keywords: UAV, Traffic Flow Monitoring, Vehicle Detection, Intelligent Transportation Systems, Background Difference, Template Matching, Generative and Discriminative Tracking

1. Introduction

1.1 Background Information

The development of Intelligent Transportation Systems (ITS) has been rapid in recent years, and traffic flow monitoring is now considered to be of great significance to the enhancement of road access efficiency, the alleviation of congestion, and the optimisation of traffic management. Traditional traffic monitoring methods principally rely on fixed sensors (e.g. ground induction coils, radar, cameras, etc.), but they have limitations such as limited coverage, poor dynamic adjustment capability, and susceptibility to environmental interference. Moreover, conventional techniques are challenging to implement real-time dynamic analysis of multi-dimensional traffic parameters (e.g. speed, density, trajectory), thereby constraining their extensive application in ITS.

The advent of Unmanned Aerial Vehicle (UAV) technology has engendered a novel solution for the monitoring of traffic. The three principal advantages of UAVs are as follows: firstly, mobility, which is characterised by the capacity for flexible adjustment of flight paths in order to adapt to different scenarios; secondly, wide-area coverage, which is exemplified by the capacity of a single aircraft to monitor a wide range of areas; and thirdly, low cost, which is evidenced by a significant reduction in deployment and maintenance costs when compared with traditional fixed equipment. For instance, as Kampf et al.[1] demonstrate, the capacity of UAVs to analyse traffic at complex intersections was validated by the continuous acquisition of traffic video at 20 m altitude by a tethered UAS in Ceske Budejovice. This succeeded in extracting spatial-temporal trajectory data for 2,516 vehicles. In addition, Ke et al.[2] carried out experiments on a motorway using visible and infrared sensors carried by a UAV and achieved real-time estimation of the mean traffic flow parameters by means of the Kanade-Lucas-Tomasi (KLT) tracker with the K-means clustering algorithm. The correctness rate reaches about 96%. The cases under consideration demonstrate that UAVs have the capacity to overcome the static deployment limitations of traditional methods, whilst concomitantly enhancing data robustness through multimodal sensing fusion.

1.2 Typical Application Scenarios and Cases

Utilising drones or unmanned aerial vehicles (UAVs), this technology has recently been adopted by a number of police agencies across the globe, as shown in Table 1.1. The key challenge in detecting traffic violations is the need for evidence. The evidence must be present at the time and place of the violation. Several countries have adopted the use of drones on the roads. Drones equipped with cameras and wireless communication devices are very effective in recording traffic violations, identifying vehicles and drivers, and notifying the police of violations. Among other use cases, drones can also be used to detect crimes in progress, terrorist activities, drivers texting or talking on the phone while driving, suspected drivers for driving under the influence of alcohol (DUI), and investigations following road accidents.

For example, during the May Day holiday in 2025, 27 drones were deployed at congestion-prone road nodes on highways by the Jiangsu Provincial Traffic Comprehensive Law Enforcement Bureau's direct detachments for monitoring highway operations and easing congestion. When the highway is slowed down or congested, the combination of fixed video monitoring and drone monitoring can more accurately determine the congestion situation and quickly report the relevant information to the command centre, providing strong support for decision-making, thus shortening the incident disposal time, reducing the spread of congestion, and enhancing the overall operational efficiency and safety level of the road network[3].

Table 1 Details of the application of drones for traffic detection on roads.

Country	Remarks
France	The French city of Bordeaux has started using drones to catch drivers who break traffic rules. The drones, because they allow police to see dangerous drivers on the road, but will not be seen by the drivers, giving police the oversight and safety precautions they need[4].
UK	Police forces in the UK use drones equipped with high-definition cameras, night vision or thermal imaging for a range of police activities such as monitoring major incidents and event and traffic management[5].
USA	The Wentzville Police Department is using unmanned drones for a variety of purposes. For example, the drone captured drivers who failed to stop at a sign at an altitude of 250 feet[6].
China	Drones are used to detect traffic offences in Jinan, the capital of east China's Shandong province. They can monitor drivers for offences such as using mobile phones and devices while driving and take clear video footage[7].

2. The Core Technology of UAV in Traffic Flow Monitoring

2.1 Conventional traffic flow detection techniques

Traditional traffic flow detection techniques rely on fixed sensors, with core methods including: radar detection technology, toroidal coil vehicle detection and ultrasonic inspection technology.

2.1.1 Radar detection technology

Vehicle detection radar measures vehicle speed by Doppler effect, analyzes time difference, frequency change and other characteristics in combination with echo signal, and calculates vehicle position, speed and other related information.

The radar is not affected by rain, snow, fog and other adverse meteorological conditions as well as light conditions, and can operate stably in a wide range of weather conditions, ensuring good detection and tracking even at night. However, in practical application, radar detection may produce interference because of its technology.

2.1.2 Toroidal Coil Vehicle Detection

Toroidal coil vehicle detection uses a few turns of metal wire wound into a toroidal coil as a sensor, which is buried in the road. When a vehicle passes over the ground-sensing coil, it changes the magnetic field around

ISSN 2959-6157

it, which causes a change in the inductance of the coil, obtaining the real-time traffic flow data required by the adaptive signaliser control system.

Coil detectors are more accurate and the technology is more mature. They are currently used more often. However, they require a certain degree of excavation of the road surface during installation, and construction and maintenance costs are relatively high. At the same time, datum drift can seriously affect detection accuracy.

2.1.3 Ultrasonic Inspection Technology

Ultrasonic detection technology uses the propagation properties of sound waves in materials to determine the presence of a target by emitting high frequency sound waves and receiving their reflected signals.

Ultrasonic detectors do not require road damage, the use of the effect is not limited by the quality of the road surface, with the advantages of convenient installation, mobile, long use time and so on. In determining the passage of vehicles, ultrasonic detectors can also show high accuracy. Its shortcoming is that its detection range distance is short, due to the temperature or windy and stormy weather, affecting the distance detection accuracy.

Table 2 Advantages and Disadvantages of Detector Technologies

	Radar detection technology	Toroidal coil detection technology	Ultrasonic Inspection Technology
Basic Principle	Using the principle of electromagnetic wave reflection, by transmitting high-frequency electromagnetic waves and receiving the target echo, calculating the distance, speed and other parameters	Based on the principle of electromagnetic induction, the toroidal coil buried on the road surface generates an inductive change when a vehicle passes, triggering a signal	Transmit high-frequency acoustic waves and detect the position of the target by the time difference between the received and reflected echoes.
Detection accuracy	High (accurate speed and distance measurements, but limited detection of stationary vehicles)	Medium (high detection accuracy exists but is susceptible to construction/weather)	Low (significant environmental interference)
Environmental adaptability	High (all-weather operation, anti-electromagnetic interference)	Medium (not affected by weather, but requires regular maintenance)	Low (receipt of weather factors evident)
Installation costs	Medium (higher equipment costs, but flexible installation)	High (high cost of road breaking construction and complex maintenance)	Low (easy to install, no need to break the road)
Maintenance cost	Medium (regular calibration required, high immunity to interference)	High (susceptible to failure due to construction/ageing, short life)	Low (low failure rate, but requires environmental compensation)
Multi-lane detection capability	High (supports multi-lane dynamic tracking)	High (single point detection, multiple coil combinations required)	Medium (single point detection at close range, multi-sensor required for multiple lanes)

2.2 Technical Analysis and Application Evaluation of UAV Vehicle Detection Methods

UAV vehicle detection is a core technology in the fields of intelligent transportation, security monitoring, etc., and its methods are mainly divided into traditional image processing algorithms (background difference method, optical flow method, template matching method, and inter-frame difference method) and deep learning models (e.g., Faster R-CNN and its optimisation variants).

2.2.1 Vehicle Detection Algorithm Based on Inter-Frame Difference

In the technical system for vehicle detection using UAV-mounted visual sensors, the Frame Difference Method (FDM) is a classic motion target detection algorithm that has become an important and fundamental technical approach due to its simple principle, high computational efficiency, and potential for real-time processing.

The core idea of this method is to extract the contour information of the moving target by analysing the differences in pixel values between two or more adjacent frames in a video sequence. This method is based on the grey scale change characteristics of the static background and the moving target within the dynamic scene over time.

In this implementation, the video stream captured by the UAV is first pre-processed. This includes image greying to reduce the data dimension, Gaussian or median filtering to suppress noise interference, and image alignment to compensate for vibration caused by the UAV platform. This ensures consistency between adjacent frames within the spatial coordinate system.

Assuming that the grey values of each pixel of the current k th and $k-l$ th frame images in the video image are $I_k(i,j)$ and $I_{k-1}(i,j)$ respectively, their difference image is

$$D_k(i,j)=\left|I_k(i,j)-I_{k-1}(i,j)\right| \tag{1}$$

For the differential image obtained as described above, individual pixel points in the image are judged by setting a threshold T to extract the motion region in the video image:

$$M_k(i,j)=\begin{cases} I_k(i,j), D_k(i,j)\geqslant T \\ 0, D_k(i,j)<T \end{cases} \tag{1}$$

The motion target detection method based on inter-frame difference method is more anti-interference and has better adaptability to the environment[8].

The UAV aerial photography scene has significant characteristics of a high-altitude perspective, and the road texture, changes in lighting (e.g. tree shade and cloud shadows) and the camera's own motion (e.g. tiny jitters when the UAV hovers) will interfere with the results of differencing. To improve robustness, three-frame differencing[9] is often used in practical applications. This involves combining the differencing results of three frames of images into a single image for a logical sum operation, thereby reducing the detection voids caused by discontinuous target motion in single-frame differencing.

The formula for the three-frame difference method is:

$$D_1(x,y)=\left|f_k(x,y)-f_{k-1}(x,y)\right| \tag{3}$$

$$D_2(x,y)=\left|f_{k+1}(x,y)-f_k(x,y)\right| \tag{4}$$

$$E_1(x,y)=\begin{cases} 1, D_1(x,y)\geqslant T \\ 0, D_1(x,y)<T \end{cases} \tag{5}$$

$$E_2(x,y)=\begin{cases} 1, D_2(x,y)\geqslant T \\ 0, D_2(x,y)<T \end{cases} \tag{6}$$

$$E(x,y)=\begin{cases} 1, E_1(x,y)\cap E_2(x,y)=1 \\ 0, E_1(x,y)\cap E_2(x,y)=0 \end{cases} \tag{7}$$

Where $f_{k-1}(x,y)$, $f_k(x,y)$ and $f_{k+1}(x,y)$ denote the grey values of the pixel points of the $k-1$ th, k th, and $k+1$ th frames of the image, $D_1(x,y)$ and $D_2(x,y)$ denote the corresponding difference results, $E_1(x,y)$ and $E_2(x,y)$ denote the binarisation results, and T is the threshold of the pre-set point. $E(x,y)$ denotes the final detected target image[10].

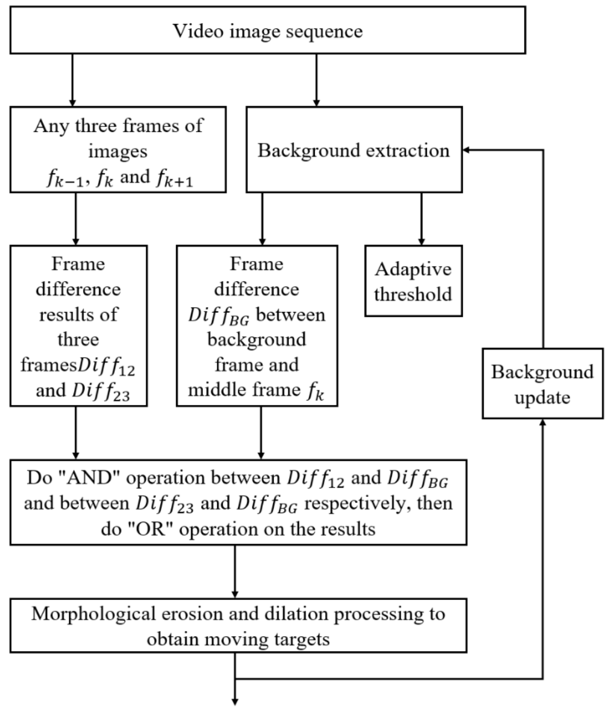

Figure 1 Flowchart of the detection algorithm for the three-frame difference method

2.2.2 Vehicle Detection Algorithm Based on Background Difference Method

In UAV vehicle detection technology systems, the background difference method is a classic motion target detection technique. Its core idea is to extract the motion target region by constructing a background model of the dynamic scene, then performing a pixel-by-pixel difference between the current frame image and the background model. Theoretically, this method can effectively detect stationary or low-speed moving vehicles, overcoming the limitations of the inter-frame differencing method, which cannot detect stationary targets. This makes it valuable for applications such as UAV traffic monitoring and intelligent inspection.

The background difference method subtracts the corresponding pixel points of the target image from the background image, and when the grey level difference between the pixel points of the target image and the background image is greater than a certain threshold, this pixel point is considered to be a foreground pixel point, and on the contrary this pixel point is considered to be a background pixel point[11].

ISSN 2959-6157

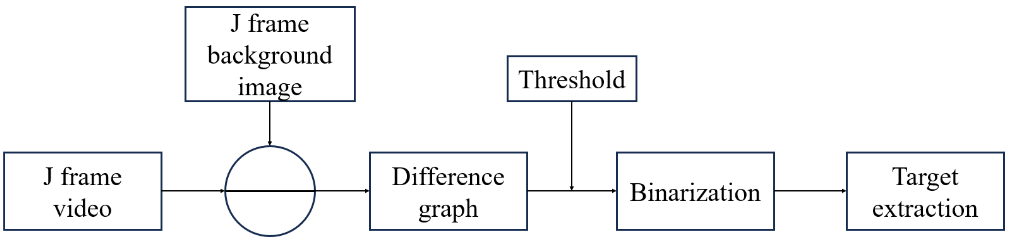

Figure 2 Background difference method process

The differential equation is:

$$D_k(x,y)=\left|B_k(x,y)-t_k(x,y)\right| \tag{8}$$

$$F_k(x,y)=\begin{cases}0, T_k(x,y)<T_0\\ 1, T_k(x,y)\geqslant T_0\end{cases} \tag{9}$$

In the formula, $B_k(x,y)$ represents the background image, $t_k(x,y)$ represents the kth frame image, $T_k(x,y)$ represents the difference image, while the value of $F_k(x,y)$ reacts to its motion, which is equal to 1 to reflect that the area where the pixel point is located is the motion area, and $F_k(x,y)$ is equal to 0 to represent the background, and T_0 is the set threshold.

The background difference method first requires a static background model[12]. Traditional methods usually use Gaussian mixture model (GMM) or inter-frame differencing to initialise the background. Taking the Gaussian mixture model as an example, the hybrid Gaussian background model is a weighted sum of a finite number of Gaussian functions, which is capable of describing the multi-peak state of the pixels (unimodal (single-peak), multimodal (multi-peak)).

Assuming that the pixel observations at each point in the image are independent of the observations at other pixel points, at a certain moment t, let the pixel observation be X_t, then the probability that the observation at moment t is X_t can be modelled by a mixed Gaussian model with K Gaussian distributions[13].

$$P(X_t)=\sum_{i=1}^{k}\omega_{i,t}\phi\left(X_t,u_{i,t},\sum\nolimits_{i,t}\right) \tag{10}$$

$$\phi\left(X_t,u_{i,t},\sum\nolimits_{i,t}\right)=\frac{1}{(2\pi)^{n/2}\left|\sum_{i,t}\right|^{1/2}} \times exp\left\{-\frac{1}{2}\left(X_t-u_{i,t}\right)^T\sum_{i,t}^{-1}\left(X_t-u_{i,t}\right)\right\} \tag{11}$$

$$\sum\nolimits_{i,t}=\delta_{i,t}^2 I \tag{12}$$

K is the number of Gaussian distribution modes, $\omega_{i,t}$ is the weight of the ith Gaussian distribution, the weight of the ith Gaussian distribution at moment t and $\sum_{i=1}^{k}\omega_{i,t}=1$, $u_{i,t}$ is the mean of the ith Gaussian distribution at moment t; $\sum_{i,t}$ is its corresponding covariance matrix; ϕ is the probability density function of the Gaussian distribution. $\delta_{i,t}$ is the variance and I is the three-dimensional unit matrix.

2.2.3 Vehicle Detection Algorithm Based on Template Matching

In UAV vehicle detection technology, the template matching method is a classical detection method based on target appearance features, and its core idea is to locate the position of the target vehicle by matching the similarity between a preset vehicle template and a local region in the real-time image. The method does not rely on the motion characteristics of the target, but uses the a priori visual features of the vehicle (e.g., silhouette, colour, texture, etc.) to achieve detection, which is suitable for scenarios where the target type is known (e.g., specific car models, specific coloured vehicles), and has a unique value of application in tasks such as capturing traffic violations by UAVs and tracking of special vehicles.

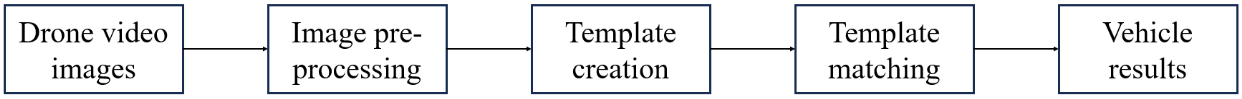

Figure 3 Flow chart of template matching method

2.2.4 Comparative analysis of interframe differencing, background differencing and template matching methods

Table 3 Comparison Table

Methods	Advantages	Disadvantages
Interframe Difference Method	- Simple calculations for real-time processing - Unaffected by changes in light - High real-time performance	- Unable to detect stationary vehicles -Low-speed vehicles are easy to miss -Noise sensitive, need morphological treatment
Background Difference Method	-High detection accuracy, preserving the internal area of the target - Adapt to complex background - Better real-time performance	-Sensitive to changes in light -Frequent updating of the background model -High computational complexity
Template Matching Method	- High noise immunity - Suitable for standardised targets - Simple to realise	- Computationally intensive and time-consuming for low-resolution images - Sensitive to changes in lighting and viewing angle - Cannot handle dynamic deformation

2.3 Methods for drone vehicle tracking

2.3.1 Generative Methods

The core idea of the generative method is to search for the region most similar to the template in subsequent frames as the tracking result by learning a feature template of the target itself. The method focuses on the intrinsic representation of the target and is suitable for scenes where the target structure is clear.

2.3.1 .1 Technical Principles and Processes

Probabilistic models (e.g. Gaussian mixture models) or templates (e.g. feature histograms) are constructed from the target's appearance features (e.g. texture, edges, colour distribution). In the UAV view, target rotation, scale variation and light interference need to be considered.

Optimisation algorithms (e.g. particle filtering, gradient descent) are used to maximise similarity functions (e.g. Bhattacharyya coefficients) within the search region. For example, particle filtering works by generating multiple candidate frames and calculating their match with the template.

2.3.1 .2 Typical Algorithms and Technology Enhancements

Generative Adversarial Network (GAN) has important applications in many fields. The generator is able to synthesise complex samples such as occlusions and deformations, and the corresponding discriminator is responsible for distinguishing between real and synthetic data, through which the model's adaptability to occlusion situations is effectively improved. For example, Iterative GAN successfully achieves facial attribute editing and reconstruction by parsing hidden variables using inverse regression, and when this technique is migrated to vehicle tracking scenarios, it can also cleverly deal with local occlusion problems. Meanwhile, the fusion of attentional mechanisms also plays a key role, like combining SENet or CBAM modules, which can enhance the weights of target critical regions (e.g., vehicle silhouette) and suppress the interference of background [15].

2.3.2 Discriminative Methods

The discriminative approach treats tracking as a binary classification problem, where the importance of contextual information is emphasised by training classifiers to distinguish between target and context.

2.3.2 .1 Technical Principles and Processes

In the field of target tracking, techniques such as classifier design, online update mechanism and feature fusion strategy are closely coordinated to ensure the tracking performance. Classifier design is based on support vector machine (SVM), correlation filter (DCF), or deep learning model (e.g., Siamese network), and the classifier is trained with positive samples in the target area and negative sam-

ISSN 2959-6157

ples in the surrounding area, which lays the foundation for accurate tracking. Meanwhile, the online update mechanism is crucial, which can dynamically adjust the classifier parameters to adapt to the target appearance changes, in which the DCF accelerates the computation through the cyclic matrix, which powerfully achieves real-time update so that the classifier can match the target state in time [15].

2.3.2 .2 Typical Algorithms and Technology Enhancements

Typical algorithms and techniques enhancements cover correlation filters (DCF), contrast learning enhancements and hybrid architectures. The correlation filter (DCF) efficiently trains filters in the frequency domain by minimising cyclic correlation loss, especially in UAV scenarios, and the ECO algorithm achieves a balance between accuracy and speed by compressing the feature dimensions [15]. Contrast learning enhancement, on the other hand, uses video sequences to generate positive and negative sample pairs, and brings the feature distance between target frames closer through contrast loss to improve the robustness of the model under occlusion and deformation. In addition, the use of hybrid architectures is also noteworthy, for example, the ASKCF algorithm combines KCF and particle filtering, KCF locates the target position, and particle filtering estimates the scale change, which effectively solves the problem of target size adaptation.

2.3.3 Comparative analysis of generative and discriminant methods

Table 4 Comparison Table of generative and discriminant methods

	Generative method	Discriminant method
Core idea	Target feature modelling and similarity optimisation	Target/contextual categorisation decision-making
Computational efficiency	Lower (bulk sampling required)	Higher (frequency domain optimisation, matrix operations)
Occlusion resistance	Weak (relies on target's own characteristics)	Strong (background context-assisted decision-making)
Background interference sensitivity	High (ignores background)	Low (explicitly distinguishes background)
Real-time	Limited (e.g. particle filtering)	Excellent (e.g. DCF)
Training data dependency	Synthetic data can be generated	Large number of labelled samples required

3. Realistic Dilemmas and Technological Research Directions

Currently, drone-based intelligent traffic monitoring faces numerous practical challenges. The incomplete technology of professional equipment makes it difficult for drones to fully meet traffic requirements in terms of payload, flight control, endurance, telemetry, data (image) transmission, and response. Insufficient environmental adaptability may lead to high detection error rates due to complex lighting conditions, obstructions, and extreme weather. Traditional radar detection technology performs poorly in adverse weather conditions and cannot accurately measure parameters such as vehicle height and length. In terms of supporting mechanisms, the development of drone applications varies across regions, and there is a lack of unified standards for pilot training and drone equipment, necessitating further research. In terms of deployment and maintenance, drones typically have a short single flight time, making it difficult to meet the demand for long-term continuous monitoring. There is also a lack of training for maintenance and service personnel, which can easily limit the functionality of drones due to mechanical failures. In complex traffic scenarios, drones need to avoid collisions and adjust their flight paths in real time, placing extremely high demands on algorithm real-time performance.

Addressing the issue of drone traffic flow, it is necessary to promote the research and development of drone technology, deepen cooperation between police and enterprises, and drive technological upgrades in line with practical needs to meet requirements for tasks, safety, and environmental considerations. Simultaneously, we should establish a supporting institutional management system, formulate equipment management standards, and establish a comprehensive support system to break down barriers to drone application. Furthermore, we must create diversified application scenarios, promote the deep integration of drones with traffic work, and cover daily patrol flights, vehicle inspections, accident investigations, and other business operations.

References

[1] Kampf, R., Kubina, M., Bartuska, L., & Soviar, J. (2022). Use of unmanned aerial vehicles for traffic surveys. *LOGI – Scientific Journal on Transport and Logistics*, 13, 163–173. https://doi.org/10.2478/logi-2022-0015

[2] Ke, R., Li, Z., Kim, S., Ash, J., Cui, Z., & Wang, Y. (2017). Real-time bidirectional traffic flow parameter estimation from aerial videos. *IEEE Transactions on Intelligent Transportation Systems*, 18(4), 890–901. https://doi.org/10.1109/TITS.2016.2595526

[3] Sujiao Law Enforcement. (2025, May). Jiangsu traffic law enforcement uses “technology + service” to ensure smooth holiday travel. *Jiangsu Legal Daily*. https://jsfzb.xhby.net/pc/con/202505/19/content_1448861.html

[4] Margaritoff, M. (2019). *Bordeaux Police Are Using Drones to Catch Reckless Drivers*. The Drive. https://www.thedrive.com/article/16073/bordeaux-police-are-using-drones-to-catch-reckless-drivers

[5] Biometrics and Surveillance Camera Commissioner. (2023). *2023 survey of law enforcement use of uncrewed aerial vehicles.* GOV.UK. https://www.gov.uk/government/news/2023-survey-of-law-enforcement-use-of-uncrewed-aerial-vehicles

[6] Faust, V. (2018). *Wentzville police using drones for traffic monitoring, other purposes.* Fox2now. https://fox2now.com/news/wentzville-police-using-drones-for-traffic-monitoring-other-purposes/

[7] Xinhua Silk Road. (2018). *Drones monitor traffic violations in east China.* Xinhua Silk Road Information Service. https://en.imsilkroad.com/p/105221.html

[8] Chen, Z., Peng, L., & Zhang, J. (2015). New moving-object detection algorithm based on the imported five-frame difference under the dynamic environment. *Journal of Jiangnan University (Natural Science Edition)*, 14(01), 34–37.

[9] Fu, L., Wang, Y., & Huang, Q. (2020). Motion vehicle target detection based on improved three-frame difference method. *Technology Wind*, (29), 69–70. https://doi.org/10.19392/j.cnki.1671-7341.202029034

[10] Ding, L., & Gong, N. (2013). Moving objects detection based on improved three-frame difference. *Video Engineering*, 37(01), 151–153. https://doi.org/10.16280/j.videoe.2013.01.040

[11] Jiao, H. (2022). Intelligent research based on deep learning recognition method in vehicle–road cooperative information interaction system. *Computational Intelligence and Neuroscience*, 2022(2), Article 4921211. https://doi.org/10.1155/2022/4921211

[12] Han, S. (2021). Vehicle detection based on improved frame difference method and background difference method. *Agricultural Equipment & Vehicle Engineering*, 59(6), 88–92. https://doi.org/10.3969/j.issn.1673-3142.2021.06.019

[13] Bai, Y., Song, Y., Zhao, Y., Zhou, Y., Wu, X., He, Y., Zhang, Z., Yang, X., & Hao, Q. (2022). Occlusion and deformation handling visual tracking for UAV via attention-based mask generative network. *Remote Sensing*, 14(19), 4756. https://doi.org/10.3390/rs14194756

[14] Fu, C., Li, B., Ding, F., Lin, F., & Lu, G. (2020). Correlation filter for UAV-based aerial tracking: A review and experimental evaluation. *IEEE Geoscience and Remote Sensing Magazine*, 10(1), 125–160. https://doi.org/10.1109/MGRS.2021.3072992

[15] Goodfellow, I. J., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., & Bengio, Y. (2014). Generative adversarial nets. In *Proceedings of the 28th International Conference on Neural Information Processing Systems – Volume 2* (pp. 2672–2680). MIT Press.