Vehicle Detection through Unmanned Vehicle

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Abstract- One of the most important requirements for traffic surveillance is vehicle detection. Cameras are typically installed in fixed locations in most Intelligent Transportation Systems (ITS), limiting their flexibility. the cameras' field of view (FOV). This paper discusses a new vehicle detection method based on airborne video analysis retrieved from a quadrotor unmanned aerial vehicle (UAV). Different detection methods for moving and static videos vehicles are used to meet traffic requirements surveillance. A feature point detects moving vehicles tracking method based on a scale invariant combination SIFT (feature transform) and an efficient clustering method. The blob information is used to identify static vehicles following automatic road extraction. In order to increase Some pre-processing methods are added to improve detection precision. into the monitoring system the results of the experiments show. Vehicle detection approaches proposed here can be implemented with a high rate of identification.

Keywords - intelligent transportation system, UAV

I. INTRODUCTION

In western China, sparse highway networks cover a large area but have a low traffic density. It is difficult to ensure traffic safety in such an environment. Furthermore, disadvantages such as bad weather and inconvenient communication increase the difficulties of the rescue, which may result in severe injuries and death. With the advancement of technology in aircraft manufacturing and imaging processing,

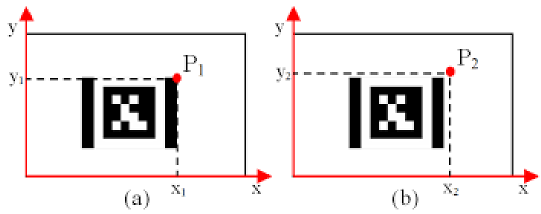
UAVs provide a new dynamic aerial platform for traffic surveillance systems.

The UAV platform has many advantages over ground-based sensors. The globe traffic information can be easily gathered from aerial video by installing visual sensors in a UAV. Furthermore, the high mobility of UAVs ensures that traffic incidents are detected in time, reducing casualties and property losses to a minimum.

However, the UAV visual surveillance system creates unique challenges for vehicle identification. Because of the high speed of the aircraft, the background in the UAV surveillance platform changes frequently, as opposed to the still background in traditional surveillance systems. To identify traffic status and incidents, the complex background must be filtered, and traffic features must be detected, both of which must be accomplished enroute, putting a high demand on the algorithm's performance.

Due to the difficulties mentioned above, we investigate an airborne video surveillance system in which moving and static vehicles are detected separately by two detection methods in this paper. In the case of moving vehicles, image feature points are extracted in each frame and then matched between two adjacent frames. Following that, an effective clustering algorithm is used to classify these feature points into three categories: background, moving vehicles moving forward, and moving vehicles moving backward. Given the impact of image noise, some pre-processing approaches have been implemented to improve detection rate. In the first place, a method based on an edge detection algorithm correctly extracts the road region for static vehicles. After removing the moving vehicles detected previously, static vehicles can be identified by selecting those features that differ from road features in the road region.

II. MOVING VEHICLE DETECTION

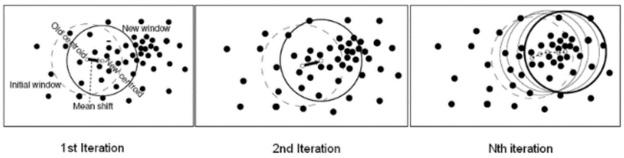


Feature point tracking

Background modelling could not be applied to UAV video surveillance system when background is fast moving. At the same time, camera vibration and speckle noise also seriously affect the accuracy of detection. Therefore, in this paper, we use the feature point tracking method to acquire a serial of image features, which are then classified into three categories: background, moving vehicles with forward direction and moving vehicles with backward direction after clustering processes.

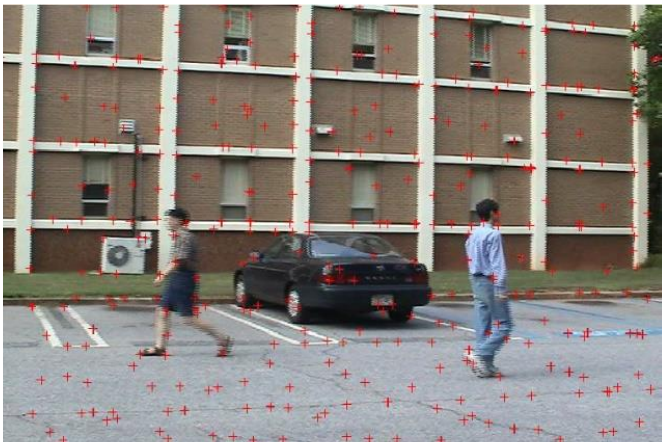
Background modelling could not be used with UAVs. When the background is moving quickly, use a video surveillance system. At the same time, camera vibration and speckle noise are present. This has a significant impact on detection accuracy. In this paper, we use the feature point tracking method to acquire a series of image features that are then classified into three categories: background, moving vehicles with forward motion.

III. FEATURE EXTRACTION AND MATCHING



SIFT algorithm

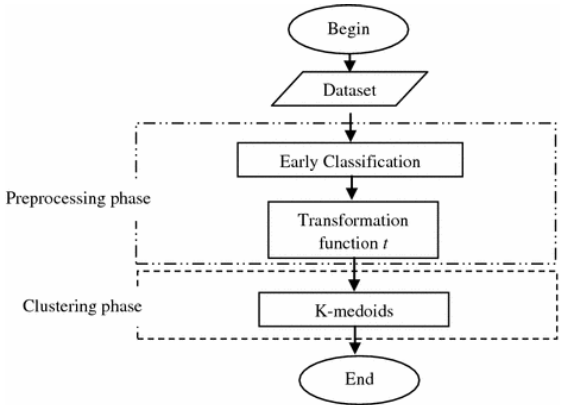
Corner features that are important image features always defined as the points of intersection between two or more. More edge segments of a picture contain a lot of information. Not only can feature point extraction be used to obtain critical image information, but also to remove the impediment of redundant information. Moravec is one of the most commonly used feature extraction methods. Harris points, KLT points, and SUSAN points. The SIFT is based on scale space theory. The algorithm has been widely adapted for corner feature extraction because of its translation, scaling, and scalability invariance rotation. To generate features at various scales-spaces, The SIFT algorithm establishes distinction-of-Gaussian (DOG). First, there is scale space, which is produced by the convolution of a with the input image, a Gaussian kernel of different scales is used.



Moravec corner detection

Following the feature extraction process, image registration using feature point matching between two adjacent frames is required. The feature's matching algorithm is typically implemented in two ways. One is based on the sum of squared intensity differences (SSD), while the other is based on normalised cross correlation (NCC). In this case, we use the KLT detector to track feature points between adjacent frames.

IV. CLUSTERING ALGORITHM



Data clustering has been widely used in data analysis as an important data mining method. The K-means algorithm is the most well-known clustering method. The average of all date points is chosen as the initial centre in K-means, and the sample data is then partitioned into different clusters iteratively. Although it is simple and fast, the results of K-means clustering are frequently sensitive to the initial clustering centres and easily fall into the locally optimal value. In this case, we use the K-medoids algorithm to cluster the feature points in order to reduce the reliance on initial centres. Instead of choosing the average of all data points as the centre in K-means clustering, K-medoids chooses the point with the shortest distances from the other points in a cluster as the centre. Because it minimises a sum of pairwise dissimilarities rather than a single dissimilarity, it is more independent and robust to noise and initial centres than K-means. The process of K-medoids clustering is as follows:

1. Randomly select k points as the medoids (O1, O2…Ok);

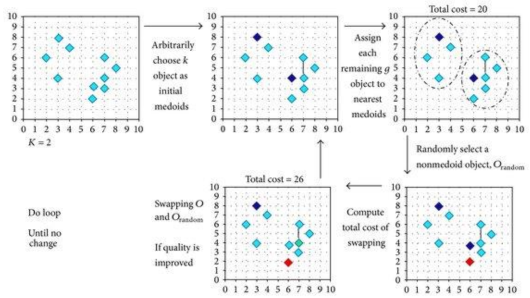
2. Associate the rest points to the closet medoid;

3. For each medoid O and each non-medoid point P, swap O and P and then compute the total cost of the configuration;

4. Select the configuration with the lowest cost;

5. Repeat steps 2 to 5 until there is no change in the medoid

The K-medoids clustering algorithm is used for the first time in this paper to distinguish moving vehicles from the background. It is obvious that the background has the most highlighting points When compared to the velocity of against this backdrop, we can easily distinguish moving vehicles with backward movement of moving vehicles in the forward direction. Then we employ K-medoids are used once more to separate every moving vehicle. In order to some steps



must be taken to reduce the rate of false positives measures to eliminate a series of disturbances. We can see that four moving vehicles have been successfully launched separated from one another.

V. STATIC VEHICLES DETECTION

When a sign of a static vehicle appears on a sparse highway network, it frequently indicates that an accident has occurred. As a result, correctly identifying static vehicles in our surveillance system is critical. At the moment, there aren't many effective methods for detecting static vehicles in a UAV surveillance system. Under the conditions of a fast-moving camera, the static vehicle will be easily misidentified as the background. To overcome these drawbacks, we first obtain road region in our system using image edge detection, which reduces detection region and the disturbance of complex background, thereby confining ROI (region of interest) in relatively simple road region. After that, we use a blob analysis algorithm to identify static vehicles by removing moving vehicles.

VI. BLOB ANALYSIS

After extracting the road, we can set the road area as the ROI, which not only reduces computation but also improves detection rate. Because a sparse highway has a low traffic density, the background has the most weight in the road region, which allows us to define a threshold for distinguishing vehicles from the road. The variance of the RGB value of the road area remains stable.

VII. EXPERIMENT RESULTS

To assess the performance of the UAV visual surveillance system discussed in the previous section, we present experimental results that put our vehicle detection methods to the test. We use a quad rotor helicopter outfitted with a camera as the UAV platform. The experiments are run on an Intel(R) Core (TM) i5 CPU running at 3.2GHz with 4GB of RAM and the Windows XP operating system. A SONY camera with a resolution of 720h576 captured the aerial video. And the frame rate is 25fps.

During the experiment, the UAV's flying height is kept between 100 and 150 metres, and its velocity is not less than 100 km/h. Every moving vehicle is identified by a green rectangle label, while every stationary vehicle is identified by a red rectangle label. We can see from the results that vehicles can be detected with varying backgrounds and road directions.

VIII. CONCLUSIONS

In this paper, we look at vehicle recognition methods from a UAV visual surveillance system in a sparse highway network. In comparison to fixed-wing aircraft, research on surveillance systems in multiple-rotor helicopters is more promising, but also more difficult. The main contribution of this paper is that both moving and stationary vehicles can be correctly recognised in this system.

More importantly, the system implements auto-alarm of traffic incidents based on detected vehicle information.

Because of the helicopter's violent vibration, we concentrate on methods that are more invariant of translation, scaling, and rotation. The experimental results show that the method can achieve good detection rate performance, with a correct detection rate of moving vehicles of at least 90% and static vehicles of at least 80%. A high detection rate ensures the viability of the next stage of our work, which includes vehicle tracking and acquisition of the automobile velocity. In the future, we will place a greater emphasis on developing a detection method for dealing with larger situations and meeting the Real-time constraints.

IX. REFERENCES

[1] HulyaYalcin, Martial Herbert, Robert Collins and Michael J.Black. “A Flow-Based Approach to Vehicle Detection and Background Mosaicking in Airborne Video,” Computer Vision and Pattern Recognition, (2005).

[2] Alejandro Angel, Mark Hickman. PituMirchandani and Dinesh Chandnani, “Methods of Analyzing Traffic Imagery Collected From Aerial Platforms,”IEEE Transactions on Intelligent Transportation Systems,Vol.4(2),pp:99-107, (2003).

[3] Ernst.I, Sujew.S, Thiessenhusen.K.U and Hetscher.M, “LUMOS-Airborne Traffic Monitoring System”IEEE Transactions on Intelligent Transportation Systems.Vol.1,pp:753-759, (2003).

[4] WANG Wen-long, LI Qing-quan and TANG Lu-liang, “Algorithm of Vehicle Detection in Low Altitude Aerial Video,” Journal of Wuhan University of Technology.Vol.32(10),pp:155-158, (2010).

[5] H.P.Moravec, “Rover visual obstacle avoidance,” International Joint Conference on Artificial Intelligence.pp:785-790, (1981).

[6] C.Harris, M.Stephens, “A combined corner and edge detector,”Proceedings of the 4thAlvey Vision Conference, pp:147-151, (1988).

[7] Smith, S.M, M.Brady.SUSAN, “A New Approach to Low Level Image processing[J],” International Journal of Computer Vision, Vol.23(1), pp:45-78, (1997).

[8] Mikolajjczyk K, Schmid C, “A performance evalution of local descriptors[J],” IEEE Transactions on Patternt Analysis and Machine Intelligence, Vol.27(10), pp:1615-1630, (2005).

[9] MyungHwangbo,Jun-Sik Kim and Kanada T, “Inertial-aided KLT feature tracking for a moving camera,”Intelligent Robots and Systems, pp:1909-1916,(2009).

[10] Danyang Cao, Bingru Yang, “An improved k-medoids clustering algorithm,”Computer and Automation Engineering(ICCAE), Vol.3,pp:132-135,(2010).

[11] Rafael C. Gonzalez, Richard E. Woods, “Digital Image Processing(Third Edition),”Pearson Prentice Hall,pp:132-135, (2008).