KNN NETWORK BASED INTELLIGENT AERIAL SURVEILLANCE SYSTEM

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Abstract- In this paper, we proposed an automatic vehicle detection system for aerial surveillance with advance use of detecting vehicle colors, and its model. It does not assume any prior information of camera heights, vehicle sizes, and vehicle colors. Vehicle classification has evolved into a significant subject of study due to its importance in autonomous navigation, traffic analysis, surveillance and security systems, and transportation management. While numerous approaches have been introduced for this purpose, no specific study has been conducted to provide a robust and complete video-based vehicle classification system based on the rear-side view where the camera's field of view is directly behind the vehicle. In this paper features including vehicle colors and local features are considered. Feature extraction performs the edge detection and corner detection using canny edge detector. Color classification executes the color a transformation. Finally KNN classifier is used for classification purpose. By finding the nearest neighbors pixelwise classification is accomplished.

Keywords - Aerial surveillance, KNN (k-Nearest Neighbor), Pixelwise classification, Feature extraction, Vehicle detection.

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I. INTRODUCTION

Aerial surveillance has a long history in the military for observing enemy activities and in the commercial world for monitoring resources such as forests and similar imaging techniques are used in aerial news gathering and search and rescue. Surveillance is the monitoring of the behavior, activities, or other changing information, usually of people for the purpose of influencing, managing, directing, or protecting. Surveillance is therefore an ambiguous practice, sometimes creating positive effects, at other times negative. It is sometimes done in a surreptitious manner. It most usually refers to observation of individuals or groups by government organizations. Surveillance cameras are video cameras used for the purpose of observing an area.

They are often connected to a recording device, IP network, and/or watched by a security guard/law enforcement officer. Cameras and recording equipment used to be relatively expensive and required human personnel to monitor camera footage. The use of surveillance cameras by governments and businesses has dramatically increased over the last 10 years. Aerial surveillance is the gathering of surveillance, usually visual imagery or video, from an airborne vehicle such as a unmanned aerial vehicle, helicopter, or spy plane. Military surveillance aircraft use a range of sensors (e.g. radar) to monitor the battlefield.

Traffic surveillance has been important to the Department of Transportation. Several options were considered for the necessity of developing a system that would enable the next generation of traffic surveillance, but unfortunately, most of them were not practical. The aerial surveillance technologies are used in variety of applications, like military department, police department traffic management and disaster management systems. Compared with other video surveillance technologies, such as fixed camera video surveillance and ground surveillance, aerial surveillance is easier and quicker to deploy, more suitable for monitoring fast moving targets and covers a larger spatial area.

II. PAST WORK

In [4], Suman Srinivasan, Haniph Latchman considered term of Software and it is critical to design an airborne moving vehicle detection method with high detection rate and low false positive rate, while performing in real time. However, such an airborne urban moving vehicle detection method is difficult to design. The most difficult issue is the camera vibration.

In [5], Anand C.Shastry proposed an airborne video registration method and sharply reduce the camera vibration. Nevertheless, the detection rate of the system based on registered image can only reach 65%. Additionally, there are some additional difficulties existing in urban traffic surveillance from an airborne platform, which make the traditional detection method in highway situation not achieve good performance. These difficulties include as follows:

(1) There are too many moving vehicles in a frame, so two adjacent vehicles may easily be regarded as one by image subtraction method. For example, Coifman0 proposed a simple but efficient subtraction method for roadway traffic monitoring from an unmanned aerial vehicle. However, this method can only fit for the situation with little traffic on the road.

(2) Due to illumination variance and complicated objects besides road, detection background is always complex and optical flow algorithm cannot meet the real time application. However, complicated urban traffic background leads to substantial computation time. Also, it brings false positive rate to image subtraction method, because of plenty of noise.

(3) Thermal noise is very serious and the algorithm based on thermal image processing cannot achieve good performance. For example, E.Michaelsen proposed a three-level-classification method based on thermal image and got good performance on highway, but it cannot perform as well on urban situation. Due to the difficulties mentioned above, airborne urban moving vehicle detection still needs further research.

S.Hinz and A.Baumgartner [7] introduces on automatic vehicle detection in monocular large scale aerial images. The extraction is based on a hierarchical model that describes the large vehicle features on different levels. The object model comprises the contextual knowledge, i,e., relation between a vehicle and other objects. For example, The pavement beside a vehicle and the sun causing a vehicle's shadow projection. In order to avoid time consuming grouping algorithms in the early stages of extraction. Then, first focus on generic image features as edges, lines, and surfaces.

The extraction strategy is derived from the vehicle model and, consequently, contains the two paradigms. They are A) Coarse to fine B) Hypothesize and test. It consists of following four steps. They are 1) Creation of Region of Interest (RoIs) 2) Hypotheses formation 3) Hypotheses validation and selection 4) 3D model generation and verification. The drawback of this system is that there is no specific vehicle models assumed, making the method flexible. However, their system would miss vehicles when the contrast is weak or when the influences of neighboring objects are present.

H.Cheng and D.Butler [8], proposed an aerial video surveillance has proved to be an effective way to collect information for a variety of applications including military operations, law-enforcement activities, disaster management and commercial applications. In this paper, propose a video

segmentation algorithm for aerial surveillance video. The algorithm uses a Mixture of Experts (MoE) consisting of a supervised image segmentation algorithm named the Trainable Sequential MAP (TSMAP) segmentation algorithm. Compared with other video surveillance technologies, such as fixed camera video surveillance and ground surveillance, aerial surveillance is easier and quicker to deploy, more suitable for monitoring fast moving targets and covers a much larger spatial area.

In this system Video segmentation can be crudely classified into three categories: They are (1) Supervised video segmentation, (2) Unsupervised video segmentation, (3) Specialized video segmentation.

In Supervised video segmentation a video frame is partitioned into non-overlapping regions according to what it has been taught. During training, sample images or videos with corresponding ideal segmentations, also called ground-truth segmentations, are presented to a supervised segmentation algorithm. In the unsupervised segmentation algorithm provides accurate region boundaries. The specialized video segmentation, such as moving object detection.

R.Lin, X.Cao, Y.Xuc [11], proposed an Urban traffic surveillance, which is designed to improve traffic management, is an important part of intelligent traffic system (ITS). In particular, airborne moving vehicle detection has become a new but hot research area since its wide view and low cost. However, airborne urban traffic surveillance is impacted by many difficulties such as camera vibration, vehicle congestion, background variance, serious thermal noise etc. Therefore, image subtraction and thermal image processing have low detection rate, while the optical flow method cannot meet the real-time application. In this paper, propose a coarse-to-fine method, which can be divided into two stages. They are (1) pre-processing (2) classification inspection.

The main disadvantage of this method is that there are a lot of miss detections on rotated vehicles. Such results are not surprising from the experiences of face detection using cascade classifiers. If only frontal faces are trained, then faces with poses are easily missed. However, if faces with poses are added as positive samples, the number of false alarms would surge.

III. PROPOSED WORK

Here, the proposed vehicle detection framework is mainly performed the training phase and the detection phase.

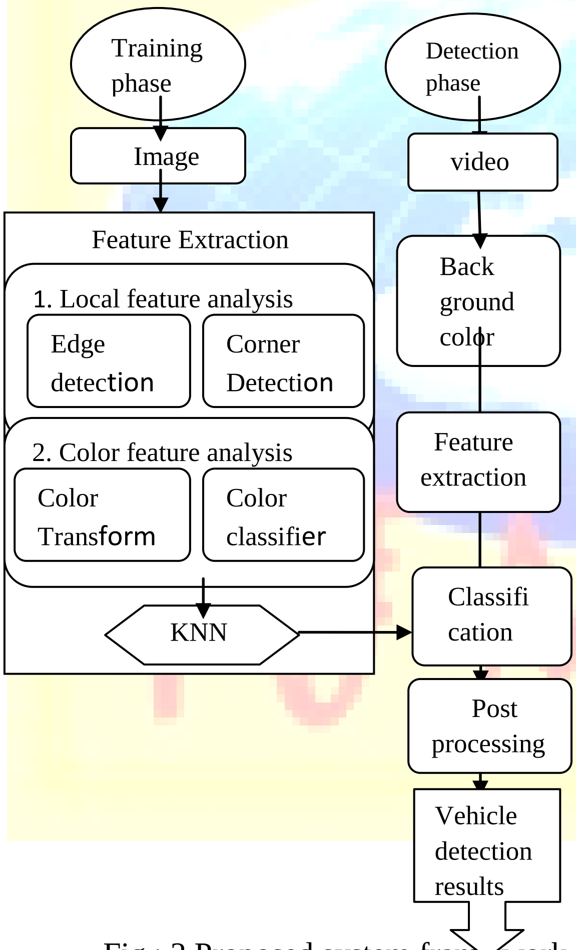


Fig : 2 Proposed system frame work

In this paper, we design a new vehicle detection framework that preserves the advantages of the existing works and avoids their drawbacks. The modules of the proposed system framework are illustrated in fig.2.

In the detection phase, first read the video signal. Then convert to the image frame format. Afterwards, perform the background color removal operations. And it is based on the color histogram. If the histogram is high, it is background color. So it is removed. Afterward, if the histogram is low, it is foreground color ie, vehicle region. Then perform the feature extraction process. The same feature extraction process is performed in both the training phase and the detection phase. In the training phase, we extract multiple features including local edge and corner features, as well as vehicle colors to train a SVM. Then k-Nearest Neighbor classifier is used. Then finally get the vehicle detection results. Here, we elaborate each module of the proposed system framework in detail.

A) Background Color Removal

It is used to remove the nonvehicle regions of the entire scene in aerial images. In fig 3, Here we construct the color histogram of each frame and remove the colors of the entire scene. Here, the colors are quantized into 48 histogram bins. Among all histogram bins, the 12th, 21st, and 6th bins are the highest and are thus regarded as background colors and are removed.

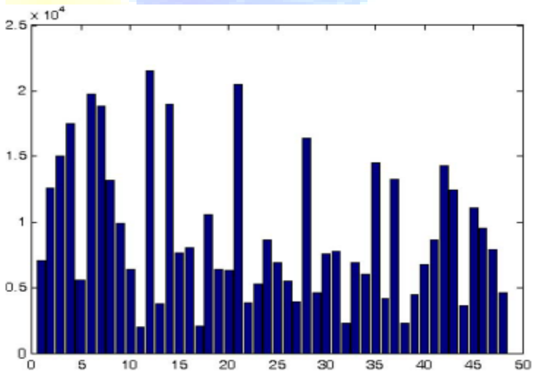
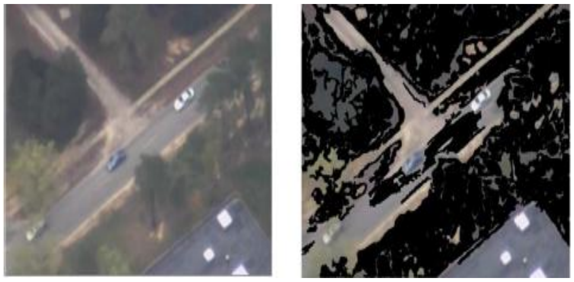


Fig. 3. Color histogram of a frame.

These removed pixels do not need to be considered in subsequent detection processes. Performing background color removal cannot only reduce false alarms but also speed up the detection process.

Here, the below fig 4, is mainly explains the background removal results.



(a) Orginal image (b) Background color Removal

B) Feature Extraction

Feature extraction is performed in both the training phase and the detection phase.

(1) Local Feature Analysis:

Local features mainly contain images that are subdivided into small small parts. Here, the Corners and edges are usually located in pixels with more information. We use the Harris corner detector to detect corners. To detect edges, we apply moment-preserving thresholding method on the classical Canny edge detector to select thresholds adaptively according to different scenes. In the Canny edge detector, there are two important thresholds, i.e., the lower threshold and the higher threshold .

$$mi = (1/n)\sum_j nj(zj)^i = \sum_j pj(zj)^i, i = 1,2,3.....$$

where nj is the total number of pixels in image f with gray value kj and $Tj = \frac{nj}{n}$.As the illumination in every aerial image differs, the desired thresholds vary and adaptive thresholds are required. The movement is calculated by pixel position and is multiplied by pixel value. ie,

Movement =Pixel position * Pixel value

2) Color transform and color classification:

The new color model is used to separate vehicle colors from non vehicle colors effectively. This color model transforms color components into the color domain (u,v) .

$$u_p = \frac{2Z_p - G_p - B_p}{Z_p}$$

$$v_p = max\left\{\frac{B_p - G_p}{Z_p}, \frac{R_p - B_p}{Z_p}\right\}$$

where(R_p,G_p,B_p) is the R,G,B color components of pixel p and $Z_p=(R_p+G_p+B_p)/3$.

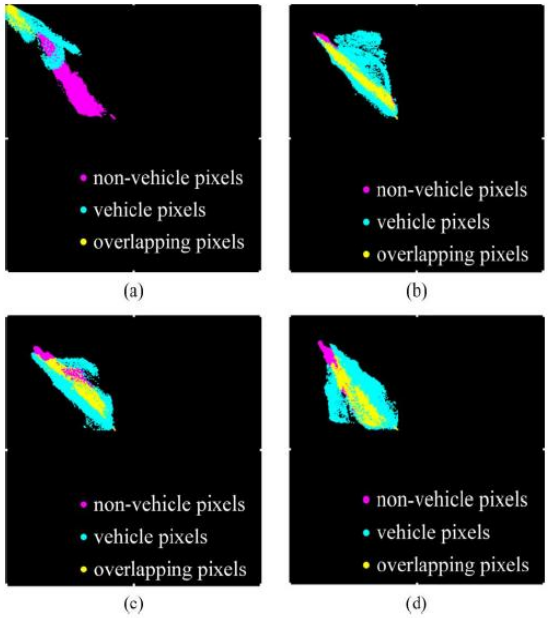


Fig. 5. Vehicle colors and nonvehicle colors in different color spaces. (a) U-V, b) R-G, (c) G-B , and (d) B-R planes.

As shown in Fig. 5, we can observe that vehicle colors and nonvehicle colors have less overlapping regions under the (U,V) color model. Therefore, we apply the color transform to obtain (U,V) components first and then use a support vector machine (SVM) to classify vehicle colors and non vehicle colors.

C) K-Nearest Neighbor (KNN):

K-Nearest Neighbor (KNN) is constructed for the classification purpose. It is based on Bays theorem. KNN gives the most accurate Comparison with each classifier. It is classified into two types. They are 1) Posterior 2) Priorior. First convert regional local features into quantitative observations that can be referenced when applying pixel wise classification via KNN.

In the training phase, extract multiple features including local edge and corner features, as well as vehicle colors to train a Support Vector Machine. In the detection phase, first perform background color removal similar to the process specified earlier. Afterwards, the same feature extraction procedure is performed as in the training phase. The extracted features serve as the evidence to infer the unknown state of the trained KNN, which indicates whether a pixel belongs to a vehicle or not. We perform pixelwise classification for vehicle detection using KNNs. The design of the KNN model is illustrated in Fig. 6. The state of v_t is dependent on the state of vt-1.Moreover, at each time slice, state has influences on then observation nodes. The observation nodes are assumed to be independent of one another.

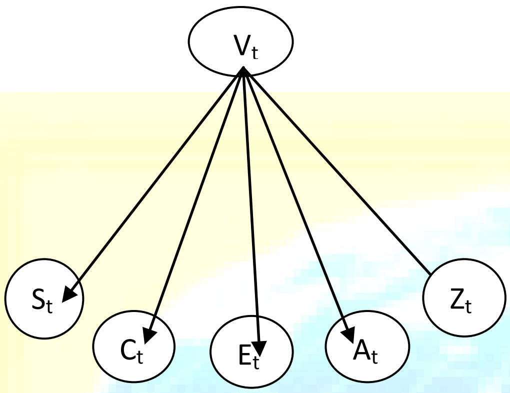


Fig 6, KNN model for pixelwise classification.

The first feature S denotes the percentage of pixels that are classified as vehicle colors by SVM, as defined. Note that, denotes to the number of pixels in that are classified as vehicle colors by SVM, i.e.,

$$S=N_{Vechile\ Color}/N*N$$

Feature C denotes to the number of pixels in that are detected as corners by the Harris corner detector.

$$C=N_{Corner}/N*N$$

The feature E denotes the number of pixels in that are detected as edges by the enhanced Canny edge detector. The pixels that are classified as vehicle colors are labeled as connected vehicle color regions.

$$E=N_{Edge}/N*N$$

The last two features A and Z are defined as the aspect ratio and the size of the connected vehicle-color region .More specifically, and feature Z is the pixel count of particular vehicle color region

A=Length/Width

In the detection phase, the Bayesian rule is used to obtain the probability that a pixel belongs to a vehicle, i.e.,

$P(V_t / S_t, C_t, A_t, Z_t, V_t\text{-}1) = P(V_t / S_t)\, P(V_t / C_t)\, P(V_t / A_t)\, P(V_t / Z_t)\, P(V_t / V_t\text{-}1)\, P(V_t\text{-}1)$

$P(V_t \mid S_t)$ is defined as the probability that a pixel belongs to a vehicle pixel at a time slice for a given observation St at time instance t. According to the naive Bayesian rule of conditional probability, the desired joint probability can be factorized since all the observations are assumed to be independent. The proposed vehicle detection framework can also utilize a K-Nearest Neighbor (KNN) to classify a pixel as a vehicle or non-vehicle pixel.

D) Post Processing

Morphological operations are used to enhance the detection mask and perform connected component labeling to get the vehicle objects. Here, the post processing is mainly used in two morphological operations. They are morphological open and morphological close. Afterward, Opening removes small objects from the foreground (Usually taken as the dark pixels)of an image, placing them in the background, while closing removes small holes in the foreground, changing small background into foreground. These techniques can also be used to find specific shapes in an image. Opening can be used to find things into which a specific structuring element can fit (edge and corner). The size and the aspect ratio constraints are applied again after morphological operations in the post processing stage to eliminate objects that are impossible to be vehicles.

IV. EXPERIMENTAL RESULTS

Experimental results are demonstrated here. To analyze the performance of the proposed system, various video sequences with different scenes and different filming altitudes are used.

When performing background color removal, we quantize the color histogram bins as 16 *16 *16. Colors corresponding to the first eight highest bins are regarded as background colors and removed from the scene.

We compare different vehicle detection methods in Fig. 6.The moving-vehicle detection with road detection method requires setting a lot of parameters to enforce the size constraints in order to reduce false alarms. However, for the experimental data set, it is very difficult to select one set of parameters that suits all videos. Setting the parameters heuristically for the data set would result in low hit rate and high false positive numbers. The cascade classifiers used in need to be trained by a large number of positive and negative training samples. The number of training samples required in is much larger than the training samples used to train the SVM classifier. The colors of the vehicles would not dramatically change due to the influence of the camera angles and heights. However, the entire appearance of the vehicle templates would vary a lot under different heights and camera angles. When training the cascade classifiers, the large variance in the appearance of the positive templates would decrease the hit rate and increase the number of false positives. Moreover, if the aspect ratio of the multiscale detection windows is fixed, large and rotated vehicles would be often missed. The symmetric property method proposed is prone to false detections such as symmetrical details of buildings or road markings. Moreover, the shape descriptor is used to verify the shape of the candidates obtained from a fixed vehicle model and is therefore not flexible. Moreover, in some of our experimental data, the vehicles are not completely symmetric due to the angle of the camera. Therefore, the method is not able to yield satisfactory results.

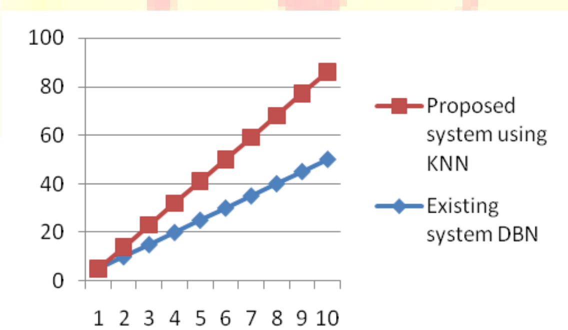


Fig : 6 Comparisons of different vehicle detection methods.

Compared with these methods, the proposed vehicle detection framework does not depend on strict vehicle size or aspect ratio constraints. Instead, these constraints are observations that can be learned by KNN. The training process does not require a large amount of training samples. The results demonstrate flexibility and good generalization ability on a wide variety of aerial surveillance scenes under different heights and camera angles. It can be expected that the performance of KNN is better than that of the DBN. The colored pixels are the ones that are classified as vehicle pixels by KNN. The ellipses are the final vehicle detection results after performing post processing. When observing detection results of consecutive frames, we also notice that the detection results via KNN are more stable. The reason is that, in aerial surveillance, the aircraft carrying the camera usually follows the vehicles on the ground, and therefore, the positions of the vehicles would not have dramatic changes in the scene even when the vehicles are moving in high speeds. Therefore, the information along the time contributed by $P(V_t / V_t\text{-}1)$ helps stabilize the detection results in the KNN.

V. CONCLUSION

In this paper, we have propose that the system framework does not assume any prior information of camera heights, vehicle sizes, and aspect ratios. This design contains a new vehicle detection framework that preserves the advantages of the existing works and avoids their drawbacks. Here, it presents an automatic vehicle detection system for aerial surveillance. In this system. We escape from the stereotype and existing frameworks of vehicle detection in aerial surveillance. A pixel wise classification method for vehicle detection is designed. The novelty lies in the fact that, in spite of performing pixel wise classification, relations among neighboring pixels in a region are preserved in the feature extraction process. Features including vehicle colors and local features are considered. In this system, region-based classification is not used which would highly depend on computational intensive color segmentation algorithms such as mean shift. The experimental results demonstrate flexibility and good generalization abilities of the proposed method on a challenging data set with aerial surveillance images taken at different heights and under different camera angle.

REFERENCES

[1] Hsu-Yung Cheng, *Member*, *IEEE*, Chih-Chia Weng, and Yi-Ying Chen "Vehicle Detection in Aerial Surveillance Using Dynamic Bayesian Networks," ieee transactions on image processing, vol. 21, no. 4, april 2012.

[2] H. Cheng and J. Wus, "Adaptive region of interest estimation for aerial surveillance video," in Proc. IEEE Int. Conf. Image Process., 2005,vol. 3, pp. 860–863.

[3]N. Cristianini and J. Shawe-Taylor, An Introduction to Support Vector Machines and Other Kernel-Based Learning Methods. Cambridge,U.K.: Cambridge Univ. Press, 2000.

[4]. L. D. Chou, J. Y. Yang, Y. C. Hsieh, D. C. Chang, and C. F. Tung, "In-tersection-based routing protocol for VANETs,"Wirel. Pers. Commun.,vol. 60, no. 1, pp. 105–124, Sep. 2011

[5] L. D. Chou, J. Y. Yang, Y. C. Hsieh, D. C. Chang, and C. F. Tung, "In-tersection-based routing protocol for VANETs,"Wirel. Pers. Commun.,vol. 60, no. 1, pp. 105–124, Sep. 2011

[6]L. Hong, Y. Ruan, W. Li, D. Wicker, and J. Layne, "Energy-based video tracking using joint target density processing with an application to unmanned aerial vehicle surveillance,"IETComput. Vis., vol. 2, no.1, pp. 1–12, 2008.

[7] S. Hinz and A. Baumgartner, "Vehicle detection in aerial images using generic features, grouping, and context," in Proc. DAGM-Symp.,Sep.2001, vol. 2191, Lecture Notes in Computer Science, pp. 45–52.

[8] H. Cheng and D. Butler, "Segmentation of aerial surveillance video using a mixture of experts," in Proc. IEEE Digit. Imaging Comput.—Tech. Appl., 2005, p. 66.

[9]R. Lin, X. Cao, Y. Xu, C. Wu, and H. Qiao, "Airborne moving vehicle detection for video surveillance of urban traffic," inProc. IEEE Intell.Veh. Symp., 2009, pp. 203–208

[10]L. W. Tsai, J. W. Hsieh, and K. C. Fan, "Vehicle detection using normalized color and edge map," IEEE Trans. Image Process., vol. 16, no. 3, pp. 850–864, Mar. 2007.

[11] R. Lin, X. Cao, Y. Xu, C. Wu, and H. Qiao, "Airborne moving vehicle detection for urban traffic surveillance," in Proc. 11th Int. IEEE Conf.Intell. Transp. Syst., Oct. 2008, pp. 163–167

[12]W. H. Tsai, "Moment-preserving thresholding: A new approach," Comput. Vis.Graph., Image Process., vol. 29, no. 3, pp. 377–393, 1985.

[13]S. Russell and P. Norvig, "Artificial Intelligence: A Modern Approach", 2nd ed. Englewood Cliffs, NJ: Prentice-Hall, 2003.

BIBLIOGRAPHY

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