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Automatic Integrated Technique for Road Detection & Tracking

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Abstract

Implementation of unmanned aerial vehicle (UAV) has recreated the detection, navigation and tracking of respective region in novel way to get accuracy and reliability in reliable way. UAV navigation, traffic monitoring, and ground–vehicle tracking attain attention due to their requirement in daily needs and usage of the UAV videos has made task easy especially in construction of roads and its associated works even in remote areas. In this paper based on two important algorithms is proposed for detection of exact region for extraction and this is done by graph-cut–based detection approach in initial stage while road tracking in automatic way is done by fast homography-based road-tracking scheme. Efficiency and performance of the proposed work is attributed to two aspects: the road detection is performed only when it is necessary and most work in locating the road is rapidly done via very fast homography-based tracking. Finally experimental results attain promising results over traditional state of art methods.

Keywords: unmanned aerial vehicle (UAV), graph-cut–based detection, fast homography, road tracking

1. INTRODUCTION

Image processing is processing of images using mathematical operations by using any form of signal processing for which the input is an image, a series of images, or a video such as a photograph or video frame; the output of images processing may be either an image or parameters related to the image. UAVs may be employed for a wide range of transportation operations and planning applications; traffic monitor, transportation, measurement of typical roadway usage, monitor parking lot utilization. UAV for surveillance is an active research topic in computer vision that tries to detect, recognize and track objects over a sequence of images and it also makes an attempt to the understand. Generally UAVs is used to follow roads, rivers, oil gas pipeline inspection, and the traffic parameter measurements. UAVs equipped with cameras are viewed as a kind of low cost platform that can provide efficient data for intelligent transport systems. With the increasing use of vehicles and their demands on traffic management, this kind of platform becomes more and more popular. Knowledge of road areas can provide users the regions of interest for further navigation, detection and data collection.

Automatic detection, tracking, and counting of a variable number of objects are crucial tasks for a wide range of applications such as security, surveillance, management of access points, urban planning, traffic control, etc. Road detection and tracking, most approaches use the color (texture) and/or structure (geometry)properties of roads. Among them, the combination of road color and boundary information have achieved more robust and accurate results than using only one of them in road detection, as shown in the work. To utilize Graph cut algorithm for road detection and homography for road tracking approach. In road detection, to utilize the Graph cut algorithm because of its efficiency and powerful segmentation performance in 2-D color images. In road tracking, propose a fast road tracking approach.

In comparison, UAV has advantages, including; there is a low cost to monitor over long distances, it is flexible for flying across broad spatial and temporal scales, and it is capable of carrying various types of sensors to collect abundant data. To collect information for the transportation system, it is important to know where the roads are in UAV videos. Knowledge of road areas can provide users the regions of interest for further navigation, detection, tracking and data collection procedures. Real time is required in many UAV based applications; major target is how to effectively combine both types of information for road detection and tracking in an efficient way. Intuitively, there are two rules to the making one integrated framework efficient. First, each component of the framework should be very fast and efficient. Second, if one component is faster than the others in achieving the same purpose, it would better make use of the fastest component as much as possible. It should be noted that these technique is not just limited to road detection and tracking. It can be also applicable to river, pipeline, or coastline detection and tracking in UAV videos**.**

2. RELATED WORK

In the literature of road detection and tracking, most approaches use the color (texture) and/or structure (geometry) properties of roads. The combination of road color and boundary information has achieved more robust and accurate results than using only one of them in road detection. Analyze the characteristics of roads in color images of urban and campus environments and algorithm is proposed to extract the candidates of road boundaries and subsequently combining the results of boundary detection with the color information in the image captured, and then present a method to precisely extract the road areas. A popular approach to the problem of road detection is the use of lane markings. Those markings are localized to acquire boundary information that facilitates the road detection process. Methods that rely on lane markings are usually fast and simple, using mainly grayscale images or videos. And second popular method in road detection applications is the use of color or brightness information to segment the road, which is enhanced by some feature extraction process such as edge detection to extract the road boundaries. To improve road detection accuracy and robustness to shadows, many researchers have utilized more complex methods by processing information related to optical flow and stereo vision acquired from camera pairs. In road detection, propose to utilize the Graph Cut algorithm because of its efficiency and powerful segmentation performance in 2-D color images. And in road tracking, aim to track the road border structure between two consecutive frames.

In a computer vision society, most developed tracking techniques, such as particle filter, optical flow ,mean shift are appearance-based methods. Mean shift this paper presents a new approach to the real-time tracking of non-rigid objects based on visual features such as color and/or texture, whose statistical distributions characterize the object of interest. The proposed tracking is appropriate for a large variety of objects with different color/texture patterns, being robust to partial occlusions, clutter, rotation in depth, and changes in camera position. It is a natural application to motion analysis of the mean shift procedure introduced earlier. The mean shift iterations are employed the target candidate that is the most similar to a given target model, with the similarity being expressed by a metric based on the Bhattacharyya coefficient. Road detection and tracking in UAVs, particularly low- and mid-altitude UAVs in this paper, which can be used for autonomous navigation and traffic surveillance and monitoring is done in accurate way. A monocular color camera is often equipped in this area, the camera can clearly capture each vehicle on the ground and also has large spatial view on traffic areas. The other research line in UAV-based road detection uses satellite or high altitude UAVs which aims to identify road network, including many junctions and roundabouts from an image. In general, region color distributions and/or boundary structures are probably the important information utilized for road detection. Road color distributions using Gaussian mixture models (GMMs) from given sample images, and then determine road pixels in each frame by checking the probabilities of pixels that fit the Gaussian mixture models.

3. PROPOSED METHOD

FAST ROAD DETECTION AND TRACKING IN UAV VIDEOS

In this techniques we applied detection to the initially segment road regions then we applied homography transformations between two consecutive frames.We applied homography transformation to project road regions in previous frames onto the current frames for tracking after that road areas are propagated by using current frames and adaptive –GMM based road detection.

A. Road Detection and Adaptive GMMs:

The road detection is nothing but to classify road pixels from non-road pixels of a frame. We can easily establish the probability that the each pixel belonging to the road (road c). By selecting the log-normal as follows we are going for the application like image segmentation.

P(road c) =log

= log (1)

=log P(c road)- log P (c nroad)

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= *log* - *log*

The above equations include GMM1 and GMM2. These are nothing but GMMs of road and non-road respectively.

As shown in equation 1 two GMMs are modeling the road and non-road pixels are are required. For each GMM k- components are designed. K is typically set to 5. This is working very well in our project. In all we require 2K components are required.

To create 2K parts, the collected road/non-road pixels to be partitioned off into K clusters. The Orchard Bouman agglomeration rule is utilized during this paper since it provides associate degree optimum answer for clusters with Gaussian distributions. The rule repeats a binary ripping procedure that splits one knowledge cluster into 2 supported the Eigen value of the variance matrix till the specified number of clusters is reached. Figure a pair of illustrates the ripping procedure. Low variance in every cluster is achieved, which benefits the separation between road and non-road pixel.

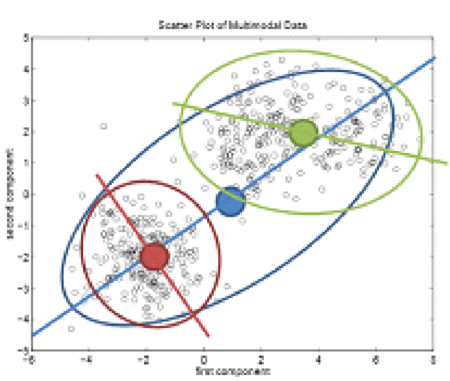

Figure 1: Illustration of the Orchard-Bouman clustering procedure in 2D data: the whole data set is split into two (red and green) based on the center of distribution (blue dot) and the estimated eigenvector (blue line).

Algorithm 1: The creation of a GMM

Input: The number of components K and a set of road (or non-road) pixels Ω.

Output: K components C1, ..., CK. 1. C m = Ω, m = 1. Cm is a cluster with the largest eigenvalue.

2. For (k = 2, ..., K)

2.1 For C m, calculate the mean value μm, the covariance matrix Σ m, the largest eigenvalue λm and the corresponding eigenvector vm of Σm.

2.2 Split Cm into two sets, Ck = {c ∈ Cm: vmc ≤ v mμm }, and Cm = Cm − Ck.

2.3 For (i = 1, ..., k)

2.3.1 For Ci, calculate the covariance matrix Σi, the largest eigenvalue λi of Σi.

2.3.2 If (λi > λm), m = i.

An UAV video perpetually spans an outsized distance, where road and non-road pixels could amendment greatly attributable to shadows and varying constructions. A static GMM trained by the off-line collections of road and non-road pixels don't

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seem to be powerful enough to explain road/non-road pixels with dynamic changes.

So we tend to update GMMs at intervals primarily based on obtained results. An easy thanks to update the GMMs is to rerun the tactic in algorithmic program I, that but is slow.

We adopt the mathematician mixture clump algorithmic program for acceleration. It clusters new pixels into K teams supported existing GMM elements that have the most important probability value manufacturing the pixels. New GMMs area unit outlined by these clustered picture element colors. This theme is delineated in Algorithm a pair of.

We have a tendency to decision GMMs with and while not this change procedure as adjustive and static GMMs, severally. Note that adjustive GMMs projected in area unit completely different. They are designed for modeling background adjustive to lighting and long-term scene changes, however just for videos captured by fixed cameras.

Algorithm 2: The procedure of updating a GMM

Input: A set of new road (or non-road) pixels Ωn, and GMM components C1o, ..., CKo : (μi, Σi), i = 1, ..., K.

Output: New GMM components C1n, ..., CKn.

1. Cn 1 = ... = CKn = NULL.

2. l max = −1, lmax records the largest likelihood value.

3. For each pixel ci in Ωn

3.1 l max = −1.

3.2 For (j = 1, ..., K)

3.2.1 Calculate the likelihood value l ji of the component Cjo producing the pixel ci: l ji = 1 √det (Σ j) 12 [(ci − μj) TΣ −j 1(ci − μj)]

3.2.2 If (lji > lmax), lmax = lji and m = j.

3.3 Cn m = Cmn ∪ {ci}

Figure 2 gives an illustration of the road detection process.

Figure 2(a) shows red and green stokes, which denote road and non-road pixels, respectively. There are 10 images scratched to provide those road and non-road pixels.

Figure 2(b) is a testing frame.

Using Eq. (1), a map representing probabilities of pixels belonging to road is obtained in Figure 2(c).

We then binarize the map. The binarization threshold can be given empirically (A typical value is 90, when the map is scaled to 0-255) or determined automatically using the Otsu algorithm to minimize within group variances. Morphology operations including erosion and dilation are performed to remove noises and fill holes. Contour analysis is applied to find large connected regions, which are the road segmentation result.

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B. Fast Homography Estimation:

In this step, we can easily estimate the homograph transformation between 2 consecutive frames. Homography transformation may be a geometrical transformation between 2 planes, defined by a 3×3 matrix.

All second plane-based transformations can be outlined by this homography matrix. It's eight degrees of freedom: three for the rotation, three for the interpretation and a pair of for the normal vector to the plane.

Thus, to calculate a homography transformation between 2 pictures, we want a minimum of four pairs of matched points.

The traditional thanks to estimate the homography transformation between 2 pictures is:

(1) Feature detection,

(2) Feature matching between 2 frames, and

(3) Homography estimation supported these matched options. Feature matching may be a terribly long step.

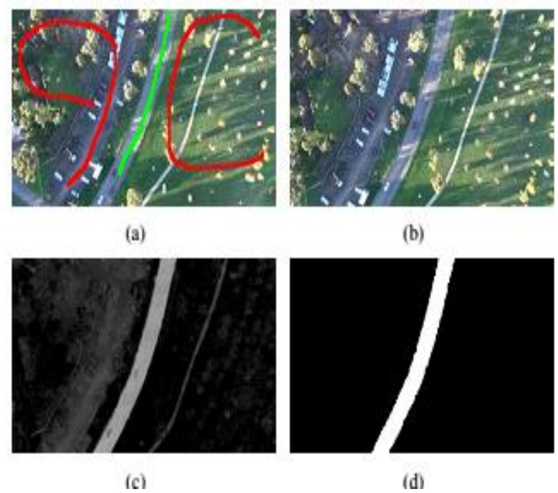

Figure 2: Road detection. (a): stoke examples for collecting road (green) and non-road (red) pixels. (b) A test frame; (c): the probability map of pixels belonging to road for (b). (d) the road segmentation result for (b).

Apply feature selection techniques to exchange the step (2), which is effective and economical.

The options with success tracked square measure treated because the matched options between 2 consecutive frames in videos. Figure 3 Provides AN illustration of feature pairs obtained by matching and selection techniques, where purpose movements in Figure 3(a) square measure similar with purpose movements in Figure 3(b).

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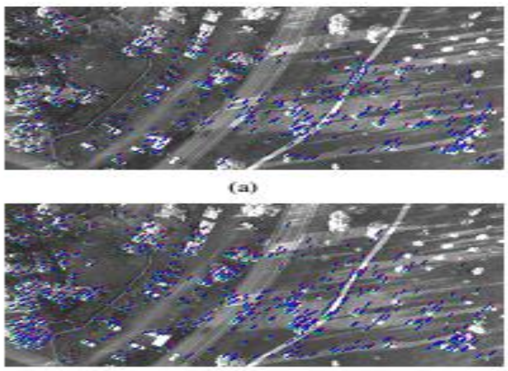
(a)
(b)

Figure 3 Feature pairs marked by green points (detected in the previous frame), red points (tracked in the current frame) and connected by blue lines, where variations between two set points in (a) are similar in (b). (a) Successfully matched features; (b) successfully tracked features.

In this work, quick options are chosen for following because they have the most effective balance between accuracy and efficient for our purpose, compared with alternative well-known features like SURF, SIFT and Harris . We find quick options during a previous frame.

Then the Lucas-Kanade technique is applied to trace these options in a current frame through estimating optical flow, as the movement between 2 frames is sort of tiny. Finally, the feature pairs with success caterpillar-tracked are used to estimate the homography transformation. The random sample accord (RANSAC) technique styles a study estimation theme. It randomly selects four pairs for matrix estimations, counts inlinear pairs that match a matrix for every estimation, and chooses the matrix with the largest range of inliers. After that, least-square fitting is performed on the inliers to provide the final transformation matrix.

C. Homography based Road Tracking:

With the homography transformation matrix H, a detected road region within the previous frame will be projected onto the present frame through remodeling the road contours within the previous frame by multiplying H. as a result of UAV movements, within the current frame, there square measure new coming back regions wherever road areas ought to be extracted. We have a tendency to solve it by playing the road detection formula delineates within the section A.

As there square measure solely little new coming back regions between 2 consecutive frames, the road detection on them is sort of quick. We have a tendency to obtain the new coming back regions within the current frame by orientating the previous frame to the present one. Once the road projection and detection, we have a tendency to merge these 2 areas to provide the ultimate segmentation result. Fig.5. shows some results.

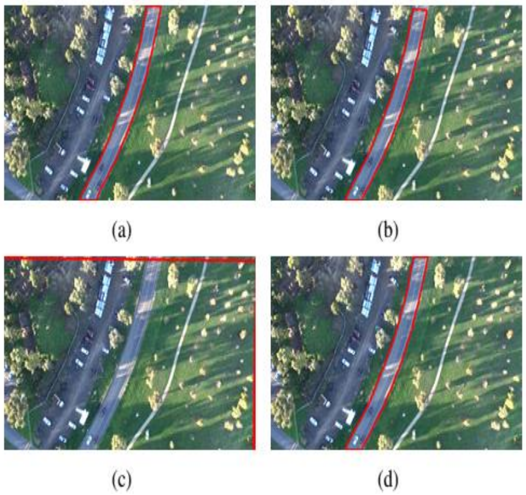

Figure 4: Road tracking by homography alignment, where the two frames (a) and (b) are not consecutive in order to illustrate the clear gap. (a): Road detection result; (b) and (c) road and image frame rectangle alignment results by homography transformation; (d) final road segmentation result.

4. RESULTS

Figure 5: Source image

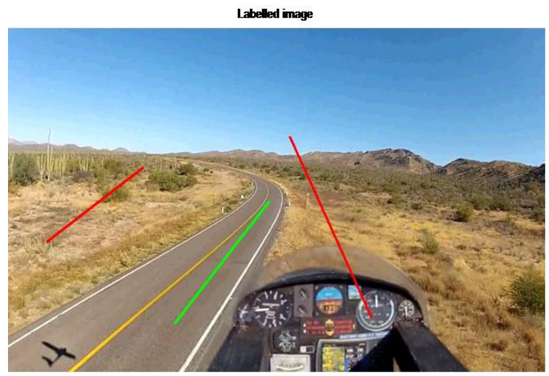

Figure 6: Labelled image

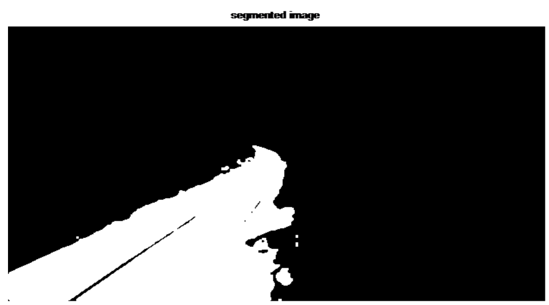

Figure 7: Segmented image

Figure 8: Segmented reference image

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Figure 9: Selected point for KLT tracking

Figure 10: Points obtained for new query image

Figure 11: Marked portions for the query image

Figure 12: Segmented before refinement

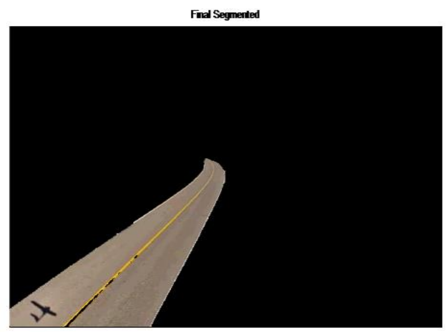

Figure 13: Final segmented

5. CONCLUSION

Road detection and tracking system on road images for unmanned aerial vehicle videos in urban area is proposed. In this paper, presented on graph cut for road detection and homography for the road tracking in the urban area. The objective is to effectively combine both types of information for road detection and tracking in urban area in an efficient way for surveillance, transportation system. For many fields, transportation, security surveillance, traffic monitoring these system performance and accuracy plays an important role. From the point of view of practical application, it is necessary to consider the robustness of road image based on graph cut algorithm and homography to scale of dataset. The problem with existing system is that it gives less accuracy, time for the road tracking.

REFERENCES

[1] B. Coifman, M. McCord, M. Mishalani, and K. Redmill, "Surface transportation surveillance from unmanned aerial vehicles," in Proc. 83rd Annu. Meet. Transp. Res. Board, 2004, pp. 1–9.

[2] [Online]. Available: http://www.list.ufl.edu/ATSS.htm

[3] [Online]. Available: http://soliton.ae.gatech.edu/people/ejohnson/

[4] E. Frew et al., "Vision-based road-following using a small autonomous aircraft," in Proc. IEEE Aerosp. Conf., Mar. 2004, vol. 5, pp. 3006–3015.

[5] H. Zhou, D. Creighton, L. Wei, D. Y. Gao, and S. Nahavandi, "Video driven traffic modeling," in Proc. IEEE/ASME Int. Conf. Adv. Intell. Mechatronics, Jul. 2013, pp. 506–511.

[6] Y. He, H. Wang, and B. Zhang, "Color-based road detection in urban traffic scenes," IEEE Trans. Intell. Transp. Syst., vol. 5, no. 4, pp. 309– 318, Dec. 2004.

[7] G. K. Siogkas and E. S. Dermatas, "Random-walker monocular road detection in adverse conditions using automated spatiotemporal seed selection," IEEE Trans. Intell. Transp. Syst., vol. 14, no. 2, pp. 527–538, Jun. 2013.

[8] Y. Boykov, O. Veksler, and R. Zabih, "Fast approximate energy minimization via graph cuts," IEEE Trans. Pattern Anal. Mach. Intell., vol. 23, no. 11, pp. 1222–1239, Nov. 2001.

[9] D. Comaniciu, V. Ramesh, and P. Meer, "Real-time tracking of non-rigid objects using mean shift," in Proc. IEEE Comput. Vis. Pattern Recog., 2000, pp. 142–149.

[10] K. Nummiaro, E. Koller-Meier, and L. Van Gool, "An adaptive colorbased particle filter," Image Vis. Comput., vol. 21, no. 1, pp. 99–110, Jan. 2003.