A RAILROAD DETECTION ALGORITHM FOR INFRASTRUCTURE SURVEILLANCE USING ENDURING AIRBORNE SYSTEMS

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ABSTRACT

Infrastructure surveillance is an important requirement for many companies. With the advancement of technology, drones can now provide an efficient tool for such applications. A possible future scenario is the automated surveillance of railroads. Whereas numerous algorithms that provide railroad detection exist, they have mainly focused either on satellite images or for small, low altitude drones which are unsuitable for our particular scenario. In this paper we propose a railroad detection algorithm tailored for large, high altitude enduring drones. More specifically, we use Hough Transform to detect lines and perform a line clustering in the Rho and Theta space. A score model is also proposed in order to identify the railroad. We test our method on several sequences supplied by Airbus Defense & Space and show our algorithm to provide a detection rate of 93.23% in average.

Index Terms— drone surveillance, enduring airborne systems, railroad detection, hough transform

1. INTRODUCTION

With the advancement of technology, new opportunities arise in the field of video surveillance. As drones are no longer limited to military applications and are even available as entertainment devices that can be controlled through modern mobile phones, automatic video surveillance of infrastructures is a real possibility. This is also the goal of the SURICATE project (SUrveillance de Reseaux et dInfrastruCtures par des systemes AeroporTes Endurants), which proposes the use of Unmanned Aerial Vehicles (UAV) for the surveillance of infrastructures such as railroads or electrical lines. This work is centered around these ideas and tackles a specific scenario: the surveillance of railroads using large high altitude enduring drones. To the best of our knowledge, this problem has not been investigated yet.

Railroad and road detection is a known problem in image processing and a large number of methods exists that propose solutions for various usage scenarios. A first use case scenario is that of roads and railroads detection in satellite images. Radu Stoica *et al.* propose an algorithm based on a Monte Carlo dynamics for finite point processes [1]. Mohammadzadeh *et al.* use a few samples from road surface and apply a particle swarm optimization to a fuzzy-based mean calculation system in order to obtain road mean values in each band of high resolution satellite color images. However, this type of scenarios are inherently different from detecting railroads or roads in images or videos acquired by drones. Our scenario requires a less complex approach. More specifically, it is desired to be as close as possible to real time usage, as the algorithm will be used for tracking and detection purposes, either for tracking the railroad with the onboard camera or providing additional data that can be used for drone orientation and flight control.

A second use case scenario which has been investigated is that of railroads detection when using small low altitude drones. The algorithm in [2] uses feature extraction in order to detect railroads in pictures. A large number of methods for generating features exist, some of the more popular include Histogram of Gradients (HOG) [3] or Scale-invariant feature transform (SIFT) [4]and [5]. However, object detection usually requires the use of learning algorithms such as Support Vector Machines (SVM) [6].

Pali *et al.* [7] propose to use Probabilistic Hough Transformation (PHT) [8] to determine the vanishing point of the railroad. They use this method to guide a small drone along a railroad. However, in our scenario the vanishing point cannot be determined as the images are acquired from a high altitude. Furthermore, the PHT may provide worse results than HT as only a subset of edge points are considered in order to improve computational time.

In this paper, we propose a Hough Transform (HT) based algorithm to detect railroads when using high altitude drones. We perform a clustering with respect to Rho and Theta in the HT. The cluster selection is performed using a scoring technique that takes into account the geometrical properties of the railroad and the length of the detected lines. We test our method using several test video sequences acquired by Airbus Defense & Space in the framework of SURICATE project. The rest of the paper is organized as follows: Section 2 describes the proposed algorithm, in Section 3 we show and discuss our results and Section 4 concludes the paper.

2. METHOD DESCRIPTION

In this section,, we describe our proposed algorithm. As previously discussed we aim at providing a robust and fast railway detection method that can be used on board UAVs for tracking and orientation purposes during infrastructure surveillance. In order to achieve this we use a sequential algorithm where each block's output is the input of the next. The whole algorithm can also be divided into two larger blocks: a line detection block and a line selection one.

In Figure 1, we depict the general scheme of the proposed algorithm. Our method can be divided into 7 steps, starting from the input image and finalizing with the detected lines coordinates. The first step in the algorithm is the edge detection. There are numerous algorithms that can be used for edge detection. Some of the more

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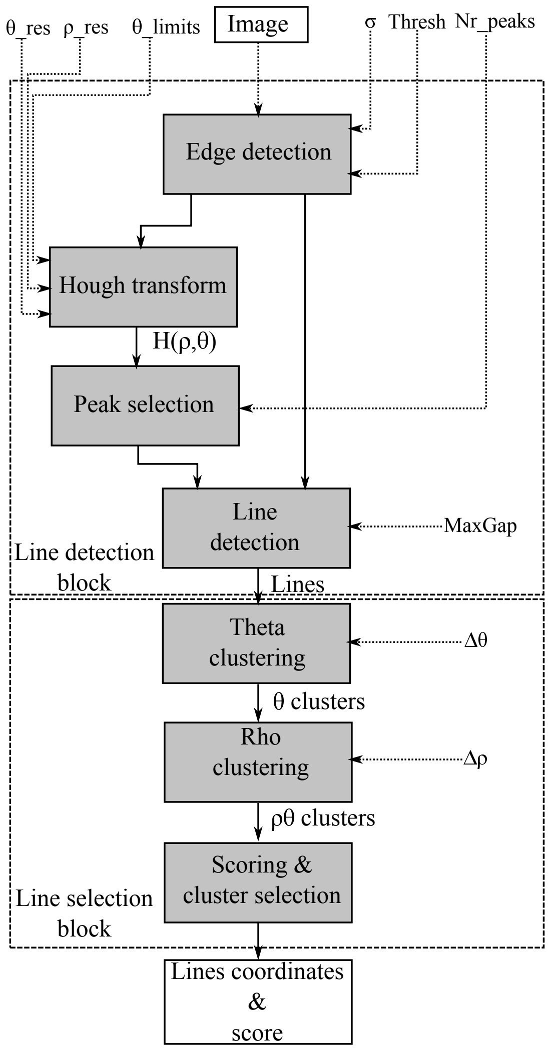


Fig. 1. Algorithm general scheme. Dotted lines indicate input data.

popular ones, that were proven over time are: Laplace, Sobel and Canny methods [9]. Unlike the first two, Canny method is less susceptible to noise and for this reason it is preferred. However, the selection of σ and Thresh parameters plays an important role and should be carefully balanced. Too much smoothing may lead to a loss of useful information, while no smoothing will lead to noise in the edge detection step.

The next step of the algorithm is the Hough Transform (HT) [10] [11]. This is a well known method for detecting straight lines in images and can work even with noisy data. Several variants of the transform exist such as those described by Leavers in [12] or [13]. Fernandes and Oliveira propose in [14] a real time implementation for HT through an improved voting scheme. Frame rates of up to 52.63 are reported.

The next two steps in the our pipeline identify the lines in the image. Firstly, a selection of peaks is performed in the transform space and then lines are identified for each of the pairs of (ρ, θ). The MaxGap parameter is used to set the maximum accepted discontinuity, in the binary edge image, when identifying a line. Once a set of lines is identified with corresponding start/end points and associated (ρ, θ) pairs, the list is passed to the next block which performs the line selection that best characterizes a railroad in the given context (UAV infrastructure surveillance).

The second part of our method is comprised of three blocks. Two clustering blocks for θ and ρ and a scoring and cluster selection block. In what follows we will describe each block in detail and discuss the particularities and issues that can be encountered.

A first thing to notice is that the clustering is performed in two steps as opposed to running a clustering algorithm, for all (ρ, θ) pairs, such as k-means [15]. The reason behind this is that each of the two parameters is bound by a specific condition. Performing this analysis separately allows us to identify the clusters efficiently by searching for a maximum with respect to the frequency of lines at each θ and ρ interval.

In the case of θ we know that railroads are parallel so lines belonging to a railroad should have the same angle. Of course, due to the nature of the HT, several concurrent lines can be identified for each rail instead of two parallel lines for each rail. This is due to peaks in the HT transform that are not always isolated. These effects are caused by the quality of the image, the precision of the edge detection method or simply by the resolution with which the HT was computed. Therefore, a small variation should be allowed for lines that belong to a railroad. This is denoted in Figure 1 by $\Delta\theta$. Identifying the θ line clusters is now simply a matter of searching for θ intervals with a high frequency of lines in a histogram computed over a quantization of the θ search domain (θ_{limits}). The minimum quantization step in this case is given by θ_{res} and the maximum step should not be higher than $\Delta\theta$. Once a cluster is identified the lines are suppressed and the procedure is repeated. The number of clusters should be limited manually and also automatically in order to avoid relatively small clusters with respect to the frequency of the peak intervals. A good form for this threshold is:

$$F(\theta_{min}^{C_k}, \theta_{max}^{C_k}) > \tau \cdot F(\theta_{min}^{C_1}, \theta_{max}^{C_1}) \tag{1}$$

where, $(\theta_{min}^{C_k}, \theta_{max}^{C_k})$ is the θ interval of the cluster, F returns the number of lines in the interval, C_1 is the first identified cluster which has the highest line frequency and τ is a constant between 0 and 1.

Once a set of θ clusters is identified we can proceed to separating each one into multiple clusters with respect to ρ. The procedure is similar to the θ case and differs in the selection of $\Delta\rho$. As rails are equally spaced, $\Delta\rho$ can be empirically determined for a given scenario or estimated using the drone camera parameters and altitude. In a similar manner with θ clustering, a stop criterion can be expressed as:

$$F(\rho_{min}^{C_k}, \rho_{max}^{C_k}) > \tau \cdot F(\rho_{min}^{C_1}, \rho_{max}^{C_1}) \tag{2}$$

The final step of the pipeline is an analysis of the clusters and a selection of the best matching ones. The first thing required is to define what makes a cluster of lines most likely to belong to a railroad. For this purpose we propose computing a score for each cluster depending on the length of the lines and the variation of θ and ρ within each one. We will separate this score into three intermediary scores: S_θ, S_ρ and S_{ll} (line lengths).

The first score S_θ should indicate the similarity of the lines angles within the cluster and also take into account the number of lines within the cluster. Even though, the angles are limited to an interval less variation should indicate a better match. Let us consider the following formulation for a single line θ score:

$$s_\theta^{C_k}(j) = \frac{\Delta\theta + \sum_{i=1}^{N} |\theta^{C_k}(i) - \theta^{C_k}(j)|}{N} \tag{3}$$

where, k denotes the cluster, N is the total number of lines within the cluster and $||$ is the absolute value. $\Delta\theta$ assures a non-zero score. This is an indication of how similar the angles are within the cluster (high value indicates increased angle variation). The S_θ score for cluster C_k can now be expressed as:

$$S_\theta^{C_k} = \sqrt{\frac{N \cdot \sum_{i=1}^{N} ll^{C_k}(i)}{\sum_{i=1}^{N} s_\theta^{C_k}(i) \cdot ll^{C_k}(i)}} \tag{4}$$

where, $ll^{C_k}(i)$ is the length of the line i in cluster C_k. This value can be interpreted as the geometric mean between the number of lines and the inverse of the $s_\theta^{C_k}$ weighted average with the length of the lines. Longer lines should be given more weight and a high number of lines increase the reliability of the detection.

A similar set of operations can be performed for ρ values in order to obtain $S_\rho^{C_k}$. Similarly to θ the lines should be relatively close to each other. We can define $s_\rho^{C_k}(j)$:

$$s_\rho^{C_k}(j) = \frac{\Delta\rho + \sum_{i=1}^{N} |\rho^{C_k}(i) - \rho^{C_k}(j)|}{N} \tag{5}$$

and $S_\rho^{C_k}$:

$$S_\rho^{C_k} = \sqrt{\frac{N \cdot \sum_{i=1}^{N} ll^{C_k}(i)}{\sum_{i=1}^{N} s_\rho^{C_k}(i) \cdot ll^{C_k}(i)}} \tag{6}$$

The final component of the score should reflect the lengths of the lines in each cluster. Considering that all clusters contain a high number of small lines (this aspect will be further discussed in the experimental section) we are interested in evaluating only the longer lines as they will provide more information about the structure of the rail. We first select all lines with a length higher than the average line length of the cluster as:

$$\mathcal{L}(ll^{C_k}) = \{i | ll^{C_k}(i) > mean(ll^{C_k})\} \tag{7}$$

The line length score $S_{ll}^{C_k}$ can be defined as:

$$S_{ll}^{C_k} = \sqrt{\frac{\sum_{i \in \mathcal{L}(ll^{C_k})} ll^{C_k}(i)}{M} \cdot N} \tag{8}$$

where M is the number of elements in $\mathcal{L}(ll^{C_k})$. Finally, score can be written as the geometric average of $S_{ll}^{C_k}$, $S_\rho^{C_k}$ and $S_\theta^{C_k}$.

$$\mathcal{S} = \sqrt[3]{S_\theta^{C_k} \cdot S_\rho^{C_k} \cdot S_{ll}^{C_k}} \tag{9}$$

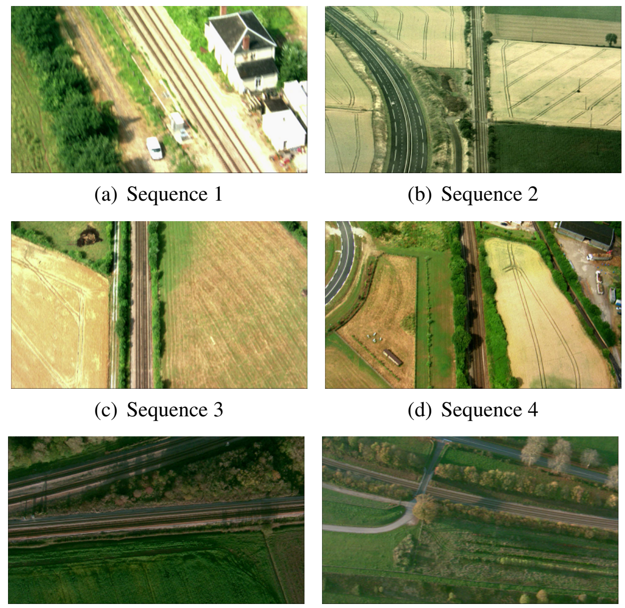
The cluster with the highest score is then selected as the railroad.

3. EXPERIMENTAL RESULTS

In this section we present our experimental results and discuss the methodology of the tests and the selection of parameters.

3.1. Testing data

As no benchmarks and video databases currently exist for our particular scenario, we use a set of video sequences acquired by Airbus Defence & Space in the framework of the SURICATE project. The video sequences were acquired in raw YUV format and contain recordings of railroads located in France, captured with large, high altitude, enduring UAVs. We extracted several sequences from the drone recordings, from various locations, with different content including roads or other geometrical structures similar to railroads. Each sequence has 300 frames and a resolution of 1920×1080.



(a) Sequence 1 (b) Sequence 2
(c) Sequence 3 (d) Sequence 4
(e) Sequence 5 (f) Sequence 6

Fig. 2. Test sequences representative frames. Each frame shows the type of content present in each of the test sequences.

3.2. Testing Methodology

For testing purposes, we implement our algorithm in Matlab. However, in the future an on-board implementation will be done in order to perform real time testing and calibration of parameters. The detection algorithm is applied on each frame. We consider the line detected if the line cluster is located over the railroad and has the correct angle. If the railroad is not entirely detected (e.g. the detected lines cover only a part of the railroad) we consider this case also as a positive detection, as having the θ and ρ intervals will provide a good indication of the railroad position and relative angle to the drone. All other cases when the detected lines fail to indicate the proper angle of the rail or are located over different structures in the image are considered false detections. In addition, we will show a step by step run of the algorithm and the intermediary results.

3.3. Parameter calibration

In our tests, we used the same parameters for all test sequences. Although, in the future an automatic calibration is preferred, as some of the parameters are strongly linked with the drone's camera and flight path. A large increase in speed can be obtained by reducing the search domain for θ. In normal conditions the UAV will have a predefined flight path in close proximity to the railroad. The relative angle of the railroad can be determined with respect to the aircraft by using the GPS and geographical information. This information can be used to drastically reduce the search angle limits (θ_{limits}) and increase the speed and reliability of the detection. However, in our experiments we used the maximum angle span from -90 to 90 degrees, relative to the image x-axis. The HT resolution for θ and ρ is also dependent on the zoom. Once the railroad is identified the camera may be zoomed in and our algorithm will indicate the relative position of the railroad in the image which can be used for tracking. The resolution in this case may be lowered as the railroad will have a larger size relative to the image size. Also, based on the degree of zoom in, camera parameters and drone altitude the $\Delta\rho$ can be easily computed as railroads have constant widths. In Table 1 we report the parameters used in our tests.

Parameter	value	Parameter	value
θ_{res}	0.4	$\Delta\theta$	3
ρ_{res}	1	$\Delta\rho$	50
θ_{limits}	[-90, 89.6]	σ	1.4
Nr_peaks	150	Thresh	0.15

Table 1. Algorithm parameters used in our tests.

3.4. Results

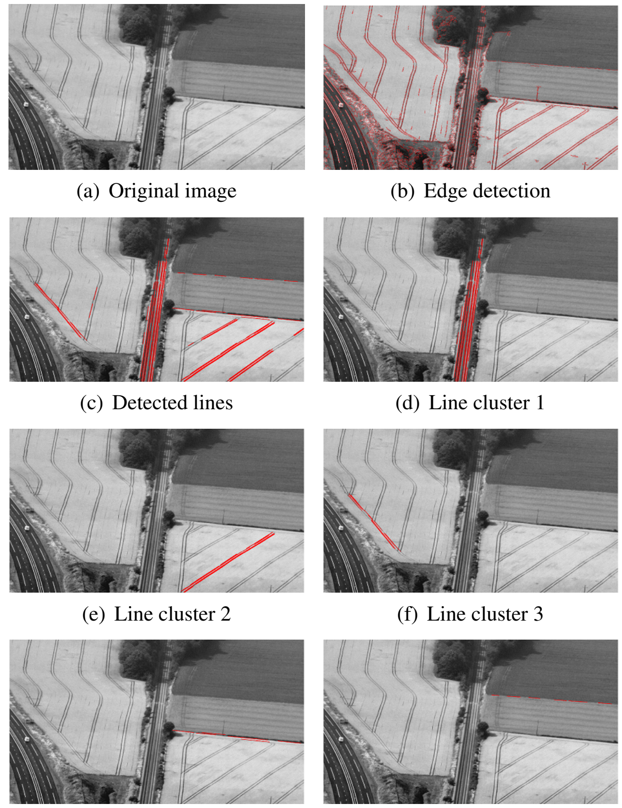
In Table 2, we report our detection rate. As can be seen we obtain a very good detection rate for the railroads. In Figure 3, we depict an example of the algorithm's behavior for frame 40 of Sequence 2. The detected clusters of lines are depicted, as well as the edge detection step. In Figure 3(c) we show all the detected lines. The reported score ($\mathcal{S}$) for the 5 clusters is: 9.0932, 5.9146, 5.9701, 4.6062 and 3.6431. As expected the first cluster which also contains the railroad has the highest score and is selected as the detected railroad.

Sequence	Det. rate(%)	Sequence	Det. rate(%)
Seq. 1	99.6	Seq. 4	72,6
Seq. 2	96.6	Seq. 5	96.3
Seq. 3	94.3	Seq. 6	100

Table 2. Algorithm parameters used in our tests.

4. CONCLUSIONS

In this paper we presented a railroad detection algorithm for surveillance of infrastructure using large, high altitude, enduring drones. The method can be used for railroad tracking with the UAV's camera and also for navigational purposes in the case of GPS or connection failure with the drone. We tested the proposed technique using a set of sequences supplied by Airbus, Defense & Space, acquired in the context of the SURICATE project which proposes infrastructure surveillance using UAVs. We were able to obtain a detection rate of 93.23 in average over all tested sequences. The algorithm was not yet integrated with the drone's on-board systems, however, this is a future work direction. Furthermore, additional improvements can be made by creating a parameter adjustment system with respect to the drone camera and flight information data. Further improvements can be made by taking into account the temporal aspect and estimating the position of the railroad in future frames thus eliminating possible erroneous detections.



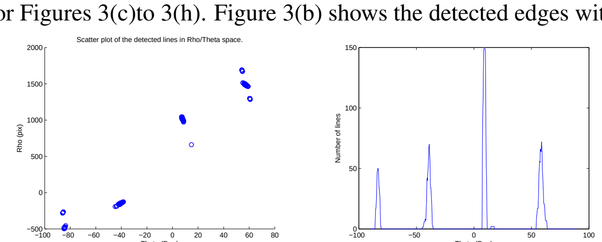
(a) Original image (b) Edge detection

(c) Detected lines (d) Line cluster 1

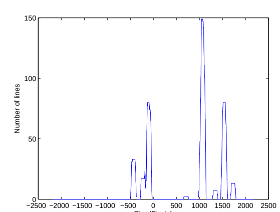
(e) Line cluster 2 (f) Line cluster 3

(g) Line cluster 4 (h) Line cluster 5

Fig. 3. An example of the detected lines and clustering process for frame 40 of Sequence 2. Red indicates the detected lines in the image for Figures 3(c)to 3(h). Figure 3(b) shows the detected edges with.



(a) Line scatter plot in Rho/Theta space (b) Theta histogram



(c) Rho histogram

Fig. 4. The line scatter plot in Rho/Theta space 4(a) and the lines histograms with respect to Theta 4(b) and Rho 4(c).

5. ACKNOWLEDGMENTS

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