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Road detection from Aerial Imagery

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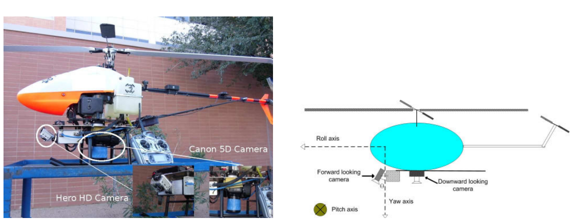
***Abstract*— We present a fast, robust road detection algorithm for aerial images taken from an Unmanned Aerial Vehicle. A histogram-based adaptive threshold algorithm is used to detect possible road regions in an image. A probabilistic hough transform based line segment detection combined with a clustering method is implemented to further extract the road. The proposed algorithm has been extensively tested on desert and urban images obtained using an Unmanned Aerial Vehicle. Our results indicate that we are able to successfully and accurately detect roads in 97% of the images. We experimentally validated our algorithm on over ten thousand (10,000) aerial images obtained using our UAV. These images consist of intersecting roads, bifurcating roads and roundabouts in various conditions with significant changes in lighting and intensity. Our algorithm is able to successfully detect single roads effectively in almost all the images. It is also able to detect at least one road in over 95% of the images containing bifurcating or intersecting roads.**

I. Introduction

There is a strong need for near real-time, geo-referenced imagery and geospatial information in the aftermath of natural disasters and humanitarian crises. One means of collection is to use Unmanned Aerial Vehicles (UAVs). Detecting roads and other man-made features is useful in low-altitude imagery for developing geo-referenced mosaics, route planning and emergency management systems. A road detection and tracking system will vastly improve the utility of UAV acquired images sets and make a significant step towards the operational deployment of mini and micro-UAV systems for geographical information systems (GIS) purposes. While road detection has been extensively studied in satellite imagery ([3], [4], [5]), large number of images obtained and the limited resolution of onboard IMU and GPS systems make road-detection from UAVs a challenging problem.



(a) Our autonomous helicopter testbed. The two cameras are shown in detail

(b) The mounting of the camera

Fig. 1: Camera mount on the UAV

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In recent years, road detection and tracking has also been extensively studied for terrain classification and ground vehicle navigation [12], [13], [9]. While there are certainly algorithms that work well on ground vehicles, they fail on aerial vehicles. This is because of the forward facing cameras on unmanned ground vehicles as compared to the downward looking cameras on Aerial Vehicles. Roads typically appear as converging lines for ground vehicles and vanishing point algorithms [8] work remarkably well on such situations [1].

A good road-detection algorithm should have the following properties:

- detect both natural and man-made road regions (i.e., roads in desert as well as urban areas)
- is invariant to changes in intensity and lighting conditions
- is sufficiently fast so that it can be further integrated into road tracking and following algorithms if necessary.

To illustrate the difficulty in road detection, two images taken from an UAV are shown in Figures 2(a) and 2(b). Figure 2(a) shows a typical image of a road region taken in a desert setting, while Figure 2(b) shows that of a road region in an urban setting. We demonstrate the difficulty of road classification by illustrating the results from three well-known methods for classification: a) Pyramidal Segmentation [2] b) Naive-Bayes (NB) Classification c) Expectation-Maximization (EM) [1]. All three methods perform well on the urban images but perform poorly on desert images (Figures 2(c) to 2(h)). The NB, EM and Pyramid-Segmentation incorrectly detect a large part of the desert as a road as can be seen in Figures 2(c), 2(e) and 2(g). All of them correctly determine the urban road regions (Figures 2(d), 2(f) and 2(h)).

II. Related Work

Methods for road detection include active contours and snakes [4], higher order moment based methods [5] and intensity based classification [6], [7]. They are computationally expensive and assume that the roads are paved such as highways, country roads and urban roads. Such roads are typically characterized by their asphalt or concrete color, or by standardized markings in or at the edges of the roads, and are hence much easier to identify than undeveloped dirt-roads occurring in the desert area. Road detection and classification from satellite imagery has been an active area of research for the past decade. Typically satellite imagery consists of roads

[1]Note that this is not the case in all situations, but in majority of cases only a single road is visible to a UGV with a forward facing camera. This is certainly not the case with UAVs where one might see multiple networks of roads. This can be seen in Figures 2(a) to 2(h)

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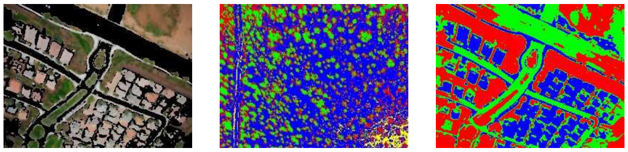
(a) A typical desert image taken from our UAV (b) A typical urban image from the same UAV (c) Region recognized by Naive Bayes as road in desert (the dark region)



(d) Region recognized by NB as road in urban area (the dark region) (e) Result of EM in desert area. (blue/dark is detected as road) (f) Result of EM in urban area. (green/bright is road)

(g) Result of Pyramidal Segmentation in desert area. (bright area is road) (h) Result of segmentation in urban area. (bright area is road)

Fig. 2: (a), (b) are original images. (c), (d) are results of Naive-Bayes classifier. (e), (f) are results of EM and (h), (i) are results of Pyramid-Segmentation.

as lines connecting points which is not the case with low-altitude aerial imagery.

There has been extensive work on road detection and classification from Unmanned Ground Vehicles (UGVs) (vanishing point detection [8], superpixel grouping [9], semi-supervised learning[10], [11]). All of them assume that the vehicle is detecting a single road, not multiple intersecting or bifurcating roads. There has been some recent work on road detection and tracking using UAVs. The authors in [14], [15] have developed an algorithm for detecting locally linear structures such as highways and rivers. Their algorithm relies on the fact that the longest linear region in the image is the road. Although the algorithm works well on detecting straight roads, it will fail on images that have intersecting or bifurcating roads as in Figure 2(b).

In this paper, we propose a new algorithm of UAV aerial road detection and exhaustively evaluate it on various datasets containing roads in desert and urban regions. We evaluate the effectiveness of the algorithm on over ten thousand images. Our algorithm is able to robustly detect roads in almost all of these images. Furthermore we are able to detect multiple roads (i.e., both bifurcating and intersecting roads) in more than 50% of the images. To the author's knowledge, this is the first paper where an exhaustive evaluation of the road classification algorithm has been performed. The rest of the paper is organized as follows: Section III describes our procedure for collecting the image data. Section IV describes the road detection algorithm. Results of the algorithm are shown in Section V.

III. Experimental Procedure

The images are obtained using our Autonomous Helicopter Testbed (Figure 1(a)). A full frame Canon 5D camera is used to obtain pictures at 1 frame/second. A second forward mounted camera is used to obtain forward looking images. Figure 1(b) depicts the mounting of the camera. The helicopter was flown over various terrains autonomously and manually on multiple days while images collected.

Some images of desert and urban roads are shown in Figure 3.They include intersecting roads, single long roads and bifurcating roads. A total of 13077 images were collected over four days of flights in various weather, temperature and lighting conditions.

(a) (b)

(c) (d)

Fig. 3: (a)&(b) show desert roads and (c)&(d) urban roads. (a) is a straight road. (b) is a road with strong curvature. (a) shows intersecting roads. (b) shows bifurcating roads.

IV. Proposed Algorithm

Our algorithm consists of the following steps: a) Possible road regions detection using a histogram based thresholding method; b) Local line segment detection using a probabilistic hough transform c) Point Clustering for detecting the final region.

The histogram based thresholding method consists of the following steps:

- Creating a histogram of the image, with n bins [2].
- Counting the number of pixels whose value is below the lower limit of bin i ($1 \leq i \leq n$). If the number is more than 95% of total number of pixels, the lower limit of bin i is the threshold. Other wise increment i until such criterion is satisfied.
- Select region above the threshold (Figure 4(c)).

This method is fast, robust and works well on desert images as can be seen from Figure 4(c). The entire road and a small part of desert not belonging to the road is selected as possible road regions. The result is much better than Naive-Bayes or EM.

[2]the number of bins depends on the size and the smoothing function used. We found 32 to be a good number

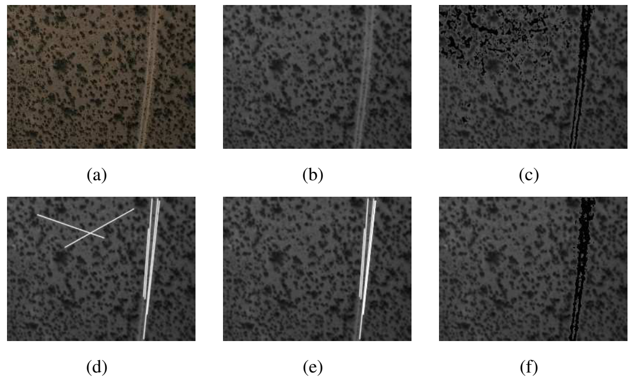


Fig. 4: Results of every step from possible road region selection to road separation. (b) is the result after pre-procession. (c) is the result after histogram based thresholding. (d) is the result of line segment detection. (e) is the result of line selection. (f) is the result from points clustering.

The next stage is to detect all possible line segments in the above detected regions. We use the probabilistic hough transform [16]. The algorithm is as follows:

- Use progressive probabilistic hough line transformation [16] on the above detected regions. The minimum length of a line segment that needs to be detected is set close to half of image's height. The separation between collinear segments is set to 1/40 of image's height. This assumes that the road consists of a relatively long straight line. This allows us to detect straight long roads but will naturally fail on curved roads. To detect curved roads we modify the algorithm to detect "chains" of intersecting lines.
- Once lines are detected, select roads using the following criteria:
  - If a line has either of its ends close to the edge of the image and has at least 3 lines that "follow" it, the line and lines "following" it are considered as belonging to the road. "Following" a line, means that the angle and distance between the lines is sufficiently small (we use 10° as a threshold).
  - If a line, whose apparent length along the image's width is larger than $0.6\times$width or along the image's height is larger than $0.6\times$height and has at least one line that "follows" it, the line and the lines "following" it are considered part of the road. [3]
- Any points that are sufficiently close to these selected lines are considered part of road. Figure 4 shows this in detail. A flowchart that describes the algorithm is presented in Figure 5.

As pointed out earlier, the assumption that the road is long and comparatively straight does not apply to curved roads. For such roads, instead of detecting long lines, we detect chains of intersecting lines. The algorithm for detecting these "chains" is as follows:

[3]These steps might seem too specific to the readers. we point out that these steps are just smoothing algorithms to combine multiple lines detected by the hough transform.

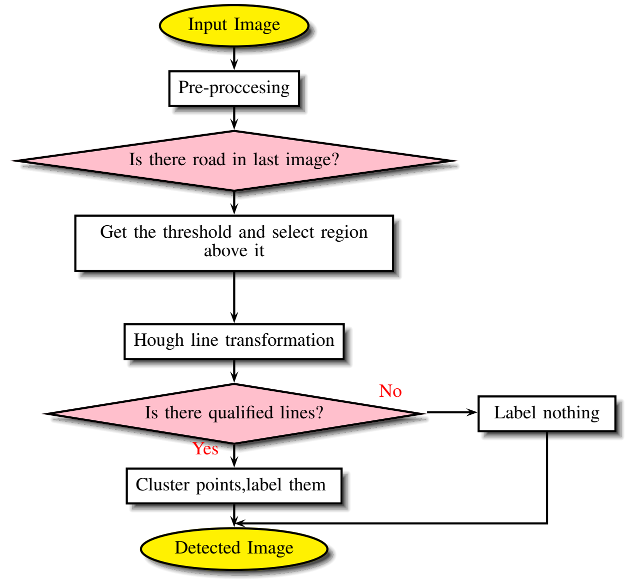


Fig. 5: Flow chart of our method

- Detect line segments using the hough transform as described above.
- choose an arbitrary line L to form a set C.
- if any line L' not in C intersects any line in C, add L' to C.
- Continue until no other line can be part of C.

Line chains C that satisfy the following criteria are considered as roads:

- Both ends of the chain are close to the edge of image. We assume that roads do not stop in the middle of the image.
- The two ends of the chain are sufficiently far apart. This is to remove spurious line chains
- The number of intersecting line pairs whose instersecting angle is above 40° is less than 5.

Figure 6(b) shows all "line chains" that are detected. Figure 6(c) shows "line chains" that satisfy the above criteria. Figure 6(d) shows the final recognized road.

V. Experimental Analysis

A. Desert Roads

Results of desert roads detection are shown in Figure 7. Our algorithm works remarkably well with all kinds of roads irrespective of road direction or intensity variation. Failure rate of the algorithm as a function of image size is shown in Figure 8. It is evident that as image size increase, the number of false negatives [4] decreases while the number of false positives and the number of mismatched roads increases [5]. This is to be expected since as the size of the mage increases much larger areas need to be checked for possible roads and

[4]false negative: a road in the image is not detected; false postive: a road is detected from an image without any road; mismatch: a non-road part of an image with road is detected while the true road not detected.

[5]Note that even though these rates are minuscule, there is a definite trend in them

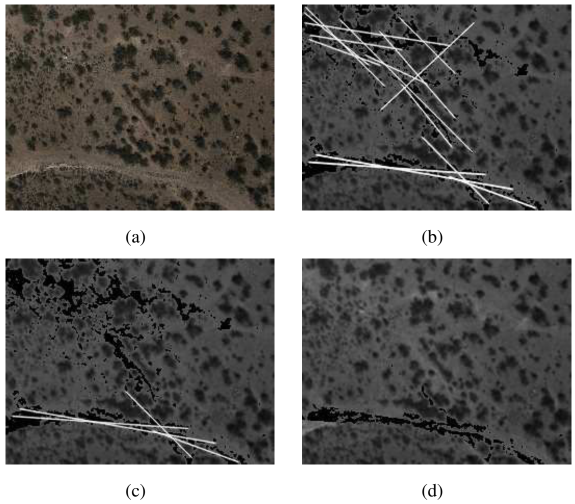


Fig. 6: Detection of roads in irregular shape. (a) is the original image. (b) shows all line chains. (c) shows line chains that satisfy our criteria. (d) is the final result.

hence the rate of false positives increases. This demonstrates the effectiveness and robustness of our algorithm.

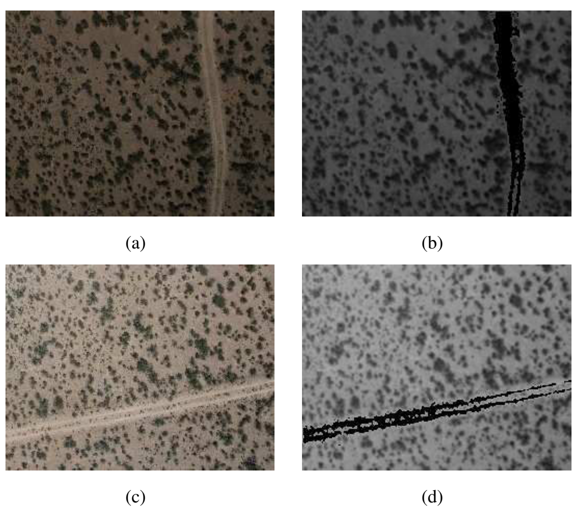


Fig. 7: Results from road detection in desert regions. Original Images are in the left column.

Results from detecting "straight" roads, roads with "turns" and "curved" roads are shown in Table I. It is evident that our algorithm is able to detect "straight" roads with 100% success rate, roads with "turns" with 95% success rate and roads with "curves" with 88% rate of success. Assuming that 30% of an image should overlap with image in next frame so that road tracking can be successful, the time allowed for road detection can be calculated as

$$t = \frac{0.7h\tan(\frac{\theta}{2})}{v} \quad (1)$$

where h is the height of the vehicle, θ is field of view of the camera and v is the velocity of the UAV. Assuming a height above ground level (AGL) of 50 meters for the UAV, velocity of 30 m/s and the field of view of the camera as

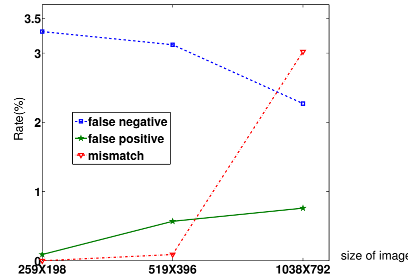


Fig. 8: Failure rate ("false positives + false negatives") as compared to Image size .

94°, the time t between images for a 30% overlap is 1.25 seconds. This is less than the runtime of our algorithm(Table II). Hence our algorithm can be used for road tracking.

	Straight roads	Roads with small turns	Roads with small curves
Success rate	100%	95.45%	88.05%
Total Images	475	154	159

TABLE I: Results from Straight, turns and curved roads.

Image Size	All Images	Average run time
259×198	15m14.917s	0.864s
519×396	16m37.790s	0.942s
1038×792	20m41.068s	1.172s

TABLE II: Running time for the entire desert road dataset.

Results from detection of roads with strong curvature are shown in Figure 9. False positive and negative matches from our road detection algorithm on desert regions with "curved" roads are shown in Table III. The algorithm works for smaller size images and produces a lot of false negatives for larger size images. This is because the underlying histogram-based segmentation algorithm is unable to detect all the road regions.

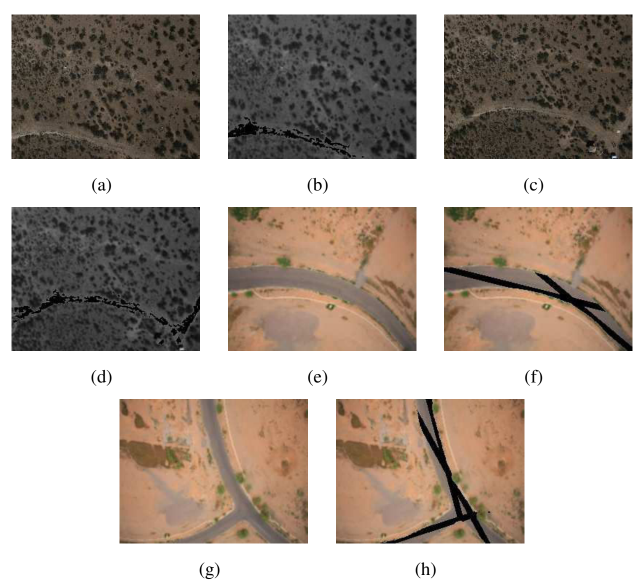


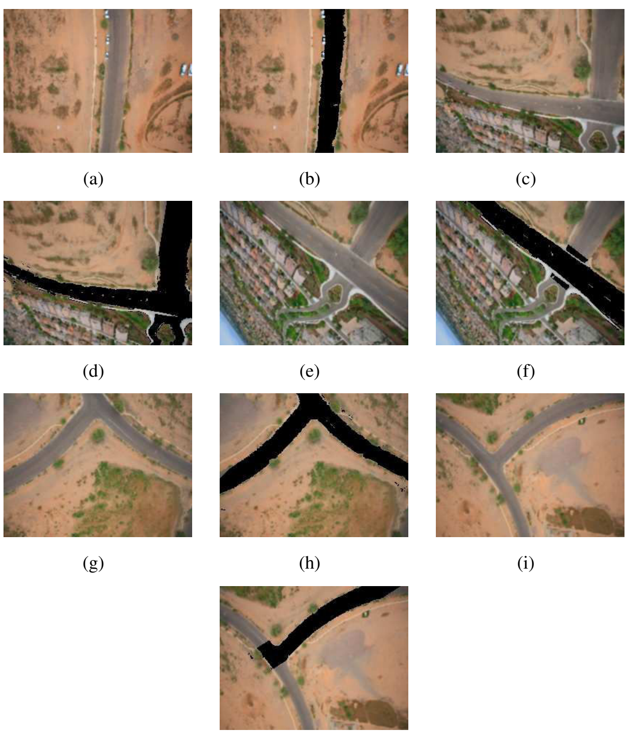
Fig. 9: Results from curved road detection in desert and urban regions. (a),(c),(e),(g) are original images.

Image Size	False Negatives	False Positives	Mismatches
259×198	0.00%	0.00%	0.00%
519×396	14.29%	0.00%	0.00%
1038×792	23.81%	0.00%	4.76%

TABLE III: False positive and negative matches from our road detection algorithm on desert regions with "curved" roads. The total number of images in these conditions are 21.

B. Urban Roads

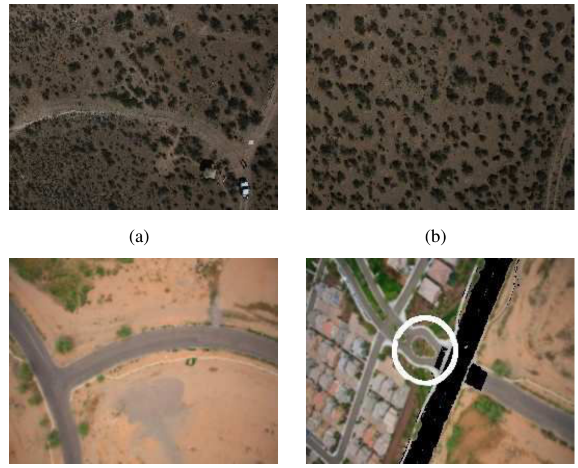
For urban roads, we use a Naive-Bayes classifier instead of histogram-based thresholding to select possible road regions.Results from road detection in "normal" conditions are shown in Figure 10. The false positive, false negative detection rate for different image sizes are shown in the first three rows of Table IV. This demonstrates that our algorithm is robust and effective for urban roads also. The first two rows of Table V [6] show the number of intersecting and bifurcating roads with one and all branches detected. Although our algorithm performs remarkably well, it does fail on images where the curvature of the road is large or there are multiple intersecting roads with roundabouts in them (Figures 11(c) and 11(d))



(a) (b) (c) (d) (e) (f) (g) (h) (i) (j)

Fig. 10: Detection result of urban road in normal condition. (a),(b) show a single road detected. (c),(d) shows intersecting roads with both branches detected. (e), (f) shows intersecting roads with only one branch detected. (g),(h) shows bifurcating roads with both branches detected. (i),(j)shows bifurcating roads with only one branch detected.

[6]'Inter both' means intersecting roads with both branches detected. 'Inter one' means intersecting roads with only one branch detected. 'Bi both' means bifurcating roads with both branches detected. 'Bi one' means bifurcating roads with only one branch detected. 'Total' means total number of images



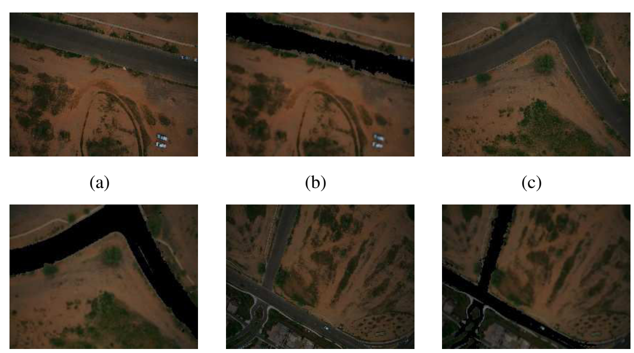
(a) (b) (c) (d)

Fig. 11: Roads where our algorithm fails in desert and urban area. The circled region in 11(d) is a roundabout.

Figure 12 are results from road detection in urban regions in "darker" conditions. The false positive, false negative detection rate for different image sizes are shown in the last three rows of Table IV. Our false positive and negative rates are negligible even in these conditions and our algorithm is robust to changes in intensity.

Image Size	False Negatives	False Positives	Mismatches
259×198	2.13%	0.00%	0.80%
519×396	2.03%	0.00%	1.58%
1038×792	1.13%	0.00%	2.25%
259×198	1.84%	0.00%	0.00%
519×396	1.84%	0.00%	0.00%
1038×792	1.84%	0.00%	0.00%

TABLE IV: False positive and negative matches from our road detection algorithm on urban regions in normal (the first three rows) and "dark" conditions. The total number of "light" images are 752 and that of "dark" images are 272.



(a) (b) (c) (d) (e) (f)

Fig. 12: Road detection in urban regions in almost "dark" conditions. (a),(c),(e) are original images, (b), (d), (e) are images with roads detected in them.

Figure 13 are the results from detecting bifurcating and intersecting roads . The third and fourth rows of Table V show the percentage of successful detection of single, intersecting and bifurcating roads. Our algorithm is able to successfully detect single roads in 99.88% of the images. We can also detect both branches of intersecting and bifurcating roads in over 50% of the images. Our algorithm fails when the curvature of the roads in the images is very large or when the roads cover a very small area in the image. Note that we penalize the algorithm unless it detects the complete road.

	Single	Inter both	Inter one	Bi both	Bi one
%	97.34%	56.90%	43.10%	55.38%	35.38%
Total	376	116	116	65	65
%	99.88%	56.23%	40.30%	48.90%	45.97%
Total	4908	1067	1067	1910	1910

TABLE V: Detection rate for single road, intersecting roads and bifurcating roads for urban roads. The first two rows are for pictures from the downward-looking camera and the other two rows are for pictures from the forward looking camera.

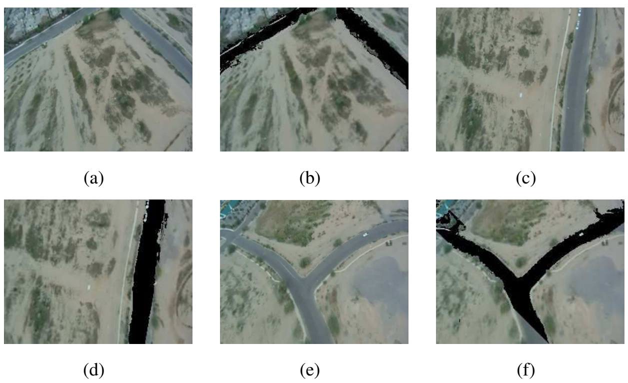


Fig. 13: Detection of intersecting, bifurcating or multiple roads in urban regions. These images were taken from the forward mounted camera. (a), (c), (e) are the original images. (b), (d), (f) are the images with the roads detected in them.

VI. Conclusion and Future Work

We have presented the design and implementation of a image based road detection algorithm from aerial images. The algorithm is robust, reasonably fast and computationally inexpensive. It relies on the assumption that roads are regions that can be approximated by locally linear line segments and differ in intensity from neighborhood regions. A histogram based thresholding method was developed to select possible road regions from the images. Furthermore a probabilistic line detection algorithm combined with a clustering method was developed to further refine the road region.

Data from four test flights and 13,000 images show that our algorithm is able to detect roads accurately and repeatably in desert and urban regions in varying intensity conditions. Furthermore it is also able to detect roads with strong curvature, intersections, bifurcations or roundabouts. Our algorithm is able to detect single roads in 99% of the images. It is also able to detect at least one road in over 95% of the images containing bifurcating or intersecting roads. Although our algorithm was not designed to track roads over a sequence of images, we were able to take advantage of the fact that roads do not appear or disappear abruptly to reduce the search window. We plan on integrating this to develop a road tracking algorithm. We believe that with proper modifications to the underlying road detection algorithm we can use this to detect rivers, valleys and other useful regions. In the future we plan to focus our attention on developing classification algorithms and integrating it with out algorithm for autonomous classification and tracking. The applications of such a system are enormous: from GIS to mapping and target tracking.

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