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Embedded system for automatic landmark detection using images captured by UAVs

Ana Laura G. Silva[a 1] and Elcio H. Shiguemori[b]
[a b]Instituto de Estudos Avançados, São José dos Campos, SP, Brazil
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Abstract

Autonomous Navigation for Unmanned Aerial Vehicle (UAVs) is a widely studied subject nowadays. There are different works that we could find in the literature that is dedicated to solving this problem. However, the UAVs has a limit for the weight that can be loaded with it which makes the use of embedded systems for real-time data processing one solution to decreased devices which should have to be carry with the vehicle during flight to send data to an ground station to process the data. This works aims to present a study with Haar-Like cascade classifier embedded in a Raspberry PI for automatic landmark detection using images captured by UAVs. The results obtained with this study prove the possibility of using the approach in embedded systems and real-time analysis.

Keywords: Automatic Landmark detection, Embedded systems, Unmanned Aerial Vehicle (UAVs).

1. Introduction

Unmanned Aerial Vehicle (UAV) has become widely used for different activities including civil or military tasks. UAVs are especially used when the presence of a pilot is a limiting factor to accomplish the mission [3].

According to [5], the biggest challenge for autonomous navigation today is to develop methods to replace the dependence on the use of satellite navigation systems (Global Navigation Satellite System). For this task use images captured during the flight could be an alternative to estimate the UAV's position [4].

Promote the real-time processing of objects classification can be a hard task since the UAV has payload limit. Use the embedded system can assist in the efficiency of autonomous aerial navigation, since the object recognize can be made during the flight, decreasing the need for others equipment that would be used to send information to the ground station.

[1]E-mail Corresponding Author: algsilv@gmail.com

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In this work we used the Haar-Like cascade classifier embedded in a Raspberry PI in order to promote an study to see what is the results to use this concept during the flight. In spite of cascade classifier is widely used in literature for face detection it is an efficient general framework for object detect [1].

2. Related Work

In [1] an comparison study was made between HOG + SVM and Haar-like classifiers. The dataset for image training was satellite and airborne images. In this study the Haar-like method showed 80% accuracy and was 35 times more faster than the other approach during the classification.

The study proved the efficiency on using Haar-like classifier as an general framework for object detection. Once proven the efficiency and velocity of the classifier to objects recognize, we developed a new study which will be described in the 5 and 6 chapters of this article where a training dataset was exposed to Haar-like to analyze the classifier in embedded systems during flight.

3. Autonomous Navigation

The act to drive an vehicle to an desired location could be define as navigation. That is, the navigation includes driving a vehicle to reaches an point while beware about obstacles in a predetermined route.

Nowadays, most of autonomous navigation are based on the integration of inertial sensors and Global Positioning System (GPS) which can fail and suffer external interference [4]. Different studies could be find in the literature that aims to find a solution to UAVs position issues [4] [6] Therefore this work focus on presents a study of Haar-like approach to identifying landmark using embedded systems.

4. Method

The Haar-like cascade classifier proposed by [7] extracts images attributes [8] and treats directly the gray levels or pixels color. All the pixels values of positive and negative areas of the filter are summed, respectively white and black region that can be observed in Figure 1, and then the subtraction of the positive region sum of negative region sum is performed and this value categorizes the sub-regions on an image.

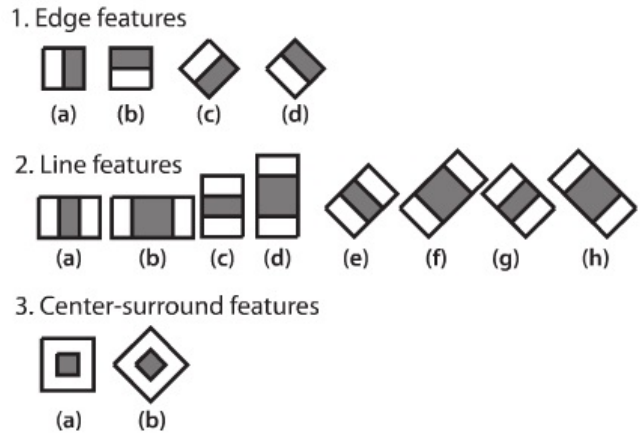

Figure 1 - Haar-like Features [11]

The cascade feature makes Haar-like an powerful classifier. A weak classifier could be combined and becomes a strong classifier (Figure 2) during the training process and this allows the classifier identify objects in several conditions [7].

Computational cost of the search is dramatically decreased by the internal architecture of the classifier which allows the rejection of a negative classification early on with the least possible rating [7]. This feature makes the method proper to embedded system use.

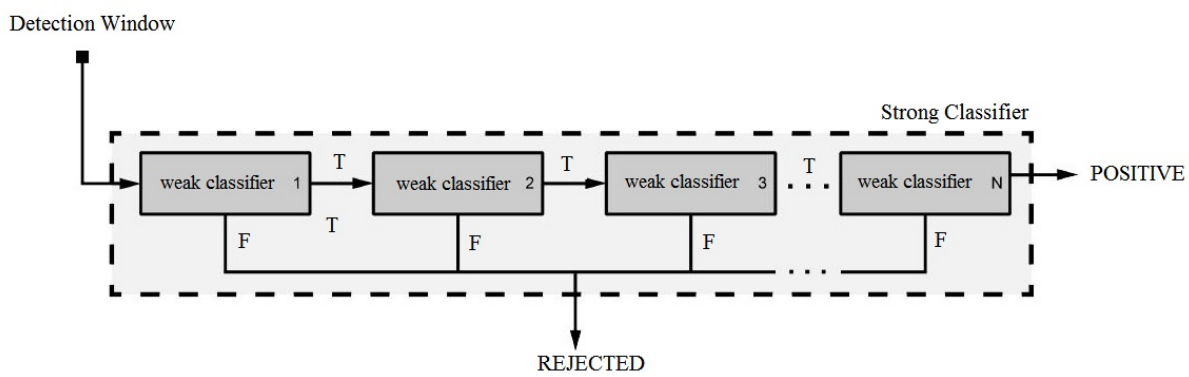

Figure 2 - Haar-like cascade classifier [1].

5. Methodology

The landmarks was chosen after the flight route definition which had a few buildings that could be used to identify the correct flight position. Most of the images to assemble the training dataset was obtained from previous route flights and Google Maps application [9] that was used for being free and easy to access.

The training dataset contained 643 positive images and 1021 negative images. Positive images were composed of square images containing building roofs in several positions Figure 3. The positive images were resized to take detection window size the in the training and the negative images remained with the actual size and different samples were extract of then.

All method used were implemented using the OpenCV library [10] in C ++ language. An 50x50 pixels detection window was used with Haar-Like and the hit rate was fixed at 99% in training.

Figure 3 - Positive samples (Authors, 2016).

6. Results

Figure 4 - Positive detection (Authors, 2016).

Two metrics [2] were used to measure the performance of the detection. The two metrics are: Accuracy and sensitivity Equation 1, Equation 2.

$$P = \frac{TP}{TP + FP} X100 \tag{1}$$

$$P = \frac{TP}{TP + FN} X100 \tag{2}$$

True positives (TP) are properly recognized roofs, false positives (FP) are regions of the image that were misclassified as roofs and false negatives (FN) are not recognized roofs.

The algorithm was tested over a 11m46s flight where was captured 41 images containing a total of 35 roofs. The Table 1 present the results. To test the algorithm an Raspberry Pi 2, ARM Cortex-7 CPU 900 MHz processor and 1GB of RAM with Raspbian operating system was used

Table 1: Classification (Authors, 2016)

Method	TP	FP	FN	Accuracy	Sensibility
Haar-like	18	19	12	48.64%	60%

5. Conclusion

Haar-like classifier algorithm depends directly on training, the variety and quantity of landmarks may affect the performance.

In this study, it was chosen three distinct landmarks, which made difficult to obtain positive images for training. The example of the chosen landmarks can be seen in the Figure 5. They are distinguished by their color and shape.

Figure 5 - Landmarks (Authors, 2016).

Sensitivity parameter is affected by the algorithm codification which allows detecting of one or more objects in the classification. As an example, the parameters of detectmultiscale function [10]. The false negatives was affected by this.

The chosen route contained other objects that influence the accuracy of the classification. Figure 6 shows resemblance between true and false positive classification.

Figure 6 - Resemblance between TP and FP (Authors, 2016).

There were variables (dataset and landmark) that influenced the algorithm classification and therefore affected directly the results of this study. One solution to increase the classification accuracy is limit the number of landmarks types and include the False Positive detections on negative dataset in a new Haar-like classifier training process.

7. Final Considerations

Although the accuracy results presented less than 50%, since the focus of this work was prove the possibility of using the Haar-like cascade classifier in embedded systems and real-time analysis and the classifier was already studied and signed as an consistent choice for the proposed classification [3] the study was considered sufficient to prove the possibility of using this classifier in embedded systems and real-time flight performed by UAVs with a great response.

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