Automatic Landmark Selection for UAV Autonomous Navigation

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***Abstract*—Landmark recognition has been showing promissing results for UAVs autonomous navigation by image. Although, the selection of landmarks has a significant influence in the results, more efficient methods to select them are necessary. The work aims to develop an algorithm that selects automatically landmarks through keypoints obtained with ORB. The algorithm is based on a modified X-means approach.**

***Keywords*-Landmark; self-adaptative cluster; ORB.**

I. Introduction

The growth of technological and computational development of the past years allowed an increasing use of Unmanned Aerial Vehicles (UAVs) autonomous navigation, mainly because of the diversity of its applications. Some examples are landmarks and objects recognition; borders and urban areas survaillance [1][2]. The use of UAV systems in civilian air space areas are still a concern to aviation authorities due to several vulnerabilities that put in risk the population. One of the main vulnerabilities is due to possible GPS failure [3] [4].

The Global Positioning System and Inertial Navigation System (GPS/INS) navigation is the most common navigation system used. It can face, though, serious drawbacks, due to GPS signal lost and attenuation, jamming and multipath, which can result in a catastrophic situation to the UAV [4]. An alternative to GPS/INS navigation is a computer vision based navigation system for UAVs [3][5].

Landmark recognition is a promising method for autonomous navigation by image [1][3][5]. It is a method that recognizes from real time images and videos, previously selected landmaks which will provide information for navigation, like the position of the aerial vehicle in a specific route [1]. A landmark can be defined as an object in an image that can be a point of recognition of the place; e.g. of possibles landmark would be constructions, houses or buildings[1]. Any object that can be differentiated from the surrounding for further recognition can be considered a landmark.

A person can easily select a landmark in a image that has the purpose of further recognition of a place. However, these selected landmarks does not necessarily have the attributes that a computer seeks to identify in a landmark. The challenges that can be faced when trying to identify a landmark in an image are many, for example variances in scale, luminosity, climate, rotation among others variables[1].

The process of a landmark recognition briefly consists in three steps [1]. Firstly, it identifies the keypoints of the query image and in the trained image; secondly, it computes the keypoints descriptors; and finally, it matches the points descriptors identified from the trained images and the query image. The trained images are the ones with landmarks previously selected. The matching process occurs based on similarities of the keypoints localized in each images; so, it is believed that the success for recognizing a landmark depends on how many keypoints it has, because it would increase the probability of inliners in the matching process.

The aim of this work is to present an automatic landmark selection system, considering the number of keypoints on each landmark. This selection of landmark is made by a self-adaptative clustering of the keypoints localized in an image [6].

A. Related work

The features localized in images for recognizing objects have been largely used in the machine vision industry for different purposes, such as registration and inspection. Zhang and Miao [7] show an approach in the use of these features for object recognition. They use a self-adaptive kernel clustering algorithm to specify clusters in a image with the purpose of obtaining better matching results. The purpose for using clusters is because these keypoints grouped describes an object in the image and increase the success of the recognition through matching keypoints.

In another work Feng et. al [8] also propose an automatic landmark selection with the purpose of a better feature matching for landmark recognition. In their case the landmarks will be selected in the lunar scenario which is significantly different from terrestrial and has similar and textureless terrain in most of its surface.

Landmark selection is mostly found in the literature for robots navigation or others non aerial perspectives [9] [10]. They show how a landmark can be useful for navigation in several areas and has become a suited technology.

II. Technical background

An aerial scenario offers vast possibilities for landmarks, so it is necessary that the computer knows how to classify these possibilities properly, for this reason a self-adaptive clustering is necessary. The classic algorithm X-means is used in this work mainly because of its characteristics of self-adaptive clustering [6]. This method permits the classification of the clusters from the samples with no supervision, which means that it can find the correct number of clusters by itself.

X-means is an extention of another classic algorithm, K-means [11]. K-means is a simple algorithm that was largely used in metric data. It basically separates the cluters in a pre defined number k. A center is given randomly at first and in further iterations is calculated until it stays fixed. In each iteration it associates every point to a center. The rule is that each point belongs to the closest center. The re-estimation of the centroid location for each iteration is made by the calculation of the center of mass for all the points associated with it. The algorithm described is used as the base of X-means that has significant improvements [6].

The number of K in the algorithm described is given previously by the user, yet in X-means this number is estimated. Now, the user sets a range where the K lies, so the output now is the number K and the final centroids. The algorithm uses a model selection criterion as a cluster separation decision [6]. This decision is made when the algorithm proposes a second division of an already set cluster. It firstly set the given minimum number of clusters with K-means. Furthermore, separately it takes each set cluster and runs again K-means with K equals 2. Finally, the resulting model is compared to the previous model by the selection criterion and set the best one. Briefly the algorithm uses K-means to separate its clusters until it reaches a maximum number of K or find the best model through its model selection criterion [6].

The model selection criterion: The model selection criterion specified for X-means is the Bayesian information Criterion (BIC) [12] [6]:

$$BIC = -2 * ln\hat{L} + k * ln(n)$$

where $\hat{L}$ is the likelihood function of the model M maximized, i.e. $\hat{L} = p(x|\hat{\theta}, M)$ and $\hat{\theta}$ are the parameters values that maximize the likelihood function; x is the observed data; n is the number of data points in x and k the number of parameters estimated [12].

The use of ORB in X-means: The keypoints localized in the input image in X-means is described by the ORB (Oriented FAST and Rotaded BRIEF) algorithm that is one of the most efficient for image processing [1]. Briefly, the points are selected based on the FAST method in ORB and its variants. As a result, ORB sets the points coordinates in the input image allowing the landmark selection algorithm work on the separation of the clusters [1].

III. Technique adaptation and implementation

Although the X-means plays its role, still its results are not enough to completely solve the needs of the selection system. Firstly, the separation of the clusters are still not ideal. Many clusters were correctly separated, yet some had keypoints that could form another cluster. We noticed that the re-separation of the cluster in X-means was correctly selecting the best model in comparison to the new created, but was not being enough to better select a landmark. Trying to solve this problem, we propose a modification in the model selection criterion (BIC) of X-means and also an additional decision variable to allow the creation of a new cluster from the separation.

We believe that a modification in BIC could lead to a better model decision and therefore to a better separation of the clusters. Some anomalies of points too distant to its related center was leading to a cluster that had points not belonging to that object. It was noticed that the results needed to consider the distances between the points of the clusters and its center in order to choose the best model and build a better cluster. So, it was added a distance factor so that it could have a stronger and more direct influence on the model criterion.

$$BIC = -2 * ln\hat{L} + k * ln(n) * log(d)$$

Where d is the sum of greatest distance between a point and its cluster in all the clusters created. For the decision of a creation of a new cluster, besides a BIC comparison to separate the cluster it also compares the distance of the centers of the new clusters created to check if was necessary to separate that cluster. For a better understanding of the algorithm developed the Fig. 1 below shows a flowchart of the algorithm.

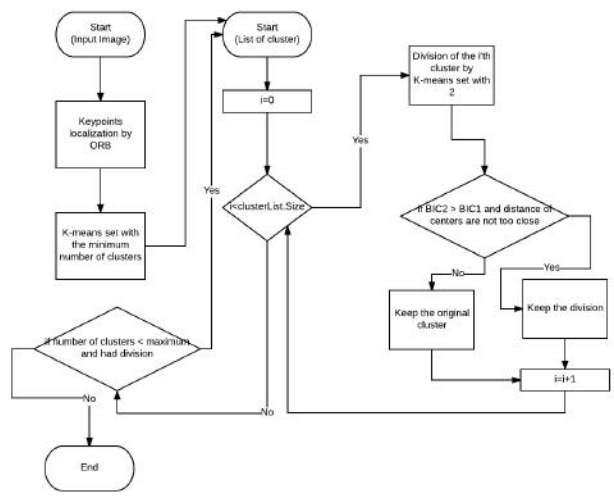

Fig. 1. Algorithm Flowchart

IV. Experiments

The goal of this work is to select automatically landmarks for UAV autonomous navigation. For this purpose, it is necessary to have previous images of the route or possible routes that the UAV will fly. Different images were used in the experiments to validate the proposed algorithm, which could be considered as images for a possible UAV flight route. Some of those images were obtained from an UAV flight around 40 meters high; others were obtained from a satellite image, in which several regions of interest were cropped to build test cases. The satellite image was obtained from INPE, in 2011.

The first experiment intended to compare the X-Means implemented as in the literature with other implementations of the X-Means. For this, the data mining tool WEKA was used [13] as it has the X-means implemented. Both were set with the same parameters, that is a minimum number of cluster equals 3 and a maximum number of 100, so the results could be compared and validated at first. ORB was used to identify the keypoints and an WEKA dataset was build using the pixel position (X,Y) of the image as attributes [13].

To validate the X-Means implemented, Fig. 2 was used. It is an image obtained by an UAV, with 1243x853 pixel resolution. The ORB keypoints were extracted and used both in WEKA and the implemented X-Means. The results are shown in Fig. 3 and Fig. 4.

Fig. 2. UAV flight image

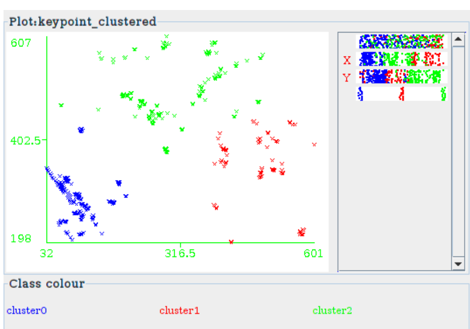

Fig. 3. Results obtained of X-Means in WEKA from the dataset of the Fig. 2

Fig. 4. Results from the implemented X-Means tested in Fig. 2

As shown in Fig. 5, the ideal separation is far from the results from the X-Means in the literature. The same image (Fig. 2), then, was used to test the proposed modified X-Means, and the results are showed in Fig. 6, it is closer to the ideal separation.

Fig. 5. Ideal separation of clusters

Fig. 6. Results from Modified X-Means in Fig. 2

The following experiments show the comparison between the results obtained from the modified algorithm and the orignal one implemented by WEKA. The images used for testing are the Fig. 7 and Fig. 8, which are cropped regions of a satellite image captured by the National Institute of Spatial Research (INPE) in Brazil, in 2011, with a spatial resolution of 1 meter per pixel. The algorithms also have the same settings on the proposed X-Means and on WEKA, with a minimum number of 3 clusters and maximum of 100. Fig. 9 shows the X-Means in WEKA results and the Fig. 10 the implemented algorithm results for Fig. 7. For Fig. 8 the results of X-Means in WEKA is in Fig. 11 and the results of the X-Means modified is in Fig. 12

Fig. 7. Cropped region 1 from the satellite image

Fig. 8. Cropped region 2 from the satellite image

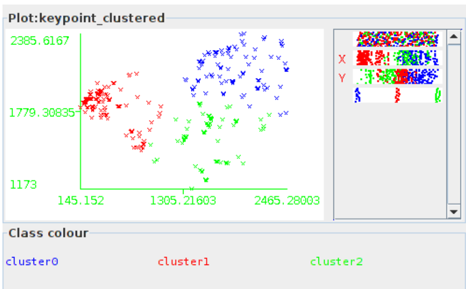

Fig. 9. Results from X-Means in WEKA using the dataset obtained from Fig. 7

The clusters identified by the algorithm were circulated in red for a better visualization of the separation on all images.

Fig. 10. Results from the Modified X-Means tested in Fig. 7

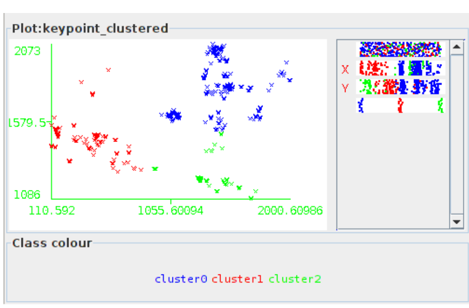

Fig. 11. Results from X-Means in WEKA using the dataset obtained from Fig. 8

Fig. 12. Results from the Modified X-Means tested in Fig. 8

V. RESULTS AND DISCUSSION

It was firstly needed to implement correctly an X-means and compare with the one in WEKA for the consistence of the algorithm built and then implement its modifications. The first experiment in the previous section showed that the implemented X-Means with no modifications in Fig. 4 had similar results compared to X-means implemented in WEKA in Fig. 3 and therefore, is a valid X-Means for further modifications.

The algorithm with the modifications in comparison with the original X-means had similar results when were tested with Fig. 2, which was in a low altitude flight and the image also has a small amount of objects. However, the modified X-Means has achieved closer results of an ideal separation than the original X-means.

In the satellite images on the other hand, the modified algorithm showed significant improvements in the separation of the clusters, as shown in Fig. 10 and Fig. 12, when compared with the results of X-means as in literature (Fig. 9 and Fig. 11). The satellite images have a greater number of objects (landmarks), which can be considered as the main reason why the number of clusters is higher.

The results presented for the modifications made in the algorithm in comparison to X-means has improvements in the separation of the clusters. Therefore, can be used to separate the bests landmarks for recognition to trace the best route for the UAV.

VI. CONCLUSION

In conclusion, UAV autonomous navigation has a wide area for application, and its technology evolution is crucial for the use in civilian areas. The use of landmark recognition is a promissing technique to improve the UAV autonomous navigation. The work developed shows that an appropriate selection of the landmark can have significant improvements for the recognition of the objects and therefore for the landmarks. The results presented by the algorithm developed showed to be a promissing algorithm to select landmarks for recognition and furthermore to become an important tool for better landmark recognition and UAV route planning based on landmarks.

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