An Approach to Navigation in Outdoor and Indoor Environments with Unmanned Aerial Vehicle Using Visual Topological Map

Paulo Honório Filho*, Suane Pires P. da Silva*, Jefferson S. Almeida*, Leandro B. Marinho†, Tiago Carneiro*
Antonio Wendell de O. Rodrigues* and Pedro Pedrosa Rebouças Filho*
*Programa de Pós-Graduação em Ciência da Computação (PPGCC),
Instituto Federal do Ceará, Fortaleza, Ceará, Brazil
Email: {paulo.honorio, tiago.carneiro}@ppgcc.ifce.edu.br, {suanepires, jeffersonsilva}@lapisco.ifce.edu.br,
{wendell, pedrosarf}@ifce.edu.br
†Programa de Pós-Graduação em Engenharia de Teleinformática (PPGETI),
Universidade Federal do Ceará, Fortaleza, Ceará, Brazil
Email: leandro.marinho@lapisco.ifce.edu.br

***Abstract*—Unmanned Aerial Vehicles (UAVs) are increasingly being applied in professional activities that require higher precision in navigating and positioning the aircraft in flight. Advanced location technologies such as GNSS (Global Navigation Satellite System) and RTK (Real-Time Kinematic), can raise the cost of demand using UAVs or still be dependent on an area with a transmission coverage. In this context, this article presents a visual navigation methodology based on topological maps comparing the performance of consolidated classifiers such as Bayesian classifier, k-Nearest Neighbor (kNN), Multi-layer Perceptron (MLP), Optimum-Path Forest (OPF) and Support Vector Machines (SVM), using attributes returned by state-of-the-art feature extractors such as Fourier, Gray Level Co-Occurrence (GLCM) and Local Binary Patterns (LBP). The results show that the combination of LBP with SVM obtained the best values in the evaluation metrics considered, among them, 99.99% of Specificity and 99.98% of Accuracy in the navigation process.**

***Index Terms*—Unmanned Aerial Vehicles, Computer Vision, Topological Maps, UAV Navigation.**

I. Introduction

Unmanned aerial vehicles (UAVs), also known as drones, are the focus of several researches for the most different purposes, since they have become attractive due to their small size, low cost and great manipulation potential [1]. In [2], UAV is employed in precision agriculture, aiming at collecting data to assist a more efficient farm and thus reduce its costs. While in [3], a method of monitoring road traffic using UVA is proposed, addressing the difficulty of managing road networks, due to their vast distances. In [4], the authors present solutions for the search of victims in natural disasters using UVAs and wireless technology.

Considering this context, the navigation of UVAs has been increasingly exploited, with the aim of elaborating more modern systems, with the ability to navigate independently [5]. For the most part, the navigation task of a UAV is performed using Inertial Navigation Systems (INS), which provides position, velocity and attitude information of the UAV [6]. However, this sensor has polarization errors, which continuously increase. Thus, additional information on the position of the vehicle was necessary from a precise navigation sensor, such as the Global Positioning System (GPS) [6]. However, since INS for accurate air navigation is very expensive, it is not popular on small aircraft and UAVs and although GPS offers accurate navigation with a cheap receiver, in some situations this system may simply not receive the satellite signal, either due to obstacles or signal block [7]–[9].

Therefore, to perform the navigation of UAVs using other resources has become a challenge, motivated by the need to obtain independent satellite alternatives [1], [5]. As an alternative to INS/GPS, one of the most commonly used means for UAV navigation is image recognition, enabling an autonomous visual-based navigation, satellite independent [10]. Among the main advantages of visual sensors is that they do not depend on external signals [11], give bountiful online information of the environment, are highly recommended for perception in dynamic environments because they have a high anti-interference capability and still make it difficult to identify the detection system because they are mostly passive type sensors [10].

With this, in this article we propose an autonomous visual navigation approach with UAVs using topological map and computational vision. The objective of this work is to present an analysis of techniques of feature extraction and machine learning consolidated, directing them to the task of localization and navigation of UAVs in external and internal environment. The feature extractors Fourier, Gray Level Co-Occurrence (GLCM) and Local Binary Patterns (LBP) together with classifiers k-Nearest Neighbor (kNN), Multi-layer Perceptron (MLP), Optimum-Path Forest (OPF), Support Vector Machines (SVM) and Bayesian Classifier were considered for this proposal. Vision-based navigation for UAV is a complicated procedure that demands fast processing times and accurate calculations to return adequate and reliable control commands to the vehicle [12]. For this reason, in order to compare the performance of each classifier, four evaluation metrics were considered: Specificity (Sp), Sensitivity (Se), Positive Predictive Value (PPV) and Accuracy (Acc). Parameters such as classification time and extraction time are also considered.

The results show that the association of the LBP extractor with the SVM classifier, operating with linear kernel, reached the highest values in the evaluated metrics, with 99.99% Specificity, 99.98% Accuracy and 99.77% of Sensitivity and PPV, proving to be an efficient and reliable approach for navigation of UAVs.

II. Materials and Methods

Figure 1 depicts the steps for carrying out the proposed approach. Firstly, the image is captured by the camera coupled to the UAV. Then, in the pre-processing step, the image is resized to decrease the cost of storage and processing in the next steps. After this, the feature extractors are applied so that the attribute vector is then used as input for the classifiers. By obeying the information present in the topological map, the classifiers perform their prediction, identifying in which class the UAV is located, called stage of cognition, and finally allowing the UAV to navigate.

The UAV employed in this approach is the Parrot Bebop Drone PF722000, as shown in Figure 2. This drone is equipped with a camera that records videos and takes photos within a 180-degree field of view. The technical Specifications of the UAV can be seen in Table I.

TABLE I: Specifications of Parrot Bebop Drone PF722000.

Connectivity	
Wi-Fi	802.11a/b/g/n/ac
Antennas	MIMO dual-band with 2 double-sets of dipole antennas for 2.4 and 5 GHz
Camera	
Sensor	CMOS 14Mpx
Streaming Resolution	1700 x 1070 pixels
Video encoding	H264
Internal memory	Flash 8 GB

Fig. 2: Parrot Bebop Drone.

A. Image Acquisition, Pre-processing and Database

The images were captured through the camera coupled to the UAV. Table I shows the technical specification of the device. Each image underwent a pre-processing after its acquisition, where they are redimensioned to decrease the storage and computational costs. However, this pre-processing does not interfere with the navigation process.

An image database was created to carry out this work. The images were captured at strategic points in the positions of the classes numbered c1 to c24, establishing the possible trajectories of the UAVs during their navigation. The database is composed of 240 images per class, totaling 5760 images, which have a resolution of 889 $\times$ 500 pixels. The sequence of the images were captured at different angles in real navigation tasks.

B. Feature Extraction and Classification

For the feature extraction, GLCM was considered with a distance $D = 1$ and direction $\theta = 0$. LBP was applied in its version with a uniform model, aiming at reducing the dimension of the problem.

Concerning the classification process, Bayesian classifier operated with the Gaussian probability density function. kNN considered $k = 5$ nearest neighbors. MLP carried out its training using the Levenberg-Marquardt method and neurons ranging from 1 to 50 in the hidden layer. For OPF, Euclidean distance was adopted. SVM used a linear kernel and a range $[2^{-2}, 2^{12}]$ for the γ parameter. The determination of MLP and SVM hyperparameters was done through cross-validation with 10-folds.

The classifiers used were chosen because they presented distinct properties among them, allowing the abagence of different aspects. Bayesian Classifier is non-parametric, kNN is distance-based, MLP consists of an artificial neural network, OPF is distance-based and SVM is a classifier that seeks to reduce empirical and structural error.

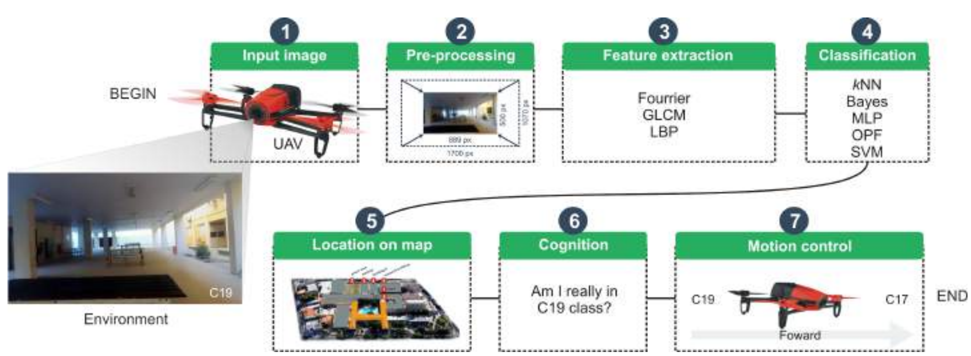

Fig. 1: Methodology of the proposed approach for the UAVs navigation.

C. Localization and Navigation

A college campus was selected for navigation because this environment includes both indoor and outdoor areas, which provides analysis of navigation in both types of environment.

Fig. 3: Topological map of the environment.

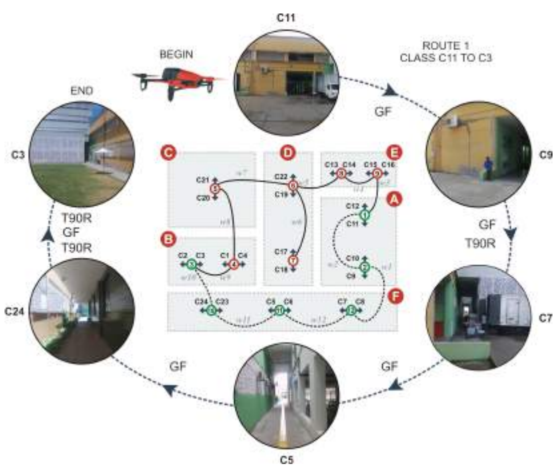

Fig. 4: Flow of route 1.

The topological map of the system is presented in the Figure 3, which is systematized in nodes numbered from 1 to 12. The images were captured in positions that are equivalent to the classes considered, which were labeled from c1 to c24. Classes define viable routes for navigation. Figure 3 shows the topological map of the environment with classes and nodes. A set of 10 routes were elaborated for navigation. The sequence of instructions employed to move the UAV in each route is displayed in the Table II, as well as the initial and final class.

For the sake of better understanding the navigation process, the flow of route 1 is shown in Figure 4. The UAV begins the navigation at class c11 (node 1) and receives two instructions to go front. After this, a command to turn 90 degrees to right followed by two more commands to go front are sent. Finally, an instruction to turn 90 degrees to the right, another to go front and another to turn 90 degrees to right are received by the UAV. In this way, UAV concludes route 1 by reaching class c3 (node 3).

TABLE II: Instructions for operating the UAV and navigation routes considered: Go front (GF), turn 90 degrees to left (T90L), turn 90 degrees to right (T90R) and turn 180 degrees (T180).

Route	Start (Class)	Commands	End (Class)
1	c11	GF, GF, T90R, GF, GF, T90R, GF, T90R	c3
2	c2	T180, GF, T90L, GF, T180	c20
3	c21	T90R, GF, T90L, T90R, GF, GF, T90R, GF	c11
4	c18	GF, T90R, GF, T90L, GF, T90L	c13
5	c13	GF, T90L, T90F, GF, T90L, GF, T90R, GF	c2
6	c3	GF, T90R, GF, T180	c20
7	c17	T180, GF, T90R, GF, GF, T90R, GF	c11
8	c23	GF, GF, GF, T180	c13
9	c4	T180, GF, T90L, GF, T90L,GF, T180	c5
10	c11	T180, GF, T90L, GF, GF, T90L, GF, T180	c18

III. Results

The domain of each combination of feature extractor with classifier on the images is analyzed according to the parameters shown in Tables III and IV. The results of navigation tests were calculated from 10 runs of each of the routes. The results were calculated on an iMac 2.5 GHz Core i5 processor with 4GB of RAM.

Table III outlines mean values and standard deviations of Specificity, Sensitivity, PPV, and Accuracy. According to this table, LBP stands out for obtaining the best values in all the metrics, being the highest values always returned when in combination with SVM(Linear), reaching 99.991% in Specificity, 99.774% in Sensitivity, 99.776% in PPV and 99.985% in Accuracy with this classifier. Also according to Table III, the worst results were returned by the combination of Fourier with MLP: 97.122% of Specificity, 42.392% of Sensitivity, 42.712% of PPV, and 94.512% of Accuracy.

Since the problem in question is a real-time application, it is important to be aware of the computational costs. Hence, Table IV shows accuracy, training time, testing time and extraction time, which are important parameters for embedded systems.

According to Table IV, kNN obtains the shortest training times when combined with all feature extractors. Values of 0.00007s, 0.00017s, and 0.00039s are observed when kNN is associated with GLCM, Fourier, and LBP, respectively. The slower classifiers in the training stage are MLP and SVM(Linear). MLP reached 3.04043s and 22.26473s in combination with GLCM and Fourier, respectively. SVM(Linear) associated with LBP completes the training in 5.49787s. Concerning the testing time, MLP is the fastest, achieving 0.01ms in association with all feature extractors. The highest testing times are observed for the combinations of kNN with all extractors, performing the task of classification in 345.74ms, 432.57ms, and 1321.10ms when associated to GLCM, Fourier, and LBP, in this order.

Still according to Table IV, we evidence that, among all the feature extractors, GLCM is the one that accomplished its task in the shortest time: 11.77s. On the other hand, Fourier is the slowest in this question, with extraction time of 18.49s. All the best values cited are shown in green in Tables III and IV.

TABLE III: Specificity (Sp), Sensitivity (Se), Positive Predictive Value (PPV) and Accuracy (Acc) obtained by features extraction and classifiers.

Feature	Classifier	Sp (%)	Se (%)	PPV (%)	Acc (%)
Fourier	Bayes(Normal)	99.591±0.024	91.802±0.471	92.589±0.373	99.223±0.045
	kNN	99.718±0.021	94.155±0.415	94.122±0.427	99.438±0.039
	MLP	97.122±0.761	42.392±15.202	42.712±16.209	94.512±1.447
	OPF(Euclidean)	99.806±0.028	95.993±0.554	95.976±0.566	99.617±0.053
	SVM(Linear)	99.611±0.024	92.226±0.475	92.167±0.491	99.259±0.045
GLCM	Bayes(Normal)	99.951±0.009	98.971±0.192	98.973±0.191	99.905±0.018
	kNN	99.839±0.012	96.500±0.242	96.502±0.236	99.672±0.023
	MLP	97.613±0.226	52.137±4.528	51.361±3.525	95.436±0.431
	OPF(Euclidean)	99.915±0.009	98.253±0.198	98.254±0.199	99.831±0.019
	SVM(Linear)	99.918±0.007	98.249±0.135	98.241±0.137	99.835±0.013
LBP	Bayes(Normal)	99.984±0.006	99.619±0.119	99.615±0.118	99.958±0.011
	kNN	99.972±0.006	99.458±0.115	99.453±0.115	99.951±0.011
	MLP	99.983±0.008	99.532±0.161	99.538±0.162	99.964±0.015
	OPF(Euclidean)	99.987±0.006	99.699±0.123	99.694±0.122	99.969±0.012
	SVM(Linear)	**99.991±0.005**	**99.774±0.069**	**99.776±0.069**	**99.985±0.007**

TABLE IV: Accuracy (Acc), training time, testing time and extraction time obtained by features extraction and classifiers.

Classifier	Acc (%)	Training time (s)	Testing time (ms)	Extraction time (s)
		Fourier		
Bayes(Normal)	99.22±0.05	0.01551±0.00184	55.96±55.94	18.49±2.84
kNN	99.44±0.04	**0.00017±0.00012**	432.57±432.37	
MLP	94.51±1.45	22.26473±6.45220	**0.01±0.01**	
OPF(Euclidean)	99.62±0.05	0.24186±0.01320	143.40±143.33	
SVM(Linear)	99.26±0.05	14.24819±5.53269	20.73±20.72	
		GLCM		
Bayes(Normal)	99.90±0.02	0.00601±0.00448	34.30±34.28	**11.77±8.67**
kNN	99.67±0.02	**0.00007±0.00002**	345.74±345.58	
MLP	95.44±0.43	13.04043±3.79468	**0.01±0.01**	
OPF(Euclidean)	99.83±0.02	0.13773±0.03154	80.30±80.26	
SVM(Linear)	99.83±0.01	5.13358±1.21721	9.53±9.53	
		LBP		
Bayes(Normal)	99.96±0.01	0.06373±0.00299	80.76±80.72	17.15±13.21
kNN	99.95±0.01	**0.00039±0.00026**	1321.10±1320.47	
MLP	99.96±0.02	2.74550±1.03566	**0.01±0.01**	
OPF(Euclidean)	99.97±0.01	0.64364±0.32249	361.82±361.64	
SVM(Linear)	99.98±0.01	5.49787±1.22487	80.91±80.87	

IV. Conclusion and Future Works

The present research work has proposed a new navigation and localization approach for UAVs. The proposed approach uses topological map and feature extraction and machine learning techniques for the construction of a system based on computational vision. The chosen place for the development of the approach has a dynamic structure, presenting outdoor and indoor areas, which allows the system to be evaluated in these two types of environment.

According to the results presented, LBP with SVM(Linear) was the combination that obtained the best values in the metrics evaluated, achieving 99.99% in Specificity, 99.77% in Sensitivity and PPV, and 99.98% in Accuracy, showing to be a robust and reliable option for the navigation task. About training and testing times, kNN presented the shortest training time, with 0.00007s, and MLP obtained the shortest test time, with 0.01ms. Among the feature extractors, GLCM achieved the shortest extraction time, with 11.77s.

For future work, other environments that are exclusively external or internal can be evaluated with our proposed methodology. In addition, other methods of feature extraction and machine learning can also be employed, such as Structural Co-occurrence Matrix (SCM) [13] and Optimum-Path Forest (OPF) [14], respectively, and still Deep Learning techniques, especially Convolutional Neural Networks (CNN) [15].

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References

[1] B. R. Stojkoska, J. Palikrushev, K. Trivodaliev, and S. Kalajdziski, "Indoor localization of unmanned aerial vehicles based on RSSI," in *IEEE EUROCON 2017 -17th International Conference on Smart Technologies, Ohrid, Macedonia, July 6-8, 2017*, 2017, pp. 120–125.

[2] I. Petkovics, J. Simon, Á. Petkovics, and Z. Covic, "Selection of unmanned aerial vehicle for precision agriculture with multi-criteria decision making algorithm," in *15th IEEE International Symposium on Intelligent Systems and Informatics, SISY 2017, Subotica, Serbia, September 14-16, 2017*, 2017, pp. 151–156.

[3] R. Reshma, T. Ramesh, and P. Sathishkumar, "Security situational aware intelligent road traffic monitoring using uavs," in *2016 International Conference on VLSI Systems, Architectures, Technology and Applications (VLSI-SATA)*, Jan 2016, pp. 1–6.

[4] T. Kobayashi, S. Seimiya, K. Harada, M. Noi, Z. Barker, G. K. Woodward, A. Willig, and R. Kohno, "Wireless technologies to assist search and localization of victims of wide-scale natural disasters by unmanned aerial vehicles," in *20th International Symposium on Wireless Personal Multimedia Communications, WPMC 2017, Bali, Indonesia, December 17-20, 2017*, 2017, pp. 404–410.

[5] B. Chen, "Navigation and control of unmanned aerial vehicles in gps-denied environments," in *13th International Conference on Control Automation Robotics & Vision, ICARCV 2014, Singapore, December 10-12, 2014*, 2014.

[6] A. Nemra and N. Aouf, "Robust ins/gps sensor fusion for uav localization using sdre nonlinear filtering," *IEEE Sensors Journal*, vol. 10, no. 4, pp. 789–798, April 2010.

[7] C. S. Y. C.-S. Yoo and I. K. A. I.-K. Ahn, "Low cost gps/ins sensor fusion system for uav navigation," in *Digital Avionics Systems Conference, 2003. DASC '03. The 22nd*, vol. 2, Oct 2003, pp. 8.A.1–8.1–9 vol.2.

[8] J. Unicomb, L. Dantanarayana, J. Arukgoda, R. Ranasinghe, G. Dissanayake, and T. Furukawa, "Distance function based 6dof localization for unmanned aerial vehicles in gps denied environments," in *2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Sept 2017, pp. 5292–5297.

[9] R. Skulstad, C. L. Syversen, M. Merz, N. Sokolova, T. I. Fossen, and T. A. Johansen, "Net recovery of uav with single-frequency rtk gps," in *2015 IEEE Aerospace Conference*, March 2015, pp. 1–10.

[10] Y. Lu, Z. Xue, G.-S. Xia, and L. Zhang, "A survey on vision-based uav navigation," *Geo-spatial Information Science*, vol. 21, no. 1, pp. 21–32, 2018.

[11] P. Kaniewski and W. Grzywacz, "Visual-based navigation system for unmanned aerial vehicles," in *2017 Signal Processing Symposium (SPSympo)*, Sept 2017, pp. 1–6.

[12] A. Cerón, I. Mondragón, and F. Prieto, "Onboard visual-based navigation system for power line following with uav," *International Journal of Advanced Robotic Systems*, vol. 15, no. 2, p. 1729881418763452, 2018.

[13] G. L. B. Ramalho *et al.*, "Rotation-invariant feature extraction using a structural co-occurrence matrix," *Measurement*, vol. 94, no. 2, pp. 406–415, 2016.

[14] T. M. Nunes, A. L. V. Coelho, C. A. M. Lima, J. P. Papa, and V. H. C. de Albuquerque, "EEG signal classification for epilepsy diagnosis via optimum path forest - A systematic assessment," *Neurocomputing*, vol. 136, pp. 103–123, 2014.

[15] Y. LeCun, B. E. Boser, J. S. Denker, D. Henderson, R. E. Howard, W. E. Hubbard, and L. D. Jackel, "Handwritten digit recognition with a back-propagation network," in *Advances in Neural Information Processing Systems 2, [NIPS Conference, Denver, Colorado, USA, November 27-30, 1989]*, 1989, pp. 396–404.