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Computer vision systems in unmanned aerial vehicle: a review

ODILON LINHARES CARVALHO MENDES[1,2], GIOVANNA MICELI RONZANI BORILLE[1]

[1]Instituto Tecnológico de Aeronáutica - ITA, Praça Marechal Eduardo Gomes, 50, Vila das Acácias, 12228-900 São José dos Campos, São Paulo, Brazil

[2]Instituto Federal do Ceará - IFCE, Campus Fortaleza, Av. Treze de Maio, 2081, Benfica, 60040-215 Fortaleza, Ceará, Brazil

<odilonlinharesmendes@gmail.com>, <ronzani@ita.br>

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Abstract. Inspections in areas of difficult access or hostile to the human, pattern recognition, surveillance and monitoring, are some of the many applications in with Unmanned Aerial Vehicles (UAV), can be a solution, opening up new perspectives for the use of this technology. The navigation and the position of the UAVs can be made by autonomous method through computational vision, which is a technology of construction of artificial systems capable of read information from images or any multidimensional data and making decisions. This work presents a review of the use of computer vision systems by UAVs, with a focus on its many applications. The main objective is to analyze the latest technologies used for the development of computer vision in UAVs, through the tools of data search, information storage and, mainly, processing and analysis of data. The researches encompass a publication of recent works, 2011 to 2019. For each work were analyzed the objectives, results and conclusions. Based in this analysis, was made a comparison between the techniques and their challenges, that are to develop systems that are robust to noise and deviations from data-driven models, and also it must have good performance regarding to computational requirements and memory space. Hence, future outlook scenarios of UAVs using computational vision are mentioned.

Keywords: Unmanned Aerial Vehicles (UAV). Computer Vision (CV). Navigation.

1 Introduction

Remove people (crew or pilot) from the aircraft is the main reason for the development and use of UAVs. The operational benefits and also questions of security have to be considered to the atention of investors and governments. The time autonomy is essential for many tasks. UAVs can operate for hours without inducing the pilot to fatigue. It is possible to fly in dangerous situations without putting people at risk. The costs of operation can be reduced. Though, barriers need to be broken so their full potential can be utilized (MCFADYEN; MEJIAS, 2016).

Many problems still remain as obstacles in operations, such as suspended load, remote sensors and adverse weather conditions management (visibility, rain etc.). These challenges are being studied by the scientific community in different parts of the world searching the best solutions to ensure the safe flight of UAVs (VALAVANIS, 2016).

The increase demand for use of UAVs will press forward the development of public and government standards to enable the integration of this tecnology into the National Airspace System (NAS). There are studies aimed at identifying the key technical, procedural, and policy areas that would best foster UAS integration into the NAS (WARGO et al., 2014).

Initially the UAVs were developed for use of defense and military, with purpose of avoiding danger to human life. With the advent of microelectronics and increased computational efficiency, micro and small UAVs have been the focus of scientific research in the robotics community (ADAMS; FRIEDLAND, 2011).

UAVs are widely used for civilian and military pur-

Table 1: Category of UAVs according to resistance, flight range, and altitude. Source: Yu & Zhang (2015)

Category	Resistance	Flight range (km)	Altitude (km)
Long/High	≥ 24	≥ 400	≥ 10
Medium	5-24	100-400	1-10
Low	≤ 5	≤ 100	≤ 1

poses. Traditionally, the determination of position and altitude has been done by combining the Inertial Navigation System (INS) with the Global Positioning System (GPS). In this configuration, GPS position updates can be used to decrease the error referring to the INS device. However, GPS signals can be easily lost or misinterpreted when UAVs are navigating obstacles such as rough terrain, urban areas, mountains or forests. The INS only accumulates errors that prevent its use alone (CHAO; GU; NAPOLITANO, 2014; FLORES et al., 2014).

Vision sensors are good against disturbances, have good motion capture capabilities and are lightweight. Many studies with respect to sensor vision navigation systems have been made, mainly due to the low cost (CHOWDHARY et al., 2013).

According to Kai, Chunzhen & Yi (2015), depending on the characteristics of weight, yield, flight range and altitude, UAVs can be classified into groups as indicated in Tables 1 and 2. UAVs can also be classified in fixed wings or rotating wing.

Table 2: Classification of UAVs by weight. Source: Yu & Zhang (2015)

Category	Weight range (kg)
Super heavy	≥ 2000
Heavy	200-2000
Medium	50-200
Light	5-50
Micro	≤ 5

In addition to these categories, there are others that can be taken into account; size, mission range, operating altitude, duration, flight principle, propulsion mode, operating condition, load capacity, or also the combination of these characteristics (AL-KAFF et al., 2017).

Autonomous UAVs need an equivalent level of safety, just like piloted aircraft. This is important because both types of aircrafts can travel at the same airspace. In order to not degrade the air traffic management system, some initiatives must be taken (CLOTHIER; WILLIAMS; FULTON, 2015). Researchers and governments in several countries are already creating regulatory measures for UAVs to operate, depending on their mission.

The main part of the UAVs is the navigation system. Autonomous navigation uses information from several subsystems to perform three essential tasks: position identification, obstacle bypass, and flight control to achieve mission objectives (AL-KAFF et al., 2017).

In order to guarantee the most detailed information possible and the lowest operating and software costs, visual sensors and computer vision (CV) have played a key role (KRAJNÍK et al., 2012). The CV guarantees low power consumption and the cost is lower compared to systems that use the combination of INS with GPS. In addition, this technology enables detailed processing of the mission environment for quick decision making.

To ensure a safe flight, systems must be able to detect other aircraft in space, providing maneuvers necessary to avoid a potential accident. Both embedded vision and intelligence devices as well as the human being are critical to avoid catastrophes (KAI; CHUNZHEN; YI, 2015).

The concept of using aerial imagery for photographs and movies has changed to more complex applications. This work presents a literature review of UAV applications using computer vision, specifying the techniques used and their latest results.

2 Computer vision

Computer vision is closely linked to artificial intelligence. Autonomous systems are able to interpret data and make decisions. In Mota et al. (2018), Petri Nets are used for modeling the trajectory that an autonomous mobile robot must execute. The development of new CV techniques associated to the development of machine learning has contributed to a significant progress in this field of study with several applications in the industry, science and military force (ANDREOPOULOS; TSOTSOS, 2013). However, the performance of these systems depends on a large amount of data, efficient processing and classification techniques for quick and accurate responses (JI, 2017).

There are four levels of computer vision tasks: detection of a item in the visual stimulus; localization of the detected item; recognition of which class the item belongs to; understanding the role of an item present in the scene (ANDREOPOULOS; TSOTSOS, 2013). These levels of tasks can be achieved through of faculty for learning semantic knowledge, the retention of contextual knowledge, and how it relates to the system and reasoning about objects and events in the environment (VERNON, 2006).

The main purpose of CV is to ensure visual information for a given application. There are levels of vision that will be addressed in detail: low-level vision, which is the acquisition and processing of images; intermediate-level vision, which is the segmentation and classification; and high-level vision, which is the conceptual understanding of visual information, generating a response (ALVES et al., 2018).

2.1 Data acquisition

There are several types of sensors and cameras that can be used for image acquisition (COUTARD; CHAUMETTE, 2011). Numerous computer vision techniques can be applied to generate image measurements for vision or vision integrated navigation. Their detection can be carried out efficiently, and under varying image scale, viewpoint, and illumination conditions (COUTARD; CHAUMETTE; PFLIMLIN, 2011). Depending on the application, it is necessary to use more robust technologies which require better software for image processing or others that do not require so much. The Traffic Alert and Collision Avoidance System (TCAS) and Automatic Dependent Surveillance – Broadcast (ADS-B) sensors can be used in all weather conditions, but the cost is high. Synthetic Aperture Radar (SAR) is a technology that can be employed both in visual meteorological conditions (VMC) and in instrumental meteorological conditions (IMC), but the accuracy needs to be improved. Laser/Light Detection and Ran- ging (LIDAR) also operates in VMC and IMC, but its field of vision is limited. There are also electro-optical, acoustic and infrared, which are inexpensive and can detect transponderless equipment, including gliders and birds, but these devices do not measure direct reach and have low IMC yields (YU; ZHANG, 2015).

2.2 Image processing

Most processing image techniques are a two-dimensional signal. This process is required for later techniques such as machine learning and pattern recognition. Specific information to the use of image purpose improves the performance of the next step which is a segmentation. The use of prior knowledge with emphasis on segmentation, for example, by editing an image texture, may become less susceptible to noise (QIAN et al., 2017). The most used techniques are: Fourier Transform (LARSSON; FELSBERG, 2011), Adaptive Threshold (ALEXANDRIA et al., 2014), Filtering (MEIER et al., 2011), Histogram (HE et al., 2013).

2.3 Segmentation

The segmentation of images divides them into multiple regions (NEUMANN; MATAS, 2013). This process focuses on finding points of interest, for example, regions containing microcalcifications on mammograms. Thus, features can be processed by artificial intelligence, such as color, intensity, shape and texture. Most general segmentation methods usually propose texture, color and edge-based features to define regions of interest (GHAMISI et al., 2012). There are several methods: thresholding (RAJU; NEELIMA, 2012), clustering (PATEL; NGUYEN; VIDAL, 2013), Otsu method (YANG et al., 2012) etc. The performance of the adopted technique can be evaluated through statistical metrics such as accuracy and processing time (EL-BAZ et al., 2013). Hinzmann et al. (2018) propose prior knowledge-free visual landing site detection for autonomous planes. The method explores texture and geometric shapes without using any prior knowledge about the environment. Aydin & Kuğu (2016) propose safe landing site detection using shuttle radar topography mission (SRTM) maps for UAVs. The method segments regions of interest called blobs, which are analyzed for landing zone detection.

2.4 Classification

There are several methods for classifying images. Artificial Neural Networks (ANN) are currently one of the main techniques applied by the scientific community (FAN et al., 2013). Several techniques can be used, such as Multilayer Perceptron (MLP) (BOUGHRARA et al., 2016), Radial Basis Function (RBF) (WANG et al., 2016), Extreme Learning Machine (ELM) (SA JUNIOR; BACKES, 2016), Fuzzy Logic (KIM; KIM; KIM, 2015), Genetic Algorithms (GA) (MOREIRA et al., 2018). Another efficient method is genetic programming (GP), that generate knowledge base vectors. GP is a computational approach to automatically develop solutions for a given problem (IQBAL; ZHANG; XUE, 2016). Huang et al. (2016) propose geological segmentation for UAV aerial images using shape-based in dominant color. The method uses fuzzy c-means clustering for classification based on color information. The method of Li (2013) explore a similarity-based texture area for finding possible landing areas. Then the features are passed to Support Vector Machine (SVM) classifier for confirming landing areas.

3 Work selection criteria

The methodology adopted to execute this systematic review is based on some steps: (1) choosing relevant research of terms associated with the subject; (2) choosing the works that will be used based on the relevance of the article; (3) applying the inclusion criterion: only works that associate computational vision in applications in the use of UAVs; (4) synthesizing the key words obtained from the selected papers and review the terms of greatest incidence, in order to optimize future work searches; and finally (5) evaluating each selected work based on the purpose of application, computational technique used, algorithm for error estimation and results.

4 Selected works

During the analysis of the work related to the use of computer vision applied to UAVs, a variation of keywords were found. In order to identify the best and most effective keywords within this line of research a statistical analysis has been applied to them and can be seen in Figure 1. It were necessary 54 works to construct the database of keywords and 35 works were discarded because they did not have significant relevance for the purpose of the review and the written language was not adequate.

The base Science Direct was chosen because it has a large collection of Physical Sciences and Engineering publications, covering a range of disciplines, from the theoretical to the applied. Practically all the necessary works for this review were found in this portal. This section will make an analysis of the best works in order to explore what is most recent research on the use of computer vision by UAVs.

The authors, year, objective and computational technique of the relevant works in this review are shown in Table 3. The estimated error technique used, if any, and the results are presented in Table 4. There is no standard data set description which can be used for evaluating the proposed system, because each work has a different objective and a form of evaluate its results. Therefore, it is shown in the table the best numerical results that can express the quality of the chosen works. The autonomous UAVs applications based on computer vision are divided in Table 5. Through this table is possible to see the research groups by area of activity. Thus, in the section "Discussion"a comparison is made of the works and point out the best technique for each application.

Meng et al. (2019) develop a technique for autonomous landing of UAVs on moving ships. They used the Inertial Measurement Unit (IMU) for attitude information with infrared to capture the landing target. The Extended Kalman Filter (EKM) was used to merge inertial information with visual and estimate position, speed and orientation at landing. Simulations showed that the method satisfies the estimation and prediction of the results. The speed error is 0.16 m/s and 6.4 m for landing position.

Huang et al. (2018) explain a method to analyze the performance of reference points based on the Inertial navigation system/Vision navigation system (INS/VNS). The Kalman filter is used to estimate the errors of navigation parameters for UAV. At the end, a simulation is done, comparing the INS/VNS method with the IMU/VNS. The results show that INS/VNS is less accurate and slower than IMU/VNS, but its real-time performance is better.

The work developed by Hu et al. (2019) present a fuzzy multiobjective surveillance model of multiple UAVs based on predictive control distributed to mobile ground targets unknown in an urban environment. EKF is combined with fuzzy to estimate the probability of predicting unknown targets. The result of the simulations shows that the proposed method is efficient compared to traditional ones. In target surveillance, there is a 92.7 % success rate compared to 70.8 % of traditional methods.

Shirzadeh et al. (2017) investigate the application of Image Based Visual Servoing (IBVS), a mechanism that controls the translational and rotational movements of a quadrotor helicopter to track mobile targets. A direct adaptive neural controller is designed to control the transition motion. The controller makes use of the neural network Radial Basis Function (RBF) to deal with the dynamics of the uncertainties of the images. The simulation results for ideal and non-ideal conditions indicate that, despite problems such as uncertainty of image depth and the mobility of the target, both in rotation and translation, the helicopter was able to reach the desired altitude to properly track the target in motion.

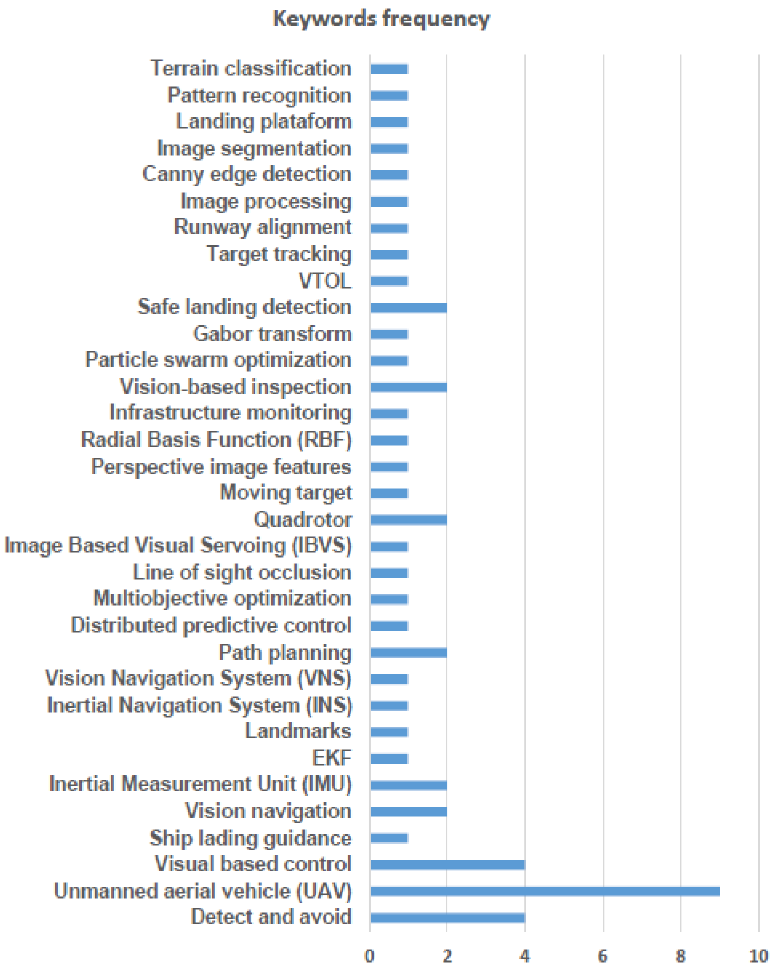

Figure 1: Keywords frequency

Table 3: Major objective and techniques

Authors	Year	Objective	Computational technique
Meng et al.	2019	Autonomous landing on a ship	IMU
Huang et al.	2018	Navigation and position	INS / VNS
Hu et al.	2019	Surveillance / Target Tracking	Fuzzy
Shirzadeh et al.	2017	Mobile Target Tracking	RBF
Phung et al.	2017	Surface Inspection	DPSO
Kaljahi et al.	2019	Landing zone detection	Gabor Transform / MCCs
Abdssameud and Janabi-Sharifi	2015	Mobile Target Tracking	IMU
Marianandam and Ghose	2014	Fixed wing UAV landing	VILS
García-Pulido et al.	2017	Landing zone detection	CPA
Eresen, Imamoglu and Efe	2012	Obstacle avoidance	Optical flow
Asl and Yoon	2016	Speed detection	IBVS
Patterson et al.	2014	Landing zone detection	SIFT / Fuzzy
Carvalho	2014	Mosaic of images	SIFT, NSSD / NCC

Table 4: Error estimation and results

Autors	Error estimation	Results
Meng et al.	EKF	Error: 0.16 m/s (speed) / 6.4 m (landing position)
Huang et al.	KF	3 landmarks errors: [30, 20, 10] m/s (speed) and [50, 50, 10] m (landing position)
Hu et al.	EKF	Error: 20 m (position)
Shirzadeh et al.	Control techniques	10 s to reach the desired target
Phung et al.	-	Improvement of 15 % in the travelling cost and 87 times in the computation time
Kaljahi et al.	Chi square distance	Recall: 0.87 / Precision: 0.93 / F-Measure: 0.90
Abdssameud and Janabi-Sharifi	Control techniques	20 s to reach the desired target
Marianandam and Ghose	Control techniques	2 degrees of error and 25 s to align on the track
García-Pulido et al.	-	Success rate (%) based on distance: 70.1 (0-2 m) / 51.4 (2-4 m) / 28.5 (4-6 m) / 26.5 (6-8 m) / 39.3 (>8 m)
Eresen, Imamoglu and Efe	PID controller	Error > 1 m: it lands automatically / Variance threshold is 1.5
Asl and Yoon	-	10 s to detect the speed automatically
Patterson et al.	-	Average accuracy of 94.7 % of hits in landing
Carvalho	-	A mosaic of 22 images and another of 25

Table 5: Autonomous UAVs applications based on computer vision

Application	Description	Related works
Landing	Autonomous landing / Landing zone detection / Fixed wing UAV landing	Meng et al. (2019); Kaljahi et al. (2019); Marianandam and Ghose (2014) García-Pulido et al. (2017); Patterson et al. (2014)
Navigation	Navigation and position / Obstacle avoidance	Huang et al. (2018); Eresen, Imamoglu and Efe (2012)
Target tracking	Surveillance / Mobile target tracking / Surface inspection / Speed detection	Hu et al. (2019); Shirzadeh et al. (2017); Asl and Yoon (2016) Abdssameud and Janabi-Sharifi (2015); Phung et al. (2017)
Mosaic	Mosaic of images	Carvalho (2014)

Phung et al. (2017) develop an efficient path planning algorithm for inspection of large surfaces using computer vision. An advanced Discrete Particle Swarm Optimization (DPSO) algorithm is proposed to solve the TSP problem, with performance improvement using deterministic initialization, random mutation, and edge switching. A GPU is also implemented, to reduce computing time significantly, while keeping the hardware requirement unchanged. The experimental results are shown in graphs and obtained from UAVs inspecting an office building and a bridge.

Kaljahi et al. (2019) develop a system that detects regions to navigate a UAV when it requires an emergency landing due to technical failures. Gabor Transform is the technique used to extract images. The Markov Chain Codes (MCCs) detects the candidate regions. Experimental results show that the proposed system surpasses the existing ones.

Abdessameud & Janabi-Sharifi (2015) approach the image-based take-off and landing control problem for UAVs. The proposed approach is based on imaging characteristics, defined in perspective along with a useful projection, and the design of a translation controller without linear velocity measurements in the presence of external perturbations. The work proved to be efficient to provide adequate visual dynamics for the control and analysis of the system.

Marianandam & Ghose (2014) present a computer vision method for landing lane alignment of fixed wing UAVs, the Vision-in-the-loop-Simulation (VILS). FlightGear and Matlab were used to develop the simulation system. Image processing is used to detect and track lane lines through Hough Transforms. A controller maneuver the UAV by responding to commands from the system that interprets the images.

Garcia-Pulido et al. (2017) develop a technique for recognizing a landing platform for UAVs using techniques based on computer vision. Comparative Partial Analysis (CPA) is the technique used. The results were satisfactory, with mean time of 1.5 s for landing target recognition.

Eresen, İmamoğlu & Efe (2012) present an autonomous flight based on computer vision with a UAV. Automatic obstacle detection is achieved by using the Optical flow technique together with a PID controller. The proposed method is tested in the virtual environment of Google Earth for four different destination points. In each case, the autonomous flight of the UAV is simulated successfully without collisions. The results show that the proposed method is a powerful candidate for vision based navigation in urban environment.

Asl & Yoon (2016) develop a technique to determine UAV speed without needing measure devices, just using computer vision information. Linear speed information is obtained from macroelectrometers. The method used is Image Based Visual Servoing (IBVS). Simulation results illustrate the effectiveness of the IBVS proposal even in the presence of noise.

Patterson et al. (2014) develop a work based on the autonomous identification of safe landing zones that can be used in the occurrence of a critical safety event. The work uses Scale Invariant Feature Transform (SIFT) and Fuzzy logic. The results are presented based on the aerial color images captured during manned flight demonstrating practical potential in the approaches. The average accuracy is of 94.7 % of hits in landings.

Carvalho (2014) present a work of automatic construction of mosaic of images from aerial images referenced in relation to the data measured by inertial, altitude and velocity measurement sensors of a UAV. The generation of the mosaic is done through C language and the OpenCV libraries. Scale-Invariant Feature Transform (SIFT), Normalized Sum of Squared Differences (NSSD) and Normalized Cross Correlation (NCC) were used. Two results are shown, one mosaic of 22 images and another of 25, fulfilling the objectives of the work.

5 Discussion

During the analysis of the works selected for this review, it was noticed that several of the proposed techniques presented potential for the development of the use of computer vision in UAVs, allowing decision making in an autonomous way. Some techniques obtained accuracy greater than 92 %, as is the case of the work developed by Hu et al. (2018) for surveillance and target tracking, which utilized Fuzzy multiobjective optimization and achieved 92.7 % success compared to 70.8 % of traditional methods.

The work presented by Patterson et al. (2014) achieve an accuracy rate of 94.7 % of hits in the detection of emergency landing zones in an autonomous way, once again using Fuzzy with Scale Invariant Feature Transform (SIFT).

Some papers have used other ways of evaluating their results, such as Meng et al. (2019), for autonomous landing by ship, which evaluated an error of only 0.16 m/s for speed and of 6.4 m for landing position.

Another way of evaluation was carried out by Garcia-Pulido et al. (2017), also for the autonomous detection of landing zone, where the average time variable for target recognition was used.

Not all papers used techniques to estimate or decrease the error rate. Some techniques were used, such as the use of GPU to improve computational performance, Chi square distance, PID controller to reduce errors, Gaussian filter and the most approached was the Kalman Filter.

Advantages can be found in the papers studied in this review. Abdessameud & Janabi-Sharifi (2015) show that perspective moments with an appropriate projection have been shown efficient to provide suitable visual dynamics for the control system design and analysis. As a result, a control scheme that exploits the full dynamics of the Vertical Take-Off and Landing (VTOL) aircraft has been proposed such that the aircraft tracks a moving target, at a specified configuration, in the presence of constant external disturbances.

In the work of Asl & Yoon (2016), stability analysis guarantees that all states of the system are bounded and the error signals converge to zero. Garcia-Pulido et al. (2017) present that in scenarios where a part of the figure is blind there are still sufficient singular regions to allow for their identification. Hu et al. (2019) prove that control input cost of UAVs and the energy consumption of sensors allows a longer time flight. Distributed predictive control is used to obtain the local optimal path of each UAV under the constraints of collision avoidance, minimum turning radius and control input. Mcfadyen & Mejias (2016) show that relative state information allows position-based visual servoing approaches in which full control of the platform is possible. Position based control is likely to provide more precise position control and better collision avoidance assureance, by leveraging abroad errange of possible control solutions compared to image-based approaches. Meng et al. (2019) prove that the proposed visual/inertial integrated landing guidance method achieves satisfied performance in state estimation and ship motion prediction.

Disadvantages can also be found in the mentioned studies. Abdessameud & Janabi-Sharifi (2015) found the problem of field of view maintenance inherent in IBVS techniques, which cannot efficiently handle large displacements. Alves et al. (2018) report the problem of lack of standardisation in knowledge based vision research. This offer numerous challenges to the development of new applications, like the identification of resourceful prior knowledge, the capture of the knowledge of interest and the process of encoding knowledge into visual learning. In the work of Carvalho (2014), the images were taken considering the aircraft in stabilized flight and the algorithm was developed without considering the corrections of altitude variation, roll and pitch of the aircraft. In addition, image processing techniques such as threshold and mathematical morphology proved ineffective for noise elimination. Eresen, İmamoğlu & Efe (2012) show that very small and very large threshold values make the vehicle blind and there exists an acceptable interval in which the autonomous flight response is satisfactory. The simulation of Huang et al. (2018) result that the landmark-based INS/VNS has lower convergence precision and slower convergence speed than those of the landmark-based IMU/VNS due to its modeling errors. Kaljahi et al. (2019) show that the proposed system considers the region of water in an image as a false candidate region. This is due to the water surface appearing as a homogeneous region for the proposed system. Also, during flight there is a high chance of capturing blurred images due to adverse climate effects and variations in height.

The work of Marianandam & Ghose (2014) do not verify robustness in the presence of crosswinds and do not to identify and track visual cues to generate appropriate control for landing the UAV. Patterson et al. (2014) prove that due to the real-time nature of the problem of SLZ detection, and the potential, hard constraints imposed by remaining battery life it may not always be practicable to include knowledge into the algorithm to provides a more reliable method of SLZ. The algorithm of Phung et al. (2017) can not provide inspection of nonplanar surfaces and incorporate online re-planning strategies to deal with inspection of built infrastructure of an irregular shape. The work of Shirzadeh et al. (2017) do not guaranteed that, in the course of movement, the visual features always remain within the camera's field of view. A problem found by Yu & Zhang (2015) is that without air worthiness certificate, the UAVs are prevented from a wider spread even though the UAV applications become increasingly urgent.

The review however showed that the latest techniques using computer vision along with UAVs have not yet solved all problems, and there is still space for research and advancement of new techniques and possibilities of use, which are always approached in the papers presented as ideas for work futures.

6 Results

In this section are mentioned the best results for each group of selected works that are divided at the Table 5. In the "Landing"group, the best-performing work is that of Patterson et al. (2014) with accuracy of 94.7 % of hits in landing. In the "Navigation"group, Huang et al. (2018) have the best results, 3 landmarks errors: [30, 20, 10] m/s (speed) and [50, 50, 10] m (landing position). In the "Target tracking"group, Shirzadeh et al. (2017) and Asl & Yoon (2016) have the same performance, 10 seconds to reach desired target and to detect the speed automatically, respectively. In the "Mosaic"group there is just one work, so comparisons can not be made.

7 Conclusion

This paper presented a review of some computer vision techniques applied to UAVs for various purposes. The survey included articles published from the year 2011 to 2019, which makes the recent review. Advantages and improvements for various tasks have been made for the use of drones. However, there is still much to be developed and studied. Different possibilities for applications appear constantly, making the subject review important to the scientific community.

In general, many study publications have shown potential for the joining of computer vision technology with UAVs. Governmental requirements still need to be broken for their full acceptance and use, especially those involving security and privacy. Therefore, a close relationship between researchers and aeronautical regulatory authorities becomes important and necessary. The full freedom to use UAVs for a wide range of applications, with the support of computer vision technology, will only be possible through the pooling of efforts between parts of the process, including researchers, government, users, engineers and partners.

For this reason, it is obvious that only with these efforts will it be possible to achieve the development and the most accurate results possible. The reduction of errors and technical limitations is a requirement for the generalization of the use of this association of technologies. The challenges are to develop systems that are robust to noise and deviations from data-driven models, and also it has to be good performance in computational requirements and memory space.

Considering the review carried out, the analysis and evaluation of the techniques with the best results was possible due to a thorough research, considering the best keywords, in a well-known academic and scientific portal. This article will be an object of study and analysis for future perspectives in the development of computer vision techniques. There is a large possibility of application based on computer vision in UAVs. The integration of knowledge representation architectures is of interest for the computer vision community. This review can lead to further progress towards the development and domain of techniques that are robust and able to generalize to novel data and visual learning tasks.

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