Location Management in a Structured Environment

Zakaria Ouchatti[1], Fouad Moutaouakkil[1], Souad Berradi[1]

Abstract: ***Unmanned Aerial Vehicles navigation usually relies on precise localization services that are commonly acquired using a GPS system. However, the GPS signal can be lost or disturbed due to bad weather, the existence of obstacles or other constraints imposed by the environment. In this context, the Inertial Measurement Unit alone becomes ineffectual for providing reliable information about the vehicle position, because of the cumulative error on calculation iterations. Subsequently it produces mission errors, which could have disastrous consequences. This work presents as a contribution an alternative navigation strategy in the hovering framework, which makes the flying craft able to overcome the localization constraints at these environments. The proposed solution consists of a system that toggles from a GPS-based localization to hybrid localization. This hybrid approach is essentially based on two methods. The first will be based on deterministic method, justified by exact data that don't overlap position estimation, as against the second will be based on a Bayesian method to calculate the relative UAV position by the combination of the IMU data and the results of image processing results using the SIF descriptor, which is most appropriate for our context.***

Keywords: Localization, Image processing, UAV, Feature extraction, control, EKF, SIFT, Camshift

1. Introduction

UAVs autonomous and semi-autonomous navigations usually rely on a robust localization services, which can be an annoying constraint when moving in some poor environment, because correct localization is generally based on methods which overcome constraints related to this environment.

However, with the development of more complex drone operating in uncontrolled and dynamic environments, the drone must continuously reconfigure itself to adapt to the external conditions and its objectives. Particularly, its control architecture must give a very powerful localization meeting the same requirements in order to ensure proper navigation without errors.

2. UAV localization solution

The location based visual characteristics is an ideal complement to the classic localization especially in urban areas [1]. In this context we propose a system allowing to the autonomous drone to locate permanently in this environment, by switching from a conventional signal of GPS to a signal coming from image processing block on order to build a geo-location map. Firstly we will propose a classification procedure for the various descriptors, according to the UAV flight modes, which meets the material constraints actually used. Afterwards ,according to scenario based on image processing we will develop a theoretical method, "correction-prediction", for calculating the position by increments imposed by vision-based processing and correcting the cumulative errors in each iteration.

2.1 Localization System

Vehicle maneuvers, with obstacle avoidance, can be performed in a local coordinate system. but planned autonomous navigation requires absolute positioning using a global coordinate system. However, for certain drone applications, the two cases can be covered as those carried out in restricted environments and these marks can be classified according to a measurement criterion. A distinction can therefore be made between "incremental" and "absolute" measures. These types generally have different and often complementary characteristics which are frequently combined in order to obtain a robust localization system. First, we will describe the incremental solutions, then the absolute solutions and finally hybrid. In each method, we will briefly discuss the advantages and disadvantages of each method in our context, while a more in-depth study can be found on the article. [2].

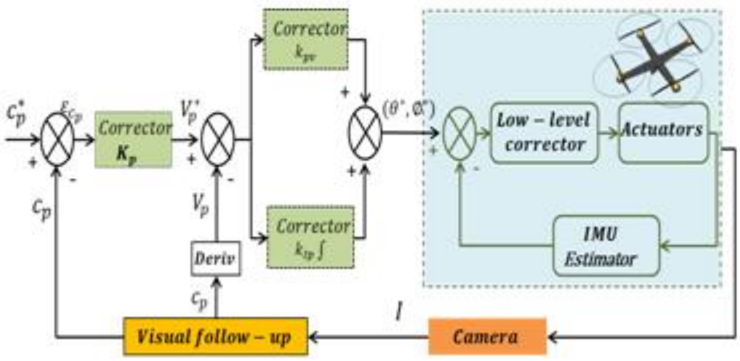


Figure 1: Translation control

The relative position is based on sensors (gyro, accelerometer ...) which provide an estimation of the incremental displacement of an object between two instants. In general, these approximations are very close to

International Journal of Science and Research (IJSR)
ISSN: 2319-7064
SJIF (2019): 7.583

each other, and so providing a good estimate. If the initial position and heading of the object are known, we can estimate the new position by knowing its movement. This sort of measures provides a good accuracy over short distances, but the accumulation of errors in the estimation of every movement causes a significant drift over long distances. In robotics, classic odometry is based on wheel rotation speed to compute the distance traveled and then change cape [3]. Despite some systematic errors (error on wheel spoke) or spot (wheel slip), this technique is reliable and simple. Movement of a mobile platform can also be estimated using one or more cameras. This technique, called optical odometry, performs matching identical points of interest between two consecutives images and rebuilt moving 3D camera [4],[5],[6]. The difference is that here we are working on a system with 6 degrees of freedom to estimate. But the computing times remain of an order of magnitude much greater than the classical odometry, which is an invalid technique for unstructured environments.

The absolute localization consists in estimating the craft position relative to some landmarks, which are themselves referenced in a Global coordinate system. The advantage of this technique is its ability to avoid drifts and error accumulations. The most common way is to use a constellation of satellites positioned in known coordinates, such as satellites that are orbiting around the Earth and are emitting radio-frequency waves. On the other hand, ground receivers can measure the travel time of these signals in order to estimate the position of these receivers (Such technique requires responses from at least 4 satellites). Up to date, Global Navigation Satellite System (GNSS) can be considered as the best means of geo-positioning in a global navigation coordinate system such as earth surface. The main system is the NAVSTAR-GPS [9] (Commonly known as GPS Global Positioning System), which also has a Russian equivalent GLONASS.

Because of the limited accuracy that a single method can achieve, it has been preferable to use hybrid solutions based on the both methods; relative measurements and absolute measurements. One possibility is to combine the two types of sensors through a coupling, such as GPS and odometer or GPS and an inertial unit. Other processes, such as map-matching or Simultaneous Localization and Mapping (SLAM) are within the scope of hybrid solutions because they cannot be related to purely relative techniques or to purely absolute techniques. Because of its wide scope or applications fields, the coupling of a GPS sensor and an inertial unit has been strongly developed by the scientific community [12], [13]. The high accuracy of the inertial location on the short displacement and the approximate position provided by the GPS allow for mutual compensation, by using two methods of coupling between these two sensors: integration through loose coupling and integration through tight coupling.

2.2 Visual command for hovering

We consider in this work a hexa-rotor drone as a mobile machine to be studied.The dynamic modeling of this type of machine was presented in the article [17]. The yaw control is identical to that proposed for the tracking task; here we simply remember the circuit diagram in Figure 2 which focuses on controlling the yaw parameter after performing the visual tracking algorithm.

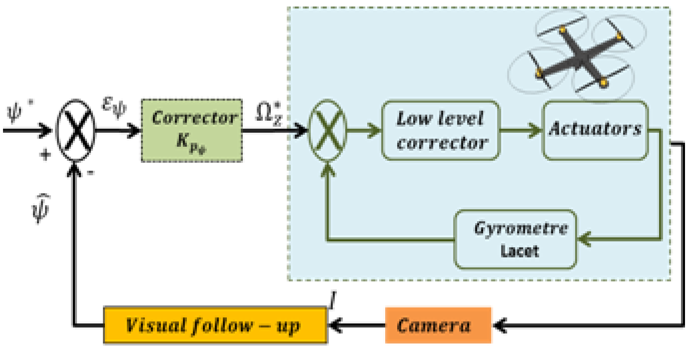


Figure 2: Lace control

To control the UAV translational movement, the position regarded as a control input corresponding to object position $c_p = (x_p, y_p)$ in the projected landmark R_p. This position c_p is obtained using an estimate of the rotation matrix R calculated from the inertial measurements through an onboard attitude option. The purpose of translation command consists in adjusting the position error defined by: $\varepsilon_{c_p} = c_p^* - c_p$ which designates the desired position of the object in the image plane.

$V_p^* = K_p \varepsilon_{c_p}$ Hierarchical command relation and K_p Proportional gain.

This speed will be controlled in an internal control loop which plays a damping role necessary for the system stability, as the speed corrector determines the attitude control (pitch and roll) to be sent to the UAV. To take the system's internal disturbances into account, a proportional integral (PI) is used to regulate the speed, and a proportional controller regulates the position error. The speed error will be defined by:

$$\varepsilon_{V_p} = V_p^* - V_p \qquad (1)$$

Where the current error V_p is obtained by a derivative filter at the position c_p. We will use a filter in the following form:

$$V_p^{(k+1)} = (1-\alpha)V_p^{(k)} + \alpha \frac{c_p^{(k+1)} - c_p^{(k)}}{\delta t} \qquad (2)$$

α determines the cutoff frequency.

The attitude set-point (θ *, φ *) sent to the drone is in the form:

$$(\theta^*, \emptyset^*) = k_{pv}\left(k_p \varepsilon_{c_p} - V_p\right) + k_{Ip} \int (k_p \varepsilon_{c_p} - V_p) \qquad (3)$$

k_{pv} and k_{Ip} are gains PI used by the speed regulator .

International Journal of Science and Research (IJSR)
ISSN: 2319-7064
SJIF (2019): 7.583

3. Vision-based localization approach

In this section we present a new arbitration concept, which consists in finding the UAV position permanently, by collaborating between the satellite measurements and the information extracted from the observation as proprioceptive data.

3.1 Arbitrator System

The Arbitration system consists of two blocks: measurement control block and tilt block. The first must be able to assess the reliability of the GPS measurement [11] and the secondary makes it possible to pass from a determined method when there is no absolute measurement noise to a method based on the position calculation by Image flux processing, where the problem of perception becomes a Problem of statistical estimation or as a Markov process.

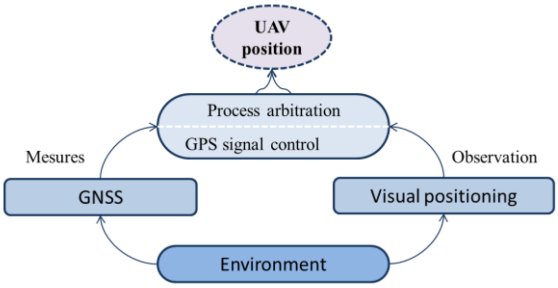


Figure 3: Arbitrator system

- ***Location in Deterministic setting***

The location in the deterministic framework consists of merging the GPS data and the IMU data to determine the position of the craft as shown in the following figure:

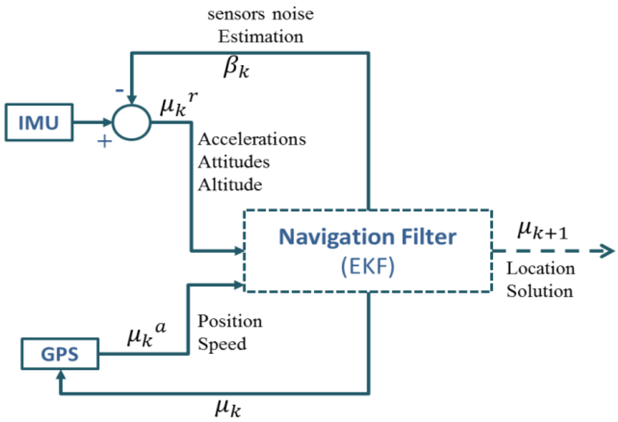


Figure 4: Deterministic localization

We note $\mu_k \epsilon E$ the parameter vector which characterizes the UAV position of the device at the instant t, $\epsilon \subset \mathbb{R}^{n_\mu}$ the space of parameters vectors. With n_μ is the number of parameters considered.

The deterministic correction function consists in finding the new parameters μ_{k+1} which minimize a distance in the measurements space B at the instant t + 1.We can, therefore, have a function that associates to each position of a measurement vector:

$$g\ :\mu(t)\epsilon E \rightarrow g\big(\mu(t)\big)\epsilon\, \mathcal{B}$$

It is assumed that the space E is provided with a distance (standard), so the problem can be written in the case of a Euclidean distance such as:

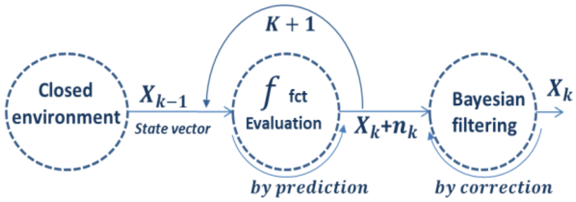
$$\mu_{k+1} = \arg\min_\mu \left\| g(\mu) - g\left(\mu_k\right) \right\|^2$$

Where $g(\mu_k)$ is a reference measurement vector, which can be taken in the previous image. The distance to be minimized is also called objective function.

- ***Localization in the Bayesian framework***

In case of loud noises or loss of the GPS signal, we'll consider the localization problem as a statistical estimation problem; we try to estimate the system state over time, according to a coupling, the sensors measures and visual observations to minimize the accumulated noise and keep a correct location. The state vector usually consists of the parameters of the position (2D or 3D) μ_k but also it can contain other parameters (ie speed, acceleration ...).

Suppose that we have a model f to evaluate the system stateX_k, which makes it possible to predict the new state of the system X_k, from the previous state X_{k-1}. This model is an approximation of the system behavior, which has an uncertainty can be modeled by a noise n_k.. We have already developed this method in the article [17], so we can summarize the method in the following diagram:



If we consider a model with constant speed $\left(v_{x_k} v_{y_k}\right)^T$ and a state vector $X_k = \left(x_k y_k z_k v_{x_k} v_{y_k} v_{z_k}\right)^T$, the state evolution can then be modeled by the following linear state-equation (4):

$$f(X_{k-1}, n_k) = AX_{k-1} + n_k (4)$$

As for a time interval Δt:

$$A = \begin{pmatrix} 1 & 0 & 0 & \Delta t & 0 & 0 \\ 0 & 1 & 0 & 0 & \Delta t & 0 \\ 0 & 0 & 1 & 0 & 0 & \Delta t \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix}$$

It's assumed that it has a measurement model or an observation model $z_k = h(X_k, b_k)$ / withb_k is the model noise.

Unlike deterministic methods, the measurement information are noisy in statistical method, this noise will be taken into account in the estimation process. Therefore the measured state variables are considered as random variables. Estimating the system state X_k from the known measurements $z_{1:k} = (z_1, \cdots, z_k)$ up to time t will be equivalent to determining a probability function$p(z_k|z_{1:k})$, which represents the probability density of the state z_k by knowing the measurements $z_{1:k}$.

Therefore, we propose an optimal recursive solution to this problem of position calculus based on two steps:

$$(X_{k-1}|Z_{1:k-1}) \xrightarrow{\text{by prediction}} p(X_k|Z_{1:k-1})$$
$$p(X_k|Z_{1:k-1}) \xrightarrow{\text{by correction}} p(X_k|Z_{1:k})$$

The prediction step uses the dynamic equation and the probability density $p(X_{k-1}|Z_{1:k-1})$to obtain the a priori probability density$p(X_k|Z_{1:k-1})$:

$$p(X_k|Z_{1:k-1}) = \int p(X_k|X_{k-1})p(X_{k-1}|Z_{1:k-1})dX_{k-1} \quad (5)$$

the correction step then calculates the posterior probability density $p(X_k|z_{1:k})$ from the likelihood function $p(z_k|X_k)$ through recursive Bayes' formula (6):

$$p(X_k|Z_{1:k}) \propto p(Z_k|X_k)\int p(X_k|X_{k-1})p(X_{k-1}|Z_{1:k-1})dX_{k-1} \quad (6)$$

The localization component calculates the position of the extracted features in the global reference frame. A last position, supplied by GPS, of the moving vehicle is necessary to alternate to a system referenced point to point using the processing of the combination {Image flow and laser odometer response}.

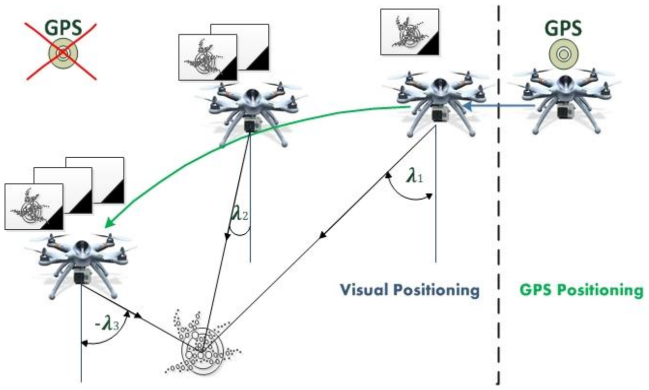


Figure 5: Concept of location method

The measuring principle on stage consists make an adjustment between a reference model of the object and measurements taken as the displacement progresses.

3.1 The proposed hybrid localization approach

In FIG. 6, we propose a system that allows an UAV to locate permanently in an uncertain environment, relying on the construction of a positioning system that switches from a conventional GPS signal to a signal comes from a visual processing block. In addition to the process of extracting features, the construction of the map relies on two additional processes for evaluating functionality and function compression. These methods allow generating an efficient map which offers high localization accuracy with less functionality; consequently it provides computational savings in memory and processing time [14], [15].

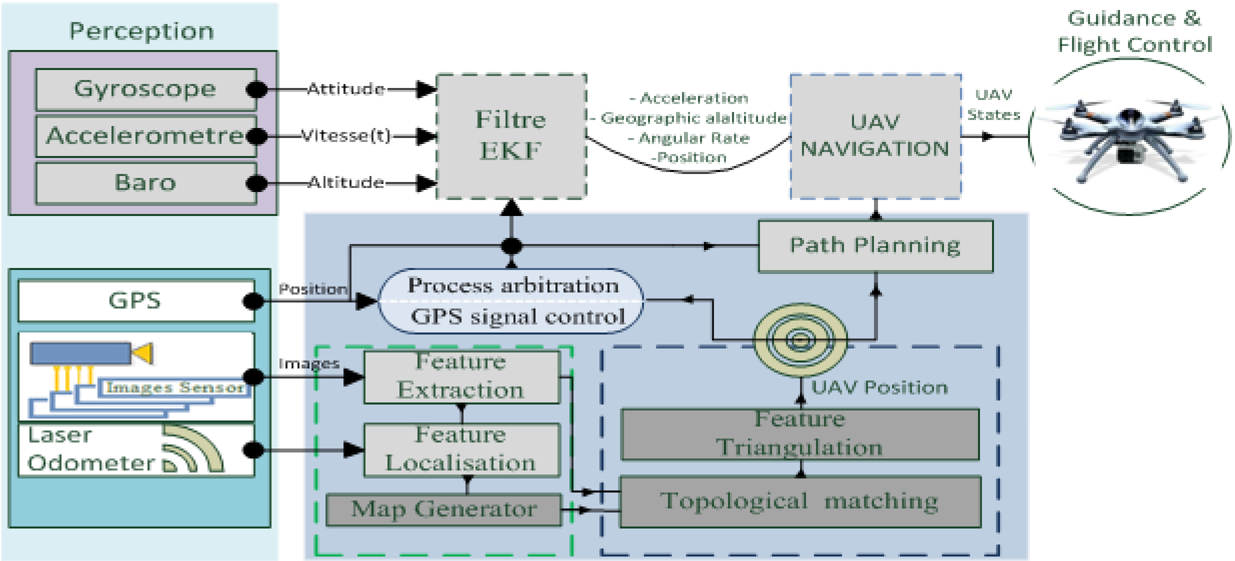


Figure 6: Localization block in proposed architecture

Moreover, the solution structure uses topological features and odometer measurements in order to combine them to build a functional map.

The structure of the proposed solution uses three main modules: feature extraction, map generation and UAV localization.

3.2 Feature detection method

The first step is based on the analysis of image sequences captured by UAV to detect a reference object,and prepare the typical characteristics which must be defined and detected. For this reason, we try to present an effective detection method applied to a series of captured images, which makes it possible to keep the object characteristics invariant to scale, to rotation, to translation and not to affect the maximum possible lighting effects.

Firstly, the approach seeks the extraction of the characteristic points of the zone to be followed and it initializes the estimation support of the global movement. A second phase corresponds to the extraction of target characteristics. It has two parts:

- The first part is the prediction of thepoint's position to follow in the current image. Using an estimator of the overall motion. In [13] it is shown that a quadratic type model is the most suitable for writing the motion of a 2D scene. For reasons of computing time, we have used is the affine model.
- Second part corresponds to the search of points using the prediction in order to refine the estimate of the target position. This step corresponds to the analysis of local motion in the image. The method is developed in Article [17]

In [16] the SIFT (Scale-Invariant Features Transform) can detect and identify similar elements between different successive images. This is a method proposed by David G. Lowe which was based on improving the approach [17]. In [7] Lowe not only presented the SIFT but also discussed the key points pairing. SIFT can be invariant to image scaling, rotating and blurring which is a key advantage of object detection from drones.

On review [8], Bay and Tuytelaars are proposed robust functions for image convolutions and the Fast-Hessian detector. The SIFT and SURF algorithms have different methods for detecting characteristic points. SIFT built an image pyramid and treats each layer with Gaussian on increasing sigma values before taking the difference. On the other hand, creates SURF sampling method is an easy process for the higher levels in the pyramid resulting images. The following results show that it works faster and produced good results.

A. Comparison Results

In order to justify the choice of the method used, we try to analyze the algorithms developed on Matlab that we have implicated in a raspberry environment 2, for satisfying the same conditions of an autonomous drone, In order to evaluate the performance of these methods according to the constraints that can be found in a real context, execution time (A), average accuracy, change of point of view (rotation) (B) (C) and illumination changes (D), consequently we come to construct the following comparative table 1,

Figure 7: Test device

Table 1: Comparison of methods

Methods	SIFT	SURF	Camshift*	A-SIFT
A	100ms	70 ms	95 ms	115ms
B	85.98%	80,88%	83,34%	80.98%
C	93,36%	94,78%	94,01%	93,36%
D	97,59%	96,46%	94,78%	96,59%
Time	Good	Best	Good	Common
Scale	Good	Good	Common	Best
Rotation	Good	Common	Good	Common
Illumination	Best	Common	Common	Good
Affine	Good	Good	Good	Good

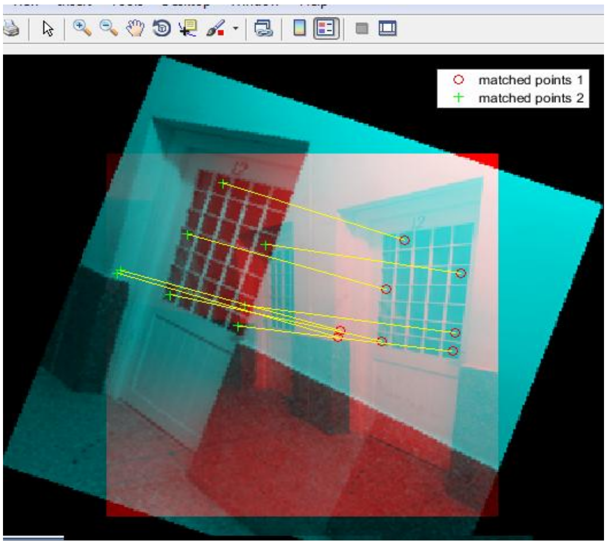


Figure 8: Roll simulation

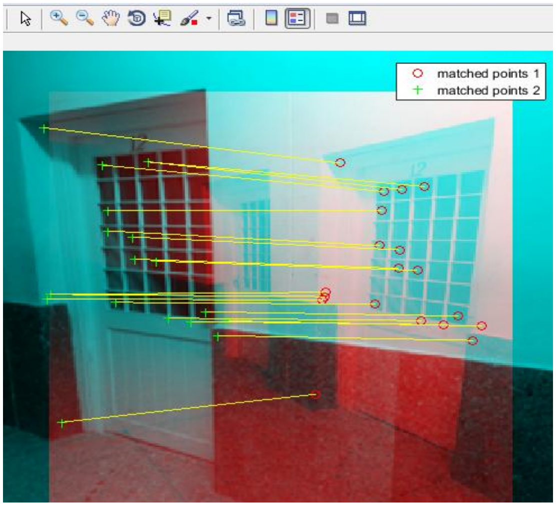


Figure 7: Translation simulation

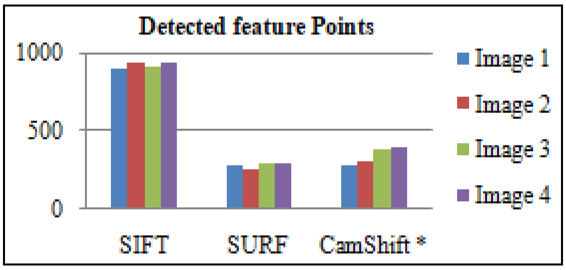


Figure 10: Detected Points-Features

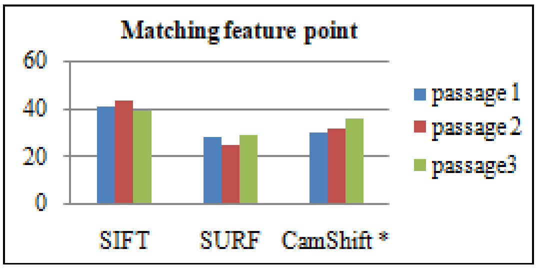


Figure 11: Correspondence Points

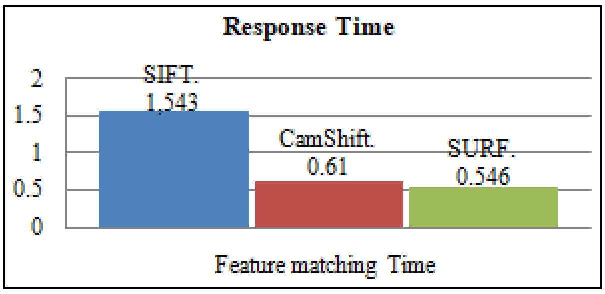


Figure 12: Response time test

The SIFT key points are the extreme points of the Gaussian scale space differences. The SIFT algorithm computes the unstable extreme point and the exact position of the pixel using the Taylor expansion and the Hessian matrix. Also in the Gaussian image, the values and direction of each neighborhood pixel is calculated to get the scale of independence key-point and direction. Since these key points are invariant to these conditions, so this method can achieve a better detection result.

B. Coordinates calculation

Below, we compare the coordinates calculated by a classical method based on the IMU alone and the method proposed in the previous section.

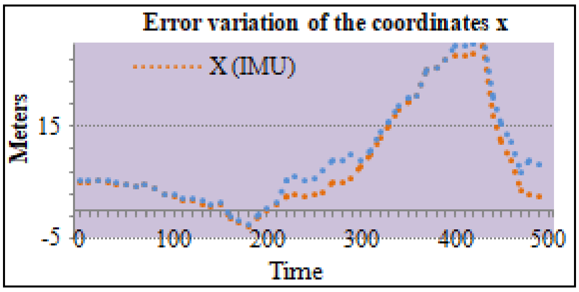


Figure 3: Variation of X Through time

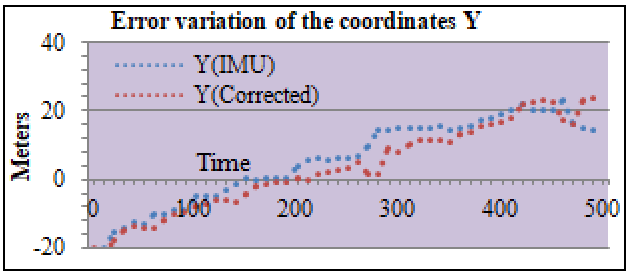


Figure 8: Variation of Y Through time

These results in Fig 14 and 15, show that, in closed places, the different improvements make tracking much less susceptible then in the classical version based on the IMU only. This is particularly noticeable for example in the variation of the estimated altitude on the displacement of a few centimeters.

4. Conclusion

We have just presented our proposed approach in the case of positioning the drone in closed areas through a visual system that can replace the GPS with the same performance,by confronting all these techniques with our context, in particular, the various constraints imposed. Our objective is to develop and validate this control architecture based on visual servoing in order to reinforce localization strategies, autonomous navigation and to have a good implementation of any object tracking tasks.The rest of our reasoning approach, which works on two aspects, UAV command and image Processing, seeks to have a greater integration of visual methods as an intelligence module compatible with any modular architecture.In order to allow a very strong imbrication between the image analysis and the control thus avoiding certain temporal constraints present in the other servo-control techniques.

Abbreviation and Acronyms

IMU: Inertial Measurement Unit
GPS: Global Positioning System
GNSS: Global Navigation Satellite System
UAV: Unmanned Aerial Vehicle
EKF: Extended Ealman Filter
SIFT: Scale-Invariant Features Transform
SURF: Speeded Up Robust Features
Camshift*: adapted Continuously Adaptive Mean Shift

References

[1] Boumehed, M., Alshaqaqi, B., &Amraoui, M. (2016). Distance and Speed Measurement and Classification of Road Traffic. International Journal of Applied Engineering Research, 11(2), 1347-1352.

[2] Jung Jongdae 2016 13th International Conference on Ubiquitous Robots and Ambient Intelligence (URAl) [Localization of AUV s Using Depth Information of Underwater Structures from a Monocular Camera] August 19~22, 2016 at Sofitel Xian on Renmin Square, Xian, China.

[3] Kelly. Some useful results for closed-form propagation of error in vehicle odometry. Technical report, CMU-RI-TR-00-20.(2000)

[4] Muller, Peter M., "Optical Flow and Deep Learning Based Approach to Visual Odometry" (2016). Thesis. Rochester Institute of Technology. Accessed from.

[5] Zhang, R., & Wheeler, M. D. (2019). U.S. Patent No. 10,309,778. Washington, DC: U.S. Patent and Trademark Office.

[6] Florez, S. R., Fremont, V., and Bonnifait, P. (2009). An experiment of a 3d real-time robust visual odometry for intelligent vehicles. In *Proc. of the 12th IEEEInternational Conference on Intelligent Transportation Systems, ITSC 2009*, pages 1 – 6, St. Louis.

[7] Vidal, J., & Lin, C. Y. (2016, June). Simple and robust localization system using ceiling landmarks and infrared light. In Control and Automation (ICCA),

2016 12th IEEE International Conference on (pp. 583-587). IEEE.

[8] J. Jung H. Myung "AUV Localization Using Visual Information of Underwater Structures" , Proc. The 12th International Conference on Ubiquitous Robots and Ambient Intelligence (URAI 2015), pp. 228-230 2015.

[9] Dudek, G., & Jenkin, M. (2016). Inertial Sensing, GPS and Odometry. In Springer Handbook of Robotics (pp. 737-752). Springer International Publishing.

[10] Mori, D., Sugiura, H., & Hattori, Y. (2019, October). Adaptive Sensor Fault Detection and Isolation using Unscented Kalman Filter for Vehicle Positioning. In 2019 IEEE Intelligent Transportation Systems Conference (ITSC) (pp. 1298-1304). IEEE..

[11] Kempke, B., Pannuto, P., Campbell, B., & Dutta, P. (2016, November). SurePoint: Exploiting Ultra Wideband Flooding and Diversity to Provide Robust, Scalable, High-Fidelity Indoor Localization. In Proceedings of the 14th ACM Conference on Embedded Network Sensor Systems CD-ROM (pp. 137-149). ACM.

[12] Strömbäck, P. (2003). Centralized GPS/INS integration for urban navigation. Scientific Report FOI-R-0847-SE, Swedish Defense Research Agency.

[13] Yoon, Y. J., Li, K. H. H., Lee, J. S., & Park, W. T. (2015). Real-time precision pedestrian navigation solution using Inertial Navigation System and Global Positioning System. Advances in Mechanical Engineering, 7(3), 1687814014568501.

[14] Luo Juan, OubongGwun, “A Comparison of SIFT, PCA-SIFT and SURF”, International Journal of Image Processing (IJIP) Volume 3, Issue 4, pp 143-152 (2009)

[15] Agrawal, P., Sharma, T., &Verma, N. K. (2020). Supervised approach for object identification using speeded up robust features. International Journal of Advanced Intelligence Paradigms, 15(2), 165-182.

[16] Lim, J., & Lee, K. (2019). 3D object recognition using scale-invariant features. The Visual Computer, 35(1), 71-84.

[17] D. G. Lowe, “Distinctive image features from scale-invariant keypoints,” *International Journal of Computer Vision*, 2004, 60 (2): 91–110.

[18] *Z.ouchatti 13th International Conference Computer Graphics, Imaging and Visualization [Deterministic method of visual servoing: robust object tracking by drone] , BeniMellal, Maroc.2016.*

Author Profile

[1]ENSEM, Hassan-II University,Casablanca, Morocco.
Zakaria OUCHATTI received à Mechatronics Engineer’s degree from National School of Applied Sciences (ENSA) in June 2014 in Tetouan, Morocco. In December 2014 he joined,as a PhD student, the System Architecture team of the National and High School of Electricity and Mechanic (ENSEM), Casablanca, Morocco. His current main research interests concern the visual servoing control in real timeof autonomous UAVs based on multi-agent systems

Fouad MOUTAOUAKKIL received the PhD in computer science from the ENSEM, Hassan-II University in November 2010, Casablanca, Morocco. in 2005, he obtained the Engineer Degree in industrial automation from the ENSEM, Hassan-II University, Casablanca, Morocco. In 2006 he rejoined the system architecture team of the ENSEM. His actual main research interests concern Remote Control over Internet Based on Multi agents

Souad Berradi received à Mechatronics Engineer’s degree from National School of Applied Sciences (ENSA) in June 2014 in Tetouan, Morocco. In December 2014 he joined, as a PhD student, the System Architecture team of the National and High School of Electricity and Mechanic (ENSEM), Casablanca, Morocco. His current main research interests concern UAV autonomy control and management.