24th COBEM - 2017

24th ABCM International Congress of Mechanical Engineering
December 3-8, 2017, Curitiba, PR, Brazil

COBEM-2017-2527
DATA ANALYSIS ABOUT FLIGHT DYNAMICS: A REVIEW TO APPLY MACHINE LEARNING TECHNIQUES IN UNMANNED AERIAL VEHICLES

Gustavo Prado Oliveira
Instituto Federal do Triangulo Mineiro – Campus Uberlândia Centro – Rua Blanche Galassi 150 – Bairro Morada da Colina - CEP: 38411-104 – Uberlândia - MG
gustavoprado@iftm.edu.br

Roberto Mendes Finzi Neto
Universidade Federal de Uberlândia - Av. João Naves de Ávila, 2121 - Bairro Santa Mônica -CEP 38400-902 - Uberlândia - MG
finzi@ufu.br

João Marcelo Vedovoto
Universidade Federal de Uberlândia - Av. João Naves de Ávila, 2121 - Bairro Santa Mônica -CEP 38400-902 - Uberlândia - MG
jmvedovoto@mecanica.ufu.br

Leonardo Sanches
Universidade Federal de Uberlândia - Av. João Naves de Ávila, 2121 - Bairro Santa Mônica -CEP 38400-902 - Uberlândia – MG
lsanches@ufu.br

Abstract. *The possibility of independent flights without human interference and the ability to make decisions without external interventions are the main attractions for a wide field of application in Unmanned Aerial Vehicles (UAV). To find the correct algorithm from Machine Learning to apply in a UAV guaranteeing the flight autonomy and recovery from flight stability quadcopter through turbulence, it is necessary to analyze all data obtained from the embedded inertial sensors from the UAV. The algorithm selection will depend on the size and type of data that is necessary working with, the insights that want to get from the data and how those insights will be used, therefore in this paper, will be necessary to compare different kind of algorithm, and take this decision. The authors would like to thank FAPEMIG (Fundação de Amparo à Pesquisa do Estado de Minas Gerais) that funded this work.*

Keywords: *Flight dynamics, data analysis, Machine Learning, Unmanned Aerial Vehicles, autonomous flight.*

1. INTRODUCTION

Technological advances in areas such as microprocessors, sensors, communication networks, have increased the development of Autonomous Unmanned Aerial Vehicles (AUAV). The possibility of independent flights without human interference and the ability to make decisions without external interventions are the main attractions for a wide range of application.

Among the UAV models studied for autonomous flight, the quadrotor is generally adopted for having advantage over the helicopter in the matter of stability and agility. Quadrotor do not require complex mechanical control linkages for rotor actuation, relying only on fixed pitch rotors and on rotor speed for vehicle control.

As can be seen in some academic papers (Bouabdallah *et al* , 2004a; Bresciani, 2008; Hoffmann et al, 2004 and Quemel, 2009), studies have already been carried out about flight stability with the use of classical control techniques, like with PID controllers (Proportional, Integral and Derivative). Both linear and non-linear controllers are used to achieve a high degree of flight stability (Bouabdallah *et al* ,2004b and Kendoul *et al* 2006). According to Waslander *et al* (2005), and Hoffmann *et al* (2004), even with the feasibility of classical control techniques, these techniques still prove to be insufficient to provide stability to a quadrotor that is subject to the complex airflow induced by its own rotors. Therefore, to guarantee its autonomous flight stability, a high degree of control complexity is required.

In order to an UAV be able to maintain flight stability under adverse atmospheric conditions, the effect of turbulence must be considered. Fluid-structure interaction phenomena, such as Vortex Induced Vibrations, can easily occur during UAV operation, creating fluid dynamics instabilities, which coupled with a flexible structure, can even lead to catastrophic structural failure (Bristeau *et a*l, 2009).

To address the problem of state estimation, UAV are usually equipped with embedded inertial sensors (gyrometers and accelerometers, see Titterton and Weston (2004)), a sonar altitude sensor (or a barometer), an absolute position or velocity sensor such as a GPS or a camera feeding vision algorithms (see e.g. Hamel and Mahony, 2007; Rondon *et al*, 2009), and a magnetometer, to measure the direction, strength, or the relative change of the magnetic field at particular location.

Numerous approaches to deal with flight control quadrotor have been applied to a great variety of problems, including vision based detection algorithms for indoor flight (Tournier *et al*, 2006 and How *et al,* 2008), dynamic programming approaches to task assignment (Bethke *et al*, 2008), autonomous tracking and regulation in indoor and outdoor settings (Hoffmann *et al*, 2007), and cooperative manipulation (Michael *et al*, 2009 and 2010). Control approaches, including feedback linearization with a high-order sliding mode observer (Benallegue *et al* 2008), and machine learning (Lupashin *et al*, 2010) have been used to perform acrobatic maneuvers despite the uncertainties. Simulation results have shown nonlinear controllers can also provide robustness to modeling errors in vertical take-off and landing drones (Hua *et al*, 2009).

Traditional control laws like Linear-quadratic regulator (LQR) and Linear-quadratic Gaussian control (LQG), show some robustness to uncertainties but not enough to those that result in actuator failure or structural damage. They also present unstable behaviors depending on different types of sensors applied to quadrotor.

Considering the information previously presented, it is necessary to define a mission or activity for the quadrotor (given distance, altitude, duration, and environment requirement), analyze a combination of appropriate sensors, which autonomy level it will have and then will be possible to analyze all quadcopter data to define which algorithm to apply to solve the problem. In order to improve the performance of quadcopters, a number of researchers have proposed learning schemes including those based on supervised, unsupervised and reinforcement learning techniques (Dunfied *et al*, 2004; Dierks and Jagannathan, 2010).

To present the most relevant studies about machine learning applied to UAV control, this paper has been organized as follows: Section 2 reviews the quadrotor dynamics, the autonomy levels and which kind of sensors can be used to guarantee the autonomy. Section 2 present the general view to machine learning techniques. Section 4 describes the experimental case setup and the generated data to be analyzed. Section 5 presents and analyses different types of algorithm. Finally, Section 6 presents the final considerations.

2. THE THEORY ENVOLVING QUADCOPTER

Quadcopters is a platform studied as Unnamed Aerial Vehicle because it provides different benefits, including the capability to fly freely in three-dimensional space, and the ability to overcome obstacles. For being a small platform that require hovering capability, quadcopters are often a good choice (Siegwart *et al*, 2011), including to maintain autonomy, depending in which kind of sensors it use.

2.1 Quadcopter dynamics

Several groups (Bouabdallah et al, 2004b and Hoffmann et al, 2007) have studied the dynamics of quadcopter. The main modeling principle is to consider the quadrotor's body rigid and with six degrees of freedom: position (p_1, p_2, p_3) in the inertial coordinate system O; and attitude, represented by the rotation matrix $\frac{O}{v}R$ between the inertial coordinate system *O* and the body-fixed coordinate system *V*, as shown in Fig. 1.

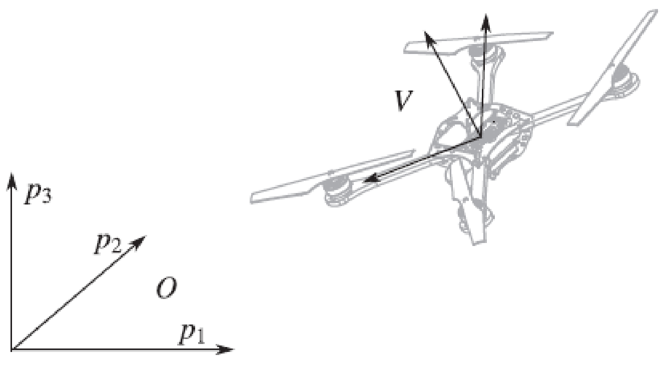

Figure 1. The inertial coordinate system *O* and the vehicle coordinate system V, used to describe the dynamics of the quadcopter

Four brushless motors are used in the quadcopter and each one incorporates a fixed-pitch propeller. The produced thrust, drag, and the resulting rotational dynamics in the body-fixed coordinate system V are

$$l\dot{\omega} = \begin{bmatrix} L(F2-F4) \\ L(F3-F1) \\ \zeta(F1-F2+F3-F4) \end{bmatrix} - \omega \times l\omega \tag{1}$$

where $\omega = (\omega_x, \omega_y, \omega_z)$ is the rotational rate of the vehicle, l is its rotational inertia, L the arm length of the vehicle, ζ the drag-to-thrust ratio of the propeller, and F1 to F4 are the individual thrust forces of each propeller. The total mass-normalized thrust produced by the four propellers is

$$a = \frac{1}{m}(F1-F2+F3-F4) \tag{2}$$

where m denotes the mass of the vehicle. The rotational kinematics are given by the first-order differential equation of the rotation matrix

$$\frac{O}{V}\dot{R} = \frac{O}{V}R\begin{bmatrix} 0-\omega_z\omega_y \\ \omega_z 0-\omega_x \\ \omega_y\omega_x 0 \end{bmatrix} \tag{3}$$

The translational dynamics of the vehicle, expressed in the inertial coordinate system O, are

$$\begin{bmatrix} \ddot{p}_1 \\ \ddot{p}_2 \\ \ddot{p}_3 \end{bmatrix} = \frac{O}{V}R\begin{bmatrix} 0 \\ 0 \\ a \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ -g \end{bmatrix} \tag{4}$$

where g denotes the gravitational acceleration.

This first-principles model of the quadcopter rotational and translational dynamics is commonly used to design and analyze algorithms such as feedback control laws and path planners (Mahony et al, 2010), and captures near-hover dynamics well.

Using quadcopter to take pictures or to shoot a movie, one of the main fighting mode is hovering. Analyzing this flight is easy to determine when the flight undergoes destabilization, because the variation of angular velocity and displacement are small, consequently it is easier to define which action should be taken.

Flight stability under adverse atmospheric conditions, have not such simple attitudes to be took, considering that to determine the flight conditions of a quadrotor, it is necessary to analyze the flight dynamics. Already in conditions of movement, a more complex control system is required, since quadcopter differs from fixed-wing aircraft.

Fixed-wing aircraft control systems include actuators, which exert forces in various directions, generate rotational forces or moments about the aerodynamic center of the aircraft, and thus rotate the aircraft in pitch, roll, or yaw (Figure 2). For example, a pitching moment is a vertical force applied at a distance forward or aft from the aerodynamic center of the aircraft, causing the aircraft to pitch up or down.

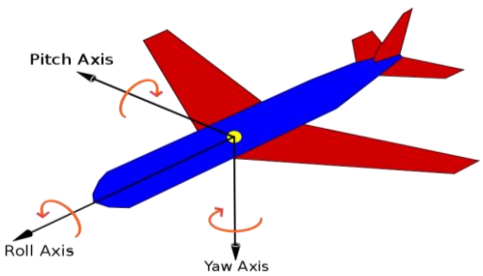

Figure 2: Pitch, roll and Yaw movement in Fixed-wing aircraft

For quadcopters, it is necessary to define pitch, yaw and roll in a different way (Figure 3). Pitch is the movement of quadcopter either forward or backward. Forward Pitch is achieved by pushing the aileron stick forward, which makes the quadcopter tilt and move forward, away from you. Backward pitch is achieved by moving the aileron stick backwards (towards you), making the quadcopter come closer to you. The same happens to roll and yaw.

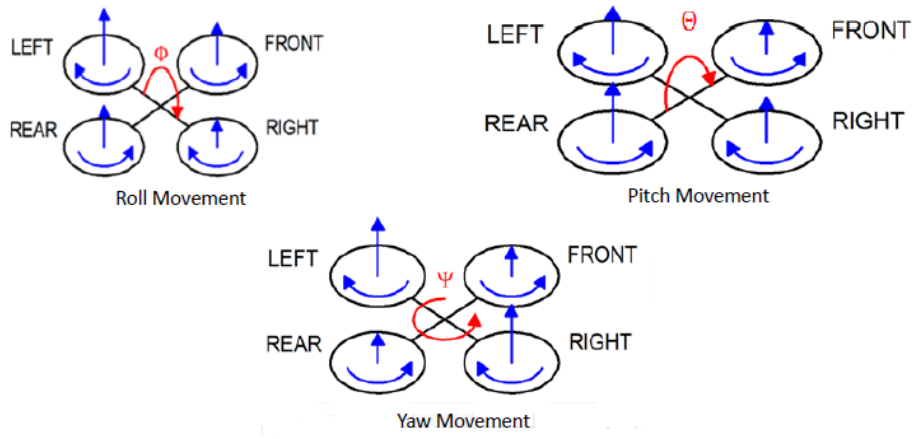

Figure 3: Pitch, Roll and Yaw movement in a Quadrotor

2.2 Autonomy

The operation of a quadrotor is generally limited by the main human factor that is the capacity to control the UAV and bandwidth. Human control capability over quadcopter has been shown to underperform inertial-based flight controllers in stabilization tasks (Cheng *et al*, 2014). Recent studies have demonstrated that manual control of MAVs in cluttered and dynamic environments is a challenging task, even for experienced operators (Wilson and. Russell, 2007; Jenkins *et al*, 2001). The limited task-load capacity of human operators limits MAV operations because the introduction of tasks such as payload management and comprehension of the acquired data require significant human resources. To summarize the activities in MAV operation is desirable that the aircraft has some autonomy level to take decisions according to the situation. The study by Young et al (2005) highlighted the importance of autonomy for MAV operation.

Before define autonomy, is necessary to measure the level of autonomy (LoA) to guarantee the safety of an autonomous MAV (Clothier and Walker 2014).

A review of various definitions and scales of autonomy that have been applied to MAVs and unnamed aircraft system (UAS) is provided by Clothier *et al* (2013). According to Elbanhawi *et al* (2017), autonomy can be separated in two categories based on “independence” and “complexity”. The first category describes autonomy as the independence of the UAS from the remote pilot (RP). The second category relates increasing autonomy to increasing complexity to resemble human intelligence.

At first, this work will focus on studding quadrotor independence, by the way various frameworks try to define UAS autonomy based on independence (Russel and Norvig, 2010), and the international Civil Aviation Organization (ICAO, 2011) referred to an Autonomous Aircacft System(AAS) simply as an aircraft that operates with no human interference.

According to Clough (2002) is necessary to describe the AAS according to diverse LoA and the decision-making to achieve the mission requirements.

The study of the hovering flight situation, i.e. when the aircraft is flown so that it maintains a constant position over the ground, is the main capability which differentiates helicopters from airplanes. Hovering is one of those flight situations that seems like it should be very simple, so to start an analysis to apply some autonomy level, it’s important to start with a simple case.

Is necessary to implements some specific operations in the quadcopter in order to guarantee some LoA and, considering the hovering situation, the following ones stand out:

- Self-level: attitude stabilization on the pitch and roll axes.
- Altitude hold: The aircraft maintains its altitude using barometric or ground sensors.
- Hover/position hold: Keep level pitch and roll, stable yaw heading and altitude while maintaining position using GNSS (Global Navigation Satellite System) or inertial sensors.

To limit this paper research review for the hover situation, we focus the data analysis using sensors applied at this flight situation, with clarification about these sensors in next session.

2.3 Sensors

To recognize the environment aiming to deal with different situations, and UAV needs to be equipped with various sensors to estimate the pose (position and attitude). According to Mohamed *et al* (2014) and Dobloi *et al* (2008), it is possible to classify sensors used in pose estimation provided by a framework as illustrated in figure 4.

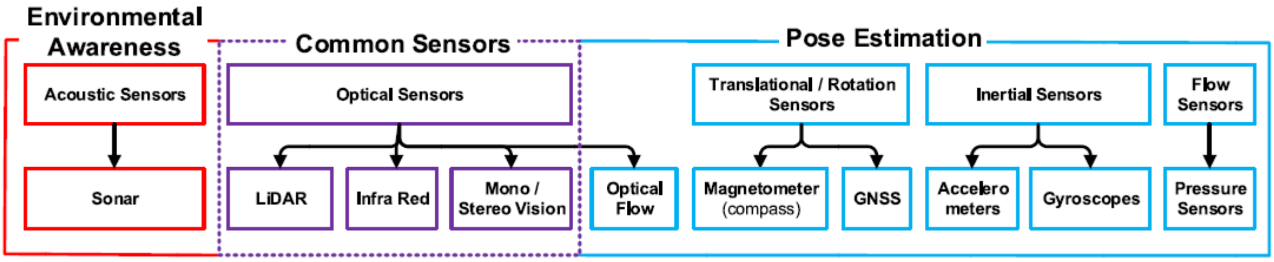

Figure 4. UAV autonomous sensors category

Focusing on hovering situation and considering the Figure 4 taxonomy, it is possible to highlight pose estimation sensors as Magnometer, GNSS, Accelerometers and Gyroscopes.

It is important to consider the turbulence intensity that increases at lower altitude (Walshe,1972). Consequently, improve UAV operation in turbulent conditions is essential to enable them to safely conduct autonomous missions and mainly ensuring that it optimizes flight stability as desired in hovering. (Mohamed, 2014 a)

Posing estimation involves localization and attitude sensors, which, respectively, can be used to determine the position and orientation of the vehicle. Inertial Navigation Units (INUs), which employ a combination of inertial, rotational, and translational sensors, are commonly used for posing estimation. Inertial-based sensors can often lack the update rate, resolution, accuracy, precision, robustness, and reliability needed for UAVs. Sensor fusion in combination with efficient and effective algorithms can lead to substantial pose estimate enhancement in addition to bounding accumulated errors. Attempts to also develop automated tuning algorithms which can be implemented on-board the vehicle may provide further enhancements (Elbanhawi *et al*, 2017).

The use of a low cost microcontrolled system like Arduino and the aforementioned sensors simplify the task to improve posing estimation and thus enhance attitude stability. The microcontroller must act like a black-box recording information related to the aircraft pose under adverse situation to prepare data for the machine learning algorithms. Figure 5, presents accelerometer and gyroscope data obtained from quadrotor fling under intense turbulence.

```
COM3 (Arduino/Genuino Uno)

Initializing SD card...card initialized.
Initializing I2C devices...
Testing device connections...
MPU6050 connection successful
a/g:    408     -44     17256   -36     137     -40
a/g:    340     68      17244   -48     131     -23
a/g:    480     -32     17260   -45     131     -51
a/g:    412     56      17296   -49     122     -45
a/g:    416     -44     17324   -76     144     -36
a/g:    460     40      17408   -68     144     -40
a/g:    392     -64     17384   -34     150     -28
a/g:    560     -32     17224   -52     118     -34
a/g:    436     68      17316   -44     135     14
a/g:    428     60      17396   -69     144     -21
a/g:    408     -68     17344   -49     116     -51
a/g:    452     -12     17280   -59     157     -42
a/g:    436     64      17356   -55     154     -20
a/g:    460     -4      17260   -53     120     -28
a/g:    468     88      17308   -65     149     -37
```

Figure 5: data taken from accelerometer and gyroscope in instability situation

Besides the data of the accelerometer and the gyroscope, information about the electrical power applied to each brushless must be recorded too. When an instability is identified, the necessary level of power change applied to each rotor can be more easily established. Finally, all this considered, the best way to approach this stability problem is implementing algorithms that apply decision making capabilities and machine learning Techniques.

3. MACHINE LEARNING

There are different definitions to explain what machine learning is, and some of them consider that machine learning is to teach machines to realize activities that are natural for a human.

According to Alpaydin (2010), machine learning is the task of programming computers to optimize a performance criterion using example data or experience. When there is a defined model to some parameters, learning will be the execution of a program to optimize those parameters using the experience or training data. The model may be predictive to obtain future data, descriptive to gain knowledge, or both.

Several real applications can use machine learning, e.g., image processing to recognize faces, movement detection, computational biology to detect tumor, natural languages processing, automotive and aerospace control, etc. To solve those problems, it is possible to use different machine learning techniques (Figure 6). The algorithm selection will depend on the size and data type necessary to work with, the insights that are required from the data and how those insights will be used.

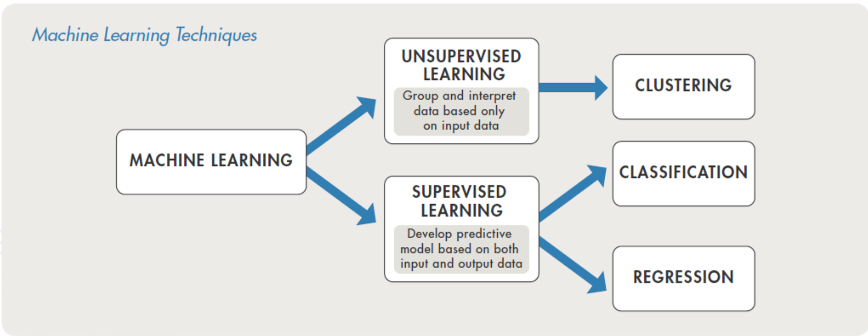

Figure 6: Machine Learning Techniques.

Alpaydin (2010), presents an example analyzing a financial situation. that consider a credit as an amount of money loaned by a financial institution, i.e. a bank, to be paid back with interest, generally in installments. It is important for the bank to be able to predict in advance the risk associated with a loan, which is the probability that the customer will default and not pay the whole amount back. This is both to make sure that the bank will make a profit and to not inconvenience a customer with a loan over his or her financial capacity. This classification is an example of a problem where there are two classes: low-risk and high-risk customers. The information about a customer makes up the input to the classifier whose task is to assign the input to one of the two classes. After training with the past data, a classification rule learned may be of the form

IF income> θ1 **AND** savings> θ2 **THEN** low-risk **ELSE** high-risk

Making some analogy to the hovering it is possible to consider the classification of two situations: normal hovering, when there is no considerable oscillation analyzing the gyroscope and accelerometer data; and turbulent hovering, when those data describes huge oscillations. Even classifying this situation is necessary to parameterize the hover to choose the correct algorithm to be applied to them, and then decide whether to accept or refuse, and act in controlling the hover situation depending on the possible parameters.

The classification cited before is a supervised learning technique whose objective is construct decision-make models based on evidences and presence of uncertainties. Therefore, it is necessary to analyze the income and outcome data and to train a model to generate a reasonable prediction of response for new incoming data.

4. RECOMMENDED HARDWARE SETUP FOR ACQUIRING TRAINING DATA

To use machine learning is necessary to define the learning problem through the learning model to indicate with huge accuracy the capture of important aspects of the learning problem. According to Schapire (2008), the learning model should answer several questions like: What is being learn?; How is the data being generated, or in other words, where does it come from?; How is the data presented to the learner?; For instance, does the learner see all the data once, or only one example at time?; What's the goal of learning in this model?

Our instance described by the set of features showed in figure 5 is composed by six variables acquired by the tri-axial gyroscope and accelerometer that get the raw 6-axis motion sensor readings (accel/gyro).

All that data necessary to guarantee hovering stability, is produced by a specialized sensor identified MPU-6050. Then is latter stored in a MicroSD card.

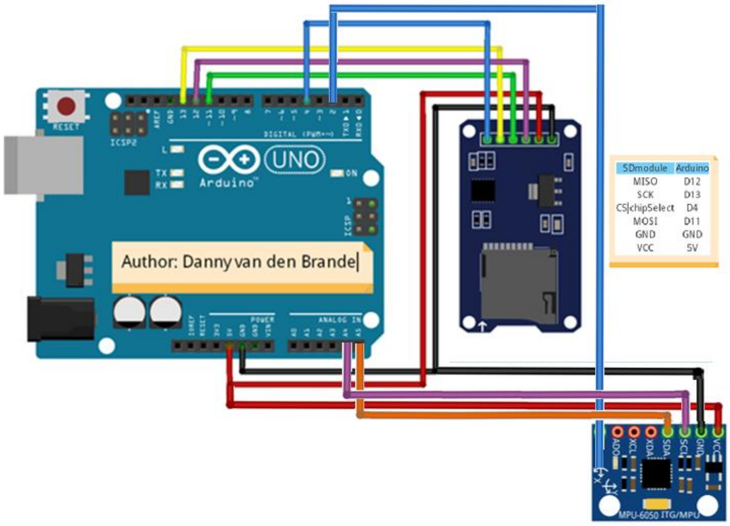

Figure 7. Arduino scheme

5. DATA ANALYZIS

The right approach to implement machine-learning starts with the definition about amount of data that will work with and what it will be used for. At first, focused at the hovering situation, it seems to delimits the search with a reduced amount of data, but even so, it requires trial and error tests to achieve the right balance of complexity, performance and precision.

Considering different existing techniques, this section will present a few selected algorithms that can be used to solve this problem.

5.1 Naïve Bayes

Naïve Bayes is a good choice when the CPU and memory resources are a limiting factor. It does not tend to overfit data, and can be trained very quickly. It also does well with continuous new data used to update the classifier (MathWorks, 2016).

Another consideration to use this algorithm is the data complexity. It is a classifier with low variance / high bias. It can work with limited set of data to train the model, being more advantageous than logistic regression and nearest neighbor algorithms in this situation.

According to Marsland (2009), the Bayes' rule is the most important equation in machine learning. It relates the posterior probability with the prior probability and class-conditional probability. It is so important because it is possible to obtain the posterior probability by calculating things that are much easier to compute. It estimates of the prior probabilities by looking at how often each class appears in the training data set and get the class-conditional probabilities from values of the feature for the training set.

5.2 k-Nearest Neighbor

K-nearest neighbors algorithm (k-NN) is a non-parametric method used for classification and regression. (Altman, N. S, 2007) In both cases, the input consists of the k closest training examples in the feature space. The output depends on whether k-NN is used for classification or regression. The main idea behind the nearest neighbor implies that if a model that describes the data is not available, it is necessary to look at similar data and choose to be in the same class as them.

K-NN is an instance-based lazy learner, which means there is no real training phase (MathWorks, 2016). K-NN starts to works when required to analyze the data training loaded into the model. When there is a new query instance, the kNN model looks for the specified k number of nearest neighbors; For instance, if k is 5, then there is a class of 5 nearest neighbors. If it is required to apply a label or class, the model takes a vote to see where it should be classed.

Considering a fully stable hovering model, the training K-NN will be short. However, if pre-defined movements are either required the definition of K-NN is far more complex. The query time will be longer and the number of training data points can increase exponentially.

5.3 Decision Trees

The main idea about decision tree is to classify down into a set of choices about each feature, starting from the root of the tree and following up to the leaves, where the classification decision or answers are.

Decision trees are popular because it is possible to turn them into a set of logical disjunctions (**if** … **then** rules) that go into program code very simply (Altman, 1992). In this study proposal, it is possible to analyze the values of the x, y and z variables of the gyroscope and for each one that has some considerable changing as instability or not hover, apply power to the motor to change this state. This may generate a set of logical disjunction around those variables.

The main disadvantage of decision trees is that they tend to overfit, but there are ensemble methods to counteract this.

5.4 Support Vector Machine

Support Vector Machin (SVM) is one of the most popular algorithms in modern machine learning because they often provide significantly better classification performance than other machine learning algorithms on reasonably sized datasets (Marsland, 2009).

This algorithm works very well if dataset has exactly two classes. Their main activity is to define the hyperplane that separate all data points of one class from another one, and the main consideration to do is to put a line in the middle of the data points in order to separate them, being almost equidistant from the data in both classes.

Is possible to use SVM with more than two classes creating a set of binary classifications subproblems, but speed will be adversely affected.

This algorithm was considered for the hovering problem due the fact it can classify hover as stable or not. SVM is very accurate in well-defined situations and tends not to overfit data. However is necessary to train the model before of use, and after this is possible to discard the training data.

6. FINAL CONSIDERATIONS

This work was focused to analyses the use of machine learning in an Unmanned Aerial Vehicle to guarantee their autonomy during specific flight situations. However, how autonomy is a complex condition to analyze for an aircraft it was very important to determine which types apply to this work.

As there is a difference in the pitch, roll and yaw movement between fixed wing aircraft and rotating wing aircraft, analyzing these movements were crucial in defining which sensors should be used to aid in capturing data for decision making. Mainly because the plurality of sensors in an aircraft influence its performance and the type of technique to be used to implement the aircraft control.

Given the data that can be used to guarantee stability in the hovering situation, and considering that this goal leads to knowing the desired data for such a situation, this research review work is directed to the use of supervised learning algorithms.

The computational power should was considered for this research review work because microcontrolled processing hardware presents limited computation resources. Algorithms like Naïve Bayes algorithm has advantage because it does not require great computational performance.

Is necessary to considering aircraft data training in terms of size and persistence in the use of SVM, which requires well-defined objectives. The same happens with the k-NN algorithm, which is also interesting in well-defined situations, but may be less efficient due to the growth trend of training data.

Decision trees are apparently interesting for the simple fact of creating a set of logical disjunction that addresses the question of defining stability or not and still be able to extrapolate to more complex definitions such as where instability is found.

Although this research review work have narrowed the number of machine learning algorithms to four, there is still the need of trial-and-error stages, applying each of these algorithms to the proposed problem, in order to define the one that best fits in solving it. As this is a review paper, it will be a future activity for this work.

7. ACKNOWLEDGEMENTS

The authors would like to thanks FAPEMIG (Fundação de Amparo à Pesquisa do Estado de Minas Gerais), CAPES, CNPq that funded this work, and the post-graduation program of the Faculty of Mechanical Engineering (FEMEC) at the Federal University of Uberlândia (UFU) where this work has been developed.

8. REFERENCES

Alpaydin, E. Introduction to machine learning, 2 ed., MIT Press, 2010

Altman, N. S.; "An introduction to kernel and nearest-neighbor nonparametric regression". The American Statistician. 46 (3): 175–185. doi:10.1080/00031305.1992.10475879, 2007

Benallegue, A. ; Mokhtari, A. and L. Fridman, “High-order sliding-mode observer for a quadrotor UAV,” Int. J. Robust Nonlinear Control, vol. 18, no. 4, pp. 427–440, 2008

Bethke, B. ; How, J. P. and Vian, J. ; “Group health management of UAV teams with applications to persistent surveillance,” in Proc. Amer. Control Conf., 2008, pp. 3145–3150.

Bouabdallah, S.; Noth, A. ; Siegwart, R.; PID vs LQ control techniques applied to an indoor micro Quadrotor, in: Proceedings of IEEE/RSJ International Conference on Intelligent Robots and Systems, Sept 28–Oct 2, Sendal, Japan, 2004, pp.2451–2456.

Bouabdallah, S.; Murrieri, P.; Siegwart, R. Design and Control of an Indoor Micro Quadrotor, 2004.

Bresciani, T.; Modelling, Identification and Control of a Quadrotor Helicopter. Department of Automatic Control, Lund University, 2008

Briesteau P.J.; Martin, P.; Salaün, E.and Petit, N.; The role of propeller aerodynamics in the model of a quadrotor UAV. In European control conference; 2009.

Cheng, Y.; Cheng, P.; Jiang, Y.F.; Hu, A snake-based scheme for path planning and control with constraints by distributed visual sensors, Robotica 32 (2014) 477–499.; P. Jiang, Y.F. Hu, A snake-based scheme for path planning and control with constraints by distributed visual sensors, Robotica 32 (2014) 477–499.

Clothier, R.; Williams, B. ; Perez, T.; A review of the concept of autonomy in the context of the safety regulation of civil unmanned aircraft systems, in ASSC 2013, pp. 15–27, 2013.

Clothier,R.; Walker, R.; Safety risk management of unmanned aircraft systems, in: K.P. Valavanis, G.J. Vachtsevanos (Eds.), Handbook of Unmanned Aerial Vehicles, Springer, Netherlands, 2014, pp. 2229–2275.

Clough, B.T.; Metrics, Schmetrics. How The Heck Do You Determine A UAV's Autonomy Anyway, Air Force Research Lab., Wright-Patterson AFB, OH, 2002.

Dierks, T.; Jagannathan S. Output feedback control of a quadrotor UAV using neural networks. IEEE Trans Neural Netw 2010;21(1):50–66.

Doboli, A.; Curiac, D.; Pescaru, D.; Doboli, S.; Tang, W.; Volosencu, C., Cities of the future: employing wireless sensor networks for efficient decision making in complex environments, State Univ. N.Y. Tech. Rep.

Dunfied, J.; Tarbouchi, M.; Labonte G. Neural network based control of a four rotor helicopter. In: International conference on industrial technology; 2004.

Elbanhawi, M.; Mohamed, A.; Clothier, R.; Palmer, J.L.; Simic, M. and Watkins, S.; Enabling technologies for auntonomous MAV operations, Progres in Aerospace Sciences (2017), http://dx.doi.org/10.1016/j.paerosci.2017.03.002.

Hamel,T. and Mahony, R.. Image based visual servo-control for a class of aerial robotic systems. Automatica, 43:1975–1983, 2007.

Hoffmann, G. ; Huang, H.; Waslander, S. and Tomlin, C. ; “Quadrotor helicopter flight dynamics and control: Theory and experiment,” in Proc. AIAA Guid., Navigat., Control Conf., Hilton Head, SC, 2007, pp. 1–20.

Hoffmann, G.; Rajnarayan, D. G.; Waslander, S. L.; et al. The stanford testbed of autonomous rotorcraft for multi agent control (starmac). In: Proceedings of the 23rd Digital Avionics Systems Conference, 2004

How, J. ; Bethke, B.; Frank, A.; Dale, D. and Vian, J. “Real-time indoor autonomous vehicle test environment,” IEEE Control Syst. Mag., vol. 28, no. 2, pp. 51–64, Apr. 2008.

Hua, M.; Hamel, T.; Morin, P. and Samson, C. “A control approach for thrust-propelled underactuated vehicles and its application to VTOL drones,” IEEE Trans. Autom. Control, vol. 54, no. 8, pp. 1837–1853, Aug. 2009.

I2Cdev Lib: MPU 6050 Class Reference. 15 July 2017. https://www.i2cdevlib.com/docs/html/class_m_p_u6050.html.

International Civil Aviation Organization (ICAO), Unmanned Aircraft Systems (UAS). Cir 328 AN/190, United Nations, Montreal, Quebec, Canada 2011.

Jenkins,D.A.; Ifju, P.G.; Abdulrahim, M.; Olipra, S. "Assessment of controllability of micro air vehicles," in: Proceedings of the Sixteenth International Conference On Unmanned Air Vehicle Systems, 2001

Kendoul, F. ; Lara, D.; Fantoni, I.; Lozano, R.; Nonlinear control for systems with bounded inputs: Real-time embedded control applied to UAVs, in: Proceedings of 45th IEEE Conference on Decision and Control, December 13 -15, San Diego, CA, USA, 2006, pp. 5888–5893.

Lupashin, S. ; Schollig, A.; Sherback, M. and D’Andrea, R. “A simple learning strategy for high-speed quadrocopter multi-flips,” in Proc. IEEE Int. Conf. Robot. Autom., May 2010, pp. 1642–1648.

Machine Learning Challenges: Choosing the Best Model and Avoiding Overfitt, 20 july 2017 <https://www.mathworks.com/tagteam/87371_92974v00_Machine_Learning_Whitepaper.pdf>, MathWorks.

Mahony, R.; Kumar,V.; Corke, P.; Multirotor aerial vehicles: modeling, estimation, and control of quadrotor. IEEE Robot Autom Mag 2012;19(3):20–32.

Marsland, S.; Machine Learning – An Algorithmic Perspective, CRC Press, 2009

Michael, N.; Mellinger, D.; Lindsey, Q. and Kumar, V. “The GRASP multiple micro-UAV testbed,” IEEE Robot. Autom. Mag., vol. 17, no. 3, pp. 56–65, Sep. 2010.

Michael, N.; Fink, J. and Kumar, V. “Cooperative manipulation and transportation with aerial robots,” in Proc. Robot.: Sci. Syst., Seattle, WA, Jun. 2009, pp. 73–86.

Mohamed, A.; Massey, K.; Watkins, S.; Clothier, R. The attitude control of fixedwing MAVS in turbulent environments, Prog. Aerosp. Sci. 66 (4//2014) 37–48.

Mohamed, A. ; Clothier, R.; Watkins, S.; Sabatini, R.; Abdulrahim, M. Fixed-wing MAV attitude stability in atmospheric turbulence, part 1: Suitability of conventional sensors (10//)Prog. Aerosp. Sci. 70 (2014) 69–82.

Quemel, P. H. R.. Modelagem e controle de quadrirrotores. In: Grupo de Robótica, Automação e Visão Computacional (GRAV), Depertamento de Engenharia Elétrica, UNB, Brasília, DF, 2009.

Rondon, E. ; Fantoni-Coichot, I.; Sanchez, A. and Sanahuja, G. Optical flow-based controller for reactive and relative navigation dedicated to a four rotor rotorcraft. In Proc. IEEE/RSJ International Conf. on Intelligent Robots and Systems, 2009.

Russell,S.J. ; Norvig, P. Artificial Intelligence: A Modern Approach, Pearson Education/Prentice Hall, 2010.

Schapire, R., Theoretical machine learning, Princeton lecture, 2008, 16 July 2017 <https://www.cs.princeton.edu/courses/archive/spr08/cos511/scribe_notes/0204.pdf>

SD Library Arduino Reference. 15 July 2017. https://www.arduino.cc/en/Reference/SD.

Siegwart, R.; Nourbakhsh, I.R.; Scaramuzza, D. Autonomous mobile robots. 2nd ed. The MIT Press; 2011.

Schölkpf, B. and Smola, A.J.; Learning with Kernels – Support Vector Machines, Regularization, Optimization and Beyound, MIT Press, 2002

Titterton, D. H. and Weston, J. L. Strapdown Inertial Navigation Technology. The American Institute of Aeronautics and Aeronautics, 2004.

Tournier, G.; Valenti, M.; How, J. and Feron, E. “Estimation and control of a quadrotor vehicle using monocular vision and moirè patterns,” in Proc. AIAA Guid., Navigat. Control Conf., Keystone, CO, 2006, pp.21–24.

Walshe,D.E.J. , Wind-excited oscillation of structures, Her. Majesty'S. Station. Off. 1972

Waslander, S. L.; Hoffmann, G. Multi-agent quadrotor testbed control design: Integral sliding mode vs. reinforcement learnig. In: 2005 IEEE/RSJ International Conference on Intelligent Robots and Systems, 2005

Wilson, G.F.; Russell, C.A.; Performance enhancement in an uninhabited air vehicle task using psychophysiologically determined adaptive aiding (December 1)Hum. Factor.: J. Hum. Factor. Ergon. Soc. 49 (2007)

Young, L.A.; Yetter, J.A.; Guynn, M.D. System analysis applied to autonomy: application to high-altitude long-endurance remotely operated aircraft, in AIAA Infotech@ Aerospace Conference, Arlington, VA, 2005.

9. RESPONSIBILITY NOTICE

The main author is the only responsible for the printed material included in this paper.