# Review of an Underwater Autonomous Vehicle (UAV) Control System and Selection Method Based on Desired Performance

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***Abstract***

*The present work was carried out within the tasks of the PID UNDEF No. 484/2019 where a light UAV was designed as an alternative to replace other similar vehicles. One of these tasks was the design of the UAV control system, for which different methods in use were reviewed and a method was proposed to select it based on the type of missions it would carry out and the desired performance. For this, a systematic review of the different control methods that are applied, their characteristics and the responses obtained by each of them was carried out. A comparison and evaluation of its performance was carried out, proposing a systematic selection method that would allow obtaining the control system with the best performance for the vehicle application. The method was contrasted with the results reported in different publications and the results obtained proved that the method used met the established requirements. The advantage of the proposed method is that the choice of the control system is made to optimize certain characteristics of the UAV's operation, depending on the vehicle and the type of task to be performed.*

## I. Introduction

### 1. The basic dynamics of the UAV

Autonomous underwater vehicles base their navigation on electric motors that provide the mobility to follow a given trajectory. Roll, pitch, yaw and thrust actions are mostly controlled by changing the thrusts of the rotors using Pulse Width Modulation (PWM) to give the desired output. The use of these unmanned underwater vehicles includes photography, inspection of submerged objects, analysis of oceanographic variables, vessel hull maintenance, fish and algae studies, and search and rescue operations, among others. Based on the various existing control schemes, the search for control configurations that optimize the navigation problems that arise for different geographical and operational contexts is a task that requires specific formal tools to choose said schemes.

Before seeing the different control methods, the mathematical model of the controlled system must be included, the UAV, the equations that govern the movement of a rigid body, it is necessary to define an inertial reference system. In this case, the Earth is taken as the inertial system reference, assuming that the acceleration of a point on the Earth's surface, due to its rotation, can be neglected in the case of these underwater vehicles. This approximation is valid, in this situation, since the movement of the Earth has little effect on marine vehicles that move at low speed, such as UAVs (Fossen, 1994). According to these considerations, the inertial reference system originating from an OT point in solidarity with the Earth is defined, where the X axis points to the north, the Y axis to the east and the Z axis to the center of the Earth.

Normally in underwater vehicles, linear and angular velocities are associated with a mobile coordinate system located in the vehicle and their time derivatives are measured with respect to the reference frame of the body. Thus, the coordinate system A joint to the UAV is defined, with origin in its center of mass (OA), where the x axes are made to coincide with the axes of inertia of the UAV, which will facilitate the dynamic analysis. The axis is taken to be coincident with the direction of advance of the UAV, it is orthogonal to and is positive towards starboard in the horizontal plane, while it is oriented downward and orthogonal to the plane, as shown in Figure 1.

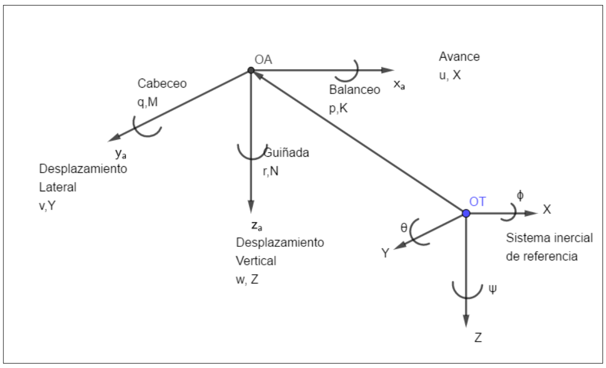


***Figure 1***

The dynamic model of an underwater vehicle can be written in its compact form as shown below by Fossen:

$$M\dot{v}+C(v)v+D(v)v+g(\eta)=\tau$$

where: M = MRA + MA is the inertia matrix including the added mass

C(v) = CRA + CA is the Coriolis matrix, including the added mass.

D(v) the damping matrix, and

g(η) represents the restoring forces

With $\tau=\tau_{dh}+\tau_m+\tau_P$ ; where $\tau_{dh}$ and $\tau_{sh}$ are the moments generated by the hydrodynamic forces $\tau_m$ , the moments generated by the effects of wind and waves $\tau_P$ , and the torques produced by the propellers or any other force exerted on the UAV.

The velocity vector υ is the generalized velocity $\upsilon=[u,v,w,p,q,r]^T$ where $u,v,w$ are the linear components of advance, roll, and roll, $p,q,yr$ are the angular components of roll, pitch, and yaw, referred to the frame fixed to the body of the vehicle.

The six position and attitude components of the UAV, which describe the movement of a marine vehicle in the six degrees of freedom 6 DOF, referred to the inertial frame, are: η = [x, y, z, φ, θ, ψ] T , where η is the vector that allows determining the position of the vehicle with respect to the fixed ground system and its orientation with respect to it, given by the Euler angles φ, θ, and ψ. (Fossen and Pettersen, 2014).

Being $J(\eta)$ the transformation matrix between the inertial and mobile reference system, the speeds of the UAV with respect to the inertial axes are expressed:

$$\begin{bmatrix}\dot{x}\\ \dot{y}\\ \dot{z}\\ \dot{\theta}\\ \dot{\phi}\\ \dot{\psi}\end{bmatrix}=[J(\eta)]\begin{bmatrix}u\\ v\\ w\\ p\\ q\\ r\end{bmatrix}$$

UAV is subjected, considering it as a rigid body and using the notation used according to SNAME (1950). for each variable:

$$X=m$$

$$Y=m$$

$$Z=m$$

$$K=I_{xx}\dot{p}+(I_{zz}-I_{yy})qr-(\dot{r}+pq)I_{xz}+(r^2-q^2)I_{yz}+(pr-\dot{q})I_{xy}+m[y_g(\dot{w}-uq+vp)-z_g(\dot{v}-\wp+ur)]$$

$$M=I_{yy}\dot{q}+(I_{xx}-I_{zz})pr-(\dot{p}+rq)I_{xy}+(p^2-r^2)I_{zx}+(pq-\dot{r})I_{yz}+m[z_g(\dot{u}-vr+\wp)-x_g(\dot{w}-uq+vp)]$$

$$N = I_{zz}\dot{r} + (I_{yy} - I_{xx})qp - (\dot{q} + pr)I_{yz} + (q^2 - p^2)I_{xy} + (qr - \dot{p})I_{zx} + m\left[x_g(\dot{v} - \wp + ur) - y_g(\dot{u} - vr + wq)\right]$$

## II. Materials and Methods.

### 2. The basics of the UAV control system

Since there are several characteristics of control systems that must be taken into account when they are applied to the control of a UAV, the use of adequate noise filtering, the characteristics of the high frequency response, the adjustment of the degrees of freedom with respect to equilibrium point, actuator saturation effects, parameter setting method and computational implementation. These considerations require the establishment of a model that includes disturbances and noise, based on the traditional model shown in Figure 2

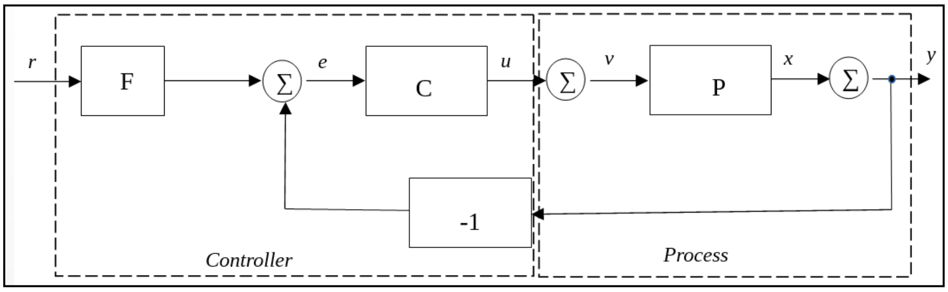


***Figure 2***

In this new model, the process P is subject to disturbances: the load disturbance *d* (which represents those effects that separate the process from its desired behavior), and the measurement noise *n* of the process variable *x* is the true physical variable that you want to control. But the control is based on the measured signal and it is corrupted by noise *n*. The controller is shown divided into two parts: the feedback compensator C and the feed-forward compensator F. The process is influenced by the controller through the control variable *u*. The process thus turns out to be a system of three inputs (*u, d, n*) and one output (*y*). Figure 3 shows the load disturbance acting at the input of the process, but in reality the disturbance can enter the process in a multitude of different ways, this representation being adopted to simplify its description.

By making a summary of the general design considerations for a controller, we can identify the basic requirements as: Stability, Ability to follow reference signals, Reduction of the effects of load disturbances, Reduction of the effects of measurement noise and Rejection of variations in process parameters and / or uncertainties in the model used. Depending on the specific application, one or more of the indicated requirements will prevail over the others. This new model features three inputs: *r, d* and *n*, which affect variables *u, x* and *y*, which are those that describe the operation of the System. Assuming that the system is linear, there are nine relationships expressible as transfer functions between the input and output variables. If with X, Y, U, D, N, R we represent the Laplace transforms of *x, y, u, d, n, r,* Leaving aside the complex argument *s* for simplicity, it can be expressed:

$$X=\frac{P}{1+PC}D-\frac{PC}{1+PC}N+\frac{PCF}{1+PC}R$$

$$Y=\frac{P}{1+PC}D+\frac{1}{1+PC}N+\frac{PCF}{1+PC}R$$

$$U=\frac{-P}{1+PC}D-\frac{C}{1+PC}N+\frac{CF}{1+PC}R$$

We observe that several of the transfer functions are equal and that all relations are expressed as combinations of a set of six functions,
as stated Åström (Åström, 2002)

$$\frac{PCF}{1+PC}\ \frac{PC}{1+PC}\ \frac{P}{1+PC}$$

$$\frac{CF}{1+PC}\ \frac{C}{1+PC}\ \frac{1}{1+PC}$$

The transfer functions in the first column
determine the responses of the process variable x and the control variable u to the command variable r. The second column gives the same signals for the case of pure feedback with error, that is, assuming F = 1. The function P / (1 + PC) in the third column defines the reaction of the process variable x to a load disturbance d, while C / (1 + PC) gives the response of the control signal to the measurement noise. The system with F = 1 is called pure error feedback control. In this case, the system is completely characterized by four transfer functions:

$\frac{1}{1+PC}$ *Sensitivity Function*

$\frac{PC}{1+PC}$ *Complementary Sensitivity Function*

$\frac{P}{1+PC}$ *Load Disturbance Sensitivity Function*

$\frac{C}{1+PC}$ *Noise Sensitivity Function*

These functions are obtained by considering the closed-loop transfer function *T* of the system and the variation suffered by the process if the process *P* experiences a small disturbance around the nominal value of its parameters:

$$T=\frac{PC}{1+PC};dT=\frac{C}{(1+PCN+PCF)^2}dP$$

$$\frac{dT}{T}=\frac{C}{1+PC}\frac{dP}{P}\rightarrow S=\frac{dT/T}{dP/P}=\frac{1}{1+PC}$$

The sensitivity function $S$ then makes it possible to express the relative variation of the closed-loop transfer function with small variations in the process. From these equations, it is observed that:

$$S + T = 1$$

So, the closed-loop transfer function $T$ is also called the *complementary sensitivity function*. This analysis is the same as if another type of Control system configuration is used, as the one represented in Figure 3, where we could obtain the same results as before if we set the condition F = A / C

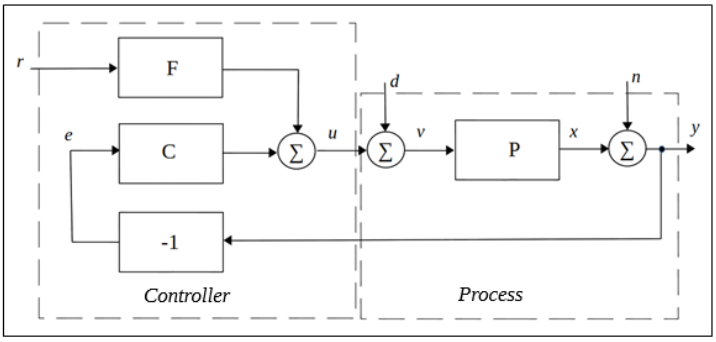


***Figure 3***

## 3. Review of the Control Systems used by UAV's

Various control algorithms have been used according to the nature of the drone dynamics. Each control scheme has advantages and disadvantages, in a first approximation the control systems used could be divided into linear and non-linear. For a first categorization, this analysis can be restricted to different control systems within these categories.

### 3.1. Proportional and Integral plus Derivative (PID) (LINEAR) control system

The PID controller was patented in 1939 by Albert Callender and Allan Stevenson of Imperial Chemicals Limited (Northwich, England). The PID controller represented a huge advance over previous automatic control methods. The PID control algorithm consists of three different parameters: the proportional, the integral, and the derivative. The proportional value depens on the current error, the integral depends on the past errors, and the derivative is a prediction of future errors. The sum of these three actions is used to adjust the process by means of a control element. Given a system whose variables are made explicit in the control loop of Figure 4

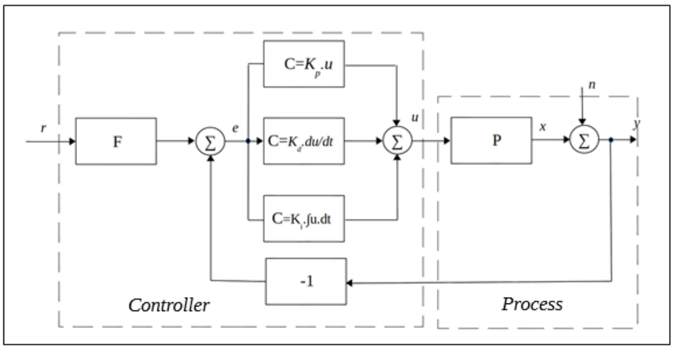


***Figure 4***

The system presents a behavior described by the equation:

$$u(t)=\mathrm{K}\left[e(t)+\frac{1}{T_i}\int_0^t e(\tau)\mathrm{d}\tau+\mathrm{T}_d\frac{\mathrm{de}(t)}{\mathrm{dt}}\right]$$

### 3.2. Gaussian Quadratic Linear Control Systems (LQR / G) (LINEAR)

The block diagram of an LQG controller for a UAV is shown in Figure 5.

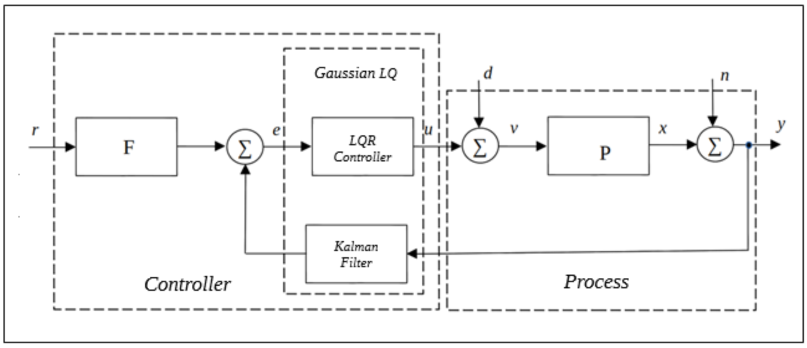


***Figure 5***

The generic description in terms of a linear dynamical system would be:

$$\dot{x}(t)=\mathrm{A}(t)x(t)+\mathrm{B}(t)u(t)+\mathrm{v}(t)$$
$$y(t)=\mathrm{C}(t)x(t)+\mathrm{w}(t)$$

Where ***x*** represents the vector of the system state variables, **u** the vector of the control inputs and **y** the vector of measured outputs available for feedback. Both the additive white noise of the system *v(t)*, as noise from the measurement w (t) affect the system. Taking into account that the objective is to find the values of the control input *u(t)* for each time *t*, this will depend only on the latest measurements *y(t')*, for *0< t'<t* , such that the following cost function is minimized:

$$J=E\left(x^T(T)Fx(T)+\int_0^T x^T(t)Q(t)+u^T(t)R(t)u(t)dt\right)$$

$$F \geq 0; Q(t) \geq 0; R(t) > 0$$

Where *E* is the expected value. *T* can be finite or infinite, but if it tends to infinity, the first term of the cost function *J* can be neglected. To keep the cost function in a finite value, *J / T* can be used instead of *J*. The LQG controller that solves the problem by posing the following equations:

$$(t)=A(t)x(t)+B(t)u(t)+L(t)\big(y(t)-C(t)x(t)\big)x$$

$$x(0)=E(0)$$

$$u(t)=-K(t)x(t)$$

The matrix *L (t)* is called the Kalman gain of the associated Kalman filter present in the first equation. For each *t* the filter generates estimates of *x (t)* using the previous measurements and inputs. The Kalman gain *L (t)* is calculated from the matrices *A (t)*, *C (t)*, the two matrices *V (t)*, *W (t)* of the white noises *v (t)* and *w (t)* and finally the matrix of the values *E [x (0)]* expected at the origin *t = 0*. These five matrices determine the Kalman gain through the matrix associated with the Riccardi differential equation:

$$\dot{P}(t)=A(t)P(t)+P(t)A^T(t)-P(t)C^T(t)W^{-1}(t)C(t)P(t)+V(t)$$

Which fulfills that in the initial instant:

$$P(0)=E\big(x(0)x^T(0)\big)$$

The solution for *P (t)* at *0 <t <T* allows the Kalman gain to be obtained as:

$$L(t)=P(t)C^T(t)W^{-1}(t)$$

$$-\dot{S}(t)=A^T(t)S(t)+S(t)A(t)-S(t)B(t)R^{-1}(t)B^T(t)S(t)+Q(t)$$

$$S(T)=F$$

Where the solution *S (t)* for *0 <t <T* allows obtaining the feedback gain as:

$$K(t)=R^{-1}(t)B^T(t)S(t)$$

It is observed that the matrix expressions of the Riccardi differential equations are similar, this is called Duality. The first equation solves the linear quadratic estimation (LQE) problem and the second solves the linear quadratic regulator (LQR) problem; Since the problem is dual, both equations solve the linear quadratic Gaussian control (LQG) problem. For this reason, the LQG problem is said to be separable, since it is solved by solving the LQE and LQR problems separately.
When *A (t)*, *B (t)*, *C (t)*, *Q (t)*, *R (t)* and the noise matrices *V (y)* and *W (t)* do not depend on t as *T* approaches infinity, the LQG controller becomes an invariant dynamical system and the second Riccardi differential equation can be replaced by the Riccardi algebraic equation. If

the discrete analysis of this problem is proposed, the solution would be reached in a similar way to that carried out in the continuous analysis.

### 3.3. Sliding Mode Control Systems (SMC) (NON-LINEAR)

Sliding mode control (SMC) is a non-linear control method that alters the dynamics of a non-linear system by applying a discontinuous control signal (or more accurately, a pre-set set of control signals) that forces the system to "slide" along a cross section of the normal behavior of the system.
Control signals follow feedback rules that are not a continuous function in time. Instead, it can change from one continuous structure to another based on its position in state space. Therefore, slider mode control is a control method with a variable structure. These control structures are designed so that the trajectories always move towards an adjacent region with a different control structure, so the final trajectory will not exist within the control structure, instead it will slide along the boundaries control structures. The movement of the system as it glides along these limits is called the sliding mode, and the locus containing these limits is called the (hyper) sliding surface. Figure 6 shows the scheme of this type of control.

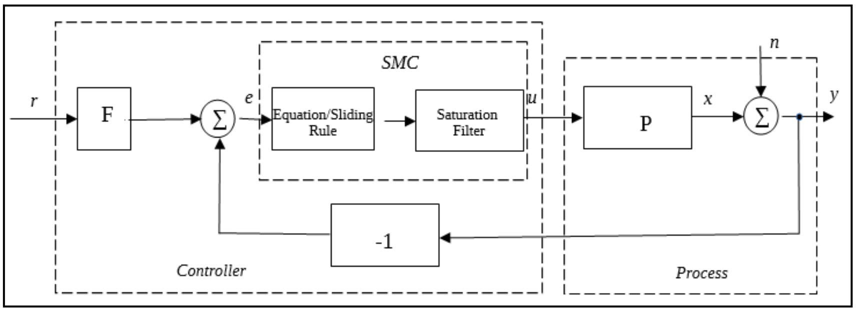


***Figure 6***

### 3.4. Backsteppig Control System (Integrator) (NON-LINEAR)

The Backstepping approach provides a recursive method to stabilize the origin of a system by feedback only. If a system is considered as follows:

$$\dot{x}=f_x(x)+g_x(x)z_1$$
$$\dot{z}_1=f_1(x,z_1)+g_1(x,z_1)z_2$$
$$\dot{z}_2=f_2(x,z_1,z_2)+g_2(x,z_1,z_2)z_3$$
$$\vdots$$
$$\dot{z}_i=f_2(x,z_1,z_2,\dots,z_{i-1},z_i)+g_2(x,z_1,z_2,\dots,z_{i-1},z_i)z_{i+1}$$
$$\vdots$$
$$\dot{z}_{k-1}=f_2(x,z_1,z_2,\dots,z_{k-1})+g_2(x,z_1,z_2,\dots,z_{k-1})z_k$$
$$\dot{z}_k=f_2(x,z_1,z_2,\dots,z_{k},)+g_2(x,z_1,z_2,\dots,z_{k-1},z_k)u$$

Where $x$ is real, *z1,…, zk* are scalars, $u$ is the scalar input to the *fx* system, *f1,…, fk* have a value of 0 at the origin (that is, *fi (0,0,…, 0) = 0)* and *g1,… .gk* are distinct from or in the domain. If it is also assumed that the subsystem is stable at its origin *(x = 0)* for some control input *ux (x)* where *ux (0) = 0*. That is, the subsystem *x* is stabilized in some way and the backstepping extends its stability to the surrounding *z* environment. It is said that in strict backstepping mode around a stable subsystem *x*: the control input *u* has its stabilizing impact on *Zn*; the *zn* state acts as a stabilizer for the previous *zn-1* state and this process continues until each *zi* state is stabilized by the *zi + 1* state. The backstepping approach tends to stabilize subsystem *x* using *z1*, then try to get *z2* to *z1* keeping control so that *x* remains stable. This procedure is continued until the control input *u* is reached. Figure 7 shows us a diagram of this type of control.

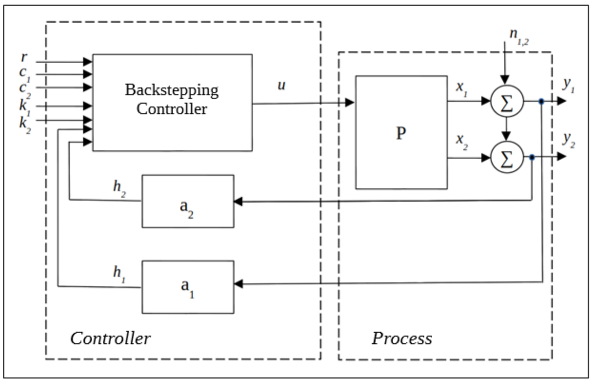


***Figure 7***

**3.4. Adaptive Algorithm Control System (NOT linear)**

Adaptive control differs from robust control in that it does not need a priori information on the limits of variation of the parameters or their variation over time. Robust control ensures that if parameter changes are within certain limits, it is not necessary to change control rules, while adaptive control deals with changing control rules and how they can change themselves. The basis of adaptive control is in the estimation of these parameters, which is a part of the system.

Common estimation methods include recursive least squares and gradient descent. Both methods provide update laws that are used to modify estimates in real time (that is, as the system works). Lyapunov stability is used to derive these actualization laws and show convergence criteria (typically persistent excitation; relaxation of this condition is studied in adaptive control of concurrent learning). Projection and normalization are commonly used to improve the robustness of estimation algorithms.

In general, it is convenient to distinguish between direct adaptive control and feedback adaptive control, these refer to the location of the estimator. A distinction must also be made between Direct Methods, Indirect Methods and Hybrid Adaptive Methods. Direct methods are those in which the estimated parameters are used directly on the controllers. In contrast, indirect methods are those in which the estimated parameters are used to calculate the required parameters of the controller. Hybrid methods are based on both parameter estimation and direct modification of control rules.A diagram of a system with direct adaptive control is show in Figure 8.

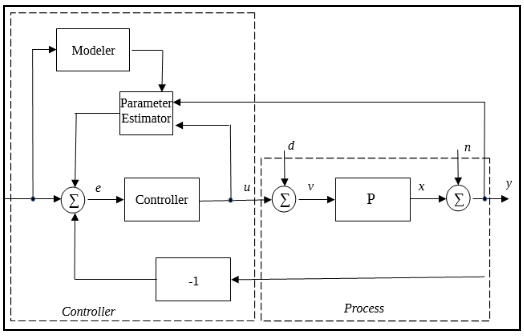


***Figure 8***

### 3.5. Control Systems with Robust Control Algorithms

Robust control is an approach to the design of controllers that explicitly deals with uncertainty, they are designed to work correctly whenever a set of uncertain parameters or disturbances is encountered. Robust methods aim to achieve robust performance and / or stability in the presence of limited model errors.

The early methods of Bode and others were quite robust, but in the 1960s and 1970s more extensive tests showed that they lacked robustness to parameter variation, prompting research to improve them. This was the beginning of robust control theory, which took shape in the 1980s and 1990s and continues today. In contrast to adaptive control, robust control is static, instead of adapting to variations measurements, the controller is designed to work assuming that certain variables will be unknown but bounded.

A controller designed for a particular set of parameters is said informally to be robust if it also performs well under a different set of parameters. High-gain feedback is a simple example of a robust control method; with a sufficiently high gain, the effect of any variation of the parameters will be negligible. From the perspective of the closed-loop transfer function, a high open-loop gain leads to substantial rejection of disturbances in the face of the uncertainty of the system parameters. But the main obstacle to achieving high profits is the need to maintain loop stability. Loop conFiguretion that allows stable operation can be a technical challenge.

Robust control systems often incorporate advanced topologies that include multiple feedback loops and direct loops. The control rules would thus be represented by high-order transfer functions required to simultaneously achieve the desired disturbance rejection performance with robust closed-loop operation.

One of the most important examples of a robust control technique is the infinite loop form in H, developed by Duncan McFarlane and Keith Glover of the University of Cambridge; This method minimizes the sensitivity of a system over its frequency spectrum, and this ensures that the system will not deviate much from expected trajectories when disturbances enter the system.

Another form of robust control is the slider mode control, which is a variation of the variable frame control. While robust control has traditionally been treated with deterministic approaches, in recent decades this approach has been criticized for being too rigid to describe actual uncertainty. Robust probabilistic control has been introduced as an alternative, which interprets robust control within the so-called scenario optimization theory. Another example is loop transfer recovery (LQG / LTR), which was developed to overcome robustness problems of linear-quadratic-Gaussian (LQG) control. Other robust techniques include quantitative feedback theory (QFT), passivity-based control, Lyapunov-based control, etc. A diagram of a Robust Control system is shown in figure 9.

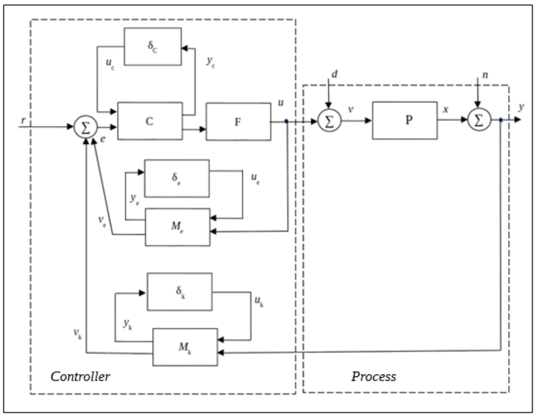


***Figure 9***

**3.6. Control systems using Optimal Control algorithms - OCA (LINEAR and NON-LINEAR)**

OCAs reduce a variable and obtain the best cost function out of a set of options. A special type of optimization is the convex optimization, which uses a mathematical optimization technique to minimize a convex variable in a convex set of variables. Most algorithms consist of the Gaussian Linear Quadratic Control (LQG) problem, which is a combination of a Kalman filter that is, a Linear Quadratic Estimator (LQE) with a Linear Quadratic Regulator (LQR). A major limitation of various optimization algorithms is, in general, their poor robustness.
Optimal control problems may be classified in continuous and discrete, we can also make a classification according to the time variable *t*, whether or not it is explicitly included in the equations of state. In this way we have problems: Autonomous: where the equation of state does not explicitly depend on time: $x = f(x, u)$ y Non-autonomous: where the variable *t* is present in the above equation: $x = f(t, x, u)$. On the other hand, the set *U* of the admissible controls can be Unbounded, Bounded or Bang-Bang, depending on whether the *U* values are bounded or not, or vary only between discrete values (for example 0 or 1).
An example of what the diagram of a system with an optimal controller would look like is shown in Figure 10

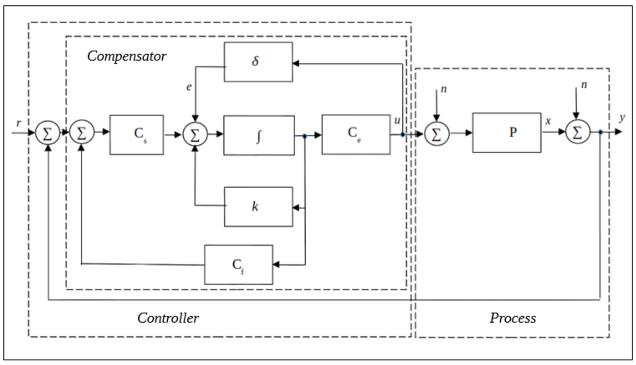


***Figure 10***

### 3.7. Control systems using feedback linearization algorithms (FL) (Non-linear)

FL control algorithms convert a non-linear system into an equivalent linear one by changing variables. Some limitations of this method are due to the loss of precision when linearizing variables and it requires having an exact model for its implementation.
Feedback linearization is an approach used to control non-linear systems. The approach proposes a transformation of the nonlinear system into an equivalent linear system through a change of variables and an appropriate control input. It applies to nonlinear systems of the form:

$$\dot{x}=\mathrm{f}(x)+\mathrm{g}(x)u$$
$$\mathrm{y}=\mathrm{h}(x)$$

Where x is a vector of real components, as is the vector of inputs u. The goal is to get a control input as:

$$u=a(x) + b(x)v$$

Which generates a linear input-output map between the new input and the output, resulting in a linear control system that can be applied by an external control circuit. In the case of FL for a single input and output system (SISO), results are obtained that can be extended to multiple input and output systems (MIMO). If both u and y are real, the objective is to find a transformation of coordinates $z = T(x)$, which transforms the equation of the system through the feedback already indicated. This leads to a new map of linear input and output relationships between each input $v$ and each output $y$. To guarantee that the transformation of the system is an equivalent representation of the original, it must be not only bijective (invertible), but must be infinitely differentiable (it admits derivatives of any order) at the origin of coordinates. A diagram of these systems is presented in Figure 11:

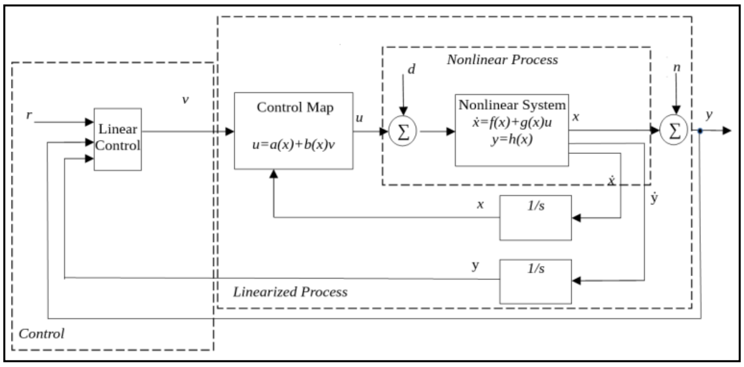


***Figure 11***

### 3.8. Control by Fuzzy Logic Control (FLC) systems (Non-linear)

The FLC is a type of control, usually of a feedback type, that is based on rules. It is aimed at improving the characteristics of "classical" control, for example, incorporating knowledge that cannot be described in the analytical model on which the design of the control algorithm is based, and that usually, in "classical" control, is left for manual modes of operation or other limit or safety mechanisms. FLC applications can be divided into two classes: Those in which the FLC is a supervisory control, that is, it complements the conventional feedback control, and those in which the FLC replaces the conventional control.

The FLC works by applying a set of rules that is combined using fuzzy logic. A rule is activated ("triggered") if the conditions described in the rule's premises are met. The evaluation of those conditions is carried out in a diffuse way, taking into account the inherent uncertainty of the available knowledge. The input variables are interpreted as linguistic variables. It is not unusual for more than one rule to be triggered for the same combination of input variables, in this case, the inference machine in a FLC acts as a parallel processor, that is, all the rules that have some degree of truth in their premises are triggered and contribute to the fuzzy set of output. Applying Mamdani's inference, the result produced by each of the rules is combined to give the result of the set, which is the union of the outputs of each of the triggered rules.

The consequents of all the triggered rules are related in the range [-1,1], being combined locally by a logical OR. A logical OR is a T conorm, for example the maximum point function. It is important to mention that any T conorm could be used for this, the max function is the most used in real time applications. The expression for the fuzzy set of the output variable given by Mamdani's inference is then:

$$\forall b \epsilon U_B : u_{B(\mathrm{CR})}(b) = \max_k \left( \min \left( u_{A(k)}(a) \mathrm{m}, \mathrm{u}_{B(k)}(b) \right) \right)$$

There are several methods to build the de-diffusion interface of a FLC, such as: center of gravity, average of the supreme or weight. The center of gravity method is the most widely used; it consists of obtaining the abscissa of the center of the area that is formed under the function that represents the combined output fuzzy set. The average of the supreme is obtained considering only the lines with the maximum membership value within the whole set. The weight method considers the value (equivalent to the degree of certainty) obtained by each of the individual triggered rules. The center of gravity of each consequent of these rules, which is previously known, (typically trapezoids or triangles) is weighted by the value of the height in each case, and a weighted average of all the consequents represented in the output set is obtained. Figure 12 shows the differences between the "classical" control process and the FLC

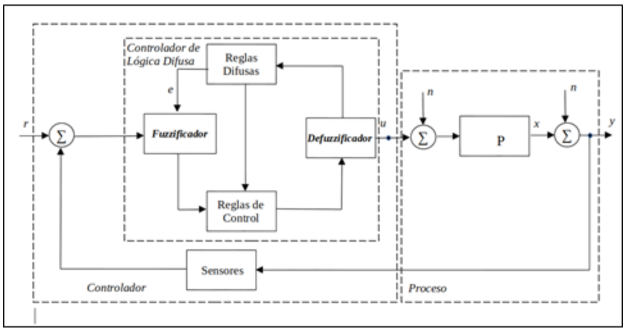


***Figure 12***

### 3.9. Control by Neural Network systems (Nonlinear)

Artificial neural networks have characteristics similar to those of the human brain. For example, they are able to learn from experience, to generalize from previous cases to new cases, to abstract essential characteristics from inputs that represent irrelevant information, etc. This means that they offer numerous advantages and that this type of technology is being applied in multiple areas. Advantages include: Adaptive Learning (ability to learn to perform tasks based on training); Self-organization (ability to create their own representation of information through learning); Fault tolerance (certain capabilities of a NN can persist after taking great damage). Real-time operation (the operation of the NNs can be carried out in parallel using special hardware); and Easy insertion into existing technology (using specialized NN chips that improve the capabilities of certain tasks, facilitating their integration into existing systems). A schematic of an NN is shown in Figure 13:

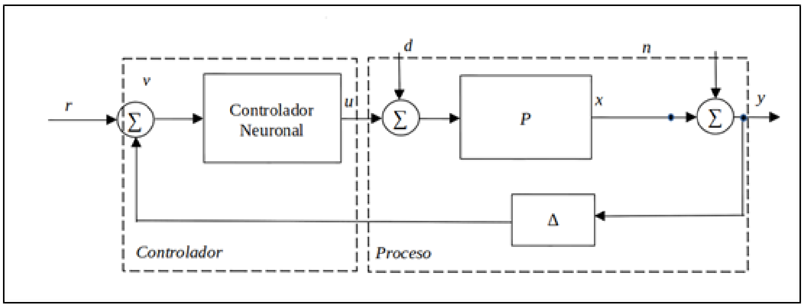


***Figure 13***

### 3.10. Control Systems using Hybrid algorithms

Clearly, the best linear and non-linear algorithms have limitations and no controller has got all the optimal characteristics. Different approaches try to solve this by combining one or more algorithms.

A hybrid algorithm is one that combines two or more algorithms that solve the same problem, either by choosing one (at the mercy of the data), or by switching between them over the course of the algorithm. This is generally done to combine desired characteristics of each, so that the overall algorithm is better than the individual components. "Hybrid algorithm" does not refer to combining algorithms to solve a problem - many algorithms are the simplest combinations of pieces - but to combining algorithms that solve the same problem and that differ in particular characteristics such as the execution time for an input size dice.

Since they arise from the previous methods described, they will not be used as a category, but are considered in the elaboration of the evaluation index.

## III Results

### 4. Assessment of UAV control methods

Table 1 compares the previous algorithms applied to the control of drones and UAVs, although it should be noted that the performance of a specific algorithm depends upon so many factors that it cannot be modeled completely. The table below helps to give a rough guide as it emerges from previously performed analysis and theoretical knowledge.

| Control Algorithm | Linearity | Good Characteristics | Bad Characteristics |
|---|---|---|---|
| Proportional and Integral plus Derivative | LINEAR | Simple, Noise Tolerant, Allows Manual Adjustment | Little adaptable, Does not reject disturbances, Requires a known model, High Power Consumption |
| Linear Quadratic Gaussian (LQR / G) | LINEAR | Adaptable, Optimizable, Rejects Disturbances | Not very robust, Not intelligent, Requires a known model, Not very precise, High Power Consumption. |
| Sliding Mode (SMC) | NON LINEAR | Adaptive, Good Tracking, Fast Convergence, Accurate, Rejects Disturbances, Requires Little Power | Non Intelligent, Does Not Allow Manual Adjustment, Does Not Tolerate Noise |
| Backstepping | NON LINEAR | Adaptive Good Tracking, Rejects Disturbances | Little Robust, Not Intelligent, Low Convergence, Complex, Does not Allow Manual Adjustment. High Power Consumption |
| Adaptive Algorithms | NON LINEAR | Adaptive, Noise Tolerant, Rejects Disturbances | Non-intelligent, Requires a known model, High Power Consumption |
| Robust Control Algorithms | NON LINEAR | Robust, Noise Tolerant, Rejects Disturbances | Non-intelligent, Low Convergence, High Power Consumption |
| Optimum Control Algorithms | LINEAR / NON LINEAR | Robust, Adaptable, Fast Convergence, Accurate | Requires a known model, High Power Consumption |
| Nonlinear Feedback Linearization Algorithms (FBL) | NON LINEAR | Good Tracking, Fast Convergence, Accurate | Not Intelligent, Does Not Allow Manual Adjustment. High Power Consumption |
| Fuzzy Logic (CLD) | NON LINEAR | Intelligent | Does not tolerate Noise, Requires a known model. High Power Consumption |
| Neural Networks | NON LINEAR | Adaptive, Intelligent, Does not require a known model | Complex, Does not allow Manual Adjustment, Does not tolerate Noise. High Power Consumption |
| Hybrid Algorithms | LINEAR / NON LINEAR | Adaptive, Intelligent, Does not require a known model | Does not allow Manual Adjustment. Does not tolerate Noise. High Power Consumption |

*y*
***orithms***

Despite the low precision in determining the characteristics of the algorithms, you can build a table that indicates in a “rough” way how each algorithm responds to certain characteristics, for example taking values: 1 = Good, 0 = indifferent and -1 = Bad. This allows building the following table:

| Control Algorithm | Characteristics | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Robustness | Adaptability | Intelligence | Tracking | Convergence | Accuracy | Simplicity | Disturbances | Model Independence | Manual Adjustment | Noise Tolerance | Power Consumption |
| Proportional and Integral plus Derivative | 0 | -1 | 0 | 0 | 0 | 0 | 1 | -1 | -1 | 1 | 1 | -1 |
| Linear Quadratic Gaussian (LQR / G)) | -1 | 1 | -1 | 0 | 0 | -1 | -1 | 1 | -1 | -1 | -1 | -1 |
| Sliding mode (SMC) | 0 | 1 | -1 | 1 | 1 | 1 | 0 | 1 | 0 | -1 | -1 | 0 |
| Backstepping | -1 | 1 | -1 | 1 | -1 | 0 | -1 | 1 | 0 | -1 | -1 | -1 |
| Adaptive Algorithms | 0 | 1 | -1 | 0 | 0 | 0 | 0 | 1 | -1 | 0 | 1 | -1 |
| Robust Control Algorithms | 1 | 1 | -1 | 0 | -1 | 0 | 0 | 1 | 0 | 0 | 1 | -1 |
| Optimal Control Algorithms | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | -1 | 0 | 0 | -1 |
| Feedback linearization Algorithms (FBL) | 0 | 0 | -1 | 1 | 1 | 1 | 0 | 0 | 0 | -1 | 0 | -1 |
| Fuzzy Logic (CLD) | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | -1 | 0 | -1 | -1 |
| Neural Networks | 0 | 1 | 1 | 0 | 0 | 0 | -1 | 0 | 0 | -1 | -1 | -1 |

***Table 2. Performance of the Algorithms***

## 5. Construction of an Index to assess UAV control methods

From Table 2, an individual applicability index (IAI) is proposed, which allows evaluating the performance of the Control Algorithm for a given application. The index is obtained by the following formula

$$IAI = \sum NC1\ (ICi) / NC$$

With:

NC = Number of features required
CI = characteristic index {1 = Good, 0 = indifferent, -1 = Bad)

This index will return a value between 1 and -1 indicating that the chosen algorithm for the desired characteristics will have a good performance if the value obtained is close to 1 or a performance if it is close to -1.

With this index, the combined use of two or more algorithms could also be evaluated, through a joint applicability index (IAC), which is obtained from:

$$IAC = \sum^{NA}{}_{1}\ (ICI_i)/NA$$

With:

NA = Number of algorithms to use

The way to evaluate this index is through the analysis of published works that describe the control system used, the application of the UAV and the results obtained. In this way, it is possible to check whether the Index reflects the performance of the control system.

## 6. Results.

### 6.1. Comparison of published results with the Index

A total of 27 publications that described the application and results of different control methods were analyzed, in each case the individual or joint applicability index was obtained as appropriate, the results were added to Table 3, where the results reported by the publications were categorized in: Good, Fair and Insufficient.

The performance of the indicator is evaluated through reports of 27 different published works, calculating the indicator in each case and indicating if it can express the result indicated by said works. (The index is calculated, and the performance of the index is compared with that reported by the paper, resulting in: 2= Matches, 1=Partially matches and 0=Does not match. The result of the evaluation is the percentage of the score obtained respect to the maximum possible score)

| Control Method | Paper | IAI | Reported Result | Result |
|---|---|---|---|---|
| **PID** | Maalouf, D. et al. 2012<br>Parameter changes | 0.5 | Good | 1 |
| | Li, Y et al., 2015<br>Follow-up control before changes in currents, Independence of the mathematical model | 0 | Fairly<br>Good | 1 |
| | Guerrero, J. et al. ,2019<br>Trajectory tracking and yaw angle changes | 1 | Good<br>Good | 2 |
| **LQR/G** | Du, G. et al., 2011<br>Navigation Precision, Number of Calculations | .5 | Good<br>Good | 1 |
| | Wang, S. et al., 2016<br>Dynamic resistance to angle changes | 1 | Good | 2 |
| | Mohamed, S. et al., 2020<br>Stability in motion control. And the response speeds | 1 | Good<br>Good | 2 |
| **SMC** | Hernández Julián, et. al., 2016<br>disturbance reduction | 1 | Good | 2 |
| | Escobar Ponce e Imba Cruz, 2018<br>Trajectory tracking against changes in disturbances | 1 | Good | 2 |
| | Medina,V. Et al., 2020<br>Precision Search Stability and Robustness | 0.66 | Good<br>Good<br>Good | 1 |
| **Backstepping** | Z hang, M. et al., 2017<br>Trajectory tracking.<br>propellant failures<br>Model uncertainty | 0.66 | Good<br>Good<br>Good | 2 |
| | Liang, X. et al., 2017<br>Seguimiento trayectorias 3D. Robustez Respuesta perturbaciones externas | 0.66 | Good<br>Good<br>Good | 2 |
| | Li, X. Et al., 2020<br>Response to nonlinear disturbances. Sturdiness | 0.5 | Good<br>Good | 1 |
| **Adaptive** | Spandan et al., 2013<br>Response to Noise, in trajectory follow-ups | 0.5 | Good<br>Insufficient | 2 |
| | Zaín et al., 2017<br>Robustness, convergence to errors in the presence of uncertainty and disturbances | 0.5 | Good | 2 |
| | Cao y Xu, 2020<br>Dynamic Unknown Trajectory Prediction | 1 | Good | 2 |
| **Optimal Control** | Chybaa et al., 2009<br>Energy consumption | 0 | Good | 1 |
| | (Rout y Subudhi, 2017<br>trajectory tracking Response to model uncertainties | 0.5 | Good<br>Good | 2 |
| | LI et al., 2020<br>Control of nonlinear trajectories. | 1 | Good | 2 |
| **FL** | Jian et al., . 2012<br>Response to disturbances | 1 | Good | 2 |
| | Moon y Lee, 2018<br>Response to uncertainties in the model | 0.5 | Good | 2 |
| | Rattanawaorahirunkul et al., 2020<br>Steady state response. Response precision. dynamic monitoring | 0.66 | Good<br>Good<br>Good | 2 |
| **Fuzzy Logic** | Ishaque et al., 2010<br>Adjustment of control parameters | 1 | Good | 2 |
| | Londhe et al., 2017<br>Trajectory control against disturbances, Robustness | 0.5 | Good | 2 |
| | Londhe y Patre, 2019<br>Stability. Steady state response. | 0 | Good<br>Good | 1 |
| **RN** | Pan et al., 1014<br>Follow-up. Response to dynamic conditions | 0.5 | Good<br>Good | 2 |
| | Ni et al., 2017<br>route planning | 1 | Good | 2 |
| | Duab et al., 2020<br>Trajectory tracking, Simplicity and Robustness | 0 | Good<br>Good<br>Good | 1 |

*Table 3. Results of the application of the control method*

The same methodology was applied for the analysis of hybrid methods, although not many publications were found. The results are shown in Table 4

| Control Method | Paper | IAI | Reported Result | Result |
|---|---|---|---|---|
| **SMC + PID** | Mohan y Asokan, 2010 Trajectory tracking with disturbances | 0.75 | Good | 2 |
| **Fuzzy + PID** | Deng et al., 2014 Adaptation of the Control to variable environments | 1 | Good | 2 |
| **Linear + Fuzzy** | Vang et al., 2016 heading control | .66 | Good | 1 |
| **Fuzzy + PID** | Li et. al., 2019 Sturdiness | 1 | Good | 2 |
| **Fuzzy + SMC** | Cai et al., 2020 movement precision | .75 | Good | 2 |

*Table 4. Results of the application of hybrid methods*

### 6.2. Analysis of the obtained results

Analyzing Table 3 and Table 4 it can be seen that of the categories that were established to classify the results, one result is observed in category Fairly and one in category Insufficient, which would generate a bias that is explained by the fact that most of the published works do not usually report bad results. The allocation of category Good was carried out based on the universality of the results shown, since in some cases they were compared with other works that used different control methods, in other cases they were compared with results of theoretical models and in other cases with other implementations of the same control method.
It can be observed that most of the results reported by the analyzed publications correspond to the results of the calculation of the IAI and IAC indices. This could lead to the use of these indices as an estimate of the results to be obtained in the application of a method, or a combination of them, for a given application.
It should also be noted that the defined intervals include the numerical values that limit them with the neighboring categories, which could give rise to some uncertainty as to which category it should correspond to, but provides guidance on the results that could be obtained. However, since some control methods could be divided according to some of their particularities and the number of features of those methods could be increased, the uncertainty could be eliminated. The possibility of correcting this uncertainty is what demonstrates the usefulness of the presented method.

## 7. Conclusions

The review carried out and the method of evaluation of a specific control system for a certain use allow us to have analysis tools for future works that can be carried out for the control of UAVs. As can be seen from this review, no algorithm has all the characteristics compared to the total number of problems that must be faced when beginning the design of a control system. It is also clear from the works analyzed that a better performance is obtained by combining different algorithms that provide the best combination of the desired characteristics, such as: robustness, adaptability, optimality, simplicity, tracking capacity, fast response and disturbance rejection, among others. others. However, this does not guarantee good overall performance; having to reach a compromise on which characteristics would be the most appropriate, for a given application. Although there is no consensus on which model would give the best overall performance, the proposed a priori evaluation method is a useful tool in selecting a combination of control algorithms.

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## 7. Bibliography

A. Benaddy, M. Bouzi and M. Labbadi, ( 2020),"Comparison of the different control Systems". Control Applications in Marine Systems CAMS04. IFAC, Ancona, Italia, pp. 203–208.

A. Budiyono (2009) Robust Control Synthesis for an Unmanned Underwater Vehicle World Academy of Science, Engineering and Technology 60

Bhattacharya D., Puttamadappa C. (2021) Designing of Adaptive Depth Control for Autonomous Underwater Vehicle Using Type-2 Fuzzy Logic Controller. In: Favorskaya M., Mekhilef S., Pandey R., Singh N. (eds) Innovations in Electrical and Electronic Engineering. Lecture Notes in Electrical Engineering, vol 661. Springer, Singapore. https://doi.org/10.1007/978-981-15-4692-1_35

Chang-Zhong Pan, Simon X. Yang, Xu-Zhi Lai, Lan Zhou (2014), An Efficient Neural Network based Tracking Controller for Autonomous Underwater Vehicles Subject to Unknown Dynamics. The 26th Chinese Control and Decision Conference (2014-CCDC) - 3300 - 3305

Chovancová, A.; Fico, T.; Duchoň, F.; Dekan, M.; Chovanec, Ľ.; Dekanová, M. (2020). Control Methods Comparison for the Real Quadrotor on an Innovative Test Stand. Appl. Sci.,10, 2064

Chybaa, M., Haberkornd, T. , Singha, S., Smithb, R. & Choic,S. (2009) Increasing Underwater Vehicle Autonomy by Reducing Energy Consumption. Ocean Engineering Volume 36, Issue 1,, Pages 62-73

Deng, Zhigang; Zhu, Daqi; Xu, Pengfei; Fang, Jianan (2014) Hybrid Underwater Vehicle:

ARV Design and Development .Sensors & Transducers; Toronto Tomo 164, N.º 2, 278-287.

Du, Gang, Zhan, Xingqun, Gu, Yunbiao, Zhai, Chuanrun, (2011), "Research on Embedded Model-Aided Autonomous Navigation for Miniature UAVs," Proceedings of the 24th International Technical Meeting of the Satellite Division of The Institute of Navigation (ION GNSS 2011),
Portland, OR,, pp. 1839-1844.

Duan, K., Fong, S. & Chen, C.L.P. (2020), Multilayer neural networks-based control of underwater vehicles with uncertain dynamics and disturbances. Nonlinear Dyn 100, 3555–3573. https://doi.org/10.1007/s11071-020-05720-5

Elham Yazdani Bejarbaneha, Mojtaba Masoumnezhadb, Danial Jahed Armaghani, Binh Thai Phamd(2020), Design of robust control based on linear matrix inequality and a novel hybrid PSO search technique for autonomous underwater vehicle , Applied Ocean Research Volume 101, 102231

Escobar Ponce, P. D., & Imba Cruz, D. I. (2018). Comparación Mediante Simulación de Tres Controladores Basados en las Estrategias de Control Tipo PID Y Modo Deslizante (SMC) Aplicadas al Seguimiento de Trayectoria de un Vehículo Autónomo Sumergible. 161 hojas. Quito : EPN.

Fossen, T. I. (1994). Guidance and Control of Ocean Vehicles, John Wiley & Sons, Inc., ISBN 0-471-94113-1, Chichester, England.

Fossen, T. I., 2011. Handbook of Marine Craft Hydrodynamics and Motion Control. John Wiley & Sons, ISBN: 978-1-119-99149-6, Nueva York,

Fossen, T. I., Pettersen, K. Y., 2014. On uniform semiglobal exponential stability (USGES) of proportional line-of-sight guidance laws. Automatica 50 (11), 2912–2917.

Hernandez Julian, Anailys & Valeriano, Yunier & Gómez, Jorge & Hernández, Luis. (2016). Controlador I-LOS considerando la distancia lookahead constante para el seguimiento de caminos curvos en UAV.

Ishaque, K., Abdullah, S.S., Ayob, S.M. et al. (2010). Single Input Fuzzy Logic Controller for Unmanned Underwater Vehicle. J Intell Robot Syst 59, 87–100 https://doi.org/10.1007/s10846-010-9395-x

Jesus Guerrero, Jorge Torres, Vincent Creuze, Ahmed Chemori, Eduardo Campos Mercado. (2019) Saturation based nonlinear PID control for underwater vehicles: Design, stability analysis and experiments. Mechatronics, Elsevier, No 61

Ji Hyun Moon and Ho Jae Lee (2018). Decentralized Observer-Based Output-Feedback Formation Control of Multiple Unmanned Underwater Vehicles. J Electr Eng Technol. No 13. Vol 1: 495-502, http://doi.org/10.5370/JEET.2018.13.1.495

Jian, Y., Zhong-hai, Z. , Wen-xia, Z. . (2012). A Feedback Linearization based Leader-follower Optimal Formation Control for Autonomous Underwater Vehicles. Institute of Oceanographic Instrument of Shandong Academy of Science, Qingdao, 266001

John, S. (2013) Artificial Intelligent-Based Feedforward Optimized PID Wheel Slip Controller. AFRICON, 12 September 2013, Pointe-Aux-Piments, 1-6.

K.J. Åström: (2002) Control System Design - Lecture Notes for ME155.California at Santa Barbara.

Li X., Ren C., Ma S., Zhu X. (2020) Compensated model-free adaptive tracking control scheme for autonomous underwater vehicles via extended state observer. Ocean Engineering, Volume 217,

Li, A., Li, Y., Cao, J., Jiang,Y., Hea, J, & Wu, H, (2020). Proximate time optimal for the heading control of underactuated autonomous underwater vehicle with input nonlinearities. Applied Ocean Research Volume 95, 102002

Li, Jiyong; Huang, Hai; Wan, Lei; Zhou, Zexing; Xu, Yang. (2019):Hybrid Strategy-based Coordinate Controller for an Underwater Vehicle Manipulator System Using Nonlinear Disturbance Observer. Robotica; Cambridge Tomo 37, N.º 10, 1710-1731

Li, Y., Yanqing, J., Wang, L., Cao, J. & Zhang, G. (2015). Intelligent PID guidance control for UAV path tracking. Journal of Central South University. 22. 3440-3449. 10.1007/s11771-015-2884-0.

Liang X, Qu X, Hou Y, Zhang J. (2017) Three-dimensional path following control of underactuated autonomous underwater vehicle based on damping backstepping. International Journal of Advanced Robotic Systems.. doi:10.1177/1729881417724179

Londhe, P.S., Patre, B.M. (2019). Adaptive fuzzy sliding mode control for robust trajectory tracking control of an autonomous underwater vehicle. Intel Serv Robotics 12, 87–102 . https://doi.org/10.1007/s11370-018-0263-z

M. Cai, Y. Wang, S. Wang, R. Wang, Y. Ren and M. Tan, (2020) "Grasping Marine Products With Hybrid-Driven Underwater Vehicle-Manipulator System," in IEEE Transactions on Automation Science and Engineering, vol. 17, no. 3, pp. 1443-1454, doi: 10.1109/TASE.2019.2957782.

Maalouf, D., Tamanaja, I., Campos, E., Chemori, A., Creuze, V., Torres,J. And Lozano, R. (2012) From PID to Nonlinear Adaptive Depth-Control of a Tethered Autonomous Underwater Vehicle.In IEEE/RSJ IROS’12, Algarve, Portugal

Mesdaghi, S., Dosaranian-Moghadam, M. (2019). 'A Fuzzy Logic Control System for Quadcopter by Human Voluntary-Physical Movements', Journal of Computer & Robotics, 12(1), pp. 39-45.

Mohan Santhakumar & Thondiyath Asokan (2010) Investigations on the Hybrid Tracking Control of an Underactuated Autonomous Underwater Robot, Advanced Robotics, 24:11, 1529-1556, DOI: 10.1163/016918610X512587

Omar A.Jasim Sandor M.Veres (2020). A robust controller for multi rotor UAVs Aerospace Science and Technology Volume 105,, 106010

P. S. Londhe, M. Santhakumar, B. M. Patre and L. M. Waghmare, (2017)."Task Space Control of an Autonomous Underwater Vehicle Manipulator System by Robust Single-Input Fuzzy Logic Control Scheme," in IEEE Journal of Oceanic Engineering, vol. 42, no. 1, pp. 13-28, https://doi.org/10.1109/JOE.2016.2548820

Pawłowski, P. y Konatowski, S. (2020). Linear controller design with the use of PSO algorithm for UAV trajectory tracking Proceedings. Radioelectronic Systems Conference 2019. Volume 11442, , Jachranka, Poland. https://doi.org/10.1117/12.2565129

R. Amin, A. A. Khayyat and K. G. Osgouie, (2010),"Neural networks control of autonomous underwater vehicle,", 2nd International Conference on Mechanical and Electronics Engineering, Kyoto, pp. V2-117-V2-121, doi: 10.1109/ICMEE.2010.5558474.

R. Prasanth Kumar, A. Dasgupta Ã , C.S. Kumar(2007) Robust trajectory control of underwater vehicles using time delay control law Ocean Engineering 34 842–849

Rapeepong Rattanawaorahirunkul , Peerayot Sanposh, Kanjanapan Sukvichai , Yodyium Tipsuwan , Phakhachon Hoonsuwan (2020) Feedback Linearization with PID Controller Design for Autonomous Underwater Vehicle Using Particle Swarm Optimization (PSO) Department of Electrical Engineering, Faculty of Engineering, Kasetsart University, Bangkok 10900, Thailand

Rout,R & Subudhi,B. (2017). Inverse optimal self-tuning PID control design for an autonomous underwater vehicle. International Journal of Systems Science Volume 48, Issue 2

Rui Wang , Shuo Wang Yu Wang (2016). A Hybrid Heading Control Scheme for a Biomimetic Underwater Vehicle. International Society of Offshore and Polar Engineers. The 26th International Ocean and Polar Engineering Conference, Rhodes, Greece 2016. IDISOPE-I-16-625

S. A. Mohamed, A. A. Osman, S. A. Attia and S. A. Maged, (2020)."Dynamic Model and Control of an Autonomous Underwater Vehicle," International Conference on Innovative Trends in Communication and Computer Engineering (ITCE), Aswan, Egypt, 2020, pp. 182-190, doi: 10.1109/ITCE48509.2020.9047757.

S. Wang, H. Jin, L. Meng and G. Li, (2016) "Optimize motion energy of UAV based on LQR control strategy," (2016) 35th Chinese Control Conference (CCC), Chengdu, 2016, pp. 4615-4620, doi: 10.1109/ChiCC.2016.7554068.

SNAME, 1950, \Nomenclature for Treating the Motion of a Submerged Body Through a Fluid". The Society of Naval Architects and Marine Engineers, Technical and Research Bulletin No. 1-5.

Spandan Roy, Sambhunath Nandy, Sankar Nath Shome, Ranjit Ray (2013) Robust Position Control of an Autonomous Underwater Vehicle: A Comparative Study. IEEE International Conference on Automation Science and Engineering (CASE)

Spandan Roy, Sambhunath Nandy, Sankar Nath Shome, Ranjit Ray, (2013). IEEE International Conference on Automation Science and Engineering (CASE).

Valeriano Medina, Y., Hernández, L., Garcia Garcia, D., Hernández Morales, L. E., Miranda Jiménez, L., & Milián Morón, O. (2020). Esquema de guiado para el seguimiento de caminos rectos en un vehículo sub-acuático. Revista Cubana De Transformación Digital, 1(2), 85-95.

X. Cao and X. Xu, (2020),"Hunting Algorithm for Multi-UAV Based on Dynamic Prediction of

Target Trajectory in 3D Underwater Environment," in IEEE Access, vol. 8, pp. 138529-138538, doi: 10.1109/ACCESS.2020.3013032.

Yun Ni, Liuying Wu, Pengfei Shi, Simon X. Yang, (2017),"A Dynamic Bioinspired Neural Network Based Real-Time Path Planning Method for Autonomous Underwater Vehicles", Computational Intelligence and Neuroscience, vol. 2017, Article ID 9269742, 16 pages,. https://doi.org/10.1155/2017/9269742

Zain Anwar Ali; Dao Bo Wang; Muhammad Aamir; Suhaib Masroor (2017) MRAC base robust RST control scheme for the application of UAV. International Journal of Modelling, Identification and Control (IJMIC), Vol. 28, No. 3,

Zhang, Mingjun; Liu, Xing; Wang, Fei. (2017). Backstepping Based Adaptive Region Tracking Fault Tolerant Control for Autonomous Underwater Vehicles. The Journal of Navigation; Cambridge Tomo 70, N.º 1. DOI:10.1017/S0373463316000370