VISIÓN ELECTRÓNICA

DEFINICIÓN DE ESTADOS EMOCIONALES EN SISTEMAS DINÁMICOS

DEFINITION OF EMOTIONAL STATES FOR DYNAMICAL SYSTEMS

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Resumen:

Este trabajo presenta una forma de lograr sistemas adaptables y autónomos, con el propósito de emular inteligencia en máquinas, de manera que estas puedan verse como entidades que tracen sus propios planes y los sigan. Sin embargo, el enfoque del artículo no es mostrar la construcción de humanoides, sino que es presentar mejoras en el control de cada actuador en una máquina, esto como primer paso para tener dispositivos inteligentes. El trabajo de cada algoritmo de control es el tomar decisiones para fijar la dinámica del sistema que dirige en un valor llamado referencia. En este sentido, el autor asocia descubrimientos recientes en neurociencia y psicología acerca de la importancia de las emociones en el proceso de toma de decisiones con el trabajo de los controladores. Como resultado, se define y prueba un grupo de emociones básicas que deberían tener los controladores.

Palabras clave:
Control de sistemas, emociones, sistemas no lineales, proceso de toma de decisiones.

Abstract:
This work is part of new scientific attempts of having adaptive and autonomous systems. That is useful to improve the intelligence of machines in order to have capable entities to trace their own plans and to follow them. Even though the focus of the paper is not to build humanoids but to improve the control of every actuator in a machine, which would be the first step to have intelligent devices in a down-up approach. The work of every control algorithm is to make decisions in order to fix the dynamic of a system on a defined reference value. The author of this paper associates recent discoveries of neuroscientists and psychologist about the importance

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of emotions in the decision-making process with the task of controllers. As a result a group of basic emotions are defined as well as tested.

Key Words:
Control Systems, Decision-Making Processes, Emotions, Non-linear Systems.

1. Introduction

Current machines cannot follow their own plans: they are programmed. To avoid losing control, redundant systems and protections are necessary because even the machine's operation can damage its own integrity. In addition, the complexity of machines has been increasing, but intelligence has not evolved at the same pace. Some solutions have been proposed in areas such as computational intelligence, which use techniques like fuzzy logic, neural networks, genetic algorithms, swarm intelligence and artificial immune systems in order to create more intelligent programs [1]. However, it is not possible to say that there is an industrial system capable of being conscious of itself, deciding what to do, and defining its own values and goals.

It is better to divide the problem—complex machines without enough intelligence—and to seek solutions from different branches of science. For instance, this work considers only two subproblems: adaptability and autonomy. About adaptation, two scenarios may be observed: the external and internal system. The external scenario takes into account changes in the environment; if the changes occur very slowly, then the machine may not notice them; in contrast, if they happen very fast, there may not be enough time to adapt to the changes or learn from them. The internal scenario includes faults and changes in the attributes of the system.

An autonomous system is a system that performs tasks in an unknown environment without human supervision. This requires making decisions to evaluate the current state and ideal situations, and determining what is desirable and what to avoid [2]. Examples of applications where adaptive and autonomous systems are needed are: (1) planetary explorations and (2) motion in environments harmful to humans. These include robotics such as unmanned aerial vehicles (UAV), which can also be ground or aquatic vehicles [3].

A big challenge for these machines is to determine how to get from a point A to point B, while within an unknown and changeable environment. The general way to deal with it is called motion planning: a route is traced and the machine must track it as close as possible. This tracking means changing the reference point for every actuator adequately, e.g., motors or hydraulic cylinders. Therefore, each physical variable—such as speed and position—must be set at specific values constantly in order to follow a precise path [4].

As in the motion of the UAV, each of the robot's actuators must determine how to go from an initial state to a desired final state, for example from zero speed to the nominal value. Therefore, the same problem obtains at a low level: machines do not have enough intelligence to make their own decisions or to follow their own plans. So solving the low level problem (i.e., making more intelligent controllers) is a good approach to solving the high level problem, that of the entire machine.

Clearly, the human body is a highly adaptive and autonomous entity in nature; humans inhabit diverse regions of the world, gain experience, learn, associate concepts, and make decisions that are useful to survival and reproduction. Humans have transformed the environment to serve own purposes and plans, and reasoning is undoubtedly one of the most powerful tools in that process.

Engineering has designed controllers based logical components, such as mathematical functions, which result in rigid algorithms known as hard computing. Psychologists and neuroscientists have proved that is not possible to reason properly without emotions. Emotions play an important role in long term memory and learning; in addition, they are essential in the human decision-making process [5].

The hypothesis of this work is that including emulated emotions in control algorithms would make them adaptive and autonomous. This should allow them to trace their plan to reach a desired value, the reference signal, without human guidance even when the environment changes.

2. Computational Models of Emotion

Researchers in cognitive science and related areas have proposed several computational models of emotions; these are useful to demonstrate or refute theories about emotions. For example, one of the most complete models, based on neuroscience, studies the interaction between attention and memory [6]. Other models represent the cognitive process of decision making, especially applied to robotics or virtual agents [7-13]. Two of them have been used in controlling dynamical systems, in a way similar to the model proposed in this paper. The first model applies neuronal nets in implementing the control algorithm [14].

The second model is more relevant, though it was not originally designed for adaptive control. In this model authors seek to reproduce the emotional learning occurring in the amygdala, and the relation of the amygdala with the orbitofrontal cortex [15]. Their equations represent the connections among elements, and the work of each component is reduced to comparisons and to the four basic arithmetic operations. It provides a helpful algorithm for real time applications.

In this section, a continuous model of emotions is taken. There exist theories that assume that emotions are discrete; these theories create sets out of basic or principal emotions. Viewing emotions as being discreet has inspired several engineering applications; some of its theorists include: Robert Plutchik, Paul Ekman, and Nico Frijda, who have defined eight, six, and six basic emotions, respectively. In control, some studies based on discrete emotions make use of anger and fear in search algorithms as well as in generation of autonomy [16, 17].

Against the discreet theories of emotions, the continuous theories focus on two aspects: one known as the appraisal theory and the other as the dimensional theory of the affection. The two main authors of the first theory are psychologists Richard Lazarus and Craig Smith. They seek to define emotions as the result of evaluating a situation; this explains why the same condition activates a variety of emotions in the same person, according to the context, or triggers different emotions in different people.

The definition of emotion takes into account the suddenness of a situation, the importance of the goal that is being sought, the control that can be gained from the situation and the available energy, among other aspects. Documents have been proposed using from five to sixteen variables [18]. Currently, some work has been done in support of this theory from neuroscience and it is complemented with the use of the nonlinear dynamic systems theory in the generation of a computational model of emotions [19].

The second point of view regarding the continuous theories of emotions is the dimensional theory. This was proposed by Russell in 1980, who measured emotional states in human beings by means of two variables: valence and arousal. Valence indicates the emotional experience from positive states such as happiness, to the negative ones such as anger. Arousal ranges from inactive such as sleepiness, to very active ones such as excitement [20]. When Russell measured such dynamical states, he represented them on a Cartesian coordinate system with the valence on the horizontal axis and the arousal on the vertical axis. Therefore, emotions occupied a circular region, and that is why this proposal is known as the Circumflex Model of Affect. Although this theory was proposed by psychologists, in the last years, it has also been supported by neuroscience [21].

Based on the Circumflex Model of Affect, a great many contributions have been made to medicine, psychology, language analysis, and music, among other fields. Recent work includes the measurement of emotional states in order to change screen colors on a mobile phone [22], and the measurement of emotional states in a player to alter the characteristics of a video game [23]. Another work in robotics is the design and construction of EDDIE (An Emotion-Display with Dynamic Intuitive Expressions). This robot regulates the action of servomotors, which control the movement of ears, eyes and mouth in the generation of emotional expressions [24]. From the analysis of this application, they concluded that the dimensional theory is useful in building a control strategy based on emotions. It has a continuous evaluation of emotions and it is easy to implement. As can be seen, the value of the model has been demonstrated in a diverse range of scientific fields.

3. Mathematical Basics

The dynamical system to be controlled must be described by means of a non-linear differential equation. The phase plane is a didactic math tool used to study the system [25]. It divides a second order differential equation into two equations, so an additional dependent variable might be defined. Usually all that is used is the first derivative of the output. For instance, the speed is the intermediate variable when the output is the position.

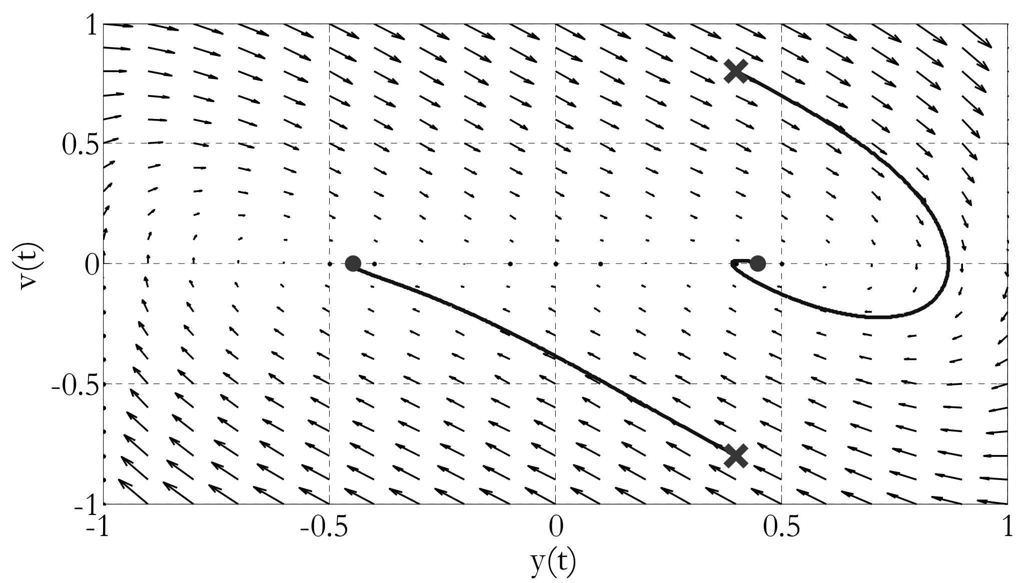
Equation (1) is an example of a non-linear system. It is rewritten as two state equations in (2), which y(t) is the output of the system, v(t) is the rate of change of y(t), and u(t) is the input.

$$\frac{d^2y(t)}{dt^2}+\frac{dy(t)}{dt}+y(t)\left(y^2(t)-0{,}2\right)=u(t) \qquad (1)$$

$$\begin{aligned}\frac{dy(t)}{dt}&=v(t)\\ \frac{dv(t)}{dt}&=-y(t)(y^2(t)-0.2)-v(t)+u(t)\end{aligned} \qquad (2)$$

The phase plane method draws a vector field. It associates a vector to every pair (y(t),v(t)). The horizontal component of the vector is v(t) and the vertical one is dv(t)/dt,

Figure 1. Motion of the Non-linear System in the Phase Plane. The arrows are the vector field of the system described by (2), with u(t) = 0. First values, marked with crosses, are defined at t = 0s, while dots are the last duples, at t = 15s. In this case, the continuous line shows how the system by itself reaches a different attractor according to its initial condition.



as described in (2). Each arrow indicates the tendency, so $(y(t+\Delta t), v(t+\Delta t))$ can be predicted by means of the current values of y(t) and v(t). Figure 1 illustrates two solutions to the non-linear system in equations (1) and (2). It can be seen that different sets of initial conditions lead the system towards different attractors.

A controller takes into account the desired value y(t), which is called the reference value, or r(t), as the main goal. If the reference does not change, then the desired v(t) will be null. The control algorithm should make decisions in order to transform current y(t), into the desired r(t). There is only one way to do it, and it is by varying u(t). The algorithm can only make three possible decisions: increasing, decreasing or maintaining u(t). However, in addition to these three options, it should also determine when, how much and how long it takes.

A phase plane "landscape," i.e., the vector field, is transformed when the actuating signal, u(t), changes. It implies that attractors change their position or even disappear from the scene. Therefore, the work is to modify the landscape adequately, forcing the motion of the system (the line in the figure 1) to reach a desired point.

4. Reference Model Definition

Having summarized a general control system, it is time to explain the particularities of emotion based control. First the reference signal is described. It should be designed to avoid rough transitions because it means an infinite rate of changes which are difficult to deal with mathematically. So original r(t) goes through a low-pass filter to even the reference. This filter is called Reference Model - RM.

The Reference Model puts together all the technical constraints that the overall system must accomplish, for instance an adequate peak response, a maximum settling time or a certain rise time. There are at least two models that satisfy the constraints and have been well tested (these are Bessel and ITAE [26]). The first one has zero overshoot, and the second one is optimal regarding energy consumption. If the type was already selected, what remains is to determine the settling time.

RM is an important component for the control architecture because it does not only produce smooth transitions, but it is the way to "teach" the system how to "behave". It is the mentor, and everything is measured having its behavior as the target or the ideal. The figure 2 shows an unstable system which becomes stable when it follows RM. A classical PI controller measures the distance between y(t) and RM output, and feeds the system proportionally.

A remarkable characteristic of the dynamic of the system is evident when X and Y axis labels are ignored. It looks like the system is chasing the RM, like a predator chases its prey. The reference model knows where to go, i.e., the reference point, while the system follows the RM. Therefore a perfect controller is one that forces the system to be just one step behind the RM. In other words, the system's goal changed from

Figure 2. System behavior goes after the Reference Model. The RM's Transfer function is 1/(S2 + S + 1), and the system is 1/(S – 1), in addition, unitary feedback is used, as well a classical PI controller with P = 2, I = 2. The simulation time is 6s, and the initial condition is (0,0). Vector field is omitted intentionally to improve clearness.

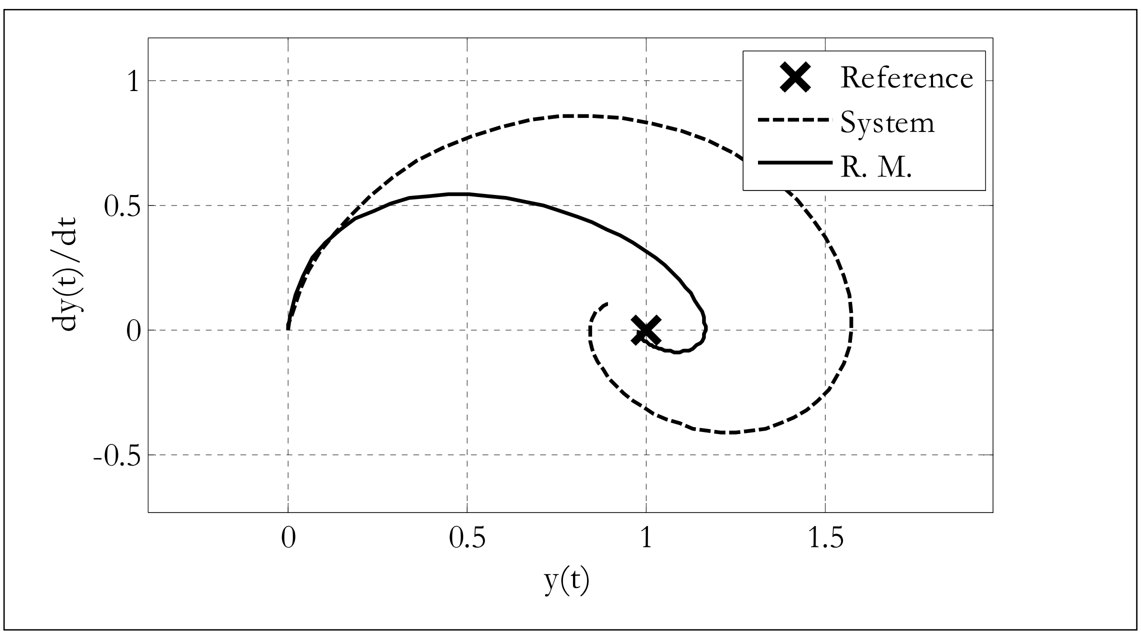
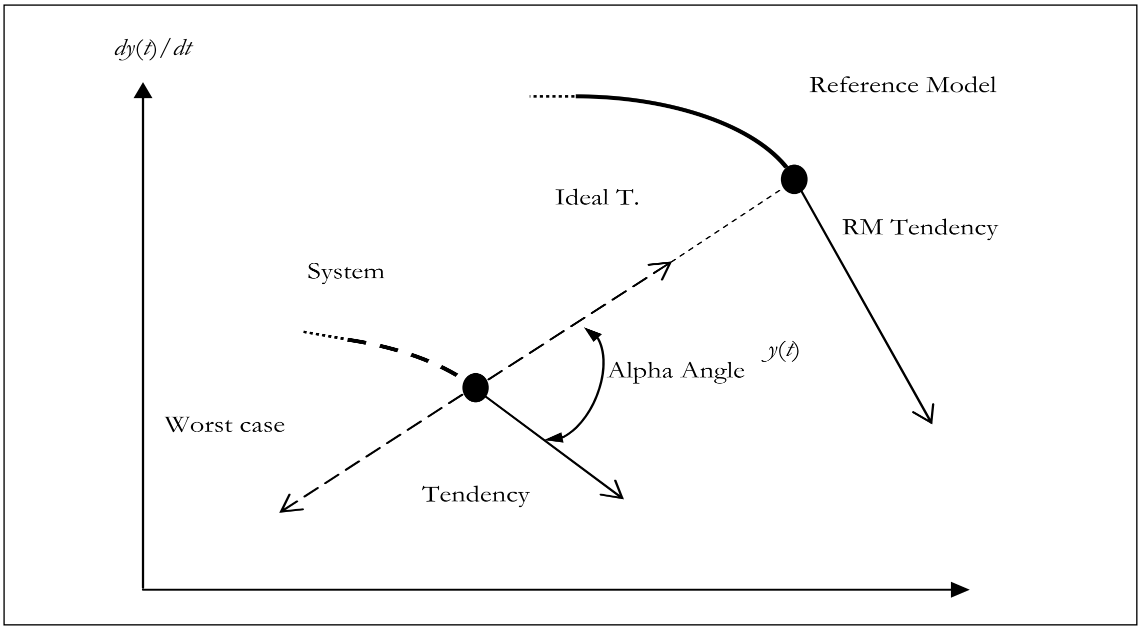


Figure 3. Vector definition according to pursuit-evasion problem. The relation between line-of-sight and tendency of the system is useful to evaluate how close the system is to the ideal tendency. That can be labeled Alpha Angle for now, but it will be related to emotional state definition.



reaching the reference point to having the same dynamic of the RM.

Pursuit-evasion actions have been considered for solving problems in evolutive computing, network security, motion planning (e.g., missile tracking systems) and cooperative robotics, among other fields [27-29]. In this case, there is an important simplification which comes from the evader behavior. It does not try to escape, on the contrary, it seeks the reference point and simultaneously acts as a mentor to the dynamical system which follows it.

Having defined the continuous nature of the process by (1) and (2), a geometric approach is selected to measure the distance from the system to the RM. In the figure 3 there is a snapshot of the dynamic at unspecified time t. It has an ideal tendency for the system, which must fall into the line of sight between the RM and the system. Although this is not the exclusive definition, it is the simplest. For example, a predictive algorithm would consider the ideal tendency towards the direction of the RM vector.

5 Definition of Emotions

The ideal emotional state for solving hard problems has been identified as the state of being calm. In brief, the more complex the task, the lower the level of emotional arousal that can be tolerated without interfering with the system's performance. This is well known as the Yerkes-Dodson law [30]. So the ideal tendency is translated as calmness. It means that the goal of the new algorithm is to reach calm, avoiding other emotions. The next step is then to define all emotional states that a controller can experience.

It is essential to say that a controller does not need all the range of emotions that are felt by humans, but just an adequate range which helps to perform the control task. This range can also be used in the learning and decision-making processes. In this work, it is assumed that there will not be emotional illnesses or behavioral disorders, such as stress, phobias, manias, and so forth. It is guaranteed because the controller just experiences one emotion at each moment; it is also limited to the same task all the time; and, finally, the controller experiences only a selected group of emotions and not all of them.

To define all the emotional states, there is an imaginary situation where a person controls a process, and he/she has experienced difficulties, challenges and results. For instance, a person is happy when his/her plans are working as expected; if not, he may be afraid. See Table 1 for definitions of emotional states. Emotions ranging from calm to anger are a function of instant behavior, without considering previous or future states. However, sleepiness and relaxation, or annoyance and frustration, depend on how long the controller has experienced calm or anger, respectively.

Notice that the definitions in Table 1 are not fully detailed. For instance, there is not any angle, range of time, or scale indicated. This is because the algorithm will have the

Table 1. Emotional State Definition

Emotion	Definition
Sleepiness	The plan has worked for a long time, and everything looks steady
Relaxation	When zero alpha has been reached and nothing has changed for certain time
Calm	Zero alpha has been reached, or the angle is small
Satisfaction	The goal, zero alpha angle, has not been reached yet, but it is permissible
Happiness	At least, the distance between system and RM is decreasing. It is going to take some time to reach the ideal angle, but it is possible
Excitement	The system does not increase or decrease, but maintains the ratio between RM and system, so it oscillates around RM
Fear	Alpha angle says that the ratio between RM and system is increasing
Anger	This is the worst case scenario. System tendency is directed to the contrary of ideal, so it looks like that the goal is never going to be achieved
Annoyance	The controller has experienced anger for some time
Frustration	It has not been possible to change the system behavior. Ratio between reference signal and system has exceeded some maximum value.

ability to change them to more convenient values according to its own experience, but this is out of the scope of this paper. Some predefined values are: calm has a null alpha angle, satisfaction is initially fixed at an alpha angle equal to 30°, happiness is found at 60°, and excitement is exactly at 90°; fear is at 135°, and anger at 180°.

6. Simulation and Analysis

The following paragraphs describe each emotion. Simulations have been done using an unstable system H(S) = 1/(S – 1), which is controlled by a classical PID, with unitary feedback. The reference signal is a step function, and initial conditions are y(0) = 0, and dy(0)/dt = 0. In addition, the output signal of the reference model is rm(t).

Figures 4 to 7 have four graphs each. The left side shows one emotion and the right side another. The upper figure illustrates the behavior in time, and the lower graph is a graph in polar coordinates where emotions are presented. The angle in polar coordinates is alpha, the radius is the absolute value of the distance between rm(t) and y(t). The figure 4 shows a system which moves away from the reference; the difference between the left and right figures is the speed.

Anger, shown on the left side of the figure 4, begins at 3s, where the slope of y(t) is maximum, so the radius increases to reach the value 200 in 15s. The figure at the right side begins at 0s, but fear is experienced after 2s. The slope is lower than in the case of anger, and the highest difference is 1.25 at

Figure 4. Anger and Fear. The Reference Model for both emotions is 1/(S2 + 2S + 1). Anger is on the left side, with P = 0.2, I = 0.2, D = 0. Fear is on the right side, with P = 0.9, I = 0.3, D = 0.

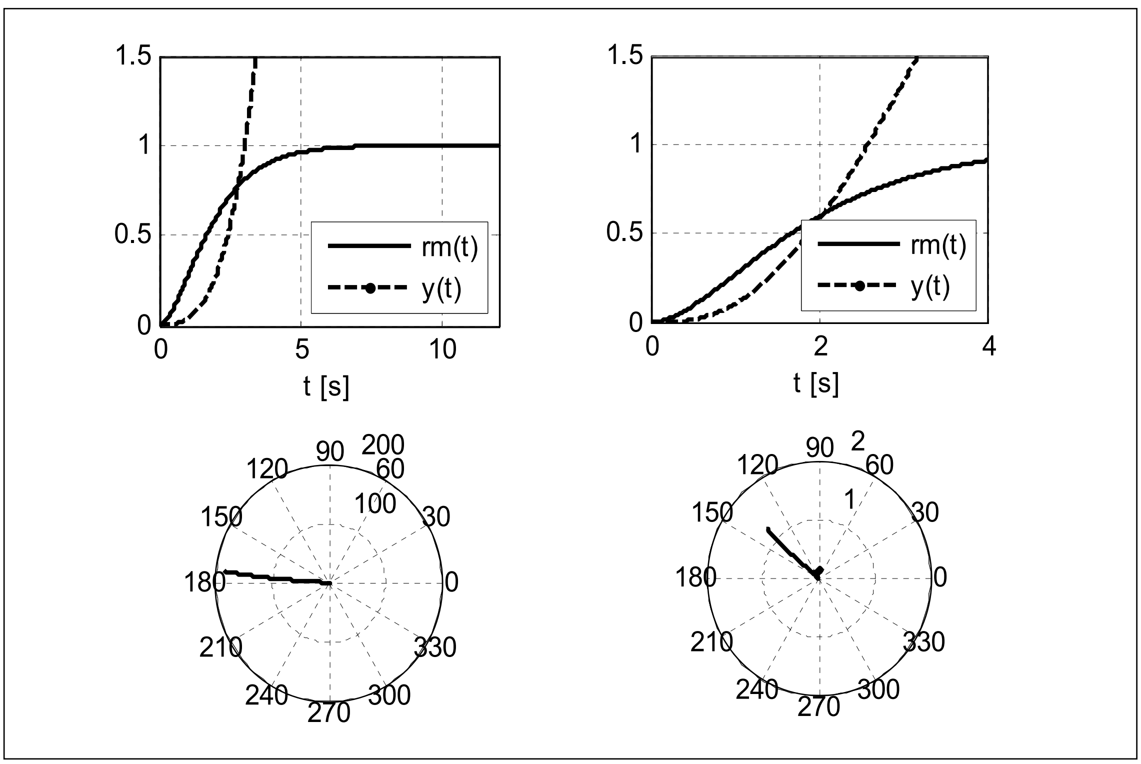
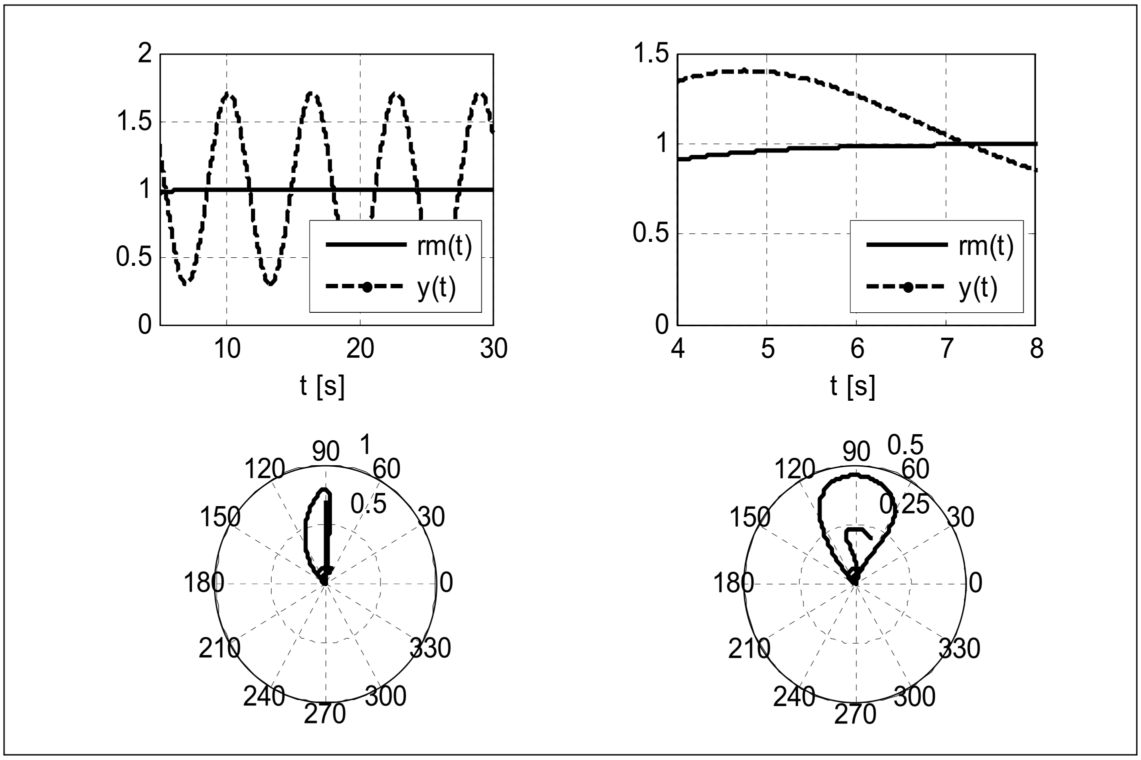


Figure 5. Excitement and Happiness. The Reference Model for both emotions is RM(S) = 1/(S2 + 2S + 1). Excitement is on the left side, with P = 1, I = 1, D = 0. Happiness is on the right side, with P = 1.5, I = 1, D = 1.



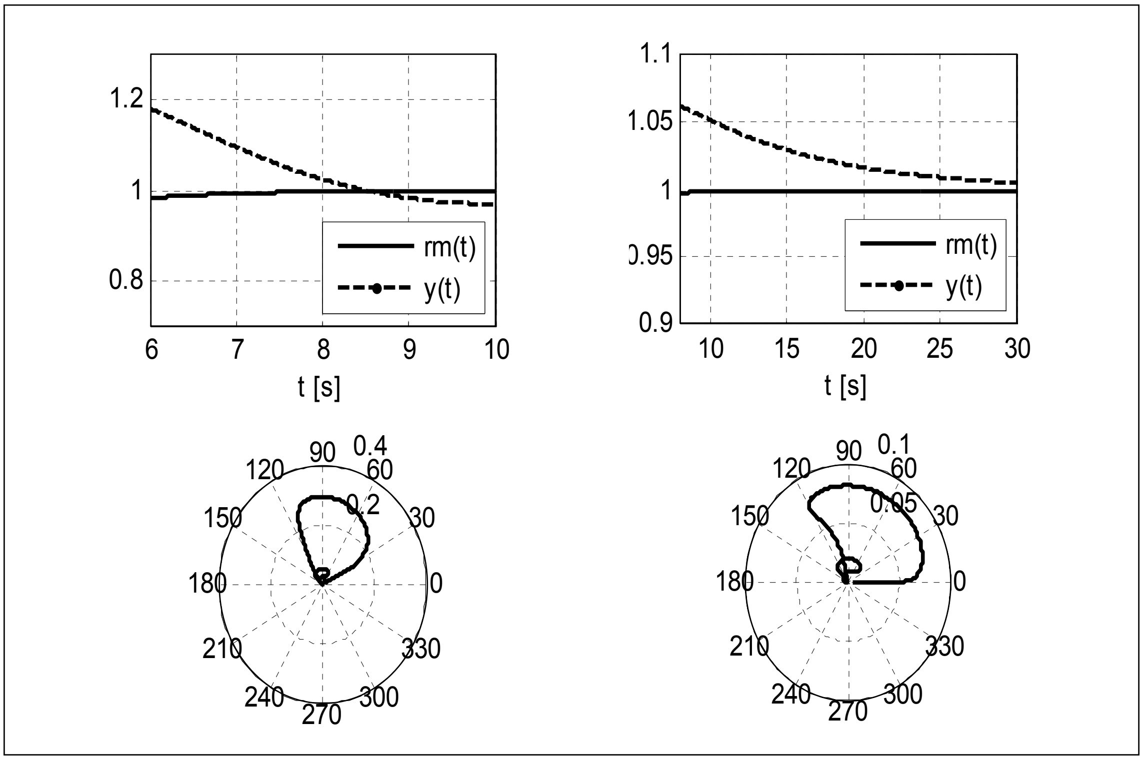
4s. Even when the radius changes, the tendency is held, therefore the emotion does not change for the simulation time. Emotion definition takes into account only current tendency, not the difference between rm(t) and y(t).

Excitement and happiness are simulated in the figure 5. Excitement is the most important emotion because it defines the limits between stable and unstable behaviors. When the step signal appears at 0s, the emotion is negative, because the RM moves towards the reference value, while the system stays still due to its inertia.

Then, the controller works and corrects, so the system follows the reference model. This implies a positive emotion, for example, happiness or satisfaction, but in the border excitement is found. Excitement is the point where the system stops moving away and begins to follow the RM. The way to achieve stability is by making sure that the controller experiences more positive emotions than excitement. In other words, to have alpha angles smaller than 90°.

The right side of the figure 5 illustrates happiness: the controller is excited at the outset, t=4.5s, then by means of the actuating signal the emotion turns to happiness at alpha angle 60°. The controller experiences this emotion until rm(t) and y(t) have the same value, at 7.3s, then a negative emotion appears, because y(t) moves away,

Figure 6. Satisfaction and Calm. The Reference Model for both emotions is 1/(S2 + 2S + 1). Satisfaction is on the left side, with P = 2.5, I = 1, D = 1. Calm is on the right side, with P = 10, I = 1, D = 1.



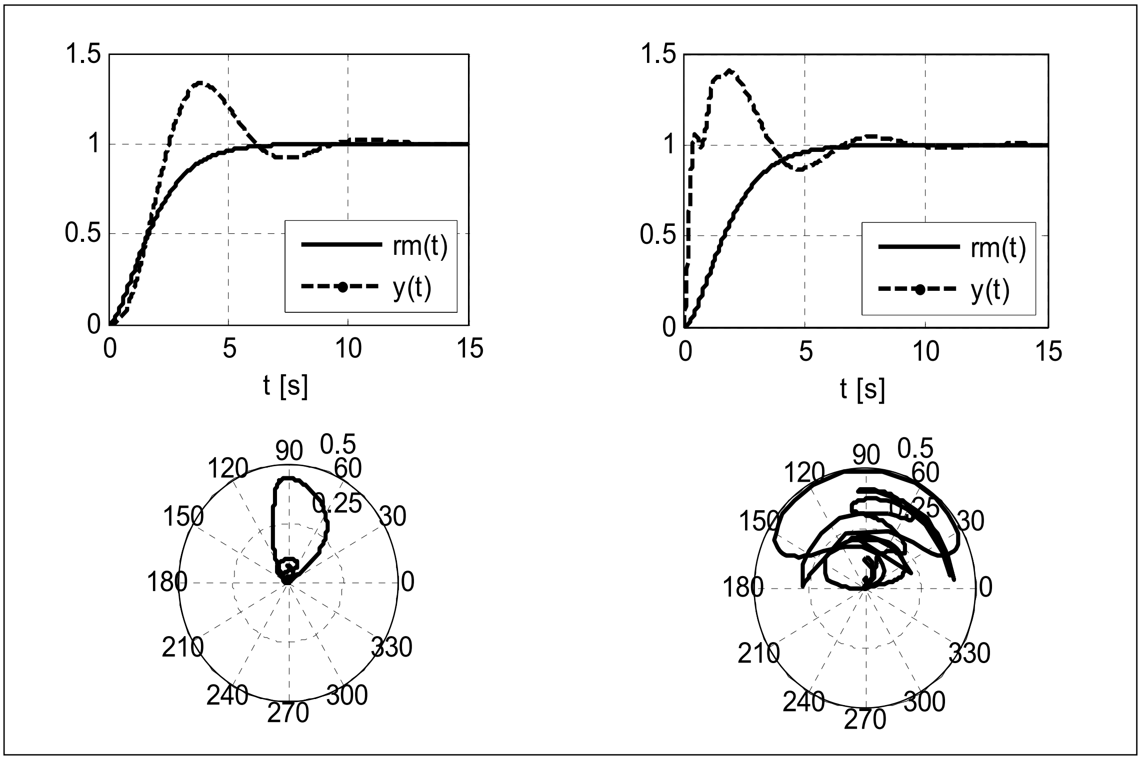
but it is not visible in the polar coordinates due to its having a very small radius. The figure 6 depicts satisfaction and calm, which are the most desirable states. Those emotions mean that the actuating signal is working as desired, so the system moves to reach the RM.

Figure 7 shows an example of a controller that is well tuned on the left side, in contrast with an undesirable performance on the right. On the left side is shown a desired system behavior. It results from the distribution of emotional states and depicts an appropriate relation between the reference model definition, the system, and controller efforts; the states oscillate but make smooth profiles. Once the overshoot has been reached, the error decreases and the system gets at a steady state at 13s.

Although the steady state is reached at 10s, on the right side of figure 7, the control tuning is not adequate because emotional states jump from the most positive side to the most negative side; this forces the actuating signal to change abruptly, increasing the possibility of having an unstable performance. The work of the actuating signal can be interpreted as making reactive decisions or trying to avoid a disaster, but not following a plan to match the dynamic of the system with the RM.

There are three possible explanations for the system performance on the right side

Figure 7. Good and bad control tuning. The Reference Model in the left side is 1/(S2 + 2S +1), and the PID controller constants are P = 1.75, I = 1, D = 0. The Reference Model in the right side is 64/(S2 + 4S + 64), and the PID constants are P = 2.5, I = 2.5, D = 1.



of figure 7. First of all, the RM is much faster than the system. Second, the RM has a lot of oscillations, so even if the system were stable, the polar coordinates would show that the emotion changes as well as the RM. Finally, the system cannot satisfy the constraints set by the RM, because it is slower than the RM. There are three solutions, one for each problem: to test a slower RM, to use standard configurations for the RM (for instance Bessel or ITAE), and not to force the system more than feasible.

7. Conclusion

It has been proved that the dynamic of a system can be seen as a set of emotional states, and they each have a unique and well-defined relation between the Reference Model and the tendency of the system. However, it is not necessary to experiment with all the repertory of human emotions, only an adequate group of them. In this paper the range from calm to anger has been adopted, taking into account the order given for the Circumplex Model of Affect. Tiredness, depression and sadness are not included as a result of the adapted range. This is useful to avoid unstable behaviors or unsatisfactory dynamics. Lastly, calm has been defined as the most desirable state due to psychologists have demonstrated that calm is the best emotional state to perform cognitive tasks.

The Reference Model is fundamental to the control algorithm. It has two jobs: to be the mentor for the dynamical system, and to be the reference to measure alpha angle. This angle measurement is made considering the relation between the line of sight and the tendency of the system; furthermore, it has been demonstrated that the Reference Model definition is essential in the tuning process. It is recommended to use a standard linear configuration such as Bessel or ITAE, also it should not be much faster or slower than the system. On the one hand the controller is forced more than feasible; on the other hand, the control algorithm would be underused.

Finally, it is concluded that excitement is the most important emotional state for a dynamical system. Excitement delimits the time when the system leaves to move away and begins to go after the Reference Model or when it leaves to go after the Reference Model and begins to move away. It could be used to measure stability because a controlled system is stable when all its emotional states are more positive than excitement, in other words, when alpha angle is lower than 90°.

In the next step of the project, definitions of emotional states are going to be used in order to test the decision-making algorithm. Therefore, systems to be controlled must be selected, for instance, the basic choice is a first or a second order systems. In particular, there will be experiments to measure the ability of the controller to force the dynamic of the system to be close to the Reference Model. This is why classical metrics in control such as overshoot, rise time and the steady-state error can be taken into account. Additionally, other measures must be added to compute adaptability and autonomy.

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