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Major Goals: The research objective of this project is to employ computational models of emotional learning observed in the mammalian limbic system to develop novel and systematic methodologies for analysis, design, and implementation of autonomous multi-agent systems (MAS) operations. The motivation comes from the interdisciplinary and complex nature of the tasks encountered in the modern society, which demand the integration of multiple complementary agents capable of self-organization and coordinate themselves. This work builds on the PI's previous results demonstrating that the implementation of Brain Emotional Learning (BEL) is effective in stabilizing a single autonomous aerial agent, as well as a team of robots, both in simulations and real-time experiments. Coordination of MAS in real-time missions is challenging because the dynamics of the robotic agents, which could be aerial, ground, water vehicles, or even a combination of them, are usually not precisely known. Furthermore, MAS operations are often subjected to external disturbances and varying operational conditions. It is hypothesized that BEL strategies will provide MAS with learning capabilities, multi-objective properties, and low computational complexity.

To achieve these goals, the proposed project focuses on the following fundamental research thrusts:
1. Adaptation of reward and sensory signals: BEL-inspired controllers must be provided with sensory signals and emotional cues, which should make sense with respect to the MAS states and objectives. It is hypothesized that, by adaptively choosing these functions by means of self-organizing methods and multi-objective goals (e.g., flocking, obstacle avoidance, energy savings) the mission will be optimally performed.
2. Stability of BEL controllers for MAS: To enhance the theoretical contribution, stability conditions for BEL-inspired feedback controllers for MAS will be investigated. At present, there is not a specific way for ensuring stability of these methods. It is hypothesized that use of Lyapunov Stability Theory, as well as numerical methods, will advance this objective.
3. Implementation of BEL-inspired MAS control: Exploiting the small computational cost and adaptive capacity of the proposed BEL control, we will show the applicability of our approach in realistic MAS applications, e.g., cooperative load transportation. A network of aerial/ground robotic vehicles will be used in a laboratory for validation purposes.

MAS control is complex by nature as it involves a large number of couplings and interdependencies between disciplines and subsystems, alongside a variety of sometimes contradicting objectives and design constraints. State-of-the-art MAS controllers often lead to a functional design, but rarely to an optimal one. This project aims at an integrated design to achieve MAS controllers with efficiency, reliability and flexibility, and at the same time, with less complexity and lower computational costs.
The integration of BEL in MAS control is still unexplored. Transformative project outcomes will advance knowledge

in the networked control systems domain, establishing foundations for future exploration of complementary methodologies to improve this field. Integrated education/outreach activities will support the Texas A&M University - Corpus Christi (TAMU-CC) Unmanned Aircraft Systems Summer Institute (UASSI), an engineering event happening every year in July, and targeting local K-12 underrepresented students. Students from the Society of Hispanic Professional Engineers (SHPE) will be involved as “mentors” for working with UASSI attendants. UASSI activities will increase awareness and inform young students of the needs in the domain of complex networks, and will increase participation of underrepresented students in engineering and computing sciences (ENCS). As a professor of an MSI/HSI, it is important to build a sustainable foundation for a successful long-term research program. A strong, sustained research environment will be created by motivating underrepresented students early in their career to obtain a university education, and to participate in research during their college careers.

Accomplishments: The major activities performed from July 03, 2018 to December 31, 2019 are summarized as follows:

• A comprehensive Literature Review and State of the Art of Brain Emotional Learning (BEL)-inspired control strategies, as described in Sections III-A and III-B.
• Design of a novel Limbic System Inspired Control (LISIC) structure, which considers a system interface whose inputs are simpler with respect to existing learning-inspired control approaches. The LISIC methodology is described in Sections III-C, III-D and III-E.
• Development of stability proofs for LISIC using Lyapunov Theory. This main result corresponds to Theorem 1 in Section III-G.
• Analysis of performance of the proposed LISIC methodologies based on numerical simulations and synthetic data. These results, which consider a nonlinear system affected by uncertainties and perturbations are included in Section III-H.
• Design of a novel LISIC strategy for Multi-Agent Systems (MAS) consensus and flocking based on an imitation of a double integrator closed-loop behavior. This novel technique, which was given the name Double Integrator LISIC (DILISIC), is described in Sections III-J and III-K
• Analysis of performance of the proposed DILISIC structure based on numerical simulations and synthetic data. These results, which consider a nonlinear MAS affected by uncertainties and perturbations, are included in SectionsIII-L.
• Development of a MAS experimental platform for validation of the proposed LISIC and DILISIC structures, as described in Section III-M.
• Training Activities, which involve a Postdoctoral Researcher, an Graduate Student, and four undergraduate students majoring in Mechanical and Electrical Engineering, as discussed Section IV-B
• Outreach activities, in form of a summer camp for underrepresented minority students (UMRs) are described in IV-C.

Four research papers about the outcomes of this project were accepted and published in international conferences and journals. These publication are:

[1] I. Rubio Scola, L.R. Garcia Carrillo , and J.P. Hespanha, “Stable robust controller inspired by the mammalian limbic system for a class of nonlinear systems”, accepted in American Control Conference (ACC), Denver, CO, USA, July 2020.
[2] J. Xie, L.R. Garcia Carrillo, L. Jin, and J.P. Hespanha, “A Robust State Estimator for Multi-Agent Systems Under Impulsive Noise and Missing Measurements”, Conference on Decision and Control (CDC), Nice, France, December 2019.
[3] I. Rubio Scola, G.A. Guijarro Reyes, L.R. Garcia Carrillo, J.P. Hespanha, and J. Xie, “Translational model identification and robust control for the Parrot Mambo UAS Multicopter”, IEEE GLOBECOM Workshop on Computing-Centric Drone Networks , Waikoloa, Hawaii, December 2019.
[4] L.R. Garcia Carrillo , and K.G. Vamvoudakis, “Deep-Learning Tracking for Autonomous Flying Systems Under Adversarial Inputs”, IEEE Transactions on Aerospace and Electronic Systems, July 22, 2019.

Two research papers about the outcomes of this project are currently under review in international conferences and journals. These publication are:

[1] I. Rubio Scola, L.R. Garcia Carrillo, and J.P. Hespanha, “Performance-guaranteed flocking control inspired by the mammalian limbic system”, submitted to IEEE Transactions on Neural Networks and Learning Systems, (Submitted on December 2019).
[2] I. Rubio Scola, L.R. Garcia Carrillo, J.P. Hespanha, and R. Lozano, “Performance-guaranteed consensus

control inspired by the mammalian limbic system for a class of nonlinear multi-agents", submitted to 21st IFAC World Congress, Berlin, Germany, July 12-17, 2020, (Submitted on November 2019).

Training Opportunities: One Postdoctoral Researcher (PR), Dr. Ignacio Rubio Scola, was funded on this project. The research responsibilities of the PR were to collaborate with the PI, Dr. Garcia Carrillo, in developing the theory for the novel LISIC and DILISIC structures. The PR also assisted the PI in advising Mr. Gabriel Alexis Guijarro, the graduate student involved in the project and Mr. Alan Garduno, the Electrical Engineering undergraduate student.

The M.Sc. student Gabriel Alexis Guijarro was being trained in research-oriented tasks, in order to prepare him for a Ph.D. program in the near future. Gabriel Alexis was also part of our outreach efforts (as explained in the attached file). Furthermore, three undergraduate students (Selena Mendoza, Nebai Tapia Lugo, and Andrew Garcia) were trained as Technical Mentors (TM) for the UAS Summer Institute (outreach effort explained in the attached file) directed by the PI.

For the last 6 months of this project, the URM undergraduate student Alan Garduno, major in Electrical Engineering, and member of the TAMU-CC SHPE, joined this project. Alan was involved in the practical aspects of building the UAS multicopter shown in Figure 14, and is being trained by the graduate student, postdoc, and PI of this project in different aspects of control systems and robotics. The ultimate goal is to recruit him for one of the STEM graduate programs available at TAMU-CC.

Results Dissemination: Unmanned Aerial Systems Summer Institute (UASSI)

On July July 22-26, 2019 the PI served as the Technical Director for the Texas A&M University - Corpus Christi (TAMU-CC) Unmanned Aerial Systems Summer Institute (UASSI) [21], see Figure 15. The goal of UASSI is to connect South Texas students to UAS technology, capitalizing on the buzz surrounding this cutting edge industry and placing South Texas students at the forefront of this field. UASSI is designed to give high-school students hands-on experience with UAS equipment and software. The objectives are to offer an introduction to: (1) UAS engineering concepts and applications, (2) Sensors and sensing techniques, (3) Flight Controllers, Robot Operating System (ROS), and OpenCV software, (4) Design, assembly, and operation of a home-made UAS platform. UASSI curriculum is based on participants building a UAS, and then using software (MAVLink, ROS) to interact with the UAS and enable it to perform an autonomous mission.

The PI recruited and trained three Technical Mentors (Selena Mendoza, Nebai Tapia Lugo, and Andrew Garcia) from TAMU-CC's Engineering programs, as well as one Technical Mentor (Gabriel Alexis Guijarro) from the M.Sc. Program in Computer Sciences. The Technical Mentors, all of them Underrepresented Minorities (URMs), provided the PI with the support needed for ensuring that all the high-school students received the appropriate guidance during the summer institute.

This 2019 TAMU-CC UASSI hosted 20 URMs students from from the Corpus Christi Independent School District (CCISD). In particular, each Technical Mentor was in charge of supervising five high school students. Through UASSI, two URM students were recruited for TAMU-CC Engineering programs. An additional benefit of UASSI is the possibility of identifying, among the Technical Mentors, potential candidates for our graduate programs. So far, two of them (Nebai Tapia Lugo and Andrew Garcia) have expressed interest in enrolling in the Computer Science M.Sc. program at TAMU-CC.

Honors and Awards: Nothing to Report

Protocol Activity Status:

Technology Transfer: Nothing to Report

PARTICIPANTS:

Participant Type: PD/PI
Participant: Luis Rodolfo Garcia Carrillo
Person Months Worked: 1.00 **Funding Support:**
Project Contribution:
International Collaboration:

International Travel:
National Academy Member: N
Other Collaborators:

Participant Type: Postdoctoral (scholar, fellow or other postdoctoral position)
Participant: Ignacio Rubio Scola
Person Months Worked: 12.00 **Funding Support:**
Project Contribution:
International Collaboration:
International Travel:
National Academy Member: N
Other Collaborators:

Participant Type: Graduate Student (research assistant)
Participant: Gabriel Alexis Guijarro Reyes
Person Months Worked: 15.00 **Funding Support:**
Project Contribution:
International Collaboration:
International Travel:
National Academy Member: N
Other Collaborators:

Participant Type: Undergraduate Student
Participant: Alan Garduno
Person Months Worked: 6.00 **Funding Support:**
Project Contribution:
International Collaboration:
International Travel:
National Academy Member: N
Other Collaborators:

Participant Type: Undergraduate Student
Participant: Selena Mendoza
Person Months Worked: 1.00 **Funding Support:**
Project Contribution:
International Collaboration:
International Travel:
National Academy Member: N
Other Collaborators:

Participant Type: Undergraduate Student
Participant: Nebai Tapia Lugo
Person Months Worked: 1.00 **Funding Support:**
Project Contribution:
International Collaboration:
International Travel:
National Academy Member: N
Other Collaborators:

Participant Type: Undergraduate Student
Participant: Andrew Garcia
Person Months Worked: 1.00 **Funding Support:**
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International Collaboration:
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Paper Title: Stable robust controller inspired by the mammalian limbic system for a class of nonlinear systems
Authors: I. Rubio Scola, L.R. Garcia Carrillo, J.P. Hespanha
Acknowledged Federal Support: **Y**

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Authors: Ignacio Rubio Scola, Gabriel Alexis Guijarro Reyes, Luis Rodolfo Garcia Carrillo, Joao Hespanha, Junfe
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Conference Location: Nice, France
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Authors: Junfei Xie, Luis Rodolfo Garcia Carrillo, Lei Jin, Joao P. Hespanha
Acknowledged Federal Support: **Y**

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Date Received: 29-Jan-2020 Conference Date: 12-Jul-2020 Date Published:
Conference Location: Berlin, Germany
Paper Title: Performance–guaranteed consensus control inspired by the mammalian limbic system for a class of nonlinear multi-agents
Authors: Ignacio Rubio Scola, Luis Rodolfo Garcia Carrillo, Joao P. Hespanha, Rogelio Lozano
Acknowledged Federal Support: **Y**

Multi-Agent Network Control
A Brain Emotional Learning-Inspired Approach

Final Report for Proposal Number: 72814-NS-II
Principal Investigator: Luis Rodolfo Garcia Carrillo, Ph.D.
Institution: Texas A&M University - Corpus Christi

Abstract

This Final Report provides a description of what was accomplished under the project goals. The reporting period is from July 03, 2018 to December 31, 2019.

I. Major Activities

The major activities performed from July 03, 2018 to December 31, 2019 are summarized as follows:

- A comprehensive *Literature Review* and *State of the Art* of Brain Emotional Learning (BEL)–inspired control strategies, as described in Sections III-A and III-B.
- Design of a novel Limbic System Inspired Control (LISIC) structure, which considers a system interface whose inputs are simpler with respect to existing learning-inspired control approaches. The LISIC methodology is described in Sections III-C, III-D and III-E.
- Development of stability proofs for LISIC using Lyapunov Theory. This main result corresponds to Theorem 1 in Section III-G.
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- Development of a MAS experimental platform for validation of the proposed LISIC and DILISIC structures, as described in Section III-M.
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[4] **L.R. Garcia Carrillo**, and K.G. Vamvoudakis, "Deep-Learning Tracking for Autonomous Flying Systems Under Adversarial Inputs", *IEEE Transactions on Aerospace and Electronic Systems*, July 22, 2019.

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[2] I. Rubio Scola, **L.R. Garcia Carrillo**, J.P. Hespanha, and R. Lozano, "Performance-guaranteed consensus control inspired by the mammalian limbic system for a class of nonlinear multi-agents", submitted to *21st IFAC World Congress*, Berlin, Germany, July 12-17, 2020, (Submitted on November 2019).

II. Specific Objectives

The research objective of this project is to employ computational models of emotional learning observed in the mammalian limbic system to develop novel and systematic methodologies for analysis, design, and implementation of autonomous multi-agent systems (MAS) operations. The motivation comes from the interdisciplinary and complex nature of the tasks encountered in the modern society, which demand the integration of multiple complementary agents capable of self-organization and coordinate themselves. It is hypothesized that Brain Emotional Learning (BEL) inspired control strategies will provide MAS with learning capabilities, multi-objective properties, and low computational complexity. To achieve these goals, the project activities are focused on answering the following fundamental research questions:

1) Adaptation of reward and sensory signals: BEL-inspired controllers must be provided with sensory signals and emotional cues, which should make sense with respect to (w.r.t.) the MAS states and objectives. It is hypothesized that, by adaptively creating these functions, the mission will be optimally performed.
2) Stability of BEL controllers for MAS: At present, there is not a specific way for ensuring stability of these methods. Lyapunov Stability Theory is being used to achieve this objective.
3) Implementation of BEL-inspired MAS control: Exploiting the small computational cost and adaptive capacity of the proposed BEL control, the applicability of the proposed solutions will be demonstrated in realistic MAS applications. A network of aerial/ground robotic vehicles will be used in a laboratory environment for validation purposes.

MAS control is complex by nature as it involves a large number of couplings and interdependencies between disciplines and subsystems, alongside a variety of sometimes contradicting objectives and design constraints. State-of-the-art MAS controllers often lead to a functional design, but rarely to an optimal one. This project explores an integrated design to achieve MAS controllers with efficiency, reliability and flexibility, and at the same time, with less complexity and lower computational costs. Novel knowledge is being generated in the networked control systems domain, establishing foundations for future exploration of complementary methodologies to improve this field.

Integrated education/outreach activities support the Texas A&M University - Corpus Christi (TAMU-CC) Unmanned Aircraft Systems Summer Institute (UASSI), an engineering event happening every year in July, and targeting local K-12 underrepresented students. Students from the Society of Hispanic Professional Engineers (SHPE) are involved as "technical mentors" for advising UASSI attendants. UASSI activities increase awareness and inform young students of the needs in the domain of complex networks of autonomous systems, and increases participation of underrepresented students in engineering and computing sciences (ENCS). A strong, sustained research environment is being created by motivating underrepresented students early in their career to obtain a university education, and to participate in research during their college careers.

III. Significant results, including major findings, developments, and conclusions

A. *Literature review and state of the art of BEL-inspired control strategies*

In recent years, computationally complex problems have been solved using biologically-inspired approaches. In [1], a computational model known as Brain Emotional Learning (BEL) was developed, which mimics parts of the brain that are known to produce emotion. The BEL framework can be used for control systems purposes as in [2], where the authors develop a BEL–Based Intelligent Controller (BELBIC) which imitates the emotional parts of the mammalian brain, namely, the amygdala, the orbitofrontal cortex (OFC), the thalamus, and the sensory input cortex. Classic control methodologies may require the knowledge of all the dynamics of the model to be controlled, but BELBIC as a model-free controller has no such a requirement. Furthermore, BELBIC has a single-layered architecture and therefore its computational complexity is in the order of $O(n)$, which is relatively small if compared to other existing learning-based intelligent controls, and therefore more appealing for real-time implementation. In [2], the authors show that BELBIC has a promising performance when dealing with noise and system uncertainty. Other groups have successfully implemented BELBIC to solve different engineering problems, see for example [3], [4], [5], [6] and [7].

Closely related, the authors in [8] demonstrated that an artificial Neural Network (NN) design with one hidden layer of nodes possessing radial Gaussian input-output characteristics is capable of uniformly approximating sufficiently smooth functions on a compact set. Exploiting this property in combination with Lyapunov stability analysis, a method for using dynamic structure Gaussian Radial Basis Functions (RBF) NN for adaptive control of affine nonlinear systems has been presented in [9]. The extension of this approach to an output feedback scheme for the control of a class of non-linear systems represented by input–output models was presented in [11]. The objective of both designs are to achieve good tracking performance when the system dynamics are unknown.

In [12], RBF are combined with NN for robust and adaptive control in nonlinear systems, where two backstepping NN control approaches are presented for a class of affine nonlinear systems in strict feedback form with unknown nonlinearities. In [13], a new adaptive control approach for uncertain systems is proposed using an input normalized NN technique which also combines RBF and NN. With a simple condition, the ultimate boundedness of the tracking error regardless of the reference signals is verified through the Lyapunov stability theory.

Recently, engineering applications have been solved by estimating nonlinearities for feedback control using NNs with associated Lyapunov stability proofs. In [14] a NN-based output feedback control has been proposed for reference tracking of underactuated surface vessels (USVs) with input saturation and uncertainties with a NN-based observer that estimates the velocity data of the USV with uncertainties. Also, in [15] an adaptive output feedback control also based on NNs is proposed to control flexible multi-link planar manipulators.

Despite its multiple benefits, BELBIC has two **main drawbacks**. The first one corresponds to the **lack of mathematical proofs of stability and performance**, and the second one corresponds to the **lack of a clear method to select the structure for connecting the BEL control structure with the system outputs**. In a recent work, the authors attempted to modify the internal BEL structure to simplify the connection with the system output, and to develop a stability proof for a class of nonlinear systems [16]. These modifications, however, lead to a structure which considerably deviates from the original BEL proposed in [1], and cannot be considered, strictly speaking, a BEL–inspired solution with all its associated benefits.

Main Contributions of this Research Project: Taking into account the research gaps and limitations identified in these previous and related works, this research project proposes the implementation of a novel Limbic System Inspired Control (LISIC) structure for (i) nonlinear agents and (ii) MAS. The original contributions encountered in the proposed LISIC structure are categorized in **three main directions**. The first one is the establishment of a novel LISIC structure capable of **increasing the control performance** of nonlinear agents performing autonomous missions. The second is the fact that LISIC is **closer to and consistent with the original BEL structure**, as originally proposed in [1], and maintaining all its benefits. A Lyapunov formulation is proposed to prove stability and performance of the novel LISIC structure for nonlinear agents. The third contribution consists on the development of the **DILISIC structure**, which consist of a system composed by a (possibly nonlinear) agent in closed-loop with a LISIC imitating double integrator agent dynamics. The DILISIC structure allows the extension of well known MAS control strategies for double integrator agents to MAS composed by agents with nonlinear models.

The following subsections introduce the computational model of BEL, and provide the theoretical background of the novel contributions of this project, i.e., LISIC structure for nonlinear agents and DILISIC for MAS.

B. The Brain Emotional Learning (BEL) computational model structure in details

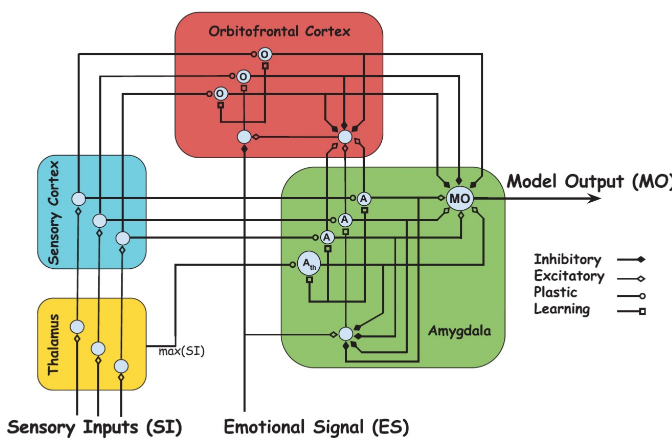

Fig. 1. A block diagram representation of the computational model describing the limbic system in the mammalian brain.

The BEL architecture is inspired by emotional learning observed in the mammalian limbic system [1], and is graphically represented as in Figure 1. This model has two main parts: *Amygdala* and *Orbitofrontal Cortex* (OFC), which are responsible for immediate learning and for inhibiting any inappropriate learning happening in the Amygdala, respectively. The BEL model output can be defined my means of the following equation

$$MO = A_{th} + \sum_{i=1}^{n} A_i - \sum_{i=1}^{n} OC_i \tag{1}$$

which consists of the subtraction of OFC outputs (OC_i) from the Amygdala outputs (A_i) and the Thalamus node (A_{th}). Here, i represents the number of sensory inputs. Amygdala and OFC outputs are computed by the summation of all their corresponding nodes, where the outputs of each node, i.e., Amygdala and OFC, can be respectively obtained as

$$A_i = V_i SI_i, \qquad OC_i = W_i SI_i \tag{2}$$

The terms V_i and W_i are the plastic weights of Amygdala and OFC, respectively, and SI_i is the i_{th} sensory input. Particularly, the term A_{th} is fed by an additional sensory input (i.e., S_{th}) which directly connects the Thalamus to the Amygdala, and is calculated as the maximum of all SI_i as follows

$$A_{th} = V_{th} \max (SI_i) \tag{3}$$

where V_{th} is the associated plastic weight. To update V_i the following equation is used

$$\dot{V}_i = \alpha SI_i \max \left(0, ES - A_{th} - \sum_{i=1}^{n} A_i\right) \tag{4}$$

where α is a learning rate parameter settable between 0 (no learning) and 1 (instant adaptation). Notice that the adjusting rule in equation (4) is monotonic, i.e., the weights V_i can not decrease. This is due to the fact that, once an emotional reaction is learned, it should be permanent, and it is the task of the OFC to inhibit this reaction if needed.

The weights W_i are updated as a function of the sensory inputs and the internal reinforcer for the OFC. This update considers two scenarios. On one hand, if $ES \neq 0$

$$\dot{W}_i = \beta \cdot SI_i \left(\max\left(0, \sum_{i=1}^{n} A_i - ES\right) - \sum_{i=1}^{n} OC_i\right) \tag{5}$$

And on the other hand, if $ES = 0$

$$\dot{W}_i = \beta \cdot SI_i \cdot \max\left(0, \sum_{i=1}^{n} A_i - \sum_{i=1}^{n} OC_i\right) \tag{6}$$

where β is a learning rate parameter similar to α, and A_i are all amygdala nodes except the thalamus node A_{th}.

C. Problem Statement: Design of a novel Limbic System Inspired Control (LISIC) Structure

Consider the class of nonlinear systems of order n described by the equation

$$x^{(n)} = f(\underline{x}) + g(\underline{x})u + d(\underline{x}, t) \tag{7}$$

where $\underline{x} = [x, \dot{x}, \ldots, x^{(n-1)}]^T \in \mathbb{R}^n$ is the state vector, $\dot{x}$ is the derivative of x w.r.t. time, $x^{(n-1)}$ is the $(n-1)^{\text{th}}$ ordered derivative of x w.r.t. time, and $u \in \mathbb{R}$ is the control input. Assume that the vector state $\underline{x}$ belongs to the compact set $\Omega_x = \{\underline{x} |\ \|\underline{x}\| \leq M_x\}$ with M_x a positive constant. Also, suppose that $g(\underline{x}) > 0$, $g(\underline{x})^{-1}$ and $f(\underline{x})$ are unknown continuous scalar functions. The term $d(\underline{x}, t)$ represents a bounded external scalar disturbance with unknown upper bound $|d(\underline{x}, t)| \leq \epsilon_d$. Assume that the desired trajectory x_d and its derivatives, up to its n^{th} order derivative, are smooth and bounded.

Define a new auxiliary variable depending on the system's tracking error and its derivatives as

$$s := s(\underline{x}) = e^{(n-1)} + \Delta_{n-1} e^{(n-2)} + \ldots + \Delta_1 e \tag{8}$$

with the tacking error $e = x - x_d$ and Δ_k $(k = 1, 2, \ldots n-1)$ are constants such that the roots of the polynomial $\lambda^{n-1} + \Delta_{n-1}\lambda^{n-2)} + \ldots + \Delta_1 = 0$ have negative real part. The derivative $\dot{s}$ is then calculated as

$$\dot{s} = f(\underline{x}) + g(\underline{x})u + q_a(t) + d(\underline{x}, t) \tag{9}$$

with $q_a = -x_d^{(n)} + e^{(n-1)} + \Delta_{n-1} e^{(n-2)} + \ldots + \Delta_1 \dot{e}$. Inspired by the feedback linearization method from [17], we propose to solve the tracking problem by selecting a control signal u that results in the following dynamics for s

$$\dot{s} = -Ks + u_r \tag{10}$$

where $K > 0$ is a real constant and u_r can be viewed as an auxiliary input that will be specified in Section III-D with the goal of improving the performance of the closed loop.

If $f(\underline{x})$ and $g(\underline{x})$ were known and $d(\underline{x}, t) = 0$, it is possible to achieve the dynamics in equation (10) with the following exact matching control law

$$u^* = -g^{-1}(\underline{x})(f(\underline{x}) + q_a + Ks - u_r), \tag{11}$$

that can be obtained by equating the right-hand sides of (9) and (10). The assumptions of boundedness of $\underline{x}$, $f(\cdot)$, $g^{-1}(\cdot)$, x_d and its derivatives up to order n ensure that the exact matching controller is bounded.

D. Improving performance of the proposed LISIC structure through an integral action

To implement the integral action, a new state $\xi(t) = \int s(t)dt$ is introduced. This augments the system in equation (10) as in [18] leading to $s_e = [s,\ \xi]^T$

$$\begin{bmatrix} \dot{s} \\ \dot{\xi} \end{bmatrix} = \underbrace{\begin{bmatrix} -K & 0 \\ 1 & 0 \end{bmatrix}}_{A_e} \begin{bmatrix} s \\ \xi \end{bmatrix} + \underbrace{\begin{bmatrix} 1 \\ 0 \end{bmatrix}}_{B_e} u_r \tag{12}$$

The term u_r can be obtained by solving the Ricatti equation

$$0 = A_e^T P_e + P_e A_e - P_e B_e R^{-1} B_e^T P_e + Q_e \tag{13}$$

$$u_r = -\frac{1}{r} B_e^T P_e s_e \tag{14}$$

where $Q_e = \text{diag}\{Q, Q_I\}$ and $R = \frac{\rho^2 r}{2\rho^2 - r}$ with $Q_e = Q_e^T \succ 0$ and $2\rho^2 > r$.

E. Development of a Gaussian radial basis function (RBF) for nonlinear function approximations

A Gaussian RBF is a real-valued function whose value depends on the distance from the origin. Gaussian RBF networks are of the form $\hat{H} = \theta^T h$, with θ a vector of adjustable weight in $\mathbf{R}^\nu$, and h a Gaussian basis function. It was shown in [8], that given any smooth scalar-values nonlinear function $H(\zeta)$ defined on a compact set Ω_ζ, which is a compact subset of $\mathbf{R}^\eta$, there exists a Gaussian RBF vector $h : \mathbf{R}^\eta \rightarrow \mathbf{R}^\nu$ and a weight vector $\theta^* \in \mathbf{R}^\nu$ such that $|H(\zeta) - \theta^{*T} h(\zeta)| \leq \epsilon\ \forall \zeta \in \Omega_\zeta$, with $\epsilon > 0$. It can be shown that arbitrary small ϵ can be achieved for a sufficiently large ν.

Taking into account the previous statements, the goal is to approximate the unknown functions $f(\underline{x})$ and $g(\underline{x})$ by means of estimates $\hat{f}(\underline{x})$ and $\hat{g}(\underline{x})$ using a combination of Gaussian RBFs that emulate the BEL structure in equation (1)

$$\begin{aligned} \hat{f}(\underline{x}) &:= \hat{f}(\underline{x}, V_f, W_f) = V_f^T \Phi_A(s(\underline{x})) - W_f^T \Phi(s(\underline{x})) \\ \hat{g}(\underline{x}) &:= \hat{g}(\underline{x}, V_g, W_g) = V_g^T \Phi_A(s(\underline{x})) - W_g^T \Phi(s(\underline{x})) \end{aligned} \tag{15}$$

where

$$\begin{aligned} V_f &= [V_{f1}, V_{f2}, \ldots, V_{fp}, V_{f\text{th}}]^T, W_f = [W_{f1}, W_{f2}, \ldots, W_{fp}]^T, \\ V_g &= [V_{g1}, V_{g2}, \ldots, V_{gp}, V_{g\text{th}}]^T \text{ and } W_g = [W_{g1}, W_{g2}, \ldots, W_{gp}]^T \end{aligned}$$

are vector of weight parameters. This formulation can be understood as follows: inside the Thalamus the input of the controller is processed by the RBFs given the SIs. A graphical depiction of this formulation is shown in Figure 2. This novel structure, which we call LISIC, is similar to the one proposed in [16] but without the bias terms. The bias terms are removed in order to maintain the original structure of the Amygdala and the OFC, as described in (1)–(2). In Section III-I we show a numerical simulation comparing the performance of BEL-based NN and classical RBF-NN.

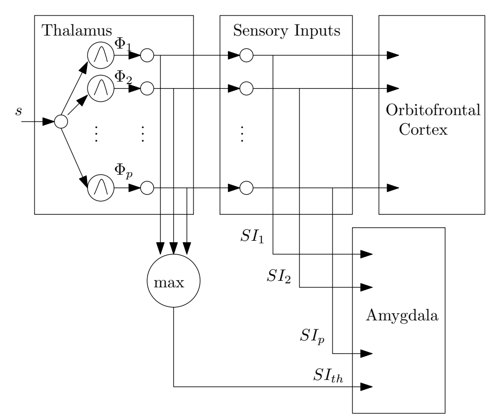

Fig. 2. Representation of the proposed LISIC interconnection between the Amygdala, OFC, and the (original and novel) Thalamus structure.

Mathematically, inside the new Thalamus formulation, the j^{th} Gaussian RBF can be represented using the structure

$$\Phi_j = \exp\left(-\frac{(s - \mu_j)^2}{\sigma_j^2}\right), \quad m = \max([\Phi_1, \Phi_2, \ldots, \Phi_p]) \tag{16}$$

$$
\dot{V}_f = \begin{cases} \alpha_f \Phi_A \max(B_e^T P_e s_e, 0) \text{ if } (\|V_f\| < \Omega_{fv}) \text{ or } (\|V_f\| = \Omega_{fv} \text{ and } \alpha_f V_f^T \Phi_A \max(B_e^T P_e s_e, 0) \leq 0) \\ \alpha_f \left(\Phi_A - \dfrac{V_f^T \Phi_A V_f}{\|V_f\|} \right) \max(B_e^T P_e s_e, 0), \text{ if } (\|V_f\| = \Omega_{fv} \text{ and } \alpha_f V_f^T \Phi_A \max(B_e^T P_e s_e, 0) > 0) \end{cases}
$$
$$
\dot{W}_f = \begin{cases} -\beta_f \Phi B_e^T P_e s_e \text{ if } (\|W_f\| < \Omega_{fw}) \text{ or } (\|W_f\| = \Omega_{fw} \text{ and } \beta_f W_f^T \Phi B_e^T P_e s_e \geq 0) \\ -\beta_f \left(\Phi - \dfrac{W_f^T \Phi W_f}{\|W_f\|} \right) B_e^T P_e s_e, \text{ if } (\|W_f\| = \Omega_{fw} \text{ and } \beta_f W_f^T \Phi B_e^T P_e s_e < 0) \end{cases}
$$
$$
\dot{V}_g = \begin{cases} \alpha_g \Phi_A \max(B_e^T P_e s_e u, 0) \text{ if } (\|V_g\| < \Omega_{gv}) \text{ or } (\|V_g\| = \Omega_{gv} \text{ and } \alpha_g V_g^T \Phi_A \max(B_e^T P_e s_e u, 0) \leq 0) \\ \alpha_g \left(\Phi_A - \dfrac{V_g^T \Phi_A V_g}{\|V_g\|} \right) \max(B_e^T P_e s_e u, 0), \text{ if } (\|V_g\| = \Omega_{gv} \textit{ and } \alpha_f V_g^T \Phi_A \max(B_e^T P_e s_e u, 0) > 0) \end{cases} \tag{22}
$$
$$
\dot{W}_g = \begin{cases} -\beta_g \Phi B_e^T P_e s_e u \text{ if } (\|W_g\| < \Omega_{gw}) \text{ or } (\|W_g\| = \Omega_{gw} \text{ and } \beta_g W_g^T \Phi B_e^T P_e s_e u \geq 0) \\ -\beta_g \left(\Phi - \dfrac{W_g^T \Phi W_g}{\|W_g\|} \right) B_e^T P_e s_e u, \text{ if } (\|W_g\| = \Omega_{gw} \text{ and } \beta_g W_g^T \Phi B_e^T P_e s_e u < 0) \end{cases}
$$

where s is the error dynamics described by equation (8), and μ_j and σ_j are the corresponding mean and smoothing factor, respectively. The RBFs are $\Phi = [\Phi_1, \Phi_2, \dots, \Phi_p]^T$ and $\Phi_A = [\Phi, m]^T$, m is the input from Thalamus, and V_{th} is its corresponding weight.

Following the universal approximation property exhibited by feed–forward NN and, in particular in our case, by Gaussian RBFs as proposed in [9] and recently reviewed in [10], there exist optimal parameters $[V_f^*, W_f^*]$ and $[V_g^*, W_g^*]$ such that $\hat{f}(\underline{x})$ and $\hat{g}(\underline{x})$ can approximate $f(\underline{x})$ and $g(\underline{x})$, respectively, on a compact set Ω_x, to an arbitrary degree of accuracy. Let the *optimal* parameters be defined as follows

$$
[V_f^*, W_f^*] = \underset{V_f \in \Omega_{fv}, W_f \in \Omega_{fw}}{\arg\min} [\sup_{\underline{\tilde{x}} \in \Omega_x} |V_f^T \Phi_A(\underline{\tilde{x}}) - W_f^T \Phi(\underline{\tilde{x}}) - f(\underline{\tilde{x}})|], \tag{17}
$$
$$
[V_g^*, W_g^*] = \underset{V_g \in \Omega_{gv}, W_g \in \Omega_{gw}}{\arg\min} [\sup_{\underline{\tilde{x}} \in \Omega_x} |V_g^T \Phi_A(\underline{\tilde{x}}) - W_g^T \Phi(\underline{\tilde{x}}) - g(\underline{\tilde{x}})|], \tag{18}
$$

For simplicity, the following formulation was used $\hat{f}^*(\underline{x}) := \hat{f}(\underline{x}, V_f^*, W_f^*)$ and $\hat{g}^*(\underline{x}) := \hat{g}(\underline{x}, V_g^*, W_g^*)$.

The errors of the approximation functions w.r.t. the real value are defined as

$$
f_e(\underline{x}) = f(\underline{x}) - \hat{f}^*(\underline{x}), \quad g_e(\underline{x}) = g(\underline{x}) - \hat{g}^*(\underline{x}) \quad \text{and} \quad \tilde{\omega} = f_e(\underline{x}) + g_e(\underline{x})u \tag{19}
$$

and the estimation errors as

$$
\begin{aligned} \tilde{V}_f &= V_f^* - V_f & \tilde{V}_g &= V_g^* - V_g \\ \tilde{W}_f &= W_f^* - W_f & \tilde{W}_g &= W_g^* - W_g \end{aligned} \tag{20}
$$

Based on the adaptation rules presented in [16], the following adaptation rules are proposed:

$$
\begin{aligned} \dot{V}_f &= \alpha_f \Phi_A \max(B_e^T P_e s_e, 0), \; \dot{W}_f = -\beta_f \Phi B_e^T P_e s_e, \\ \dot{V}_g &= \alpha_g \Phi_A \max(B_e^T P_e s_e u, 0), \; \dot{W}_g = -\beta_g \Phi B_e^T P_e s_e u \end{aligned} \tag{21}
$$

where $\alpha_f > 0$, $\alpha_g > 0$, $\beta_f > 0$, and $\beta_g > 0$. The proposed update laws for the nodes of the Amygdala respect the principle that its weights are always increasing, while the OFC weights can both decrease and increase preventing inappropriate behaviour of the Amygdala.

F. Parameter Projection for Boundedness

In order to guarantee the boundedness of the time varying weights V_f, W_f, V_g, and W_g we use the parameter projection algorithm. When the parameter is inside the desired region, or in the region boundary but moving towards the interior of the region, we use the equations (21). However, if the parameter is outside the desired region, or in the region boundary but moving towards the outside of the region, we use the gradient projection algorithm described in [19], and then the new set of adaptation rules are the ones described in equation (22).

Assumption 1: The optimal adaptive parameters V_f^*, W_f^*, V_g^*, and W_g^* belong to the following compact sets, respectively: $\Omega_{fv} = \{V_f^* | \|V_f^*\| \leq M_{fv}\}$, $\Omega_{fw} = \{W_f^* | \|W_f^*\| \leq M_{fw}\}$, $\Omega_{gv} = \{V_g^* | 0 < \delta \leq \|V_g^*\| \leq M_{gv}\}$, and $\Omega_{gw} = \{W_g^* | 0 < \delta \leq \|W_g^*\| \leq M_{gw}\}$. Here, δ, M_{fv}, M_{fw}, M_{gv}, and M_{gw} are positive constants.

At this point it is possible to guarantee the stability and the degree of performance of the closed loop system by means of the statements in **Theorem 1**.

G. Introduction of Theorem 1 – Performance and stability proof based on Lyapunov Theory

Theorem 1: Consider the nonlinear system in equation (7) with the following control law

$$u = -\hat{g}^{-1}(\underline{x})(\hat{f}(\underline{x}) + q_a + Ks - u_r) \tag{23}$$

where $\hat{f}$ and $\hat{g}$ are given by equation (15), with BEL-based adaptive laws as described in equation (22), and u_r as defined in equation (14). Under this scenario, the H_∞ tracking performance criteria in equation (24) is fulfilled for a pre-given attenuation level ρ, and the error function s remain bounded.

$$\begin{aligned}\int_0^T s_e^T Q_e s_e dt \leq \frac{1}{\alpha_f}\tilde{V}_f(0)^T\tilde{V}_f(0) + \frac{1}{\beta_f}\tilde{W}_f(0)^T\tilde{W}_f(0) + \frac{1}{\alpha_g}\tilde{V}_g(0)^T\tilde{V}_g(0) + \frac{1}{\beta_g}\tilde{W}_g(0)^T\tilde{W}_g(0) + s_e^T(0)P_e s_e^T(0)\\ + \rho^2\int_0^T \omega^T\omega dt\end{aligned} \tag{24}$$

where ω is the worst-case uncertainty of the system and is defined as

$$\omega = \tilde{\omega} + d + (|\tilde{V}_f^T\Phi_A + \tilde{V}_g^T\Phi_A u|)\text{sign}(\tilde{\omega} + d) \tag{25}$$

Proof: The P_e matrix from equation (13) is positive definite and can be decomposed as

$$P_e = \begin{bmatrix} P & P_2 \\ P_2^T & P_3 \end{bmatrix} \tag{26}$$

Pre- and post-multiplying equation (13) by s_e:

$$\begin{aligned}&2s_e^T A_e^T P_e s_e - s_e^T P_e B_e R^{-1} B_e^T P_e s_e + s_e^T Q_e s_e = 0 \Rightarrow\\ &-KsB_e^T P_e s_e + P_2 s^2 + P_3\xi s - s_e^T P_e B_e \frac{1}{r} B_e^T P_e s_e = -\frac{1}{2}(s_e^T Q_e s_e + s_e^T P_e B_e \frac{1}{\rho^2} B_e^T P_e s_e)\end{aligned} \tag{27}$$

Using equations (9), (15), (19), and (23), and after some algebraic manipulations, the derivative of s in closed loop can be written as

$$\begin{aligned}\dot{s} =& (\hat{f}^*(\underline{x}) + f_e(\underline{x}) + (\hat{f}(\underline{x}) - \hat{f}(\underline{x}))) + (\hat{g}^*(\underline{x}) + g_e(\underline{x}) + (\hat{g}(\underline{x}) - \hat{g}(\underline{x})))u + q_a + d\\ =& \tilde{f}(\underline{x}) + \tilde{g}(\underline{x})u + \tilde{w} - Ks + u_r + d\end{aligned} \tag{28}$$

with $\tilde{f}(\underline{x}) = \hat{f}^*(\underline{x}) - \hat{f}(\underline{x})$ and $\tilde{g}(\underline{x}) = \hat{g}^*(\underline{x}) - \hat{g}(\underline{x})$ leading to

$$\dot{s} = \tilde{V}_f^T\Phi_A - \tilde{W}_f^T\Phi + \tilde{V}_g^T\Phi_A u - \tilde{W}_g^T\Phi u - Ks + u_r + \tilde{\omega} + d \tag{29}$$

with a term u_r of the form

$$u_r = -\frac{1}{r}B_e^T P_e s_e = -\frac{1}{r}(Ps + P_2\xi) \tag{30}$$

To prove stability, the following Lyapunov function is implemented

$$V_x = \frac{1}{2\alpha_f}\tilde{V}_f^T\tilde{V}_f + \frac{1}{2\beta_f}\tilde{W}_f^T\tilde{W}_f + \frac{1}{2\alpha_g}\tilde{V}_g^T\tilde{V}_g + \frac{1}{2\beta_g}\tilde{W}_g^T\tilde{W}_g + \frac{1}{2}s_e^T P_e s_e \tag{31}$$

whose derivative is:

$$\dot{V}_x = -\frac{1}{\alpha_f}\tilde{V}_f^T\dot{V}_f - \frac{1}{\beta_f}\tilde{W}_f^T\dot{W}_f - \frac{1}{\alpha_g}\tilde{V}_g^T\dot{V}_g - \frac{1}{\beta_g}\tilde{W}_g^T\dot{W}_g + \dot{s}_e^T P_e s_e \tag{32}$$

from equation (20), the derivatives with respect to time of the optimal values are zero (e.g. $\dot{\tilde{V}}_f = -\dot{V}_f$). In particular, using equation (29)

$$\begin{aligned}\dot{s}_e^T P_e s_e &= \dot{s}(Ps + P_2\xi) + P_2 s^2 + P_3 s\xi = \dot{s}B_e^T P_e s_e + P_2 s^2 + P_3 s\xi\\ &= (\tilde{V}_f^T\Phi_A - \tilde{W}_f^T\Phi + \tilde{V}_g^T\Phi_A u - \tilde{W}_g^T\Phi u - Ks + u_r + \tilde{\omega} + d)B_e^T P_e s_e + P_2 s^2 + P_3 s\xi\end{aligned} \tag{33}$$

From equations (32) and (33), $\dot{V}_x$ can be rewritten as

$$\begin{aligned}\dot{V}_x =& \tilde{V}_f^T(\Phi_A B_e^T P_e s_e - \frac{1}{\alpha_f}\dot{V}_f) - \tilde{W}_f^T(\Phi B_e^T P_e s_e + \frac{1}{\beta_f}\dot{W}_f)\\ &+ \tilde{V}_g^T(\Phi_A B_e^T P_e s_e - \frac{1}{\alpha_g}\dot{V}_g) - \tilde{W}_g^T(\Phi B_e^T P_e s_e + \frac{1}{\beta_g}\dot{W}_g)\\ &- KsB_e^T P_e s_e - \frac{1}{r}B_e^T P_e s_e B_e^T P_e s_e + P_2 s^2 + P_3 s\xi + (\tilde{\omega} + d)B_e^T P_e s_e\end{aligned} \tag{34}$$

In a first case when the update laws in equation (22) are equivalent to equation (21), and using equation (27), it is possible to simplify as

$$\begin{aligned}\dot{V}_x \leq &-\frac{1}{2}(s_e^T Q_e s_e + s_e^T P_e B_e^T \frac{1}{\rho^2} B_e P_e s_e) \\ &+ \tilde{V}_f^T \Phi_A (B_e^T P_e s_e - \max(B_e^T P_e s_e, 0)) + \tilde{V}_g \Phi(B_e^T P_e s_e u - \max(B_e^T P_e s_e u, 0)) + (\tilde{\omega} + d) B_e^T P_e s_e \end{aligned} \tag{35}$$

Now, in a second case when the update laws are defined by the second line of equation (22), for each dynamic of the NN weights we obtain

$$\begin{aligned}\dot{V}_x \leq &-\frac{1}{2}(s_e^T Q_e s_e + s_e^T P_e B_e^T \frac{1}{\rho^2} B_e P_e s_e) + (\tilde{\omega} + d) B_e^T P_e s_e \\ &+ \tilde{V}_f^T \Phi_A (B_e^T P_e s_e - \max(B_e^T P_e s_e, 0)) + \tilde{V}_g^T \Phi_A (B_e^T P_e s_e u - \max(B_e^T P_e s_e u, 0)) \\ &+ \tilde{V}_f^T \frac{V_f^T \Phi_A V_f}{\|V_f\|} \max(B_e^T P_e s_e, 0) + \tilde{V}_g^T \frac{V_g^T \Phi_A V_g}{\|V_g\|} \max(B_e^T P_e s_e u, 0) \\ &- \tilde{W}_f^T \frac{W_f^T \Phi W_f}{\|W_f\|} B_e^T P_e s_e - \tilde{W}_g^T \frac{W_g^T \Phi W_g}{\|W_g\|} B_e^T P_e s_e u \end{aligned} \tag{36}$$

We analyse the new term depending on V_f, using equation (20) and the respective conditions in equation (22)

$$\begin{aligned}\tilde{V}_f^T \underbrace{\frac{V_f^T \Phi_A \max(B_e^T P_e s_e, 0)}{\|V_f\|}}_{:=\zeta_1 > 0} V_f &= \tilde{V}_f^T V_f \zeta_1 = (V_f^{*T} - V_f^T) V_f \zeta_1 = V_f^{*T} V_f \zeta_1 - \|V_f\|^2 \zeta_1 \\ &\leq (\|V_f^*\| - \|V_f\|)\|V_f\|\zeta_1 \end{aligned} \tag{37}$$

We know that in this case $\|V_f\| = \Omega_{fv}$, $\|V_f^*\| \leq \Omega_{fv}$, and we can conclude that

$$\tilde{V}_f^T \frac{V_f^T \Phi_A V_f}{\|V_f\|} \max(B_e^T P_e s_e, 0)) \leq 0 \tag{38}$$

A similar analysis can be done for V_g, W_f, and W_g. It is concluded that the projection algorithm does not modify the Lyapunov eq. (35) because all the new terms are negative.

Considering equation (35) and knowing that $a \max(b, 0) \leq \max(ab, 0)$ then

$$\dot{V}_x \leq -\frac{1}{2}(s_e^T Q_e s_e + s_e^T P_e B_e^T \frac{1}{\rho^2} B_e P_e s_e) + (\tilde{V}_f \Phi_A + \tilde{V}_g \Phi u)(B_e^T P_e s_e - \max(B_e^T P_e s_e, 0)) + (\tilde{\omega} + d) B_e^T P_e s_e \tag{39}$$

Defining the worst case perturbation as

$$\omega = \tilde{\omega} + d + |\tilde{V}_f \Phi_A + \tilde{V}_g \Phi u| \text{sign}(\tilde{\omega} + d) \tag{40}$$

the following is obtained

$$\dot{V}_x \leq -\frac{1}{2}(s_e^T Q_e s_e + s_e^T P_e B_e^T \frac{1}{\rho^2} B_e P_e s_e) + \omega B_e^T P_e s_e \tag{41}$$

Adding and subtracting $\frac{1}{2}\rho^2\omega^2$ the following is obtained

$$\begin{aligned}\dot{V}_x &\leq -\frac{1}{2} s_e^T Q_e s_e - \frac{1}{2}(\frac{1}{\rho} B_e P_e s_e - \rho\omega)^2 + \frac{1}{2}\rho^2\omega^2 \\ \dot{V}_x &\leq -\frac{1}{2} s_e^T Q_e s_e + \frac{1}{2}\rho^2\omega^2 = -\frac{1}{2} s^T Q s - \frac{1}{2}\xi^T Q_I \xi + \frac{1}{2}\rho^2\omega^2 \\ &\leq -\frac{1}{2} s^T Q s + \frac{1}{2}(\rho^2 - \lambda_{max}(Q_I)\frac{\|\xi\|^2}{\|\omega\|^2})\omega^2 \end{aligned} \tag{42}$$

By integrating equation (42) from $t = 0$ to $t = T$, the H_∞ tracking performance criteria in equation (24) is attained. If $\omega \in L_2$, using Barbalat's Lemma [20] it can be proved that the error function s asymptotically converges to zero. ■

Figure 3 illustrates the overall architecture of the proposed LISIC structure enhanced with a PI feedback.

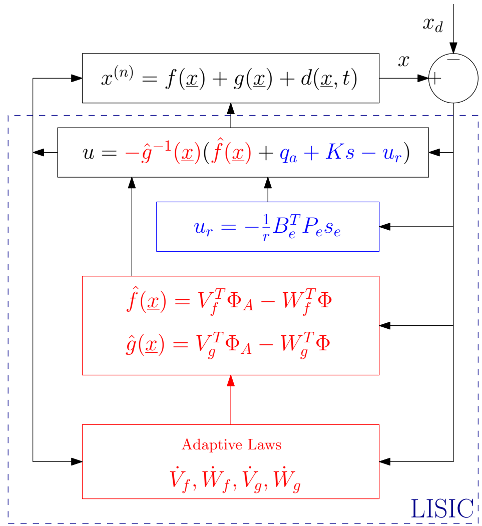

Fig. 3. A block diagram representation of the proposed LISIC structure enhanced with a PI feedback.

H. Performance analysis of the LISIC structure based on numerical simulations

The performance of the proposed LISIC structure is demonstrated and compared with respect to the controller from [16]. Towards this goal, the same numerical example proposed in [16] is implemented, which consists on the stabilization of an inverted pendulum. The system under consideration has the following dynamics

$$\begin{aligned} \ddot{x} &= \frac{g\sin(x) - a_p m_p l \dot{x}^2 \sin(2x)/2}{4l/3 - a_p m_p l \cos(x)^2} + \frac{a_p \cos(x)}{4l/3 - a_p m_p l \cos(x)^2} u + d \\ y &= x + \nu \end{aligned} \tag{43}$$

with $g = 9.81$, $m_p = 1$, $M = 10$, $l = 3$, $a_p = 1/(mp + M)$, $\nu = 0$, $d(0 \le t < 20) = 0$, $d(20 \le t < 30) = 15$, $d(t \ge 30) = 0$, $\underline{x}(0) = [0.2, 0.2]^T$, and a sampling time of $T_s = 0.001$.

We use 5 nodes for the LISIC with tuning parameters $\rho = 0.2$, $r = 0.075$, $K = 1$, $Q = 10$, and $Q_I = 1000$, and the reference is $x_d = \frac{\pi}{30}\sin(t)$. The NN weights are initialized as $V_f(0) = V_g(0) = 0.$ and $W_f(0)$ and $W_g(0)$ take random values between -0.01 and 0.01, while $\xi(0) = 0$.

Figure 4 shows the output of the system with respect to the reference, as calculated directly from the methodology proposed in [16]. Notice the effect of a perturbation in the output derivative between $t = 20$s and $t = 30$s. Figure 5 shows the same scenario, but now making use of the proposed novel LISIC structure, which considers the addition of the integral action. LISIC exhibits faster convergence and superior performance against the the perturbation.

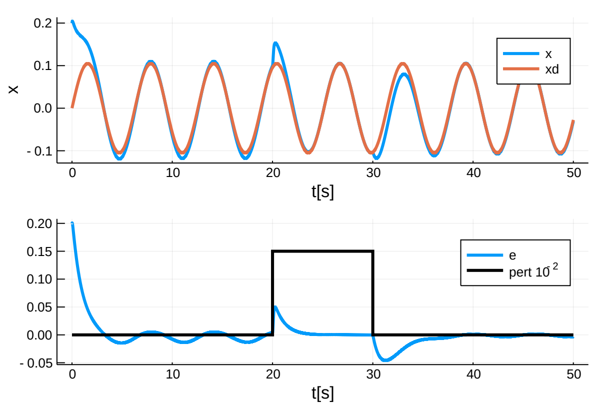

Fig. 4. BEL with a proportional feedback in u_r from [16]

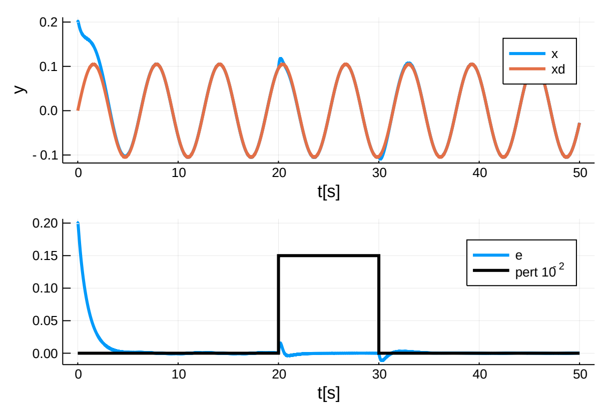

Fig. 5. Proposed LISIC structure with an integral action in u_r

I. Numerical benchmark between BEL-based NN and a RBF NN

Figure 6 illustrates the performance of a BEL-based NN, compared with respect to a classical RBF NN, for the numerical example presented in Section III-H. In this simulation, both NN are tuned with the same parameters as in Section III-H (including the robust term), but for the RBF NN all the amygdala part (V_f and V_g) are removed. Notice the faster convergence of the BEL-based NN with respect to the classical RBF-NN.

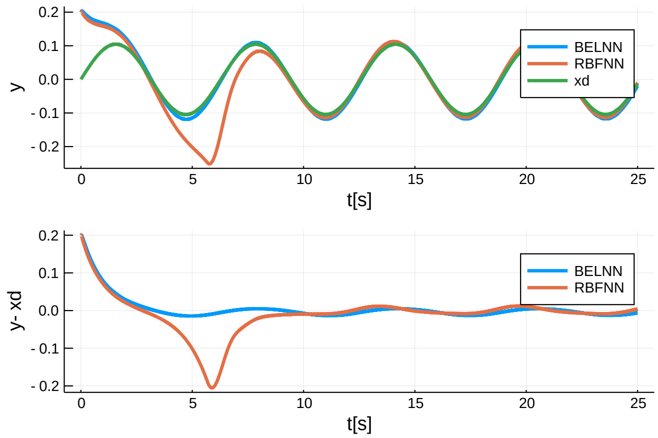

Fig. 6. Comparison of numerical results of a BEL-based NN with respect to a classical RBF NN with same tuning parameters and the robust term u_r.

J. A novel LISIC structure for MAS consensus and flocking operating under uncertainties and disturbances

In terms of MAS consensus and flocking, the main objective is to design a control signal u_i for each agent i, in such a way that the collective motion of all the agents exhibits an emergent behavior arising from simple rules that are followed by individuals, and does not involve any central coordination. For the novel framework proposed in this research work, each agent i is designed to incorporate a LISIC structure to support the overall consensus controller. The objective of each LISIC$_i$ control structure is to identify and compensate model differences between what was theoretically supposed when tuning the MAS controllers and the real practical conditions encountered in the system.

A great part of the literature in MAS consensus and flocking is focused on developing results when considering double integrator agents, see for example [22], [23] and [24]. These results, however, are not applicable when dealing with real–time systems having specific dynamics models, and furthermore, uncertain parameters. In order to use and implement in real–time the well established consensus and flocking techniques available for double integrators, we develop a novel framework that interfaces the LISIC structure with the MAS by means of a novel reference model of a double integrator, which creates a virtual reference for the s variable. The proposed interconnection framework, which we call the *Double Integrator*–LISIC (DILISIC) is shown in Fig. 7. The DILISIC system is composed by an agent in closed-loop with a LISIC, imitating the desired double integrator dynamics.

Remark 1: In the absence of model mismatches and/or disturbances, the LISIC strategy should not interfere with the nominal MAS control.

K. Designing the double integrator closed-loop behavior

We propose to use the LISIC structure to compensate the differences between the model of each agent and a nominal system described by a double integrator. This approach facilitates the implementation of a consensus–inspired control strategy specifically designed for second order nonlinear agents, which in our case will be controlled by means of LISIC.

As a first step, consider a reference model representing the double integrator dynamics

$$\ddot{x}_d = u_{DI} \tag{44}$$

where the subscript $(\cdot)_{DI}$ indicates the double integrator system that the LISIC closed-loop should imitate, and we must assume that $u_{DI} \in C^{n-2}$. Next, the system output is compared with the reference model that represents the double integrator dynamics

$$e = x_d - y \tag{45}$$

$$x^{(n)} = f(\underline{x}) + g(\underline{x})(u_{DI} + u_{LISIC}) \tag{46}$$

where u_{LISIC} comes from the controller in equation (23) and u_{DI} is defined in equation (44).

The DILISIC closed-loop system can now be rewritten as

$$x^{(n)} = f(\underline{x}) + g(\underline{x})u_{LISIC} + \underbrace{g(\underline{x})u_{DI} - u_{DI}^{(n-2)}}_{d(\underline{x},t)} + u_{DI}^{(n-2)} \tag{47}$$

For the particular case of a second order system we have

$$\ddot{x} = f(\underline{x}) + g(\underline{x})u_{LISIC} + g(\underline{x})u_{DI} - u_{DI} + u_{DI} \tag{48}$$

If the functions $f(\underline{x}) = 0$ and $g(\underline{x}) = 1$, then the systems in equations (44) and (48) are identical. If both systems have the same initial conditions, then there is no need for compensation and the LISIC controller output should be $u_{LISIC} = 0$.

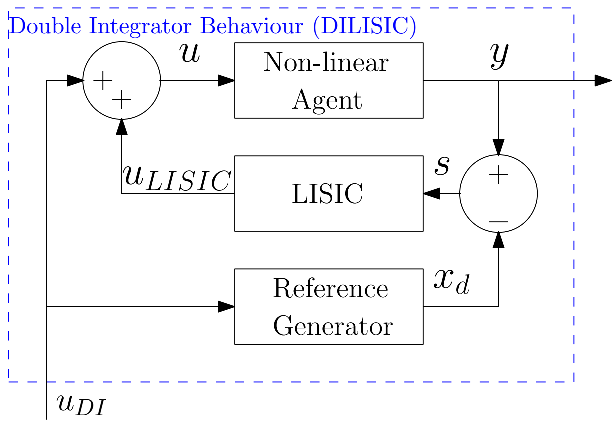

Fig. 7. DILISIC structure: a LISIC structure imitating the double integrator behavior. A non-linear agent is in closed loop with a LISIC controller that corrects the error variable s between the system output y and a double integrator system that generates x_d from u_{DI}.

With the DILISIC structure imitating double integrator agents, we can directly apply consensus techniques for double integrator agents.

L. Performance analysis of the DILISIC structure based on numerical simulations

The performance of the proposed controller for nonlinear MAS is validated in a set of numerical simulations. The application chosen for this purpose consists on the stabilization, consensus, and flocking of a group of ten inverted pendulums, with dynamics as described in equation (43). The initial conditions of the pendulums are $\underline{x}_i(0) = [q_{0,i}, 0]^T$, with $q_{0,i}$ equally distributed between -0.75rad and 0.75rad. The sampling time is fixed at $T_s = 0.001$. To increase the challenge of performing this task, a perturbation affecting all the agents appears at $d(50 \geq t) = 2$.

The tuning parameters of DILISIC are $r = 0.2$, $\rho = 0.075$, $K = 1$, $Q = 10$, and $Q_I = 10$. The reference signal is $x_d = \frac{\pi}{30}\sin(t)$. The RBF parameters are $\mu = 10^4$ and $\sigma = 10^4$. The weight parameters are initialized as $V_f(0) = V_g(0) = 0$, with $W_f(0)$ and $W_g(0)$ taking random values between -0.1 and 0.1, and $\xi(0) = 0$. The conventional MAS controller from [23], [24] was adopted as the supporting foundational controller for the novel strategy proposed here, and was tuned with parameters: $c_1^\alpha = 2 \cdot 10^4$, $c_2^\alpha = 2\sqrt{c_1^\alpha}$, $c_1^\beta = 3 \cdot 10^4$, $c_2^\beta = 2\sqrt{c_1^\beta}$, $c_1^\gamma = 200$, $c_2^\gamma = 2\sqrt{c_1^\gamma}$, $c_1^{sc} = 2 \cdot 10^4$, $c_2^{sc} = 2\sqrt{c_1^{sc}}$. The adaptation rate was implemented with $\alpha_{ij} = 30$. Parameters for sigmoidal function $a = 20$, $b = 50$ and $\epsilon = 0.1$.

In the simulation, the group of agents are tasked to follow a Center of Mass (CoM) reference in consensus and flocking modes, and in the presence of disturbances. Figure 8 shows the positions of the MAS composed by the ten one–dimensional agents, which can be seen maintaining a security distance from each other. The effect of the disturbance is more evident in Figure 9 at around 50sec, which shows the time evolution of the CoM of the MAS formation w.r.t. the desired reference. Finally, the angular velocity of the MAS is shown in Figure 10, were it is also possible observe the disturbance effect.

A more challenging scenario was designed, in which the agents are affected by the presence of obstacles and external disturbances. The numerical results in Figure 11 show the evolution of the angular position of the ten agents. At time $t = 23$s, an obstacle appears at position $x = 0.8$rad. Notice that, as soon as the obstacle appears, the separation distance between agents is adjusted and successfully maintained to the desired values. The CoM state is modified at the same time, see Figure 12, allowing the agents to maintain the desired inter-agent separation. Still, the tracking of the CoM under consensus conditions is successfully accomplished. After a few seconds, a perturbation appears at time $t = 40$s, which simulates an uniform force in the positive x axis, and affects all the agents simultaneously. Notice again from Figure 11 that each agent rejects the perturbation, and from Figure 12 that the MAS can effectively follow the CoM. The agent velocities, which are shown in Figure 13, exhibit small corrections between $t = 23s$ and $t = 40s$. These are due to the presence of the obstacle. On the other hand, the large variation at time $t = 40$s is due to the presence of the disturbance. Notice that the proposed controller is able to stabilize the agents in the MAS according to the proposed requirements.

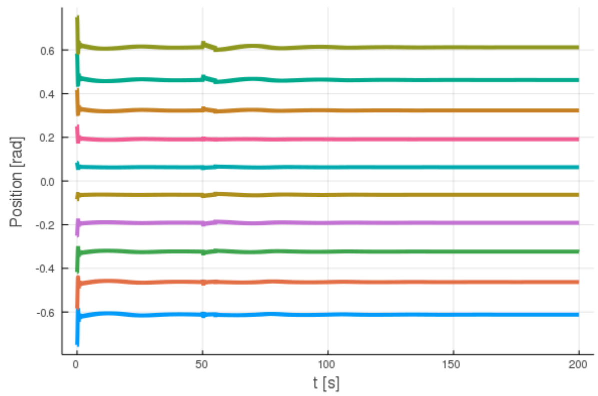

Fig. 8. Positions of a 10-agent MAS (1D agents) following a constant reference, and maintaining a security distance from each other.

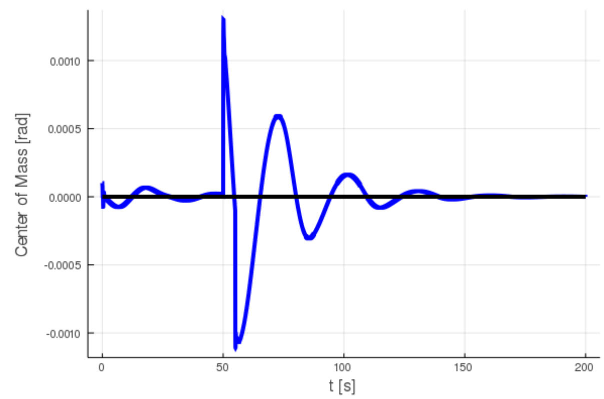

Fig. 9. Time evolution of the CoM of the MAS formation (blue) w.r.t. the desired reference (black). At time $t = 50$sec a perturbation modify the formation, then it reaches asymptotically the reference

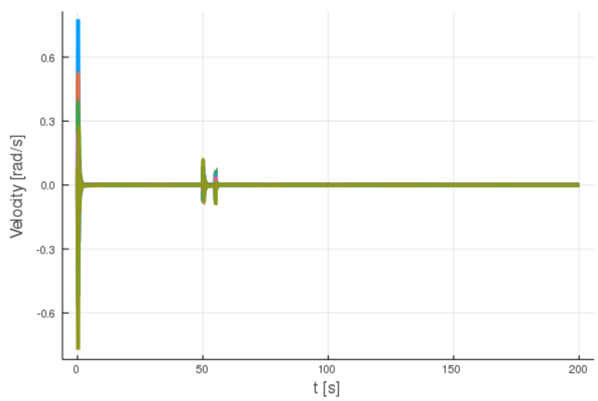

Fig. 10. This figure illustrates the angular velocity of the MAS, in the first seconds the effect of the initial conditions of the agents to reach flocking is shown. Later, at time $t = 50$sec, notice the effect of a perturbation rejection, first when the perturbation appears and then when the perturbation disappears.

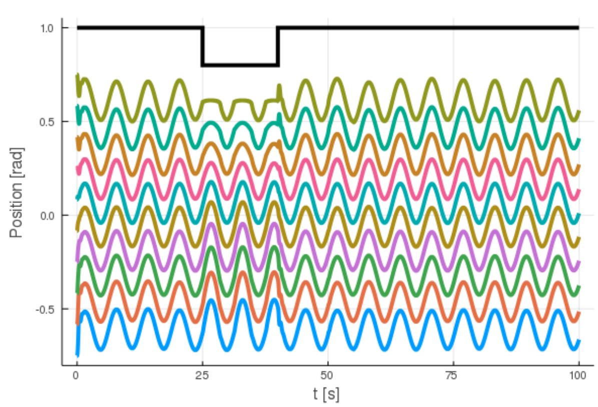

Fig. 11. Positions of a 10-agent MAS (1D agents) following a sinusoidal reference, and maintaining a security distance from a wall-type obstacle (black line). The obstacle appears at time $t = 23$s, with position $x = 0.8$rad.

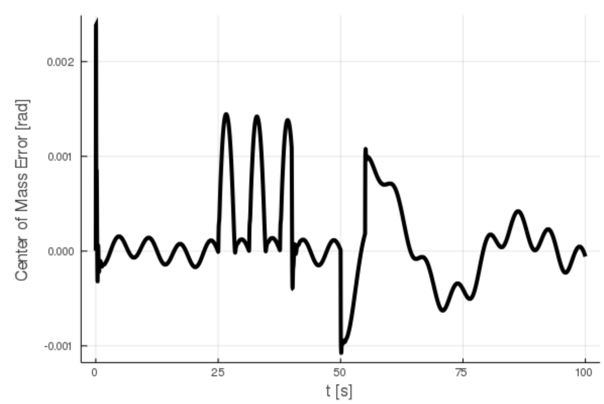

Fig. 12. Time evolution of the error between the CoM of the MAS formation and the desired reference. Notice the vertical axis scale, the CoM follows very close the reference.

M. Development of a MAS experimental platform for validation purposes

The graduate student involved in this project (Gabriel Alexis Guijarro Reyes) is working with one undergraduate student (Alan Garduno, Major in Electrical Engineering) on the development of a novel home made UAS prototype, see Fig. 14. The platform is equipped with a combination of sensors and actuators, enabling the UAS to stabilize itself, sense its surrounding

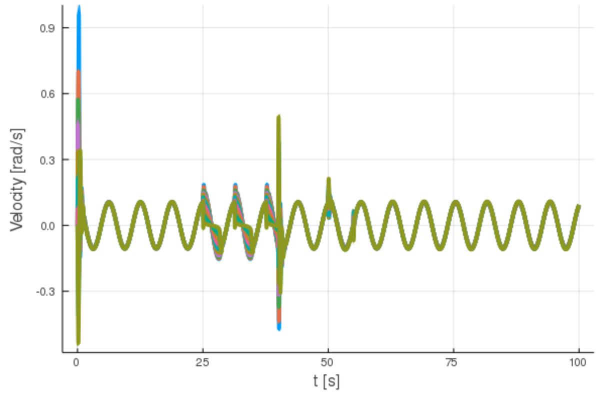

Fig. 13. Angular velocity of the MAS. Notice the effect of the obstacle between $t = 23s$ and $t = 40s$, and the disturbance at around $t = 40s$.

environment, and communicate with neighboring agents as well as with a Ground Control Station (GCS). At present, the LISIC and DILISIC algorithms introduced in Sections III-C and III-J are being discretized for its online implementation in the autopilot onboard the UAS. The goal is to be able to demonstrate the applicability and performance of LISIC and DILISIC for stabilizing MAS with uncertain dynamics and affected by external perturbations.

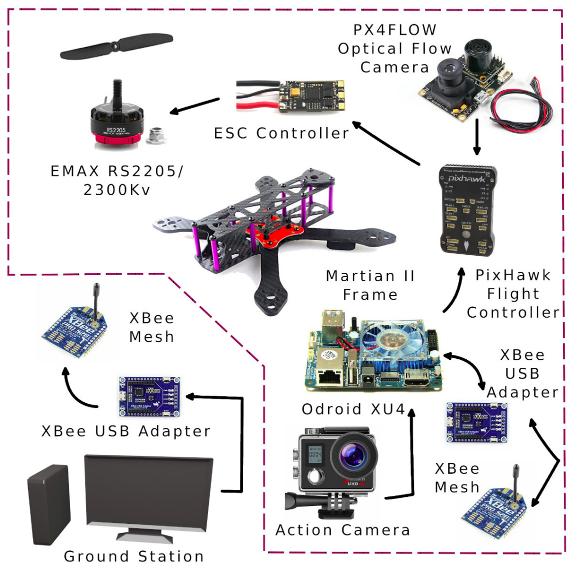

Fig. 14. The novel MAS experimental platform for validation purposes. A fleet of home made multi rotrocraft UAS is currently under development for validation of LISIC and DILISIC algorithm under real–time experimental scenarios. The platform is equipped with a combination of sensors and actuators, enabling the UAS to stabilize itself, sense the environment, and communicate with neighboring agents as well as with the GCS.

IV. Key outcomes and other achievements

Four research papers about the outcomes of this project were **accepted and published** in international conferences and journals. These publication are:

[1] I. Rubio Scola, **L.R. Garcia Carrillo**, and J.P. Hespanha, "Stable robust controller inspired by the mammalian limbic system for a class of nonlinear systems", accepted in *American Control Conference (ACC)*, Denver, CO, USA, July 2020.

[2] J. Xie, **L.R. Garcia Carrillo**, L. Jin, and J.P. Hespanha, "A Robust State Estimator for Multi-Agent Systems Under Impulsive Noise and Missing Measurements", *Conference on Decision and Control (CDC)*, Nice, France, December 2019.

[3] I. Rubio Scola, G.A. Guijarro Reyes, **L.R. Garcia Carrillo**, J.P. Hespanha, and J. Xie, "Translational model identification and robust control for the Parrot Mambo UAS Multicopter", *IEEE GLOBECOM Workshop on Computing-Centric Drone Networks*, Waikoloa, Hawaii, December 2019.

[4] **L.R. Garcia Carrillo**, and K.G. Vamvoudakis, "Deep-Learning Tracking for Autonomous Flying Systems Under Adversarial Inputs", *IEEE Transactions on Aerospace and Electronic Systems*, July 22, 2019.

Two research papers about the outcomes of this project are currently **under review** in international conferences and journals. These publication are:

[1] I. Rubio Scola, **L.R. Garcia Carrillo**, and J.P. Hespanha, "Performance-guaranteed flocking control inspired by the mammalian limbic system", submitted to *IEEE Transactions on Neural Networks and Learning Systems*, (Submitted on December 2019).

[2] I. Rubio Scola, **L.R. Garcia Carrillo**, J.P. Hespanha, and R. Lozano, "Performance-guaranteed consensus control inspired by the mammalian limbic system for a class of nonlinear multi-agents", submitted to *21st IFAC World Congress*, Berlin, Germany, July 12-17, 2020, (Submitted on November 2019).

A. Fundamental conclusions derived from the research findings

For the first part of this project (July 2018 to March 2019), the research activities focused on the development of a novel BEL-inspired control framework which includes an integral action for increasing robustness. This original method was given the name of *Limbic System–Inspired Control (LISIC)*. In particular, the advantage of using RBFs in the computational model of the Thalamus, as proposed in this project, is that this novel formulation facilitates the implementation of BEL–inspired control strategies where the structure for the Sensory Input (SI) connection is already solved. Similarly, for the Emotional Signal (ES) connection a great advantage is attained, since the imposed integral action structure greatly simplifies the tuning of the BEL to a single parameter tuning, i.e., the tuning of Q_I. Furthermore, the corresponding Lyapunov stability proofs and performance analysis were developed. The novel LISIC structure developed in this research project closely follows the original BEL computational model structure described in the seminal work in [1]. Maintaining the original structure is important in order to keep consistency with complementary developments from the Neuropsychology community. It is expected that this desirable characteristic will allow future collaborations between researchers from the Control Systems, the Artificial Intelligence, and the Neuropsychology communities.

The second part of the project (April 2019 to December 2019) was devoted to the development of the DILISIC structure. As previously explained, a great part of the literature on MAS consensus considers double integrator agents. Despite being effective controllers from a theoretical point of view, in a real world scenario a double integrator would never be appropriate for representing the real robotic agents. In order to apply the consensus techniques for double integrator agents we developed a novel framework that interfaces the LISIC structure with the MAS by means of implementing a reference model of a double integrator to create a virtual reference for the error variable. The proposed interconnection framework, which we call DILISIC is composed by an agent in closed-loop with a LISIC, ultimately imitating the desired double integrator dynamics. An important characteristic of this method is that in the absence of model mismatches and/or disturbances, the LISIC strategy does not interfere with the nominal MAS control. In summary, the LISIC structure compensates the differences between the model of each agent in the MAS and a nominal system described by a double integrator. Ultimately, LISIC and DILISIC facilitate the online and real–time implementation of consensus–inspired control strategies specifically designed for second order nonlinear agents, which are extensively found in the literature.

B. Training opportunities

One Postdoctoral Researcher (PR), Dr. Ignacio Rubio Scola, was funded on this project. The research responsibilities of the PR were to collaborate with the PI, Dr. Garcia Carrillo, in developing the theory for the novel LISIC and DILISIC structures. The PR also assisted the PI in advising Mr. Gabriel Alexis Guijarro, the graduate student involved in the project and Mr. Alan Garduno, the Electrical Engineering undergraduate student.

The M.Sc. student Gabriel Alexis Guijarro was being trained in research-oriented tasks, in order to prepare him for a Ph.D. program in the near future. Gabriel Alexis was also part of our outreach efforts (as explained in the following subsections). Furthermore, three undergraduate students (Selena Mendoza, Nebai Tapia Lugo, and Andrew Garcia) were trained as **Technical Mentors** (TM) for the UAS Summer Institute (outreach effort explained in the following subsections) directed by the PI.

For the last 6 months of this project, the URM undergraduate student Alan Garduno, major in Electrical Engineering, and member of the TAMU-CC SHPE, joined this project. Alan was involved in the practical aspects of building the UAS multicopter shown in Figure 14, and is being trained by the graduate student, postdoc, and PI of this project in different aspects of control systems and robotics. The ultimate goal is to recruit him for one of the STEM graduate programs available at TAMU-CC.

C. *Integrated education/outreach activities*

Unmanned Aerial Systems Summer Institute (UASSI)

On July July 22-26, 2019 the PI served as the **Technical Director** for the Texas A&M University - Corpus Christi (TAMU-CC) Unmanned Aerial Systems Summer Institute (UASSI) [21], see Figure 15. The goal of UASSI is to connect South Texas students to UAS technology, capitalizing on the buzz surrounding this cutting edge industry and placing South Texas students at the forefront of this field. UASSI is designed to give high-school students hands-on experience with UAS equipment and software. The objectives are to offer an introduction to: (1) UAS engineering concepts and applications, (2) Sensors and sensing techniques, (3) Flight Controllers, Robot Operating System (ROS), and OpenCV software, (4) Design, assembly, and operation of a home-made UAS platform. UASSI curriculum is based on participants building a UAS, and then using software (MAVLink, ROS) to interact with the UAS and enable it to perform an autonomous mission.

The PI recruited and trained three **Technical Mentors** (Selena Mendoza, Nebai Tapia Lugo, and Andrew Garcia) from TAMU-CC's Engineering programs, as well as one **Technical Mentor** (Gabriel Alexis Guijarro) from the M.Sc. program in Computer Sciences. The Technical Mentors, all of them Underrepresented Minorities (URMs), provided the PI with the support needed for ensuring that all the high-school students received the appropriate guidance during the summer institute.

This 2019 TAMU-CC UASSI hosted 20 URMs students from from the Corpus Christi Independent School District (CCISD). In particular, each Technical Mentor was in charge of supervising five high school students. Through UASSI, two URM students were recruited for TAMU-CC Engineering programs. An additional benefit of UASSI is the possibility of identifying, among the Technical Mentors, potential candidates for our graduate programs. So far, two of them (Nebai Tapia Lugo and Andrew Garcia) have expressed interest in enrolling in the Computer Science M.Sc. program at TAMU-CC.

D. *Discussion of stated goals not met*

Overall, the LISIC structure was formulated and its stability was demonstrated, allowing the publication of a number of papers. However, there are still two goals that need more work in order to be fully accomplished.

The fist goal is the real-time implementation of DIELIC in a real–time MAS platform. The main reason why this goal was not fully accomplished is because an effective discretization of equations (22) should be done first, taking into account a specific sampling time. The fact that the autopilots onboard the home made UAS prototypes (currently under development) have limited computational power is being carefully considered as we plan the execution of this goal.

The second goal that was not fully met is the formal proofs of stability for consensus and flocking of MAS with a DIELIC controller running on each agent. As can be seen from the results reported in the previous section, the MAS simulations indicate that stability is indeed possible. In order to investigate the conditions allowing the fulfilment of this goal, the DIELIC equations are being studied in combination with the MAS consensus/flocking equations for double integrator agents, see for example the conventional algorithms in [23] and [24]. Ultimate goal is to derive solid stability proofs, similar to the ones already obtained (and published) for the originla LISIC structure.

V. Work in progress and future tasks

A. *Stability proofs for DILISIC structure for MAS*

As of now, the novel DILISIC approach for consensus and flocking for MAS is well understood under numerical simulations. Still, this technique requires a deeper analysis in terms of performance and stability profs. The immediate future research efforts will explore these goals.

B. *Real-time implementation of the proposed BEL-structure*

The ultimate goal is to test the DILISIC structure in a distributed MAS testbed. Once the stability proofs are ready, the applied research objective will be to develop the discretization of the proposed method for real time implementation purposes.

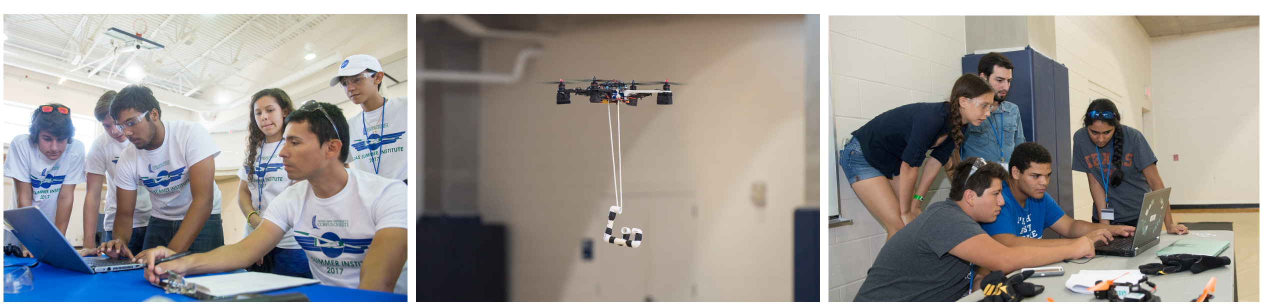

Fig. 15. Unmanned Aerial Systems Summer Institute (UASSI): the PI, in collaboration with Technical Mentors, guide the high school students on how to build the UAS and use ROS to operate the UAS and sensor equipment.

C. Publications in preparation

At present, one international journal publication is being prepared, which will include the first steps towards the real-time implementation of the DIELIC for consensus and flocking of MAS. The MAS testbed will be composed by a fleet of multi rotorcraft UAS, which can be seen in Figure 14. The tentative title for this publication is:

- I. Rubio Scola, G. A. Guijarro Reyes, **L.R. Garcia Carrillo**, and Joao P. Hespanha, "Performance-guaranteed consensus control inspired by the mammalian limbic system for a class of nonlinear multi-agents: Theory and Practice", to be submitted to *IEEE Transactions on Neural Networks and Learning Systems*, Special Issue on "Adaptive Learning and Control for Autonomous Vehicles".

The deadline for submitting this manuscript to the IEEE TNNLS special issue is July 30, 2020.

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