Available online at www.sciencedirect.com

ScienceDirect

IFAC PapersOnLine 50-1 (2017) 6934–6939

Implementation of Brain Emotional Learning-Based Intelligent Controller for Flocking of Multi-Agent Systems

Mohammad Jafari, * **Ric Fehr,** ** **Luis Rodolfo Garcia Carrillo,** *** **Eduardo Steed Espinoza Quesada,** **** **Hao Xu,** †

* *Department of Electrical and Biomedical Engineering, University of Nevada, Reno, NV 89557-0260 USA (e-mail: mo.jafari@nevada.unr.edu).*
** *Department of Electrical and Biomedical Engineering, University of Nevada, Reno, NV 89557-0260 USA (e-mail: ricfehr3@nevada.unr.edu)*
*** *Department of Electrical Engineering, School of Engineering & Computing Sciences, Texas A&M University - Corpus Christi, 6300 Ocean Drive, Unit 5797, Corpus Christi, TX 78412-5797 USA (e-mail: luis.garcia@tamucc.edu)*
**** *Polytechnic University of Pachuca, Hidalgo, Mexico 43830, (e-mail: steed@upp.edu.mx)*
† *Department of Electrical and Biomedical Engineering, University of Nevada, Reno, NV 89557-0260 USA (e-mail: haoxu@unr.edu)*

Abstract:
The Brain Emotional Learning Based Intelligent Controller (BELBIC) is a neurobiologically-motivated intelligent controller based on a computational model of emotional learning in mammalian limbic system. The learning capabilities, multi-objective properties, and low computational complexity of BELBIC make it a very promising tool for implementation in real-time applications.
Our research combines, in an original way, the BELBIC methodology with a flocking control strategy, in order to perform real-time coordination of multiple Unmanned Aircraft Systems (UAS). The characteristics of BELBIC fit well in this scenario, since almost always the dynamics of the autonomous agents are not fully known, and furthermore, since they operate in close proximity, they are subjected to aggressive external disturbances. Numerical and experimental results based on the coordination of multiple quad rotorcraft UAS platforms demonstrate the applicability and satisfactory performance of the proposed method.

Keywords: Reinforcement learning control, adaptive neural and fuzzy control, embedded computer control systems and applications, knowledge based control, tele-robot.

1. INTRODUCTION

Aiming at the coordination of Multi-Agent Systems (MAS), numerous control strategies have been proposed by research groups from different communities, see for instance (Reynolds (1987); Olfati-Saber (2006); Ortega et al. (2015); Xu and Garcia (2015); Jafari (2015); Muñoz et al. (2016)) and the references therein. The mathematical model of *flocking*, which explains the aggregated motion of an immense number of self-driven entities (agents) and is exhibited by birds, fish, bacteria, insects, and many other living beings who interact as a group, is adopted in most of these MAS control approaches (O'Loan and Evans (1999)).

Three basic rules were introduced in the seminal work proposed by Reynolds (1987) for simulating the flocking behavior: *separation*, *alignment*, and *cohesion*. Recently, researchers have shown interest towards the improvement of the flocking behavior of MAS (Zhang et al. (2014); Li et al. (2014); Dong and Huang (2015); Jafari et al. (2015); Ghapani et al. (2016)).

Related Works

Diverse critical aspects should be considered in the real-time implementation of control strategies on mobile robotic platforms, for example, energy expenses and actuator saturation. For instance, a decentralized strategy for performing formation maneuvers by groups of mobile robots considering the actuator saturation issue was introduced in Lawton et al. (2003). A flocking control approach taking into account bounded control inputs is proposed in Liu and Yu (2009). Gasparri et al. (2012) and Leccese et al. (2013) proposed a swarm aggregation for MAS, taking into consideration the actuator saturation. Additionally, Ke et al. (2009) investigated a leader-following

10.1016/j.ifacol.2017.08.1219

tracking problem for MAS with a varying-velocity leader and input saturation. Closely related, a decentralized connectivity-maintenance strategy for mobile networks with bounded inputs was introduced in Dimarogonas and Johansson (2008). Recently, Chen et al. (2015) presented an energy function-based method for estimating the required control force for preserving network connectivity and for collision avoidance purposes.

Flocking methodologies available in the literature are generally addressing (i) the control effort optimization, (ii) the capability of environmental noise handling, and (iii) the handling of model uncertainty. However, most of these strategies are not considering two critical aspects for real-time implementations: the inclusion of multi-objective properties, and the downsizing of the computational complexity of the algorithm. In fact, by incautiously targeting multiple goals, concurrently with the flocking problem, the computational complexity of the overall problem is not appropriate for a real-time application.

A few methods have tackled the problematic related to computational complexity in MAS control. For example, in recent years neurobiologically-motivated approaches have been extensively employed to overcome such problems. The Brain Emotional Learning Based Intelligent Controller (BELBIC) is one of such techniques, which takes inspiration on the computational model of emotional learning in mammalian brain introduced in Moren and Balkenius (2000). BELBIC imitates those parts of the brain which are responsible for inducing emotion, i.e., the *amygdala*, the *orbitofrontal cortex*, the *thalamus*, and the *sensory input cortex*. BELBIC has two main inputs: *Sensory Inputs* (SI) and *Emotional Signal* (ES). The flexibility on determining both SI and ES makes this controller a favorable tool for solving multi-objective problems in real-time applications (Beheshti and Hashim (2010)). In addition, the computational complexity of BELBIC is on the order of $O(n)$,because it has a single layered architecture. Due to its multiple benefits, diverse techniques based on BELBIC have shown to be very promising for dealing with model uncertainties, environmental noises, and disturbances (Jafari et al. (2013b); Lucas et al. (2004)).

Main Contribution

Our contribution is the design and experimental validation of a novel flocking control for practical MAS applications. To fulfill this goal, we employ the computational model of emotional learning in mammalian limbic system, i.e., BELBIC, in combination with a flocking control strategy. The design and experimental validation of the BELBIC-inspired flocking for MAS presented here is an original work, which has shown very promising results. To deal with uncertainty, we take advantage of the learning capabilities of BELBIC, inherently enhancing the flocking strategy in a computationally feasible way. The proposed BELBIC-inspired MAS design provides a practically implementable controller of low complexity with multi-objective properties such as: (i) minimization of the control effort, (ii) handling of system/model uncertainty, and (iii) noise/disturbance rejection. Therefore, our solution is capable of keeping the flocking performance as satisfactory as possible in terms of formation control, obstacles avoidance, and target tracking, while at the same time is practically appropriate for real-time systems. To demonstrate the effectiveness of the proposed approach, a set of numerical simulations and experimental results based on a team of UAS are presented. Furthermore, a comparison between the proposed method and a conventional flocking technique is provided, where it is possible to observe the improved flocking performance achieved by BELBIC.

This paper is organized as follows. The problem formulation, as well as preliminaries about flocking and BELBIC are presented in Section 2. The main contribution is introduced in Section 3, which corresponds to the BELBIC-inspired flocking control. Section 4 and Section 5 present numerical simulation and experimental results, respectively. Conclusions and future directions of our work are provided in Section 6.

2. PROBLEM FORMULATION AND PRELIMINARIES

2.1 Flock Modelling

Consider n agents, with double integrator dynamics, evolving in an m dimensional space ($m = 2, 3$). The equations of motion of each agent can be described as

$$\begin{cases} \dot{q}_i = p_i \\ \dot{p}_i = u_i \qquad i = 1, 2, ..., n \end{cases} \tag{1}$$

where u_i is the control input, q_i is the position, and p_i is the velocity of the agent i, respectively. The flock topology is modeled by means of a dynamic graph $\mathcal{G}(\upsilon, \varepsilon)$ which consists of a set of vertices $\upsilon = \{1, 2, ..., n\}$ representing the agents, and edges $\varepsilon \subseteq \{(i, j) : i, j \in \upsilon, j \neq i\}$ representing the communication link between a pair of agents. The neighborhood set of agent i is described by

$$N_i^\alpha = \{j \in \upsilon_\alpha : \| q_j - q_i\| < r, j \neq i\} \tag{2}$$

where r is a positive constant expressing the range of interaction between agents i and j, and $\|\cdot\|$ is the Euclidean norm in $\mathbb{R}^m$. The geometric model of the flock, i.e., the α-lattice (Olfati-Saber (2006)) is accomplished by solving the following set of algebraic constraints

$$\| q_j - q_i\| = d \quad \forall j \in N_i^\alpha \tag{3}$$

where the positive constant d describes the distance between two neighbors i and j. In order to resolve the singularity problem caused at $q_i = q_j$ in the collective potential function, equation (3) can be rewritten as

$$\| q_j - q_i\|_\sigma = d_\alpha \quad \forall j \in N_i^\alpha \tag{4}$$

where $d_\alpha = \| d\|_\sigma$, and $\| \cdot\|_\sigma$ is the σ-norm which is represented by $\| z\|_\sigma = \frac{1}{\epsilon}[\sqrt{1 + \epsilon\| z\|^2} - 1]$, and $\epsilon > 0$ is a positive constant. For a vector z, the σ-norm represents a map from $\mathbb{R}^m$ to $\mathbb{R} \geq 0$. The new map $\| z\|_\sigma$ is differentiable everywhere, while the Euclidean norm $\| z\|$ is not differentiable at $z = 0$.

Considering the above conditions, a smooth collective potential function is defined as

$$V(q) = \frac{1}{2} \sum_i \sum_{j \neq i} \psi_\alpha(\| q_j - q_i\|_\sigma)$$

where $\psi_\alpha(z)$ is a smooth pairwise potential function determined by $\psi_\alpha(z) = \int_{d_\alpha}^{z} \phi_\alpha(s)ds$, with $\phi_\alpha(z) = \rho_h(z/r_\alpha)\phi(z - d_\alpha)$, and $\phi(z) = \frac{1}{2}[(a+b)\sigma_1(z+c) + (a-b)]$, with $\sigma_1(z) = z/\sqrt{1+z^2}$. Notice that $\phi(z)$ is an uneven sigmoidal function with $0 < a \leq b$, $c = |a-b|/\sqrt{4ab}$ to guarantee that $\phi(0) = 0$. In addition, $\rho_h(z)$ is a scalar bump function which smoothly varies between $[0,1]$. A possible choice for determining $\rho_h(z)$ is (Olfati-Saber (2006))

$$\begin{cases} 1, & z \in [0,h) \\ \frac{1}{2}\left[1+\cos\left(\pi\frac{(z-h)}{(1-h)}\right)\right], & z \in [h,1] \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

The full flocking control algorithm $u_i = u_i^\alpha + u_i^\beta + u_i^\gamma$ introduced in Olfati-Saber (2006) makes all agents to form an α-lattice configuration, while at the same time avoiding obstacles, and following a specific trajectory. The algorithm consists of the following main components: (i) u_i^α which is the interaction term between two α-agents i and j, (ii) u_i^β which is the interaction term between the α-agent and an obstacle (named the β-agent), and (iii) u_i^γ which is a goal term and represents a distributed navigational feedback component. Each one of these components is explicitly expressed as follows

$$u_i^\alpha = c_1^\alpha \sum_{j\in N_i^\alpha} \phi_\alpha(\| q_j - q_i\|_\sigma)\mathbf{n}_{i,j} + c_2^\alpha \sum_{j\in N_i^\alpha} a_{ij}(q)(p_j - p_i)$$

$$u_i^\beta = c_1^\beta \sum_{k\in N_i^\beta} \phi_\beta(\| \hat{q}_{i,k} - q_i\|_\sigma)\hat{\mathbf{n}}_{i,k} + c_2^\beta \sum_{k\in N_i^\beta} b_{i,k}(q)(\hat{p}_{i,k} - p_i)$$

$$u_i^\gamma = -c_1^\gamma \sigma_1(q_i - q_r) - c_2^\gamma(p_i - p_r)$$

where c_1^α, c_2^α, c_1^β, c_2^β, c_1^γ, and c_2^γ are positive gains. The pair (q_r, p_r) represents the γ-agent, which is the virtual leader of the flock and is described as

$$\begin{cases} \dot{q}_r = p_r \\ \dot{p}_r = f_r(q_r, p_r) \end{cases} \tag{6}$$

The terms $\mathbf{n}_{i,j}$ and $\hat{\mathbf{n}}_{i,k}$ are vectors determined by

$$\mathbf{n}_{i,j} = \frac{q_j - q_i}{\sqrt{1+\epsilon\| q_j - q_i\|^2}}, \qquad \hat{\mathbf{n}}_{i,k} = \frac{\hat{q}_{i,k} - q_i}{\sqrt{1+\epsilon\| \hat{q}_{i,k} - q_i\|^2}}$$

The term $b_{i,k}(q)$ is the element of the heterogeneous adjacency matrix $B(q)$, and the term $a_{ij}(q)$ is the element of the spatial adjacency matrix $A(q)$, which are expressed as $b_{i,k}(q) = \rho_h(\| \hat{q}_{i,k} - q_i\|_\sigma / d_\beta)$ and $a_{ij}(q) = \rho_h(\| q_j - q_i\|_\sigma / r_\alpha) \in [0,1], j \neq i$. In these two equations $r_\alpha = \| r\|_\sigma$, $a_{ii}(q) = 0$ for all i and q, $d_\beta = \| d^{'}\|_\sigma$, and $r_\beta = \| r^{'}\|_\sigma$. The term $\phi_\beta(z)$ is a repulsive action function which smoothly vanishes at $z = d_\beta$, and is described as $\phi_\beta(z) = \rho_h(z/d_\beta)(\sigma_1(z - d_\beta) - 1)$.

Finally, similar to equation (2), it is possible to determine the set of β-neighbors for an α-agent i as

$$N_i^\beta = \{k \in \upsilon_\beta : \| \hat{q}_{i,k} - q_i\| < r^{'}\}$$

where r', a positive constant, is the range of interaction of an α-agent with obstacles.

2.2 Brain Emotional Learning-Based Intelligent Controller

BELBIC is a neurobiologically-inspired technique based on a computational model of the emotional learning exhibited in the mammalian limbic system, which was introduced in Balkenius and Morén (2001). A graphical representation of this computational model is presented in Figure 1. The model has two primary parts: (i) the *Amygdala*, which is responsible for immediate learning, and (ii) the *Orbitofrontal Cortex*, which is responible for inhibiting any inappropriate learning happening in the Amygdala.

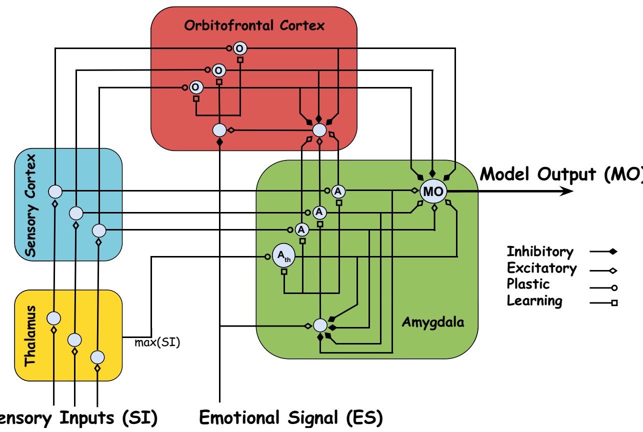

Fig. 1. Computational model of emotional learning (Balkenius and Morén (2001)).

The Sensory Inputs (SI) and the Emotional Signal (ES) are the two inputs to the BELBIC model. The output of this model can be described by the following equation

$$MO = \sum_l A_l - \sum_l OC_l \tag{7}$$

which is determined by subtracting the Orbitofrontal Cortex outputs (OC_l) from the Amygdala outputs (A_l). In this equation, l represents the number of sensory inputs.

The outputs of the Amygdala and Orbitofrontal Cortex are computed by adding all their corresponding nodes, see Figure 1, where the outputs of each node are expressed as

$$A_l = V_l SI_l \tag{8}$$

$$OC_l = W_l SI_l \tag{9}$$

where W_l is the weight associated to the Orbitofrontal Cortex, V_l is the weight associated to the Amygdala, and SI_l is the l^{th} sensory input.

In order to update V_l and W_l we use

$$\Delta V_l = K_v SI_l \max\left(0, ES - \sum_l A_l\right) \tag{10}$$

$$\Delta W_l = K_w SI_l\,(MO - ES) \tag{11}$$

where K_v and K_w are the learning rates of the Amygdala and the Orbitofrontal Cortex, respectively.

There is another input to the Amygdala, which directly comes from the Thalamus. This input is computed by finding the maximum of all SI and can be described as

$$A_{th} = V_{th} \max(SI_l) \tag{12}$$

Several techniques have been employed for tuning the BELBIC parameters (Dorrah et al. (2011); Jafarzadeh et al. (2008); Garmsiri and Najafi (2010); Jafari et al. (2013a,b); Lucas et al. (2004)). In this paper, a heuristic approach is employed for determining the BELBIC parameters.

2.3 Flocking Control Objectives

The problematic and goal of this research can be summarized as follows. Consider the flocking model expressed in

Section 2.1, in combination with the BELBIC methodology presented in Section 2.2. The objective is to design a feasible control signal u_i for each agent i, in such a way that the motion of the agents in the flock exhibits an emergent behavior caused by a set of simple rules, which are executed by each agent independently, and do not require any central coordination. Moreover, the proposed controller should keep a low level of complexity, in order to be practically implementable in the real-time flocking of multiple unmanned aircraft systems (UAS) platforms.

Ultimately, the proposed methodology will enable the flock to track a virtual leader (i.e., the γ-agent), while avoiding collisions with every other agent in the group, and while avoiding obstacles encountered in the environment. Furthermore, the proposed BELBIC flocking strategy should be able to satisfy multiple control objectives, such as (i) minimization of the control effort and energy expenses, (ii) robustness against environmental noise/disturbances, and (iii) model uncertainty handling. All of these previous requirements should be attained without increasing the complexity of the system.

3. BELBIC-INSPIRED FLOCKING OF MAS

The BELBIC architecture implemented in this work is shown in Figure 2.

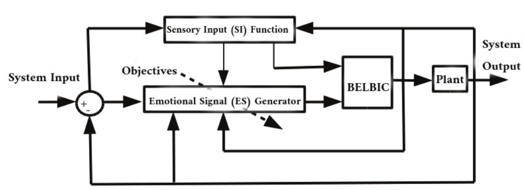

Fig. 2. BELBIC in the control loop of a MAS.

The general form of the SI and the ES signals are

$$SI = G\left(y, e, u, r\right) \tag{13}$$

$$ES = F\left(y, e, u, r\right) \tag{14}$$

where e, u, y, and r, are system error, control effort, system output, and system input, respectively. Specific control objectives can be implicitly determined by choosing the appropriate ES. For example, it is possible to choose the ES in such a way to optimize the energy expense, to preserve network connectivity, or to attain superior target tracking performance, among others.

The BELBIC-inspired flocking focuses on minimizing the control effort and the energy of the flock, while at the same time taking into account the actuator saturation. By doing this, we will accomplish a practical controller well suited for implementation in real-time applications. In order to fulfill the above mentioned objectives, the ES is designed in such a way that the increase in control effort will express a *negative emotion*, e.g., stress. Therefore, the more stress emanated from the system, the more the system performance will be considered as not satisfactory.

The employed sensory inputs (SI_i) and emotional signal (ES_i), for each agent i, are expressed as follows

$$SI_i = K^{\alpha}_{SI} u^{\alpha}_i + K^{\beta}_{SI} u^{\beta}_i + K^{\gamma}_{SI} u^{\gamma}_i \tag{15}$$

$$ES_i = K^{\alpha}_{ES} u^{\alpha}_i + K^{\beta}_{ES} u^{\beta}_i + K^{\gamma}_{ES} u^{\gamma}_i \tag{16}$$

where K^{α}_{SI}, K^{β}_{SI}, K^{γ}_{SI}, K^{α}_{ES}, K^{β}_{ES}, K^{γ}_{ES} are positive constants. By assigning different values to these gains, the influence of ES on the system behavior will change. Since this work emphasizes the reduction of both the overall control effort and the energy of the system, identical values are assigned to all the gains.

In a real-time scenario, the MAS could face unexpected events. The designer can take advantage of the adaptability of the equation (16) in order to successfully achieve different flocking objectives. For example, the pseudo-code in **Algorithm** 1 assigns a specific value to the gain K^{β}_{ES} depending on the situation faced by the flock, specifically (i) flocking in presence of obstacles, or (ii) flocking in obstacle-free environment.

Then, from the equations (15)-(16), the BELBIC-inspired flocking of MAS is expressed as

$$\begin{aligned} u^{BEL}_i &= \sum_i V_i.SI_i - \sum_i W_i.SI_i \\ &= \sum_i V_i.\left(K^{\alpha}_{SI}.u^{\alpha}_i + K^{\beta}_{SI}.u^{\beta}_i + K^{\gamma}_{SI}.u^{\gamma}_i\right) \\ &\quad - \sum_i W_i.\left(K^{\alpha}_{SI}.u^{\alpha}_i + K^{\beta}_{SI}.u^{\beta}_i + K^{\gamma}_{SI}.u^{\gamma}_i\right) \end{aligned} \tag{17}$$

where $i = 1, ..., n$, and n is the number of agents.

Algorithm 1 : Adaptive gain K^{β}_{ES}.

if agent i senses an obstacle **then**
  set K^{β}_{ES} = predefined value
else
  set $K^{\beta}_{ES} = 0$
end if

In summary, the BELBIC-inspired flocking methodology for MAS is presented as a pseudo-code in **Algorithm** 2.

Algorithm 2 : The BELBIC-based flocking for MAS.

Initialization:
Set $V_i = 0$, $W_i = 0$, and $V_{th} = 0$, for $i = 1, ..., n$.
Define ES_i = Objective function, for $i = 1, ..., n$.
for each iteration $t = t_s$ **do**
  for each agent i **do**
    Compute $SI_i = K^{\alpha}_{SI} u^{\alpha}_i + K^{\beta}_{SI} u^{\beta}_i + K^{\gamma}_{SI} u^{\gamma}_i$
    Define K^{β}_{ES} using **Algorithm** 1
    Compute $ES_i = K^{\alpha}_{ES} u^{\alpha}_i + K^{\beta}_{ES} u^{\beta}_i + K^{\gamma}_{ES} u^{\gamma}_i$
    Compute $A_i = V_i SI_i$
    Compute $OC_i = W_i SI_i$
    Compute $A_{th} = V_{th} \max\left(SI_i\right)$
    Compute $BEL_i = \sum_i A_i - \sum_i OC_i$
    Update V_i
    Update W_i
    Update V_{th}
  end for
end for

4. SIMULATION RESULTS

The performance of the BELBIC-inspired flocking of MAS is studied in this section. Simulation results for the 3-dimensional obstacle-free environments is addressed here. A total of 50 agents were employed, with initial velocities equal to zero, and initial positions randomly distributed in a squared area.

The following parameters are used through all the simulations: $r = 1.2d_\alpha$, $d' = 0.6d_\alpha$, $r' = 1.2d'$, and $d_\alpha = 4$. For the σ-norm, the parameter $\epsilon = 0.1$, for $\phi(z)$ the parameters $a = b = 5$, for the bump function $\phi_\alpha(z)$ we use $h = 0.2$.

Flocking in a 3-dimensional Obstacle-Free Environment

Figure 3 shows the 50 UAS in their initial positions, at $t = 0s$. Figure 4 shows the UAS at $t = 70s$ where they have successfully formed a 3D connected network.

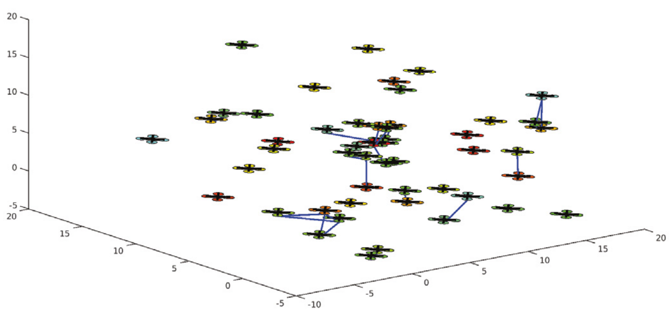

Fig. 3. BELBIC-inspired Flocking of MAS in a 3D obstacle-free environment, at $t = 0s$.

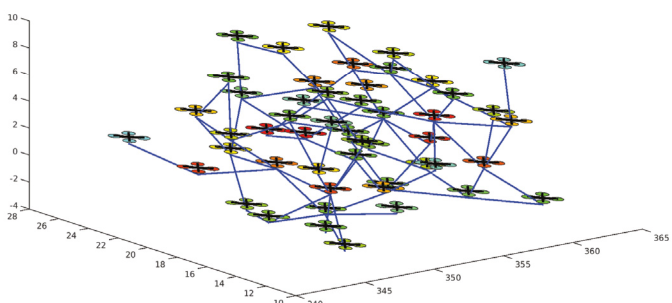

Fig. 4. BELBIC-inspired Flocking of MAS. Simulation in a 3D obstacle-free environment. At $t = 70s$ the 50 UAS have successfully formed a 3D connected network.

For comparison purposes, a similar experiment was performed, but using the flocking algorithm in Olfati-Saber (2006) instead of the BELBIC-inspired flocking. Table 1 presents some characteristics of the control signals generated by both the conventional and the BELBIC-inspired flocking, in a 3D obstacle-free environment.

Table 1. Characteristics of the control signals generated by both flocking strategies.

	Flocking in (Olfati-Saber (2006))	BELBIC-inspired Flocking
Max Value	37.8306	6.0529
Min Value	-5.8222	-1.7141
Mean Value	0.1343	0.1366
Standard Deviation	$1.0979E-04$	$1.0183E-04$

5. EXPERIMENTAL RESULTS

This section presents experimental results showing the performance of the BELBIC-inspired flocking for MAS. The platform implemented for validation of the proposed algorithm is available at the Unmanned Systems Laboratory from the University of Nevada Reno, and the Unmanned Systems Laboratory from Texas A&M University - Corpus Christi. The aerial robots correspond to the Bebop drone, manufactured by Parrot.

Real-time Experiments

The ultimate goal of this experimental application is to maintain a satisfactory flocking of the MAS, even when the model of the UAS is uncertain, and when unknown external factors affect the performance of the agents. In this experiment, a total of four UAS were employed, with initial velocities equal to zero, and positions randomly distributed in a squared area. The following parameters are used for the experiment: $r = 1.2d_\alpha$, $d' = 0.6d_\alpha$, $r' = 1.2d'$, while $d_\alpha = 2m$. For the σ-norm the parameter $\epsilon = 0.1$, for $\phi(z)$ the parameters $a = b = 5$, for the bump function $\phi_\alpha(z)$ we used $h = 0.2$, and for $\phi_\beta(z)$ we used $h = 0.9$.

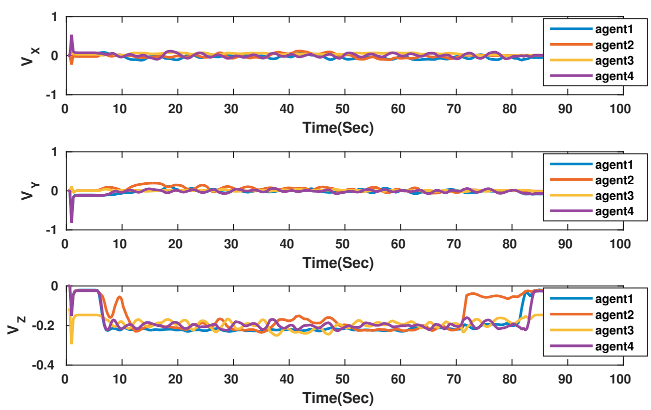

Fig. 5. BELBIC-inspired flocking of MAS: consensus in UAS velocities in (X, Y, Z) axis.

Figure 5 plots the velocities of the four UAS in (X, Y, Z) axis. It can be seen that all the agents agreed on the same speed, successfully accomplishing the objective of our experimental application.

6. CONCLUSIONS

A neurobiologically-motivated intelligent controller based on a computational model of emotional learning in mammalian limbic system was proposed for flocking control of MAS. The methodology, called BELBIC-inspired flocking, was designed and implemented in the real-time coordination of multiple UAS platforms operating in close proximity, and subjected to aggressive external disturbances. Numerical and experimental results of the BELBIC-inspired flocking demonstrated the effectiveness of the proposed approach, as well as its applicability to real-time systems.

The current direction of this research is focused on implementing the BELBIC-inspired flocking for the coordination of multiple UAS cooperatively performing the autonomous transportation of loads with uncertain characteristics.

REFERENCES

Balkenius, C. and Morén, J. (2001). Emotional learning: A computational model of the amygdala. *Cybernetics & Systems*, 32(6), 611–636.

Beheshti, Z. and Hashim, S.Z.M. (2010). A review of emotional learning and it's utilization in control engineering. *Int. J. Adv. Soft Comput. Appl*, 2(2), 191–208.

Chen, Z., Fan, M.C., and Zhang, H.T. (2015). How much control is enough for network connectivity preservation and collision avoidance? *IEEE transactions on cybernetics*, 45(8), 1647–1656.

Dimarogonas, D.V. and Johansson, K.H. (2008). Decentralized connectivity maintenance in mobile networks with bounded inputs. In *Robotics and Automation, 2008. ICRA 2008. IEEE International Conference on*, 1507–1512. IEEE.

Dong, Y. and Huang, J. (2015). Flocking with connectivity preservation of multiple double integrator systems subject to external disturbances by a distributed control law. *Automatica*, 55, 197 – 203.

Dorrah, H.T., El-Garhy, A.M., and El-Shimy, M.E. (2011). Pso-belbic scheme for two-coupled distillation column process. *Journal of advanced Research*, 2(1), 73–83.

Garmsiri, N. and Najafi, F. (2010). Fuzzy tuning of brain emotional learning based intelligent controllers. In *Intelligent Control and Automation (WCICA), 2010 8th World Congress on*, 5296–5301.

Gasparri, A., Oriolo, G., Priolo, A., and Ulivi, G. (2012). A swarm aggregation algorithm based on local interaction for multi-robot systems with actuator saturations. In *2012 IEEE/RSJ International Conference on Intelligent Robots and Systems*, 539–544. IEEE.

Ghapani, S., Mei, J., Ren, W., and Song, Y. (2016). Fully distributed flocking with a moving leader for lagrange networks with parametric uncertainties. *Automatica*, 67, 67 – 76.

Jafari, M. (2015). *On the Cooperative Control and Obstacle Avoidance of Multi-Vehicle Systems*. Master's thesis, University of Nevada, Reno.

Jafari, M., Sengupta, S., and La, H.M. (2015). *Adaptive Flocking Control of Multiple Unmanned Ground Vehicles by Using a UAV*, 628–637. Springer International Publishing, Cham.

Jafari, M., Shahri, A.M., and Elyas, S.H. (2013a). Optimal tuning of brain emotional learning based intelligent controller using clonal selection algorithm. In *Computer and Knowledge Engineering (ICCKE), 2013 3th International eConference on*, 30–34. IEEE.

Jafari, M., Shahri, A.M., and Shouraki, S.B. (2013b). Attitude control of a quadrotor using brain emotional learning based intelligent controller. In *Fuzzy Systems (IFSC), 2013 13th Iranian Conference on*, 1–5. IEEE.

Jafarzadeh, S., Motlagh, M.J., Barkhordari, M., and Mirheidari, R. (2008). A new lyapunov based algorithm for tuning belbic controllers for a group of linear systems. In *Control and Automation, 2008 16th Mediterranean Conference on*, 593–595. IEEE.

Ke, P., Hou-Sheng, S., and Yu-Pu, Y. (2009). Coordinated control of multi-agent systems with a varying-velocity leader and input saturation. *Communications in Theoretical Physics*, 52(3), 449.

Lawton, J.R., Beard, R.W., and Young, B.J. (2003). A decentralized approach to formation maneuvers. *IEEE Transactions on Robotics and Automation*, 19(6), 933–941.

Leccese, A., Gasparri, A., Priolo, A., Oriolo, G., and Ulivi, G. (2013). A swarm aggregation algorithm based on local interaction with actuator saturations and integrated obstacle avoidance. In *Robotics and Automation (ICRA), 2013 IEEE International Conference on*, 1865–1870. IEEE.

Li, S., Liu, X., Tang, W., and Zhang, J. (2014). Flocking of multi-agents following a leader with adaptive protocol in a noisy environment. *Asian Journal of Control*, 16(6), 1771–1778.

Liu, B. and Yu, H. (2009). Flocking in multi-agent systems with a bounded control input. In *Chaos-Fractals Theories and Applications, 2009. IWCFTA'09. International Workshop on*, 130–134. IEEE.

Lucas, C., Shahmirzadi, D., and Sheikholeslami, N. (2004). Introducing belbic: brain emotional learning based intelligent controller. *Intelligent Automation & Soft Computing*, 10(1), 11–21.

Moren, J. and Balkenius, C. (2000). A computational model of emotional learning in the amygdala. *From animals to animats*, 6, 115–124.

Muñoz, F., Quesada, E., Steed, E., La, H.M., Salazar, S., Commuri, S., and Garcia Carrillo, L.R. (2016). Adaptive consensus algorithms for real-time operation of multi-agent systems affected by switching network events. *International Journal of Robust and Nonlinear Control*.

Olfati-Saber, R. (2006). Flocking for multi-agent dynamic systems: Algorithms and theory. *IEEE Transactions on automatic control*, 51(3), 401–420.

O'Loan, O. and Evans, M. (1999). Alternating steady state in one-dimensional flocking. *Journal of Physics A: Mathematical and General*, 32(8), L99.

Ortega, G., Munoz, F., Espinoza, E.S., Garcia, L.R., and Ordaz, P. (2015). Implementation of leader-follower linear consensus algorithm for coordination of multiple aircrafts. In *2015 Workshop on Research, Education and Development of Unmanned Aerial Systems (RED-UAS)*, 25–32. IEEE.

Reynolds, C.W. (1987). Flocks, herds and schools: A distributed behavioral model. *ACM SIGGRAPH computer graphics*, 21(4), 25–34.

Xu, H. and Garcia, L.R. (2015). Distributed near optimal flocking control for multiple unmanned aircraft systems. In *2015 International Conference on Unmanned Aircraft Systems*, 879–885. IEEE.

Zhang, Q., Li, P., Yang, Z., and Chen, Z. (2014). Adaptive flocking of non-linear multi-agents systems with uncertain parameters. *IET Control Theory & Applications*, 9(3), 351–357.