A human-machine symbiotic system for the extraction of high-level behaviors from a macroscopic view of swarms

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AFOSR Program Review:

Computational Cognition and Machine Intelligence Program

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A human-machine symbiotic system for the extraction of high-level behaviors from a macroscopic view of swarms

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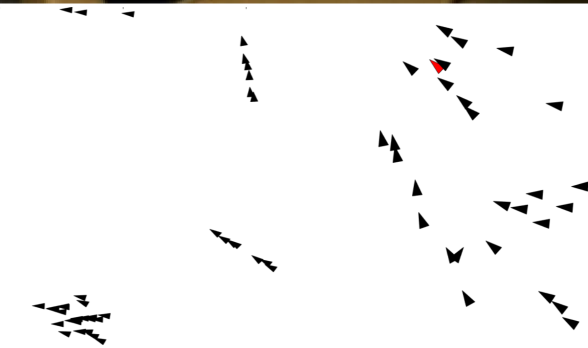
Objective:
- Identify underlying **brain perception** mechanisms of **high-level latent multi-agent** behaviors
- Define computational principles and methods for **human-aided macroscopic analysis of swarms**
- Develop and test human-machine symbiotic system for comprehensive **situation awareness**

Approach:
- Record and analyze evoked ElectroEncephaloGraphic (EEG) signals where human operators **observe latent swarming behaviors**
- Combine image segmentation and feature extraction methods with **EEG-based extraction of behaviors** and models
- Develop **mixed situation awareness** between humans and machine for deconstructing and predicting behaviors

DoD Benefits:
- Form a symbiosis between human and machine systems for comprehensive situation awareness, collaborative assumptions about adversarial agents, and shared decision making

Progress:
- Identified brain patterns related to visual perception of collective and swarming behaviors
- Developed new methods for EEG feature extraction, fusion and classification in motor and speech imagery
- Developed methods for simulating stochastic leader-follower swarming behaviors and reconstructing latent controller for enhancing human perception



Simulated leader-follower behaviors

List of Project Goals

1. Correlate brain activation patterns and gaze tracking to collective high-level behaviors

2. Extract areas of interest and perform human-aided analysis of behaviors using machine intelligence

3. Fit models and control programs to agent groups

4. Present extracted models to the human, predict future behaviors and close the loop

Progress Towards Goals (or New Goals)

1. Correlate brain activation patterns and gaze tracking to collective high-level behaviors
   A. Swarm cohesion as a variable explained in EEG
   B. Improving EEG classification using new features
   C. Explaining mutual adaptation in human-machine EEG-based interfaces
2. Extract areas of interest and perform human-aided analysis of behaviors using machine intelligence
   A. Automatic identification of swarm leader from macroscopic behaviors
3. Fit models and control programs to agent groups
   A. Automatic extraction of control strategies
4. Present extracted models to the human, predict future behaviors and close the loop

Outline

HORC

- Related Work - Inspiration for the project
- EEG feature descriptors and discriminant analysis under Riemannian Manifold perspective
- Metrics for mutual adaptation between humans and machines
- Automatic identification of swarm leader from macroscopic behaviors

Related Work

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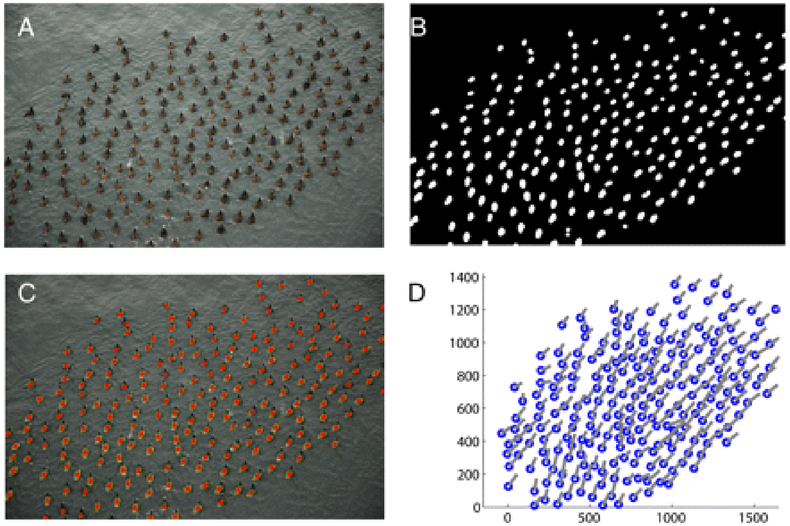
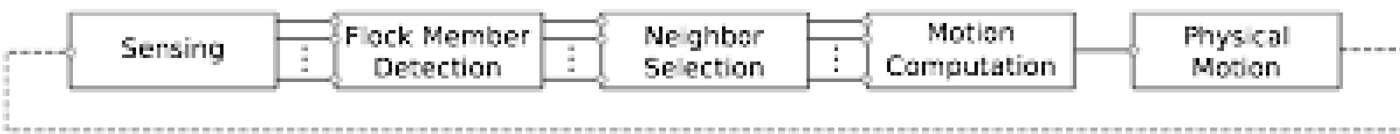
- Analysis of individual roles and rules to explain swarming in biological swarms [1], [2]

- Extraction of flocking models by explaining behaviors of each agent and its neighbors [3]



Agents detection and velocities calculation [1]



Flocking motion model extraction [3]

[1] Ryan Lukeman, Yue-Xian Li, and Leah Edelstein-Keshet. Inferring individual rules from collective behavior. Proceedings of the National Academy of Sciences, 107(28):12576–12580, 2010.
[2] Yael Katz, Kolbjørn Tunstrøm, Christos C Ioannou, Cristián Huepe, and Iain D Couzin. Inferring the structure and dynamics of interactions in schooling fish. Proceedings of the National Academy of Sciences, 108(46):18720–18725, 2011.
[3] Benjamin T Fine and Dylan A Shell. Unifying microscopic flocking motion models for virtual, robotic, and biological flock members. Autonomous Robots, pages 1–25, 2013.

Related Work

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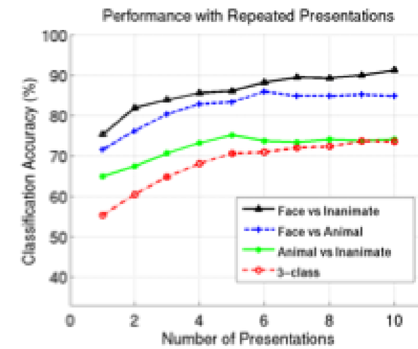
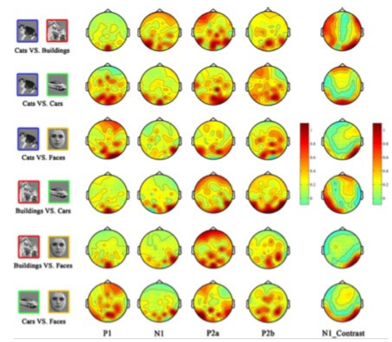
Object and behavior recognition - A brain skill (?)

- Static image categorization using brain-aided approaches has promising results [4]
- ERPs can be used for static image classification [5]
- A single trial EEG-based brain machine interface (BCI) is used to detect objects of interest of arbitrary classes from an initial subset of images. [6]
- Deep learning to develop a visual object classifier where the feature descriptors are extracted from EEG signals rather than from the conventional raw pixel level. [7]



EEG-based Image classification [4]



ERP differences across 4-category objects [5]

[4] Pradeep Shenoy and Desney S Tan. Human-aided computing: utilizing implicit human processing to classify images. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, pages 845–854. ACM, 2008.

[5] Changming Wang, Shi Xiong, Xiaoping Hu, Li Yao, and Jiacai Zhang. Combining features from erp components in single-trial eeg for discriminating four-category visual objects. Journal of neural engineering, 9(5):056013, 2012.

[6] Jun Wang, Eric Pohlmeyer, Barbara Hanna, Yu-Gang Jiang, Paul Sajda, and Shih-Fu Chang. Brain state decoding for rapid image retrieval. In Proceedings of the 17th ACM international conference on Multimedia, pages 945–954. ACM, 2009.

[7] Concetto Spampinato, Simone Palazzo, Isaak Kavasidis, Daniela Giordano, Mubarak Shah, and Nasim Souly. Deep learning human mind for automated visual classification. arXiv preprint arXiv:1609.00344, 2016.

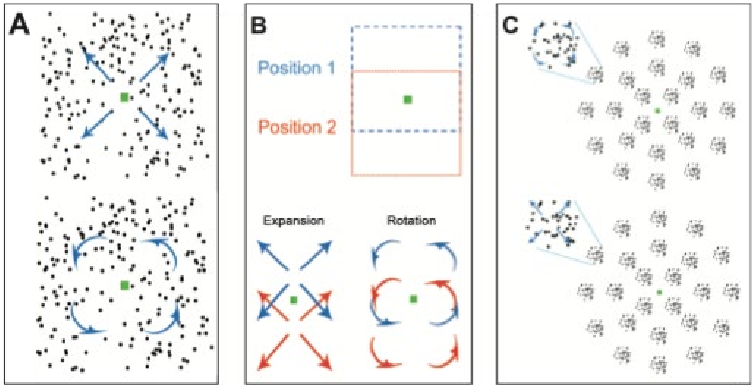
Related Work

From static images to swarming behaviors

- EEG alpha waves are correlated to direction of uniform and accelerated visual motion in [8]

- Examining the brain via functional Magnetic Resonance Imagining (fMRI) demonstrated that optical flow of a pattern of moving dots, such as expansion and rotation, elicits selective responses in the visual areas of the brain [9]

- In [10], Muller et al. found that the EEG gamma power band is modulated differently in coherent versus incoherent motion.



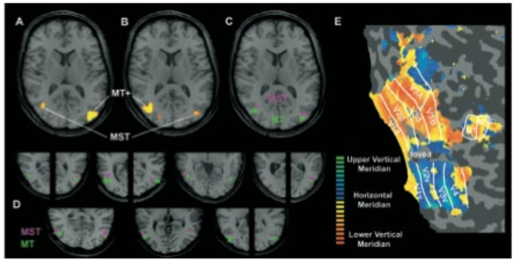
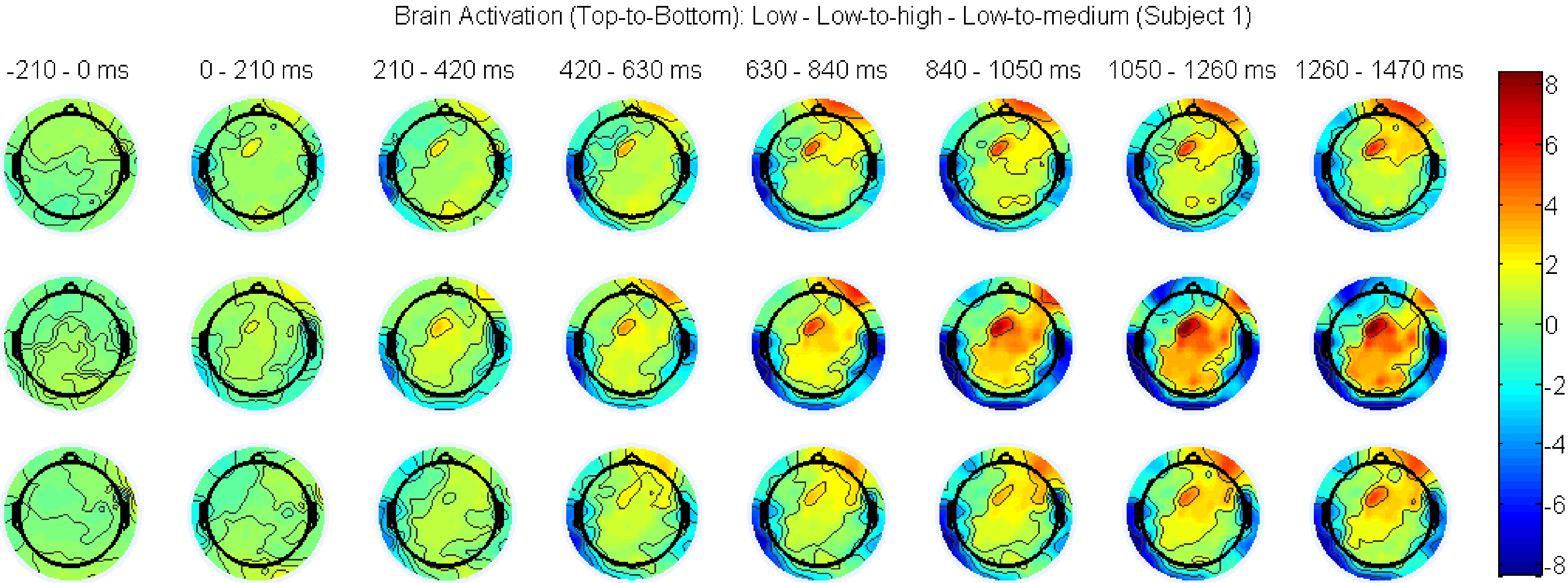


FIG. 2.

Igor A Shevelev, Viktorina M Kamenkovich, Nina B Kostelianetz, and George A Sharaev. Recognition of direction of uniform and accelerated visual motion and eeg alpha wave phases. FEBS letters, 392(2):169–174, 1996.
Matthew B Wall, Angelika Lingnau, Hiroshi Ashida, and Andrew T Smith. Selective visual responses to expansion and rotation in the human mt complex revealed by functional magnetic resonance imaging adaptation. European Journal of Neuroscience, 27(10):2747–2757, 2008.
Matthias M Müller, Markus Junghöfer, Thomas Elbert, and Brigitte Rochstroh. Visually induced gamma-band responses to coherent and incoherent motion: a replication study. NeuroReport, 8(11):2575–2579, 1997.

Results

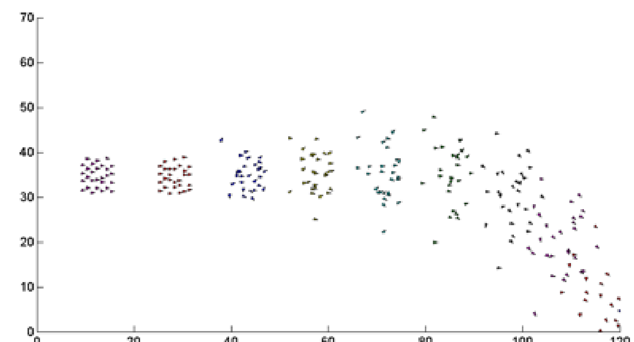
Brain representation of swarm cohesion



1st row: low cohesion

2nd row: low -> high cohesion

3rd row: low-> medium cohesion



George Karavas, Daniel T. Larsson and Panagiotis Artemiadis, “A hybrid brain-machine interface for control of robotic swarms: Preliminary results”, in 2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp. 5065 – 5075, 2017

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EEG feature descriptors and discriminant analysis under Riemannian Manifold perspective

Problem Definition and Research Gap

- The energy of EEG signals is simultaneously distributed in 3 domains: Time–Space–Frequency.

- Classical approaches in one way or another extract the feature descriptor into a vector in Euclidean space, therefore fail to notice a very distinctive characteristic of data: their structure -- the manifolds and the interrelation across the tensor dimensions.

Chuong H Nguyen and Panagiotis Artemiadis, "EEG Feature Descriptors and Discriminant Analysis under Riemannian Manifold perspective," Neurocomputing, 275, pp. 1871-1883, 2018.

EEG feature descriptors and discriminant analysis under Riemannian Manifold perspective

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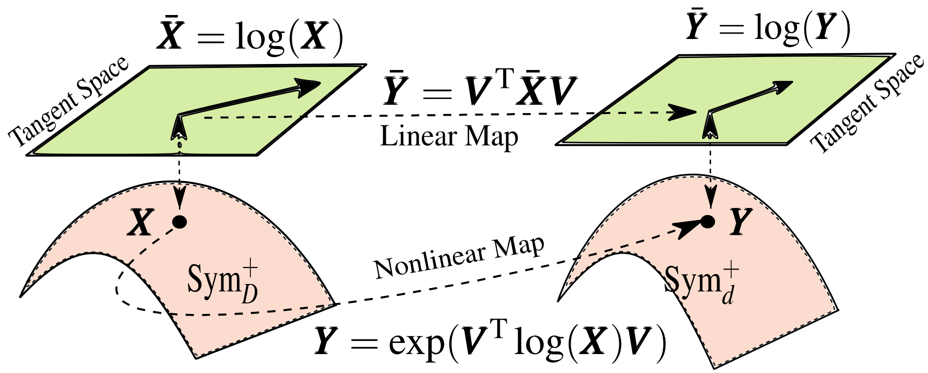
Features in Reimannian Manifold

- Tangent space distance
- Log-Euclidean distance
- Kullback-Leibler (KL) divergence
- Stein divergence
- Von Neumann divergence

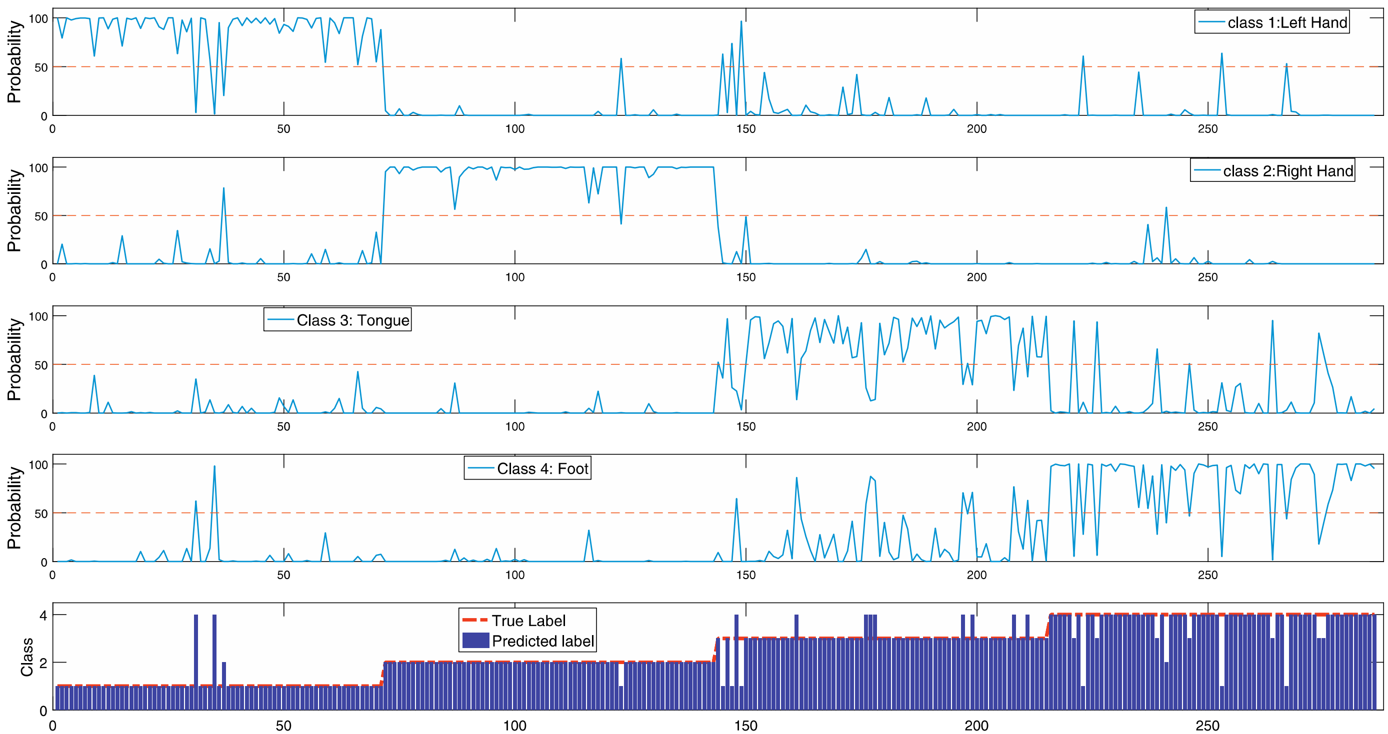


Transform map and Jacobian matrix.

Distance	Transform map	Jacobian $\frac{\partial d^2}{\partial V}(X, Y)$
Log Euclid	$\hat{X} = V^T \log(X) V$	$4(\log(X) - \log(Y))V(\hat{X} - \hat{Y})$,
LogDet	$\hat{X} = V^T X V$	$(XV\hat{X}^{-1} - YV\hat{Y}^{-1})(\hat{X} - \hat{Y})(\hat{X} + \hat{Y})^{-1}$
Kullback–Leibler	$\hat{X} = V^T X V$	$(XV\hat{X}^{-1} - YV\hat{Y}^{-1})(\hat{X}\hat{Y}^{-1} - \hat{Y}\hat{X}^{-1})$
Von Neumann	$\hat{X} = V^T X V$	$2(\Delta + \Delta^T),\ \Delta = 2(X - Y)VV^T(\log(X) - \log(Y))V$

Chuong H Nguyen and Panagiotis Artemiadis, "EEG Feature Descriptors and Discriminant Analysis under Riemannian Manifold perspective," Neurocomputing, 275, pp. 1871-1883, 2018.

- The approach was evaluated by using the datasets IIa from the BCI competition IV [11]. The datasets consist EEG signals from nine subjects, each was asked to perform four different motor imagery tasks: Left hand, right hand, tongue and foot.



[11] G.P.C. Brunner, R. Leeb, G.R. Muller-Putz, A. Schlogl, BCI Competition 2008 Graz Data Set A, Technical Report, Institute for Knowledge Discovery, and Institute for Human–Computer Interfaces Graz University of Technology, Austria, 2008, doi:10.1109/TBME.2004.827081.

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Metrics for mutual adaptation between humans and machines

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- Use EEG signals and combine **motor with speech imagery** to allow for tasks that involve **multiple degrees of freedom** (DoF).
- Utilizes the covariance matrix descriptor as feature, and the Relevance Vector Machines (RVM) classifier.
- The novel contributions include:

(1) a new method to select representative data to update the RVM model, and

(2) an online classifier which is an adaptively-weighted mixture of RVM models to account for the **users' exploration and exploitation processes** during the learning phase.

(3) Instead of evaluating the subjects' performance solely based on the conventional metric of accuracy, we analyze their skill's improvement based on 3 other criteria, namely the **confusion matrix's quality, the separability of the data, and their instability**.

Chuong H. Nguyen, George K. Karavas and Panagiotis Artemiadis, "Adaptive multi-degree of freedom Brain Computer Interface using online feedback: towards novel methods and metrics of mutual adaptation between humans and machines for BCI," PloS one 14.3, e0212620, 2019.

Metrics for mutual adaptation between humans and machines

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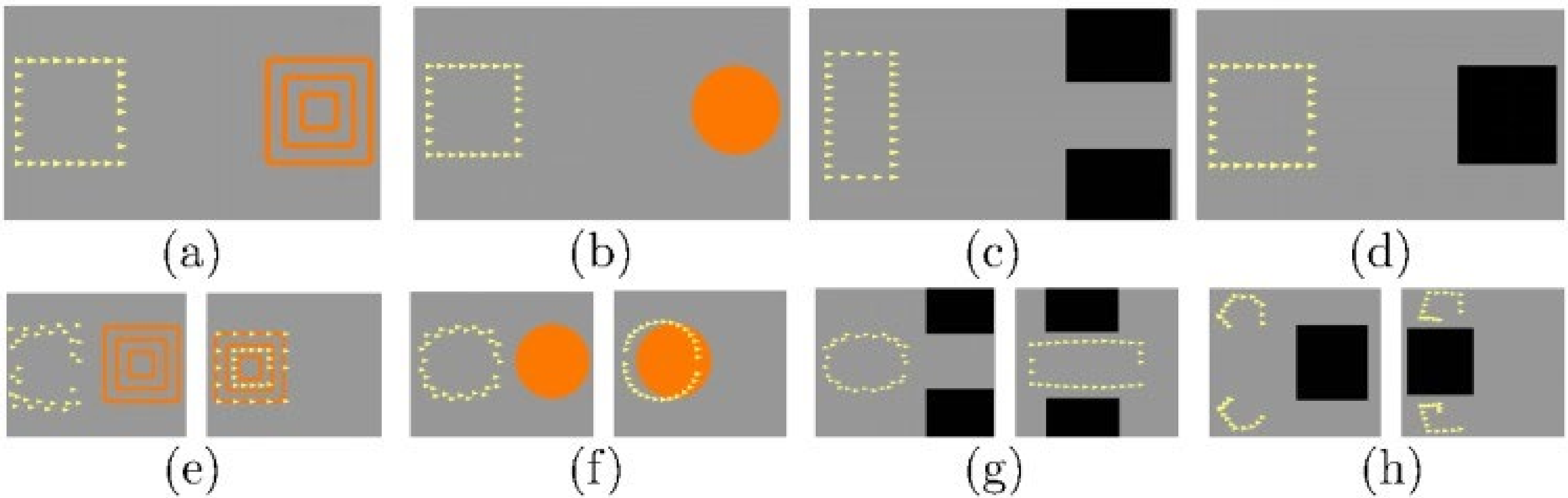

Figs (a) and (b) **control the swarm density** and the shape of the formation, respectively. Figs (c) and (d) assign the task of imagining saying the words “concentrate” (class 2) and “split” (class 4) to concentrate and split the swarm, respectively. Fig (e,f,g,h) show the system’s feedback to the corresponding imagery of the users.

Chuong H. Nguyen, George K. Karavas and Panagiotis Artemiadis, "Adaptive multi-degree of freedom Brain Computer Interface using online feedback: towards novel methods and metrics of mutual adaptation between humans and machines for BCI," PloS one 14.3, e0212620, 2019.

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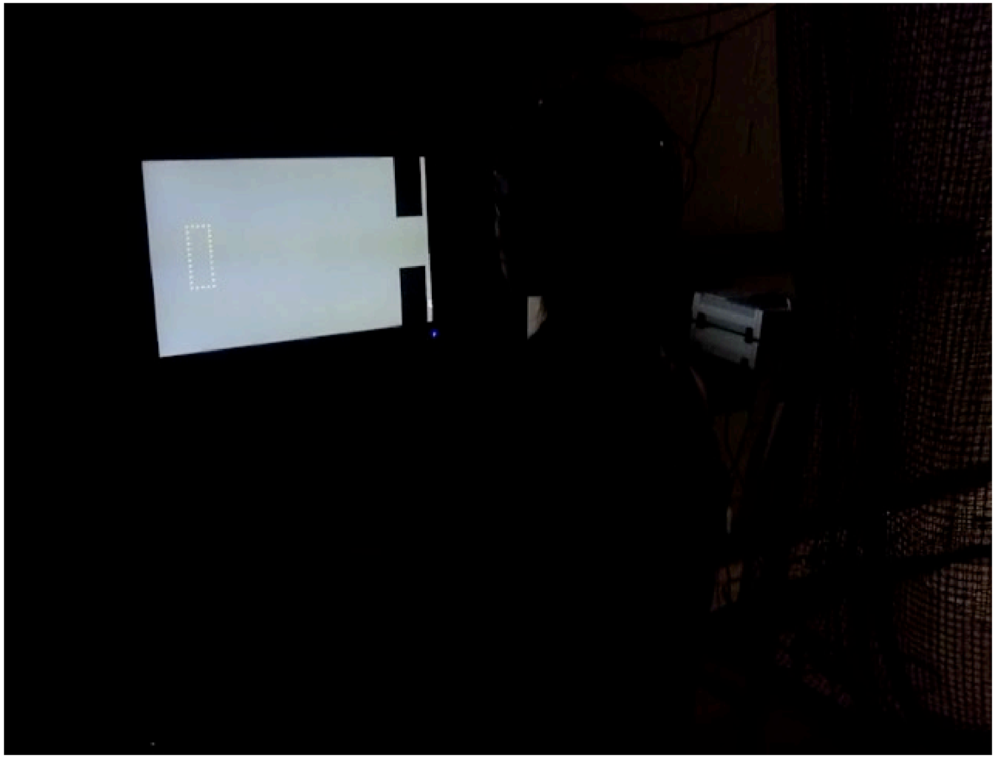
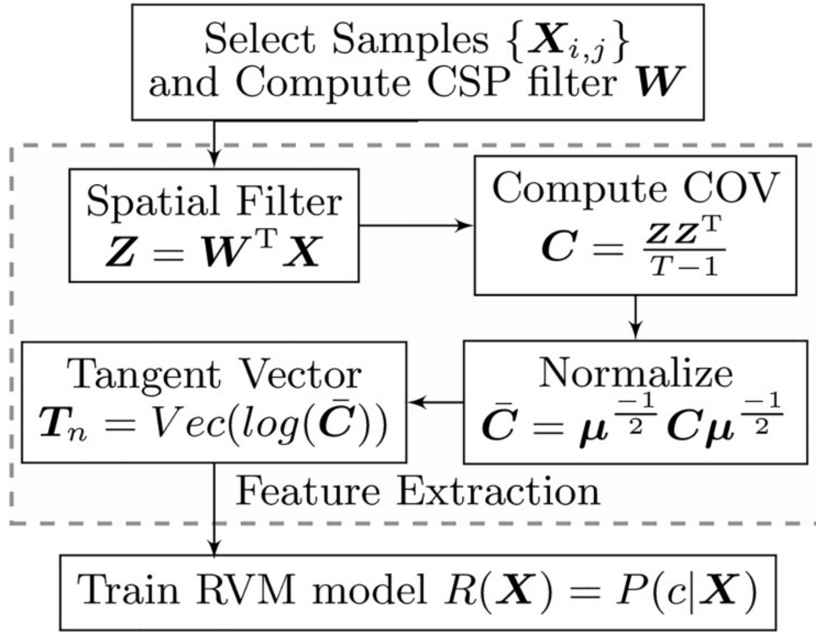
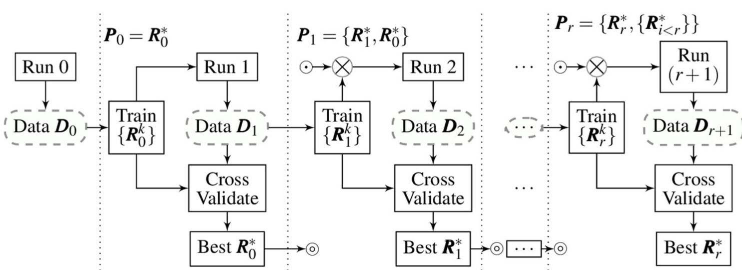
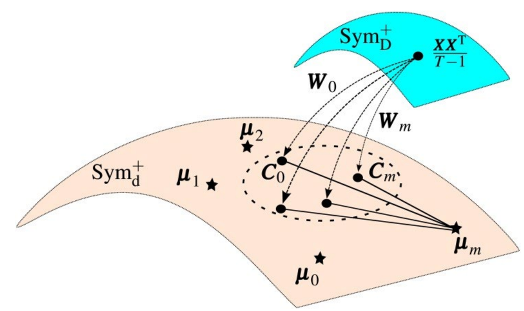


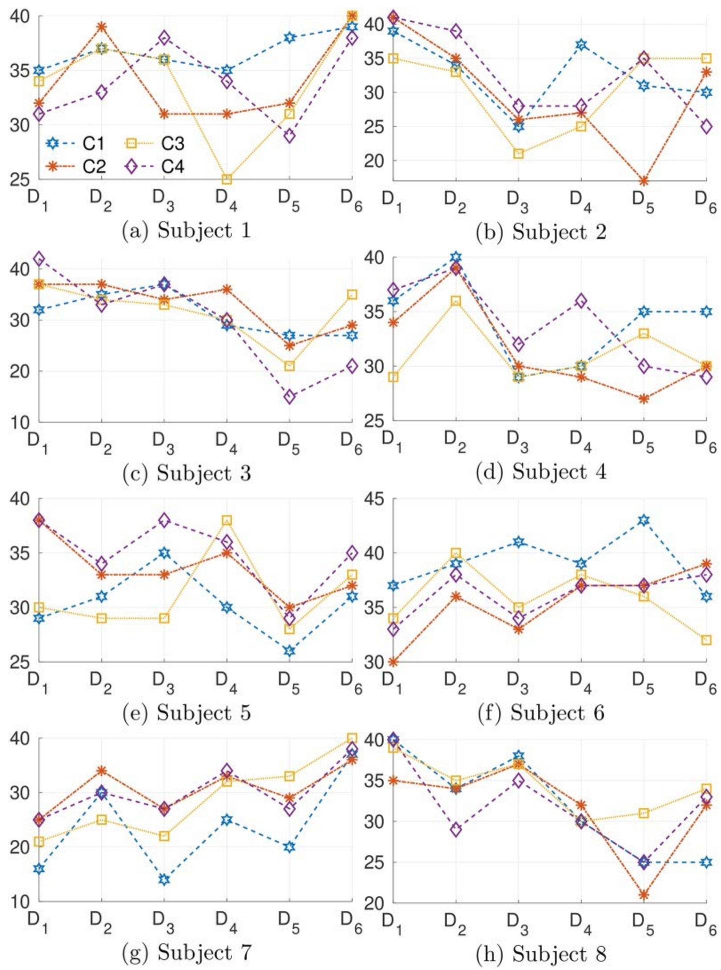






Chuong H. Nguyen, George K. Karavas and Panagiotis Artemiadis, "Adaptive multi-degree of freedom Brain Computer Interface using online feedback: towards novel methods and metrics of mutual adaptation between humans and machines for BCI," PloS one 14.3, e0212620, 2019.

Metrics for mutual adaptation between humans and machines



- ***Reducing instability*** from run 1 to run 4 or even run 5, which indicates that the users became more familiar to the systems and tried to apply what they had learned, e.g. ***exploitation***.
- In run 6, we observe the increase of instability

Data instability for each class along the runs.

Chuong H. Nguyen, George K. Karavas and Panagiotis Artemiadis, "Adaptive multi-degree of freedom Brain Computer Interface using online feedback: towards novel methods and metrics of mutual adaptation between humans and machines for BCI," PloS one 14.3, e0212620, 2019.

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Controller reconstruction and leader identification

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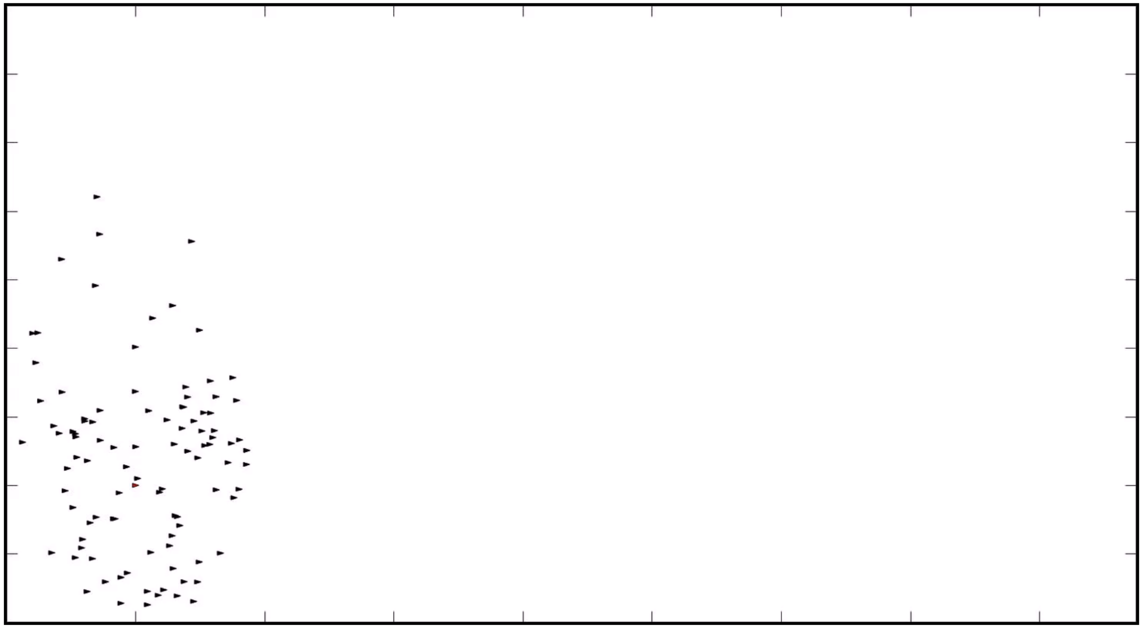
Problem Statement

- *Given macroscopic behavior of a multi-agent system with a single leader, devise method for tracking and identifying leader in real-time*
- *Identify leader-followers controllers and simulate/predict future behavior*



Controller reconstruction and leader identification

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Motivation

- ***Leader-based control of swarm behavior: Explicit leadership vs Tacit leadership [1]***

- *In explicit leadership via flooding, every agent matches the speed and direction of the leader*
- *In tacit leadership via consensus, every agent matches the average speed and direction of neighbors within sensor range*

- ***Performance of flooding and consensus [2] :***
- *Flooding method is observed to be more effective in moving the swarm between goal points.*
- *However, consensus method showed advantages in improving overall connectivity and cohesion of the swarm.*

[1] Amraii, Saman Amirpour, Phillip Walker, Michael Lewis, Nilanjan Chakraborty, and Katia Sycara. "Explicit vs. tacit leadership in influencing the behavior of swarms." In 2014 IEEE International Conference on Robotics and Automation (ICRA), pp. 2209-2214. IEEE, 2014.
[2] P. Walker, S. A. Amraii, M. Lewis, N. Chakraborty, and K. Sycara, “Human control of leader-based swarms,” in Proc. IEEE Int. Conf. Syst. Man, Cybern., 2013, pp. 2712–2717.

Controller reconstruction and leader identification

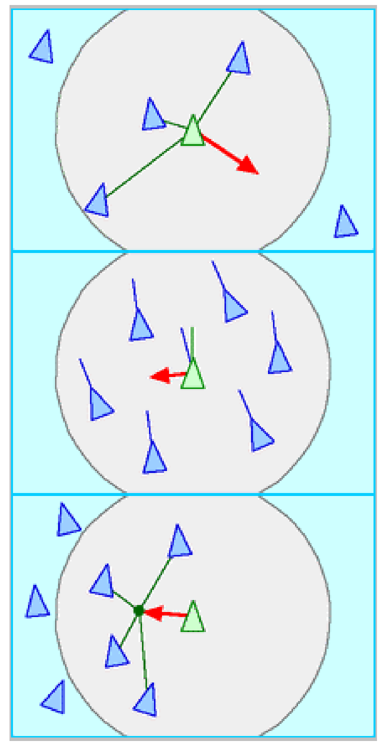
Methods

- *Assume general enough behaviors, as explained in Craig Reynolds model [3]*

- Separation : Each agent experiences separation force from other agents in its neighborhood

- Alignment : Each agent tries to move in the average velocity direction of other agents in its neighborhood

- Cohesion : Each agent tries to move to the average position of other agents in its neighborhood



$$\vec{F}_{i\_separation} + \vec{F}_{i\_alignment} + \vec{F}_{i\_cohesion} = \vec{F}_i$$

[3] Reynolds, Craig W. "Flocks, herds and schools: A distributed behavioral model." In Proceedings of the 14th annual conference on Computer graphics and interactive techniques, pp. 25-34. 1987.

Controller reconstruction and leader identification

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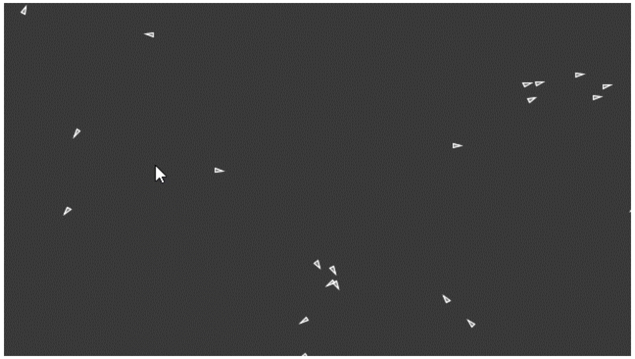
Methods

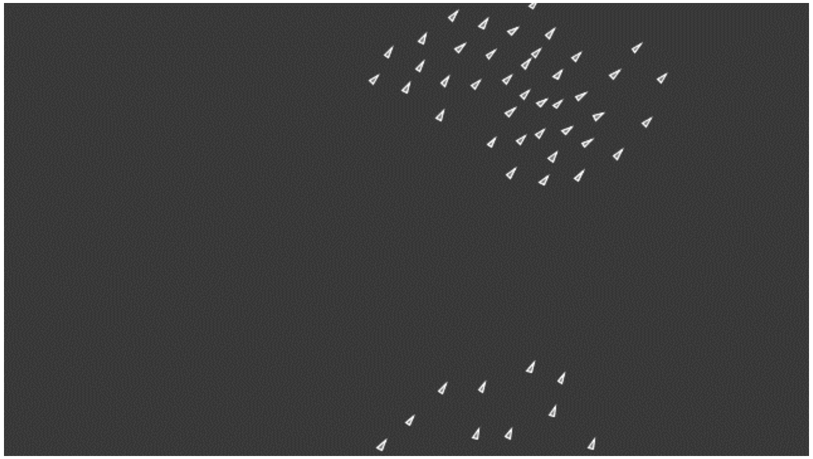
- *Assume general enough behaviors, as explained in Craig Reynolds model [3]*

Separation behavior with 20 agents



Alignment behavior with 20 agents

Cohesion behavior with 20 agents



Combined

Controller reconstruction and leader identification

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Approach

- *Create simulation with the following assumptions*

  - Leader is given a fixed trajectory
  - Other members do not exert force on the leader
  - Leader has a bigger neighborhood radius than other members
  - Agents communicate with each other and follow rules of flocking algorithm

- ***Given the simulated position of all agents, create an optimization problem to identify the leader***

Controller reconstruction and leader identification

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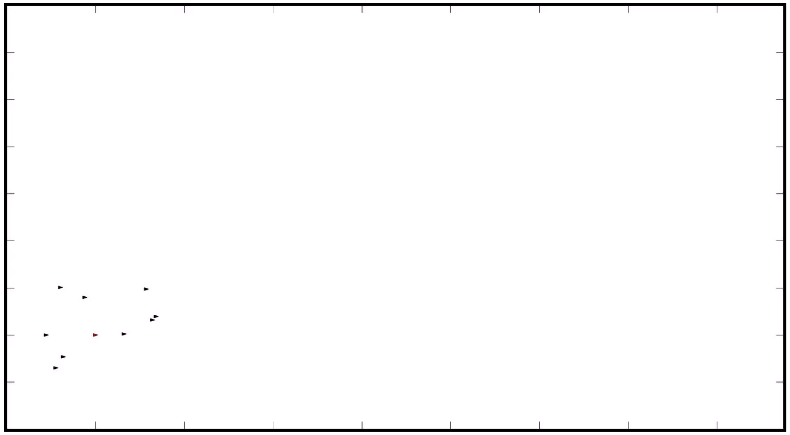
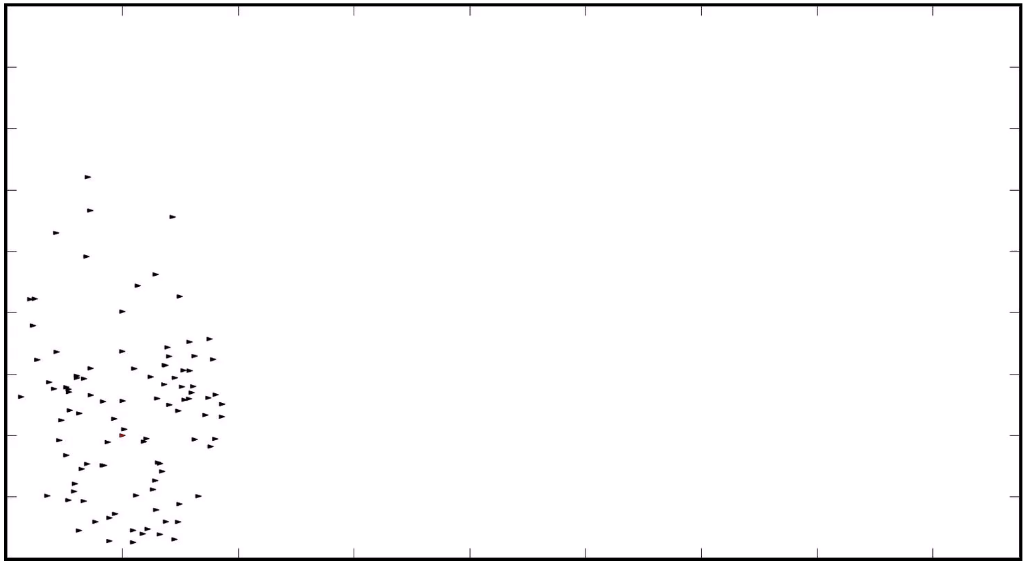
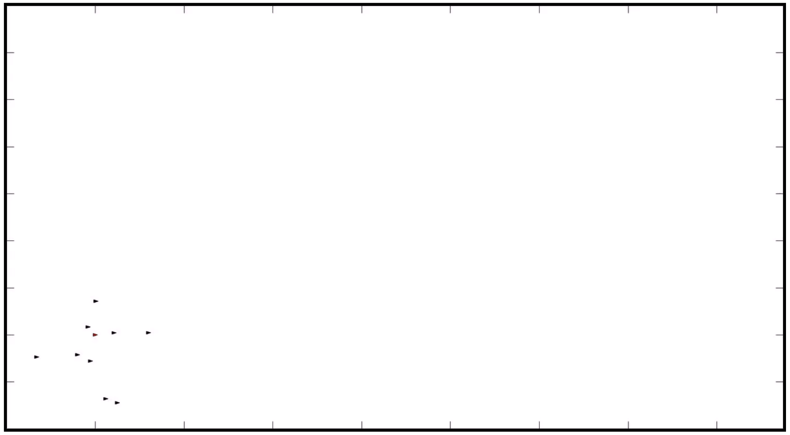
Example cases







Controller reconstruction and leader identification

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Approach

Let $\vec{D}_i^t$ be the position of agent *i* recorded from the simulation at time frame t and $\vec{d}_i^t(L)$ be the predicted position with *L* being the parameter to be optimized
L: the weight factor of the leader to agents force

We define the total cost over T-1 steps for N agents as

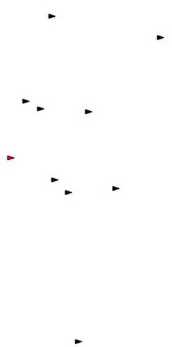
$$\text{Total Cost} = \sum_{t=1}^{T-1} \sum_{i=1}^{N} \left\| \vec{D}_i^{t+1} - \vec{d}_i^{t+1}(L) \right\|$$

Assuming each one of the agents to be the leader, find the agent for which the leader weight factor *L* minimizes the above cost

Controller reconstruction and leader identification

Early results

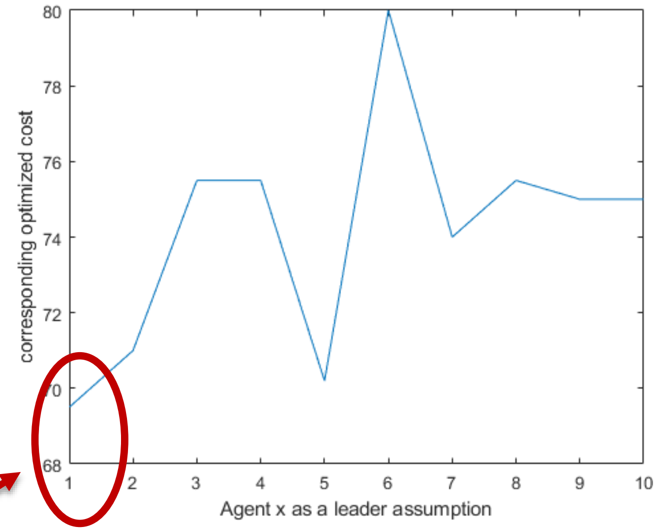
Simulation



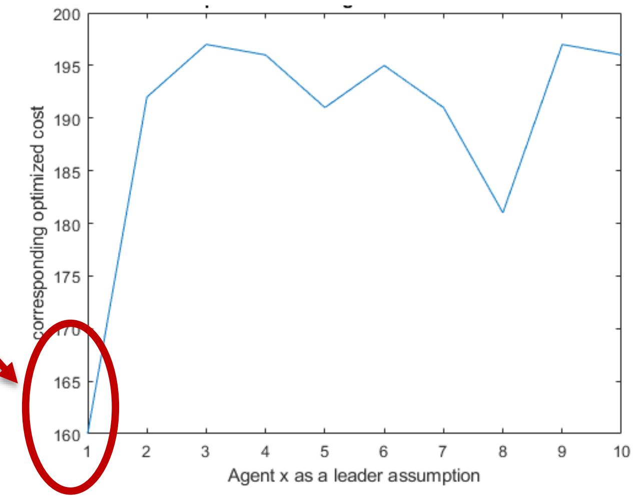
Agent 1 is the leader

Minimum cost - Prediction

Using first 150 time samples



Using first 300 time samples



A human-machine symbiotic system for the extraction of high-level behaviors from a macroscopic view of swarms

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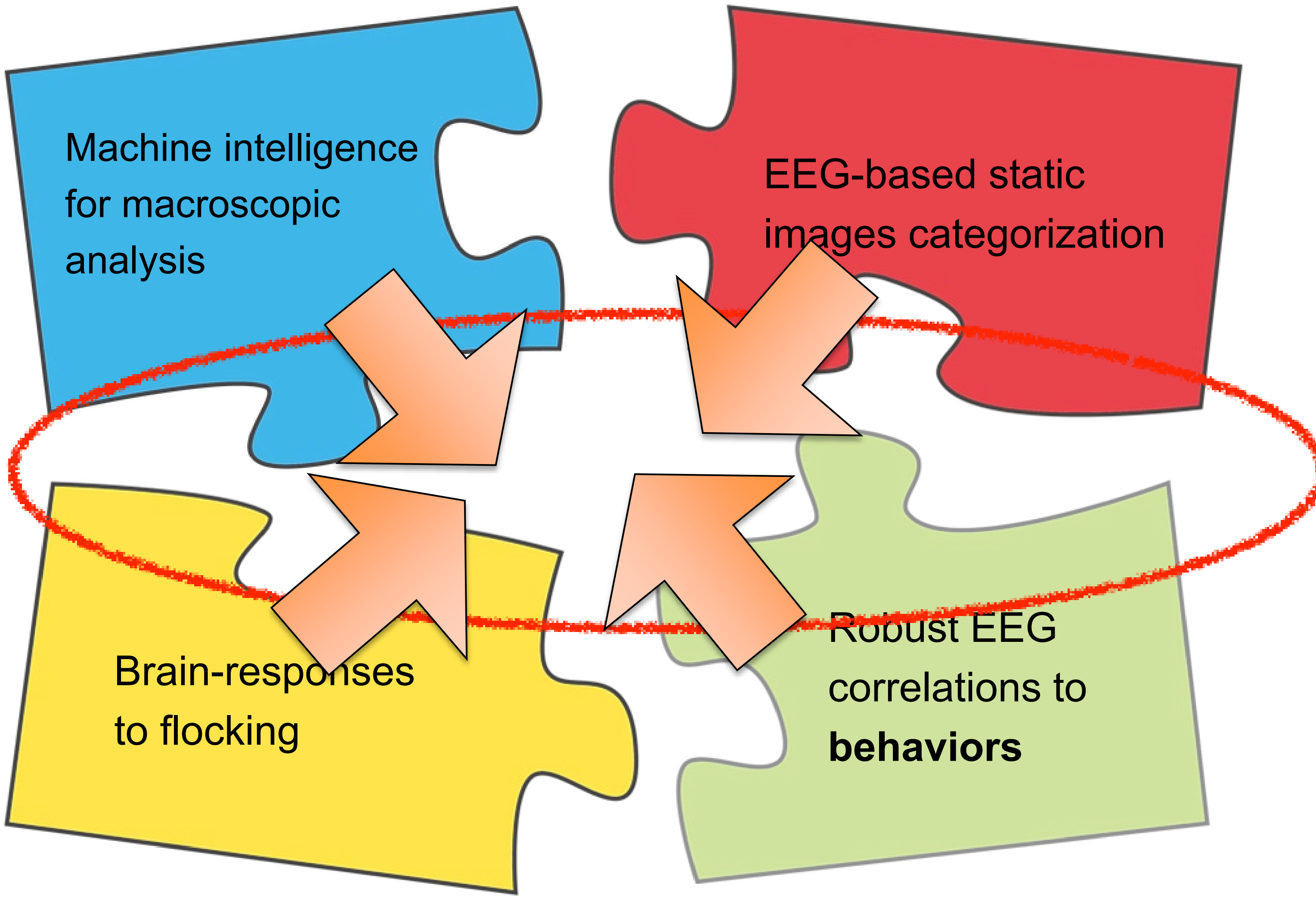

List of Publications, Awards, Honors, etc. Attributed to the Grant

- Daniel Larsson, Chuong Nguyen, Panagiotis Artemiadis, “Modeling and Control of Mid-flight Coupling of Quadrotors: A new concept for Quadrotor cooperation,” In the Proc. of the IEEE International Conference on Unmanned Aircraft Systems (ICUAS), September 2020, Athens, Greece, 2020.
- Panagiotis Artemiadis, Chuong H. Nguyen, George K. Karavas, ``Brain-computer interface methods for imagined speech using Reimannian manifold feature classification," in N. G. Hatsopoulos, J. S. Pezaris (editors) Proceedings of AREADNE 2020, Santorini, Greece, 16-20 June 2020, published by The AREADNE Foundation, Inc., Cambridge, Massachusetts, USA, 2020.
- Chuong H. Nguyen, George K. Karavas and Panagiotis Artemiadis, "Adaptive multi-degree of freedom Brain Computer Interface using online feedback: towards novel methods and metrics of mutual adaptation between humans and machines for BCI," PloS one 14.3, e0212620, 2019.
- Chuong H Nguyen and Panagiotis Artemiadis, “EEG Feature Descriptors and Discriminant Analysis under Riemannian Manifold perspective,” Neurocomputing, 275, pp. 1871-1883, 2018.
- Chuong H Nguyen, George K Karavas and Panagiotis Artemiadis, “Inferring imagined speech using EEG signals: a new approach using Riemannian manifold features,” Journal of Neural Engineering, 15.1, 016002, 2018.
- Panagiotis Artemiadis and Georgios Konstantinos Karavas, "Systems and methods for hybrid brain interface for robotic swarms using EEG signals and joystick inputs", U.S. Patent No. 10,712,820. 14 July. 2020.
- Panagiotis Artemiadis and Daniel Larsson, “Systems and methods for dynamics, modeling, simulation and control of mid-flight coupling of quadrotors”, U.S. Patent No. 10,642,285. 5 May. 2020.

2 peer-reviewed conf. papers, 3 journal papers, 2 issued patents