Extended Swarming with Embodied Neural Computation for Human Control over Swarms

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Abstract. With the rise of robot swarms, it has become a relevant problem how humans can control them. Extended swarming is a potential approach in which robot swarms are treated as self-organising extensions of human bodies. Swarm control takes the form of controlling the observable swarm body while robot chains connect the human operator to relevant aspects of the environment. Inspired by how natural bodies are controlled by a nervous system, we here investigate how the swarm body's self-organisation can be influenced by robot chains acting as embodied neural traces while remaining under human high-level control. Three design principles are proposed for such embodied neural computation. First, the swarm body's self-organisation is controlled both by top-down human control and bottom-up sensor inputs alike to the hierarchical control architecture of the nervous system. Second, robots participating in robot chains are treated as rate-coded neurons rendering the chains as embodied neural traces which offers intuitive control possibilities for the human. Third, neural and swarm self-organisation are integrated by utilizing the swarm's communication network as a scaffolding for neural function influencing swarm dynamics. This process is interpreted as embodied Hebbian learning. Human control over the swarm is demonstrated in a grid-based search-and-rescue simulation with the objective of selecting the most valuable subregion defined by accumulated victims in need. We evaluate how using embodied trace relevance in terms of neural activation improves completion time to finding the highest-value trace as well as how attracting units to relevant traces increases their robustness.

Keywords: Human-swarm interaction · Extended swarming · Swarm robotics · Embodied neural computation · Bio-inspiration

"A signal comes in saying, 'threat!' Something has appeared that can be detected by the changes it induces, for example alterations in the electrostatic field. At once, the flying swarm forms into this 'cloud-brain' or whatever it is..."

The Invincible, Stanisław Lem [13]

1 Introduction

In swarm robotics, minimalistic robots rely solely on local information without global leadership to promote flexibility, scalability, and robustness against node failures [4]. Therefore, swarms are especially envisioned for scenarios with large and dynamic environments such as Search-and-Rescue (SaR) missions.

However, deploying robot swarms to real-world problems requires human operators to be in control of swarms. While humans require fused information about the robot swarm and means to control it, the traditional swarm definition explicitly excludes the generation of global information and centralised leadership. Human-Swarm Interaction (HSI) therefore develops swarm control methods invariant to swarm size in order to join the natural centralised human cognition with the distributed synthetic intelligence of robot swarms [6, 11, 12], the latter being referred to as centralisation-decentralisation trade-off.

A potential approach to HSI is Extended Swarming (ES) which focuses on designing the joint agent as a whole [6]. The joint agent describes the combination of human and swarm as a goal-seeking unit itself. In ES, the observable robot swarm is treated as a self-organising but controllable body extending the human's sensor-act range [20, 21]. Human control takes the form of influencing aspects of the extending body based on the virtual pheromone approach [19, 20], e.g., by adjusting the swarm body's dispersion. The extending body is also streaked with shortest-path robot chains connecting the human operator to relevant aspects of the environment [1, 5, 21], such as victims in need. The underlying motivation of ES is that the embodied swarm network performs the computation itself while being under human high-level control. In comparison to fully centralised control, swarms as world-embedded, or embodied, distributed networks can compute in parallel, are more robust, can adapt to the environment, and can use the spatial location of their nodes for computation [5, 19, 21].

In this work, we investigate the benefit of designing robot chains as embodied neural traces given that real bodies are also controlled by the nervous system. For us, Embodied Neural Computation (ENC) refers to treating each robot participating in chains as embodied neurons that self-organise by an embodied form of Hebbian learning into embodied neural traces and has the following motivations. First, the brain provides an approach to the centralisation-decentralisation trade-off and applying neural principles to ES could be of use for HSI [6]. Second, given the brain controls the body, neural parameters could offer human control possibilities over the swarm body. Third, embodied neural activity could be used to represent chain relevance, similar to virtual pheromones in swarm robotics for site selection [1]. Fourth, the ES vision aims at integrating the extending swarm body into the human nervous system function in the long run, with a neural swarm possibly simplifying such a cyborg integration [6].

This paper provides the following contributions. In Sec. 2, the ES approach to swarm control and sensor fusion is summarized based on a SaR mission requiring the joint agent to select the most relevant subregion with victims in need. Then, ENC is introduced into the extending swarm body (Sec. 3). We first survey previous work on treating swarms as embodied neural systems and extract three design principles for ENC: Embodied hierarchical control, robots as embodied neurons, and Embodied Hebbian Learning (EHL). In embodied hierarchical control (principle 1), the swarm body's self-organisation is influenced by both bottom-up sensor inputs and top-down human operator commands [6]. If robots participating in robot chains are treated as neurons, the swarm body is streaked with embodied neural traces while neural parameters offer intuitive control over the swarm body for ES (principle 2). In order to integrate swarm and neural self-organisation, the liquid-slow swarm body communication topology is treated as a scaffolding for locking robot nodes to relevant information traces for fast-solid neural information processing [22]. This process is interpreted as EHL (principle 3) influencing the swarm body's self-organisation which also can be modulated by the human. Finally, Sec. 4 demonstrates how ES with ENC provides swarm control possibilities for HSI invariant to swarm size in the context of a grid-based SaR simulation. The completion time of establishing relevant traces is evaluated showing that taking trace relevance in terms of neural activation into account improves completion time. In addition, we demonstrate how utilizing neural activation for attracting robots increases trace robustness.

2 Extended Swarming

2.1 Model Assumptions

Consider a SaR scenario as an experimental testbed in which the joint agent's goal is to decide which subregion featuring victims in need are of the highest relevance (best-of-N problem), while we here focus on the interplay between the human operator and the swarm. The joint agent $A = h \cup S$, h being the human operator node and S the swarm, operates on the region $\mathbb{D}$, $\mathbb{D}$ here being a two-dimensional grid plane $\mathbb{N}^2$, that includes static objects of interest $o \in O$, i.e., the victims, being located at position (x_o, y_o) with relevance $\gamma \in [0, 1]$. For this work, h is a static node with position (x_h, y_h). The swarm of size N is a collection of homogenous simple robot nodes $S = \{r_1, ..., r_N\}$. A robot r with position (x_r, y_r) has the basic local state $[\theta_r, v_r]$ with $\theta_r \in [0, 2\pi]$ being the heading direction and $v_r \in \{0, 1\}$ the speed while $v_r = 1$ corresponds to 1 m/s. Joint agent nodes $a \in A$ are able to sense other members h, r' and objects o, and estimate the relative bearings $\hat{\delta}_h, \hat{\delta}_{r'}, \hat{\delta}_o$ to them if nodes are in their bearing sensor range $d_{ij} \leq d_{\hat{\delta}max}$, d_{ij} being the Euclidean distance between two nodes a_i and a_j. In addition, A nodes can estimate the object relevance $\hat{\gamma}$ if in their state sensor range $d_{ij} \leq d_{\hat{\gamma}max}$. The A nodes can also selectively send messages at a particular angle, such as possible with directed infrared communication [19].

Robot movements are based on an object attractor force and a dispersion force being summed to θ_r. The object attraction force attracts robots towards O if $d_{ij} \leq d_{\hat{\delta}max}$, while $v_r = 0$ for all $(x_r, y_r) = (x_o, y_o)$. The dispersion force repels robots away from each other if $d_{ij} \leq d_{disp}$ resulting in a regular dispersion pattern if the swarm is initiated as aggregated.

The A nodes with positions (x_a, y_a) establish communication edges if $d_{ij} \leq d_{com}$ yielding the swarm body Euclidean graph G_{body} at the current time. In the following, G_{body} is used to superimpose virtual pheromone fields Φ and the extending shortest-path tree G_{tree}.

2.2 Extending Swarm Control

In ES, the region $\mathbb{D}$ is explored via the swarm body being controlled by the virtual pheromone approach [19] as adapted by Rockbach [20]. At predefined points in time, a source node $\phi \in A$ injects a message into G_{body} containing a hop counter $c^{\phi} \in \mathbb{N}$, which is distributed to connected nodes while being incremented by 1 at each hop. Here the hop counter c is used instead of estimating the Euclidean distance to nodes as this suffices [19]. Each node a only accepts the message with the lowest hop count, thereby ensuring a radial distribution of the pheromone message into the network, while also saving the bearing $\hat{\delta}^{\phi}$ to the transmitting node. The result of this virtual pheromone breadth-first distribution is a world-embedded potential field described by $\Phi^{\phi} = \{(x_a, y_a, c_a^{\phi}, \hat{\delta}_a^{\phi}) | a \in A\}$. Thus, a pheromone field is an embodied shortest-path tree with ϕ as source.

A Φ-potential field is used for robot particle allocation by defining a negatively charged field centre ϕ^- for attraction or a positively charged centre ϕ^+ for repulsion with allocations being triggered based on a hop count distance threshold τ^{ϕ}. An extending behaviour is given by a distance condition to the field centre ϕ such as $c^{\phi} < \tau^{\phi}$ and the resulting attraction or repulsion action to ϕ being released with probability p^{ϕ}. Triggered robots follow the attraction or repulsion gradient as given by their local state $(c_a^{\phi}, \hat{\delta}_a^{\phi})$.

The extending posture is given by condition $c^h > \tau^h$ with action h^- and releaser $p^h = 1$ and is used to radially constrain the dispersion of S based on the distance to h (Fig. 1a). The human can control the extending swarm dispersion by adjusting τ^h, which is communicated via G_{body} to all connected robots, invariant to the swarm size. $\tau^h = 0$ results in a swarm aggregated at h, a "contracted pose", while a larger τ^h allows the swarm to further disperse onto $\mathbb{D}$, referred to as "extended pose". Thus, the extending posture encapsulates the robots inside the swarm body and ensures the connectivity of G_{body}. Φ^r-fields have a selected robot as source. If the above extending posture is combined with condition $c^r > \tau^r$ and action r^-, the extending posture is oriented towards (x_r, y_r) with strength p^r (Fig. 1c). Finally, if the source is a robot sensing an object, condition $c^o < \tau_o$ with action o^- "grasps" the object by allocating robots towards o with recruiting depth τ^o and allocation force p^o (Fig. 1d).

2.3 Extending Swarm Fusion

Based on Rockbach et al. [21], swarm fusion in the context of ES requires the establishment of robot chains between h and all sensor robots r^o estimating object relevance. The collection of shortest paths between h and all reachable r^o is the fusion graph G_{tree}, $G_{tree} \subset G_{body}$. As described above, swarm control is based on virtual pheromones distributed as an embodied shortest-path tree. Since each r contains the local bearings towards h, a shortest path between h and r^o is found if r^o injects a return message which is forwarded based on the local bearings. Each robot receiving such a return message is a node of the shortest path and therefore restricts its movement $v_r = 0$ for all $r \in G_{tree}$. Given the swarm dynamics, new robot positions lead to a shortening of paths with time since only the nodes participating in a shortest path stop while other nodes continue their exploration [6].

G_{tree} represents a directed radial tree topology pointing towards h extending its sensor range while each r^o injects object relevance $\hat{\gamma_o}$ into its individual chains (Fig. 1a). The fusion graph contains three types of nodes; sensor robots r^o injecting $\hat{\gamma_o}$, relay robots forwarding the injections, and fusion robots integrating information from multiple o. The fusion nodes emerge as a function of object distance resulting in a hierarchical embodied fusion topology [21]. After G_{tree} self-organisation, the human h can follow the observable path with the integrated relevance estimation leading to the highest-value subregion.

3 Embodied Neural Computation

3.1 Background

We provide a short overview of treating robot swarms as embodied neural systems given the aim of introducing neural logic to ES. Augmenting a swarm with neural logic requires an understanding of the relationship between swarms and neural systems as well as how these can be exploited for design. Swarm cognition proposes that both swarms and neural systems are decentralised computing networks that share similarities on the computational level [2, 24]. However, swarms and neural systems are also fundamentally distinct; swarm agents move in space with very flexible connections whereas neurons do not [22], resulting in faster information processing for neural systems. Integrating the two systems therefore means integrating different time scales. In general, they both can be treated as graphs G; here G_{body} represents the swarm's liquid interactions and G_{tree} the solid-neuronal, while a neural graph is called a connectome [4, 23].

In swarm engineering, limited work has considered how the potential overlap between swarms and neural systems could be exploited. Holland et al. [9] described the idea that the computation capabilities of drones could be linked together into an "ultraswarm"; into an artificial nervous system. An approach called "Mergeable Nervous System" to reconfigurable robotics was proposed by Mathews et al. [14]. Their proposal augments decentralised intelligence with a semi-centralised control unit (brain robot) and is similar to ES where the human operator constitutes the brain [6]. Otte [18] formalized and implemented a robot swarm as a distributed neural network that can classify scattered stimuli such as pixels making up an image. A hippocampus-inspired swarm model for navigation was also discussed where robots were treated as neurons and groups of robots formed reciprocal connected networks [16]. Finally, Hasbach and Bennewitz [6] proposed constraining robot positions based on superimposed neural activity in the context of ES. In the following, three principles for Embodied Neural Computation (ENC) are extracted and elaborated; embodied hierarchical control, embodied neurons, and Embodied Hebbian Learning (EHL).

3.2 Principle 1: Embodied Hierarchical Control

The nervous system has been abstracted as a hierarchical fusion and control architecture with fast, low-level, bottom-up, sensor-driven loops being modulated by slow, high-level, top-down, cognition-driven loops [6]. Neural fusion, more commonly called convergence, is illustrated by Hubel and Wiesel [10] who showed how the vision system first encodes simple local visual features of a visual scene that are sequentially fused over layers to more complex global representations. The self-organising hierarchical fusion topology G_{tree} represents embodied neural convergence if the plane $\mathbb{D}^2$ is seen as a visual scene with stimuli O. The swarm not only fuses local objects hierarchically into a global percept at h but the emergence of fusion nodes as a function of object distance [21] also represents an embodied instance of the Gestalt law of proximity [3], stating that stimuli close in space are more likely being grouped together in the visual percept.

In turn, neural hierarchical distributed control refers to top-down modulatable low-level sensor-motor loops [6] which is best exemplified for ES by decentralised octopus arms acting semi-autonomously [8]. In ES, local sensor information at sensor and fusion nodes is used to directly trigger robot allocations via pheromone fields close to objects, economising time by not relying on human control inputs [20]. For example, an object "seen" at the low level can trigger the swarm body "reflex" of "reaching out" to that object via using Φ^o for robot attraction. By utilizing a repulsion pheromone field, the swarm body can also be triggered to retract from an object. Such a reaching out or retraction behaviour represents the swarm's fine motor skills, alike to limbs or tentacles. Gross motor activity is achieved by orienting the pose as a function of Φ^r or Φ^o, or by changing the extension, such as if o is a threatening stimulus for the A leading to a contracted pose [20]. Finally, h controls the swarm bodies' self-organisation top-down via τ and p for extending posture control as well as by the neural parameters discussed in the following.

3.3 Principle 2: Robots as Embodied Neurons

Each $r_i \in G_{tree}$ is treated as a single world-embedded neuron [6, 16] given the embodied computation viewpoint. Thus, robot chains now represent embodied neural traces. r_i is a neural rate-coding unit [15] receiving excitatory inputs $u_{ji}^{in} \in [0, 1]$ from other nodes j computing an output activation $u_i^{out} \in [0, 1]$ via

$$u_i^{out} = f(W * \mathbf{u}^{in} + u^{bias}) \quad (1)$$

where $\mathbf{u}^{in}$ is the input activation vector and W the weight matrix with $w_{ji} \in [0, 1]$, $u^{bias} \in \mathbb{Z}$ is the bias of the neuron defining its resting activity, and f is the neuron's activation function. Here, $f(u)$ is a saturating linear unit with an adjustable activation threshold $M_u \in [0, 1]$; $f(u) = 0$ for $u < 0$, u for $0 \leq u \leq M_u$, and 1 for $M_u > u$. Given the intended scalability in swarm robotics, the same virtual weight w, bias u^{bias}, activation function f, and activation threshold M_u are assumed for all robots so that the complexity for storing the neural parameters is 1 rather than $N^2 - N$ (assuming no self-connections), while w, M_u, u^{bias} are under human influence as long as $r_i \cup c \in G_{tree}$. By using directed communication at a particular angle, h can also selectively update the neural parameters for a particular trace. New meanings are given to these neural parameters in the context of ES. Assuming the same weight w, the weight becomes the swarm body's distance sensitivity [21] with $w < 1$ decreasing forwarded activity u^{out} with each hop. M_u in turn defines the swarm body's activation sensitivity, ignoring activities below its threshold. The bias u^{bias} is used to excite or suppress specific neural traces, e.g., if h pays attention to a particular trace. In sum, G_{tree} is a simplified connectome over which bottom-up neural activity spreads while being under human top-down control via w (distance sensitivity), M_u (activation sensitivity), and u^{bias} (trace attention).

3.4 Principle 3: Embodied Hebbian Learning

Neural learning is a form of self-organisation. In the neural sciences, it is well known that learning is a result of the interdependence between neural structures and neural activities [23]. More specifically, Hebbian learning [7] is described as "neurons that fire together, wire together, and neurons that do not fire together, do not wire together.", referring to trace stabilization and forgetting by updating W based on neuronal activity u^{out}.

In its embodied version, $G_{tree} \subset G_{body}$ represents the embodied connectome based on which neural activity spreads. To implement EHL, the connectome is updated by influencing the positions of robots since they in turn define G_{tree} [6]. From a swarm robotics perspective, this is a special case of an exploration-exploitation trade-off; should a robot participate in a current chain ("neural trace stabilisation" via $v_r = 0$) or rather continue exploration ("neural trace forgetting" via $v_r = 1$) [17]? In contrast to the virtual weight w, these embodied connection weights $\omega \in \{0, 1\}$ are binary since robots can be either connected or not, while node distance may be utilized for some applications [16]. EHL is implemented via

$$P(v_i = 0) = l(u_i^{out}) \tag{2}$$

where $P(v_i = 0)$ is the robot's stopping probability and l is the embodied learning function. Here, $l(u) = 1$ for $u > M_l$ and $\epsilon u + (1-\epsilon)$ for $u \leq M_l$ with parameter $M_l \in [0, 1]$ being the embodied one-shot learning threshold immediately stabilising relevant traces and $\epsilon \in [0, 1]$ being the embodied learning rate defining the stability of flexible traces for adjusting exploration-exploitation dynamics. Note that trace stability depends on the joint probability of the individual robot stopping probabilities. If $M_l = 0$ or $\epsilon = 0$, all traces are stabilized.

The above EHL locks robots to relevant traces over time while trace brittleness represents forgetting. However, brittleness can also result from undesired factors, such as robot failures. Therefore, $u_i^{out} > M_l$ traces are protected from undesired brittleness by attracting further units for redundancy based on trace pheromone fields with condition $c^T < \tau^T$ and robot particle attraction T^-, T being the nodes of G_{tree},

$$\tau^T = \alpha u_i^{out} \tag{3}$$

$$p^T = \beta u_i^{out} \tag{4}$$

with the recruiting depth τ^T and allocation probability p^T being coupled to neural importance via scaling factors $\alpha \in \mathbb{R}^{\geq 0}$ and $\beta = [0, 1]$. Thus, the density around traces inside the swarm body is updated as a function of neural activity.

To conclude, EHL describes swarm pose self-organisation as a function of neural activation while the swarm pose enables specific neural activity in the first place. The human can control EHL by adjusting the embodied neural learning parameters M_l (one-shot learning), ϵ (learning rate), α (recruiting depth), and β (recruiting probability).

4 Computational Investigation

4.1 Simulation Setup

In order to investigate human control over the self-organising swarm body and to evaluate the establishment of embodied neural traces in ES with ENC, we implemented a simulation in MATLAB 2020b with a $\mathbb{D}^2 = 100\,\mathrm{m} \times 100\,\mathrm{m}$ grid. h is placed at $(50\,\mathrm{m}, 50\,\mathrm{m})$ and N robots are initiated inside $10\,\mathrm{m}$ around h. The simulation parameters are $d_{com}, d_{\hat{\delta}max} = 10\,\mathrm{m}$, $d_{\hat{\gamma}max} = 0.5\,\mathrm{m}$, and $d_{disp} = 6\,\mathrm{m}$.

4.2 Demonstration of Swarm Body Control

The top-down controlled bottom-up self-organisation in ES with ENC is demonstrated through the following examples. Assume a SaR unit A being deployed in area $\mathbb{D}^2$ with unknown victims O, $\gamma = 1$ being a high need of attention according to triage. Victim pairs are placed in all four directions (Fig. 1), three with equal distance to h but different criticality (east $\gamma = 1$, west $\gamma = 0.25$, south $\gamma = 0.1$), and one pair ($\gamma = 1$) further away to the north. h must chose which direction to attend to based on the enactive exploration of $\mathbb{D}^2$ with the swarm body. Neural parameters are initialised with $w = 0$, $M_u = 0.25$, $u^{bias} = 0$ and EHL parameters with $M_l = 0.5$, $\epsilon = 0$, $\alpha = 0.8$, and $\beta = 1$.

The swarm body with $N = 150$ robots disperses onto $\mathbb{D}^2$ until the commanded stretching limit is reached ($\tau^h = 3$ hops), leading to trace stabilisation for the three close victim pairs (Fig. 1a). Given the threshold $M_u = 0.25$, the swarm body assigns no relevance to the southern perception at h. Based on the EHL setup, all traces are stabilised, but only the high-value trace to the east is strengthened by the swarm bodies' bottom-up dynamics. Instead of following the provided swarm body estimation, h however becomes attentive of the western region instead. Selective top-down attention to the west is implemented by inducing $u^{bias} = 1$ into the western direction while suppressing the other traces by $u^{bias} = -2$. The bottom-up dynamics now strengthen the western trace while some units remain locked to the relevant eastern victims on standby (Fig 1b).

The victims located at the peripheral of the northern region are not perceived via $\tau^h = 3$. h explores the region by orientating the swarm body towards north via a robot source field with $\tau^r = 5$, $p^r = 1$, and the robot source position at the border of the dispersion while stretching to $\tau^h = 5$ and deactivating trace robustness via $\alpha = 0$ (Fig. 1c). The swarm body is now pushed towards the north and the two victims are perceived while h remains connected to the previously found victims. By activating distance sensitivity $w = 0.6$ and switching off the bias $u^{bias} = 0$, the north is perceived as irrelevant given the distance, although both eastern and northern victims are in critical states. In addition, the western direction is now also filtered by the activation threshold given its relevance in regard to its distance. The perception of the global scene has been adapted by enactive top-down parameter selection influencing the swarm body's bottom-up self-organisation. h now feels that the global percept is reliable and releases a full bottom-up grasping reaction via Φ^o for first-responder action while oneself being guided by the eastern trace towards the victims in need (Fig. 1d). The traces to the other sites remain intact, enabling h to monitor the dynamics of the other victims without delay and adapt to new situations as necessary.

4.3 Evaluation of Embodied Hebbian Learning

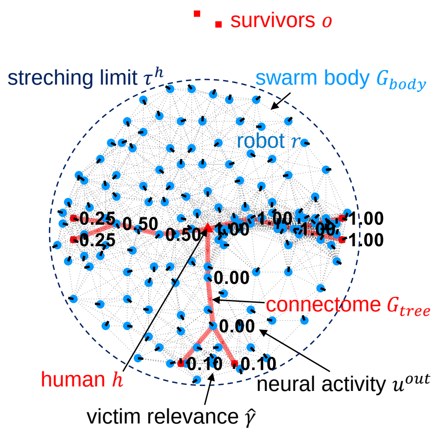
In order to evaluate trace self-organisation via EHL, four objects $\{o_1, o_2, o_3, o_4\}$ are randomly initiated, each in a $20\,\mathrm{m} \times 20\,\mathrm{m}$ area located in one of the four corners of $\mathbb{D}^2$. One randomly chosen o_i is relevant ($\gamma = 1$) while the other three are of low relevance ($\gamma \leq 0.5$). The swarm body disperses onto the grid without stretching constraint τ^h and a correlated random walk force is added so that robots sometimes break the dispersion to explore remote regions. The neural parameters are $w = 1$, $M_u, u^{bias} = 0$ with EHL parameters $M_l = 0.5$, and $\alpha, \beta = 0$. The task for S is to establish a connection to the relevant object.

Fig. 2 shows completion time until a connection to the relevant object o_i is found for $\epsilon = 0$ (no forgetting) and $\epsilon = 0.1$ (forgetting) with 100 samples each. For limited resources, forgetting irrelevant traces increases the performance to find the relevant object [17]. However, this increased performance comes with the cost of increased brittleness of low-value traces. Specifically, connection probability, defined as the ratio of the number of connected trace time steps to the total number of time steps during the search period, is 0.38 for $\epsilon = 0$ and 0.06 for $\epsilon = 0.1$ at $N = 80$.

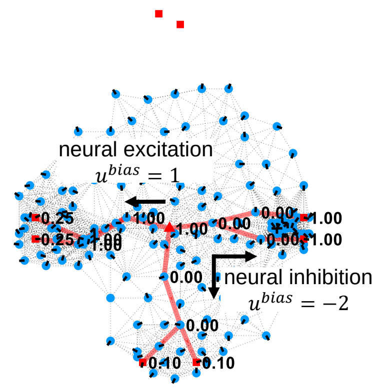
To investigate trace robustness, robot failures are introduced with an individual failure probability of 0.1 at each time step. Fig. 3 shows the connection probabilities to a relevant o_i with $\gamma = 1$, randomly placed with a maximal distance of 20 m to the arena border and observed over 100 time steps after a connection was first established with 100 samples. Both attraction depth and probability increase the robustness of the relevant trace.

5 Conclusion

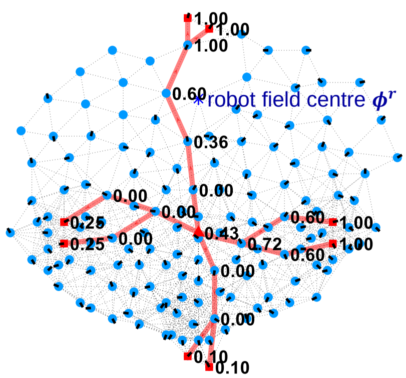
In Extended Swarming (ES) as an approach to Human-Swarm Interaction (HSI), the swarm's embodied nature is utilised for hierarchically fusing local estimates about the world while the swarm itself embodies a potential field that is used



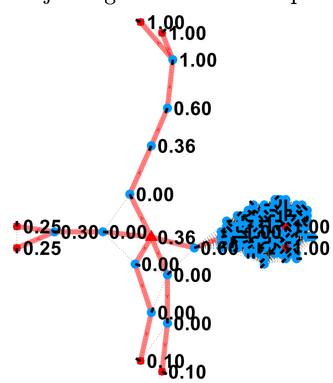
(a) The swarm body strengthens the eastern trace based on bottom-up dynamics.



(b) The western trace is strengthened based on injecting neural biases top-down.



(c) The swarm body is oriented north based on top-down robot field Φ^r control.



(d) The eastern objects are "grasped" by top-down releasing the fine motor skill.

Fig. 1: Examples showing human control over the swarm body's self-organisation.

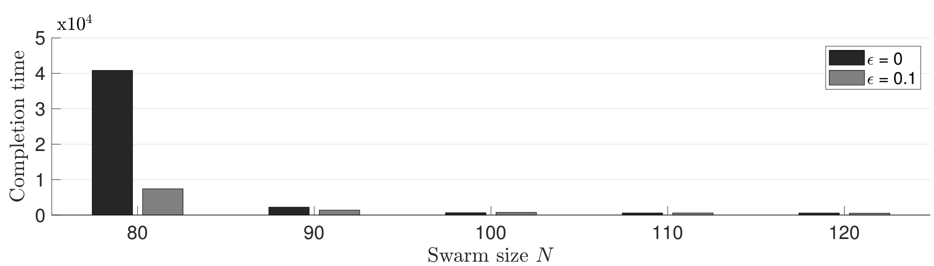


Fig. 2: Speed to relevant trace establishment improves with trace forgetting.

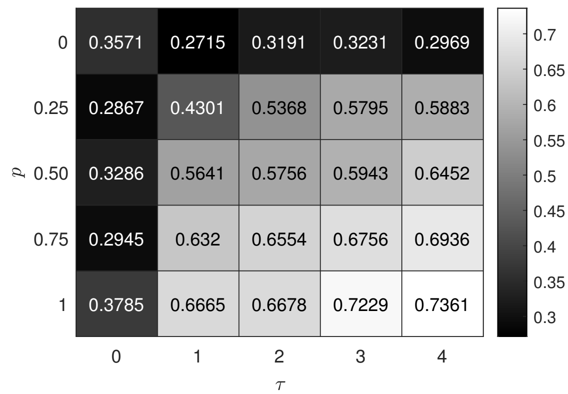


Fig. 3: Connection probability of a relevant trace for $N = 100$ and $\epsilon = 0$ over different recruiting depths τ^T and probabilities p^T.

for swarm control. This work proposed three design principles for Embodied Neural Computation (ENC) in the context of ES. First, the swarm body's self-organisation is controlled by both bottom-up sensor estimates and top-down human control inputs. Second, robots participating in robot chains are treated as embodied neurons offering intuitive control possibilities in the context of ES. Third, swarm and neural level are integrated by using the swarm's communication topology as a scaffolding for neural function that in turn influences robot movements which is interpreted as Embodied Hebbian Learning (EHL). We demonstrated how the approach establishes human control over the swarm extension in a search-and-rescue simulation. It was also shown how EHL improves completion time for finding the highest-value robot chain and how chain robustness can be strengthened. A parameter sensitivity analysis should be conducted next to explore the model in greater detail. Currently, our approach remains theoretical and requires real-world validation. However, we have demonstrated how robot swarms can not only be envisioned as autonomous agents, but also as controllable extensions of humans with embodied neural-like computation.

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