

UniSwarm-SSVEP: Dynamic Content Mapping for Efficient SSVEP-Based Swarm Robot Control

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ABSTRACT: Steady-state visual evoked potential (SSVEP)-based brain-computer interfaces (BCIs) are widely used for device control, but static one-to-one stimulus-command mapping limits scalability in swarm tasks, and simply increasing the number of stimulus targets may reduce recognition performance. This paper proposes UniSwarm-SSVEP, a swarm robot control system with a Dynamic Content Mapping Module (DCMM). By updating stimulus meanings according to the current control state, DCMM allows tens of physical targets to be mapped to hundreds of logical commands and supports flexible switching among single-vehicle, subgroup, and whole-swarm control modes. To validate this mechanism, we constructed a 20-target UniSwarm-SSVEP test system for a 153-command swarm control task. Under FBCCA, UniSwarm-SSVEP achieved an average accuracy of 91.56% and a standard information transfer rate (ITR) of 143.46 bits/min. Task-discriminant component analysis (TDCA)-based validation further improved the accuracy to 95.78% and the standard ITR to 268.80 bits/min, demonstrating the scalability and decoding compatibility of the proposed system.

INTRODUCTION

Brain-computer interfaces (BCIs) enable direct interaction between users and external devices by decoding neural activity [4]. Among noninvasive BCI paradigms, steady-state visual evoked potential (SSVEP)-based BCIs have been widely used owing to their high signal-to-noise ratio (SNR), high information transfer rate (ITR), and low training burden [1,2]. These advantages have made SSVEP-BCIs an effective approach for controlling robotic arms, unmanned vehicles, and other external devices [3,10,11,15]. However, most existing SSVEP-based control systems still suffer from inefficient utilization of brain-control resources. In this study, brain-control resources mainly refer to the user's stable attention, gaze capacity, and reliable EEG responses. Conventional SSVEP interfaces usually adopt a static stimulus-command mapping mode, in which each physical stimulus target is assigned to a fixed command meaning throughout the task. As the number of controlled devices, command types, or control scopes increases, this static mapping mode requires more physical targets or more complex interface switching, thereby consuming additional visual and neural

resources for command selection rather than efficient device control.

Previous studies have attempted to improve BCI-based swarm control through SSVEP-controlled robot swarms, VR-based heterogeneous swarms, VR-assisted UAV formations, shared control, and predefined group commands [5-12]. Although these approaches improve interaction to some extent, many of them still follow the static one-to-one mapping strategy exemplified in [13]. Under this framework, systems can usually broadcast predefined commands to the whole swarm or to limited groups, but flexible switching among individual robot control, group coordination, and global commands remains difficult without expanding the physical stimulus set. However, previous multi-target SSVEP studies have shown that classification accuracy and communication speed tend to decrease as the number of simultaneously displayed targets increases [14].

To address this limitation, this study proposes UniSwarm-SSVEP, an SSVEP-based swarm robot control system with a Dynamic Content Mapping Module (DCMM). Different from static mapping, DCMM dynamically updates the control object and command scope associated with each stimulus according to the current system state. Therefore, the same physical stimulus target can represent different individual robots, robot groups, or global commands in different contexts. This mechanism decouples the number of physical stimuli from the size of the logical command space, enabling scalable swarm scheduling while maintaining a compact and stable visual interface.

To evaluate the effectiveness of the proposed dynamic mapping mechanism, we designed a baseline comparison between UniSwarm-SSVEP and a 153-target static-mapping baseline constructed according to the strict one-to-one stimulus-command relationship in [13]. In this implementation, we used FBCCA to compare the static-mapping baseline system with UniSwarm-SSVEP and highlight the advantage of dynamic content mapping. In addition, task-discriminant component analysis (TDCA) was further introduced to examine whether dynamic content mapping can be combined with a high-performance decoder for shorter decision windows [16]. This experimental design verifies the advantage of dynamic mapping from both baseline comparison and algorithm-enhanced validation. This offers a practical engineering solution for high-efficiency scheduling swarm devices via brain control.

MATERIALS AND METHODS

1. overall architecture

The overall architecture of the system is as Figure 1 shows:

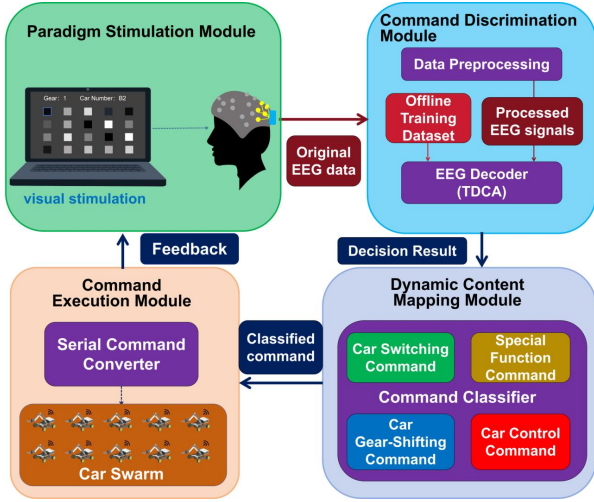


Figure 1: The overall architecture of UniSwarm-SSVEP. The system consists of four main modules: the Paradigm Stimulation Module, the Command Discrimination Module, the Dynamic Content Mapping Module and the Command Execution Module.

1.1 Paradigm Stimulation Module

This system adopts an SSVEP paradigm as the stimulation interface. The interface is divided into four functional regions: the Car Control Region, the Car Gear-Shifting Region, the Special Function Region and the Car Switching Region. Stimulus coding adopts the classic SSVEP frequency coding scheme, and the stimulus is presented in the form of a picture sequence to enhance the visual locking effect and improve signal quality.

1.2 Command Discrimination Module

The Command Discrimination Module supports interchangeable SSVEP decoders. In this study, filter bank canonical correlation analysis (FBCCA) served as the training-free baseline decoder, while task-discriminant component analysis (TDCA) served as the calibrated high-performance decoder [16]. The following section briefly introduces the TDCA formulation, because FBCCA is a standard correlation-based method and is used here only as the controlled baseline.

TDCA is one of the best-performing algorithms for current low-frequency SSVEP signal recognition. After augmenting the training data twice in both spatial and temporal dimensions, a shared spatial filter for different classes of signals is solved using two-dimensional linear discriminant analysis.

Calculate the between-class scatter matrix S_b and the

within-class scatter matrix S_w of the training data across all categories.

$$S_b = \frac{1}{N_f} \sum_{n=1}^{N_f} (\bar{A}_n - \bar{A}) (\bar{A}_n - \bar{A})^T$$

$$S_w = \frac{1}{N_f N_t} \sum_{n=1}^{N_f} \sum_{i=1}^{N_t} (A_n^{(i)} - \bar{A}_n) (A_n^{(i)} - \bar{A}_n)^T \quad (1)$$

$$\bar{A}_n = \frac{1}{N_t} \sum_{i=1}^{N_t} A_n^{(i)}, \quad \bar{A} = \frac{1}{N_f} \sum_{n=1}^{N_f} \bar{A}_n \quad (2)$$

After simplification, the optimization objective of TDCA is shown in Equation (3), where W is the spatial filter to be solved, and $\hat{W}$ is the estimate of W . Derived from the optimization problem, the first N_k eigenvectors of $\hat{W}$ can be used to construct the TDCA spatial filter W .

$$\hat{W} = \underset{W}{\operatorname{argmax}} \frac{\operatorname{tr}(W^T S_b W)}{\operatorname{tr}(W^T S_w W)} \quad (3)$$

After zero-padding a single test signal, the correlation coefficient ρ_n between the second-order augmented test signal and the spatially filtered template signal is calculated. The category corresponding to the maximum value of ρ_n is taken as the recognition result, as shown in Equation (4).

$$\rho_n = \operatorname{corr}(\hat{W}^T A', \hat{W}^T \bar{A}_n) \quad (4)$$

1.3 Dynamic Content Mapping Module

The Dynamic Content Mapping Module (DCMM) is the core component that distinguishes UniSwarm-SSVEP from conventional static-mapping SSVEP interfaces. It receives decoded labels from the Command Discrimination Module and interprets them according to the current control state, including the control scope, group index, car index, and gear state. Therefore, the semantic meaning of each physical stimulus target is dynamically updated rather than fixed. Thus, the same physical stimulus target can represent different commands in individual, group, or global control contexts.

After a decoded label enters DCMM, car-control and special-function labels are converted into executable commands for the currently selected object, whereas gear-shifting and car-switching labels update the system state and refresh the stimulus interface. In this way, DCMM forms a closed-loop process among EEG decoding, state transition, command generation, and interface updating, as illustrated in Figure 2.

The command expansion capability of DCMM can be described by the equivalent number of commands that would be required in a static-mapping interface:

$$\begin{aligned} Target_{sw} &= Target_{grp} \times (M+1) + 1 \\ Target_{car} &= Target_{ctrl} + Target_{gear} \\ N_{eq.} &= Target_{car} \times Target_{sw} \end{aligned} \quad (5)$$

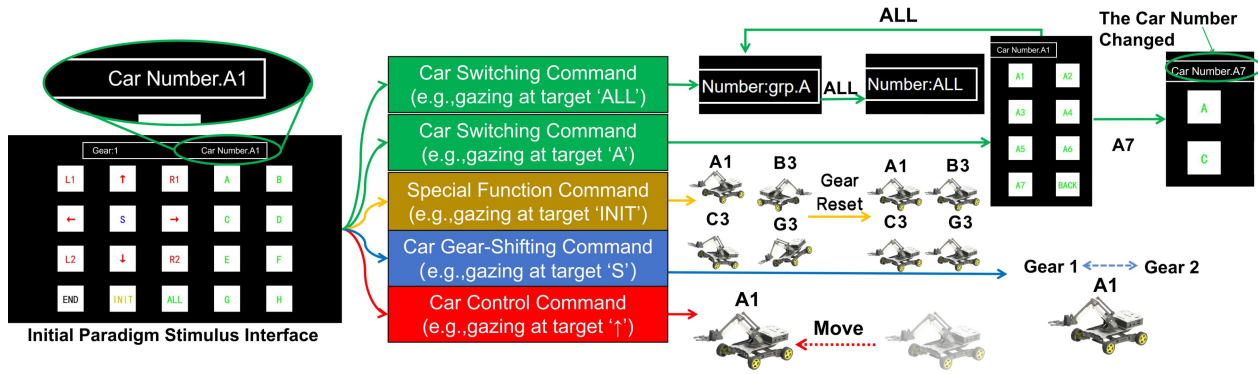


Figure 2: Functional architecture and dynamic content mapping logic of DCMM. Starting from the initial stimulus interface, decoded labels are interpreted according to the current control state. Car-switching commands, such as selecting “ALL” or a specific car label, update the control scope or selected vehicle; special-function commands perform synchronization operations; gear-shifting commands update the gear state; and car-control commands generate executable motion commands for the current object. After each state transition, the stimulus labels are refreshed, allowing the same physical target to represent different commands in individual, group, or global control contexts.

where $Target_{sw}$ denotes the number of selectable swarm control objects or scopes, $Target_{grp}$ denotes the number of car groups, and M denotes the total number of cars in each group. For each group, the selectable objects include M individual cars and one group-level scope, while the additional “+1” represents the ALL scope for global swarm control. $Target_{car}$ denotes the number of command targets available for each selected object, where $Target_{ctrl}$ is the number of control-command targets and $Target_{gear}$ is the number of gear-shifting targets. N_{eq} is the equivalent number of commands under a static-mapping interface. This formulation reflects the general expansion mechanism of DCMM: a limited number of physical stimulus targets can be reused across different control states to generate a much larger logical command space.

For the online experiment described in Section 2.3, the 12-car swarm was divided into four groups. Substituting the corresponding numbers of selectable control scopes and command targets into Equation (5) gives $N_{eq} = 153$. In the 20-target UniSwarm-SSVEP interface, 13 targets were directly related to task execution, whereas the remaining seven targets were reserved for modular design and future extension. Therefore, the 153-command value is specific to the experimental configuration used in this study, rather than a fixed upper limit of DCMM.

1.4 Command Execution Module

This module is responsible for communicating with the lower computer of the car swarm, receiving the specific control commands forwarded by the Command Dispatch Module, and sending them to the target cars via Wi-Fi to achieve precise motion control.

2. Experimental Design

2.1 Experimental Design

The experiment consisted of two parts: offline algorithm verification and online task testing. We collected EEG

signals from the same 15 subjects for both the offline and online experiments. The subjects were mainly students aged 18-25 years, including 9 males and 6 females. Each subject was asked to read and sign an informed consent form before the experiment. The Institution Review Board of Beijing University of Post and Technology approved this study.

2.2 Offline Experiment

2.2.1 Offline Data Acquisition

In the offline experiment, EEG signals were recorded using twenty stimulus blocks with distinct frequencies. The frequency range was 8-16 Hz with an interval of 0.4 Hz, and the phase difference between adjacent targets was 0.35π . In each trial, the subject was required to gaze at the specified stimulus block according to the cue. Each trial lasted 2 s, with an inter-trial interval of 1 s. Each block contained one trial for each of the 20 frequencies, and 4 blocks were conducted per experiment.

2.2.2 Offline Experimental Design

The offline data were used to evaluate the signal characteristics and algorithm performance of the system. EEG topographic maps were analyzed to examine the visual response patterns across subjects. In addition, FBCCA and TDCA were applied to the offline dataset to compare their classification performance and determine the decision window used for the subsequent online validation.

2.3 Online Experiment

To evaluate the dynamic content mapping mechanism, the same 15 subjects controlled 12 cars arranged into four groups and completed predefined individual-, group-, and global-level control tasks. According to the calculation in Section 1.3, this online configuration corresponded to 153 equivalent commands.

For the baseline comparison, we constructed a 153-target static-mapping baseline following the one-to-one stimulus-command relationship in [13]. UniSwarm-SSVEP used a 20-target dynamic interface to complete the same command set, whereas the baseline

represented the 153 commands with 153 static stimulus targets. Figure 3 compares the stimulus interfaces of the 153-target static-mapping baseline and the 20-target UniSwarm-SSVEP system.

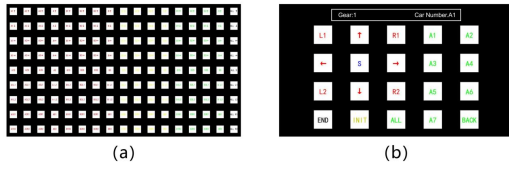


Figure 3: Stimulus interfaces used in the online comparison. (a) is the 153-target static-mapping stimulus interface, while (b) is the dynamic-mapping stimulus interface of UniSwarm-SSVEP.

In this comparison, we used FBCCA to compare the static-mapping baseline system with UniSwarm-SSVEP and highlight the advantage of dynamic content mapping. TDCA was evaluated only within UniSwarm-SSVEP for subsequent algorithm-enhanced validation, because its calibration time increases with the number of targets or classes [16,17], making it impractical for the 153-target static baseline.

In this experimental design, the number of additional gaze shifts to vehicle-switching stimulus blocks was one quarter of the number of direct vehicle-control commands.

RESULTS

1. Signal Characteristic Analysis

To examine the visual response characteristics of the acquired EEG signals, the EEG topographic maps of the 15 subjects under 10 Hz stimulation are shown in Figure 4.

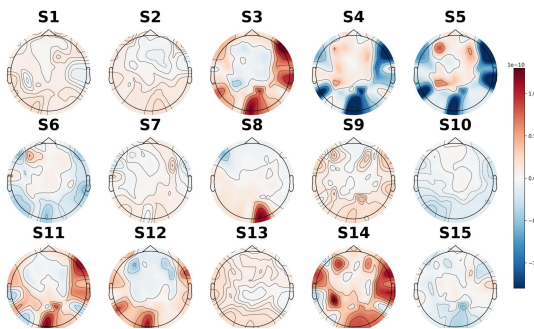


Figure 4: EEG topographic maps of the 15 subjects under 10 Hz stimulation. Most subjects showed clear occipital responses, indicating that the stimulation paradigm elicited stable visual responses across participants.

2. Offline Algorithm Performance Validation

To validate the superiority of the TDCA algorithm and determine its optimal stopping point, we conducted an offline analysis of classification accuracy across varying time windows. Specifically, both the FBCCA and TDCA algorithms were applied to the

offline dataset, with decisions made at 0.1 s intervals. The reported accuracy represents the average performance across 15 trials for each time window. Figure 5 illustrates the accuracy trajectories of the FBCCA and TDCA algorithms as a function of time window length. The results indicate that TDCA demonstrates a significant advantage over FBCCA, particularly in short time windows.

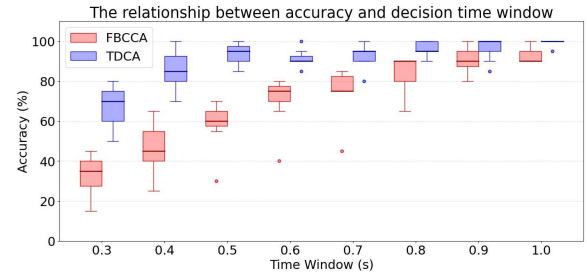


Figure 5: Classification accuracy of FBCCA and TDCA across decision windows. TDCA reached its highest performance around 0.8-1.0 s.

3. Online System Performance

Based on the online experiment described in Section 2.3, Table 1 summarizes the accuracy, standard ITR, and effective ITR of the static-mapping baseline and UniSwarm-SSVEP under FBCCA, together with UniSwarm-SSVEP under TDCA. All summary values are reported as mean $\pm$ standard deviation across subjects.

3.1 Baseline Comparison Between Static and Dynamic Mapping

This subsection focuses on the FBCCA-based comparison between static and dynamic mapping.

3.1.1 Classification Accuracy

Previous multi-target SSVEP studies have shown that classification performance tends to decrease as the number of simultaneously displayed stimulus targets increases [14]. This tendency was also reflected in the 153-target static-mapping baseline. As shown in Table 1, the static-mapping baseline achieved an average accuracy of $30.67 \pm 7.15\%$ across 15 subjects. In comparison, UniSwarm-SSVEP maintained an average accuracy of $91.56 \pm 6.02\%$ while realizing the same 153 equivalent commands with a 20-target dynamic interface.

This result suggests that dynamic content mapping can reduce the dependence of online recognition performance on the size of the logical command space. By reusing a compact set of physical stimulus targets across different control states, UniSwarm-SSVEP avoids the need to display all command targets simultaneously and preserves a simpler visual layout for online selection.

3.1.2 Standard ITR and Effective ITR

We used information transfer rate (ITR) to quantify the communication efficiency of the two systems.

$$ITR = \frac{60}{T} \left(\log_2 N + P \log_2 P + (1-P) \log_2 \frac{1-P}{N-1} \right) \quad (6)$$

Table 1: Comparison of Accuracy and ITR in Online Experiments

Sub ID	static-mapping baseline(FBCCA)		UniSwarm-SSVEP(FBCCA)			UniSwarm-SSVEP(TDCA)		
	Acc (%)	ITR (bits/min)	Acc (%)	ITR (bits/min)	ITR _{eff} (bits/min)	Acc (%)	ITR (bits/min)	ITR _{eff} (bits/min)
1	20.00	29.48	93.33	147.40	205.47	100.00	294.68	395.86
2	26.67	44.22	90.00	137.13	194.04	93.33	251.26	350.22
3	30.00	52.10	100.00	172.88	232.24	100.00	294.68	395.86
4	23.33	36.67	96.67	158.79	270.65	100.00	294.68	395.86
5	30.00	52.10	93.33	147.40	205.47	100.00	294.68	395.86
6	20.00	29.48	80.00	110.02	187.53	83.33	202.07	294.51
7	26.70	44.22	90.00	137.13	194.04	100.00	294.68	395.86
8	40.00	77.51	90.00	137.13	194.04	90.00	233.74	330.74
9	36.67	68.76	100.00	172.88	232.24	100.00	294.68	395.86
10	40.00	77.51	90.00	137.13	194.04	93.33	251.26	350.22
11	33.33	60.28	86.67	127.57	183.18	93.33	251.26	350.22
12	26.67	44.22	83.33	118.55	172.78	90.00	233.74	330.74
13	43.33	86.52	93.33	147.40	205.47	100.00	294.68	395.86
14	33.33	60.28	100.00	172.88	232.24	100.00	294.68	395.86
15	30.00	52.10	86.67	127.57	183.18	93.33	251.26	350.22
Avg	30.67	54.36	91.56	143.46	205.77	95.78	268.80	368.25
(Mean±SD)	±7.15	±17.44	±6.02	±19.42	±25.78	±5.27	±31.05	±33.43

Where N denotes the number of physical stimulus targets, P denotes the classification accuracy, and T denotes the average target selection time. The static-mapping baseline and UniSwarm-SSVEP both used a 1.5 s decision window; therefore, T was set to 1.5 s for standard ITR calculation.

Under the standard ITR metric, the static-mapping baseline achieved 54.36 ± 17.44 bits/min, whereas UniSwarm-SSVEP achieved 143.46 ± 19.42 bits/min. This result indicates that UniSwarm-SSVEP had higher information transfer capability when completing the same online control task.

To further describe the equivalent command capacity enabled by dynamic content mapping, we additionally calculated effective information transfer rate (ITR_{eff}) by replacing the physical target number N with the equivalent command number $N_{eq.}$ from Equation (5).

$$ITR_{eff} = \frac{60}{T_{eq.}} \left(\log_2 N_{eq.} + P \log_2 P + (1-P) \log_2 \frac{1-P}{N_{eq.}-1} \right) \quad (7)$$

For this supplementary metric, according to the experimental design described in Section 2.3, the adjusted selection time of UniSwarm-SSVEP was set to 1.875 s to account for the additional gaze shifts to vehicle-switching stimulus blocks. Under this supplementary metric, UniSwarm-SSVEP (FBCCA) achieved an effective ITR of 205.77 ± 25.78 bits/min, further reflecting the command-capacity gain provided by dynamic content mapping.

3.2 Algorithm-Enhanced Validation With TDCA

To further examine whether dynamic content mapping can be combined with a high-performance decoder, we applied TDCA to UniSwarm-SSVEP. TDCA improves class separability in short EEG windows through subject-specific templates and task-discriminant spatial

filtering, as described in Section 1.2. According to the offline analysis, TDCA reached its highest performance around 0.8-1.0 s, and the optimal decision window for subsequent online validation was further determined as 0.88 s.

As shown in Table 1, UniSwarm-SSVEP (TDCA) achieved an average accuracy of $95.78 \pm 5.27\%$, a standard ITR of 268.80 ± 31.05 bits/min, and an effective ITR of 368.25 ± 33.43 bits/min. Compared with UniSwarm-SSVEP (FBCCA), TDCA further improved both recognition accuracy and communication efficiency under the same dynamic mapping framework.

DISCUSSION

1. Core Advantages of Dynamic Content Mapping in Scalable BCI Systems

The core advantage of dynamic content mapping is that it expands the logical command space while maintaining a compact physical stimulus interface. In this study, the 20-target UniSwarm-SSVEP interface realized 153 equivalent commands in a 12-car task, but this value is not the upper limit. The same interface can theoretically support up to eight groups of seven cars, corresponding to a 56-car swarm and about 600 equivalent commands; adding more vehicle-switching commands could further expand this space. Compared with the multi-target SSVEP system reported in [14], UniSwarm-SSVEP also achieved higher accuracy, indicating that DCMM improves scalability without sacrificing recognition performance.

Under the same FBCCA decoder, UniSwarm-SSVEP outperformed the static-mapping baseline in both accuracy and standard ITR. These results indicate that DCMM reduces the visual and neural burden caused by displaying a large number of targets simultaneously,

while preserving efficient command selection.

2. Limitations and Future Work

Current limitations include the restriction to young adults and homogeneous car clusters, necessitating further validation across diverse ages, neurophysiological states, and heterogeneous robot types. Future work will optimize stimulus paradigms and decoding algorithms to enhance robustness, extending the system to schedule mixed swarms including cars, UAVs, and robotic manipulators.

CONCLUSION

This paper proposed UniSwarm-SSVEP, an SSVEP-BCI swarm robot control system based on dynamic content mapping. To validate the proposed dynamic content mapping mechanism, we constructed a 20-target UniSwarm-SSVEP test system for a 153-command swarm control task, involving single-vehicle control, subgroup coordination, and whole-swarm control. In the online comparison under the same FBCCA decoder, UniSwarm-SSVEP achieved an average accuracy of 91.56%, a standard ITR of 143.46 bits/min, and an effective ITR of 205.77 bits/min, outperforming the 153-target static-mapping baseline. The TDCA-based validation further improved the average accuracy to 95.78%, with a standard ITR of 268.80 bits/min and an effective ITR of 368.25 bits/min. These results indicate that UniSwarm-SSVEP provides a practical and scalable approach for efficient SSVEP-based swarm robot control.

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