Autonomous Robots (2023) 47:833–847
https://doi.org/10.1007/s10514-022-10079-0

Motion-based communication for robotic swarms in exploration missions

Corentin Boucher[1] · Rebecca Stower[2] · Vivek Shankar Varadharajan[3] · Elisabetta Zibetti[2] · Florent Levillain[4] · David St-Onge[1]

Received: 30 November 2021 / Accepted: 27 November 2022 / Published online: 30 January 2023

Abstract

Many people are fascinated by biological swarms, but understanding the behavior and inherent task objectives of a bird flock or ant colony requires training. Whereas several swarm intelligence works focus on mimicking natural swarm behaviors, we argue that this may not be the most intuitive approach to facilitate communication with the operators. Instead, we focus on the legibility of swarm expressive motions to communicate mission-specific messages to the operator. To do so, we leverage swarm intelligence algorithms on chain formation for resilient exploration and mapping combined with acyclic graph formation (AGF) into a novel swarm-oriented programming strategy. We then explore how expressive motions of robot swarms could be designed and test the legibility of nine different expressive motions in an online user study with 98 participants. We found several differences between the motions in communicating messages to the users. These findings represent a promising starting point for the design of legible expressive motions for implementation in decentralized robot swarms.

Keywords Expressive motion · Robotic swarm · Exploration algorithms · Legibility · User study

✉ Corentin Boucher
corentin.boucher.1@etsmtl.net

Rebecca Stower
becstower@gmail.com

Vivek Shankar Varadharajan
vivek-shankar.varadharajan@polymtl.ca

Elisabetta Zibetti
ezibetti@univ-paris8.fr

Florent Levillain
florent.levillain@utc.fr

David St-Onge
david.st-onge@etsmtl.ca

1 Department of Mechanical Engineering, Ecole de Technologie Supérieure, 1100 Notre-Dame W, Montreal, QC 100190, Canada

2 CHArt-LUTIN Laboratory RNSR 200515259, Department of Psychology, Université Paris 8, Rue de la Liberté, Paris 93526, Saint Denis, France

3 Department of Computer and Software Engineering, Polytechnique de Montréal, 1000 Chemin Polytechnique, Montreal, QC 100190, Canada

4 Costech laboratory EA2223, Université de Technologie de Compiègne, Rue du Dr Schweitzer, 60200 Compiègne, France

1 Introduction

Human-Robot teams offer many benefits in real-world deployment scenarios such as exploration of unknown environments. Multi-robot systems controlled by a human operator can allow access to spaces where humans may be unable to reach (such as other planets or underwater), and are able to cover large areas more efficiently. How to effectively design and deploy such systems is therefore quickly becoming an area of interest. For example, in 2017 DARPA launched its OFFensive Swarm-Enabled Tactics (OFFSET) program where teams have to locate and secure multiple simulated items of interest relevant to the urban operational scenario (Chung, 2021).

In such contexts, swarm robots offer an advantage over single-robot systems, which are not able to effectively cover large areas and present a critical single point of failure for the mission. Although centralized multi-robot management is one solution, robotic swarms, i.e. with decentralized control, have been identified as more efficient (Schranz et al., 2020). Swarm control algorithms, often referred to as 'behaviors', are generally distributed, leveraging the processing power of all units combined, which greatly decreases the load on each robot. Furthermore, swarm robots rely on local interactions, both with their neighbors in the swarm and with their surroundings in the environment; a strategy that makes them more robust to dynamic mission contexts. The programming challenges of swarm behaviors has been addressed already in several works (St-Onge et al., 2020), leading to numerous successful realistic deployments (McGuire et al., 2019).

Robotic swarms are bio-inspired: swarms unfold in various forms in nature, from bird flocks to ant colonies, and they have always been subject to humanity's fascination. How can complex behaviors, such as efficient nest designs, emerge from the combination of millions of local actions performed by individuals? Theraulaz shows in (Theraulaz, 2014) that part of the explanation comes from sharing simple information about their current task to the neighboring individuals of the swarm (sometimes referred to as stigmergy). However, this information is invisible to most observers, as is knowledge of the group cohesion rules, which makes understanding what a biological, or robotic, swarm is doing very challenging (Dorigo et al., 2021). In the case of robot swarms, this lack of unified understanding of swarm behavior is especially problematic; unconstrained and dynamic environments, as well as complex mission objectives means user input is still needed for the effective fulfillment of missions.

Adding to this complexity, there are physical constraints in exploration missions that can hinder communication with the swarm. The perception and understanding of motion features characterizing different global states of a swarm are necessarily influenced by their task (swarm functional motion and environment). For this work, we therefore focus on the context of exploration conducted by an aerial swarm and we deploy a communication strategy integrated in the mission-specific control.

An additional factor to consider that is especially relevant for exploration is the position from which the operator interacts with the swarm. In fact, both physical and remote interactions are possible - the operator may be either in the field looking up at the aerial swarm, or remotely monitoring the swarm on a mission planner. For example, the operator could be looking at a dozen or more Unmanned Aerial Vehicles (UAVs) directly in the sky, or through a mission planner. In both cases, the operator has to always be aware of what is happening in the mission and make quick decisions regarding the actions of the swarm.

Consequently, in addition to recent work that introduces new ways to improve prediction and control over swarms by the operator, we need to consider the *behavior* of the swarm in terms of its legibility to the user. In this context, legibility refers to the ability of a robot, or a group of robots, to communicate its intent to the user (Capelli et al., 2019a, 2019b). The challenge then becomes how to orchestrate large numbers of individual robots in a coherent way that is both, efficient for the mission, and legible to the operator.

One way of addressing this challenge is through group expressive motion. By expressive motion, we mean the collective movement of the robot swarm, which can then be harnessed for a communicative purpose. Such motions allow for providing feedback to the operator in scenarios where other means of communication, such as sound, lights or other signals, are not effective. Thus, the swarm expressive motion acts as a kind of natural interface for the user to interpret the current status of the swarm.

Popular swarm algorithms (flocking, aggregation, shape formation, etc.) already have an intrinsic expressivity, as reflected by the potential of collective movements to trigger emotional meanings (Santos & Egerstedt, 2021; St-Onge et al., 2019). However, in these works, the swarm was mostly presented as a communication agent, without any other realistic mission/task to fulfill. Additionally, while emotional reactions to expressive motions or the ability of a group of robots to communicate its intention to the user has been researched (Santos & Egerstedt, 2021; St-Onge et al., 2019), no work, to the authors' knowledge, has been done on the interpretation of mission-specific messages. Also, there is a lack of swarm control algorithms allowing for a modular approach to exploration giving the operator some feedback on the mission.

This article therefore aims to explore how group expressive motions can be used to communicate feedback about the swarms collective state to the operator. We focus on the design of swarm movements and dynamic behaviors with the general goal of improving the user's capacity to recognize and predict the swarm's behavior. We first consider the control of a robot swarm using swarm-oriented programming and present a novel algorithm targeted at including feedback for the operator in a preexisting exploration algorithm in a completely decentralized way. Second, we discuss the design of nine different expressive motions intended to communicate certain messages to the user (initiating communication, no problem, low battery, broken communication, operator intervention needed, closing communication). Finally, we present the results of a user study which explored the relationship between the designed animations and the different communicative messages.

2 Related work

One of the main challenges of controlling robot swarms comes from the fact that understanding swarm behavior is not necessarily intuitive and can place a high cognitive load on the operator. In addition, the need to track multiple individual objects at the same time can have a high impact on operators situational awareness (Memar & Esfahani, 2018), where the operators ability to perceive, understand, and predict the behavior of the robots in the swarm is diminished.

To this end, several works have investigated how to minimise this cognitive load. For example, Hocraffer and Nam (2017) state in their meta-analysis that increasing the autonomy of the swarm in a human-system interface scenario reduces the cognitive load put on the user, thus improving their situational awareness. Additionally, Podevijn et al. (2016) successfully demonstrated that increasing the number of robots does not influence the cognitive load required from a user if the control is performed on the swarm as a whole. In this case, collective behaviors like flocking and aggregation, two of the many decentralized control algorithms that can be found in the literature (Brambilla et al., 2013), have the potential to be really effective in helping the operator.

Adding multiple types of feedback modalities can also help reduce the cognitive workload of the operator and improve their situational awareness (Menda et al., 2011). Other works have also succeeded in improving task efficiency and general communication between the swarm and the operator by using augmented reality (Walker et al., 2018) or blinking lights (May et al., 2015). However, these tools are not always available in the field, meaning other types of feedback are also necessary for the operator in any given mission.

In sum, the existing literature demonstrates that robot swarms which are autonomous, collectively controlled, and exploit multiple modalities of communication are most effective at minimising the cognitive workload and increasing situational awareness of the operator. Leveraging collective swarm behaviors offers one such modality where these benefits are able to be exploited, as emergent group motions elicit communication which relies on the group's collective movement (Levillain et al., 2018). However, in order to successfully implement such collective group motions, it is necessary to first understand how such behaviors are perceived by users.

2.1 Legibility of swarm behaviors

Finding a way to design readable robot intentions has long been a subject of research. Experts in cinematic animations have researched animation principles to improve robots expressivity by means of creating expressive reactions to task outcomes (Takayama et al., 2011).

Already, some work has investigated how collective movements of a swarm are perceived by users. In particular, synchronized movements and the tendency to form figures helps to convey information to the operator (Levillain et al., 2019). Motionless formations have also been tested using drones trying to guide humans with arrows or stop signs (Grispino et al., 2020). Again, results showed that humans could interpret the message from the group of robots and act accordingly.

Multiple works have shown that the basic emotions can be represented by different motions (St-Onge et al., 2019) (Santos & Egerstedt, 2021). For example, fear can be represented by a fast aggregation of the swarm and sadness by a slow flocking motion. Different movement characteristics like speed, smoothness and synchronization have also been shown to have a direct effect on users emotional responses (Dietz et al., 2017).

Furthermore, research investigating the ability of a group of robots to communicate its intention to the user, or legibility, show that motion-variables such as trajectory and dispersion are relevant for the correctness of the communication between the user and that the stiffness, a variable of attraction or repulsion force from a certain point that can result in quick stop and start or change of directions, is relevant for the rapidity of communication (Capelli et al., 2019a, 2019b). While Capelli et al. considered fully connected swarms, i.e. where each robot knows where all others are at all time, there is also a need to consider progressive fully scalable algorithms that can adapt to any number of robots and network topology.

Legibility is also mentioned in recent work from Kim and Follmer (2021), where they found that a rendezvous behavior-based motion is legible and some other motion characteristics, control, trajectory and density, have an effect on legibility. The authors come to the conclusion that in order to create a legible swarm motion, the combination of multiple motion variables will be required.

Thus, multiple motion characteristics (speed, synchronization, trajectory) have been identified as contributing to the legibility and successful interpretation of swarm behaviors. Here, we aim to build upon these findings by directly manipulating different swarm movements and analysing how they are perceived by users. Our work provides a full stack implementation for autonomous exploration missions with motion-based feedback to the operator and an extended user-based validation of several communicative motions.

3 Implementation of swarm control

Decentralized control is a difficult concept to grasp which may explain why real swarm are difficult to understand. To control the robots in a truly decentralized way, we use Buzz, a swarm oriented programming language for heterogeneous robot swarms (Pinciroli & Beltrame, 2016a). This section describes the use of Buzz language and the adaptation of two swarm algorithms to fulfill the mission of exploration while communicating with the operator through expressive motions. This stack will effectively facilitate a real world robot swarm deployment in the future.

3.1 Swarm-oriented programming

Buzz sees a robot swarm as a group of different interacting robots. Each of the robots run a Buzz Virtual Machine (BVM) which permits the use of the same Buzz scripts on all robots simultaneously while incorporating a neighbor communication framework. Buzz is based on the concept of situated communication, a form of inter-robot communication that positions the robot sending the message in the receiver's frame. This permits all the robots to know where any robot is positioned so long as the communication chain between all the robots is active.

This programming language creates the flexibility needed in the implementation by using different swarm-based primitives allowing for swarm management. The work done in (Pinciroli & Beltrame, 2016b) explains in more detail how the swarm construct was built and its purpose. As is described in their work : "the swarm construct of Buzz allows the programmer to tag a set of robots according to a certain condition". By using the swarm construct, we were able to divide the robots of the swarm in sub-swarms based on their condition, for example their availability. A sub-swarm can then be requested to complete different tasks unconditionally from the other sub-swarms. Other constructs are also available to help build the behavior script such as the neighbors construct that contains information about the robots within communication range and the stigmergy construct (Pinciroli et al., 2016) that is a tuple space to broadcast messages between the robots, robust to heavy packet loss and propagated in gossip-like manner.

To be able to deploy robotic swarms in the real world, we need a tool to help run and control the robots on a lower level. We use Robot Operating System (ROS) as it is widely used in robotics and has proven to be reliable. We thus use ROSBuzz, the ROS implementation of the Buzz Virtual Machine (BVM) (St-Onge et al., 2020). ROSBuzz puts ROS and Buzz together with a ROS node which includes the BVM while using the Micro-Air Vehicle Link (MAVLink) protocol, available with the MAVROS implementation, to communicate between swarm members. Using a launch file, the user only needs to point to a certain Buzz behavior and ROSBuzz will start the main ROS loop with the necessary configuration parameters and callback functions for subscribers, publishers and services. The Buzz script will then be executed in the BVM and will receive ROS messages through the MAVROS communication.

To test the behaviors before deploying the code on real robots, we use the Gazebo simulator. We use 12 robots which each run the same Buzz scripts to execute the exploration while providing feedback for the operator. The two adapted algorithms used to fulfill that task are described in the following sections: the exploration algorithm and the acyclic graph formation algorithm. We then describe how they were redesigned to be combined in a full stack implementation.

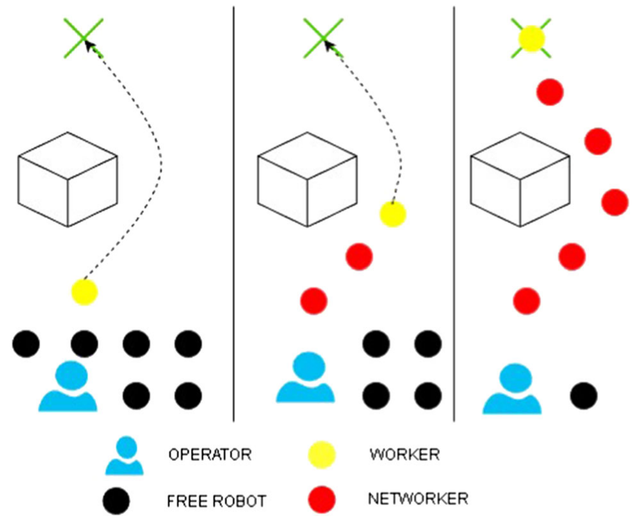

Fig. 1 Progressive formation of a chain to complete a task, inspired from (Varadharajan et al., 2020)

3.2 Exploration algorithm

As our work targets semi-autonomous deployment of a robotic swarm to explore an unknown (no map available) region, we built upon the "chain formation" algorithm published recently (Varadharajan et al., 2020). The original algorithm creates a progressive chain formation where all the robots follow the worker, the head robot, towards a goal. The robots creating the chain are called networkers and their only task is to maintain connectivity between the worker and the groundstation as shown in simulation in Fig. 1. To increase robustness to robot and network failure, the networkers can create multiple connectivity links. The worker first elects networker(s) to start creating the chain as shown in the simulation in Fig. 2. Then each networker will elect another robot to continue the chain and keep connectivity with the groundstation until the worker reaches its target.

Once a goal is set by the operator and sent to the swarm, the worker computes the path to the goal and transmits it to the networking robots that it elects, thus streamlining the communication between the robots. The worker is also the first to encounter any obstacles and is responsible for making any necessary adjustments. When more robots are required to extend the chain, the request goes through the networkers until a free bot joins the chain. Whenever the chain has the expected number of robots, the robots will move towards their goal. From that point on, all robots check if the distance between them and their parent is smaller than the critical communication distance. We compute a speed vector that prevents future collisions while approaching the goal and

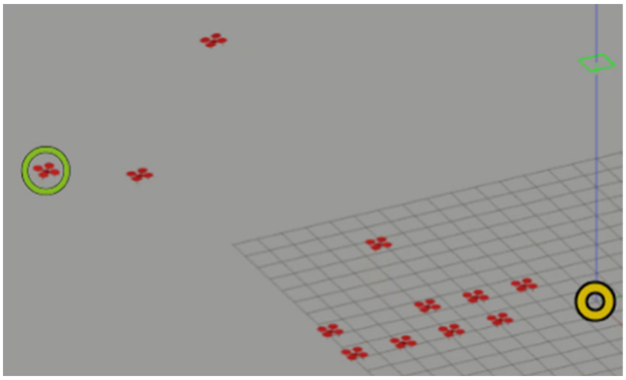

Fig. 2 UAVs simulated in Gazebo using realistic kinematic and dynamics. Four have taken off, the worker (green circle) and 3 networkers called as the worker move away from the groundstation (yellow circle) (Color figure online)

maintaining an acceptable communication range Au_i. The control law of each robot is recalled from (Varadharajan et al., 2020), which itself extended and adapted the collision avoidance control law of (van den Berg et al., 2008):

$$Au_i = \left\{ u_i^{'} \left\| u_i^{'} \right\| < u_i^{conn} \right\} \tag{1}$$

with

$$u_i^{conn} = \min_{j \in P \cup C} \frac{(d_s - d_{ij})}{2\Delta t}, \tag{2}$$

the maximum speed allowed to stay within range, and

$$u_i = \arg \min_{u_i^{'} \in Au_i} \sum_{j \in N_i^{close}} \alpha \frac{1}{tvo_j(u_i^{'})} + \left\| u_i^{pref} - u_i^{'} \right\|. \tag{3}$$

Where the function $tvo_j(u_i^{'})$ calculates a penalty according to potential future collisions with close neighbors (N_i^{close}) and $\left\| u_i^{pref} - u_i^{'} \right\|$ is a penalty for deviation from the preferred trajectory. This law was shown to be sufficient to always provide a collision-free motion of the chain to allow for the worker to reach its goal.

In order to be robust to individual robot failures, a periodic communication coming from the worker informs each individual in the swarm of its position in the chain and the position of its neighbors. This way, if the communication is broken, the robots are able to know which robot is no longer responding and where to fix the chain. The robots surrounding the faulty one will approach each other (retract the chain) to repair the communication.

3.3 Acyclic graph formation

Fig. 3 Example chain with a worker (green circle) and 10 networkers forming 2 links to the groundstation (yellow circle) (Color figure online)

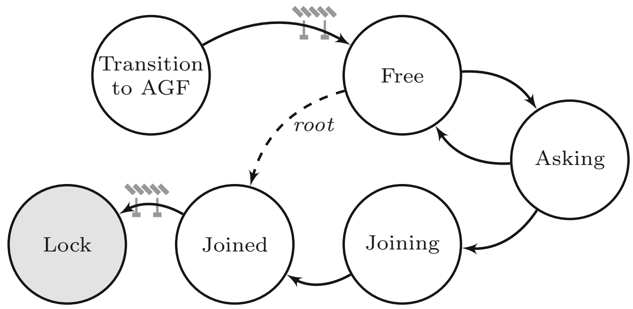

Fig. 4 The behavior law of the progressive graph formation algorithm represented as a finite state machine, adapted from (Li et al., 2019). Every robot joining the mission will experience states *Transition to AGF*, *Free*, *Asking*, *Joining* and *Joined*. Before switching to state *Free* and *Lock* the robots wait for consensus in a transition barrier state

To communicate with the operator using expressive motions, we need a flexible strategy granting us the ability to design any motion. The strategy is two-fold: we first form a graph, with as many robots as available and required, and we then start a periodic motion from that formation. For the first part, we leverage a decentralized progressive shape formation algorithm published recently, the acyclic graph formation (AGF) (Li et al., 2019). AGF algorithm positions the robots according to a predetermined graph shared among the whole fleet: all robots possess the graph representation, but none is initially assigned to a specific position. The formation is built relative to a *root* position, which can either be a robot or a relative distance to any robot before the formation. The overall shape is built dynamically and iteratively: each new robot joins the shape only after being granted permission by one of the parents, using local communication exclusively. As shown in Fig. 4, the acyclic graph formation algorithm works as a finite state machine to get the robots from a free state, when they leave the exploration chain, to a lock state in which they can perform the expressive motion.

As a newcomer to the graph formation, robot i knows the position of its parents (j and k) in its local reference frame, and uses them to calculate its goal, based on its knowledge of the graph to produce. To reach its targets, an adapted Lennard-Jones potential law is used:

$$u = f(F_p + F_a) \tag{4}$$

This law calculates the forces F_j and F_k adding up to form the attraction force F_a while simultaneously all neighbor robots position are used to compute a repulsion force F_p.

3.4 Exploration with motion feedback

Both algorithms leveraged in this work were developed in Buzz. We adapted and combined them to give feedback to the operator while the robots are conducting an exploration mission. Whenever a communicative motion is triggered, the swarm splits itself into subswarms. This requires several new mechanisms: 1. to create *specialized* subswarms, 2. to cope with the interference between the two algorithm usage of neighboring message primitives, 3. to maintain consensus among the subswarms, and, 4. to allow for smooth back-and-forth transitions between split and united swarm.

To deploy specialized swarms we used the swarm management primitives in Buzz to switch from one behavior to the other; *a first realistic demonstration of the swarm-based programming functionality*. Multiple sub-swarms are created in the exploration algorithm (chain formation), one for essential robots to maintain the connectivity and one for each of the other links. These redundant links serve to increase the chain formation algorithm robustness and the robots coverage, and, with sub-swarm, create the possibility to control each link separately. When needed, a subgroup of robots can be switched to a new behavior and complete another side task before coming back to their initial exploration task, as long as a minimum number of robots stays to maintain connectivity. However, the 'chain formation' algorithm does not include any means of differentiating the networkers, as they are all identical. We included a swarm ID (number) in the request message sent by the worker robot to the joining networkers. This swarm ID is then passed along to the next robots joining the chain. When accepting the request, the new networker joins the swarm of its parent so that the networkers are now regrouped into sub-swarms for each link. This novel functionality grants the possibility to use these redundant links (only one link is mandatory to maintain connectivity) for different side-tasks while a primary chain keeps the connectivity.

Both graph and chain formations rely on periodical message exchanges between all neighboring robots, which are propagated to the whole swarm. While these exchanges are optimised within each solution, their combination unnecessarily overcharges the communication infrastructure (tailored to long range, low bandwidth peer-to-peer radio devices). Furthermore, both algorithms based their awareness of the other robots position in formation through simply *receiving* messages from others, whatever their content. The received messages actually build up a *swarm members list*, but when both algorithms run side-by-side, they must ignore the robots which are not part of their formation, unless for collision avoidance. More specifically, if the robots which are part of the acyclic graph formation sub-swarm are still considered by the chain, a robot failure in the main chain may not be repaired due to the wrong assumption of a redundant link. We implemented a state backup mechanism that keeps all the relevant variables in memory, warns the surrounding workers of their intention to leave, and then disconnects themselves from the chain formation messaging threads. It is only after that the AGF messaging services are started.

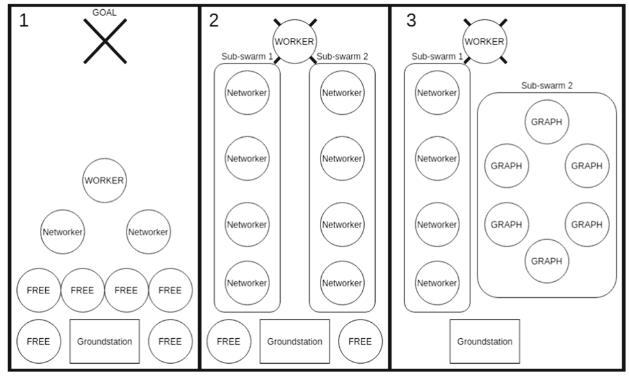

Fig. 5 Main steps to complete the exploration and feedback with the expressive motion: 1-launching the mission, 2-chaining up to the target, 3-half the networkers switched to a circle formation to inform the operator

The lead robot (worker) is the first to be informed of any challenging situations (communication lost, blocked passage, etc.), thus it maintains a *status* variable with the rest of the swarm through Buzz's stigmergy (distributed shared database). A subswarm predetermined as non-essential (redundant link to the chain), will wait to reach consensus on that status which can then trigger a communicative action at any time in the mission. At the end of an expressive motion sequence, the robots resume their position and state in the chain formation, calling back a stack of state variables backed up before the transition and re-enabling its communication protocol. The full process is shown in Fig. 3.

The free state in the original AGF provides a mechanism to avoid collision with any other robots, in the graph or not, while circulating around the graph to optimise their availability. However, in our context this state is replace by the chain formation and its control law, also covering for collision avoidance.

Both algorithms use the *barrier* mechanism: a safe idle state to wait for all the swarm to be ready for the next state transition. The mechanism was adapted in order to be apply to sub-swarm instead of the whole fleet. For instance, the last barrier in AGF (see Fig. 4) let the robots transit to the lock state, where we implemented the periodic motion, only when all others are in position.

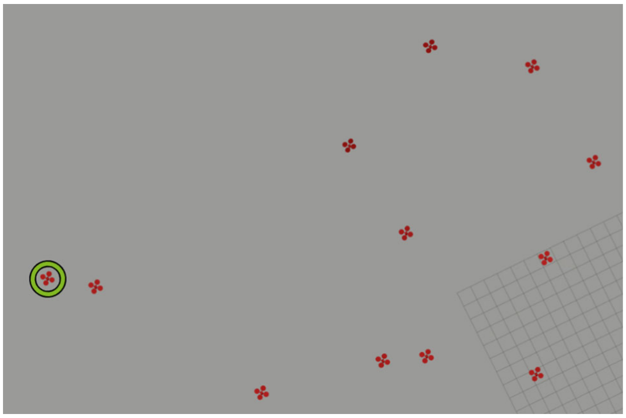

Fig. 6 One sub-swarm in the chain formation with the worker (green circle) at the goal while the other is in the acyclic graph formation

In AGF, all positions are labelled and positioned as node in the graph, thus allowing the designer to give commands to each node individually. From this initial formation, we can generate cyclic motion, slight translation, vibration, twitches and play with different velocity for each robots undergoing these motions. To illustrate the complete integration of the algorithm, we propose to look into a rather simple case: a swarm informing the operator that it reaches its target. Figure 5 summarize the three main steps: 1- The chain formation is starting with the worker taking off followed by two networkers link heads, 2- The worker reached its target and the one set of networkers are preparing to switch to AGF, 3- The AGF is creating a predesigned expressive motion while one link still maintains connectivity. Figure 6 shows the last step from simulation.

3.5 Simulation validation

The set of predesigned expressive motion for mission-specifc messages are circumstantial in that they arise at certain moments of mission to specify specific status or request of the swarm, without altering the continuous states of the swarm and the progress of the exploration mission itself. We ran several simulations with various goal position, maps and launching various expressive motions; all missions succeeded in reaching their goal. Figure 7 shows that even with communication challenges (increasing number of packet lost), the combined algorithm succeed.

As our complete solution never alters the critical components of the chain formation, it has no effect its the success rate. However, it can slow down the exploration, in order to allow for input from the operator.

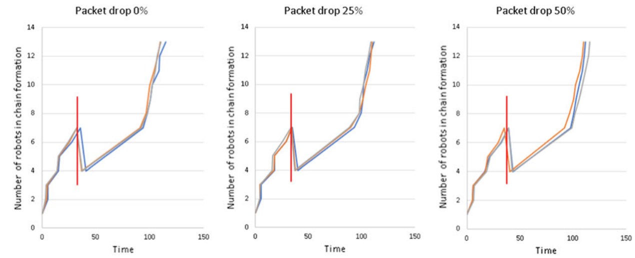

Fig. 7 Robustness to packet lost of the combined chain formation and acyclic graph formation. The red lines show when the expressive motions are triggered (Color figure online)

4 Design of expressive motions

The above implementation makes it possible to deploy a wide range of expressive motion within a robust, safe and efficient real world exploration mission. However, before implementing expressive motions on the robots, we must first design meaningful motions adapted to this exploration mission context. We propose a framework to do so: 1. Identify the key information to communicate to the operator during the an exploration mission operated by the swarm, 2. gather a focus group to design 2D animations considering usual mission constraint, and 3. validate with a user study that the swarm behaviors depicted in the 2D animation are designed in a way that they can be easily identified and understood by any operator, from any location (Lee, 2001) so that they are ideally interpretable across contexts and missions and not limited to a specific configuration or type of robot. This section describes how we designed nine 2D animation sequences potentially interpretable by operators as one of the six mission-specific messages that emerged as relevant for an usual swarm exploration mission.

Previous research on swarms as a display suggests that there are two main ways to use a swarm to convey a message (Kim & Follmer, 2017). The first way of communicating messages is by positioning the swarm as an iconic form where the user can understand the shape or icon shown by the swarm. The second is by performing abstract motions which can be compared to humans body language in order to convey information. Both of these concepts are used while designing the expressive motions, with an emphasis on the abstract motion.

From our previous work (Levillain et al., 2019), we concluded that 6 types of messages were particularly important in an exploration scenario. Those mission-specific messages are: initiate communication with the operator, close communication, no problem to report, intervention needed, low battery, and broken communication in the connectivity chain. We designed one or two expressive motion for each message type.

The design process started with discussions in a focus group of experts in psychology and art to obtain a first set of motions characteristics that each type of message should contain. From other works, such as (Santos & Egerstedt, 2021) and our previous research (St-Onge et al., 2019), we extracted the main shape and motion features that each message type could leverage. Shape features include roundness and angularity or iconic form, whereas motion variables can be divided into synchronisation (both spatial and temporal), velocity and trajectory. All of these variables can be manipulated in order to influence the swarm state (message) perceived by the operator.

Through an iterative process, nine animations were created and improved from the focus group feedback. A small user study with nine robotics students helped determine which motions were effective and which ones needed more refining or a complete redesign. In the end, nine motions representing six types of mission-specific messages were developed for further testing. All of the animations are included in a supplementary materials video. See Table 1 for a summary of the identified communicative messages, their associated expressive motion features and which sequence they correspond to in the user study.

The first animation designs relate to the communicative goal of *initiating communication* with the operator. From the expert discussions we concluded that a signal designed to realize a phatic communication, a language function designed to establish communication between the speaker and listener without having the purpose of transmitting a message (Jakobson, 1963), should have the purpose of attracting and maintaining the operator's attention. We already have some evidence from (St-Onge et al., 2019) that movements with high speed and a uniform deployment are often associated with a state of surprise. We then decided to make a cyclic motion which can be repeated until the swarm attracts the user's attention. This information is intended to form expectations "here and now" of the forthcoming communication and it is meant to be used by the operator as a cue to infer the communication intent of the swarm. This ostensive signal is thus meant to be the first perceptible signal that allows the operator to perceive the swarm as an agent (Brinck & Balkenius, 2019). From these characteristics, we created two motions where the goal is to provide a clear visual perceptive signal to the operator to initiate the human-swarm communication. In the first motion, six robots form a circle that grows bigger and then smaller with time, like a pulse (see Fig. 8). In the second one, six robots make a straight line where the distance between the robots increases and decreases with time, similar to the first motion. These motions represent Sequences 1 and 4, respectively in the user study (Sect. 5).

When designing the communicative goal: *close communication*, we needed to represent that the swarm is returning to its normal mode of operation, thus breaking any previous activated structure in its collective dynamics. We thought that

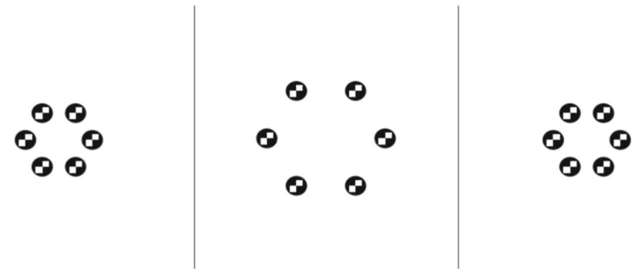

Fig. 8 Motion designed to initiate the communication between the swarm and the operator: initial formation in circle (left), followed by radial translation of each robots (middle and right). Represents sequence 1

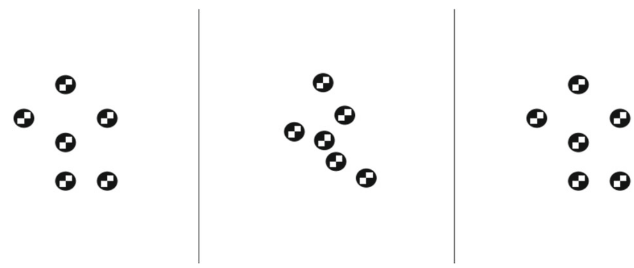

Fig. 9 Motion designed to get the user to intervene: initial tree-like formation (left), followed by rotational motion of three robots around the center one while all others are stationary. Represents sequence 2

quickly scattering the robots in different directions looking random with no further motion would mark this transition in a salient way. In addition, the fact that the robots stop after moving quickly reinforces the signal that the communication is over. See Sequence 9 in the user study.

To tell the operator there is *no problem to report* in the mission (Sequence 7 in the user study), a soothing movement should be performed by the robots. To create this, we thought that a circular shape moving slowly in a simple pattern would fit the characteristics and would not alert the operator. Thus, this motion starts as a circle, similar to the first motion to initiate the communication, but with the robots moving along the circumference slowly.

Getting the operator to *intervene* requires an element of urgency in the movement. We assumed that movements identified in a previous study (St-Onge et al., 2019) as having a component of fear, with rapid and short oscillations, would be adequate to represent this state of emergency. For the first motion designed to convey this message, all the robots meet at the same location (with active collision avoidance) and then disperse in all directions in a way designed to look erratic. The second motion puts a small number of robots in "panic" mode where they move quickly around the other robots that are vibrating while staying still (see Fig. 9). These motions represent Sequences 5 and 2, respectively, in the user study (Sect. 5).

Table 1 List of motion characteristics and corresponding sequences with each of the 6 identified mission-specific messages

Mission-specific message	Group Characteristics		Sequence/s
	Shape	Motion	
Initiate Communication	Circle/line	Slow oscillations	Sequence 1 Sequence 4
Close Communication	Line	Randomly dispersing stopping	Sequence 9
No Problem	Circle	Slow oscillations rotating counterclockwise	Sequence 7
Intervention Needed	Cluster	Tremor rapid oscillations	Sequence 2 Sequence 5
Low Battery	Wave	Progressively come to a halt	Sequence 3 Sequence 6
Broken Communication	Line	Broken synchronization	Sequence 8

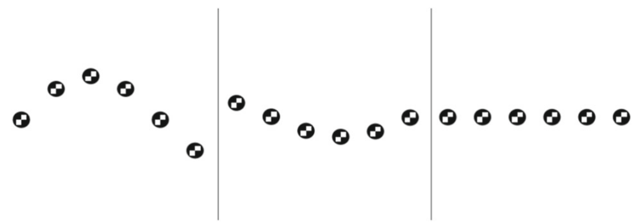

Fig. 10 Motion designed to represent a low battery or battery problem within the fleet: initial wave formation (left), followed by a decreasing sinusoidal movement up to a straight line. Represents sequence 6

To represent a *battery problem or low batteries* for the group of robots, we emphasized the aspect of losing energy. Movements gradually slowing down or motion losing amplitude were identified as potential visual markers of this message. Our first motion is then a diagonal line, representing the battery level of the robot, where each robot "falls" one at a time until they are forming a straight line. A second one shows a sinusoidal with a high amplitude slowly decreasing until it reaches an immobile straight line (see Fig. 10). These motions represent Sequences 3 and 6, respectively, in the user study (Sect. 5).

Finally, to represent a *broken communication* link between the robots (Sequence 8), the collective motion needs to represent a loss of synchronization or the loss of symmetry in a motion. This would show that a robot or two groups of robots are not communicating together properly. So, we designed this motion to feel like a "no problem" message at the beginning by having a straight line pulsating until a robot drops and half the line stops moving while the other continues to pulsate. This way, the broken communication is clearly shown by the dropped robot and the broken synchronization in the motion.

5 User study and evaluation

In this section we explore the legibility of the aforementioned expressive motions. Through a preliminary user study, we aim to investigate if it is possible to elicit different perceptions through these motions and if information (i.e., the 6 selected pragmatic messages) can be effectively communicated through one or more of the 9 designed sequences.

The study was approved by the research ethics committee at École de technologie supérieure in Montreal. 98 participants were recruited via word of mouth (email and social media). Participation was completely voluntary and participants did not receive any compensation.

The study was conducted entirely online and took approximately 15 minutes to complete. After first indicating their consent to participate, participants proceeded to the main survey, where they viewed each of the 9 animations in one of three different orders. For each animation, the participants were asked to rate the messages they thought the robot swarm was intending to communicate (initiating communication, closing communication, no problem, intervention needed, low battery, broken communication). Responses were recorded on a 5-point Likert scale for each of the six identified messages (1 = *strongly disagree*, 5 = *strongly agree*). The original and translated versions of the questions for each message can be seen in Table 2.

Even though we designed the sequences with a specific message in mind, we don't discredit the significance of a different perceived message. Since there are limited findings on the perceived intent of robotic swarms expressive motions in the literature, we cannot with confidence predict how the motions will be perceived and the user study might show different results than expected from the design of the motions. As such, we conducted the user study from an exploratory perspective without specific *a priori* hypotheses for which messages will be associated with each motion (Scheel et al., 2021).

5.1 Analysis plan

All analyses were conducted using R version 4.0.0 (2020-04-24)– "Arbor Day" (R Core Team, 2021).

For this study, we transformed the mean ratings of each participant into a ranked order of 1-6 for each message, where 1 = *highest ranked message* for each animation and 6 = *lowest ranked message*. This allowed us to clearly differenti-

Table 2 Questionnaire items for each of the 6 identified mission-specific messages

Mission-specific message	French	English
Initiate Communication	Les robots indiquent leur intention d'initier une séquence de communication	The robots are indicating their intention to begin communicating
Close Communication	Les robots indiquent que la séquence de communication s'achève	The robots are indicating that the communication sequence has ended
No Problem	Les robots indiquent qu'il n'y a pas de problème en cours	The robots are indicating that there is currently no problem
Intervention Needed	Les robots indiquent qu'une intervention de l'opérateur sur le terrain est nécessaire	The robots are indicating that an operater intervention is necessary
Low Battery	Les robots indiquent qu'ils n'ont plus assez d'autonomie	The robots are indicating that they don't have enough battery
Broken Communication	Les robots indiquent qu'ils ne parviennent plus à communiquer entre eux	The robots are indicating that they can no longer communicate between themselves

Table 3 Friedman's tests for each animation sequence. All $df = 5$

Sequence	Kendall's W	χ^2	p
Sequence 1	.20	97.35	$< .001$
Sequence 2	.29	141.92	$< .001$
Sequence 3	.11	52.80	$< .001$
Sequence 4	.14	66.52	$< .001$
Sequence 5	.22	106.88	$< .001$
Sequence 6	.18	86.02	$< .001$
Sequence 7	.20	98.31	$< .001$
Sequence 8	.16	79.13	$< .001$
Sequence 9	.12	58.59	$< .001$

ate between the legibility of each message for the respective motions.

We then performed Friedman tests for each of the expressive motions to determine if there was a difference in how the messages were ranked. For all sequences, there was an overall difference in the rankings of the six different messages, see Table 3. This indicates that for each sequence, there was at least one message which was ranked significantly differently to one or more other messages.

For each expressive motion, we then performed post-hoc pairwise comparisons using Wilcoxon's signed rank tests. Due to the exploratory nature of the analyses, we chose a less conservative correction (Holm), rather than Bonferroni (Bender & Lange, 2001). We used the most highly ranked message/s for each motion as a baseline for comparison. The results from each expressive motion are described below (also see Fig. 11). For tables describing the full post-hoc analyses see (Boucher et al., 2021).

5.2 Results and discussion

The post-hoc comparisons of the six message rankings for each sequence suggests that the expressive motions can be separated into 3 groups; those which had a single clear message which was ranked higher than the others (Sequences 4, 5, and 6, as well as partially Sequence 9), those which had 2 messages which were (equally) ranked higher than the rest (Sequences 1,2, and 7), and those which could not reliably differentiate between messages (Sequences 3 and 8).

Among the more distinctive motions, Sequences 4 and 6 were both associated with initiating communication. Both of these animations demonstrate a repetitive, almost wavelike motion, which could be associated with waiting for something to start. This motion might also be seen as a loading spinner, similar to what is shown in the loading screens of many programs and which are also likely to be familiar to the users.

For Sequence 5, "Intervention Needed" was the most highly ranked message. In this case, the "huddling" of the robots together could indicate a sense of fear (St-Onge et al., 2019) in the robots that the users interpreted as requiring intervention to resolve.

Sequences 4 and 5 also both involve an easily visible aggregation to a common point. This result could provide evidence that humans use the Gestalt properties of swarm

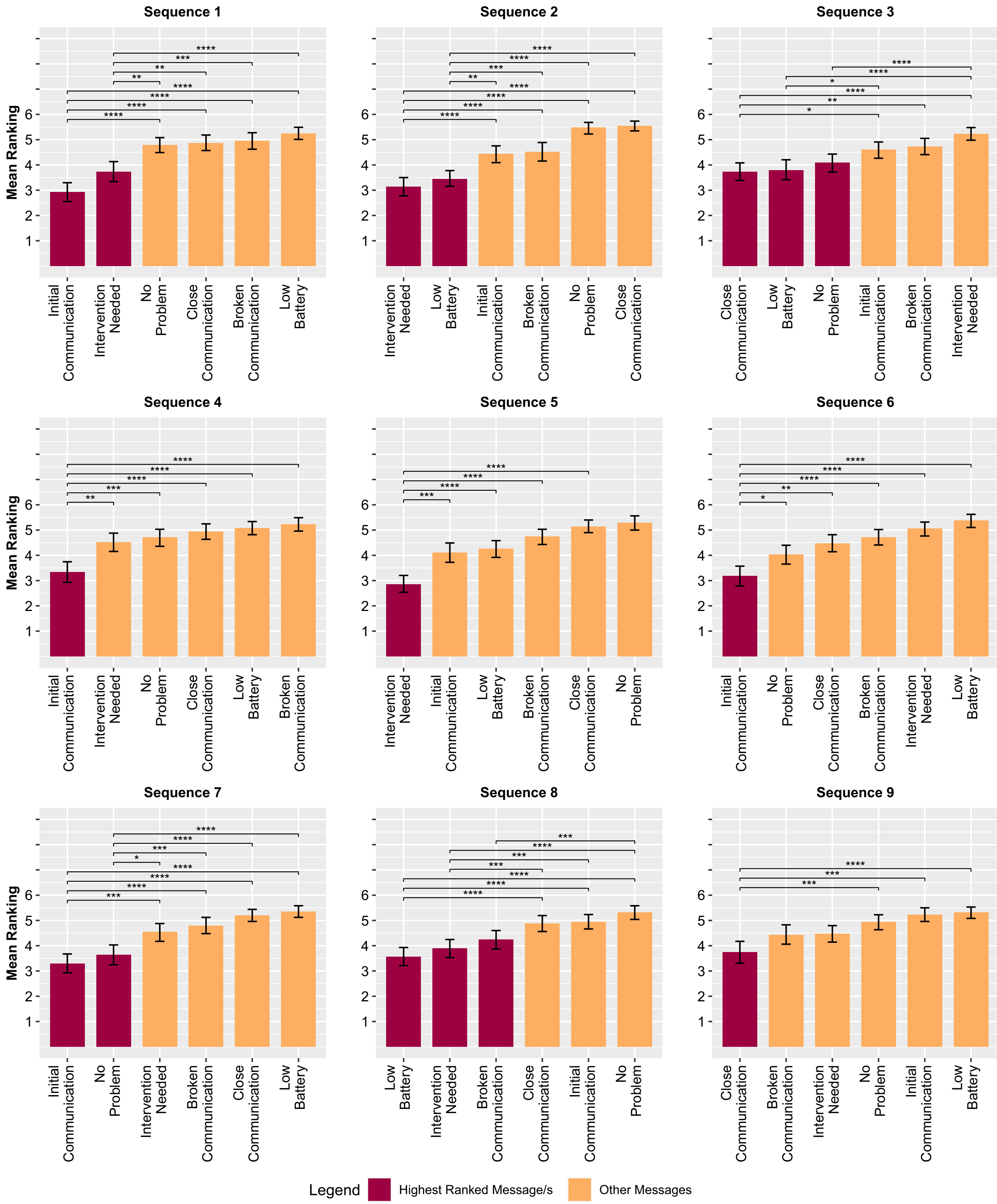

Fig. 11 Post-hoc comparisons (with Holm's correction) for the most highly ranked message/s for each animation. * significant at the $p < .05$ level, ** significant at the $p < .01$ level, *** significant at the $p < .001$ level

behaviors such as common alignment, common velocity, and proximity to recognize different behaviors.

The rankings for Sequences 1, 2, 7, and 9 were somewhat more ambiguous. For example, Sequence 1 was most often ranked as intending to either initiate communication or signalling that an intervention from the operator was needed, with both messages ranking significantly higher than all other messages. This is in line with the idea of cyclic motion signifying a loading screen that represents initiating a communication, as is also shown with Sequences 4 and 6, and also the fact that a type of aggregation shows the need for an intervention. This sequence thus needs to be clearer to represent only one message.

For Sequence 2, The low battery and intervention needed messages were most highly ranked, although there was no difference between the two. This animation was characterised by short, sharp, and fast motions intended to communicate a sense of fear (St-Onge et al., 2019). Although these results indicate some success in attracting the attention of the user and signalling that an action needed to be taken, the confusion between the different types of messages suggests more clarity is needed on *what* these actions specifically should be.

For Sequence 7, the "Initiate Communication" message was ranked significantly higher than all messages except "No Problem". In turn, the "No Problem" message was also ranked significantly higher than all other messages. Similar to Sequences 4 and 6, the pulsing motion of this sequence could be associated with waiting. Conversely, the circular rhythm and slow motion should push a sentiment of calmness and peacefulness where the user should retain that there is no problem to report. Normally, this motion should be used after having already initiated the communication which might change the way users interpret this sequence.

Sequence 9, although not completely clear-cut, showed a potential tendency towards the "Close Communication" message, which was ranked significantly higher than the "No Problem", "Initiate communication" and "Low Battery" messages, but not "Intervention Needed" or "Broken Communication". In this animation, the dispersion of the robots into an undefined pattern and the immobility of the robots are the characteristics that should push the user to perceive that the communication is over. Perhaps a longer time of immobility, which wasn't available during the test since the animation was in a loop, would push the user in perceiving the motion as a "Close Communication" message more clearly.

The worst performing animations were Sequence 3 and Sequence 8, neither of which showed consistent rankings for the six different messages.

Sequence 3 showed no difference in the rankings between "Close Communication", "Low Battery", and "No Problem" messages. The "Close Communication" message was ranked higher than the "Initiate Communication", "Broken Communication" and "Intervention Needed" messages. In turn, the "Low Battery" message was ranked higher than the "Initiate Communication", "Broken Communication" and "Intervention Needed" messages, but not the "No Problem" message. The "No Problem" message was ranked higher than the "Intervention Needed" message, but not "Initiate Communication" or "Broken Communication".

This sequence depicted a slow, waterfall like motion and was initially designed with the idea of low battery in mind. However, the slow movements potentially conveyed a sense of calmness (Dietz et al., 2017), which is the antithesis of some the other animations which depicted faster and more abrupt movements associated with a sense of urgency. The contrast between the fast/sharp movements and slow/calm movements potentially explains the confusion in this animation with the no problem and close communication messages, both of which imply that no action is needed to be taken.

Sequence 8 demonstrated almost equal rankings between "Low Battery", "Intervention Needed" and "Broken Communication", with no significant difference between the three. Although the "Low Battery" and "Intervention Needed" messages were ranked higher than the "Initiate Communication", "Close Communication" and "No Problem" messages, the "Broken Communication" message was only ranked significantly higher than the "No Problem" message. In this case, although the deviation of a single robot from the swarm was associated with disruption, it was not necessarily clear to the participants what the meaning of the disruption was.

6 Concluding remarks

In addition to the technical and practical advantages offered by swarm robots in exploration contexts (e.g., greater spatial coverage, lower cost, greater fault tolerance), group behaviors of the swarm can be leveraged as a means of communicating the swarm collective state to an operator. Successful implementation of such group expressive motions would allow for minimizing the cognitive load of the operator and increasing situational awareness, therefore allowing for more efficient mission deployments.

Consequently, the goal of this paper was threefold, first, to present a novel algorithm implementing swarm expressive motions in an exploration based-context, second, to design sequences of expressive motions for the purpose of communicating different mission-specific messages to an operator, and third, to conduct preliminary user testing on the legibility of these motions for the swarm-operator communication purpose.

The presented algorithm improves on existing work as it combines two swarm algorithms with different functionalities to include visual feedback for the operator. This allows for the possibility for the swarm to communicate different mission-specific messages through expressive motions in exploration missions. The possibility to maintain connectivity with a chain between the lead worker and the groundstation all while using robots from the same swarm as sub-swarms to fulfill other tasks, here expressive motions, is an advantage over what was previously done in Buzz. The implementation was done and fully functional in simulation. A video of the whole process is available in our supplementary materials video.

The results from the user study demonstrate that some swarm behaviors are potentially easier to recognize than others. The most highly ranked mission-specific messages across all the animations tended towards initiating communication or needing intervention (both were one of the top ranked messages in 4 out of the 9 animations). In fact, many of the animations showed confusion between the "Intervention Needed" message and one or more of the other messages. This could suggest that the concept of "Intervention" was too broad and overlaps with other, more specific actions. For example, communicating low battery of the robots signals that an action is needed such as putting the robots on charge, which in itself could be considered an intervention.

Conversely, the "No Problem", "Low Battery", and "Broken Communication" messages were among the lowest ranked for all the animations, which could imply that these messages were more difficult to communicate. In the case of "No Problem" it could be that this message is counter intuitive to the participants expectations of the interaction where they might not necessarily perceive a need for an explicit cue confirming that nothing is wrong. Signalling the lack of any need for intervention could also be dependent on the kind of action being executed by the robots and what kind of movement is typical for that task. Potentially, it might be less cognitively demanding for the operator to assume a default "no problem" status, assuming that messages signalling an action is needed are sufficiently clear.

That being said, the difficulty in communicating the "broken communication" and "low battery" messages highlights the complexities in establishing such clean-cut feedback to the operator. Given also the high overlap of many of the messages with the "Intervention Needed" message it could be that specific error messages are more difficult to interpret compared to more global status indicators. It would be worth investigating further if operators prefer having specific motions associated with specific actions needed (e.g., putting the robots on charge, repairing communication, replacing one or more robots in the swarm) or if a global signal for intervention by the operator is sufficient.

6.1 Future research

For future work, further research on the motion characteristics of each animation would provide a better understanding of why certain expressive motions were successful while others were not. The blueprint for that research would be to identify what are the motion characteristics in a given animation and compare it with the message perceived by the users. Hopefully some tendencies allow to identify what motion characteristics were most efficient in order to improve the expressive motions.

A second path to future work is to conduct a similar user study, but with real robots. 2D animations can give a good idea of a collective motion perceived intent, but they don't act the exact same way as robots. The user also doesn't always have the same point of view while watching robots, for example from the side instead of from the top, and doesn't have the same immersion into the mission. A real exploration scenario with the sound of the robots and the imperfect robot motions would possibly change the perception the user would get from the expressive motions. In the context of exploration, these findings demonstrate the utility of swarm expressive motions in communicating feedback to an operator and identify several directions for how such motions can be designed so as to improve their legibility.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s10514-022-10079-0.

Acknowledgements This work was supported by the Fonds de recherche du Québec Nature et technologies (FRQNT), École de technologie supérieure (ÉTS) and by the University of Paris Lumières Innovative Project Grant UPL-PEERM 232512-2021.

Declarations

Conflict of interest There is no conflict of interest.

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Corentin Boucher is a Master's student at École de technologie supérieure (ÉTS). He is passionate about robotics and works primarily in human robots-interactions. He has a multidisciplinary background with a bachelor degree in mechanical engineering and a technical diploma in technology of physics engineering. His work is primarily focused on the development of exploration algorithms of mobile robots, but he is also interested in collaborative robotic arms and the multiple possibilities that come with this technology.

Rebecca Stower is a postdoctoral researcher in the social robotics lab (SORO) at the Division of Robotics, Perception, and Learning at KTH Royal Institution of Technology in Stockholm, Sweden. She graduated with her PhD in psychology in 2021 as part of the ANIMATAS H2020 Marie Sklodowska Curie European Training Network (2018-2022). She is interested in the role of failures during human robot interactions, and how this affects people's attitudes and behaviours towards robots. She is also highly involved with interdisciplinary research and the open science movement.

Vivek Shankar Varadharajan is a Postdoctoral researcher in the Department of Computer Engineering and Software Engineering at Polytechnique Montréal. Varadharajan obtained his Ph.D. in robotics from Polytechnique Montréal in 2022, and he has a master's degree in Automation and Robotics from the Technical University of Dortmund. He is a full-stack robotics developer with vast experience in equipping robotic platforms with SLAM algorithms, navigation/traversability algorithms, and robotic behaviors. Varadharajan's research interests include distributed robotics, multi-robot systems, machine learning, artificial intelligence, and Cyber-Physical systems. He has won several prizes in technical competitions, hackathons, poster presentations, and demonstrations during his study. He was a team member of CoStar that took part in the DARPA subterranean challenge along with members from NASA Jet Propulsion Laboratory. He has supervised many interns and masters students in their research.

Elisabetta Zibetti is assistant professor teaching cognitive psychology at the University of Paris 8 since 2003. She obtained a PhD in cognitive psychology in 2001 (University of Paris 8, France and University of Barcelona Spain). She is currently do her research at the CHART-LUTIN laboratory exploring the psychological mechanisms allowing natural and artificial systems to understand and adapt to a specific situation, as well as to engage into collaborative interactions. Her research lies at the intersection of cognitive psychology and human-robot interaction (HRI), investigating the psychological assessment of humanoid robots and more generally behavioral artifacts.

Florent Levillain is an assistant professor at Université de technologie de Compiègne, and a research associate at Ensadlab. Florent is a specialist of social cognition, investigating intersubjectivity and the emergence of joint attention. He is collaborating with designers and artists to investigate the nature of movement expressivity, producing frameworks and experimental protocols to explain the relationship between behavioral organisation and expressivity.

David St-Onge is an associate professor in the Department of Mechanical Engineering at École de technologie supérieure, in Canada. He holds a PhD in mechanical engineering, space robotics and a master's degree on aircraft control. He worked for a decade in the field of interactive media (theatre, museums, festivals and circus): as the production director of a workshop, and as an R&D engineer. He is currently conducting research on robotic swarms' control through expressive motions (human and robots) and cognitive ergonomy in robot teams operation.