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# Human Perception of Swarm Fragmentation

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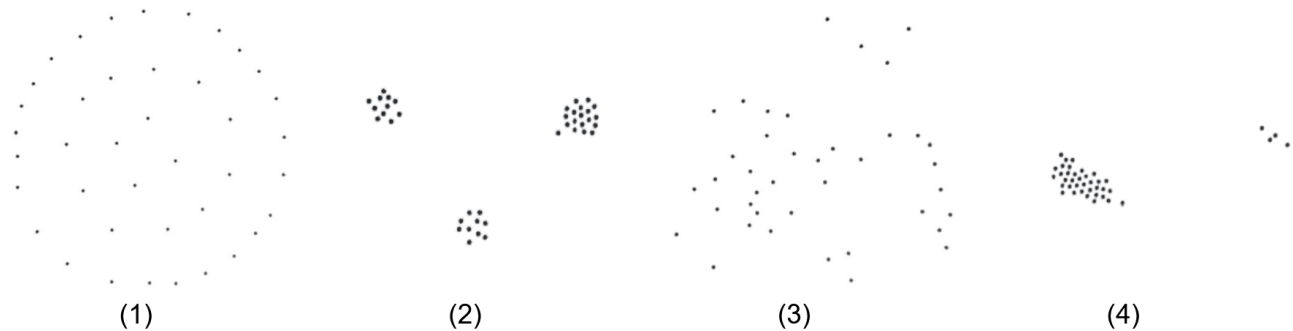


Figure 1: Fragmentation example for each behaviour : (1) expansion, (2) densification, (3) swarming, (4) flocking

## ABSTRACT

In the context of robot swarms, fragmentation refers to a breakdown in communication and coordination among the robots. This fragmentation can lead to issues in the swarm self-organisation, especially the loss of efficiency or an inability to perform their tasks. Human operators influencing the swarm could prevent fragmentation. To help them in this task, it is necessary to study the ability of humans to perceive and anticipate fragmentation. This article studies the perception of different types of fragmentation occurring in swarms depending on their behaviour selected amongst swarming, flocking, expansion and densification. Thus, we characterise human perception thanks to two metrics based on the distance separating fragmented groups and the separation speed. The experimentation protocol consists of a binary discrimination task in which participants have to assess the presence of fragmentation. The results show that detecting fragmentation for expansion behaviour and anticipating fragmentation, in general, are challenging. Moreover, they show that humans rely on separation distance and speed to infer the presence or absence of fragmentation. Our study paves the way for new research that will provide information to humans to better anticipate and efficiently prevent the occurrence of swarm fragmentation.

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## CCS CONCEPTS

• **Human-centered computing** → **User studies**; Graphical user interfaces; • **Computing methodologies** → *Multi-agent systems*; **Perception**; **Self-organization**.

## KEYWORDS

Human-Robot Interaction, Human perception, Robotic swarm, Swarm Intelligence

## ACM Reference Format:

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## 1 INTRODUCTION

Robot swarms are autonomous and self-organised systems that possess properties that make them useful for carrying out complex tasks beyond the abilities of a single robot. However, in scenarios where multiple swarm behaviours are required depending on the situation [6] (e.g. reach an area using a flocking behaviour, then spread out using an expansion behaviour and finally cover it dynamically using a swarming behaviour), or where specific real-time adjustments are required (e.g. densify the swarm to pass through a hole), human intervention/assistance may sometimes be necessary. Human beings can adopt different roles when interacting with a robot swarm [19]: *supervisor* (high-level control, actions on the medium/long-term), *operator* (low-level control, actions on the

short-term), *mechanic* (physical control, solves physical problems), *peer* (part of the swarm, interacts passively and actively while performing its tasks) and *bystander* (only an observer of the swarm functioning). Our goal is to offer to an *operator* means of control to influence a self-organised swarm efficiently, preventing undesirable effects that negatively affect the swarm. One of these undesirable effects is the swarm fragmentation [14, 15], which corresponds to a loss of communication and coordination among robots in the swarm. Fragmentation can be observed when the swarm loses one or more robots or splits into several groups. Sometimes, causing fragmentation is necessary as it allows the group to be divided to perform concurrently different tasks. However, when the fragmentation is not intended, it is harmful to the swarm and can, in the worst case, stop the swarm’s self-organisation as a whole: the loss of all interactions between robots prevents the emergence of collective behaviours such as flocking or area coverage [8]. Fragmentation can occur for various reasons such as the apparition of technical problems, changes in the environment, coordination problems between the robots, wrong initial parameter settings or unfitting control by the operator [10]. When an operator interacts with the swarm’s robots, (s)he interferes with their self-organising behaviour, potentially causing an unwitting fragmentation, for example, if (s)he reacts at the wrong time or frequency [13]. If the swarm is to be controlled by an operator who can cause or prevent fragmentation, it is first necessary to check whether and under what conditions humans can perceive (i.e. detect or anticipate) swarm fragmentation. In order to test several fragmentation situations, the use of multiple behaviours is necessary. It will allow us to check if different behaviours may impact the human perception of fragmentation differently. Moreover, in order to know what information humans may use to perceive fragmentation, we define two metrics characterising two aspects of the swarm: the separation speed and distance of the fragmented groups. It will allow us to see if these aspects are important to perceive fragmentation as a human being. We first review the literature related to fragmentation and human perception of swarms in section 2, before detailing our experimental protocol in section 3 and presenting our results in section 4. Finally, we provide an interpretation of the results and discuss limitations and perspectives in section 5, and we conclude in section 6.

## 2 RELATED WORKS

As fragmentation can be harmful to the integrity of the swarm, developing solutions to avoid it is necessary. The first solution may be to reinforce communications within the swarm, by limiting the individual autonomy of the robots or by establishing strict relationships between them, preventing the robots from wandering off and losing track of the rest of the group [17, 23, 24].

Rather than constraining the self-organisation, an alternative is to ask an operator to monitor the swarm and interact if necessary. Previous works on Human Swarm Interaction (HSI) show that it is only necessary to interact with the swarm when needed and at the right time. In [6], the authors show that human intervention reduced the efficiency of the swarm, seemingly due to a massive intervention from the operator. Moreover, the concept of *Neglect Benevolence* [11–13, 28] implies that it is sometimes necessary to wait for the right moment before exercising control in order to get

the swarm to perform a task as efficiently as possible. This also implies waiting for the right time to avoid harmful scenarios for the swarm. However, the operator must understand the swarm’s dynamics and its impact on the swarm behaviour to figure out what the right time is.

More generally, we can assume that to avoid swarm fragmentation, the operator must first be able to anticipate it, or at least to perceive it, before applying the right control to prevent it or to correct it. Regarding human perception capabilities of swarms, previous studies show that a human can discriminate between flocking, rendezvous and dispersion behaviours [27], as well as swarming [7]. In addition, the concept of *Legibility* [3, 4] shows that the trajectory of a swarm is more predictable, without the need to add additional information, when the swarm is dense, rigid and adopts a direct trajectory. Moreover, the study from [20] shows that a human is also able to identify and differentiate in a very efficient way between a self-organised pattern and a pattern simulated by random dots, but struggles to discriminate it when the dots form a solid rigid structure. The authors suggest that humans can identify the overall movement of the swarm, but not its nature. For example, humans do not seem to be able to determine whether the swarm’s movement is self-organised or simulated (i.e. agents do not interact and follow a predefined trajectory, mimicking the desired self-organised behaviour). In [9], the authors show that an increase in the number of robots and their speed influences how the time is perceived by the participants, which appears to be faster. More broadly, previous works on human perception show that a human can make visual discrimination among moving points, for example by identifying a point moving in a fixed direction while all the other points are moving randomly [29]. In cognitive sciences, the *Gestalt theory* [26] suggests that people have a natural tendency to perceive objects in their environment in terms of global shapes or coherent sets rather than isolated parts. In particular, the notion of *Perceptual Grouping* describes the ability of humans to “perceive some elements of the visual field as “going together” more strongly than others”. This notion encompasses several object properties such as *Common Fate*, *Synchrony* or *Proximity*. *Common Fate* [22, 25, 26] refers to the ability of a human to perceive among points going in random directions, moving points that are close and heading towards the same point or direction as if they had a common destiny. This identification is influenced by some factors that can be found in [25], such as the proximity of the points, the similarity of their movement or their number. *Synchrony* [26] refers to the tendency to group elements that change simultaneously, even if they are not following the same direction. *Proximity* [1] refers to the tendency to group together elements near to each other, than others further away. In another HSI study [21], the authors used *Gestalt theory* principles to study how humans perceive the cohesion of a swarm and showed that this perception of cohesion is linked to the proximity of the robots, the synchronisation of their movements and their tendency to follow a leader. As fragmentation is a loss of swarm cohesion, these results give us a good indication of the factors that can prevent humans from perceiving fragmentation. However, to our knowledge, nothing in the literature has shown that humans can perceive swarm fragmentation. As fragmentation causes the appearance of several groups that do not communicate, humans may be capable of perceiving them using agents’ position

(e.g. *proximity*) and movement (e.g. *common fate*). However, it is still unclear whether this subjective grouping represents the actual state of the swarm, or whether it misleads the human about the real nature of the interactions within the swarm. Humans could, for example, misperceive fragmentation in swarm behaviours exhibiting agents with long-distance sensing capacities and erratic movement. On the contrary, they might misperceive a cohesive swarm in behaviours exhibiting agents with short-distance sensing capacities and homogeneous movement and position.

### 3 EXPERIMENT ON SWARM FRAGMENTATION PERCEPTION

This study aims to investigate the ability of humans to perceive swarm fragmentation. More precisely, two research questions are addressed here: 1) How swarm fragmentation is perceived depending on different swarm behaviours? 2) Do humans use the distance between agents and the speed at which they separate to assess whether there is fragmentation? To answer these questions, we create a binary discrimination task in which participants have to determine whether the presented simulated swarms displayed fragmentation. Videos are used to display the swarm, showing expansion, densification, flocking and swarming behaviour.

#### 3.1 Swarm simulation

Studies from [27] and [7] show that humans can discriminate between densification, expansion, flocking and swarming behaviours in a swarm. In this study, we chose to use the same behaviours, for which we detail our implementation below, to obtain diverse fragmentation situations and to see if distinct behaviours have an impact on the human perception of swarm fragmentation. The four behaviours are defined as follows:

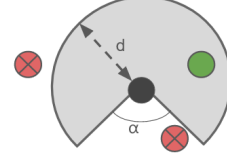
- In **densification** behaviour, swarm agents move closer to each other, causing an increase in swarm density.
- **Expansion** is the opposite of densification. Swarm agents move away from each other, causing a decrease in swarm density. This behaviour is useful for achieving area coverage.
- **Flocking** is the coordinated movement (i.e. similar speed and direction) of an aggregate of autonomous agents.
- **Swarming** is the opposite of flocking. Agents move without any coordination, going in all directions and at different speeds. However, they stay aggregated.

To obtain all these behaviours, we implemented the *Boids* model [16], on the Unity game engine. Our implementation uses a motion system based on virtual forces, which does not take into account the mass of the simulated robots. Acceleration ( $\vec{A}$ ), speed ( $\vec{S}$ ) and position ( $\vec{P}$ ) are represented by two-dimensional vectors, as the agents are mobile robots that navigate on a plane.

$$\vec{S}(t) = \vec{S}(t-1) + \vec{A}(t) \times \Delta t$$

$$\vec{P}(t) = \vec{P}(t-1) + \vec{S}(t) \times \Delta t$$

Each agent has a field of view and a blind spot. Neighbours in the agent's field of view are perceived only if they are not in the agent's blind spot (see Figure 2). We call  $N$  the set of the agent's neighbours and  $\vec{P}_a$  the position of the neighbour  $a$ . In this controller,



**Figure 2: Perception capability of an agent. Only agents in the perception area are perceived. The letter  $d$  represents the field of view size and  $\alpha$  the blind spot angle.**

the acceleration of an agent at time  $t$  is obtained by adding the forces resulting from six predefined rules:

- (1) Cohesion rule: brings the agent closer to its neighbours

$$\vec{Cohesion}(t) = \left( \frac{\sum_{a \in N} \vec{P}_a(t)}{neighboursCount} - \vec{P}(t) \right) \times cI$$

- (2) Separation rule: keeps the agent away from its neighbours

$$\vec{Separation}(t) = \frac{\sum_{a \in N} \frac{\vec{P}(t) - \vec{P}_a(t)}{\|(\vec{P}(t) - \vec{P}_a(t))\|}}{neighboursCount} \times sI$$

- (3) Alignment rule: aligns the agent's speed and direction with its neighbours

$$\vec{Alignment}(t) = \frac{\sum_{a \in N} \vec{S}_a(t)}{neighboursCount} \times aI$$

- (4) Random movement rule: allows the agent to move on its own, randomly (Here,  $X$  and  $Y$  are two different numbers randomly generated between  $-0.5$  and  $0.5$ , which change each time the rule is called).

$$\vec{RndMovement}(t) = \vec{V}(X; Y) \times rml$$

- (5) Friction rule: reduces agent speed over time

$$\vec{Friction}(t) = -\vec{S}(t) \times fI$$

- (6) Overlapping avoidance rule: prevents agents from overlapping

$$A = \{a \in N, \|\vec{P} - \vec{P}_a\| < sd\}$$

$$\vec{Avoid}(t) = \sum_{a \in A} \frac{\vec{P}(t) - \vec{P}_a(t)}{\|(\vec{P}(t) - \vec{P}_a(t))\|} \times oI$$

The rules' intensity can be adjusted at any time, as well as the size of the field of view and of the blind spot angle. This allows to seek a specific swarm state and then update the agents' parameters to obtain the desired swarm behaviour. Table 1 details the bounds of each parameter and the values used to obtain a flocking behaviour.

To achieve densification or expansion, it is necessary to create an imbalance between the intensities of the cohesion ( $cI$ ) and separation ( $sI$ ) rules: in favour of  $cI$  for densification, and  $sI$  for expansion. To obtain the flocking behaviour, increasing the intensity of the alignment rule ( $aI$ ) is necessary. It is also important that  $sI$  is not too strong compared to  $cI$ , preventing the agents from staying together. The same goes for swarming, where the agents must remain in a group. However, it is necessary to decrease  $aI$  to a minimum and

**Table 1: Example of values used to obtain a flocking behaviour**

Variable	Value	Bounds	Description
$cI$	2	$[0;\infty[$	cohesion intensity
$aI$	4	$[0;\infty[$	alignment intensity
$sI$	1	$[0;\infty[$	separation intensity
$rmI$	0	$[0;\infty[$	random movement intensity
$fI$	0.1	$[0;1]$	friction intensity
$oI$	20	$[0;\infty[$	overlapping avoidance intensity
$sd$	0.09	$[0;\infty[$	safety distance (in meters)
-	1	$[0;\infty[$	perception radius (in meters)
-	0	$[0;360]$	blind spot (in degrees)

increase the intensity of the random movement rule ( $rmI$ ), allowing agents to move more freely, without aligning themselves with their neighbours. Finally, agents must be aggregated (i.e. form a single swarm) in the initial state to obtain each of these collective behaviours. The swarm used in this study is composed of 40 agents, whose behaviour comes from the rules we previously presented. The agents move within an area bounded by impassable walls and with no obstacles. This area measures  $7 \times 7$  units and is white to contrast with the colour of the agents, which are represented by black cylinders with a diameter of 0.08 units. The observation is made from a distance of 7.0 units with a birds-eye view aligned normally to the plane<sup>1</sup>. Using a bird's-eye perspective eliminates some of the factors that can influence human perception, such as perspective or occlusion. This view from above is often used in previous works on perception (e.g. [18, 27]). In this swarm simulation, when an agent does not perceive any neighbour and is not perceived by any other agent, it becomes isolated and fragmentation appears in the swarm. An isolated agent is not the only possible source of fragmentation. Sometimes the swarm divides into two or more groups, and all agents have neighbours belonging to their respective groups. Replacing agents with nodes and their neighbours with adjacent nodes makes it possible to define a graph that connects the agents. Consequently, if only a disconnected graph with two or more components can be obtained, it implies that the swarm is fragmented, because there is no coordination or communication possible between the two groups. Figure 1 shows an example of fragmentation for each swarm behaviour.

### 3.2 Metrics

To characterise the human perception of swarm fragmentation, we defined two metrics inspired by the way humans group individualities according to the *Gestalt theory*. The first metric defines the distance separating fragmented groups. The second metric defines the separation speed of two fragmented groups. If several fragments appear, the two metrics qualify the higher score they can measure between two fragments.

**3.2.1 Distance visibility score.** Based on the notion of *Proximity* from the *Gestalt theory*, humans seem to group individualities that are close to each other. Fragmented groups often move away from

<sup>1</sup>see the video provided as supplementary material

each other, increasing the distance between them. However, the distance among agents of a single group remains unchanged. Consequently, a difference may appear between inter-group distance and intra-group distance. So, we defined a metric measuring this difference to verify whether it affects the human perception of swarm fragmentation. For this purpose, we measured the inter-group and intra-group distances when a fragmentation occurred. To measure the inter-group distance, clusters are identified, based on the perception of the agents, in a fragmented swarm. Once the different clusters are obtained, we seek the distance between two close clusters calculated as follows:

- (1) We look for the smallest distance between two clusters among all the clusters.
- (2) The two closest clusters are merged to form a larger one.
- (3) The operation is repeated so that only two clusters remain.
- (4) The smallest distance between the two remaining clusters is defined as the inter-group distance.

To measure the intra-group distance, we identify the cluster containing the most agents and average the distance of the  $K$  Nearest Neighbours (KNN) of each agent ( $K=3$ ). Finally, we divide the inter-group distance by the intra-group distance to obtain the distance value visibility score.

**3.2.2 Separation speed.** Based on the notion of *Common fate* from the *Gestalt theory*, humans seem to group together elements that are heading toward the same point. Consequently, when two distinct directions are perceived, two distinct groups may be identified. The more the directions are different and the speed of the agents is high, the faster the groups will separate from each other. So, we defined a metric to verify whether separation speed affects the perception of swarm fragmentation. As humans prefer to see coherent sets rather than isolated parts, this metric measures the separation speed of fragmented groups based on the separation speed of their centre of mass at the time of the fragmentation. To do this, we identified the group leaving the aggregate and measured the separation speed of its centre of mass compared to the centre of mass of the rest of the swarm. In the case where multiple groups were separating, we took the group that was moving away the fastest.

### 3.3 Experimental protocol

Since the dynamics of swarms are very sensitive to the initial state and random disturbances, it is difficult to replay a simulation identically from one subject to another. Consequently, to ensure that all participants view the same content, we selected and recorded videos of the swarm simulation at 60 frames per second. There are two types of videos, those containing a swarm fragmentation, whose presence has been verified using a function based on the agents' perceptions throughout the video, and those that do not. Fragmentation never appears at the same time across different videos. Moreover, the videos are classified into four categories according to the displayed swarm behaviour: expansion, densification, flocking and swarming (see section 3.1). All videos begin with a fully aggregated swarm, meaning that there is no fragmentation at the initial state. Furthermore, once the swarm agents' parameters are adjusted to exhibit the desired swarm behaviour, they don't change during the recording of the video. Among these parameters, we find the intensity of the rules, as well as the perception radius

([0.6;1] meter), the blind angle ([0;180] degrees), and the speed of the agents ([0.1;0.3] m/s), which varies between videos. Varying the perception radius and the blind angle prevents participants from retaining a reference distance as a fragmentation distance. This also allows us to approach a real context where robots have different perception ranges and angles depending on their sensors [5]. Finally, the videos end once the swarm appears to be stabilised, thus preventing the swarm's dynamics from causing to the participants an impression of imminent fragmentation. Additionally, when a fragmentation occurs, the group does not reform, the fragmentation is present until the end of the video.

**3.3.1 First task.** The first task of the participants is to watch videos presented in random order and determine if the video they are watching contains fragmentation or not. There are 48 videos with varying lengths between 6s and 50s, for a total duration of 19 minutes. A progress bar is constantly displayed on the screen indicating the percentage of time left before the end of the video. Each of the categories presented in section 3.3 is represented by 12 videos, 6 of which contain fragmentation and 6 of which do not. In the videos containing a fragmented swarm, the fragmentation occurs on average 11.6 seconds after the beginning of the video (with a minimum of 2 seconds), and there are on average 12.3 seconds left until the end of the video (with a minimum of 3.15 seconds). This gives participants a reasonable amount of time to react and answer. To avoid differences in learning, all participants watch the videos until the end. There is a pause between each video, which ends with a participant's input to launch the next video. While viewing a video, the user can press one of the two buttons to answer the question "Is there a fragmentation in this video?". Participants are aware that we choose to record a negative answer if they don't give any answer. We make this choice because (1) they are informed beforehand that they should give the correct answer as quickly as possible, as soon as they think that either a fragmentation has occurred (or will occur) or no fragmentation has occurred (or will not occur), and (2) they always have access to the remaining time in the video. In addition, participants are warned that their answer is final. In this task, the participants' answers are collected and marked as correct or incorrect, according to their alignment with the result of the numerical calculation verifying the presence of fragmentation. Response times of participants are also recorded to assess how effective they are at anticipating fragmentation.

**3.3.2 Second task.** The second task of the participants aims to collect qualitative data on the participants' perception of the swarm's dynamics and to identify important factors that contribute to the human perception of fragmentation in a swarm. This task involves watching 8 additional videos, two of each category. They differ from the other task in that they not only show the behaviours and fragmentation previously used but also additional fragmentation situations, with properties from other categories. In this way, we can identify which properties seem to be important in their perception and how they interact. Among these videos, two have particular characteristics to check if participants are sensitive to them. One contains a swarm that perpetually splits into several groups and reassembles into one aggregate. The other contains an already fragmented swarm. This task takes the form of an interview, recorded with the prior agreement of the participants. The

participants' speech and the content viewed are recorded, giving us a context for their comments. This recording is deleted after analysis, as agreed with them. During the interview, participants express themselves freely and can watch the videos as many times as necessary. However, in some situations, the interviewer may trigger comments by asking them open and non-oriented questions: "Can you describe what you see?" if they don't express themselves spontaneously, or "Can you detail your reasoning?" if their answer is too brief. After watching and commenting on the 8 videos, the participants were asked three final oral questions: "What strategy do you use to identify fragmentation?", "What makes it easy to see whether or not there is going to be fragmentation?" and "What makes it difficult to see whether or not there is going to be fragmentation?". At the end of the task, we asked the participants to write down the elements that indicate whether or not that there is or will be fragmentation. The interviews and written comments are analysed after all participants have taken part in the experiment. The interviews are viewed, and the terms used by the participants are collected manually and classified in a table according to whether they indicate the presence or absence of fragmentation. In addition, the answers to the last 3 questions are also collected, indicating the participants' strategy, and what they found easy and hard. The obtained results are discussed in section 5.

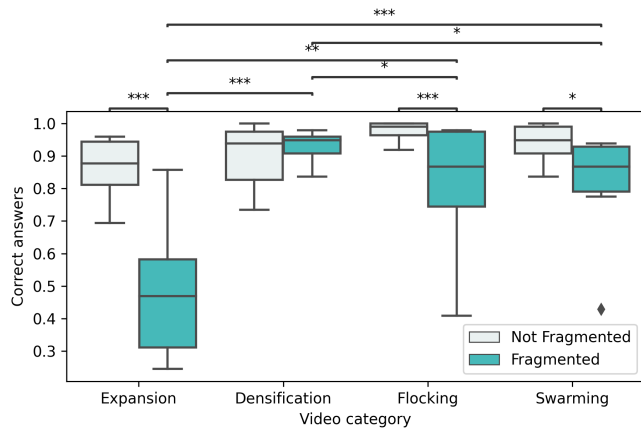
**3.3.3 Preparations.** A total of 49 participants took part in the experiment, of which 60% were male and 40% were female. The participants ranged in age from 20 to 80 (median of 27). We chose participants without prior knowledge of robot swarms. We assumed that studying their perception provides us with a fundamental basis which can be generalised. All participants had a correct or corrected vision. Collected data were anonymised. The study was conducted in a quiet room exclusively dedicated to the study for its duration. The ethics committee of the authors' institution has approved this experimental protocol.

## 4 RESULTS

Two factors were tested in this experiment. First, we checked the impact of the swarm behaviour on human perception. Non-parametric tests were used, as the experiment uses a within-subject pattern and as a Shapiro test has confirmed that data do not follow normal distribution. The Friedman test followed by a Nemenyi post-hoc were used to check differences in correct answers and anticipation among categories. Secondly, we checked the relationship between the proposed metrics (see sections 3.2.1 and 3.2.2) and the rate of correct answers, thanks to a logistic regression approach.

### 4.1 Impact of swarm behaviour on correct answers

Firstly, we verified if the swarm behaviour has an impact on the rate of correct responses from participants. Regarding the mean score for each category, densification (91%), flocking (89%) and swarming (87%) have similar results, but the expansion category scored lower (67%). Then, for each video category, the results are differentiated according to whether or not there is fragmentation, forming eight categories. Figure 3 shows the obtained results. The Friedman test performed on the eight categories shows statistically significant



**Figure 3: Correct answer rate according to the category of videos and whether they are fragmented or not**

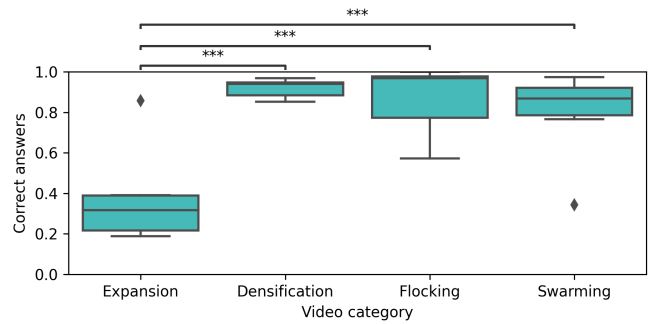
differences in correct answers ( $Q=124.68, p<0.001$ ). The Nemenyi post-hoc test shows:

- Fragmentation from the expansion category was found to be significantly harder to identify than either densification ( $p<0.001$ ), flocking ( $p=0.003$ ) or swarming ( $p=0.001$ ).
- Fragmentation from the densification category was found to be significantly easier to identify than either expansion ( $p<0.001$ ), flocking ( $p=0.011$ ) or swarming ( $p=0.023$ ).
- Videos containing fragmentation from the expansion category were found to be significantly harder to identify than videos containing no fragmentation within the same category ( $p<0.001$ ). Similar effects were found for flocking ( $p<0.001$ ) and swarming ( $p=0.032$ ). Only the densification category was found to have no significant difference between the scores for fragmented and non-fragmented swarms ( $p=0.804$ ).

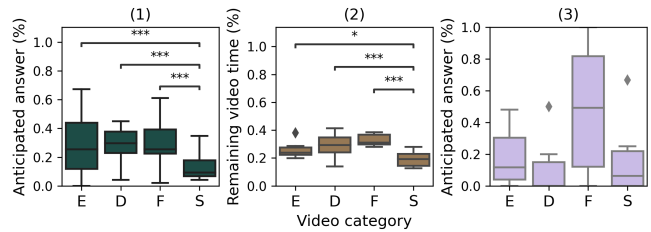
Focusing only on the videos showing a fragmented swarm, we looked further at the perception of fragmentation without taking into account the anticipated responses. Figure 4 shows the obtained results. Regarding the mean score for each category, densification (91%), flocking (87%) and swarming (79%) have similar results, but the expansion category scored lower (37%). The Friedman test shows statistically significant differences in correct answers ( $Q=63.44, p<0.001$ ). The Nemenyi post-hoc test shows that fragmentation from the expansion category was found to be significantly harder to perceive than either densification ( $p<0.001$ ), flocking ( $p<0.001$ ) or swarming ( $p<0.001$ ).

#### 4.2 Impact of swarm behaviour on anticipation

Secondly, we verified if the swarm behaviour has an impact on the participants' anticipation. The recorded response times are used to compute the anticipated responses and the percentage of video remaining at the time of the responses for all participants. Other analyses using directly the response times were not possible, because the videos are not equivalent (see section 3.3). First, we looked at the anticipation rate of responses on videos containing fragmentation (cf. Figure 5.1). Regarding the mean anticipation rate for each category, expansion (29%), densification (28%) and flocking



**Figure 4: Rate of correct answers given after fragmentation occurrence in videos containing a fragmentation, according to video category**

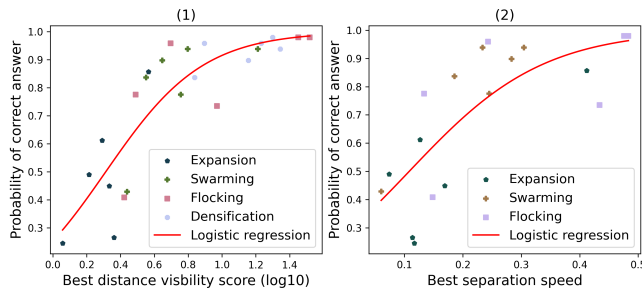


**Figure 5: (1) Rate of answers (right or wrong) given before fragmentation in videos containing a fragmentation, according to video category (2) Percentage of video remaining at the time of response for videos containing no fragmentation by category (3) Anticipation rate of wrong answers for fragmented swarms in each category (E) Expansion (D) Densification (F) Flocking (S) Swarming**

(30%) have similar results, but the swarming category scored lower (14%). The Friedman test shows statistically significant differences in fragmentation anticipation ( $Q=37.82, p<0.001$ ). The Nemenyi post-hoc test shows that fragmentation from the swarming category was found to be significantly less anticipated than either expansion ( $p<0.001$ ), densification ( $p=0.001$ ) or flocking ( $p<0.001$ ).

Then, we looked at the percentage of video remaining specifically on the videos that contain non-fragmented swarms. Regarding the mean for each category, expansion (26%), densification (29%) and flocking (33%) have similar results, but the swarming category scored lower (19%). The Friedman test shows statistically significant differences in percentage of video remaining ( $Q=44.23, p<0.001$ ). Figure 5.2 shows the obtained results. The Nemenyi post-hoc test shows that answers from the swarming category were found to be less anticipated than either expansion ( $p=0.043$ ), densification ( $p<0.001$ ) or flocking ( $p<0.001$ ).

Finally, we looked at the wrong answers given due to anticipation from videos containing fragmented swarms (cf. Figure 5.3). As the number of wrong answers is different for each category, the Friedman test cannot be used. Instead, we used the non-parametric alternative of the One-way ANOVA, the Kruskal-Wallis test. Regarding the mean anticipation rate for each category, expansion (18%), densification (12%) and swarming (17%) have similar results, but the



**Figure 6: (1) Probability of correct answer as a function of the best distance visibility score achieved by the video (2) Probability of correct answer as a function of the best separation speed achieved by the video**

flocking category scores higher (48%). However, the Kruskal-Wallis test gives us no significant result ( $Q=7.69$ ,  $p=0.054$ ).

### 4.3 Effect of distance visibility score

To verify if the distance separating fragmented groups may influence the human perception of fragmentation, we did a logistic regression of the rate of correct answers as a function of the *distance visibility score* metric defined in section 3.2.1. To spread the data correctly, a log of 10 is applied to the distance score.

As shown in Figure 6.1, characterising the videos by the best score they achieve significantly impacts the rate of correct answers ( $p<0.001$ ,  $\alpha=3.4662$ ,  $SE=0.263$ ). Moreover, we also tested the distance score at the time of response. It significantly impacts the rate of correct responses ( $p<0.001$ ,  $\alpha=3.5850$ ,  $SE=0.328$ ).

### 4.4 Effect of separation speed

To verify if the separation speed of fragmented groups may influence the human perception of fragmentation, we performed a logistic regression of the rate of correct answers as a function of the *separation speed* metric (see section 3.2.2). By observing the results, we noticed that this metric does not allow us to characterise the videos showing densification behaviours, because the mass centres of the different groups do not move. The densification category is therefore removed from the analysis for this section.

As shown in Figure 6.2, characterising the videos by the highest separation speed they achieve significantly impacts the rate of correct responses ( $p<0.001$ ,  $\alpha=8.6938$ ,  $SE=0.843$ ). Moreover, we also tested the speed of separation at the time of response. It significantly impacts the rate of correct responses ( $p<0.001$ ,  $\alpha=10.3325$ ,  $SE=1.075$ ).

## 5 DISCUSSION

This section aims to discuss the results presented in section 4. It is structured as follows: first, the results of each behaviour will be discussed, followed by the results of the two metrics and the qualitative results, to finally conclude.

**Swarm behaviours.** Firstly, participants perceive fragmentation with greater difficulty in expansion category videos. Some videos in this category score 22%, which is significantly lower than the 50% that would be expected if participants were responding randomly. These results suggest that the information presented in these videos

gives the impression that the swarm is not fragmented. When a swarm is expanding, it tends to spread homogeneously and regularly, both in terms of movement and position. Even when agents become isolated, they continue their trajectory with inertia, which remains homogeneous with the others, and stop at the same time because agents are homogeneous and have the same maximum speed. These results are consistent with the *Gestalt theory* presented in section 2, especially with the concepts of *Synchrony* and *Proximity*. To summarise, swarms that expand homogeneously and fragment provide conflicting information about their true state. This could be problematic because expansion allows for area coverage, a useful behaviour in practical applications [2]. Furthermore, we observe that participants identify fragmentation more easily in videos containing fragmented swarms from the densification category. Indeed, the movement of agents grouping towards the swarm's centre of mass facilitates its identification, notably thanks to the notion of *Common Fate*. In the case where fragmentation occurs, multiple centres of gravity are perceptible, making the identification of multiple groups simpler as 67% of subjects reported in the qualitative feedback. Furthermore, due to the nature of densification behaviour, the distance between agents in the swarm decreases, without changing the distance at which communication between two agents breaks down. As a result, the difference between the two is as remarkable as the gap widens. Similarly, the videos in the flocking category were found to have significantly good results as shown in Figure 3. Taking only answers given when the fragmentation already occurs, results are even better than the densification category as shown in Figure 4. This difference can be explained by the results presented in Figure 5. Indeed, half of the wrong answers came from bad anticipations (i.e. participants wrongly answered that no fragmentation would occur). These results are consistent with the literature [1, 26]: flocking behaviour exhibits several *Perceptual Grouping properties* such as *Common fate*, *Synchrony* and *Proximity*, and shows little or no evidence of any risk of fragmentation that might make participants doubt. In a real context, this is not a problem because the operators can reevaluate their choices continuously. However, these results show that participants do not seem to perceive the fragility of the swarm. Otherwise, it was observed that videos in the swarming category make participants more cautious than for other categories. Indeed, they are less likely to anticipate their response, whether it is anticipating the fragmentation or responding before the end of the video (see Figure 5). This can be explained by the fact that swarms within this category have erratic behaviour, making it difficult to perceive divergent agents. In addition, when fragmentation occurs, it is often unexpected according to the participants. The qualitative feedback shows that they found it difficult to answer the videos from the swarming category and tend to say "You never know what will happen".

**Metrics.** When considering the introduced metrics, the difference between inter-group and intra-group distances seems to influence the probability that a participant responds correctly (see Figure 6.1). As participants do not have access to the agents' perception distance, they must use other cues to determine the fragmentation. Since the swarm is composed of agents with homogeneous behaviour, the appearance of a remarkable difference in distance is a useful cue to identify the appearance of a second group. This also justifies



why it is difficult to perceive fragmentation in the expansion category, as fragmented agents tend to stay at a homogeneous distance from each other, there is no remarkable distance. The choice of this metric is also reinforced by qualitative results. Indeed, 57% of participants mentioned comparing the distance between groups to the inter-group distance to estimate if they perceived fragmentation. Similarly, the separation speed of the centres of mass appears to influence the probability that a participant correctly identifies the video (see Figure 6.2). However, as the densification behaviour does not involve the movement of its centres of mass, humans probably rely on other clues for this behaviour. Using these two metrics, we have shown that humans seem to use separation distance and speed to infer the presence or absence of swarm fragmentation. Determining the existence of other clues will be the subject of future works.

**Qualitative results.** Of the 19 explicit strategies obtained from the participants, 26% involved looking at the swarm as a whole, 57% keeping an eye on the outside, and 42% spotting anomalies. Some participants seemed to be more sensitive to anomalies arising from the distance between agents, and others to the movements of the agents. Moreover, of the 29 responses obtained, 58% of the participants reported finding it easier to evaluate videos displaying dense swarms moving in a common direction, specifically videos in the flocking and densification categories. They also found it easier to assess the fragmentation when the inter-group distance is very marked (17%), opposite directions are visible (41%) and the group separates quickly (37%). Conversely, of the 31 responses obtained, 80% reported finding it difficult to evaluate videos with expanding swarms, as the agents have a homogeneous behaviour and positioning and there is no clue to assess a fragmentation distance. In addition, they found it difficult to evaluate videos containing swarms in a swarming behaviour (32%) because fragmentation is deemed unpredictable (19%). In both cases, the task seemed more difficult when the swarm density was low (29%). Finally, when several contradictory pieces of information are visible, the participants seemed to choose the non-fragmentation answer. This qualitative result may explain the different obtained results within the same category between fragmented and no fragmented videos for expansion, swarming and flocking (section 4.1). In the expansion category, agents show a dispersion behaviour, but homogeneous and synchronised. In the swarming category, agents show erratic behaviour, but they keep being attracted to a centre of gravity. In the flocking category, agents move together in a coordinated way but sometimes show few instabilities inside the swarm. Only the densification category show different results, probably because its fragmentation is neat and visible almost from the start as multiple centres of gravity appear in term of movement and density.

**Synthesis.** Our results strengthen results from [21] and the assumption from [20] suggesting that *“motion perception of swarms is supported by a global motion system that is not specialized for the biological nature of the individual agents and their interaction, but instead, capitalize on the motion redundancy from multiple individuals to code the overall pattern.”* As long as agents are moving in the same way, they are seen as part of the same group even if they no longer interact and only apply the inertia of their past interaction, as shown by the results from the expansion category. However, even if the four behaviours came from the same self-organisation method, the redundancy of the agent movement is neither evidence

of the cohesion of the swarm nor proof that the agents interact. As such, this redundancy is not enough to inform humans about the stability of the aggregated swarm. Consequently, we suggest that humans need supplementary information to anticipate fragmentation and understand its causes in order to prevent it.

**Limitation and future work.** The experimentation in this document has been conducted under perfect conditions and does not take into account the issues that an operator may encounter in real conditions. Changes in the operator’s point of view can modify the perception of distances and complicate the perception of certain fragmentation. Additionally, in a real environment, there could be variations in brightness, colours, and elements, as well as occlusion that could hinder the operator’s perception of the robots. In future experiments, the impact of several parameters may need to be studied. In particular, the number of robots, their speed, the size of their blind spot or their perception range could affect the way an operator perceives fragmentation. In addition, the influence of the operator’s background would also need to be evaluated in future work. Moreover, it would be interesting to study more specifically the anticipation abilities of fragmentation in humans. Additionally, reproducing this experiment with a swarm of drones would allow us to see the impact of a 3D-navigating swarm on fragmentation perception. Moreover, testing a greater variety of behaviours would help to refine the obtained results. Finally, the use of eye tracking could help us to know what the human is looking at in the swarm.

## 6 CONCLUSION

In this document, we studied the human perception of fragmentation by presenting 49 participants with a discrimination task among videos containing swarms that fragment or not. The results show that humans perceive correctly swarm fragmentation (around 90% of the time) for flocking, densification and swarming. Yet, they have difficulties perceiving fragmentation when the swarm adopts an expansion behaviour, as it does not present any cue that would allow the estimation of a loss of communication among agents. In addition, the results show that it is difficult for humans to correctly anticipate fragmentation in all categories of behaviour. Moreover, humans take more time to respond and struggle to anticipate fragmentation when the swarm adopts a swarming behaviour, as the erratic movement of the agents prevents the anticipation of the appearance of fragmentation. We also have shown that the inter/intra-group distance and the separation speed metrics influence the chances of correctly identifying swarm fragmentation, suggesting that humans use among other cues distance separating groups to perceive fragmentation, as well as the separation speed of groups centre of mass. These results highlight the situations where it is most difficult for an operator to perceive and anticipate fragmentation. We have also proposed metrics to quantify and qualify these situations. These results provide a better understanding of the internal logic of robot swarm operators and will guide future research to provide relevant information for robot swarm control.

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<sup>2</sup><https://siaa.univ-brest.fr/artuisis/>

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