# Studying Collective Behaviour from an Algorithmic Perspective

March 28, 2019

**Abstract**

This paper reports on the setup and first results of and experimental platform to study human collective behaviour. More precisely, the setup is composed of a set of optic-fiber lit wearable jackets located in real time in a delimited area. It interacts with a group of participants wearing the jackets and engaged in the resolution of a collective task. The twist of this approach is consider tasks that would typically be realised by computers, and to consider the group as an information processor, therefore enabling an algorithmic perspective on collective behaviour.

## 1 Introduction

The system we study is the group of participants, on which we can write information (by coloring the jackets) and read information (by recording the individual positions). In other words, we interface a group of individuals. In this exploratory approach, we observe the resulting object from an algorithmic perspective: understanding how a machine (the group) manipulates information.

The only behaviour required from the group is a simple optimization task, namely to seek the display of the greenest possible light on each vest as often as possible. Using a computer interfaced with the group, we are then able to capture the group's optimization behaviour in a variety of environments (or models) that we control. By controlling the rules of appearance of certain colors, we can change the nature of the optimization problem prosed to the group, and record its response. We believe this is an interesting perspective as it allows to have a system treating information without ever having to program it: the ability to ask a group to solve algorithmic problems without ever having to introduce of frame them provides us with a live system treating binary information as "naturally as possible".

A common approach in computer science and in particular in artificial intelligence is to ask a computer to realize human tasks. Comparing the way humans and computers realize the same task is useful: first as a metric of the computer performance against the human, and second because understanding the reference behaviours of the humans (where they succeed, where they fail, possibly their strategies) can sometimes be exploited to improve computer behaviours. The Turing test[xx] for instance precisely compares computer and humans engaged in a human task (chatting), and interestingly enough some of the programs that are best at fooling humans also emulate typos and human errors to do so[xx]. Conceptually as well, neural and hopcroft networks, or Hebbs rule [big book neural] directly originate from analogies with the human brain.

The purpose of this approach is to shift from this rich yet populated paradigm and pursue the opposite direction: have humans behave like computers. We envision three sorts of benefits:

**Algorithmic perspective on CB** Collective Behaviour, as a process emerging from individuals engaged in a collaboration, shares as a field many concepts with distributed algorithmics. Notions like locality/globality of views, the spreading of information and consensus are common to both fields. Yet many tools developped in the algorithm world have no counterpart in collective behavioural perspective (like asymptotic complexity, convergence time, global and local minimas). Studying the collective behaviour on algorithmic tasks might allow to leverage some of these notions to better understand collective behaviour.

**Collective Behaviour perspective on Algorithmics** Despite its success, algorithmics has only recently grown as a major research field thanks to the invention of computers. Biological systems on the other hand realise the current state of an evolution strong of (XXX) thousands of years of collaboration in treating information. The communication patterns and structures usually found in algorithmic systems (such as gossip, leader election) are not always found in biological system traces.

Biological systems are used to a much harsher environment model than computer systems (with no determinism, questionnable synchrony, unreliable network, failures), and understanding some of the rules than guide their collaboration might greatly benefit resilient algorithmic designs.

**Transparency** Since both treat information, a natural question that arises is: do traces of biological collaboration look like distributed algorithms execution traces ?

This is a difficult question, since the relationship linking an algorithm and its traces is mostly known (and understood) in one direction: from the algorithm to the traces.

These questions will also structure the presentation of this document: after introducing the hardware setup Section 2, we will detail the experimental procedures that we conducted Section 3 before

## 2 Materials

Two essential components allow us to interface with a human group: a precise localisation system, and a set of optical fiber woven vests. A computer orchestrates the communication between those components and associates positions with colors.

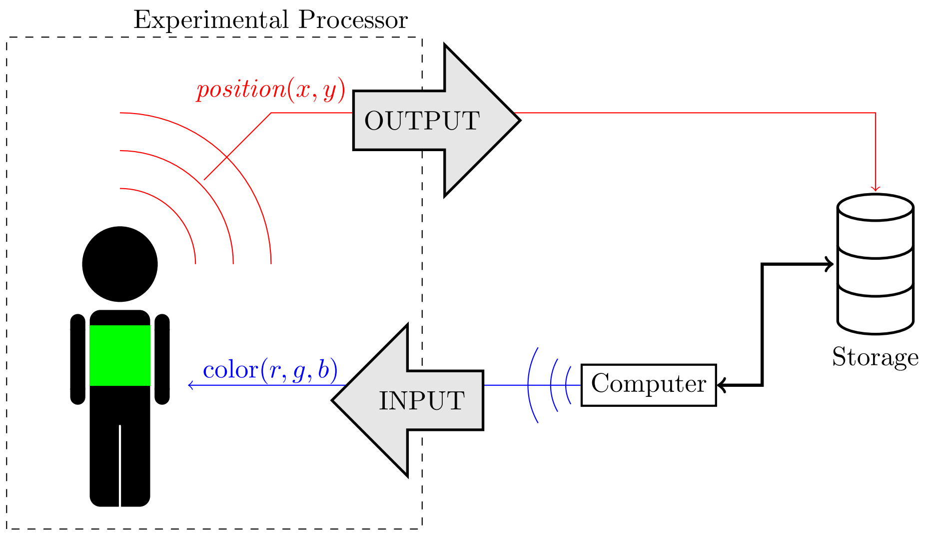


Figure 1: Illustration of the approach: the group of participants is tracked in real time, and the positions of the participants are transformed into colors displayed on the participants to form a feedback loop. By manipulating the rules that bind participants positions to colors, it is possible to study the collective resolution of different problems.

## 3 Methods

We hereafter describe the experimental protocol we developped around the system. It is roughly composed of three stages that structure the experience of participants. In a first stage, participants are welcomed, equipped with the vests, and very shallowly instructed about their expected behaviour during the experiment. The second stage is the data acquisition phase, where participants are left on their own trying to fullfill a set of tasks. This phase is followed by a third phase in which we unequip participants and engage in a conversation with them.

### 3.1 Experimental Area

The system is deployed in a $8 \times 8m$ square area specially prepared for the experience. The guiding principle of this preparation is to isolate as much as possible the future group of participants from any exterior input, so that the collected data reflects the processes taking place *within* the group rather than exterior events that would be difficult to capture and account for at data exploitation time. In thermodynamic words, we seek to characterize an adiabatic system composed of the room and its participants.

To achieve this, we chose a room that is far from exterior activity (to avoid external sound inputs), and blinded all windows and openings so that visual information only comes (directly or indirectly) from the recorded inputs of the system. Similarly, the room is as empty as possible so that participants are not artificially attracted by one direction or another.

For practical reasons, we allow two exceptions to this approach:

- During first and last phases (hereafter described), since the system is not running, vests are not emitting any light. A central lighting is lit to allow the experimentators to equip participants with a good visibility. In addition, having two lightings setups (central lighting *vs* obscurity and vests at runtime) provides a visual information to participants about the phase they are in.

- A corner of the square experimental room is reserved for the mandatory experimental setup components. It consists in a small desk and a chair on which the experimentator sits during phase 2. This allows the experimentator to overview the system and participants during this phase and acts as a safety guarantee. A rack storing unused vests is also there. The footprint of this area is kept minimum.

### 3.2 Phase 1: Participant Setup

This first phase is driven by two objectives from our experimentator perspective. The first one, practical, is to equip each of the participants with one vest. The second one, scientific, is to manage to instruct participants in a neutral yet convincing way.

Equipping each participant with vests is a tedious process during which participants often ask about the objectives of the experiment. The answers to those questions is always "those questions will get answered after the experience". This phase is also the occasion to check that each vest is working correctly and has sufficent battery for the runtime. Depending on group size, this phase takes between one and five minutes.

At the end of this phase, participants are asked to gather in the center of the experimental area. This allows the system to differentiate vests being worn by participants from spare vests located on the rack. This also allows a last check of the vests connectivity to the system.

Once they are gathered, the experimentator provides the group with its instructions. The instructions are:

> In this experiment, you have one task: find the green. This experiment is devided in 3 landscapes. In each of these landscapes, you want the greenest possible color on your vest. You can move anywhere in the room. When the lights go off, the experiment will start.

Again, any questions from the participants (*e.g.* how to achieve the green ?) are not answered ("Those questions will be answered after the experience").

There exists here a tension between the scientific objective to keep each participant "as neutral as possible", and maintain a reapeatable process across the different participant groups taking on the experiment. On one hand, these objectives tend to "de-humanize" participants – not answering their questions, only providing direct orders. On the other hand, participants come here benevolently, mostly out of good will and curiosity, and seek a fulfilling social experience. Preserving this good will is essential for the experience, as a single participant refusing to seek the green color would compromise the experience[1]. A balance between friendlyness and authority is seeked by the experimentator.

The light is then turned off and the experience itself begins.

### 3.3 Phase 2: Experience

We devide the experience in three phases we call "landscapes". Each of these landscapes corresponds to an algorithmic problem. Each landscape is implemented in the controller by a different logic that will bind the received positions to the colors displayed at each participant. We selected those tasks according to the following criteria XXXX

Each task runs for a fixed time of 150 seconds. After this time, all vests turn off for 2 seconds, and blink yellow for 3 seconds so that participants realize a new landscape will start. In addition, the experimentator says loudly "you are entering the next landscape".

Let us formalise the model. For each experience, we consider a set of $P$ of $|P| = n$ participants. At each timestep $t$, each participant is characterized by a position $p_i^t = (x_i^t, y_i^t)$ and a color $c_i^t = (r_i^t, g_i^t, b_i^t)$. A landscape $\mathcal{L}$ is a function producing the colors of the next timestamp depending on the previously recorded positions of the participants, that is such that $\{c_i^t, 1 \leq i \leq n\} = \mathcal{L}(\{P^{t'}, t' < t\})$.

**Gradient Descent** In this landscape, each participant is considered independently of the others (that is, at any given time $t$, participant $i$'s color only depends on its position $x_i^t, y_i^t$). More precisely, this function is implemented as a set of pictures $p_1, p_2 \dots$ that are $60 \times 60$ arrays of pixels. At any given time, each participant gets virtually located on the active picture $p_t$ and gets the color of the pixel he is virtually located on $p_t[x][y]$.

The picture $p_t$ generated to ensure a smooth transition between a set of 12 keyframes that are represented Figure**??**.

G:trop complique, plus simple ou shema

**Rationale:** Gradient descent is a standard optimisation problem. The goal is to maximise a benefit function $f$ defined over a domain $D$. In our case $D = [|0, 60|]^2$ is the experimental area, and the goal is to find $(x_m, y_m) \in D$ s.t. $\forall (x, y) \in D, f(x, y) \leq f(x_m, y_m)$.

This is a central problem in machine learning, and our current understanding is currently being debated G:pas exact, trouver formulation plus souple

[1]this happened once with a college class.

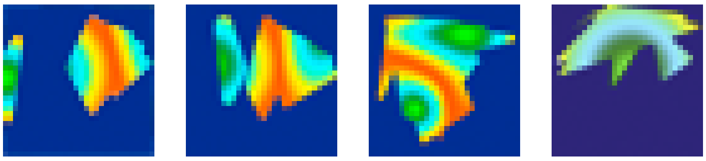


Figure 2: Keyframes used for generating the pictures $p_t, t > 0$.

| Id | $n$ | Pos. Collected | Duration(s) | Collection ratio | Month/Day |
|---|---|---|---|---|---|
| 1 | 8 | 3562 | 450 | 0.989 | 9/ 5 |
| 2 | 8 | 3563 | 450 | 0.989 | 9/ 5 |
| 3 | 8 | 3521 | 450 | 0.977 | 9/ 5 |
| 4 | 4 | 1786 | 450 | 0.992 | 10/ 12 |
| 5 | 4 | 1773 | 453 | 0.979 | 10/ 12 |
| 6 | 9 | 4019 | 450 | 0.992 | 10/ 12 |
| 7 | 9 | 4018 | 450 | 0.992 | 10/ 12 |
| 8 | 5 | 2238 | 450 | 0.994 | 10/ 12 |
| 9 | 7 | 2664 | 450 | 0.845 | 10/ 13 |
| 10 | 12 | 5288 | 450 | 0.979 | 10/ 13 |
| 11 | 9 | 4012 | 450 | 0.990 | 10/ 13 |
| 12 | 12 | 5290 | 450 | 0.979 | 10/ 13 |
| 13 | 12 | 5257 | 451 | 0.972 | 10/ 31 |
| 14 | 13 | 5621 | 450 | 0.960 | 10/ 31 |
| 15 | 13 | 5730 | 450 | 0.979 | 10/ 31 |

Table 1: Data collection campagn consists in 15 standardized runs collected during Sept. and Oct. 2018. The number of positions is computed after filtering, once reconstructed trajectories are interpolated at $1Hz$. Comparison to the theoretical maximum value (participants $\times$ duration) shows a good collection ratio.

**Maximal Matching**

**Graph Embedding**

## 4 Results

What do we want to say ?

- Is the system accurate ?
- Physicist approach: acceleration wrt color: black box hypothesis = "are people mimising/optimising their green color"
- What is a good convergence criteria ?
- Do people converge ?
- How fast is the convergence ?
- How is the convergence speed scaling wrt group size ? Do other criterias impact convergence ?
- How homogenous are the groups ? Individual contribution wrt group size ?
- Computer science: we need to discuss optimality criteria. Do we want to "simulate" behaviour also ? What is optimality criteria ? (maybe we should simply not adress this point)

G:A structuring approach might be to fade from a "black box" to a "white box", that is to gradually exploit in our analysis the knowledge we have about the system (e.g. *i* we just see people moving *ii* we look at how people optimise green color because this is what they are asked *iii* we exploit (unobservable) knowledge about the system's optimum solutions.

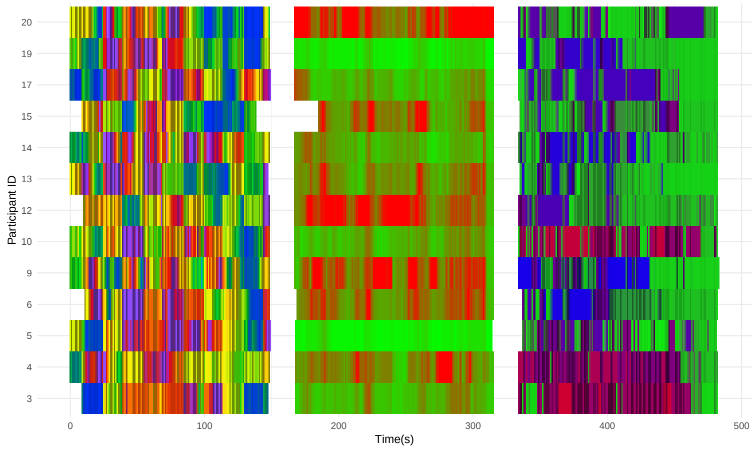


Figure 3: Temporal perspective on session 15: each participants colors is represented as a row. Cell ($t$,$i$) contains the color of participant $i$ at time $t$. The three distinct blocks correspond to the three algorithms. An empty cell denotes a missing position.

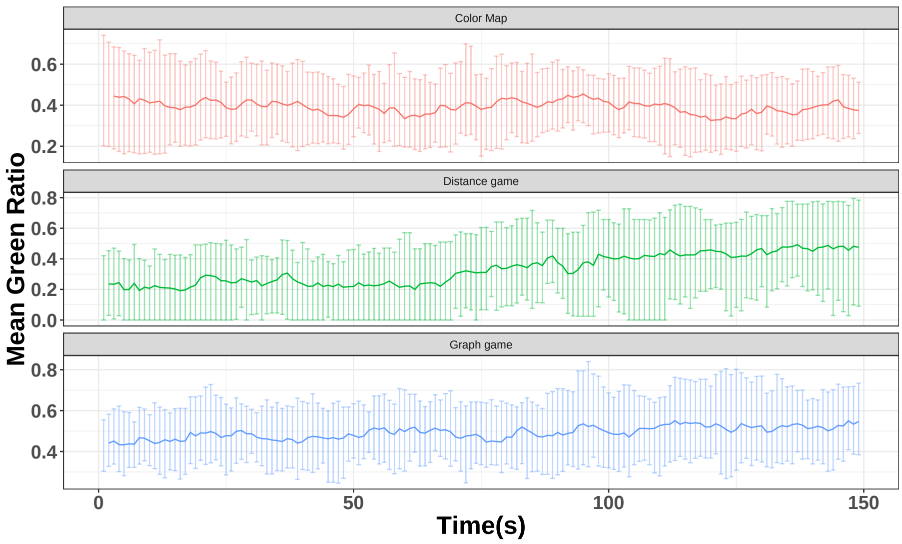


Figure 4: Temporal perspective on group success. Mean green is the average quantity of green throughout each session. ColorMap is difficult by definition. Graph Game is tougher than distance Game

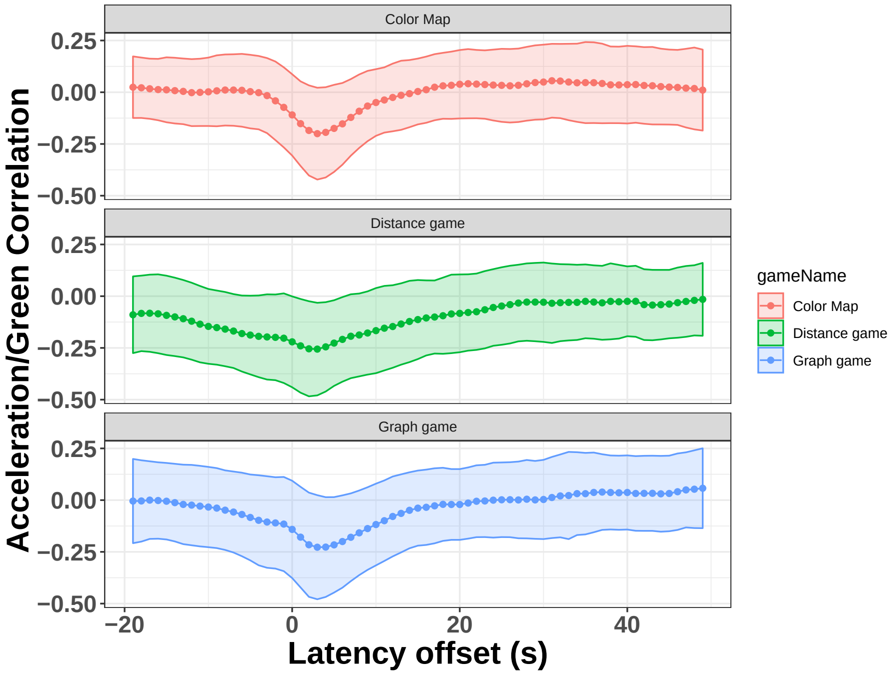


Figure 5: This figure reports the correlation between individuals green color at time $t$ and their acceleration at time $t + x$ for each of the different landscapes. The drop around 3 seconds corresponds to the latency of the whole feedback loop (individual+sensing+computing+displaying)

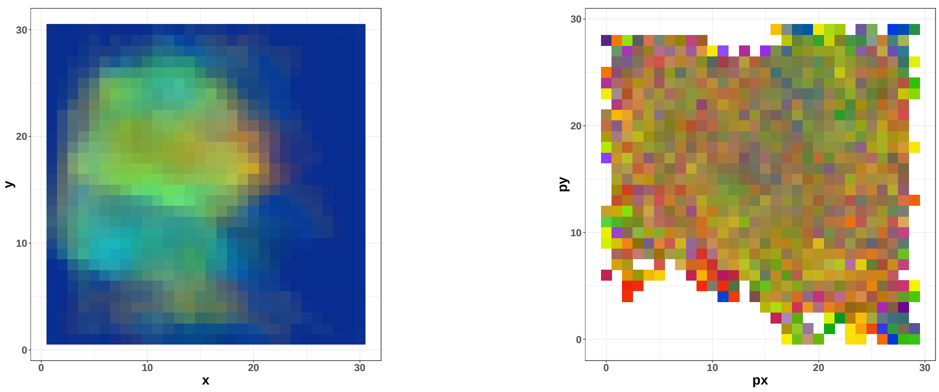


Figure 6: This plot exhibits a problem we have with gradient descent landscape. (right) average pixel color of the reference images used. In other words, the average color over the whole picture cycle. (left) average displayed colors during the actual experience. Note the empty lower left corner (experimental area).

# 5 Discussion

Lessons learned on the design of experiments. How would we improve the connection between the "physicist perspective" and the CS one. How could we conciliate black and white box ?

What is the impact of our experimental setup ? Don't we "turn groups into showing something we can measure" and could it be avoided (maybe: more "controlled" input to groups should lead to better resolution, and this would be a highres instrument. However, we do not really know how to exploit this information.

G:I believe the CS level of data analysis will be polluted by different factors. If we decide to include it, a paragraph on the lessons learned on collective tasks might be good. We could also go for the "preliminary" results route, and use this paper as a call for ideas about different tasks to ask participants.

# 6 Conclusion