The Dancing Swarm: Using Laban Effort Parameters for Generating Expressive Swarm Behaviour

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Abstract

With robots increasingly being used for artistic expression in interactive performances, this research investigates the production of expressive swarm behaviour that could form the basis for an interactive performance between a dancer and a swarm of drones. We contribute a mapping of Laban Effort parameters - a common movement analysis framework - onto a particle swarm and integrate it into an interactive prototype. The system accepts human motion as input and generates responsive swarm behaviour with the Boids algorithm as the foundational behaviour model. In a user study evaluating the mapping (N=17), we show that the Space and Time parameters were recognised significantly better than Weight and Flow, suggesting that parameters connected to embodied cues such as intention and emotion are more challenging to computationally implement, and need further refinement. The novel mapping, along with the interactive system and user study insights, offers an initial step towards practical applications in choreography development, interactive performance, or art installations, as well as designing expressive frameworks with human-guided swarm control.

CCS Concepts

• **Computing methodologies** → *Model development and analysis*; • **Human-centered computing** → *Interaction paradigms*.

Keywords

Human–Robot Interaction, Swarm Robotics, Laban Movement Analysis, Expressive Movement

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1 Introduction

With computational systems entering the artistic realm, an increasing number of practitioners are exploring the intersection between technology and creativity. In the context of human-robot interaction and expressive movement mapping, expressive robot swarms remain understudied, despite their high coordination and fluidity. The end goal of this research is to generate expressive swarm behaviour in response to real-time human movement dynamics. To achieve this, we build on the Laban Movement Analysis (LMA) framework, widely used in theatre and dance, and more recently in robotics [2, 15, 16]. In this framework, movement is analysed over five dimensions; Body, Effort, Space, Shape, and Phrasing [24]. Among these, Effort is most widely adopted to analyse movement in the context of human-robot interaction, as it focuses on the intentionality and dynamic qualities of a movement. Since the goal of this research is to explore the expressiveness rather than the mechanics of movement, we decided to focus on the Effort dimension only. Effort is broken down into four Laban Effort Parameters presented in Fig. 3.

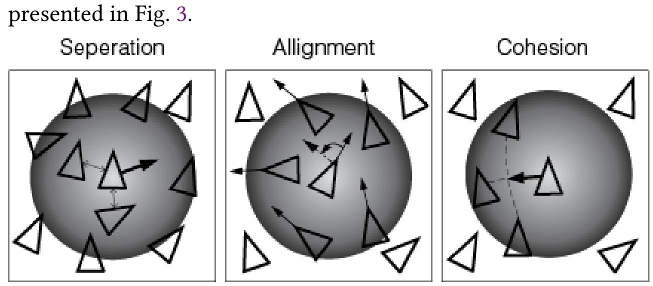

Figure 1. Visualisation of the three rules followed in Boids algorithm. Figure adapted from Noury Bouraqadi [8]

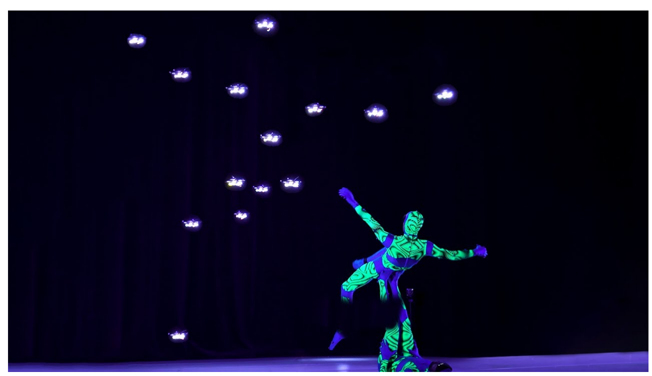

Figure 2. Example of an interactive dance performance with a swarm of drones. Photo by Kim Vos (2023)

Similar projects applying LMA for movement analysis of agents primarily use machine learning (ML) models and focus on predicting [13] and motion generation [18] for a single humanoid agent rather than several agents building a particle cloud. The goal of our paper is to fill this research gap and propose an effective system that computationally maps Laban Effort parameters on particle swarm behaviour. Additionally, we aim to show an example application for

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the mapping by creating an interactive system that captures human motion and reflects the expressive qualities of human movement in a swarm in real time. We summarize the contributions of this paper as follows.

- ⋆ A novel framework for mapping Laban Effort parameters onto swarm behaviour, and insights on its perceived accuracy.
- ⋆ An application of the mapping in an interactive system.

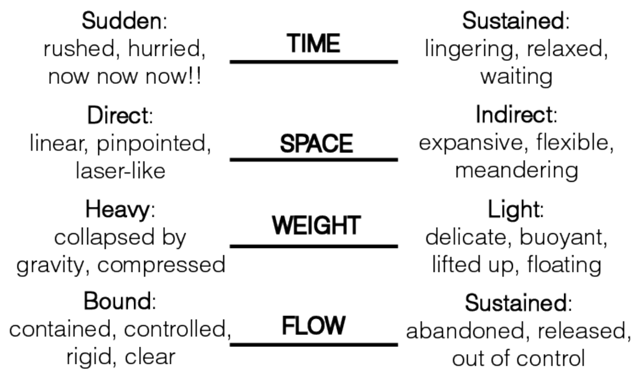

Figure 3. Explanations of the opposite poles for Laban Effort Parameters. Figure adapted from Knight and Simmons [15]

2 Related Work

2.1 LMA in Computational Systems

Laban Movement Analysis is traditionally carried out manually by experts; however, due to the increased application of LMA in various fields, alternative methods are being explored. Guo et al. trained ML algorithms for Laban annotation of pre-recorded video [14], Swaminathan et al. used a Dynamic Bayesian Network, which infers Laban Shape Qualities of movement input in real-time [22]. In contrast, our implementation only focuses on Effort. A computational approach, allowing for lower latency generation and enabling real-time execution of tasks, is more appropriate for our system. Both Erkoc [13]. and Turab [23] present a novel method for computationally obtaining LMA Effort parameters. In addition to extracting LMA Efforts, research has also been done on mapping LMA to agents. These primarily consist of humanoids [2, 9, 12]. Furthermore, some research exists on mapping LMA on non-humanoids like a robotic arm [19] and a single aerial robot [10]. In this research, we extend the expressivity from single agents to group behaviour.

2.2 Responsive swarms

When designing responsive swarms, we must consider how to keep them responsive without becoming unstable. Mateo et al. found that maximum efficiency is reached by designing agents that pay attention to a limited set of neighbours [17]. Siean et al. conducted a systematic literature review of scientific papers that examined the interaction between operators and drone swarms. They proposed several future research directions, such as expanding interaction modalities beyond limited hand gestures and increasing the number of agents in a swarm [21].

2.3 Swarms in the performing arts

Swarms have been used in artistic settings in the past. Besides reactive installations [1, 4, 5], swarm behaviours have also been used in dance shows. Bisig and Unemi explored swarms as choreographic elements for dance performances [6]. The performances discussed in the paper used virtual swarms projected on dancers and screens, following Boids-type algorithms mixed with limited independent reactions triggered by the body tracking camera. Despite the interactive component, the performances predominantly showed predefined swarm behaviours and scripted choreography. The authors concluded that the spontaneous and autonomous qualities of a swarm could be better experienced if the dance performance contained more elements of improvisation, which is exactly what the framework in this paper enables.

3 Methodology

This section describes our method for mapping Laban Effort parameters onto a particle swarm and the design of a user study to evaluate the perceived accuracy of the mappings.

3.1 Method overview

The Boids algorithm [20], where each simulated agent - "Boid" - follows a set of three rules summarised in Fig. 1, serves as the core behavioural model of our swarm implementation. The Separation, Alignment and Cohesion rules were implemented, along with an added force of Randomness to compute the steering direction of each particle. These rules were applied locally based on the positions and velocities of neighbouring particles. Steering forces and velocity were manipulated by the Efforts through the following parameters:

Space: Represents how directed the movement is. In the implementation, it manipulated the weight of Alignment and Separation forces, with lower values (directed space) increasing Alignment and decreasing Separation.

Weight: Represents how compressed the movement is. It manipulated the weight of the Cohesion force, with lower, compressed values increasing cohesion (grouping, clustering together) and higher values decreasing the cohesion force.

Flow: Represents how free the movement is. It manipulated the strength of randomness, the level of damping, and jitter in the swarm movement.

Time: Represents how fast the movement is. It manipulated the speed of the particles.

Noise: Random noise over three channels was used to obtain the initial position of all particles in the first frame.

The Laban parameters influenced the forces and the velocity that were used to compute the new position of all particles and update the table storing the positions. An overview of the mapping can be found in Fig. 4. The tables provided input for the rendering logic to update the positions of the particles in the render. Programming the Laban to Swarm framework was done in the TouchDesigner environment [11]. TouchDesigner is a node-based visual programming language that is used for interactive multimedia content in real-time. The core of the mapping Laban Efforts on particle movement lies in the script that was updating x, y and z coordinates of all particles every frame. It took the input of slider values representing four Laban Effort parameters, as well as random noise over three channels. Sliders were interactive, and the value was chosen on the range between 0 and 1, with both extremes representing the opposite poles of the respective Laban Effort parameter. Source code for the mapping can be found on GitHub[1].

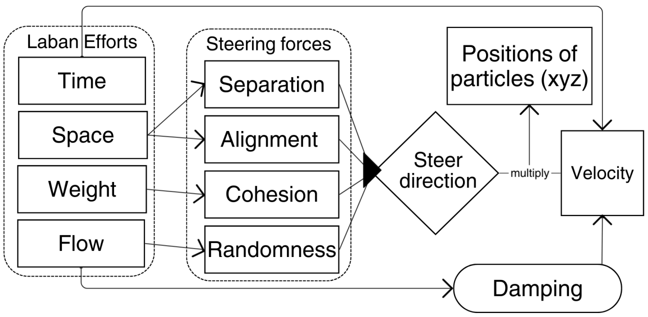

Figure 4. Visual representation of Laban Effort to Swarm mapping for each particle

3.2 Study design

To evaluate the accuracy and usability of the proposed mapping, a user study was carried out with 17 participants (3 males, 14 females, 0 other; average age 41, range 20-80). All participants had at least 5 years of experience with performing or martial arts, and 9 were already familiar with Laban movement analysis before the survey.

After reading the informed consent, all participants were given a quick tutorial on LMA. Next, they watched ten 5-second videos showing expressive swarm behaviors and evaluated each of them in terms of Space, Weight, Flow and Time using sliders ranging from 0 to 100. The videos were chosen to show balanced parameters, including at least two occurrences of all four Effort parameters at low, medium and high in a randomized order for each participant to avoid order bias. Lastly, there was a slider where participants could estimate their level of confidence in the evaluation and 4 open-ended questions about their ideas of mapping Laban parameters on a swarm. The complete questionnaire can be found online[2].

4 Results

4.1 Mapping Accuracy

To determine the general accuracy of the mappings, the overall median absolute error (MedAE) was computed to be 24. When comparing MedAE of different parameters, Time had the lowest value of 15, followed by Space with 16. Flow and Weight both had a high MedAE of 31 and 31.5, respectively. A box plot of absolute errors for all parameters can be found in Fig. 5.

Additionally, the percentage of correct classification among different Effort parameters was computed by assigning both original and participants' values to a low, mid or high bin and marking the classification correct if the bins matched. Similarly, as with MedAE, Time and Space were recognised best with the correct classification of 53% and 56%, respectively. Flow was correctly recognised 32% of the time and Weight 28%, showing poorer recognition.

The differences in the correct classification of different Efforts were computed by creating a contingency table and performing a Chi-square test ($p<0.0001$). To further test statistical significance, we performed Fisher's exact test between all pairs of parameters. While there is no significance between Space and Time nor between Weight and Flow, there is a significant difference in the number of correct classifications between both Space and Time compared to both Weight and Flow. In the correct classification percentage and MedAE error calculation, Weight and Flow also had a higher interquartile range (IQR) of 41 and 37 than Time and Space, with IQRs of 29 and 22. When comparing the average MedAE and percentage of correct classification between people with and without prior knowledge of LMA, we observe that the differences are not statistically significant. On average, the participants ranked their confidence in the ratings to be 56%.

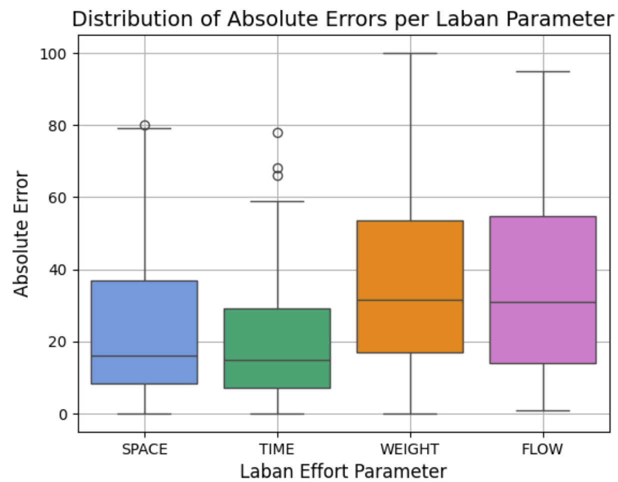

Figure 5. Boxplot of MedAE over different Effort Parameters

4.2 Qualitative survey data

Data on participants' perception of the movement were collected through open-ended questions, where they described how they imagine contrasting forms of particle movement across several dimensions. The opinions included some interesting metaphors, valuable for Effort modeling in the future collected in Table 1.

Table 1. Participant's metaphors for imagined swarm behaviour

Effort Component	Participant Example
Direct Space	Group walk in the army
Indirect Space	Group contact improvisation
Sudden Time	A moth in the light
Sustained Time	Frozen snail coming to life
Strong Weight	Demi plié and side jump with force
Light Weight	Flying swan arms
Bound Flow	Focused walk toward someone at a club
Free Flow	Frightened birds

5 Integration into Interactive System

To demonstrate an application of the mapping, an interactive system was constructed. It requires a camera to capture a video stream

[1]https://github.com/zjgb/AKOBxSiouxThesis
[2]https://vuamsterdam.eu.qualtrics.com/jfe/form/SV_eFNPMokVmQZTcbk

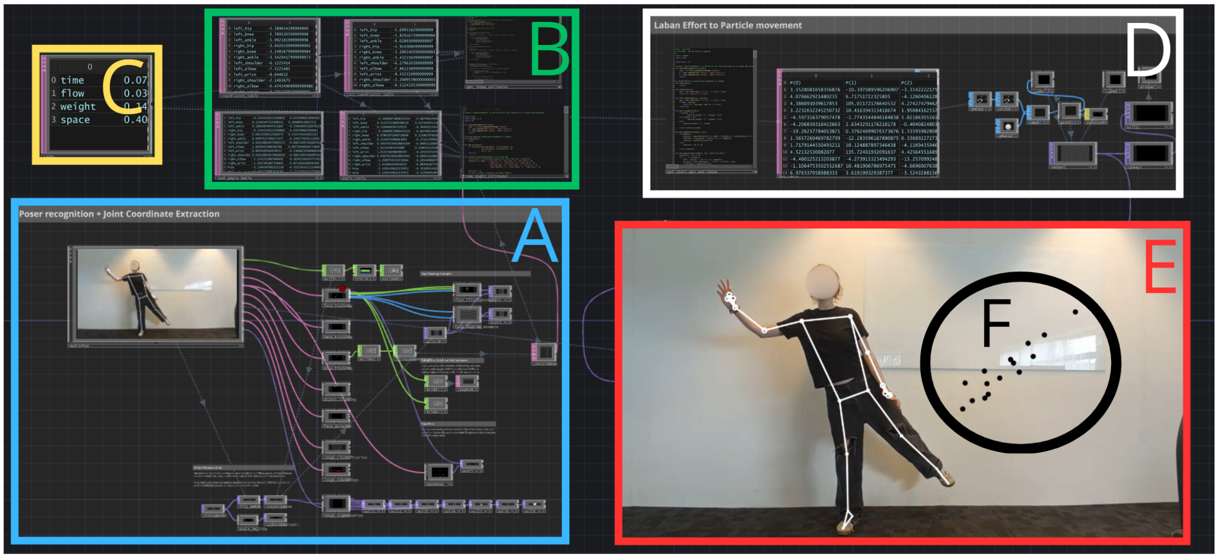

Figure 6. Overview of the Interactive system. Code available at https://github.com/zjgb/AKOBxSiouxThesis

with human motion (Fig. 6.A). The frames are processed by MediaPipe plugin [7] that recognises the body pose and extracts x, y, z coordinates of the joints. The poses of the current and last frame serve as an input for a Python script that computationally extracts Laban Effort parameters for every frame (Fig. 6.B). The method was adapted and modified to work in real-time from Turab et al. [23] for Weight and Time and from Erkoc et al. [13] for Flow and Space. The parameters are stored (Fig. 6.C) and at this point, the mapping framework from 3.1 is integrated into the system (Fig. 6.D), taking extracted Laban Efforts as input rather than slider values. Finally, it overlays the particle render (Fig. 6.F) with the input video, creating an interactive Human-Swarm experience (Fig. 6.E). Evaluation of the integrated system is left for future work.

6 Discussion

The aim of this paper was to address the gap in research and create a meaningful mapping framework between Laban Effort parameters and Swarm behaviour. With the Boids algorithm as the core behavioural model integrated with the principles of Laban movement analysis, we successfully constructed such a framework. This proved to be a relatively challenging task due to swarms lacking some complex, embodied factors typically used to identify Effort factors in human movement. The evaluation suggests that we proposed a solid framework that achieved reliable accuracy. Space and Time parameters achieved a significantly higher recognition rating than Weight and Flow. Feedback from the participants familiar with Laban theory suggests that this is likely due to the factors like emotion and intention, associated with Flow and Weight used to evaluate the Laban factors on human motion. Additionally, Weight requires embodied cues like Context, Body and Gravity, so it is particularly difficult to recognise in particles. On the other hand, Space and Time were recognised fairly accurately. They are connected to the speed and trajectory of the movement with less embodied cues. Participants also provided some useful metaphors of different swarm movement that could be used to choreograph swarm behaviours in the future, potentially using generative AI.

6.1 Future work

The user evaluation indicated that Space and Time could be used in complex systems, while Weight and Flow need refinement to be applied effectively. To gain more insight, we conducted an exploratory interview with a Laban expert. Building on their recommendations, Weight could be refined by adding some form of context, like making the swarm drop to the ground or lightly float, and Flow could be refined by breaking up the swarm in a few groups and then regrouping them again for 'Free Flow' and having the swarm move as a whole group for 'Bound Flow'. Additionally, the system could be expanded to other Laban components, especially Shape to have a more concrete mapping on a swarm and further explore the already existing Shape and Effort link [3]. Alternatively, the system could explore different combinations of predefined factor poles or just stick to 2 or 3 Efforts at the same time, just like human movement.

6.2 Application and scientific relevance

This research expands the field by developing a computational approach and introducing LMA mapping on a swarm. An example application was already constructed by integrating it with a framework that computationally extracts human motion and maps in on a particle cloud in real-time. This is a meaningful contribution for creative technology community, as this framework can be extended to drones for an improvisational dance performance or integrated as a part of other movement-based installations. Alternatively, it could assist choreography creation or movement education once refined and verified by more experts. In general, its findings can be used to design more expressive robotic swarms in projects where humans guide or interact with swarms and other scenarios where swarm dynamics need to reflect or respond to human movement.

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