# In-Formation Flocking: An Approach to Data Visualization Using Multi-Agent Formation Behavior

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**Abstract.** This paper presents *in-formation flocking*, a novel information visualization technique that extends the original information flocking concept with dynamic and data-driven visual formation behavior generation. This approach extends the emergent swarming properties of a decentralized multi-agent system in order to represent complex time-varying datasets through visually-recognizable formations and motion typologies. In-formation flocking is capable of representing volatile and inherently chaotic time-varying datasets while sustaining a comprehensible representation at a global level as well as revealing more detailed patterns in subsets of the data. This paper demonstrates the capabilities of in-formation flocking to historical stock market data.

**Keywords:** data visualization, swarming, flocking, boids, motion, emergence, multi-agent systems, self-organization, artificial life

## 1 Introduction

Behavioral rule-based *flocking* is a well-known computer graphics technique that provides a conceptual means for visually simulating the natural phenomenon of aggregate motion in birds, fish and other animals. The principle of computational flocking simulation assigns each individual group member or *boid*, short for bird object, with a fixed set of behavior rules [1]. Flocking is an example of an emergent process, which demonstrates complex behavior that arises from a collection of entities that were not individually and explicitly programmed to do so. The recursive interactions of each single entity to those in its immediate environment cause a process which, on a holistic level, can lead to perceivable complex behaviors and an increase in order of the whole collection of entities.

In this paper, the apparent order generated by emergence is exploited to represent patterns reflecting relationships in complex, time-varying datasets. Accordingly, we believe that self-organization principles such as flocking can be used for visualizing abstract data, as it is theoretically possible to group similar data entities without the need for supervision, pre-calculating data similarity matrices or predetermined data mapping algorithms. *In-formation flocking*, an extension of the information flocking

[2, 3] approach, aims to generate more readily recognizable flocking motion typologies. Instead of representing data tendencies by separating apparently randomly-moving clusters, in-formation flocking is capable of making dynamic patterns and clusters more apparent by integrating the process of decentralized *formation flying*. Formation flying, as exhibited by birds, describes the synchronized movement of a group in readily distinguishable shapes. Formation flying is believed to be reflective of the underlying internal relationships and energy considerations within the social hierarchy of a flock [4]. Here, the in-formation flocking concept aims to exploits the visually perceivable order as an additional, readily distinguishable visual cue for representing dynamic similarities in complex, time-varying datasets.

We believe in-formation flocking is capable of representing highly volatile, even potentially chaotic, time-varying datasets. By exploiting the concept of emergence and self-organization, this research proposes an alternative data mapping technique that is not predefined or predetermined as in common data mapping techniques within the field of information visualization. In-formation flocking is capable of providing a global and local view of the whole dataset over time based on animating readily recognizable and interpretable motion typologies.

## 2 Background

The original *information flocking* approach applies emergent spatial clustering behavior of boids to the field of data visualization by assigning a unique data object to each boid [2]. As the three basic behavior rules are extended with an additional data similarity rule, boids with similar data objects tend to flock towards each other. As an emergent result, underlying similarity relationships between data objects are revealed through the formation of separate spatial clusters. More recently, the information flocking concept has been extended to complex and time-varying datasets, and the representation of dynamic data tendencies by distinct dynamic motion typologies [3]. Other research has combined the information flocking algorithm with foraging behavior, enabling clusters of data items to be found according to their spatial position and density [5]. In contrast, our research is not concerned with data mining applications, but focuses on generating more readily discernable, self-organizing information displays.

The boids concept is an example of a *decentralized multi-agent system*. An *agent* is a system situated within an environment, which senses its immediate environment and can act on it autonomously, over time, to achieve a set of objectives [6]. Some agents can collaborate with others, can perceive and respond to changes, and can exhibit goal-directed behavior. A *multi-agent system* consists of multiple agents, mostly because they pursue different goals, or because the environment is too complex for a single agent to observe efficiently. A *decentralized multi-agent system* contains numerous equal agents that have communication links with those in their neighborhood, either directly or through the environment, but always in absence of a centralized coordinator. In visualization, several agent-based approaches have been used to display internal properties, such as the relationships between agents for monitoring and engineering purposes [7]. Multi-agent systems have been implemented to structure the data flow, such as for the generation of information visualizations of complex fuzzy systems [8], or to determine the choice of the most effective visualization method depending on the dataset and user tasks [9]. Self-organizing systems have been used to create emergent spatial organizations which reveal relationships between data objects. The *Narcissus* approach, for instance, aims to integrate behavioral rules into agents in order to aid the comprehension of both high-level and low-level structures using distinctive emergent shapes [10].

*Motion* is a powerful graphical cue that is capable of attracting attention, maintaining motivation and facilitating comprehension, learning, memory and efficient communication in the contexts of learning or knowledge discovery. Generally, animated objects follow predefined paths or trajectories defined by specific mathematical functions or user-defined control points. Alternatively, motion can be generated by behavior rules, which are inherently unpredictable and more suitable to convey interpretative behavior. Some researchers have demonstrated that even simple motion cues can reveal causal relationships, as launching, entraining and triggering [11]. Ware et al. have demonstrated the rich expressive visual language of motion in the context of information visualization [12]. Lethbridge and Ware [13] used behavior functions based on distance, velocity and direction to model complicated relationships such as pulling, pushing, chasing, escaping, repulsion, collision and anticipation.

Conceptual flocking models reveal that overall group structures in animals are directly affected by transformations at local levels [14]. That is, high-level aggregate movement is dictated by a decentralized system of individuals. This concept has been applied to the decentralized *formation* of robots in space [15-17]. Fredslund and Mataric employ a *neighbor-referenced* approach, which requires that robots attempt to stay at a fixed distance and angle from their so-called robot *friend* [17]. This approach only requires one robot – the friend – to determine the heading of another, rather than more centralized approaches such as *unit-center-referenced* (i.e. robots determine their positions relative to a centre average) and *leader-referenced* (i.e. positions are determined relative to a single leader). Thus, in neighbor-referenced formation, a single *conductor* or *leader*, is able to 'drag' a whole formation forward through the downward filtering of iterative friend relationships [17]. Other researchers have compared the appropriateness and optimization of each of these three techniques to the problem of *obstacle avoidance* [15, 16].

## 3 In-Formation Flocking Approach

In our in-formation flocking approach, each boid represents a unique data object, retrieved from a time-varying dataset. As illustrated in Figure 1, each boid has a limited field of perception, and is able to communicate only with boids in its immediate vicinity. Each boid is governed by an identical set of behavior rules, which are executed in parallel for the whole boid collection. These rules determine the visual characteristics of a boid, such as its speed and direction. The rules take into account any time-varying changes in the data object which the boid represents, as well as the relative positions, velocities and data values of the boids in its immediate neighborhood. During the visualization, the data values for each boid are updated to match the data values of the next successive iteration in the time-varying dataset, according to a virtual timeline. As a result, each boid is continuously governed by a small set of behavior rules which are directly affected by its own data values as well as those of its immediate boid-neighbors.

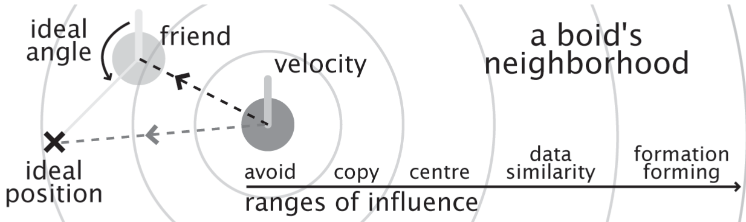


**Fig. 1.** A boid (center), its view of the neighborhood and its flocking rules ranges of influence.

These local, data-driven influences between pairs of boids cause an emergent pattern of visual formations to appear on a global scale. Notably, boids can consider local information only, and have no reference to the global pattern they may be part of. These patterns are able to represent dynamic dataset alterations, as they are essentially formed out of the interactions between pair-wise members according to their relative data values. The visualization is self-organizing and based on the dynamic properties of the underlying data phenomena rather than a traditional, predetermined data mapping rules that directly translate data values into visual form.

### 3.1 Behavior Rules

Each boid obeys five behavior rules, which are determined by pair-wise comparisons between boids. A behavior rule is only invoked when a boid is in the field of vision of another boid. The fields of vision are ordered by size, where $d_{avoid} < d_{copy} < d_{centre} < d_{similar} < d_{formation}$ so that the behavior rules act as sequential steps and do not overlap.

**Rule 1. Collision Avoidance.** Each boid avoids any other boid which is within the collision avoid range $d_{avoid}$. This rule withholds boids to visually overlap, as it causes them to actively move away from each other when nearby.

**Rule 2. Velocity Matching.** Each boid copies the direction and speed of any other boid which is within the velocity matching range $d_{copy}$. This rule causes groups of boids to move towards a similar general direction.

**Rule 3. Flock Centering.** Each boid moves towards the perceived center of gravity of all neighboring boids, present within the centering range $d_{centre}$. This rule causes localized flocking to occur, so that little internal order occurs over time.

**Rule 4. Data Similarity.** Each boid moves towards any other boid with a similar data object within a distance range $d_{similar}$ and a data range of $q_{similar}$. This rule groups boids that experience similar data changes [2, 3]. It is proportional to distance, so that boids far away move more quickly towards each other than those nearby.

**Rule 5. Formation Forming.** Each boid attempts to reach a spot that is positioned at a specific distance and angle from the most similar boid within a formation finding range $d_{formation}$ and a data range of $q_{similar}$ [15, 17]. This rule causes visually distinguishable formations to form containing multiple boid members.

The different weighting factors $w_r$ are applied to the vector outcome $v_r$ of each behavioral rule, depending on the importance of its relative influence. A new velocity $v_{new}$ is calculated using these vectors, and added to the current velocity. $d$ is the distance between a boid and its neighbor in a pair-wise comparison.

$$v_{new} = d.v_{flocking} + \frac{v_{formation}}{d}$$
$$with \begin{cases} v_{flocking} = -w_{avoid}.v_{avoid} + w_{copy}.v_{copy} + w_{center}.v_{center} + w_{similar}v_{similar} \\ v_{formation} = w_{formation}v_{formation} \end{cases} \quad (1)$$

## 3.2 Formation Flocking

The in-formation flocking approach extends the original information flocking algorithm [2, 3] with an additional formation-making rule. This rule generates formations consisting of boids that have experienced similar data value changes between successive time steps. In order to exhibit in-formation flocking (or formation forming) behavior, a boid's data change must be greater than a *minimum relative data value difference threshold* $q_{change}$, which is the relative change in data values between the current and previous time steps of the time-varying dataset.

$$q_{change} = \frac{(q_{current} - q_{previous})}{q_{previous}} \quad (2)$$

If the difference between a pair of boids' $q_{change}$ is less than the minimum data value difference threshold, normal *information flocking* behavior will be exhibited, that is similar boids will move together in independent flocks. Only if $q_{chang}$ between a pair of boids is more than the predefined minimum threshold value will formation forming be invoked, described by the following steps.

For a predefined data attribute, each boid attempts to find another boid that contains the most similar data values, here called *friend*. Accordingly, once the boid-to-friend relationship is established, the boid becomes its friend's *follower L* (friend and follower terminology is borrowed from [17]). As a restricting rule, each boid may only have one single friend $F$ and one single follower $L$. More specifically, for a boid $X$ with data change $q_X$ to become the friend of a boid $A$ with a data change $q_A$, where $q_{similar}$ is the maximum largest difference between the value of two points:

$$\begin{cases} q_X \geq q_A \\ |q_A - q_X| \leq q_{similar} \end{cases} \quad (3)$$

A data splitting rule internally orders resulting groups. If boid $X$ already has a follower $F$ with change $q_F$, boid $A$ may only split this relationship if it is more similar:

$$|q_A - q_X| \leq |q_L - q_X| \quad (4)$$

As boids split their friend-follower relationships when 'more similar' boids have been detected in its neighborhood in an iterative fashion, formations are ordered by data similarity along the chain of friends and followers, providing a chain-like representation of data similarity. This process of friend- and follower-determination happens continuously, so that the formations constantly change as all data values are continuously updated over time.

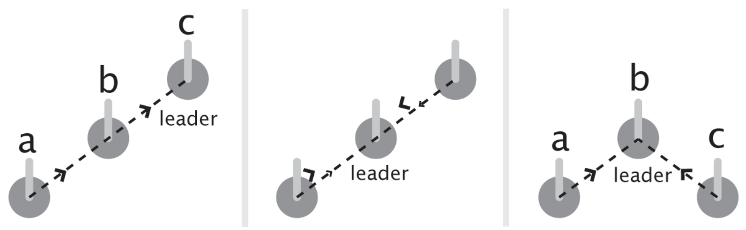


**Fig. 2.** Reversal of relationships in a friend-follower chain to generate a 2-sided formation.

The aim of each boid in a formation is to stay close to an "ideal position" relative to its friend as defined by a distance and an angle, proportional to the data attribute. This relatively simple means of formation-forming would obviously result in a single, straight line. Our approach of formation forming, however, entails that a wedge-like shape with two arms to either side is produced by specifying a single boid as a *leader*, which in turn is followed to the left and right side by a number of boids, as shown in Figure 2 Accordingly, one half of the boids in the formation must reverse their friend-follower relationships, and follow their followers rather than their friends. Because of the data splitting rule, all boids are ordered emergently by data similarity from left to right (or vice versa) along both the wedges. As shown in Figure 3, in the case of a formation with an even number of boids, one of the middle boids must follow the other directly (orthogonally) to the side.

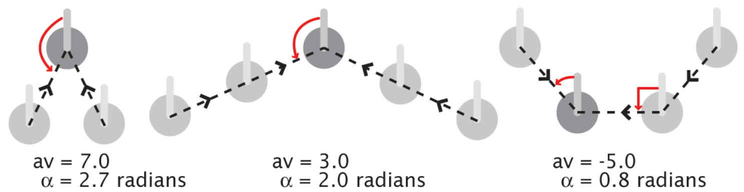


**Fig. 3.** Wedge and inverted-wedge shapes reflect positive and negative data value averages. A sharper angle between arms reflects larger variation in data change for the whole group.

The angle at which each boid follows its friend is controlled by an averaged data value of the whole group. This average is determined by the boids in a decentralized manner, in which each boid in a formation recalculates and passes on a new average from its friend to its follower. The angle *a* of a wedge is determined by the *average data value av* and a predefined maximum average data value *max*.

$$a = \frac{p}{2}.\left(1 + \frac{av}{max}\right) \quad \textbf{(5)}$$

Figure 3 shows the emergent result of this algorithm: a *negative* numerical average value will construct an inverted-wedge: boids move in the opposite direction than the direction of the wedge. Accordingly, a *sharp* peak (i.e. small wedge angle) indicates a high average data change while an almost *wide* angle or horizontal line (i.e. large wedge angle) conveys close to no variation in the boids' data values.

The ideal distance $d_{ideal}$ between a boid and its friend is determined by their relative data similarity, proportional to the maximum difference $q_{similar}$. The distance $d_{step}$ is interpolated between a minimum $d_{min}$ and maximum $d_{max}$ in which a friend must lie in.

$$d_{ideal} = d_{min} + \frac{|q_A - q_X|}{d_{step}} \qquad \text{with} \quad d_{step} = \frac{q_{similar}}{d_{max} - d_{min}} \tag{6}$$

Using knowledge of a friend's position $F_{pos}$ and velocity *vel*, in addition to the angle *a* to follow a boid *A* calculates its ideal formation position $B_{formation}$. The boid then calculates its new position $B_{new}$ according to $B_{formation}$ in the following manner.

$$\begin{aligned} \vec{B}_{formation} &= (\cos a \,.\, vel_x - \sin a \,.\, vel_y, \sin a \,.\, vel_x + \cos a \,.\, vel_y) \\ \vec{B}_{new} &= \vec{B}_{formation} + \vec{F}_{pos} - \vec{A}_{pos} \end{aligned} \tag{7}$$

The resulting angles are scaled depending on the relative position of a boid along a wedge to generate a unified curved-like wedge rather than a sharp difference between the two arms, as illustrated in Figure 4 In addition, members of a formation are connected by a continuous spline. Both these visual features emphasize formations as distinct, continuous shapes rather than two separate sequences of objects [18].

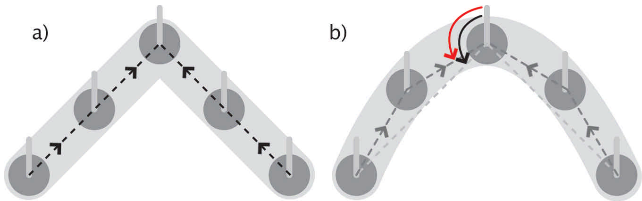


**Fig. 4.** Altering the relative formation angle from a straight line (a) to a continuous curve (b).

## 4 Data Analysis Scenario

The in-formation flocking approach was implemented for a large, complex, time-varying dataset: the historical US stock market opening and closing prices, and volume traded, over a one-year period of the 500 leading US companies [19]. Our current prototype application, programmed in Java3D, includes several interactive sliders. These interactive tools were especially required while developing for fine-tuning the weights and threshold values towards the most optimized emergent results.

Each boid represents a single stock market quote company. The formation flocking represents the percentage change in closing price over a day. The *minimum data value change threshold* for a closing quote price change is 3%. The maximum difference $q_{similar}$ between the data value of a boid and its friend is fixed at 0.1%. The volume traded each day is represented by the relative size of the boid.

Several patterns and tendencies can be perceived using the in-formation flocking approach. Firstly, data-similar groups of boids which have experienced relatively large changes in value are highlighted through formation forming. The number of boids involved in each formation shows the extent to which the similarity is common. The shape of the wedge reflects the average across the formation, which can then be compared with other groups. This shape is emphasized by the use of a continuous, underlying curve, in order to link members of a group, and differentiate between the shapes of emerging flocks (for example, formations *a* and *b* in Figure 5).

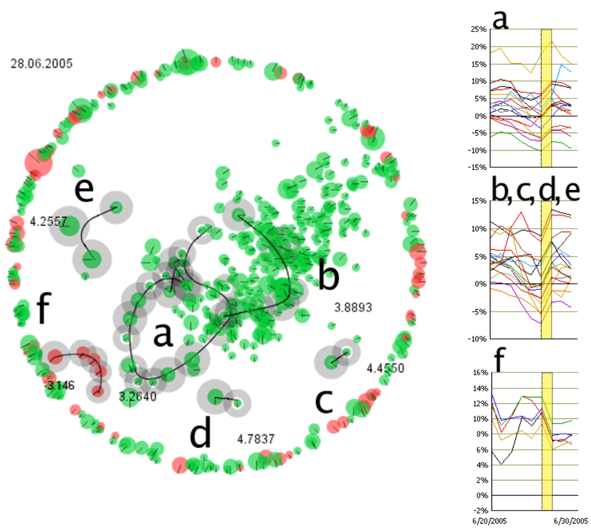


**Fig. 5.** Components of in-formation flocking after 250 iterations: separate groups emerge on 28 June 2005, with differentiating features: size, angle, and direction, versus traditional price history line charts. Each formation represents stocks which have experienced almost identical stock price changes (identical / parallel stock price changes, as highlighted in yellow on the line charts). (Charts are based on MSN *MoneyCentral* http://moneycentral.msn.com).

The traditional line charts in Figure 5 highlight the correlations between the data changes and formation representations. For example, chart *f* shows the almost identical, steep drop in price experienced by all the boids in formation *f* at exactly the same time. Although all groups from *a* to *e* have experienced similar, parallel increases in price as can be perceived from charts *a* to *e*, the formations clearly show five separate subsets which cannot be readily seen in the charts. Formation *c* corresponds to the pair of lines at the top of chart *b* to *e*; this is due to the similar starting and ending points of the line for that particular day. Although the line charts might seem more comprehensible in showing stocks which have experienced similar price changes, they only show a small subset of the total of 37 stock quotes in the dataset. In contrast, in-formation flocking is able to depict the whole dataset while highlighting meaningful data patterns as they happen and change over time.

The current prototype allows several different subsets of data similarity to be visually depicted, through the use of motion typology and color coding. Figure 6 shows the in-formation flocking on one of the worst days experienced by the stock market in 2005. Several distinguishable groups emerge: a large group of boids move in formation *c*, two smaller formations *a* and *b*, a green and red cluster, and a large red flock which has separated itself from the others. The visual focus lies on the emerging formation *c*, which correlates with a large group of similarly-changing boids between the values of -3.5% and -2.9% for that day (see histogram). A histogram of the stock market on the day reveals that the spatial separation of the large red group from the others is representative of the dip that occurs around -0.7%.

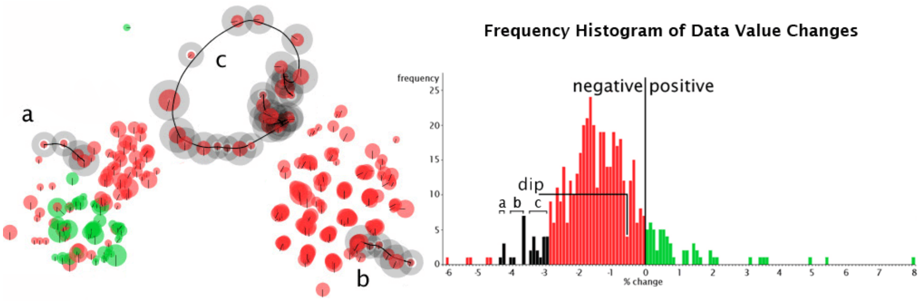


**Fig. 6.** The state of the stock market on 22 February 2005, as shown by its constituent subsets of data changes, versus a frequency histogram of data value changes. Formations *a* and *b* represent two groups of stocks experiencing large data changes (less than -4%); formation *c* reveals a large emerging group experiencing changes of between -3% and -4%, while two red information flocking clusters highlight the distinct dip as seen in the histogram.

In Figure 7, there are three formations consisting of stock quotes which have all experienced large positive price changes of over 3%. Formation *a* is a flock which has experienced a high average data of 5.6%, represented by a narrow wedge angle. In contrast, formation *b* and *c* convey a wider angle between the wedges, as they experienced an average data change of 3.0% and 3.5%, respectively. The relative distance between boid members in each formation conveys the relative similarity linking the boids and their friends. For instance, in formation *b*, boid PD is much closer to its friend, NSC, than NSC is to its friend UST. This data dependency is also reflected in the data tables, showing how PD versus NSC percentage change (0.007) is smaller than NSC to UST (0.05).

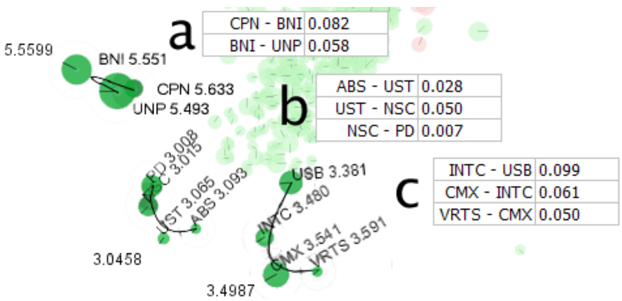


**Fig. 7.** Shape comparison between different formations on 21 December 2004, as related to the group average. The tables show differences in change between boids and their friends.

Figure 8 shows the difference in formation patterns when altering the weight values for the minimum relative data value difference threshold *mt* and maximum difference *md*. Increasing the minimum threshold causes less boids to satisfy the rule for minimum change thus creating low numbers of groups exhibit in-formation behaviors (Figure 8, *a* and *b*). Decreasing the minimum threshold causes more groups to form (*d*). Increasing the maximum difference creates longer chains of boids (*a* and *c*), whilst decreasing the difference causes shorter chains groups to form (*b* and *d*).

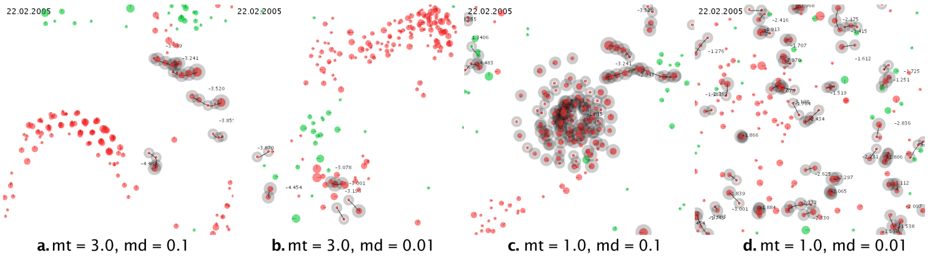


**Fig. 8.** Formations differences by adjusting *minimum threshold (mt), maximum difference (md).*

## 5 Discussion

The in-formation flocking approach highlights several important characteristics.

**Decentralized Multi-Agent System for Data Visualization.** The agent-based methodology supports the dynamic nature of time-varying datasets as each individual 'data object' continuously adapts to a changing neighborhood of data values. The decentralized approach is fundamentally different from the normal data mapping method in data visualization, as the resulting visual cues are emergent and inherently unpredictable. It forms the first step towards data visualizations that self-organize, capable of recognizing and highlighting data patterns in an unsupervised fashion

**Motion Typology as a Visual Cue.** The use of movement enhances the connectedness between similar boids through uniform velocity and direction, and through the formation of shapes and wedges. Dissimilar clusters of boids can also be differentiated by comparing motion typologies. In this work, the use of motion is necessitated by the nature of time-varying data, which can be studied over time in order to create an understanding of complex, dynamic trends that happen in parallel.

**Application Domain.** We claim that in-formation flocking is most appropriate for representing noisy or highly volatile time-varying datasets with hundreds of data items. Datasets with underlying (but not explicitly-defined) group-structures between data objects could also be effectively represented by both in-formation and information flocking. These methods are specifically useful in recognizing short- and long-term trends and tendencies that were not known before.

**Parameter Dependency.** Emergent pattern quality is highly dependent on predefined algorithmic parameters, which generally need to be fine-tuned in relation to specific dataset characteristics by a process of trial-and-error. However, even these characteristics generally change over time within a dataset (e.g. volatility of data alterations, data size) questioning the validity of keeping these parameters constant.

**Performance.** The current implementation has not been optimized for any performance issues in the context of computational efficiency or visual rendering, as we instead focused on demonstrating the in-formation flocking concept. As a worst-case scenario, the performance for $n$ boids is $O(n^2)$ dramatically increasing the number of calculations needed as the number of boids increases. As ascertained through experimentation, a visualization of about a thousand items slows down the frame rate between one and two frames per second on a computer equipped with a Pentium M 2.0GHz processor. Improvements in processing speed could be achieved by updating only a portion of the boids at each iteration, delegating the calculation and rendering tasks between two processors, or requiring only one boid in a pair-wise comparison to perform the necessary calculations.

**Formation Flying.** As mentioned previously, research in the field of biology suggests that the shape and angle at which birds fly in formation is variable to the relationship between birds and to energy considerations within the flock [4]. Although this research does not aim to create an accurate simulation of natural phenomena, it may be beneficial to integrate knowledge about the physics of and social reasons for formation flying in order to create a truly biologically-valid data visualization. The use of phenomena discovered in nature as a metaphor for information visualization may aid the understandability and learnability of the approach for users. In particular, the use of artificial life insights also demonstrates how interdisciplinary knowledge can enrich the field of data visualization [20].

## 6 Conclusion

This paper presented a novel approach of visualizing complex, time-varying datasets using a decentralized, multi-agent formation flocking metaphor. It extends the original notion of information flocking [2, 3] with the concept of in-formation flocking, which is implemented as a single, relatively simple, additional behavior rule. As a result, each boid continuously searches and positions itself relative to data-similar friends, resulting in visual formations that can interpreted in the context of time-varying data tendencies and trends. The relative distance between boids in a formation reflects their degree of similarity, while the wedge angle of the formation visualizes the average data variation experienced by the group. Thus, the shape of each formation in addition to the spatial clustering of boids creates an overall representation of data patterns within time-varying datasets.

With the future integration of algorithmic optimizations, in-formation flocking could be applied in real-time to time-varying datasets consisting of thousands of items. Future developments could integrate additional features to convey underlying data phenomena (e.g. news stories) as flock obstacles or attractors. The application could be enhanced by including dynamic user querying and filtering, and the ability to trace data values or formations. Behavioral rules could be made more flexible to increase the number of emergent characteristics for representing a larger range of data attributes. Further research should focus on user evaluations to analyze the potential for this approach in the context of complex pattern discovery for time-varying datasets and the use of motion typologies for interpreting dynamic data patterns.

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