VISUALISING COLLABORATION IN VERY LARGE DESIGN TEAMS

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Abstract

The scale of design teams for complex engineering products poses problems associated with the representation of the activities and interactions of designers on a social level. Conventional project management representations of organisation charts and graphs about deliverables are not likely to offer understandable overviews about how the team is performing on a social level. The aim of this article is to describe a new way to represent design activities through information visualisation using rules relating to language-based descriptions of actions, events, and objects in design team communication. We developed new methods in the field of information visualisation to represent patterns in design team communication that may indicate the social accounting of teamwork. We tested the method on a conversation during the conceptual design of a consumer artefact by a well-described team in the research literature to test whether our visualisation method could uncover some dynamics of teamwork.

Keywords: Design teams; collaborative design; computational linguistics; information visualisation; design team management

1 Introduction

Engineering is no longer a localised operation. Temporal and spatial dispersion means that inter-organisational and virtual engineering design teams rely principally upon ICT systems for communication [1]. Their group dynamics are difficult to manage since conversations over computer-mediated communication can be easily misconstrued. The problem is not that teams do not communicate; often, they communicate too much. Most studies find that the implementation of electronic communication increases the overall amount of communication [2]. As a consequence, they may spend more time working on relationships rather than “getting the job done.” Identifying the factors that influence successful teams in engineering design is a serious topic. But the methods employed to identify them are problematic. Organisational behaviour methods for team performance management rely heavily on discourse analysis [3], controversial psychometric evaluations [4], and human coaches – methods that are often unrealistic for practical implementations and cannot deal with the real-time nuances of team collaboration. Finally, these methods tend to treat the design team as a unit of analysis and a unit of observation – rather than offer the design teams introspective methods. There are several studies (e.g., [5]) which indicate that the analysis of one’s own behaviour is a prerequisite for modifying inadequate social processes.

The aim of the research is to develop an information visualisation method that would allow design teams to assess their teamwork dynamics. Our interest is not to visualize how design information relates but instead to reflect how the designers relate to one another. By making it easy and practical for reflection-in-action on the social effectiveness of team collaboration, we believe that the likelihood of high-performing teams is increased, leading to more productive outcomes.

There have been precedents in the area of examining the interrelatedness of design teams. Notable examples in engineering and product design include the following. The Virtual Design Team (VDT) research project [6] developed a mathematical model of activity interdependencies and associated coordination requirements for design teams. Within an information processing view of an organisation, the model calculates work loads and efficiencies for different organisational designs. While the VDT model assumed an ideal organisation, a recent study based on design structure matrices highlighted the potential misalignment between product architecture and the communication and organisational interfaces between product design teams [7]. Our primary point of departure from these studies is that we pay close attention to the *content* of communication between design team members and explicitly model, based on the content, how each communicative act is similar to, and perhaps influenced by, other communicative acts. Each team member is seen as behaving independently but influenced by external factors including the ideas and design concepts of other designers, the organisational structure, and the current state of the designed artefact. The collection of the team members and their actions and influences of their actions could be regarded as an actor-network [8]. Consequently, the visualisation is intended to characterise the team as it is actually performing (on a social level) given the situation.

The creation of any information visualisation system requires five stages: 1) The identification (or establishment) of an abstract data set which captures the relevant phenomena of interest; 2) The selection of an information visualisation metaphor and or tool that may be capable of revealing the phenomena from the data set in a human understandable way; 3) Mapping between the phenomena and the information visualisation metaphor; 4) Implementation; and 5) The evaluation of the visualisation according to various metrics such as case studies of the discoveries and awareness of information afforded to viewers by the visualisation [9]. In this bench-scale study, we focused on the creation of a data set that captures the way that designers relate to one another through the content of their language-based communication and the development of an appropriate information visualisation technique. In both instances, we paid careful regard towards scalability such that our techniques could apply to design teams consisting of more than 100 and even thousands of members. Our approach is through the instrumentation of computational methods that take advantage of advanced computational linguistics and information visualisation to enable explorations into the dynamics of engineering design teamwork. We tested our information visualisation on a small data set to verify the suitability of our approach and present our findings herein.

Before proceeding to a description of our method, it is worth considering whether computation, rather than social or cognitive science for example, is a satisfactory approach for understanding human behaviour in design. Using computers to understand humans is a primary research aim of artificial intelligence (AI). A common approach is to model humans as a knowledge-based system where the knowledge is encoded by semiotics and operated upon by information processing systems [10]. This is also the standard approach taken in design cognition research which provides an explanatory framework for how designers think based on rules and representations of the cognitive structures in individual designer's minds. We could categorise these as the symbol system approach in AI research. Alternatively, there exist methods in modelling human behaviour that uses participant activity as the way to model their behaviour.

This distinction could be described by contrasting the ways in which information retrieval research has been carried out. The field of information retrieval deals with methods for structuring and retrieving information from full-text documents. The classic approach is to organise and index the full-text documents from the perspective of a person who could have read all of the documents in the corpus and conceptually chunked them. There is a fundamental premise of a person's state of mind and how a person would categorize information. A contemporary approach takes an alternative view; what if, instead of positing a mental model, the information retrieval activities of people were modelled? This is the basis of link-based analysis techniques in information retrieval where the relationship between a set of documents is computed by a link structure derived from the conferred authority to a document as determined by authors of other documents [11] and serves as the basic architecture of Google, the Web's most popular search engine [12].

Similarly, our approach is based on associating relations among components of knowledge stored in each designer's mind (i.e. experience) and the larger body of experience held by the team as represented by the language-based communication expressed by the designers. The theoretical work of the Russian school of constructional psychologists such as Vygotsky and Bakhtin has influenced our research (e.g. [13]) in analysable features of the words expressed by (groups of) designers during their work, especially how design concepts and knowledge were produced through discursive construction. This influence is also seen in research in "mapping" out the relationships between people in online communities [14].

In this paper, we explore the dimension of *idea cohesiveness* as one dimension of teamwork dynamics to assess the relations among components of knowledge stored in each designer's mind and the larger body of experience held by the team. We start with the concept of idea cohesiveness because similarities between ideas may indicate shared understanding, a critical social dimension for effective teamwork. Other social accounting metrics of teamwork include leadership, social cohesion, and knowledge sharing. We present in the next section our computational linguistics and information visualisation method to represent the interconnectedness of the participants, not just from a frequency of communication standpoint but rather from influence, contribution and idea uptake perspectives.

2 Methodology

2.1 Information Flocking

Visualisation, the representation of data graphically rather than textually, uses the high bandwidth human perceptual and cognitive capabilities to detect patterns and draw inferences from visual form. Information visualisation has emerged over the past fifteen years as a distinct academic field that is inspired by the fields of computer science, psychology, semiotics, graphic design, cartography and art. Information visualisation addresses the need to represent the structure of and the relationships within abstract datasets, which are characterised by their lack of a natural notion of position in space.

In this research, we used the concept of *information flocking*, originally introduced by Proctor and Winter [15], to represent the dynamics of teamwork and collaboration. This information visualisation technique is based on the mathematical simulation of flocking birds or swarming fish, a method that is normally used by the computer graphics community to simulate specific real-world effects in computer animations or virtual worlds. Flock behaviour has already been simulated to generate a mathematical model of dynamic formations to characterise swarms with respect to the implementation parameters of wireless, ad-hoc network communications systems [16]. Their research demonstrated how different sorts of swarm behaviour, such as ordered or chaotic, tight or loose, and global or regional can be used to analyse the communication link establishment performance in communication networks. Flock behaviour is also an effective search strategy for exploratory geographical analysis, for instance to detect visual clusters in large collections of points [17]. Swarm behaviour is an example of a new kind of social intelligence model, called Particle Swarm Optimization (PSO), that, like other evolutionary computation algorithms, can be applied to problem solving, learning and optimization problems in the fields of system design, pattern recognition, biological system modelling, signal processing, decision making, simulation and identification, and so on [18].

In practice, the swarming motion typology is generated by a small set of behaviour rules originally introduced by Reynolds [19], who successfully modelled the movements of so-called boids (or bird-objects) within a flock. A plausible functional explanation for social flocking behaviour describes how animals at the edge of the herd are more likely to be selected by predators [20]. Accordingly, boids would 'selfishly' attempt to move as close to the centre of the herd as possible, and thus, in information visualisation terminology, spatially 'cluster'. In fact, such boids act as simple, decentralised agents; they are situated, viewing the world from their own perspective rather than from a global one, and their actions are determined by both internal states as well as external influences. The original information flocking method applied principles of self-organisation and behaviour simulation to represent data patterns in static datasets by spatially clustering data objects that are similar or related. We have extended this original information flocking method to include distinguishable motion typologies that are able to depict dynamic tendencies and long- as well as short-term evolutions in large, time-varying datasets [21].

Because design ideas and concepts are introduced and changed dynamically during the life cycle of the design process, we believe that self-organisation by flocking is a more apt metaphor than classical concept clustering algorithms which mostly operate on a priori non-time-varying datasets.

2.2 Motion Typology as Visual Cue

The information flocking visualisation technique attempts to exploit the cognitive capabilities of the human visual system to directly relate simple motion typologies to complex behavioural reasoning. Results from different psychological studies suggest that motion holds promise to convey meaning and thus is capable to describe how different elements are related. However, motion is still an underutilized vehicle for displaying informational values, as most current visualisation techniques still use static patterns, even to represent time-varying datasets. However, motion can be considered as a visual attribute of an object that represents information, and thus be treated along with other, more common visual cues, such as size, colour and position.

Psychophysical evidence has shown that, within certain limits, humans tend to resolve motion with emotional connotations. Michotte [22] suggests that causal relationships can be perceived directly when specific simple animation techniques are used, such as launching, entraining and triggering. Lethbridge and Ware [23] used simple behaviour functions based on distance, velocity and direction to model complicated behavioural relationships such as pulling, pushing, chasing, escaping, repulsion, collision and anticipation. Heider and Simmel [24] demonstrated that observers attribute high-level intentions and even emotions to movements of simple, geometric shapes. In the context of visualising design collaboration, the dynamic motion of boids that represent team members may reveal patterns of teamwork dynamics such as leadership, cohesion, influence, and direction.

2.3 Implementation

Each single boid represents one unique team member and is placed in a three-dimensional virtual space. Each boid is capable of perceiving other boids in its close vicinity. In fact, the direction and speed of each boid A with position $\vec{p}_A$, is dependent on all the boids X with position $\vec{p}_X$ in its neighbourhood, following specific behaviour rules.

- **Collision Avoidance**. A boid will pull away from nearby boids to avoid collision. If the distance between boid A and any boid X is within the collision avoidance range d_{CA}, a directional vector pointing away is calculated, of which the strength is inversely proportional to the distance between these boids.

$$\|\vec{p}_X - \vec{p}_A\| \le d_{CA} \Rightarrow \vec{v}_{CA} = \sum_X \frac{|\vec{p}_X - \vec{p}_A|}{\|\vec{p}_X - \vec{p}_A\|}. \tag{1}$$

- **Velocity Matching**. A boid will attempt to move with approximately the same average speed as the boids in its neighbourhood. If the distance between boid A and any boid X is smaller than a specific velocity matching threshold d_{VM}, but larger than d_{CA}, boid A should attempt to take over the direction of boid X, and this for all boids in its neighbourhood.

$$\left.\begin{array}{l} \|\vec{p}_X - \vec{p}_A\| \le d_{VM} \\ \|\vec{p}_X - \vec{p}_A\| > d_{CA} \end{array}\right\} \Rightarrow \vec{v}_{VM} = \sum_X \vec{v}_X \tag{2}$$

- **Flock Centring**. A boid will attempt to move towards the centre of the flock (as the boid perceives it). For all boids X in its neighbourhood, if the distance between $\vec{p}_X$ and $\vec{p}_A$ is smaller than the flock centring limit, boid A should try to direct itself towards the perceived centre of gravity of all boids X combined.

$$\left.\begin{array}{l} \|\vec{p}_X - \vec{p}_A\| \le d_{FC} \\ \|\vec{p}_X - \vec{p}_A\| > d_{CA} \end{array}\right\} \Rightarrow \vec{v}_{FC} = \sum_X |\vec{p}_X - \vec{p}_A| \tag{3}$$

Following these traditional flocking rules, the boids will spatially reorganise and cluster following a swarming behaviour, which is an 'emergent' and coherent effect, as each individual boid is not specifically instructed to do so. The information flocking technique will adjust this behaviour to provoke spatial clustering and similarity in dynamic movements according to the dynamically changing data values that the boids represent. Accordingly, in addition to the previously mentioned traditional flocking rules, the boids are determined by the following data similarity rule.

- **Data Similarity**. A boid will attempt to stay close to boids that are in its neighbourhood and are interconnected in the context of the data values that it represents. Data similarity, in this case the connectedness between design collaborators, is determined by calculating the difference between the data values that the boids represent. Consequently, the strength of the attracting force is proportional to the distance between the boids and the connectedness between design participants.

$$\|\vec{p}_X - \vec{p}_A\| < d_{DS} \Rightarrow \vec{v}_{DS} = \sum_X (A,X).|\vec{p}_X - \vec{p}_A|.\|\vec{p}_X - \vec{p}_A\| \tag{4}$$

$0 < w_{CA}, w_{VM}, w_{FC}, w_{DS} < 1$ are weights applied to Collision Avoidance, Velocity Matching, Flock Centering, and Data Similarity behaviours respectively. $\vec{v}_A, \vec{v}_{CA}, \vec{v}_{VM}, \vec{v}_{FC}, \vec{v}_{DS}$ denote the accumulated velocity vectors. After each boid has checked the four behaviour rules for all boids in its neighbourhood, the flocking algorithm normalises for large accumulation vectors. Next, the final new direction and speed of boid A is determined by adding all four accumulation vectors, scaled by weight factors that denote the importance of each behaviour rule within the context of the preferred global behaviour of the boid.

$$\|\vec{v}_x\| > 1 \Rightarrow normalize(\vec{v}_x) \rightarrow x = \{CA, VM, FC, DS\} \tag{5}$$

$$\vec{v}_A = -w_{CA}.\vec{v}_{CA} + w_{VM}.\vec{v}_{VM} + w_{FC}.\vec{v}_{FC} + w_{DS}.\vec{v}_{DS} \tag{6}$$

In practice, the Flock Centering and Velocity Matching weighting factors are relatively small, to avoid any erratic movement or spatial splitting of the global flock, and to provide the data similarity rule enough room to cluster similar boids. One should note that the flock never attains a static equilibrium, and instead is determined by continuing swarming characteristics. Accordingly, it is necessary to stabilize this behaviour as much as possible by fine-tuning both the different weighting factor values and the according threshold distances. The exact numerical values of these variables are determined through a process of trial and error, as the information visualisation designer is mostly unable to foresee the exact outcomes of the numerical values due to the shear multitude of simultaneous local interactions between all boids.

Each boid represents the succession of states of a single team member for a series of time spans within the whole design process timeline. In practice, this means that for approximately each second during the visualisation, a boid simulates and represents about 6 seconds worth of design discussion. The user is capable of pausing and rewinding the boids' movements, to explore and navigate the three-dimensional world in order to replay and discover specific time-varying tendencies. In addition, a user can choose to enclose the boids in three-dimensional mesh shapes to augment the visual perception of spatial proximities and directional trends. Accordingly, by driving the rule-based boid behaviours by the values stored in the data set (numerical values depict the interconnectedness of the participants from an influence, contribution and idea uptake perspectives) during an accelerated timeline simulation, individual (e.g. chaotic or stably atomic boid behaviour) as well as global similarities (clustering or avoidance between boid groups) and dynamic tendencies become visualised. Where they differ, the boids diverge. The speed of convergence and divergence is captured in the "strength of ties" of the relation.

2.4 Dataset

Generally speaking, there is no data that is stored by a company that would necessarily capture the teamwork dynamics. Because the information visualisation metaphor of flocking generates the emergent behaviour of spatial reorganisation and clustering, the data should not itself directly calculate the clustering of one team member to another. The direct calculation of cohesion is commonly taken in studies of social networks wherein the metrics used to compute the network are based on, for example, the frequency of communication between people or the organisational distance between people. Regardless, the data is synthetic and must be generated from a primary data source, such as electronic communication. The data set for this research was generated from a transcript of a design team conversation. To quantify measurements of interconnectedness using our metaphor of information flocking, three rules are proposed.

- **Rule 1.** The baseline is the number of words per communicative act (Rule 1). A communicative act could be a document, an e-mail, or an utterance during a synchronous conversation (i.e., the primary data source). It is reasonable to assume that in constructive teamwork, the amount of communication each person contributes is, to a first-order approximation, equivalent. Clearly, an imbalance exists if one or more persons dominate.

- **Rule 2**. However, counting words is a fairly rudimentary way of encoding the amount of information and the similarity between two information sources that produced that information. As a refinement, Rule 2 is based on the information content of each speaker's utterance using Shannon's formulation of information entropy [25]. This rule encodes the similarity of the information sources (the team members) that produced the utterances. Suppose we have a set of possible design concepts, ideas and issues, what we propose to call the *design space*. Further, suppose that the design space is expressed semantically as lexicalized concepts in each communicative act. We can calculate the probability of occurrence of a lexicalized concept in the communicative act using the equation $p_i = \frac{tf_i}{idf_i}$ (7) where *tf* is the term frequency (number of occurrences) of a lexicalized concept in a communicative act *i* and *idf* is the inverted document frequency, the number of times a lexicalized concept appears over all recorded communicative acts. We can then quantify the amount of information contained in a message using Shannon's measure of information entropy:

$$H = -K \sum_{i=1}^{n} p_i \log_2 p_i \tag{8}$$

Similar information sources (team members) should produce similar amounts of information.

- Rule 3. This rule encodes the semantic coherence of the utterance with the current ("running average") semantic space of the conversation where the semantic space has been processed by latent semantic analysis [26]. Latent Semantic Analysis (LSA) is a computational linguistics tool which provides one way to model the "psychological similarity between thoughts" based on language [27]. The theory of LSA is that terminological patterns in text occur based on the entire range of words chosen. Word and document meanings derive from these "latent" terminological patterns. The coherence χ between two communicative acts a_m and a_n is given by $\chi_m^n = \frac{a_m \cdot a_n}{\|a_m\| \|a_n\|}$ (9) where the communicative acts are mathematically represented using the standard vector model for full-text documents. For our calculations, a_n is the current "average" communicative act, that is, the centroid of all of the vectors representing the communicative acts.

In summary, the rules for measuring inter-relatedness and the ranges of possible values are:

Rule 1: Word count per communicative act $[0,\infty)$

Rule 2: Information entropy $[0, \max_{p_1 \ldots p_n} H(p_1 \ldots p_n)]$

Rule 3: Running semantic coherence [-1,1]

Thus, the data set is formed by the tuple {*ID, Speaker, Time, InformationMeasure*}. The boids flock together when the *InformationMeasure* values become similar and repel when they digress. Various groups of flocks and boid motion typologies may appear based on different values and orders of magnitude of the *InformationMeasure*.

The dataset for our prototype is the transcript of (I)van, (J)ohn and (K)erry from the mountain bike backpack design problem at the 1994 Delft Protocols Workshop [28]. The qualitative profile of the team is that John is generates the most ideas and is the most active in driving the direction of the team. Ivan manages the design process and keeps track of the time; he summarizes but weakly influences the team. Kerry has the most domain knowledge and appears to make specific contributions to the functional specification. Given the qualitative profile of the team, John's influence and ability to build upon the ideas of his team maters would mean that his boid would be most active and attract Ivan and Kerry. The relatively smaller contribution of Kerry means that her boid representation would cluster less often (that is, the other boids would not tend to cluster around Kerry) and generally be more distant from Ivan and Kerry. Ivan, being the time keeper, process manager and summariser, should be fairly close to both John and Kerry.

3 Results

One should note that the actual capabilities of the information flocking visualisation system can only be demonstrated with large groups: the 3 participants scenario shown in this paper is intended to illustrate how the system operates rather than to show images of representative visualisations. Later, we present a artificially synthesised image based on this data set. We should note that that the data values in the visualisations shown will not always correspond directly to the positions of the boids in the images. Because the time scale and the *InformationMeasure* values will fluctuate faster than the boids can adapt to the new situation, the boids need some adaptation time to reach their ideal (according to the behaviour rules) relative positions. The lag in adaptation means that that, in the backpack design team data set, one boid could be completely outside the global flock but have an instantaneous data value in the middle of the other two. The reason is that, for example, a short time (e.g., < 1 second) before, but for a longer period, one outsider had a non-similar data value (e.g. 0) while the other two were related (e.g. 0.6 and 0.63). This lag in spatial and motion adaptation is not necessarily negative; in fact, small random, noise iterations in the dataset are thus filtered out rather than being shown as sharp, ‘chaotic’ movements which could confuse the viewer. Only long-term or very significant correlations are picked by the spatial positions and movement typologies of the boids.

In the data set, there are three team members, Ivan (I), John (J), and Kerry (K). Each team member is represented as a single boid as shown in Figure 1.

Figure 1 Each team member is represented as a boid.

Over time, the team members produce design communication and new *InformationMeasure* values are calculated. Spatial ‘trails’ behind the boids are generated by connecting the points in space that the boids pass through, and enable the viewer to perceive a short history and judge the motion typology; for instance, one can perceive when boids ‘turn away’ (ideas diverging) by perceiving a curve of 180 degrees in the trails, or when boids move in the same direction (ideas converging). Figure 2 shows the motion trails for the boids prior to their position shown in Figure 2. When the boids are selected (clicked), larger static ‘ribbons’ appear that function as spatial timelines with historical time codes and respective data values on top of them. They can be used to trace back when large spatial movements occurred, or to see locally interactions in time such as when the boids crossed, diverged and merged.

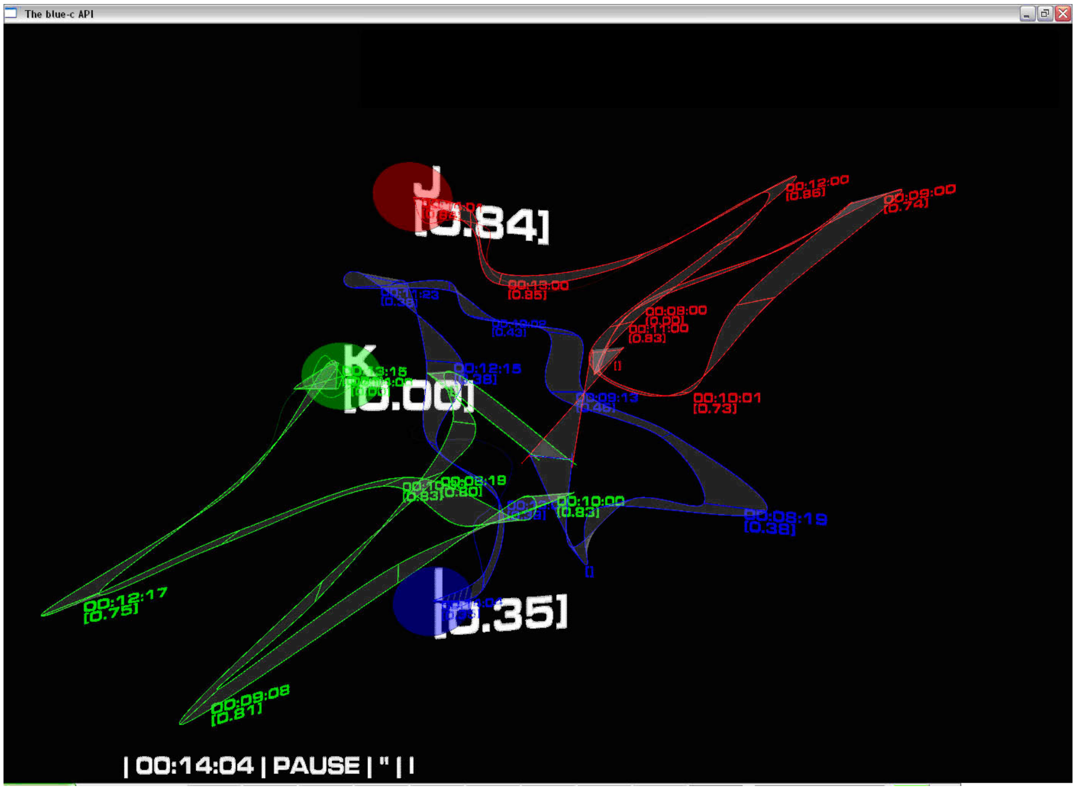

Figure 2 Motion trails for boids.

The boids may also be encompassed in a 'mesh' form where the mesh indicates the relative active flocking radius. When the boids flock or repulse over time, as shown in Figure 3a when J and K 'mesh' but not 'I', then their volume meshes 'rip of' and appear to 'repulse' as 'blobs' away from one another as shown in Figure 3b when J and K have 'broken away' from I. This visual feature also enhances the recognition of subflocks, and grouped directional movements. In addition, it eases the comprehension of the spatial constellations as relative distances might be difficult to judge on a screen-based three-dimensional world projection.

Figure 3 (a) Boids in mesh representation; (b) Boids in a transition mesh.

Over an extended period of time, the flocking behaviour of the group becomes more evident as the trails for the boids intersect and overlap. shows how the trails for I and k intersect with J at (approximately the middle of the image) during the period of time from 13:00 minutes to 17:00 minutes.

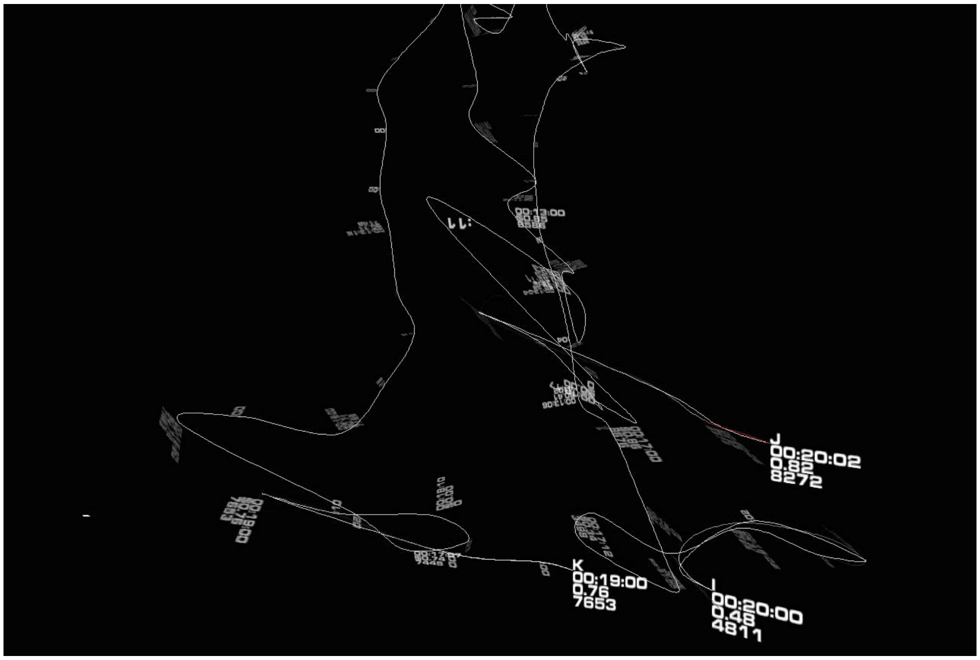

Figure 4 Intersecting motion trails.

The visualisation was run over the Delft Mountain Bike Backpack protocol study applying the behaviour rules and the rules for the measurement of the 'strength of ties.' We conducted a qualitative observational analysis to assess which of the three 'strength of ties' rules revealed motion typologies that most closely match our understanding of this team's dynamics related to the production of shared understanding and design concepts and as published elsewhere (e.g. [29] and [30]). The resulting animated visualisations (as opposed to the static images shown here) indicate that the measurement of "strength of ties" based on semantic coherence (Rule 3) appears to most accurately model the qualitative profile of the team. The information entropy (Rule 2) method is also satisfactory and faster to calculate. However, the expected spatial collective and individual behaviours of the boids is not evident for Rule 1 because the wide variation of the values prevented the boids from 'settling' into flocks.

Figures 5 and 6 demonstrate our first efforts to visualise large groups of design collaborators, as the information flocking methodology seems to be ideal to visually depict the time-based tendencies of large, dynamically changing data sets. One should also note that considerable calculation performance issues are involved when simulating flocking behaviour for large groups, next to other issues of querying, caching and parsing a large, time-varying data set during runtime.

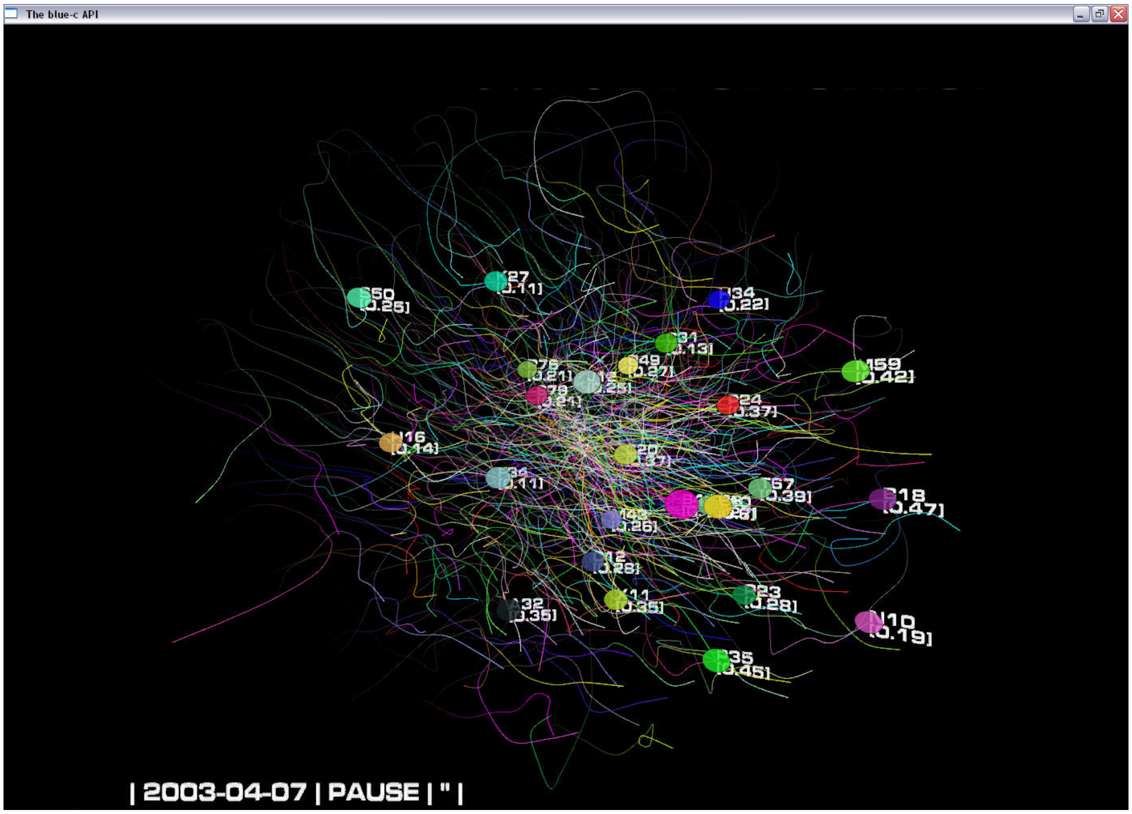

Figure 5 Large scale dataset & flocking.

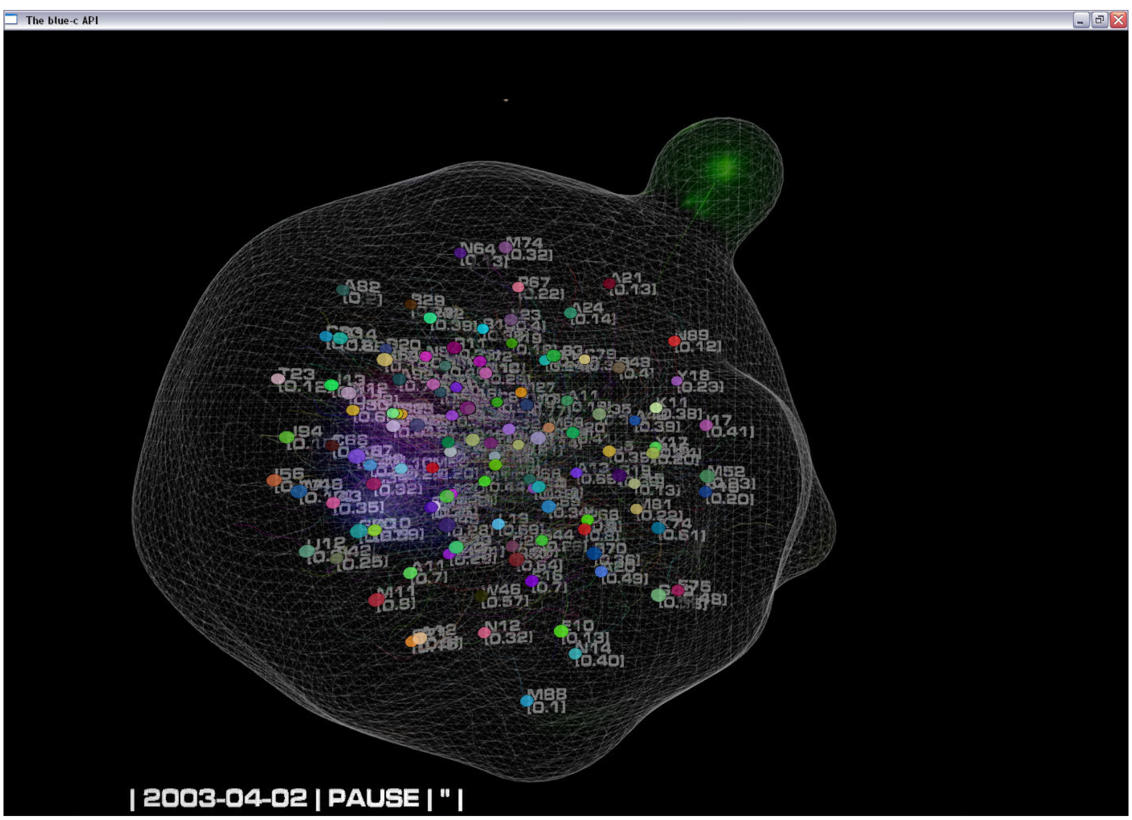

Figure 6 Spatial separation in large dataset over time.

4 Conclusions

Inevitably, one might ask what theoretical or pragmatic advances our research may provide. The study of very large design teams (on the scale of the number of people involved in the design of commercial aircraft for example) has often eluded design researchers (or been avoided by us) particularly in the establishment of models of design cognition that scale into hundreds of designers working roughly ‘together.’ In the design research literature, human behaviour in design is typically situated in one of three categories. The first are studies of individual designers. At this level of analysis, factors such as competency with technical design methods and tools, domain knowledge, and availability of information resources figure into a designer’s mental model. When we turn to a consideration of the behaviour of design teams and individuals’ behaviour within them as in a distributed cognition paradigm, then the cognitive system consisting of more than one individual may have cognitive properties that differ from the cognitive properties of individuals who participate in these systems. Both of these categories presume the existence of a shared representation. That representation might be localized (the designer’s mental imagery) or distributed (e.g., a shared understanding), implicit or explicit. For the most complex design problems, it appears as if this presumption of a representation of the artefact is invalid [31] and have lead some researchers to question the existence of such representations. Do designers actually have an internal representation of the artefact beyond what is necessary to complete a specific design task at a given moment in time? Can a shared understanding exist among hundreds of designers working on the design of an aircraft? Non-cognitive models such as swarm intelligence in which collective behaviour emerges in the absence of a shared cognitive representation of the artefact and localized representations serve as mechanisms for self-organization may better explain very large scale design teams. This is a nascient area of research in the field of design science. Visualisations developed by applying models of particle flocking to large-scale design activities such as the one presented in this paper may offer a new way to understand the design practices of very large scale design teams.

Accordingly, this research should be considered a working, experimental prototype for evaluating and representing such large-scale, large-number design collaborations. We believe that insights from the field of information visualisation provide more straightforward and less information dense descriptions of events in design team conversations. The mapping of the attraction and repulsion of boids appeals to most engineers’ understanding of basic spatial self-organisation of creatures, making the communication of teamwork dynamics more transparent. This is central in our exploration of the links and paths which correspond to design thinking. Given the evidence demonstrating the role that reflection plays in enabling teams to make decisions rationally to proceed, perhaps these visual descriptions will also offer a more lucid and aesthetic way to assess team collaboration as a supplement to the standard but rather clinical Gantt charts. By seeing tendencies toward idea cohesion through the motion typologies of the boids, the designers may recognise implicit and explicit many-to-many relationships in a more accessible format than design structure matrices.

We are currently investigating other rules for measuring interrelatedness such as the semantic distance between team members as well as evaluating the visualisations through case studies of large scale design teams. In addition, we are working on more basic approaches of the information flocking methodology, for instance by limiting the representation to a two-dimensional space and offering specific user interfaces for specialised tasks. The basic concept outlined in this paper – information visualisation of the interrelatedness of engineering design teams from the perspective of influence, contribution and idea uptake –appears to be a promising way to assess the interconnections between team members by leveraging the computational methods of computational linguistics and information visualisation.

References

[1] E. F. McDonough-III, K. B. Kahn, and G. Barczaka, "An investigation of the use of global, virtual, and colocated new product development teams," *Journal of Product Innovation Management*, vol. 18, pp. 110-120, 2001.

[2] S. R. Hiltz, K. Johnson, and M. Turoff, "Experiments in group decision-making: Communication process and outcome in face-to-face computerized conferences," *Human Communication Research*, vol. 13, pp. 225-252, 1986.

[3] H. H. Clark and S. E. Brenan, "Grounding in communication," in *Perspectives on socially shared cognition*, L. B. Resnick and S. D. Teasley, Eds. Washington, D.C.: American Psychological Association, 1991, pp. 127-149.

[4] D. J. Wilde and J. Berberet, "A Jungian Theory for Constructing Creative Design Teams," presented at 7th International Conference on Design Theory and Methodology (DTM), Boston, MA, 1995.

[5] J. A. Cannon-Bowers, S. I. Tannenbaum, E. Salas, and C. E. Volpe, "Defining competencies and establishing team training requirements," in *Team effectiveness and decision making in organizations*, R. A. Guzzo and E. Salas, Eds. San Francisco: Jossey Bass, 1995, pp. 333-380.

[6] Y. Jin and R. E. Levitt, "The virtual design team: A computational model of project organizations," *Computational and mathematical organization theory*, vol. 2, pp. 171-196, 1996.

[7] M. E. Sosa, S. D. Eppinger, and C. M. Rowles, "The misalignment of product architecture and organizational structure in complex product development," *Management Science*, vol. 50, pp. 1674-1689, 2004.

[8] M. Callon, J. Law, and A. Rip, "Mapping the dynamics of science and technology: sociology of science in the real world." Basingstoke: Macmillan, 1986.

[9] C. Plaisant, "The challenge of information visualization evaluation," in *AVI '04: Proceedings of the working conference on Advanced visual interfaces*. New York: ACM Press, 2004, pp. 109-116.

[10] A. Newell, *Unified theories of cognition*. Cambridge, MA: Harvard University Press, 1990.

[11] J. M. Kleinberg, "Authoritative Sources in a Hyperlinked Environment," *Journal of the ACM*, vol. 46, pp. 604-632, 1999.

[12] S. Brin and L. Page, "The anatomy of a large-scale hypertextual Web search engine," *Computer Networks and ISDN Systems*, vol. 30, pp. 107-117, 1998.

[13] A. Dong, "Quantifying coherent thinking in design: a computational linguistics approach," in *Design Computing and Cognition '04*, J. S. Gero, Ed. Dordrecht: Kluwer Academic Publishers, 2004, pp. 521-540.

[14] W. Sack, "Conversation Map: An Interface for Very Large-Scale Conversations," *Journal of Management Information Systems*, vol. 17, pp. 73-92, 2000.

[15] G. Proctor and C. Winter, "Information Flocking: Data Visualisation in Virtual Worlds Using Emergent Behaviours," in *Virtual Worlds*, vol. 1434, *Lecture Notes in Computer Science*, J.-C. Heudin, Ed. Berlin: Springer-Verlag GmbH, 1998, pp. 168-176.

[16] B. A. Kadrovach and G. B. Lamont, "A particle swarm model for swarm-based networked sensor systems," in *SAC '02: Proceedings of the 2002 ACM symposium on Applied computing*. New York: ACM Press, 2002, pp. 918-924.

[17] J. Macgill and S. Openshaw, "The use of Flocks to drive a Geographic Analysis Machine," presented at 3rd International Conference on GeoComputation (GeoComp98), Bristol, UK, 1998.

[18] R. C. E. Y. Shi and J. Kennedy, *Swarm Intelligence*. San Francisco: Morgan Kaufmann, 2001.

[19] C. W. Reynolds, "Flocks, Herds, and Schools: A Distributed Behavioral Model," in *SIGGRAPH '87: Proceedings of the 14th annual conference on Computer graphics and interactive techniques*. New York: ACM Press, 1987, pp. 25-34.

[20] W. D. Hamilton, "Geometry for the Selfish Herd," *Journal of Theoretical Biology*, vol. 31, pp. 295-311, 1971.

[21] A. Vande Moere, "Time-Varying Data Visualization Using Information Flocking Boids," presented at IEEE Symposium on Information Visualization (INFOVIS'04), Austin, TX, 2004.

[22] A. É. Michotte, *The perception of causality*. New York: Basic Books, 1963.

[23] T. C. Lethbridge and C. Ware, "A Simple Heuristically-Based Method for Expressive Stimulus-Response Animations," *Computers and Graphics*, vol. 13, pp. 297-303, 1989.

[24] F. Heider and M.-A. Simmel, "An experimental study of apparent behaviour," *American Journal of Psychology*, vol. 57, pp. 243-259, 1944.

[25] C. E. Shannon, "A Mathematical Theory of Communication," *The Bell System Technical Journal*, vol. 27, pp. 379-423 and 623-656, 1948.

[26] A. Dong, "The latent semantic approach to studying design team communication," *Design Studies*, pp. to appear, 2005.

[27] T. K. Landauer, "Latent semantic analysis: A theory of the psychology of language and mind," *Discourse Processes*, vol. 27, pp. 303-310, 1999.

[28] N. Cross, H. Christiaans, and K. Dorst, "Analysing Design Activity." Chichester: John Wiley & Sons Ltd, 1996, pp. 480.

[29] R. C. Valkenburg, "Shared understanding as a condition for team design," *Automation in Construction*, vol. 7, pp. 111-121, 1998.

[30] G. Goldschmidt, "The Designer as a Team of One," in *Analysing Design Activity*, N. Cross, H. Christiaans, and K. Dorst, Eds. Chichester: John Wiley & Sons Ltd, 1996, pp. 65-91.

[31] T. A. W. Jarratt, C. M. Eckert, and P. J. Clarkson, "Providing an overview during the design or complex products," in *Design Computing and Cognition '04*, J. S. Gero, Ed. Dordrecht: Kluwer Academic Publishers, 2004, pp. 239-258.

Acknowledgements

This research was supported in part by an Australian Research Council Grant DP0557346.

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