Walkers—Encoding Multivariate Data into Human Motion Sequences

Iain Carson, Uta Hinrichs, Aaron Quigley
University of St Andrews
St Andrews, Scotland
ic48,uh3,aquigley@st-andrews.ac.uk

ABSTRACT

The human perceptual system is highly efficient and effective at processing visual information, even at a pre-conscious level. Data visualisation leverages these functions to extract meaning and patterns from data, reducing cognitive load. Yet, the design of visualisations that represent multivariate data is still a challenge — as the number of data attributes increases, so does the complexity of visualisations, with it, the complexity of analysis processes potential users are facing. Many algorithms exist that support dimension reduction, leading to simpler, yet less nuanced visualisations in 2D space. We propose a novel way of presenting complex multivariate data using dimensional reduction that leverages humans' ability to quickly process and decipher even complex sequences and compositions of motions to extract social cues. By encoding data into biomechanical motion of abstract figurines—*"walkers"*—and then using Point Light Displays to convey their motion in isolation, our proposed technique for data visualisation results in subconscious dimensional reduction and pattern recognition, enabling a meaningful overview of complex multivariate data with little cognitive effort. In this workshop paper, we introduce *walkers* as a novel visualisation concept and describe how this idea could be integrated into potential immersive analytics application scenarios. We also discuss the research questions that the idea of encoding data into biomechanical motion raises in the context of immersive analytics.

CHI'19, May 2019, Glasgow, UK

ACM ISBN . . . $15.00
https://doi.org/

CCS CONCEPTS

• **Human-centered computing → Visualization theory, concepts and paradigms**;

KEYWORDS

Data Visualisation, Multidimensional Visualisation

ACM Reference format:
Iain Carson, Uta Hinrichs, Aaron Quigley. 2019. Walkers—Encoding Multivariate Data into Human Motion Sequences. In *Proceedings of ACM SIGCHI conference, Glasgow, UK, May 2019 (CHI'19),* 6 pages.
https://doi.org/

INTRODUCTION

Most humans are naturally able to extract information from even a fraction of a second of watching biomechanical movement, such as gender [11], weight and relaxedness [15]. More subtle information (such as intent and emotion - namely sadness, anger, joy, fear, and romantic love) is also discernible [4] even from Point Light Displays (PLDs), designed to isolate biomechanical motion from other confounding biometrics.

Fundamental research states that the processing and recognition associated with viewing biomechanical motion is "a highly mechanical, automatic type of visual data treatment that is most important" [8], as it occurs extremely rapidly, from a "bottom-up" cognitive process [13], and with little conscious effort.

Although recognising and extracting cues from biometric observations is natural, the extracted information is largely "sensory" or "emotional", which does not suit accurate representation of data, limiting the usefulness of anthropomorphic data visualisation efforts, such as Chernoff faces [3] and explaining some of its most common criticisms[12].

Instead, the objective of the herewith presented encoding and approach is not to represent precise data points for interpretation, but to explore the communicative and explorative power of the social cues extracted from observation of biomechanical motion. Consequently, issues such as value ambiguity and non-orthogonality that render similar visualisations traditionally weak, are unimportant.

By encoding multidimensional data into biomechanical motion, the interactions of the data manifest themselves as extracted social cues; a form of dimensional reduction.

To the authors' knowledge, gait has to-date not been used as an encoding mechanism for such means, and the following explanation and examples establish the presented visualisation technique as a unique approach to multivariate analysis with distinct and discrete advantages to prior and alternative efforts.

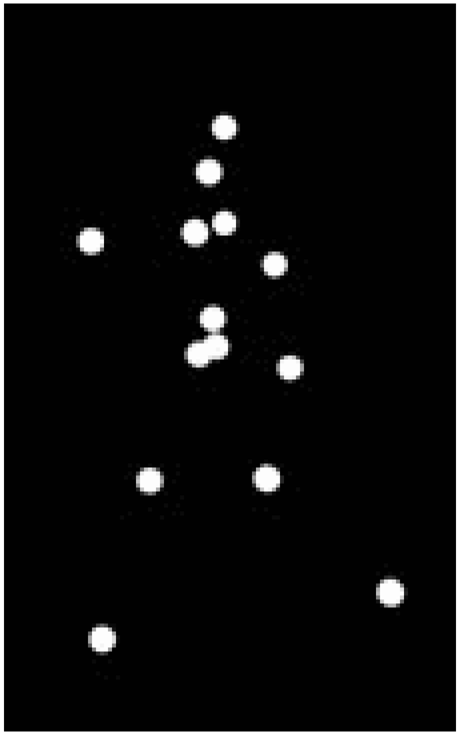

Figure 1: Example of a Point Light Display walker.
The biomechanical motion of such a walker, with as few as 12 points, may be used to encode complex, multidimensional data, allowing extremely fast dimensional reduction and potentially easing the cognitive load of classification.

RELATED WORK

Biomechanical motion has received significant research attention from both a human perception perspective [8, 9, 11, 13] and a biometrics and data-driven perspective [2, 14]. Further, training of humans in classification and complex pattern recognition techniques is still highly relevant in many situations where machine learning algorithms are unable to match human performance, from chicken sexers [6] to earthquake data interpretation [16]. To date, synthesised biomechanical motion has not been applied to immersive analytics, and may prove a novel, natural way of interacting with multidimensional data.

Chernoff Faces

Encoding data into biologically recognisable features occurs probably most famously in the form of Chernoff Faces [3], which display multivariate data in the shape of a human face. Chernoff Faces have since been employed in unsupervised learning (clustering) tasks [1, 7], the purpose for which they were originally designed. As Lange states[9], "Recent behavioral and imaging studies indicate a close relationship of face and biological-motion perception in healthy adult". This reinforces the potential of biomechanical gait in similar clustering or recognition tasks. However, we are keen to differentiate this technique from the approach taken by Chernoff, as the below-proposed encoding mechanism highlights the social cues extracted from basic biomechanical motion.

The Empathic Visualisation Algorithm (EVA)

Loizides [10] takes the approach of generating realistic faces with expressions encoded directly to key output variables of the data. They argue that if the "mapping is arbitrary..." (as in the case of Chernoff Faces for example) "...then this method has no intrinsic value". In opposition, we argue that the emotional signal arising from the complex interaction of multiple variables is an effortless dimensional reduction; highly valuable in a holistic evaluation scenario or classification task. That said; carefully-considered, hierarchical (as opposed to arbitrary) encoding is certainly advantageous in both circumstances.

Furthermore, the technique relies on the principle that "emotion in the face reflects importance in the data", which requires that the important features of the data are known before they can be usefully represented. This is therefore a visualisation technique optimised for communication of specific trends or patterns in the data, rather than the overall effect of their interactions.

MECHANISM

Biomechanical motion is unique enough to identify an individual biometrically (like a fingerprint) [5], indicating a large and complex underlying information space in which we can encode our data.

There is a wide spectrum between abstract and realistic biomechanical motion, ranging from the PLD walkers described above, to fully-clothed photo- or video-realistic animated characters featuring rich expressions. An investigation into the perception and effectiveness of the visualisation along the "realism" axis would be an interesting endeavour in itself, however in this perspective, we focus on the social cues extracted from isolated biomechanical motion, mainly to avoid many of the issues associated with Chernoff faces.

Johansson's original experiments [8] showed that a dot pattern of just 12-15 points allow recognition and interpretation of biomechanical motion. We propose using such anthropomorphic animated dot patterns for data representation to minimise noise in the generated graphics.

The overall skeletal structure and gait will be a combination of deliberate social encodings and micro-adjustment of points and motion driven directly by raw data:

Skeletal structure. The underlying skeletal structure of a walker dictates the baseline neutral pose and relative positions of the individual points in the light display. This can be used to represent immutable information belonging to the datapoint. While no dynamic information is present in the skeletal structure, a uniqueness about the formation leading to recognition of individuals may assist in the development and recognition of unique empathy for the datapoint.

Social axes. Complex axes directly encoding social patterns such as Happy/Sad, Relaxed/Nervous are defined in frameworks [15]. Light use of these may assist in displaying especially influential data attributes, or representing known important interactivity between data attributes.

Individual Point Light Motion. Raw data attributes may be directly linked to the presence, angles, spatial range, or frequencies of individual points and their motion cycles.

It is unclear to what degree the perception of the "human-ness" or even "healthiness" of the walker is useful or distracting, and whether symmetry (or lack thereof) arising from separate encoding of information from the left to right of the body provides opportunities for rich data representation, or must be carefully controlled to avoid masking more subtle interactions.

APPLICATIONS AND EXAMPLES

Personal Medical Data Display

The vital signs, blood chemistry and other biological parameters of patients under critical or extended care are often continuously monitored. By encoding this multivariate data into a walker, a unique perspective on the data as achieved: Individual vital signs or measurements that may separately not be a cause for concern (and therefore not trigger any threshold-based alarms) may in combination be significant, manifesting as a social cue or characteristic of the walker's gait.

Stock monitoring

A multitude of historical stock measurements such as open price and turnover alongside expert prospecting results, Twitter sentiment analysis and news spins, is encoded into walkers as rich multivariate data, with each walker representing a single stock. Users are then asked to judge the predicted success of the stock in a year's time, and provided with feedback as to their accuracy. In time, is it possible for the future success or failure of a stock to manifest as subtle social cues arising from the current data?

Technology and Immersive Analytics

Walkers could be positioned and distributed in an AR/VR space around a data analyst, where the space offered allows many walkers to be viewed simultaneously, without obscuring each other, in life size. The 3D perspective would give a rich view of the walkers, reducing the need to manipulate them for perspective as a 2D monitor would require. One can imagine being surrounded by walkers, able to perform complex comparisons of multivariate data. While accurate evaluation of specific data properties of the walkers may be difficult, a continuous exposure to the sets may result in an intuitive, holistic evaluation of outliers, trends or otherwise invisible data interactions.

FURTHER AND FUTURE WORK

Implementation and studies

As mentioned above, the immersive environment offered by AR and VR would be well-suited to testing the proposed encoding principles. We envision running studies to evaluate the limitations, encoding axes, and overall effectiveness of the technique, and would welcome suggestions or related work that may guide our approach.

Limitations

We are keen to discuss potential limitations of these visualisations with researchers familiar with immersive visualisation and human perception. Solutions for the presentation of large point clouds, or hugely multivariate (100points+) datasets would also be interesting. Questions also arise around the manifestation of subtle interactions, and whether false associations are produced, or important signals drowned by distracting or prioritised biomechanisms.

Immersive Analytics

The visualisation approach presented here does not have to be limited to faces and gait; there are many other perceptual processes which could find application, such as language, illusion, musical interpretation or physical motion. Many of these have the potential to simplify interpretation of datasets requiring complex dimensional reduction or pattern recognition, perhaps leading to novel insights and decision making. We would welcome the opportunity to bring this novel perspective to the Immersive Analytics workshop at CHI 2019 in the form of illustrations, approaches and related work for discussion.

REFERENCES

[1] A. Astel, K. Astel, M. Biziuk, and J. Namieśnik. 2006. Clasification of drinking water samples using the Chernoff's Faces visualization approach. *Polish Journal of Environmental Studies* 15, 5 (2006), 691–697. https://doi.org/10.1080/10426500307868

[2] Jeffrey E Boyd and James J Little. 2005. *Biometric Gait Recognition*. Springer Berlin Heidelberg, Berlin, Heidelberg, 19–42. https://doi.org/10.1007/11493648_2

[3] Herman Chernoff. 1973. The Use of Faces to Represent Points in K-Dimensional Space Graphically. *J. Amer. Statist. Assoc.* 68, 342 (1973), 361–368.

[4] Tanya J. Clarke, Mark F. Bradshaw, David T. Field, Sarah E. Hampson, and David Rose. 2005. The perception of emotion from body movement in point-light displays of interpersonal dialogue. *Perception* 34, 10 (2005), 1171–1180. https://doi.org/10.1068/p5203

[5] Patrick Connor and Arun Ross. 2018. Biometric recognition by gait: A survey of modalities and features. *Computer Vision and Image Understanding* 167, January (2018), 1–27. https://doi.org/10.1016/j.cviu.2018.01.007

[6] David Eagleman. 2011. *Incognito: The Secret Lives of the Brain.*

[7] Linda L. Golden and Mayur Sirdesai. 1992. Chernoff Faces: a Useful Technique For Comparative Image Analysis and Representation. *ACR North American Advances* NA-19 (1992). http://www.acrwebsite.org/volumes/7279/volumes/v19/NA-19

[8] Gunnar Johansson. 1973. Visual perception of biological motion and a model for its analysis. *Perception & Psychophysics* 14, 2 (1973), 201–211. https://doi.org/10.3758/BF03212378 arXiv:19433921

[9] Joachim Lange, Marc De Lussanet, Simone Kuhlmann, Anja Zimmermann, Markus Lappe, Pienie Zwitserlood, and Christian Dobel. 2009. Impairments of Biological Motion Perception in Congenital Prosopagnosia. 4, 10 (2009). https://doi.org/10.1371/journal.pone.0007414

[10] A. Loizides and M. Slater. 2002. The empathic visualisation algorithm (EVA) - An automatic mapping from abstract data to naturalistic visual structure. *Proceedings of the International Conference on Information Visualisation* 2002-January, February 2002 (2002), 705–712. https://doi.org/10.1109/IV.2002.1028852

[11] George Mather and Linda Murdoch. 1994. Gender discrimination in biological motion displays based on dynamic cues. *Proc. R. Soc. Lond* B, 258 (1994), 273–279.

[12] Robert Kosara. 2007. A Critique of Chernoff Faces. https://eagereyes.org/criticism/chernoff-faces

[13] Ian M. Thornton, Ronald A. Rensink, and Maggie Shiffrar. 2002. Active versus passive processing of biological motion. *Perception* 31, 7 (2002), 837–853. https://doi.org/10.1068/p3072

[14] Nikolaus F. Troje. 2002. Decomposing biological motion: A framework for analysis and synthesis of human gait patterns. *Journal of Vision* 2, 5 (2002), 2. https://doi.org/10.1167/2.5.2

[15] Nikolaus F. Troje. 2002. The little difference: Fourier based gender classification from biological motion. *Dynamic Perception* (2002), 115–120.

[16] Tao Zhao, Vikram Jayaram, Atish Roy, and Kurt J. Marfurt. 2015. A comparison of classification techniques for seismic facies recognition. *Interpretation* 3, 4 (2015).