557

Sketching maps

Comparison between digital diagrammatic sketches of urban connectivity and actual maps of landscape fabric.

EDUARDO RICO CARRANZA, & KAYVAN KARIMI,

UCL, LONDON, UK

ABSTRACT

Digital Participatory Platforms (DPPs) are tools allowing general members of the public to express themselves through design actions. This field is rapidly expanding and has the potential to democratize SS theory, making it visible and relevant to many. Tools that allow participants to develop simple diagrams of urban form can be of help since these types of drawings are easy to make and relate directly to some of the abstractions behind SS theory. However, even if we general members of the public can develop these drawings, the relation between these types of drawings and the reality they may intend to represent has not been mapped sp far.

To address this issue we propose an experiment where we compare 200 drawings produced by professionals as part of a participatory process with real scale maps of London parks. We develop an analytic method for the lines of these two datasets using geometric feature extraction and dimensionality reduction representation in a t-SNE scatter graph. Results indicate that, for some types of landscapes, the algorithm effectively matches sketches and map morphologies. In other cases, the geometries of sketches and maps of some landscapes are inherently different since designers tend to develop "cartoons" of their designs, forcing curvature of items or forgetting small details which end up being added into the design in later stages. This would suggest the need to develop sophisticated layers of detail in addition to digital tools if they are to adequately translate between a syntactic approach to design and real-life map results.

KEYWORDS

Sketching, Geometrical analysis, Drawing landscapes

1 INTRODUCTION

Digital Participatory Platforms (DPPs) (Falco and Kleinhans, 2018) are tools that allow general members of the public to engage in participation emphasizing co-production and what (Senbel and Church, 2011) call “design empowerment”. The number of DPPs has recently grown substantially, mostly linked to current improvements in web-based interactive systems, which include 3D configurators, collage systems and GIS-based methods of design and data collection. However, none of these tools seems adequate for SS Theory, which relies on abstract and simple forms of diagrams, such as centerline diagrams or similar. While the tools that would allow such data collection are easy to come by, there are no experiments on the usability of these types of diagrams and, more importnatly, how these drawings may relate to the reality they are meant to represent.

In this paper, we develop an experiment comparing what people produce when asked to develop diagrams of urban form with the real maps of the spaces they may represent. We carry out this work by collecting drawings via a digital sketching tool for a planning project and comparing them with maps of areas of London using geometrical analysis and dimensionality reduction techniques. This work is an addition to existing methods of semantic analysis of drawing, in this case, an analysis of SS basic diagrams attending to their nature as fragments of urban form.

1.1 CURRENT WORK ON SEMANTIC ANALYSIS OF DRAWINGS

A substantial amount of work currently exists in the field of sketch processing, trying to understand the meaning and nature of drawings for various purposes. These levels of semantics, begin in the most basic levels, trying to understand the nature, style or quality of single lines, and grow as they try to obtain meaning from the entire drawing composition.

The first level of semantic understanding would correspond to Sketch-Based Interfaces and Modelling (SBIM) groups techniques, which try to improve on existing mouse-based drawing technologies (Cruz and Velho, 2010), most typically in the field of industrial and product design. Some techniques address the need to improve the quality of lines and transform them into smooth splines or even 3D geometries without trying to understand the meaning or the aim of the drawing. This typically begins with filtering (reducing points) and fitting (adjusting overall curves) or removal of “oversketching” (turning bundles of semi-coincident strokes into single lines) as described by (Cruz and Velho, 2010). “Beautification” techniques (Igarashi et al., 1997), (Murugappan et al., 2009) reconstruct strokes according to a catalogue of robust geometries (circles, parallels, tangents). 3D Predictive Stroke techniques (see Adobe Sketchbook) do similar work helping to identify cylinders, extrusions and cubes from strokes and authors (Li et al., 2016) support direct conversion of wireframes into 3D shapes.

Other techniques work on understanding the semantic meaning behind a drawing for further use. Sketch-Based Image Retrieval (SBIR) techniques use different machine learning methods to interpret the meaning of sketches using both geometrical characteristics of traces as well as their temporal nature (Xu et al., 2020) and managing to retrieve related images or even generate the photorealistic versions of the drawing. Working at the semantic level, within the urban realm, (Broelemann et al., 2016), (Schwering and Wang, 2015) and SketchMapia application (Spatial Intelligence Lab, University of Münster, 2020), present methods for analyzing scanned sketch map drawings. Strokes are categorized semantically as part of a graph of related items which is then related to georeferenced information. Furhtermore authors such as (Kim and Penn, 2004) and (Canakcioglu, 2015) relate sketch maps to SS analysis and understand their configurational essence.

However, the techniques outlined do not apply to more diagrammatic forms of design drawings such as desire lines or others which are the lines we could expect to use in SS outline design. Work is required to understand how the drawings that people develop when they sketch urban networks relate to actual pieces of urban form. To address this gap, the following section outlines a series of research questions and methodology followed in our experiment.

2 RESEARCH QUESTIONS AND METHODOLOGY

To understand the relation between maps and drawings, we formulate two research questions that help us develop our experiment. These relate to the nature of sketches and ways in which hew can measure their morphology and how these methods help us trace relations between sketches and maps.

Research Question 1: Does a geometrical analysis of lines help identify distinct groups of sketches produced by participants? We hypothesize that the geometry of a group of lines (sketch, sections of a map or other) encodes information that allows a computer to group and classify lines or groups of lines in distinct and recognisable categories.

To answer this question we develop, we develop the first dataset of sketches and analyse their quality using Geometrical Features Extraction applied to their lines. This dataset is composed of a series of 340 sketches produced by general members of the public as well as design professionals using a digital tool (web-based 700pix*700pix HTML canvas). To generate this dataset, participants were asked to generate drawings of lines representing "desire lines" of the paths for a proposal for the UCL East Marshgate site (**Error! Reference source not found.**). The site can be accessed at www.drawscapes.com. Drawings were cleaned and smoothened to removed excessive jaggedness. We then extract a series of geometrical features for maps and sketches with some modifications necessary to adapt to the nature of the dataset as shown in *Morphological characterization of landscape using context-rich geometrical features extracted* *from path centre lines* (Rico et al., 2021). This consists of 8 features for each line (Length, Neighbours, Tortuosity, Curvature, Parallelism, Orthogonality, Axiality) and their Average Surrounding values (Figure 2) estimated with 6 topological steps.

We use a technique called dimensionality reduction to represent the datasets and assess their properties and distribution. For all data entries (sketches or parklets) defined in N-dimensional space (N=16 features), these techniques generate a parallel series of points in a 2D space where the distance between points and variance between coordinates best approximate those in the N-dimensional space. We use T-Stochastic Neighbourhood Embedding (commonly known as t-SNE) for this purpose (sklearn.TSNE, 2020). Visualizing the 2D data points produced by the t-SNE helps us understand visually the natural clusters and distribution of parameters in the dataset

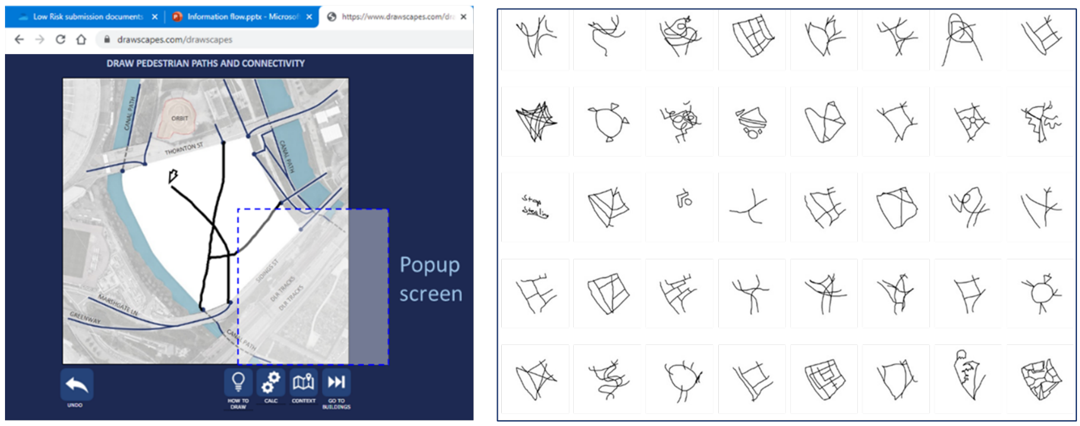

Figure 1 Drawing interface (left) and typical results (right)

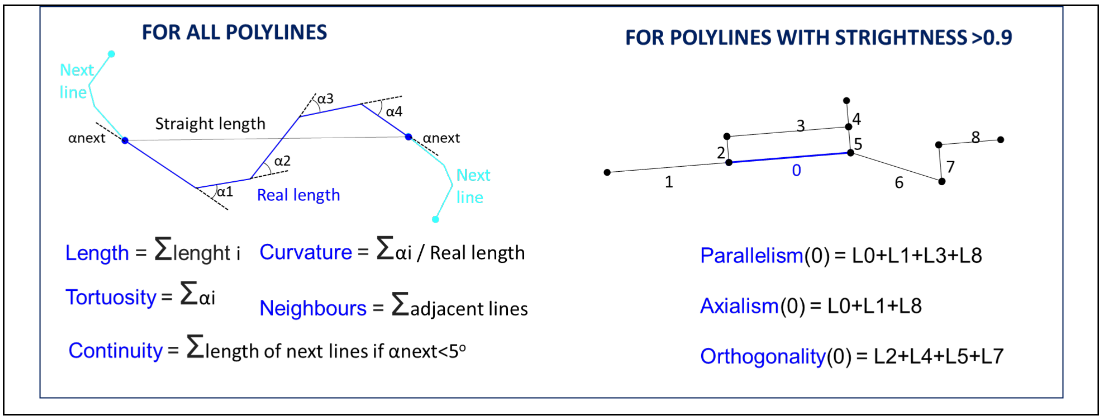

Figure 2 Geometrical Feature Extraction

Research Question 2: Does the information extracted from lines point to a relationship between sketches and real-life maps? We hypothesize that sketches and map data have similar geometric characteristics. When using GFE on a dataset composed of sketches and lines obtained from maps the computer will match or join similar sketches and similar parks together. In the case of t-SNE representation, sketches and park sections with similar characteristics will be clustered together.

To assess this hypothesis we develop a dataset of map lines that can be used as a comparison. Given the small scale of the proposed masterplan, its layout are likely to be informed by public space, landscape as well as built form. The reference dataset should include straight-axial, grid-like structures, curvy and more informal. Landscape datasets are likely to include these features and therefore we use a dataset of lines from 40 of the largest parks in London, obtained from OSMaps and pre-processed for calculation. For the case of the map dataset, we extract pieces of coherent fabric as shown in what we call "parklets" (Figure 3) by performing the first clustering on the feature space and spatial clustering in real space.

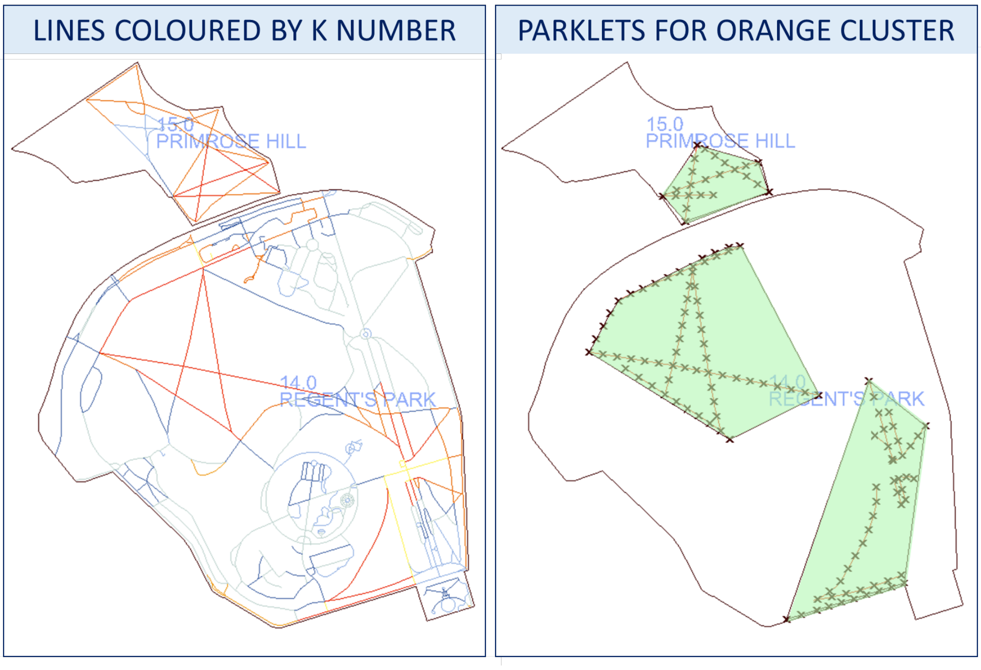

Figure 3 Feature clusters (left) and extraction of parklets (right)

Once we obtain a set of parklets, we carry out t-SNE embedding visualizations for a dataset of sketches, a combination of sketches and parks as well as sketches and parklets. We assess how close or "mixed" the two datasets are by drawing the convex hull in the 2D space of the parks or parklets and estimate the proportion of sketches within them (see shaded area in t-SNE in Figure 6). Low percentage inclusion values indicate distant (ie unrelated) datasets while high inclusion indicates that the datasets have common characteristics. We also identify the nearest neighbour for each sketch in the feature space and evaluate the cosine similarity as well as the average for all sketches.

We finally use the work carried out in (Rico et al., 2021) where we label the lines of the parks in 6 historical categories (Heath, Picturesque, Baroque, Contemporary, Formal-renaissance, Building-parterre) and carry out a classification of the sketches using three methods: the closes park in feature space, the closes parklet in feature space and via a Random Forest Classifier based on the line features. We then predict the character of the sketch (averaging its features) and compare these results with the manual classification of the sketches as developed by the research team. Embedding tests and classification are repeated for a varying number of features, starting with all 16 described above down to only 3. These features as well as the results are shown in Figure 4.

	TEST NUMBER									
VARIABLE	1	2	3	4	5	6	7	8	9	10
Length	1	1		1	1	1			1	
Tortuosity	1	1		1	1	1			1	
Curvature	1	1		1	1	1			1	
Continuity	1	1					1			
Neighbours	1	1					1			
Parallelism	1	1		1		1		1		
Orthogonality	1	1		1		1		1		
Axiality	1	1		1		1		1		
Av. Surr. Length	1		1	1	1					1
Av. Surr. Tortuosity	1		1	1	1					1
Av. Surr. Curvature	1		1		1		1			1
Av. Surr. Continuity	1		1				1			
Av. Surr. Neighbours	1		1	1						
Av. Surr. Parallelism	1		1	1	1					
Av. Surr. Orthogonality	1		1	1	1					
Av. Surr. Axiality	1		1	1	1					
PARKS										
Average cosine similarity	0.8837	0.8855	0.8822	0.9185	0.9664	0.9574	0.8407	0.9159	0.9896	0.9895
% sketches in hull	0.67	0.63	0.39	0.72	0.65	0.68	0.05	0.42	0.60	0.57
Classification accuracy	0.29	0.29	0.29	0.29	0.33	0.32	0.32	0.30	0.34	0.33
PARKLETS										
Average cosine similarity	0.8958	0.8984	0.8949	0.9245	0.9679	0.9670	0.9210	0.9125	0.9953	0.9912
% sketches in hull	0.58	0.19	0.04	0.30	0.84	0.78	0.15	0.45	0.84	0.71
Classification accuracy	0.31	0.33	0.32	0.29	0.34	0.31	0.36	0.32	0.33	0.35
CLASSIFIER										
Classification accuracy	0.30	0.35	0.31	0.34	0.30	0.34	0.33	0.34	0.36	0.33
Classification accuracy(*)	0.69	0.56	0.80	0.70	0.69	0.55	0.67	0.52	0.51	0.74

(*) Refers only to a RF model trained and tested on the annotated park lines using 70/30 Train/Test split

Figure 4 Testing schedule showing variables chosen (above) and results (below) for parks, parklets and RF classifier. Shaded colour coding in rows below is added for clarity to denote higher and lower values.

3 RESULTS

Figure 5 shows the results of the t-SNE embeddings carried out for 340 drawings using the average GFE for lines inside each drawing. Drawing clusters are distinct and well-formed, with most groups showing a certain consistency in terms of style and distance between them is large. This means that representation produced by the GFE seems to be enough for the algorithm to distinguish clear types and identify differences and similarities. However, some clusters do not work equally well with some “alien” sketches interspersed in the mix.

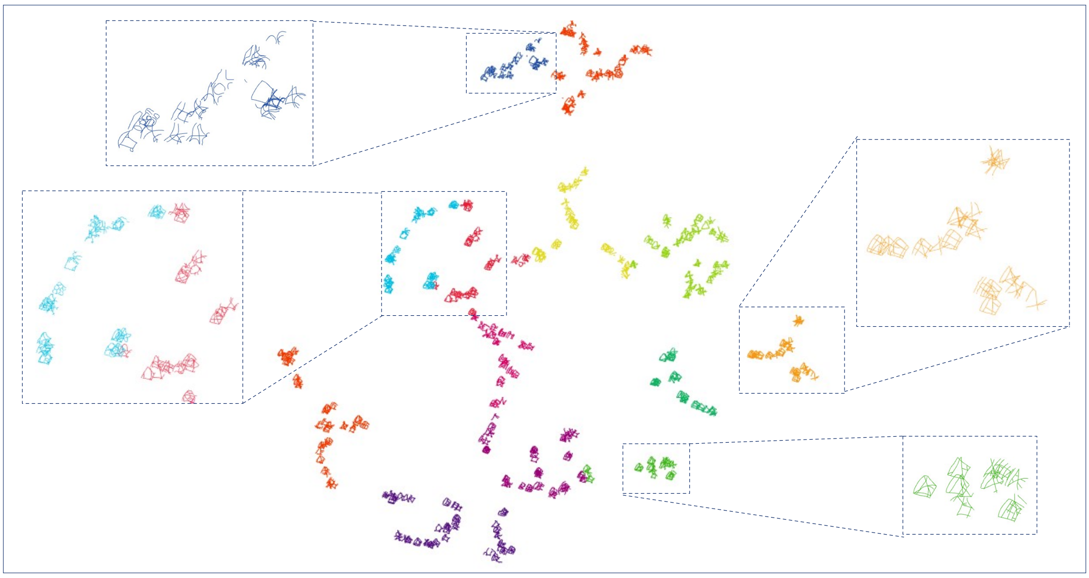

Figure 5 t-SNE groupings for sketches using GFE

Looking at the quality of the embeddings (Average cosine similarity and % in convex hull in Figure 4) we see improvements when using fewer variables. Test 5 (9 variables) and Test 9 (only 3 variables) work best than Test 3 (samples in Figure 6). It seems that the algorithm works better when partially “blind” to some details. Moreover, some of the features (number of neighbours or continuity) depend on the cleanliness of lines and proper topological connectivity, hard to achieve in hand sketches with no “snap” function. Comparing results from parks and parklets would indicate that the latter perform better, probably since these are, inherently more coherent than parks (ie they have removed mixed types).

Looking at the frequency of predicted categories and comparing them with the annotated set (Figure 7) we can see how all classifiers are seeing a large proportion of picturesque sketches. This is telling us that the translation of sketch lines to the historical realm is relatively skewed due to geometrical details (small curvatures or similar) that read most sketches under one particular category. If we compare this distribution against the original (annotated by the researcher) it can be seen that there is a marked difference in the visual classification of sketches and the real historical counterpart. The relationship between the style of sketches and the historical style cannot be always traced using geometry but may need some form of mediation or manual labelling, which shows in low overall classification values.

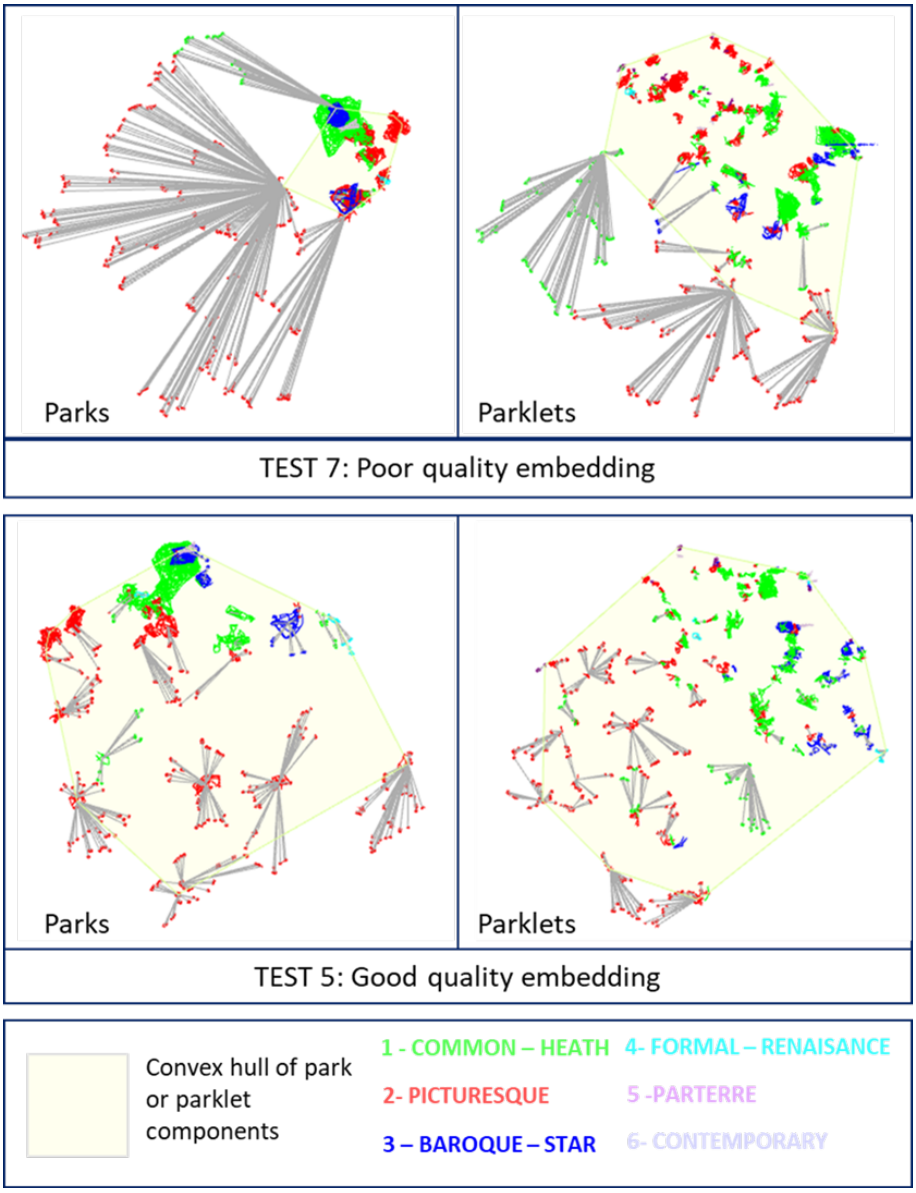

Figure 6 t-SNE including sketches and parklets using all GFE variables

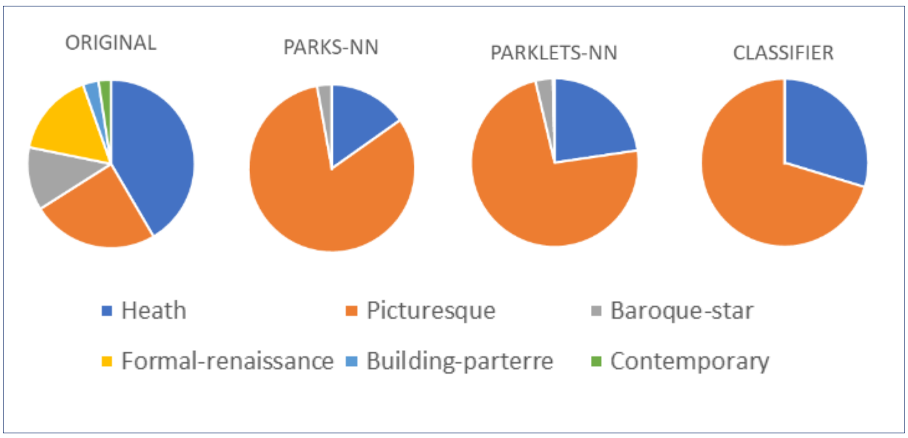

Figure 7 Frequency of predicted categories

4 CONCLUSIONS

The result analysed seems to indicate that the drawings that people generate when asked to develop diagrams have geometrical characteristics with structural coherence that can be understood by practitioners. However, there are aspects and nuances of the drawings that do not come well represented since the t-SNE groups some drawings inconsistently. When it comes to the comparison between sketches and drawings, there are features related to the accuracy of the drawing methods that skew the categorisation of sketches towards picturesque or heath types, hence ignoring categories that rely on orthogonal structures or have straight lines. This points out further research on how to use techniques of sketch processing, such as smoothing or simplification, that may help users generate more realistic drawings of urban form, relevant for SS analysis data gathering. Methods that generate an intermediate step in the correspondence between drawings and maps via manual data labelling or similar.

REFERENCES

Broelemann, K., Jiang, X., Schwering, A., 2016. Automatic understanding of sketch maps using context-aware classification. Expert systems with applications 45, 195–207.

Canakcioglu, N., 2015. Can cognitive maps of children be analysed by space syntax? 12, 127–140.

Cruz, L.M.V., Velho, L., 2010. A Sketch on Sketch-Based Interfaces and Modeling, in: 2010 23RD SIBGRAPI - Conference on Graphics, Patterns and Images Tutorials. Presented at the 2010 23RD SIBGRAPI - Conference on Graphics, Patterns and Images Tutorials, pp. 22–33. https://doi.org/10.1109/SIBGRAPI-T.2010.8

Falco, E., Kleinhans, R., 2018. Digital Participatory Platforms for Co-Production in Urban Development: A Systematic Review. International Journal of E-Planning Research 7, 52–79. https://doi.org/10.4018/IJEPR.2018070105

Igarashi, T., Matsuoka, S., Kawachiya, S., Tanaka, H., 1997. Interactive Beautification: A Technique for Rapid Geometric Design.

Kim, Y.O., Penn, A., 2004. Linking the Spatial Syntax of Cognitive Maps to the Spatial Syntax of the Environment. Environment and Behavior 36, 483–504. https://doi.org/10.1177/0013916503261384

Li, C., Lee, H., Zhang, D., Jiang, H., 2016. Sketch-based 3D modeling by aligning outlines of an image. Journal of Computational Design and Engineering 3, 286–294. https://doi.org/10.1016/j.jcde.2016.04.003

Murugappan, S., Sellamani, S., Ramani, K., 2009. Towards beautification of freehand sketches using suggestions, in: Proceedings of the 6th Eurographics Symposium on Sketch-Based Interfaces and Modeling, SBIM '09. Association for Computing Machinery, New York, NY, USA, pp. 69–76. https://doi.org/10.1145/1572741.1572754

Rico, E., Karimi, K., Neri, I., 2021. Morphological characterization of landscape using context-rich geometrical features extracted from path centre lines. Presented at the XXVIII International Seminar on Urban Form ISUF2021: URBAN FORM AND THE SUSTAINABLE AND PROSPEROUS CITIES, Glasgow.

Schwering, A., Wang, J., 2015. Invariant spatial information in sketch maps - a study of survey sketch maps of urban areas. Journal of Spatial Information Science 11, 31–52.

Senbel, M., Church, S.P., 2011. Design Empowerment: The Limits of Accessible Visualization Media in Neighborhood Densification. Journal of Planning Education and Research 31, 423–437. https://doi.org/10.1177/0739456X11417830

sklearn.TSNE, 2020. sklearn.manifold.TSNE — scikit-learn 0.24.1 documentation [WWW Document]. URL https://scikit-learn.org/stable/modules/generated/sklearn.manifold.TSNE.html (accessed 3.24.21).

Spatial Intelligence Lab, University of Münster, 2020. Sketchmapia - Overview [WWW Document]. URL https://www.uni-muenster.de/Geoinformatics/en/sketchmapia/ (accessed 9.1.20).

Xu, P., Song, Z., Yin, Q., Song, Y.-Z., Wang, L., 2020. Deep Self-Supervised Representation Learning for Free-Hand Sketch. arXiv:2002.00867 [cs].