

Towards a Human-Centred Cognitive Model of Visuospatial Complexity in Everyday Driving

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Abstract

We develop a human-centred, cognitive model of visuospatial complexity in everyday, naturalistic driving conditions. With a focus on visual perception, the model incorporates quantitative, structural, and dynamic attributes identifiable in the chosen context; the human-centred basis of the model lies in its behavioural evaluation with human subjects with respect to psychophysical measures pertaining to embodied visuoauditory attention. We report preliminary steps to apply the developed cognitive model of visuospatial complexity for human-factors guided dataset creation and benchmarking, and for its use as a semantic template for the (explainable) computational analysis of visuospatial complexity.

1 Introduction

Autonomous driving research has received enormous academic & industrial interest in recent years. As the self-driving vehicle industry develops, it will be necessary—in a manner similar to sectors such as medical computing, computer aided engineering and design—to have an articulation and community consensus on aspects such as representation, interoperability, data archival & retrieval mechanisms, and human-centred performance benchmarks. We posit that this will be necessary towards fulfilling essential legal and ethical responsibilities, such as those pertaining to representation and realisation of rules and norms, verifiable performance of normative behaviour, and technology capabilities vis-a-vis human-centred expectations.

Human-Centred Benchmarking and Standardisation. Within autonomous driving, the need for standardisation and ethical regulation has most recently garnered interest internationally, e.g., with the Federal Ministry of Transport and Digital Infrastructure in Germany (BMVI) taking a lead in eliciting 20 key propositions (with possible legal implications) for the fulfilment of ethical commitments for automated and connected driving systems [21]. In spite of major investments in self-driving vehicle research, issues related to human-centred design, human-machine interaction, and standardisation have been barely addressed, with the current focus in driving research primarily being on two basic considerations: *how fast to drive*, and *which way and how much to steer*. This is necessary, but inadequate if autonomous vehicles are to become commonplace and function with humans: not everything in autonomous vehicles is about realtime control/decision-making; several human-machine interaction requirements (e.g., for diagnostic communication, universal design) also exist. The 20 key propositions elicited by the German federal ministry BMVI highlight a range of factors pertaining to safety, utilitarian considerations, human rights, statutory liability, technological transparency, data management and privacy etc. Ethically driven standardisation and regulation will require addressing challenges in foundational human-centred AI technology,

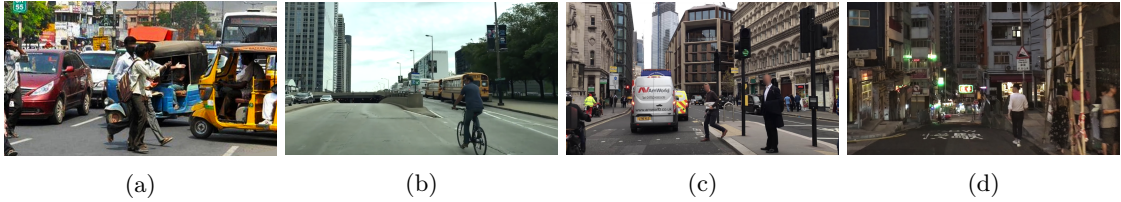


Figure 1: Multimodal communication in complex streetscape scenes: **(a)** Pedestrian gesturing and head rotation (Mumbai); **(b)** Cyclist’s head rotation (Chicago); **(c)** Pedestrian stepping to the street and monitoring attention of the driver (London); **(d)** Pedestrian moving to the side of the street (Hong Kong).

e.g., pertaining to semantic visual interpretation, natural / multimodal human-machine interaction, high-level data analytics (e.g., for post hoc diagnostics, dispute settlement) [35, 34]. This will necessitate –amongst other things– human-centred qualitative benchmarks relevant to different facets of machine (visual) intelligence, and incorporation of multifaceted hybrid AI solutions to fulfil such requirements. We claim that what appears as a spectrum of complex challenges (in autonomous driving) are actually rooted to one fundamental methodological consideration that needs to be prioritised, namely: the design and implementation of human-centred technology based on a *confluence* of techniques and perspectives from AI+ML, Cognitive Science & Psychology, Human-Machine Interaction, and Design Science. Like in many applications of AI, such an integrative approach has so far not been mainstream also within autonomous driving research.

Multimodal Interaction: The Case of Visuospatial Complexity. The central focus of the research presented in this paper is to develop a systematic methodology for the development of human-centred benchmarks for visual sensemaking and multimodal interaction for the domain of autonomous vehicles. Our work is driven by a bottom-up interdisciplinary approach –combining techniques in AI, Psychology, HCI, and design– for the study of embodied multimodal interaction in diverse ecologically valid conditions, with a particular emphasis on low-speed driving and complex urban environments (possibly also with unstructured traffic and people dynamics). We emphasise driver behaviour, as well as behaviour of other users such as pedestrians, bicyclists, bikers whilst focussing on natural interactions (e.g., gestures, joint attention) amongst involved stakeholders.

Key Contribution. We present a *cognitive model of visuospatial complexity* in everyday driving situations that may be used as a basis to *design, evaluate, standardise, and test & validate* visuospatial sensemaking capabilities of computational models of visual intelligence (for autonomous vehicles). We posit that our methodology can be used as a basis of developing human-centred benchmark datasets for visual sensemaking in autonomous driving encapsulating key cognitive principles founded on empirically established (context-specific) embodied multimodal interaction patterns under naturalistic driving conditions in everyday life [1, 24]. The proposed model of visuospatial complexity is based on *quantitative, structural, and dynamic* roadside attributes identifiable from the stimuli under consideration. As an example application of our model, we report work-in-progress concerning the development of one instance of a dataset where the central emphasis is on the evaluation of visuospatial complexity of driving stimuli. Both our proposed methodology and its human evaluation are driven by behavioural research in visual and spatial cognition methods as pursued within cognitive and environmental psychology. Such bottom-up interdisciplinary studies combining AI, psychology, HCI, and design are needed to better appreciate the complexity and spectrum of varied human-centred challenges in autonomous driving.

2 Naturalistic Human Factors in Everyday Driving

We approach cognitively motivated human-factors in autonomous driving from the viewpoint of visual attention (e.g. visual search, change detection), spatial cognition (e.g. cognitive mapping), and multimodal communication (e.g. joint attention, gesturing). We conduct systematic behavioural studies with a representative set of scenarios that encompasses challenging, hazardous, or cognitively demanding events in the urban set-up. The scenarios involve a range of visuospatial complexity levels in streetscape that reflects different areas of the world.

Multimodal Interactions (in the Streetscape) Multimodal interactions are highly varied and they can convey very different meanings depending on the task, the environmental setting, or other social, and dynamic factors. Even if they seem everyday monotonic events, they are complex problems for today’s autonomous systems. Embodied interactions (e.g., on the street) use a combination of communication modalities such as gestures and speech to pass a message or solve a conflict (Fig. 1a), or head rotations and eye contact to establish joint

MODALITIES	Examples
SPEECH	Ask - Warn - Shout - Scold - Give directions
HEAD MOVEMENTS	Turn towards the street - Tilt to a direction - Nod for disapproval - Slide for notice - Protrusion for warning
FACIAL EXPRESSIONS	Smiles - Frowns - Wrinkle - Eye Rolling - Cut Eye - Eyebrows Raising - Lips Movement - Mouth Movement
GESTURES	Emblematic (hitchhiking, stop) - Iconic (direction of movement) - Deictic (pointing) - Beat (irritation, gratitude)
BODY POSTURES	Crossing arms - Idle - Stand with the back to the street - Lean towards - Stand besides a car/bike
GAZE	Eye contact - Seek attention - Follow other's gaze - Follow a moving object - Aversion - Point towards a direction
AUDITORY CUES	Honking - Car engine - Traffic light sound - Brakes - Siren - Voice
PRACTICAL ACTIONS	(Select Sample)
Cyclist standing beside the bike while putting on the helmet indicates he will start cycling soon - Pedestrian on a wheelchair beside the street with hands on the wheels indicates his intention to cross - Pedestrian pushing the button for the traffic light, not monitoring the traffic and relying on auditory cues - Driver switching the light on and off to indicate that the cyclist can cross, combined with a nudge to the direction of movement - Driver slowing down/accelerating indicates intentions to give / take priority.	

Table 1: Multimodal interactions in the streetscape.

attention (Fig. 1b) (Table 1). A practical action when observed by an agent can be considered both as a physical action as well as a message (e.g., a pedestrian stepping on the street indicating willingness to get priority; Fig. 1c). Consequently, street users receive and comprehend different implicit cues that may alter their behaviour based on their observations and their expectations of being observed (e.g. a pedestrian is moving to the side of the street based on the auditory cue of a car approaching and the estimation of street's width; Fig. 1d).

Visuospatial Complexity Visual complexity and its effect on visual attention and cognition has been investigated by different disciplines - including cognitive science, psychology, computer science, marketing [12]. Several definitions have been proposed as well as several methodologies to measure it or measure specific attributes of it (e.g. visual saliency, spatial frequency, subband entropy) [16, 19, 26]. Visual complexity has been broadly defined as the level of detail and intricacy contained within an image or a scene [32]. With the term visuospatial complexity we consider the combination of visual and spatial characteristics that both coexist in dynamic naturalistic scenes where a person acts. In addition to the visual related features such as colour, contrast, number of objects etc., we also study the size and the structure of the space, the connection of its parts, etc. Visual attention is being controlled involuntary by external stimulus features (exogenous) such as luminance, and colour; as well as by voluntary internal cognitively relevant features of the world (endogenous) such as people, objects [8]. Visual search refers to an intentional look in the scene and the visuospatial complexity of the scene is highly correlated to visual search performance and the visual attention patterns as they evolve over time [10]. However, it is challenging to separate the bottom-up from the top-down cognitive processes (such as visual search, attentional priming, foraging) throughout a naturalistic visual attention task in driving, and therefore to establish which dimension of complexity (low-level scene properties, or high-level semantic properties) affect the visual attention patterns [29, 3, 40, 18, 17]. For this reason it is necessary to establish a taxonomy of attributes and parameters (pertaining to visuospatial complexity) quantifying the levels of complexity reliably based on their effects on people's performance and visual attention patterns.

3 Visuospatial Complexity in Everyday Driving: A Human-Centred Model

Developing a taxonomy and model of visuospatial complexity necessitates the identification of objective physical attributes that affect visuospatial perception and cognitive functions, such as *visual search* in everyday activities (e.g., driving, walking, cycling). However, the majority of existing empirical evidence is based on studies focusing on static real-world scenes, or abstract shapes and symbols [13, 15, 14]. For our taxonomy of attributes, we focus on naturalistic dynamic scenes, and we take into consideration recent work about attentional synchrony on dynamic real-world scenes demonstrating the effect of the dynamic attributes on visual attention [31, 20]. We categorise the attributes into **(A1–A3)**:

A1. Quantitative Attributes. Objective environmental factors – referring to low-level (*lines, edge, contour*) and middle-level (*corners, orientation*) features of the scene – and their relation to visual perception and cognition, have been a topic of research on computational image processing [7, 30]. Psychophysical and neurophysiological research has shown that these attributes are part of early human visual processing [31]. Moreover, the physical space and its functional *clutter* are general properties of all scenes that are immediately accessible to humans [23]. *Clutter* refers to overabundance of information, including the *number* of components of the scene, their *variety*, as well as the *density* of the viewed entities from the current perspective. Additionally, *luminance* and *colour*, and their respective retinotopic gradients (contrast), are typically employed in computational models

VISUOSPATIAL COMPLEXITY	Description
Quantitative attributes	
SIZE	[Width / Depth / Height] The dimensions of the physical space, the area covered by the visual stimulus.
CLUTTER	
Quantity	No. components (objects, people, shapes etc.)
Variety of Colours	No. colours
Variety of Shapes/Objects	No. shapes / objects
Objects Density	No. objects in a defined area
Edges Density	No. edges of objects in a scene / visual area
Luminance	Amount of light emitted / reflected from the scene
Saliency	Particularly prominent objects based on characteristics of colour, luminance and contrast
Target-background similarity	Compare similarity in luminance, contrast, structure, or spatial and orientation information
Structural attributes	
Repetition	Recurrence of the same element of group of elements or characteristics on a line, a grid or a patterns in space
Symmetry	Resilience to transformation and movement. Types: reflectional, rotational, translational, helical, fractal
Order	Organised elements based on a recognised structure, Varies from poorly organised to highly organised
Homogeneity/Heterogeneity	The state of being all the same kind/ diverse. Varies from single shape repeated to multiple distinct shapes
Regularity	Variations in a placement rule across a surface or line; Varies from simple polygons to abstract shapes
Openness	The ratio between empty and full space
Grouping	No. elements that are part of a group
Dynamic attributes	
Motion	No. people or objects moving in the scene
Flicker	Abrupt changes over-time (in luminance, colours, etc.)
Speed Direction	The rate of change of position with respect to time Move or facing towards

Table 2: Taxonomy of attributes for Visuospatial Complexity

of *saliency*. Similarities between a target with the background in various low-level features or in the spatial arrangement also correlates with visuospatial complexity [26].

A2. Structural Attributes. Structural attributes refer to the relations that the elements form due to positioning in space, or the overall distribution in the viewing scene. Many times structural attributes of the scene can mitigate the effects of visuospatial complexity increasing due to low-level quantitative attributes. High regular arrangements of elements in space or in the scene are related to low visuospatial complexity, and more randomised arrangements contribute to higher complexity levels [9]. *Repetition*, *symmetry*, *order*, and *grouping* are related to a decrease in spatial complexity [38, 27]. Likewise, *heterogeneity* (e.g., a single shape repeated vs. multiple distinct shapes), *regularity* of shapes and objects (e.g., simple polygons vs. more abstract shapes), *openness* (i.e., relation between full and empty space) and their relationship to complexity have been investigated in the fields of urban design and architecture [5, 27].

A3. Dynamic Attributes. Studies of visual attention on videos reveal a significant impact of dynamic features of the scene such as *motion* and *flicker* on top-down as well as bottom-up cognitive processes. Even the same environment can be perceived as more complex due to an increase in velocity of the observer. Taking into consideration dynamic aspects in scene analysis promotes gaze allocation prediction, as previous studies suggest that dynamic cues are predominant, and reliable predictors for greater number of people [20]. Concerning top-down processes, clusters of attention often coincide with semantically rich objects such as eyes, hands, vehicles, etc. On the other hand, cortical analysis shows a selective response to moving elements on the scene, meaning that we are able to notice moving objects even if we are not looking for them [25]. *Flicker*, i.e., abrupt changes in luminance over time, has been shown to pop-out independently of observers attention. Moreover, *speed* and *direction* are related to motion but they have different dependences on the way they are encoded during a cognitive task [8, 20].

The role of visuospatial complexity on visual attention depends on the kind of stimuli employed and on the way in which visuospatial complexity is defined, manipulated, and measured. Consequently, there are more significant factors influencing the role of visuospatial complexity on human behaviour that we do not consider in this paper but we cannot ignore. The nature of the *task* or aspects of *familiarity*, *working memory*, as well as *previous knowledge* of the context, are some them. For instance, semantic grouping of the scene based on previous knowledge during driving indicating where targets expected to appear. Additionally, studying dynamic scenes reveals the significance of *time* on visual attention, and a continuous interplay between low-level and high-level cognitive functions that affect the visual search performance. Analysing visual attention over time shows that first fixations are more influenced by environmental properties, but after the first 200ms fixation locations are determined predominantly by top-down processes [29].

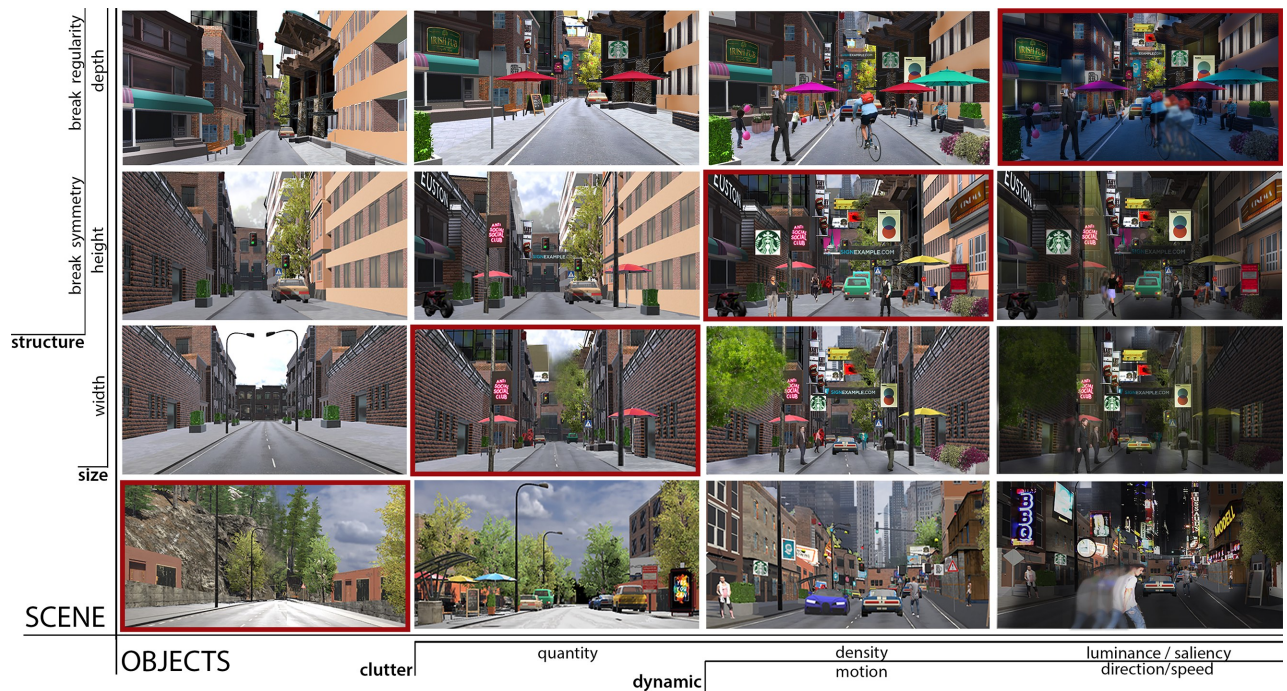


Figure 2: Sample of VR scenes that varies on the level of Visuospatial Complexity. The scenes are developed based on one urban environment with the combining of a number of attributes provided in Table 2, and it is not an exhaustive representation of the possible outcomes. The scenes are organised in a matrix as follows: the attributes that shape the scene itself are listed on the vertical axis, while the attributes related to objects are introduced on the horizontal axis. In every new line in both direction a new attribute is introduced in addition to the existed ones. The combination provides a new scene. The marked scenes are used for the empirical study of Section 4.

Towards a model of visuospatial complexity. Visuospatial complexity is a function of not only individual factors but also interactions between them. For instance, clutter can increase complexity, however high complexity may also be achieved with a combination of low clutter and low contribution of structural attributes (e.g. order, heterogeneity). A systematic analysis of different combinations of attributes can provide a better understanding of the aggravation or counterbalance dynamics between the attributes and their effect on human behaviour. To empirically define a model of visuospatial complexity for dynamic naturalistic scenes, we use the taxonomy introduced in Table 2 to develop a number of scenes in virtual reality (VR) that differ on the combination of attributes involved, as well as on the degree of each attribute the scene contains (Fig. 3a).¹ This way we create a matrix of possible scenes (Fig. 2), and use a number of them as the dynamic stimulus for our empirical study. The matrix provides an indication for a scale of visuospatial complexity based on the current knowledge from the literature on the effect of individual attributes on human behaviour. However, the empirical result of our study will be used to confirm or decline this indication, and further investigate the *weight* of each attribute to the overall effect on human behaviour (Fig. 3b). To represent these interactions between the attributes and their contribution to the overall complexity level we are developing a dynamic bubble diagram (Fig. 3c) that demonstrates the correlation coefficients of visuospatial complexity attributes and the behavioural metrics. We expect a stronger correlation between the visual search inefficiency and factors of clutter than size or structural attributes. Additionally, we expect quantitative attributes to have a negative correlation with visual search performance, while the structural ones to have a positive correlation. Although this effect can be counterbalanced.

4 Visual Search in the Streetscape: An Ongoing Empirical Study

A visual search task in driving. Driving performance has been shown to depend on visuospatial complexity in this case the streetscape, but also on the complexity of the driving task, and other factors that affect cognitive resources, such as individual differences, fatigue, age, dual task requests, etc [11, 39]. We are primarily concerned about the extent of which environmental factors of the dynamic scene affect the driving performance, such as

¹An important aspect not considered in this paper is high-level *event perception* [37]; presently, work is also in progress to include high-level event segmentation primitives complementing the developed visuospatial complexity model.

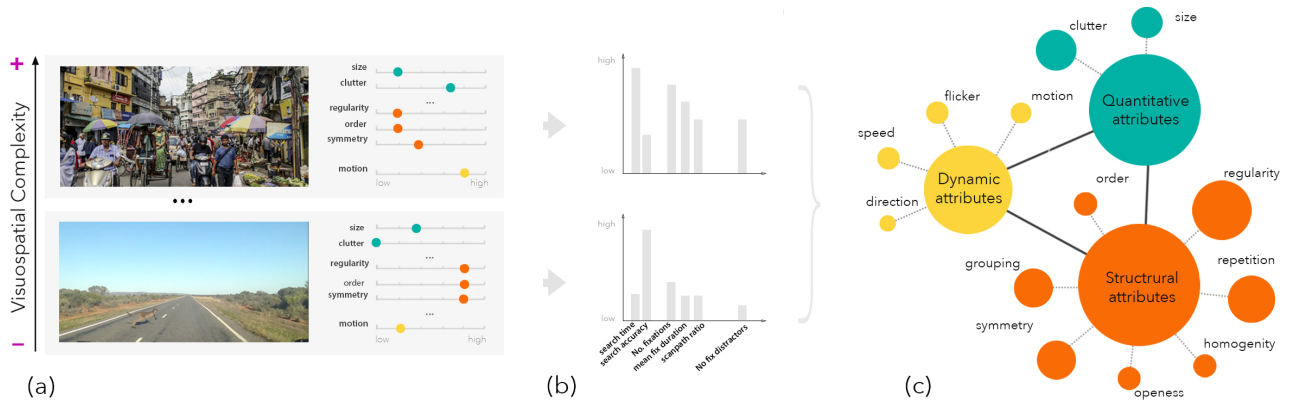


Figure 3: Visuospatial complexity model: **(a)** In the top row a high complex scene, and in the bottom row a low complex one, accompanied by the degree of the involved attributes; **(b)** behavioural metrics from the empirical study; **(c)** the bubble diagram representing the dynamic relations between the attributes of visuospatial complexity based on the effect they have on human behaviour.

locating and responding to traffic, directions or warning signs, hazard detection, and vehicle control etc. These actions are closely connected to visual perception and visual search processes. Visual search in driving primarily refers to detection of signs, obstacles, or road users, as well as situation awareness, including perception of hazard.

Four scenarios in four levels of visuospatial complexity. We collect and analyse a list of scenarios with dynamic scenes in streetscape that differ on the events and the interactions between the street users involved. The scenarios are collected from online video footage, following the indications about hazard situations published on Accidence Research report by the German Insurance Association [2], and categorised based on the nature of the incident (Table: 1). For the behavioural study in progress we choose four scenarios that differ on the multimodal interaction event and the practical actions used (Table: 1), and we replicate them in VR environment, in four different levels of visuospatial complexity. One example scenario on *inattentive crossing by pedestrian* is presented in Fig. 4. It is a typical scenario of pedestrian on a low traffic street with no official indication for crossing such as zebra crossing or traffic light. The pedestrian who is crossing more than one lane, firstly deviates from his path on the sidewalk and then he performs a slow speed crossing, while he is altering his visual attention states multiple times, between monitoring traffic (t_1), crossing the street being inattentive (t_2), sharing attention with a driver (t_3), and continue to cross the next lane being visually inattentive (t_4). The visual search task for the driver is to detect the pedestrian and elaborate on his behaviour. The pedestrian - considered from the driver’s point of view as the dynamic visual target - passes gradually from the peripheral view of the driver to the fovea area, while he is changes orientation and speed.

As the visual search process can be divided in different stages (early phase of search guidance, verification component), no single metric can describe the effect of visuospatial complexity on a search process entirely; rather it a combination of several metrics for performance and physiological measurements such as eye-tracking which can provide a more precise assessment of the effect of visuospatial complexity on human behaviour. We collect eye-tracking data from the participants, as well as reaction time, and accuracy to the target (Table 3)². For the analysis we define areas of interest and distractors according to the nature of the scene and the interactions involved. We further combine the results from the physiological and performance measurements and use them to trace the effect of visuospatial complexity levels. We expect the combination of measurements to provide insights about the attentional cost and the underline cognitive processes affected by visuospatial complexity.

5 Outlook

The road ahead (in autonomous driving) presents several opportunities: next-generation developments to achieve (legal) deployment and user / ethical acceptability require attention to a wider spectrum of autonomous driving

²The study is conducted using HTC Vive Pro Eye headset with embedded eye-tracking device. Unity Game Engine was used for the VR simulation of the scenes. VR is currently firmly established as an experimental tool; it combines a high degree of control with high level of ecological validity, and has shown important benefits for basic psychology and neuroscience research, especially on aspects of visual perception and spatial cognition [6, 22, 28, 41].

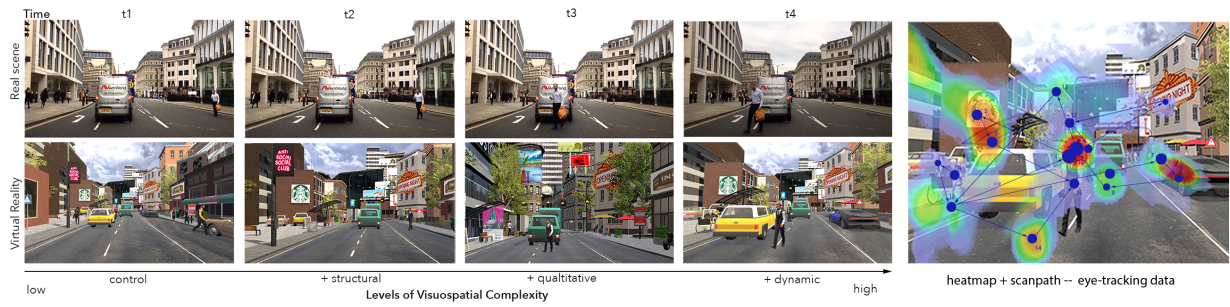


Figure 4: Example scenarios as it evolves over time (t1-t4), in the real scene (top) and in a virtual scene (bottom). The development of the VR scenes in four levels of complexity are demonstrated on the horizontal axis (based on Figure 2). Starting from a control scene, in every new scene towards right, new attributes from a new category (2) are introduced in addition to the existed ones. On the right, a sample heatmap of eye-tracking data for one VR scene.

METRICS	Description – Correlation with visuospatial complexity
Performance Evaluation	
Search time	domain specific measurement related to the task (e.g. detection of pedestrians, detection of objects)
Accuracy	
Physiological measurements – Eye-tracking	
Latency of first saccade	indicates confusion and uncertainty
Total number of fixations	large number indicates decreased search efficiency
Number of fixations on distractors in AOIs	larger when the target’s location is in high complex area
Number of fixations excluding those on distractors	indicate that other aspects like high variation contribute to complexity
Scanpath ration	big length of scanpath indicates poor search efficiency
Mean fixation duration	longer fixation duration indicates difficulty in processing information
Final saccade length	indicates how easily noticeable the target is in the peripheral vision

Table 3: Summary of metrics used for visual search evaluation and assessment of visuospatial complexity effects

challenges from the viewpoint of human-centred technology design encompassing natural human-machine interaction, industry-wide benchmarking, standardisation and statutory validation of technology components. The work reported in this paper is being conducted in synergy with research in computational *cognitive vision* [4], particularly in relation with the development of integrated vision and semantics solutions for active, explainable visual sensemaking for autonomous vehicles [35, 34]. The empirically founded model developed in this paper also constitutes the basis for computational assessment and analysis of visuospatial complexity. Towards this, we use the empirical results to develop a declaratively grounded computational model integrating KR and vision ([36, 33]) towards: **a)** learning behavioural models from empirical data, i.e., using (statistical) relational learning to induce weighted dependencies and constraints within the model, and **b)** utilising the computational model to examine and construct benchmarking datasets ensuring variety in driving conditions, naturalistic multimodal human interaction events, challenging and diverse environments, etc. Our goal is that a computational model of visuospatial complexity may provide a measure for the complexity of benchmarking datasets/scenarios and thus serve as a guideline to develop realistic human-centred evaluation criteria. We posit that such interdisciplinary studies are needed to better appreciate the complexity and spectrum of varied human-centred challenges in autonomous driving.

References

- [1] M.V. Angrosino, *Naturalistic Observation*, Qualitative essentials, Left Coast Press, 2007.
- [2] GDV: The German Insurance Association, *Compact Accident Research*, 2017.
- [3] E. Awh, A.V. Belopolsky, and J. Theeuwes, ‘Top-down versus bottom-up attentional control: a failed theoretical dichotomy.’, *Trends Cogn. Science*, **16**(8), 437–443, (2012).
- [4] M. Bhattt and J. Suchan, ‘Cognitive Vision and Perception: Deep Semantics Integrating AI and Vision for Reasoning about Space, Motion, and Interaction’, in *ECAI 2020*, (2020).
- [5] G. Boeing, ‘Measuring the complexity of urban form and design’, *Urban Design International*, **23**(4), 281–292, (2018).
- [6] C.J. Bohil, B. Alica, and F.A. Biocca, ‘Virtual reality in neuroscience research and therapy’, *Nature Rev Neurosc*, **12**, (2011).
- [7] M.J. Bravo and H. Farid, ‘A scale invariant measure of clutter’, *Journal of Vision*, **8**(1), (2008).
- [8] M. Carrasco, ‘Visual attention: The past 25 years’, *Vision Research*, **51**(13), 1484–525, (2011).

- [9] F. Doyon-Poulin, B. Ouellette, and J.M. Robert, 'Review of visual clutter and its effects on pilot performance: New look at past research', in *Digital Avionics Systems Conference (DASC)*. IEEE/AIAA 31st, (2012).
- [10] M.P. Eckstein, 'Visual search: A retrospective', *Journal of Vision*, **14**(5), 1–36, (2011).
- [11] J. Edquist, *The Effects of Visual Clutter on Driving Performance*, Ph.D. dissertation, Monash University, 2009.
- [12] A. Cavalcante et al., 'Measuring streetscape complexity based on the statistics of local contrast and spatial frequency', *PLoS ONE*, **9**(2), (2014).
- [13] A. Forsythe, 'Visual complexity: Is that all there is?', *Engin Psychology and Cognitive Ergonomics, HCII*, 158–166, (2009).
- [14] A. Gartus and H. Leder, 'Predicting perceived visual complexity of abstract patterns using computational measures: The influence of mirror symmetry on complexity perception', *PLoS ONE*, **12**(11), (2017).
- [15] S. Harper, E. Michailidou, and R. Stevens, 'Toward a definition of visual complexity as an implicit measure of cognitive load', *ACM Transactions on Applied Perception*, **6**(2), 1–18, (2009).
- [16] J. Henderson, M. Chanceaux, and T. Smith, 'The influence of clutter on real-world scene search: Evidence from search efficiency and eye movements', *Journal of Vision*, **9**(1)(32), 1–8, (2009).
- [17] Á. Kristjánsson and Á.G. Ásgeirsson, 'Attentional priming: recent insights and current controversies', *Current Opinion in Psychology*, **29**, 71 – 75, (2019).
- [18] T. Kristjánsson, I.M. Thornton, A. Chetverikov, and Á. Kristjánsson, Á., 'Dynamics of visual attention revealed in foraging tasks', *Cognition*, **194**, (2020).
- [19] C. Madan, J. Bayer, M. Gamer, B. Lonsdorf, and T. Sommer, 'Visual complexity and affect: Ratings reflect more than meets the eye', *Frontiers in Psychology*, **8**, (2018).
- [20] P.K. Mital, T. Smith, R.L. Hill, and J.M. Henderson, 'Clustering of gaze during dynamic scene viewing in predicted by motion', *Cognitive Computing*, **3**, 5–24, (2011).
- [21] BMVI: Fed Ministry of Transport & Digital Infrastructure, *Report by the ethics commission on automated and connected driving*, Germany, 2018.
- [22] B. Olk, A. Dinu, D. J. Zielinski, and R. Kopper, 'Measuring visual search and distraction in immersive virtual reality.', *Royal Society open science*, **5**, (2018).
- [23] S. Park, T. Konkle, and A. Oliva, 'Parametric coding of the size and clutter of natural scenes in the human brain', *Cerebral Cortex*, (2014).
- [24] A.T. Reader and N.P. Holmes, 'Examining ecological validity in social interaction: problems of visual fidelity, gaze, and social potential', *Culture and brain*, **4**(2), 134–146, (2016).
- [25] R. Rosenholtz, 'A simple saliency model predicts a number of motion popout phenomena', *Vision Research*, **39**(19), (1999).
- [26] R. Rosenholtz, Y. Li, and L. Nakano, 'Measuring visual clutter', *Journal of Vision*, **7**, (2007).
- [27] N.A. Salingaros, 'Complexity in architecture and design', *Oz Journal*, **36**, 18–25, (2014).
- [28] P. Scarfe and A. Glennerster, 'Using high-fidelity virtual reality to study perception in freely moving observers', *Journal of Vision*, **15**(9), (2015).
- [29] H. Schütt, L. Rothkegel, H. Trukenbrod, R. Engbert, and F. Wichmann, 'Disentangling bottom-up versus top-down and low-level versus high-level influences on eye movements over time', *Journal of Vision*, **19**(3), (2019).
- [30] Y. Semizer and M.M. Michel, 'Natural image clutter degrades over search performance independently of set size', *Journal of Vision*, **19**(4), 1–16, (2019).
- [31] T. Smith and P. Mital, 'Attentional synchrony and the influence of viewing task on gaze behavior in static and dynamic scenes', *Journal of Vision*, **13**(8), 16–16, (2013).
- [32] J.G. Snodgrass and M. Vanderwart, 'A standardized set of 260 pictures: Norms for name agreement, image agreement, familiarity, and visual complexity.', *Journal of Experimental Psychology: Human Perception and Performance*, **6**, 174–215, (1980).
- [33] J. Suchan, M. Bhatt, and C. Schultz, 'Deeply semantic inductive spatio-temporal learning', in *26th International Conference on Inductive Logic Programming*, eds., James Cussens and Alessandra Russo, volume 1865, (2016).
- [34] J. Suchan, M. Bhatt, and S. Varadarajan, 'Out of sight but not out of mind: An answer set programming based online abduction framework for visual sensemaking in autonomous driving', in *IJCAI 2019*, pp. 1879–1885, (2019).
- [35] J. Suchan, M. Bhatt, and S. Varadarajan, 'Driven by commonsense: On the role of human-centred visual explainability for autonomous vehicles', in *ECAI*, (2020).
- [36] J. Suchan, M. Bhatt, S. Vardarajan, A.A. Seyed, and S. Yu, 'Semantic Analysis of (Reflectional) Visual Symmetry: A Human-Centred Computational Model for Declarative Explainability', *Advances in Cognitive Systems*, **6**, 65–84, (2018).
- [37] B. Tversky and J. M. Zacks, *Oxford handbook of cognitive psychology*, chapter Event perception, 83–94, Oxford: Oxford, 2013.
- [38] P.A. van der Helm, 'Simplicity versus likelihood in visual perception: From surprisals to precisals.', *Psychological Bulletin*, **126s**, 770–800, (2000).
- [39] M. Wierda, *Vision in Vehicles - V*, chapter Beyond the eye: cognitive factors in drivers' visual perception, 97–105, 1996.
- [40] C.C. Williams and S.M. Castelano, 'The changing landscape: High-level influences on eye movement guidance in scenes', *vision*, **3**(33), (2019).
- [41] C.J. Wilson and A. Soranzo, 'The use of virtual reality in psychology: A case study in visual perception', *Advances in Computational Psychometrics*, (2015).