CREATIVE NAVY

Objective assessment of user interfaces

Cømpass
the AI that measures visual complexity

Solution overview

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Cømpass is a tool that measures the visual complexity of user interfaces. It uses computer vision and machine learning to evaluate the factors that make an interface complex and thus difficult to use.

The approach is based on consistent research in cognitive science and computer science. We have analysed a large number of complexity factors for GUIs, weeding out the ones without predictive value.

Cømpass is a reliable, objective, and efficient way to measure visual complexity in user interfaces.

Why develop a GUI assessment tool?

With the rapid spread of the Internet and new technologies to use it, human behaviour in digital environments grows in importance for the computational social sciences[28].

While this type of technology is widely used in a personal setting, more importantly it has become the basis for emergency response systems, health care applications, automobiles with digital systems, disaster relief systems, industrial and professional systems that affect productivity. People interact in digital environments via graphic user interfaces (GUI), which strongly influence users' behaviours and attitudes in these interactions[29].

Professional designers and amateurs alike intuitively know that simplicity is one of the most important features of an interface that is easy to use. This is backed by consistent research in cognitive science and computer science, which has successfully uncovered what simplicity means in practice and how it supports user experience.

Designers working to create better user interfaces find it most challenging to assess potential design solutions while also predicting ease of use. The situation is further complicated by the fact that improving a single UI component doesn't result in an improved design. A large number of good design decisions that coalesce is vital.

Being able to quickly and objectively assess the visual complexity of a user interface speeds up the user experience improvement process. Furthermore, it leads to more robust designs of far superior quality. In effect, the tool does away with guess work and subjectivity, supporting a mature, evidence-based design.

Medical GUIs

A primary area in which Cømpass will add value is interfaces used by medical professionals. In this niche, decisions are often made under time pressure due to urgency or work overload. Improving the interfaces by reducing complexity and making them more accessible for human processing will boost productivity, reduce error incidence and allow users to stay focused on the patients they care for. The healthcare industry is known for high development costs and barriers to user testing. Any alternative method to improve user interfaces will make a major contribution.

Real time dashboards

In applications with one dashboard view which integrates information in real time, complexity runs high. Oftentimes all that information is necessary for the users' decision-making process, so the onus is on interface designers to reduce complexity by finding better ways to display information. In this context, Cømpass will provide designers with an objective and time efficient way to measure the visual complexity of different design solutions.

Embedded GUIs

Embedded GUIs can be found in any device's touch displays, excluding laptops and mobile devices. Typically, they are an integral part of stand alone devices (such as tools or appliances), but they can also consist of a monitor integrated into a larger object (such as industrial machinery or a display in a control room). These interfaces have to allow for seamless touch and play interaction. More often than not, display specifications impose severe limitations on what an interface can do. Reducing complexity in these devices improves productivity and reduces training costs.

Professional web apps

Professionals use applications throughout the day to complete work related tasks. They will benefit greatly from interfaces that are easier to deal with. On the one hand, less complex design reduces onboarding and training efforts. On the other hand, once a user is actively using the interface, less complexity diminishes cognitive load and prevents fatigue. This improves productivity and reduces the likelihood of errors.

Interfaces for the elderly

Research has shown that the elderly have a particularly difficult time dealing with complex interfaces. The manner in which they perceive and process an interface as a visual stimulus is unique, impacting their decision-making process, and catching designers off guard. Therefore, developing Cømpass to evaluate interfaces from the perspective of usability for the elderly population will enable designers to assess design solutions as fast as they are iterated.

Consumer apps

Even though consumer apps often follow design patterns and best practices consistently, large numbers of users warrant a level of design optimization that is only possible by measuring interfaces objectively and reliably. Cømpass will be especially useful for interfaces that have an unusual level of complexity or where users have to go into an interaction blind.

How GUI complexity affects user performance

The ubiquitous spread of digital devices results in constant interactions with multiple computer-based systems, which puts a lot of pressure on the human cognitive system and raises serious challenges that can hinder the quality of interactions[30], information processing[31] and the productivity level[32] of one's work.

Firstly, visual complexity has a direct impact on task completion. Studies conducted with professional user interfaces (for example in the control of air traffic[21] and healthcare applications[1]) have found that the more complex the interface, the longer it takes users to solve tasks. The user error rate also rose significantly[2] due to the high cognitive load[1] caused by visual complexity. Cognitive load is easily influenced by the burden of information processing placed on the user.

Secondly, visual complexity has a significant effect on emotional arousal: the higher the visual complexity, the higher the intensity of the negative emotions triggered[18]. Not only is this unpleasant, but in turn, negative emotions affect task performance, for example by hijacking attention, affecting working memory, and decreasing exploratory behaviour in search and recognition tasks[3].

Multiple studies in the field of digital environments suggest that the complexity of the graphical user interface influences behavioural outcomes such as communication effectiveness[33], flow[34], usability[2], arousal, pleasantness[35], and attitudes[36].

Interfaces with lower cognitive load support users in creating value while they use professional devices or applications. Better interfaces improve productivity, prevent errors, and reduce training costs.

Reaching a high level of informational relevance can be challenging in an environment where data is constantly progressing[37]. The importance of measuring the interaction between the graphical user interfaces and the cognitive demands becomes essential as it allows one to predict unwanted consequences that might lead to negative externalities. Therefore it is beneficial for designers to have a tool that measures visual complexity in an objective manner.

GUI complexity can be measured

Perception of user interfaces is subjective, to a certain extent. However, studies in the fields of cognitive science, human-computer interaction, and computer science have revealed an array of interface design factors that affect user performance. They can be measured in an objective manner[4,18].

Studies also stress the importance of a thoughtful graphic user interface for an optimal human-system interaction. Some general principles have been put forth, for example that the graphical user interface of a computer-based system should include only safety and quality-enhancing attributes while disqualifying features that tend to increase the unneeded workload[38].

A significant research effort has sought to identify the factors that affect user performance. Some researchers have looked at individual design details, such as imagery[5,7], icons[6], visual banners[8], 3D graphics[9], etc. Others have evaluated complete GUIs in both professional applications[1, 10, 21] and web interfaces[4, 2, 23, 27].

Additionally, researchers have tested measurement methods applied to the factors identified. They found that when several methods are used simultaneously to indicate the overall visual complexity of an interface, strong predictions can be made about users' performance when engaging with an interface and their subjective impression of the interface[18].

Evidence suggests that these factors are consistent across cultures[11, 12].

Factors that predict GUI complexity

Research consistently shows that predictions become more reliable when several factors are used concurrently as a composite measure of visual complexity. There is significant diversity in terms of which factors are combined and how they are measured. Broadly speaking, these factors fall into five categories.

Complexity as intricacy

A simple but effective way to think about visual complexity is to examine the number, characteristics, and variety of interface elements, such as buttons, labels, titles, shapes, graphics, etc.[13] Aspects such as alignment of elements, balance, density, the size of objects, and consistency have predictive value[13, 14, 15]. This approach can be elaborated further based on the concept of the local density of components[16].

Grouping

These types of factors address how elements work together, even when the number of elements stays the same[17]. In essence, it relies on measurements such as symmetry, regularity of connectedness, and lacunarity[19, 20]. It also includes the relations between elements which can indicate the level of relevance said elements have to one another (where an increase in relations lowers information complexity)[21]. Even a simple model consisting of five measurements (alignment, balance, density, size, and grouping) can predict user satisfaction with an accuracy of 88.8%[22].

Structural features

These measurements examine how a view of the interface is divided into areas. A number of factors act as reliable indicators of this aspect of user interfaces. For example, the top-left corner, where a chunk rendering of the page is created based on cues, allows the user to identify divisions. The top-left corner of a box is taken into account if it fulfils a series of criteria[23].

Visual hierarchy

Visual hierarchy determines a GUI's potential to guide people's attention in a beneficial sequence[24]. From a technical perspective, the importance of visual hierarchy is explained by the premotor theory of attention, which predicts that overt and covert processes involving eye movements provide users with information about what they are seeing and shifts the focus of their attention[25, 26].

When visual hierarchy is not clear in an interface, users find it difficult to understand their task and concentrate on it.

Visual design

The properties of colour directly affect visual complexity[18]. Some of the factors found to be relevant for visual complexity are: the number of colours, colour harmony, contrast ratios, brightness variance and texture [23, 13, 27]. In essence, the use of colour determines the discriminability of information[24].

The role of computer vision

If user interfaces had to be coded before they could be evaluated, it would be too late for a tool such as Cømpass to have any meaningful impact for users. Luckily, that's not the case. Evaluating interfaces based on design file picture exports allows designers to receive feedback while actively seeking and testing solutions.

This is why computer vision is a core component of our tool. We use image processing for feature extraction, after which the data collected goes to metric calculation. Features vary for each of the factors discussed above, and thus a key part of our research is identifying the right types of metrics. Developing image processing and computer vision techniques with high accuracy is essential in order to achieve high efficiency.

Machine learning is used to ensure element recognition accuracy and to develop prediction models. We collect and label data to train and test datasets, after which we extract features in order to develop prediction models. Subsequently, we train the models until they reach a satisfactory accuracy level. The final step is testing the models against the test datasets.

Automation makes feature extraction faster and more effective. Machine learning develops the generalisation capability of a prediction model, thus enabling exceptional performance with new, unseen data prediction[23]. The major advantage of machine learning in this application is that it extracts features using statistical analysis, in other words without human manipulation. Moreover, visual complexity analysis is carried out by imitating human behaviours[18].

References

1. A. Lorenz and R. Oppermann, "Mobile health monitoring for the elderly: Designing for diversity," Pervasive and Mobile Computing, vol. 5, no. 5, pp. 478-495, Oct. 2009
2. Tuch, A. N., Bargas-Avila, J., Opwis, K., and Wilhem, F. 2009. Visual complexity of websites: Ef- fects on users' experience, physiology, performance, and memory. *Int. J. Hum. Comput. Stud. 67*, 703–715.
3. Tuch, A. N., Kreibig, S., Roth, S., Bargas-Avila, J., Opwis, K., and Wilhem, F. H. 2011. The role of visual complexity in affective reactions to web pages: Subjective, eye movement, and cardiovascular responses. *IEEE Trans. Affective Comput. 2*, 4, 230-236.
4. Song, G. 2007. Analysis of web page complexity through visual segmentation. In *Proceedings of the 12th International Conference on Human-Computer Interaction.* Lecture Notes in Artificial Intelligence, vol. 4553, Springer, 114–123.
5. Forsythe, A. 2009. Visual complexity: Is that all there is? In *Proceedings of the 13th International Conference on Human-Computer Interaction.* Lecture Notes in Artificial Intelligence, vol. 5639, Springer, 158–166.
6. Forsythe, A., Sheehy, N., and Sawey, M. 2003. Measuring icon complexity: An automated analysis. *Behav. Res. Methods Instrum. Comput. 32*, 2, 334–342.
7. Rosenholtz, R., Li, Y., and Nakano, L. 2007. Measuring visual clutter. *J. Vision 7*, 2, 1–22.
8. Pieters, R., Wedel, M., and Batra, R. 2010. The stopping power of advertising: Measures and effects of visual complexity*. J. Market. 74*, 5, 48–60.
9. Gero, J. S. and Kazakov, V. 2004. On measuring the visual complexity of 3d objects. *J. Des. Sci. Technol. 12*, 1, 35–44.
10. Donderi, D. C. 2006. Visual complexity: A review. *Psychol. Bull. 132*, 1, 73–97.
11. J.G. Snodgrass, M. Vanderwart, A standardized set of 260 pictures: norms for name agreement, image agreement, familiarity, and visual complexity, J. Exp. Psychol.: Hum. Learn. Memory 6
12. L. Soren, Usability Requirements in a Tender Process, in: Proceedings 1998 Australasian Computer Human Interaction Conference, Adelaide, SA, Australia
13. J. Koch, A. Oulasvirta, Computational layout perception using gestalt laws, in: Conference Extended Abstracts on Human Factors in Computing Systems, California, USA, May 2016
14. Miniukovich, A. De Angeli, Quantification of interface visual complexity, in: International working conference on advanced visual interfaces, Como, Italy, 27–30 May 2014
15. A. Riegler, C. Holzmann, UI-CAT: Calculating User Interface Complexity Metrics for Mobile Applications, in: 14th International Conference on Mobile and Ubiquitous Multimedia, Linz, Austria, 30 November–2 December 2015.
16. T.S.Tullis: Screen design Handbook of Human-Computer Interaction, Second completely revised edition. (eds) M.Helander, Landauer, P.Prabhu, 1997
17. Miyoshi, Tetsuya and Atsuo Murata. "A method to evaluate properness of GUI design based on complexity indexes of size, local density, aliment, and grouping." *2001 IEEE International Conference on Systems, Man and Cybernetics. e-Systems and e-Man for Cybernetics in Cyberspace (Cat.No.01CH37236)* 1 (2001): 221-226 vol.1.
18. Eren Akça, Ömer Özgür Tanriöver, A comprehensive appraisal of perceptual visual complexity analysis methods in GUI design, Displays, Volume 69, 2021
19. M.L. Mack, A. Oliva, The perceptual dimensions of visual simplicity, J. Vis. 4 (8) (2004)
20. M. Moshagen, M.T. Thielsch, Facets of visual aesthetics, Int. J. Hum Comput Stud. 68 (10) (2010)
21. J. Xing, Information complexity in air traffic control displays, Applications and Services Lecture Notes in Computer Science vol. 4553 (2007)

22. K.A. Alemerien, Metrics and tools to guide design of graphical user interfaces, Dissertation, North Dakota State University, 2014.
23. Ou Wu, Weiming Hu, and Lei Shi. 2013. Measuring the Visual Complexities of Web Pages. ACM Trans. Web 7, 1, Article 1 (March 2013)
24. Urano, Yoko & Kurosu, Aaron & Henselman-Petrusek, Gregory & Todorov, Alexander. (2021). Visual Hierarchy Relates to Impressions of Good Design.
25. Soazig Casteau, and Daniel T. Smith. 2020. Covert attention beyond the range of eye-movements: Evidence for a dissociation between exogenous and endogenous orienting. Cortex, 122
26. Calden Wloka, Iuliia Kotseruba, and John K. Tsotsos. 2018. Active fixation control to predict saccade sequences. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition
27. K. Reinecke, T. Yeh, L. Miratrix, R. Mardiko, Y. Zhao, J. Liu, K.Z. Gajos, Predicting Users' First Impressions of Website Aesthetics With a Quantification of Perceived Visual Complexity and Colorfulness, in: CHI Conference on Human Factors in Computing Systems, Paris, France, 27 April–3 May 2013.
28. Lazer, D., Pentland, A., Adamic, L., Aral, S., Barabasi, A. L., Brewer, D., ... & Van Alstyne, M. (2009). Social science. Computational social science. Science (New York, NY), 323(5915), 721-723.
29. Lee, K. W., & Lee, Y. C. (2012). Design and validation of an improved graphical user interface with the 'Tool ball'. Applied ergonomics, 43(1), 57-68.
30. Jha, A. P., Stanley, E. A., Kiyonaga, A., Wong, L., & Gelfand, L. (2010). Examining the protective effects of mindfulness training on working memory capacity and affective experience. Emotion, 10(1), 54.
31. Ash, I. K., Cushen, P. J., & Wiley, J. (2009). Obstacles in investigating the role of restructuring in insightful problem solving. The Journal of Problem Solving, 2(2).
32. Cheriff, A. D., Kapur, A. G., Qiu, M., & Cole, C. L. (2010). Physician productivity and the ambulatory EHR in a large academic multi-specialty physician group. International journal of medical informatics, 79(7), 492-500.
33. Geissler, G., Zinkhan, G., & Watson, R. T. (2001). Web home page complexity and communication effectiveness. Journal of the Association for Information Systems, 2(1), 2.
34. Huang, M. H. (2003). Designing website attributes to induce experiential encounters. Computers in Human Behavior, 19(4), 425-442.
35. Deng, L., & Poole, M. S. (2010). Affect in web interfaces: A study of the impacts of web page visual complexity and order. Mis Quarterly, 711-730.
36. Kumar, N., & Kumar, J. (2016). Measurement of Cognitive Load in HCI Systems Using EEG Power Spectrum: An Experimental Study. Procedia Computer Science, 84, 70-78.
37. DesRoches, C. M., Campbell, E. G., Vogeli, C., Zheng, J., Rao, S. R., Shields, A. E., ... & Jha, A. K. (2010). Electronic health records' limited successes suggest more targeted uses. Health affairs, 29(4), 639-646.
38. Mazur, L. M., Mosaly, P. R., Moore, C., Comitz, E., Yu, F., Falchook, A. D., ... & Marks, L. B. (2016). Toward a better understanding of task demands, workload, and performance during physician-computer interactions. Journal of the American Medical Informatics Association, 23(6), 1113-1120.