HCI for Elderly, Measuring Visual Complexity of Webpages Based on Machine Learning

1st Zahra Sadeghi
Shahid Beheshti University
Tehran, Iran
z.sadeghib@gmail.com

2nd Elaheh Homayounvala
Goldsmiths, University of London
London, UK
e.homayounvala@gold.ac.uk

3rd Mostafa Borhani
Shahid Beheshti University
Tehran, Iran
mo_borhani@sbu.ac.ir

***Abstract*—The increasing number of elderly persons, aged 65 and over, highlights the problem of improving their experience with computers and the web considering their preferences and needs. Elderlies' skills like cognitive, haptic, visual, and motor skills are reduced by age. The visual complexity of web pages has a major influence on the quality of user experience of elderly users according to their reduced abilities. Therefore, it is quite beneficial if the visual complexity of web pages could be measured and reduced in applications and websites which are designed for them. In this way a personalized less complex version of the website could be provided for older users. In this article, a new approach for measuring the visual complexity is proposed by using both Human-Computer Interaction (HCI) and machine learning methods. Six features are considered for complexity measurements. Experimental results demonstrated that the trained proposed machine learning approach increases the accuracy of classification of applications and websites based on their visual complexity up to 82% which is more than its competitors. Besides, a feature selection algorithm indicates that features such as clutter and equilibrium were selected to have the most influence on the classification of webpages based on their visual complexity.**

***Index Terms*—visual complexity, webpages, human computer interaction, user-interface, machine learning, personalization**

I. INTRODUCTION

To make computer devices an integral part of our lives, the good design of User Interfaces (UI), in the field of Human-Computer Interaction (HCI), has become an important issue today. Useful UIs have to be adapted to users who use them [1] to increase the quality of experience based on different subjective parameters such as visual complexity. This is of critical importance for user communities with special needs such as elderlies, especially by increasing the number of senior citizens in the world.

Research studies about elderlies mentioned normal brain aging results in an average decline in some functions like, cognitive functions such as the speed of thinking and working memory and also motor functions [2] The following can be noted as reasons for paying more attention to the preferences and needs of elderly people [3] to improve their experience.

- Many cognitive, physical, and motor skills are reduced with aging [3].
- Given the fact that elderlies are the largest population of the coming decades, also, very little information is gathered about the performance of older users with the computer system [4].
- Design based on the preferences and needs of the elderly may result in a better design of UI for other users [5].

Generally, users' visual preferences such as preferring simple websites with little text and few images or preferring complex websites with many colors, images, and text, indicate which website complexity they can work with most efficiently. The visual complexity of a website has a notable negative impact on search efficiency and information recall [6] and also user interfaces with low visual complexity tend to have higher aesthetics, usability, and accessibility and result in more user satisfaction [7]. On the other hand, since improving older users' experience with computers and the web and considering their preferences and needs are gaining more importance, and there is a strong link between speed of visual information processing and cognitive aging [8], and also almost all users assess website design and complexity very quickly, within 1 second, and these evaluations remain surprisingly consistent over time [9], so this study aims to provide a model to evaluate visual complexity of webpages, that could increase the speed of visual discrimination [8], and identify the most important parameters for complexity evaluation. This study can provide guidelines for UI designers on how to reduce complexity for older users' websites and provide a personalized experience for them. Related work and research methods and results are presented in the next sections.

II. RELATED WORK

Reducing or revoking the unnecessary elements from the UI design, content, and code is the main goal of measuring visual complexity. Website aesthetics is an effective factor for attracting online users. According to a series of studies in recent years, users judge the aesthetics of websites in a short time after they saw it. On the other hand, if one understands a website as an unappealing website, he/she would like to leave it and do not trust it at all [10]. Berlyne [11] discovered the relationship between visual complexity and the appeal of a web page [10]. It is significant to know which website features help people's perception of visual complexity. The visual complexity of webpages has many effects on human perception and feeling. Users comfortably search and recognize tasks on low visually complex pages [12]. Fig. 1 shows two web pages with high and low visual complexity.

Fig. 1. A high visual complexity page (Left). A low visual complexity page (Right) [9].

Age-related problems such as cognitive and motor skills problems influence older users' experience with visual devices. Some of these problems are reported based on reviewing the literature in this domain.

According to previous studies, it is difficult for elderly people to distinguish the contrast difference between colors. The background color of the screen should not be white and should not be too bright. The designer of UI for the elderly has to avoid using colored text on a colored background [1], [4]. Elderly people often have weakening experiences in many aspects of their vision, including visual acuity, dark adaptation, and weakened recognition of color contrast.

The use of touch screens among older people is much more popular than keyboard input, the probability of accidental user input is more, so it is best to align the page elements to the center [1]. Much attention has been recommended by [5] to be careful when placing elements on the edge of the page. In general, it is better to place elements in the center because it is very difficult for an elderly person to work with user interfaces that their elements are on its edges.

The centrality of the elements and colorfulness is very important in the UI design for elderly people. The equilibrium and clutter of UI are also among important parameters for elderlies and are metrics related to the visual complexity [8], [9].

Colorfulness and centrality of the elements are very significant features of UIs related to elderlies. These features are also related to clutter and equilibrium that are among the important parameters of the visual complexity of UIs [1], [4].

We found a gap in the literature to improve the interactions of the elderly people with the computer by measuring visual complexity and reducing it in UIs. Since, manual measurement and reduction of the complexity is an expensive and time-consuming task, this work focuses on the automatic measurement of visual complexity to reduce time and cost. On the other hand, many previous works have analyzed the visual complexity from the perspective of human-computer interaction (HCI) and finally measured it with this approach [13], [15], [22], [23]. And only a few studies have used a combination of human-computer interaction and machine learning to estimate visual complexity. Wu et al. [12] revealed that this combination could lead to better results; yet, they employed supervised learning algorithms and did not reach high accuracy in the prediction of visual complexity. The current study presents a new model for measuring visual complexity by using studies in HCI and machine learning.

III. Research Study

This study first identified important visual complexity parameters for elderlies as summarized in Table. I.

TABLE I
COMPLEXITY METRICS RELATED TO ELDERLIES AND UI DESIGN RECOMMENDATIONS

Recommendations	Related complexity metrics
It is difficult for the elderly to distinguish between color and contrast between colors. The background color of the screen should not be white and should not be too bright. Avoid using colored text on a colored background [1], [4].	Figure-ground contrast
In the design of the interface for the elderly, the simplicity of the user interface is very important and the icons should be simple [1], [4].	Clutter
Be careful when placing elements in the edge, generally, it is better the elements be near the center of the frame [4].	Equilibrium
All elements should not have the same color (the order of color is all colors not only black and white) [4].	Color variability

Some of the typical metrics of visual complexity are illustrated in Table. II.

TABLE II
THE METRICS OF VISUAL COMPLEXITY

Metric	Description
Number of quadtree leaves	Quadtree decomposition divides an image into origins Recursively until the algorithm stops, and returns the number of leaves [13].
Clutter	The amount of information perceived from the picture (the number of image objects and color variation affects the clutter of image) [14].
Balance	In an image, if the right and left, as well as the top and bottom part of it, has the same number of components, independent of their spatial distribution, it is a balanced image [15].
Equilibrium	The centering of image elements around the image's midpoint is called equilibrium that is dependent on their spatial distribution [15].
Number of images	A simple search in the HTML code of a web page can return the number of images.
Number of font-sizes	A simple search in the HTML code of a web page can return the number of font-sizes.

As we can see in Table. II, the centrality of the elements and colorfulness influence elderlies and they are related to equilibrium and clutter of the UI that are important metrics of visual complexity. Measuring visual complexity and diminishing it in UIs can improve older people's interactions with the computer. Therefore, measuring and assessing visual complexity are important issues for application and webpages. Measuring the visual complexity of applications and web pages is an expensive and time-consuming task. This work focuses on the automatic measurement of visual complexity to reduce time and cost. Subjectively measuring the visual complexity of web pages can be done reliably [16]. This paper presents a machine learning approach to use limited subjective measurements to build a model to classify unlabeled websites with increased accuracy.

In this study, an automatic approach based on machine learning was proposed to measure the visual complexity as an effective criterion on elderly experience with webpages. A set of features and some labeled data are needed to train the proposed machine learning algorithms. Typically, preparing the training samples is a difficult and time-consuming task. Therefore, this work proposed a semi-supervised algorithm to reduce the number of needed labeled data in training however it has a great performance in the test. In this study, the UI feature set is customized to measure visual complexity for elderly people.

Since single machine learning algorithms did not provide good classification accuracies, an ensemble co-training algorithm is utilized in this study. First learning machines are trained using labeled data and then the most accurate algorithm is used to classify a subset of unlabeled data. Interactively the unlabeled subset is deleted from the unlabeled data set and it adds to labeled data set with corresponding labels in the next round. This process continues until all data is labeled by the proposed algorithm. Fig. 2 demonstrates the overall research process in this study.

A. Data preparation

Homepages typically give users the first impression of the website [12], so they are usually designed to attract users. In this work, a 600 screenshot of websites were collected (100 Persian and 500 English websites) from corporation webpages, universities, and personal websites. Screenshots and HTML source code of each homepage were collected. The features of these pages' screenshots and HTML source codes were extracted using the approaches introduced in the feature extraction section. In the user study part, 21 Iranian participants were asked to label these screenshots from the visual complexity point of view. The subjective rating process was performed by using software developed for this study which showed each of these 600 homepages with five buttons on the right of them and the participants expressed their opinion about the visual complexity by pressing one of these buttons. Due to the fact that visual complexity is not difficult to understand, participants were taught only how to use labeling software using 4 main screens, two with high visual complexity and the others with low visual complexity. Each page was shown for five seconds, and the participant selected a score from 1, 2, 3, 4, and 5, as the label of the page where 5 means the homepage is very complex, and 1 means it is very simple. These scores of 1 to 5 are later mapped to numbers -2, -1, 0, 1, and 2 in our calculations. This issue is worth considering that we asked the Iranian participants to conduct this experiment, and we all know that some nationalities may prefer different website styles regarding the characters are different, and the writing and reading styles are also different. Therefore, for future work, we suggest using participants of different nationalities.

The perception of the visual complexity of a web page is subjective and it might be different from one user to another, so this work considered the inter-user disagreement of visual complexity by asking several users to rate each category of webpages. The participants were divided into three equal groups. Each group, consisting of 7 users, rated three different categories of webpages. Each category consists of 180 pages.

Each training website is rated by several users. Typically, each website received 7 rates even though each of them should have one visual complexity label. Each web page got a visual complexity label using the suggested method by [17].

$$l = \begin{cases} +1\ (high\ complexity) & \Sigma_{i=-2}^{2} ur(i) * \frac{i}{5} \geq \frac{\sigma}{2} \\ -1\ (low\ complexity) & \Sigma_{i=-2}^{2} ur(i) * \frac{i}{5} \leq -\frac{\sigma}{2} \end{cases} \tag{1}$$

σ is the category gap between high and low complexity which in this category equals 0. l shows the category of the web page. $ur(-2)$ is the number of users who rate the page by "-2". In other words, l indicates the weighted mean of the users' rates.

B. Feature Selection

In this work, two feature categories, Visual features and HTML features based on elderly restrictions are extracted.

1) Virtual Features: In this category of features, four features balance, equilibrium, number of quadtree leaves, and clutter were calculated.

Quadtree decomposition due to the minimum color or intensity entropy, divides an image into regions, recursively until the algorithm stops, and returns the number of leaves. The number of leaves shows the number of areas that are no longer divisible [13]. The second metric that calculated in this research is clutter. Clutter defined as "a crowded or disordered collection of things". This metric affects the ability of individuals to find and identify an object on a webpage. The clutter of a webpage was calculated according to the method proposed in [14]. This metric has an important effect on the elderly. The input image converts to an optimal number of color clusters. The number of proto-objects reached by the number of obtained clusters. Eventually, the proto-object model calculates visual clutter perception by a simple count of the number of proto-object extracted from an image.

The third metric is the balance. A balanced presentation makes a sense of stability and confidence in a witness, while an unbalanced exhibition makes a feeling of stress [18]. Balance in a web page is attained by making the same weight of screen elements, left and right, top and bottom. The balance was

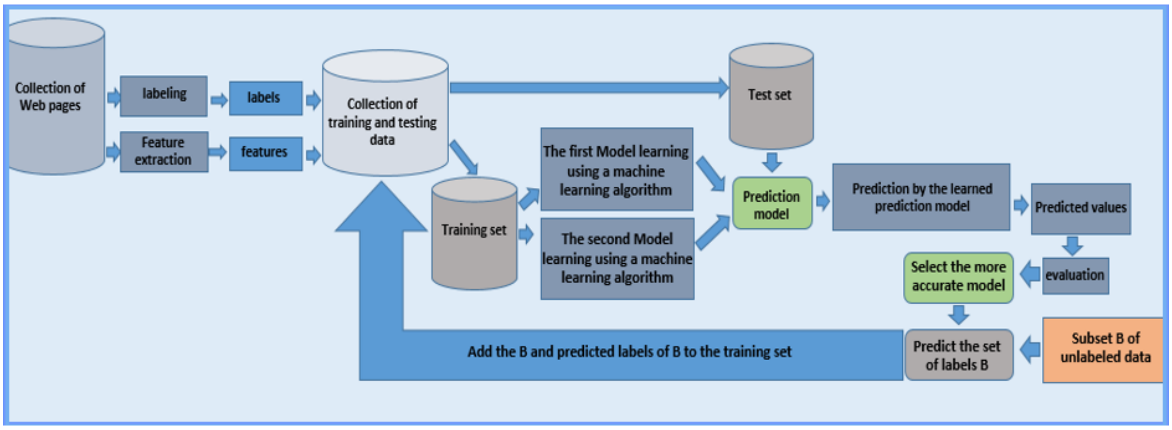

Fig. 2. Overall research process

calculated in this paper according to the formula mentioned in [15]. The formula is

$$BM = (w_L - w_R, w_T - w_B) \tag{2}$$

BM is the amount of balance, w_L is the weight on the left side (LHS), w_R is the weight on the right-hand side (RHS), w_T is the weight on the top, and w_B is the weight on the bottom.

The weight of a layout is the numerical sum of the weight of its components:

$$w = \Sigma_i a_i b_i \tag{3}$$

a_i is the area of an object and b_i is the distance between the vertical axis and its vertical central line.

The final feature that calculated in this research is equilibrium. Equilibrium can be defined as the centering of interface elements around the midpoint of the image [15]. Then a layout is in equilibrium when the center of the frame locates on the layout center.

The equation is:

$$EM = (x_c, y_c) - (x_0, y_0) \tag{4}$$

EM is the amount of equilibrium, and (x_0, y_0) is the center of the layout, and (x_c, y_c) is the center of the frame and is a fixed value. Equation (5) can be used to calculate (x_0, y_0) in which a_1, a_2, $a_3 \ldots$ area of a set of objects at points (x_1, y_1), (x_2, y_2), $(x_3, y_3) \ldots$:

$$(x_0, y_0) = \left(\frac{\Sigma_i a_i x_i}{\Sigma_i a_i}, \frac{\Sigma_i a_i y_i}{\Sigma_i a_i} \right) \tag{5}$$

2) HTML Features: In this paper, the number of font-size and the number of images are considered as two metrics. They are calculated by analyzing the HTML code of webpages. The Matlab code that calculates the number of images and font-size of a webpage takes the HTML code of the web page as input and returns the values of these two variables as output.

C. Machine Learning Algorithms in Training

Semi-supervised classification methods used the small set of labeled instances and unlabeled instances to train the classifier. In this study three algorithms of machine learning are considered. Studies have shown that two machine learning algorithms, random forest (RF) and support vector machine (SVM), are good algorithms for predicting unseen data for visual complexity [12].

1) Support Vector Machine: Support vector machines (SVMs) is one of the most popular machine learning classifiers. Supposing that the categories are linearly separable, this algorithm divided the categories with maximum margin. The purpose of this group of algorithms is to distinguish complex patterns in data [19], [20]. Multi-View (MV) SVMs including MV Least Squares SVM (MV-LSSVM) [21], MV Twin SVM (MvTSVMs) [24], MV Scaling SVM [25] Classifications can incorporate information from all views in the training phase while still permit modeling the views differently.

2) Random Forest: Random Forests (RF) are a grouping of decision trees that randomly choose features and the class of a test example is predicted by voting of the single trees [26].

This study employed a novel ensemble co-training that combines the power of Random Forest and Support Vector Machine methods for semi-supervised learning [27]. At the beginning, selected both algorithms RF and SVM are trained with existing labeled samples. Then, iteratively, both algorithms are evaluated and the best one is chosen to label the most confident predictions. This procedure is reiterated until all instances have a label.

IV. Result

The final result before and after using a co-training algorithm named RFSVM are shown in Table. III.

TABLE III
Classification precisions of SVM, RF and SVMRF algorithms

SVM	RF	RFSVM
0.5244	0.6303	0.7507

These numbers are the best accuracies of each algorithm after 60 runs of training. As shown in the above table, the proposed ensemble co-training algorithm can well predict the visual complexity of user interfaces. Therefore, the webpages with high visual complexity can be identified, and ultimately their complexity can be reduced. Also according to Table. III, RF is more suitable than SVM in terms of visual complexity classification.

As mentioned in this work, six features were considered. If subsets of these features were considered results reported in Table. IV are obtained. Table. IV shows the three highest feature selection algorithms with the highest classification accuracies.

TABLE IV
SUBNETS OF FEATURES WITH THE HIGHEST CLASSIFICATION ACCURACIES

First feature	Second feature	Third feature	RFSVM
Number of images	Clutter	-	0.8203
Balance	Number of quadtree leaves	Clutter	0.8120
Number of images	Number of font-sizes	Number of quadtree leaves	0.8024

As predicted, clutter is one of the most influential factors of the visual complexity for the elderly. This feature also includes many items like color variations and the number of objects on the website. Fig. 3 shows the distribution of the websites labeled as being of low and high visual complexity in 3D space based on the values measured for the features of clutter, balance, and number of quadtree leaves. As shown in the figure, these features can classify websites accurately.

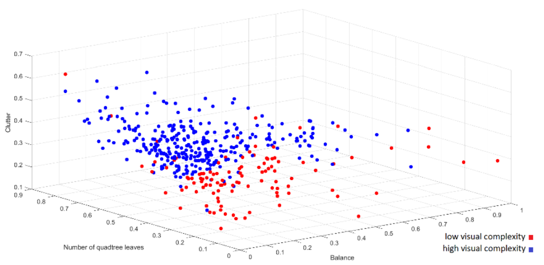

Fig. 3. Distribution of low and high visual complexity websites based on the number of quadtree leaves, clutter, and balance

V. CONCLUSION

Improving interaction between the elderly and computer systems is very important. Some of the skills are reduced by age so this category of users must be given more attention. Based on previous works some of the factors of visual complexity affecting the elderly are identified. Initially, this paper measured the visual complexity of webpages. Six effective features including clutter, number of images, number of quadtree leaves, number of font-sizes, balance, and equilibrium are considered in this measurement. This work also discusses the subjective property of visual complexity. The user rating results showed that there are large disagreements among the raters. This study proposed a method that combines the power of Random Forest and Support Vector Machines for semi-supervised learning or the power of Random Forest and SVM. After this step, appropriate accuracy was obtained to predict visual complexity. In this article, subsets of features with the best classification accuracy are also presented. Clutter was one of the most important features of the visual complexity of the elderly.

ACKNOWLEDGMENT

I would like to thank Dr. Nick Hine, professor of Goldsmiths, university of London for his extremely helpful comments on the paper.

REFERENCES

[1] D. Williams, M. A. U. Alam, S. I. Ahamed, and W. Chu, "Considerations in designing human-computer interfaces for elderly people," in Quality Software (QSIC), 2013 13th International Conference on, 2013, pp. 372-377.
[2] S. Ray and S. Davidson, "Dementia and cognitive decline," A review of the evidence. Age UK, vol. 27, pp. 10-12, 2014.
[3] J. M. Morris, "User interface design for older adults" Interacting with Computers, vol. 6, pp. 373-393, 1994.
[4] J.-M. Díaz-Bossini and L. Moreno, "Accessibility to mobile interfaces for older people," Procedia Computer Science, vol. 27, pp. 57-66, 2014.
[5] A. C. de Barros, R. Leitão, and J. Ribeiro, "Design and evaluation of a mobile user interface for older adults: navigation, interaction and visual design recommendations," Procedia Computer Science, vol. 27, pp. 369-378, 2014.
[6] A. Baughan, T. August, N. Yamashita, and K. Reinecke, "Keep it Simple: How Visual Complexity and Preferences Impact Search Efficiency on Websites," in Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems, 2020, pp. 1-10
[7] A. Miniukovich, S. Sulpizio, and A. De Angeli, "Visual complexity of graphical user interfaces," in Proceedings of the 2018 International Conference on Advanced Visual Interfaces, 2018, pp. 1-9.
[8] S. J. Ritchie, E. M. Tucker-Drob, and I. J. Deary, "A strong link between speed of visual discrimination and cognitive ageing," Current biology, vol. 24, pp. R681-R683, 2014.
[9] S. Pengnate, R. Sarathy, and J. Lee, "The engagement of website initial aesthetic impressions: an experimental investigation," International Journal of Human–Computer Interaction, vol. 35, pp. 1517-1531, 2019.
[10] K. Reinecke, T. Yeh, L. Miratrix, R. Mardiko, Y. Zhao, J. Liu, et al., "Predicting users' first impressions of website aesthetics with a quantification of perceived visual complexity and colorfulness," Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, pp. 2049-2058, 2013.
[11] D. E. Berlyne, "Curiosity and learning," Motivation and emotion, vol. 2, pp. 97-175, 1978.
[12] O. Wu, W. Hu, and L. Shi, "Measuring the visual complexities of Web pages," ACM Transactions on the Web (TWEB), vol. 7, p. 1, 2013.
[13] X. S. Zheng, I. Chakraborty, J. J.-W. Lin, and R. Rauschenberger, "Correlating low-level image statistics with users-rapid aesthetic and affective judgments of web pages," in Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, 2009, pp. 1-10.
[14] C.-P. Yu, D. Samaras, and G. J. Zelinsky, "Modeling visual clutter perception using proto-object segmentation," Journal of vision, vol. 14, pp. 4-4, 2014.
[15] D. C. L. Ngo, A. Samsudin, and R. Abdullah, "Aesthetic measures for assessing graphic screens," J. Inf. Sci. Eng, vol. 16, pp. 97-116, 2000.
[16] R. E. Wood, "Task complexity: Definition of the construct," Organizational behavior and human decision processes, vol. 37, pp. 60-82, 1986.
[17] O. Wu, H. Zuo, W. Hu, and B. Li, "Multimodal Web Aesthetics Assessment Based on Structural SVM and Multitask Fusion Learning," IEEE Transactions on Multimedia, vol. 18, pp. 1062-1076, 2016.

[18] S. S. Reilly and J. W. Roach, “Improved visual design for graphics display,” IEEE Computer Graphics and Applications, vol. 4, pp. 42-51, 1984.
[19] N. Cristianini and J. Shawe-Taylor, An introduction to support vector machines and other kernel-based learning methods: Cambridge university press, 2000.
[20] Borhani M, Ghassemian H ”Kernel grouped multivariate discriminant analysis for hyperspectral image classification,” International Symposium on Artificial Intelligence and Signal Processing, Springer, pp 3-12, 2013.
[21] L. Houthuys, R. Langone, and J. A. K. Suykens, “Multi-View Least Squares Support Vector Machines Classification,” Neurocomputing, vol. 282, pp. 78–88, 2018.
[22] Michailidou E, Harper S, Bechhofer S, ”Visual complexity and aesthetic perception of web pages,” Proceedings of the 26th annual ACM international conference on Design of communication, pp 215-224, 2008.
[23] Miniukovich A, De Angeli A, ”Quantification of interface visual complexity,” Proceedings of the 2014 international working conference on advanced visual interfaces, pp 153-160,2014.
[24] X. Xie, “Multi-view semi-supervised least squares twin support vector machines with manifold-preserving graph reduction,” International Journal of Machine Learning and Cybernetics, pp. 1–11, 2020.
[25] J. Xu, J. Han, F. Nie, and X. Li, “Multi-View Scaling Support Vector Machines for Classification and Feature Selection,” IEEE Transactions on Knowledge and Data Engineering, vol. 32, no. 7, pp. 1419–1430, 2020.
[26] L. Breiman, ”Random forests,” Machine learning, vol. 45, pp. 5-32, 2001.
[27] C Aridas, S Kotsiantis, ”Combining random forest and support vector machines for semi-supervised learning,” Proceedings of the 19th Panhellenic Conference on Informatics, 2015.