Segmentation of Dashboard Screen Images: Preparation of Inputs for Object-based Metrics of UI Quality

Jiří Hynek and Tomáš Hruška
Brno University of Technology, Faculty of Information Technology, IT4Innovations Centre of Excellence, Božetěchova 1/2, Brno, Czech Republic
{ihynek, hruska}@fit.vut.cz

Keywords: dashboard, page segmentation, object-based metric

Abstract: Using object-based metrics to analyze design aspects of user interfaces (UI) is a suitable approach for the quantitative evaluation of the visual quality of user interfaces. Balance or Symmetry are examples of such metrics. On the other hand, we need to deal with the problem of a detection of objects within a user interface screen which represent the inputs for the object-based metrics. Today's user interfaces (e. g., dashboards) are complex. They consist of several color layers, and it is complicated to segment them by well-known page segmentation methods which are usually used for the segmentation of printed documents. We also need to consider the subjective perception of users and principles of objects grouping (as Gestalt laws). Users usually group simple objects (graphical elements and shapes) into coherent visually dominant objects. We analyzed the experience of 251 users manually segmenting dashboard screens and designed a novel method for the automatic segmentation of dashboard screen images. The method initially focuses on the reduction of image colors which represents image layers. Then, it detects the primitives which makes a screen layout. Finally, the method processes the screen layout using the combination of the top-down and bottom-up segmentation strategy and detects visually dominant regions.

1 INTRODUCTION

Dashboard is a frequently used term connected with business intelligence and management information systems. Malik (2005) defines it as 'a rich computer interface with charts, reports, visual indicators, and alert mechanisms that are consolidated into a dynamic and relevant information platform.' According to Few (2006), dashboard should visualize only 'the most important information needed to achieve one or more objectives; consolidated and arranged on a single screen so the information can be monitored at a glance.' Dashboards are a favorite tools used by many organizations to comprehensively present their key performance indicators which help to evaluate the progress and benefit of business activities (Eckerson, 2010). Since dashboards support decision-making, they have become popular among a wide range of users for the management of personal activities and analysis of personal data.

The rising diversity of dashboards has led UI designers and researchers to think about the principles of high-quality dashboard design. For instance, Few (2006) provided design heuristics based on the knowledge of famous books regarding design and graphics e. g. (Tufte, 2001; Ware, 2012). Their application, however, usually requires presence of specialist in UI design. For this reason, researchers try design quantitative metrics measuring UI characteristics which play role during the application of design heuristics. For example, Hynek and Hruška (2016) measured colorfulness of UI to distinguish highly colorful and distracting dashboards. Such measuring can be performed automatically during the design phase. On the other hand, these metrics are usually simple. They focus on simple visual UI attributes. They do not consider screen in such level as a human would perceive it.

One possible step in making the metric-based evaluation more reliable is to process a screen similarly as it is perceived by human brain – not as a matrix of pixels but as a group of objects within a scene as described by Baker et al. (2009). Then, we evaluate the objects in a screen (widgets) and their properties (e. g., size or position) as described by Charfi et al. (2014). We can measure advanced characteristics of a screen as the characteristics connected with layouts. For instance, Ngo et al. (2003) have published 13 ad-

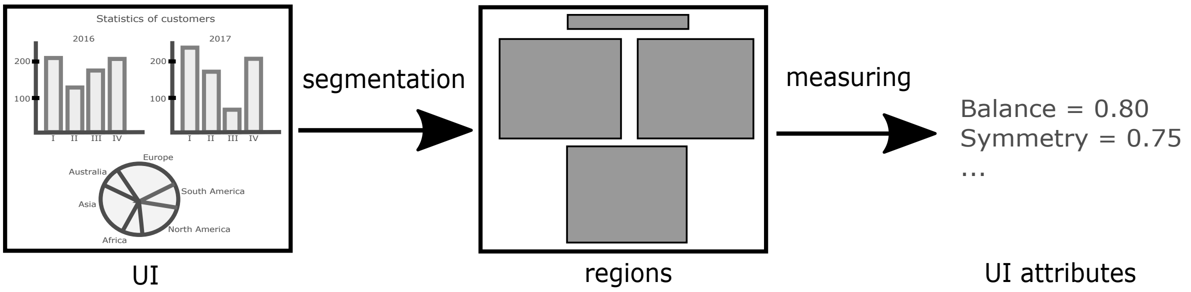


Figure 1: In the beginning, we have a screenshot of a user interface. We need to find a suitable segmentation method to specify regions representing the visually dominant objects corresponding with the user perception. Then, we can use these regions as inputs for object-based metrics measuring characteristics of the user interface.

vanced object-based metrics measuring aesthetic aspects of a screen. Figure 2 demonstrates an example of the Balance metric which measures the distribution of optical weight in a picture. An example of practical application of Ngo's metrics is the tool QUESTIM designed by Zen and Vanderdonckt (2014). Users can use the tool without special knowledge of UI design. They manually specify object regions according to their visual perception, and the tool calculates the values of Ngo's metrics using dimensions of the regions (Figure 1).

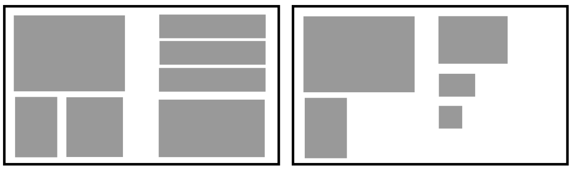


Figure 2: Example of two screens which can be compared using the Balance metric. The left screen is balanced since the weight of the regions is uniformly distributed among screen sides. The right screen is unbalanced due to the greater weight of its left side.

The weakness of the object-based metrics is the ambiguous definition of objects. The tool QUESTIM depends on the user's subjective perception of objects. Two users will most likely specify object regions in a slightly different way which may lead to ambiguous results. Moreover, dashboards are complex user interfaces with emphasis on graphical presentation of data. They consist of several layers (e. g., toolbars or menus). Their complexity makes it more difficult to design a segmentation algorithm which would reflect the average user perception (Hynek and Hruška, 2018). We cannot easily segment them into background and foreground which means, we cannot use common segmentation methods, e. g., methods used for the segmentation of printed documents.

This paper focuses on the problem of segmentation of dashboard into regions which we can use as inputs for object-based metrics. It provides a brief state of the art regarding visual perception of objects and existing page segmentation methods. Then, it describes an experiment analyzing user perception of the visually dominant objects (represented by their boundaries – regions). We use the knowledge to design an algorithm for the dashboards segmentation. Finally, we compare the results of the experiment with the results of the segmentation algorithm and suggest improvements.

We work with raster screenshots of dashboards. We focus more on the way the UI is presented to users than how the UI is implemented (e. g., web-page). Our goal is to analyze and understand what is actually seen by users on the screen. In contrast to the standard page segmentation algorithms, users are not able to process all graphical elements of the screen at once. They preattentively cluster simple elements into larger coherent parts as it is explained by Gestalt laws (Wertheimer, 1938). Information about the segmentation using structural description of UI can be found in (Burget, 2016; Feng et al., 2016).

2 PERCEPTION OF OBJECTS

The visual receptors of eyes – rods and cones – detect light and send it as electrical impulses via neurons to the brain which constructs an image of the perceived view (recognition of objects such as points, edges, or patterns and the comparison thereof) (Gibson, 1950). The initial construction of the image is done preattentively without the user's attention (in less than 200 ms (Healey et al., 1996)). After the initial recognition of objects, the brain tries to comprehend the recognized objects, organize them and add meaning to them. Baker et al. (2009) call it *sensemaking*. Only a fraction of what the viewer focuses on is also the object of the viewer's attention (Few, 2006). This fact corresponds with the limited[1] capacity of a brain's

[1] 3 - 9 items (Few, 2006), 3 - 5 items (Johnson, 2013)

short-term memory which stores the objects of the actual focus of attention.

Since the viewers can focus on a limited number of objects, they preattentively cluster simple graphical objects into a larger visual group. The problem of object ordering and grouping was described by Gestalt psychology in the early 20th century (Wertheimer, 1938). It provides several laws – e. g., the law of proximity, similarity, enclosure, closure, and continuity (Figure 3). We expect that we should consider these laws in the segmentation of screen. However, a missing mathematical model of Gestalt laws complicates the conversion of the laws into computer algorithms which would automatically predict how a user perceives the displayed screen. The problem of quantitative description of Gestalt laws is still the aim of researchers (Jäkel et al., 2016).

We also need to consider the subjective perception. Every viewer can process a different number of items at the same time. Orlov et al. (2016) performed an eye tracking study to analyze the effect of change of a number of objects in a dashboard on the perception of the dashboard. Also, every viewer has a different experience which also affects the visual perception (Johnson, 2013).

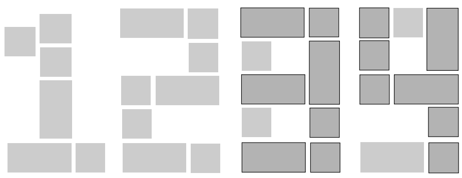


Figure 3: An example of the Gestalt laws of proximity, similarity and continuity. Readers will most likely cluster the rectangles and recognize the digits.

Finally, visually emphasized objects together with background elements (larger-scale, solid surfaces and structures) make a scene of visual representation (Henderson and Hollingworth, 1999). Every object within the scene can be described by its visual characteristics (Baker et al., 2009). We can analyze and evaluate the suitability of these characteristics after a successful and objective segmentation of the screen.

3 PAGE SEGMENTATION

Researches have developed many different segmentation methods for the purpose of computer processing and archiving of printed documents. Mao and Kanungo (2001); Shafait et al. (2006) provide a methodology for performance comparison of segmentation methods, and they compare the most famous ones. Kise (2014) classifies segmentation methods according to page layout, objects of analysis, primitives of analysis and strategy of analysis.

Page layout can contain non-overlapping and overlapping page elements. The overlapping layout analysis is significantly more difficult. It uses the extraction of features and classification of page components based on unsupervised or supervised learning (Jain and Zhong, 1996; Etemad et al., 1997). There exist dashboards with overlapping elements (Figure 5-a). The reason might be the need to fit data into one screen or just exaggerated creativity of the designer. However, it is not common, and dashboards usually contain elements arranged in simple non-overlapping rectangular or Manhattan layout.

Objects of analysis specify whether we analyze the background or foreground of the page. Printed documents usually consist of black foreground (e. g., text) and white background which can be separated by image thresholding (Sezgin and Sankur, 2004; Russ, 2016). On the other hand, dashboards often consist of hierarchically arranged frames, and the background is represented by multiple colors or color gradients (Figure 5-a). Minaee and Wang (2016) presented an example of the advanced method for separation of foreground and background.

Primitives of analysis represent elements of the page foreground or background processed by the segmentation analysis. We can consider single pixels as primitives, but common segmentation methods usually work with larger groups – e. g., connected components or projection profiles of the page image (Kise, 2014). This research works with the group of same color pixels represented by their rectangular boundaries (*regions*). We use heuristics to organize the regions in a tree structure representing the page layout.

The page layout consists of a hierarchy of page primitives. There are two **strategies of the layout processing** – the top-down and bottom-up strategy. The top-down strategy starts with a page and divides it into page primitives representing leaves of the layout tree, e. g. Recursive XY-cut (Nagy and Seth, 1984; Ha et al., 1995). On the contrary, the reversed bottom-up strategy starts with simple primitives of the page (e. g., groups of pixels) and join them into larger coherent groups, e. g. connected components-based methods (Simon et al., 1997).

We can assume that the dashboard screenshots can be captured in high quality if needed. However, whereas printed documents are usually very similar, the appearance of dashboards varies in many visual aspects. There exist various dashboard templates using different layouts, widgets, colors, and styles which complicates to design a universal segmentation algorithm.

4 ANALYSIS OF HUMAN PERCEPTION

The first part of the research was focused on the user perception of visually dominant objects. We performed an experiment to understand the principles of objects grouping and ambiguity of user perception. We gathered 130 image samples of various dashboards and divided them into 13 groups of 20 samples (every sample was contained in two groups). Then, we uniformly distributed the groups among users who provided us with descriptions of regions representing their subjective perception of the objects within a dashboard (*user description*).

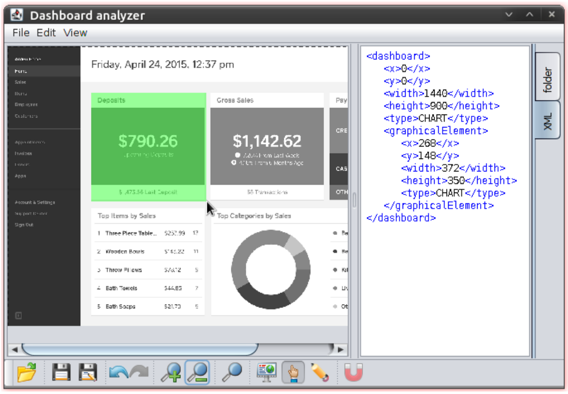


Figure 4: An example of the specification of regions using the Java application. The green area represents a selection of a visual region drawn by a user. The XML description presented on the right is re-generated with every change of regions in the canvas. It contains a specification of the dashboard and one region.

We selected the users among third-year students ($\sim$ 20 years old) of the Information Systems course at the Brno University of Technology, Faculty of Information Technology. We dedicated one lecture to familiarizing the students with the term dashboard and fundamental principles of data visualization and visual perception. Then, they used a simple Java application to load a dashboard, draw the perceived regions and generate the XML description of the specified regions (Figure 4). The application did not allow them to specify regions hierarchically (regions within regions) since we focused only on the top-level objects. 251 of 361 students decided to participate. They provided us with 5,020 user descriptions of regions in total ($\sim$ 39 user descriptions for every dashboard).

Then, we took the gathered user descriptions of the same dashboard and combined them into one *average description* representing the probabilities $p_i \in \langle 0,1\rangle$ of region occurrences in every pixel i of the dashboard. Figure 5-b shows a visualization of such an average description in the grayscale color space. We used these graphical representations to observe similarities and differences of the users' perceptions.

Then, we compared the average description with the user descriptions. We calculated the difference $\delta_i^{(u)} \in \langle 0,1\rangle$ between p_i and logical value $v_i^{(u)} = \{0,1\}$ representing the occurrence of a region in a user description provided by a user u for the every pixel i of a dashboard d:

$$\delta_i^{(u)} = \mid p_i - v_i^{(u)} \mid \tag{1}$$

and the average difference $\delta_d^{(u)} \in \langle 0,1\rangle$ of all pixels in the dashboard d:

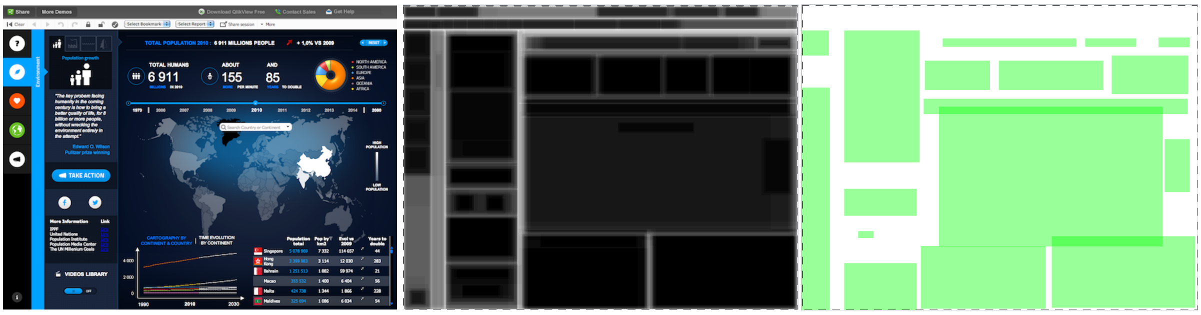
$$\delta_d^{(u)} = \frac{\sum_{i=0}^{n} \delta_i^{(u)}}{n} \tag{2}$$

We used the values $\delta_d^{(u)}$ for their later comparisons with the value $\delta_d^{(\mathrm{alg})}$ of the *segmentation descriptions* made by the segmentation method (Section 6).

4.1 Conclusions of Experiment

The detailed results of the experiment including all user and average descriptions are available in Appendix. The average descriptions indicated that the users segmented the dashboard screens similarly. We observed a strong influence of the Gestalt law of enclosure. The users tend to group the screen elements which are explicitly grouped by visually emphasizing frame. These frames are usually represented by borderlines or a different background, and they form a rectangular boundary of the widgets. Few (2006) showed that designers could avoid to use these boundaries because viewers will group the widget parts since they are usually close together (the Gestalt law of proximity). We can confirm this fact since our samples contain widgets without borders as well and the users grouped them. We used the knowledge during the design of the segmentation method (Section 5).

On the other hand, the users specified objects differently in the management areas (toolbars or headers; the left and upper part of Figure 5-b). Some users considered these areas as solid regions. Other users split them into smaller coherent regions (such as buttons or labels). It means that the segmentation algorithm does not need to be so strict with the segmentation of these areas. However, it the should try to make the value $\delta_d^{(\mathrm{alg})}$ lower than the values $\delta_d^{(u)}$. After the dashboard segmentation, we should use sufficiently robust object-based metrics which are able to consider certain differences caused by the subjective perception of users or imprecision of the segmentation.



(a) Dashboard image (b) Average perception (c) Segmentation

Figure 5: Figure (a) presents an example of colorful dashboard containing overlapping objects. Figure (b) presents the average description of probabilities of region occurrence. The higher color intensity represents a higher probability of the region occurrence. Figure (c) presents the result of the segmentation algorithm. Readers can notice segmentation problems – e. g., insufficient recognition of widgets in the header. Source of dashboard: softwareadvice.com

5 THE METHOD FOR SEGMENTATION OF DASHBOARDS

The method for the segmentation of dashboards consists of seven phases (Figure 7). The following subsections briefly describe the phases. Readers of this paper can evaluate the phases using the source code which is available online (see Appendix). We implemented the segmentation method in Java language as a part of the tool for analysis of dashboard quality shown in Figure 4.

5.1 Image Preprocessing

In the beginning, we convert the dashboard bitmap into the 8-bit grayscale color space representing color intensity to reduce the number of colors to 256. Then, we locate the areas represented by color gradients and replace the values of all the pixels of the area by the average grayscale value of the area. We search the areas by using a flood-fill-based algorithm. We add a neighboring pixel into the flood-fill queue if the difference between the color values of neighboring pixels is lower than a threshold t. We determine the optimal threshold t heuristically by analysis of the color histogram of the bitmap (Figure 6).

Finally, we posterize the image from the 8-bit to the [4 to 6]-bit color space. We search the optimal parameter of the posterization by analysis of color histograms similarly as the threshold t.

5.2 Selection of Color Layers

Then, we take the preprocessed bitmap and select the most frequently used colors of the bitmap. We do the selection iteratively. We sort all colors according to their frequency of occurrence and process colors from the most frequently used one. We are adding colors to a list of the most frequently colors until the occurrence of i-th color is higher than a heuristically chosen limit l_1 (0.1%, 5%, or 10% of the screen area) and summarized occurrence of all pixels in the list is lower than a limit l_2 (50%, 60%, or 70% of the area, respectively to l_1).

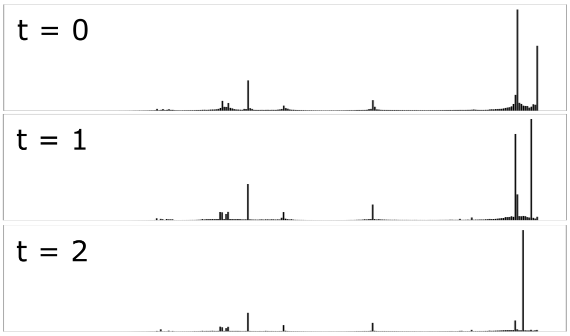


Figure 6: We iteratively increase the value t and analyze changes of the histogram indicating a possible loss of important information. The first histogram contains two dominant colors represented by the two highest bars. The reduction of color gradients using the threshold $t = 1$ keeps the areas using the dominant colors distinguished. However, using $t = 2$ reduces the two colors into one (there is a possibility that visually different areas were joined). Hence, we use the threshold $t = 1$ in this case.

If the bitmap contains only one dominant color we can easily separate background and foreground (we replace the dominant color with the white color representing the background, the values of the remaining pixels are changed to the black color representing the foreground).

If the bitmap contains more than one dominant color (usually up to 10), the bitmap most likely contains more layers (e. g., widget frames). We sort the dominant colors according to their frequency (from

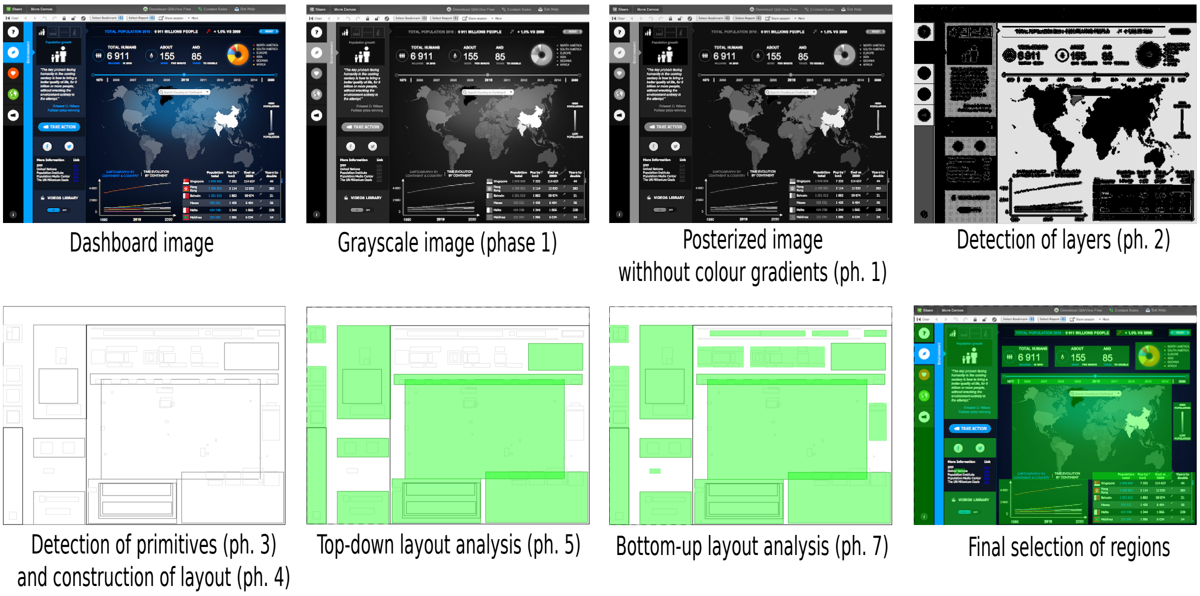


Figure 7: An example of the segmentation of a colorful dashboard containing overlapping regions. Firstly, we preprocess the image, reduce the number of colors and detect color layers. Then, we construct layout and find the visually dominant regions (represented by green rectangles). Readers can notice that the method ignores some widgets, especially in management areas. Phase 6 is not shown since the method did not detect any highly overlapping regions.

the highest to the lowest) and append a virtual color representing all the remaining colors to the end of the sorted list. Then, we map the list of n colors to the range of n uniformly distributed grayscale values (from the white color to the black color).

The result of the phase is a bitmap represented in the number of dominant colors + 1. The grayscale colors represent the layers of the bitmap which are suitable to detect page primitives and construct the page layout.

5.3 Detection of Page Primitives

The third phase detects page primitives in the bitmap. Firstly, we use a flood-fill-based algorithm to select the areas of pixels represented by the same color (layer). Then, we convert the areas into a set of regions representing rectangular boundaries of the areas. We keep the information about the layers as attributes of the regions. Also, we measure the share of the number of pixels within its boundary and keep the value as another region's attribute. We store these attributes for the heuristics in selection of dominant regions (Section 5.5). Finally, we filter tiny regions.

5.4 Construction of Layout

The fourth phase converts the set of regions into a tree structure representing the page layout. In the beginning, we initialize the tree by creating the root node representing the area of the dashboard (the top-level region). Then, we go through the set of regions and append the regions into the tree according to the following rules.

(1) If a region r_1 is located within r_2 represented by a node n_2, we compare r_1 with the children of n_2. (2) If r_2 is located within r_1, we create a node n_1 representing r_1, attach n_1 to the same parent as n_2 and reattach n_2 to n_1. (3) If r_1 intersects r_2 or there is no region in actual scope, we create a node n_1 representing r_1 and attach n_1 to the parent node of actual scope.

The final tree contains hierarchically organized regions (from the top-level region representing a dashboard to the leaves representing small objects). Note that one region can be represented by more than one node in the tree (overlapping layout).

5.5 Top-down layout analysis

The next phase takes the tree of regions and searches the visually dominant regions which correspond with the user perception. We start with the top-level node and look for a sidebar and header which are frequently occurred regions in dashboards. Then, we continue with the largest region representing the body of the dashboard and analyze its children. We sort the children according to their size and analyze their attributes gathered during the detection of primitives. Small data regions (usually represented by the foreground layer) are filtered. Very large regions which occupy the majority of the screen area are segmented (we analyze their children). Remaining medium-size regions are considered as visually dominant regions.

Since we focus only on the large regions representing widget frames, the strategy works well with the dashboards which consist of the widgets surrounded by an explicit boundary. The body of such a dashboard contains a small number of large regions which are detected by top-down analysis. The users tend to recognize these regions similarly since there is a strong influence of the Gestalt law of enclosure.

On the second hand, if a dashboard contains the widgets without explicit specification of their boundaries, the body of such a dashboard consists of a large number of small regions representing parts of widgets. Users tend to cluster these regions with correspondence to the Gestalt law of proximity. Our top-down analysis ignores these regions because the regions are too small. Hence, we keep the tree of regions for the phase 5.7, which uses the reversed bottom-up strategy to cluster small regions located in the remaining area of the dashboard.

5.6 Analysis of Overlapping Regions

Since there are dashboards with non-rectangular layouts, it is possible that the result of the previous phase could contain overlapping regions. We detect all intersections and compare the area of every intersection with the areas of the intersected regions. If the area of the intersection represents most of the area of one region (e. g., a region within another region or 2 highly overlapping regions, usually 33%), we join such regions into one region. Else, we ignore the intersection. The result of the phase is a list of visually dominant regions with a reduced number of intersections.

5.7 Bottom-up layout analysis

The last phase focuses on the areas of the dashboard which does not contain any visually dominant region recognized in the previous phases. These areas might contain small regions which together creates larger regions perceived by users with correspondence to the Gestalt law of proximity.

We take the tree of regions representing the layout of the dashboard and analyze it by using the bottom-up strategy. We measure vertical and horizontal gaps between the small regions and join the regions if the gaps are smaller than a heuristically chosen threshold. The regions detected in this phase together with regions detected in the previous phases represent the result of the dashboard segmentation.

6 EVALUATION AND RESULTS

Readers can find all results in Appendix.

6.1 Visual Analysis

Firstly, we compared the segmentation results with the average descriptions visually to understand the main problems caused by the computer segmentation. We usually inaccurately segmented the dashboards represented in low resolution or skewed by image compression. The algorithm also had occasional problems with the segmentation of management areas (e. g., toolbars and headers) which were ambiguously perceived by users. Sometimes, the method incorrectly clustered small regions into larger, so the result insufficiently reflected the Gestalt law of proximity. Readers can notice these problems in Figure 5-c.

Our method works well with the dashboards which contain widgets surrounded by an explicit border. We successfully reduced the number of colors and detected layout primitives in most of the cases.

6.2 Comparison with User Perception

Then, we used the data gathered in the experiment analyzing the user perception (Section 4). Firstly, we segmented all 130 dashboard samples using the segmentation method and measured 130 values $\delta_d^{(\mathrm{alg})}$ as described in Section 4. Then, we compared these values with the values $\delta_d^{(u)}$ representing differences between average description and user descriptions.

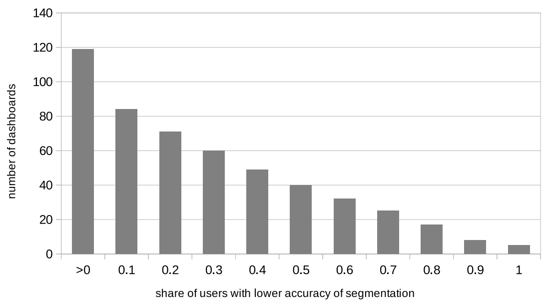


Figure 8: The numbers of dashboards where $\delta_d^{(\mathrm{alg})} \leq \delta_d^{(u)}$ for particular share of users u. Vertical axis shows the number of dashboards. Horizontal axis represents the share of users for which $\delta_d^{(\mathrm{alg})} \leq \delta_d^{(u)}$.

The segmentation descriptions created by the segmentation method are at least as close to the average descriptions ($\delta_d^{(\mathrm{alg})} \leq \delta_d^{(u)}$) as 33.90% of 5,020 descriptions provided by users. Figure 8 shows that 119 of 130 dashboards were segmented at least as close to the average description as they were segmented at least by one user. The closer to the average description the segmentation description is the better it averages perception of users.

6.3 Measuring Balance

Finally, we used the descriptions of regions to measure Balance (BM) of the 130 dashboards according to the formula designed by Ngo et al. (2003). We calculated 130 average values $\mathrm{BM}_d^{(\mathrm{users})}$ using the user descriptions, and 130 $\mathrm{BM}_d^{(\mathrm{alg})}$ using the segmentation descriptions. Average distance between those values $\delta_{\mathrm{BM}}^{(\mathrm{users,alg})}$ is 0.100 ($\sigma = 0.086$). We can consider this value as low compared to the range of $\mathrm{BM} \in \langle 0, 1 \rangle$. However, we should not neglect this deviation.

We also calculated the standard deviation for every value $\mathrm{BM}_d^{(\mathrm{users})}$. Average value of these 130 standard deviations is 0.119 ($\sigma = 0.051$) which is similar to the value $\delta_{\mathrm{BM}}^{(\mathrm{users,alg})}$. This means that there is an unneglectable deviation between the values of BM based on different user descriptions. Hynek and Hruška (2018) discuss this problem in detail.

7 LIMITATIONS

We integrated the designed method into the existing tool for analysis of dashboard user interfaces presented in Figure 4. We assume that the method could be applied to other tools using object-based metrics (e. g., QUESTIM designed by Zen and Vanderdonckt (2014)). Users can use it for the initial detection of regions. Then, they can arrange possible inaccuracies in the selections of regions manually. There is also a possibility to train parameters of segmentation according to the users' further corrections of regions.

The readers should, however, consider the following limitations. Firstly, we used the limited number of dashboard samples for the experiment of user perception and evaluation of the segmentation results. We should consider other samples (not only dashboards) to improve the segmentation method. Secondly, the results also depend on the limited group of users who provided us with the subjective description of regions. The group consisted of similar users (technical students). We assume that a higher diversity of users (e. g., art-skilled users) might provide us with a more objective view regarding visual perception. Finally, we should evaluate the results of the segmentation method with other metrics than Balance.

There are several possible improvements to the segmentation method which we suggest to do in the future. We could improve the image preprocessing. The heuristics analyzing image histograms could be replaced with more advanced machine learning techniques using the histograms or dashboard samples as the training set. We should also improve the heuristics used in the top-down and bottom-up analysis of dashboard layout and improve the correlation between the segmentation and Gestalt laws (especially the law of proximity). Finally, we should focus more on the overlapping layouts and low-quality image samples.

8 CONCLUSIONS

This paper dealt with the problem of segmentation of user interfaces into regions which can be used as inputs for object-based metrics of UI quality. We focused on dashboards which usually contain complex widgets and charts which makes dashboards difficult to segment. In contrast to printed documents, dashboards consist of a hierarchy of frames using different colors. The widgets often overlap each other. It is also much more challenging to consider the principles of human perception (e. g., Gestalt laws).

We performed the experiment analyzing the user perception of visually dominant regions in dashboards. We used this knowledge to design the method for the dashboard segmentation. The method consists of several phases. In the beginning, we preprocess a dashboard image, select dominant colors to distinguish dashboard layers and detect the layout primitives – regions. Then, we use the regions to construct the dashboard layout. Finally, we process the layout to find visually dominant regions. We process the layout two times. The top-down strategy selects large widgets explicitly surrounded by frames (the Gestalt law of enclosure). The bottom-up strategy clusters small regions into remaining visually dominant widgets (the Gestalt law of proximity).

We used the method to segment 130 dashboards and compared the results with the average description of regions provided by the users. Most of the samples were segmented similarly to the average descriptions. There were samples which were more difficult to segment (e. g., Figure 5). However, the goal of the research was to present the influence of user perception in the segmentation of user interfaces. Also, we wanted to design and implement a prototype of the segmentation method. We successfully integrated the method in the existing tool for the analysis of dashboards. In the future, we would like to improve the heuristics used for image preprocessing and analysis of dashboard layout and extend the method applicability to other kinds of user interfaces.

ACKNOWLEDGEMENTS

This work was supported by The Ministry of Education, Youth and Sports from the National Programme of Sustainability (NPU II) project "IT4Innovations excellence in science – LQ1602".

REFERENCES

Baker, J., Jones, D., and Burkman, J. (2009). Using visual representations of data to enhance sensemaking in data exploration tasks. *Journal of the Association for Information Systems*, 10(7):2.

Burget, R. (2016). Information extraction from the web by matching visual presentation patterns. In *International Semantic Web Conference*, pages 10–26. Springer.

Charfi, S., Trabelsi, A., Ezzedine, H., and Kolski, C. (2014). Widgets dedicated to user interface evaluation. *International Journal of Human-Computer Interaction*, 30(5):408–421.

Eckerson, W. W. (2010). *Performance dashboards: measuring, monitoring, and managing your business*. John Wiley & Sons.

Etemad, K., Doermann, D., and Chellappa, R. (1997). Multiscale segmentation of unstructured document pages using soft decision integration. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 19(1):92–96.

Feng, H., Zhang, W., Wu, H., and Wang, C.-J. (2016). Web page segmentation and its application for web information crawling. In *Tools with Artificial Intelligence (ICTAI), 2016 IEEE 28th International Conference on*, pages 598–605. IEEE.

Few, S. (2006). *Information dashboard design*. O'Reilly Sebastopol, CA.

Gibson, J. J. (1950). The perception of the visual world.

Ha, J., Haralick, R. M., and Phillips, I. T. (1995). Recursive xy cut using bounding boxes of connected components. In *Document Analysis and Recognition, 1995., Proceedings of the Third International Conference on*, volume 2, pages 952–955. IEEE.

Healey, C. G., Booth, K. S., and Enns, J. T. (1996). High-speed visual estimation using preattentive processing. *ACM Transactions on Computer-Human Interaction (TOCHI)*, 3(2):107–135.

Henderson, J. M. and Hollingworth, A. (1999). High-level scene perception. *Annual review of psychology*, 50(1):243–271.

Hynek, J. and Hruška, T. (2016). Pixel-based analysis of information dashboard attributes. In *East European Conference on Advances in Databases and Information Systems*, pages 29–36. Springer.

Hynek, J. and Hruška, T. (2018). Application of object-based metrics for recognition of well-designed dashboards. *International Journal of Human–Computer Interaction*, pages 1–13.

Jain, A. K. and Zhong, Y. (1996). Page segmentation using texture analysis. *Pattern recognition*, 29(5):743–770.

Jäkel, F., Singh, M., Wichmann, F. A., and Herzog, M. H. (2016). An overview of quantitative approaches in gestalt perception. *Vision research*, 126:3–8.

Johnson, J. (2013). *Designing with the mind in mind: simple guide to understanding user interface design guidelines*. Elsevier.

Kise, K. (2014). Page segmentation techniques in document analysis. In *Handbook of Document Image Processing and Recognition*, pages 135–175. Springer.

Malik, S. (2005). *Enterprise dashboards: design and best practices for IT*. John Wiley & Sons.

Mao, S. and Kanungo, T. (2001). Empirical performance evaluation methodology and its application to page segmentation algorithms. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 23(3):242–256.

Minaee, S. and Wang, Y. (2016). Screen content image segmentation using sparse decomposition and total variation minimization. *arXiv preprint arXiv:1602.02434*.

Nagy, G. and Seth, S. (1984). Hierarchical representation of optically scanned documents.

Ngo, D. C. L., Teo, L. S., and Byrne, J. G. (2003). Modelling interface aesthetics. *Information Sciences*, 152:25–46.

Orlov, P. A., Ermolova, T., Laptev, V., Mitrofanov, A., and Ivanov, V. (2016). The eye-tracking study of the line charts in dashboards design. In *VISIGRAPP (2: IVAPP)*, pages 205–213.

Russ, J. C. (2016). *The image processing handbook*. CRC press.

Sezgin, M. and Sankur, B. (2004). Survey over image thresholding techniques and quantitative performance evaluation. *Journal of Electronic imaging*, 13(1):146–166.

Shafait, F., Keysers, D., and Breuel, T. M. (2006). Performance comparison of six algorithms for page segmentation. In *International Workshop on Document Analysis Systems*, pages 368–379. Springer.

Simon, A., Pret, J.-C., and Johnson, A. P. (1997). A fast algorithm for bottom-up document layout analysis. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 19(3):273–277.

Tufte, E. R. (2001). *The Visual Display of Quantitative Information*. Graphic Press.

Ware, C. (2012). *Information visualization: perception for design*. Elsevier.

Wertheimer, M. (1938). Laws of organization in perceptual forms.

Zen, M. and Vanderdonckt, J. (2014). Towards an evaluation of graphical user interfaces aesthetics based on metrics. In *Research Challenges in Information Science (RCIS), 2014 IEEE Eighth International Conference on*, pages 1–12. IEEE.

APPENDIX

Attachments are available at: `http://www.fit.vut.cz/~ihynek/dashboards/visigrapp-2019`