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Research Article

Quantifying the Visuo-Perceptual Segregation Between Ortabayır and Levent District in Istanbul through Semantic Segmentation

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ABSTRACT

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Urban segregation has always been a critical problem affecting citizens' socio-cultural equality. Although the issue has been widely investigated, recent methodological perspectives based on machine learning techniques can provide alternative viewpoints while contributing to precise findings. This study highlights the urban segregation problem in the context of Levent and Ortabayir districts in Istanbul while reviewing the existing literature on the relevant issue of segregation. The study aims to elaborate on the visual and perceptual segregation between Levent and Ortabayir while providing quantitative evidence. This study applies semantic segmentation of street view images and scene ratings to quantify visuo-perceptual segregation. The dataset for semantic segmentation contains 150 street view images for both Levent and Ortabayır regions. Seven semantic label criteria are decided, such as nature, pavement, road, sky, buildings, people, and cars, to outline the basic visual qualities of the urban environment. The street view scenes are evaluated on a 7-Likert scale by fifty raters who are asked to focus on the scenes' safety and beauty perceptual qualities. We applied comparison analysis to detect the statistical similarities and variations and correlation analyses to investigate the associative trends between virtual and perceptual variables. This study distinguishes itself from the existing literature by adopting the machine learning method to asses the segregation problem between Levent and Ortabayir through semantic labels. Our approach contributes to the literature with its methodology and the quantitative, precise segregation findings. This study confirms the segregation between Levent and Ortabayir with their visual and perceptual qualities and illustrates the discrete visuo-perceptual features of both regions. This study shows that segregation appears in the selected regions on both inter-regional and intra-regional scales.

1. Introduction

Over the last ten years, urban areas have become complex entities with interactions affecting the engagement of citizens with cities. The urban setting, with its complex interactions and all physical domains of the urban environment, including both mobile and static entities, has been the source of urban big data (UBD) [1, 2]. In their study, Wang and Yin review the UBD literature and illustrate the significant scale and variety of research on UBD [3]. A considerable volume of UBD literature proves that UBD has been one of the major research areas to interpret the complex system of the urban, infer the reasoning behind the correlations and interactions within urban, and predict future urban data.

According to Tohidi and Rustamov, artificial intelligence (ML) techniques have become an important tool for analyzing and managing UBD [4]. Thodi and Rustamov emphasized that spatial data is key in efficiently providing urban services, ensuring public safety, and resource management as cities grow. However, Nikparvar

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and Thill argue the need for a valid method to use machine learning in geospatial data [5].

UBD functions as a source for defining and solving urban-related problems. On the other hand, integrating ML into UBD research provides data-driven decisions that reveal patterns of urban design-related issues. Rabari and Storper suggest using ML to benefit from UBD for urban policies and urban planning processes [6]. UBD can be used for IoT applications to fulfill urban sustainability objectives [7, 8]. Hu et al. proposed that the UBD be used to determine the housing policies in the city effectively [9].

On the other hand, UBD shows the capability to predict the future of cities [3]. Almukhalfi et al. utilizes deep learning for city traffic management [10]. Hameed et al. adapt a multimodel urban air quality assessment method using deep learning techniques [11]. Kiwelekar et al. elaborates on deep learning techniques for geospatial and urban data analysis while focusing on remote sensing technology for urban scale analysis [12]. UBD fosters and facilitates the understanding of the city's historical development while revealing the visual perceptual elements of urban heritage.

Alacam et al. utilize the Cyclegan algorithm to transform the old maps of Istanbul into modern satellite maps, and this conversion can convey valuable insights into spatial changes and development phases of the Urban environment from the past to the present [13]. Understanding the historical layers of the urban environment is part of UBD's urban heritage. Karadağ proposes an ML approach (cGAN) to understand and predict the missing parts of the architectural heritage data [14]. This method can contribute to elaborating the missing parts of the urban heritage data.

Literature on street view image and UBD supports the idea that besides planning and deciding the urban policies, UBD helps to understand the citizens' perceptions and assess the qualities of urban liveability. Through data-driven studies on urban areas and their effects on quality of life, urban planning can be improved [15]. On the other hand, a thorough understanding of how people perceive and engage with urban settings through UBD is pivotal to ensuring the livability of cities [15].

Correlations between citizen perception and the urban components can convey the underlying structure of the interactions, the reasoning the citizen needs, and their anticipation of the possible solutions to the livability of the cities. The physical infrastructure of the neighborhood in the urban environment shapes the perception and the interaction of the citizens with the urban area. In particular, the visual perception of urban infrastructure affects the citizens' perspective on the city. Therefore, visual perceptual components are inevitable parts of the UBD and must be addressed in an adequate urban planning process. On the other hand, visual perceptual components clarify the distinct features of the regions and enhance the understanding of the identity of the regions.

Recently, street-view images have become one of the major resources for UBD studies to understand the qualities of the city and its effects on the citizens [3, 16]. Li et al. assessed the green areas in the urban environment [17]. Hu et al. analyzed the differences in urban land usage using street-view images [18]. Jiang et al. [19] and Seiferling et al. [20] applied image processing to the urban street view to quantify the number of trees in urban areas.

Yin et al. [21], Yin and Wang [22], and Chen et al. [23] estimated the pedestrian density and analyzed the usage of the pavements by applying urban street view image processing. Kang et al. utilized a classification algorithm to understand the different types of buildings in the street view [24]. Liu et al. assess the quality of the urban environment with street-view images [25]. Li et al. analyzed the correlation between the green area distribution and the socioeconomic level of the citizens using street view image processing [26]. Weber et al. analyzed the perception of urban streets using street-view image processing [27]. Gebru et al. estimated the demographic typology of the urban neighborhood by analyzing the street view images [28]. Ki and Lee studied the effects of green areas on the citizen's psychology using street-view image processing [29]. Hu et al. analyze the citizen's perceptions using street views [30].

Recent literature on analyzing street view images benefits the semantic segmentation method for extracting meaningful data. Suzuki et al. investigate the relationship between urban views and real estate prices in Tokyo through semantic segmentation of visual components of street views [31]. Gao et al. propose to evaluate the quality of a given street space by segmenting street view images as an input to urban design decisions [32]. Kim et al. use semantic segmentation on Google Street Views to detect changes in the urban environement [33]. Xia et al. analyze the sky factor of the streets through street view image segmentation to develop a comfortable street atmosphere [34]. Xia et al. measure the green view index with segmented street views to contribute to the urban design process [35].

In conclusion, this introduction overviews the literature on solutions for urban-related problems through UBD, street view images, and semantic segmentation techniques. The following section details the study's problem statement: understanding the perceptual urban segregation problem through street view images. Section 2 outlines the methodology of the research in this paper. Section 3 explains the study's findings, and section 4 concludes.

1.1. Problem statement

Urban segregation, which affects citizens' quality of life, is challenging for urban policymakers and planners. Measuring urban segregation provides valuable insight for accurately reading the problem. Luca et al. state the importance of measuring inequalities in metropolitan areas with timely and adequate data to propose accurate solutions for the urban segregation problem [36].

Istanbul, the economic, social, and historic center of Turkey, is one of the examples of UBD sources [37]. Urbanization speed in Istanbul constantly transforms the cityscape, creating complexities and contradictions between adjacent regions and making it difficult to distinguish the regions' identities, components, and problems. Such a complex region in Istanbul, Büyükdere Street creates multiple urban identities and lifestyles around itself. The street passes through the Levent and Ortabayır districts and impedes the distinct identities of these two adjacent regions. This research focuses primarily on the Levent and Ortabayir regions, which present a significant segregation problem. Altınok explains the socioeconomic urban contradiction of the district encapsulates the Levent and Ortabayır districts and analyzes the region in three headings: slum structures, half-slum structures, and apartment blocks [38].

Ozbaki and Onder analyze the region by conducting the space syntax method to understand the morphological differences among the regions, Levent, Çeliktepe, Ortabayır, Telsizler, and their surroundings and define the region as unplanned gentrification [39]. Ozbaki and Onder demonstrate that the studied adjacent districts, which have different socio-economical and cultural levels, are not integrated morphologically. Agirbas utilizes space syntax to analyze the Levent, Çeliktepe, and Ortabayır regions, and according to Agirbas, the regions are spatially segregated [40]. Gulen discusses the insufficiency of the region's urban infrastructure [41]. Gur and Heidari applied questionaries in the region, and their results revealed the different socioeconomic identities of the habitants in the adjacent regions [42]. Terzi and Bölen [43] and Koç [44] argue that gentrification in the region could not provide a liveable or sustainable environment. Karabey discusses that the constant changes in the region have violated the event's identity and the surrounding environment [45]. The literature regarding the Levent and Ortabayır regions reveals a significant challenge of segregation influenced by socioeconomic, morphological, and typological characteristics.

Furthermore, the visuo-perceptual infrastructure of the surrounding neighborhoods of Büyükdere Street has changed dramatically. This substantial difference is obvious from the scenes at the street level of the regions. Quantifying the visual-perceptual segregation of the areas can facilitate informed policy development, which can help targeted strategies to prevent segregation while contributing to social awareness and fair and equal decisions for resource allocation in urban planning and sustainable planning. Besides, quantitative findings allow for uncovering the dwellers' engagement, interactions, perception, and emotions with the metropolitan regions.

The existing literature on urban segregation tends to focus on socio-spatial segregation rather than the perceptual segregation problem directly related to the visual infrastructure of the urban environment. Besides, existing literature typically relies on space syntax or survey-related methodologies. This research differs from the literature in that it focuses on the perceptual segregation problem of two adjacent regions in Istanbul and utilizes a recent method combining semantic segmentation and scene grading methods.

The following section explains how we adapt the semantic segmentation and scene grading methods to extract visual-perceptual data using street view images.

2. Methodology

In this paper, we assess the visuo-perceptual segregation by conducting semantic segmentation and Likert scale grading of the Levent and Ortabayir street view images. The first step of the segregation assessment is collecting street view images for both regions, Levent and Ortabayir, from Yandex panoramas. We collected 150 street-view photos for each area. After collecting the street view images, we applied semantic segmentation and Likert scale grading of the regions on these images. For semantic segmentation, we decide on seven visual perceptual labels. These visual labels are building pavement, vehicle, sky, nature, human, and road. The semantic segmentation algorithm captures the entities from a street view image and assigns related color labels. Once the color labels are assigned, we can convert these label percentages of the street views using the label pixel color ratio to the overall pixel of the image. All the label pixel color percentages are recorded in a spreadsheet. Parallel to the segmentation process, human raters are asked to rate the street view images of both regions with a 7-Likert scale based on their safety and beauty qualities. After rating, each image's Likert points are listed in another spreadsheet file. Both regions' safety, beauty, and visual label features were compared. Following the comparison, we investigate the correlation between visuo-perceptual features. Figure 1 summarizes the research method process.

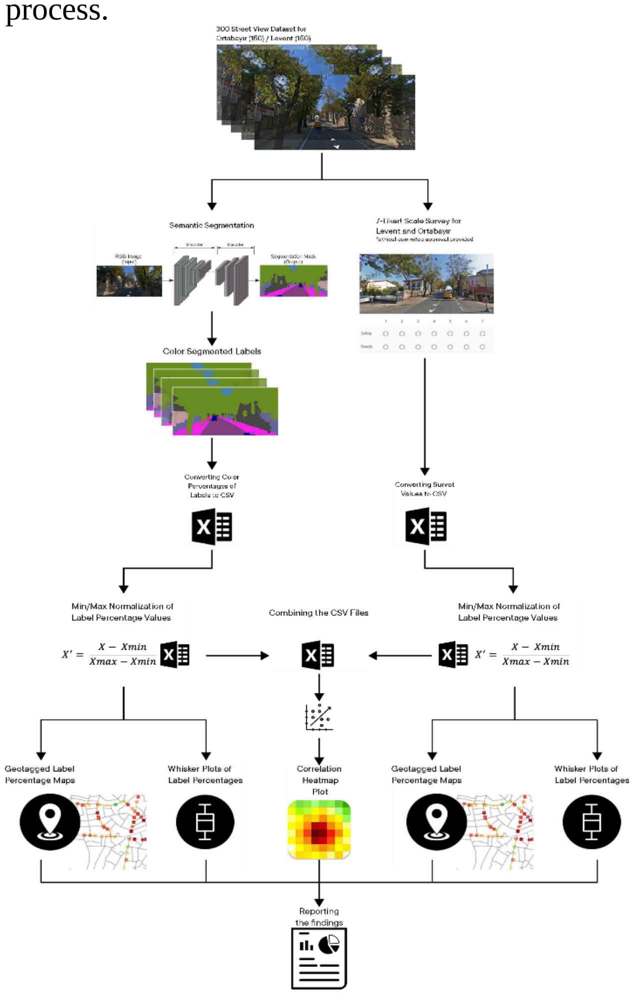

Figure 1. Research Process (By Author(s))

2.1. Levent and Ortabayır image dataset

Street-level image acquisition is the main part of the dataset creation process. The dataset was formed using Levent and Ortabayır street view images captured from Yandex panoramas. Each neighborhood should be fully represented in the collected images. Hence, images that best explain the surrounding district are chosen on the streets in both directions: east-west and north-south.

In the Ortabayir district, Talat Paşa Street, which aligns through the east-west axis, is chosen as the basis of the district as this street is the region's main street. Parallel to this street, Dutluk Street is chosen. Perpendicular to these streets: Benek Street, Eski Belediye Street, Erkılıç Street, Sarıgöl Street, Bacadibi Street, and Çakmak Street are selected on the north-south directional axis of the region. In Levent, Levent Street is chosen as the basis of the region, which is the main street of this district and aligns in the east-west direction. The other streets in this region are mostly perpendicular to this street, and the most important streets are chosen as Çamlık Street, Sümbül Street, Yenisülün Street, Karanfil Street, and Çamlık Street. Figure 2 represents the locations of the images on the selected streets for both the Ortabayir and Levent districts.

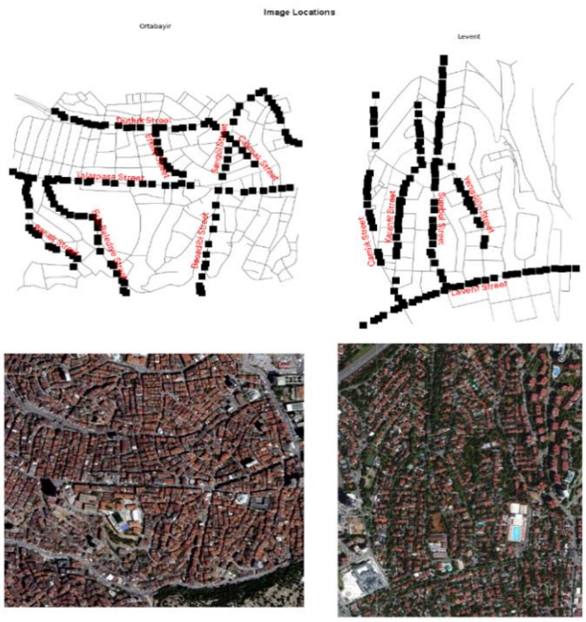

Figure 2. Locations of the street level images, left Ortabayir, right Levent (By Author(s))

2.2. Semantic segmantation

Feature extraction is the process of extracting meaningful features or attributes from a dataset. The process aims to create a simpler and more informative representation of more complex data that contributes to the efficient analysis of the dataset. Semantic segmentation extracts pixel-level associated features with semantic class labels and segments the image according to its the structural, color and textural features. Once the color-labeled image is created, the percentages of the related class within the scene can be calculated using color pixel values.

In our semantic segmentation task, we employed a transfer learning strategy on the U-net architecture, which is a semantic segmentation algorithm developed by Ronneberger et al. [46]. Transfer learning is the task of reusing a pre-trained algorithm for prediction. U-net architecture is a deep-learning architecture on which the algorithm is trained using pixel color values with their distribution on the image and the pixel locations. This architecture is a localization algorithm, enabling us to assign color labels to their respective locations on the original image. The U-net model we used in our transfer learning process was trained on pavement, automobile, sky, nature, human, and road features. As a result, the U-net model can predict and assign color labels on street-level images based on the locations of these predefined labels (Figure 3).

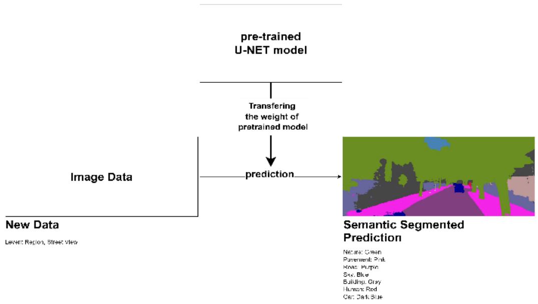

Figure 3. Transfer Learning Architecture (By Author(s))

Figure 4 represents the results of the semantic color label prediction for both the Levent and Ortabayir regions. After obtaining the color labels, we saved them with their in-image-occurrence percentage as a spreadsheet. We obtain the numeric color percentage values for each street view image to compare the regions numerically.

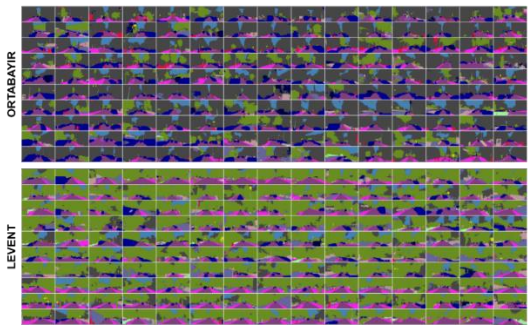

Figure 4. Semantic Segmentation Result for Both Ortabayır and Levent (By Author(s))

Table 1. Segmentation and perception mean values

Mean Values	built score	paved score	auto score	sky score	nature score	human score	road score	beauty	safety
Levent	0.149302	0.450318	0.117909	0.205806	0.756088	0.02517	0.341202	0.70544	0.80191
Ortabayir	0.615347	0.397133	0.327853	0.310626	0.23865	0.141278	0.386497	0.14085	0.24161

2.3. Scene rating for the street level images

Scene rating allows raters to evaluate a scene from an aesthetic, functional, or perceptual perspective. This rating is used to understand the scene's perceived quality and measure the impact of the specific design elements and their content. The data collected is evaluated using various statistical analysis methods. These analyses reveal the overall perception of the scenes, differences in rates' preferences, and the impact of spesific design elements. The results provide useful feedback for design applications while considering the development of the user experience.

This study applies fifty raters' street-level scene ratings based on their visual attractiveness and security features. Visual attractiveness is the measure of the aesthetical appeal of the environment. Security features are the variable related to feeling safe perception. Both features can enhance the quality of the habitat of the citizens.

We utilized Google Forms for the image rating interface with 300 street-level images of the selected neighborhoods. Raters used a 7-point Likert scale to rate the images' beauty and safety levels from 1 (poor) to 7 (high). Fifteen thousand answers were collected for each safety and beauty factor. We stored the scores for each street-level image in a spreadsheet document.

2.4. Assesment method

We applied comparison analysis to detect the statistical similarities and variations and correlation analyses to investigate the associative patterns between visual and perceptual variables. Using both methods together facilitates a comprehensive analysis of the variable's relations, similarities, and differences. Moreover, comparative findings can be validated with statistical correlation analysis, which supports the generalization of the findings. While comparison reveals meaningful similarities and differences between different groups, correlation analyses examine the relation between variables to determine the correlation's direction and strength.

The variables collected for comparison and correlation are both visual and perceptual values as build_score, paved_score, auto_score, sky_score, nature_score, human_score, road_score, beauty_score, and safety_score of both regions.

The values collected from semantic segmentation and ratings were compared using geotagged labels and whisker plots. Geotagged labels show the locational variations of the data, while whisker plots represent the mean and variance pattern of the data. Both the geotagged data and the whisker plot reveal the visual variability and define the visual characteristics of the regions. Using correlation analysis, we investigate the dependency status among the nine scores listed above. Correlation analysis reveals the effects of visual elements on the perception of safety and beauty in Levent and Ortabayır.

3. Results and Discussion

3.1. Visuo–Perceptual comparison

In visuo-perceptual comparison, visual stands for the color-labeled visual urban entities from semantic segmentation results, and perceptual stands for the scores, which are the ratings for beauty and safety perceptions of the selected regions. From semantic segmentation labels, visually segmented urban entities are listed respectively as built, paved, auto, sky, nature, human, and road scores. Perceptual entities are beauty and safety scores. Table 1 demonstrates the mean values of all the scores with the corresponding region. According to the mean values, built, auto, sky, human, and road scores of the Ortabayir region show higher values than the Levent region.

In contrast, the paved, nature, beauty, and safety scores of the Levent region are higher than the Ortabayir region's corresponding scores. Upon an in-depth investigation of the values, both regions' paved, sky, and road scores represent close results. A notable discrepancy is obvious for both regions' built, nature, beauty, and safety scores. This result illuminates the segregated characteristics of both regions to be "built, nature, beauty, and safety scores." While higher safety and beauty scores in the Levent region in comparison to Ortabayir reflect a liveable neighborhood, the high nature score in the Levent region and a high built score in the Ortabayir region are proofs of the significant level of visual segregation between regions. Whisker plot covers all the maximum, minimum, and mean values and demonstrates the variance of the values. *Variance* can be defined as the difference between the minimum and maximum values of the plot.

High variance represents high variability, and low is vice versa. Figure 5 demonstrates the whisker plot for both regions. The variance of the built score, auto score, nature score, human score, and road score exhibits higher values in Ortabayir than in Levent. In terms of visual entities among the streets of Ortabayir, there are more different characteristics than Levent, and Levent streets are more visually consistent than Ortabayir. The human score mean and variance values represent considerably small values for the Levent region. The evidence from human_score suggests that a quieter residential area than Ortabayir characterizes the Levent neighborhood.

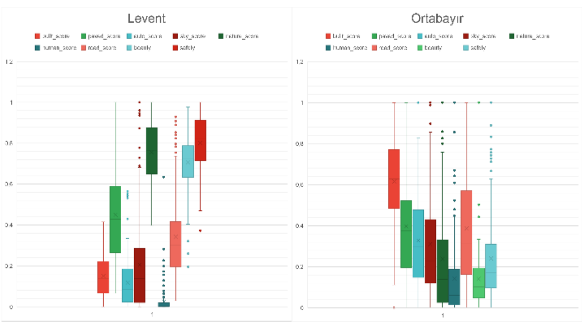

Figure 5. Whisker Plots for Visuo-Perceptual Features of both Ortabayır and Levent (By Author(s))

Geotagged values represent the variability of scores based on locations. At first glance, in Figure 6, we can see the sharp difference between Levent and Ortabayir in terms of build_score, nature_score, beauty, and safety scores. The build score for the Levent region decreases through the north direction of the region. In the ortabayır region, building scores are getting higher around the road intersections than in the other areas. The Paved score for both regions is equally distributed along the streets, except the north and south parts of Levent regions show higher pavement scores. Auto_score in Ortabayir shows almost equal distribution along the roads; conversely, the Levent region's western part shows higher values than its east parts. Sky score was distributed almost equally for both regions.

Except for the western part of the Levent region, the Levent region shows lower values for sky score. In Ortabayir, except for Talat Paşa Street, other streets show drastically low nature values. In the Levent region, the nature score gets higher values than Ortabayir, while the western part of the Levent gets lower nature values, and this might be the reason why the sky score is higher in the part of the west of the Levent Region. The nature score mostly comes from tree vegetation, and trees mostly cover the sky and decrease the sky score in street view perspectives. The human score shows its highest values in Talatpaşa Street in the Ortabayir region. The other streets have lower values.

In comparison, Ortabayir demonstrates a more dense human score than Levent. Road scores were distributed almost equally for regions other than the northern part of the Levent region. Beauty and safety scores show an obvious difference between Levent and Ortabayir. In the Levent region, safety and beauty scores show relatively higher values than in Ortabayir. Interestingly, the geotagged map of beauty and safety scores suggests that Talatpaşa Street, among the other selected streets in Ortabayir, dominates the positive beauty and safety score. The safety and beauty scores decrease on the north-south axes in the Ortabayir region**.** Upon detailed inspection of the safety values, Talatpaşa

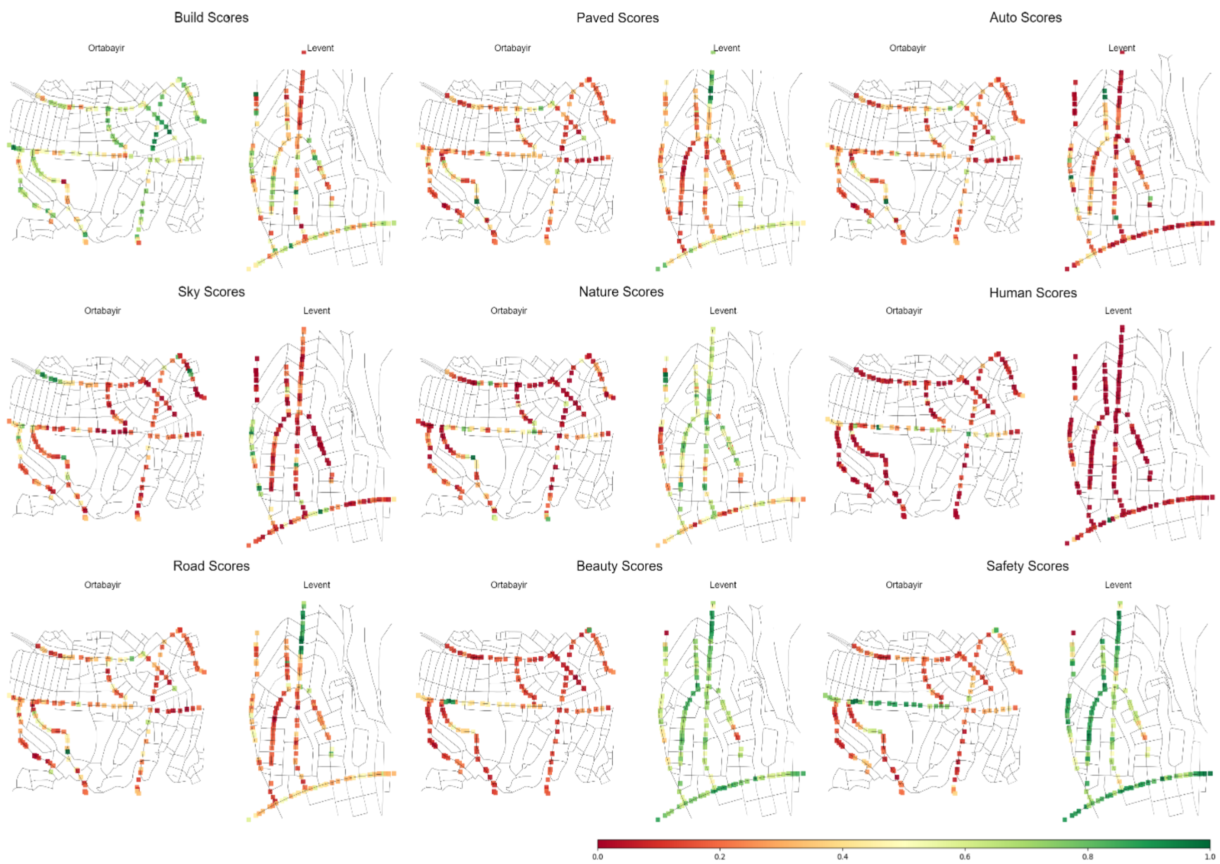

Figure 6. Geotagged variable values for Levent and Ortabayir Regions (By Author(s))

Street in Ortabayir and the streets of Levent get almost equal values.

3.2. Visuo-Perceptual correlation

The concept of correlation explains the relationship of two variables while showing the negative and positive correlations. A positive correlation indicates that two variables increase in parallel by the correlation coefficient ratios. Conversely, a negative correlation means an increase in one variable decreases the other variable.

Visuo-perceptual correlation represents the pairwise relations of visual elements of street view images and perceptual scores. Both the visual and perceptual elements are the variables of the correlation analysis. The variables are built_score, paved_score, auto_score, sky_score, nature_score, human_score, road_score, beauty and safety scores. Visuo-perceptual correlation analysis is constructed upon three heatmaps; two show regional correlations of Levent and Ortabayir separately, and the other one shows the region's variables correlated. The region-based correlation heatmaps show region-based correlation characteristics. Region-based heat maps point to the differences and similarities of the correlation characteristics of the regions; on the other hand, combining correlations with both regions' variables provides a holistic perspective on the visual-perceptual variables' relations independent of the regions.

Figure 7 illustrates the Levent correlation heatmap. Levent correlation has 20 negative and 16 positive correlations. Among all correlations, two negative and two possitive correlations are obvious. Nature_score correlates negatively with built_score and sky_score, and the correlation coefficients are considerably higher than those of other negative correlations. When nature_score increases, built_score and sky_score decrease, naturally. However, the contrast between built and natural scores mostly defines the characteristics of the region.

Interestingly, nature_score has no considerable positive or negative effect on perceptual beauty and safety scores in the Levent region. Heatmap offers that when the paved score increases, the road score also increases. However, this finding has yet to provide a significant outcome. Organically, safety and beauty have a positive correlation.

Levent Correlation	built_score	paved_score	auto_score	sky_score	nature_score	human_score	road_score	beauty	safety
built_score	1								
paved_score	-0,264000714	1							
auto_score	0,006465349	-0,364315729	1						
sky_score	-0,032575198	-0,01532694	0,233071648	1					
nature_score	-0,612273108	-0,276500622	-0,204792275	-0,495600251	1				
human_score	0,167388914	0,024665905	-0,058024598	0,014018091	-0,18225546	1			
road_score	-0,26656381	0,902805428	-0,223109588	0,06256852	-0,283773168	-0,009606189	1		
beauty	-0,171400984	0,208882772	-0,138297817	-0,044102057	0,053291295	0,021122112	0,172387101	1	
safety	-0,037134926	0,168775698	-0,050179793	0,133884632	-0,139635674	0,101249666	0,143375179	0,794347154	1

Figure 7. Correlation matrix for Levent Region Values (By Author(s)).

Ortabayir correlation shows parallel results with Levent correlations except for slight differences among correlation coefficients. Figure 8 shows 20 negative and 16 positive correlations for Ortabayir. Interestingly, in Ortabayir, built_score and sky_score correlate negatively with all the variables, which may result from the crowded building landscape in the Ortabayir region. The highest negative correlation of built_score is with nature_score in the Ortabayir region. The built environment is one of the key elements in the Ortabayir region and affects the natural landscape negatively. The highest positive correlations are the natural correlations between paved-road and safety-beauty scores. The human score is another variable positively correlated with beauty and safety scores in the Ortabayir region, which differs from the Levent region.

Ortabayir Correlation	built_score	paved_score	auto_score	sky_score	nature_score	human_score	road_score	beauty	safety
built_score	1								
paved_score	-0,293068977	1							
auto_score	-0,340806493	-0,080011871	1						
sky_score	-0,305020008	-0,203539873	0,095010142	1					
nature_score	-0,767252262	0,030765568	-0,073515823	-0,038032171	1				
human_score	-0,158660686	0,14371763	-0,106176373	-0,13243355	0,148206313	1			
road_score	-0,287953196	0,816941757	0,198342427	-0,143853672	-0,047466312	0,025012244	1		
beauty	-0,222386653	0,185725375	-0,07807458	-0,047805995	0,243064987	0,347892092	0,07202541	1	
safety	-0,259280638	0,194920518	-0,119148088	-0,015715813	0,272209081	0,509923372	0,049926962	0,814638943	1

Figure 8. Correlation matrix for Ortabayir Region Values (By Author(s)).

Figure 9 shows the correlation of the combined values of both regions. Negative correlations of built_score and positive correlations of nature_score stand out among all the variables. While built_score negatively affects the beauty, safety, and nature scores, nature_score positively affects safety and beauty scores. On the other hand, auto_score correlates negatively with nature, safety, and beauty scores. Paved score positively impacts beauty and safety scores, although no correlation is observed for human scores.

All Correlation	built_score	paved_score	auto_score	sky_score	nature_score	human_score	road_score	beauty	safety
built_score	1								
paved_score	-0,38394649	1							
auto_score	0,301718244	-0,311229566	1						
sky_score	-0,012439275	-0,112195989	0,17122472	1					
nature_score	-0,936436118	0,21567925	-0,458379207	-0,19530258	1				
human_score	0,297376654	-0,042400264	0,098022015	-0,042155629	-0,325774035	1			
road_score	-0,28076947	0,872019419	-0,081032157	-0,039610859	0,089263876	-0,059562653	1		
beauty	-0,806663829	0,355689963	-0,435840879	-0,098174827	0,809225288	-0,209585638	0,218189664	1	
safety	-0,739576371	0,336381734	-0,406638277	-0,041388674	0,726397019	-0,041887019	0,193197407	0,92126004	1

Figure 9. Correlation matrix for combined values for both regions (By Author(s)).

4. Conclusion

This study applies the state-of-the-art method to quantify the urban fabric by semantically segmenting the street-level images and collecting the perceptual ratings of the selected urban regions. The visuo-perceptual comparison and correlation analysis of the Levent and Ortabayir regions shed light on the characteristics of the regions and illustrate the visuo-perceptual segregation of both regions. Even though the literature on Levent and Ortabayir regions repeats the regions' segregation issue, this study emphasizes the visuo-perceptual segregation and quantifies visual-perceptual similarities and differences. From this perspective, the study contributes to the urban design problem of the selected region by providing objective quantitative evidence on segregation. In the comparison and correlation analysis, different periods of street-level images may enhance the reliability of the study, which is its main limitation. Street-level images show only a particular time period for the regions. So, the time effect on the visual and especially the perceptual part is neglected in this study.

This study confirms the segregation between Levent and Ortabayir with their visual and perceptual qualities and illustrates the discrete visuoperceptual features of both regions. Results show that the Levent region has quiet surroundings due to its human and car scores; moreover, Levent has more consistent visual-perceptual qualities than the Ortabayir region. In contrast, the considerable variance of variables in the Ortabayir region suggests a high level of diversity in visuo-perceptual qualities. Hence, along with the visuo-perceptual segregation issue, which is an inter-regional problem, the non-homogeneous construct of the regions becomes another challenging problem, the intra-regional segregation problem, for urban design. Segregation appears on both inter-regional and intra-regional scales.

In conclusion, this study represents the sharp visuo-perceptual segregation between Levent and Ortabayir regions. The densities of nature and built scores define the characteristics of both regions. Moreover, perceptual analyses illustrate that nature scores and built scores affect the perception of urban regions.

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The Declaration of Ethics Committee Approval
This study does not require ethics committee permission or any special permission.

The Declaration of Research and Publication Ethics
The authors of the paper declare that they comply with the scientific, ethical and quotation rules of SAUJS in all processes of the paper and that they do not make any falsification on the data collected. In addition, they declare that Sakarya University Journal of Science and its editorial board have no responsibility for any ethical violations that may be encountered, and that this study has not been evaluated in any academic publication environment other than Sakarya University Journal of Science.

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