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Technical Section

Saliency-aware color harmony models for outdoor signboard[☆]

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ABSTRACT

This paper introduces a geometric approach for assessing color harmony of a signboard, and color coherence of a signboard with the environment. We propose to incorporate visual saliency as an inherent color characteristic residing in the image space, to better cope with the attention mechanism when people view a scene. In doing so, our color harmony models consider saliency-weighted color differences and area balance in CIELab color space. We collect 5.2 K valid subjective ratings on 375 diverse signboards in the real world, and translate them into quantitative measures for model construction. Experimental results show that our models improve the overall performance, especially for modeling color coherence between a signboard and the environment. The study also reveals that color combinations with similar chroma but distinctive lightness lead to harmonic signboards, while simple color patches in accordance with local context contribute to environment-coherent signboards.
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1. Introduction

Improving design quality of outdoor signboard can benefit a variety of applications, such as to convey brand information to customers [1,2], and to create people-friendly streets [3,4]. However, despite its importance, there have been few studies conducted on understanding what factors affect people's impression of outdoor signboard, which are considerably hindered by particular challenges including the lack of dataset, the diversity of signboard design, and the complexity of street environments. As such, some study [5] considers simple heuristics of only a small amount of color combinations, which fails to account for the complex reality.

The advancement of various sensing technologies and data services promotes large-scale quantitative measurements of urban environments. For instance, Google Street View (GSV) [6] service provides visual aspect information of urban space from different geographic positions. There have been continuous efforts on unveiling fine-scale characteristics of urban streets using GSV images, including to support interactive visual exploration of street views (*e.g.*, [7,8]), and to examine human perceptions on visual elements in street views (*e.g.*, [9,10]). Adding on to this line of trend, we build a new dataset of diverse signboards collected from various cities in the world.

With the data, this work seeks to strengthen our understanding of human perception on signboard design. We primarily focus on examining color harmony for outdoor signboards, since color is a provocative visual stimuli and plays an important role on signboard design [11]. We decompose the problem into two subtasks: (i) to explore color harmony of a single signboard, and (ii) to analyze color coherence of a signboard with the street comprising the signboard. This is nevertheless a challenging task. First, the design space of color usage is huge, thus identifying categories of harmonic color combinations (*e.g.*, [12–14]) is infeasible. Second, the complex street environment where an *outdoor* signboard belongs to calls for effective color extraction and modeling algorithms. Last but not least, most if not all studies on color harmony derive color features in certain color spaces, whilst omits the fact that people perceive colors in an image space.

This work introduces a geometric approach, which has been widely employed in the graphics and vision communities to evaluate human perception on colors (*e.g.*, [15–17]), for building color harmony models for signboards. Despite its popularity, most of existing studies conduct geometric analysis on noiseless images, whilst neglecting the complex lighting and shading conditions in the street. To address the limitations, we propose to incorporate visual saliency, which is an inherent color characteristic residing in the image space, to better cope with the attention mechanism when people view a scene. Given a street-view image with multiple signboards as inputs, we extract a set of primary

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color patches for each signboard and the street, using a k-means clustering weighted by the saliency of pixels attached to each color patch. From the primary color patches, we derive a list of color features including saliency-weighted color differences and area balances, in CIELab color space. Next, we employ LASSO regression to construct color harmony models that fit the color features with human judgments of signboard design by architects. Our study shows that conventional color usage guidelines, such as that colors harmonize with minor chroma difference but large lightness difference, also apply to outdoor signboard design. Moreover, our study also suggests that many Asian cities can improve their street landscapes by adopting simple color patches similar to the context of the street.

The main contributions of this work include:

- We build a new dataset of diverse real-world signboards in different cities, and diverse perception ratings on color harmony of signboard design by different human subjects. The dataset will be released publicly to foster future research on color harmony as well as signboard design.
- We introduce saliency-aware color harmony models for assessing color harmony of a signboard, and color coherence of a signboard with the environment. Experimental results demonstrate that saliency-weighted color features can improve the overall performance, especially when modeling color coherence between a signboard and the environment.
- Our study reveals important color characteristics that affect human perception on signboards, and different practices of signboard design over geography. Based on the findings, we propose several design recommendations for improving signboard design.

2. Related work

2.1. Signboard design

Baker [18] categorized elements of a store environment into three types: social factors, design factors, and ambient factors. Follow-up studies (*e.g.*, [11,19]) revealed that store environment would mediate consumer emotions and affect their purchase behaviors. Signboard, as a design factor firstly perceived by consumers, exerts a substantial effect on consumer perception and subsequent feelings of a store. For example, Henderson et al. [1] found that signboards that are perceived as elaborate, natural, and harmonious bring positive effect on store impression. As such, store owners often feel the need for remodeling and replacing outdoor signboards [2].

Signboards are also important elements of street scenes, which should be considered as a public product. Signboard design shall assort with the street landscape, to make the street looks appealing. In contrast, poorly designed and visually unattractive signboards would hamper people's willingness to enter a market space [20]. Many efforts have been conducted to improve signboard design, to strengthen the city identity and attractiveness of the business area [4]. Therefore, signboard design is not only a stand-alone study, but shall also be considered from the perspective of being an ingredient of the street [3].

Though critical for store perception and street appealingness, assessment on the visual perception of signboards is mostly neglected. Won et al. [5] conducted a closely related study, revealing the impact of color combinations on harmony and legibility of signboards. However, they categorized all perceived colors into 18 average color names [21], yielding a small amount of color combinations. Moreover, human perceptions on color names may be inconsistent for some shades of a color or across different cultures [22,23]. Instead, this study builds upon color features in a geometric manner, therefore our proposed color harmony models can be more reliable and generalizable.

2.2. Color harmony models

Color is a provocative visual stimuli that affect much of what we perceive and feel about an image. Due to its ubiquity, color has been extensively exploited in many applications. A color appearance model seeks to describe the perceptual aspects of human color vision in a mathematical way [24], by modeling vision agnostic of many of the complexities that may affect people's perception of colors in practice. Color harmony reflects the aesthetic pleasure of certain color combinations. It can be adopted as a key metric to assess the aesthetic quality of photograph and video images [25,26]. Nevertheless, color harmony is a subjective property that can be altered by culture and education backgrounds of viewers. Therefore many studies have been carried out to transform harmony evaluation from subjectively to objectively. A widely adopted approach is Matsuda's harmonic color templates [12], which include 8 types of hue distributions (*e.g.*, I type, V type) and 10 types of tone distributions (*e.g.*, value contrast, triangle contrast) in Munsell color space [27]. Based on the templates, many design tools for improving color harmony of images were developed, *e.g.*, [13,14].

An alternative approach is the Moon and Spencer model [28], which suggests that harmonic colors satisfy the following conditions: (i) the interval between any two colors is unambiguous, and (ii) colors are so chosen that the points representing them in a (metric color) space are related in a simple geometric manner. More specifically, harmonic colors give sensations of *identity* - the same color, *similarity* - a resembling color, or *contrast* - a target color that is significantly different from a chosen color. Since the harmonic color templates can also be defined in a geometric manner, the Moon and Spencer model can be regarded as a more general approach. Several studies [29,30] revealed close associations between Matsuda's templates and the postulates of the Moon and Spence model. Follow-up studies examine more geometric features and metrics, and develop color perception models for various types of images, including graphic art and design [15,16] and data visualization [31–34].

Our study also adopts the geometric approach, by considering color differences and area balance in the CIELab color space. Nevertheless, due to dynamic street environment, outdoor signboards exhibit more complex geometric patterns than graphic designs and visualizations. Existing models are not directly applicable on our dataset. Instead, we propose to take visual saliency - an inherent color characteristic that reflects how people view a scene, into consideration when computing the color features. Experimental results demonstrate superior performance by considering the saliency.

2.3. Visual saliency

Humans can rapidly direct gaze and select the most relevant information from an image. Understanding and modeling the attention mechanism has attracted increasing attentions in vision studies. Saliency reflects which areas of an image will draw a viewer's attention, by analyzing the visual features of an image. The past 20 years have witnessed a rapid development of saliency detection techniques, from conventional image processing methods [35] to recent deep learning approaches [36]. The ultimate goal of these techniques is to capture the structure and function of the human visual cortex. Taking an input image, saliency detection techniques output a saliency map that assigns a value of a human viewer's attention to each pixel in the image [37]. Studies have shown that saliency can be utilized as a visual guide for various graphics applications, such as to improve graphics [38] and visualization [39] design.

This work adopts a conventional saliency model [35] to compute saliency maps, and takes saliency into consideration when measuring color features. In doing so, we combine human perceived color features in both image space and color space. We demonstrate the effectiveness of our approach using quantitative comparisons to ablation color harmony models without considering saliency.

3. Background and research goals

This work is motivated by practical requirements from a collaborating urban planner specializing in data-informed urban design. In his work, the collaborator is often asked to assess *Q1 if a signboard is well designed or not*, and *Q2 whether a signboard accords with the street*. Among many components including text, logo, and color that affect the quality of signboard design, we opt to start by analyzing color harmony, in consideration of the following facts. First, color is an intrinsic visual element of all signboards, whilst text and logo may not be available in certain signboards. Second, people's perceptual assessment on text and logo would require basic knowledge of the language and the culture, hindering large-scale data analysis. In contrast, color harmony is mainly determined by color combinations [28], thus being more independent on culture and education backgrounds. This allows us to conduct quantitative comparative analysis-a fundamental approach in urban design, on designs of signboards from different cities in the world.

Though numerous efforts have been conducted on modeling color harmony, we found few to no studies specific to outdoor signboards. Won et al. [5] simplified the problem by analyzing harmony ratings of only a limited number of color combinations. Instead, we seek to build more reliable and generalizable models, to support:

- **G1**: to identify what color combinations make an outdoor signboard look harmonic, for Q1.
- **G2**: to determine what color features make an outdoor signboard look coherent with a street, for Q2.

4. Data preparation

To build color harmony models for outdoor signboards, we prepare a new dataset including street-view images, signboards, and color harmony judgments by human subjects.

4.1. Street views and signboards

We developed an automatic approach to crawling street-view images, followed by manual annotation of signboards in the images. First, we downloaded a street area from OpenStreetMap,[2] and applied a flood-fill algorithm that recursively went through the entire street network every 50 m, starting from a randomly selected location. The step outputs a list of sampling locations with geographic information of latitude (*lat*) & longitude (*lon*). We passed each pair of (*lat, lon*) into GSV API, and downloaded side-view images that are perpendicular to the street direction at each sampling position. Next, we utilized a manual labeling tool [40] to annotate signboards in each street-view image. Before annotating, we omitted the following signboards, as suggested by the collaborating architect: (i) too small signboards that are not clearly visible; (ii) signboards placed on see-through windows or doors; (iii) temporary signboards that may be replaced daily; and (iv) incompletely displayed signboards or signboards in tilted perspectives.

To support comparative analysis of diverse signboards, we decided to crawl street-view images from different cities. We selected eight well-known commercial streets in the world, including Sai Yeung Choi Street in Hong Kong (denoted as *HK 1*), Tung Lo Wan Road in Hong Kong (*HK 2*), Ximending in Taipei (*Taipei*), Itaewon-dong in Seoul (*Seoul 1*), Myeong-dong in Seoul (*Seoul 2*), Shinsaibashi-Suji Shopping Street in Osaka (*Osaka*), Fifth Avenue in New York City (*NYC*), and Via Monte Napoleone in Milan (*Milan*). More streets were selected in Asia, as Asian cities typically have more signboards in commercial streets, and many of them can be improved.

Table 1 presents the number of street views and signboards in each street. Notice that the streets are sorted in descending order by the average number of signboards in each image. Clearly, Hong Kong streets have higher average numbers of signboards than the other streets. In total, we collected 120 street-view images and 394 signboards from eight different streets.

4.2. Color harmony judgments

To enrich diversity of color harmony judgments, we recruited eight architects (3 males, 5 females, age: 22.75 ± 0.46) as participants to rate the signboards. They are all certified architects in China with professional degrees of bachelor or master of architecture. The participants are well trained in urban design and color usage, with professional experience in street renewal projects and street design codes. Their feedbacks can be utilized as guidelines for improving signboard design. The participants have no color vision deficiency, in fact, are sensitive to color difference. The architecture training promotes that all the participants have similar aesthetic perspective and color preferences beyond cultural background. The study was eligible for exempt research as it involves minimal to no risks to the participants, as reviewed by the research ethics board in the school.

We asked the participants to rate on *color harmony of the signboard*, and *color coherence of the signboard with the street*, to collect judgments for **G1** and **G2**, respectively. Due to the COVID-19 pandemic, the study was performed virtually using a web interface as shown in Fig. 1. The interface included a street-view image on the left, with all the signboards being rated marked in different colors. Questions for the signboards were presented on the right. Here, we used 7-point Likert scale questions ranging from '1-absolutely inharmonic' to '7-absolutely harmonic'. We randomly ordered the street-view images among the participants to counter-balance effects of the first impression bias. The participants were reminded to take a break every 30 min and at any time when they felt tired.

We collected a total of 6,304 color harmony judgments (8 participants $\times$ 394 signboards $\times$ 2 questions). On average, each participant spent about 3.2 h to finish the study, with the average time to complete one image was 1.6 min and one signboard was 29.2 s. At the end of the study, we asked the participants to describe their strategy for making the judgments. Each participant was compensated with CNY ¥200.00 ($\sim$USD $30) after the study.

4.3. Data cleaning

Next, we cleaned up the collected dataset by removing inconsistent color harmony judgments. We measured the consistency from the following two perspectives.

(1) Consistency between repeated measurements. We conducted repeated measurements, and computed the test-retest reliability of each participant, to evaluate whether the subjective judgments by the same participant were consistent. We selected a random set of 40 samples from the 394 signboards, and asked the participants to re-rate the samples after two weeks of the first study. Next, we calculated the Pearson correlation coefficient, for each participant's judgments obtained from the before and after

[2] www.openstreetmap.org.

Table 1
Number of street-view images and signboards in each street studied in this work.

	HK 1	HK 2	Taipei	Seoul 1	NYC	Milan	Osaka	Seoul 2	SUM
Street view	20	19	13	16	14	11	13	14	120
Signboard	87	77	50	51	39	28	30	32	394
Average	4.35	4.05	3.85	3.19	2.79	2.54	2.31	2.29	3.28

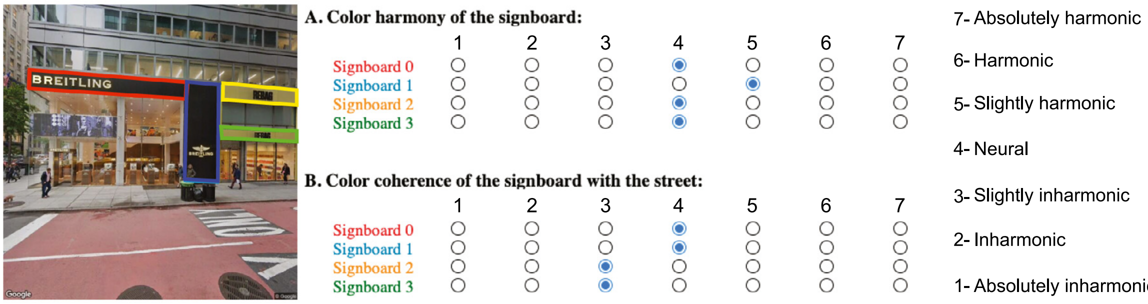


Fig. 1. The interface for collecting color harmony judgments from people.

experiments. The coefficient value ranges in $[-1, 1]$, where 0 indicates no relationship and +/-1 indicate perfect positive/negative correlations between two sets of observations.

- The results of six participants had strong positive correlations with the coefficients greater than 0.75.
- The results of one participant had a moderate correlation with the coefficient of 0.54 for color coherence judgments. In the follow-up meeting, the participant explained that he was not careful enough in the second study, whilst the judgments for the first study were more reasonable.
- The results of one participant had low correlation coefficients around 0.3 for both color harmony and color coherence judgments, and the participant could not explained the reason. Therefore, we excluded the judgments by the participant for further analysis.

(2) Consistency among participants. For each signboard, we further analyzed the variances of color harmony judgments among the remaining 7 participants. Here, we checked the consistency based on the measurements of standard deviation (*SD*) of color harmony judgments (SD_{har}), and that of color coherence judgments (SD_{coh}). The mean $\mu_{SD_{har}}$ of SD_{har} is 1.15 with a standard deviation $\sigma_{SD_{har}}$ of 0.35, while $\mu_{SD_{coh}}$ of SD_{coh} is 1.22 with a standard deviation $\sigma_{SD_{coh}}$ of 0.38. Both $\mu_{SD_{har}}$ and $\mu_{SD_{coh}}$ are small, indicating that most signboards received consistent ratings by different participants. Yet, there were some outliers with *SD* values above $\mu_{SD} + 2\sigma_{SD}$. We identified 9 signboards as SD_{har} outliers, and 10 signboards as SD_{coh} outliers. These 19 signboards were removed from the dataset. We took the remaining 375 signboards for further analysis.

In the end, there remain 5250 valid color harmony judgments (7 participants × 375 signboards × 2 questions).

5. Saliency-aware color harmony models

We represent a street-view image (Fig. 2(a)) as an RGB image $I_{st} \in \mathbb{R}^{3\times W\times H}$ with dimensions $W \times H$. The image I_{st} has multiple signboards $\{SB_1, \ldots, SB_n\}$, and each signboard SB_i contains a set of pixels $\{p_j^{SB_i}\}$. We apply a conventional saliency model [35] to compute a saliency map (Fig. 2(b)) $I_{sal} \in \mathbb{R}^{W\times H}$ for the image I_{st}, where a pixel $p_{sal} \in \mathbb{R}^+$ denotes the saliency value that reflects how much the pixel draws a viewer's attention. We then crop the region in the saliency map for each signboard SB_i, yielding a set of saliency values $\{p_{sal_j}^{SB_i}\}$ corresponding to $\{p_j^{SB_i}\}$. Based on the inputs, we derive a list of saliency-weighted color features to construct color harmony models.

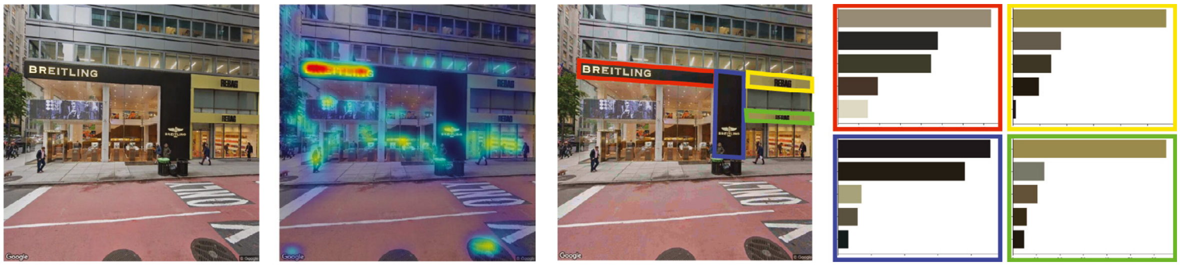
5.1. Color representation

To build color harmony models, we select a suitable color space that correlates well with human judgments. Here, we use CIELab [41], a color space comprised of three primary axes, L* (lightness), a* (the amount of red or green), and b* (the amount of blue or yellow), for two reasons. First, CIELab color space adopts a simple grid-based scheme, bringing about the computational simplicity of color difference. Second, CIELab is a three-dimensional perceptual color space based on opponent process theory [42], where perceived difference correlates well with Euclidean distance in CIELab color space. The properties make CIELab a popular color space commonly used in practice, such as to model color compatibility [15] and color difference [17].

We use OpenCV-Python[3] library that specifies L*, a*, and b* in the range [0, 255]. There are however too many unique colors in the color ranges, rendering difficulty in processing the colors. We choose to bin the colors, in a way that has a minimal effect on human judgments, meanwhile improves computation efficiency. In consideration of the Just Noticeable Difference (JND) [43], we use a bin size of 8 units for which each bin size has a radius of 1∼2 JND, so humans can hardly differentiate the colors within the same bin. For each bin we take the central color c_i, and we compute a value $sal(c_i)$ that counts the saliency of all pixels associated with c_i. Fig. 2(c) shows the street view by mapping original colors in Fig. 2(a) to the corresponding colors after binning. Marginal differences can be observed, yet the number of colors to be processed is dramatically reduced from millions to 32,876.

Though the number of color bins becomes smaller, we see $sal(c_i)$ for most color bins are zero. This is because typically a small number of colors is used when designing signboards, which are referred as primary color patches in this work. In line with previous works (*e.g.*, [44,45]), we apply a *weighted k*-means clustering to derive primary color patches. To make the clustering deterministic, instead of being sensitive to initialization [46], we perform *k*-means clustering as follows. First, we initialize the first mean as the color c_i with the largest saliency $sal(c_i)$. Then we attenuate all other weights $sal(c_j)$ by a decaying factor in accordance to the distance from c_i to c_j. Next we choose the color with the highest saliency, repeating the process until *k* initial means have been chosen. For each cluster, we compute a saliency-weighted mean color patch C_i, with a saliency $sal(C_i)$

[3] https://pypi.org/project/opencv-python/.



(a) Original street view (b) Saliency map (c) Street view after color binning (d) Extracted color patches of signboards

Fig. 2. Procedure of extracting primary color patches for signboards in an input street-view image.

summing up all color saliences in the cluster. Similarly, we also extract a set of color patches that dominate human-perceived colors for a street view. We find that $k_{sb} \in [3, 7]$ works well for typical signboards, and choose $k_{sb} = 5$ by default; and $k_{st} \in [10, 20]$ works well for street views, and choose $k_{st} = 15$ by default. Fig. 2(d) presents extracted color patches with associated saliences for the signboards in Fig. 2(c). All signboards have a dominant color (typically background) and a few subordinate colors.

5.2. Color features

5.2.1. Color harmony features

Given primary color patches $\{C_i^{sb}\}$ of a signboard, we compute two types of color features in terms of *color difference* and *area balance*, to model color harmony of a signboard.

- *Color difference*. Harmonic colors give sensations of identity, similarity, or contrast [28]. All the sensations can be modeled as difference between colors: If the difference is small, two colors are regarded as similar or even identical, whilst large difference indicates contrast colors. Here we compute geometric distance of pairwise colors to capture the color difference.
  First, *separate components difference* [47] measures the differences of two colors in CIELCh color space-a cubic representation of CIELab color space. Specifically, L^* denotes lightness component as the same in CIELab, C^* denotes chroma (relative saturation), and h° denotes hue angle. The difference of $C_i^{sb}\&C_j^{sb}$ in a component can be computed as absolute difference, *e.g.*, lightness difference is $\Delta L^*(C_i^{sb}, C_j^{sb}) = |L^*(C_i^{sb}) - L^*(C_j^{sb})|$. We also compute $\Delta C^*(C_i^{sb}, C_j^{sb})$ and $\Delta h^\circ(C_i^{sb}, C_j^{sb})$, and take all components differences into consideration.
  Second, *holistic difference interval* is defined as the Euclidean distance between $C_i^{sb}\&C_j^{sb}$ in CIELab color space:
  $$\Delta E(C_i^{sb}, C_j^{sb}) = (\Delta L^*(C_i^{sb}, C_j^{sb})^2 + \Delta a^*(C_i^{sb}, C_j^{sb})^2 + \Delta b^*(C_i^{sb}, C_j^{sb})^2)^{1/2}, \quad (1)$$
  where ΔL^*, Δa^*, and Δb^* denote the differences of $C_i^{sb}\&C_j^{sb}$ in L^*, a^*, and b^* components, respectively.
  Both separate components difference and holistic difference interval are computed for a pair of colors. For the color patches $\{C_i^{sb}\}$, we compute pairwise difference for each pair of colors, and then take the *minimum*, *weighted average*, and *maximum* differences into consideration. Specifically, the weighted average differences are computed based on the sum of saliences of the pairwise colors.
- *Area balance*. Proper balance of (color) areas is an empirical rule in design. Munsell [27] stated that 'the stronger the color ... the smaller must be its area; while the larger the area, the grayer the Chroma'. Moon and Spencer [28] also encouraged a balance of the product of each area and adaption point when viewing a color patch. Here we consider features related to area balance as follows.
  First, the participants' feedbacks indicate that 'salient colors' have a major influence on color harmony judgments, and saliency reflects which areas of an image will draw a viewer's attention. We compute the saliency $sal(C_i^{sb})$ captured by the color patch C_i^{sb}, by adding up saliences of all pixels attached to C_i^{sb}. We adopt the concept of information entropy to measure the balance of saliency, as follows:
  $$H_{sal}(\{C_i^{sb}\}) = -\sum_i P(sal(C_i^{sb})) \cdot \log P(sal(C_i^{sb})), \quad (2)$$
  where $P(\cdot)$ denotes the probability of a color patch in terms of its saliency.
  Next, Granger [48] deducted that Moon and Spencer's postulate on area balance of color patches [28] can be quantitatively described in Munsell's term [27], as the *scalar moment* (*mom*). Specifically, the scalar moment can be computed as the product of the area and adaption point of a color patch: $s\left\{(chroma)^2 + 64(value - 5)^2\right\}^{1/2}$, where s denotes the area of a color. Here we adopt saliency $sal(C_i^{sb})$ to represent the area of C_i^{sb}, thus the scalar moment is computed as:
  $$mom(C_i^{sb}) = sal(C_i^{sb})\left\{C^*(C_i^{sb})^2 + 64(L^*(C_i^{sb}) - 5)^2\right\}^{1/2}, \quad (3)$$
  where C^* and L^* indicate the chroma and lightness in the CIELCh space, respectively. Next, we compute the information entropy based on the scalar moments for all color patches in $\{C_i^{sb}\}$.

5.2.2. Color coherence features

Given primary color patches $\{C_i^{sb}\}$ of a signboard and $\{C_i^{st}\}$ of the scene, we also compute color features of *color difference* and *area balance*, to model color coherence of a signboard with the environment.

- *Color difference*. The color difference metrics are computed for pairwise color patches. Here we need to compute differences for two sets of color patches $\{C_i^{sb}\}$ and $\{C_j^{st}\}$, for which we use Hausdorff distance d_H. Since Hausdorff distance is directional, we compute both $d_H(\{C_i^{sb}\}, \{C_j^{st}\})$, and $d_H(\{C_i^{st}\}, \{C_j^{sb}\})$. We compute Hausdorff distances for all the color differences described above.
- *Area balance*. The pixels of a signboard is a subset of the pixels of the street. In this way, we can compute *information gain* in both saliency and scalar moment described above, by comparing the entropy before and after adding the signboard in the street view.

In summary, we calculate a total of 14 features for modeling color harmony of a signboard, and 10 features for modeling color coherence of a signboard with the street.

5.3. Model construction

We employ LASSO regression to fit two linear models, one for color harmony of signboards, and another one for color coherence of signboards and streets. LASSO regression attempts to model the judgments as a weighted sum of features and an intercept $r(\boldsymbol{t}) = \boldsymbol{w}^T\boldsymbol{x}(\boldsymbol{t}) + \beta$, where $r(\boldsymbol{t})$ denotes the predicted rating, $\boldsymbol{x}(\boldsymbol{t})$ denotes the feature vector, $\boldsymbol{w}$ denotes the feature weights, and β is the intercept. The regressors are trained with L_1 regularization as follows:

$$\min_{\boldsymbol{w},\beta} \left\{ \sum_i (\boldsymbol{w}^T\boldsymbol{x_i} + \beta - r_i)^2 + \lambda\|\boldsymbol{w}\|_1 \right\}, \tag{4}$$

where $\boldsymbol{x_i}$ is the feature vector, and r_i is the average judgment for the ith signboard. LASSO performs feature selection by penalizing potential models by the L1 norm of their feature weights. In this way, LASSO will find a model that both predicts the target scores well, and also tells which features are more important. We use 10-fold cross-validation combined with stratified sampling, to ensure that the split samples have similar distributions of signboards from different streets.

Table 2 presents the statistics comparison of fixed and LASSO regressors in modeling color harmony and color coherence of outdoor signboards. Here we take a fixed regressor that outputs the mean judgments of all signboards as the baseline technique, and a LASSO regressor without considering saliency as the ablation technique. We compute the mean absolute error (MAE) and mean squared error (MSE) of each regressor with cross-validation. From this table, our approach of LASSO regressor with saliency significantly outperforms the baseline technique: our results achieve 19% decrease in MAE and 28% decrease in MSE in terms of color harmony, and 20% decrease in MAE and 30% decrease in MSE in terms of color coherence. Comparing to the ablation technique, our approach achieves comparable results in modeling color harmony of a signboard, yet much better performances in modeling color coherence of a signboard with the street, with 9% decrease in MAE and 13% decrease in MSE.

We have also compared to the results by O'Donovan color harmony model [15], using the pretrained weights learned from online color themes (*i.e.*, Kuler, COLOURLovers, and MTurk) and that trained on our dataset. The results are as follows:

- *Pretrained weights*: O'Donovan color harmony model with pretrained weights produce much worse results, *i.e.*, the one on Kuler has MAE 3.599, COLOURLovers has MAE 5.079, and MTurk has MAE 3.929. The results indicate that the pretrained models on online color themes are infeasible for the signboard use case, and the new dataset is necessary for accessing outdoor signboards.
- *Weights trained on our dataset*: O'Donovan color harmony model trained on the signboard dataset has better results, with MAE of 0.469 and MSE of 0.367. Nevertheless, the model uses 334 dimensional color features derived from four color space: RGB, CIELab, HSV, and CHSV, yet our dataset contains valid harmony ratings for only 375 signboards. It is easy for the model to overfit. Besides, O'Donovan model adopts individual color features that may be affected by different lighting conditions in street-view images. As such, we stick to our model with the selected color features.

6. Model-based data analysis

All color features in the LASSO regressors are regularized to the range [0, 1], so the learned weights are directly comparable and give a sense of which features are most predictive. Appendix B lists the learned feature weights, while the details of the weights for each run are given in Supplementary Table S3. Note that some weights are empty fields, because the feature exhibits strong correlations with some other feature and we select only one feature between them. It is also important to remember that examining individual weights gives only a partial picture of the predictor's behavior.

Table 2
Statistics comparison of fixed and LASSO regressors in modeling color harmony and color coherence of outdoor signboards.

	Color harmony		Color coherence	
	MAE	MSE	MAE	MSE
Fixed regressor (Baseline)	0.916	1.229	1.059	1.575
LASSO w/o saliency (Ablation)	**0.735**	**0.874**	0.938	1.263
LASSO w/ saliency (Our)	0.741	0.880	**0.852**	**1.100**

6.1. Important features for color harmony

For color harmony, color difference features are the most predictive. Among the separate component differences, the most important feature is average lightness difference, indicating a preference for colors with variable lightness and distances between them are sufficient. Next, average chroma difference is also very important with a big negative weight, indicating that colors with similar chroma tend to be harmonic. However, the weights of hue difference are marginal, showing that any hues used together can be harmonic. These findings are consistent with conventional color usage guidelines [49,50] that acknowledge the importance of setting lightness and chroma properly. When combining all separate components together, the minimum holistic difference interval shows a large negative weight, whilst average interval is not very important. This suggests that signboards with at least two similar colors tend to be harmonic.

Area balance features, on the other hand, are less important for color harmony. In fact, the ablation LASSO regressor (see Table 2) without considering saliency and subsequent area balance features shows even better performance. This suggests that area balance shall not be of primary concern for harmonic signboard design.

Fig. 3 compares minimal holistic difference interval (a) and scalar moment entropy (d) of signboards in *Milan* and *HK 1*. Among the streets, signboards in *Milan* receive the highest average color harmony ratings (r_{har} = 5.78), whilst those in *HK 1* receive much lower ratings (r_{har} = 4.379). Fig. 3(a) shows a strong correlation of minimal holistic difference interval and color harmony, whilst the correlation of scalar moment entropy and color harmony is not obvious in Fig. 3(d). In Fig. 3(a), the minimal holistic difference intervals of *Milan* signboards is constrained in a small range, whilst those of *HK 1* signboards are spread out. The signboards with large minimal holistic difference intervals are typically rated of low harmony. Taking *HK 1* signboards in Fig. 3(c) for example, the top signboard uses blue–white, and the bottom signboard uses black–magenta color combinations. Both color combinations exhibit big holistic difference intervals, and also separate color differences in chroma. In contrast, *Milan* signboards in Fig. 3(b) have small holistic difference intervals, benefiting from small chroma differences.

6.2. Important features for color coherence

Color differences also play a major role in color coherence between a signboard and the environment. Specifically, Hausdorff distance of the holistic difference interval from signboard colors

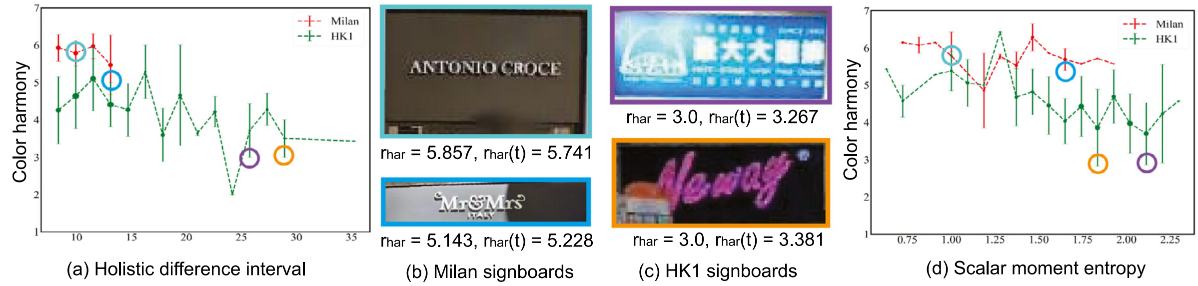


Fig. 3. Comparing minimal holistic difference interval (a) and scalar moment entropy (d) of signboards in *Milan* and *HK1*. Example signboards in *Milan* and *HK1* are presented in (b) & (c) respectively, together with user ratings r_{har} and predicted ratings $r_{har}(t)$.

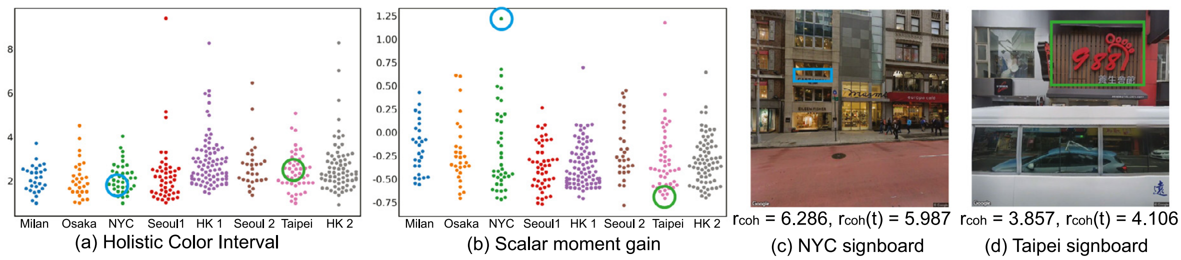


Fig. 4. Comparing color coherence over geography. Distributions of signboard-street holistic color intervals (a) and scalar moment gains (b) in the streets. An example signboard from NYC (c) is coherent with the street, whilst another one from Taipei (d) is incoherent.

to street colors has a large negative weight, indicating a preference of small color difference between signboards and streets. Yet, sufficient lightness difference is preferred, as the lightness difference shows a large positive weight. Other color differences exhibit similar weights as those in the LASSO regressor for color harmony, suggesting consistent color usage guidelines for both color harmony and color coherence. One interesting observation is that Hausdorff differences from signboard colors to street colors are much bigger than those from street colors to signboard colors. The finding coincides with a common practice that signboards typically catch people's attention before the environment.

The gain in scalar moment has a higher positive weight for color coherence, indicating that a signboard making street colors more balanced is more likely to be perceived as coherent with the street. Taking a signboard from *NYC* (Fig. 4(c)) and another one from *Taipei* (Fig. 4(d)) for example, both signboards have small color differences with the street (Fig. 4(a)), whilst the *NYC* signboard has a much higher gain in scalar moment than the *Taipei* signboard. The difference contributes to a higher coherence ratings for the *NYC* signboard (r_{coh} = 6.286) than that of the *Taipei* signboard (r_{coh} = 3.857). The correlation of scalar moment gain and color coherence makes our saliency-aware LASSO model outperforms the ablation LASSO model without considering saliency.

From Appendix A, *Milan* signboards are the most coherent with the street, whilst those in *HK 1*, *Taipei*, *Seoul 2*, and *HK 2* have lower color coherence ratings. Fig. 4(a) presents the distributions of Hausdorff distances of the holistic color difference from signboard to street colors. The holistic color difference distributions in *Milan* and *Osaka* are concentrated to small values, in comparison to the other streets. In Fig. 4(b), distributions of scalar moment gains are shown. Here, signboards in more coherent streets typically have more scalar moment gains than those in less coherent streets. Interestingly, compared to *Osaka* and *NYC*, *Seoul 1* has more concentrated scalar moment gains, which may explain why a smaller standard deviation is achieved in *Seoul 1* signboard predictions.

7. Discussion

Experimental results show that overall, color difference features play more important roles than area balance features in both color harmony and color coherence. This may explain why recent studies (*e.g.* [29,30]) on color harmony mostly focus on assessing color differences instead of area balance. Moreover, the results also reveal that our saliency-aware color harmony model achieves better performance when modeling color coherence, but only produces similar predictions when modeling color harmony, than ablation techniques without considering saliency. A possible reason is that signboards studied in this work typically occupy a relative small region in the image space, and the enclosed pixels exhibit small saliency variations. Thus saliency makes a marginal change to the color difference features for color harmony. The situation changes when modeling color coherence, which considers saliency over an entire street view. The difference indicates that saliency indeed affects human perception, and shall be considered when assessing color harmony, especially for images of complex environments.

Our results clearly show variations of color harmony and color coherence ratings over geography. Signboards in Asian cities typically receive low ratings, especially those in *HK1*, *HK2*, and *Taipei*. Interestingly, these three cities have highest average number (∼4) of signboards in each image. We suspect that store owners in these streets consider too much of the noticeability of signboards, hence choose to use more saturated colors; see examples in Fig. 3(c) and Supplementary Material Table S1 & S2. The saturated colors, as from our analyses, harm both color harmony and color coherence. An exception city is *Osaka* in Japan. We see most of the signboards in *Osaka* use just one or two colors, and are designed in similar styles with the context. Similar designs are observed in *Milan* and *NYC*. Consequently, signboards in these three cities receive high ratings for both color harmony and color coherence. A deep investigation shows that signboard colors in these cities are limited to close colors of the local context.

7.1. Design recommendations

Next we discuss our results disaggregated by the main characteristics that define the research goals of this work.

7.1.1. Towards harmonic signboard design

Holtzschue [50] stated that harmonic colors can use any combinations of hues, as long as lightness and chroma are set accordingly. Ou and Luo [47] also claimed that colors with small chroma differences tend to be harmonic, whilst many literatures (*e.g.*, [15,47]) agreed on the strong effect of lightness difference. Recently, Won et al. [5] revealed that hue difference has minor effect-as the same with Holtzschue's statement, and lightness difference has significant impacts, on color harmony of signboard. Yet, the authors did not find much effect of chroma differences on color harmony of signboard. This is probably because the authors transformed colors to a limited number of color names, hereby the experiments were constrained to a few color combinations. Instead, our results coincide with existing statements, in a stronger sense with quantitative values. Specifically, the weights of average lightness and chroma differences rank the top two in 14 color harmony features we analyzed, whilst the weights of hue difference is minimal. One thing needs notice is that the lightness and chroma differences here are average values, rather than the minimal differences. In most cases, average color differences reflects difference between background and text/logo colors.

We distill the following recommendation:

R1: *For harmonic signboard design, background and text/logo color combinations with distinctive lightness difference and small chroma difference are better.*

7.1.2. Towards environment-coherent signboard design

To certain extent, making a signboard coherent with the street means to suppress the noticeability of the signboard, which is contradictory to the purpose of attracting customers. However, as important elements of a street landscape, outdoor signboards should be coherent with the environment, from the perspectives of urban planning and city management. Yet, few to no studies explicitly assess what factors make an outdoor signboard look coherent with the street. This work fills the gap and we reveal interesting findings. First, the results show that the weights of color coherence features are relatively similar to those of color harmony features, meaning that conventional color usage guidelines for color harmony can also be applied to improve color coherence. Specifically, small holistic difference intervals and chroma difference, and large lightness difference, are preferred. Hence using an LED lamp to brighten signboards is effective. Second, adding a signboard that makes the street colors look more balanced has a slight impact on color coherence, in comparison to the color difference features. Measuring the change of saliency or scalar moment entropy is rather challenging, calling for new techniques such as virtual reality.

Therefore we distill the following recommendation.

R2: *For environment-coherent signboard design, colors that are similar to the street colors, and more lightness, are better. New techniques that allow comparison of streets before and after adding signboards are encouraged.*

7.2. Applicability

In collaboration with an urban planner, this work was initiated to improve color design for outdoor signboards. We develop color harmony models that quantify harmony and coherence ratings of certain color combinations in a geometric manner, meeting the research goals identified in Section 3. With the models, one can find out which signboards are poorly designed, identify reasons, and come up with feasible solutions for improvement. Here, we consider a version of this process in which we first identify poorly- and well-designed signboards in the same street, and next we can improve poorly-designed signboards by mimicking well-designed ones.

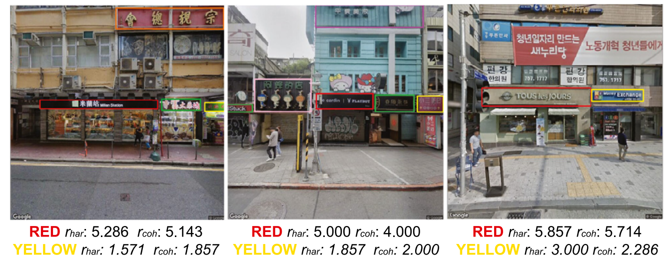


Fig. 5. Improvements of poorly designed signboards (yellow) can be accomplished by mimicking well-designed ones (red) in the neighborhood.

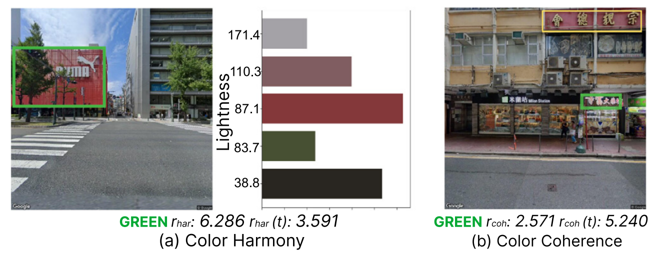


Fig. 6. Failure examples with high prediction errors. (a) The signboard is obscured by trees, resulting in a reduction in the average lightness of the extracted color patch and consequently a low harmony prediction. (b) The signboard marked in green shares similar colors with the street, resulting in a high coherence prediction, yet it receives a low coherence rating from human.

Fig. 5 presents three such examples, where poorly-designed signboards are marked in yellow and well-designed ones are marked in red. The poorly- and well-designed signboards are located besides each other, sharing a common context with the same street and lighting conditions. Based on our models, those poorly-designed signboards make common mistakes such as using saturated colors, or color combinations with big chroma differences. To improve the harmony and coherence ratings, one can consider adopting color combinations of well-designed signboards in the neighborhood, which are adapted to the local context with less saturated colors.

Nevertheless, it is not feasible to ask the local business owners to change the signboards immediately. Instead, the findings achieved in this study would be an important supplement for establishing street design codes, which is an interesting direction to promote precise urban governing, especially in East Asia [3,4]. The municipal city appearance and environmental sanitation administrative department could ask local business owners to renew their signboards every 5∼10 years by following the code. Moreover, newly-opened shops have to follow the code as well. In this way, the color coherence of a street would be largely improved in a decade.

7.3. Limitations and future work

There are several limitations of the current work.

- First, we assume that the number of primary color patches is fixed and we adopt a straightforward color patch extraction method, which may degrade the quality of color extraction.

Fig. 6(a) presents a failure case of our model caused by inaccurate color patch extraction. The trees on the road obscure the signboard and introduce green and dark brown colors, leading to a reduction in the average lightness of the extracted color patches and consequently a low harmony prediction. A possible future work thus involves dynamically adjusting the number of colors, or employing deep-learning techniques (*e.g.*, [51,52]) to derive colors. In such ways, we can improve the accuracy of color metrics and consequently the quality of models.

- The current work considers only two-aspect color features of color difference and area balance. Though saliency implicitly reflects many factors, we would like to explicitly examine additional features such as color distinctness, contrast, and adjacency, which may also have significant effects on color harmony and coherence. For example, in Fig. 6(b), the signboard marked in green shares similar colors to the street, resulting in a high coherence prediction. However, the colors are not distinctive from the environment, thus the signboard receives a low coherence rating from humans.
- Currently, the color harmony models are built upon CIELab color space, which was designed to be perceptually uniform but do not accurately quantify small- to medium-size color difference. A possible alternative is to use CIEDE2000 [53] that copes well with human judgments in both local patches and global space. Besides, it is worthy of combining color features of many different color spaces together, such as that in [15]. Nevertheless, this will require us to collect more color harmony judgments, to prevent overfitting the model.
- Our current method is to obtain professional consensus through the professional judgment of small samples, so we do not need too large samples and can avoid the deviation caused by cultural background to a certain extent. Nevertheless, this yields a small dataset on color preference for outdoor signboards. We are going to build a targeted website to collect a large sample of the preferences of locales in typical cities around the world for further exploration.
- With a larger dataset, we envision to employ advanced deep learning techniques to model the color harmony. In this way, we can get rid of the tedious process of selecting proper color spaces and features. Nevertheless, deep learning models lack interpretability and may not be much helpful for establishing color design codes. Instead, we may first take advantage of deep learning models to narrow down the search space, and construct more interpretable models using conventional LASSO regression.
- Last but not least, we will extend the applicability of this work. On one hand, we are working on an augment reality (AR) project that aims to help users improve color designs of outdoor signboards. This is nevertheless a challenging task, due to the complexity of street environment and lighting conditions. On the other hand, we would like to examine if the harmony models can be applied to other fields, such as to improve color coherence for multiple-view visualization design [54]. This can give more color palettes than prefabricated ones like ColorBrewer [55].

8. Conclusion

We have presented an in-depth assessment on what color features contribute to color harmony and color coherence of outdoor signboards. The findings are revealed with novel color harmony models that take into account the color features in CIELab color space, and saliency as an inherent color characteristic in the image space. The benefits of introducing saliency are prominent, especially for modeling color coherence of a signboard with the environment. This is because saliency depends on many factors such as color distinctness [35] and therefore reflects which areas draw a viewer's attention, which is essential for complex environment. We apply our saliency-aware color harmony models to a new dataset comprising of diverse signboards from various streets worldwide, and diverse subjective ratings by eight architects. Experimental results show that many conventional color usage guidelines (*e.g.*, to choose proper lightness and chroma differences) apply to signboard design, and also reveal new insights such as that adapting simple color patches in accordance with the local context can improve signboard design.

Table A.3
User ratings and predicted ratings of color harmony for the streets.

Street name	User ratings	Predicted ratings	MAE	MSE
NYC	5.568 ± 0.527	4.890 ± 0.384	0.726	0.680
Seoul1	5.035 ± 0.843	4.734 ± 0.398	0.729	0.724
Seoul2	4.300 ± 1.043	4.442 ± 0.739	0.721	0.886
Milan	5.780 ± 0.534	5.238 ± 0.399	0.649	0.597
Japan	5.456 ± 0.863	4.875 ± 0.631	1.013	1.503
Taipei	4.057 ± 1.106	4.501 ± 0.584	0.893	1.309
HK2	4.115 ± 1.070	4.684 ± 0.516	0.781	1.052
HK1	4.379 ± 0.941	4.545 ± 0.610	0.580	0.549

Table A.4
User ratings and predicted ratings of color coherence for the streets.

Street name	User ratings	Predicted ratings	MAE	MSE
NYC	5.527 ± 0.734	4.968 ± 0.465	0.819	0.977
Seoul1	5.255 ± 0.909	5.061 ± 0.368	0.705	0.762
Seoul2	4.266 ± 1.298	4.658 ± 0.727	0.933	1.262
Milan	6.020 ± 0.538	5.114 ± 0.331	0.984	1.304
Japan	5.670 ± 0.928	5.058 ± 0.514	1.017	1.338
Taipei	4.117 ± 1.192	4.747 ± 0.610	0.928	1.404
HK2	4.073 ± 1.084	4.487 ± 0.773	0.818	1.093
HK1	4.309 ± 1.184	4.347 ± 0.773	0.809	0.980

CRediT authorship contribution statement

Yanna Lin: Methodology, Software, Formal analysis, Writing – original draft. **Wei Zeng:** Conceptualization, Resources, Writing – original draft, Supervision. **Yu Ye:** Conceptualization, Writing – review & editing, Supervision. **Huamin Qu:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. User ratings and predicted ratings of color harmony and color coherence for the streets

See Tables A.3 and A.4.

Appendix B. Feature weights of our LASSO regressor (top) considering saliency and ablation LASSO regressor (bottom) without saliency.

See Tables B.5 and B.6.

Table B.5
Feature weights of Our LASSO regressor considering saliency.

	Color harmony				Color coherence		
	Feature	Channel	Metric	Weights	Feature	Metric	Weights
Color difference	**Separate Components Difference**	Lightness	Max.	–	**Hausdorff distance**	**Street-sign.**	**1.238**
			Min.	0.083		**Sign.-street**	**3.865**
			Average	**2.128**			
		Chroma	Max.	–		Street-sign.	0.395
			Min.	−0.131		**Sign.-street**	**−1.684**
			Average	**−1.441**			
		Hue	Max.	–		Street-sign.	−0.336
			Min.	−0.139		**Sign.-street**	**−0.775**
			Average	−0.231			
	Holistic Difference Interval	Color	Max.	–		**Street-sign.**	**−1.461**
			Min.	**−0.925**		**Sign.-street**	**−4.313**
			Average	−0.239			
Area balance	**Saliency**	Saliency	Entropy	−0.462	Saliency gain	Entropy difference	−0.453
	Scalar Moment	Saliency, Chroma, Lightness	Entropy	−0.483	Scalar moment gain	**Entropy difference**	**1.167**

Table B.6
Feature weights of ablation LASSO regressor without saliency.

	Color harmony				Color coherence		
	Feature	Channel	Metric	Weights	Feature	Metric	Weights
Color difference	**Separate Components Difference**	Lightness	Max.	–	**Hausdorff Distance**	**Street-sign.**	**−0.711**
			Min.	−0.314		Sign.-street	0.397
			Average	**1.986**			
		Chroma	Max.	–		Street-sign.	**0.919**
			Min.	−0.359		Sign.-street	**−1.343**
			Average	**−0.876**			
		Hue	Max.	–		**Street-sign.**	**−0.755**
			Min.	**−0.624**		**Sign.-street**	**−2.359**
			Average	−0.397			
	Holistic Difference Interval	Color	Max.	–		**Street-sign.**	**0.707**
			Min.	**−1.260**		**Sign.-street**	**−1.902**
			Average	−0.293			

Appendix C. Images of signboards and street views, user ratings, and code of our LASSO regressor model.

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.cag.2022.04.012.

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