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Analyzing color harmony of food images

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Abstract

Color of food images play a key role in human perception of food quality and calories, as well as in food choice. In this paper we investigate the use of computational methods for color harmony analysis of food images. To this end we propose a computational pipeline that includes color segmentation, color palette extraction and color harmony prediction. Such a pipeline makes it possible to analyze the emotions elicited by pairs and multiple combinations of food dishes.

Introduction

Monitoring of daily food intake is one of the most relevant topic in the health and fitness domain [1]. Recently several automatic or semi-automatic tools have been introduced to speed up the diet monitoring process, such as computer vision tools for food recognition, localization and segmentation [2, 3, 4]. While a plenty of literature has been published for the automatic interpretation of food images, few papers deal with the emotional aspects related to the food content and more in particular to its color content.

Previous studies demonstrated the importance of food color analysis in food human perception especially related to food choice [5, 6]. Foroni et al. [7] revealed that color of food correlates with the way humans perceive food quality and calories. Results of these studies suggest that humans are biased towards attributing significantly less energy to greener food and that humans are more motivated by food with more reddish nuances since they elicit more arousal. Other studies demonstrated that color play a key role in food choice by influencing taste thresholds, sweetness perception, food preference, pleasantness, and acceptability [5, 6]. Harmony is an attribute that measures how much a combination of colors are perceived pleasant when seen in combination by a human being. Since, food images are mostly made of several colors, we investigate how the harmony of a color combinations within food images influences human emotions.

We analyze color of food images by exploiting the concept of color themes [8] (also known as color palettes or swatches). Given an image, a color theme is a set of the most relevant colors, usually 5 [9, 10], to that image. Then we exploit color harmony and color emotion models to describe the color palette with respect to emotion and sensation elicited by the color combinations. Our preliminary investigations on a food image database show that color harmony can be a useful measure to predict human perceived emotions.

Proposed analysis pipeline

This section describes the pipeline proposed for automatically analyzes color and harmony of food color images. Figure 1 shows main modules involved: 1) food region segmentation to extract the food content from an image; 2) color palette extraction; 3) computation of the color harmony from a color theme.

Food Segmentation

For our investigations we adopted the GUNet architecture presented for the first time by Mazzini in [11, 12] and that demonstrated to be very effective for food segmentation [4]. The network follows an encoder-decoder design. The encoder has a multibranch structure to encode features at multiple resolutions: the first branch is the deepest one, encoding the most abstract features whereas the second branch is shallower by design in order to encode fine details without being too computational heavy. The first part of the decoder is a Fusion Module. It is composed by a first part where signals are pre-processed independently followed by a second part where signals are jointly processed and information coming from multiple resolution branches is fused together. The Decoder ends with a layer named Guided Upsampling Module that efficiently upsample the feature map. The output of the network is a binary mask of the pixels that belong to the food regions. Using this mask, we select all the color pixels with which to compute the food color palette as described in the next subsection.

Color Theme extractions

In the field of visual and graphic art design the choice of an attractive set of colors (also called color theme or color palette) can be a very complex process [8]. The perceived quality of a color decision can be affected by subjective-culture, trending fashions, and individual preference [13, 14]. Artists and designers often choose colors by taking inspiration from other pre-made color themes [15, 16, 17] or themes extracted from images [14]. A color theme of an image is a finite set of color (usually about 5) that best represents an image [8].

Color themes are useful in many tasks such as image recoloring, color blending, photo segmentation and editing, image enhancement and manipulation [18]. Color theme can be also adopted as signatures (or feature vectors) for the indexing of images in a content-based image retrieval system [19, 20, 21]. A user can query the system by choosing a color, or a set of colors, and then retrieve a set of images that are relevant to that query, or in another way a set of images for which the colors of the query are representative [19, 22].

Whatever is the application domain, being able to automatically extract a color theme from an image can facilitate color-related applications such as color picking interfaces, color mood transfer from one image to another, or color harmonization [14, 20, 23, 24]. Human beings are able to recognize millions of colors and more important they are able to describe an image by selecting just a few of them [25, 26]. While human beings perform this task quite effortlessly, algorithms does not

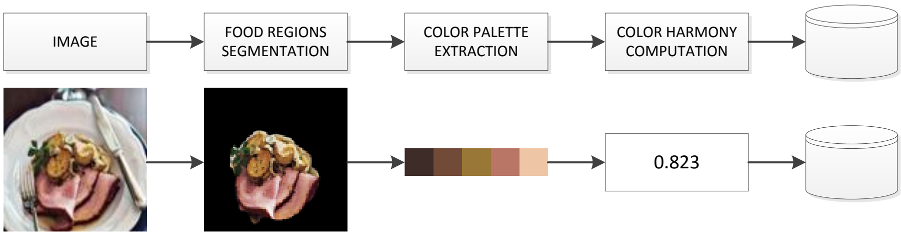

Figure 1. *Pipeline of the proposed color harmony extraction strategy. The food image is firstly segmented using a food localization CNN to discard the background pixels. Then the five most relevant colors are extracted from the segmented region to form the food color palette. Finally, a color harmony model is applied to compute the degree of harmony of the color in the palette.*

perform this task easily especially from the computational-cost point of view.

A plenty of automatic color theme extraction methods have been presented in the last years. There are methods based on clustering [25, 9, 27], that are unsupervised, while other methods are supervised, such as the one by Lin et al. [8]. They presented a regression model trained on user-defined color themes. Very recently a deep-learning based solution has been presented for a discrete-continuous color gamut representation that extends the color gradient analogy to three dimensions and allows interactive control of the color blending behavior [18]. Mellado et al. presented a graph-based palette representation to find a theme as a minimization problem [28].

The evaluation of color theme goodness, that is how much a set of colors is representative of a given image, involves human beings and therefore is highly subjective. Such evaluations are time consuming and not costless. To overcome the limits of subjective evaluations, computational metrics based on the Earth Mover's distance (EMD) have been adopted [29].

To the scope of this paper we extract color themes exploiting the K-means algorithm and CIELab version of the image as input. Since K-means is influenced by the initialization step, we have chosen initial seeds uniformly over a set of colors ordered from the brightest to darkest. Once the color palette is obtained, in order to have a smaller number of colors, we mapped the colors of the theme to the color names defined by the ISCC-NBS system proposed in the 1955 by the Inter-Society Color Council and the National Bureau of Standards (NBS, now NIST) [30]. The system was designed to describe colors in non-technical, everyday terms that anybody could understand. The backbone of the system is based on the following 13 names: Pink, Red, Orange, Brown, Yellow, Olive, Yellow green, Green, Blue, Purple, White, Gray, Black. From these names, other subcategories have been derived and the final number of colors is 267 [31].

Color Harmony

Color combinations play an important role in how an image is emotionally perceived. Some colors may be perceived pleasant or unpleasant if viewed paired with other colors. Color harmony is an attribute of a set of colors that are perceived when seen in combination. This attribute has been exploited, for example, for color selection in interior design [32], in computer graphics [33] where images are recolored according to palettes of harmonic colors. Also, color harmony has been experimented in [34] for enabling novel modalities for retrieval and browsing of images in large collections. In recent years, using psycho physical scaling methods, predictive models of colour harmony have been developed such as those derived by Ou and Luo [35], Solli and Lenz [36], Nayatani and Sakai [37], Szabó et al. [38].

The computational model used in this work is based on the work on colour pairs firstly introduced by Ou and Luo in [35]. In psycho physical experiments, observers were presented with color pairs, and harmony scores were assessed for each color pair using category scaling. The final model describe the color harmony in terms of hue, chromaticity and lightness similarities. Since different cultural backgrounds may bias color harmony, this model has been further refined in [39] where more psycho physical data is collected from 12 regions to derive a Universal Color Harmony model that should works across different population. The actual model used in this work is as follows: given two $L^*a^*b^*$ colors, the harmony score CH_U between them takes into account four elements: the hue similarity ($CH_{\Delta H}$), the chroma similarity ($CH_{\Delta C}$), the lightness difference ($CH_{\Delta L}$) and the high lightness contribution (CH_{Lsum}). Computationally the model is defined as a combination of the four elements:

$$CH_U = CH_{\Delta H} + CH_{\Delta C} + CH_{\Delta L} + CH_{Lsum} \tag{1}$$

with

$$CH_{\Delta H} = -0.7tanh(-0.7 + 0.04\Delta H^*_{ab}) \tag{2}$$

$$CH_{\Delta C} = -0.3tanh(-1.1 + 0.05\Delta C^*_{ab}) \tag{3}$$

$$CH_{\Delta L} = 0.4tanh(-0.8 + 0.05\Delta L^*) \tag{4}$$

$$CH_{Lsum} = 0.3 + 0.6tanh[-4.2 + 0.028(L^*_1 + L^*_2)] \tag{5}$$

where Δ^*_L is the CIELab lightness difference; ΔC^*_{ab} is the CIELab chroma difference; ΔH^*_{ab} is the CIELab hue difference.

Since the model defines an harmony score between two colors, we need to extend it for a set of colors. For the purpose of this work, we followed a simple approach. Given a color palette, the harmony of the colors in the palette is given by averaging the harmony scores computed between every pairs of color combinations in the palette. Since the model defines an harmony score between two colors, we need to extend it for a set of colors. For the purpose of this work, we followed a simple approach. Given a color palette, the harmony of the colors in the palette is given by averaging the harmony scores computed between every pairs of color combinations in the palette.

Case studies

In this section, we illustrate two preliminary case studies about the use of color harmony applied to food images. In the first one, we show how food images can be related to each other with respect to the color harmony. To this end we exploit network graphs to visualize these relations. The second one is a possible application of color harmony to create menus of food dishes that, on the overall, have the most harmonic colors.

Dataset

We select images from the publicly available Yummly28K food dataset [40]. This dataset contains 27,638 food images and with respect to other existing datasets in the literature, in addition

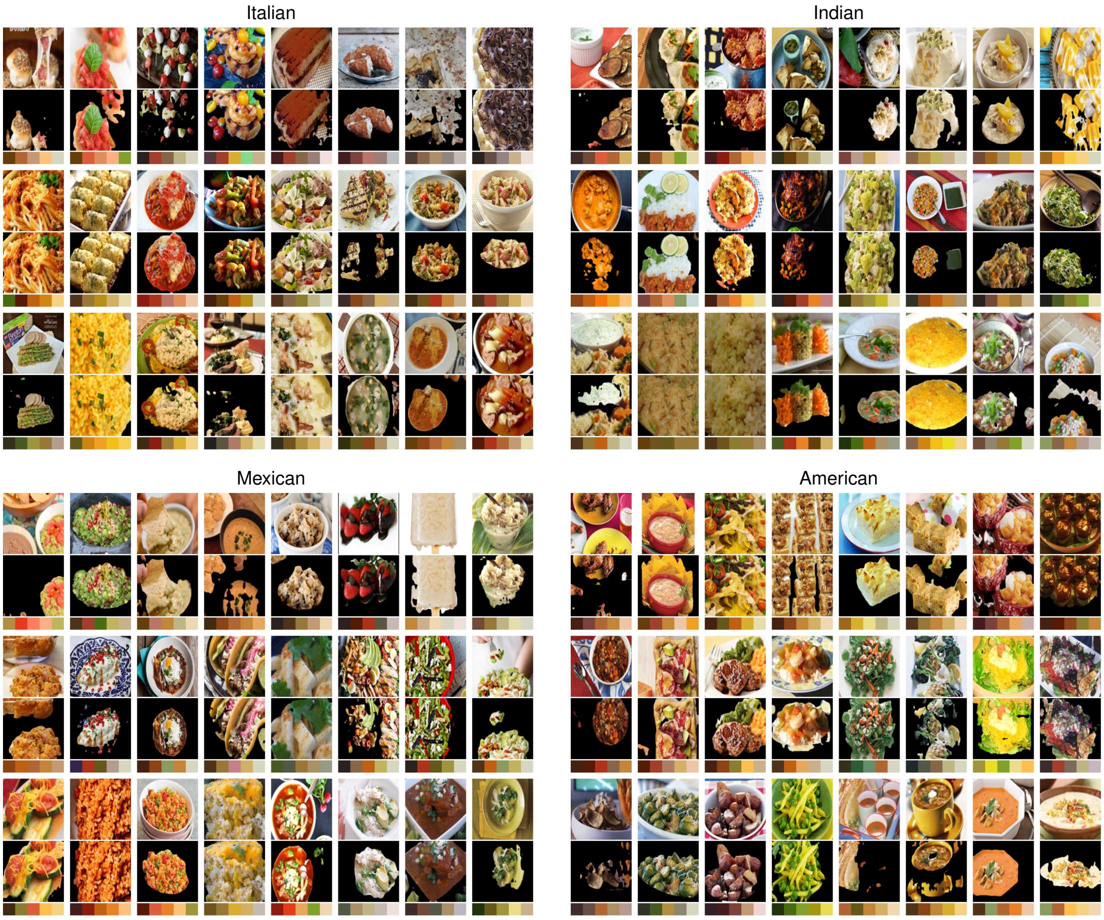

Figure 2. Images of the four cuisines considered in this work. The food segmentation results and the computed color palettes are also shown. Each course has four images. Courses are: Appetizers and Desserts (top rows), Main Dishes and Salads (middle rows), Side Dishes and Soups (bottom rows).

to images, it includes name of the recipe, ingredients, cuisine and course type associated to each image. These information could be useful to perform analysis across different cuisines as well as with respect to the different courses. The dataset contains 16 kinds of cuisines and 13 possible courses. Since not all the cuisines have the same courses and that the courses/cuisines do not always contains the same number of images, in order to maximize the number of course and images, we selected a subset of four cuisines and six courses. Specifically, the selected cuisines are: Italian, Indian, Mexican, and American. The six courses are: Appetizers, Soups, Main Dishes, Salads, Side Dishes, and Desserts. For each Cuisine/Course combination we randomly selected four food images from the available ones. Each image is processed with the proposed pipeline. Figure 2 shows the images in each cuisine group along with the segmentation results and their color palettes. We can see that the food segmentation stage effectively select the pixels of food regions with few minor errors on some images, and the extracted color palettes are effectively representative of the segmented images.

Color Harmony Graphs

In this first investigation, given the images in a cuisine, we want to analyze how they are related with respect to the color harmony. To this end we employ a data visualization using network graphs, where each node is an image and each link represents color harmony between two images. Figure 3 shows color harmony graph computed for each cuisine. Each graph illustrates the color harmony between pairs of food images. Nodes are the food images. Darker and wider links indicate higher color harmony values between the corresponding nodes. For ease of readability, only the strongest links (i.e. strongest color harmony image pairs) are shown. This visualization helps us to see patterns (if any) and relations among the images.

As it can be seen, the topologies of the graphs are quite different. For the Italian cuisine, there are some “satellites” images belonging to the desserts course. This means that, among the considered images, the desserts are considered by the model not very harmonic with the others. This is also shown by the width of their links. For the Indian cuisine, the graph is quite compact and connected with a couple of image that are considered very harmonic with many others. Few links show low level of harmony, thus indicating that, on the overall, the colors in the images are harmonic. In the case of the Mexican cuisine, we can see that there is a single image showing strong color harmony connections. It is an ice cream that exhibits strong harmonic connection with food from the different courses. This could be because its color palette contains neutral colors. Finally, for the American cuisine, we have no particular observation with patterns similar as in the other graphs. In all the graphs we can see that images with similar colors are near each other with different degree of color harmony connecting them.

Color Harmony Menus

Here we investigate a possible application of the color harmony: given a set of courses, we want to understand which combination of dishes is the best in terms of color harmony. We

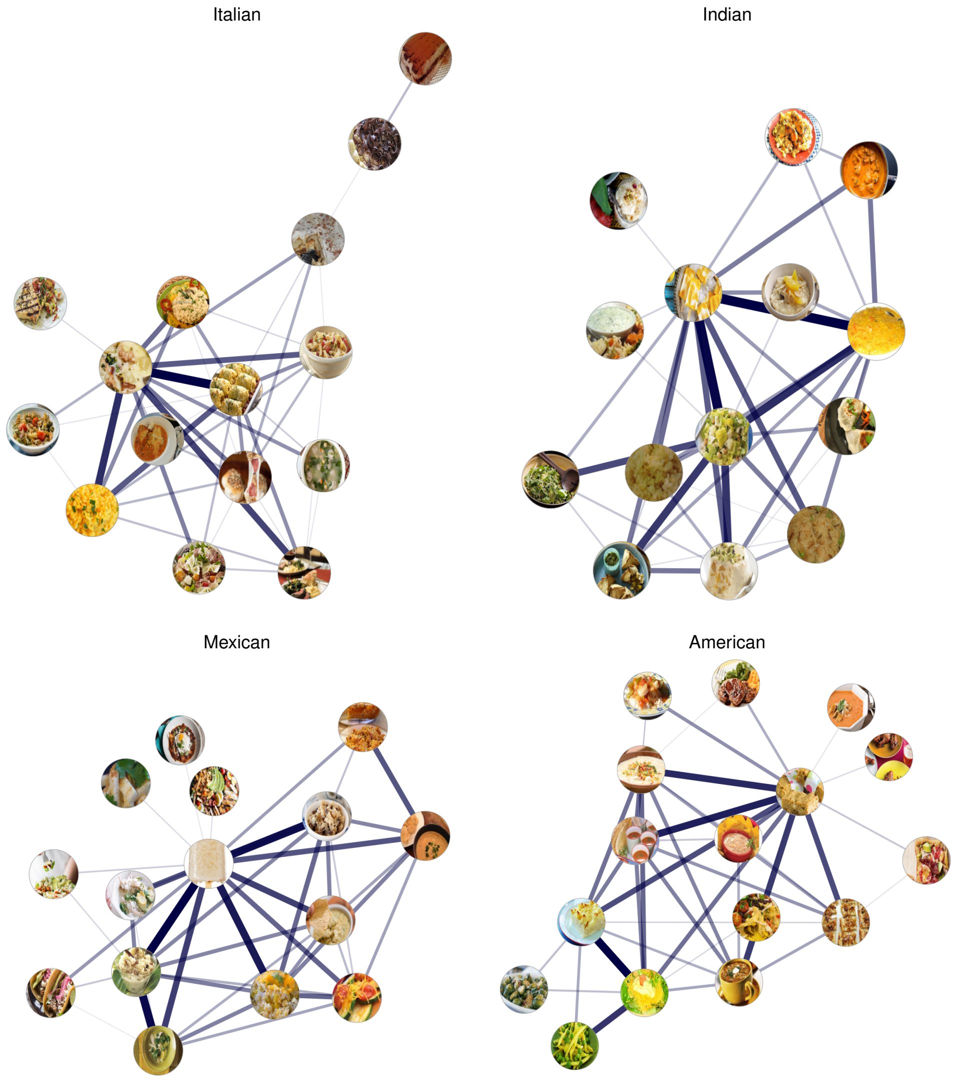

Figure 3. *Color harmony graphs showing harmony between each pair of food images in a cuisine. Only the strongest connections (i.e. strongest color harmony image pairs) are shown for readability. Darker and wider links indicate higher color harmony values.*

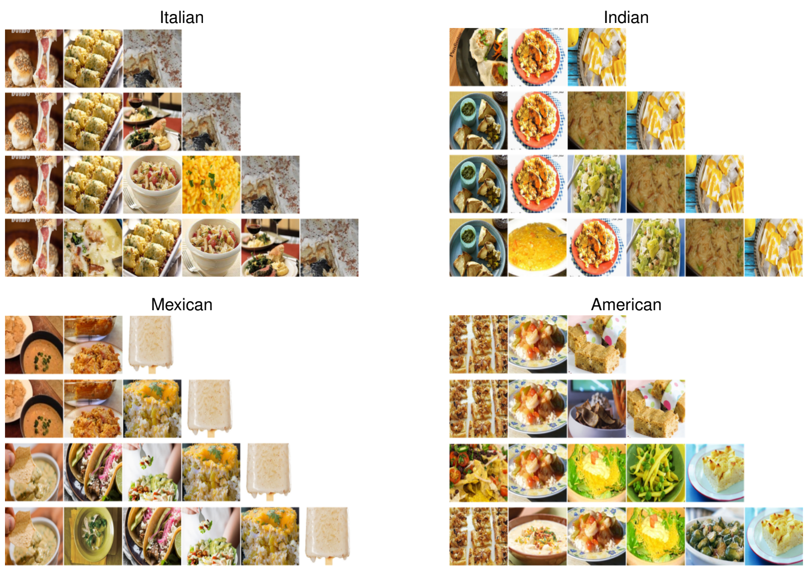

Figure 4. *Color Harmony Menus. The figure shows the most harmonic menus varying the number of courses in each menu. For the names of the courses see Table 1. Please note that the background of the food images is not taken into account by the algorithm.*

Figure 5. The most non-harmonic menus for the four cuisines.

generate several menus, each one of different courses. The selection of the best food combination in terms of color harmony is conducted exhaustively.

The courses in each menu ranges from 3 to 6. Table 1 shows the courses included in each menu. Not all the menus are reasonable in a real scenario given the available courses. Notwithstanding that we want to see how the final selection changes when many images are considered. Figure 4 shows the different menus created on the four selected cuisines.

Table 1. Menu compositions for the case study.

Menu	Courses					
3	Appetizer	Main Dish	Dessert			
4	Appetizer	Main Dish	Side Dish	Dessert		
5	Appetizer	Main Dish	Salad	Side Dish	Dessert	
6	Appetizer	Soup	Main Dish	Salad	Side Dish	Dessert

If we analyze the menus created for the four cuisines, we can see a similar behaviour. The food selected in the 3-course menu are often retained in the larger menus (with some exceptions). This is probably due to the exhaustive search of the most harmonic images. The most harmonic images are the more important and the subsequent ones less influence the selection. Moreover, the selected images are strongly related to what we have observed in the harmonic graphs. The images with strong connections are the ones that have the highest probability to be selected for the menus. In order to assess if the selected menus are indeed the most harmonic ones, we have further performed a test involving human judgments. For this test, we have considered only the six-course menus. For each cuisine, we have generated another menu by considering the most non-harmonic dishes. Figure 5 shows the generated menus. We have then presented to the users both the harmonic and the non harmonic menu and asked them to choose which one they prefer in terms of colors. At the end of the test, we collected the results and computed how many users selected the harmonic menus in Figure 4. Table 2 shows the results of this test performed on 13 users. For the Mexican, Italian and American menus, the users effectively preferred the most harmonic menu between the two. For the Indian cuisine, both menus were considered equally not very harmonic. These results could be explained by considering the difference in cultural background. Most of the subjects in the experiment have a Western cultural background while Indian dishes are composed according to the Indian cultural color-emotions associations. On the contrary, if we look at Figure 3, we can see that, according to the color harmony model used, the Indian cuisine shows the most compact graph compared with the other cuisines. More subjective experiments, with people from different cultural backgrounds, are required in order to better evaluate the association of color and harmony in the context of food.

Table 2. User test of harmonic vs. non-harmonic menu.

Cuisine	Italian	Indian	Mexican	American
Harmonic vs. non-Harmonic	76.9%	46.1%	69.0%	86.6%

Conclusions

In this paper we analyzed color and harmony of food images. Two case studies involving pairs (harmony graphs) and multiple combinations (harmony menus) of food images have been performed. Results on harmony graphs show that this visualization is helpful for analyzing collection of food images and for highlighting patterns and relations between food images and courses. Results on harmony menus revealed that the computational model of harmony prediction is suitable to create harmonic menus of different courses in substantial accordance with human perception. Different menus could be created by considering one or more dishes as the preferred ones and let the pipeline search for the remaining ones to create an overall harmonic menu. Another possible are of investigation could be the evaluation of the color harmony across cuisines and courses. We intend to extensively investigate these use cases in the future. Moreover, it would be interesting to test the influence of the background colors and texture with respect to the food regions.

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