Investigating human color harmony preferences using unsupervised machine learning

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Abstract

Color harmony patterns are relationships between coexisting colors where human psycho-perceptual visual pleasantness is the judging criterion. They play pivotal role in visualization, digital imaging and computer graphics. As a reference we assumed Itten model where harmony is expressed in terms of hue. The paper demonstrate investigation on color harmony patterns using clustering techniques.

Our source data was Adobe Kuler database consisting of hundreds of thousands of color palettes prepared for creative purposes. For the color palettes dissimilarity measurement we propose to use Jaccard distance additionally treating colors as the elements of a fuzzy set. Then, in the next step, separate colors are grouped within each group of palettes to specify each scheme of relations. The results are schemes of relationships between color within palettes.

Introduction

The general harmony concept, according to Merriam-Webster dictionary, is: *"pleasing or congruent arrangement of parts"*. The most common strict model is the music harmony, which we will refer to. It describes coexistence of two or more sounds as consonances and dissonances by their pitch (frequency) relation and its psycho-perceptual reception. Since the harmony is aesthetic and artistic subject therefore both consonances and dissonances may be used for aesthetic purposes. Moreover there is cultural impact on aesthetic perception of harmony. Color harmony is the important and open task on the art and science edge with vital importance for the visualization, electronic imaging and computer graphics as it results in visual pleasantness of the resulting images. Color harmony is topic of ongoing discussion and research effort but there is still no common consensus on definition of color harmony [2][9], although one can find useful and practical proposals.

The proposed method stems from [11] which was based upon linguistic variables for color quantification. Our contribution is the proposal how to numerically describe a palette with a fuzzy set and how to measure similarity of palettes with a formal method with respect to their cyclic nature. Next, we applied the measure with machine learning to discover patterns within large community based data set [1]. The crowd sourcing of a data is nowadays present in human centric research. In color research such an approach can be found in [4] or [10].

Background

Color theory models [11] at most are based on the psychoperceptual color models like Munsell or their approximations like HSV colorspace. Such models consist of quantitative information described visually as length on axis: V - value (lightness), S - saturation (or C - chroma - relative saturation) and qualitative information H - hue expressed as angle on color wheel.

Our research is based on Itten's model where color harmony is dependent on the *hue* relationship between coexisting components only. This idea was investigated by Matsuda as it is described in [11] - hue harmonic templates are demonstrated in Fig. 2. The key concept of a harmonic *color scheme* (or *template* equivalently) is a relative distribution of hues of colors that defines angular relationship between them. Colors located within marked boundaries are considered harmonic according to the given template. A template as a whole can be rotated freely. This model was successfully used to investigate harmonic patterns to support color decision [11], image enhancement [3] and visualization [12].

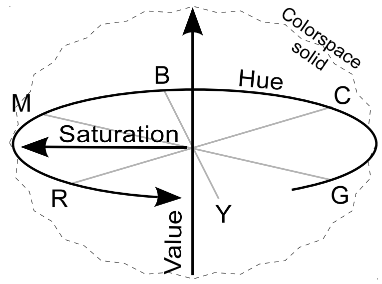

Figure 1. *Hue Saturation Value color model*

There are also two notable concerns related to the color space we used. First - to be compliant to the HSV convention - we used degrees as a measure of angles instead of radians. Second - even more important and not so obvious - as there are some discrepancies [8] related to HSV model we used cylindrical model (with absolute saturation), not the conical with relative saturation (chroma). For the interpretation of final results it does not matter as the hue angles are intensity and lightness agnostic.

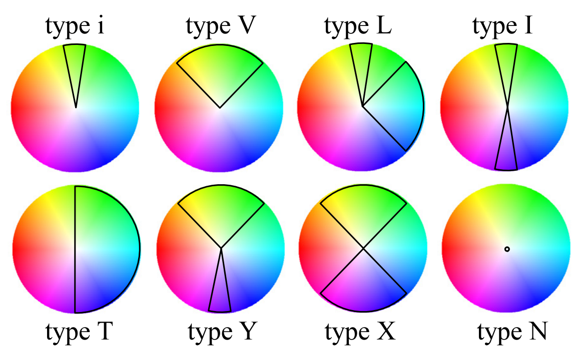

Figure 2. *Examples of harmonic templates on hue wheel. They can be rotated as the angles of color patterns are relative*

Investigation method

The data

The source of color data was Adobe Kuler database. It is a web application intended to "*Explore, create and share color themes*" [1], it is also integrated into Creative Suite package so it allows designers to cooperate with the others in creation of palettes for conventional publications, websites and interactive applications as well. The web interface allows to define own palette on base of an image or manually. Kuler offers palette creation using predefined palette templates or a custom color set. These predefined templates should be rediscovered in resulting patterns as an experimental confirmation of the method.

The database can be accessed using dedicated API through RSS in XML files. We downloaded 450415 color palettes containing from 2 to 5 color patches but this amount is still growing. Among the others each palette contains information about number of downloads and user rating (0-5). Each color is stored in two ways: original color space and hex RGB for web presentation.

We had no control over the whole process of data collection so using such an industry maintained and community fed database lead to some drawbacks. First, there exists a risk that data can be contaminated with nonsense entries by malevolent person, to solve this problem one can use active data cleaning [4]. Our proposal is to use noise resistant algorithm (DBSCAN) and surplus number of clusters which would gather noisy results. This approach connected with the massive amount of entries of the database would prevent wrong entries to have influential impact on the obtained results. The second drawback is the fact that we do not know anything about color representation and viewing conditions of certain subjects. Nevertheless, since the Adobe CS software incorporates the color management and on the other side the minimalistic sRGB standard is assumed for the web applications and the Kuler delivers web hex representation of RGB, therefore assuming that all the results are in consistent sRGB would be the proper choice. We selected, for further processing, a 437,450 element subset, consisting of 5 color palettes only as dominant ones.

Overview of the method

The outline of our research method is relatively simple as it consists of four basic steps, where each step uses the results of the proceeding one as input data. The palettes data is processed as follows:

1. normalize the raw data set - rotate each palette to start with $0°$ angle, on the basis of the first palette item,
2. cluster palettes to obtain consistent groups of palettes,
3. cluster single colors to form consistent ranges of hue relative angles within each harmonic scheme,
4. manually ensemble different schemes as they differ only in rotation in order to have equivalent meaning.

Steps 2 and 3 listed above are further explained in the following subsections and illustrated in Fig. 3. Resulting values are relative angles of groups of hues (both distances and widths) within a single harmonic pattern. For the first stage of grouping (of palettes) there was fuzzy Jaccard distance used as a dissimilarity measure. For in-palette hue grouping we used absolute angular distance. Another important fact is that thanks to the statistical nature of grouping algorithms it is possible to filter out noise that can appear as single non-schematic palettes or as incidental single hues as it is depicted in Fig. 4. Obtained patterns describe relative difference of colors within palette selected by users - e.g. users often choose opponent colors what is reflected by I type in Fig. 2 so the template will be fulfilled by e.g. red-green, blue-yellow or orange-cyan.

Fuzzy set based hue distance measurement

The problem how to compare two color palettes plays pivotal role in our research. The methods we had to reject:

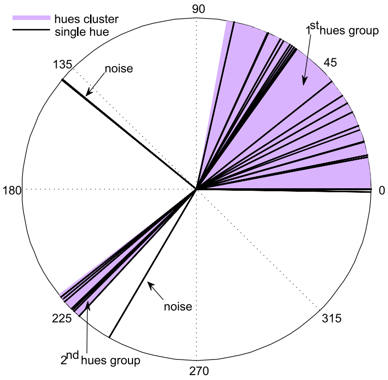

Figure 4. *Exemplary palette cluster with groups of hues and individual hue instances*

- sum of minimal angles between components, (quasi distance)
- simple cosine distance,
- minimal sum of angular distances between components for all permutations of them

After testing above heuristic methods we decided to employ fuzzy sets [5] with Jaccard distance. Each palette consists of several hues in range $\langle 0°, 360°)$ degrees. Since there is no special order within such a palette it should be considered as a mathematical set. To compare two such sets we spanned a fuzzy set over palette hues using triangle membership function of a width $30°$. The choice of such a width was motivated by the fact that all principal colors (RGBCMY) are equally distributed on the hue wheel with $60°$ step whereas one can easily identify additional in-between entities such as *orange*, *violet*. Another notable fact is that whole domain is cyclic so after reaching the limit of $360°$ it continues from $0°$. The Jaccard distance between two sets compares the cardinality ('size') of common part to overall cardinality of both considered sets. It is given with:

$$d_J(A,B) = 1 - J(A,B) = 1 - \frac{|A \cap B|}{|A \cup B|}, \tag{1}$$

where: A, B are compared sets, $J()$ is Jaccard similarity index. In terms of fuzzy set theory a sum and intersection are named S-norm and T-norm respectively. There are proposed various forms of them but we decided to use the simplest and the most generic methods:

$$S(A,B)(x_i) = max(\mu_A(x_i), \mu_B(x_i)), \tag{2}$$
$$T(A,B)(x_i) = min(\mu_A(x_i), \mu_B(x_i)), \tag{3}$$

where: A, B are fuzzy sets, $\mu_A(x_i), \mu_B(x_i)$ are membership functions for x_i elements. Finally, the cardinality operator for the fuzzy sets has a form:

$$|A| = \sum_{i=1}^{N} \mu_A(x_i). \tag{4}$$

In further considerations w assume isosceles triangular membership functions of 30 degrees width as in Fig. 5.

Grouping palettes

The classical hierarchical agglomerative algorithm [7] was applied to palettes clustering. The method starts treating each data object that is analyzed as a separate group. Next, the two closest groups are merged iteratively until one group containing all the data objects is created.

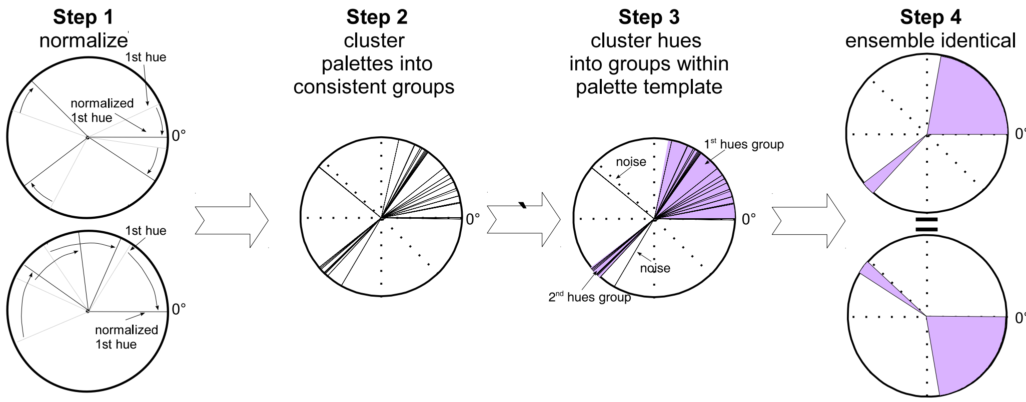

Figure 3. *Flowchart of a proposed approach*

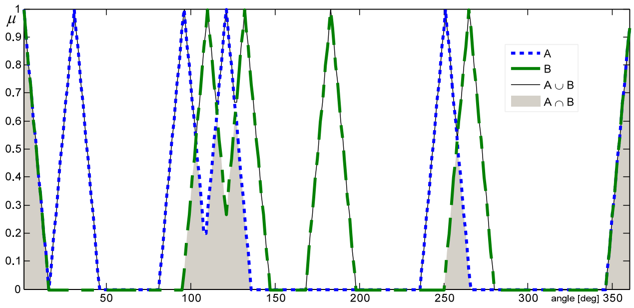

Figure 5. *Fuzzy Jaccard index computation*

There are several approaches how to calculate the distance d between the two groups. One of the possibilities is *average link* method which defines this distance as:

$$d(C_i, C_j) = \frac{1}{|C_i|\,|C_j|} \sum_{x_k \in C_i, x_m \in C_j} d(x_k, x_m), \tag{5}$$

where $|C_i|$ is a number of data objects creating cluster C_i.

The result of the method is a hierarchy of partitions which can be visualized in a form of dendrogram - a tree structure showing how the groups were merged in the consecutive iterations. A dendrogram can show if the clustering results are balanced in terms of groups cardinality and if we can obtain several well separated groups.

The algorithm processes distance matrix calculated for the analyzed data objects. In the case of palettes clustering the distance is calculated using the method described in previous subsection.

Grouping in-palette colors

The goal of in-palette colors clustering is to reveal the regions on a hue wheel which are densely filled in by the color values. Thus, density-based DBSCAN algorithm [6] was applied to perform this task. DBSCAN algorithm utilizes two parameters: ε is a radius that defines the neighbourhood of each data object, m defines how many neighbours located within ε radius of a data object make this neighbourhood dens. The clusters are built on the basis of dens regions in data. Additionally the algorithm creates a group of data objects that do not belong to any dens cluster and classify them as noise. It is a valuable feature in case of a given application. The goal of the analysis is to reveal harmonic templates on hue wheel, which are defined by dens clusters. The rest of the color values are classified as noise.

The algorithm processes distance matrix calculated for the analysed data objects. The in-palette colors that are clustered are one dimensional vectors containing a single hue value. Therefore, the distance between colors was calculated simply as a value of an angle between the colors on a hue wheel.

Experiments

Due to large computational complexity - just for the synthesis of distance matrix it is: $o(n) = (n^2 - n)/2$ - we performed two attempts to the data analysis: preliminary - using small amount and finally on relatively large subset of the original data.

Preliminary analyses

First to verify if we rely on the proposed approach we performed preliminary grouping using relatively small amount of the data - we have drawn 1000 random samples from the overall set. As it is visible in the corresponding dendrogram (Fig. 6) the proposed measure conforms hierarchical clusterization very well. The results are grouped in 30 clusters representing identified schemes.

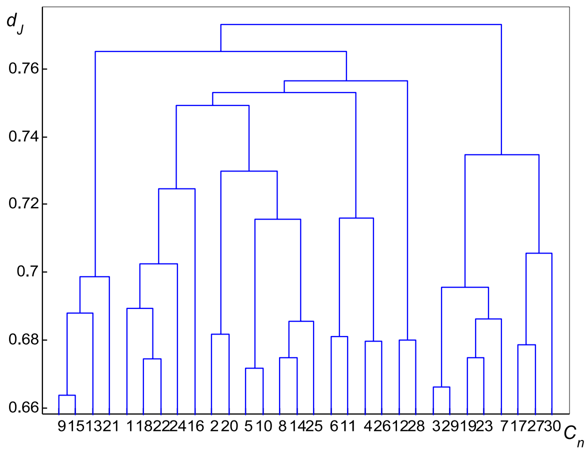

Figure 6. *Dendrogram of preliminary data set*

This step was performed several times using various data sets of 1000 palettes. The results of tests were quite consistent. Obtained templates (according to dendrogram in Fig. 6) are presented in Fig. 7. We had to deal with clusterization parameters: number of palette clusters and DBSCAN parameters: width of hue neighborhood ($\varepsilon = \pi/8$) and minimal cluster size ($m = 10$). In the final clustering the necessary number of palette clusters was identified by iterative incrementation of the number of clusters until there was no more than one *'junk'* cluster collecting

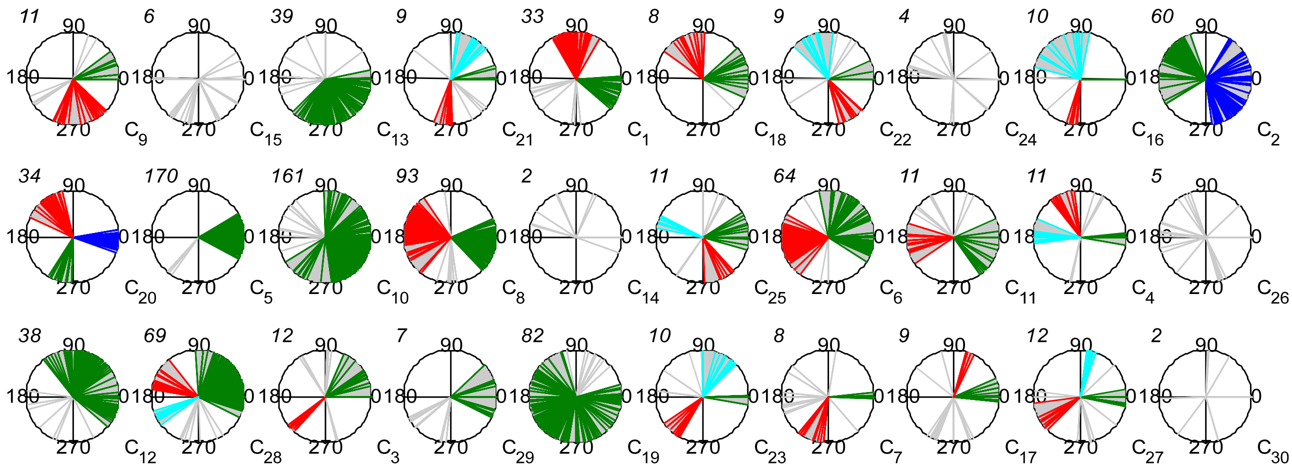

Figure 7. *Preliminary palette template clusters (C_n) accompanied with cardinalities*

Tab. 1. Preliminary cluster ensembles

Class	Pattern	Cluster numbers C_n
non-patterns	noise	15, 24, 14, 26, 30
	'junk'	10, 19
	uncertain	16, 28
known patterns	L-type	9, 1, 18, 7, 17
	V-type	5, 29
	T-type	13, 12
	Y-type	3
	X/Y (?)	8, 6, 11
	X-type	2
new patterns	regular triad	20, 25, 23, 27
	irregular triad	21, 22, 4

ungrouped palettes (consisting of color groups wider than *T-type* in Fig. 2). Furthermore, one can easily observe the clusters that are necessary to be ensembled. Clusters such as C_{13} and C_{12} - differing only by a hue angle - are equivalent as all angles in the pattern should be considered as relative. Such a behavior results from ambiguous meaning of initial normalization.

Resulting clusters can be interpreted as it is shown in the Tab. 1. One can note two desired properties - using the machine learning methods we observe results well corresponding to the known patterns (Fig. 2) but we also observe other patterns so the proposed method is able to discover new knowledge. Raw resulting clusters were heuristically interpreted and ensembled by authors.

The above results shows the most of known patterns. There are also identified common triad patterns. There are visible 5 of 7 reference chromatic patterns (as the method is irrelevant to achromatic *N-type*). The lack of registration of two known patterns can be caused by small amount of the source data. On the other hand they can be considered as a special cases (subsets) of more general ones - i as a subset of V and I as a subset of Y - so these patterns can be clenched in wider ones. There are other questions related to unknown or uncertain patterns as well. Are there any patterns in quite numerous (*'junk'*): C_{10} and C_{19}? As Ittens theorem of color harmony is based on regular patterns in hue wheel: shall we consider C_{16} and C_{28} clusters as asymmetric patterns or poorly determined cases of regular patterns? Answering above questions is non-trivial and it is a matter of a special interest of us as it can bring new knowledge. To answer them it seems to be necessary to perform the analysis but using larger number of palettes and larger number of target clusters.

Final analysis

For the needs of final analysis we have drawn 9000 palettes being approximately 2% subset of overall number of collected ones. Such a data were processed in the pipeline described previously. For this amount of data, iteratively increasing, we determined 120 clusters to be the necessary number to differentiate patterns from the 'junk'. Using these data we identified all but one known chromatic patterns and numerous other significant patterns. The results in Fig. 8 demonstrate resulting clusters which are heuristically ensembled and interpreted in Tab. 2.

Tab. 2. Final cluster ensembles

Class	Pattern	Cluster numbers C_n
non patterns	noise	5, 7, 11, 37, 39, 48, 63, 65, 74, 83, 105
	'junk'	-
known patterns	L-type	26, 45, 49, 84, 108, 112
	i-type	13, 23, 33, 69, 96, 110, *and may be in T-type*
	T-type	1, 25, 80, 103, 107, 114
	V-type	*may be in T-type*
	Y-type	38, 41, 60, 64
	X-type	18, 20, 79
	I-type	59, 4(?), *and may be hidden in X and Y-type*
new patterns	cross shape (+)	12, 50, 53, 78, 94
	fork shape (Ψ)	75, 98, 118
	Ł shape (Ł)	70, 97, 116
	p/q shape (P)	3, 22, 24, 32, 52, 56, 68
	triad (Δ)	2, 17, 31, 42, 54, 57, 66, 104, 106, 111, 115
	irreg. triad (Σ)	9, 10, 27, 28, 34, 36, 40, 43, 44, 47, 55, 58, 61, 71, 77, 85, 86, 91, 93, 95, 102, 113
	K shaped (K)	6, 8, 14, 15, 16, 19(?), 29, 30, 67, 76, 82, 87, 89, 90, 100, 101, 117, 120
uncertain	disputable	51(P), 62(X), 88(P/L), 99(P/L), 109(K/X)
	unknown	21, 35, 46, 1, 92, 119

The Tab. 2 contain: noise/'junk', identified patterns (see Fig. 9) and 'uncertain' results. There appeared both well-known templates and new templates. Precision of the proposed clas-

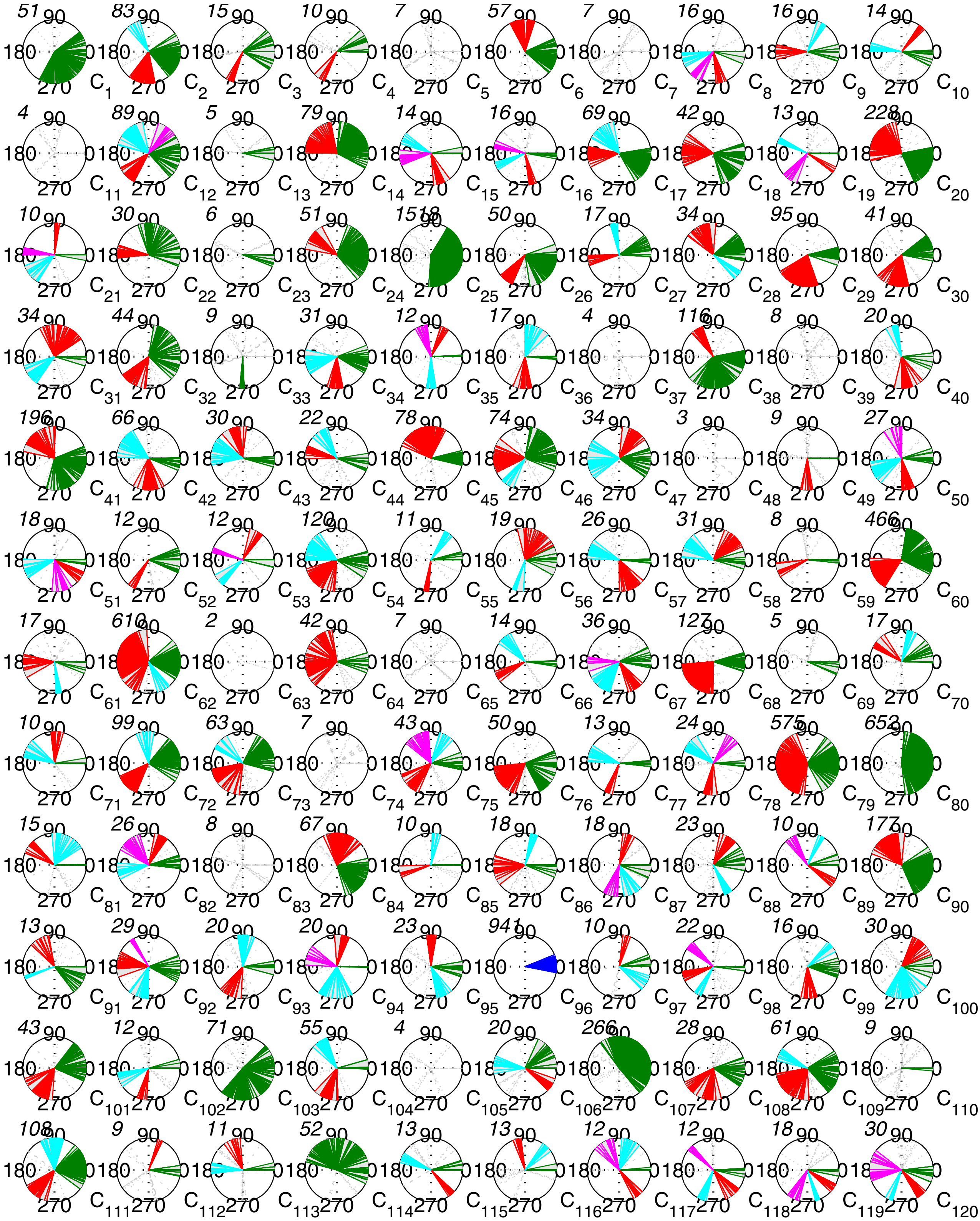

Figure 8. *Final palette template clusters (C_n) accompanied with cardinalities*

sification of patterns within ensembles might be considered as disputable as it was done heuristically by visual examination of the results. Although human interpretation is common practice in unsupervised learning.

The last group of results in Tab. 2 is interesting since it contains ambiguous results - templates which assignment to specific type would be disputable (although they are similar) and results which probably might be separate, rare templates but we did not decide to declare them due to their small cardinality.

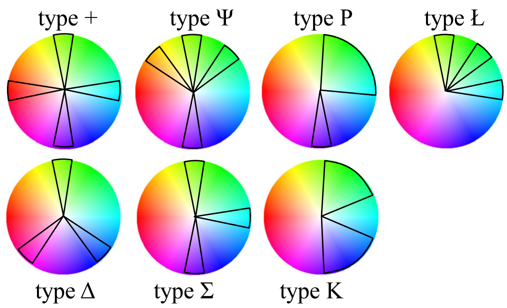

Figure 9. *Discovered harmonic templates*

Conclusions

As it was shown in results of final analysis the main goal of the paper, to qualitatively discover new harmonic templates, was achieved. We have proven usefulness of the proposed approach to employ grouping algorithms. The proposed method of comparing color palettes using fuzzy sets apparently resulted in rational outcomes when applied to compare palette templates.

Since our investigation was oriented on qualitative aspects and method testing there were no considerations on the precise determination of shape of certain templates. They were obtained heuristically and are given 'as is' without strict rules on relationship between angles and angle ranges. Moreover, it is impossible to specify them precisely, without algorithmic formulation of the ensembling stage. That topic will be a subject of our further research. Another field for future development is to include saturation and lightness into pattern investigation.

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