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Texture Characterization by Grey-Level Co-occurrence Matrix from a Perceptual Approach

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Abstract

Texture, along with color, is one of the most important characteristics of a material defining its appearance. While color had been studied for a long time and continues being an interesting topic, the analysis of texture has traditionally been postponed, mainly because of its difficulty, and remains a challenge. Depending on the application, different approaches to texture characterization have been proposed in the bibliography. In this work, texture is considered in the context of visual perception and the second order statistical measurements based on the Grey-Level Co-occurrence Matrix (GLCM) have been computed for a database of texture images (KTH-TIPS and KTH-TIPS2). In the literature, there is no available information about the number of features needed for texture characterization, although no less than five parameters are typically employed. In our previous work, the selection of the optimal texture features was studied through Principal Component Analysis (PCA), using only those that are statistically significant describing the studied textures. In this work, the texture features obtained were analyzed from a perceptual point of view.

(Keywords: Image Processing, Texture Descriptors, Grey-Level Co-occurrence Matrix, Principal Component Analysis)

Introduction

The influence of texture on color perception is well known and has far-reaching industrial relevance [1,2]. Nevertheless, texture samples have not yet been thoroughly studied in color science. Although viewing conditions include, among other parameters, the sample surface structure (texture), the reference conditions exhibits 'Sample structure: visually homogeneous' [3].

A first step to include texture in color science must be the texture characterization through numerical values, which is the goal of this work. State-of-the-art texture descriptors show that texture is characterized mainly through its spatial properties with grey level images, although some methods also includes the colorimetric characteristic of the texture [4,5]. A variety of texture descriptors exits in literature, based on different ways to treat the analysis of textures, as for example the descriptors based on the Texton theory, the Wavelet approach, the Fourier approach, etc. [6,7]. In recent years, a variety of texture description approaches has been proposed [8-12]. Latest papers combine multiple texture descriptors assessing their complementarity, but at the cost of increase the dimensional final image representations [13].

In this work, we were interested in characterizing texture to be related to the way the human visual system perceives it. One of the very first approach to texture analysis was defined by Haralik [14]. It is still widely used in image segmentation and object recognition, applied mainly for classification of defined datasets and texture extraction [15-17]. In addition, Julesz [18] concludes that GLCM matches the human perception response to textures the best. Haralik's method is based on second order statistical measurements through the Grey-Level Co-occurrence Matrix (GLCM). In an image, the GLCM is built by the frequency of occurrence of each two neighboring pixel combination. Thus, the features extracted from a texture, by this method, assume that the information in an image is contained in the overall spatial relationship of grey levels of neighboring pixels. Globally, 22 of these features describing the texture can be computed from GLCM. At the moment, there is no available information about either nor the number of features needed for texture characterization or the relationship with texture perception. In literature, usually only five among the 22 are used, which are: *Contrast*, *Homogeneity*, *Dissimilarity*, *Energy* and *Entropy* [19], but no reasons are exposed for that selection.

In a previous work [20], we employed Principal Component Analysis (PCA) to reduce the number of possible texture features based on redundancy, and propose only those that are statistically significant for a given dataset. As a conclusion, we proposed five features as the most important describing the considered textures, which are: *Difference Entropy*, *Sum of Squares: Variance*, *Correlation*, *Information Measure Correlation 2*, and *Information Measure Correlation 1*, which are different from those usually used, listed in previous paragraph.

The goal of this work was to study if the proposed texture features are related to the visual perception of them, through the result of a psychophysical experiment.

Method

Texture images used in this work were extracted from KTH-TIPS and KTH-TIPS2 [21-22], whose names stand for "Kungliga Tekniska Högskolan - Textures under varying Illumination, Pose, and Scale". These databases extend the so-called CUReT texture database, by providing variations in scale (9 different scales, but only 8 are common in TIPS and TIPS2), pose (three poses of the camera) and illumination (three and four illumination conditions for KTH-TIPS and KTH-TIPS2 respectively), and by imaging four different texture samples within every texture category in KTH-TIPS2. The original CUReT database is a collection of 61 real-world surfaces, with its name standing for "Columbia-Utrecht Reflectance and Texture Database" [23].

For the goal of this work, using the whole database was not necessary. Only the images obtained as a combination of the frontal position of the camera and all illumination positions (from the front, from the side at roughly 45° and from the top at roughly 45°, plus fluorescent ambient lab light only in TIPS2), and scale #5 (distance between sample and camera of 28 cm) were considered. In total, 206 images were chosen 30 from KTH-TIPS (10 types of textures *3 illumination positions) and 176 from KTH-TIPS2 (11 types of textures *4 types of sample per texture *4 illuminations).

For the computation of GLCM, and subsequently the 22 texture features, the orientation and displacement between neighbor pixels had to be established. On the one hand, as the GLCM can be computed for four different orientations (horizontal 0º, vertical 90º, and two diagonals 45º and -45º), in this work the average of the four directions was used as suggested in the literature. On the other hand, displacement of the GLCM is the distance between two pixels whose repetition is examined. It can be only one pixel distance or up to any reasonable value. Our results in a previous work [24] suggest that the distance which gives the maximum Contrast (one of the feature computed from GLCM) should be the best for the computation of the GLCM, as it could mean that there is a big difference between the two pixels selected to be neighbors, lowering the possible averaging effect. This conclusion gives us a possibility to define a new criterion for the computation of GLCM, that we call the Maximum Contrast Distance (MCD) criterion. By implementing this criterion the majority of texture features exhibit constant behavior with the change of scale, as it recomputed the distance for the feature calculations with every distance and it adjusts the change that the change of scale is introducing [24].

Under these considerations, the 22 texture features were computed from the GLCM, using MATLAB®. The GLCM was computed in the CIELAB *L** channel, because several works proved that the majority of texture information is located on this channel [25]. Since all the 22 features are correlated to some extent, they should provide redundant information. Therefore, the selection of the best set of features becomes a dimensionality and redundancy reduction task. By applying PCA to the extracted texture features 5 principal component (PC) were found, which correspond to the following features:

PC1: *Difference Entropy*.
PC2: *Sum of Squares: Variance*.
PC3: *Correlation*.
PC4: *Information Measure Correlation 2*.
PC5: *Information Measure Correlation 1*.

It is interesting to note that PCA also gives a biplot containing all the samples and all the features together. For the purpose of the psychophysical experiment performed, the Squared Cosine observed from the PCA biplot.was used to select the samples best described by each factor.

A visual experiment was performed to compare the perceptual results with the computed features. The observers were asked to order a set of images according to their texture strength. One set of texture images was considered per each one of the texture features (PC) selected by PCA, mentioned above, as can be seen in Fig. 1. Each group has 8 samples selected varying the most in only one PC, while the others should be as constant as possible, except groups 1 and 2 that have 7 samples. To give the observers a benchmark, a solid gray sample was added to the each one of the 5 groups. In addition, the average sample of the dataset (value zero of the Square Cosine) was also added (with a dark gray square in Fig. 1).

Observers were warned to focus on the texture itself, rather than the nature of the image, and try to response as spontaneous as possible. As color influences the perception of texture, and vice versa, to allow the observers to focus on texture as much as possible, selected color samples (43 images) were mapped to gray using the LCH mapping method [26], by taking into account the pixel deviation to the mean chroma and luminance values. Additive mapping was used for each sample, and the mean luminance value was set to CIELAB L^*=70 so that it is different from the neutral gray (L^*=53) used as background. As images were displayed, after mapping, mean luminance in Adobe RGB color space was normalized by adjusting the image histogram [24].

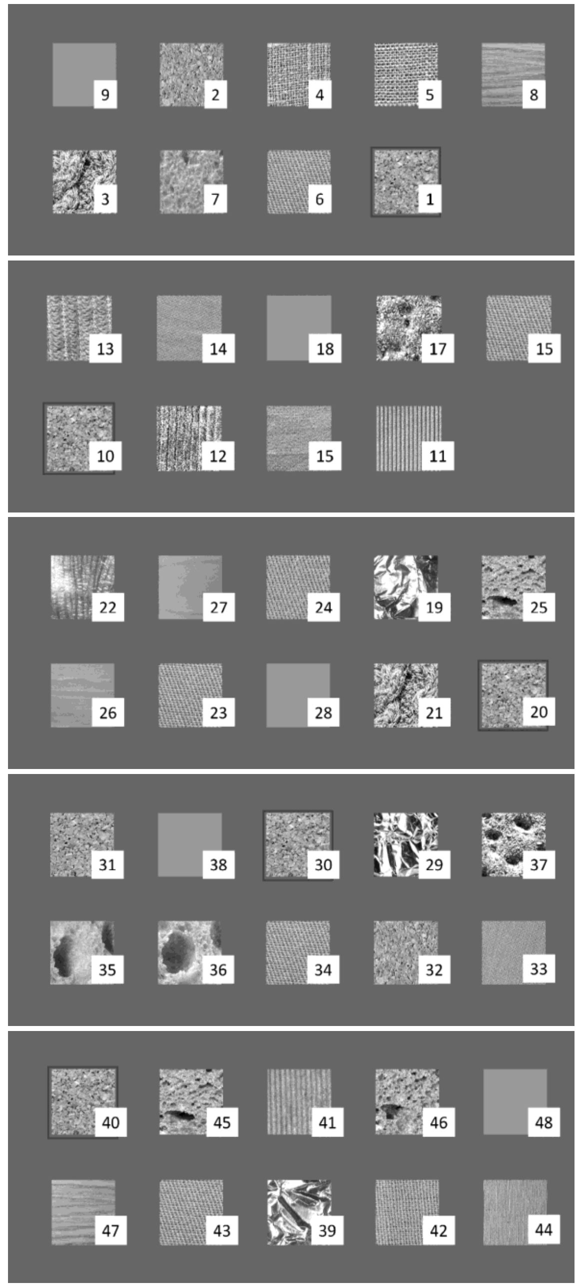

Figure 1. Set of images in each of the five group. Numbers and grey square were not displayed in the experiment, and was used for analysis of the results.

Table 1 shows the 22 features for the samples of the group 1. The five selected features are marked in blue. Please, note that the feature corresponding to group 1 is “denth”.

Table 1. Texture features for the 9 samples of the group 1. Last two columns shows mean and deviation (blue for features selected by PCA, red for most changing, green for highest correlation, and yellow for the finally selected feature).

Feature	Sample									Mean	Deviation
	1	2	3	4	5	6	7	8	9		
autoc	34.43	34.50	33.84	34.26	34.43	34.74	34.96	34.86	36.00	34.67	0.60
contr	1.72	1.82	6.71	4.13	2.39	2.21	0.89	0.35	0.00	2.25	2.07
corm	0.00	-0.01	0.03	-0.08	-0.13	-0.05	0.01	0.12	0.00	-0.01	0.07
corrp	0.00	-0.01	0.03	-0.08	-0.13	-0.05	0.01	0.12	0.00	-0.01	0.07
cprom	12.23	13.89	135.86	35.45	9.41	11.46	2.65	0.93	0.00	24.65	43.03
cshad	-1.79	-1.96	-7.42	-2.05	-0.15	0.43	-0.10	-0.02	0.00	-1.45	2.44
dissi	0.92	0.93	2.05	1.57	1.21	1.16	0.66	0.33	0.00	0.98	0.62
energy	0.14	0.14	0.03	0.05	0.07	0.07	0.19	0.44	1.00	0.24	0.31
entro	2.49	2.52	3.75	3.36	2.85	2.84	2.04	1.23	0.00	2.34	1.14
homom	0.65	0.65	0.45	0.50	0.56	0.57	0.70	0.84	1.00	0.66	0.17
homop	0.62	0.62	0.37	0.44	0.51	0.53	0.69	0.84	1.00	0.62	0.20
maxpr	0.29	0.30	0.07	0.10	0.13	0.13	0.37	0.63	1.00	0.33	0.31
sosvh	35.11	35.22	37.02	36.14	35.44	35.66	35.23	34.85	35.81	35.61	0.66
savgh	11.74	11.75	11.62	11.73	11.76	11.80	11.83	11.80	12.00	11.78	0.10
svarh	103.73	103.64	93.01	97.68	102.77	102.88	110.25	118.18	144.00	108.46	15.10
senth	1.64	1.66	2.35	2.03	1.71	1.75	1.37	0.95	0.00	1.50	0.68
dvarh	1.72	1.82	6.71	4.13	2.39	2.21	0.89	0.35	0.00	2.25	2.07
denth	1.23	1.25	1.79	1.57	1.32	1.29	0.97	0.66	0.00	1.12	0.53
inf1h	0.00	0.00	0.00	-0.01	-0.02	-0.01	0.00	-0.07	0.00	-0.01	0.02
inf2h	0.04	0.03	0.05	0.15	0.21	0.17	0.05	0.25	0.00	0.11	0.09
indnc	0.91	0.91	0.82	0.85	0.88	0.88	0.93	0.96	1.00	0.90	0.06
idmnc	0.98	0.97	0.92	0.95	0.97	0.97	0.99	0.99	1.00	0.97	0.03

Because of the selection criterion, it is expected that the biggest change, and consequently the biggest standard deviation, occur for the feature that is selected to be the representative for that group. However, this is not the case as all the five features are changing (even all the 22 features), as can be seen in Table 1 for the group 1. Similar results were obtained for the rest of the groups.

For visual experiment, the selected images were displayed, using JavaScript code, on calibrated LCD HP 2510i monitor in a dark room. Calibration was performed by a GretagMacbeth Eye-One Display. The white point was set to chromacity coordinates - 0.3244,0.3418 with a luminance of 248.5 cd/m^2. Black point luminance was 0.247 cd/m^2. All the values were measured with a spectrophotometer spectroradiometer (Photo Research 704). Monitor resolution was set to its native, 1920x1080px. In order to remove any external influence the screen was isolated with gray panels, as can be seen in Fig. 2. The images were presented in two rows on a grey background (L^*=53), as shown in Fig. 2. Each image sample subtended 7.5° of visual angle from the position of the observer, which was approximately 45 cm from the monitor.

Figure 2. Setup and performance of the experiment.

A panel of 28 observers (16 experts and 12 non-experts) with normal or corrected vision and normal color vision (tested with Ishihara test) participated in the experiment in the age range between 21 and 51 years. From the 16 experienced observers 11 are female and 5 male while from the non-experts 8 are female and 4 are male. This makes a total of 19 female and 9 male observers.

The observers were adapted to the grey background for 2 min before each session. In the experiment observers were instructed to arrange presented images according to their texture visibility, where the first in order should be image with no texture (solid color) starting in the upper left corner of the scale (Fig. 2). Accordingly, the last one should be an image where texture is most noticeable in the bottom right corner of the scale. Observers were allowed to drag and drop images, changing their positions. There were not time-limited. The current order was stored in a database using AJAX call to Ruby on Rails application. Database system used was PostgreSQL. The observers were asked to perform two repetitions on two different days.

Results

To check the observer's reliability, the *STRESS* and *PF3*, have been applied to the results [27]. The intra observer variability has been calculated between the two repetitions the observers performed for each of the five groups of images and their mean was calculated. The inter observer variability was obtained by calculating the measures for the global mean scale from all the observers for a given group and each observers mean scale. Then the mean of the five was obtained. The intra-observer variability was 24.47 (standard deviation 15.71) and 23.59 (standard deviation 10.83), and the inter-observer variability was 31.83 (standard deviation 6.59) and 27.01 (standard deviation 4.07), *PF/3* and *STRESS* values respectively. The *STRESS* and *PF\3* were shown to be in the desired range according to the literature [28].

Table 2. Mean and standard deviation of sample position for the five groups of samples (blue for the average sample of the dataset, green for the highest position, and red for the lowest position inside the group).

Group 1	**Sample**	1	2	3	4	5	6	7	8	9		**Sum deviation**
	Mean position (deviation)	5.38 (1.27)	5.13 (1.30)	7.91 (2.24)	6.58 (1.31)	6.98 (1.37)	5.66 (1.87)	4.13 (2.10)	2.23 (0.80)	1.00 (0.00)		12.26
Group 2	**Sample**	10	11	12	13	14	15	16	17	18		
	Mean position (deviation)	5.45 (2.20)	5.34 (1.56)	6.42 (1.70)	6.04 (1.78)	3.98 (2.59)	5.11 (1.53)	4.17 (2.20)	7.49 (2.47)	1.00 (0.00)		16.03
Group 3	**Sample**	19	20	21	22	23	24	25	26	27	28	
	Mean position (deviation)	7.17 (2.57)	6.70 (1.54)	8.64 (1.71)	6.02 (2.02)	6.34 (1.78)	6.40 (1.95)	7.62 (1.20)	3.02 (0.31)	2.09 (0.30)	1.00 (0.00)	13.38
Group 4	**Sample**	29	30	31	32	33	34	35	36	37	38	
	Mean position (deviation)	7.79 (2.95)	5.25 (1.63)	5.55 (1.39)	4.62 (1.58)	4.06 (3.06)	4.77 (2.42)	6.77 (2.02)	7.23 (2.08)	7.96 (2.07)	1.00 (0.00)	19.20
Group 5	**Sample**	39	40	41	42	43	44	45	46	47	48	
	Mean position (deviation)	7.62 (3.19)	6.60 (1.55)	4.32 (1.41)	6.55 (1.75)	6.34 (1.82)	4.74 (2.30)	7.58 (1.95)	7.81 (1.80)	2.43 (1.05)	1.00 (0.00)	16.80

Table 2 shows the mean position (average of all observers) of each sample within a group and its standard deviation. Last column shows the sum of deviations. The smallest deviation between the observers appears in the group 1. This would suggests that for these samples, corresponding to PC1, the observers have the most constant discrimination. This can be expected because these samples represent the ones with the biggest variation. Therefore, this group can be considered as the easiest for the observers.

Table 3. Coefficient of correlation between22 features and the mean order (green for maximum correlation and blue for the features selected by the PCA).

Features	Group 1	Group 2	Group 3	Group 4	Group 5
autoc	0.8142	0.7165	0.5694	0.3187	0.6825
contr	0.7160	0.5446	0.676	0.4882	0.6674
corrm	0.2934	0.0612	0.0114	0.2328	0.0002
corrp	0.2934	0.0612	0.0114	0.2328	0.0002
cprom	0.3875	0.3839	0.4158	0.5541	0.4616
cshad	0.3452	0.3247	0.3154	0.6963	0.2978
dissi	0.9157	0.6885	0.8822	0.6389	0.7843
energ	0.7932	0.6938	0.9088	0.6691	0.7957
entro	0.9479	0.7694	0.9541	0.8376	0.8868
homom	0.9659	0.7206	0.9454	0.7047	0.8255
homop	0.9706	0.7152	0.9414	0.7002	0.8174
maxpr	0.9170	0.6831	0.9112	0.7374	0.8242
sosvh	0.2616	0.1129	0.1125	0.2776	0.0858
savgh	0.7551	0.8191	0.8307	0.7332	0.7624
svarh	0.8581	0.7827	0.9437	0.8076	0.8572
senth	0.9056	0.801	0.9338	0.9055	0.8722
dvarh	0.7160	0.5446	0.676	0.4882	0.6674
denth	0.9298	0.7769	0.9579	0.7603	0.8749
inf1h	0.1258	0.0056	0.0007	0.0781	0.0001
inf2h	0.0151	0.0203	0.1657	0.1551	0.0249
indnc	0.9491	0.7093	0.9156	0.6751	0.8019
idmnc	0.7666	0.5699	0.7229	0.5135	0.6814

Furthermore, the low sample positions (red in the table) have in general low deviation while high sample positions have big deviation (green). This can suggest that the observers are more constant in deciding about weaker textures, whereas strong textures are perceived differently. This finds analogy with color discrimination, as it is known that small color differences are discriminated and quantified more easily than big color differences.

It is interesting to see that the average sample (blue) is more or less around the middle of the scale for every experiment, supporting the PCA findings about the average sample of the dataset used.

Table 3 summarizes the correlation (R^2 coefficient) between the 22 features and the mean order that the experiment provides, to see how important are the features perceptually and which ones are the most important for each set of samples. Green shadow marks the features with high correlation for each experiment while blue marks the features selected by PCA to be representative for the group, for which the highest correlation would be expected. However, the results show that the feature with the highest correlation is not the feature selected by the PCA for each group. This suggests that the results the PCA provides are not perceptual, meaning that visually other features are more important for the observers. Thus, PCA gives different features for a mathematical description of the texture, but does not provide features more related with the perception of the texture.

Looking at Table 4, which shows the correlation between all the features and the PCs, it can be seen that PCA indicates which features are redundant, especially for PC1. However, it cannot select precisely the one that has the biggest perceptual importance. This means that the perceptual and feature scale are not the same in a sense that small numerical change in a feature (which is considered in PCA analysis) might mean a big perceptual change and vice versa. For example, in Table 1, which shows the features computed for the set of samples of the group 1, the feature “homop” has quite small standard deviation, but it is the feature most correlated with perception in that group (see Table 3). On the other hand, the feature “cprom” has very high deviation (see Table 1) but very low correlation with perception (see Table 3). This means that a small change in “homop” is visually more significant for the discrimination of the samples than a big change in “cprom”. Conclusively, PCA works properly for dimensionality reduction, but it cannot select the perceptually best features. Besides, the interpretation of the principal planes is not clear from the PCA results, as the samples of the used texture dataset are much centered and do not have a sufficient variation. Thus, the projection of the samples does not separate the given set of samples completely and moreover visually.

However, it can be concluded that the features that are perceptually more significant are the ones having the highest correlation in each group, showed in the brackets (see Table 3):

PC1: *Homogeneity* (0.9706)
PC2: *Sum Average* (0.8191)
PC3: *Difference Entropy* (0.9579)
PC4: *Sum Entropy* (0.9055)
PC5: *Entropy* (0.8868)

This selection would mean that, from the perceptual point of view, in general, the *Entropy* is quite an important feature and it also exhibits big deviation compared to the mean in the five groups, as obtained in a previous work [29]. On the other hand, this selection shows the redundancy of the features one more time. Looking at the three formulas for different entropy calculations, the redundancy between them is clear. Thus, two (PC1 and PC2) of the five features selected according to the results can be kept and the other three (PC3, PC4, and PC5) should be chosen according to other criteria to remove the redundancy. As *Sum Entropy* has the highest correlation from the three with all the other groups, it can be kept as it is a good feature to explain all the images and it is different from *Homogeneity* and *Sum Average* (Table 3).

Table 4. Correlation between the texture features and the PC (green for high correlation). (Table 21)

Feature	PC1	PC2	PC3	PC4	PC5
autoc	-0.521	0.823	0.147	-0.113	-0.122
contr	0.897	0.096	0.284	-0.202	0.199
corrm	-0.151	-0.240	0.789	0.299	-0.451
corrp	-0.151	-0.240	0.789	0.299	-0.451
cprom	0.737	-0.047	0.546	-0.239	0.264
cshad	0.605	-0.178	0.530	-0.179	0.324
dissi	0.975	0.170	0.047	-0.064	0.070
energ	-0.819	-0.163	0.267	-0.278	0.316
entro	0.948	0.172	-0.056	0.110	-0.217
homom	-0.943	-0.218	0.215	-0.089	0.083
homop	-0.949	-0.221	0.189	-0.075	0.063
maxpr	-0.842	-0.186	0.290	-0.259	0.266
sosvh	-0.367	0.886	0.212	-0.160	-0.088
savgh	-0.488	0.836	0.139	-0.117	-0.129
svarh	-0.684	0.681	0.166	-0.190	0.033
senth	0.943	0.114	0.082	0.129	-0.265
dvarh	0.897	0.096	0.284	-0.202	0.199
denth	0.979	0.142	-0.020	-0.008	-0.079
inf1h	-0.225	0.244	0.145	0.747	0.519
inf2h	0.012	0.348	0.092	0.835	0.367
indnc	-0.977	-0.191	0.042	0.012	-0.021
idmnc	-0.926	-0.119	-0.226	0.167	-0.169

Based on internal computations, *Sum variance* can be a better feature than *Difference Entropy* as it has higher correlations with all perceptual scales and it is different from *Homogeneity*, *Sum Entropy* and *Sum Average*. Finally, for the fifth feature *Maximum Probability* can be selected as it has higher correlation with the majority of the perceptual scales and it is different from *Homogeneity*, *Sum Entropy*, *Sum Variance* and *Sum Average*. Therefore, the new and final list of features is (correlation value in the brackets):

PC1: *Homogeneity* (0.9706)
PC2: *Sum Average* (0.8191)
PC3: *Sum Variance* (0.9437)
PC4: *Sum Entropy* (0.9055)
PC5: *Maximum Probability* (0.8242).

Even though PCA was shown to be not related to perception, it provided initial steps towards finding the features with high perceptual correlation. Firstly, it allowed selecting the samples for the visual experiment and computing the features with the highest perceptual correlation. The final set of perceptually most important features was then proposed based on having independent features with the highest perceptual correlation.

Aknowlegments

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