Perceptual similarity between color images using fuzzy metrics

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Abstract

In many applications of the computer vision field measuring the similarity between (color) images is of paramount importance. However, the commonly used pixelwise similarity measures such as Mean Absolute Error, Peak Signal to Noise Ratio, Mean Squared Error or Normalized Color Difference do not match well with perceptual similarity. Recently, it has been proposed a method for gray-scale image similarity that correlates quite well with the perceptual similarity and it has been extended to color images. In this paper we use the basic ideas in this recent work to propose an alternative method based on fuzzy metrics for perceptual color image similarity. Experimental results employing a survey of observations show that the global performance of our proposal is competitive with best state of the art methods and that it shows some advantages in performance for images with low correlation among some image channels.

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1. Introduction

Many applications in the fields of image processing and computer vision use image similarity measures for different purposes [1]. In some cases the objective is the very measurement of the similarity itself globally or partially in the images, but other times the similarity is used to assess the performance of an image processing method. For instance, in image filtering, the common process to measure the performance of a filtering method is the following: an original image is corrupted artificially with noise, then it is filtered with the method under study and it is measured how similar is the filtered image to the original one. This allows to properly adjust filter parameters for optimal performance, to assess different filter configurations as well as to compare the performance of different filtering methods. An analogous approach is used in other image processing procedures such as image compression, image demosaicing or video de-interlacing. Therefore, the similarity measure used highly influences the whole process.

The most common similarity measures used in this context are based on a pixelwise approach, such as the Mean Absolute Error (MAE), the Mean Squared Error (MSE), the Peak Signal to Noise Ratio (PSNR) or the Normalized Color Difference (NCD) (which is the MSE in the Lab color space). However, these measures do not match well with perceptual observations and, as the MSE, some of them have other concerns [2].

During the last twenty years series of works have addressed the problem of defining image similarity measures that match human perceptual similarity. First works in this issue include the Weighted Signal to Noise Ratio (WSNR) [3] which simulates the human visual system properties by filtering both the reference and distorted images with contrast sensitivity functions and then compute the SNR. Other measures [4, 5] assess shifts in image luminance, differences in the frequency domain and changes in edges. Instead of luminance, some metrics [6, 7, 8] specifically target color in images. Other metrics [9, 10] embed a hidden signal in an image, introduce an impairment and measure its quality. Besides, to detect similarity between images their histograms have been used [11, 12].

More recently, in [13, 14] a similarity measure for gray-scale images that matches well with perceptual similarity has been introduced (UQI-Universal Quality Index and SSIM-Single-scale Structural Similarity Index). This method could be applied in color images in a componentwise fashion, that is, independently in each color channel and then averaged. However, it is well-known that the correlation among the color image channels should be taken into account and this approach cannot provide optimal performance [1], as we show in this paper. This similarity measure is extended to the Multiscale Structural Similarity Index (MSSIM) in [15]. In turn, in [16], a color comparison criterion is combined with MSSIM. In the approach [17], SSIM scores are weighted by region type. And, in [18], a two staged wavelet based

Visual Signal to Noise Ratio (VSNR) was defined based on the low-level and the mid-level properties of human vision.

In this paper, we introduce a method for color image similarity that matches perceptual similarity. Our method follows a procedure inspired in [13, 14] as follows: the images are processed with sliding patches so that a number of small image portions are compared and the similarity between two images is obtained by averaging the similarities of all portions. In each pair of patches three different factors are compared separately and then combined: contrast, structure and luminance. The particular expressions used in [13, 14] for these three factors cannot be directly generalized from gray-scale images to color images, so we propose our own expressions to measure them. Experimental results employing perceptual similarity observations show that our approach is able to outperform classical similarity measures, is competitive with best state-of-the-art methods, and shows some advantages in performance for images with low correlation among some image channels.

In the following section we detail the proposed method. Section 3 contains the experimental results and discussion. Finally, Section 4 presents the conclusions.

2. Proposed image similarity measure

Let $\mathbf{X}$ denote a RGB image and W be the sliding patch of finite size $q \times q = n$ used to process the image. The image pixels in W, $\mathbf{X}_W$, are denoted as $\mathbf{x}_i(l), i = 1, ..., n$ where $l = 1, 2, 3$ denotes the R, G, and B channels, respectively. Notice that $\mathbf{x}_i$ can be processed as a three component vector.

We measure the similarity between images $\mathbf{X}$ and $\mathbf{Y}$ as the average of the similarities of the image patches $\mathbf{X}_W$ and $\mathbf{Y}_W$ obtained when sliding the patch along every image row. To measure the similarity between two patches in the same image location we measure three different similarities: contrast, structure and luminance. In so doing, we need to measure the similarities between all image color pixels $\mathbf{x}_i$ and $\mathbf{y}_i$ in $\mathbf{X}_W$ and $\mathbf{Y}_W$, respectively, and the mean color vector in each patch, $\overline{\mathbf{x}_W}$ and $\overline{\mathbf{y}_W}$. We denote these similarities by $M_{\mathbf{x}_i}$ and $M_{\mathbf{y}_i}$ and we measure them by employing the fuzzy metric used in [19, 20, 21, 22] for its high sensitivity to edges as follows.

$$M_{\mathbf{x}_i} = M(\mathbf{x}_i, \overline{\mathbf{x}_W}, t) = \prod_{l=1}^{3} \frac{\min(x_i(l), \overline{\mathbf{x}_W}(l)) + t}{\max(x_i(l), \overline{\mathbf{x}_W}(l)) + t}, \quad i = 1, ..., n, \tag{1}$$

where $t > 0$ and

$$\overline{\mathbf{x}_W} = \frac{1}{n} \sum_{j=1}^{n} x_j, \quad l = 1, 2, 3 \tag{2}$$

Through an analogous computation in the image $\mathbf{Y}$ we obtained the similarities $M_{\mathbf{y}_i}, i = 1, \ldots, n$. Notice that $M_{\mathbf{x}_i}$ and $M_{\mathbf{y}_i}$ are fuzzy similarities that take value in $[0, 1]$.

2.1. Contrast

Contrast can be seen as the largest difference observed in $\mathbf{X}_W$ and $\mathbf{Y}_W$. We can measure contrast in $\mathbf{X}_W$ using $M_{\mathbf{x}_i}$ as $C_{\mathbf{X}_W} = \max(M_{\mathbf{x}_i}) - \min(M_{\mathbf{x}_i}), \quad i = 1, ..., n$, and analogously for $\mathbf{Y}_W$. Then, the fuzzy similarity between the contrasts is given by

$$SC(\mathbf{X}_W, \mathbf{Y}_W) = 1 - |C_{\mathbf{X}_W} - C_{\mathbf{Y}_W}|. \tag{3}$$

2.2. Structure

Structure describes how the differences between the pixels in a patch are distributed spatially. Therefore, for this aspect we average the fuzzy similarities of $M_{\mathbf{x}_i}$ and $M_{\mathbf{y}_i}$ as follows.

$$SS(\mathbf{X}_W, \mathbf{Y}_W) = \frac{\sum_{i=1}^{n} 1 - |M_{\mathbf{x}_i} - M_{\mathbf{y}_i}|}{n}. \tag{4}$$

2.3. Luminance

To compare image luminance we propose to use spherical coordinates computed from RGB values [23]. Luminance correspond with the radius parameter given by

$$L\mathbf{x}_i = \sqrt{\mathbf{x}_i(1)^2 + \mathbf{x}_i(2)^2 + \mathbf{x}_i(3)^2} \tag{5}$$

The luminance similarity between $\mathbf{X}_W$ and $\mathbf{Y}_W$ is obtained through the corresponding expression in [13] as

$$SL(\mathbf{X}_W, \mathbf{Y}_W) = \frac{2\overline{L_{\mathbf{X}_W} L_{\mathbf{Y}_W}}}{\overline{L_{\mathbf{X}_W}}^2 + \overline{L_{\mathbf{Y}_W}}^2} \tag{6}$$

where $\overline{L_{\mathbf{X}_W}}$ and $\overline{L_{\mathbf{Y}_W}}$ are the mean luminance in each patch. In the case that $\overline{L_{\mathbf{X}_W}} = \overline{L_{\mathbf{Y}_W}} = 0$ we assign $SL(\mathbf{X}_W, \mathbf{Y}_W) = 1$.

Finally, the similarity between $\mathbf{X}_W$ and $\mathbf{Y}_W$ results from combining the three previous measures as follows

$$S(\mathbf{X}_W, \mathbf{Y}_W) = SC(\mathbf{X}_W, \mathbf{Y}_W)^\alpha \cdot SS(\mathbf{X}_W, \mathbf{Y}_W)^\beta \cdot SL(\mathbf{X}_W, \mathbf{Y}_W)^\gamma \tag{7}$$

where $\alpha, \beta, \gamma > 0$ are parameters used to adjust relative importance of three components. As commented above, the average of all $S(\mathbf{X}_W, \mathbf{Y}_W)$ provides the similarity between $\mathbf{X}$ and $\mathbf{Y}$, that will be high only if the three similarities are high.

Finally, we would like to point out that in each processing patch the number of operations is proportional to the number of pixels, so for the whole method we have also a linear computational cost.

3. Experimental study

In order to study the performance of our proposal and also to compare with other approaches we make a comparison with respect to a survey of perceptual observations as follows.

We have chosen the four color bmp images in Figure 1: Goldhill, Lenna, Baboon, and Parrots. To better appreciate low resolution differences we have taken a small part of 68x68 pixels of the original images. We have applied a series of 10 different distortions to each of the test images. The distortions applied over the image Parrots along with the software use in each case, which are shown in Figure 2, are the following.

1. jpg compression of ratio 20% (MS Picture Manager)
2. Increase brightness by 15% (MS Picture Manager)
3. Increase contrast by 15% (MS Picture Manager)
4. Gaussian blur with radius 1.5 (Corel Draw X5)
5. Addition of 5% of impulsive noise (imnoise function from Matlab)
6. Addition of white Gaussian noise with standard deviation equals to 10% of the maximum value in the channels (imnoise function from Matlab)
7. Filtering of original image with [24]
8. Addition of Gaussian noise as in 6) and filtering with [24]
9. Filtering of original image with Vector Median Filter (VMF) [25]
10. Addition of 5% of impulsive noise as in 5) and filtering with Vector Median Filter (VMF) [25]

In the survey, we asked independent observers to rank the 10 distorted images with respect to its similarity to the original image ($1st$ the most similar, $10th$ the least). We did this through a questionnaire available on the internet address [27] to get as many answers as possible. We received 108 complete answers. We processed them to remove outliers using boxplot and we found 4 outliers that could be due to the observer not paying enough attention or to wrong understanding. Finally, we average the ranks obtained by each of the distorted images and we re-scale the average rankings to the interval [1, 10].

Next, we measure the similarity between all distorted images and the original one with the usual similarity measures MAE, MSE, NCD, as well as with Structural Similarity Index (SSIM) [13, 14] (used by averaging after component-wise application in each channel), FSIMc [26], CMSSIM [16] and the proposed method (Fuzzy Color Structural Similarity, FCSS). To assess the match between these measures and the survey perceptual observations, we re-scaled similarity measures results to the interval $[1, 10]$. In this way we can measure the similarity between each measure ranking and the perceptual ranking.

For our proposal we try different parameter settings and one providing a nice overall performance is the following: $t = 256$, patch size $q = 4$ and $\alpha = \beta = \gamma = 1$.

Tables 1 - 8 show the ranks obtained in our survey for each image and those provided by the methods in the comparison. To measure the match between perceptual observations and the similarity measures we computed the Root Mean Squared Error (RMSE) [1] and the correlation coefficient r between the re-scaled ranks of each similarity measure and the re-scaled ranks of the visual observations.

From these results we can see that performance of SSIM, FSIMc and FCSS is much better than the rest of the methods. CMSSIM only works well for Goldhill image, which suggests that it is too sensitive to the image features. SSIM exhibits a very high performance ($r > 0.9$) in two cases (Goldhill and Lenna) but much lower ($r < 0.8$) in another two cases (Baboon and Parrots). FSIMc performs very well for GoldHill and Lenna ($r > 0.9$), well for Parrots ($r \sim 0.8$), but worse for Baboon image, where its performance drops with respect to FCSS ($r < 0.8$). On the other hand, FCSS exhibits a consistent high performance in all cases ($r \in [0.80, 0.90]$) and it is better than SSIM for Baboon and Parrots images and better than FSIMc for Baboon image.

In order to understand these pretty high differences in the performance of SSIM and FSIMc for different images we analyzed several features of the images and we realized that there is significant differences with respect to their correlations among the image channels. These correlations are shown in Table 9. We see that correlations in Goldhill and Lenna images are high in all cases, whereas in Parrots and Baboon appear some medium and low correlations respectively. This implies that SSIM is only able to provide high performance when the correlation among the color channels is high in all cases. However, when for a couple of channels the correlation is not high, SSIM performs worse. This is most probably due to the component-wise application of SSIM. FSIMc performs better from this point of view and still performs well in the presence of some medium correlations (Parrots), but its performance drops for the Baboon image were the correlation between the R and B channels is very low and the rest are not high. We see that FSIMc is sensitive to low correlations between channels which probably means that its capability to take into account correlation can be improved. On the other hand, FCSS performance is independent from the correlation among the image channels which in turns indicates proper correlation management. This is interesting for practical applications and also for possible adaptations to other types of multichannel images and future research.

These results justify the need of keeping active the research on specific methods for color image similarity.

4. Conclusions

In this paper we have proposed a method to measure the similarity between two color images that uses fuzzy metrics. The similarity between the images takes into account three factors: structural similarity, contrast similarity, and luminance similarity. The method takes into account the correlation among the image channels by processing the images as vector fields. Experimental results employing a survey of observations show that the global performance of our proposal is competitive with best state of the art methods and that it shows some advantages in performance for images with low correlation among some image channels, which is interesting for future research.

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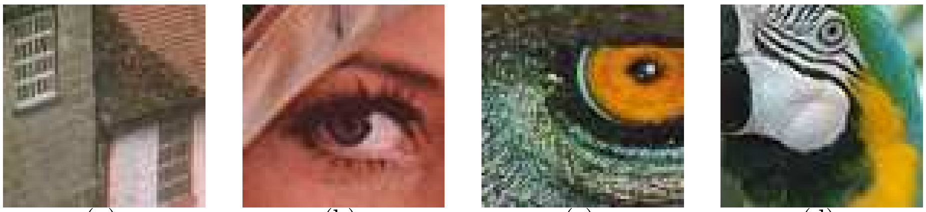

(a) (b) (c) (d)

Figure 1: Images for tests: (a) Goldhill, (b) Lenna, (c) Baboon, and (d) Parrots.

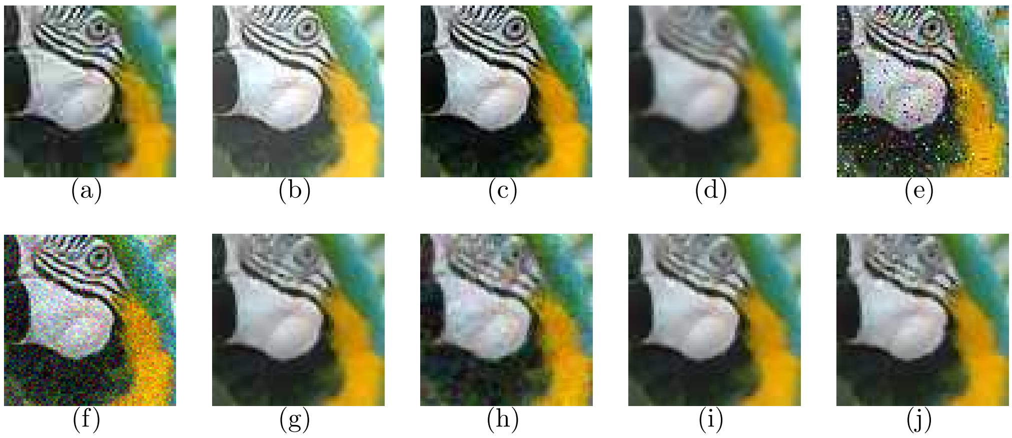

Figure 2: Distortions applied to the image Parrots: (a) jpg compression of ratio 20% (MS Picture Manager), (b) Increase brightness by 15% (MS Picture Manager), (c) Increase contrast by 15% (MS Picture Manager), (d) Gaussian blur with radius 1.5 (Corel Draw X5), (e) Addition of 5% of impulsive noise (Matlab according to [1]), (f) Addition of white Gaussian noise with standard deviation equals to 10% of the maximum value in the channels (Matlab according to [1]), (g) Filtering of original image with [24], (h) Addition of Gaussian noise as in (f) and filtering with [24], (i) Filtering of original image with Vector Median Filter (VMF) [25], (j) Addition of 5% of impulsive noise as in (e) and filtering with Vector Median Filter (VMF) [25].

Table 1: Performance comparison for Goldhill image. * denotes re-scaled ranking/similarity to the interval $[1, 10]$. RMSE and r denote the Root Mean Squared Error and correlation coefficient, respectively, between the re-scaled ranks of each similarity measure and the re-scaled ranks of the visual observations.

Effect	Survey	Survey*	MAE	MAE*	MSE	MSE*	SSIM	SSIM*
1	5.952	7.03	10.677	2.41	196.675	2.01	0.638	6.75
2	2.615	2.93	37.169	10.00	1382.581	10.00	0.949	1.64
3	1.038	1.00	5.754	1.00	47.118	1.00	0.988	1.00
4	6.212	7.35	8.242	1.71	129.801	1.56	0.741	5.05
5	8.375	10.00	6.798	1.30	958.967	7.15	0.468	9.53
6	8.192	9.78	20.326	5.17	646.569	5.04	0.447	9.88
7	4.596	5.36	8.017	1.65	166.062	1.80	0.692	5.86
8	8.279	9.88	15.341	3.75	389.531	3.31	0.440	10.00
9	4.596	5.36	8.129	1.68	164.759	1.79	0.687	5.93
10	5.144	6.04	8.553	1.80	178.725	1.89	0.675	6.13
RMSE		0		5.318		4.744		0.884
r		1		-0.108		0.124		0.960

Table 2: Performance comparison for Goldhill image

Effect	Survey	Survey*	NCD	NCD*	CMSSIM	CMSSIM*	FSIMc	FSIMc*	FCSS	FCSS*
1	5.952	7.03	0.071	2.58	0.654	5.64	0.889	7.31	0.895	4.58
2	2.615	2.93	0.130	5.16	0.923	1.24	0.995	1.00	0.931	2.62
3	1.038	1.00	0.036	1.00	0.920	1.29	0.993	1.09	0.961	1.00
4	6.212	7.35	0.045	1.41	0.937	1.00	0.877	8.03	0.872	5.86
5	8.375	10.00	0.120	4.72	0.489	8.33	0.863	8.81	0.796	10.00
6	8.192	9.78	0.239	10.00	0.447	9.02	0.843	10.00	0.829	8.20
7	4.596	5.36	0.046	1.48	0.925	1.20	0.911	5.96	0.896	4.52
8	8.279	9.88	0.149	5.99	0.387	10.00	0.857	9.19	0.888	4.96
9	4.596	5.36	0.046	1.45	0.927	1.16	0.908	6.15	0.895	4.57
10	5.144	6.04	0.049	1.59	0.921	1.27	0.906	6.29	0.897	4.46
RMSE		0		3.916		3.260		0.853		1.971
r		1		0.574		0.805		0.958		0.873

Table 3: Performance comparison for Lenna image

Effect	Survey	Survey*	MAE	MAE*	MSE	MSE*	SSIM	SSIM*
1	6.423	6.88	8.864	2.35	140.249	1.66	0.755	4.57
2	4.337	4.49	37.396	10.00	1398.719	10.00	0.930	1.73
3	1.288	1.00	7.229	1.92	69.314	1.19	0.975	1.00
4	5.731	6.08	5.319	1.40	60.199	1.13	0.878	2.58
5	9.154	10.00	6.266	1.66	937.370	6.94	0.456	9.44
6	8.788	9.58	20.248	5.41	641.076	4.98	0.422	10.00
7	3.279	3.28	3.809	1.00	40.924	1.00	0.894	2.32
8	8.327	9.05	12.938	3.45	266.176	2.49	0.560	7.75
9	3.240	3.23	3.902	1.02	40.890	1.00	0.891	2.36
10	4.433	4.60	4.436	1.17	52.697	1.08	0.872	2.67
RMSE		0		4.624		4.223		1.811
r		1		0.157		0.377		0.930

Table 4: Performance comparison for Lenna image

Effect	Survey	Survey*	NCD	NCD*	CMSSIM	CMSSIM*	FSIMc	FSIMc*	FCSS	FCSS*
1	6.423	6.88	0.084	3.07	0.544	7.56	0.907	5.42	0.925	2.88
2	4.337	4.49	0.148	5.46	0.702	8.97	0.997	1.00	0.934	2.44
3	1.288	1.00	0.072	2.61	0.671	10.00	0.993	1.18	0.963	1.00
4	5.731	6.08	0.037	1.30	0.922	1.17	0.926	4.46	0.925	2.88
5	9.154	10.00	0.110	4.06	0.531	8.07	0.841	8.62	0.778	10.00
6	8.788	9.58	0.269	10.00	0.428	9.84	0.813	10.00	0.813	8.32
7	3.279	3.28	0.030	1.03	0.955	1.01	0.958	2.91	0.943	1.97
8	8.327	9.05	0.159	5.88	0.399	9.82	0.869	7.29	0.901	4.02
9	3.240	3.23	0.029	1.00	0.958	1.00	0.957	2.97	0.943	1.98
10	4.433	4.60	0.032	1.14	0.951	1.15	0.948	3.40	0.939	2.18
RMSE		0		3.292		3.900		1.543		2.578
r		1		0.640		0.386		0.929		0.850

Table 5: Performance comparison for Baboon image

Effect	Survey	Survey*	MAE	MAE*	MSE	MSE*	SSIM	SSIM*
1	5.615	6.20	17.536	4.19	523.011	3.94	0.599	7.81
2	3.077	3.30	37.451	10.00	1403.372	10.00	0.894	1.88
3	1.067	1.00	8.603	1.59	96.246	1.00	0.938	1.00
4	7.519	8.38	14.082	3.18	376.375	2.93	0.665	6.49
5	8.933	10.00	6.596	1.00	1059.051	7.63	0.616	7.48
6	6.510	7.23	19.657	4.81	604.993	4.50	0.648	6.83
7	5.404	5.96	13.289	2.95	433.458	3.32	0.637	7.06
8	6.577	7.30	19.487	4.76	665.686	4.92	0.490	10.00
9	4.952	5.45	13.390	2.98	433.040	3.32	0.639	7.02
10	5.346	5.90	14.103	3.19	474.321	3.60	0.618	7.43
RMSE		0		4.383		3.395		1.673
r		1		-0.271		0.217		0.783

Table 6: Performance comparison for Baboon image

Effect	Survey	Survey*	NCD	NCD*	CMSSIM	CMSSIM*	FSIMc	FSIMc*	FCSS	FCSS*
1	5.615	6.20	0.205	5.26	0.363	9.52	0.887	6.68	0.864	5.89
2	3.077	3.30	0.189	4.61	0.729	2.72	0.994	1.00	0.893	3.83
3	1.067	1.00	0.103	1.00	0.696	3.35	0.991	1.17	0.934	1.00
4	7.519	8.38	0.127	1.99	0.822	1.00	0.824	10.00	0.805	10.00
5	8.933	10.00	0.128	2.07	0.470	7.53	0.887	6.66	0.841	7.51
6	6.510	7.23	0.319	10.00	0.400	8.84	0.874	7.37	0.851	6.79
7	5.404	5.96	0.130	2.14	0.770	1.97	0.868	7.67	0.840	7.54
8	6.577	7.30	0.243	6.84	0.338	10.00	0.837	9.34	0.836	7.82
9	4.952	5.45	0.128	2.06	0.801	1.39	0.867	7.72	0.843	7.36
10	5.346	5.90	0.135	2.37	0.749	2.36	0.866	7.77	0.843	7.32
RMSE		0		3.907		3.64		1.874		1.337
r		1		0.211		0.357		0.782		0.859

Table 7: Performance comparison for Parrots image

Effect	Survey	Survey*	MAE	MAE*	MSE	MSE*	SSIM	SSIM*
1	5.240	6.15	13.044	2.91	346.224	2.65	0.749	5.52
2	2.663	2.99	37.285	10.00	1395.746	10.00	0.886	2.19
3	1.038	1.00	9.179	1.78	109.858	1.00	0.935	1.00
4	6.865	8.15	11.966	2.60	443.218	3.33	0.809	4.06
5	8.029	9.58	6.503	1.00	1098.513	7.92	0.585	9.49
6	6.240	7.38	19.517	4.81	595.748	4.40	0.564	10.00
7	5.192	6.10	7.515	1.30	286.272	2.23	0.876	2.42
8	8.375	10.00	16.690	3.98	569.456	4.22	0.613	8.80
9	5.115	6.00	7.670	1.34	291.128	2.27	0.874	2.46
10	6.240	7.38	8.651	1.63	328.090	2.53	0.857	2.89
RMSE		0		5.341		4.266		2.688
r		1		-0.285		0.118		0.739

Table 8: Performance comparison for Parrots image

Effect	Survey	Survey*	NCD	NCD*	CMSSIM	CMSSIM*	FSIMc	FSIMc*	FCSS	FCSS*
1	5.240	6.15	0.115	3.71	0.544	7.67	0.894	6.14	0.887	3.73
2	2.663	2.99	0.175	5.94	0.702	5.12	0.989	1.12	0.890	3.49
3	1.038	1.00	0.088	2.71	0.671	5.62	0.991	1.00	0.924	1.00
4	6.865	8.15	0.060	1.66	0.922	1.58	0.905	5.53	0.849	6.53
5	8.029	9.58	0.112	3.60	0.531	7.88	0.838	9.12	0.802	10.00
6	6.240	7.38	0.284	10.00	0.428	9.53	0.821	10.00	0.832	7.82
7	5.192	6.10	0.042	1.00	0.955	1.06	0.950	3.14	0.898	2.95
8	8.375	10.00	0.187	6.41	0.399	10.00	0.862	7.82	0.843	6.94
9	5.115	6.00	0.042	1.01	0.958	1.00	0.948	3.27	0.895	3.14
10	6.240	7.38	0.047	1.20	0.951	1.12	0.939	3.75	0.891	3.44
RMSE		0		4.518		4.104		2.270		2.283
r		1		0.125		0.221		0.804		0.801

Table 9: Correlation in image channels

Channels	Goldhill	Lenna	Baboon	Parrots
RG	0.92	0.89	0.69	0.9
RB	0.89	0.78	0.1	0.5
GB	0.97	0.96	0.7	0.75