New Principle Component Analysis Based Colorizing Method

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Abstract: *Although many modern imaging systems are still producing grayscale images, colored-images are more preferred for the larger amount of information they are carrying. Computing the grayscale representation of a color image is a straightforward task, while the inverse problem has no objective solution. The search through out literature has not revealed much history of the past works. In this paper, after a brief review of related research, a new dimension-reduction method is proposed for natural color images and approved by both quantitative (PSNR) and subjective tests. Based on it a new class of colorizing methods is proposed and two sample formulations are presented, where the authors are aware of many other formulations available. Subjective test shows dominancy of our proposed method when our method is much faster than others. Our method is leading in face image colorizing where other methods have failed. Such colorization method can be used greatly in medical image processing, surveillance systems, and information visualization.*

Keywords: Image Colorizing, Principle Component Analysis (PCA), Color Attributes

1 Introduction

Colored images are more preferred not only for their better visual appeal but also for the larger amount of information they are carrying.

Computing the grayscale representation of an image in hand is a trivial task, but when dealing with the inverse problem, the task shows itself a more complicated job, to be performed with some levels of human intervention.

Having in mind the enormous amount of classical heritage such as the first photograph, the *lumiere* brothers have taken or the early movies of *Charles Chaplin*, a user-friendly tool that converts the non-colored images to colored ones shows itself more useful. The commercial motivations towards such *colorizing* process are not less than humanistic ones. Even nowadays, many imaging systems are still producing the old-style grayscale (Many types of medical images) or green-scale (Infrared images [2]) images. Colorizing remote sensing images, medical images (Just for better illustration), surveillance images (For highlighting possible dangers as the baggage inspection performed in the airports), and weather images are just a few examples.

Authors have performed a widespread search in the literature containing personal contact to the authors of the very few papers found in the field. We have just found a few previous works in the field. Rather than the classic *pseudocoloring* task proposed by Gonzalez [4], the only noteworthy works are published by Welsh [1] and Yan [2].

In this paper, we call the image to be colorized as the *source* image and the image from which the color information is extracted as the *mood* image. In all formulas, variables indexed by 1 belong to the source image where index 2 is deduced to the mood image. Variables indexed by 1 with the *prime* symbol are those relating to the source image after colorizing task takes place. All vectors in this paper are column vectors.

After some consideration about information packing abilities of PCA, we propose a new category of colorizing methods that inputs both source and mood images in a segmented fashion. Then by principle component analysis and a little linear algebra work, it adds the color content of the mood image to the source image. To make a ground truth for comparing different algorithms, some conditions and measurements are proposed. Two sample formulas of the category are proposed and analyzed subjectively and quantitatively by means of PSNR.

2 Related Work

Colorizing in its general meaning is assigning three-dimensional color information vectors to one-dimensional luminance or brightness values, in order to satisfy some subjective or quantitative goals. It is clear that there is no absolute solution for this problem.

The simplest solution ever raised for the colorizing problem is pseducoloring first introduced by Gonzalez and Wintz [4] in which, 255 three-dimensional color vectors are enlisted in a color map and then applied to the source image by simple look up table processing. Of course, pseducoloring seems to be fully automated but the choice of a proper color-map needs human intervention. Although pseducoloring is an appropriate method for such tasks for which it was first purposed as highlighting explosives in the baggage inspection equipment at an airport, but the process that generates the color map for the general problem discussed here is yet another problem.

Welsh [1] uses $l\alpha\beta$ color space, proposed by Ruderman [5]. Ruderman's aim was to minimize correlation between color channels of natural scenes. After some considerations to gain a device-independent color space, the work describes using principle component analysis to compute maximal decorrelation between the three axes and proposes the $l\alpha\beta$ color space as a result. $l\alpha\beta$ is based on data-driven human perception research that assumes the human visual system to be ideally suited for processing natural scenes. Reinhard [3] expresses that the $l\alpha\beta$ color space has never been applied otherwise or compared to the other color spaces.

Welsh states that the problem of transferring color information to a grayscale image has no exact objective solution and that the goal in the field is reducing the human labor required for the task. He chooses the $l\alpha\beta$ color space and adds color content (α,β information) to single l information present in the source image. Rather than some extra neighborhood information processing, his work generally assumes that the image is divided into distinct luminance clusters where each region is covered by a distinct texture. In addition, he assumes that similar material on the source and mood image are in the same range of intensity. As he states in his paper, the method does not work very well with the face images, as the L_2 measure he has used is not always a sufficient measure in classifying the difference between skin and lips. Although the method works very slowly, (15 seconds to 4 minutes in a Pentium III 900 MHZ processor using optimized MATLAB code) the paper proposes the use of larger window size, which declines the overall speed. Although Welsh's method is not intended to be real-time, the whole work is easy to apply.

Yan [2] has focused on colorizing infrared home videos. He states that all commercial camcorders available in the market are equipped with a *night shot* tool along with a *still shot* with flash. The work's genius idea is the use of the still imaging part of the camera as the mood-image acquiring tool. As he expresses, amateur users of such cameras do not use professional lightings and the flash of the cameras cannot function continuously because of battery capacity considerations. The paper does not express his own colorizing approach, but it seems that it's main emphasize is applying Welsh's work on temporally distributed images. Of course, there are three colorized movies in the Welsh's site, having in mind that Welsh has reported his work to fail on face images, were home video mainly consists of such scenes.

We want to emphasize on the main shortcoming of both Welsh and Yan's work. They have considered that there is a one-by-one correspondence between grayscale information and color vectors. As stated before this is the main idea in pseudocoloring, and is not true in ordinary images were different parts of the image belong to different materials.

3 Principle Component Analysis

The idea of reducing the color space dimension is not a new idea; many researchers have reported benefits of illumination coordinate rejection [6].

PCA (Principle Component Analysis) [7] is widely used in signal processing, statistics, and neural networks. In some areas, it is called the (discrete) Karhunen-Leove transform or the Hotelling transform.

The basic idea behind PCA is to find the components $s_1,\ldots,s_n$ so that they explain the maximum amount of variance possible by n linearly transformed components. By defining the direction of the first principal component, say w_1, by (1), PCA can be represented in an intuitive way.

$$w_1 = \arg\left(\max_{\|w\|=1}\left[E\left\{\left(w^T x\right)^2\right\}\right]\right) \tag{1}$$

Thus, the principal component analysis is the projection of data on the direction in which the variance of the projection is maximized. Having determined the first $k-1$ principal components, w_k is determined as the principal component of the residual as in (2).

$$w_k = \arg\left(\max_{\|w\|=1} \left[E\left\{ \left(w^T \left[x - \sum_{i=1}^{k-1} w_i w_i^T x \right] \right)^2 \right\} \right] \right) \tag{2}$$

The principal components are then given by $s_i = w_i^T x$. In practice, the computation of w_i can be simply accomplished using covariance matrix $C = E\{(x-\bar{x})(x-\bar{x})^T\}$. Now w_n is the eigenvector of C corresponding to the n[th] largest eigenvalue.

The basic goal in PCA is to reduce the dimension of data. Thus, one usually chooses $n << m$. Indeed, it can be proven that the representation given by PCA is an optimal linear dimension reduction technique in the mean-square sense. Such a reduction in dimension has important benefits. First, the computational overhead of the subsequent processing stage is reduced. Second, noise may be reduced, as the data not contained in the n first components may be mostly due to noise.

4 Proposed Algorithms

In this section after a brief concentration on the direct problem of converting a color vector to a grayscale value, our method for reverse problem is described.

4.1 Color to Grayscale Transformation

Many measures of intensity have been proposed in the literature with different meanings and reasons, and no one has been standardized generally (For a few examples look at [8], [9], and [10]). A few samples are listed in Table 1. For generalization, we call such measure the *achromatic norm* or easily the *norm*.

To use linear algebra methods we limit our work to linear norm functions generally shown as $\langle \vec{v} \rangle$ as described in (3) where the vector $\vec{N}$ is *a posterior* defined satisfying the condition $\langle \vec{1} \rangle = 1$.

Table 1. Few examples of different intensity components.

Color space	Intensity component
HSI[8], $Ohta$[9]	$I = \frac{R + G + B}{3}$
HSV[10]	$V = \max(R, G, B)$
$YCbCr$	$Y = c_1 R + c_2 G + c_3 B$
YIQ	$Y = 0.30R + 0.59G + 0.11B$
YUV	$Y = 0.299R + 0.587G + 0.114B$

$$\langle \vec{V} \rangle = \vec{N}' \vec{V} \tag{3}$$

The above-defined norm function satisfies two simple but important conditions, Stated in (4) and (5). The proofs are easily obtained by definitions and a little linear algebra work.

$$\langle \alpha \vec{v}_1 + \vec{v}_2 \rangle = \alpha \langle \vec{v}_1 \rangle + \langle \vec{v}_2 \rangle \tag{4}$$

$$\mathrm{E}\{\langle \vec{x} \rangle\} = \langle \mathrm{E}\{\vec{x}\} \rangle \tag{5}$$

4.2 Proposed Colorizing Methods

Our general view to the colorizing problem is illustrated in figure 1 as a user-guided process of liquefying the color content of a given image (the mood image) and purring it onto a grayscale image (the source image).

As the transformation from a 3-D color vector to a single intensity number is not reversible, so there could be many extremely different colors with the same appearance in the grayscale image. One method to distinguish such fake points is to use some neighborhood information as Welsh has worked out. His method is based on a suspicious assumption that color regions of the same material are in the same range of intensity. Having in mind the desperate performance he has reported, along with the wide range of images in which the method fails, containing the major category of face images, the need for a completely different method arises.

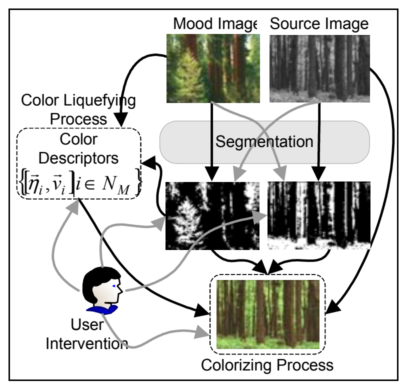

Figure 1: General idea behind colorizing as a user-guided process of liquefying the color content of a given image and purring it onto a grayscale image.

To withdraw the shortcomings of Welsh's work, we separated the color extraction and segmentation phases. Rather than Welsh's work that combined the two segmentation phases for the mood and the source image that are entirely different (one working on a color image whilst the other one is essentially working on grayscale images), We assumed that regarding to the problem in hand the source image has been separated into a few segments describing the content of the points in the physical phenomenon. Such segmentation could be the result of an entirely different pre-processing widely discussed in the literature. Each segment is responsible for a distinct region, for example Wood and Leaf in the image under process in Figure 1. Segmentation of the mood image is much easier because user must only highlight middle-sized rectangular areas of each predefined color mood. For generality, we have assumed that both the mood image and the source image are segmented completely.

When the regions in the mood image were highlighted, the color content must be extracted. In our work, we suggest using PCA for that job. When an area in the image is said to be the representative of i-th region, the two parameters $\vec{r}_i$ and $\vec{v}_i$ are computed as the mathematical expectation of the color information of the region and the eigenvector of the covariance matrix of the color information of the region corresponding to the largest eigenvalue respectively (The direction of the first principle component).

The selected region then can be represented by a one-dimensional representation in contrast with the ordinary three-dimensional representations, with the aid of the above-described statistical parameters, as the vector $\vec{C}$ is represented by the vector $\vec{C}'$ in (6). Note that the $\vec{C}'$ space is now a shifted version of a one-dimensional vector space.

$$\vec{C} = \vec{\mu} + \begin{bmatrix} v_{1_x} & v_{2_x} & v_{3_x} \\ v_{1_y} & v_{2_y} & v_{3_y} \\ v_{1_z} & v_{2_z} & v_{3_z} \end{bmatrix} \begin{bmatrix} \alpha \\ \beta \\ \gamma \end{bmatrix} \rightarrow \vec{C}' = \vec{\mu} + \alpha \begin{bmatrix} v_{1_x} \\ v_{1_y} \\ v_{1_z} \end{bmatrix} \tag{6}$$

A test was planned in order to investigate the amount of data lost in this operation. Eight homogenous regions in standard sample images were considered, then the PSNR of the reconstructed image $\vec{r} + \alpha\vec{v}_1$ was computed as (7) along with a new parameter κ_X defined to show the ratio of information available in a given channel X belonging to $\{R, G, B, PC_1, PC_2, PC_3\}$ as described in (7). As the transformation from RGB space to the space defined by principle components is a unitary transform, it can be shown that $\sigma_R^2 + \sigma_G^2 + \sigma_B^2 = \sigma_{PC_1}^2 + \sigma_{PC_2}^2 + \sigma_{PC_3}^2$. The Complete results are shown in the results part of the paper.

The high PSNR (32 averagely with standard deviation of less than four) shows that such dimension reduction is objectively considerable.

There is no objective parameter proposed for comparing different colorizing tasks in the literature, but some conditions and measures seem to be appropriate. We propose three conditions to be met by a perfect colorizing process, as $\langle I_1' \rangle = \langle I_1 \rangle$, $\vec{\eta}_1' \parallel \vec{\eta}_2$, and $\vec{v}_1' = \vec{v}_2$.

The first condition states that converting the colorized source image back to grayscale representation should revert it. The second condition along with the third one tries to ensure that the same color information, which was extracted from the mood image, is available in the source image after colorization takes place.

$$\begin{aligned} \hat{\sigma}_x &= \sqrt{\frac{1}{MN}\sum_{x=1}^{M}\left(\sum_{y=1}^{N}\left(\left(I_x[x,y] - \hat{I}_x[x,y]\right)^2\right)\right)} \\ \sigma_x &= \sqrt{\frac{1}{MN}\sum_{x=1}^{M}\left(\sum_{y=1}^{N}\left(\left(I_x[x,y] - \bar{I}_x\right)^2\right)\right)} \\ \sigma &= \sqrt{\frac{\sigma_R^2 + \sigma_G^2 + \sigma_B^2}{3}}, \hat{\sigma} = \sqrt{\frac{\hat{\sigma}_R^2 + \hat{\sigma}_G^2 + \hat{\sigma}_B^2}{3}} \\ \kappa_X &= \left[100\frac{\sigma_X}{\sqrt{3}\sigma}\right], PSNR = 20\log_{10}\left(\frac{255}{\hat{\sigma}}\right) \end{aligned} \tag{7}$$

Two quantitative measures that could be defined to compare different colorizing tasks are the algorithm speed and human sense. Algorithm speed can be described as the color extraction price and operation per pixel complexity. Human sense could be measured by means of impairment (Table 2) and goodness (Table 3) scales [11].

Table2. Impairment scales [11].

1	Not noticeable
2	Just noticeable
3	Definitely noticeable but only slight impairments
4	Impairment not objectionable
5	Somewhat objectionable
6	Definitely objectionable
7	Extremely objectionable

Table3. Goodness scales.

5	Excellent
4	Good
3	Fair
2	Poor
1	Unsatisfactory

We propose a new category of colorizing methods, which reconstruct the color information by a function of $\vec{\eta}_1, \vec{\eta}_2, \vec{C}_1, \vec{v}_2$ generally stated as (8), satisfying the three conditions.

$$\vec{C}_1' = \Phi_{\vec{\eta}_1, \vec{\eta}_2, \vec{v}_2}\left(\left\langle \vec{C}_1 \right\rangle\right) \tag{8}$$

Many different formulations were worked out and applied by the authors, two formulations that seemed to be more appropriate are proposed in (9) and (10), Where in both $\langle \vec{v}_2 \rangle$ is assumed unity. Authors are aware of huge number of such formulations. To show the versatility of the category, two other formulations are stated in (11) and (12), in which user can tune the parameter λ, to control the amount of color added to the image ($\lambda = 0$ adds no color to the source image resulting in the same grayscale image). (11) And (12) are not discussed in this paper. Considering the two samples (9) and (10) the entire category can be estimated.

$$\vec{C}_1' = \vec{\eta}_2 + \left(\left\langle \vec{C}_1 \right\rangle - \left\langle \vec{\eta}_2 \right\rangle \right) \vec{v}_2 \tag{9}$$

$$\vec{C}_1' = \frac{\left\langle \vec{\eta}_1 \right\rangle}{\left\langle \vec{\eta}_2 \right\rangle} \vec{\eta}_2 + \left(\left\langle \vec{C}_1 \right\rangle - \left\langle \vec{\eta}_1 \right\rangle \right) \vec{v}_2 \tag{10}$$

$$\vec{C}_1' = \vec{C}_1 + \lambda \left(\vec{\eta}_2 - \vec{C}_1 + \left(\left\langle \vec{C}_1 \right\rangle - \left\langle \vec{\eta}_2 \right\rangle \right) \vec{v}_2 \right) \tag{11}$$

$$\vec{C}_1' = \vec{C}_1 + \lambda \left(\vec{\eta}_1 - \vec{C}_1 + \left(\left\langle \vec{C}_1 \right\rangle - \left\langle \vec{\eta}_1 \right\rangle \right) \vec{v}_2 \right) \tag{12}$$

As $\left\langle \vec{v}_2 \right\rangle$ is considered unity, it is easy to see that in both (9) and (10), $\left\langle \vec{C}_1' \right\rangle = \left\langle \vec{C}_1 \right\rangle$, fulfilling the first condition. In addition, as $E\left\{ \left\langle \vec{C}_1 \right\rangle - \left\langle \vec{\eta}_1 \right\rangle \right\}$ is equal to zero, it is convenient that in (10), $\vec{\eta}_1' = \left(\left\langle \vec{\eta}_1 \right\rangle \big/ \left\langle \vec{\eta}_2 \right\rangle \right) \vec{\eta}_2$ complying with the second condition in contrast with (9) that does not comply ($\vec{\eta}_1' = \vec{\eta}_2 + \left(\left\langle \vec{\eta}_1 \right\rangle - \left\langle \vec{\eta}_2 \right\rangle \right) \vec{v}_2$). It can be proved that the third condition is valid in both (9) and (10) as expressed in (13).

$$\left.\begin{aligned} &\vec{C}_1' - \mathrm{E}\left\{\vec{C}_1'\right\} = \left(\left\langle \vec{C}_1 \right\rangle - \left\langle \vec{\eta}_1 \right\rangle \right) \vec{v}_2 \\ &C = \mathrm{E}\left\{ \left(\vec{C}_1' - \mathrm{E}\left\{\vec{C}_1'\right\} \right) \left(\vec{C}_1' - \mathrm{E}\left\{\vec{C}_1'\right\} \right)' \right\} \end{aligned}\right\} \Rightarrow$$
$$C = \sigma_1^2 \vec{v}_2 \vec{v}_2' \Rightarrow \tag{13}$$
$$\left.\begin{aligned} &Rank(C) = 1 \\ &C\vec{v}_2 = \left(\sigma_1^2 \vec{v}_2' \vec{v}_2 \right) \vec{v}_2 \end{aligned}\right\} \Rightarrow \vec{v}_1' = \vec{v}_2$$

Both (9) and (10) cost three subtractions, three additions and three multiplications for each pixel in colorization phase.

To test the proposed colorizing methods, attempts were made to colorize sample images of Welsh paper with our two proposed methods, and a subjective test was applied to the results. Twenty-six girls and boys of age 17 to 27 were asked to reorder the three images (Welsh's synthesized image and the result of (9) and (10)) in terms of goodness. The subjects were unaware of the algorithms but were literate people. Neither the source image nor the mood image was exposed to the subjects, but they were able to scroll in the monitor in order to watch any of the three images at any time they wanted. The images were shown in a randomly ordered fashion and no timing threshold was set. The answers were given as strings containing 1,2,3 along with the *comma* and *slash*. For example, 1/2,3 was defined to mean, first image is the best, and second and third are the same in the next place. Subjects were not allowed to contribute the results. When the subjects performed the ordering task, the orders were changed to scores (0..3) and statistical analysis was preformed on them. Results are shown in the result section.

To test the algorithm in special problem of face colorizing, three standard images (Lena, Girl and Barbara) were selected and were manually segmented into six distinct segments of skin, hair, lip, cloth1, cloth2 and *don't care* (Background). The claim was that our algorithm satisfies the user when preformed on face images, when Welsh has reported his method to fail in this field. Segmented images are shown in Figure 2.

(a) (b) (c)

Figure 2: Segmented version of test images for face colorizing, a: Girl, b: Lena, c: Barbara.

The grayscale version of the three images were colorized twelve times, once with the color information of Lena and then by Girl, each colorization performed twice, once by (9) and then by (10). Results are shown in the result section.

A subjective test was performed on the results, containing two questions of Impairment and goodness. Of course, as the background was leaved grayscale in all synthetic images, the background of the original image was made grayscale too. To find out the quality of the method dealing with the special problem of face colorizing, both questions were asked twice, once for the entire image and then only for the face area. As the color version of Barbara was not available, only the goodness question was asked. In addition, PSNR analysis was performed on Lena and Girl images. Results are shown in the result section.

5 Dataset

Standard images were used for both the homogenous region reconstruction test and the face-colorizing test. The standard images in region reconstruction were Baboon, Lena (Full version), Girl, and Peppers; the test images in face reconstruction part were Lena (Small version), Girl, and Barbara.

6 Experimental Results

Eight swatches were used in dimension reduction test are shown in Figure 3, one-dimensional version images are shown in Figure 4. Numerical results are printed in Table 4.

Two samples of Welsh are shown in figure 5, along with the colorized images by (9) and (10).
The algorithms were developed in Matlab 6.5 with highly optimized code, on an 1100 MHZ Pentium III personal computer with 256MB of RAM. For a 256*256 image containing eight regions, the color extraction phase was performed in 2 seconds averagely, when the color transfer phase got another 2 seconds

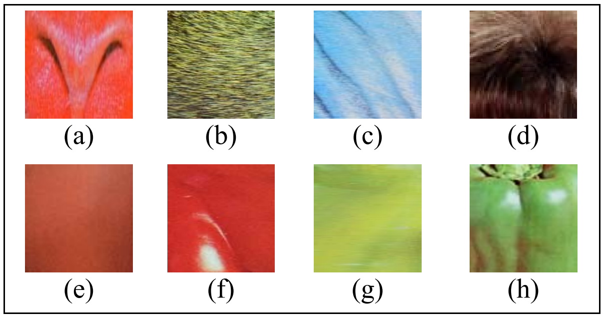

Figure 3: eight homogenous regions in standard images selected to estimate proposed dimension reduction method. a: Nose of Baboon, b: Wool of Baboon, c: Lateral part in nose of Baboon, d: Hair of Girl, e: Skin of Lena, f: Red pepper of Peppers, g: Yellowish-Green pepper of Peppers, h: Green pepper of Peppers (Images are not proportionally resized).

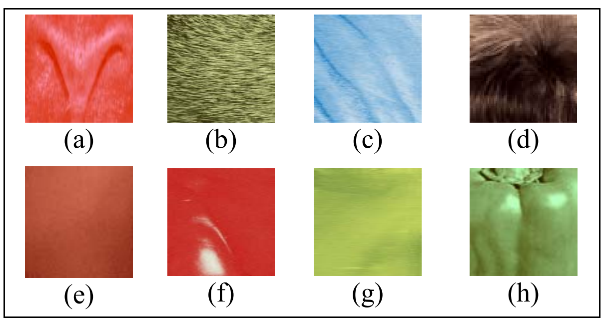

Figure 4: Results of dimension reduction process on samples of fig. 4 (Images are not proportionally resized)

Table 4. Statistical parameters of dimension reduction applied on sample images.

	a	b	c	d	e	f	g	h	ı	c
PSNR	25	30	30	35	38	34	33	28	32	4
κ_R	52	58	79	65	63	21	68	42	56	17
κ_G	44	62	46	57	55	71	54	65	57	9
κ_B	72	52	38	48	53	66	49	63	55	10
κ_{PC_1}	84	97	89	99	97	98	88	94	93	5
κ_{PC_2}	51	18	44	10	22	18	44	27	29	14
κ_{PC_3}	13	7	7	3	4	7	13	18	9	5

The subjective test on Welsh samples gave the following results. When the average score for Welsh's algorithm was 1.833, (9) was given 2.119, and (10) was given 2.429, making the average score for our methods about 2.27 (all out of 3).

Colorized version of Lena, Girl, and Barbara are shown in Figure 6. PSNR values of colorizing Lena and Girl with each other in both proposed methods are listed in table 5. Results of subjective test on face colorizing in a normalized (0..100) fashion are listed in table 6.

Table 5. PSNR values for Lena and Girl colorizing tests.

Mood	Lena		Girl	
Source	(6)	(7)	(6)	(7)
Lena	26	26	18	21
Girl	14	13	28	28

Table 6. Subjective Results of face colorizing tests.

		Image		Face	
		I[1]	G[2]	I	G
S=M[3]	(9)	67	75	82	90
	(10)	75	87	88	98
S<>M[4]	(9)	35	72	45	80
	(10)	40	83	52	96
No S[5]	(9)		60		80
	(10)		78		95

7 Discussion

It is clear in Table 4 that in contrast with RGB channels with κ of around 50, in PCA channels the information mostly gathers in the first channel (90 compared with 30 and 10).
Comparison of κ_{PC_1} in the first and the fourth samples (the extreme values of κ_{PC_1}) are valuable. While shades in the nostrils of the Baboon, distributes the information in the three channels of PCA, the information densely focuses in PC1 channel in the hair sample. This means scattered images do not give bad results for sure. In addition, it must be emphasized that skin sample has gained κ_{PC_1} of 97, so face components (d and e) tend to respond to such dimension reduction averagely better.
The average PSNR of 32 in table 4 shows that the proposed dimension reduction process is a reasonable reconstruction scheme. The low standard deviation (four) between different PSNR values proves the method to respond uniformly. The highest PSNR has been gained in the fifth sample, the skin. This is why we are concentrating on face images, containing big areas of skin. The worst result is obtained in the first sample because of the dark shades of the nostrils.

[1] Impairment
[2] Goodness
[3] Mood image is the colored version of the source image.
[4] Mood image is not the colored version of source image.
[5] Colored version of source image was not available (the case with Barbara image).

As Welsh uses the luminance as the segmentation criteria, his method is completely depending on the similarity of the source and mood images. Such dependency does not exist in our work. Using the intensity as the matching feature sometimes makes an odd artifact in Welsh's synthesized images as a discontinuity of color appearance. Such effect could be easily recognized in the background of samples shown in figure 5 (5-c, 5-h).

Our methods perform PCA for each sample; in contrast with Welsh's work that is based on the $l\alpha\beta$ color space, that has performed PCA on a set of sample images once. Theoretically, we are working on a better base of uncorrelatedness.

The three conditions defined in the method section try to build a ground truth for new algorithms. Our first method, justifies only two of the methods, where our second proposed method justifies all. Welsh's method holds the first condition, as he just transfers α, β components, leaving the l value unchanged, but he has given no attention on the other two conditions. It must be emphasized that the l component of $l\alpha\beta$ is not a linear norm function.

Our method works about 20 times faster (Our 4 seconds measurement, versus 15 seconds to 4 minutes record of Welsh in similar systems), though he offers to use larger window sizes. Considering the speed of algorithms, our algorithm is dominant.

Our methods were recognized subjectively, 16% and 32% better respectively than Welsh were, resulting in 24% better score averagely. Our second proposed method was about 15% better than our first method.

Table 5 shows that both methods are similar in PSNR sense. It is clear that colorizing each image by its color information gives better results, though the meaning of PSNR test must be considered carefully. Many objectionable images with high values of PSNR can be produced.

In face images, our methods were approximately scored 83 out of 100, which means the synthetic images are averagely thought *good*. In impairment scales, the colorized images were considered *not objectionable* (60.5 out of 100). Face region is averaged 23% higher than the whole colorized area, when method (10) has gained 18% more scores than (9). Also it must be emphasized that colorizing with the same color content of the source image gives better results, but not much better (less than 6%), the same fact rules in the scores given to the case of comparing *S<>M* (Refer to footnote of previous page) with *No S* case.

8 Conclusion

A new dimension-reduction method was proposed that maps the three-dimensional vector space of color information to a shifted one-dimensional vector space. The transform was approved by both quantitative (PSNR) and subjective tests. Based on the dimension-reduction method a new class of colorizing methods was proposed and two samples were considered, where there are many other formulations available. Subjective test shows dominancy of our proposed method whilst our method is twenty times faster. As Welsh has reported his method to fail in face-image colorizing, a test was performed on standard face images and was shown to be leading both regarding to quantitative tests and subjective tests. Conditions and measurements were proposed for comparison of future colorizing methods.

References

[1] Tomihisa Welsh, Michael Ashikhmin and Klaus Mueller, "Transferring Color to Grayscale Images", proceedings of ACM SIGGRAPH 2002, San Antonio, pp. 277-280, July 2002

[2] Wei-Qi Yan, Mohan S Kankanhalli, "Colorizing Infrared Home Videos" , IEEE, 2003

[3] Erik Reinhard, Michael Ashikhmin, Bruce Gooch, and Peter Shirley, "Color Transfer between Images", IEEE Computer Graphics and Applications, September/October 2001, pp. 34-41

[4] Gonzalez R.C. and Wintz P., "Digital Image Processing", Addison-Wesley Publications, 1987

[5] D.L. Ruderman, T.W. Cronin, and C.C. Chiao," Statistics of Cone Response to Natural Images: Implications for Visual Coding", J. Optical Soc. Of America, vol. 15, no. 8,1998, pp. 2036-2045

[6] Min C. Shin, Kyong I. Chang, Leonid V. Tsap, "Does color space transformation make any difference on skin detection?", http://citeseer.nj.nec.com/542214.html

[7] Aapo Hyvarinen, "Independent Component Analysis: Algorithms and Applications", IEEE transaction on Neural Networks, April 1999

[8] Smith A. R., "Color Gamut Transform pairs", Computer Graphics 12, August 1978

[9] T-Y Shin, "The reversibility of six geometric color spaces", Photogrammetric Engineering and Remote Sensing, October 1995

[10] Y. I. Ohta, Y. Kanade and T. Saki, "Color information for region segmentation", Computer graphics and image processing, July 1980

[11] Anil K. Jain, "Fundamentals of Digital Image Processing", Prentice-Hall International, Inc., 1989

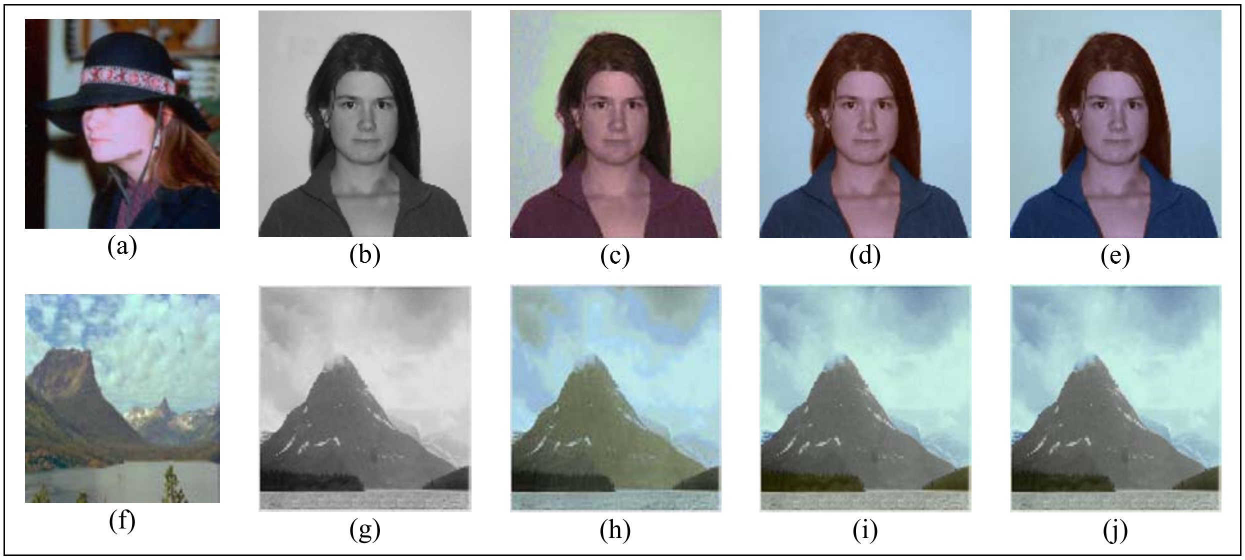

Figure 5: Two samples of Welsh along with the results of our methods. (a),(f) Mood images, (b),(g) Source images, (c),(h) Results of Welsh, (d),(i) Results of (9), (d),(j) Results of (10). (a),(b),(c),(f),(g),(h) Adopted from Welsh [1].

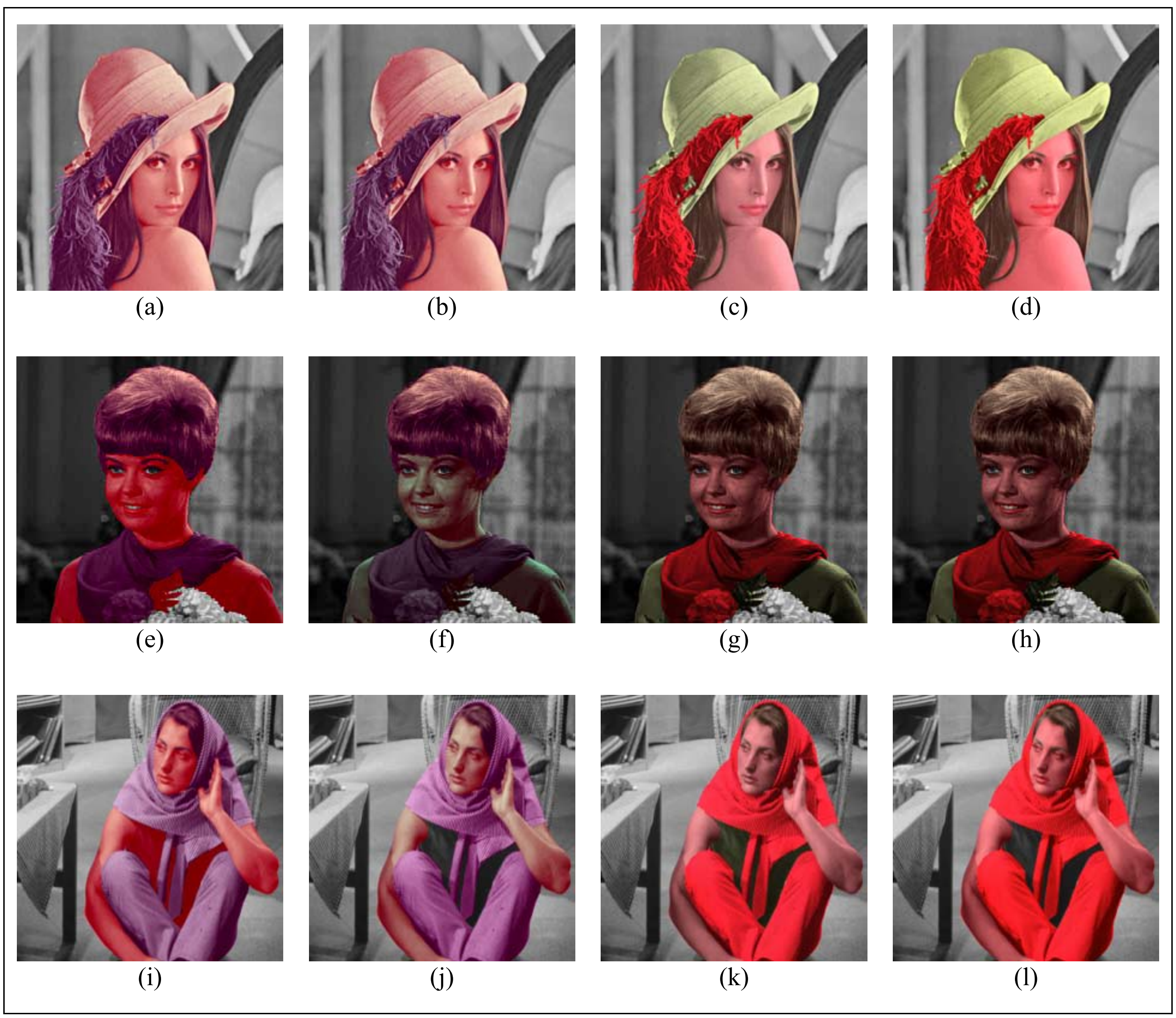

Figure 6:. Results of colorizing face images, (a),(b),(e),(f),(i),(j): Colorized with color information extracted from Lena image. (c),(d),(g),(h),(k),(l): Colorized with color information extracted from Girl image. (a),(e),(i),(c),(g),(k): Colorized based on (6). (b),(d),(f),(h),(j),(l): Colorized based on (7).