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Optimized Color Based Compression

[1]K.P.SONIA FENCY, [2]C.FELSY

[1]PG Student, Department Of Computer Science Ponjesly College Of Engineering Nagercoil,Tamilnadu, India

[2]Asst. Professor, Department Of Computer Science Ponjesly College Of Engineering Nagercoil,Tamilnadu, India

Abstract: **In colorization-based coding colorization-based coding, the encoder chooses a few representative pixels (RP) for which the chrominance values and the positions are sent to the decoder, where as in the decoder, the chrominance values for all the pixels are reconstructed by colorization methods. The main issue in colorization-based coding is how to extract the RP well therefore the compression rate and the quality of the reconstructed color image becomes good. By formulating the colorization-based coding into an L_1minimization problem, it is guaranteed that, given the colorization matrix, the chosen set of RP becomes the optimal set in the sense that it minimizes the error between the original and the reconstructed color image. In other words, for a fixed error value and a given colorization matrix, the chosen set of RP is the smallest set possible. This system will provide method to construct the colorization matrix that colorizes the image in a multiscale manner. This, combined with the proposed RP extraction method, allows us to choose a very small set of RP. There is no need to adopt geometric methods in this system also this system does not requires no extra RP extraction and the reduction.**

Keywords: **Representative Pixels (RP); Orthogonal Matching Pursuit (OMP); Joint Photographic Expert Group (JPEG).**

I. INTRODUCTION

Recently a new compression technique for color images, which is based on the use of colorization methods, has been proposed [1]–[4]. Previously, several colorization methods [5] have been proposed to colorize grayscale images using only a few representative pixels provided by the user. The main task in colorization based compression is to automatically extract these few representative pixels in the encoder. In other words, the encoder selects the pixels required for the colorization process, which are called representative pixels (RP) in [4], and maintains the color information only for these RP. The position vectors and the chrominance values are sent to the decoder only for the RP set together with the luminance channel, which is compressed by conventional compression techniques. Then, the decoder restores the color information for the remaining pixels using colorization methods.

The main issue in colorization based coding is how to extract the RP set so that the compression rate and the quality of the restored color images become good. Several methods have been proposed to this end [1]–[4]. All these methods take an iterative approach. In these methods, first, a random set of RP is selected. Then, a tentative color image is reconstructed using the RP set, and the quality of the reconstructed color image is evaluated by comparing it with the original color image. Additive RP are extracted from regions where the quality does not satisfy a certain criterion using RP extraction methods, while redundant RP are reduced using RP reduction methods. However, the set of RP may still contain redundant pixels or some required pixels may be missing. The main contribution of this paper is that we formulated the RP selection problem into an optimization problem, that is, an L_1 minimization problem. The selection of the RP is optimal with respect to the given colorization matrix in the sense that the difference error between the original color image and the reconstructed color image becomes minimum with respect to the L_2 norm error. Furthermore, the number of pixels in the RP set is also minimized by the L_1 minimization. The optimal set of RP is obtained by a single minimization step, and does not require refinement,i.e.,any additional RP extraction/reduction methods.

Therefore, there is no need for iteration. Furthermore, there is no need to use a geometric method such as defining line segments or squares as in [1]–[4].The optimization problem can also be considered as a variational approach, and

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therefore, the rich research results of the variational approach in image processing can be used in the colorization based coding problem. This system proposes a construction method of the colorization matrix, which, combined with the proposed RP extraction method, produces a high quality reconstructed color image. It will be shown experimentally that the proposed scheme compresses the color image with higher compression rate than the conventional JPEG standard as well as other colorization based coding methods, and is comparable to the JPEG2000 standard even without using complex entropy coding for the proposed method.

- ***Related works***

The related works for this system can be given by,

A. Levin's Colorization Technique

In [5], Levin *et al*'s propose a colorization algorithm, which reconstructs the colors in the decoder using the color information for only a few representative pixels (RP) and the gray image which contains the luminance information. For example, using the YCbCr color space, the colorization problem reconstructs all the Cb and Cr components, given the Y luminance component and the Cb and Cr information for a few RP. Following the notation in [4], denoted **y** as the luminance vector, **u** as the solution vector, i.e., the vector containing the color components to be reconstructed in the decoder, and **x** as the vector which contains the color values only at the positions of the RP, and zeros at the other positions. The vectors **y**, **u**, and **x** are all in raster-scan order. The cost function defined by Levin *et al*. is $J(\mathbf{u}) = \|\mathbf{x} - A\mathbf{u}\|$ (1) which has to be minimized with respect to **u**. Here, $A = I\text{-}W$, where I is an $n \times n$ identity matrix, n is the number of pixels in **u**, and W is an $n \times n$ matrix containing the *w_rs* weighting components. The minimizer of (1) can be explicitly computed.

B. Colorization-Based Compression Techniques

As mentioned in the introduction, the main function of colorization based coding is the extraction of the RP. Previous colorization based coding methods use an iterative approach to extract the RP. In these approaches, first, an a priori temporary set of RP is usually selected. This *a* priori selection is manual and causes a redundant or insufficient set of RP. Therefore, redundant RP have to be eliminated, and required RP have to be additionally extracted by additional RP elimination extraction methods.

In [1] and [2], new pixels are added to the initial set of RP by iterative selection based on machine learning, while in [3], the RP is selected iteratively constrained to a set of color line segments. In [4], redundant RP are reduced and required RP are extracted iteratively based on the characteristics of the colorization basis. However, after using these additional RP extraction/reduction methods, it is still not guaranteed that the resulting set of RP is optimal. After each step of RP extraction, the A matrix is constructed, and the A^{-1} matrix is obtained by taking the inverse of A. Then, a tentative color image is reconstructed by (3) which is then compared with the original image.

C. L_1 Minimization Model

In many applications, it is necessary to obtain a highly sparse signal **x**, i.e., a signal with very few nonzero components, which produces the measurement **b**, given a certain system (matrix) A: $A\mathbf{x} = \mathbf{b}$. This problem can be formulated as an L_0 minimization problem norm measures the number of nonzero components in **x**. However, this problem is very difficult to solve, since it is a combinatorial optimization problem with prohibitive complexity. Recently, it has been established theoretically that the solution **x** can be obtained also as a solution of an L_1 minimization problem if A satisfies the L_1 minimization problem can be solved easily by tractable linear programming. The L_1 minimization was popularized by the work in [6] and is now widely used in the image processing area, especially in the total variation minimization and the compressive sensing area.

Stability results have been established for the L_1 minimization model in [8]–[11]. One of the major contributions of this system is that formulated the RP selection problem into an L_1 minimization problem.

II. SYSTEM DESIGN

The overall system diagram of the proposed method. The details of the components are described in the following . In the encoder, the original color image is first decomposed into its luminance channel and its chrominance channels. The luminance channel is compressed using conventional one-channel compression techniques, e.g., JPEG standard, and its discrete Fourier or Wavelet coefficients are sent to the decoder. Then, in the encoder, the colorization matrix C is constructed by performing a multi-scale mean shift segmentation on the decompressed luminance channel. The decompressed luminance channel is used to consists with that in the decoder. Using this matrix C and the original chrominance values obtained from the original color image, the RP set is extracted by solving an optimization problem, i.e., an $L1$ minimization problem.

This RP set is sent to the decoder, where the colorization matrix C is also reconstructed from the decompressed luminance channel. Then, by performing a colorization using the matrix C and the RP set, the color image is reconstructed. While most colorization based coding methods try to extract the RP set by using an iterative approach, formulate the RP selection problem into an $L1$ minimization problem. An essential prerequisite for this is that the colorization matrix has to be determined beforehand. This will first explain why the $L1$ minimization problem suits the RP selection problem well. Then, we propose a method to determine the colorization matrix from the given luminance channel before the RP selection. By formulating the colorization based coding into an $L1$ minimization problem, we obtain the following benefits:

1) Compared to the sets of RP obtained by other conventional colorization based coding methods, which are updated at each iteration, the set of RP in our method is obtained only once and requires no update.

2) Compared to other colorization based coding methods, our method needs no extra RP extraction/reduction.

3) It is mathematically guaranteed that the RP set is optimal with respect to the given matrix C in the sense that it minimizes the number of RP due to the $L1$ norm. If using (10) or (11), then it is also optimal (with respect to given matrix C) in the sense that it makes the square error in (10) minimum. When solved with the BP/OMP solver, the solution becomes a local optimal minimum of (11).

4) There is no need to adopt geometric methods into the proposed method.

5) By formulating the problem of RP selection as an optimization problem, this have designed a way to adopt existing optimization techniques to the problem of RP selection.

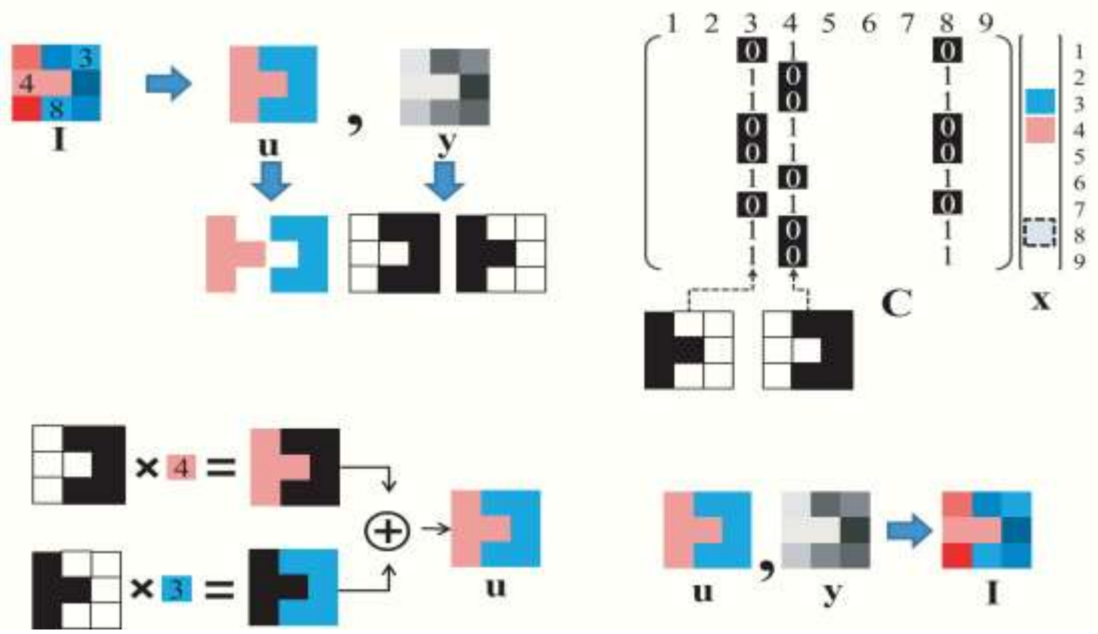

Fig. 1. Constructing of colorization matrix

This can be explained using exemplary 3 × 3 image (**I**) in that after decomposing the image (**I**) into the luminance channel (**y**) and the color components (**u**), the color components is mainly constituted two colors (as can be seen in **u** in Fig. 2(a)). This means that the color image can be reconstructed in the decoder using a minimum of two color values and the luminance channel sent from the encoder. Therefore, sending the color information of the third and the fourth pixels could be enough to reconstruct the color image if C sufficiently reflects the effect of the color information on the colorized image.

To obtain such colorization matrix C, segmentation is performed on the luminance channel, which results in two segmented regions corresponding to the two main color components. Then, the matrix C is constructed considering the segmentation result, as from the matrix C, for example, that the color information of the third pixel has a full effect on the pixels which positions correspond to those having the value '1' in the third vector, while it has no effect on the pixels which positions correspond to those having zero values. Furthermore, the third and the fourth vectors together have an effect on all the pixels in the image. Therefore, using this C in the RP extraction, the solution vector **x** is obtained such that has only two nonzero values, since a third value would be superfluous.

In the decoder, the color components of all the other pixels are recovered using the two nonzero color component values and combined with the luminance channel, the color image is reconstructed (Fig. 2(d)). From this simple example, we see that an important step to obtain the matrix C is the segmentation on the luminance channel in the encoder.Important role is the construction of the colorization matrix. why this system uses multi-scale segmentation,

1) Mean shift Segmentation: This the meanshift segmentation [12] due to its several desirable properties.The mean shift segmentation uses two parameters where one decides the photometric distances between the pixels inside the segmented regions, and the other decides the spatial distances. Therefore, using the meanshift segmentation, it can easily generate segmented regions of different photometric and spatial characteristics.

Other segmentation techniques may also work with the proposed compression framework if they are tuned to suit well with the proposed method.

2) Multiscale Segmentation: It perform a multi-scale meanshift segmentation to construct the colorization basis. The reason that we use a multi-scale segmentation is that there the possibility that some regions in the colorized image may lack either the Cb or the Cr components when using a single scale segmentation. This is due to the fact that even though the RP for both the Cb and Cr components have to be selected for every segmented region, some may not be selected due the L_1 minimizing constraint. A multi-scale mean shift segmentation is performed at different scales by using kernels with different bandwidths. A kernel with large bandwidth segments the image into large segments, while a kernel with smaller bandwidth segments the image into smaller segments.

This will result in segmented regions, the segmented regions of the upper row in with the weight applied, where a brighter pixel corresponds to a larger weight. Using the weight, applied colorization basis results in colorization with larger weights in the centers of the segmented regions. Obviously, the minimization process in (10) or (11) will select the RP set corresponding to the column vectors containing large segmented regions with large priority, since the L_2 error grows if they are not chosen.

This will colorize the reconstructed image at course scale. Since the RP corresponding to the large-scaled segmented regions are chosen with large priority, the image becomes fully colorized leaving no regions lacking the Cb or Cr components.

After the RP corresponding to large-scaled segmented regions are selected, further RP corresponding to smaller regions are selected according to the errors they reduce. This will add detailed colors to the reconstructed color image the decoder. Figure 5 shows the reconstructed color images reconstructed with different numbers of RP and different numbers of scales. The different scales are constructed by using different spatial and range parameters in the mean shift segmentation .It can be seen that the image reconstructed with a small number of RP is colorized at somewhat course scale, since they correspond to the large-scaled segmented regions, while detailed colors appear in the colorized image when more RP are involved. Table I shows the framework of the proposed method pseudo codes. We omitted the compression/ decompression process on the luminance channel for simplicity.

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III. RESULTS AND DISCUSSION

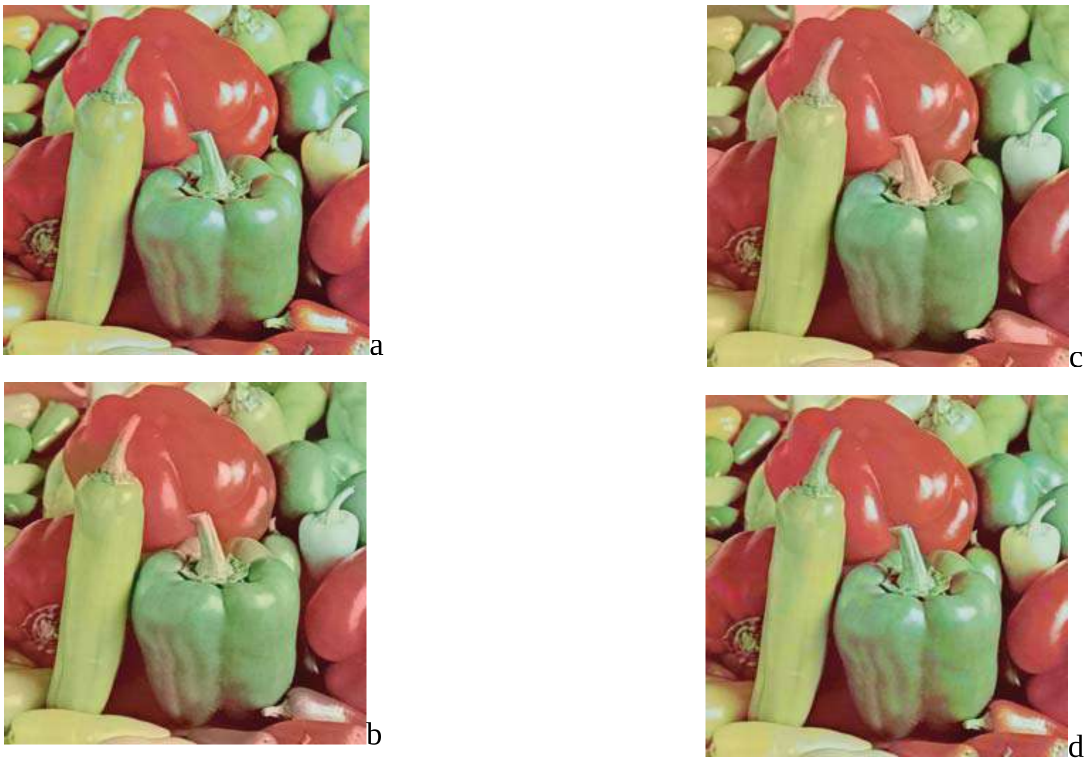

Fig.2. Experimental results with the 256*256 (a)orginal. (b)Cheng *et.al.* (c)Ono et *al.* (d) Proposed

Fig.3. Experimental results with the 256*256 (a)orginal. (b)Cheng *et.al.* (c)Ono et *al.* (d) Proposed

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This explains the details of the implementation of the proposed method. When constructing the matrix *C*, we used a 16-scale segmentation, which means that we performed the mean shift segmentation with 16 different spatial and range resolutions, i.e., a combination of four different spatial and four different range resolutions. The parameters h_s and h_r control the spatial and the range resolutions, respectively, and large values of h_s and h_r result in large scaled segmented regions. The meaning of h_s and h_r is the same as in [12].The parameters (h_s , h_r) used in each scale are as follows: Scale 1: (51, 408), Scale 2: (51, 204), Scale 3: (51, 102), Scale 4: (51, 51), Scale 5: (25.5, 204), Scale 6: (25.5, 102),Scale 7: (25.5, 51), Scale 8: (25.5, 25.5), Scale 9: (15.3, 122.4),Scale 10: (15.3, 61.2), Scale 11: (15.3, 30.6), Scale 12: (15.3), Scale 13: (10.2, 81.6), Scale 14: (10.2, 40.8), Scale(10.2, 20.4), Scale 16: (10.2 ,10.2).

The order of the positions of the colorization basis vector sin *C* is determined by the scale and the mode. That is, colorization basis vectors are classified first into 16 different parts in *C* according to the scale. After that, in each part, colorization basis vectors are ordered again according to raster scan order of the modes of the corresponding segmented regions. Here, the mode refers to the local maxima of assumed probability density function of the feature space the segmented region [12].

Using the same procedure, same matrix *C* can be reconstructed in the decoder using luminance channel sent from the encoder, and therefore, the intended colorized image can be reconstructed using RP set also sent from the encoder.It is observed that the positions of the RP in **x** for the and the Cr components are almost the same, and therefore, encode the positions only for the Cb components.

This compared the proposed method with the JPEG and the JPEG2000 standards, as well as two conventional colorization based coding methods, the method of Cheng *et al*. [1] and the method of Ono *et al*. [4]. We used a 4:1:1 color format, which means that the size of the reconstructed Cb and Cr chrominance images are one-fourth of the luminance image. To make the visual comparison easy, this constructed the colors with a very small number of coefficients (or RP) for all the methods. In the comparison with conventional colorization based coding methods, we used an uncompressed luminance channel in the reconstruction of the color image for all methods. The proposed method surpasses other colorization based coding methods by a large amount, and using a compressed luminance channel makes no difference in the comparative result. In the comparison with the JPEG/JPEG2000 standards, used a compressed luminance channel. Using a compressed luminance channel deteriorates the PSNR a little compared with that using an uncompressed luminance channel. For conventional colorization based codings, used bytes to encode each RP, where 2 bytes are used to encode the x and y coordinates, and 2 bytes to encode the Cb and Cr chrominance values. We used a total of 175RP at the start the iteration. However, for the method of Ono *et al*., the number of RP changes after each iteration, and therefore, it was not easy to make the final file size similar to that of ours. For the proposed method, we used (11) with $L = 200$, e., we used a total of 200RP. We could use more RP than conventional colorization based coding methods, since we need a smaller number of bits encode the RP. However, the quality of the reconstructed color image is much better with the proposed method even when using the same or even a smaller number of RP. Thus, we use 28 bits to encode each RP, where 12 bits are used to determine the position of the RP in **x**, and 2 bytes (16 bits) For the comparison with the JPEG/JPEG2000 standards uses standard JPEG/JPEG2000 encoders. The file sizes of the images compressed with JPEG/JPEG2000 standards are the sums of the compressed luminance channel and the chrominance values together. With the proposed method, the file size is the sum of the compressed luminance channel and the RP set.

Here, this compared the total file sizes of the different methods and therefore, to match the total file sizes, the sizes of the compressed luminance channels are not the same between the different methods. We further reduced the number of bits used.

For the comparison with the JPEG/JPEG2000 standards, we used standard JPEG/JPEG2000 encoders. The file sizes of the images compressed with JPEG/JPEG2000 standards are the sums of the compressed luminance channel and the chrominance values together. With the proposed method, the file size is the sum of the compressed luminance channel and the RP set. Here, this compared the total file sizes of the different methods, and therefore, to match the total file sizes, the sizes of the compressed luminance channels are not the same between the different methods.

Further reduced the number of bits used JPEG2000 standard. To show that the proposed compression framework has potential to further increase its performance varied the proposed method a little, by putting some extra small-scaled wavelet basis vectors in the colorization matrix *C*, together with the basis vectors generated by the mean shift segmentation.

This does not increase the file size of the encoded image, due to the fact that wavelet basis vectors can be generated without the knowledge about the image. The chances that the L_2 difference error reduces are now increased, since C contains more column vectors, and (11) will choose the optimal linear combination of the column vectors with respect to the L_2 difference error. Therefore, the PSNR values increases and surpasses the performance of the JPEG2000 application.

IV. CONCLUSION AND FUTURE ENHANCEMENT

In this system formulated the colorization based coding problem into an optimization problem. By formulating the problem as an optimization problem we have opened the way to tackle the colorization based coding problem using several well-known optimization techniques. Furthermore, proposed a method to compute the colorization matrix which can colorize the image with a very small set of RP. Experimental results show that the proposed method surpasses other colorization based coding methods to a large extent in quantitative as well as qualitative measures. The proposed method also surpasses the JPEG standard, and is comparable to the JPEG2000 standard. However, the problem of computational cost and use of large memory remains, and has to be further studied.

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