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Expansion In Valorization Based Confining

J.N.CHANDRA SEKHAR
Assistant Professor, Dept of CSE, KKR & KSR Institute of Technology and Sciences, Guntur, A.P, India.

M. NAGARAJU
Assistant Professor, Dept of CSE, KKR & KSR Institute of Technology and Sciences, Guntur, A.P, India.

Abstract: **Colorization is a process of adding colors to a black and white image. 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) 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.**

I. INTRODUCTION

A new compression technique for color images, which is based on the use of colorization methods, has been proposed. Previously, several colorization methods like YUV Color space algorithm 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 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 image become good. Earlier, several methods like Semi-supervised learning, Graph-based learning, Transductive and Inductive learning have been proposed. 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 L1 minimization problem. The optimization problem can also be considered as a variational approach, and therefore, the rich research results of the variational approach in image processing can be used in the colorization based coding problem.We also propose a construction method of the colorization matrix, which, combined with the proposed RP extraction method, produces a high quality reconstructed color image.

II. EXISTING SYSTEM

Recently, a new compression technique for color images, which is based on the use of colorization methods, has been proposed. Previously, several the encoder selects the pixels required for the colorization process, which are called representative pixels (RP) by segmenting the image into squares, 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.

colorization methods have been proposed to colorize grayscale images using only a few representative pixels provided by the user. 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 image become good. Several methods have been proposed and 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.

Disadvantages of Existing System:

- The techniques that have been used to extract the Representative Pixels (RP) follow the iterative approach.
- Initially, user has to determine the sample RP and has to compare with the original image.
- If there is error, then again there involves several RP extraction and RP reduction process.
- The above process has to be repeated until the correct image is obtained.

But still, there obtains the redundancy of pixels and also some important pixels might be missing in the RP set.

III. RELATED WORKS

To understand the proposed method, three major related works have to be explained.

A. Levin's Colorization Technique: In Literature survey, 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 Literature survey we 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.

***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.

IV. LITERATURE REVIEW

Instead of performing a frequency transformation, we store a grayscale version of the image and color labels of a few representative pixels. Using the stored information, we learn a model which predicts the color for the rest of the pixels.

Semi-Supervised Learning

Semi-supervised learning refers to the problem of learning from labeled and unlabeled data. A graph G consists of an ordered and finite set of n vertices V denoted by {v1,v2,…..,vn}, and a finite set of edges $E \subset V \times V$.

A vertex Vi is said to be a neighborhood of another vertex Vj if they are connected by an edge.

Transductive and Inductive Learning:

In transductive learning, one is given a labeled training set and an untrained test set. The idea is to perform predictions only for the given test points.

In inductive learning, the goal is to output a prediction function which is defined on the entire space.Inductive algorithms can easily be used to predict labels on closely related images, transductive algorithms are unsuitable.

Graph Regularized Experimental Design

Another key step in learning based image compression is to select the most representative pixels. An active learning algorithm, called Graph Regularized Experimental Design (GRED), for this purpose based on LapRLS.

Often estimates of the parameters (w) are of interest together with predictions of the responses (y) from the fitted model. The variances of the parameter estimates and predictions depend on the particular experimental designs used and should be as small as possible.

Recently, a novel approach to color image compression based on colorization has been resented. Although the conventional method of colorization-based coding outperforms JPEG in terms of subjective quality, the decoded chrominance components lose the local oscillation that the original images had. A large number of color assignations is required to restore these oscillations. We focus on the local correlation that exists between luminance and chrominance in separated texture components, and we present a new colorization-based coding method. Experimental results showed that our coding method can restore the oscillation and improve the coding efficiency compared with the conventional method.

Colorization-based Coding by Cheng et al

Cheng et al's colorization-based coding uses an active learning approach to extract RP automatically. Their methods perform better than JPEG for color components.

The steps of their method are given below.

1. Divide original image into clusters by image segmentation algorithm.

2. Extract RP randomly from each cluster.

3. Conduct colorization by using temporary RP.

4. Search for clusters that have high error between original and colorized images.

5. Extract more RP from high-error clusters.

6. Repeat 4–5.

The above algorithm produces redundant pixels. So, the following method has to be followed.

1. Setting of initial RP
2. Redundancy reduction of RP.
3. Extraction of required pixels for RP.

Colorization is a computer assisted process of adding color to a monochrome image or movie.

The process typically involves segmenting images into regions and tracking these regions across image sequences. Neither of these tasks can be performed reliably in practice.

Here, neighboring pixels in space-time that have similar intensities should have similar colors. For this purpose the formulization of quadratic function is done and is obtained an optimization problem that can be solved efficiently using standard techniques.

The algorithm is given a input an intensity volume Y(x,y,t) and outputs two color volumes U(x,y,t) and v(x,y,t). Thus, Y(r) is the intensity of a particular pixel.

The encoder and the decoder share a collection of random vectors (Xk) where the Xk's are independent Gaussian vectors with standard normal entries. We can imagine that the encoder would send the seed of a random generator so that the decoder would be able to reconstruct those "pseudorandom" vectors.

Encoder: To encode a discrete signal f, the encoder simply calculates the coefficients yk=<f,Xk> and quantizes the vector y.

Decoder: The decoder then receives the quantized values and reconstructs a signal by solving the llinear program.

V. PROPOSED METHOD

While most colorization based coding methods try to extract the RP set by using an iterative approach, we 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. We 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.

A. Overall System Diagram

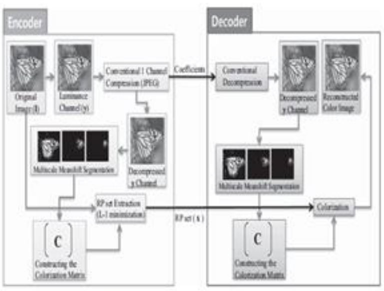


Fig. 1. Overall system diagram from encoder to decoder of the proposed compression framework.

Figure 1 shows the overall system diagram of the proposed method. The details of the components are described in the following subsections. 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 meanshift segmentation on the decompressed luminance channel. The decompressed luminance channel is used to consist 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.

B. Formulating the RP Extraction Problem into an L1 Minimization Problem

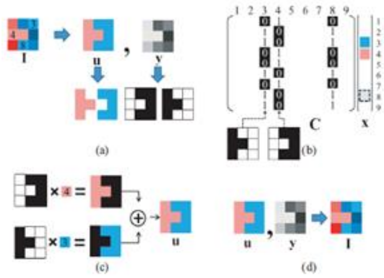


Fig. 2. Exemplary image of reconstructing the colorization matrix. (a) Decomposing the image, (b) constructing the colorization matrix, (c) reconstructing the chrominance channels, and (d) reconstructing the color image.

The colorization process can be expressed in matrix form as follows:

$$\mathbf{u} = C\mathbf{x} \qquad \text{……(6)}$$

Here, C represents the matrix which performs a colorization process on **x** to obtain the colorized image **u**. Here, **u** is a one dimensional vector of size n, representing the image in raster scan order which has n pixels. The Levin's colorization method can be expressed by (6) with C = A−1, where C is a square matrix of size n × n. In the proposed method, C has the size n×m, where m is the size of **x**, and normally m < n. Other colorization methods can also be expressed by (6) using different C matrices. In the colorization process, C and **x** are given and **u** is the solution to be sought. In contrast, in colorization based coding, the problem in the encoder is to determine **x** when C and **u** are given. For the aim of compression, we seek to obtain a sparse vector **x**. Therefore, we formulate the problem of selecting the RP as an L0 minimization problem

$$\underset{\mathbf{x}}{\operatorname{argmin}} |\mathbf{x}|_0, \ \text{s.t. } \mathbf{u}_0 = C\mathbf{x}. \qquad (7)$$

Unfortunately, the matrix C does not satisfy the RIP (Restricted Isotropy Property) condition. Therefore, the problem in (7) cannot be changed directly into an equivalent L1 minimization problem. To change the L0 minimization problem in (7) into an equivalent L1 minimization problem, we have to manipulate the matrix C to satisfy the RIP condition. We multiply a random gaussian matrix RG, which derives its entries from a zero-mean gaussian distribution, to C (and to **u**0) to obtain the matrix RGC which satisfies the RIP condition. The size of RG is l ×n, where normally l < n. This results in the following L0 minimization problem

$$\underset{\mathbf{x}}{\operatorname{argmin}} |\mathbf{x}|_0, \ \text{s.t. } R_G\mathbf{u}_0 = R_G C\mathbf{x} \qquad (8)$$

which can be changed into the following equivalent L1 minimization

$$\underset{\mathbf{x}}{\operatorname{argmin}} |\mathbf{x}|_1, \ \text{s.t. } R_G\mathbf{u}_0 = R_G C\mathbf{x}. \qquad (9)$$

Equation (9) is an optimization problem and can be solved by linear programming such as the Basis Pursuit (BP) or Orthogonal Matching Pursuit (OMP) .Since (9) is an optimization problem, the various results from variational methods can be incorporated into the colorization based coding problem. For example, (9) can also be reformulated as an unconstrained problem

$$\underset{\mathbf{x}}{\operatorname{argmin}} |\mathbf{x}|_1 + \lambda \| R_G\mathbf{u}_0 - R_G C\mathbf{x}\|^2 \qquad (10)$$

which can be solved by various algorithms developed for unconstrained problems, e.g., the Bregman iterative algorithm in Literature survey. Other weighted L2 norms that consider the image characteristics can be used instead of the normal L2 norm in (10). The unconstrained problem (10) is a more practical choice, since the linear constraint in (9) is too strong a constraint, and therefore, the BP solver will often fall into an unsolvable state. For the unconstrained problem, the solution varies as the parameter λ varies. In fact, we can alternatively solve the following problem, such that we can control the number of nonzero components as we are minimizing the error between the reconstructed and the original color images

$$\underset{\mathbf{x}}{\operatorname{argmin}} \|\mathbf{u}_0 - C\mathbf{x}\|^2, \ \text{s.t. } |\mathbf{x}|_0 \le L \qquad (11)$$

whereL is a positive integer that controls the number of nonzero components in **x**. The number L can be determined by the desired compression rate, i.e., if we want a large compression rate, then L is set to a small number. The above problem can be solved either by the BP or the OMP solver. 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, we have designed a way to adopt existing optimization techniques to the problem of RP selection. There is one more main difference between the proposed method and other colorization based coding methods 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. Segmentation Techniques in the Construction of the Colorization Matrix As has been seen in the previous section, segmentation plays an important role in the construction of the colorization matrix. In this section, we explain why we have to use a multi-scale segmentation.

1) **Mean shift Segmentation**: In this paper, we use the meanshift segmentation in Literature survey 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, we 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 suite well with the proposed method.

2) **Multiscale Segmentation**: We perform a multi-scale meanshift segmentation to construct the colorization basis. The reason that we use a multi-scale segmentation is that there is the possibility that some regions in the colorized image may lack either the Cb or the Cr components when using singlescale 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 to the L1 minimizing constraint.

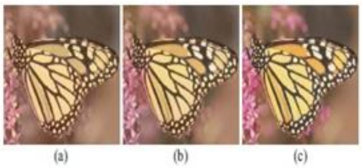


Fig. 5. Colorization results by using the RPs corresponding to (a) scale 1-4, (b) scale 1-8, and (c) scale 1-12, where the scales are as defined in Section 4.

5.2 ALGORITHMS

ENCODER

1) **Input:** Original color image. I
2) **Decomposition:** Decompose I into its luminance channel (y) and original chrominance images uCb0 and uCr0.
3) Perform multi-scale meanshift segmentation on y to obtain segmented regions _kj,

   j = 1, . . .nk , ∀k .
4) Construct column vectors c j, k using _kj , j = 1, . . . nk , ∀k .
5) Concatenate the column vectors construct c j,k to construct the colorization matrix C.
6) Using the Orthogonal Matching Pursuit (OMP) obtain theRP set x for u0 = uCb0 and u0 = uCr0.
7) **Output:** Final RP set x = {xCbk ,xCrk } (optimal with respectto the matrix C).

DECODER

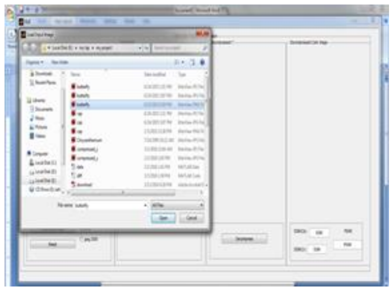
1) **Input:** Luminance channel (y), RP set $x=\{x^k_{Cb},x^k_{Cr}\}$.
2) **Reconstruction:**
   a) Reconstruct the matrix C by performing multi-scale meanshift segmentation on y.
   b) Reconstruct the color components by

      $u_{Cb}=Cx_{Cb}$ **and** $u_{Cr}=Cx_{Cr}$
   c) Reconstruct color image I by combining the luminance channel y and the color components u_{Cb} and u_{Cr}.
3) **Output:** Reconstructed color image I.

VI. RESULTS

7.1: Screen Shot after running gui.m

Screen shot for reading image



Screen shot after loading image

Screen shot after Reconstruction of image in decoder

VII. CONCLUSION

In the proposed system, I have formulated the colorization based coding problem into an optimization problem. By formulating the problem as an optimization problem I have opened the way to tackle the colorization based coding problem using several well-known optimization techniques. Furthermore, I proposed a method to compute the colorization matrix which can colorize the image with a very small set of RP. However, the problem of computational cost and use of large memory remains, and has to be further studied.

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www.mathworks.in

AUTHOR's PROFILE

J.N.ChandraSekhar, Asst.Professor, Area of Interests: Data Mining, Big Data, Soft Computing, Digital Image Processing.

M.NAGARAJU, Assistant Professor, Area of Interests: Data Mining, Big Data, Network Security, Artificial Intelligence.

