International Journal of Engineering Research and General Science Volume 3, Issue 2, March-April, 2015
ISSN 2091-2730

A Novel Approach for Compression Using Optimized Colourisation Method

Remya R Mohan, Sobin Francis, Ambily P K

Department of ECE, IHRD College of Engineering Poonjar, CUSAT, Kerala, India

Email: remyar784@gmail.com

Abstract- Colorization is a process of adding a color to a gray scale image. In this paper formulating a colourisation based compression into an optimisation method, ie, L1- Minimization method. That means instead of performing frequency transformation we can store grayscale version of image along with some color information of a very few pixels. The encoder selects pixels required for colourisation which is user defined and sends its position vectors and color labels to decoder along with compressed luminance component of image. These pixels are known as Representative Pixels (RP). Then, the decoder restores the color information for the remaining pixels using suitable colorization methods.The main function of this coding is the extraction of RP. By formulating RP selection into L1 minimization problem we can reconstruct image with high PSNR value. Also to improve visual quality separate encoding for geometry and texture can be performed. Thus it avoids the loss of local oscillation between original and reconstructed image. Geometry and texture separation is done by total variation regularisation. The texture components are compressed into coefficients that represent correlation between luminance and chrominance values and geometry components are compressed by formulating RP selection problem into L1 minimization problem.

Keywords— Colourization, L1-minimization, Texture, Geometry, Compression, Representative pixels, Total Variation Regularisation, Encoder, Decoder, PSNR,SSIM.

INTRODUCTION

The basic objective of image compression is to find an image representation in which pixels are less correlated. Recently, machine learning based approach has been proposed for image compression instead of frequency transformation. From a machine learning perspective, two fundamental problems are there. One is how to select the most representative pixels, which is essentially an active learning problem. The selected pixels, together with the gray scale image are stored as the encoding process. Another is how to combine color and gray scale information of the pixels to learn a model, which is essentially a semi-supervised learning problem. The learned model is used to recover the color image as the decoding process. It is observed that, in many images, there is a great deal of color coherence. In particular, most images consist mainly of regions of smoothly varying color. This suggests that colors at a subset of locations can be stored and the necessary gradients can be subsequently generated through a process of optimization. Since the information amount for representing positions and color values of these locations is small, a novel approach to image compression by using colorization (called colorization-based coding) has been proposed. The main task in semi-supervised learning 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.

Colorization based coding utilizes the fact that the required number of pixels having color information is small. The main issue in colorization based coding is how to extract the RP set so that the compression rate and the quality ofthe restored color image become good. Another issue is how to restore the chrominance components without losing the local oscillation that the original images had. Due to these a novel method is needed for image compression which gives better quality and good compression ratio.

RELATED WORK

Cheng et al: Cheng *et al*'s colorization-based coding uses an active machine learning approach to extract RP automatically. It is better than JPEG std for color components. The steps of this 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.

Additionally, Cheng *et al* apply some extension to Levin's colorization to suit their approach. However, their colorization-based coding cannot reduce the redundant RP if the initial RP (extracted at step 2) already have redundancy.

Colorization-Based Compression Techniques: The function of colorization based coding is the extraction of the RP. Existing methods use an iterative approach to extract the RP. In those 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.

Levin's Colorization: The concept of Levin *et al*'s colorization algorithm is neigh boring pixels that have similar intensities should have similar colors. Consider the YCbCrcolor space. Y is the luminance component corresponding to $\boldsymbol{y}$, and Cb or Cr is the color component corresponding to $\boldsymbol{u}$. Let n be the number of pixels in the original image and r be an identifier of the pixels in raster-scan order ($1 \leq r \leq n$). $\boldsymbol{u}$is assumed to be a one-dimensional vector that contains a color component restored by colorization (denoted as the restoration color component) and is arranged in column in raster-scan order. $\boldsymbol{x}$ is assumed to be a one-dimensional vector that contains RP values, and $\boldsymbol{x}$ has non-zero values only for RP. $u(r)$ and $x(r)$ are the r-th elements of $\boldsymbol{u}$ and $\boldsymbol{x}$ respectively. $\Omega = \{ r/x(r) \neq 0\}$ is a set of positions of RP. Obviously, $|\Omega|$ is the number of RP that have a specific color value, and it corresponds to the amount of information in-colorization based coding. Let $y(r)$ be a luminance component at the r-th pixel. $s \in N(r)$ denotes that the s-th pixel is belonging to the neighbour (defined as 8 surrounding pixels) of the r-th pixel. Levin *et al* defined a cost function as

$$J(u) = \sum_{r \neq \Omega}^{\infty} \left(\mathrm{u(r)} - \Sigma \mathrm{wrsU(s)}\right)^2 + (\Sigma \mathrm{U(r)} - x(r))^2$$

PROPOSED METHOD

The overall system diagram is shown below. In encoder, the original color image is first decomposed into its luminance channel and its chrominance channels. The luminance channel is compressed using JPEG std. and its discrete Fourier or Wavelet coefficients are sent to the decoder. Then for each component Y,Cb and Cr , geometry and texture are separated using total variation regularization to get geometry components Y_g,C_{bg} and C_{rg} and texture components Y_t,C_{bt},C_{rt}. Also, in the encoder, a colorization matrix C is constructed by performing multi-scale mean shift segmentation on the geometry component. 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. Here the algorithm used is Orthogonal Matching pursuit algorithm (OMP).

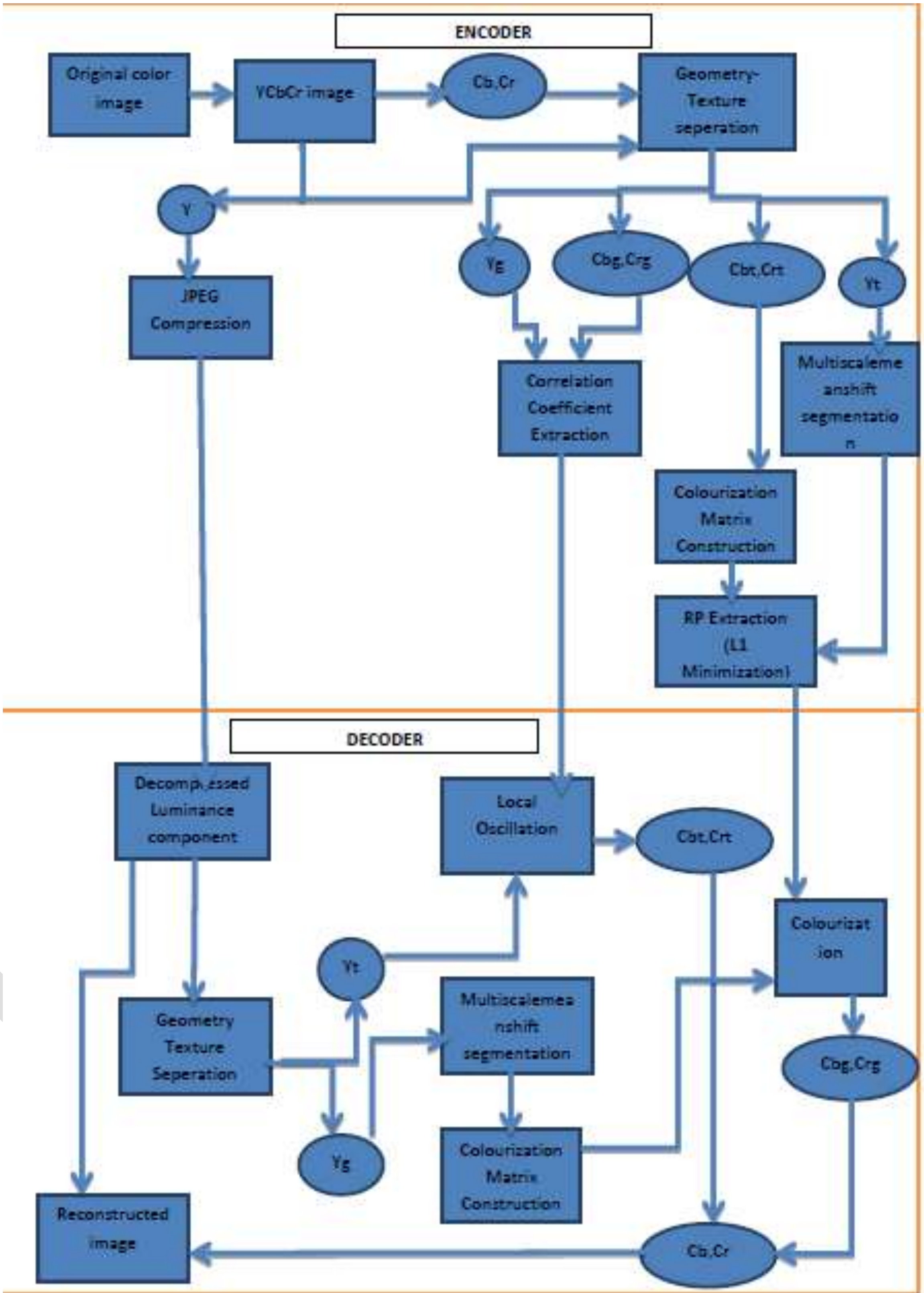


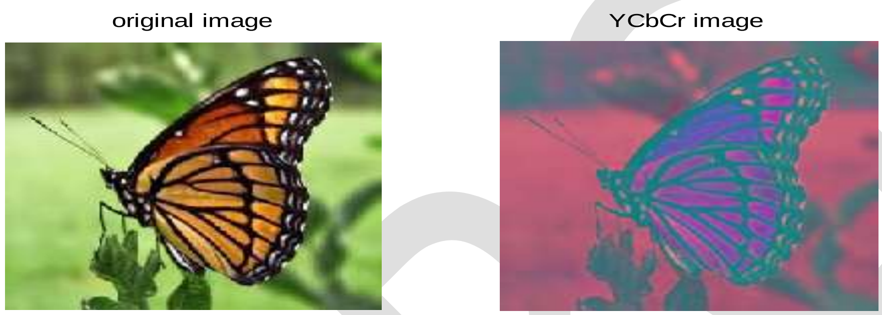
Fig 1: Overall System Diagram

This RP set is sent to the decoder, where the colorization matrix C is also reconstructed from the luminance channel of geometry component. Then, by performing a colorization using the matrix C and the RP set, the color components of geometry part is

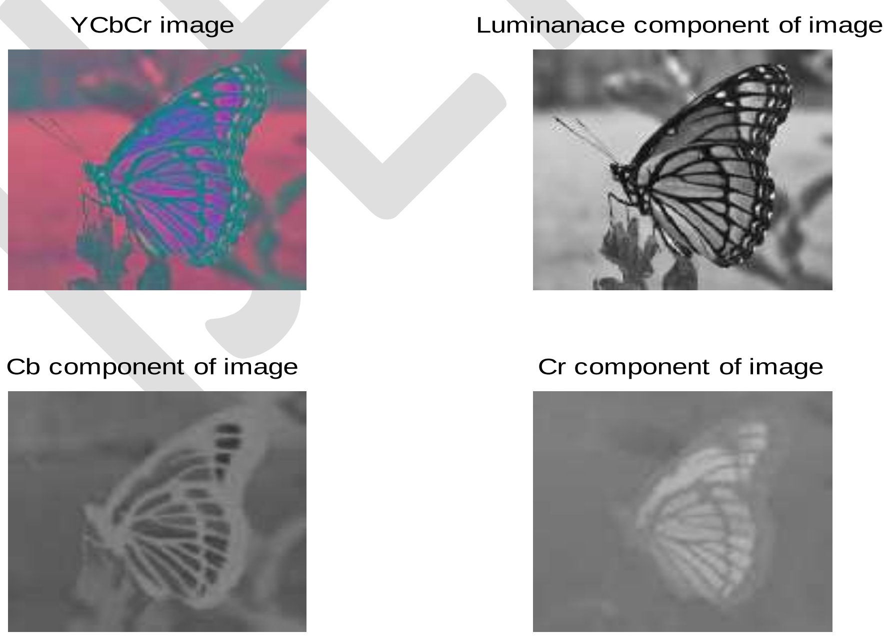
International Journal of Engineering Research and General Science Volume 3, Issue 2, March-April, 2015
ISSN 2091-2730
reconstructed. For color coding of texture part, correlation coefficients a_{cb} and a_{cr} are extracted. Using texture part of luminance (Y_t) and correlation coefficients (a_{cb} and a_{cr}), texture part of chrominance (C_{bt},C_{rt}) are reconstruct-ed. All components of geometry and texture are combined to restore the image.

RESULT

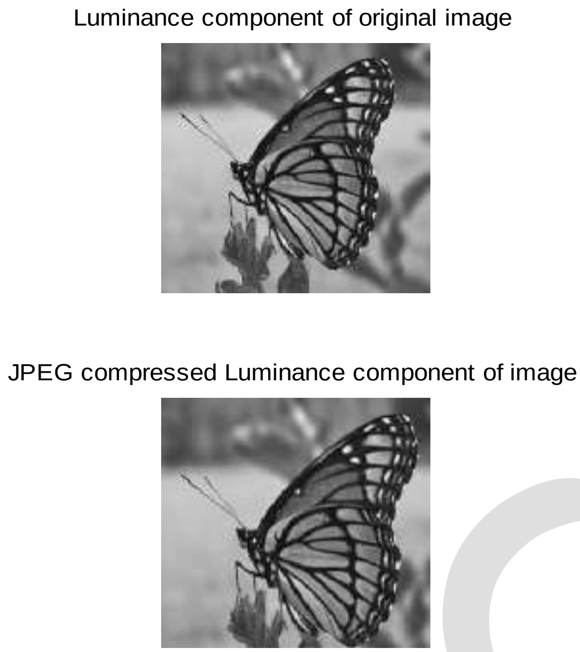
To make the visual comparison easy, we constructed the colors with a very small number of coefficients (or RP) for all the methods. In the comparison with conventional colorization based coding methods, we used an uncompressed luminance channel in the reconstruction of the color image for all methods. 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.
Figures show the results of the implementation in MATLABR2013a:



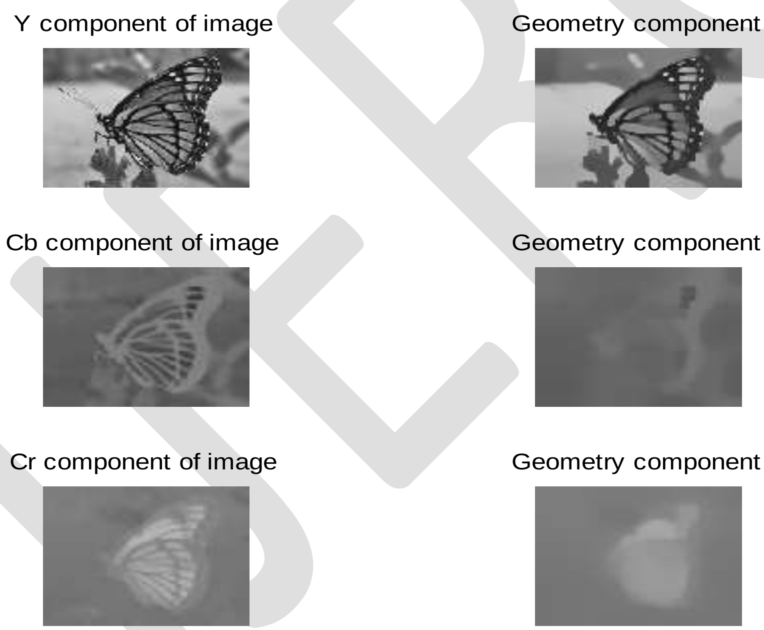
Step 1: Original image is converted into YCbCr. (Figure 2)



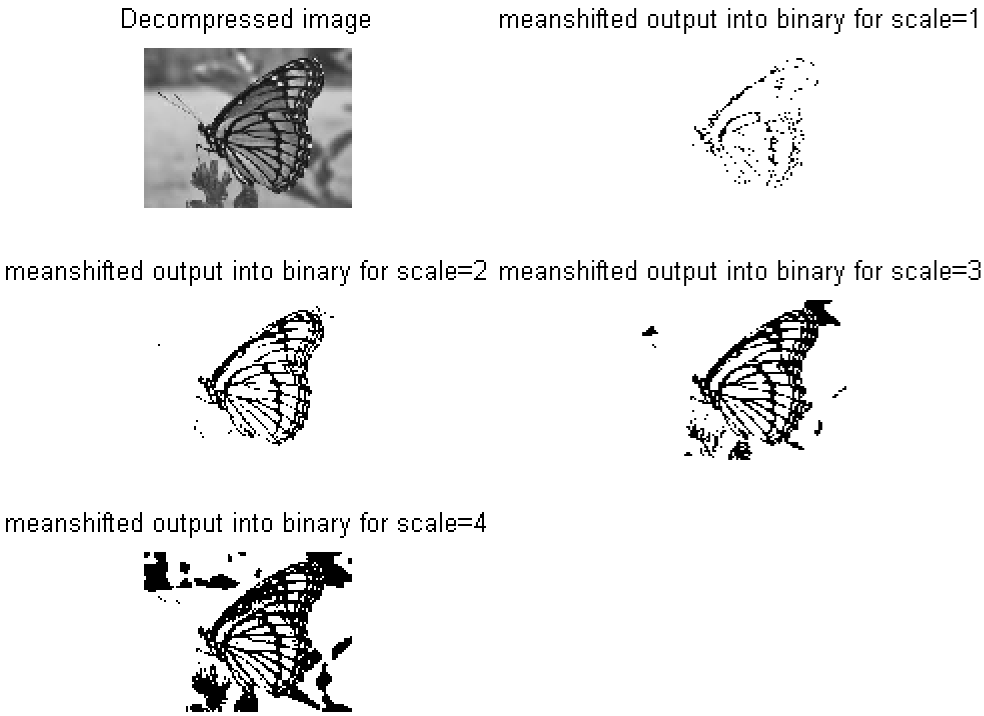
Step 2: Decompose I into its luminance channel and original chrominance images. (Figure 3)



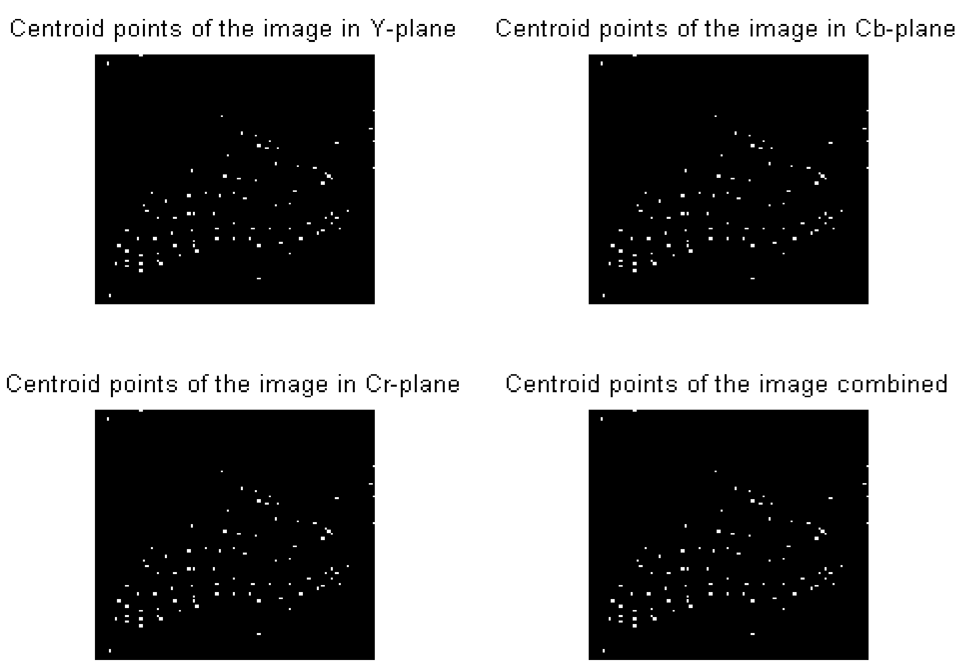
Step 3: Perform JPEG compression on the luminance component of original image. (Figure 4)



Step 4: Geometry component of Y,Cb,Cr channels. (Figure 5)



Step 5: The colourization matrix is constructed by performing multiscale mean shift segmentation on the luminance component. (Figure 6)



Step 6:Using this matrix and chrominance values perform Orthogonal Matching Pursuit (OMP) algorithm to get Representative Pixels (RP) and these pixels are send to the decoder .(Figure 7)

Y component of image

Texture component of image

Cb component of image

Texture component of image

Cr component of image

Texture component of image

Step 7: Find Correlation Between luminance and chrominance components of the texture part. (Figure 8)

Original image

Reconstructed image

Step 8: In decoder, using these RP set and the same colourization matrix, constructed in encoder and the correlation coefficient reconstruct original image. (Figure 9)

PSNR and SSIM

The peak signal-to-noise ratio (PSNR) and structural similarity (SSIM Structural Similarity Index Matric) value as an objective evaluation of image quality for comparison. PSNR is defined as

$$\mathrm{PSNR} = 10 * \log 10(\frac{256^2}{\mathrm{mse}})$$

where MSE is Mean Square Error.

SSIM isthe image quality assessment based on the degradation of structural information, better for the human visual estimation than traditional image qualityassessments such as PSNR. SSIM between images X and Y is defined as

SSIM = {(2µxµy + C1) + (2σxy + C2)}/{(µx2 + µy2 + C1)(σx2 +σy2 + C2)}

Where µx is the average of X and µy is the average of Y. σxy is the covariance of X and Y. σx is the variance of X and σx is the variance of Y. C1 andC2 are constants. Result numbers are averages of PSNR and SSIM of thethree RGB components. Using a compressed luminance channel deterioratesthe PSNR a little compared with that using an uncompressed luminancechannel.

Results obtained in command window

- Size of colourization matrix= [10000 9606]
- The PSNR Value = 25.7824
- SSIM = 0.9026
- Elapsed time is 54.788464 seconds.

CONCLUSION

Compression Using Optimized Colourisation Method was implemented and analysed. In this method, the geometry and texture of an image are separated using total variation regularization. The texture components are compressed into coefficients that represent the correlation between luminance and chrominance, and the geometry components are compressed by formulating the RP selection pro-lem into an L1 minimization problem. The compression performance and visual quality was evaluated using SSIM and PSNR values. Using this method, the compression gain becomes high and the reconstructed image has good visual quality. The speed of execution of proposed system is slow. The method can be improved further by increasing the speed of algorithm. Also the proposed method can be extended from still images to video too.

ACKNOWLEDGMENT

I would like to express my deepest gratitude to God Almighty in completing this thesis and also express my heartfelt thanks to parents, professors and friends who extended their sincere support for the fulfillment of both theoretical and practical work of my paper.

REFERENCES:

[1] Sukho Lee, Sang-Wook Park, Paul Oh, and Moon Gi Kang, "*Colorization-Based compression using optimization*" IEEE Transactions On Image Processing, Vol. 22, No. 7, Pp. 2627-2636, July 2013.

[2] L. Cheng and S. V. N. Vishwanathan, "*Learning to compress images and videos*," in Proc. Int. Conf. Mach. Learn., vol. 227. 2007, pp. 161–168.

[3] X. He, M. Ji, and H. Bao, "*A unified active and semi-supervised learning framework for image compression*," in Proc. IEEE Comput. Vis. Pattern Recognit., Jun. 2009, pp. 65–72.

[4] T. Miyata, Y. Komiyama, Y. Inazumi, and Y. Sakai, "*Novel inverse colorization for image compression*," in Proc. Picture Coding Symp., 2009, pp. 1–4.

[5] A. Levin, D. Lischinski, and Y.Weiss, "*Colorization using optimization*," ACM Trans. Graph., vol. 23, no. 3, pp. 689–694, Aug. 2004.

[6] J AntoniBuades, Triet M. Le, Jean-Michel Morel, and Luminita A. Vese, "*Fast Cartoon + Texture Image Filters,*" IEEE Transactions On Image Processing, Vol. 19, No. 8, August 2010.

[7] Li XuQiong Yan Yang Xia JiayaJia ,"*Structure Extraction from Texture via Relative Total Variation*" Department of Computer Science and Engineering, The Chinese University of Hong Kong

[8] S. Ono, T. Miyata, and Y. Sakai, "Colorization-based coding by focus-ing on characteristics of colorization bases," Dec. 2010

[9] D. Comaniciu and P. Meer, "Mean shift: A robust approach toward feature space analysis," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 24, no. 5, pp. 603–619, May 2002.

[10] J. A. Tropp and A. C. Gilbert, "Signal recovery from random meas-urements via orthogonal matching pursuit," *IEEE Trans. Inf. Theo-ry,*vol. 53, no. 12, pp. 4655–4666, Dec. 2007.

[11] G. K. Wallace, "The jpeg still picture compression standard," *Com-munications of the ACM*, Apr. 1991.

[12] W. Yin, S. Osher, D. Goldfarb, and J. Darbon, "Bregman iterative algorithms for *L*1-minimization with applications to compressed sensing,"*SIAM J. Imag.Sci.*, vol. 1, no. 1, pp. 143–168, 2008.

[13] E. Candés and T. Tao, "Near optimal signal recovery from random projections: Universal encoding strategies," *IEEE Trans. Inf. Theory*, vol. 52, no. 12, pp. 5406–5425, Dec. 2006.

[14] S. S. Chen, D. L. Donoho, and M. A. Saunders, "Atomic decomposition by basis pursuit," *SIAM J. Sci. Comput.*, vol. 20, no. 1, pp. 33–61, 1998.

[15] E. Candés, J. Romberg, and T. Tao, "Stable signal recovery from incomplete and inaccurate information," *Commun. Pure Appl. Math.*, vol. 59, no. 8, pp. 1207–1233, 2005.