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Colorization-Based Image Compression using L1 Minimization

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Abstract: This paper defines the colorization-based coding issue into a streamlining issue, i.e., a L1 minimization issue. In colorization-based coding, the encoder picks a couple of delegate pixels (RP) for which the chrominance qualities and the positions are sent to the decoder, even though in the decoder, by colorization techniques the chrominance values for every one of the pixels are recreated. The primary issue in colorization-based coding is the way to remove the RP, hence the pressure rate and the nature of the reproduced shading image turns out to be well appeared. By figuring the colorization-based coding into a L1 minimization issue, it is ensured that the given colorization grid and the picked arrangement of RP turns into the ideal set as it minimizes the lapse between the first and the remade shading image. As such for a given colorization grid, the picked arrangement of RP is the smallest set conceivable. The proposed strategy beats ordinary colorization-based coding strategies, the JPEG standard and it is similar with the JPEG2000 pressure standard, both in terms of the pressure rate and the nature of the reproduced shading image.

Index Terms: DCT Co-efficient, Representative pixels (RP) set, image compression, Sparse L1 minimization.

1. INTRODUCTION

As more and more visual data is being exchanged, there is an ever increasing demand for better pressure rate which will diminish system activity. In The pressure procedure for shading images, colorization techniques taking into account. The fundamental assignment in colorization based pressure is to separate these delegate pixels in the encoder. At the end the encoder chooses the pixels needed for the colorization process, which are called agent pixels (RP) in, and keeps up the shading data just for these RP[1]. The position vectors and the chrominance qualities are sent to the decoder just for the RP set together with the luminance channel, which is packed by customary pressure procedures. At that point, the decoder restores the shading data for the remaining pixels utilizing colorization systems. The fundamental Issue in colorization based coding is the means by which to remove the RP set, so that the pressure rate and the nature of the restored shading image turn out to be great. This paper represents RP determination issue into an advancement issue i.e., a L1 minimization issue. The choice of the RP is ideal concerning the given colorization grid as in the distinction blunder between the first shading image and the remade shading image gets to be least regarding the L2 standard mistake. In addition to the quantity of pixels in the RP set is additionally minimized by the L1 minimization. The ideal arrangement of RP is acquired by a solitary minimization step, and does not require any refinement i.e., any extra RP extraction/lessening strategies[2]. The advancement issue can be considered as new approach. In this paper we propose a strategy to focus the colorization lattice from the given luminance channel before the RP determination.

II. EXISTING METHOD

Colorization – the procedure of adding color to a grayscale image or video sequence. The existing algorithms are tedious and labor-intensive. A particularly relevant Levin algorithm [3], which we now present using notation that makes it easy to see connections to semi-monitored learning. Given a grayscale image with a few color patches, it enforce the constraint that two neighboring pixels should have same colours if their intensities are similar. The predictor is forced to take on user-specified values on the all pixels where colour information is usable, by the lossy function $\Delta[f(xi),yi] = \begin{cases} 0 & \text{if } f(x) = yi \\ \infty & \text{, otherwise} \end{cases}$. The weights ω are computed using a normalized radial basis function or a second-order polynomial, that takes the similarities in the intensity values. The above algorithm is a graph-based transductive semi-supervised learning algorithm and its objective functions are similar to of Levin algorithm. It is worthwhile mentioning that Levin use their algorithm to perform colorization on a video sequence, hence the temporal information is also takes into account i.e., two pixels are

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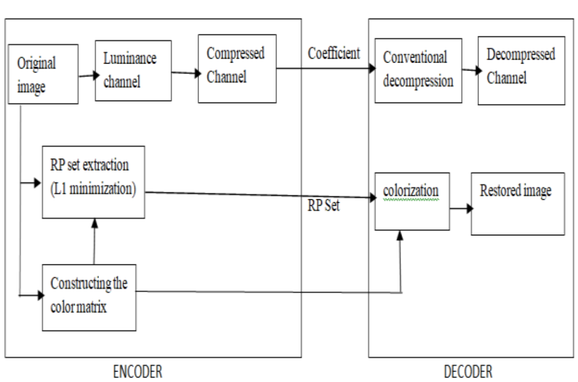
deemed neighbors if either they are near to each other on a single frame or if they appear at the same position on two consecutive frames. For our application, this approach stands from several drawbacks. Firstly the size of the optimization problem grows with the number of related figures thus making it unsuitable for real-time compression[5]. Secondly the algorithm spreads color information from frame to frame[1]. A better approach is to learn how to predict color on a single frame and reuse this model to pre figure on all closely related frames and thirdly when streaming data on the Internet, there is a need to compact on demand since all the frames might not be available. Learning to Compress Images and Videos appropriately proposed algorithm addresses all these issues. Our weight issue fits neatly in this structure Because the pictures are subjected to a game plan of shading pixels (checked cases) and a course of action of grayscale pixels (unlabeled specimens).

III. PROPOSED METHOD

The colorization has been proposed for shading a given grayscale image from a couple of pixels that have shading data. We indicate these pixels as agent pixels (RP), and RP can be spoken to by the positions and shading estimations of these pixels. Since the data sum for speaking to positions and shading estimations of RP is little, a novel way to deal with image pressure by utilizing colorization (called colorization based coding) has been looked. An encoder removes RP from a unique shading image and transmits RP and all luminance parts (packed by the routine encoder) to a decoder. At that point, the decoder restores a shading image by colorization. Clearly, to execute colorization-based coding, programmed RP extraction is needed, and which extraction system is picked decides the execution of the colorization based coding technique.



Block Diagram

Cheng proposed colorization based coding that concentrates RP in view of a machine learning methodology. Cheng Technique [5] adds new pixels to the RP by iterative choice beginning from haphazardly chose starting RP. Notwithstanding if the introductory RP as of now have some repetition, there is no methodology for diminishing it. Conversely, system chooses competitor RP (which could be extricated as RP) as the first step.

At that point RP's are separated from the applicant pixels by successive determination which ensures optimality of the machine learning information. On the other hand if the hopeful pixels don't at first incorporate the pixels needed for smothering coding lapse, such pixels cannot be removed at any stage by this strategy. Besides strategy does not utilize the shading parts of the first image (meant as unique shading segments) to remove RP. In view of this, their system may not remove the obliged pixels for RP much of the time. Interestingly, the colorization based coding strategy proposed by Komiyama[6] extricates RP as an arrangement of shading line portions. By limiting the RP to an arrangement of shading line fragments, the data sum for speaking to RP is diminished definitely while subjective quality is kept up. In any case, they didn't assess their strategy with any target quality metric.

In this application, we minimize the metrics on the image gradient, where the image is a Shepp-Logan phantom of dimensions 256 × 256. Using $\ell 1{-}2$, we observed that 8 projections suffice for exact recovery, while IRLS for $\ell 1/2$ minimization takes 10. Still at 8 projections, the relative recovery error is a factor of 2 × 106 larger under the split Bregman for $\ell 1$.However, this does not mean $\ell 1$ norm is superior to $\ell 1{-}2$ in terms of sparsity promoting[4]. On the contrary it will be shown numerically that $\ell 1{-}2$ penalty consistently outperforms $\ell 1$. Besides possible technical issue, one explanation is that the RIP is just a sufficient condition to guarantee that a measurement matrix A fits for exact reconstruction. It can happen that two matrices have exactly the same performance and yet one satisfies RIP whereas the other does not they only extract linearly independent columns from the sensing matrix A, whether A satisfies any RIP or not.

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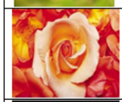
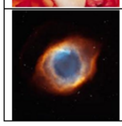
IV.RESULTS

Original image	Compression ratio	PSNR		MSE	
		With sparse L1	Without sparse L1	With sparse L1	Without sparse L1
	42.127	30.028	35.877	8.133	16.801
	40.562	39.887	36.627	6.681	14.135
	40.644	39.148	35.611	7.911	17.862

Comparing PSNR and MSE for different inputs based on L1 minimization

Taking an image which is resized into 256X256, which of 65,536 pixels, Hence by formulating the *L1* optimization problem we reduced it into 676 pixels. With a finer quality of the image. The quality of the image is measure in terms of the PSNR and MSE values.

$$PSNR = 20\, log_{10} \frac{255}{MSE}$$

$$\text{MSE}=\sqrt{\frac{\sum_{x=0}^{W-1}\sum_{y=0}^{H-1}\left(f(x,y)-f(x,y)\right)^2}{WH}}$$

V. CONCLUSION

In this paper the colorization problem is formulated into an optimization problem, Thereby optimization problem has given a way to tackle the colorization based coding problem using several well-known optimization techniques. In this proposed a method, the colorization matrix which can colorize the image with a very small set of Representative pixels (RP) is computed. The proposed method surpasses the JPEG standard and is comparable to the JPEG2000 standard in terms of performance. Additionally in this algorithm the mean scale segmentation can be used for further improvements.

VI. References

[1] R. Chartrand and V. Staneva Restricted isometry properties and nonconvex compressive sensing, Inverse Problems, 24 (2008), 035020 (14pp).

[2] R. Chartrand and W. Yin, Iteratively Reweighted Algorithms for Compressive Sensing, IEEE international conference on acoustics, speech, and signal processing, 2008.

[3] S. Chen, D. Donoho, and M. A. Saunders, Atomic decomposition by basis pursuit, SIAM J. Sci. Computer., 20 (1998), pp. 33-61.

[4] X. Chen, F. Xu, and Y. Ye, Lower Bound Theory of Nonzero Entries in Solutions of ℓ2-ℓp Minimization, SIAM J. Sci. Computer., Vol. 32, No. 5, pp. 2832-2852, 2010.

[5] X. Chen and W. Zhou, Convergence of the reweighted ℓ1 minimization algorithm for ℓ2-ℓp minimization, to appear in Comp. Optim. Appl.

[6] A. Cohen, W. Dahmen, and R. Devore, Compressed Sensing and Best k-Term Approximation, Journal of the American Mathematical Society, Vol 22, No. 1, pp. 221-231, 2009.