Coding Techniques for CFA Data Images

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Abstract

In this paper we present a comparison between different approaches to CFA (Colour Filter Array) images encoding. We show different performances offered by a new algorithm based on a vector quantization technique, JPEG-LS a low complexity encoding standard and classical JPEG. We also show the effects of CFA image encoding on the colour reconstructed images by a typical image generation pipeline. A discussion about different computational complexity and memory requirement of the different encoding approaches is also presented.

1. Introduction

The wide diffusion of digital still cameras and mobile imaging devices observed in last few years leads us to face with the problem of using reliable coding techniques for storing or transmitting digital images. Although common coding techniques offer good performances on full color images, most of these do not offer the same performances if we encode images captured by digital sensors in CFA format. So we have focused our attention to the problem of CFA images encoding using both new approaches and classical ones. In particular we have developed our experimental activity on the widely diffused CFA Bayer pattern scheme [1][3][10][11][12]. Classical coding techniques in this case do not always offer satisfying performances. In this work a useful comparison between various compression techniques (standard and not) is presented in order to evaluate the relative performance for CFA images. The opportunity to adapt classical approaches or develop ad-hoc ones for this kind of images encoding process is also considered. The comparison is realized between the techniques presented in [2], classical JPEG [13] and JPEG-LS [6][7][14].

In our recent work [2] is proposed a vector quantization technique for CFA images encoding that offers a good trade-off between required computational resources and final quality. For sake of comparison the relative performance of both JPEG and JPEG-LS have been measured adopting properly the relative features able to manage effectively CFA image (as described in the experimental section).

The rest of the paper is structured as follows. Next Section describes CFA image structure and different encoding approaches adopted. Section 3 reports all experiments while a conclusion section ends the papers tracking direction for future research.

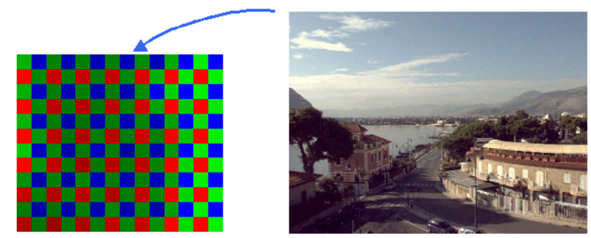

Figure 1. Bayer pattern structure.

2. Encoding techniques on CFA

A Bayer pattern image of size *NxN* contains *(N*N)/2* green pixels, *(N*N)/4* red pixels and *(N*N)/4* blue pixels. It is the output image acquired by a photo-sensors array through a particular micro-lens filtering pattern. The Bayer pattern structure is shown in figure 1.

Several reasons support a research in CFA image encoding. The most important, are concerning lower computational resources needed respect to full color image encoding and storage saving. Both these resources are generally limited on low-cost imaging devices. Typical applications for CFA encoding could be developed for example on still pictures and video transmission, constrained by limited resources (bandwidth, memory).

2.1 A vector quantization technique

An effective CFA compression technique has been presented in [2]. A uniform vector quantizer [5][9], processes the input vector $(X_1,\dots,X_n)$ applying the same quantization step Q to each sample X_i (with $1\leq i\leq n$) according to the following formula:

$$VQ(X_i)=floor(X_i/Q)*Q,\ \forall i : 1\leq i\leq n. \qquad (1)$$

Resulting quantizer vector $(Y_1,\ldots,Y_n)$ contains the *reconstruction points* for all samples of the n-dimensional space that falls in the range $Y_i \leq X_i \leq Y_i+Q,\ \forall i : 1 \leq i \leq n$.

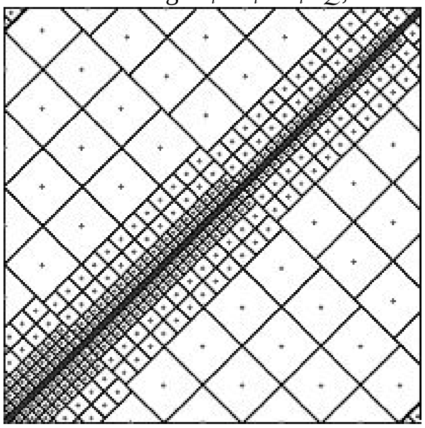

Figure 2. Non-uniform partitioning of the 2-D histogram using the proposed adaptive quantizer.

Given a 2-D image, it is described by a 2-dimensional vector of luminance values falling into the range [0,255], each pair of adjacent pixel could be mapped into a 2-D histogram, which could be partitioned in regular cells, corresponding to the fixed quantization step.

An adaptive quantizer could be defined exploiting basic Human Visual System (HVS) properties. In particular, two considerations should be taken into account: quantization errors are less visible along edges and HVS discriminates better at high luminance levels. In the 2-D representation of the image, points falling along the diagonal correspond to pixels of *homogeneous regions*, while points far from the diagonal are generated by pixels of *edge-regions*. Thus, a non-uniform vector quantizer could reduce the perceptual irrelevancy performing a finer quantization near the bottom left corner diagonal of the histogram using bigger cells, as showed in figure 2. The proposed scheme, that maintains the bayer pattern structure, is showed in figure 3.

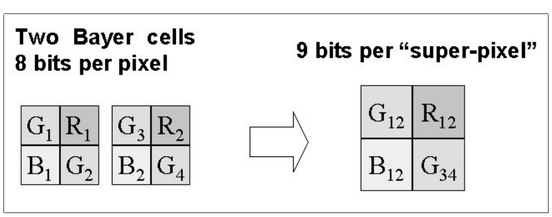

Figure 3. Pixel pairs construction scheme.

This approach assumes that there is a stronger correlation among nearest green pixels, so given a pair of image rows, green pairs are built using a zig-zag scanning order, while red and blue pixels are associated to the nearest adjacent pixel. Resulting "superpixels" represent reconstruction points. Moreover, a code is assigned to each superpixel corresponding to a pair $<C_i,C_j>$ of pixels in a color component, applying an appropriate function f:

$$C_{ij}=f(<C_i,C_j>) \qquad (2)$$

The proposed vector quantizer is defined by 512 reconstruction points, so a 9-bits code is assigned to each pair of pixels in the original image and a bitrate of 4.5bpp (bit per pixel) is achieved. Defining f in a way that codes assignment is related to the distribution of reconstruction points in the 2-D space, residual redundancy has been eliminated by iterated compression performed applying a lossless DPCM [8] algorithm to the "codes-image". Thus, the compression is performed in three steps. First, the input vector is quantized to the nearest reconstruction point. Second, the binary code associated with the reconstruction point is outputted. Then the resulting codes are further compressed using DPCM. The inverse operation (the dequantization) is a two-steps process: from the binary code to the "codes-images", back to the reconstruction point. See [2] for further details.

2.2 JPEG-LS

JPEG-LS is an ISO/ITU standard [7] for low complexity lossless and near lossless encoding for continuous tone images. It is based an a fixed prediction encoding approach based on a neighborhood gradients followed by a Golomb type encoding, which is optimal for typical prediction error statistic distributions. JPEG-LS standard offers a lossless mode operation and a near-lossless one, in which every sample in the reconstructed image is guaranteed to differ from the corresponding value on the original image by up to a preset value, δ. See [7] [14] for more related details.

2.3 JPEG

As a classic reference, it was useful a comparison with this widely known algorithm [13] due to the fact that all the devices generally have on-board JPEG coding engine.

To assess the performance in term of rate/distortion capabilities we used [4], that allows obtaining a given bitrate analyzing the activity/energy already present in input bayer data.

3. Experiments and discussions

A large data set of 30 CFA images for each of the three resolutions considered (CIF-352x288, VGA-640x480, 1000x800) captured by different CMOS sensors was used to compare different approaches in terms of PSNR at different compression ratios.

In order to adapt both JPEG and JPEG-LS encoding schemes to the CFA image characteristics, which contain intrinsic high spatial frequencies, a plane slicing pre-processing step was used. This step was performed applying the encoding algorithms not to the whole CFA image, but separately to the different color planes, as represented in figure 4. This approach, which preserves local chromatic correlation, offered a good improvement in both cases in term of compression ratio without a significant computational overhead.

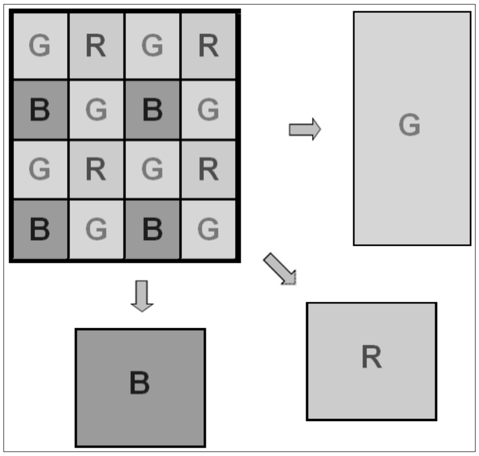

Figure 4. Bayer pattern plane slicing process.

This improvement is evident as reported in figures 5, 6, which summarize the average improvements obtained both for JPEG-LS and JPEG for a VGA resolution data set. For JPEG-LS, from lossless encoding up to an error δ=3, is reported the compression ratio in terms of bitrate. At the same error level, which means about the same PSNR, a good improvement is evident for the compression ratio. This improvement is due to the nature of this encoding algorithm, which adopts a dual encoding mode (predictive/run-length). On low entropy regions/images the encoder switches more frequently to the run-length mode, which offers better compression performance. For the same reasons better improvements were obtained on higher resolution images, which contain larger low entropy regions. Also the encoding process complexity decreases by adopting the pre-slicing step, as will be explained in section 3.3. For JPEG encoding the results are reported in term of PSNR at fixed bitrate. A better improvement is evident for higher compression ratios (≤2.0 bpp). Also for this encoding approach the improvement increases on higher resolution images. At max resolution of our data set (1000x800) and lower bitrate (0.25 bpp) was obtained an average improvement of 48% in terms of PSNR. An adaptation to the CFA images nature, performed by an appropriate rows and columns indexing, has limited the computational overhead of this pre-processing step for both JPEG and JPEG-LS encoding algorithms.

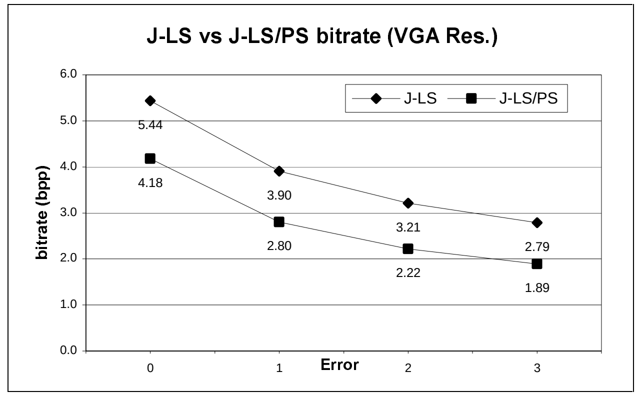

Figure 5. Average bitrate obtained at different error levels with JPEG-LS encoding, without (J-LS) and with plane-slicing step (J-LS/PS).

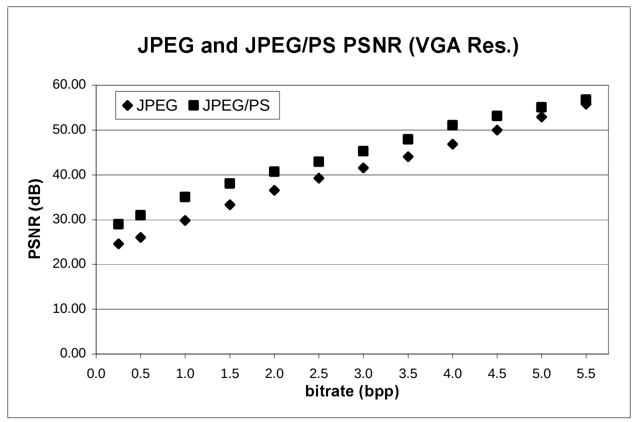

Figure 6. Average PSNR obtained at fixed bitrates with JPEG encoding, without (JPEG) and with plane-slicing step (JPEG/PS).

3.1 Performances of CFA images encoding

For all approaches the testing phase on CFA images was performed comparing in terms of PSNR the decoded image with the original one, acquired by the CFA sensor. For JPEG-LS and JPEG encoding it was always adopted the pre-processing plane-slicing step, as mentioned above. In particular for JPEG-LS encoding we have tested, for the near lossless mode, different error levels obtaining good performances in terms of PSNR at low bitrates. These performances increase with higher resolutions due to the larger low entropy regions present in such images. For values of δ>3 this encoding approach produces evident artifacts on the decoded image, as uniform runs on low entropy regions, due to the fact that it was designed to reduce statistical redundancies and not psycho-visual ones. These artifacts are still evident in some cases with high PSNR (~40 dB), which often were obtained in near-lossless encoding (δ<4). An example is showed in figure 7. For this reason we focused our attention only on lossless and near-lossless mode, for δ values up to 3.

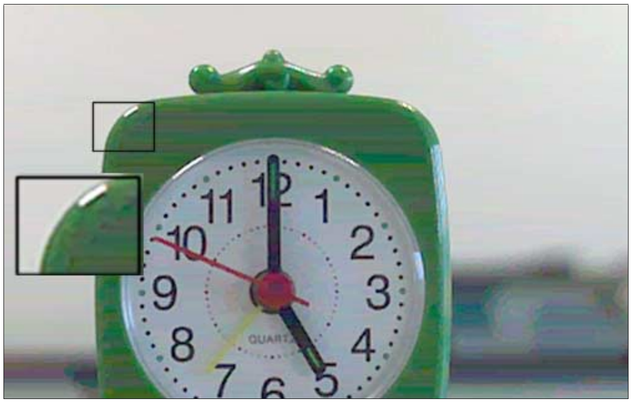

Figure 7. Full color image generated after a JPEG-LS CFA encoding with error δ=5. (PSNR=39.13 dB). On detail window artifacts are evident.

Figures 8, 9, and 10 summarize average results at different resolutions for the entire data set.

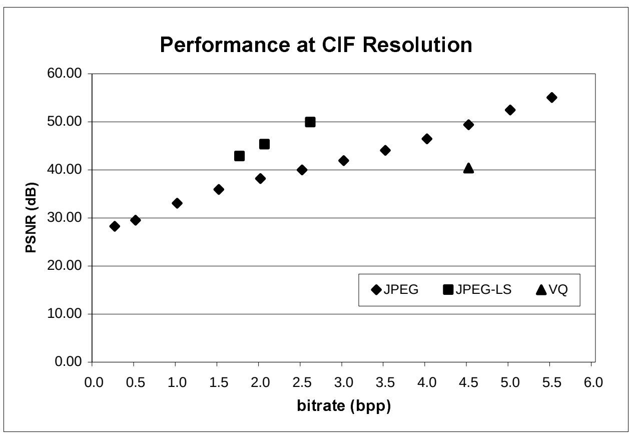

Figure 8. Average PSNR (dB) for different compress ratios with different encoding algorithms at CIF resolution.

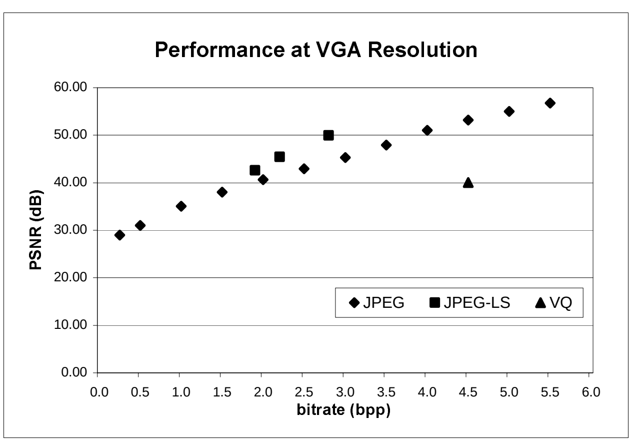

Figure 9. Average PSNR (dB) for different compress ratios with different encoding algorithms at VGA resolution

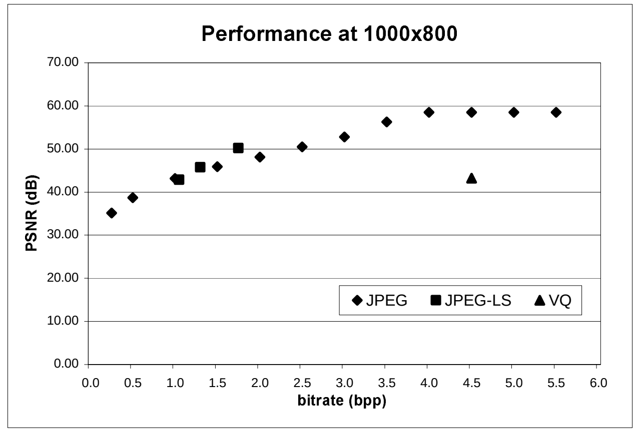

Figure 10. Average PSNR (dB) for different compress ratios with different encoding algorithms at 1000x800 resolution.

In particular, for JPEG-LS encoding the three data points are referred to error levels (δ=1, 2, 3). All different approaches show for bitrates higher than 1.5 bpp good performances in terms of PSNR. At similar bitrates JPEG-LS generally offers better performance than JPEG algorithm. Moreover for JPEG-LS encoding we observed higher variance on compression ratios at different error levels, depending on the image characteristics. This could be a limit for applications with bitrate constraints. On the contrary the VQ approach, has showed more resolution independence, always at high levels of PSNR. At a bitrate of 4.5 bpp, which is fixed for the VQ approach, JPEG algorithm has shown better performance. JPEG also allows, at visually lossless PSNR levels (~40 dB), more scalability in terms of compression ratios than other approaches.

3.2 Performances on colour reconstructed images

It is useful showing how an encoding process on CFA images influences the quality on final colour reconstructed images, which are obtained by an IGP (Image Generation Pipeline) process with a typical parameters set. In figure 11 is shown a full color image generation process. Main steps of the pipeline used for the tests are: defect correction, white balancing, noise reduction, color interpolation. Figure 12 describes the testing and performance evaluation criteria. In table 1 the effects on colour reconstructed images are summarized for the encoding approaches at different resolutions in terms of PSNR for the pair decoded-original CFA images compared with the same index for the pair of full colour images obtained with or without the CFA encoding process. In particular, the data for JPEG-LS encoding were obtained at an error level δ=2, for JPEG at a fixed bitrate of 2.0bpp. Average results show that a visually lossless approach to CFA encoding has not excessive influence on the output full colour images. For the VQ encoding method, which is specifically designed to IGP reconstruction, the final full color image is always re-aligned to the corresponding RGB-Image obtained without co-decoding (by JPEG or JPEG-LS, however in a lossy way) the original raw data.

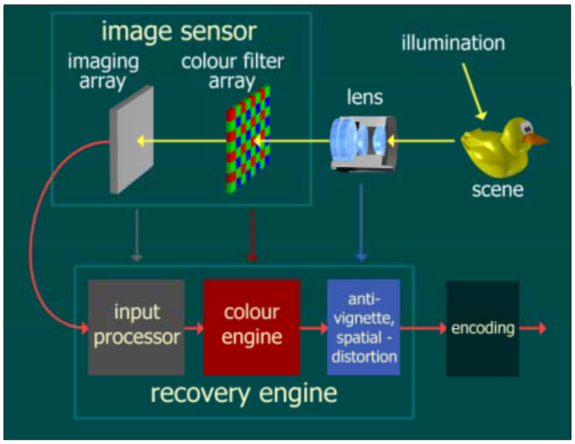

Figure 11. Image generation pipeline dataflow.

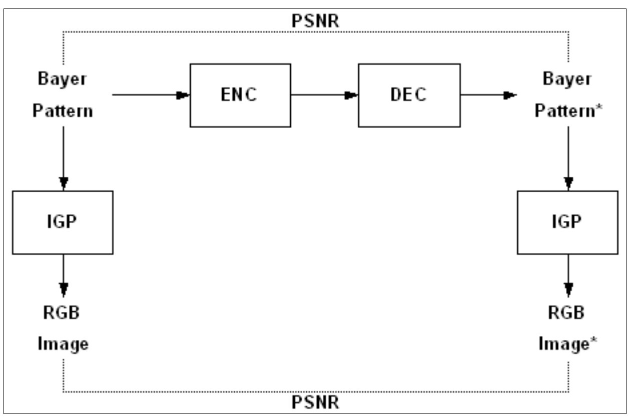

Figure 12. Performance evaluation criteria for full colour images.

	VQ		JPEG-LS		JPEG	
	CFA	RGB	CFA	RGB	CFA	RGB
CIF	40.39	41.74	45.36	45.53	38.18	37.17
VGA	40.07	40.92	45.46	44.80	40.66	40.89
1000x800	43.25	44.45	45.72	42.19	48.14	46.85

Table 1. Average PSNR (dB) for CFA encoded images and colour reconstructed ones.

3.3 Computational complexity

Our experimental phase was also devoted to obtain a complexity assessment both on computational and memory requirement aspects. As mentioned before, such aspects are relevant on mobile consumer devices. Our assessments, summarized in table 2 are expressed in OPP (operations per pixel) and MR (memory requirement) related to the encoding buffer size, without frame storing. While for VQ and JPEG computational resources are substantially independent from the image characteristics, JPEG-LS complexity decreases for low entropy regions/images and for higher error level preset, due to the fact that in these conditions the encoder, which adopts a dual encoding mode (predictive/run-length), switches more frequently to the less expensive run-length mode. Thus for this encoder the data reported are related to the worst case. In the average case a 50% improvement was registered by comparing the average encoding time to the worst case.

VQ		JPEG-LS		JPEG	
OPP	MR	OPP	MR	OPP	MR
10.5	~8000	~90	~1100	~30	~5000

Table 2. Complexity assessments: Operations per pixel and memory requirements (bytes).

4. Conclusions and future works

A comparison between several compression algorithms applied to Bayer pattern images has been presented. In particular, a non-standard "vector quantization"-based approach was compared with JPEG and JPEG-LS standard algorithms. All these techniques have high performance in terms of compression quality at high bitrates without perceptual loss. Moreover, compression does not affect further stages of IGP that take compressed data as input in order to obtain a full color image in a typical digital camera architecture. Performances were evaluated also in terms of computational complexity, a basic evaluation criteria for "bayer-oriented" compression algorithms. JPEG-LS gives the highest values of PSNR, but it is also the most resolution sensitive both in terms of compression ratios and computational resources, while VQ-based method is the best trade off between complexity and compression quality.

The testing activity presented in this paper suggests us that other further investigations on ad-hoc techniques could be made. In particular, encoding procedures could be adapted to process several kinds of CFA data images, extending the study on the case of other filter array schemes. Furthermore, more attention could be focused on the effects that CFA encoding has on the full colour images generation process, considering also different color-depth resolutions (more than classical 8-bit/pixel).

5. References

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