World Academy of Science, Engineering and Technology
International Journal of Computer and Information Engineering
Vol:10, No:4, 2016

A Survey on Lossless Compression of Bayer Color Filter Array Images

Alina Trifan, António J. R. Neves

Abstract—Although most digital cameras acquire images in a raw format, based on a Color Filter Array that arranges RGB color filters on a square grid of photosensors, most image compression techniques do not use the raw data; instead, they use the rgb result of an interpolation algorithm of the raw data. This approach is inefficient and by performing a lossless compression of the raw data, followed by pixel interpolation, digital cameras could be more power efficient and provide images with increased resolution given that the interpolation step could be shifted to an external processing unit. In this paper, we conduct a survey on the use of lossless compression algorithms with raw Bayer images. Moreover, in order to reduce the effect of the transition between colors that increase the entropy of the raw Bayer image, we split the image into three new images corresponding to each channel (red, green and blue) and we study the same compression algorithms applied to each one individually. This simple pre-processing stage allows an improvement of more than 15% in predictive based methods.

Keywords—Bayer images, CFA, losseless compression, image coding standards.

I. Introduction

MOST modern digital cameras allow the acquisition of images as raw data that have a pixel distribution following the Bayer pattern [1]. A Bayer filter mosaic is a type of Color Filter Array (CFA) for arranging RGB color filters on a square grid of photosensors. Its particular arrangement is used in most single-chip digital image sensors used in digital cameras, camcorders, and scanners to create a color image. The filter pattern is 50% green, 25% red and 25% blue, usually called BGGR, RGBG, GRGB, RGGB, etc. depending on the position of the filters.

For display purposes and better human visualization, interpolating or demosaicing algorithms are used, that convert the raw image to a certain color space, like RGB, YUV or HSV [2]. This is a digital image processing technique used to reconstruct a full color image from the incomplete color samples output from an image sensor overlaid with a CFA. Most modern digital cameras acquire images using a single image sensor overlaid with a CFA, so demosaicing is part of the processing pipeline required to render these images into a viewable format. However, in most of them, it is possible to retrieve images in a raw format, allowing the user to demosaic them using software, rather than using the camera's built-in firmware.

Compression algorithms usually operate on the already converted images and so far there have not been many attempts to directly compress the raw data. An interpolation followed by compression approach is inefficient from different perspectives. Interpolation comes with a redundancy cost that will be carried further in the compression step. Moreover, digital cameras could be more power efficient and provide increased resolution images if the interpolation process would be shifted to an external processing unit.

In this paper we present a survey on the lossless compression algorithms applied to raw images. We present comparative results obtained by applying the compression algorithms directly to the raw data and results obtained after having split the raw image into three corresponding channels: Red, Green and Blue, compressing them individually.

The paper is structured in 7 sections, first of them being this Introduction. We present previous attempts on raw image compression in Section II. Section III describes the lossless compresion standards that have been used in this survey. Section IV describes four successful compression algorithms that have been used in this survey. In Section V, we describe the procedure for splitting a Bayer image and we provide experimental results in Section VI. Conclusions are drawn in Section VII and last, but not least, the institutions that have supported this work are acknowledged.

II. Related Work

Coding techniques for full color images have been explored for a long time and there are currently a considerable number of algorithms that provide good compression results, depending on the type of application in which they are needed. Bayer data compression is however, a more recent concern in the image coding research community and the traditional coding techniques applied to these images do not lead to reasonable compression results.

Lossless coding techniques have the advantage of preserving the information and they provide low compression rates. On the other hand, lossy coding techniques have higher compression rates and they discard the information that is not visually relevant. Lossy compression approaches for CFA images can be found in [3] and [4]. In [5] proposed compression scheme allows performing a near-lossless compression of CFA images, by reducing both mathematical and perceptual redundancies.

In some applications, original CFA images are required for a better imaging quality and the interpolation step is done aposteriori. Techniques based on adapting the JPEG [6] standard algorithm to the Bayer data are presented in [7] and [8] but they lead to a lossy compression. These approaches are based on subsampling the image to convert Bayer pattern in the YCbCr color space. The main drawback is the bandwidth required by these approaches.

Alina Trifan and António J. R. Neves are with the Universidade de Aveiro, IEETA/DETI-IRIS Laboratory, Aveiro, Portugal (e-mail: alina.trifan@ua.pt, an@ua.pt).

A more recent approach for lossless Bayer image compression has been presented in [9]. Their solution is based on decorrelating the mosaic data using the Mallat wavelet packet transform and the coefficients are then compressed by adaptive Rice code. In [10] and [11], a prediction-based lossless CFA compression scheme that employs context matching technique to rank the neighboring pixels for predicting the current pixel is presented. To our knowledge, the results presented in [11] in terms of compression rate have been the best up to this moment. However, we provide experimental results in this paper showing that using a simple pre-processing stage, the use of predictive coding standards can obtain competitive results.

III. Lossless Compression Standards

In this section, we present the state-of-the-art standards that allow lossless coding of digital images, namely JPEG-LS [12], JPEG2000 [13], JBIG [14] and PNG [15]. They have been developed with different goals in mind: JPEG-LS is dedicated to the lossless compression of continuous-tone images; JPEG2000 was designed with the aim of providing a wide range of functionalities; JBIG is more focused on progressive lossless compression of binary and low-precision gray-level images; PNG was developed for lossless compression of computer graphics images, however supporting also grayscale and true-color images.

JPEG-LS [12] is the state-of-the-art International Standard for lossless and near-lossless coding of continuous tone still images. It has been developed by the Joint Photographic Experts Group (JPEG) with the aim of providing a low complexity lossless image standard that could be able to offer better compression efficiency than lossless JPEG. The core of JPEG-LS is based on the LOw COmplexity LOssless COmpression for Images (LOCO-I) algorithm [16], that relies on prediction, residual modeling and context-based coding of the residuals. Most of the low complexity of this technique comes from the assumption that prediction residuals follow a two-sided geometric probability distribution and from the use of Golomb codes, which are known to be optimal for this kind of distributions.

JPEG2000 [13] is the most recent international standard for still image compression. This standard is based on wavelet technology and embedded block coding (EBCOT) of the wavelet coefficients [17], providing very good compression performance for a wide range of bit rates, including lossless coding. Moreover, JPEG2000 allows the generation of embedded codestreams, meaning that from a higher bit rate stream it is possible to extract lower bit rate instances without the need for re-encoding.

Joint Bi-level Image Experts Group (JBIG) [14] was issued in 1993 by the International Organization for Standardization / International Electrotechnical Commission (ISO/IEC) and Telecommunication Standardization Sector of the International Telecommunication Union (ITU-T) for the progressive lossless compression of binary images. The major advantages of JBIG over other existing standards are its capability of progressive encoding and its superior compression efficiency. The term "progressive encoding" means that the image is saved in several "layers" in the compressed stream. Even though JBIG was designed for bi-level images, it is possible to apply it to grayscale images by separating the bitplanes and compressing each individually, as if it was a bi-level image.

Portable Network Graphics (PNG) [15] is an extensible file format for the lossless, portable, well-compressed storage of raster images. Color-indexed, grayscale, and truecolor images are supported, with optional transparency (alpha channel). PNG is designed to work well in online viewing applications, such as the World Wide Web, allowing a progressive display option using a 2-D interlacing algorithm. This algorithm, named Adam7, uses seven passes to send the complete picture. In the first pass only 1 out of 64 pixels is transmitted, which results in a good approximation of the original image. PNG is robust, providing both full file integrity checking and simple detection of common transmission errors.

These four standard image encoders cover a great variety of coding approaches. In fact, whereas JPEG2000 is transform based, JPEG-LS relies on predictive coding, JBIG relies on context-based arithmetic coding and PNG uses a dictionary based approach. This diversity in coding engines might be helpful for drawing conclusions regarding the appropriateness of each of these technologies for the case of raw Bayer image compression.

IV. Specific Lossless Compression Methods

Besides the study about the efficiency of lossless compression standards with raw Bayer images, we provide in this paper experimental results showing the efficiency of some successful image compression algorithms developed specifically for some types of images. We were interested in cover the most important techniques, namely prediction coding, transform coding, bitplane decomposition and binary tree decomposition.

CALIC [18] is a context-based lossless compression method. It is based on a large number of modeling contexts to condition a non-linear predictor. It uses the previous scan lines of coded pixels to do the prediction and form the context. In order to achieve high performance in binary images or binary portion in encoding images, CALIC operates in two modes: Binary and continuous tone modes. The algorithm selects one of the two modes on the fly during the coding process, depending on the context of the current pixel. Arithmetic coding is used to to entropy coding of prediction residuals.

In [19] was presented a sophisticated bitplane decomposition approach that was successfully developed for the compression of microarray images. The bitplane decomposition technique is very useful on image compression. On one hand, it allows some bi-level compression methods, such as JBIG, to be applied to typical grayscale images. The compression method is applied to each bitplane after the decomposition. On the other hand, it is possible to create sophisticated models, as the ones presented in [19] that take advantage of this decomposition. This algorithm uses information of the previous bitplanes (the MSBPs) to improve the compression performance of the LSBPs.

EIDAC [20] is a compression method that has been used with success for coding images with a reduced number of intensities (simple images). The images are compressed on a bitplane basis, from the most to the least significant bitplane. The causal finite-context model that drives the arithmetic encoder uses pixels both from the bitplane currently being encoded and from the bitplanes already encoded.

Another approach of image decomposition, based on binary-tree decomposition, was developed with success for the compression of medical images [21] and microarray images [22]. In this decomposition approach, the intensity levels of a given image are organized in a binary-tree structure, where each leaf node is associated with an image intensity.

V. Splitting the Raw Bayer Image on Channels

Fig. 1 shows a typical Bayer arrangement of color filters. As it can be seen, the green information has double the size of the red or blue information. This is due as an attempt to mimic the physiology of the human eye, which is more sensitive to green light. To obtain a full-color image, various demosaicing algorithms can be used to interpolate a set of complete red, green, and blue values for each pixel. These algorithms make use of the surrounding pixels of the corresponding colors to estimate the values for a particular pixel.

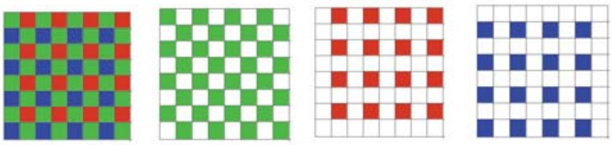
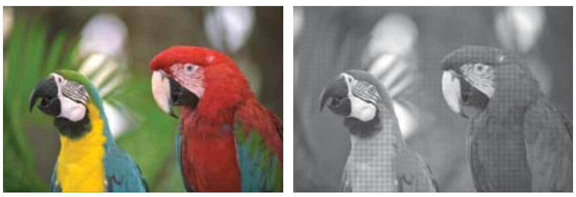


Fig. 1 Bayer arrangement of color filters



(a) (b)

Fig. 2 An example of Bayer image: (a) An RGB image, (b) The same image in Bayer format

(a) (b) (c)

Fig. 3 Result of the channel split: (a) An image containing the red channel (first order entropy: 4.866), (b) The image regarding the green channel (first order entropy: 4.838), (c) An image containing the blue channel (first order entropy: 4.912 bpp)

Fig. 2 shows an RGB image and the corresponding single channel raw Bayer image. This image is obtained from the RGB version considering the information about red, green or blue of each pixel, depending on their position on the image, as presented in Fig. 1.

As we can see, despite the RGB image represents a natural scene, the corresponding raw Bayer image lost the property of an image with smooth transitions of the pixels values due to the transition between pixels that represent different colors. The grayscale version of the RGB image has a first order entropy of 4.186 bits, while the corresponding raw Bayer image has first order entropy of 7.552 bits. This is a challenge for image compression algorithms designed for natural images and in this paper we pretend to present a detailed study about this effect in the most important algorithms presented in the literature.

In order to reduce the effect described above, we present in this paper a simple pre-processing algorithm that separates the raw Bayer image into three images, each one containing the pixel values of each primary color. An example of the result of splitting the raw Bayer image can be seen in Fig. 3.

The algorithm for the channel split, taking as input a Bayer image with the configuration presented in Fig. 1, works as follows:

```
Input: Bayer image
Output: three grayscale images: red, green and blue

/* For all the pixels in the RGB image */
for(p = 0 ; p < image.cols * image.rows ; p++)
{
  row = p / image.cols;
  col = p \% image.cols;

  if(row \% 2 == 0) /* even rows */
  {
    if(col \% 2 == 0) /* even columns */
    {
      /* Red channel */

      redImage[rIdx] = image[p*3+2];
      rIdx++;
    }
    else
    {
      /* Green channel */

      greenImage[gIdx] = image[p*3+1];
      gIdx++;
    }
  }
  else /* odd rows */
  {
    if(col \% 2 == 0) /* even columns */
    {
      /* Green channel */

      greenImage[gIdx] = image[p*3+1];
      gIdx++;
    }
    else /* odd columns */
    {
          /* Blue channel */

      blueImage[bIdx] = image[p*3];
      bIdx++;
    }
  }
}
```

Fig. 4 Twenty-four digital color images from the kodak set (refers as image 1 to image 24, from top-to-bottom and left-to-right)

VI. Experimental Results

In order to perform the experiments reported in this paper, twenty-four 24-bit color images from the Kodak image set [23] of size 512×768 each, as shown in Fig. 4, were sub-sampled according to the Bayer pattern presented in Fig. 1 to form a set of 8-bit testing raw Bayer images.

Table I shows the compression results, in bits per pixel, for the 24 images of the Kodak image set [23]. In this table, we present experimental results regarding the use of four standard image coding methods. JBIG results were obtained using version 2.0 of the JBIG-Kit package [24]. The results for the JPEG-LS standard were obtained using version 2.2 of the SPMG JPEG-LS codec [25]. JPEG2000 lossless compression was obtained using version 5.1 of JJ2000 codec with default parameters for lossless compression. The results regarding PNG were obtained using the pnmtopng tool from the NetPbm package [26].

According to the results depicted in Table I, it seems that, globally, JPEG-2000 is the best image coding standard when applied directly to the CFA images, being PNG the algorithm with worst behavior.

After the transformation presented in Section V, JPEG-LS obtained the best results. We can obtain a considerable improvement on the compression of 15%. Based on the experimental results presented in this table, we can point out that only JPEG-LS and PNG benefits from this transformation, which can be explained due the properties of the algorithms used for compression. These algorithms benefits with the properties of natural images, with smooth transitions between pixels, which is not the case of the raw Bayer images because of the transition between colors. On the other hand, JPEG-2000 and JBIG obtain better results when dealing directly with raw Bayer images since their algorithms can deal better with the non-uniform properties of these type of images. However, they stay bellow JPEG-LS when using the pre-processing stage.

Table II shows the compression results, in bits per pixel, for the 24 images of the Kodak image set. In this table, we present experimental results regarding the use of four specific image compression algorithms, the binary tree decomposition method presented in [21] and [22], the bitplane decomposition method presented in [5], EIDAC [20] and CALIC [18]. These results have been obtained with our implementation of the referred algorithms, except CALIC that was provided by the authors.

According to the results depicted in Table II, the best results regarding compression of raw Bayer images were obtained with the binary tree decomposition algorithm, being the worst results obtained with EIDAC.

It is important to point out that only CALIC and EIDAC takes advantage of the pre-processing presented in Section V. The algorithms based on image decomposition are less sensitive to the properties of the raw Bayer images and obtain interesting results, close to the ones obtained with the state-of-the-art method for this type of images presented in [11]. This gives a hint about future developments regarding the compression of this type of images.

In order to present a theoretical limit in the compression of these images, we present in Tables I and II lossless compression results for the grayscale version of the images, obtained from the RGB version after demosicing. We can notice that there are, theoretically, room for improvement in the compression of these images since the best results obtained with or without the presented pre-processing are still 0.5 bpp or more far from the grayscale compression results.

VII. Conclusions and Future Work

In this paper, we have presented a detailed study on the use of lossless compression algorithms on Bayer Color Filter Array Images. The results shown lead to the conclusion that a simple pre-processing algorithm that split the Bayer image into the three color components provides a considerable improvement on the results in terms of the compression rate regarding prediction based methods. Moreover, we present experimental results showing that algorithms based on image

TABLE I

Compression Results (in bpp) Using the Standard Image Compression Methods Studied in This Paper. Column Labeled "Bayer" Lefers to The Compression of the Raw Bayer Image, While column Labeled "Split" Refers to the Compression of the Three Images Obtained After the Proposed Pre-Processing Algorithm. Just for Comparison and Considering a Theoretical Lower Bound, Column "Gray" Refers to the Compression of the Grayscale Version of the Images Obtained Directly from the Original RGB Color Image

Image	JPEG-LS			JPEG-2000			JBIG			PNG		
	Bayer	Split	Gray	Bayer	Split	Gray	Bayer	Split	Gray	Bayer	Split	Gray
01	6.400	5.977	5.266	5.824	6.165	5.437	6.152	6.290	5.437	6.476	6.209	5.495
02	6.789	4.632	3.981	5.178	4.835	4.166	4.888	4.886	4.166	6.424	4.951	4.310
03	5.887	4.043	3.464	4.212	4.235	3.551	4.454	4.379	3.551	5.999	4.552	3.977
04	6.687	4.789	4.129	4.943	4.914	4.182	5.211	5.178	4.182	6.617	5.149	4.494
05	6.461	6.067	5.168	5.956	6.406	5.301	6.234	6.421	5.301	6.563	6.347	5.607
06	5.885	5.165	4.564	5.192	5.336	4.670	5.500	5.553	4.670	6.012	5.364	4.838
07	5.971	4.334	3.603	4.486	4.611	3.752	4.768	4.767	3.752	6.080	4.852	4.148
08	6.292	6.197	5.284	5.902	6.401	5.523	6.187	6.423	5.523	6.510	6.438	5.512
09	5.076	4.446	3.904	4.394	4.564	4.001	4.750	4.781	4.001	5.549	4.752	4.221
10	5.394	4.557	3.912	4.562	4.767	4.086	4.887	4.908	4.086	5.759	4.888	4.290
11	5.370	5.041	4.391	4.987	5.260	4.551	5.333	5.369	4.551	5.946	5.352	4.719
12	5.621	4.350	3.800	4.483	4.543	3.913	4.729	4.698	3.913	6.072	4.669	4.149
13	6.749	6.501	5.962	6.370	6.713	6.108	6.730	6.847	6.108	6.762	6.620	6.112
14	6.287	5.649	4.901	5.562	5.906	5.039	5.967	6.066	5.039	6.428	5.860	5.211
15	6.320	4.326	3.867	4.673	4.539	3.942	4.767	4.605	3.942	6.406	4.801	4.363
16	5.289	4.657	4.054	4.545	4.831	4.170	4.948	5.073	4.170	5.453	4.927	4.319
17	4.955	4.719	4.085	4.547	4.931	4.201	5.056	5.162	4.201	5.264	5.068	4.464
18	6.175	5.705	5.079	5.564	5.895	5.157	6.041	6.107	5.157	6.471	6.000	5.368
19	5.459	5.080	4.445	4.898	5.159	4.535	5.408	5.444	4.535	5.901	5.322	4.683
20	4.309	3.357	3.113	3.937	3.605	3.286	3.665	3.613	3.286	4.195	3.584	3.481
21	5.459	4.995	4.503	5.024	5.168	4.619	5.332	5.376	4.619	5.938	5.216	4.753
22	6.183	5.202	4.543	5.199	5.339	4.619	5.620	5.592	4.619	6.405	5.459	4.822
23	6.766	4.047	3.493	4.523	4.145	3.521	4.603	4.483	3.521	7.016	4.491	3.931
24	5.720	5.374	4.597	5.226	5.671	4.791	5.547	5.625	4.791	5.968	5.740	5.013
Average	5.896	4.967	4.338	5.008	5.164	4.463	5.282	5.319	4.764	6.092	5.275	4.678

TABLE II

Compression Results (in bpp) Using Some Successful Image Compression Methods Studied in This Paper. Column Labeled "Bayer" Refers to the Compression of the Raw Bayer Image, While Column Labeled "Split" Refers to the Compression of the Three Images Obtained After the Proposed Pre-Processing Algorithm. Just for Comparison and Considering a Theoretical Lower Bound, Column "Gray" Refers to the Compression of the Grayscale Version of the Images Obtained Directly from the Original RGB Color Image

Image	CALIC			EIDAC			Binary Tree decomposition			Bitplane decomposition		
	Bayer	Split	Gray	Bayer	Split	Gray	Bayer	Split	Gray	Bayer	Split	Gray
01	6.134	5.859	5.222	6.164	5.814	5.450	5.700	5.775	5.319	5.885	5.920	5.341
02	6.385	4.520	3.913	4.624	4.888	4.395	4.468	4.422	3.966	4.515	4.546	3.957
03	5.329	3.964	3.363	5.334	4.309	3.803	4.016	3.986	3.454	4.318	4.195	3.490
04	6.222	4.698	4.032	5.991	5.182	4.671	4.735	4.757	4.210	5.066	4.899	4.264
05	6.149	5.966	4.980	6.344	6.050	5.530	5.762	5.907	5.222	5.993	6.024	5.162
06	5.570	5.119	4.525	5.676	5.297	4.859	5.129	5.143	4.654	5.280	5.255	4.617
07	5.359	4.292	3.553	5.524	4.701	4.133	4.306	4.353	3.723	4.598	4.457	3.712
08	5.962	6.048	5.214	6.117	6.051	5.653	5.682	5.884	5.321	5.875	6.054	5.320
09	4.731	4.355	3.845	5.310	4.751	4.354	4.381	4.427	3.976	4.692	4.602	4.037
10	4.885	4.469	3.850	5.499	4.861	4.424	4.488	4.535	4.001	4.821	4.725	4.101
11	5.166	4.969	4.340	5.582	5.193	4.754	4.949	4.940	4.457	5.216	5.143	4.495
12	5.403	4.286	3.762	5.497	4.692	4.264	4.342	4.303	3.869	4.597	4.482	3.900
13	6.451	6.399	5.873	6.365	6.258	6.005	6.229	6.304	5.931	6.417	6.406	5.906
14	5.960	5.559	4.796	6.099	5.751	5.254	5.514	5.566	4.973	5.689	5.702	5.027
15	5.745	4.219	3.768	5.704	4.677	4.331	4.167	4.181	3.792	5.172	4.433	3.882
16	4.974	4.614	4.021	5.564	5.010	4.496	4.598	4.674	4.148	4.884	4.921	4.389
17	4.676	4.655	4.000	5.513	5.115	4.576	4.641	4.718	4.118	4.863	4.862	4.145
18	5.696	5.571	4.928	6.311	5.919	5.508	5.582	5.597	5.099	5.845	5.717	5.058
19	5.141	4.975	4.374	5.988	5.367	4.970	5.020	5.032	4.545	5.297	5.183	4.600
20	3.973	3.302	3.049	4.328	3.599	3.432	3.300	3.299	3.070	3.627	3.433	3.187
21	5.380	4.914	4.433	5.692	5.238	4.833	4.970	4.980	4.554	5.205	5.106	4.564
22	5.724	5.079	4.428	6.230	5.454	5.013	5.179	5.157	4.674	5.581	5.327	4.662
23	6.143	3.960	3.397	6.023	4.579	3.999	4.130	4.110	3.546	4.869	4.421	3.664
24	5.349	5.249	4.461	5.825	5.341	4.871	5.071	5.134	4.579	5.367	5.377	4.872
Average	5.521	4.877	4.255	5.721	5.171	4.732	4.848	4.883	4.383	5.153	5.050	4.431

decomposition can provide competitive results comparing to the state-of-the-art specific methods presented in literature. As a future work, we will use the conclusions of this study to develop more sophisticated pre-processing algorithms and specific methods to compress this type of images.

Acknowledgments

This work was developed in the Institute of Electronic and Telematic Engineering of University of Aveiro and was partially supported by FEDER through the Operational Program Competitiveness Factors - COMPETE and by National Funds through FCT - Foundation for Science and Technology in a context of a PhD Grant (FCT reference SFRH/BD/85855/2012) and the project FCOMP-01-0124-FEDER-022682 (FCT reference PEst-C/EEI/UI0127/2011).

REFERENCES

[1] B. Bayer, "Color imaging array," Jul. 20 1976, uS Patent 3,971,065. (Online). Available: http://www.google.pt/patents/US3971065

[2] R. Kimmel, "Demosaicing: image reconstruction from color ccd samples," *IMAGE PROCESSING, IEEE TRANSACTIONS ON*, 1999.

[3] X. Xie, G. Li, Z. Wang, C. Zhang, D. Li, and X. Li, "A novel method of lossy image compression for digital image sensors with bayer color filter arrays." in *ISCAS (5)*. IEEE, 2005, pp. 4995–4998.

[4] K. Chin Chye, M. Jayanta, and M. Sanjit K., "New efficient methods of image compression in digital cameras with color filter array," *IEEE Transactions on Consumer Electronics*, vol. 49, no. 4, 2003.

[5] B. Arcangelo, V. Filippo, B. Antonio, and C. Salvatore, "Predictive differential modulation for cfa compression." in *Proceedings of the 6th Nordic Signal Processing Symposium - NORSIG*, 2004.

[6] G. K. Wallace, "The jpeg still picture compression standard," *Commun. ACM*, vol. 34, no. 4, pp. 30–44, Apr. 1991.

[7] L. Sang-Yong and O. Antonio, "A novel approach of image compression in digital cameras with a bayer color filter array." in *Proceedings of ICIP 2001 – International Conference on Image Processing*, 2001.

[8] Y. Tsai, K. Parulski, and M. Rabbani, "Compression method and apparatus for single-sensor color imaging systems," Oct. 1991, uS Patent 5,053,861.

[9] Z. Ning and W. Xiaolin, "Lossless compression of color mosaic images." in *Proceedings of ICIP 2004 – International Conference on Image Processing*, 2004.

[10] K.-H. Chung, Y.-H. Chan, C.-H. Fu, and Y.-L. Chan, "A high performance lossless bayer image compression scheme." in *ICIP (2)*. IEEE, 2007, pp. 353–356.

[11] K.-H. Chung and Y.-H. Chan, "A lossless compression scheme for bayer color filter array images." *IEEE Transactions on Image Processing*, vol. 17, no. 2, pp. 134–144, 2008.

[12] M. J. Weinberger, G. Seroussi, and G. Sapiro, "The loco-i lossless image compression algorithm: Principles and standardization into jpeg-ls," *IEEE TRANSACTIONS ON IMAGE PROCESSING*, vol. 9, no. 8, pp. 1309–1324, 2000.

[13] A. Skodras, C. Christopoulos, and T. Ebrahimi, "The jpeg2000 still image compression standard," *IEEE Signal Proc. Mag*, 2001.

[14] V. Kyrki, "Jbig image compression standard," 1999.

[15] T. Boutell, "PNG (Portable Network Graphics) Specification Version 1.0," RFC 2083 (Informational), Internet Engineering Task Force, March 1997.

[16] M. J. Weinberger, G. Seroussi, and G. Sapiro, "Loco-i: A low complexity, context-based, lossless image compression algorithm," 1996.

[17] M. J. Weinberger, G. Seroussi, I. Ueno, and F. Ono, "Embedded block coding in jpeg 2000." in *ICIP*, 2000, pp. 33–36.

[18] X. Wu and N. Memon, "Context-based, adaptive, lossless image coding," vol. 45, no. 4, pp. 437–444, Apr. 1997.

[19] A. J. R. Neves and A. J. Pinho, "Lossless compression of microarray images using image-dependent finite-context models," *IEEE Trans. on Medical Imaging*, vol. 28, no. 2, pp. 194–201, Feb. 2009.

[20] Y. Yoo, Y. G. Kwon, and A. Ortega, "Embedded image-domain compression using context models," in *Proc. of the IEEE Int. Conf. on Image Processing, ICIP-99*, vol. I, Kobe, Japan, Oct. 1999, pp. 477–481.

[21] A. J. Pinho and A. J. R. Neves, "Progressive lossless compression of medical images," in *Proc. of the IEEE Int. Conf. on Acoustics, Speech, and Signal Processing, ICASSP-2009*, Taipei, Taiwan, Apr. 2009.

[22] L. M. O. Matos, A. J. R. Neves, and A. J. Pinho, "Compression of microarrays images using a binary tree decomposition," in *Proc. of the 22th European Signal Processing Conf., EUSIPCO-2014*, Lisbon, Portugal, Sep. 2014, pp. 531–535.

[23] "Kodak image set," http://r0k.us/graphics/kodak/, accessed: 2015-10-5.

[24] "Jbig kit," http://www.cl.cam.ac.uk/~mgk25/jbigkit, accessed: 2015-10-5.

[25] "Jpeg-ls software," http://sweet.ua.pt/luismatos/codecs/jpeg_ls_v2.2.tar.gz, accessed: 2015-10-5.

[26] "Png software," urlhttp://netpbm.sourceforge.net/, accessed: 2015-10-5.