SPARSE MODELLING AND PREDICTIVE CODING OF SUBAPERTURE IMAGES FOR LOSSLESS PLENOPTIC IMAGE COMPRESSION

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ABSTRACT
This paper studies the lossless compression of rectified light-field images captured by plenoptic cameras, exploiting the high similarity existing between the subaperture images, or views, composing the light-field image. The encoding is predictive, where one sparse predictor is designed for every region of a view, using as regressors the pixels from the already transmitted views. As a first step, consistent segmentations for all subaperture images are constructed, defining the regions as connected components in the quantized depth map of the central view, and then propagating them to all side views. The sparse predictors are able to take into account the small horizontal and vertical disparities between regions in corresponding close-by views and perform optimal least squares interpolation accounting implicitly for fractional disparities. The optimal structure of the sparse predictor is selected for each region based on an implementable description length. The encoding of the views is done sequentially starting from the central view and the scheme produces results better than standard lossless compression methods utilized directly on the full light-field image or applied to the views in a similar sequential order as our method.

Index Terms — lossless compression, light-field coding, depth map warping, plenoptics, sparse prediction

1. INTRODUCTION
Plenoptic cameras have received recently wide attention as an alternative to e.g. stereo camera setups in capturing 3D information from a scene. Plenoptic imaging, also referred to as light-field or holoscopic imaging, was first introduced as a concept by Lippmann in [1]. The plenoptic camera differs from a conventional camera by having an array of microlenses interposed in between the main lens and the sensor, enabling the sensing of angular information which has proven useful in numerous applications such as 3D optical microscopy, computer vision applications, 3D underwater imaging and medical imaging [2].

Recently there is a wide interest in studying the compressibility of the captured light-field, e.g. a new study action known as JPEG PLENO [3] was started by the JPEG group and a related challenge for lossy compression of plenoptic measurements was organized at ICME 2016. The lossless compression case was not extensively studied, while the lossy case is already carefully investigated see e.g., [4] and [5] and the references therein.

In plenoptic applications, the sensed image captured by the photosensor of a plenoptic camera is processed in a chain consisting of demosaicing, de vignetting, alignment to a square grid and rectification, and the result is rearranged into a 5D light-field structure \( L_P \), where an element \( L_P(i, j, x, y, c) \) has the following indices: \( i, j \in \{1, \ldots, N\} \) are indices for a certain pixel under a microlens (hence addressing a particular subaperture image) and \( x, y \) correspond to the spatial pixel location in the subaperture image. Hence, there are \( N \times N \) subaperture images (views) of size \( \xi \times \eta \) where the \((i, j)\)th view is \( A_{ij} \) with elements \( A_{ij}(x, y, c) \) at the pixel \((x, y)\) and color component \( c \in \{0, 1, 2\} \) denoting hereafter a component in RGB space. For example we experiment with plenoptic images from Lytro Illum, where \( N = 15, \xi = 434 \) and \( \eta = 625 \). We refer to the view with index \((i, j)\) as \((8, 8)\) as the center view and to the other 224 views as side views. The task considered in this paper is to compress simultaneously \( N \times N = 225 \) views losslessly, where the close-by views are extremely similar.

We utilize the redundancy between one side view and its neighbours by proposing a predictive scheme where one optimal sparse predictor is designed for each region from a segmentation of the side view. The segmentations of all side views are based on the quantized depth map and are obtained in the first stage, by propagating the regions using optimal disparities along \( x \) and \( y \) coordinates and suitably filling the missing regions that may result after warping. In the encoding stage, done sequentially over all side views, one region of a side view is predicted using an optimal sparse predictor having as regressors pixels from several side views, accounting for small integer or fractional disparities.

For obtaining the light-field from the camera measurements we use the rectification tools described in [6], but any other rectification method can be used and the decoder does not need to known which method was used and does not need to repeat the rectification processing. If the task would be to encode the initial sensor image (instead of the rectified light-field image as we do here) the decoder has to re-run the whole rectification process, which is not possible when some of the processing steps from sensor image to rectified light-field image are not known at the decoder.

Our method makes use of the depth information of the scene, which is encoded along in the bitstream efficiently using [7]. The depth map for plenoptic images can be estimated with numerous methods, see e.g. [8]. In this paper we use the depth map provided by the camera manufacturer’s software, namely Lytro Desktop.

Plenoptic images captured with a focused plenoptic camera were compressed losslessly by Ferra [9], where the compression of the non-rectified image obtained directly at the sensor is studied. As opposed to [9], we investigate the compressibility of light-field after the rectification of the sensor measurements and we exploit the redundancy of the subaperture images.

In Section 2 the general structure of the proposed method is given. In Section 3 the predictive scheme is discussed in detail. Section 4 illustrates the performance of the method and Section 5 concludes the paper.
2. COMPRESSION ARCHITECTURE

2.1. Definitions and notations

For the central view \((i_c, j_c)\) we are given an estimation of the depth map which we quantize on \(K\) levels resulting in a \(\Omega \times \eta\) quantized depth map \(Z_{i,j}(x,y) \in \{0,1, \ldots, K-1\}\) where 0 is the closest depth and \(K - 1\) is the farthest. Similarly \(Z_{i,j}\) is the quantized depth map associated to the view \((i,j)\) and is obtained with Alg. 1, see below. The set of pixels of any view, is denoted \(\Omega = \{(0, \ldots, \xi-1) \times \{0, \ldots, \eta-1\}\}.\) The depth map \(Z_{i,j}\) induces a partition \(\{\Omega_{ij}^0, \ldots, \Omega_{ij}^{K-1}\}\) of \(\Omega\), where \(\Omega_{ij}^0 = \{(x,y)| Z_{ij}(x,y) = k\}\) (hence \(Z_{ij}\) is a label image for the partition \(\{\Omega_{ij}^0, \ldots, \Omega_{ij}^{K-1}\}\)).

We find useful to work also with a finer partition, where each set \(\Omega_{ij}^k\) is split into its connected components \(\{\Phi_{ij}^k\}, l = 0, \ldots, c_{ij}^k\).

We introduce the horizontal and vertical disparity of a region \(\Omega_{ij}^k\) in the following way. The horizontal disparity \(\delta_{ij}^k\) and the vertical disparity \(\mu_{ij}^k\) warp a region \(\Omega_{ij}^k\) of the view \(A_{i,j}\) into a region \(\Omega_{ij}^k\) of the view \(A_{ij}\) such that for any non-occluded pixel \((x,y) \in \Omega_{ij}^k\), ideally \(A_{i,j}(x,y) \approx A_{ij}(x + \delta_{ij}^k, y + \mu_{ij}^k)\).

2.2. Encoding scheme

The encoder processes the views sequentially, starting with the central view \(A_{i,j}\), which is encoded independently using the lossless mode of JPEG 2000. Also the quantized depth map \(Z_{i,j}\) is encoded, using CERV algorithm [7]. Then each side view \(A_{ij}\) is encoded conditionally on the already transmitted views, as described in the following.

First, we construct the partition of a side view into regions \(\{\Omega_{ij}^0, \ldots, \Omega_{ij}^{K-1}\}\) by using the partition of the central view \(\{\Omega_{ij}^0, \ldots, \Omega_{ij}^{K-1}\}\) (having the label image \(Z_{ij}\)) and warping each region with disparities found by minimizing the Mean Square Error (MSE) in the color views:

\[
(\delta_{ij}^k, \mu_{ij}^k) = \arg \min_{\delta, \mu} \sum_{(x,y) \in \Omega_{ij}} (A_{i,j}(x,y) - A_{ij}(x + \delta, y + \mu))^2.
\]  

Using these disparities, the constant depth regions of the center view are warped to the side view as described in Alg. 1. The warping operation may create a set of missing pixels due to occlusions, denoted by \(\Phi\). We found an easy and effective way of treating missing pixels by allocating them to the nearby region (with respect to the coordinates \(x\) and \(y\)) located at the farthest depth, as described in steps 2.2–2.4 in Alg. 1. The regions in a partition and the partition propagation are illustrated in Fig. 1.

The chosen effective processing order for the views, also mentioned in e.g. [10], that discusses the compression of similar ploenopxic images, is a spiral sequence depicted in Fig. 2. We denote \(\Gamma_{ij}\) the set of pairs \((i',j')\) indexing the views that are available when designing a predictor for the view \(A_{ij}\); e.g. when predicting the view \((9,7)\), we have \(\Gamma_{9,7} = \{(8,7), (7,8), (7,7), (8,7)\}\), see Fig. 2. Since the number of available regressors grows as we move along the spiral, we limit the cardinality \(\Gamma\) so that \(|\Gamma| \leq 5\) by choosing the nearest views i.e. the views \((i',j')\) for which \(|i - i'| + |j - j'|\) is smallest.

The processing flow for encoding one region \(\Omega_{ij}^k\) is depicted in Fig. 3 where the best disparities given by (1) first are transmitted for the whole region \(\Omega_{ij}^k\). Then the region is split into its connected components (see Fig. 1c) and each of them is encoded in a predictive way, described in Fig. 4. All regions smaller than 50 pixels are merged into a single region (one for each side view), treated as any other region \(\Phi_{ij}^k\).

Algorithm 1 Partition propagation from central view \((i_c, j_c)\) to side view \((i,j)\).

| Input: Depth map for the center view \(Z_{i_c,j_c}\) which labels the partition \(\{\Omega_{ij}^0, \ldots, \Omega_{ij}^{K-1}\}\); disparities \(\delta_{ij}^k\) and \(\mu_{ij}^k\), for \(k = 0, \ldots, K - 1\). |
| 1. For \(k = K - 1, \ldots, 0\) |
| 1.1 Set \(x' = x + \delta_{ij}^k\) and \(y' = y + \mu_{ij}^k\). |
| 1.2 Insert \((x', y')\) into \(\Omega_{ij}^k\). |
| 2. Fill missing pixels \(\Phi = \Omega \setminus \{\Omega_{ij}^0, \ldots, \Omega_{ij}^{K-1}\}\) to form partition: |
| For \(k = K - 1, \ldots, 0\) |
| 2.1 Dilate the set \(\Omega_{ij}^k\) with a disk of radius \(r\) to obtain region \(\Phi_1\), |
| 2.2 \(\Phi_2 = \Phi \cap \Phi_1\) (pick from dilated region only missing pixels). |
| 2.3 \(\Omega_{ij}^k = \Omega_{ij}^k \cup \Phi_2\) (allocate to set \(\Omega_{ij}^k\)). |
| 2.4 \(\Phi = \Phi \setminus \Phi_2\) (discard \(\Phi_2\) from missing pixels). |
| Output: \(\{\Omega_{ij}^0, \ldots, \Omega_{ij}^{K-1}\}\). |

Figure 1: (a) Segmentation of the depth map of the center view in \(K = 32\) quantization levels. The three connected components (regions) forming the region \(\Omega_{ij}^3\) at depth \(Z = 3\) are shown in black. (b) Propagation of the depth segments to the side view \((10,4)\). Region \(\Omega_{10,4}\) is shown in black. c) Location of the three connected component regions: \(R_{ij}^{0,0}\) (orange), \(R_{ij}^{3,1,4}\) (blue), and \(R_{ij}^{3,2}\) (red) overlaid over the color side view image.

3. SPARSE DICTIONARY DESIGN AND SPARSE MODELLING

A specific sparse predictor is designed for the pixels in the finest partition, e.g. for a region \(R_{ij}^k\), where prediction of the color components at \((x,y)\) is done conditionally on the causal neighborhood of this pixel and also on the neighborhoods of the pixel in the available side views \((i',j')\) in \(\Gamma_{ij}\). The prediction is done independently for each color component. For the region \(R_{ij}^k\) we introduce the sparse modeling problem as

\[
\min_{\theta} \| y - D\theta \|_2 \text{ s.t. } \|\theta\|_0 \leq \kappa
\]

and describe the elements in dictionary \(D\) and in the desired vector \(y\) one row at a time where each row corresponds to a pixel \((x,y) \in R_{ij}^k\).

Let \(r\) be the row in \(D\) and \(y\) corresponding to the pixel \((x,y) \in R_{ij}^k\). The element \(r\) of the desired vector is

\[
y_r = A_{ij}(x,y,c).
\]

The elements of the \(r\)-th row of the matrix \(D\) are in order

1. The constant element 1 compensating for the bias.
2. The N,W,NW and NE causal neighbors of \((x,y)\) from the current view (e.g. the north element is \(A_{ij}(x,y-1)\)).
3. For all views \((i',j') \in \Gamma_{ij}\):
   - A row vector consisting of the elements of \(A_{i',j'}\) from the full \(3 \times 3\) neighborhood of \((x,y)\) (e.g. if we denote \(C = A_{i',j'}\), the row vector is \(\{C_{x,y}, C_{x-1,y}, C_{x-1,y-1}, C_{x,y-1}, C_{x,y+1}, C_{x+1,y}, C_{x+1,y-1}, C_{x+1,y+1}\}\) where we omitted the index for color and denote as subscripts the pixel indices).
An example of the elements of a row in $D$ is shown in Fig. 5. When a pixel from the $3 \times 3$ neighborhood does not belong to the region $R_{ij}^k$ the value at that pixel is replaced with the value of the nearest pixel in the neighborhood that belongs to the region (in the same way as in [11]).

### 3.1. Sparse prediction with code length based order selection

As is well known, the problem (2) is non-convex and fast algorithmic solutions require a relaxation e.g. by solving the $\ell_1$-norm instead of the 0-norm or by using a greedy algorithm to select relevant regressors from the dictionary one at a time. For the compression, it is crucial to have fine granularity when increasing the sparsity degree (or order $\kappa$) which is why we opt to use Orthogonal Matching Pursuit (OMP) with a model order selection criterion as follows. Optimal order $\hat{\kappa}$, i.e. the number of nonzero coefficients in $\theta$, for prediction is chosen using code length optimization, i.e.

$$\hat{\kappa} = \arg\min_{\kappa} \text{CL}_{\kappa} + \text{CL}_{\text{mask}} + \text{CL}_{\theta_{\kappa}},$$

where $\text{CL}_{\kappa}$ is the number of bits required to code the prediction residuals while $\text{CL}_{\text{mask}}$ corresponds similarly to the binary sparsity mask and $\text{CL}_{\theta_{\kappa}}$ to the nonzero predictor values.

The compression scheme uses context modeling and arithmetic coding. Ignoring the effect of contexts, the code length when the residuals $r = [y - D\theta_{\kappa}]$ are entropy coded with adaptive arithmetic coding with Laplace’s rule of succession is

$$\text{CL}_r = -\log_2 \left( \frac{1}{n_s} \prod_{i=1}^{n_s} n_i! \frac{n_s!}{(n_s - 1)!} \right)$$

where $n_s$ is the number of symbols, in this case $n_s = 511$, $n_i$ is the final count of occurrences for symbol $i$ in the residual vector $r$, and $n$ is the size of the region $R_{ij}^k$.

The mask is transmitted to the decoder by simply sending a zero if the sparse coefficient is zero and a one otherwise. Thus $\text{CL}_{\text{mask}} = n$ where $n$ is the number of regressors, typically $n = 50$. The cost of coefficients is $\text{CL}_{\theta_{\kappa}} = 10\kappa$ since the coefficients are quantized to 10 bits.

The sparse prediction is summarized in Alg. 2.

### 3.2. Entropy coding

As also seen in Fig. 4, after the predictive decorrelation stage, the predictor coefficients are encoded with Golomb-Rice coding and the binary sparsity mask is simply copied as a side information header. The prediction residuals are coded using context modeling and adaptive arithmetic coding similar to [11]. We compute contexts using quantized gradients classified into 16 different contexts.

Overall the information needed to be sent to the decoder is: the color components of the central view $A_{i,j}$, encoded by JPEG 2000; the quantized depth map of the center view $Z_{i,j}$; for each $(i,j)$ the disparities $\hat{\delta}_{ij}$ and $\hat{\mu}_{ij}$; for each $(i,j)$ the prediction residuals $r$, i.e. prediction mask, predictor coefficients and residuals.
Table 1: Compressed file sizes in mega bytes (MB).

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<th>AVC</th>
<th>CALIC</th>
<th>FP8</th>
<th>proposed</th>
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4. RESULTS

For experimental results, data from Light-Field Image Dataset\(^1\), containing raw data captured with a LightF-D... f, is used. We select the same subset of images as in the recent challenge at ICME 2016.

We compare the performance of the proposed compressor to existing generic tools for compressing $L_2$ losslessly. The views can be treated as a pseudo-video-sequence and compressed with HEVC or AVC using their lossless modes. For maximizing their performance we used the preset 'veryslow' and the same spiral.

4. RESULTS

For experimental results, data from Light-Field Image Dataset\(^1\), containing raw data captured with a Lytro Illum camera, is used. We select the same subset of images as in the recent challenge at ICME 2016.

We compare the performance of the proposed compressor to existing generic tools for compressing $L_2$ losslessly. The views can be treated as a pseudo-video-sequence and compressed with HEVC or AVC using their lossless modes. For maximizing their performance we used the preset 'veryslow' and the same spiral (see Fig. 2) sequence as for our method.

Another approach is to rearrange the views in a single image $I$ such that $I((x-1)N+i, (y-1)N+j, c) = A_i(x, y, c)$, where $i = 1, \ldots, N$, $j = 1, \ldots, N$, $x = 0, \ldots, \xi - 1$, $y = 0, \ldots, \eta - 1$ and $c = 0, 1, 2$ [10]. This structure can be efficiently compressed with tools such as JPEG 2000, CALIC [12] or FP8 compressor\(^2\).

Our encoder and decoder were implemented with a combination of Matlab and C. The reported file sizes are directory sizes containing all the necessary files for decoding and lossless decoding was checked. The size of the raw 24 bit data is 183 MB and the compressed sizes are given in Table 1. Results for JPEG2000 or JPEG-LS are not shown because CALIC outperforms them for all the images. It can be seen that our coding scheme achieves for every image the best results, improving significantly the compression rate over the generic compressors.

5. CONCLUSIONS

We conclude that partitioning the side views according to the quantized depth map provides essential regions, for which optimal LS sparse predictors can be designed to capture very efficiently the similarities between the current view and its neighbor views, resulting in a very efficient overall predictive coding. Being able to handle regions with arbitrary shapes, our method is more flexible and outperforms the methods operating over rectangular blocks.

6. REFERENCES


\(^{1}\)Available at [http://mmspg.epfl.ch/EPFL-light-field-image-dataset](http://mmspg.epfl.ch/EPFL-light-field-image-dataset).

\(^{2}\)Available at [http://matthmahoney.net/dc/text.html#1532](http://matthmahoney.net/dc/text.html#1532).