Light field image processing: overview and research issues

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1. Introduction

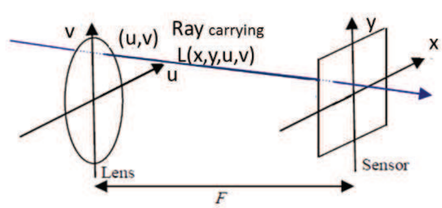
Light field (LF) imaging first appeared in the computer graphics community with the goal of photorealistic 3D rendering [1]. Motivated by a variety of potential applications in various domains (e.g., computational photography, augmented reality, light field microscopy, medical imaging, 3D robotic, particle image velocimetry), imaging from real light fields has recently gained in popularity, both at the research and industrial level.

Research effort has been dedicated to the practical design of systems for capturing real-world light fields which go from cameras arrays [2-5] to single cameras mounted on moving gantries and plenoptic cameras [6,7] based on the principle of integral imaging first introduced by Lipman in [8]. The commercial availability of plenoptic cameras and the equipment of recent smart phones with several cameras, with a single specialized sensor, or with a wafer-level-optics camera array [9], which can, to some extent, capture light fields, even if they are not as angularly dense as those captured by plenoptic cameras, has given a novel momentum to light field research. The flow of rays captured by light field acquisition devices is in the form of large volumes of data retaining both spatial and angular information of a scene, which enables a variety of post-capture processing capabilities, such as re-focusing, extended focus, different viewpoint rendering and depth estimation, from a single exposure.

While offering unprecedented opportunities for advanced image analysis, creation and editing features, real light fields capture poses a number of challenging problems. The data captured by light fields cameras is not only big in volume and of high dimension, which is an issue for storage and communication, but also overwhelming in several other aspects such as the need for high processing power and the angular-spatial resolution trade-off inherent to light field capture devices. The volume of data inherent to light fields is an issue for user interaction which requires near real-time processing, potentially on devices having limited computational power. Editing with a tractable complexity and in a consistent manner the large number of views cannot be solved with a straightforward application of now well-known 2D images editing algorithms. After a brief recall of the plenoptic function and of light fields capturing devices, this paper gives an overview of the main research directions addressing the above challenging problems.

2. Plenoptic function and real light fields capturing devices

Light field capturing is about sampling the plenoptic function which is a 7D function $L(x,y,z,\phi,\theta,\Lambda,t)$ describing the light rays emitted by a scene and received by an observer at a particular point (x,y,z) in space, following an orientation defined by the angles (ϕ,θ), with a wavelength Λ, at a given time instant t. For a static light field, the 7D plenoptic function can be simplified into a 4D representation called 4D light field in [10] and Lumigraph in [11], describing the radiance along rays by a function $L(x; y; u; v)$ of 4 parameters at the intersection of the light rays with 2 parallel planes, as shown in Fig.1.left. This simplification is done assuming constant radiance of a light ray from point to point, and given that an RGB sampling of the wavelength is performed by the color filters coupled with the CCD sensors.



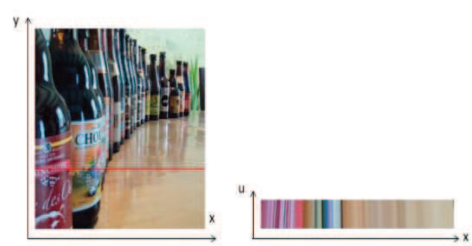


Fig. 1: (left) *Illustration of the two planes parameterization of the 4D static (one time instant) light field; (right) Rendered image at one focus; and epipolar image corresponding to horizontal red line in left image.*

The light field can be seen as capturing an array of viewpoints (called sub-aperture images in particular in the case of micro-lens based capturing devices) of the imaged scene with varying angular coordinates u and v. A photograph at a particular focus is computed from the 4D data by integrating the light across epipolar images. An epipolar image represents a 2D slice of the 4D light field (e.g. a (x,u) slice in Fig. 1.right). The epipolar image shown in Fig.1.right gives an observation of the light field at a constant y-value corresponding to the red line in the picture. Each vertical line in the epipolar image represents the light field observed at varying sub-apertures (u) of the main lens and at a given pixel location x.

Camera arrays have thus been naturally designed to capture the set of views, offering a high spatial resolution for each view but a low angular resolution (limited set of views) hence a large baseline. Targeted applications include long range depth estimation, change of viewpoint and view synthesis, such as AR content capture or movie post production. Camera gantries have also been built in which a single camera moves along a plane and takes captures at regular time intervals.

While camera arrays capture the scene from different viewpoints, hence with a large baseline, plenoptic cameras use an array of micro-lenses placed in front of the photosensor to separate the light rays striking each microlens into a small image on the photosensors pixels, and this way capture dense angular information with a small baseline. Plenoptic cameras are now available on the market with first generation Lytro cameras that typically target consumer photography via their refocusing feature, and the Raytrix cameras that instead target the industrial market with accurate, monocular depth estimation. Two optical designs have been considered for plenoptic cameras, the so-called "plenoptic 1.0" design, called unfocused plenoptic camera, in which the main lens focuses the subject on the lenslet array [6], and the "plenoptic 2.0" design [7], also called focused plenoptic camera, in which the image plane of the main lens is the object plane of the lenslet array (see Fig. 2).

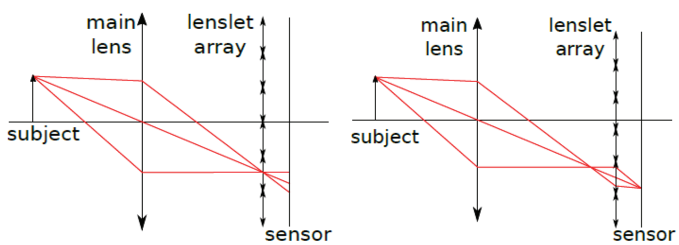


Fig. 2: *(left) plenoptic 1.0 optical design; (right) plenoptic 2.0 optical design.*

In the unfocused camera, the light emitted by one point in the 3D scene is spread over several pixel sensors of the raw lenslet data. Every pixel behind a lenslet corresponds to a different angle. Extracting views from the raw lenslet data captured by plenoptic cameras involves several processing steps [12]: devignetting which, with white images, aims at compensating for the loss of illumination at the periphery of the micro-lenses, color demosaicing, alignment of the sensor data with the micro-lens array, and converting the hexagonal sampling grid into a rectangular sampling grid.

3. Compression of the large volumes of light field data

Given their significant demand in terms of storage capacity, the problem of light field compression rapidly appeared as quite critical in the computer graphics community using light fields for image rendering. Early solutions considered for synthetic light fields were based on classical coding tools, JPEG-coding schemes [11], vector quantization [13], or wavelet coding [14] applied on each view of the 2D array separately. While the separate encoding of each view naturally allows random access to any sample of the light field, the compression factor of these solutions is however hardly exceeding 20. Predictive coding inspired from video compression techniques have then been considered for further increasing the compression factor [15], in which a few views are encoded in Intra while the other views are encoded as P-images where each block can be predicted from one of the neighboring Intra views with or without disparity compensation. Motivated by the objective of random access and progressive decoding, which is not enabled by predictive schemes, the authors in [16] consider instead a wavelet transform applied in the 4 dimensions of the light field, while a Principal Component Analysis (PCA) is used in [17]. Solutions for light field compression have then evolved following advances in mono-view and multi-view video compression (e.g. using MVC) [18].

The emerging devices for capturing real light fields also record very large volumes of data. To take only a few examples, a Lytro Illum camera captures 61 Mpixels (15×15×625×434 pixels) while a camera array, as for example a rig of 4×4 cameras of spatial resolution 2048×1088px captures 35 Mpixels. Each pixel of course has three color components represented on 8 bits. Research for compressing real light field data has evolved along two main directions. The first type of approaches consists in directly compressing the raw lenslet data after de-vignetting and demosaicing (e.g., [19-26]) and the second type of approaches compresses the views extracted from the lenslet data (e.g., [27-29]) or captured by a camera array.

Most solutions proposed for directly encoding the lenslet data aim at exploiting spatial redundancy or self-similarity between the micro-images. The micro-image is the set of pixels behind each micro-lens and is also sometimes called elemental image. Spatial prediction modes have thus been proposed for unfocused cameras in [19] based on a concept of self-similarity compensated prediction [23][24], or using locally linear embedding techniques in [20]. Bi-directional spatial prediction modes have also been added in HEVC for encoding elemental images captured by a focused 2.0 camera [25] and by an unfocused camera [26]. The authors in [22] instead partition the raw data into tiles which are then encoded as a pseudo-video sequence using HEVC.

While the first category of methods only applies to light fields captured by micro-lens based plenoptic cameras, a second category of methods consists in encoding the set of sub-aperture images (or views) extracted from the lenslet images or captured by camera rigs. The authors in [27] form a pseudo-sequence by using a lozenge scanning order and encode this pseudo-sequence using HEVC inter-coding, while in [28] a coding order and a prediction structure inspired from those used in the multi-view coding (MVC) coding standard is proposed, showing significant performance gains compared with HEVC-Intra. In [27] and [28], inter-view correlation is exploited via motion estimation and compensation methods, as in video coding, whereas the authors in [29,30] use homographies and 2D warping instead of classical predictive coding to remove inter-view redundancy. The approach in [30] actually aims at reducing the dimension of the captured data via a low rank approximation of views aligned by homographies which are jointly optimized with the low rank model. This approach called HLRMA [30] yields, with the data set of the ICME 2016 challenge, an average PSNR gain of 2.24 dB compared with a direct encoding of the views as a video sequence scanned following a lozenge scan order starting from the central view, while the pseudo-sequence approach of [28] yields an average gain of 1.78 dB.

The need for efficient compression solutions has motivated the JPEG-Pleno group to launch an initiative for defining a light field compression standard [31], for both data captured by plenoptic cameras and by camera arrays. The standardization phase is on-going with the goal of having an international standard in January 2019.

4. Handling the spatial and angular resolution trade-off

Plenoptic cameras and smart phones equipped with multiple camera sensors can capture both spatial and angular information of light rays from a single capture [6]. However, since the sensor is limited, it is difficult to have both a dense angular and spatial light field sampling. The angular sampling is related to the number of sensor pixels located behind each microlens for Plenoptic cameras while it corresponds to the number of cameras on the wafer for mobile devices. This trade-off between angular and spatial resolution leads to a significantly lower spatial resolution compared to traditional 2D cameras [6].

A first category of approaches consists in resampling the light field to reconstruct sub-aperture images with resolutions higher than the number of micro-lenses. The authors in [32] use the super-resolution discrete focal stack transform to super-resolve the focal stack of a light field. In the same vein, a light field reconstruction approach is proposed in [33], where the de-multiplexed sub-aperture images are first interpolated with barycentric interpolation to adapt to the hexagonal layout of the micro-lenses, and then refined using pixels of neighboring views using ray interpolation. The resulting light field still contains aliasing, which is unnatural. They hence use the dictionary-based single-image super-resolution method proposed in [34] to restore each sub-aperture image separately.

A second category of methods exploits the depth information to increase both spatial and angular super-resolution. Based on the image formation model of the plenoptic camera, the authors in [35] us a depth map to estimate the reflectance in a Bayesian framework where a Markov Random Field prior was used to regularize the solution. The authors in [36] estimate disparity maps locally using epipolar plane image analysis and then use a variational model for the synthesis of super-resolved novel views. A patch-based approach was proposed in [37] where they model the light field patches using a Gaussian mixture model using disparity as prior. The spatial resolution of the 4D light field is then restored using linear minimum mean square estimation (LMMSE). Nevertheless, these methods rely on the accuracy of the disparity estimation algorithm used, which generally fail to restore reliable disparity maps in real-world light fields. Moreover, a significant number of occluded regions make their restoration difficult and generally lead to blur artefacts in regions with large parallax.

Machine learning is used in [38 - 40] to super-resolve real-world light fields of higher quality. Deep convolutional neural networks (DCNN) were used in [38] for both spatial and angular super-resolution. This method first employs a spatial DCNN to restore each sub-aperture image separately followed by another DCNN to synthesize novel views. The resulting sub-aperture images are incoherent across sub-aperture images since they are restored separately. Deep learning was used in [39] to synthesize new views from a sparse set of input views. More specifically, a cascade of two DCNNs is used where the first one learns the disparity while the second one learns the synthesis of novel views. The authors in [40] have used principal component analysis (PCA) and ridge regression (RR) to learn a linear mapping between low- and high-resolution patch-volumes, which are a stack of collocated 2D patches from each sub-aperture image. This method exploits the light field structure and restores sub-aperture images that are more coherent.

5. Light field user interaction and editing

User interaction and light field editing (e.g., segmentation, object removal and inpainting, colorization) now common with 2D images are made difficult for light fields due to the big volume of data to be processed. Besides the computing complexity, one difficulty resides in the fact that the edits on one view must in addition be consistent across views.

Graph-cut used with Random Markov Fields (RMF) is a well-known tool for 2D image segmentation. It has thus been naturally considered for co-segmentation of multiple views using different models such as an appearance model based on color in [41] or on other cues in [42]. However, its complexity quite rapidly increases with the volume of data (number of views and dimension of each view). This is the reason why multi-view co-segmentation methods usually consider a limited number of views. In addition, with dense light fields, the baseline being much smaller, the views are much more correlated. Hence, label consistency can be more strongly enforced.

The problem of dense light field segmentation has been addressed in a semi-supervised manner allowing the user to enter scribbles on the central view. These scribbles are used in [43] to learn a joint color and depth classifier with a random forest technique. The result of the classification is then regularized using a variational approach to segment each ray using its 4D spatial and angular neighborhood. The segmentation of 9x9 views of size 768x768 however takes over 5 minutes. The authors in [44] use the same structure with an anisotropic 4D neighborhood and a SVM classifier to learn the color model, further increasing the computational load. A graph structure merging several rays coming from the same scene point is proposed in [45] which allows dividing the number of nodes by around 50, hence significantly decreasing the computational load of the regularization (9x9 views of size 768x768 are segmented in 4 to 6 sec.).

Light field editing has been essentially tackled from the angle of edits propagation in a consistent manner from one view to the other ones. The goal is to enable user interaction with the whole light field while entering inputs on one view only. A 3D voxel-based model of the scene with an associated radiance function is proposed in [46] to propagate pixel edits and illumination changes. Stroke-based editing is also described in [47] where the edits are propagated in a downsampled version of the light field to reduce the computational load.

Object removal is a complex editing task requiring the development of inpainting techniques. While 2D image inpainting has been widely addressed in the literature, there are few works on light fields inpainting. A first category of approaches inpaint one view of the light field using a 2D method and then propagates the inpainting to the other views in a consistent manner. One example of such approach is described in [48] where an exemplar patch-based method is used for the central view. For the other views, instead of searching a best matching patch in the known region of the view to inpaint, the patch is searched in the first inpainted view in order to ensure a better consistency across views. Instead of propagating the inpainting from one view to the others, the authors in [49] describe a 4D patch-based method where the consistency is ensured by minimizing a 4D patch bi-directional similarity measure. All these methods progress patch per patch in a greedy fashion and suffer from a high computational complexity. In addition, they may not ensure a global coherence on the entire light field. The authors in [50] suggest instead using a variationnal framework to define constraints on the epipolar images with the help of disparity information raising other questions related to the estimation of disparity for the region to be inpainted. Despite these preliminary works, the problem of fast light field inpainting which would enable user interaction, with a global coherence on the entire light field remains a difficult problem.

6. Conclusion

This paper gave a quick overview of main research trends in relation to a few critical problems in light field image processing. Given the very big volume of highly redundant data, even with static light fields, it became rapidly evident that progress in this area requires developments which go beyond a straightforward application or extension of well-known 2D imaging techniques. Even if most works focused on static light fields, the volume of high dimensional data becomes even more critical with video light fields for which the above problems remain largely open.

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