

# Saliency Guided Depth Calibration for Perceptually Optimized Compressive Light Field 3D Display

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## Abstract

Multi-layer light field displays are a type of computational three-dimensional (3D) display which has recently gained increasing interest for its holographic-like effect and natural compatibility with 2D displays. However, the major shortcoming, depth limitation, still cannot be overcome in the traditional light field modeling and reconstruction based on multi-layer liquid crystal displays (LCDs). Considering this disadvantage, our paper incorporates a saliency guided depth optimization over a limited display range to calibrate the displayed depth and present the maximum area of saliency region for multi-layer light field display. Different from previously reported cascaded light field displays that use the fixed initialization plane as the depth center of display content, our method automatically calibrates the depth initialization based on the saliency results derived from the proposed contrast enhanced saliency detection method. Experiments demonstrate that the proposed method provides a promising advantage in visual perception for the compressive light field displays from both software simulation and prototype demonstration.

## 1. Introduction

Technologies based on 3D have been increasingly applied in commercial products. However, these technologies, based on binocular parallax using lenticular sheets or parallax barriers suffer from discrepancy between visual accommodation and convergence; this can cause visual confusion and fatigue as the eyes focus on the screen but converge at the apparent distance of the image. To solve this problem, volumetric displays [51, 48] and holographic displays [32] have been developed. A huge amount of data would be involved to provide a true 3D image with both correct fo-

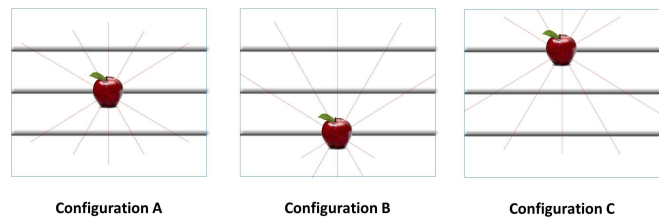


Figure 1. Different depth initialization for the same target light field, here the configuration A is used by [47, 18], configuration B is from [13] and configuration C is [28].

cus and parallax cues and this prevents these technologies from being widely accepted for daily usage. In addition to these pure optical or physics-based techniques, a computational 3D display technology known as compressive light field display has also been investigated [15, 47, 14] for solving the problem. They not only take the advantages of various emerging display technologies such as multi-layer displays and high-speed temporal modulation, but also make use of promising computer vision and pattern recognition algorithms such as sparse reconstruction and compressive factorization, which effectively compress the display data from multi-view images to multi-layer images. Moreover, the compressive light field 3D display is compatible with 2D displays since parallax barriers and lenticular sheets are not used in this display method.

However, this kind of computational multi-layer display, including our three-layer light field 3D display, shares the same limitation; the maximum depth range of multi-layer display theoretically has an upper bound and cannot be more than twice the distance between the outer layers [23]. Considering the unsatisfactory depth range limitation of multi-layer liquid crystal displays (LCDs), and the bigger depth range in the light field capture, some depth

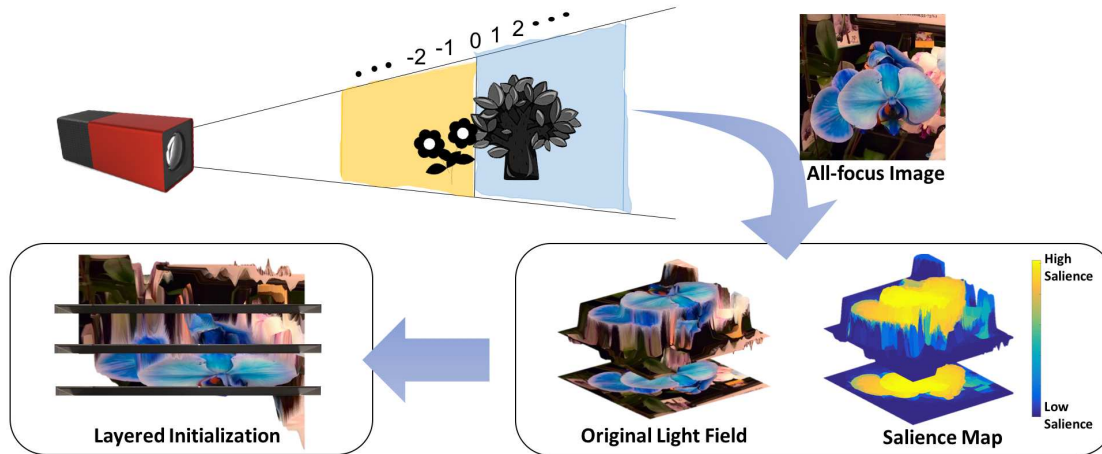


Figure 2. The framework of the saliency guided depth calibration for perceptually optimized compressive light field 3D display, including light field capture, saliency detection, depth initialization, layered decomposition and perceptually optimized light field display.

range may have to be ignored in the light field modeling and reconstruction, this paper has proposed a saliency-guided depth calibration for perceptually optimized compressive light field 3D display.

In this paper, we use a three-layer prototype as an example, but the proposed method also can be extended to other multi-layer displays with more LCD layers. In contrast to existing work on cascaded light field displays that only use the fixed depth initialization configuration [47, 13, 28] as shown in Fig. 1, the proposed method will firstly detect the higher saliency objects in the light field capture region based on a proposed contrast enhanced saliency detection method, then maps these objects into the compressive display depth region of multi-layer LCDs as much as possible. The framework of the proposed saliency guided depth calibration for optimized display is shown in Fig. 2. The experimental results show that an improved display is produced by the proposed optimization framework.

In this paper, Section 2 introduces the related work of saliency detection and compressive display of light fields and Section 3 discusses the contrast enhanced saliency detection method. Section 4 proposes saliency-guided depth calibration for three-layer light field displays. The experimental results are reported in Section 5 and Section 6 summarizes the existing contributions and anticipates future work.

## 2. Related Works

Before proposing the optimized framework and methods, related work regarding saliency detection [6] and multi-layer light field display [46] is introduced in this section.

### 2.1. Saliency Detection on Light Field

**With vs. Without Learning.** Recently, several studies have developed learning methods in saliency analysis [53, 27, 21]. For example, Judd et al. [21] use the standard support vector machine (SVM) classifier to formulate saliency detection as a binary classification problem. Li et al. [27] propose a saliency detection framework using dense and sparse coding representations as features, and integrate this framework via the Bayes formula. Multilayer learning networks [53, 35] approaches also have been researched to acquire the hierarchies of representations to detect the saliency objects. However, these approaches suffer from parameter sensitivity and normally require large-scale manually annotated data to train effective models.

State-of-the-art saliency detection approaches for light field, with the exception of Li et al. [25], use the image's selected foreground to build the dictionaries, and detect the saliency objects with a weighted sparse coding framework. Most other works still use the scheme without machine learning. A combined light field saliency detection algorithm, based on foreground, background and contrast cues, is proposed in [26]. Zheng et al. [52] further propose a deeper light field saliency detection method for light field by inducing the depth image into the optimization framework. To avoid the parameter sensitivity and manual annotation, this paper implements light field saliency detection by a framework without learning.

**Foreground vs. Background Priors.** Many saliency detection schemes exploit contrast cues, i.e., saliency objects are expected to exhibit high foreground contrast within certain context [39]. Koch and Itti [19] use center-surround foreground contrast of low level features to detect saliency. More local methods to compute the foreground contrast within a small neighborhood of pixels are proposed by using color difference [7], edge orientations [29], or curva-

tures [40]. Global methods, considering statistics of the entire image and rely on features such as power spectrum [16], color histogram [9] and element distributions [36], are also proposed for foreground contrast detection.

Although the center-surround foreground approaches are proven highly effective, Wei et al. [44] suggest that background priors are equally important. In fact, one can eliminate the background to significantly improve foreground detection. Yang et al. [50] observe that connectivity is an important characteristic of background and use a graph-based ranking scheme. Since most existing approaches rely on color contrast, when the foreground and background have similar color, these approaches can easily fail. Thus, our approach resolves this issue by using a contrast enhanced salience detection method on the light field based on selected color contrast cues, depth contrast cues and background cues.

**Intrinsic vs. Extrinsic cues.** When detecting salience objects, a key step is to distinguish salience targets from distractors. Toward this end, some approaches propose to extract various cues only from the input image itself to pop-out targets and suppress distractors (i.e., the intrinsic cues) [17, 41, 34, 40]. However, other approaches argue that targets and distractors may share some common visual attributes and the intrinsic cues are often insufficient to distinguish them. Therefore, they incorporate extrinsic cues such as user annotations [6], depth map [52] or statistical information [24] of similar images to facilitate detecting salient objects in the image.

This paper will focus on the salience detection on light field, in which some important extrinsic cues already appear within the all-focus image, such as depth image, re-focus images and dense multi-view images. Thus, the proposed approach could be listed within the same classification as extrinsic cues.

## 2.2. Multi-layer Display

Multi-layer display is a type of extension of normal liquid crystal (LC) display which stacks multiple LC layers illuminated with a uniform backlight, as shown in Fig. 3. The traditional additive volume method will show a 3D scene at different depths to generate 3D display [5]. Further, Bell et al. [4] proposed a two-layer 3D display system and discussed the implementation details like moiré reduction by diffuser for this system. For light field display, a theoretical simulation for multi-layer light field display is proposed in [12], and its implementation is introduced in [13]. Compressive display [46] is a kind of multi-layer light field display which has complete theoretical modeling and analysis, as well as several prototype implementations, such as polarization display [22] and tensor display [47].

In this paper, we will follow the light field modeling in

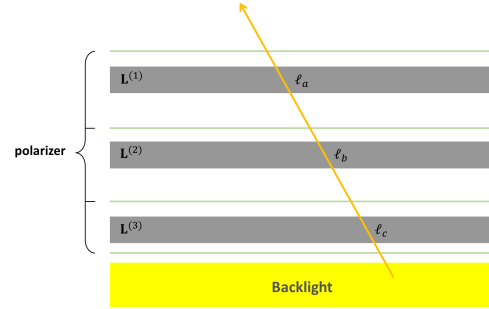


Figure 3. Polarization-based attenuation light field displays.

[47, 42, 43, 38] to introduce the proposed perceptually optimized compressive light field 3D display. The detailed modeling will be introduced in the following subsection.

## 2.3. Light Field Modeling

The compressive display is used to depict a discrete light field, which allows for optimal decomposition of a light field into light-attenuating layers [45]. The modeling framework for both glasses-free [47] and head-mounted stereoscope [18] could be considered as a fixed stack of  $N$  light-attenuating layers illuminated by a uniform backlight.

As shown in Fig. 3, we demonstrate a three-layer attenuation configuration. The reconstructed light field  $R$  for this three-layer tensor display can be written as:

$$[\mathbf{L}^{(1)}, \mathbf{L}^{(2)}, \mathbf{L}^{(3)}] = \mathbf{L}^{(1)}(\lambda_a)\mathbf{L}^{(2)}(\lambda_b)\mathbf{L}^{(3)}(\lambda_c), \quad (1)$$

where  $\mathbf{L}^{(n)}(\lambda_i) \in [0, 1]$  is the transmittance at the pixel  $\lambda_i$  of layer  $n$ . The transmittances for the front, middle and rear layers are given by  $\mathbf{L}^{(1)}(\lambda_a)$ ,  $\mathbf{L}^{(2)}(\lambda_b)$  and  $\mathbf{L}^{(3)}(\lambda_c)$ , respectively, for a light field ray shown in the figure.

By generalizing Eq. (1), the optimal three-layer reconstructed light field can be acquired by solving a constrained optimization problem [22] as follows:

$$\arg \min_{\{0 \leq \mathbf{L}^{(1)}, \mathbf{L}^{(2)}, \mathbf{L}^{(3)} \leq 1\}} \frac{1}{2} \left\| \mathbf{T} - \mathbf{W} \circ [\mathbf{L}^{(1)}, \mathbf{L}^{(2)}, \mathbf{L}^{(3)}] \right\|^2. \quad (2)$$

Here,  $\circ$  is the product of a Hadamard (elementwise) matrix,  $\leq$  denotes the element-wise matrix inequality operator and  $\mathbf{T}$  denotes the target 3D light field to be reconstructed.  $\mathbf{W}$  is a sparse three-order tensor, only with 0/1 elements, which controls the optimized view angle of reconstruction light field [30].

Eq. (2) corresponds to non-negative matrix factorization. Therefore, we can apply any non-negative matrix factorization algorithm to its solution [31, 8]. However, after applying a Fourier transform into this light field expression, Lanman, D., et al. [23] get the theoretical upper-bound

depth of field (DoF) of this three-layer display, which is twice separation layer distance. This means that during the light field reconstruction, we have to map the original camera-captured depth range to the limited multi-layer display depth range, where the former is much larger than the latter [47, 13].

### 3. Contrast Enhanced Saliency Detection

The pipeline of the proposed saliency detection approach for display optimization is shown in Fig. 2 and the detailed saliency detection algorithm is described in the following subsections.

#### 3.1. Preprocessing

The contrast-enhanced saliency is based on the light field color, depth and focus cues on the super-pixel [3]. Here, the super-pixels are segmented from the all-focus image  $\hat{I}$ . The minimum preprocessing unit of the following analysis is based on super-pixels. The total number of super-pixels  $M$  is set to 300 following [52].

After segmenting the all-focus image to super-pixels, we further try to select a best image with the highest color contrast as well as background cues. Here, we denote  $\{I^i\}$ ,  $i = 1, \dots, N$  as the re-focus images based on the Lytro camera. Following that, we use  $(x, y)$  to index a traditional pixel and  $p$  to index a super-pixel region.

We start by detecting the in-focus regions in each re-focus image  $I^i$  and use them as the focusness prior. The focus value  $\mathcal{F}(x, y)$  is measured at pixel  $(x, y)$  based on the focusness detection technique [37]. Thus, the focus value of a super-pixel  $p$  can be computed from the average of all pixels within the superpixel  $p$ :

$$\mathcal{F}(p) = \sum_{(x,y \in p)} \frac{\mathcal{F}(x, y)}{Z_p}, \quad (3)$$

where  $Z_p$  is the total number of traditional pixels in super-pixel  $p$ . Thus, a super-pixel level focusness map,  $\mathcal{F}^i$ , can be generated for each re-focus image  $I^i$ . Furthermore, the focus value of the whole image could be integrated to two 1D focusness distributions along the  $x$  and  $y$  axes as:

$$D_x = \frac{1}{\alpha} \sum_{y=1}^h \mathcal{F}(x, y), \quad D_y = \frac{1}{\alpha} \sum_{x=1}^w \mathcal{F}(x, y). \quad (4)$$

Next, we set out to find one re-focus image with the highest background cues which could be used to detect the non-saliency region as well as show the high contrast with saliency region. For this purpose, we compute the background likelihood score  $BLS(I^i)$  based on each re-focus image  $I^i$  by U-shaped filtering  $D_x$  and  $D_y$ :

$$BLS(I^i) = \rho \cdot \left[ \sum_{x=1}^w D_x^i(x) \cdot \mathcal{U}(x, w) + \sum_{y=1}^h D_y^i(y) \cdot \mathcal{U}(y, h) \right], \quad (5)$$

$$\mathcal{U}(x, w) = \left( \frac{1}{\sqrt{1 + (\frac{x}{\alpha})^2}} + \frac{1}{\sqrt{1 + (\frac{w-x}{\alpha})^2}} \right). \quad (6)$$

Here, this filter has a 1D bandpass filtering function along the axis, and  $w = 360$  is equal to the width of test images in the Lytro1 dataset, while  $h$  is the length and  $\alpha = 28$  controls the bandwidth.  $\rho = \exp(\lambda * i/N)$ , in which  $\lambda = 0.2$  is the weighting factor of a layer in terms of depth, and  $N$  is the total number of slices in the focus stacks. Then,  $I^*$  is chosen from the focusness maps for its highest BLS. While also let the re-focus image  $\mathcal{F}^*$  with the highest BLS among focus stacks takes the place of all-focus image used in traditional methods [52, 26] due to the high color contrast cues in super-pixel level. Benefiting from the focused foreground, it will provide a better performance for the final saliency map than an all-focus image.

#### 3.2. Contrast Enhanced Salient Segmentation

After completing the preprocessing work for super-pixel segmentation that is focusness map generation chosen and color image chosen, we integrate focusness background cues, color contrast and depth contrast for generating the final saliency result.

**Background Cues.** To enhance the saliency contrast, a background probability  $Pb$  on the focusness map  $\mathcal{F}^*$  is calculated through:

$$Pb(i) = 1 - \exp\left(-\frac{A_{val}(p_i)^2}{2} \cdot \|C - A_{pos}(p_i)\|^2\right), \quad (7)$$

where  $A_{val}(p_i)$  is the average value of super-pixel  $p_i$  on the focusness map  $\mathcal{F}^*$  and  $A_{pos}(p_i)$  defines normalized average coordinates of super-pixel  $p_i$ .  $\|C - A_{pos}(p_i)\|$  defines the L2-norm distance of measuring the spatial information of super-pixels related to the image center  $C$ . Therefore, regions that belong to the background have higher background probability  $Pb$  on  $\mathcal{F}^*$ .

**Contrast.** Here, we use the similar method to calculate the color contrast saliency  $M_C$  and depth contrast saliency  $M_D$  with different inputs, but the same processing unit:

$$M_C(i, j) = \|A_{col}(P_i) - A_{col}(P_j)\|D(i, j), \quad (8)$$

$$M_D(i, j) = \|A_{dep}(P_i) - A_{dep}(P_j)\|D(i, j), \quad (9)$$

where  $i, j = 1, \dots, K$ ,  $K$  is the total number of super-pixels.  $A_{col}(p_i)$  is the average color value of super-pixel  $p_i$  in LAB color space on a selected color re-focus image  $I^*$  and  $A_{dep}(p_i)$  is the average depth value of  $p_i$  on the depth image.

$D(i, j)$  is the spatial factor for controlling the pair-wise distance of super-pixels and is given by:

$$D(i, j) = \exp\left(-\frac{\|A_{pos}(p_i) - A_{pos}(p_j)\|^2}{2\sigma_w^2}\right), \quad (10)$$

where,  $A_{pos}(p_i)$  and  $A_{pos}(p_j)$  are the normalized average coordinates of super-pixel  $p_i$  and  $p_j$ , separately.  $\sigma_w$  is specified as 0.67 throughout our experiments.

**Combined Saliency Metric.** Finally, we incorporate background probability into the contrast enhanced saliency as follows:

$$M = \beta M_D + (1 - \beta)M_C, \quad (11)$$

$$M_{com} = M * P_b. \quad (12)$$

Here,  $M$  is from the focussness background cues and  $S^*$  is the weighted saliency based on color contrast saliency and depth contrast saliency.  $\beta = 0.3$ .

**Post-optimization.** Like the state-of-the-art work [52], we also applied saliency optimization algorithm [54] onto the contrasted enhanced saliency map as post-optimization:

$$S_{opt} = OPT(M_{com}). \quad (13)$$

Here, when use the post-processing, the combined saliency map is used as a 2D image input for the post-optimization, and the output is a 2D optimized saliency map. Experimental results in Supplementary Materials show that the proposed algorithm can be better than the state-of-the-art by either using, or not using post-processing.

## 4. Perceptually Optimized Light Field 3D Display via Saliency Guided Depth Initialization

### 4.1. Saliency Guided Depth Initialization

Different to the previous mentioned configurations [47, 13, 28, 18] with manually fixed initialization, the proposed method will automatically determine the relative position of

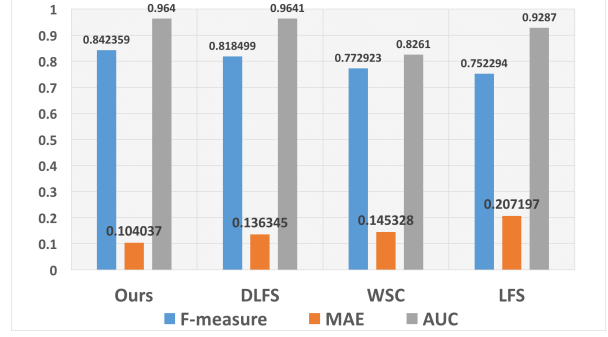


Figure 4. Performance comparisons of ours vs. DLFS, LFS, WSC by F-measure, MAE and AUC.

three layers in order to improve the performance of the 3D display. The distance between each two layers is fixed to  $Dis_L$  at 15 mm.

According to [2], assume the captured depth range is  $R_C$ , and the ideal displayed depth range is  $R_D$ , thus  $R_D$  could be calculated as follows:

$$R_D = \frac{PS_L}{PS_C} \cdot R_C, \quad (14)$$

where the  $PS_L$  is the pixel size of the LC screen of our multi-layer light field display prototype,  $PS_C$  is the micro-lens size of the Lytro camera related to one light field pixel.

According to [10], assume the real displayed depth range is  $R_L$ , and the pixel size of prototype is  $PS_L$ , so  $R_L$  could be calculated as follows:

$$R_L = \frac{2 \cdot Dis_L}{PS_L}. \quad (15)$$

The performance of 3D display will surely be good if  $R_L \geq R_D$ . However, in general,  $R_L < R_D$ , therefore, part of the image will be out of range of the real displayed depth ( $R_L$ ) and resulting in performance decreasing because of the missing key content of the image. That is, the saliency region of the image, which contains the content of most interest for human eyes, should be presented as much as possible in the real displayed depth range. The new constrained optimization problem is shown as following:

$$\mathbf{T}_{di} = \arg \max_{T'} S_{dis}(T'). \quad (16)$$

Here,  $S_{dis}(T')$  is used to calculate the saliency region whose depth range could be initialized in  $2 \cdot Dis_L$ : that is, substantially between the first layer and the rear layer.  $\mathbf{T}_{di}$  is the depth-adjusted target light field. This is different to the fixed depth initializations used in [47, 13, 28, 18], which is shown in Fig. 1, separately,  $\mathbf{T}_{di}$  is the optimized light field in which we try to keep the saliency objects displayed in the actual displayed depth region as much as possible. For example, if the initialization center of the displayed light field is in the middle layer, the performance of

	Precision	Recall	F-measure	MAE	AUC
<i>WSC</i>	0.809866	0.670907	0.772923	0.145328	0.8261
<i>LFS</i>	0.810021	0.607887	0.752294	0.207197	0.9287
<i>DLFS</i>	0.827058	0.791206	0.818499	0.136345	<b>0.9641</b>
<i>CESD</i>	<b>0.856693</b>	0.802748	<b>0.851966</b>	<b>0.097374</b>	0.8977
<i>CESD+DLFS</i>	0.851779	<b>0.812412</b>	0.842359	0.104037	0.9640

Table 1. Evaluation results of ours vs. DLFS, LFS, WSC by Precision, Recall, F-measure, MAE and AUC.

the proposed display will be equated to three-layer tensor display [47]; however, the optimization also can handle the cases where the saliency objects are not in the center of the DoF of light field as shown in Fig. 2. Here, the Eq. (16) is solved by Simulated Annealing (SA) algorithm [33].

## 4.2. Light field Reconstruction

After acquiring the perceptually optimized initialization of target light field, we still consider the light field reconstruction problem as a constrained optimization problem for the following reason:

$$\arg \min_{\{0 \leq \mathbf{L}^{(1)}, \mathbf{L}^{(2)}, \mathbf{L}^{(3)} \leq 1\}} \frac{1}{2} \left\| \mathbf{T}_{di} - \mathbf{W} \circ [\mathbf{L}^{(1)}, \mathbf{L}^{(2)}, \mathbf{L}^{(3)}] \right\|^2, \quad (17)$$

where, the  $\mathbf{T}_{di}$  is the depth-adjusted target light field with the optimized initialization. In this paper, three layered images are generated by least squares with linear constraints and bounds (LSQLIN) [11] and its GPU speed-up version based on the simultaneous algebraic reconstruction technique (SART) algorithm [22] is also released with supporting material.

## 5. Experimental Results

We compare our approach with state-of-the-art techniques for both saliency detection and layered 3D display on a public light field dataset [26].

### 5.1. Saliency Detection

Based on the ground truth (GT) released with the light field dataset [26], we follow the canonical precision-recall curve (PRC), F-measure, mean absolute error (MAE) and area under the curve (AUC) methodologies to evaluate the accuracy of the detected saliency. For details about these evaluation methods we refer the reader to [52]. For objectively showing the benefit of proposed contrast enhanced approach, the parameters setting in our implementation is the same as [52, 26], although the proposed approach is not as sensitive to the fixed parameters. The proposed light field saliency detection results are mainly compared with the algorithms that also use light field as input, which are based on Weighted Sparse Coding (WSC) [25], depth combined

contrast (DLFS) [52], and tailored Light Field Saliency (LFS) [26]. However, they are also compared with the algorithms using an all-focus image as the input, which is based on global-contrast (RC) [9], Low Rank Matrix Recovery (LRMR) [36], Graph-Based Manifold Ranking (GBMR) [50], focusness-based (UFO) [20] and Hierarchical Saliency (HS) [49].

Table 1, Fig. 4 and Fig. 6 show the results of the four comparison architectures. The PRC of our unified approach achieves a state-of-the-art result, and the best Precision, Recall, F-measure, and MAE results are shown where the proposed approach is used on the public dataset. *CESD* in Table 1 refers to our contrast enhanced saliency detection method, and the difference between *CESD* and *CESD+DLFS* is the focusness images generated from pre-processing, where *CESD+DLFS* method directly exploits the focusness results from DLFS.

Our approach can handle highly challenging cases such as the ‘Blue Bird’ scene in LFS where the deemed saliency regions have a similar color/texture to the non-saliency regions. Notice that both our precision and recall values are higher than other methods, with favorable F-measure and MAE in most cases. This indicates that our algorithm is capable of locating the most salient regions with a high confidence. Fig. 5 shows that our technique also produces more visually available results, e.g., it generates more complete and accurate contours.

### 5.2. Light Field Display

**Hardware Implementation:** The hardware prototype was built using three Asus VG248QE 24’ LCDs and two NVIDIA Quadro graphic cards, which can demonstrate  $1920 \times 1080$  resolution images or videos with a 144Hz refresh rate.

The display prototype shown in Fig. 7 uses the three-layer structure of Fig. 3. Following the structure of existing prototypes, the front and middle polarizers are orthogonal, and each polarizer has to be orthogonal to the next. Additionally, the distance between each pair of LCD screens is 15 mm.

**Software Simulation:** Under the Windows 10 operating

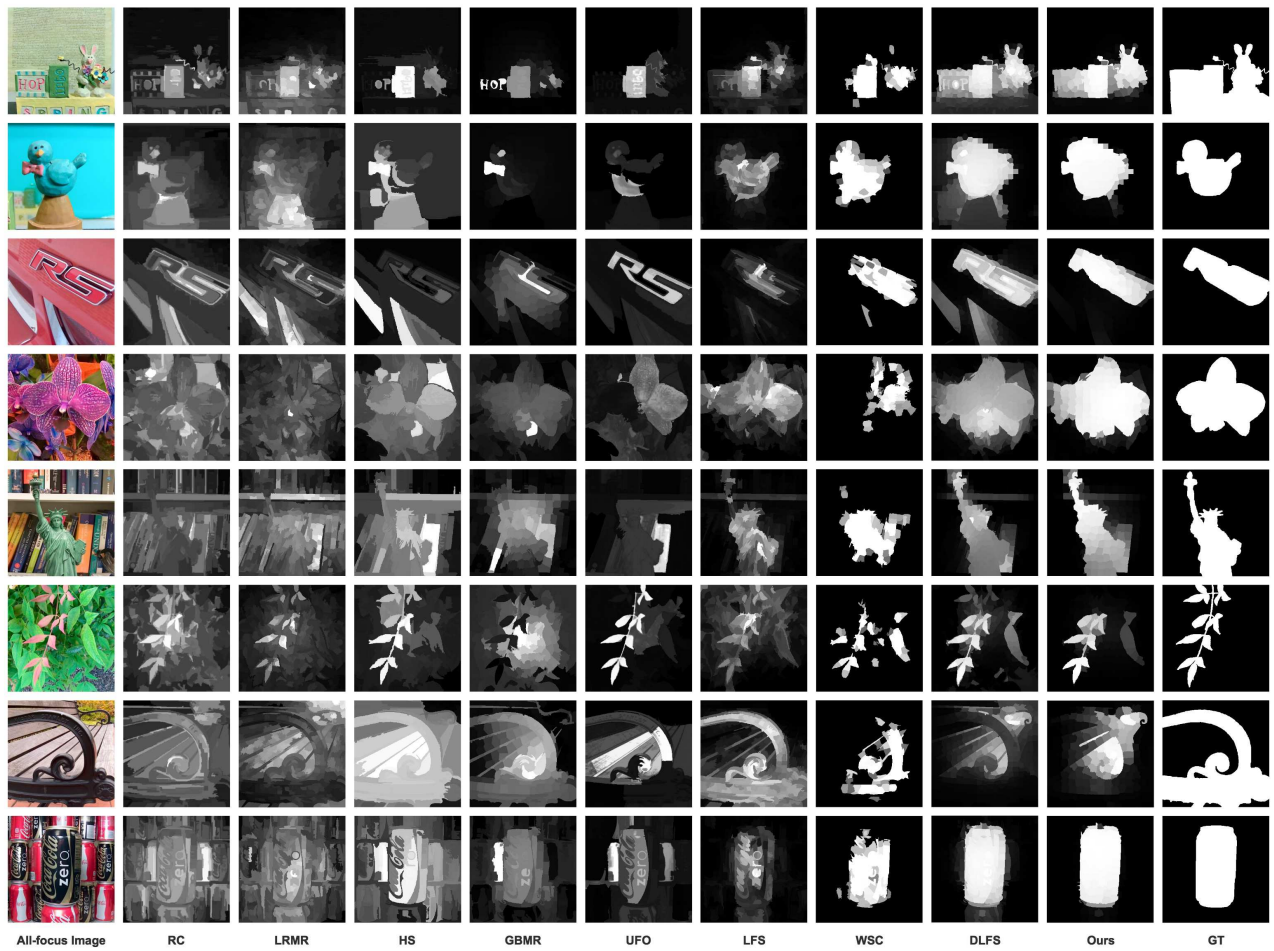


Figure 5. Visual comparisons of different saliency detection algorithms vs. ours on a light field dataset.

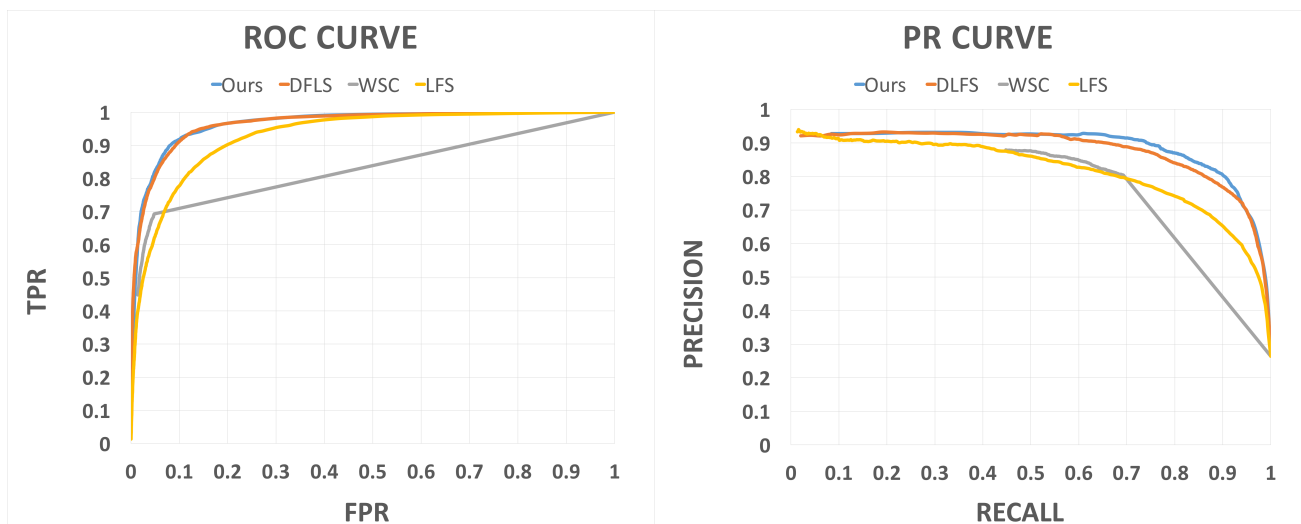


Figure 6. Performance comparisons of ours vs. (a) DLFS, (b) WSC and (c) LFS. The left is the receiver operating characteristic (ROC) curve with true positive rate (TPR) against the false positive rate (FPR) and the right is the precision recall (PR) curve.



Figure 7. Hardware prototype of compressive light field display.

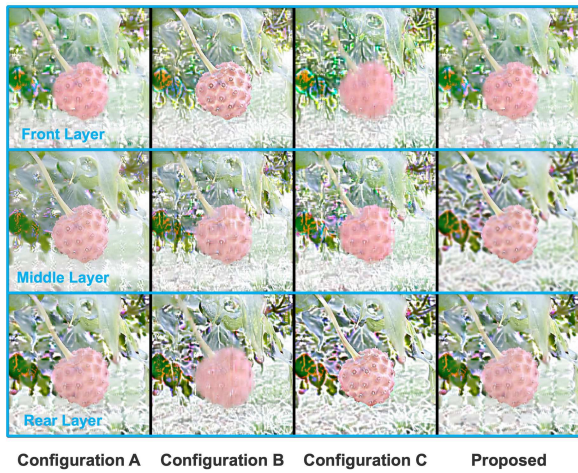


Figure 8. Software-generated layered images for different configurations: the first column is with configuration A, and second column is with configuration B, the third column is based on the configuration C, and the fourth column is from the proposed method. Note that the proposed method's average sharpness is much better than other configurations.

system, the software stimulation is implemented based on the light field database [26] captured by a Lytro1 camera, using an Intel CPU Core (3.4 GHz) PC with 32G RAM. Initialized configuration and related parameters are: i) the views, and of each light field content of this dataset is extracted from the raw data (\*.LFP) with Lytro desktop software [2] and related toolbox [1], ii) based on the Lytro camera capture configuration, the optimized view angle is  $[-3, +3]$  for both horizontal and vertical directions, iii) the time-multiplexed modulation of light field reconstruction is not used in the proposed prototype. Following the above preferences, the average processing time of light field modeling and optimizing steps in MATLAB is approximately 20 minutes. The layered pictures for each configuration are shown in Fig. 8. Note that the simulated result of the proposed initialization optimization (IO) method is better than any other fixed configuration for the salient object.

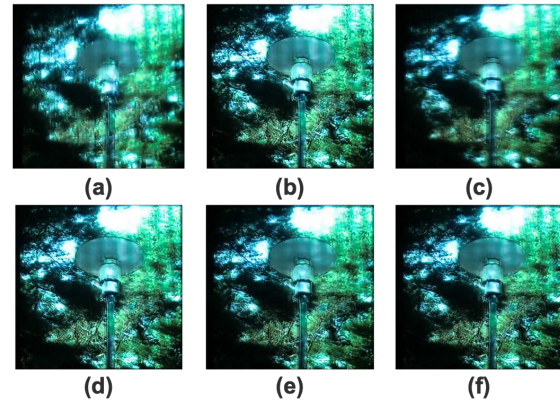


Figure 9. The frontal photograph of overall display performance in different configurations with one content from Lytro1 dataset [26]: here, (a) configuration A [47, 18] (b) configuration B [13], (c) configuration C [28], (d) optimized with proposed salience detection, (e) optimized with saliency ground truth, (f) the original captured image.

### 5.3. System Performance

The practical performances of variable prototype configurations with different depth initialization are shown in Fig. 9. Although the visual effect of frontal photographs is limited by luminance and moiré effects, it can be found that our approach provides a more distinct and natural scene than anchor methods.

The proposed method has undergone comprehensive subjective measurement by 12 subjects where the performance of optimized depth initialization was viewed as the best with 75% cases, which was found to match people visual perception better, at least 22%, than the other fixed depth initializations, which only match the maximum 53%. More experimental results and supplementary material can be found in the Supplementary Materials.

## 6. Conclusion

This paper has proposed a salience-guided depth optimization for multi-layer light field displays. The best depth initialization is automatically chosen based on the contrast enhanced salience detection approach and salience-guided depth initialization framework. Experiments demonstrate that the proposed method provides a promising perceptual advantage. In the future, we plan to improve the light field display by introducing a just noticeable differences algorithm to the visual attributes of the optimization framework.

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