Aliasing Detection and Reduction in Plenoptic Imaging

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Abstract

When using plenoptic camera for digital refocusing, angular undersampling can cause severe (angular) aliasing artifacts. Previous approaches have focused on avoiding aliasing by pre-processing the acquired light field via pre-filtering, demosaicing, reparameterization, etc. In this paper, we present a different solution that first detects and then removes aliasing at the light field refocusing stage. Different from previous frequency domain aliasing analysis, we carry out a spatial domain analysis to reveal whether the aliasing would occur and uncover where in the image it would occur. The spatial analysis also facilitates easy separation of the aliasing vs. non-aliasing regions and aliasing removal. Experiments on both synthetic scene and real light field camera array data sets demonstrate that our approach has a number of advantages over the classical prefiltering and depth-dependent light field rendering techniques.

1. Introduction

The availability of light field camera array and commercial plenoptic cameras has given rise to many solutions to traditionally challenging computer vision and graphics problems, ranging from multi-view stereo matching [27, 31, 11], to panoramic synthesis [29, 28] and image matting [10]. A plenoptic camera is essentially a multi-view acquisition device with the goal to acquire discrete samples of the 4D light field. The camera baseline in the light field camera array [28, 25, 26] is generally larger than the one in the light field camera such as Lytro [18] and Raytrix [23]. A unique capability of plenoptic camera is after-shot dynamic refocusing via wide-aperture filtering [8] or Fourier slicing [20]. However, the number of views (or the angular resolution) is often deemed insufficient to produce high quality refocused images. As a result, the refocused images will exhibit strong aliasing artifacts due to angular undersampling.

The cause of aliasing in light field refocusing has been thoroughly studied in both the spatial and frequency domains [13, 4, 3, 19]. In the spatial domain, the aliasing artifacts occur at the out-of-focus regions and are attributed to insufficient number of ray samples. To reduce aliasing, prefiltering [13] can be used to reduce the spatial artifacts.

In the frequency domain, Chai et al. [4] presented a comprehensive analysis on the tradeoff between sampling density and depth resolution. They further suggested that a sufficient condition to avoid aliasing artifacts is to limit the disparity of all scene elements to ±1 pixel. Further, one can minimize aliasing by positioning the geometry proxy plane [8] at the depth that corresponds to the average of the minimum and maximum disparity.

In reality, implementing the sufficient aliasing-free condition is difficult. To ensure the disparity less than one pixel, the camera/microlens baseline should be ultra small, and often even smaller than the camera/microlens sizes. The condition is not necessary either. Consider a light field of a constant color wall. Even if the light field is severely undersampled, the refocused results will not exhibit aliasing. In contrast, if the wall is highly textured, the refocused image will exhibit aliasing and the aliasing pattern depends on the wall texture and the sampling pattern. This implies that a scene-dependent analysis is needed to properly characterize aliasing.

Our work is also motivated by the need for improving the visual quality in the refocused rendering. Reducing aliasing using a denser microlens array will reduce the effective image resolution. For example, in Lytro, the effective resolution is 0.7 megapixel even using a 11 megapixel sensor. In
fact, balancing between the spatial and angular resolution is still an open problem in light field imaging [7]. Recent solutions [2, 6] that first recover scene depth and then use it in rendering have shown promising results. However, reliable scene geometry estimation via stereo matching [27, 31, 11] or volumetric reconstruction [5] is still difficult.

In this paper, we present a different solution that first detects and then removes aliasing at the light field refocusing stage. Specifically, we reconstruct a set of refocused images by randomly selecting/excluding certain angular views. We then compare the coefficient of variation of reconstructed scene points, with high-variance points indicating aliasing. For the aliasing regions, we use lower-frequency terms of the decomposition for reconstructing the refocused image. Experiments on both synthetic scene and real light field camera array data sets demonstrate that our approach has a number of advantages over the classical prefiltering and depth-dependent light field rendering techniques.

2. Related work

Modeling and reducing aliasing in light field rendering is a long term problem in image-based rendering. The recent commodity light field cameras have renewed the interest on exploring the problem. Earlier approaches rely on light field prefiltering that can implement either physically by using a wide aperture camera or computationally by first oversampling the light field and then applying a low-pass filter [13]. Prefiltering can also be combined with dynamic light field reparameterization to reduce aliasing at any focal depth [8]. The prefiltering technique can effectively reduce aliasing but will also introduce excessive blur in the refocused image, especially when the light field is undersampled. Stewart et al. [24] compensated over-blurring by combining multiple linear filters to simultaneously reduce aliasing and maintain image sharpness. Zwicker et al. [33] alleviated aliasing in 3D displays by interpolating more views than what the display acquires. Ng [20] suggested that the spatial domain rendering and aliasing reducing algorithms can be more efficiently implemented in the frequency domain by band limited filtering and slicing.

With the availability of the commodity light field cameras such as Lytro [18] and Raytrix [23], one can dynamically control the angular sampling depending on scene composition, desired photographic effects, etc. The Raytrix and the Adobe plenoptic can dynamically change the microlens-to-sensor space for trading between spatial and angular resolutions [22, 17, 7]. However, due to limits on sensor sizes/ resolution and microlens baselines, generating a high spatial resolution image has to sacrifice the angular resolution. As a result, the aliasing artifacts at the out-of-focus regions can be severe in the focused plenoptic camera [17], even with smart image demosaicing [32]. It is also possible to use depth-dependent light field rendering [16] to reduce aliasing. However, these techniques require solving the scene reconstruction problem, which is traditionally challenging and slow.

Light field cameras can also be implemented using coded apertures. Liang et al. [14] developed a programmable aperture photography system that can obtain a full resolution light field via view-dependent depth estimation. Bishop et al. [2] introduced an anti-aliasing filter that also incorporates multi-view depth information. Levin et al. [12] have shown that, if scene depth information is known, one can use mixture-of-Gaussians derivative priors to recover a nearly aliasing-free light field. All these techniques attempt to avoid aliasing before light field rendering whereas we aim to detect potential aliasing regions and then reduce aliasing at the rendering stage.

3. Angular Aliasing Analysis and Detecting

We start with studying the cause of aliasing in light field imaging in the spatial domain. For clarity, we focus our analysis on light field camera array in which the angular sampling is generally sparse due to the large camera baseline. The analysis can be applicable to plenoptic cameras such as Lytro and Raytrix by mapping each microlens to a pinhole camera in the array.

3.1. Aliasing in Refocusing

The digital refocusing technique using the light field data is commonly referred to as synthetic aperture photography [8, 25]. In general, synthetic aperture produced by the camera array is much larger than the one produced by Lytro or Raytrix. We assume each constituent camera in the array is pinhole in which each ray represents an angular sample of the scene. To synthetically focus on an arbitrary focal surface, one can query and then integrate corresponding rays from all cameras, similar to gathering rays using a thin-lens with a wide aperture, as illustrated in Figure 2.

Conceptually, the main difference between synthetic and real aperture imaging is that, the real one acquires all light rays passing through the camera whereas the synthetic one

![Figure 2: Refocusing Using a Real vs. Synthetic Aperture.](image-url)
only gathers a subset of rays, i.e., ray samples. Therefore, the synthetic aperture case can be viewed as a sampled version of the thin-lens system. Let \( L_p \) be the complete set of incident rays from a 3D space point \( p \) and \( R(\theta) \) be a ray of \( L_p \) with angle \( \theta \). The real aperture image \( I_p \) is represented as \( I_p = \int_{L_p} R(\theta)d\theta \). In the camera array case, the synthetic image \( I'_p \) is,

\[
I'_p = \int_{L_p} R(\theta)\delta(\theta - n\Delta x)d\theta,
\]

\[
= \sum_{L_p} R(\theta) - \sum_{L_p} R(\theta)\delta(\theta - n\Delta x)
\]

(1)

where \( \delta(\cdot) \) is a Dirac’s delta function and \( \Delta x \) is the sampling interval, \( n \in \mathbb{N} \). If taking the sampling noise \( \varepsilon \) into consideration, the relationship between \( I'_p \) and \( I_p \) is

\[
I'_p = I_p - I_p \ast \delta(\theta - n\Delta x) + \varepsilon.
\]

(2)

Eqn. (2) reveals that aliasing is caused by \( I_p \ast \delta(\theta - n\Delta x) \). If we know the camera array setting, we can derive a maximum aliasing-free sampling interval \( \Delta x^* \) (or a minimum sampling rate \( S_x^* \)), i.e., to any sampling interval \( \Delta x < \Delta x^* \), the term \( I_p \ast \delta(\theta - n\Delta x) \) could be negligible. For simplicity, we denote \( S_{x^*} = \frac{1}{\Delta x^*} \) and \( S_x = \frac{1}{\Delta x} \). The aliasing artifact hence is determined by the sampling ratio \( R \),

\[
R = \begin{cases} 
\frac{S_x}{S_{x^*}} < 1 & \text{if aliasing} \\
\frac{S_x}{S_{x^*}} \geq 1 & \text{if non-aliasing}
\end{cases}
\]

(3)

Next, we employ the classical two paralleled-plane model [13] and analyze the relationship between \( S_{x^*} \) and \( S_x \) in the 2D light field space [15]. As shown in Figure 3, all rays originating from an arbitrary surface are parameterized by the camera plane \( V \) and image plane \( T \). On the camera plane \( V, 1/\Delta x \) is equivalent to the number of cameras. We choose the central camera \( v_0 \) as the reference one. Assume all cameras focus at a specific 3D point \( p \) whose depth is \( z \). If \( p \) is not a real physical point in the space, all rays passing through \( p \) can be traced back to the actual surface (\( \Delta z \) away from \( p \)). We mark this region \( D_{region} \) in color. The boundary of \( D_{region} \) can be determined by two lines of \( v_0p \) and \( v_0f \), where \( v_0 \) represents the outermost camera on \( V \).

Assume that the scene is Lambertian and camera array is uniformly distributed, for each camera \( v_x \) within \( v_0 \) and \( v_a \), to sample \( t_x \) is equivalent to sampling between \( t_a \) and \( t'_a \) in camera \( v_a \). If camera counts between \( v_0 \) and \( v_a \) is less than the pixel counts between \( t_a \) and \( t'_a \), the aliasing artifacts will appear perceivably, as shown in the top right of Figure 3. On the image plane \( T, t_a \) and \( t_0 \) is a pair of correspondence of \( p \) in camera \( v_a \) and \( v_0 \) respectively. Thus we have,

\[
t_a = t_0 - \frac{f}{z}(v_a - v_0) = t_0 - \frac{fA}{z} \]

(4)

where \( A \) is the aperture size.

From the similitude relationship in Figure 3, we can derive \( |t_a - t'_a| \) as,

\[
|t_a - t'_a| = \frac{f A}{z^2 + z\Delta z}
\]

(5)

Therefore, the expected sampling interval \( \Delta x^* \) can be derived as \( 1/|t_a - t'_a| \). Regarding \( \alpha_t \) as the frequency of the texture on the image plane \( T \), we can derive \( \tilde{R} \) as,

\[
\tilde{R} = \frac{S_x}{S_{x^*}} = \frac{S_x}{\alpha_t|t_a - t'_a|} = \frac{1}{f} \frac{z^2 + z\Delta z}{\alpha_t}
\]

(6)

where \( \rho = \frac{S}{\alpha_t} \) denotes the sampling density on the camera plane. The term of \( \frac{1}{\alpha_t} \) is the property of camera array while \( \frac{z^2 + z\Delta z}{\alpha_t} \) depend on the scene geometry and texture. It is important to note that our analysis is different from the frequency aliasing analysis [4] in a number of ways. [4] explains if aliasing could be aliased but neither guarantees that aliasing would occur or reveal where in the image it would occur. In contrast, our derivation explicitly states which part of the image will exhibit aliasing. Second, [4] derives the sufficient condition on aliasing-free rendering in the narrow aperture case (e.g., bilinear interpolation for view synthesis) whereas we derive the necessary sampling ratio to guarantee aliasing free rendering in the wide aperture (refocusing) filter. In particular, our analysis reveals that the aliasing-free sampling rate \( S_{x^*} \) is scene geometry and texture dependent, which is the first explicit derivation that correlates aliasing with scene composition in the spatial domain.

Eqn. (6) shows that there are four cases that angular aliasing would be minimum.
1) $\Delta z = 0$. In this case, the focal plane coincides with actual scene geometry and the sampling rate $S_x$ is always sufficient.

2) $S_x \to +\infty$ or $A \to 0$. In this case, the sampling density $\rho \to +\infty$. For example, imaging using a real thin-lens or using a pinhole camera will be aliasing free.

3) $f \to 0$. If the plane $V$ and $T$ are close enough, $|t_a-t'_a|$ can be extremely small. Thus, the angular aliasing can be avoided due to the low resolution of rendering image.

4) $\alpha_t \to 0$. If the scene is textureless or the texture is highly smooth (very low frequency), the refocused results will not produce major aliasing at the out-of-focus regions.

If both scene geometry and texture are known, one can handle aliasing reduction at the rendering stage. For example, the depth-dependent rendering methods [30] assume that $\Delta z$ is known in Eqn.(6) and can estimate the size of the defocus blur kernel for conducting spatial blurs to emulate angular blurs. However, these techniques require depth estimation. In Section 3.3, we present a depth-free aliasing reduction scheme purely based on adaptive sampling.

### 3.2. Aliasing Detection

Recall that for a given scene within a finite range of distance, to a specific rendering point $p$, $S_x$ is a constant while $R$ would vary with $S_x$. We denote $U$ as all possible imaging results of points $p$, $U = \{I'_p(S_x)|S_x \in [0, +\infty)\}$, denote $\Omega$ as all angular aliasing results $\Omega = \{I'_p(S_x)|S_x \in [0, +\infty), S_x < S_{x^*}\}$, and $\Omega'$ the possible over-sampled conditions. Obviously, $U = \Omega \cup \Omega'$ and $\Omega \cap \Omega' = \emptyset$. As shown in Figure 4, the red shaded area $\Omega'$ corresponds to aliasing sampling conditions, whilst the blue shaded area represents aliasing-free sampling conditions. By Eqn.(3), $R > 1$ iff $I'_p(S_x) \in \Omega'$ and the aliasing term $I_p * \delta(\theta - n\Delta z)$ is near zero. In this case, we have the following corollary.

**Corollary:** $\forall S_{x_i}, S_{x_j} \geq S_{x^*}$, corresponds to $I'_p(S_{x_i})$ and $I'_p(S_{x_j}) \in \Omega'$, then $|I'_p(S_{x_i}) - I'_p(S_{x_j})| \leq 2\varepsilon$.

In particular, when $S_{x_i} = S_{x_j}$ and $S_{x_j} \in \Omega'$, the corollary still holds, i.e., all possible observations $I'_p(S_{x_i})$ (here $x_i$ refers to different sampling pattern with the same sampling rate) will appear similar. In this case, aliasing detection is equivalent to solving the following problem.

**Aliasing detection:** For a given $S_{x_0}$, if $\exists(S_{x_i}, S_{x_j})$, satisfying $S_{x_i}, S_{x_j} \leq S_{x_0}$ and $|I'_p(S_{x_i}) - I'_p(S_{x_j})| > 2\varepsilon$, then $I'_p(S_{x_0}) \in \Omega'$.

If we set $S_{x_0} = S_{x^*}$, there is only one sampling pattern, i.e., the full aperture condition. Consequently, we cannot directly apply the aliasing detection scheme without altering the distribution of camera array. Therefore, we need to slightly relax and false positive in aliasing detection. The image quality can be significantly improved with a proper selected $\gamma$, especially when using the camera array system.

### 3.3. Aliasing-Reduction in Refocusing

Once we have aliasing-detection result, we can conduct aliasing-reduction at the light field refocusing stage. Recall that to implement Algorithm 1, we need to generate a collection of synthetic aperture images (SAIs). This can be achieved by randomly blocking some constituent cameras as different sampling patterns. The SAIs are synthesized by
has revealed that the aliasing artifacts depend on image plane. Thus, we build a Gaussian maskMap
created from images at high pyramid level. To decide the
least significant at higher pyramid levels. The key idea here
is to replace the aliasing region with non-aliasing ones ex-
placing the pixel can cause severe seaming boundaries prob-
lem. Therefore, we conduct a gradient domain fusion pro-
cess [21]. We stitch different image regions by their gradi-
ents and then solve for the Poisson equation. The complete
aliasing-reduction algorithm is summarized in Algorithm 2.

### 4. Experimental Results

All experiments are conducted on the light field data ac-
quired by the 8 × 8 camera array in which angular aliasing is
most severe. The elemental CCD camera (CK-IH046C) has a
752 × 576 resolution and 37.0° field of view. The
baseline between two adjacent cameras is 70mm, as shown in
Figure 2. As shown in Figure 5(a)–(b), each sub-image is
captured by an element camera in the array. Due to the
large baseline between cameras, the acquired light fields are
undersampled in the angular domain. Generating the SAIs
using traditional interpolation and integral techniques [25]
results in severe aliasing, as shown in Figure 5(c)–(d).

Section 3.2 has revealed that the aliasing artifacts depend
heavily on the sampling patterns. Using different patterns,
the SAIs exhibit significantly different aliasing structures.
In contrast, the aliasing-free points remain nearly the same
despite pattern changes. For better illustration, we select
several typical pixels and show their variations using differ-
ten sampling patterns in Figure 5(e)–(f). For example, the
blue aliasing-free points have coherent appearance whereas
the red aliased points apparently exhibit large variations un-
der different sampling patterns.

### Algorithm 1: Aliasing Detection in Refocusing Stage.

```
Input: The target point I_p(S_{x_0});
Output: I_p(S_{x_0}) ∈ Ω or I_p(S_{x_0}) ∈ ∇.
1: P_γ(S_{x_0}) = \{S_x | (1 - γ)S_{x_0} ≤ S_x ≤ S_{x_0}\};
2: for i = 1 to N do
3:   S_{x_i} = random_i(P_γ(S_{x_0}));
4:   Create I_p(S_{x_i}) using SAI algorithm in [25];
5: end
6: Compute C_v via Eqn.(7);
7: if (C_v > T) then
8:   return I_p(S_{x_0}) ∈ Ω; /* aliasing */
9: else
10:  return I_p(S_{x_0}) ∈ ∇; /* non-aliasing */
11: end
```

### Algorithm 2: Aliasing Reduction in Light Field Refocusing.

```
Input: The aliased image I_{org}, maxLevel = 3;
Output: The aliasing-reduced image I_{res}.
1: Initialization. I_{res} ← I_{org}, I_{pym}(0) ← I_{org}, binary mask maskMap ← 1;
2: for l = 1 to maxLevel do
3:   I_{pym}(l) ← I_{pym}(l - 1) [1];
4:   foreach pixel p of the image I_{pym}(l) do
5:     if (maskMap(p) == 1) then
6:       Aliasing detecting on I_p(l) using Algorithm 1;
7:       if I_p(l) ∈ ∇ then
8:         maskMap(p) = 0; /p non-aliasing flag/*
9:     end
10: end
11: I_{res} = Fusion(I_{pym}(l), I_{res}, maskMap) [21];
12: end
```

![Figure 5. Comparisons of aliasing vs. aliasing-free pixels in different synthetic aperture images.](image)

(a) and (b) show the multiview data acquired with a camera array. (c) and (d) show the traditional light field refocusing images. (e) and (f) show the refocused results with 100 different sampling patterns.
and Figure 9.

In Figure 6, we introduce new aliasing frequency and cause false positives arbitrarily large since relaxation in the sampling space can introduce new aliasing frequency and cause false positives in our detection. Therefore, we generally need to tradeoff between detection accuracy and robustness. In Figure 7, we show two examples for illustration. Group 2 is false-negative-detection and group 4 is false-positive-detection.

In Figure 8, we plot the aliasing detection results with respect to parameter $N$ (the number of sampling patterns) from 20 to 150. We observe that the detection is more stable with a large $N$. For example, $N \geq 100$ is sufficient for an $8 \times 8$ camera array. The relaxation factor $\gamma$ determines the upper bound of $N$. However, we cannot set $\gamma$ arbitrarily large since relaxation in the sampling space can introduce new aliasing frequency and cause false positives in our detection. Therefore, we generally need to tradeoff between detection accuracy and robustness. In Figure 9, we show two examples for illustration. Group 2 is false-negative-detection and group 4 is false-positive-detection.

For our camera array system, $\gamma = 0.2$ is sufficient as shown in group 3.

5. Conclusion and Future Work

We have presented a new aliasing detection and reduction scheme for light field refocusing. Our analysis is based on spatial-domain analysis that directly associates aliasing with scene geometry and texture. To detect aliasing, we reconstruct a set of refocused images where certain angular views are randomly selected/excluded, hence simulating a random programmable aperture. We then compare the coefficient of image variation across these apertures for detecting aliasing. Once we detect aliasing, we apply a multiscale gradient fusion technique that replaces the aliased regions with aliasing free ones.

There are a number of future directions we plan to explore. Our experiments are restricted to the camera array where the camera baseline is large and aliasing is more problematic. An immediate future step is to apply our algorithm on the Lytro and Raytrix cameras. Since angular
sampling rates are much higher in these light field cameras than the camera array, a large $\gamma$ can be applied for aliasing detection and reduction. We also plan to estimate the relevant parameters adaptively and to accelerate our algorithm with parallel programming.

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References

Figure 8. Aliasing detection using different $N$s. Left: two sets of aliasing detection results with different $N$s. Right: the plot shows the difference of the results using $N$ and $N - 1$ vs. $N$.

Figure 9. Aliasing detections using different $\gamma$s. (a) shows a sample aliased image produced by light field refocusing. We highlight the aliased and aliasing-free regions in red. (b) shows the closeup views of the regions. (c) shows the aliasing detection and reduction results using different $\gamma$s.