Light Field Denoising, Superresolution and Stereo Camera Based Refocusing Using A GMM Light Field Patch Prior

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Light Field

Light intensity at each point \((x,y,z)\) and at all directions \((\theta,\phi)\)

Figure courtesy Adelson et al. 1992
Linear inversion problems on light field

- Light field denoising
- Spatial super-resolution
- Angular super-resolution
- Deblurring
- Refocusing from stereo images
Common characteristics

Linear, under-determined system

\[ Y = HX + n \]

- **Y**: Observed data vector
- **H**: Processing task matrix
- **X**: Light field data vector
- **n**: Noise vector

Hence, need for good light field priors
Light field priors

• Global priors
  – Low-frequency based priors
    • Agnostic of the structure of light field data
    • Variational formulations (Paolo Favaro)
  – GMM prior (Levin et. al. 2008)
    • Conditioned on depth, texture is a Gaussian variable
      – Inference is computationally expensive
A simpler patch based prior

Example light field patches

Advantages of using patch (local) prior

– Efficient learning and inference
– Performance characterization
– Close form expressions
Low-dimensional structure of light field patches of diffuse scenes
An example light field data

Light field represented as a 2-D array of images
Light field patches at different depth have different pixel disparities.
View #2

Light field patches at different depth have different pixel disparities

- Patches with large pixel disparity
- Patches with small pixel disparity
Light field patches at different depth have different pixel disparities.
Light field patches at different depth have different pixel disparities.
Light field patches at different depth have different pixel disparities.
Common characteristics of many processing tasks

Linear, under-determined system

\[
\begin{align*}
Y &= HX + n \\
\text{Observed data vector} &= \text{Processing task matrix} \\
\text{Light field data vector} &= \text{Noise vector}
\end{align*}
\]

Hence, need for good light field priors
Dimensionality of a patch depends on its pixel disparity

2-D light field patch of size $n \times s$ with a disparity of $d$ pixels between views

Intrinsic (true) dimension of the $n \times s$ patch = $n + d(s-1)$

For a 4-D patch, intrinsic dimension varies quadratically with disparity

Intrinsic dimension of a $n_1 \times n_2 \times s_1 \times s_2$ patch = $(n_1 + d(s_1-1))(n_2 + d(s_2-1))$
Low-dimensional structure of patches of lambertian subject

Ratio of intrinsic to ambient dimension Vs. pixel disparity for 16×16×5×5 patches

Compression and smoothing is an easy problem for lambertian light fields

Can reliably process LF if the observation model is under-determined (at most) by a factor of 5
GMM Patch Prior and Inference Algorithm
Overview of GMM patch prior

Choose a patch size

Quantize pixel disparity into discrete values

For each disparity, learn Gaussian patch prior

Assuming uniform prior for disparity values, the overall prior is a GMM prior
Choice of patch size

Patch size depends on the maximum disparity value between views
Large disparity requires large patch size

Problem with large patch size
Learning and Inference become computationally hard

Our data had maximum pixel disparity of 4 pixels/view
We choose 16×16 spatial patch dimension (overall 16×16×5×5 patch size)
Generating data for learning GMM model parameters

- Quantize disparity into discrete values \( (d_i, i=1,2,...,M) \)
  - We quantize into (-5:1:5)
- For each disparity value, generate artificial light field data from images using rendering pipeline.
- Extract light field patches
- Learn mean and covariance of Gaussian prior

\[
P(x \mid d_i) = N(x \mid m_i, \Sigma_i)
\]
GMM patch prior

- Assume uniform prior for mixture weights
  - Physically specifying an imaging volume
- Overall patch prior is GMM

\[
P(x) = \frac{1}{M} \sum_{i=1}^{M} N(x \mid m_i, \Sigma_i)
\]

Reminder

The model for patches is a GMM. Given a disparity, then the model is a simple Gaussian random variable.
Processing task as observation model

- Observation likelihood \( P(y \mid x) = \mathcal{N}(Hx, \Sigma_n) \)
- MAP inference is computationally expensive
  - We propose an efficient algorithm
An efficient inference algorithm

Extract patches from observed data

Estimate disparity for each patch

Final reconstruction via LMMSE estimator
Disparity estimation step

• For disparity $d_i$
  – $y$ (observed patch) is a Gaussian variable
    
    \[
    P(y \mid d_i) = N(y \mid Hm_i, H\Sigma_i H^T + \Sigma_n)
    \]
  – Compute the subspace spanned by the top few PCA vectors

• Disparity estimation step
  – Given an observed patch $y$
  – Compute its distance from each of the subspaces
  – Allocate it the disparity with minimum distance
Final reconstruction via LMMSE

• Observed patch $y$ with (estimated) disparity $d$
• For inferring $x$ (light field patch) from $y$
  – prior $P(x/d)$ is Gaussian
  – likelihood $P(y/x)$ is Gaussian
  – Thus, the posterior $P(x/y,d)$ is also Gaussian
  – MMSE estimator is the posterior mean
    • Linear Estimator also known an LMMSE

$$\hat{x} = m_d + \sum_d H^T (H\sum_d H^T + \Sigma_n)^{-1} (y - Hm_d)$$
Light field processing applications
Light field denoising

$H$ is the identity matrix
Light field superresolution

\[ Y = HX + n \]

- **Y**: Observed patch
- **H**: Processing task matrix
- **X**: Light field patch
- **n**: Noise vector

\[ H \] is the subsampling matrix
Spatial super-resolution

Input low-resolution LF data

Super-resolved LF using GMM (24.2 dB)

Super-resolved LF using bicubic interpolation (21.6 dB)
Light Field Refocussing from Stereo Camera
Light field from stereo

$Y = \begin{bmatrix} \text{observed patch} \end{bmatrix} H \begin{bmatrix} \text{light field patch} \end{bmatrix} + \begin{bmatrix} \text{noise vector} \end{bmatrix}$

$H$ is the particular selection of rows from the identity matrix.

Input stereo pair
Refocusing from stereo pair

Input stereo pair

Reconstructed LF of angular dimension 5×5
Focus at front two soldiers
Focus at the middle soldier
Focus at the rear wall
Another result on refocusing from stereo pair

Input stereo pair

Reconstructed LF of angular dimension 5×5
Focus at the front card
Focus at the middle card
Focus at the rear cards
Conclusion

• Unified framework for light field processing
• Patch based approach
  – Low-dimensional structure of LF patches
    • Indicates achievable compression factor during sensing
  – GMM patch prior
  – Efficient reconstruction algorithm