Multiview Depth Image Enhancement

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Opponent: Jalil Taghia and Haopeng Li

Internal seminar, Communication Theory, KTH

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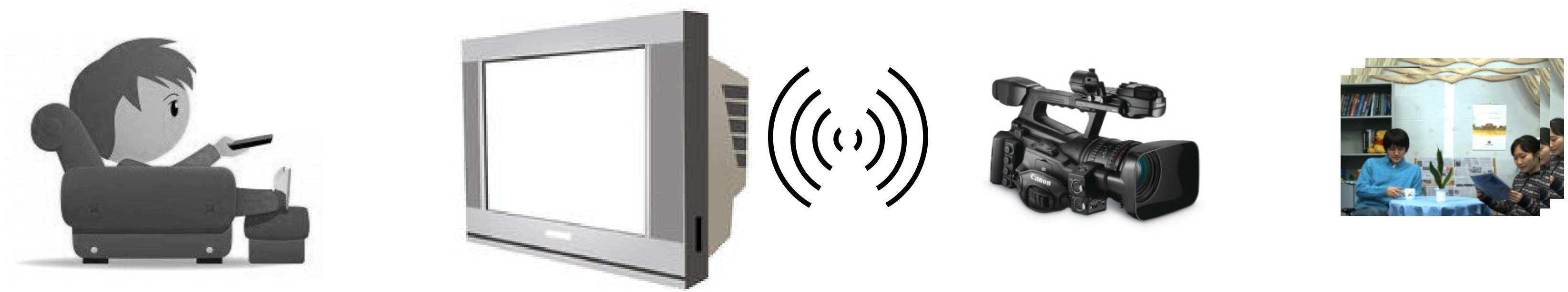
Motivation & Background

Conventional Television

User

Display

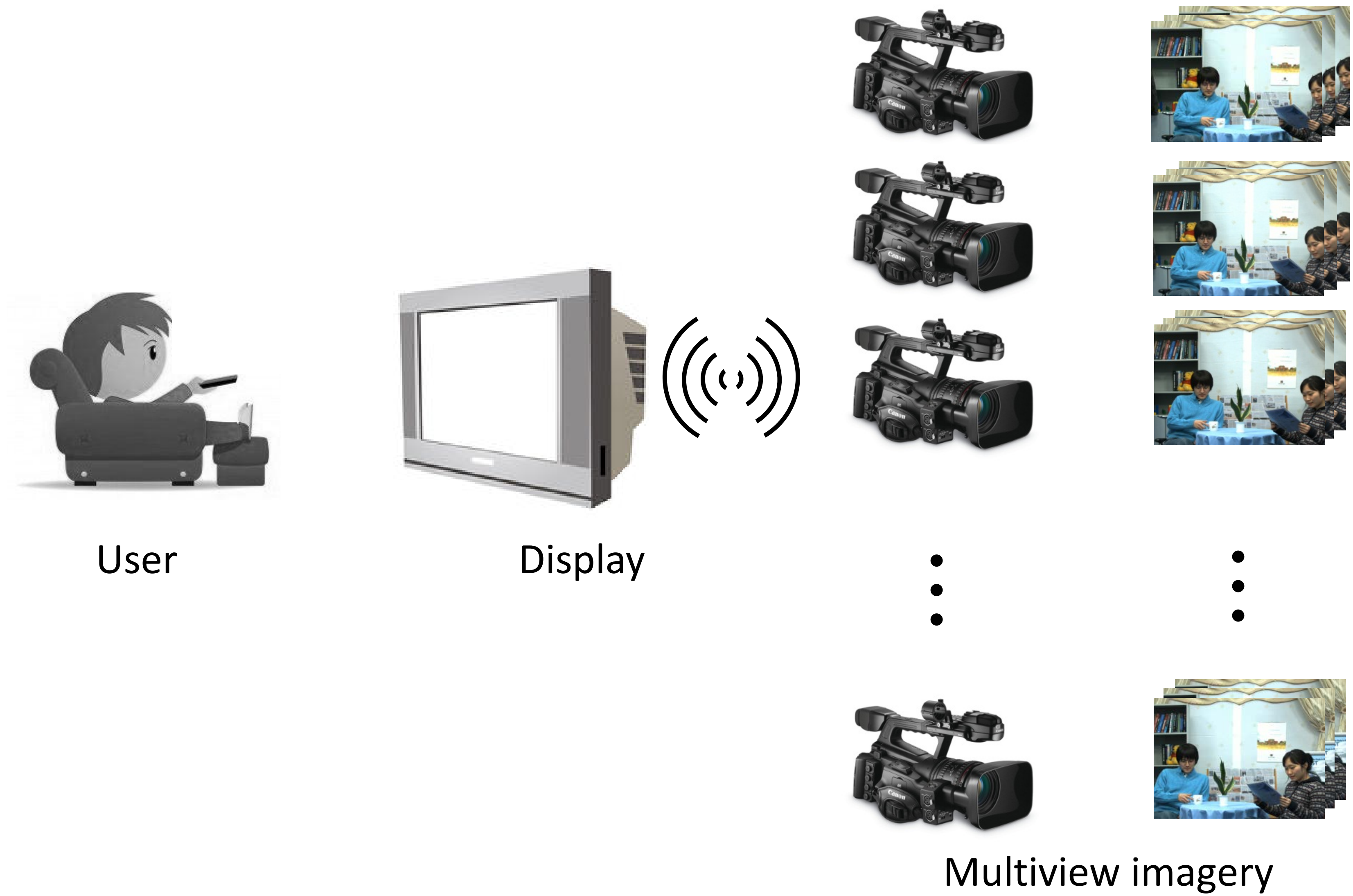
Conventional Television



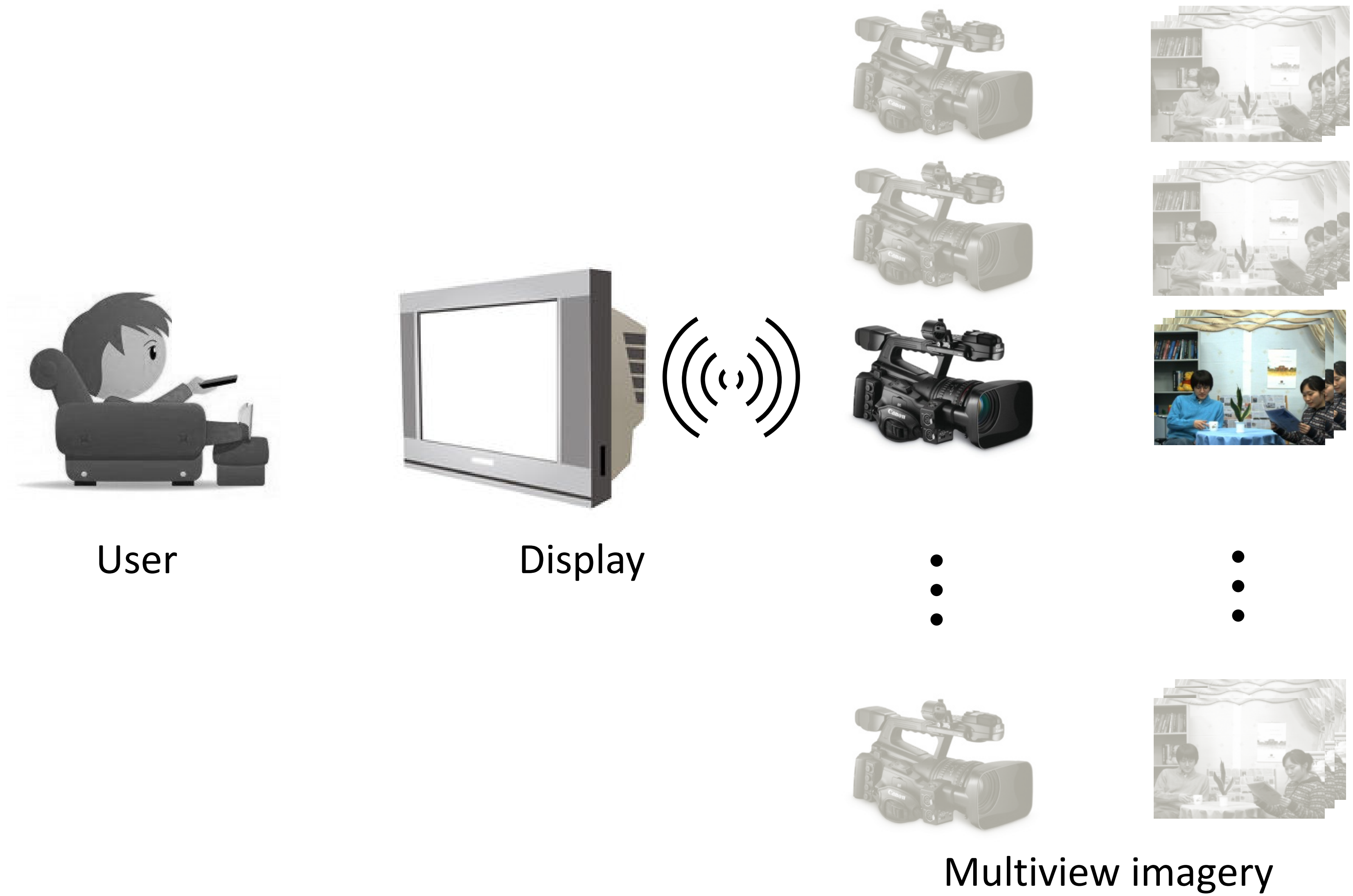
User

Display

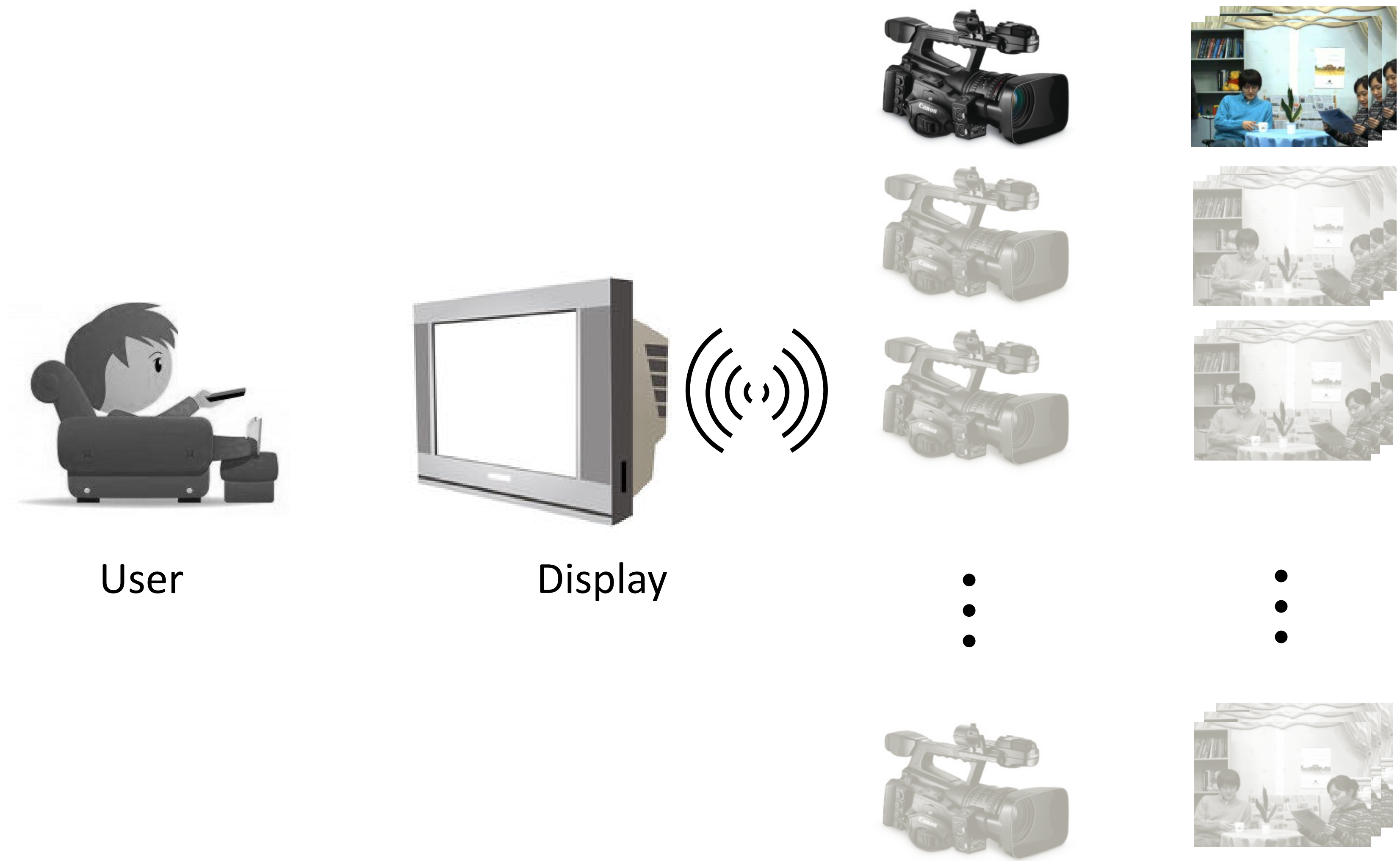
Free-viewpoint Television



Free-viewpoint Television



Free-viewpoint Television

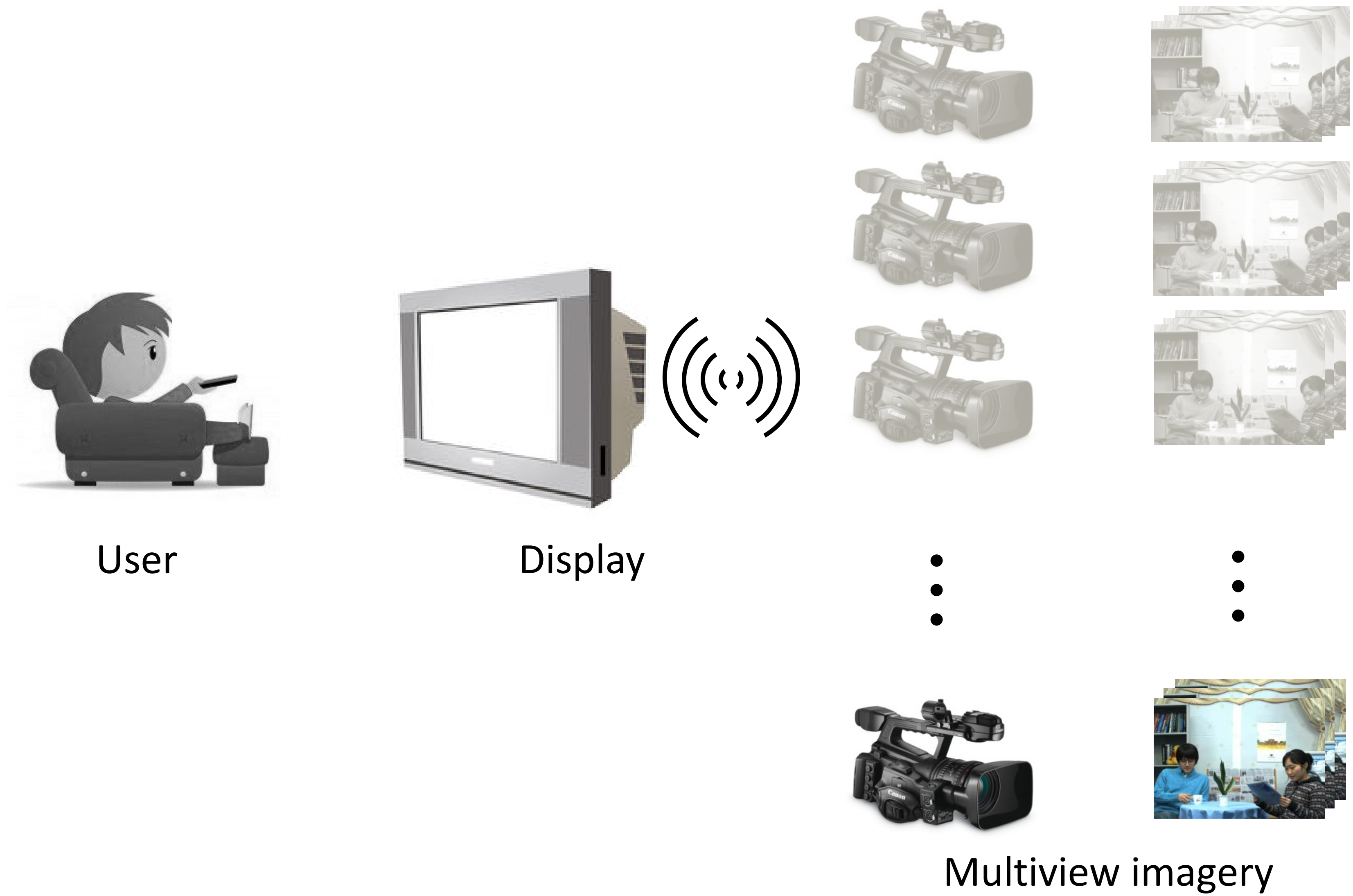


User

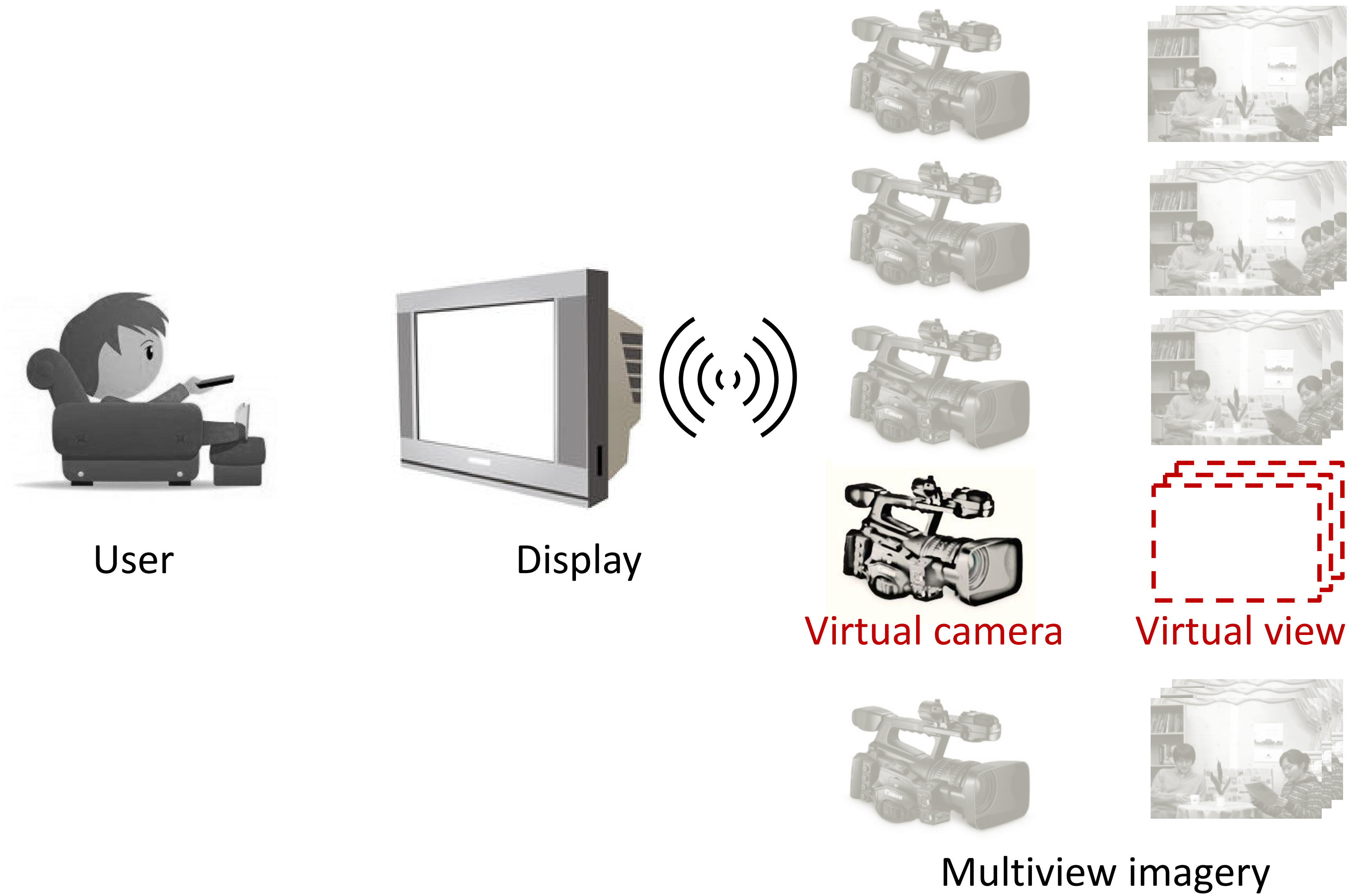
Display

Multiview imagery

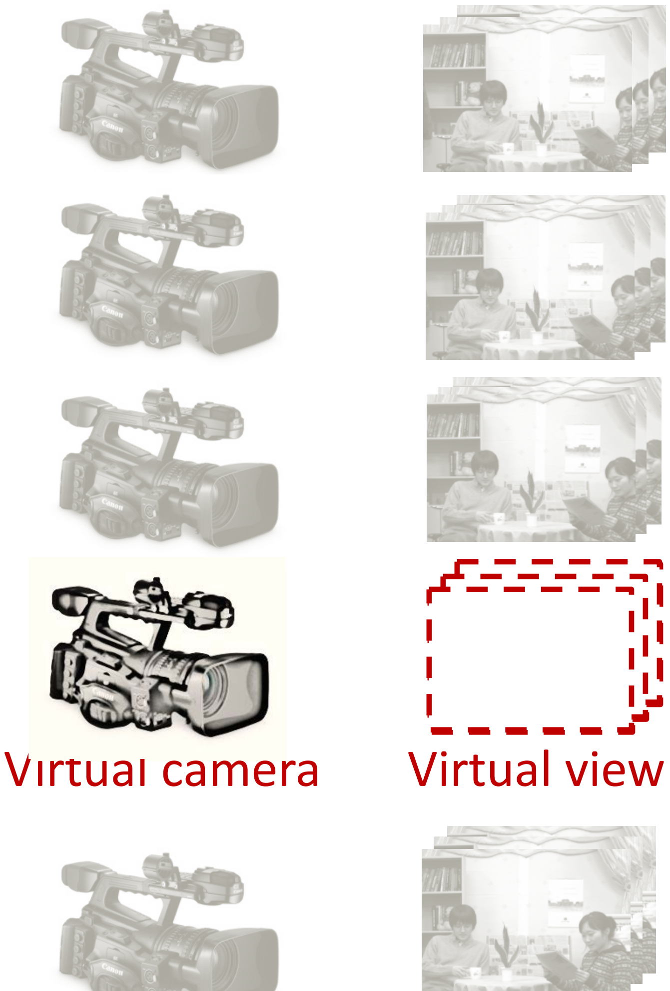
Free-viewpoint Television



Free-viewpoint Television



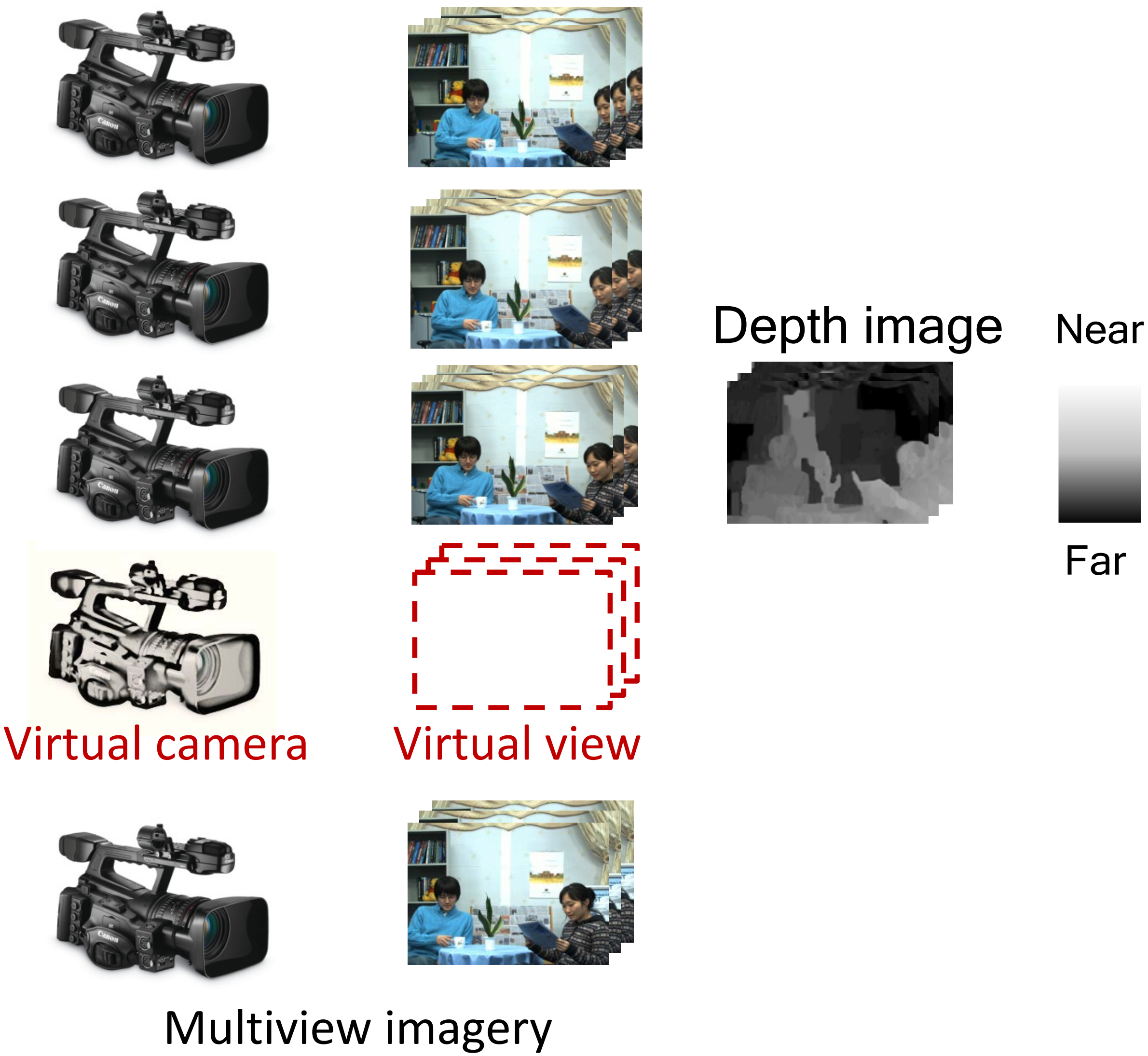
Virtual View Synthesis



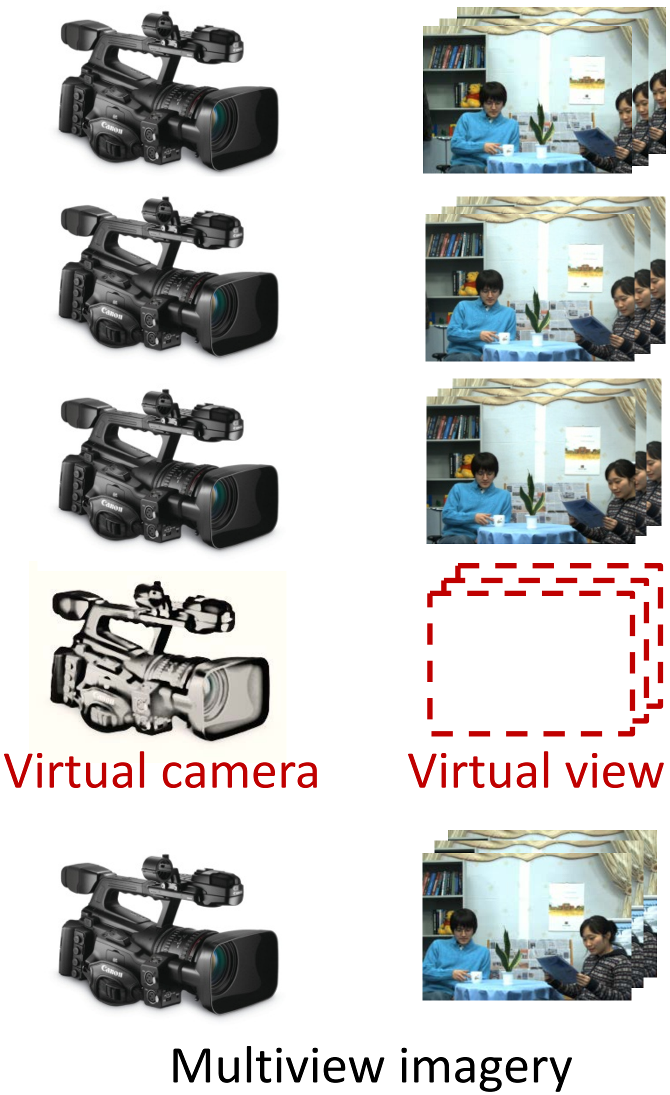
Multiview imagery

Depth Image Based Rendering

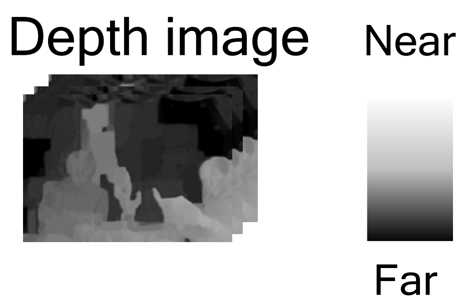
Depth Image Based Rendering



Depth Image Based Rendering



- Depth pixels represent shortest distance between object points and the camera plane
- To be estimated from multiview imagery



Depth Image Based Rendering

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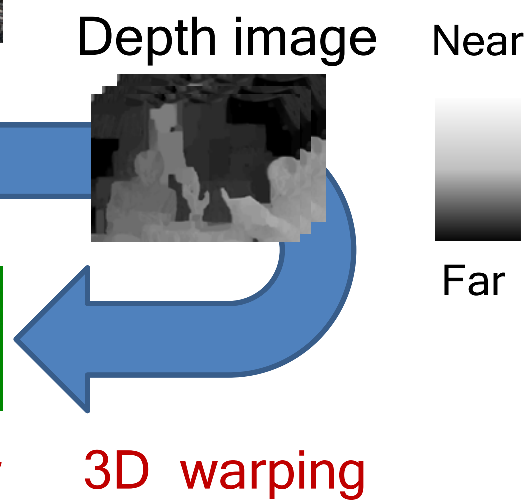
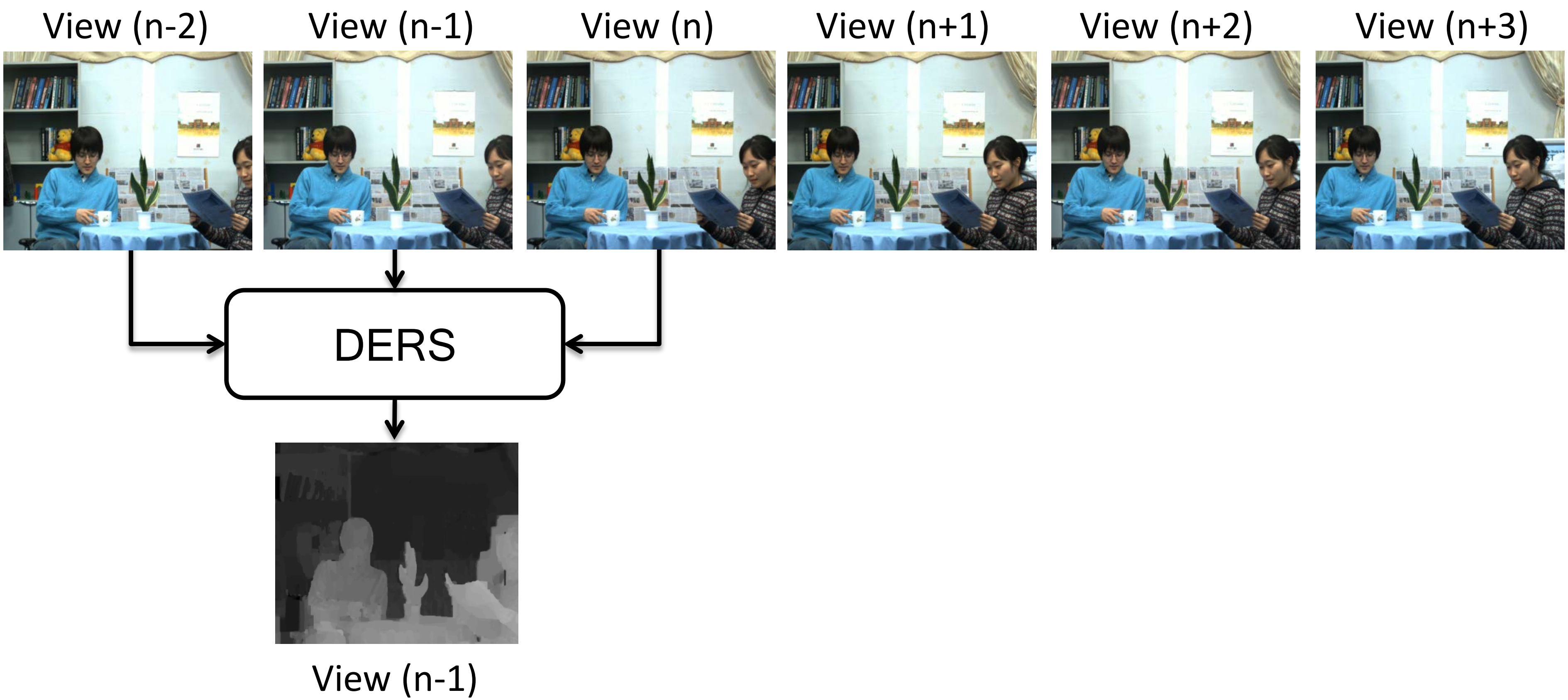


Depth Image Estimation

MPEG Depth Estimation Reference Software (DERS)



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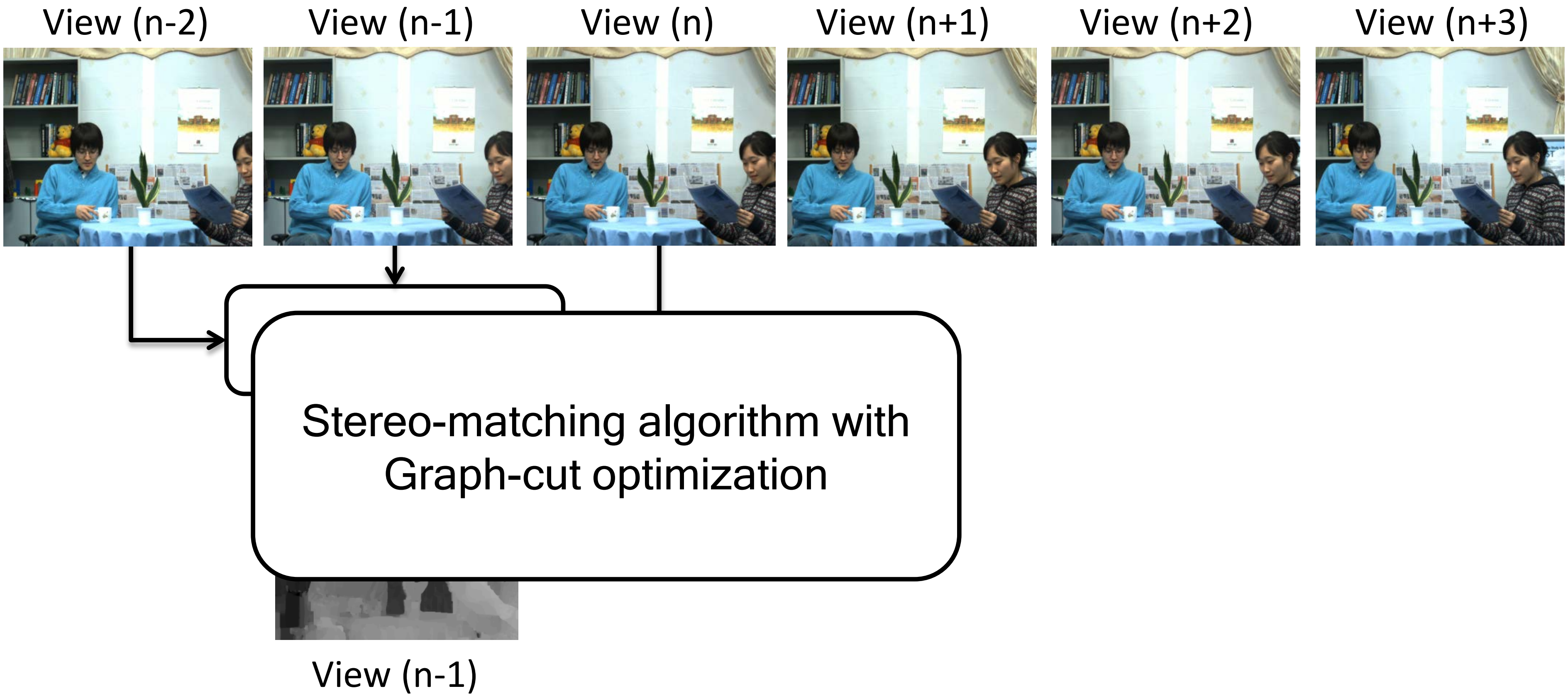

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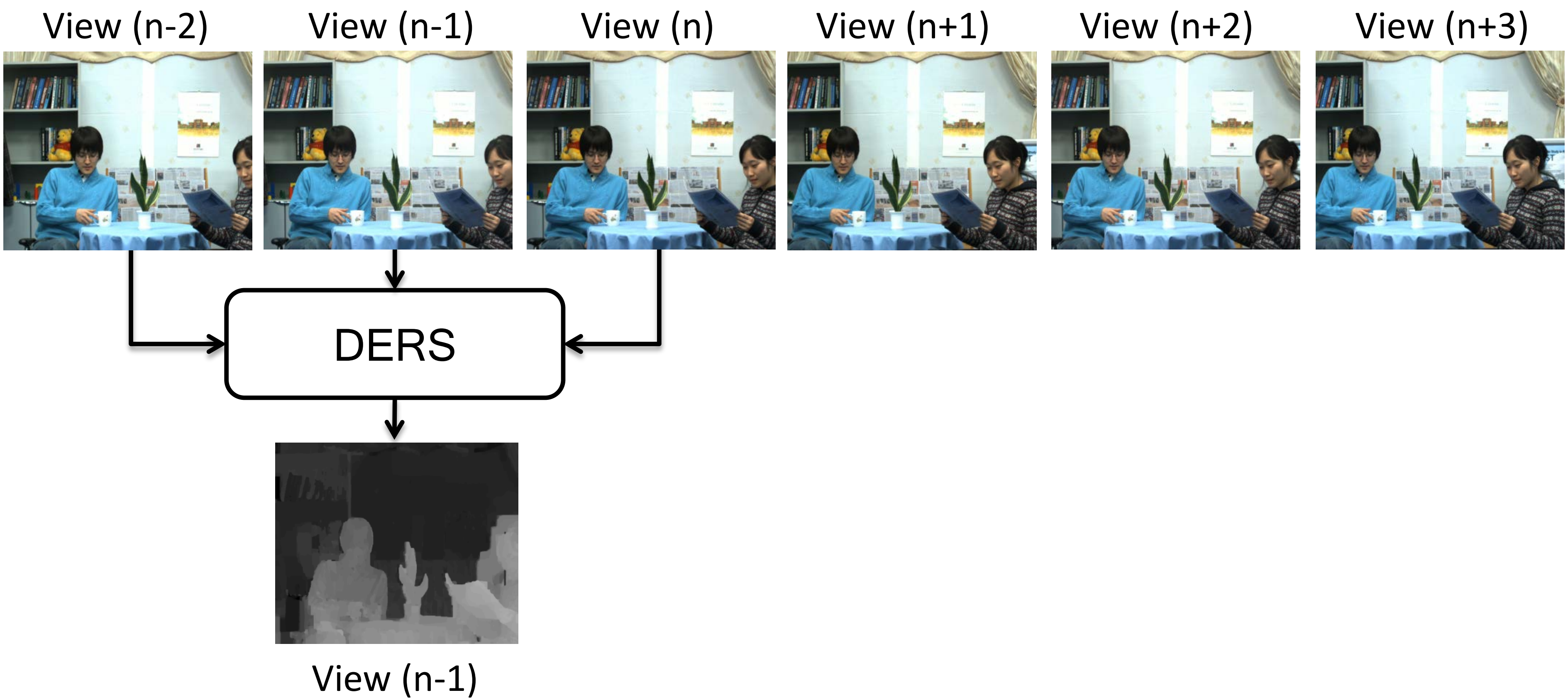

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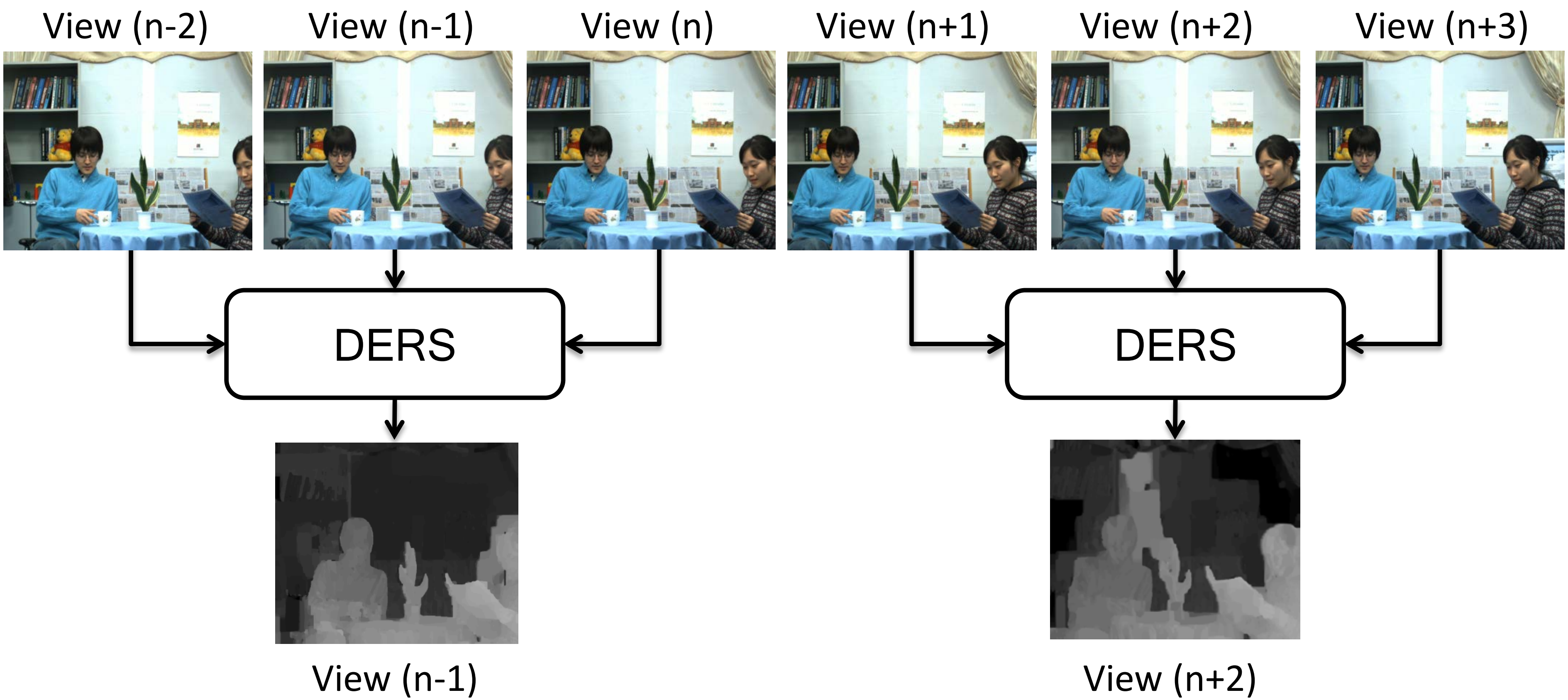

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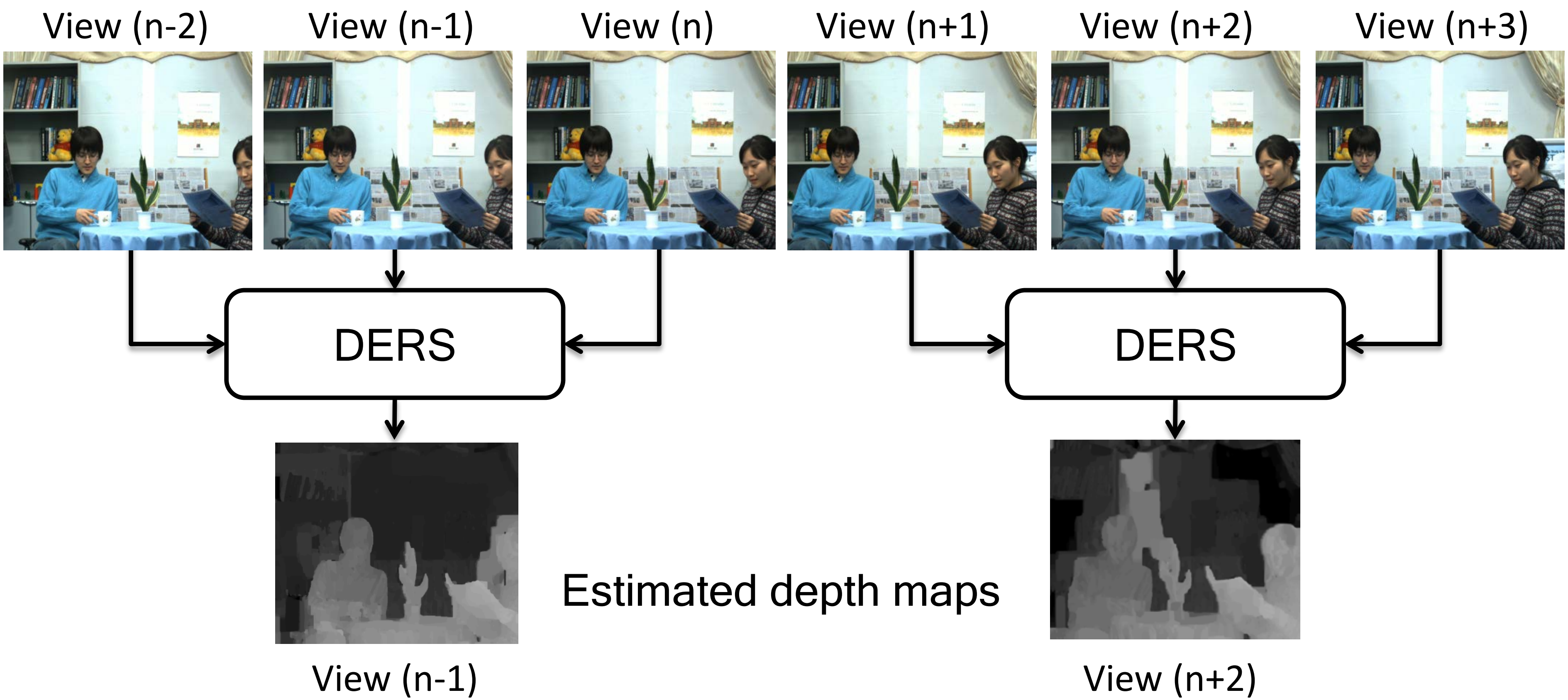


Depth Image Estimation

MPEG Depth Estimation Reference Software (DERS)

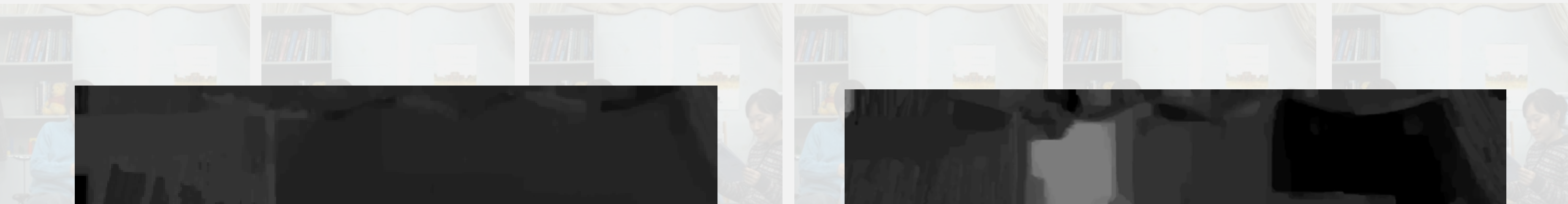
View (n-1) View (n+2)

Note: we assume a 1D-parallel camera arrangement

Depth Image Estimation

MPEG Depth Estimation Reference Software (DERS)

View (n-2) View (n-1) View (n) View (n+1) View (n+2) View (n+3)



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Depth Image Estimation

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Depth Image Estimation

MPEG Depth Estimation Reference Software (DERS)

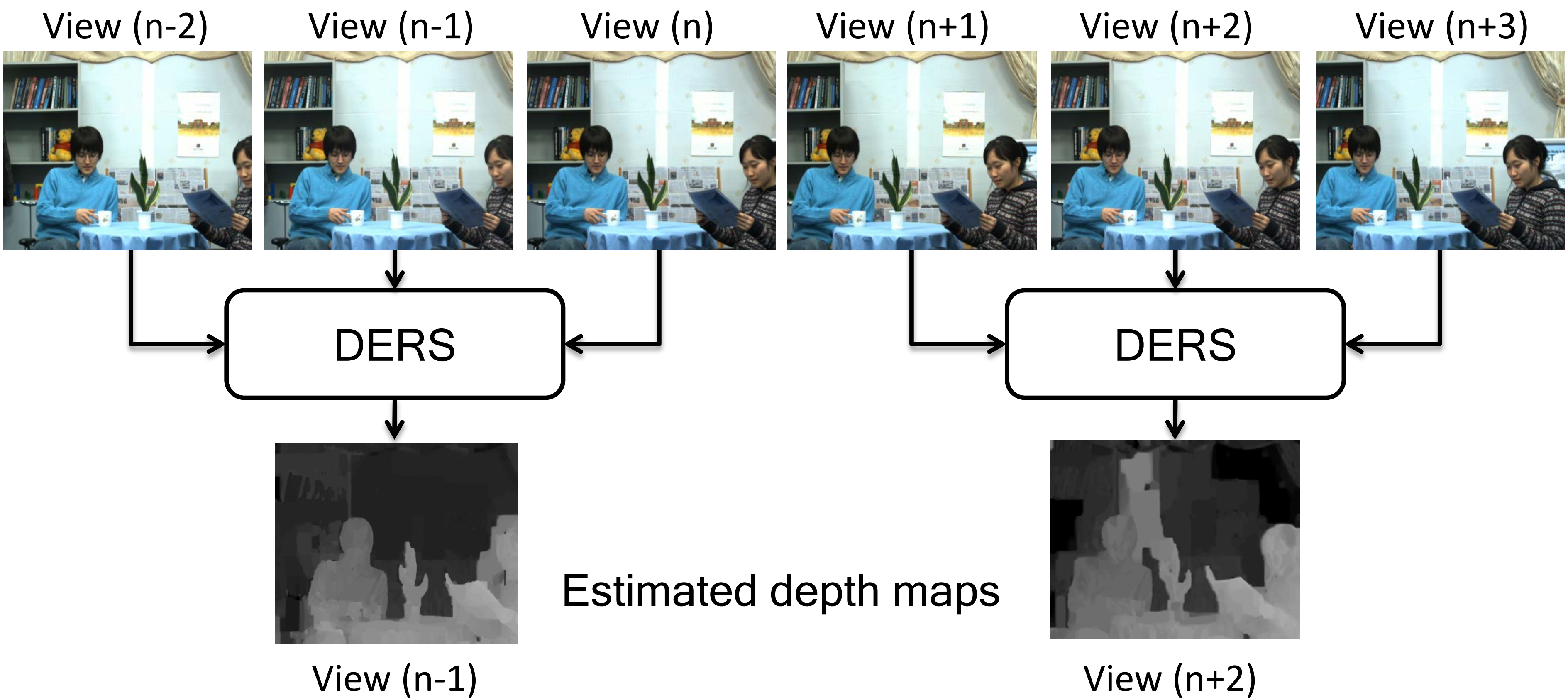
View (n-2) View (n-1) View (n) View (n+1) View (n+2) View (n+3)

View (n-1) View (n+2)

Problem: Inter-view depth inconsistency

Note: we assume a 1D-parallel camera arrangement

MPEG Depth Estimation Reference Software (DERS)



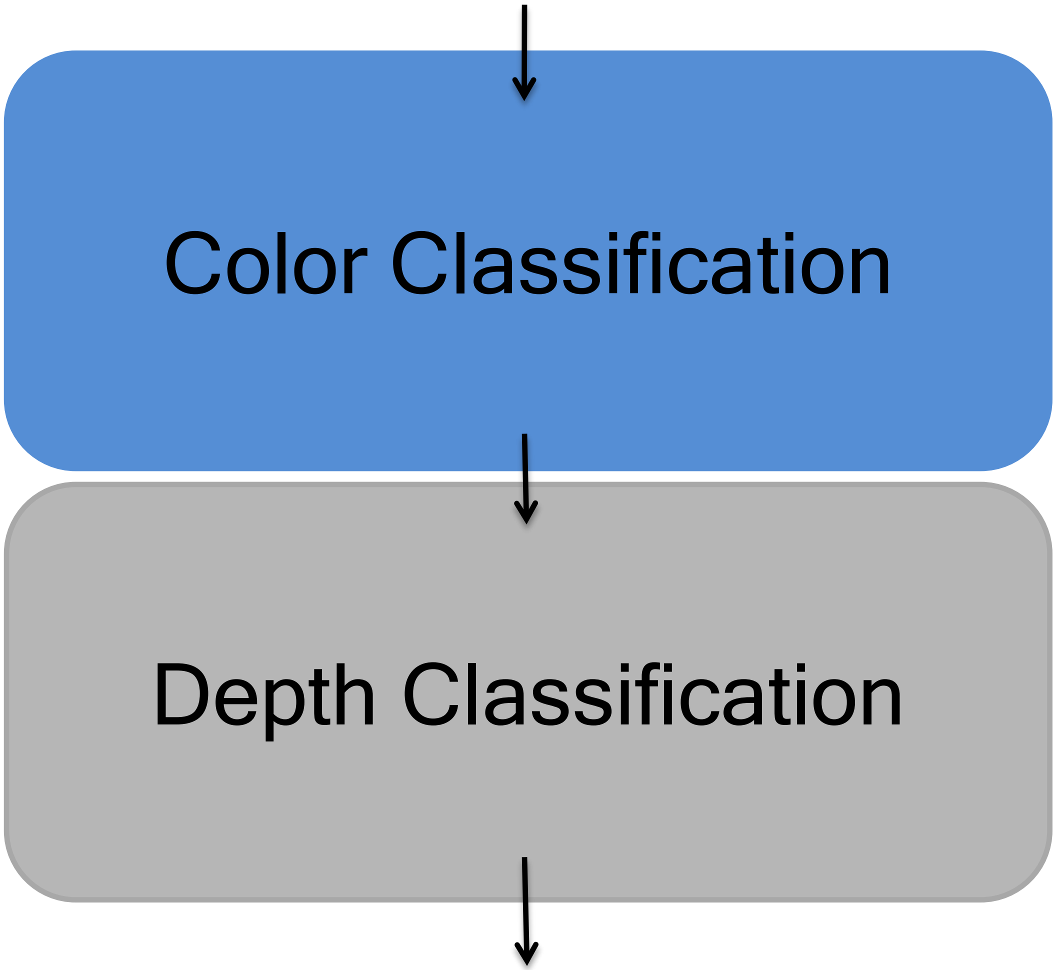
Problem: Inter-view depth inconsistency

Note: we assume a 1D-parallel camera arrangement

Depth Enhancement Framework

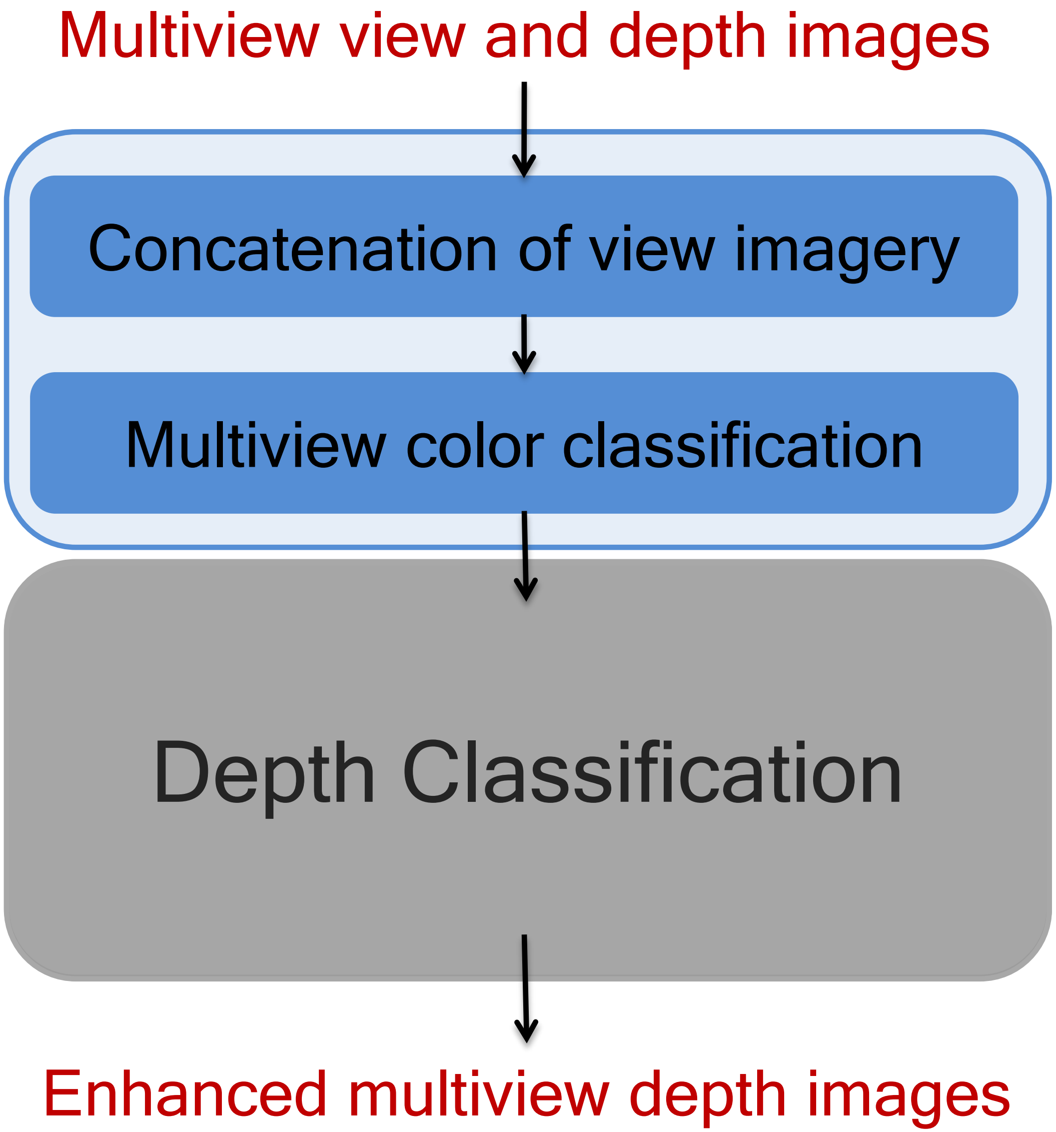
Overview of Depth Enhancement Framework

Multiview view and depth images

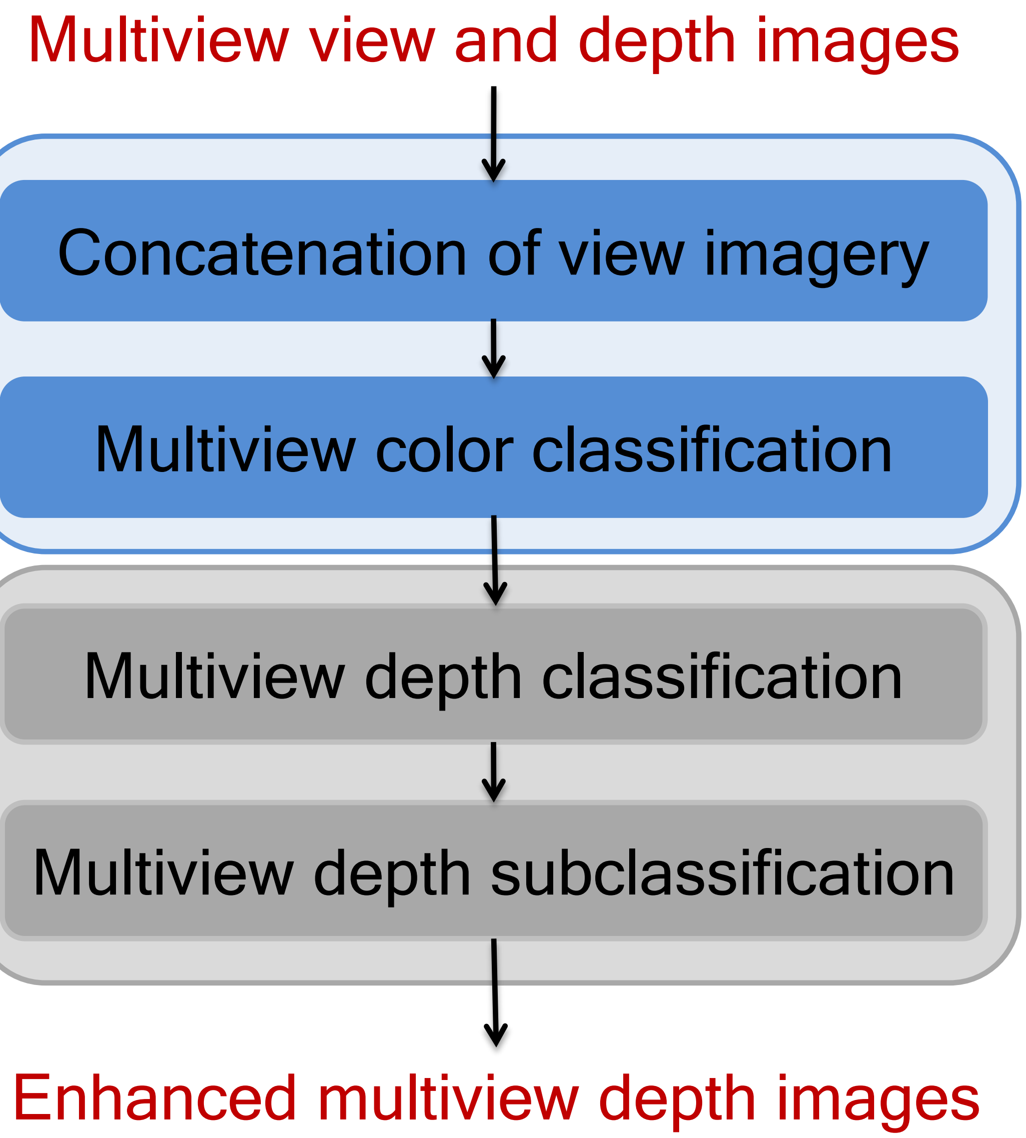


Enhanced multiview depth images

Overview of Depth Enhancement Framework



Overview of Depth Enhancement Framework



Concatenation of View Imagery

• • •

View (n-1)

View (n)

View (n+1)

View (n+2)

• • •

Concatenation of View Imagery

View (n-1) View (n) View (n+1) View (n+2)

View (n-1) View (n) View (n+1) View (n+2)

Multiview Color Classification

View (n)

View (n+1)

…

…

RGB Color space

Multiview Color Classification

View (n)　　View (n+1)

...

...

xyz Chromatic color space

Multiview Color Classification

View (n) View (n+1)

...  ...

xyz Chromatic color space

- Insensitive to the absolut luminance
- A pixel is described by a vector of three chromaticity coefficients $[x\ y\ z]^T$, where

$$x+y+z = 1$$

Multiview Color Classification

Why variational Bayes inference (VI)?

- The goal of classification is to partition an image into regions each of which has a reasonably homogeneous visual appearance
- Usually, clustering algorithm, such as Expectation-Maximization suffers from one major drawbacks that the number of clusters has to be known
- Variational Bayes inference automatically select the number of clusters

[1] C. M. Bishop, Pattern Recognition and Machine Learning, 1st ed. New York: Springer, 2006.

Multiview Color Classification

Why Dirichlet mixture model with variational Bayes inference (VI-DMM) ?

- The pixel vector in the chromaticity space has
  - nonnegative elements
  - bounded by the interval [0,1]
  - sum to one
  - efficiently modeled by utilizing non-Gaussian distributions
- Assume that these pixel vectors are Dirichlet distributed
- VI-DMM is used to capture the all underlying cluster in multiview imagery
- It reduces complexity

[2] Z. Ma, P. K. Rana, J. Taghia, M. Flierl, and A. Leijon: Bayesian estimation of Dirichlet mixture model with variational inference, submitted, 2013.

Multiview Color Classification

Newspaper

Balloons

Kendo

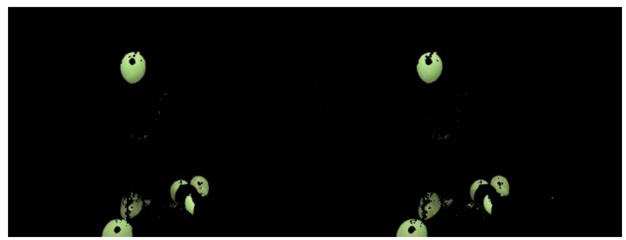
Input multiview data

Multiview Color Classification

Newspaper | Balloons | Kendo



Input multiview data


Using Dirichlet mixture model with variational Bayes inference

Multiview Color Classification

Newspaper Balloons Kendo

Input multiview data

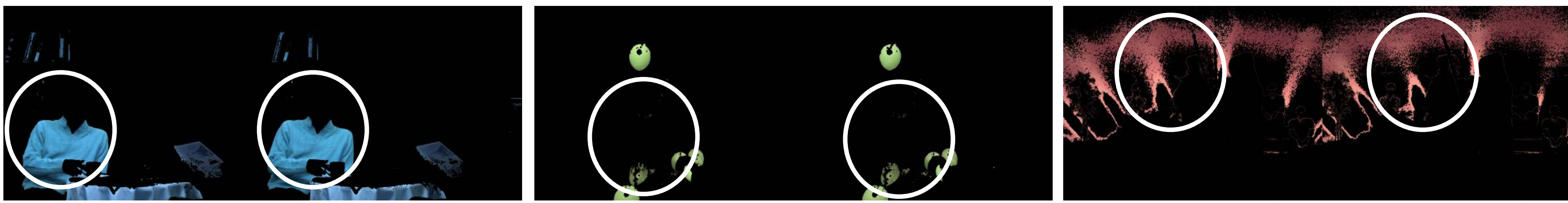
Using Dirichlet mixture model with variational Bayes inference

Using Gaussian mixture model with variational Bayes inference

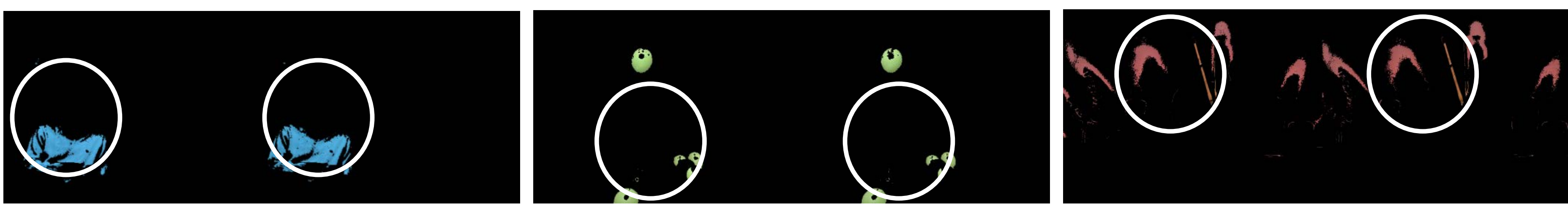
Multiview Color Classification

Newspaper | Balloons | Kendo

Input multiview data



Using Dirichlet mixture model with variational Bayes inference



Using Gaussian mixture model with variational Bayes inference

Multiview Depth Classification

Exploiting the per-pixel association between color and depth

Multiview Depth Classification

Exploiting the per-pixel association between color and depth

View image Depth image

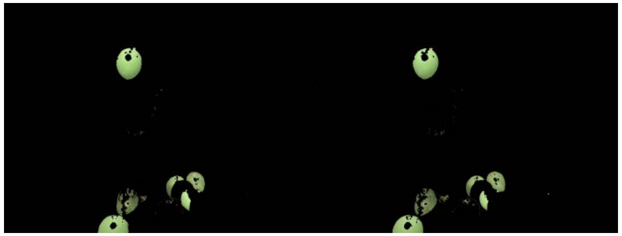
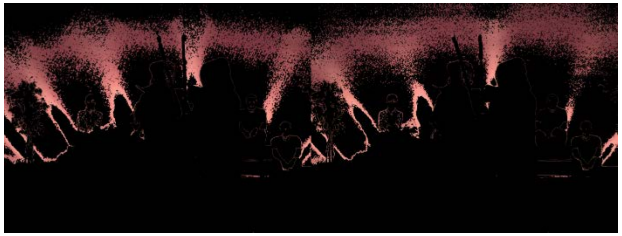
Concatenated view imagery Concatenated depth imagery

Multiview Depth Classification

Newspaper Balloons Kendo



Input multiview data

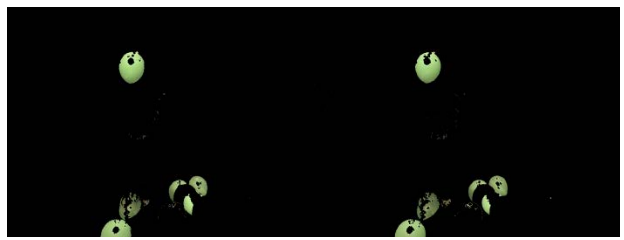
Using Dirichlet mixture model with variational Bayes inference

Multiview Depth Classification

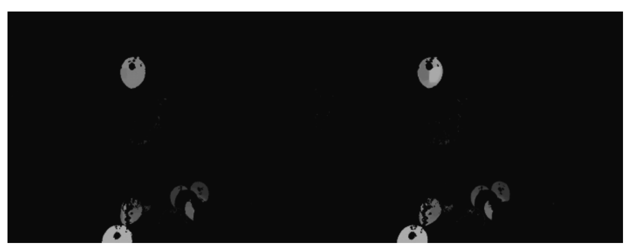
Newspaper | Balloons | Kendo



Input multiview data


Using Dirichlet mixture model with variational Bayes inference

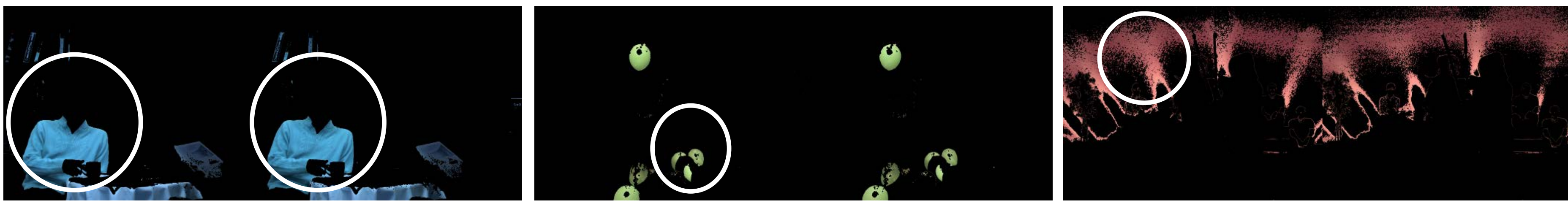




Depth clusters

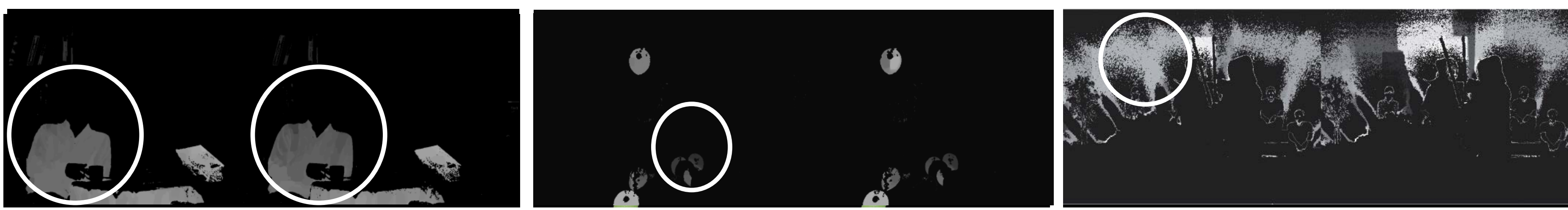
Multiview Depth Classification

Newspaper | Balloons | Kendo

Input multiview data



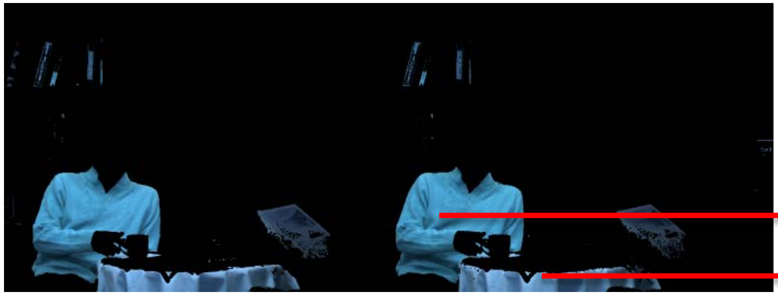
Using Dirichlet mixture model with variational Bayes inference



Depth clusters

Multiview Depth Subclassification

Difference between color and depth clusters



Members have similar colors pixels

Members may have different depth values

- Why?
  - due to foreground and background depth difference
  - due to inter-view inconsistency

Multiview Depth Subclassification

Mean-shift Clustering

- A nonparametric clustering technique
- Does not require prior knowledge of the number of clusters
- Does not constrain the shape of the clusters
- Assigns the mean to depth pixels irrespective of the originating viewpoints
- Bayesian approaches imply higher computational complexity

Experimental Results

Experimental Results

MPEG 3DTV multiview data set

Newspaper
(1024 X 768)

Lovebird1
(1024 X 768)

Kendo
(1024 X 768)

Balloons
(1024 X 768)

Poznan street
(1920 X 1088)

Experimental Results

Multiview data set	Initial number of mixture components	Active number of mixture components (after convergence)	
		VI-GMM	VI-DMM
Lovebird1	100	31	24
Kendo	100	34	15

Depth Image-Based Rendering

MPEG View Synthesis Reference Software (VSRS) 3.5

Enhanced depth map

Left

Enhanced depth map

Right

Depth Image-Based Rendering

MPEG View Synthesis Reference Software (VSRS) 3.5

Enhanced depth map

Left

Reference view

Enhanced depth map

Right

Reference view

Depth Image-Based Rendering

MPEG View Synthesis Reference Software (VSRS) 3.5

Enhanced depth map

Left

Reference view

3D warping

Warped view

Enhanced depth map

Right

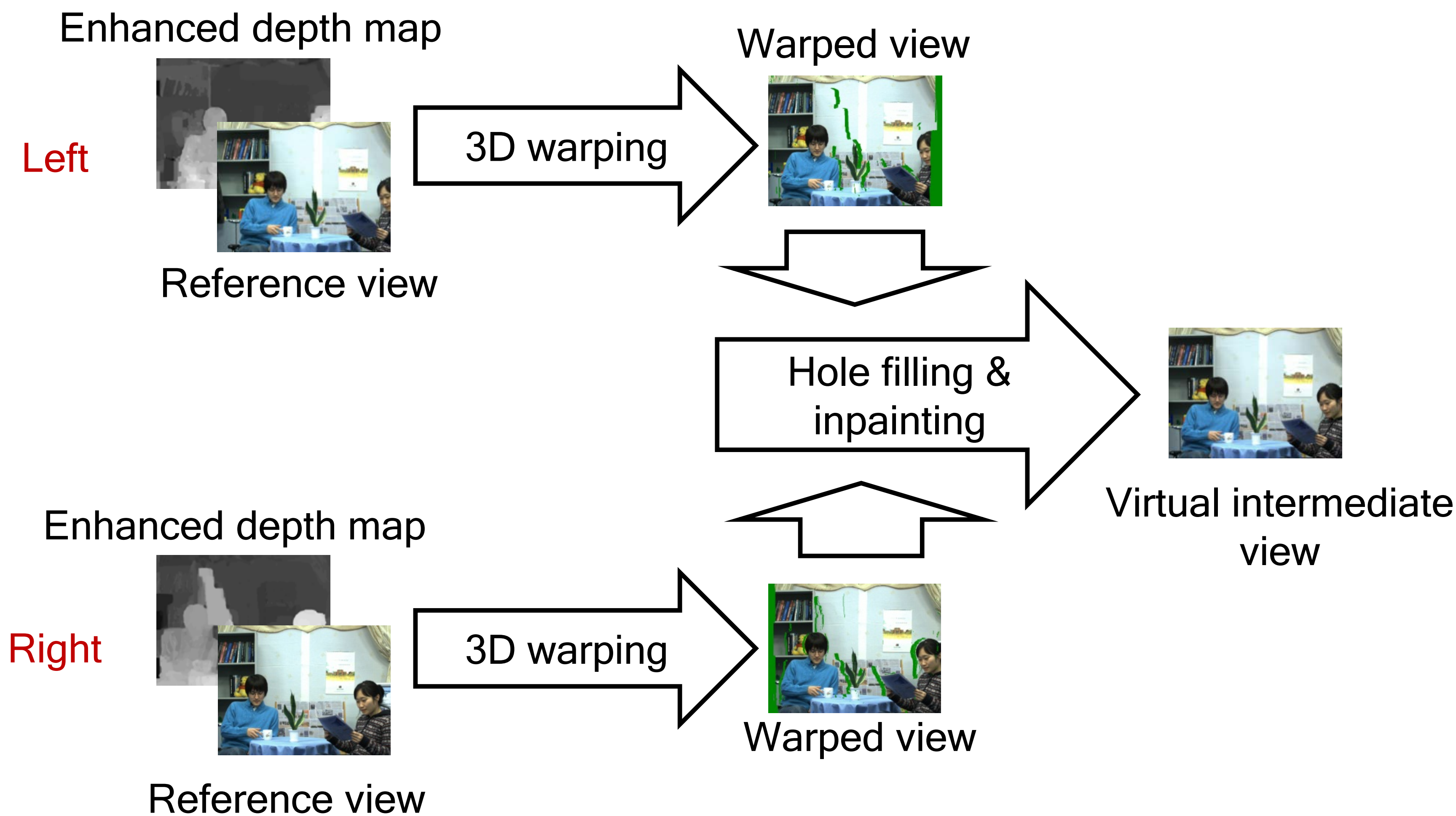
Reference view

3D warping

Warped view

Depth Image-Based Rendering

MPEG View Synthesis Reference Software (VSRS) 3.5



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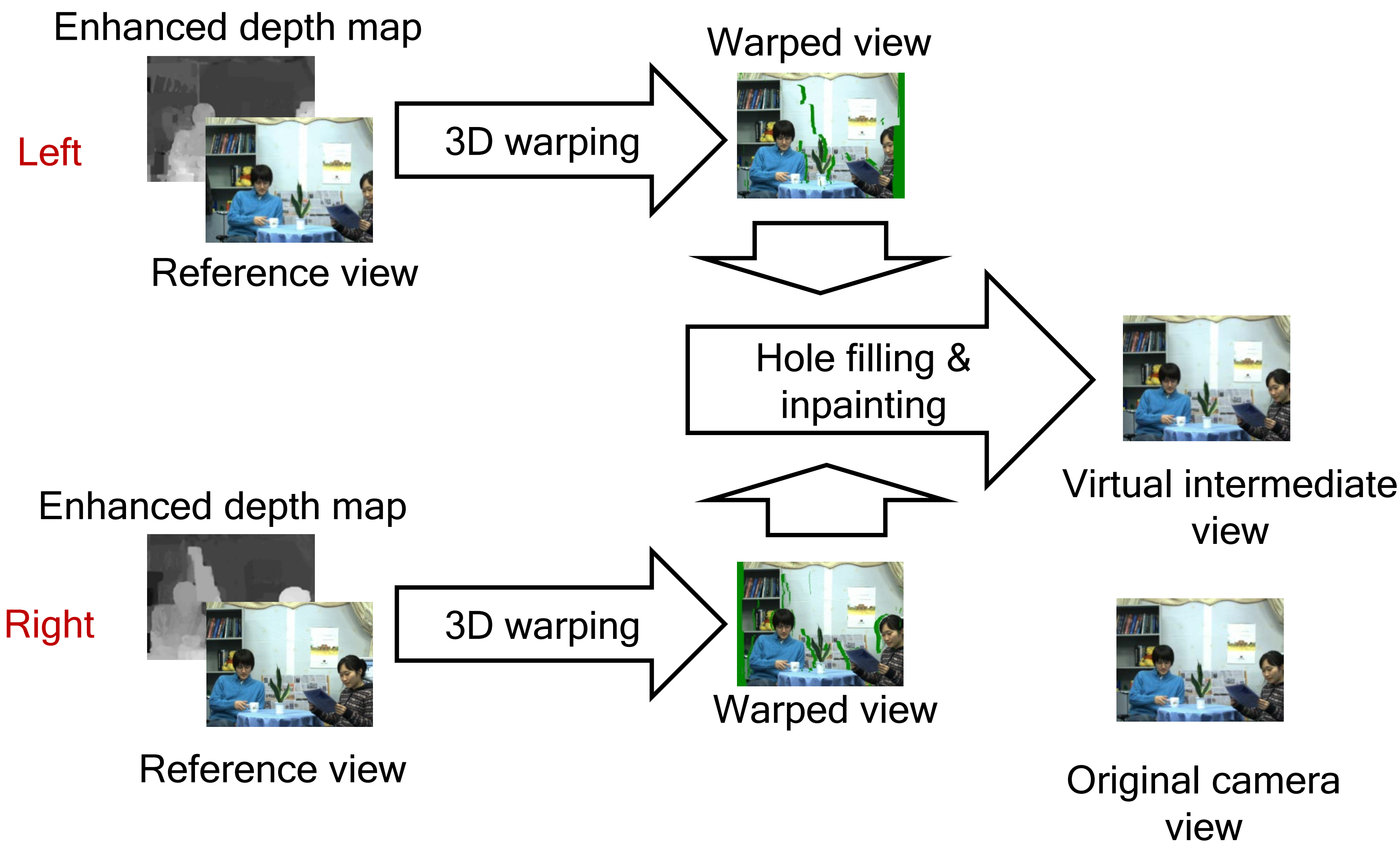

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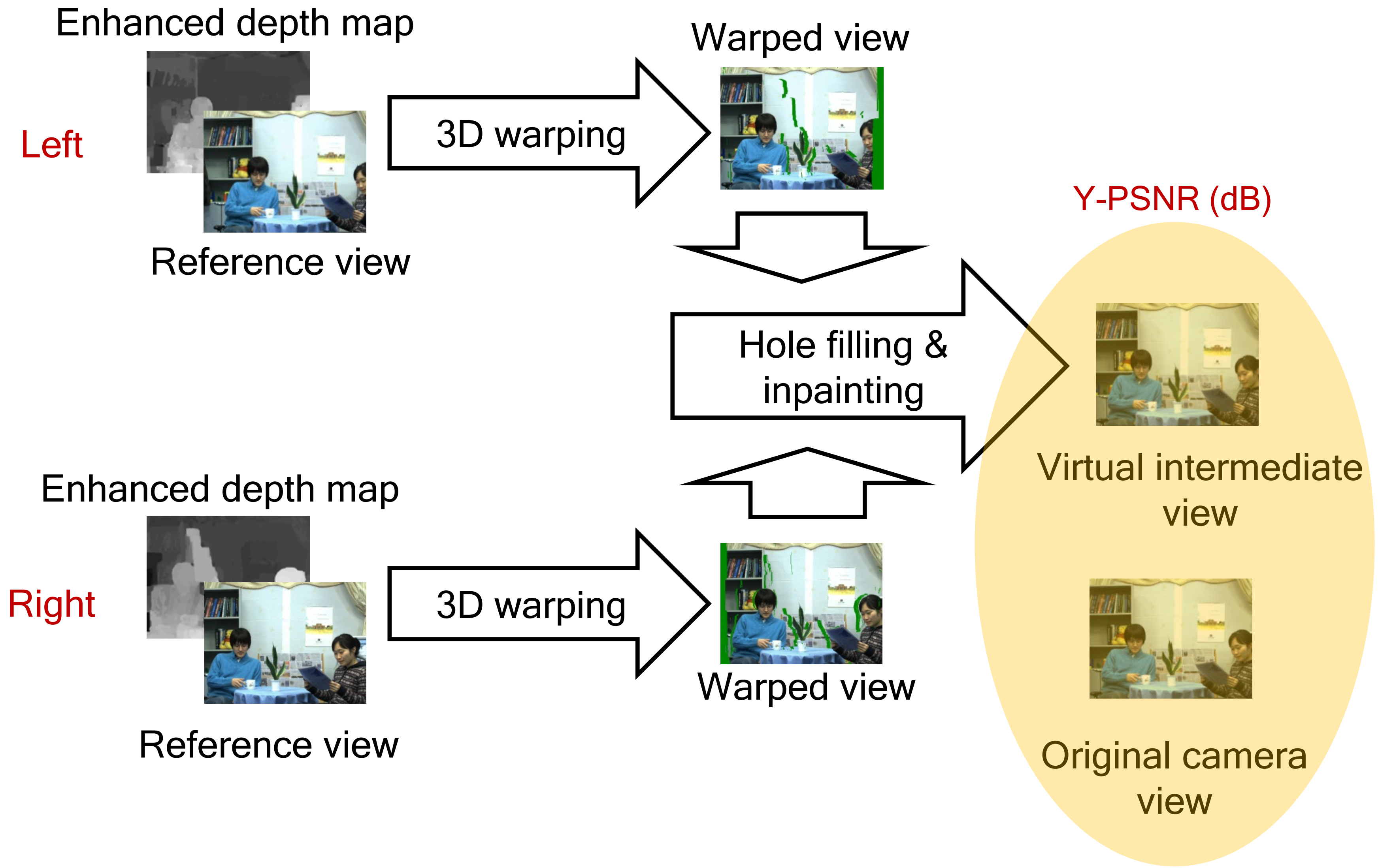

Objective Results

Test sequence	Input view pair	Virtual view	Y-PSNR [dB]		
			With MPEG depth maps	With VBIGMM + K-Means depth maps	With VBIDMM + Mean-shift depth maps
Newspaper	(4, 6)	5	32.00	32.10	32.11
Kendo	(3, 5)	4	36.54	36.72	39.35
Lovebird1	(6, 8)	7	28.50	28.68	29.04
Balloons	(3, 5)	4	35.69	35.93	36.02
Poznan Street	(3, 5)	4	35.56	35.58	35.72

- K-means sub-clustering
  - Number of cluster : 12

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Subjective Results

Test sequence: Kendo

With MPEG depth map

With VBDMM Mean-shift depth map

Subjective Results

Test sequence: Kendo

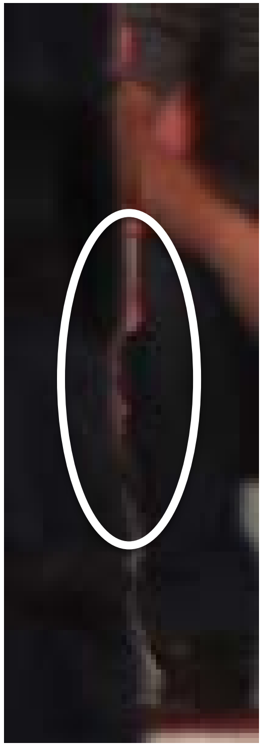
With MPEG depth map

With VBDMM Mean-shift depth map

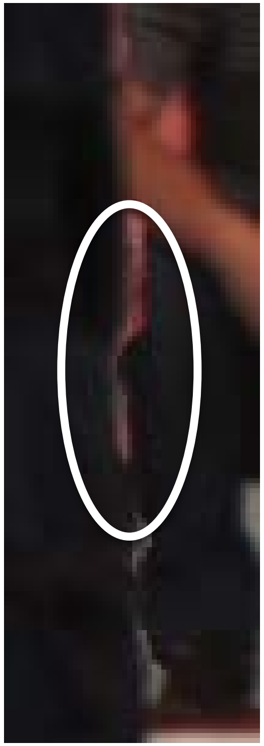
Subjective Results

Test sequence: Kendo

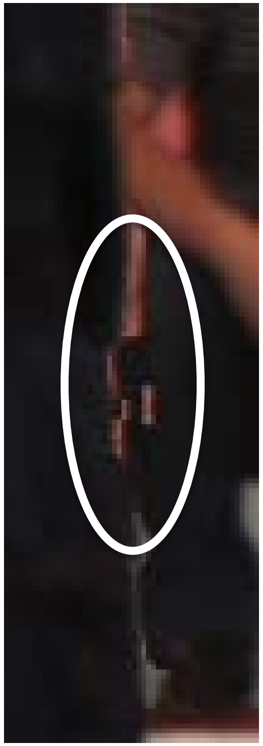
Original



With VBDMM + Mean-Shift depth maps



With VBGMM + K-Means depth maps

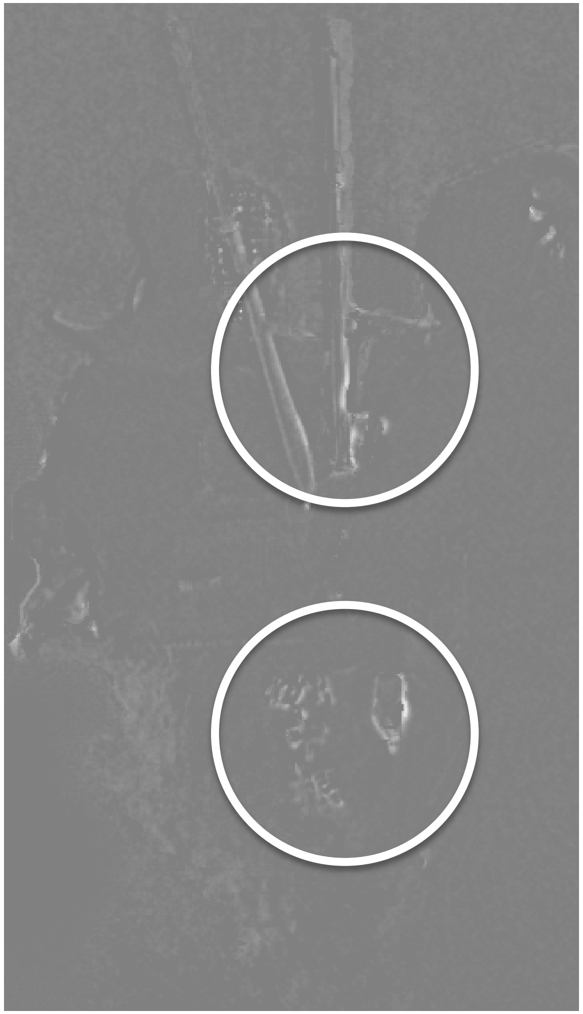


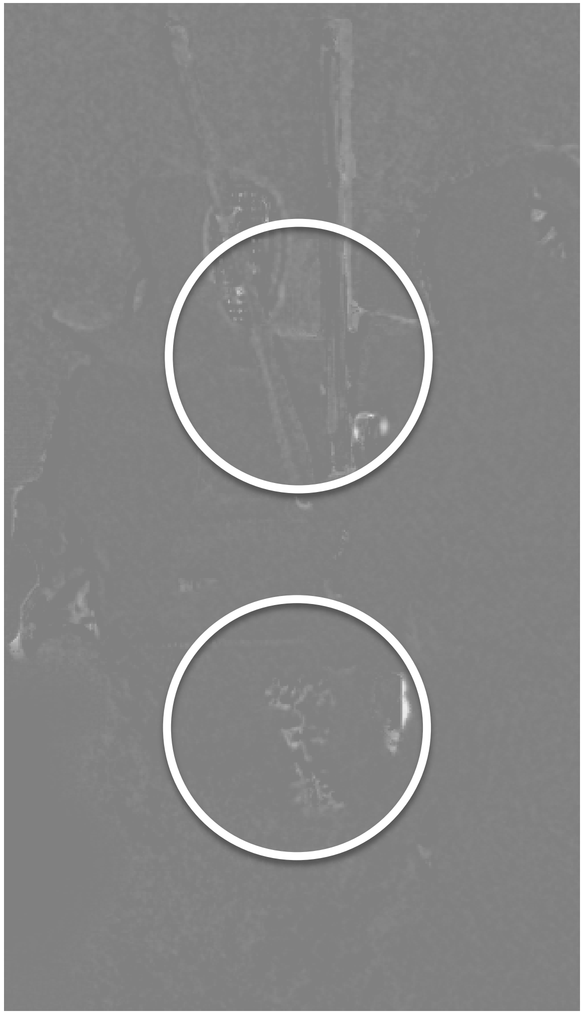
With MPEG depth maps

Subjective Results

Test sequence: Kendo

With VBGMM
K-Means
depth maps





With VBDMM
Mean-Shift
depth maps

Subjective Results

Test sequence: Lovebird 1


With MPEG depth map


With VBDMM Mean-shift depth map

Subjective Results

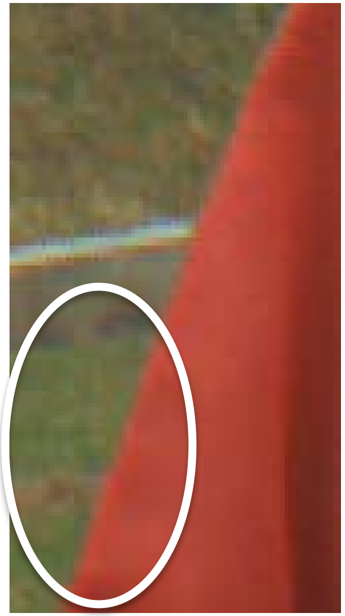
Test sequence: Lovebird 1

With MPEG depth map

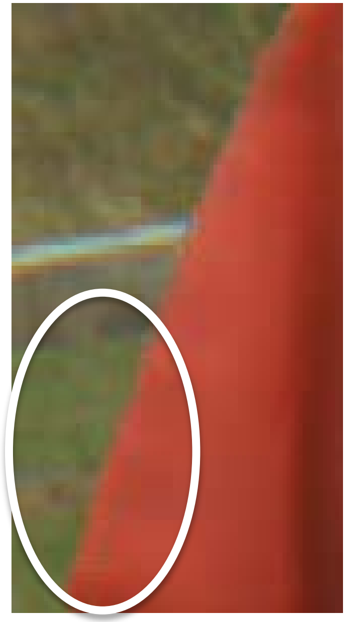
With VBDMM Mean-shift depth map

Subjective Results

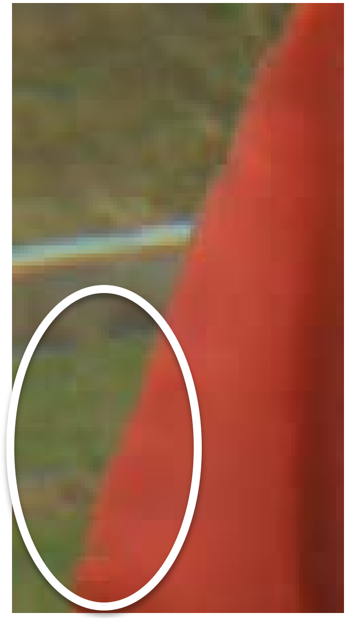
Test sequence: Lovebird 1



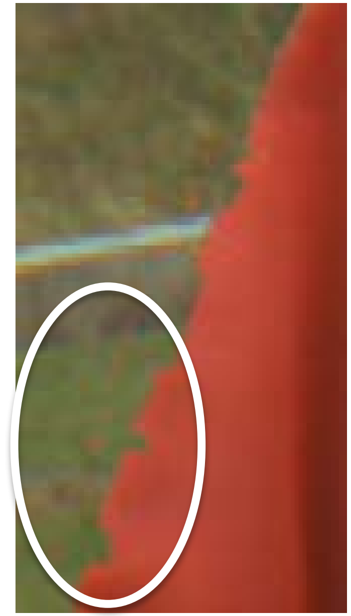
Original



With VBDMM Mean-Shift depth maps



With VBGMM K-Means depth maps



With MPEG depth maps

Subjective Results

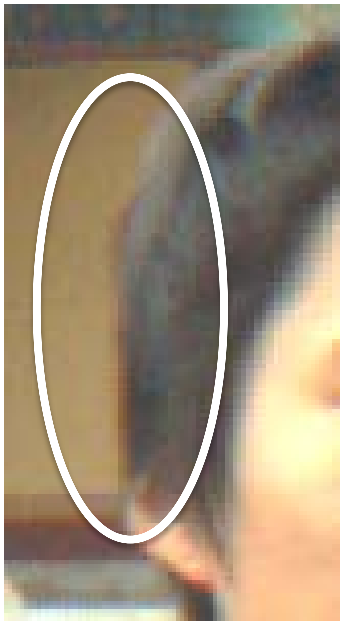
Test sequence: Lovebird 1

With MPEG depth map

With VBDMM Mean-shift depth map

Subjective Results

Test sequence: Lovebird 1



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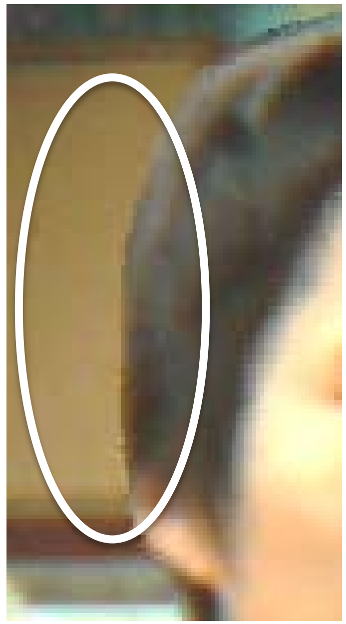
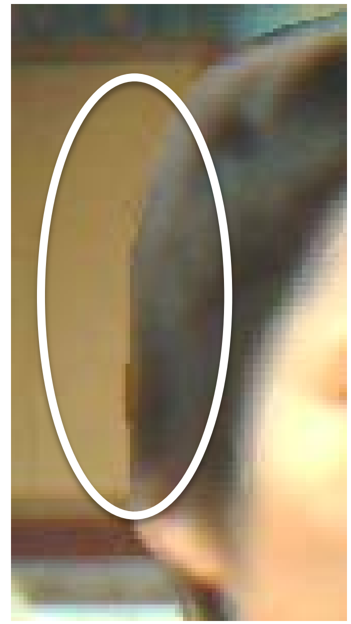


With VBDMM Mean-Shift depth maps



With VBGMM K-Means depth maps

With MPEG depth maps

Conclusions

- The inter-view depth consistency and hence, the free-viewpoint experience improve
- The per-pixel association between depth and color is exploited by classification
- Depth subclassification improves depth maps and hence, view rendering quality
- Both objective and subjective results improve

[3] P. K. Rana, Z. Ma, J. Taghia, and M. Flierl: Multiview Depth Map Enhancement by Variational Bayes Inference Estimation of Dirichlet Mixture Models, IEEE ICASSP, 2013.

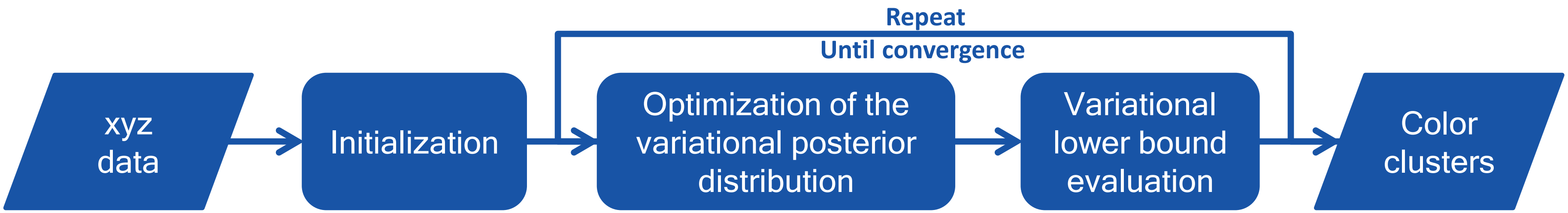
Future Directions

- A fully probabilistic multiview depth image enhancement
  - With color classification performance
  - With computational efficiency
  - Improve depth sub-clustering

Thank You

Multiview color classification

Dirichlet mixture model with variational Bayes inference



[1] C. M. Bishop, Pattern Recognition and Machine Learning, 1st ed. New York: Springer, 2006.

[2] Z. Ma, P. K. Rana, J. Taghia, M. Flierl, and A. Leijon, "Bayesian estimation of Dirichlet mixture model with variational inference," IEEE Trans. PAMI, submitted, 2013.

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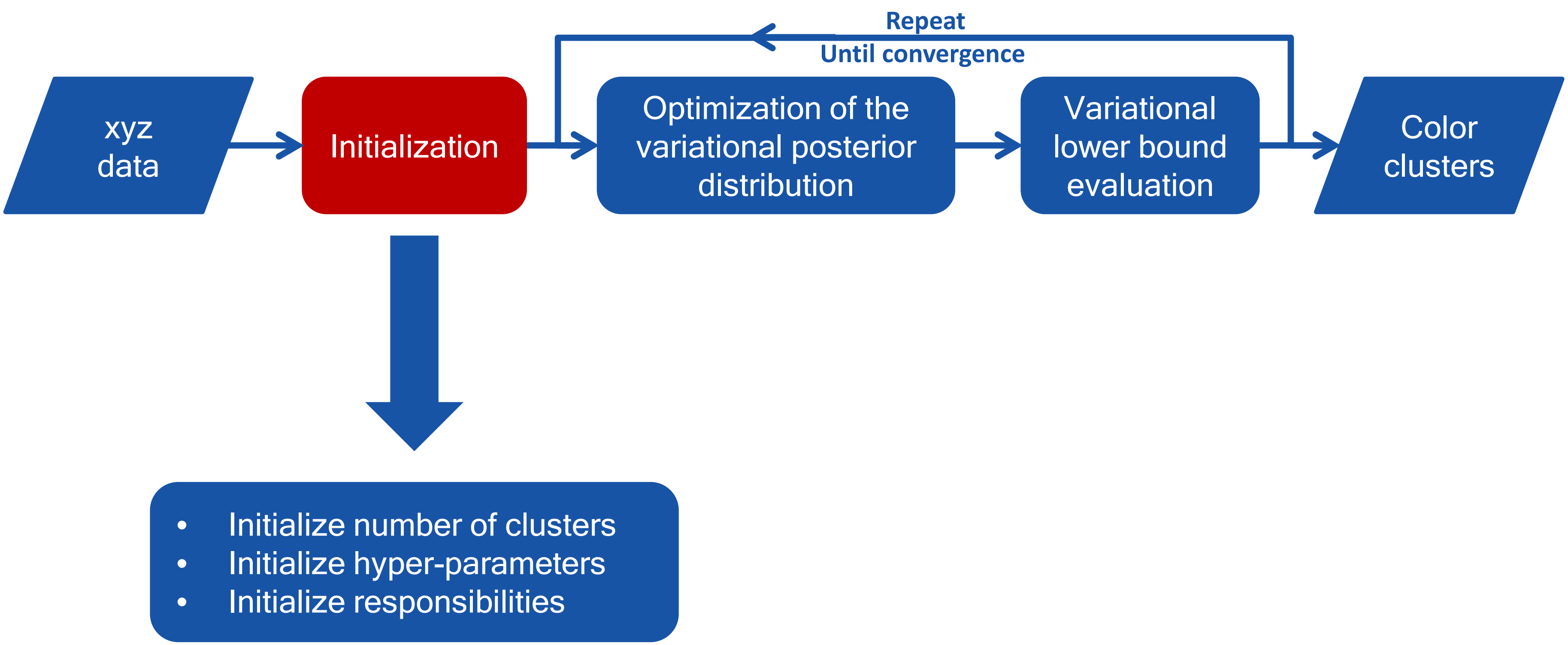
Multiview color classification

Dirichlet mixture model with variational Bayes inference



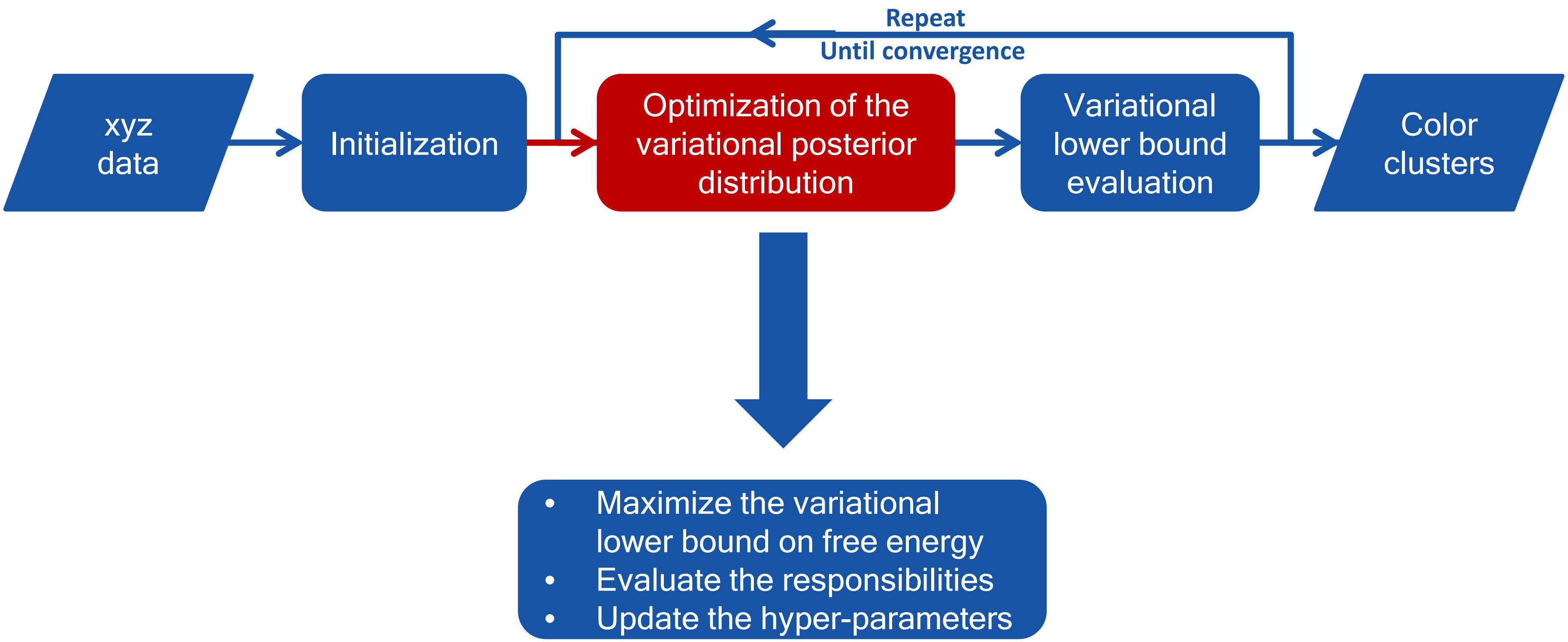
[1] C. M. Bishop, Pattern Recognition and Machine Learning, 1st ed. New York: Springer, 2006.

[2] Z. Ma, P. K. Rana, J. Taghia, M. Flierl, and A. Leijon, “Bayesian estimation of Dirichlet mixture model with variational inference,” IEEE Trans. PAMI, submitted, 2013.

Y

Multiview color classification

Dirichlet mixture model with variational Bayes inference



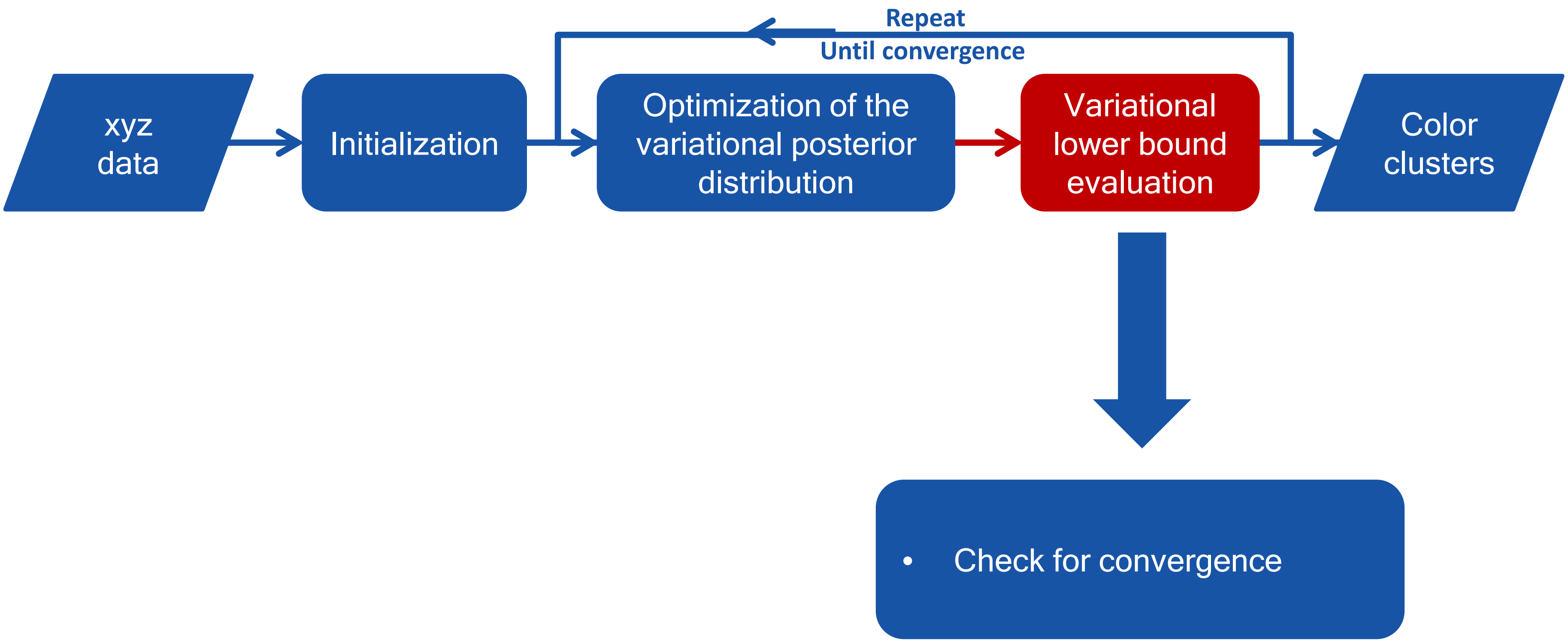
[1] C. M. Bishop, Pattern Recognition and Machine Learning, 1st ed. New York: Springer, 2006.

[2] Z. Ma, P. K. Rana, J. Taghia, M. Flierl, and A. Leijon, "Bayesian estimation of Dirichlet mixture model with variational inference," IEEE Trans. PAMI, submitted, 2013.

Y

Multiview color classification

Dirichlet mixture model with variational Bayes inference

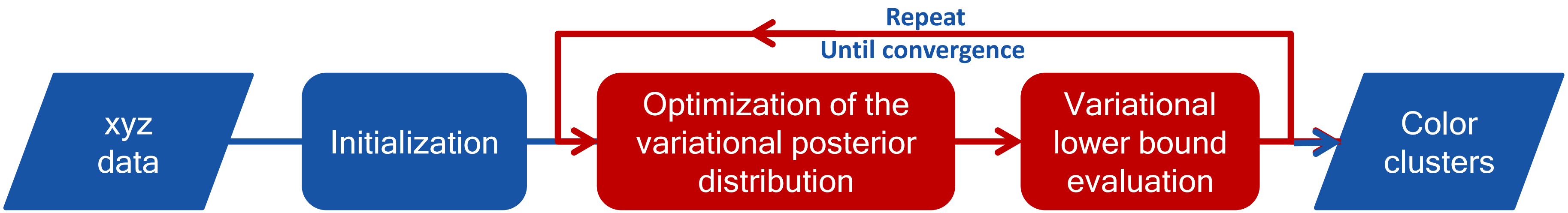


[1] C. M. Bishop, Pattern Recognition and Machine Learning, 1st ed. New York: Springer, 2006.
[2] Z. Ma, P. K. Rana, J. Taghia, M. Flierl, and A. Leijon, "Bayesian estimation of Dirichlet mixture model with variational inference," IEEE Trans. PAMI, submitted, 2013.

Y

Multiview color classification

Dirichlet mixture model with variational Bayes inference



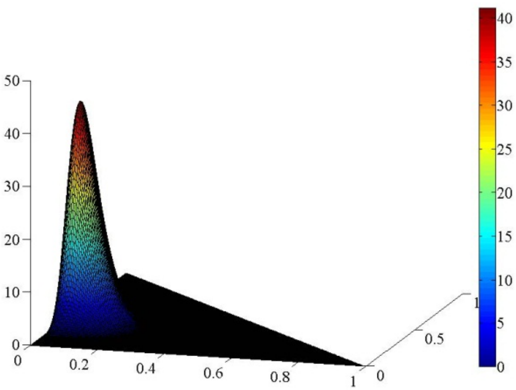
[1] C. M. Bishop, Pattern Recognition and Machine Learning, 1st ed. New York: Springer, 2006.

[2] Z. Ma, P. K. Rana, J. Taghia, M. Flierl, and A. Leijon, "Bayesian estimation of Dirichlet mixture model with variational inference," IEEE Trans. PAMI, submitted, 2013.

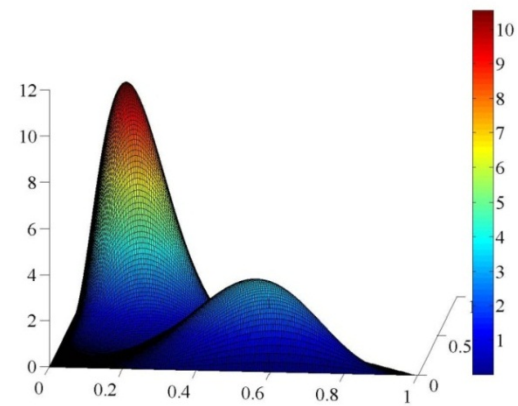
Y

Dirichlet Plot Details

- For probability density function of Dirichlet distribution $\alpha = [2\ 10\ 15]$
- For probability density function of Dirichlet mixture model parameters $\alpha_1 = [6\ 2\ 4]$ and $\alpha_2 = [3\ 8\ 5]$ with mixture weights $\pi_1 = 0.3$ and $\pi_2 = 0.7$, respectively.



Probability density function of Dirichlet distribution



Probability density function of Dirichlet mixture model

Z

Subjective Results

Test sequence: Newspaper

With MPEG depth map

With VBDMM Mean-shift depth map

X

Subjective Results

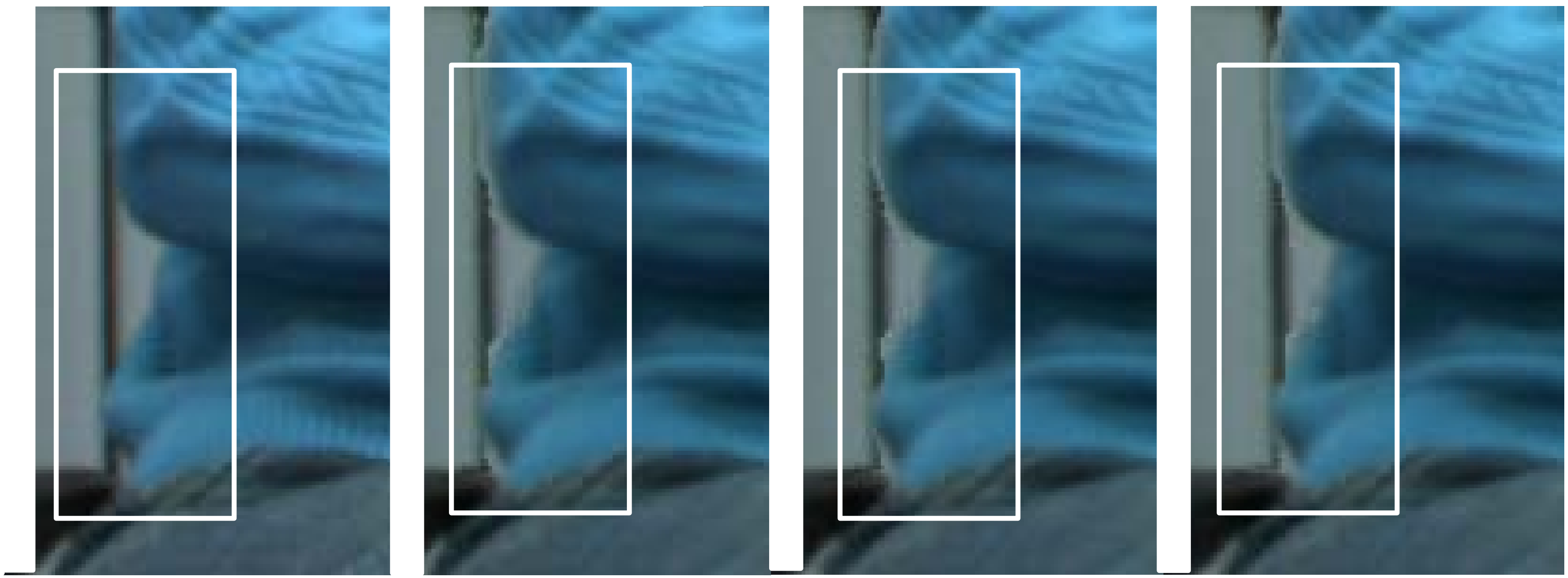
Test sequence: Newspaper

With MPEG depth map

With VBDMM Mean-shift depth map

Subjective Results

Test sequence: Newspaper



Original depth maps | With MPEG depth maps | With VBGMM K-Means depth maps | With VBDMM Mean-Shift depth maps

Subjective Results

Test sequence: Newspaper

With MPEG depth map

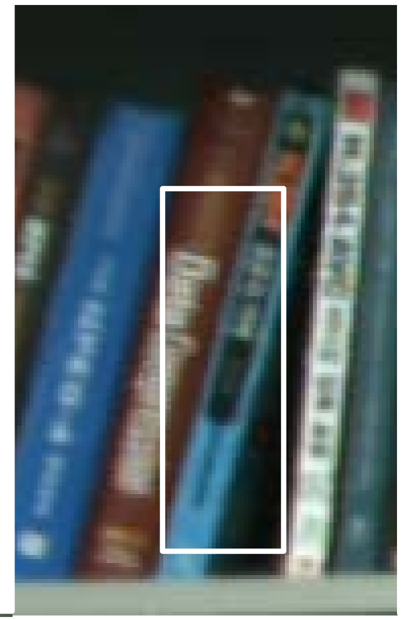
With VBDMM Mean-shift depth map

Subjective Results

Test sequence: Newspaper

Original
depth maps

With MPEG
depth maps



With VBGMM
K-Means
depth maps

With VBDMM
Mean-Shift
depth maps

Subjective Results

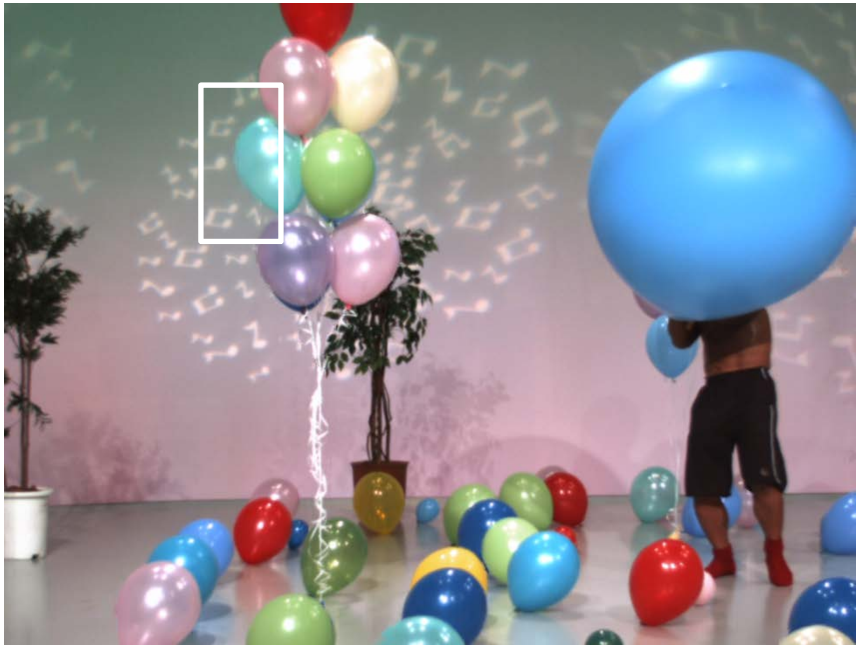
Test sequence: Balloons

With MPEG depth map

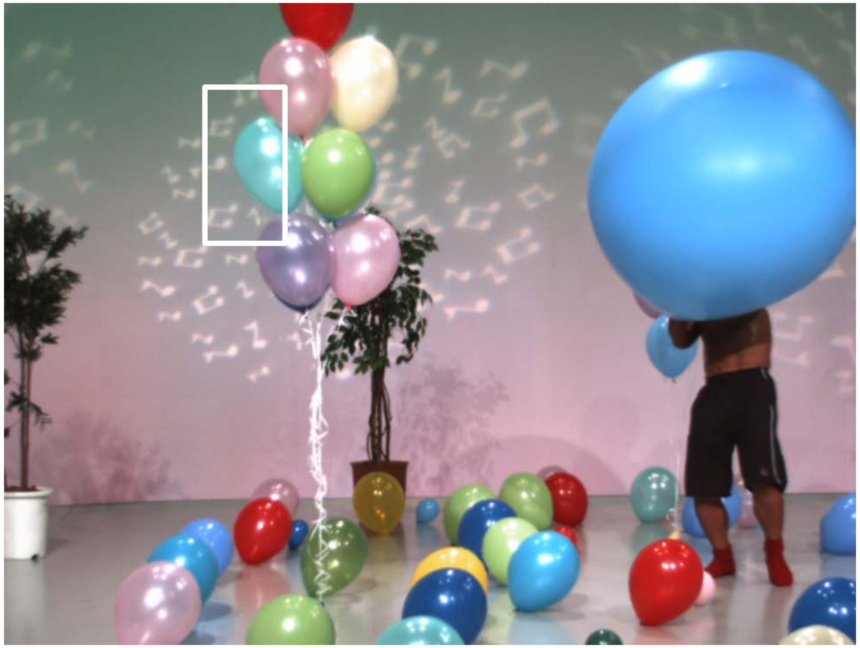
With VBDMM Mean-shift depth map

Subjective Results

Test sequence: Balloons



With MPEG depth map

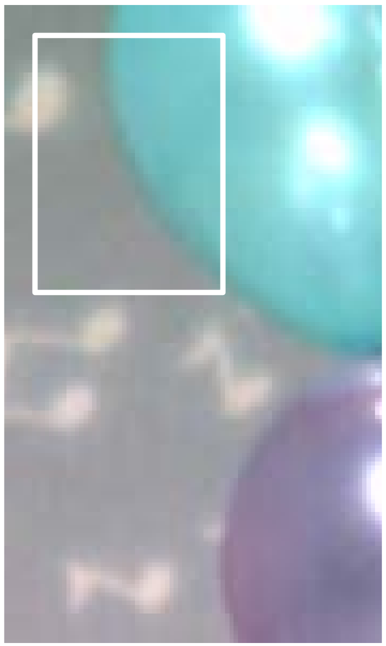


With VBDMM Mean-shift depth map

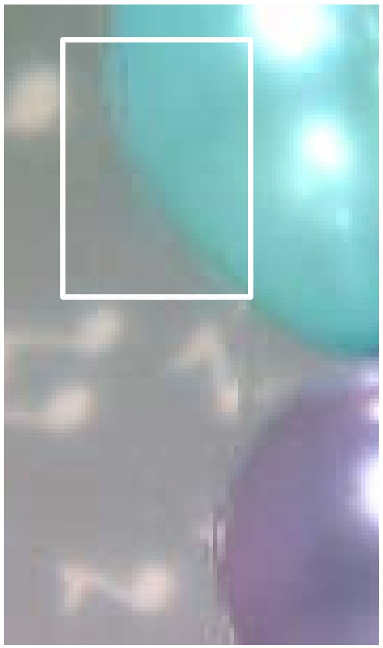
X

Subjective Results

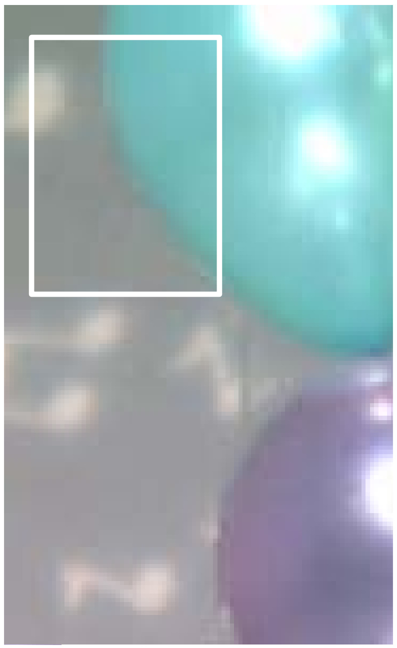
Test sequence: Balloons



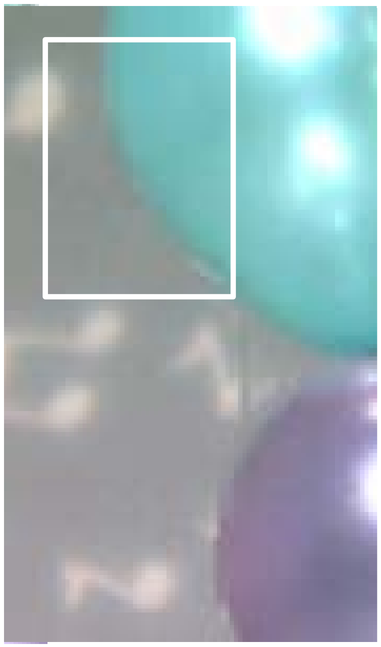
Original
depth maps



With MPEG
depth maps



With VBGMM
K-Means
depth maps



With VBDMM
Mean-Shift
depth maps

X

Subjective Results

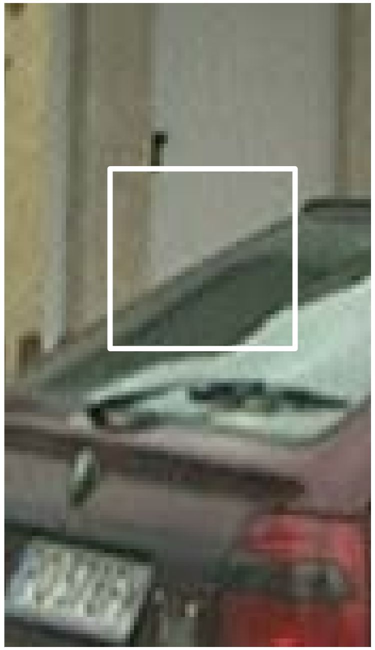
Test sequence: Poznan Street

With MPEG depth map

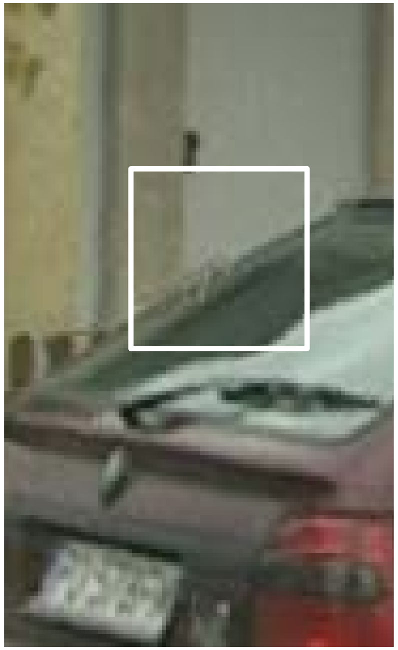
With VBDMM Mean-shift depth map

Subjective Results

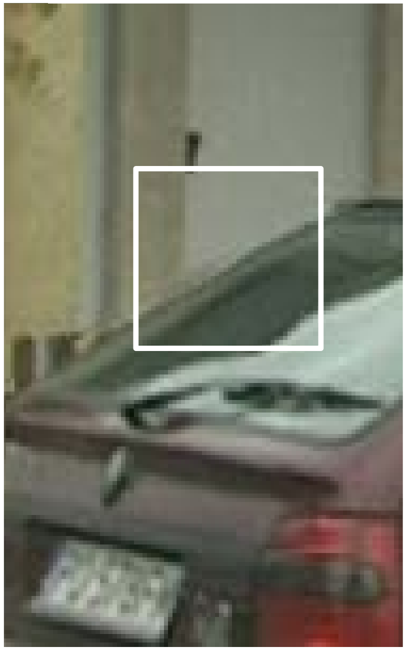
Test sequence: Poznan Street



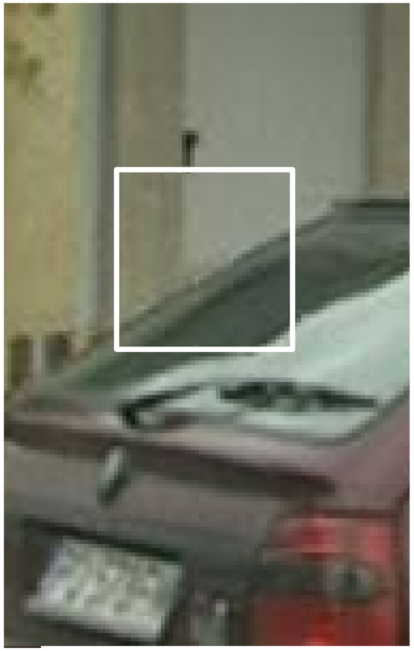
Original depth maps



With MPEG depth maps



With VBGMM K-Means depth maps



With VBDMM Mean-Shift depth maps

Subjective Results

Test sequence: Poznan Street

With MPEG depth map

With VBDMM Mean-shift depth map

Subjective Results

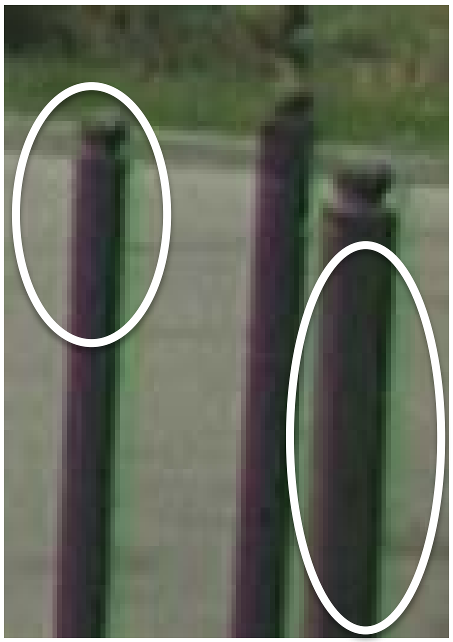
Test sequence: Poznan Street

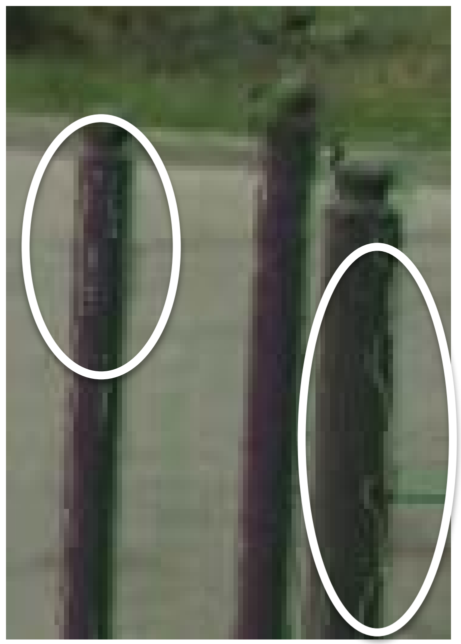
With MPEG depth map

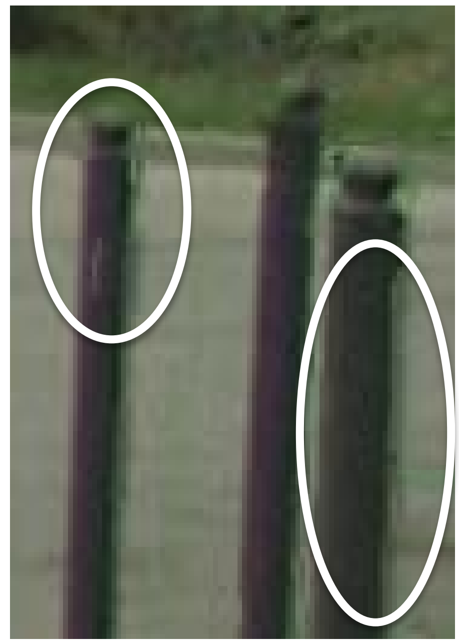
With VBDMM Mean-shift depth map

Subjective Results

Test sequence: Poznan Street


Original


With MPEG depth maps


With VBGMM K-Means depth maps


With VBDMM Mean-Shift depth maps

x