Multiview Depth Image Enhancement for Free-viewpoint Television

Pravin Kumar Rana, Zhanyu Ma, Jalil Taghia, and Markus Flierl

Opponents: Nasser Mohammadiha, Haopeng Li and, Jalil Taghia

Internal seminar, Communication Theory, KTH

June 27, 2013

Motivation & Background

Conventional Television

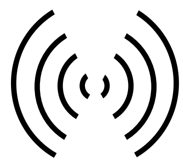
User

Display

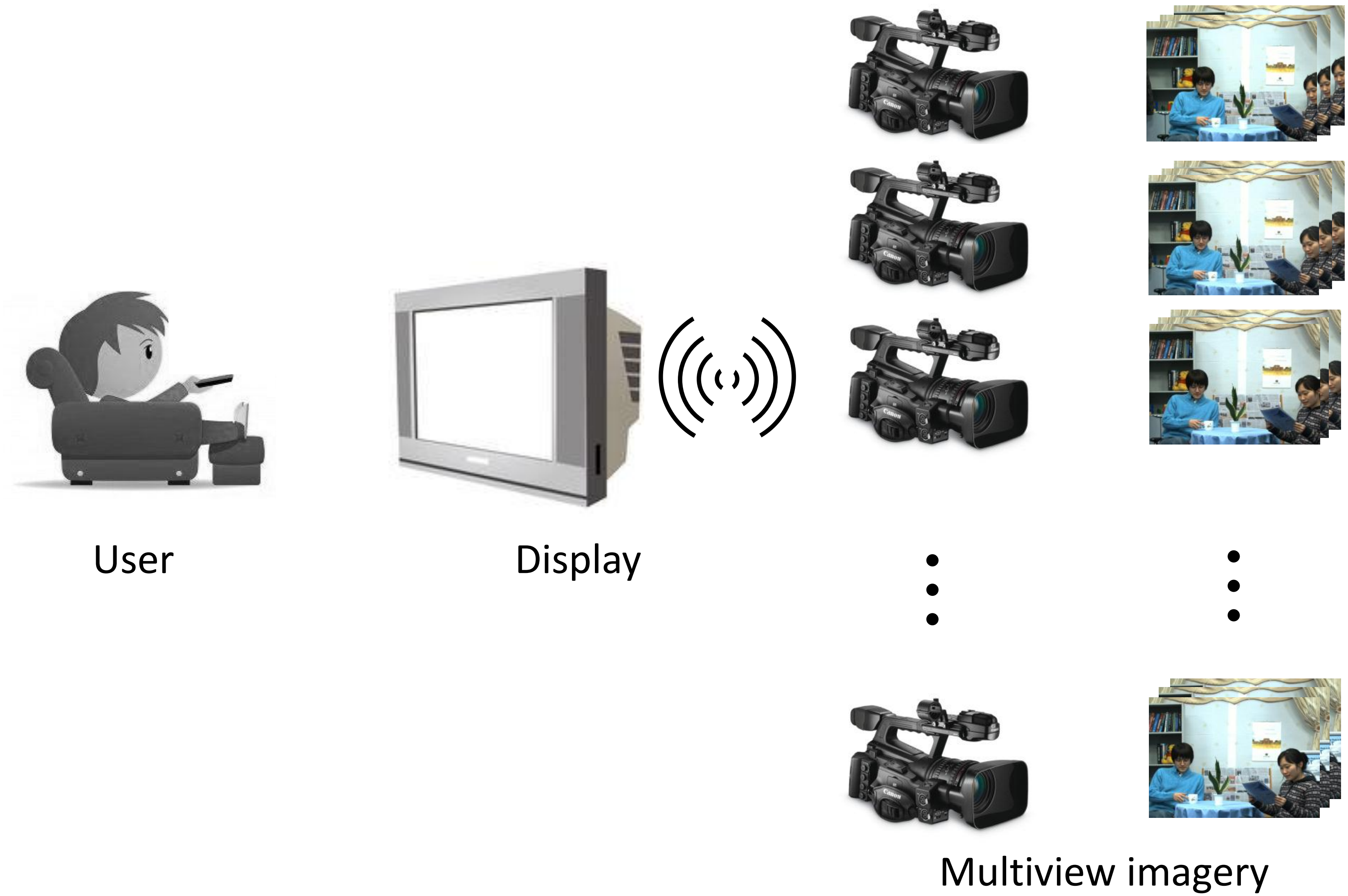
Conventional Television

User

Display



Free-viewpoint Television



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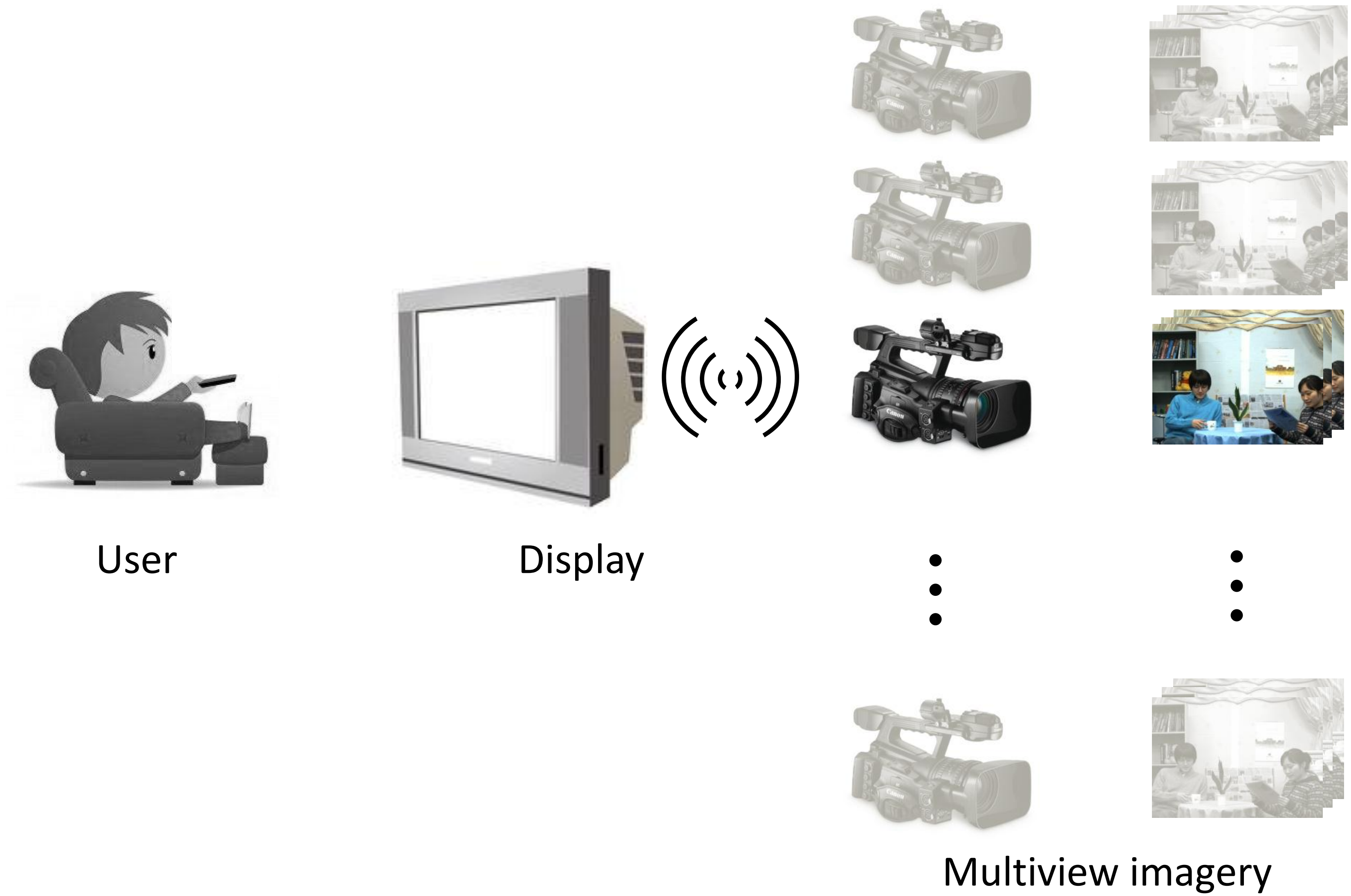

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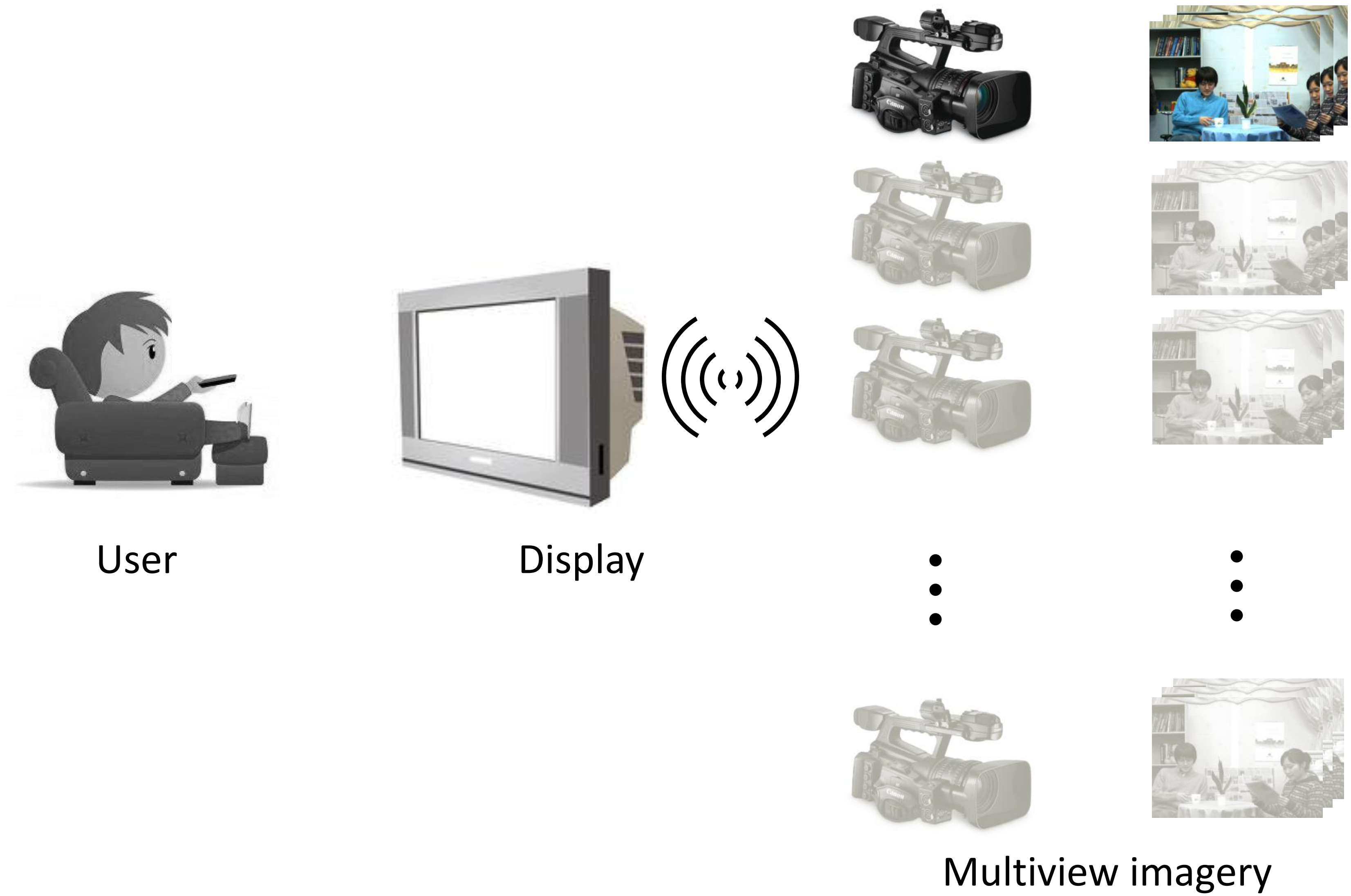
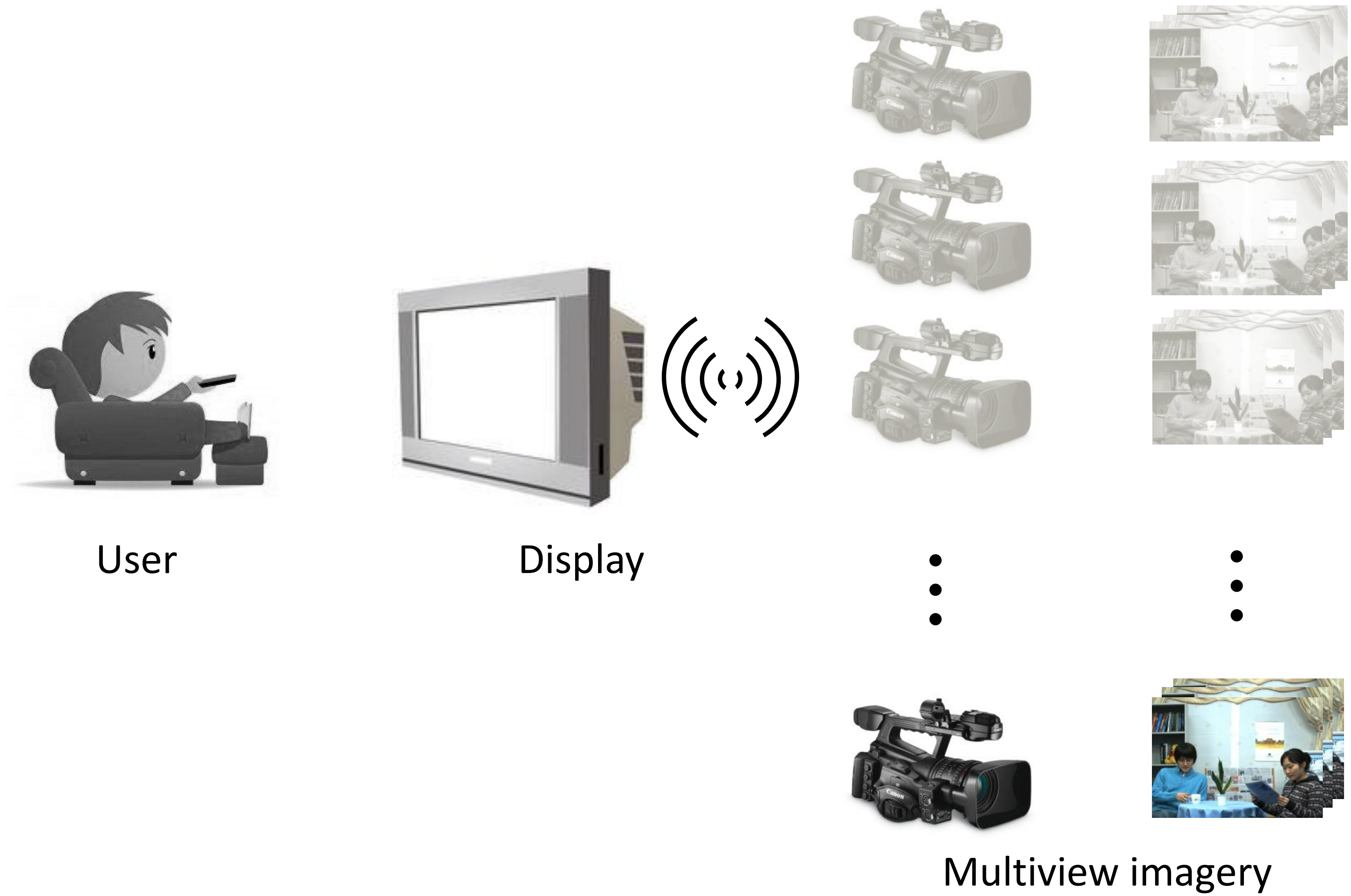


Free-viewpoint Television



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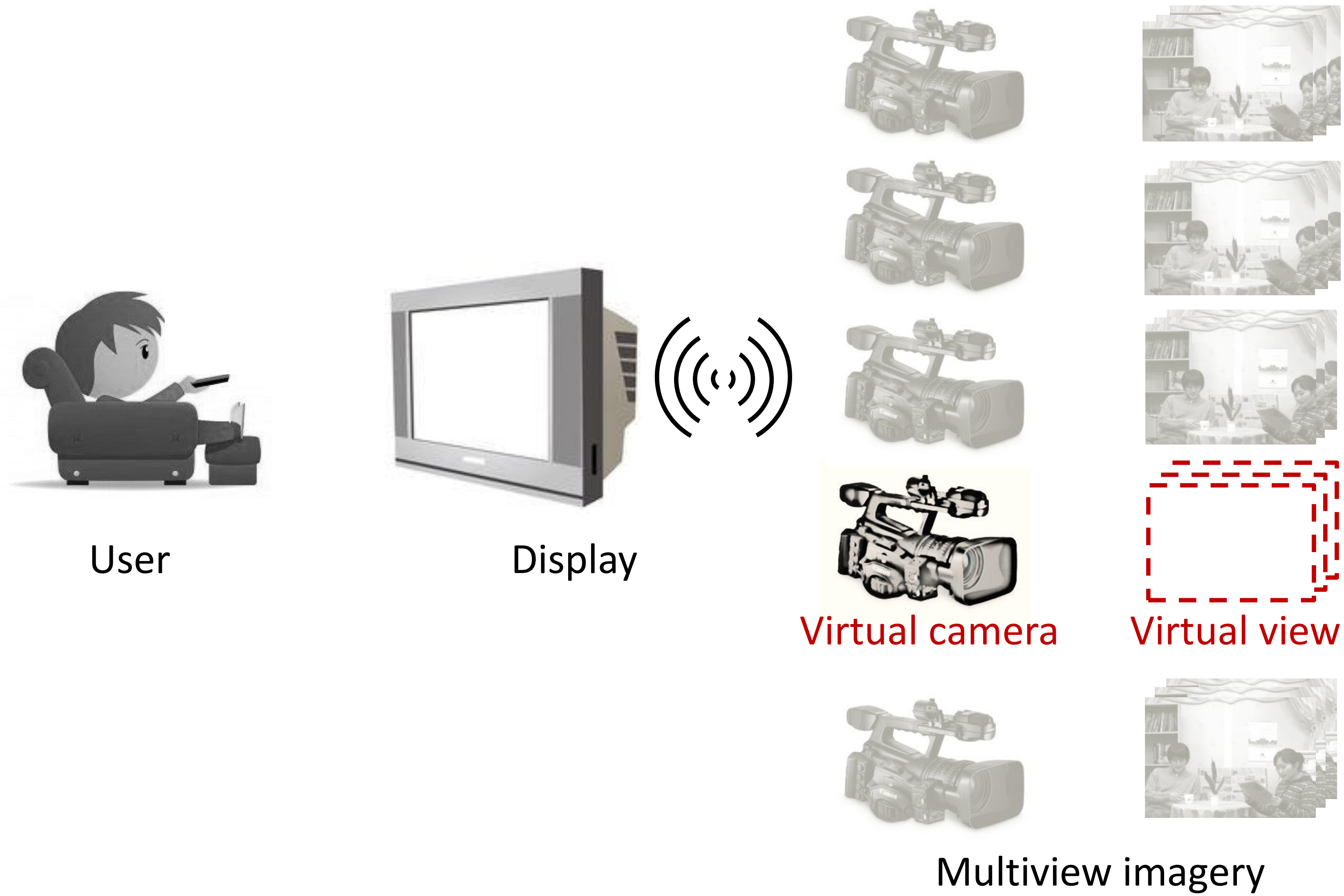
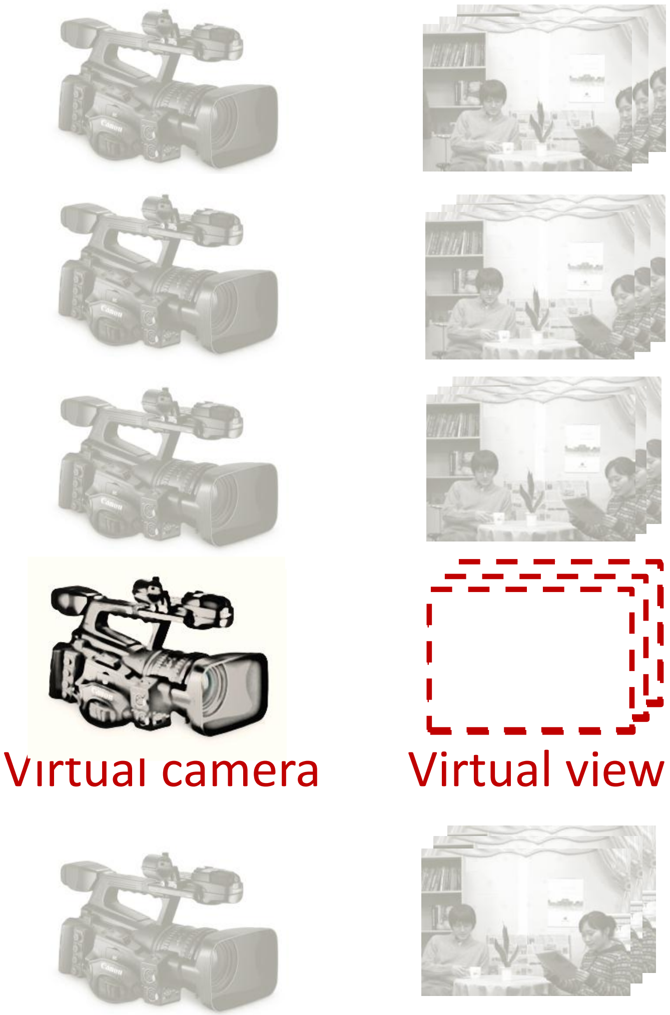


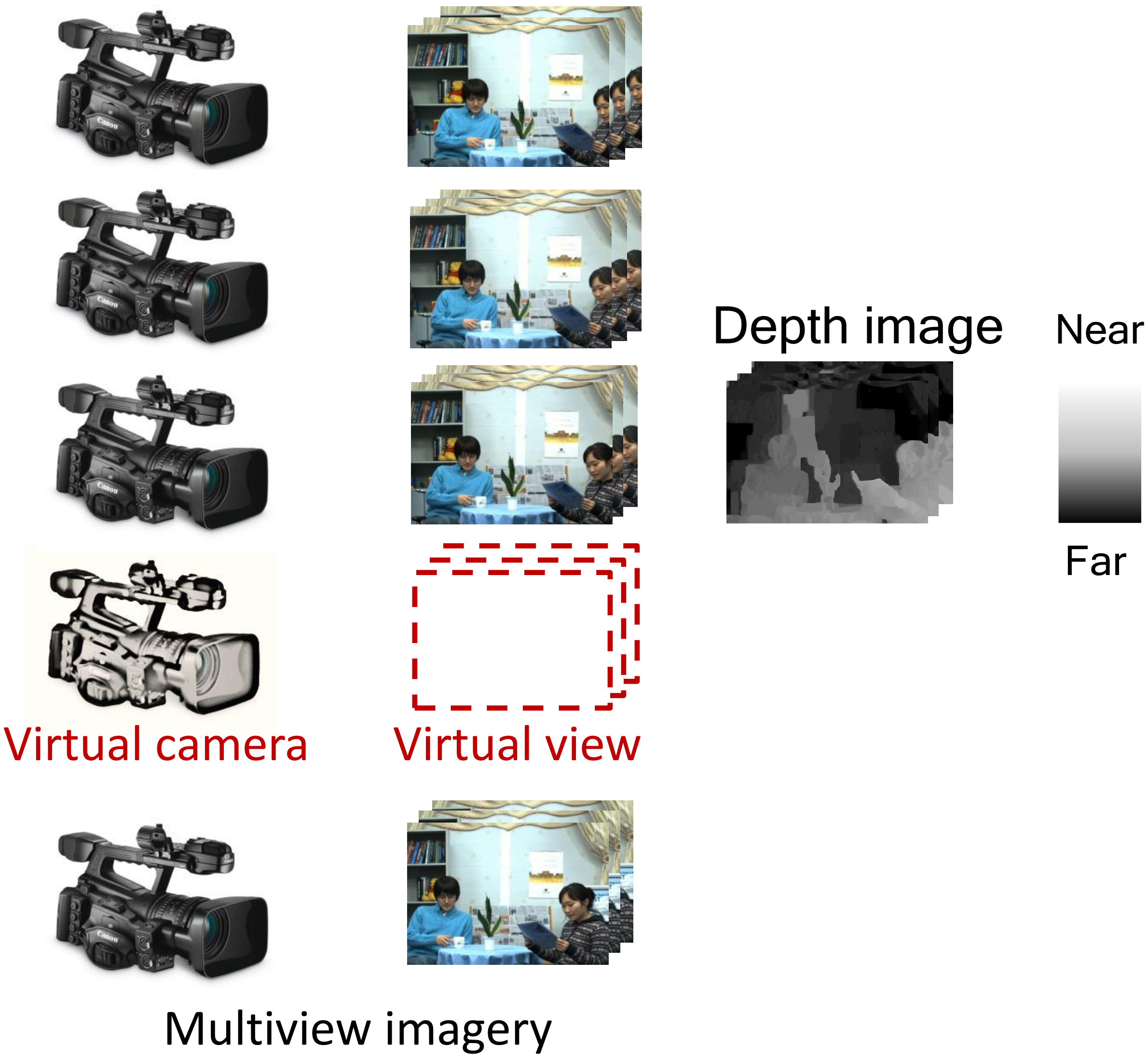
Virtual View Synthesis



Multiview imagery

Depth Image Based Rendering

Depth Image Based Rendering



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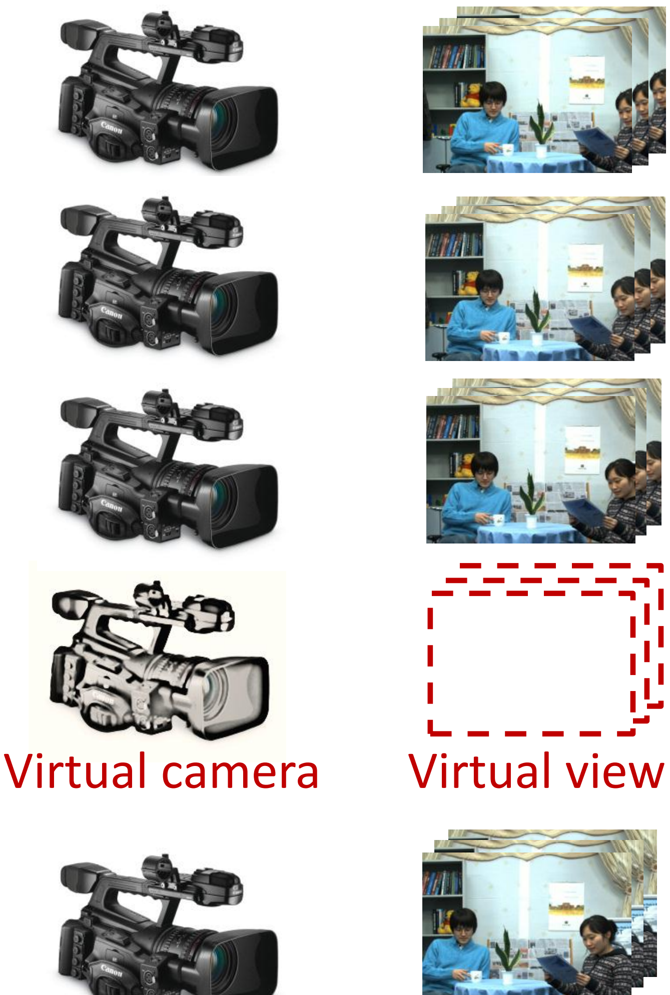

Multiview imagery

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

Depth image

Near

Far

Depth Image Based Rendering

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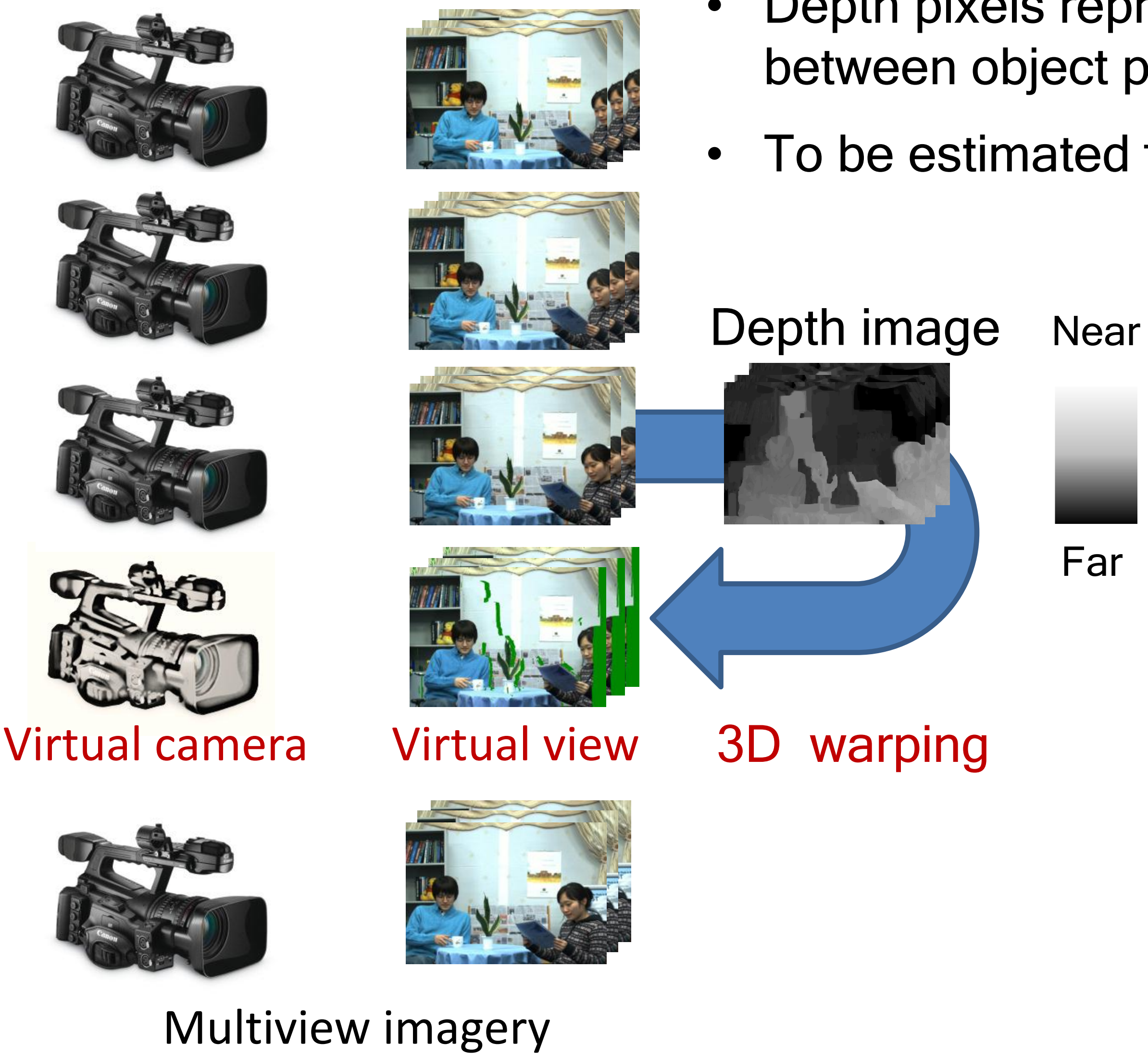
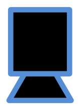
- To be estimated from multiview imagery



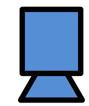
Depth Image Based Rendering

3D Warping

Physical camera
parameters



Virtual camera
parameters



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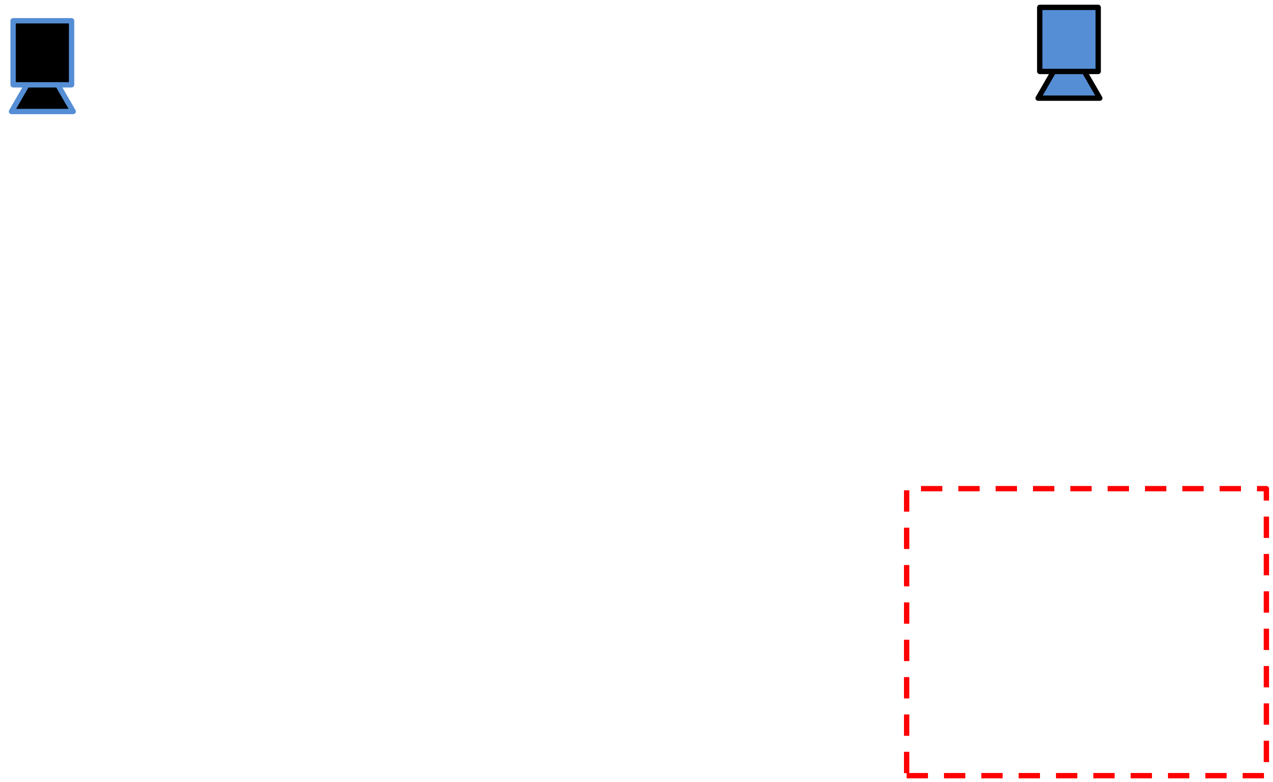

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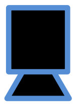

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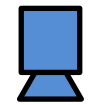

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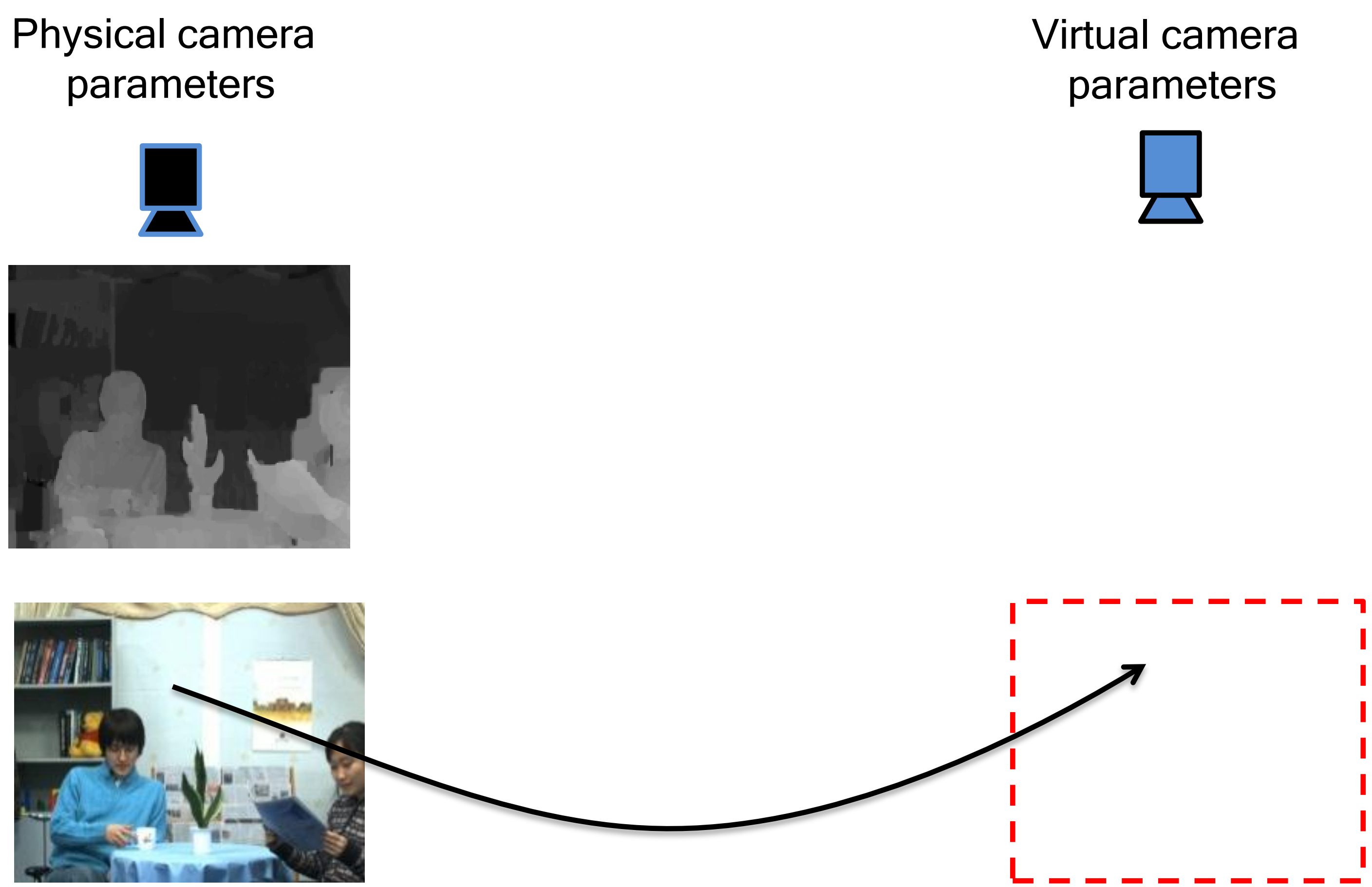

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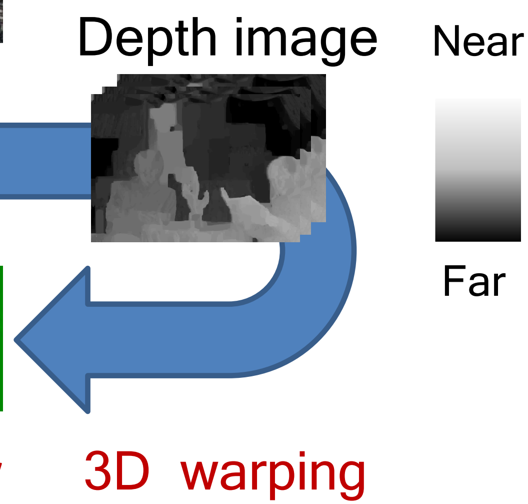
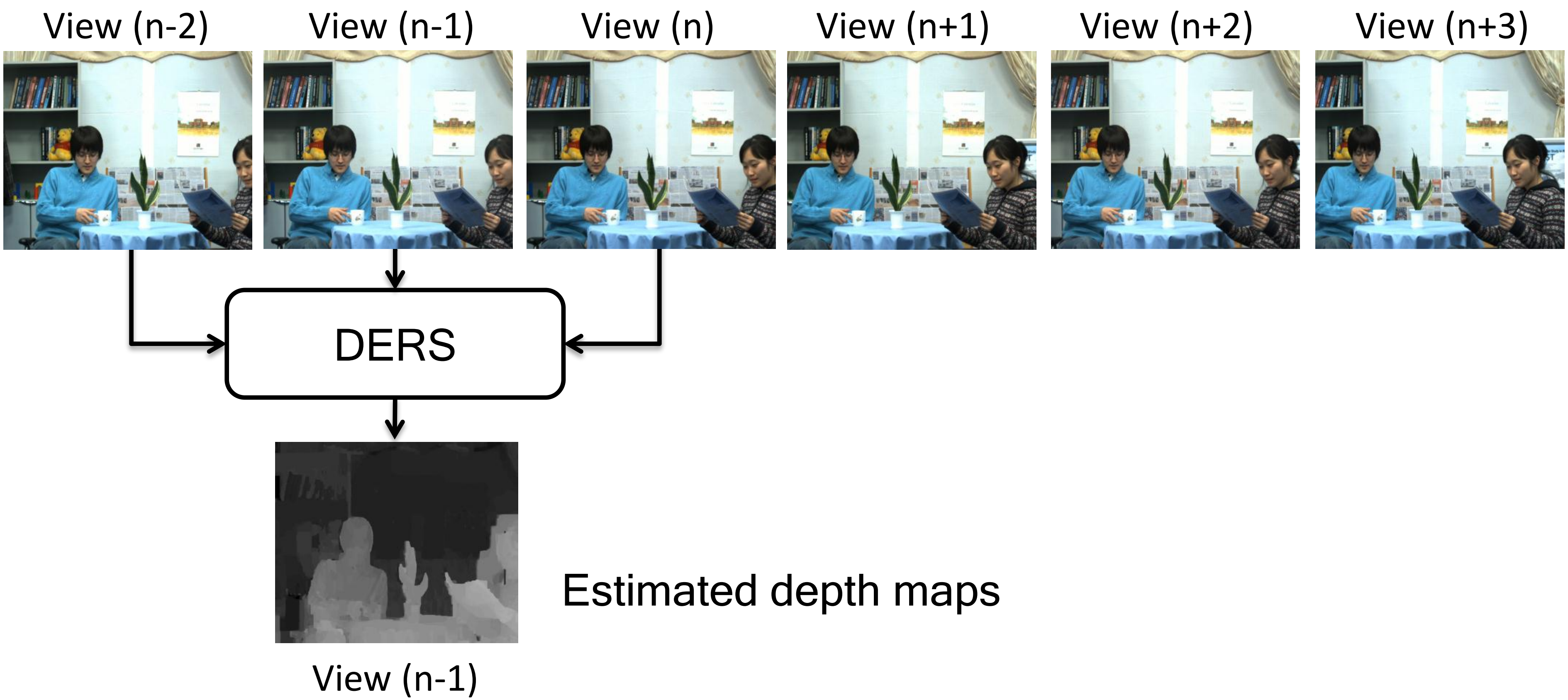


[1] C. Fehn: Depth-image-based rendering DIBR, compression, and transmission for a new approach on 3D-TV, SPIE, 2004.

Depth Image Estimation

MPEG Depth Estimation Reference Software (DERS)



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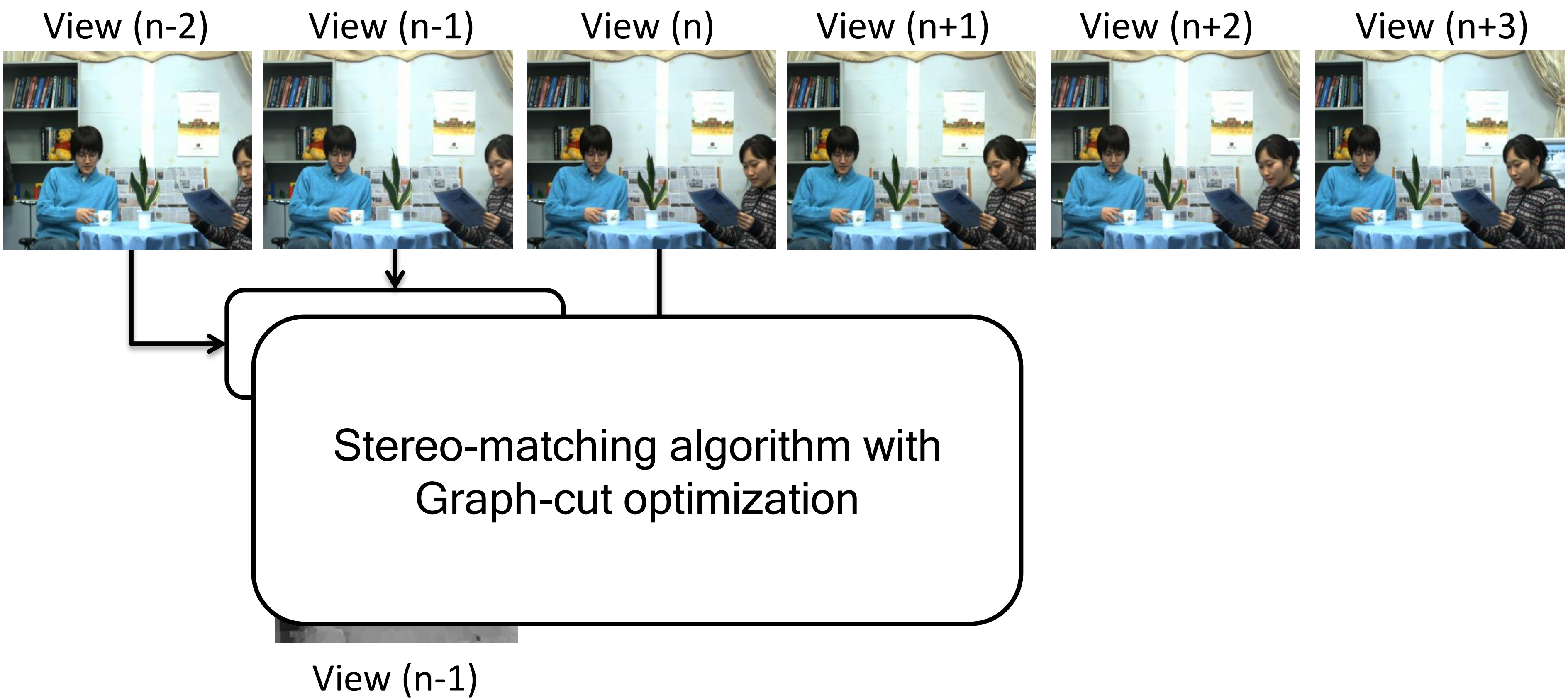

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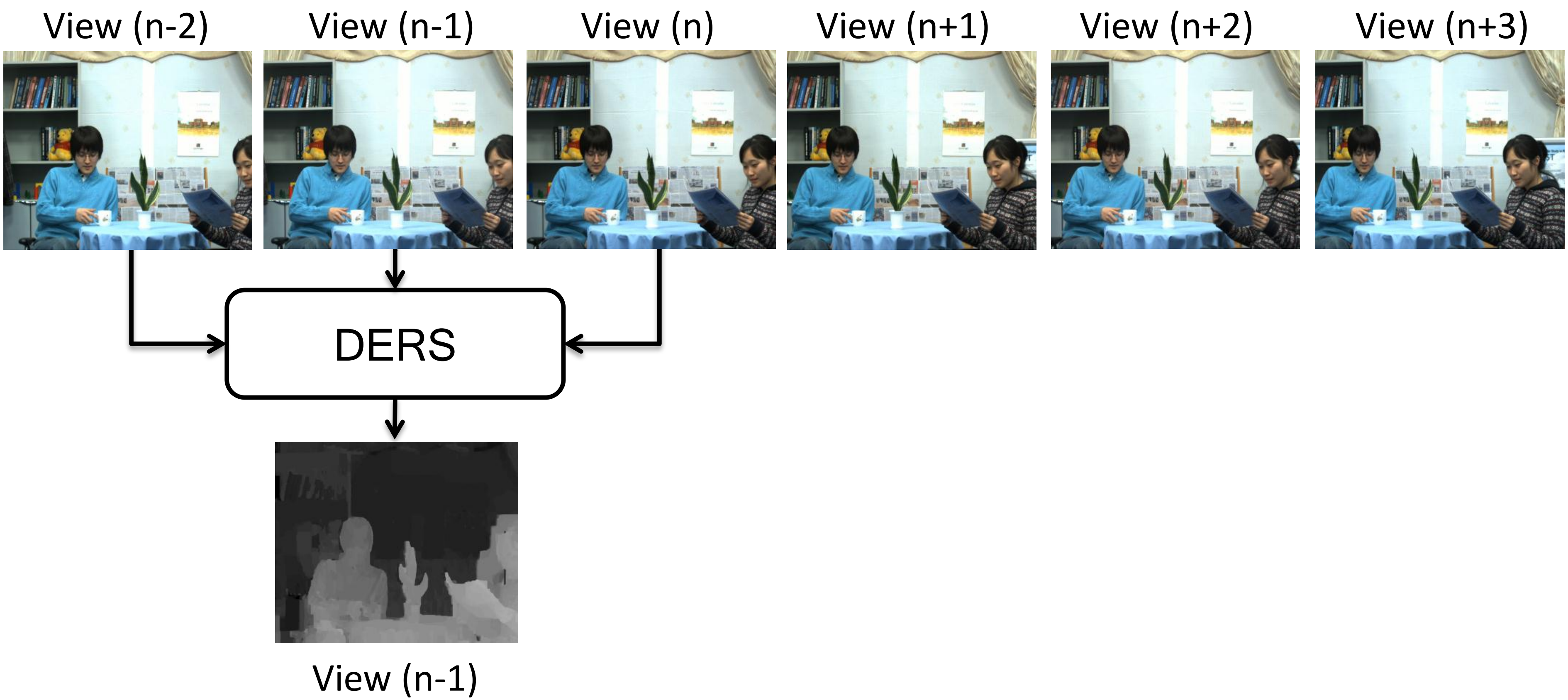

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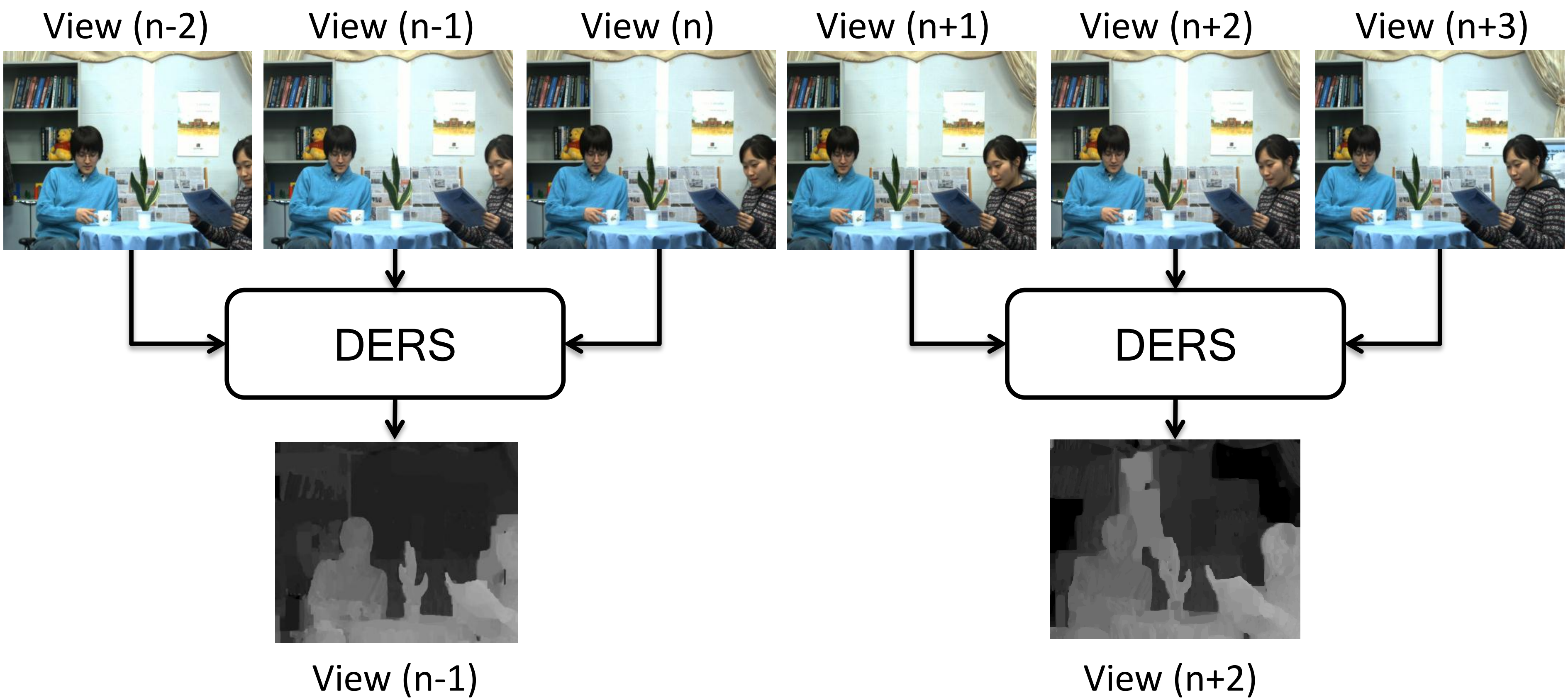

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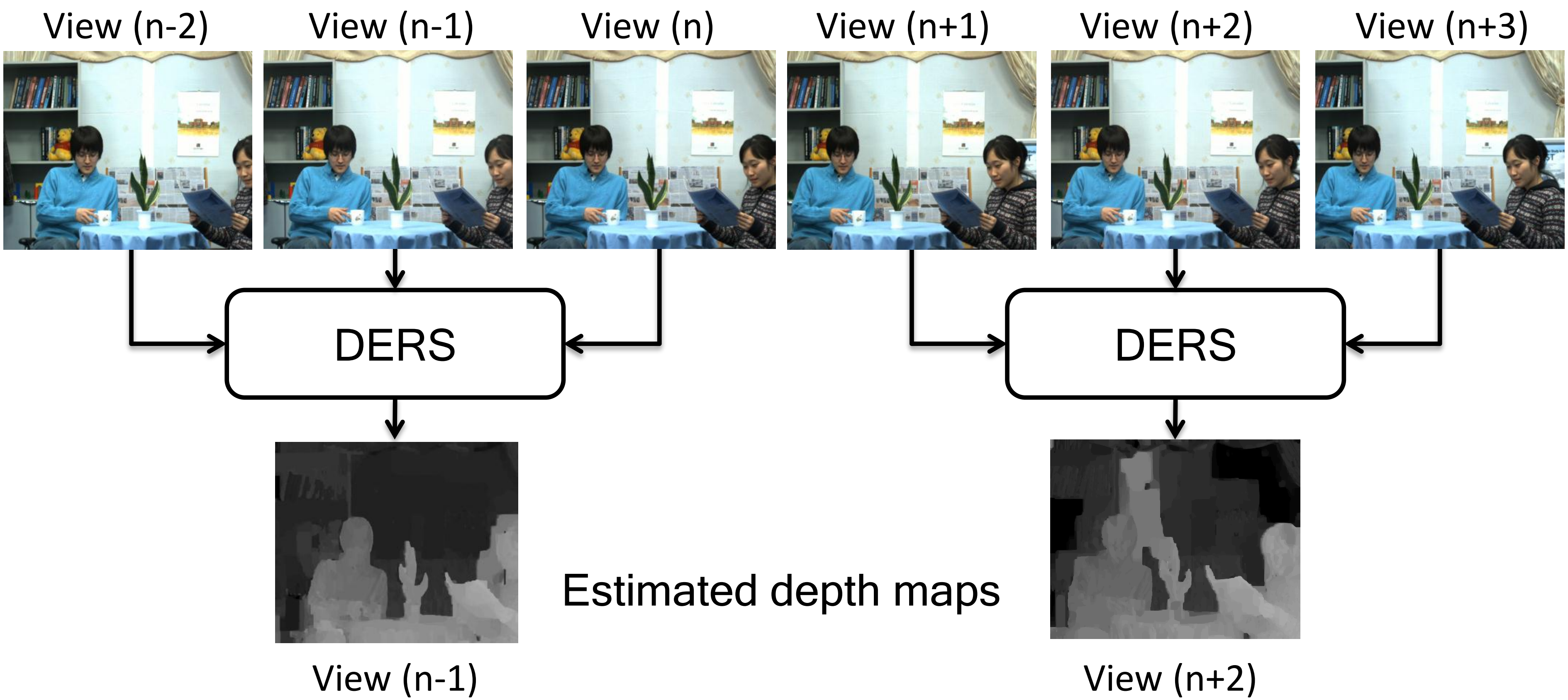
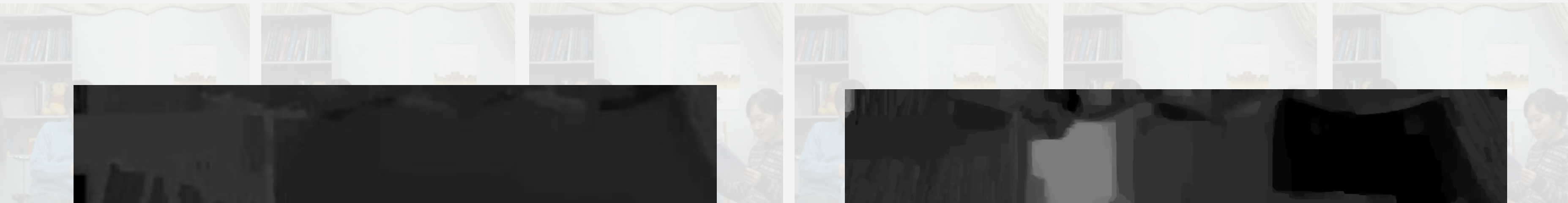


Depth Image Estimation

MPEG Depth Estimation Reference Software (DERS)

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



View (n-1)

View (n+2)

Note: we assume a 1D-parallel camera arrangement

Depth Image Estimation

MPEG Depth Estimation Reference Software (DERS)

Note: we assume a 1D-parallel camera arrangement

Depth Image Estimation

MPEG Depth Estimation Reference Software (DERS)

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Depth Image Estimation

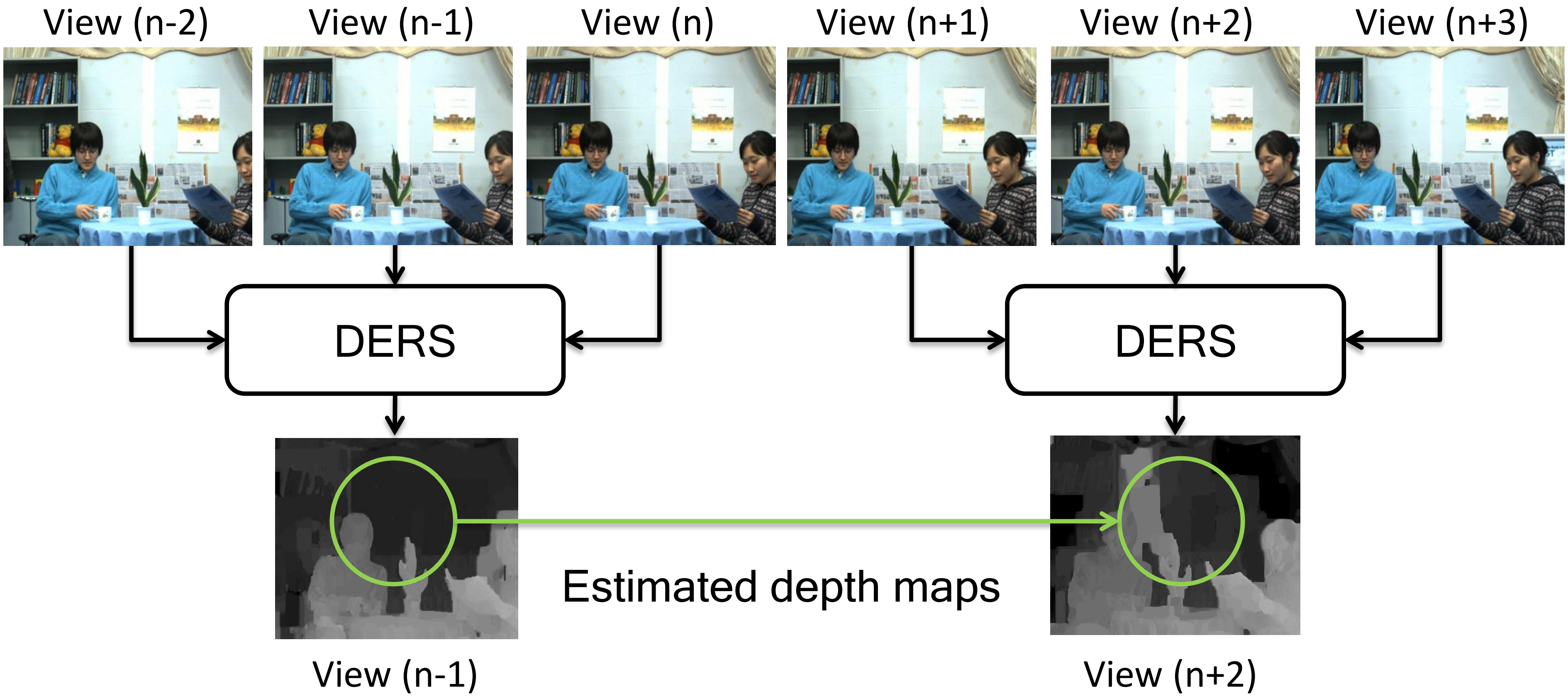
MPEG Depth Estimation Reference Software (DERS)

Problem: Inter-view depth inconsistency

Note: we assume a 1D-parallel camera arrangement

Depth Image Estimation

MPEG Depth Estimation Reference Software (DERS)

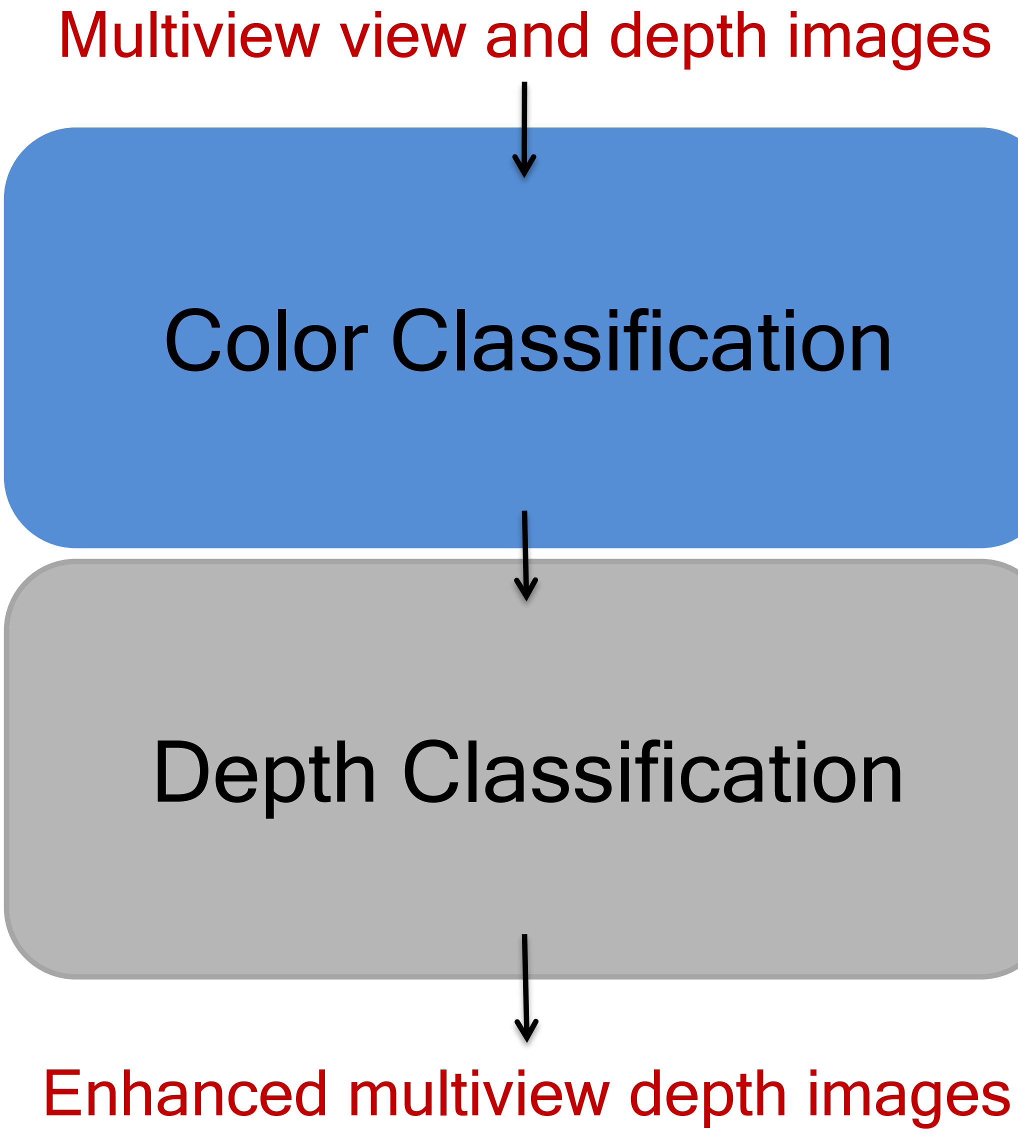


Problem: Inter-view depth inconsistency

Note: we assume a 1D-parallel camera arrangement

Depth Enhancement Framework

Overview of Depth Enhancement Framework



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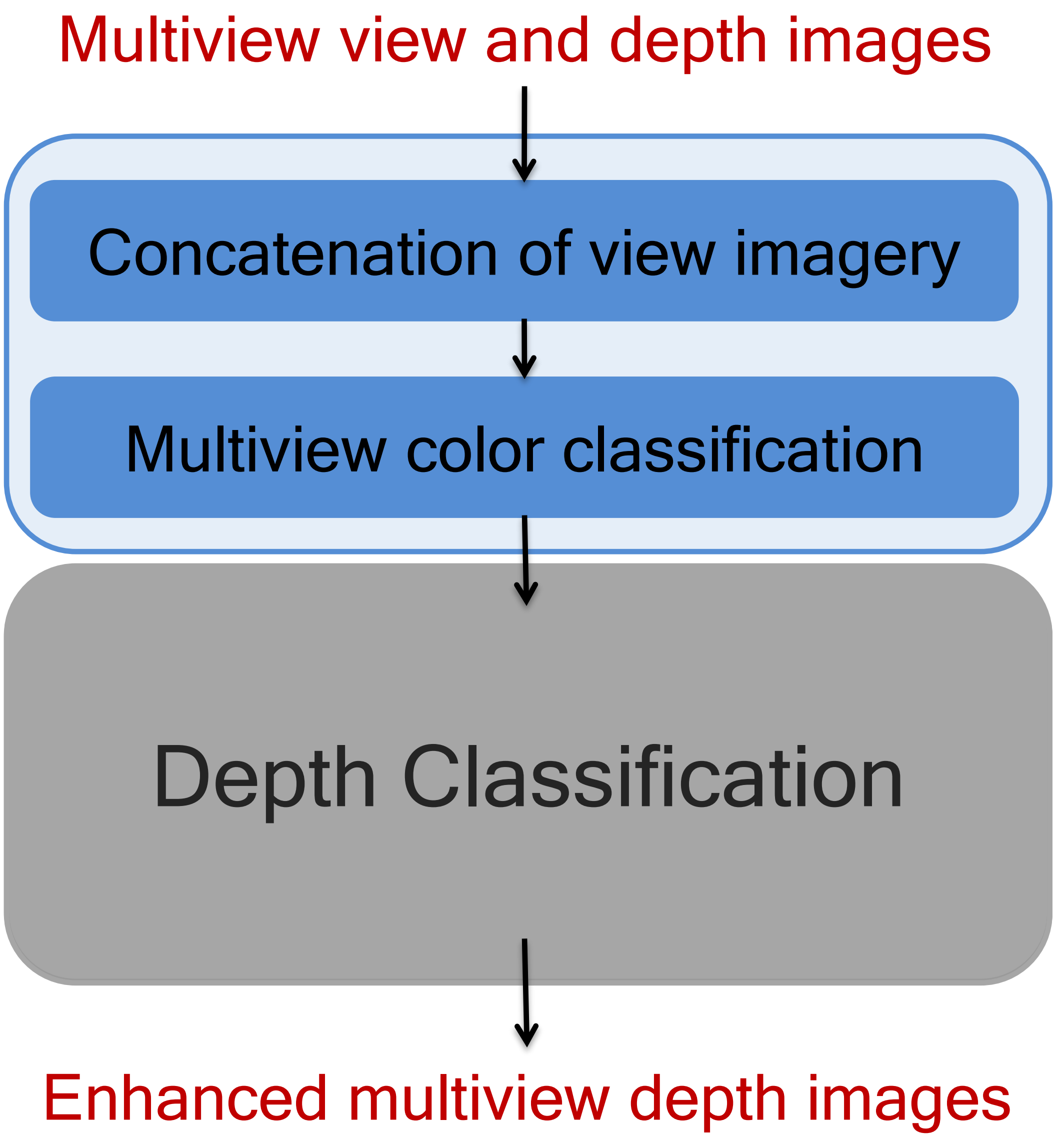

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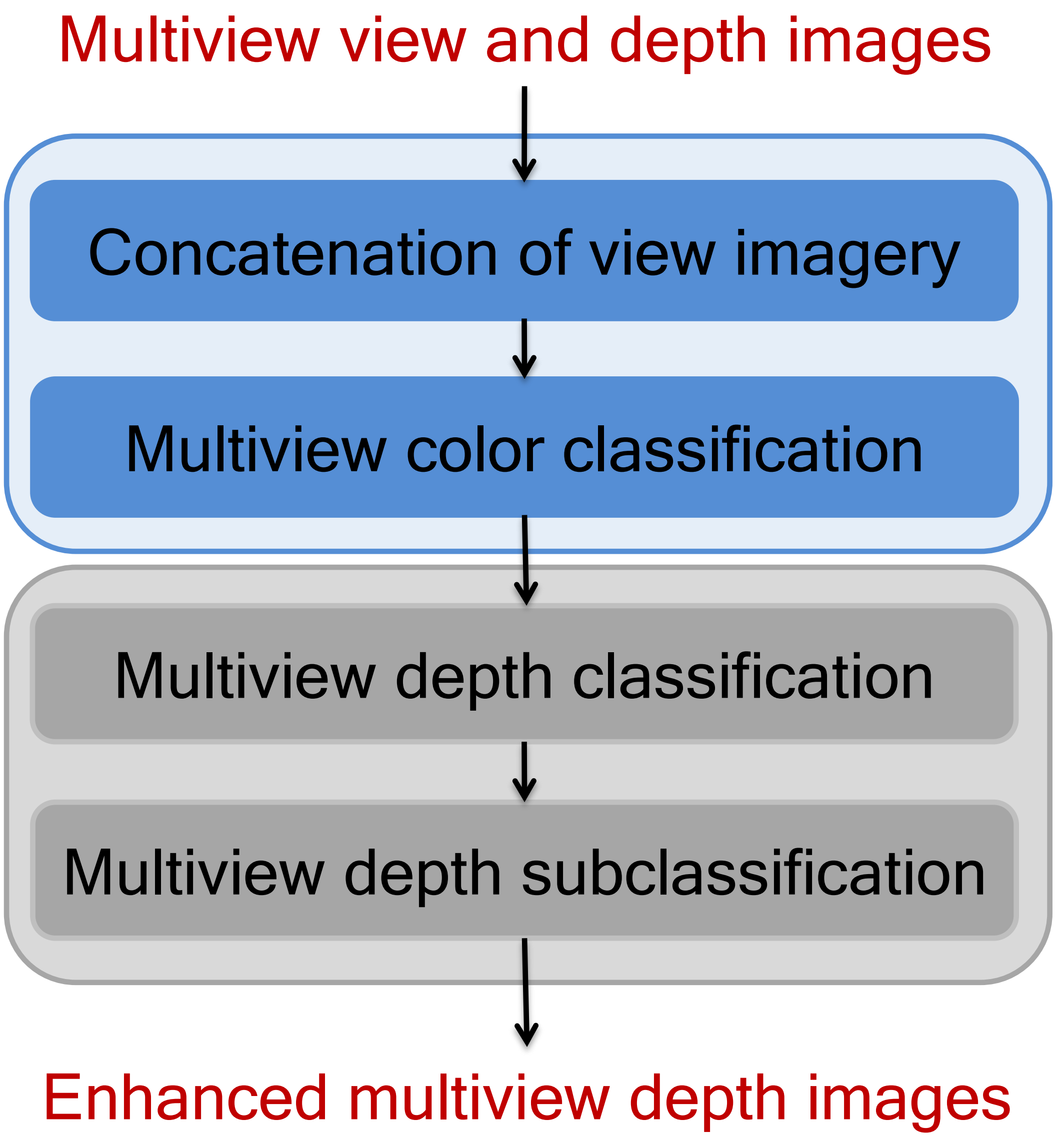


Concatenation of View Imagery

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

View (n-1)

View (n)

View (n+1)

View (n+2)

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

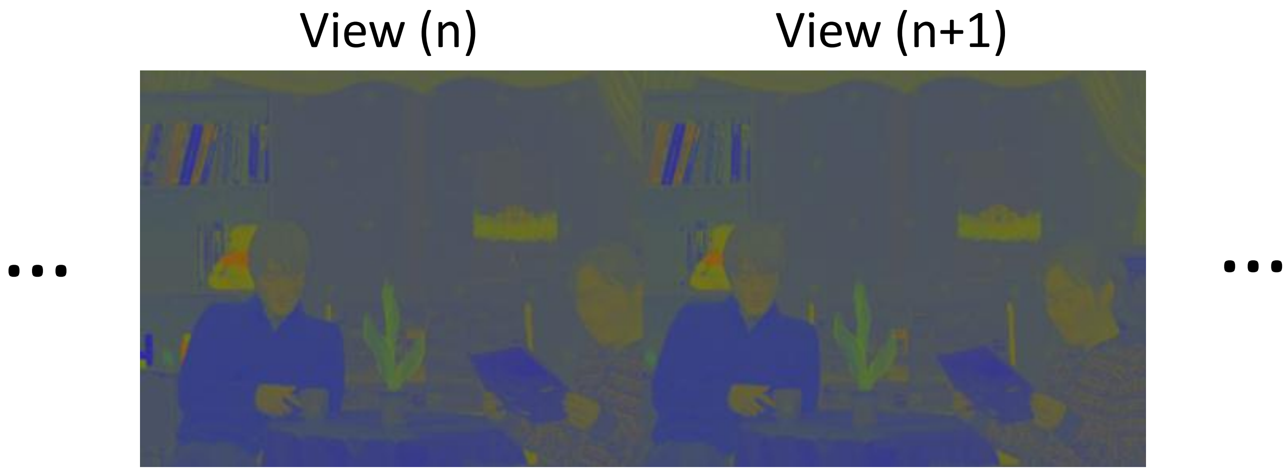
View (n) View (n+1)

...

...

xyz Chromatic color space

Multiview Color Classification



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 suffers from one major drawbacks that the number of clusters has to be known
- Bayesian approaches automatically and optimally select the number of clusters
- Use of variational inference (VI) framework for Bayesian approaches gives an analytically tractable solution

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

Multiview Color Classification

Why Dirichlet mixture models (DMM) ?

- The pixel vector in the chromaticity space has
  - nonnegative elements
  - bounded by the interval [0,1]
  - sum to one

- Assume that these pixel vectors are Dirichlet distributed

- DMM with variational inference is used to capture all underlying color clusters in multiview imagery

- It reduces complexity

[3] P. K. Rana, J. Taghia, and M. Flierl: A Variational Bayesian Inference Framework for Multiview Depth Image Enhancement, IEEE ISM, 2012.

[4] 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

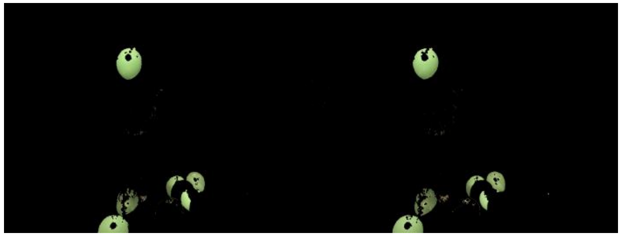
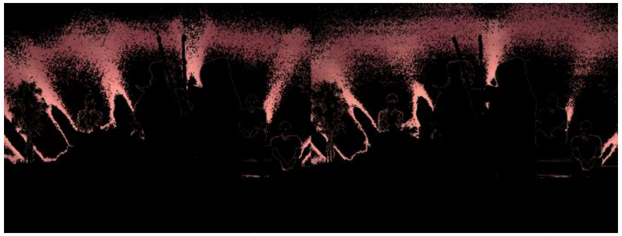
Input multiview data

Multiview Color Classification

Newspaper | Balloons | Kendo



Input multiview data

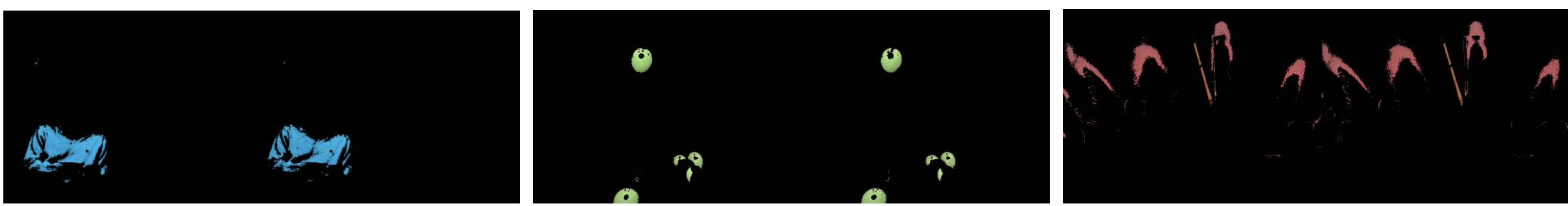
Using VI-DMM

Multiview Color Classification

Newspaper | Balloons | Kendo

Input multiview data

Using VI-DMM



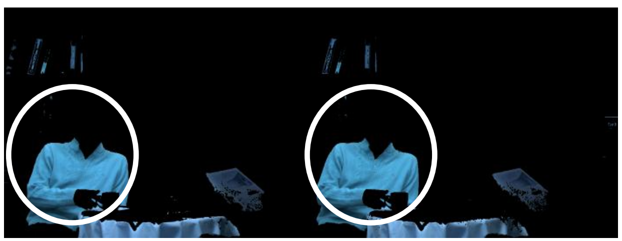
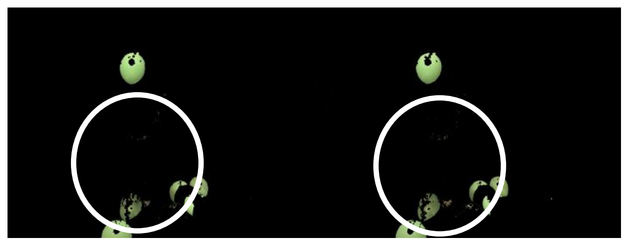
Using VI-GMM

Multiview Color Classification

Newspaper | Balloons | Kendo



Input multiview data


Using VI-DMM



Using VI-GMM

Multiview Depth Classification

Exploiting the per-pixel association between color and depth

View image   Depth image

Multiview Depth Classification

Exploiting the per-pixel association between color and depth

View image　　Depth image

Concatenated view imagery　　Concatenated depth imagery

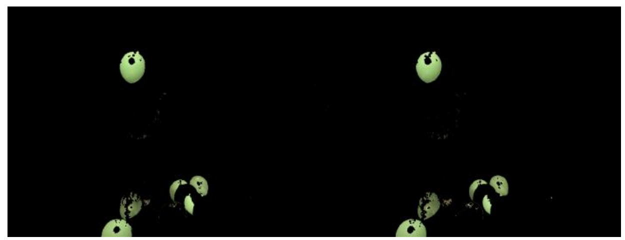
Multiview Depth Classification

Newspaper

Balloons

Kendo

Input multiview data



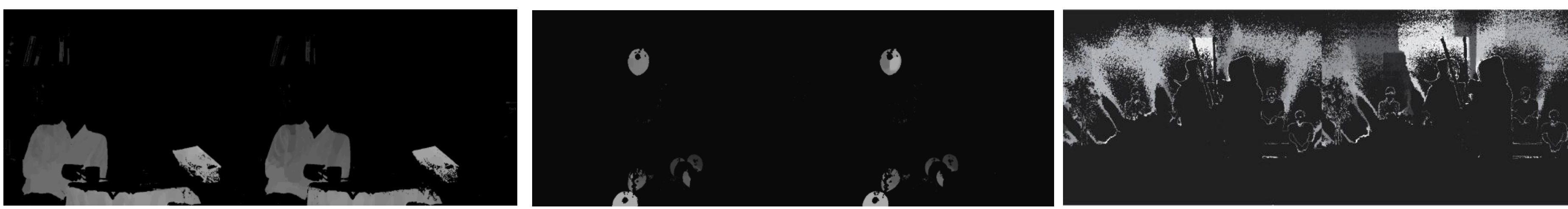
Using VI-DMM

Multiview Depth Classification

Newspaper | Balloons | Kendo

Input multiview data

Using VI-DMM



Depth clusters

Multiview Depth Classification

Newspaper | Balloons | Kendo

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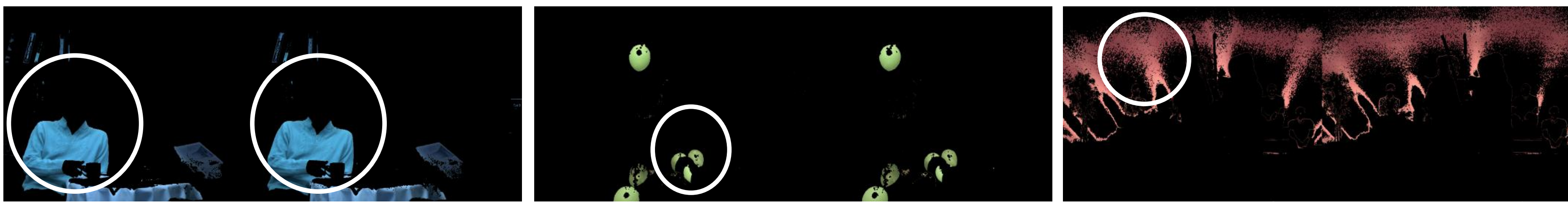

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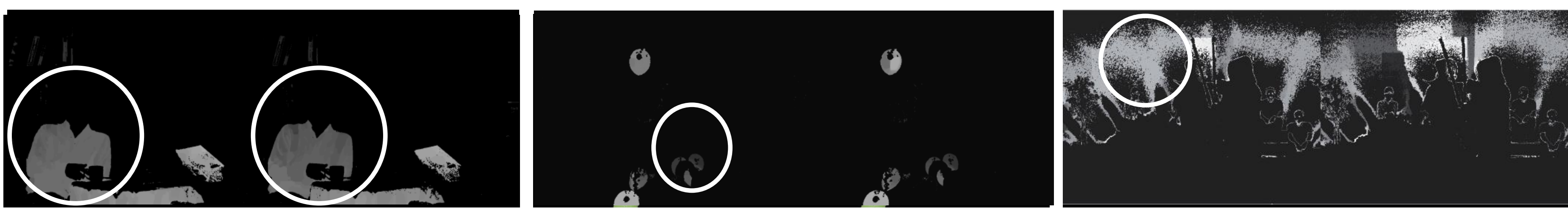

Depth clusters

Multiview Depth Subclassification

Difference between color and depth clusters

- Members of color cluster have similar colors pixels
- Members of depth cluster 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
- Knowledge of the number of clusters not required
- Assigns the mean to depth pixels irrespective of the originating viewpoints
- Generative model based approaches imply higher computational complexity

[5] D. Comaniciu and P. Meer: Mean shift: A robust approach toward feature space analysis, IEEE Trans. Pattern Anal. Mach. Intell., 2002.

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

Left

Enhanced depth map

Reference view

3D warping

Warped view

Right

Enhanced depth map

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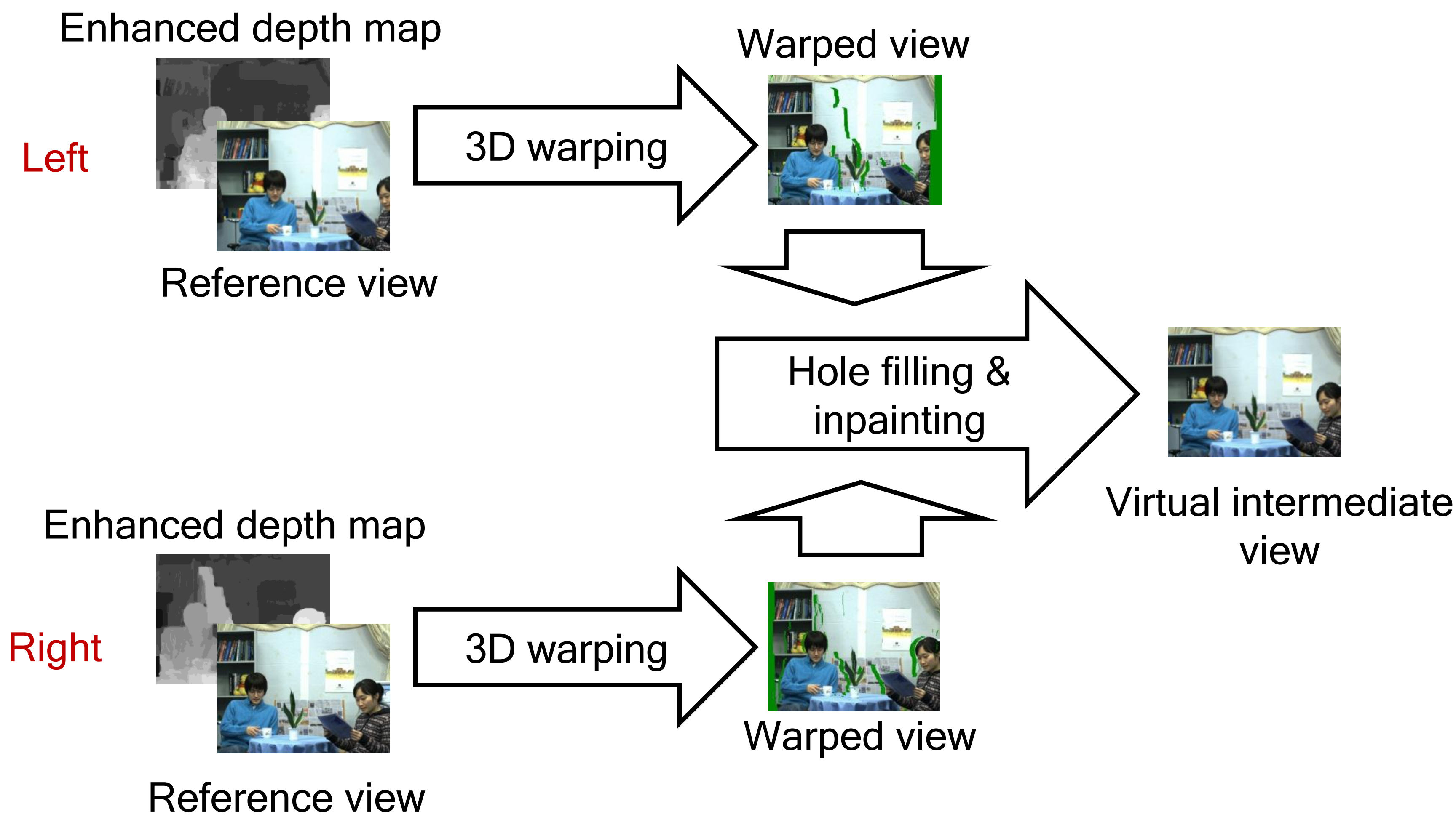
Depth Image-Based Rendering

MPEG View Synthesis Reference Software (VSRS) 3.5



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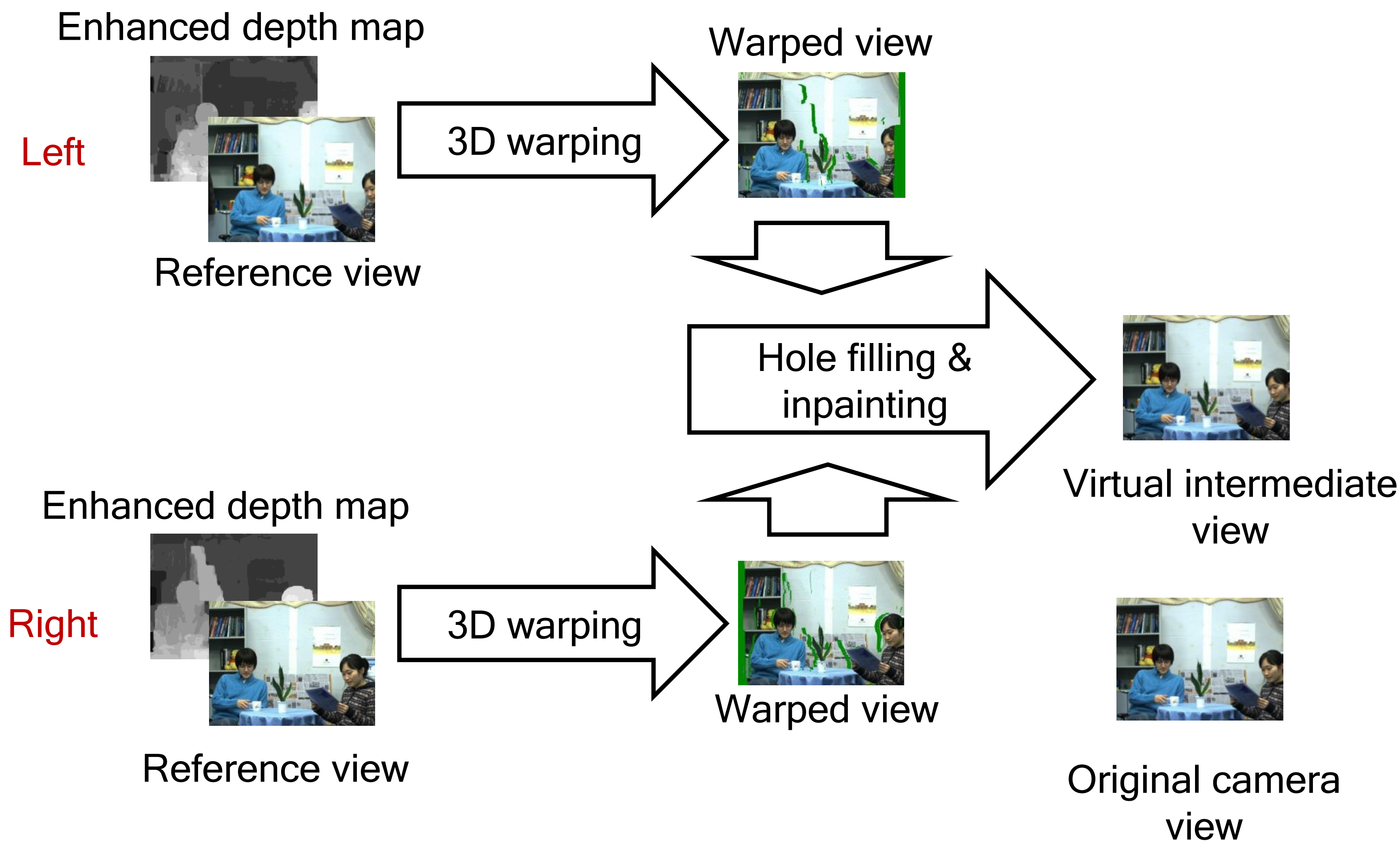

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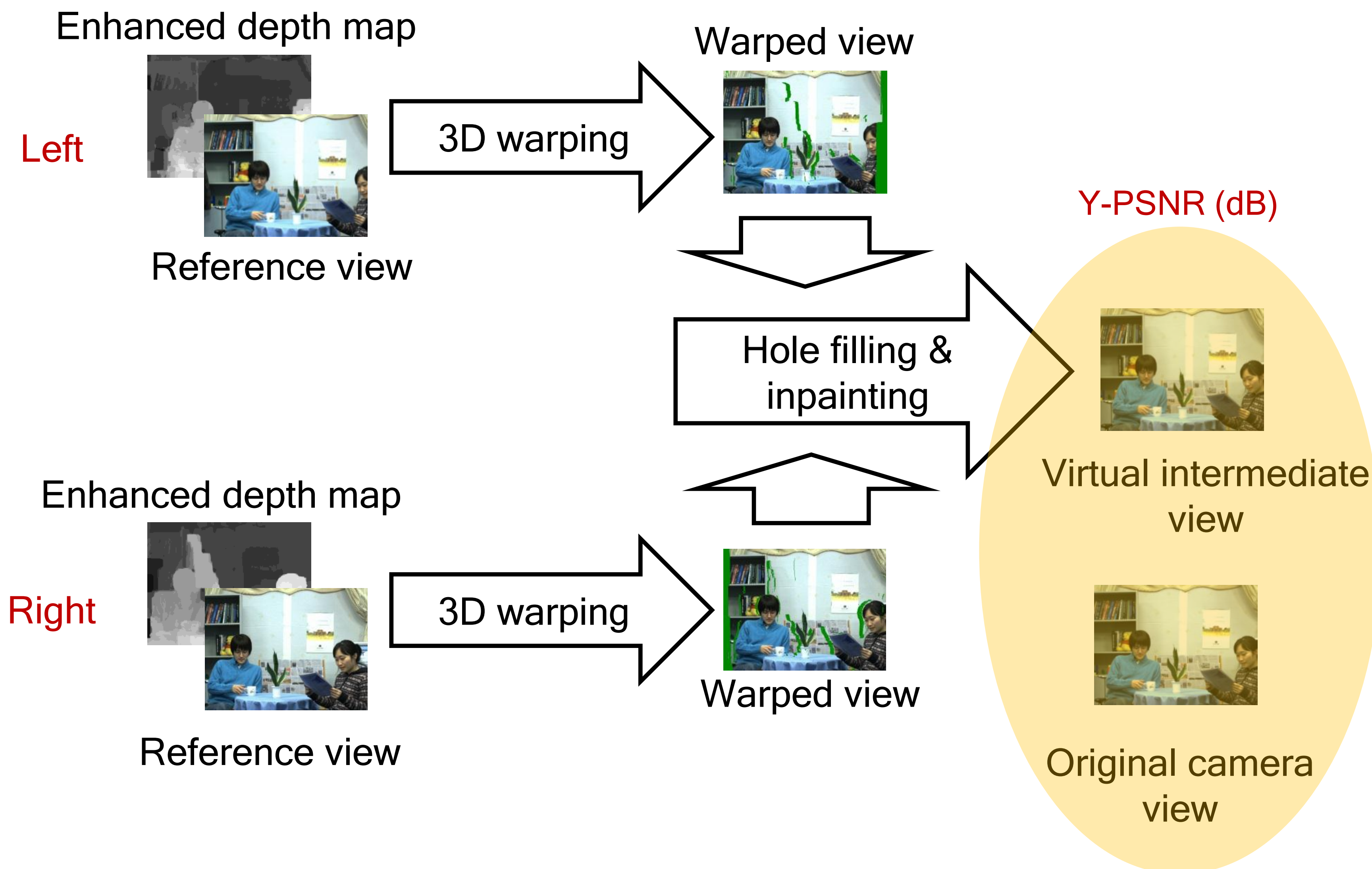

Objective Results

Test sequence	Input view pair	Virtual view	Y-PSNR [dB]		
			With MPEG depth maps	With VBIGMM + K-Means depth maps [3]	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

[3] P. K. Rana, J. Taghia, and M. Flierl: A Variational Bayesian Inference Framework for Multiview Depth Image Enhancement, IEEE ISM, 2012.

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Objective Results

Test sequence	Input view pair	Virtual view	Y-PSNR [dB]		
			With MPEG depth maps	With VI-GMM + K-Means depth maps [3]	With VI-DMM + 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

[3] P. K. Rana, J. Taghia, and M. Flierl: A Variational Bayesian Inference Framework for Multiview Depth Image Enhancement, IEEE ISM, 2012.

Subjective Results

Test sequence: Kendo

With MPEG depth map

With VI-DMM+Mean-shift depth map

Subjective Results

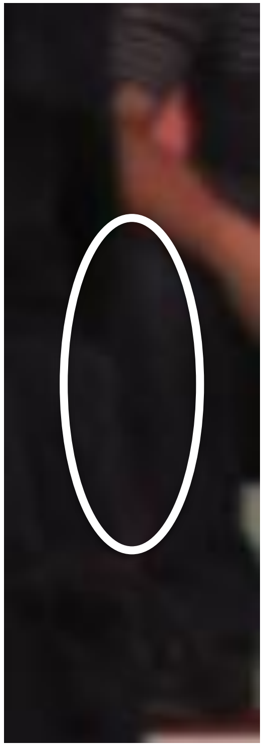
Test sequence: Kendo

With MPEG depth map

With VI-DMM+Mean-shift depth map

Subjective Results

Test sequence: Kendo



Original

With VI-DMM + Mean-Shift depth maps

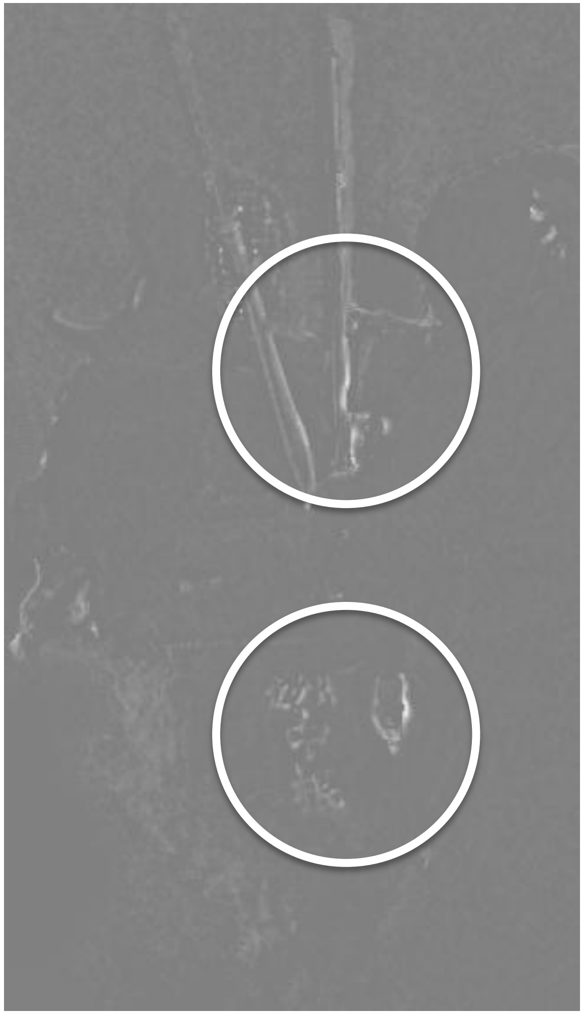
With VI-GMM + K-Means depth maps

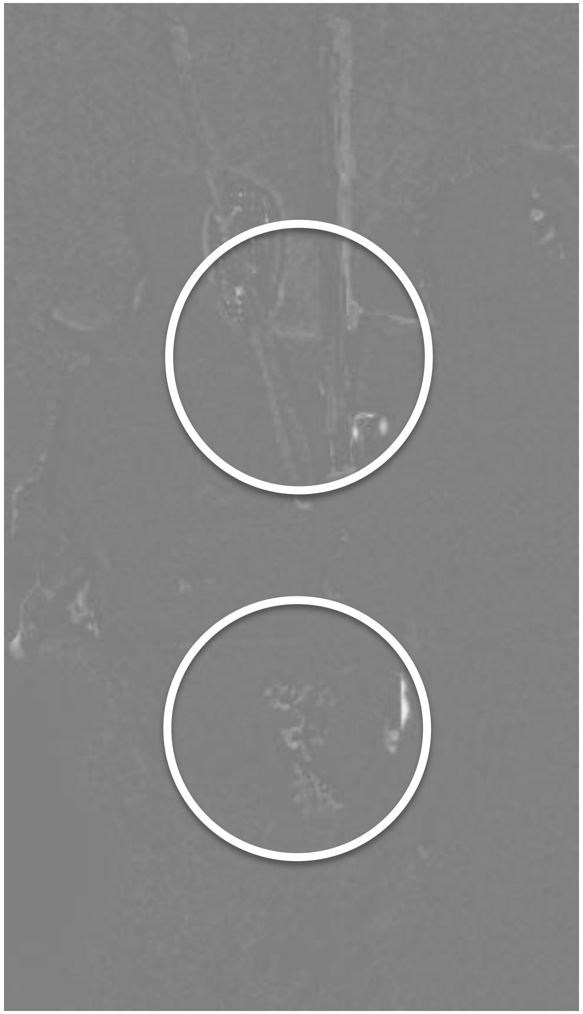
With MPEG depth maps

Subjective Results

Test sequence: Kendo

With VI-GMM +K-Means depth maps





With VI-DMM +Mean-Shift depth maps

Subjective Results

Test sequence: Lovebird 1

With MPEG depth map

With VI-DMM+Mean-shift depth map

Subjective Results

Test sequence: Lovebird 1

With MPEG depth map

With VI-DMM+Mean-shift depth map

Subjective Results

Test sequence: Lovebird 1

Original

With VI-DMM
+Mean-Shift
depth maps

With VI-GMM
+K-Means
depth maps

With MPEG
depth maps

Subjective Results

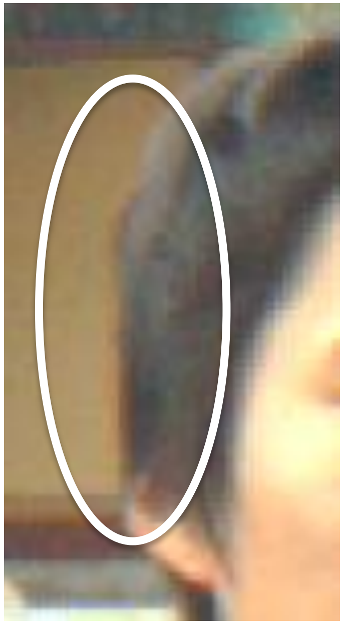
Test sequence: Lovebird 1

With MPEG depth map

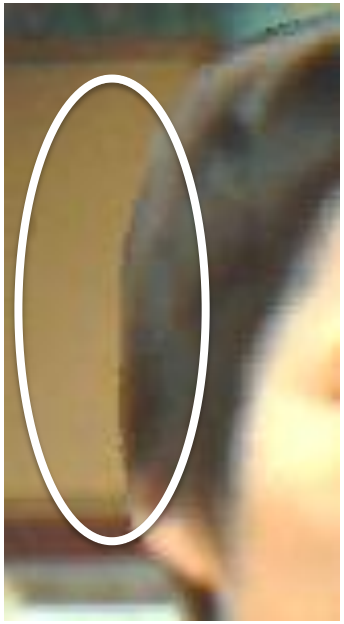
With VI-DMM+Mean-shift depth map

Subjective Results

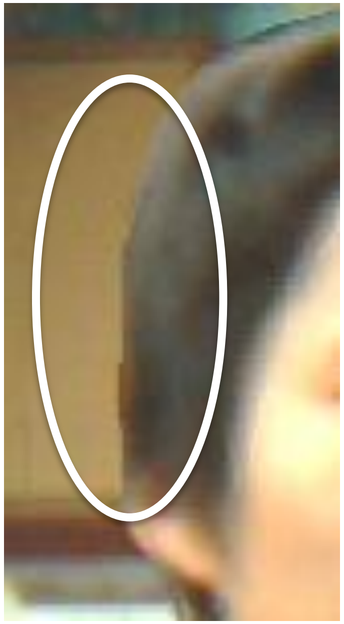
Test sequence: Lovebird 1



Original



With VI-DMM +Mean-Shift depth maps



With VI-GMM +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

[6] 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.

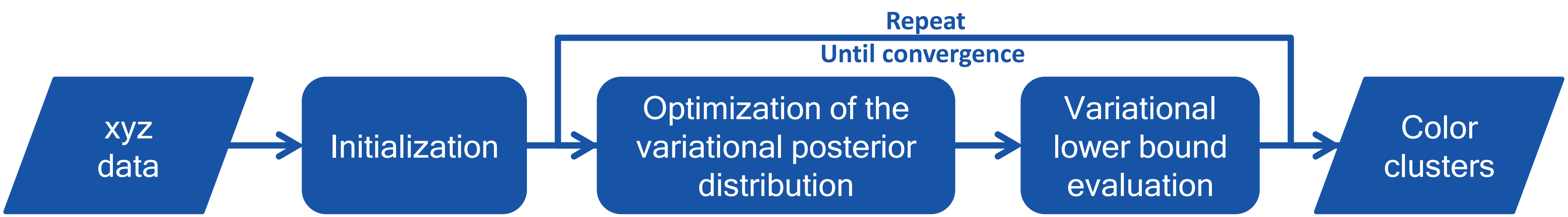
Future Directions

- A fully probabilistic multiview depth image enhancement
  - With improved computational efficiency
  - With improved depth subclassification

Thank You

Multiview color classification

Dirichlet mixture model with variational Bayes inference



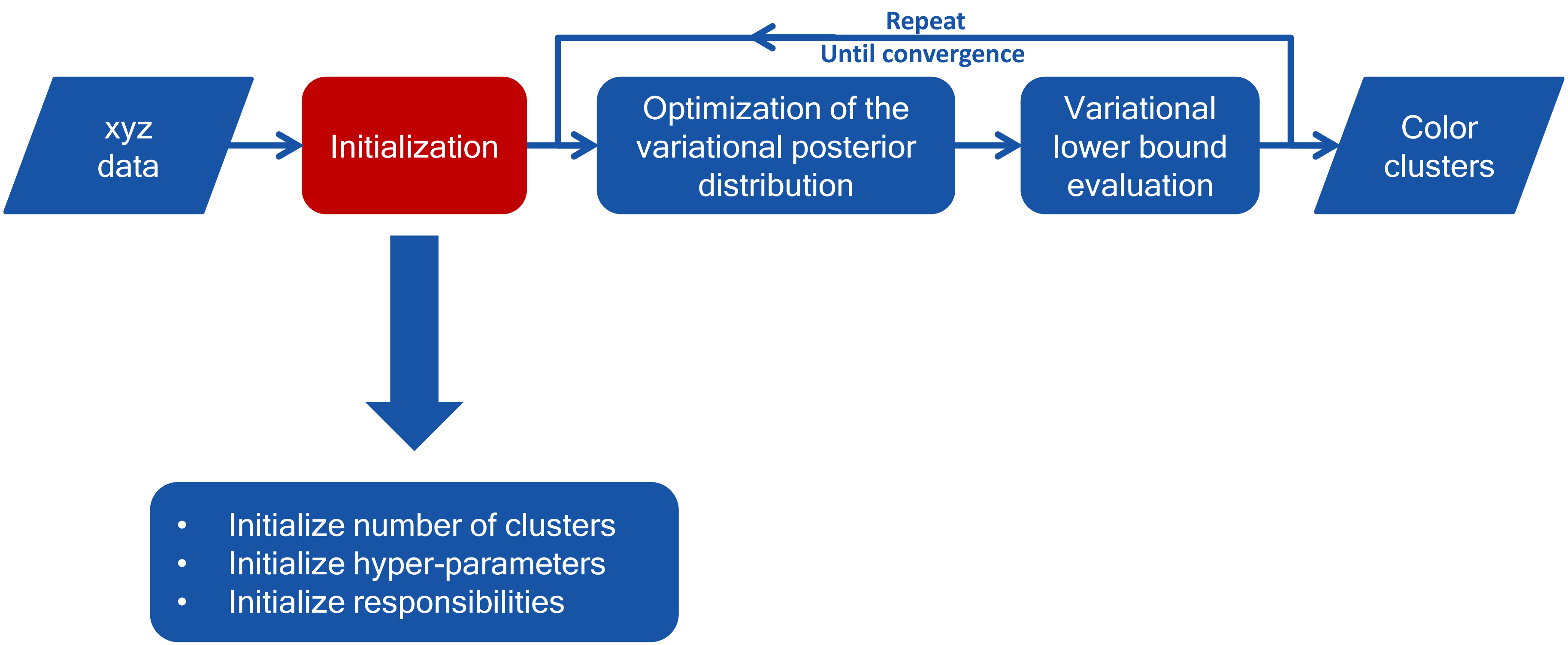
[1] C. M. Bishop, Pattern Recognition and Machine Learning, 1st ed. New York: Springer, 2006.

[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.

Y

Multiview color classification

Dirichlet mixture model with variational Bayes inference



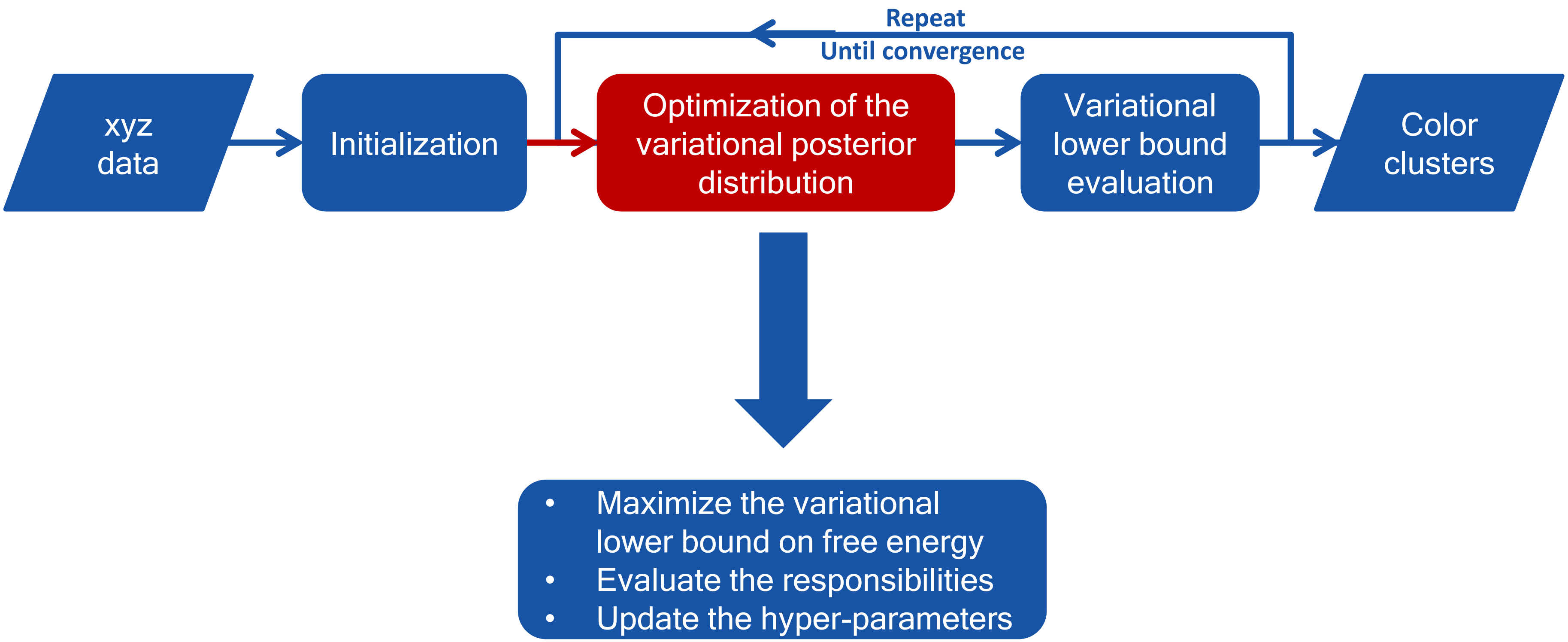
[1] C. M. Bishop, Pattern Recognition and Machine Learning, 1st ed. New York: Springer, 2006.

[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



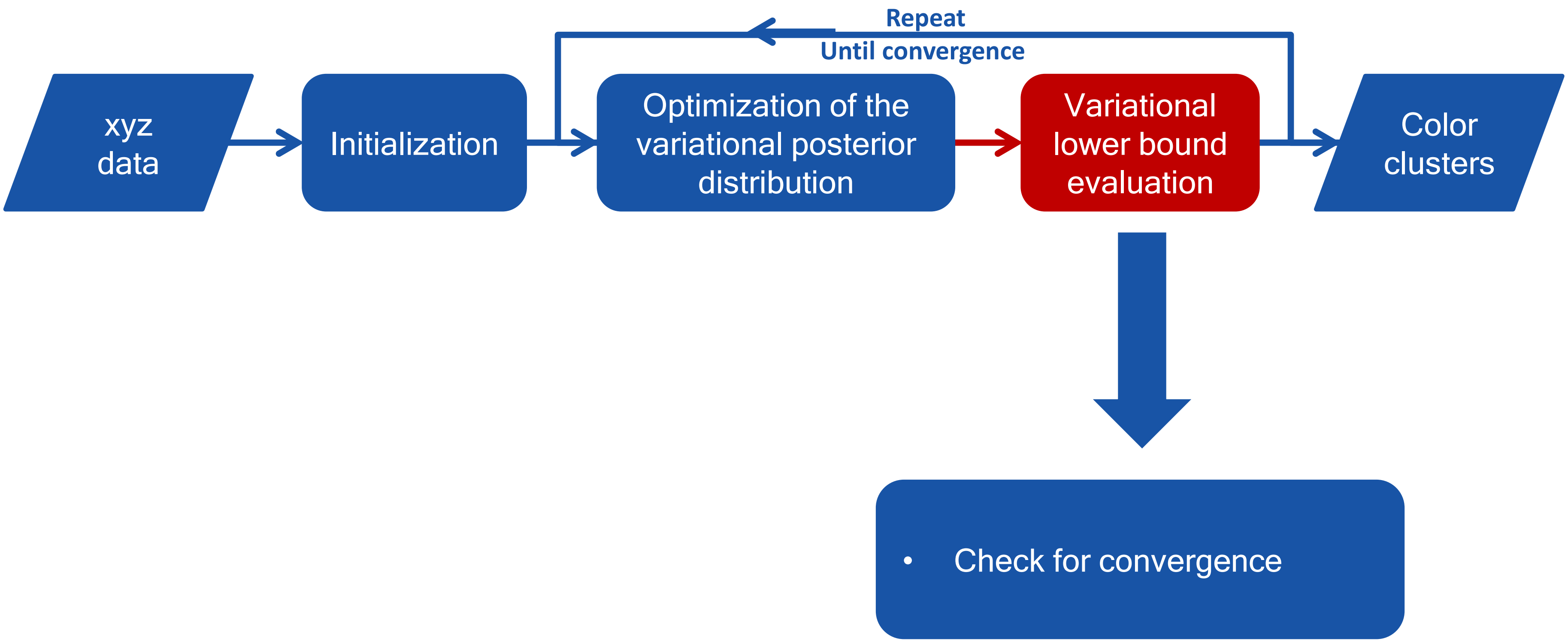
[1] C. M. Bishop, Pattern Recognition and Machine Learning, 1st ed. New York: Springer, 2006.

[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

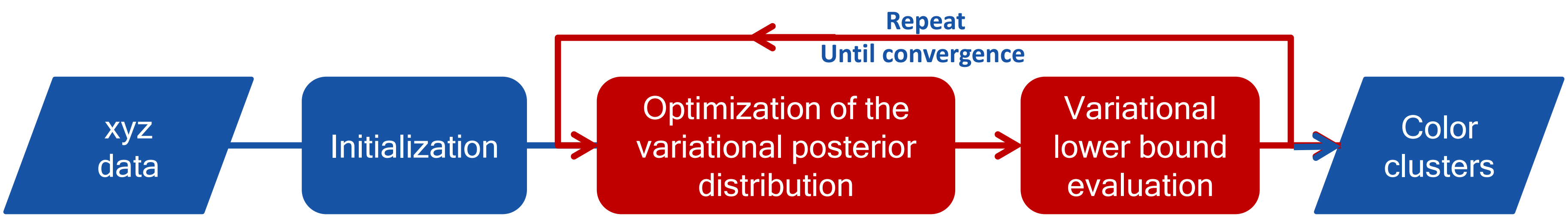


[1] C. M. Bishop, Pattern Recognition and Machine Learning, 1st ed. New York: Springer, 2006.
[2] Z. Ma, P. K. Rana, J. Taghia, M. Flierl, and A. Leijon, "Bayesian estimation of Dirichlet mixture model with variational inference," IEEE Trans. PAMI, submitted, 2013.

Y

Multiview color classification

Dirichlet mixture model with variational Bayes inference



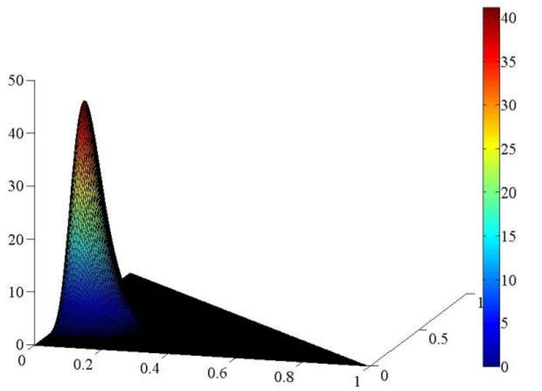
[1] C. M. Bishop, Pattern Recognition and Machine Learning, 1st ed. New York: Springer, 2006.

[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.

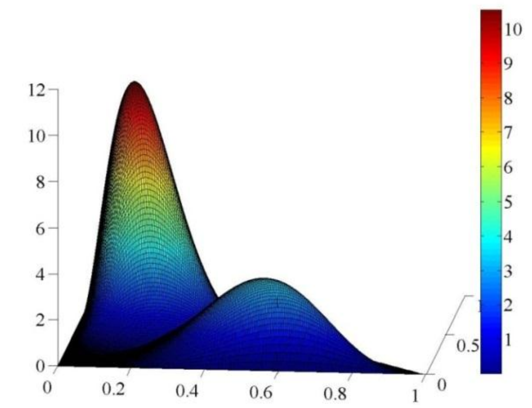
Y

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

Subjective Results

Test sequence: Newspaper

With MPEG depth map

With VBDMM Mean-shift depth map

Subjective Results

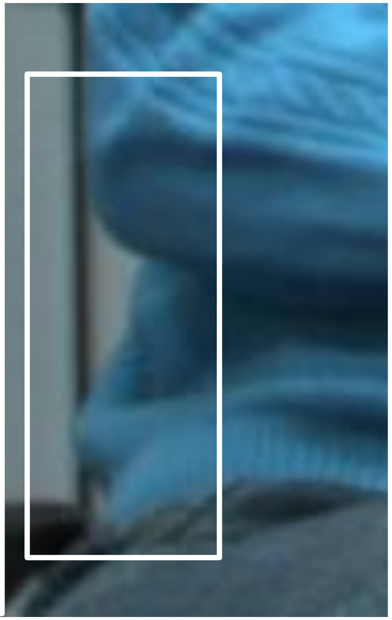
Test sequence: Newspaper

With MPEG depth map

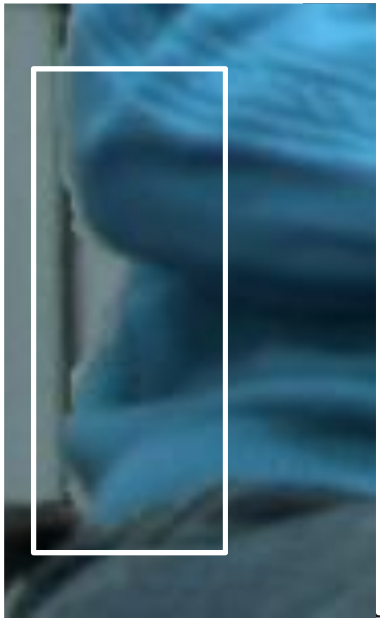
With VBDMM Mean-shift depth map

Subjective Results

Test sequence: Newspaper



Original
depth maps



With MPEG
depth maps

With VBGMM
K-Means
depth maps

With VBDMM
Mean-Shift
depth maps

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

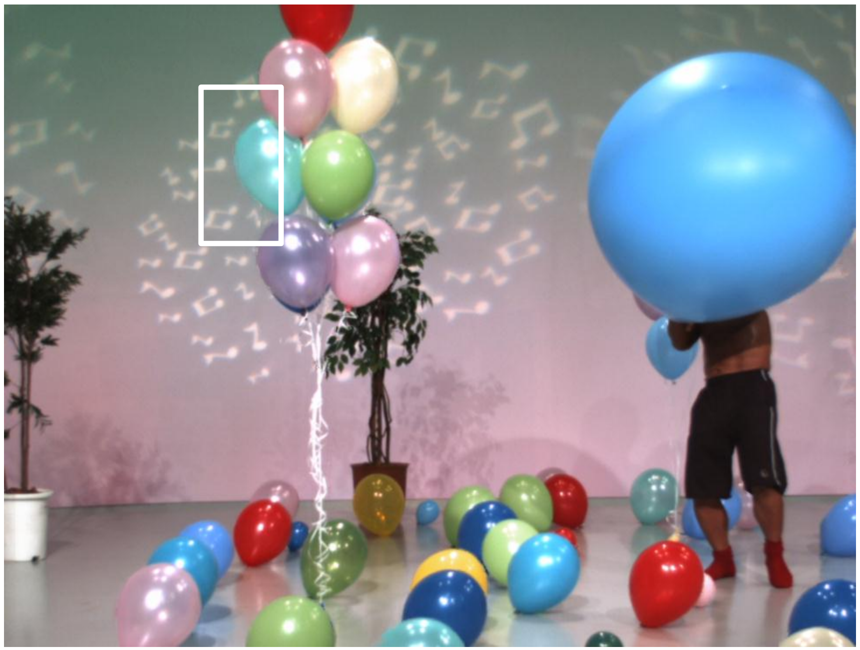
Test sequence: Balloons

With MPEG depth map

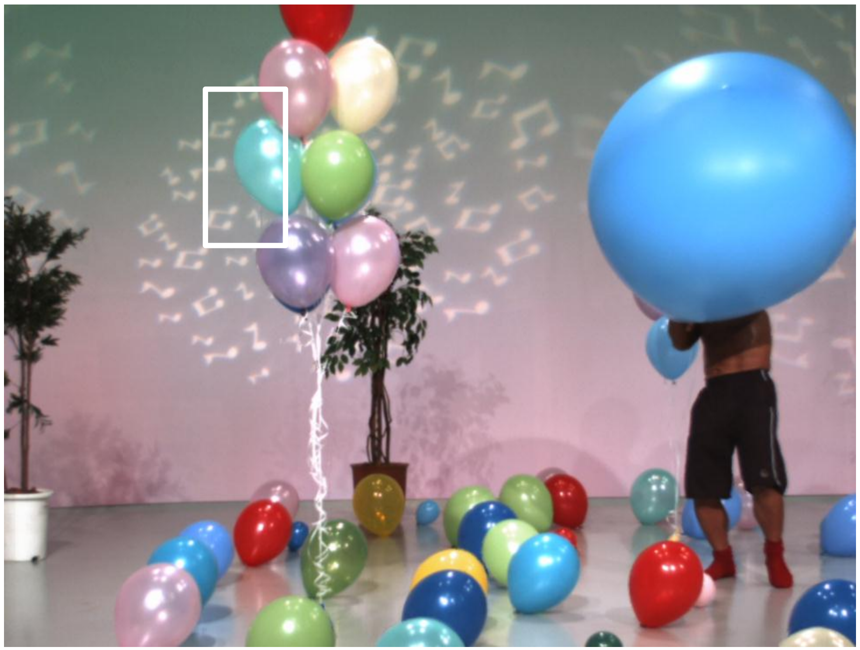
With VBDMM Mean-shift depth map

Subjective Results

Test sequence: Balloons



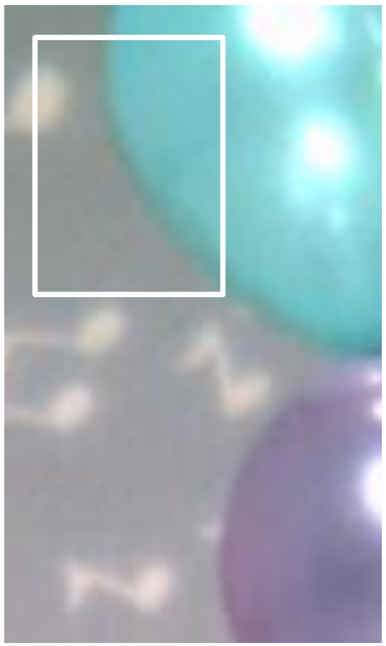
With MPEG depth map



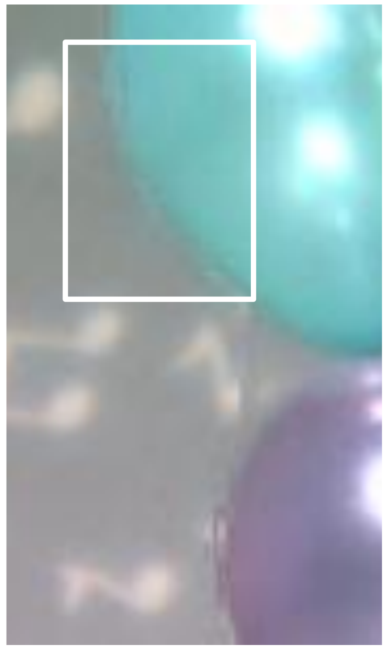
With VBDMM Mean-shift depth map

Subjective Results

Test sequence: Balloons

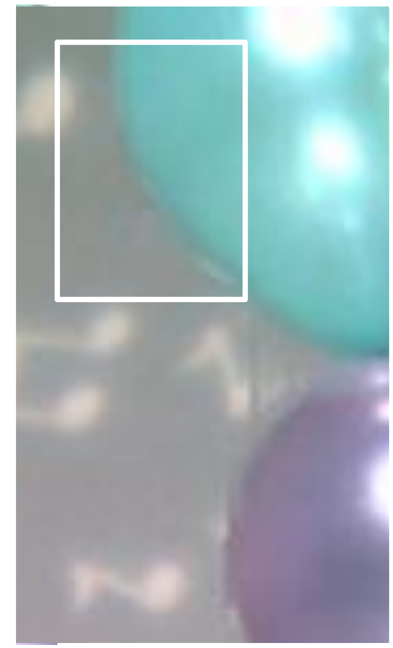


Original
depth maps



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

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

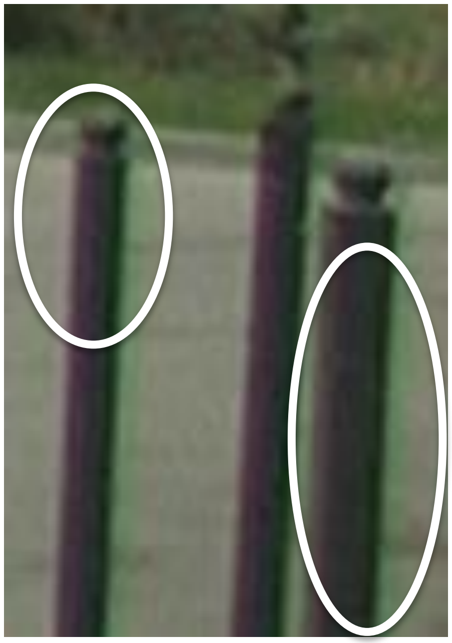
Test sequence: Poznan Street

With MPEG depth map

With VBDMM Mean-shift depth map

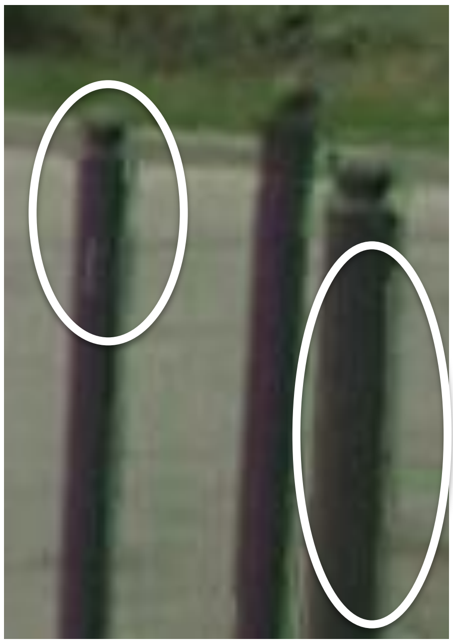
Subjective Results

Test sequence: Poznan Street

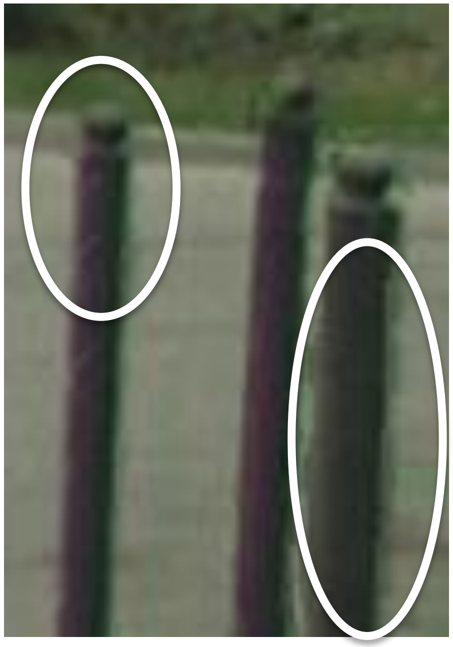


Original

With MPEG
depth maps



With VBGMM
K-Means
depth maps



With VBDMM
Mean-Shift
depth maps