IEEE International Conference on Acoustics, Speech, and Signal Processing

# Multiview Depth Map Enhancement by Variational Bayes Inference Estimation of Dirichlet Mixture Models

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KTH Royal Institute of Technology
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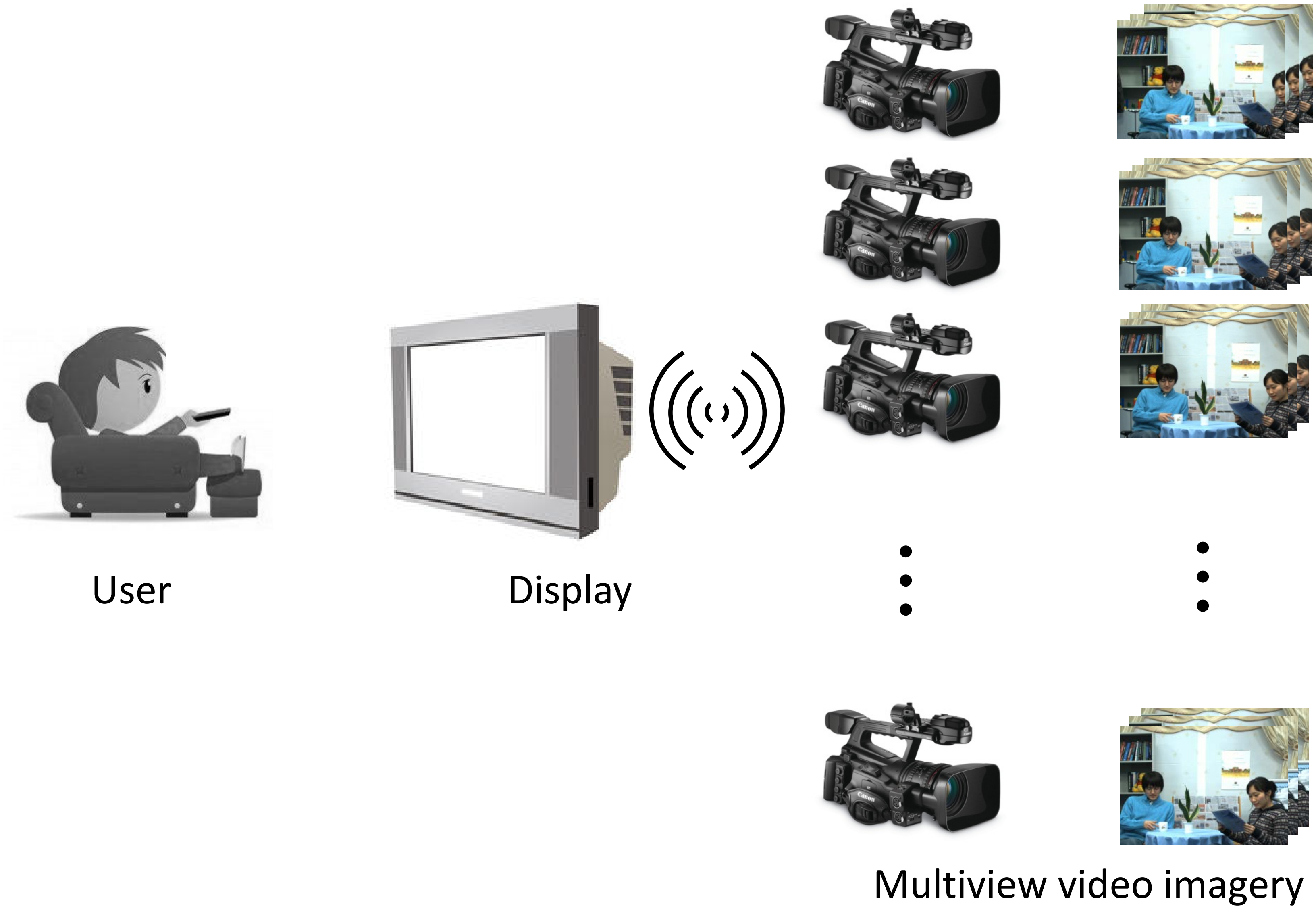
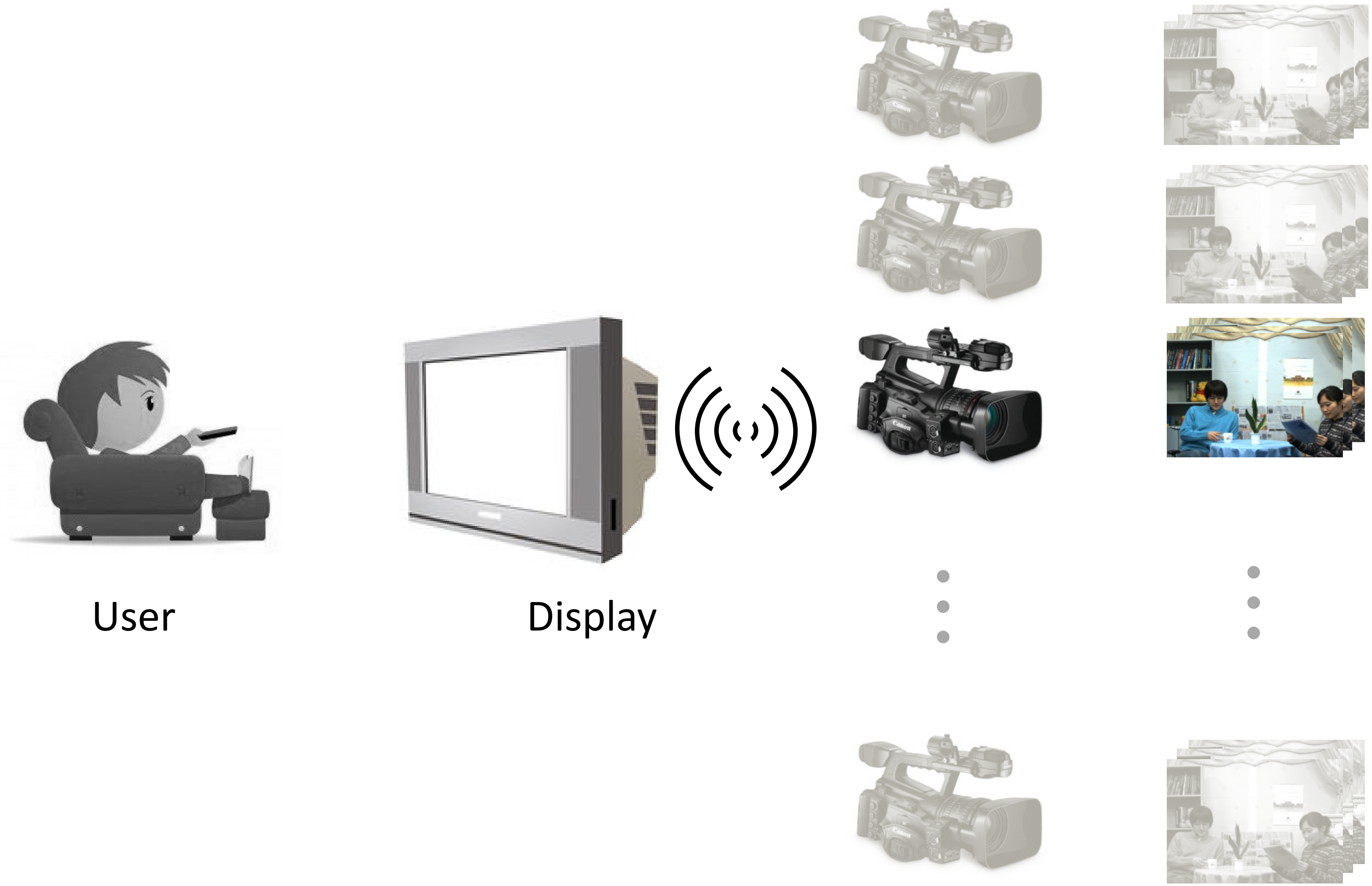
May 31, 2013

# Motivation and background

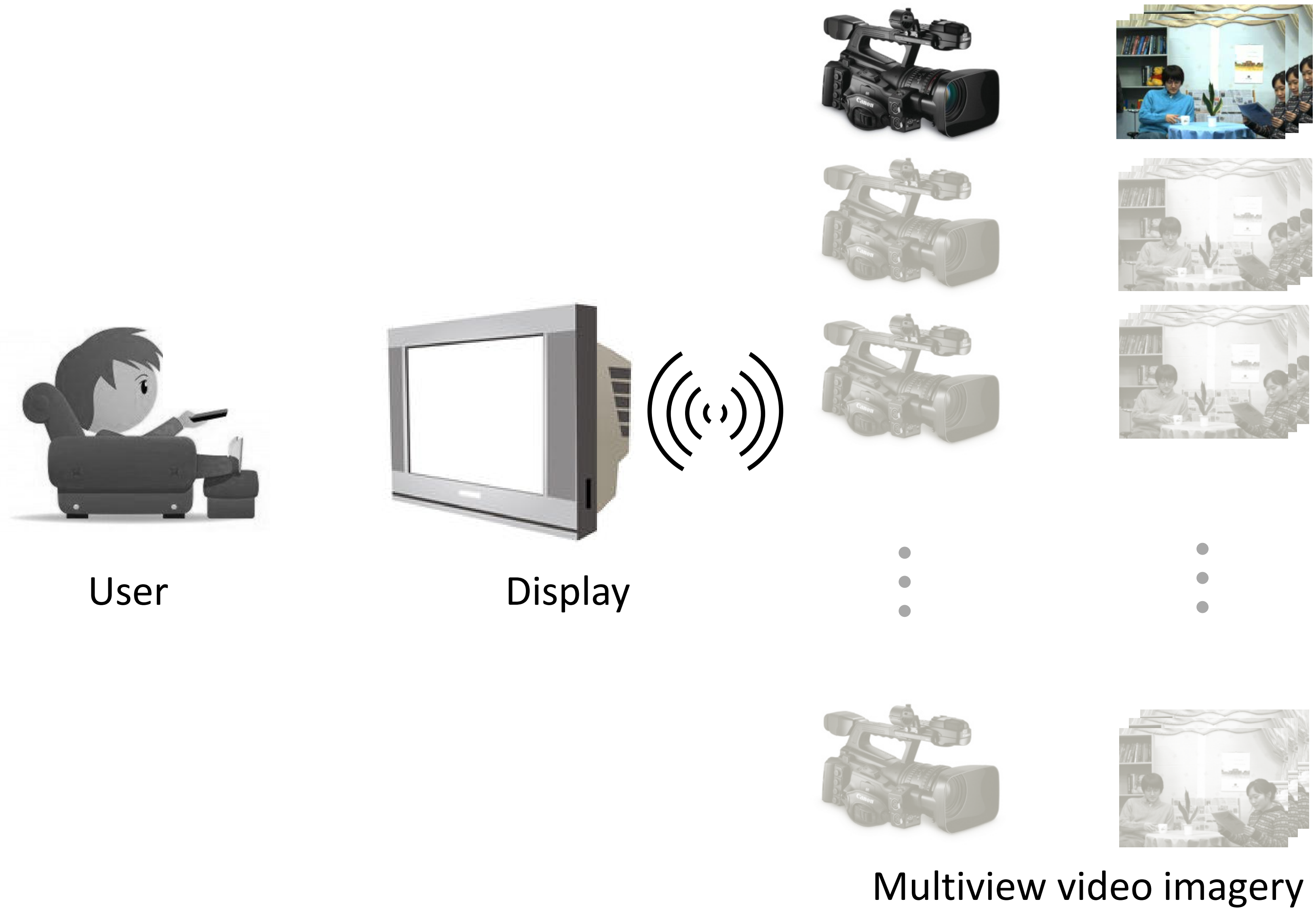
# Free-viewpoint television



# Free-viewpoint television



# Free-viewpoint television



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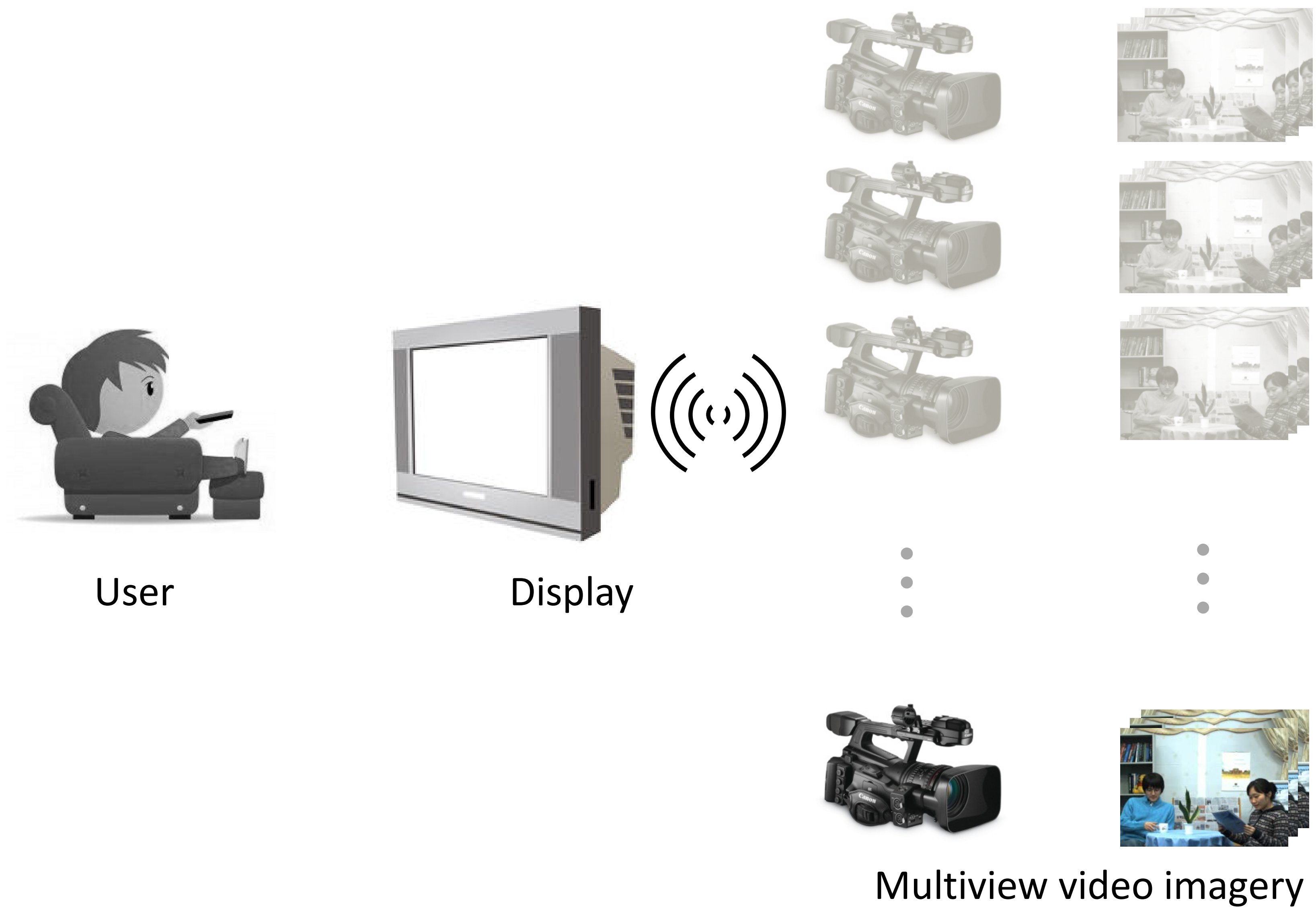
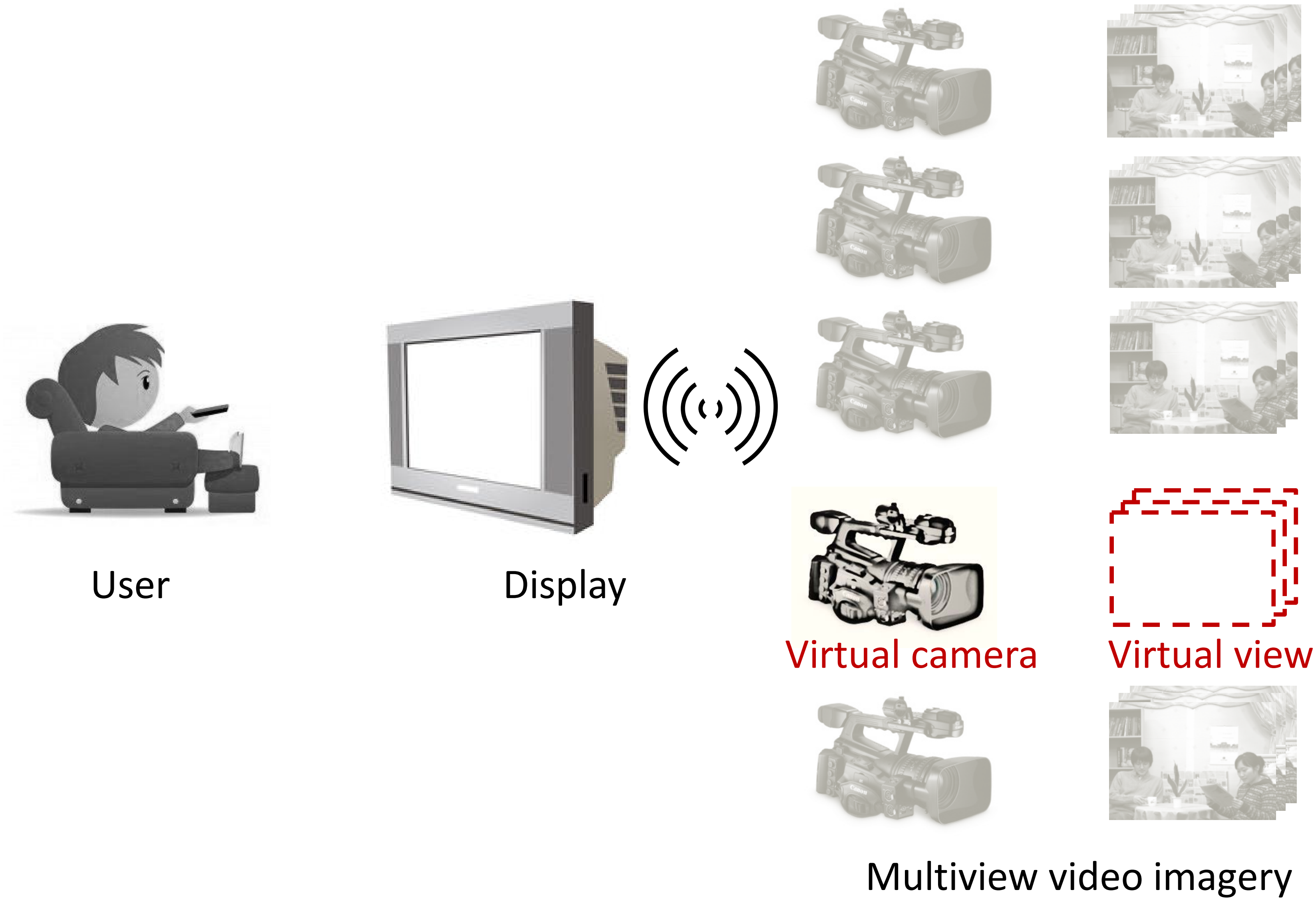
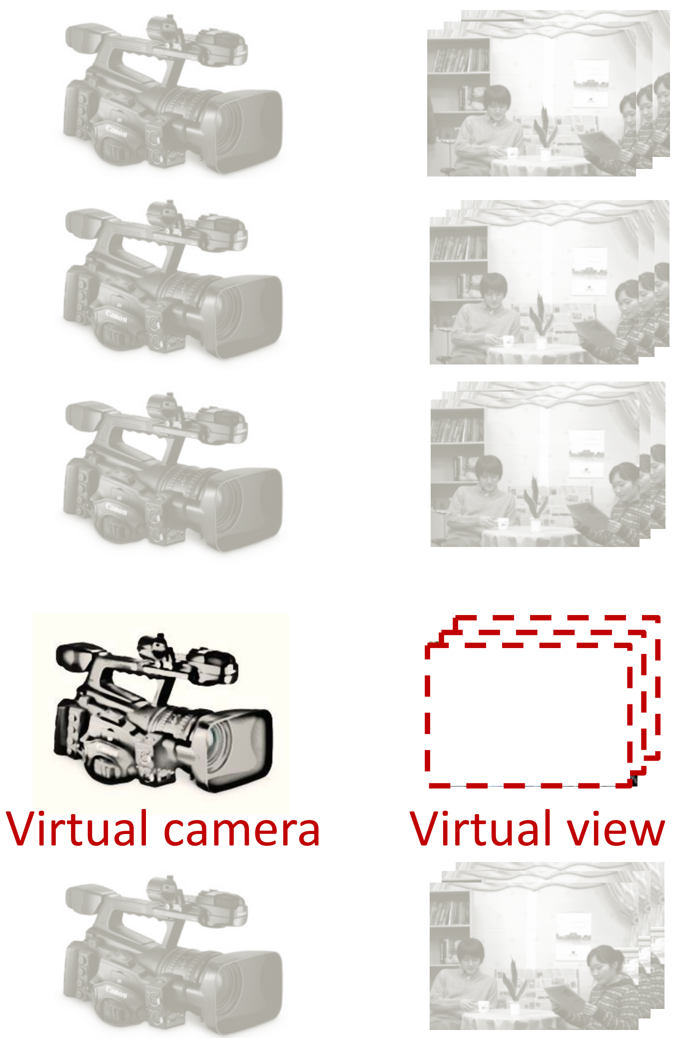


# Free-viewpoint television

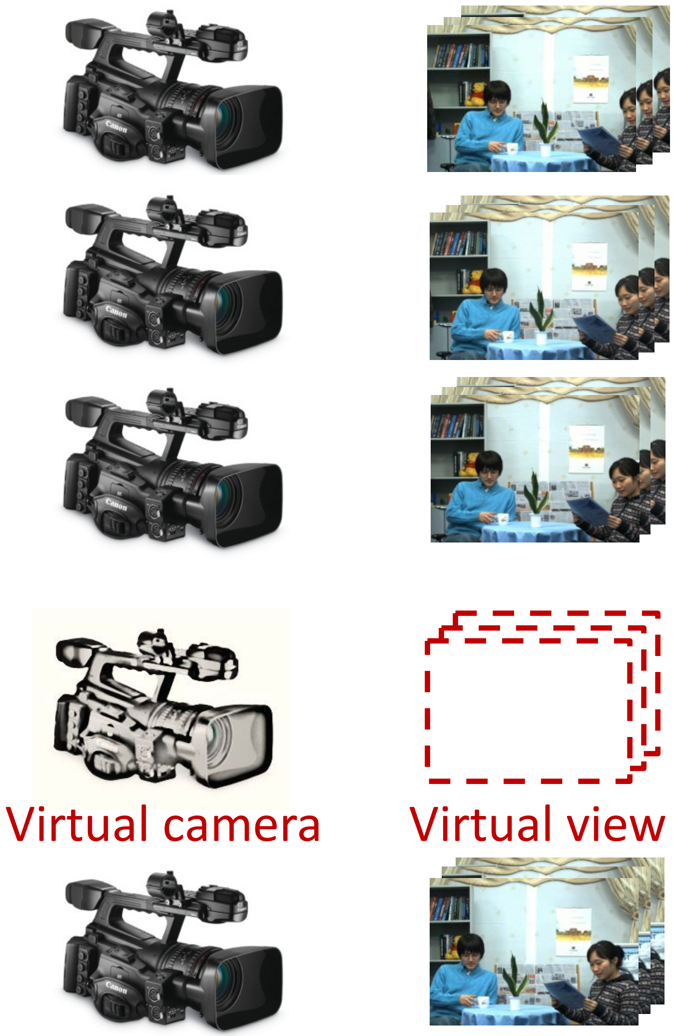


# Depth image based rendering




Multiview video imagery

# Depth image based rendering




Multiview video imagery

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

Depth image

Near

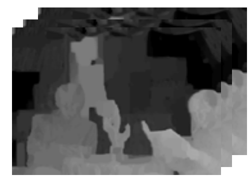
Far

3D warping

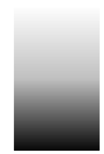
# Depth image based rendering

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

Depth image



Near



Far

3D warping

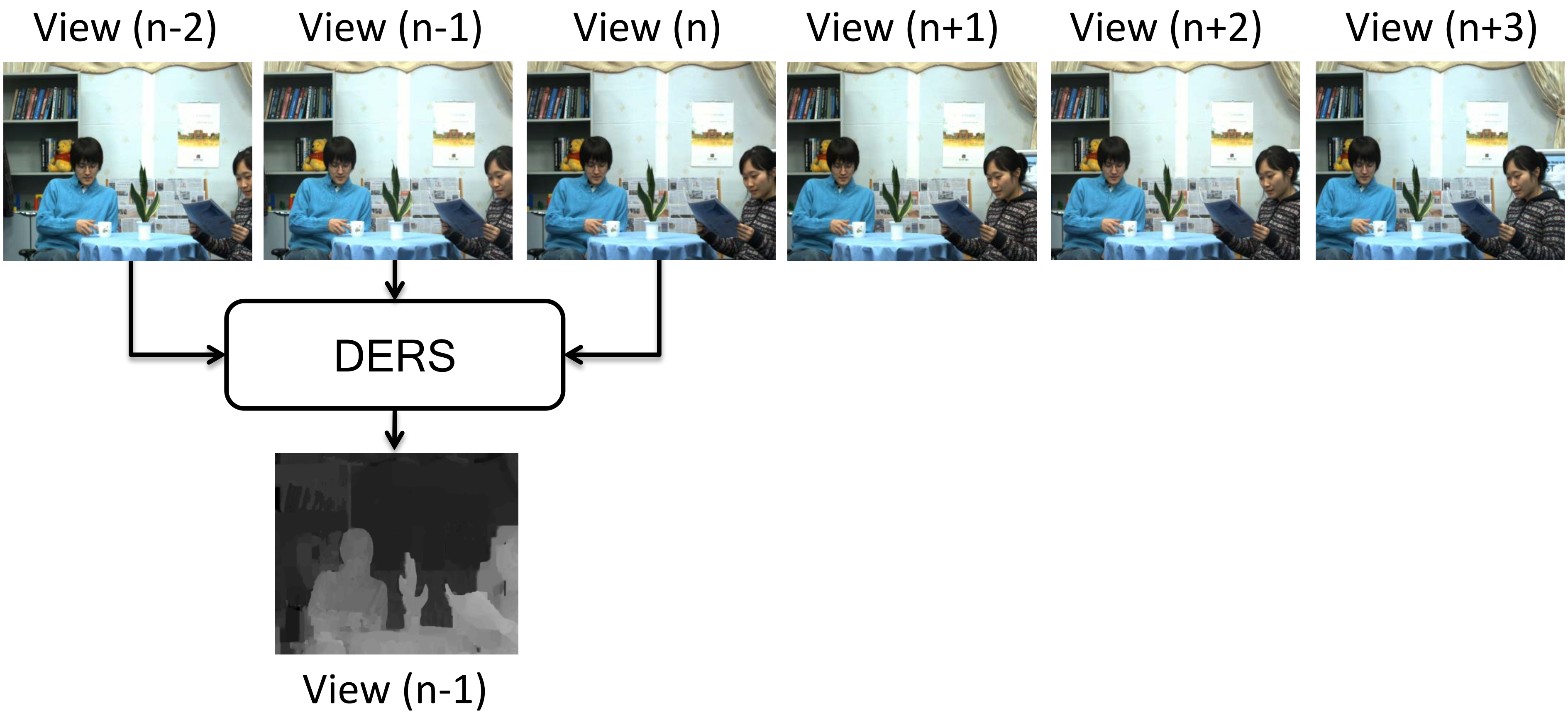
Virtual camera

Virtual view

Multiview video imagery

# Depth estimation

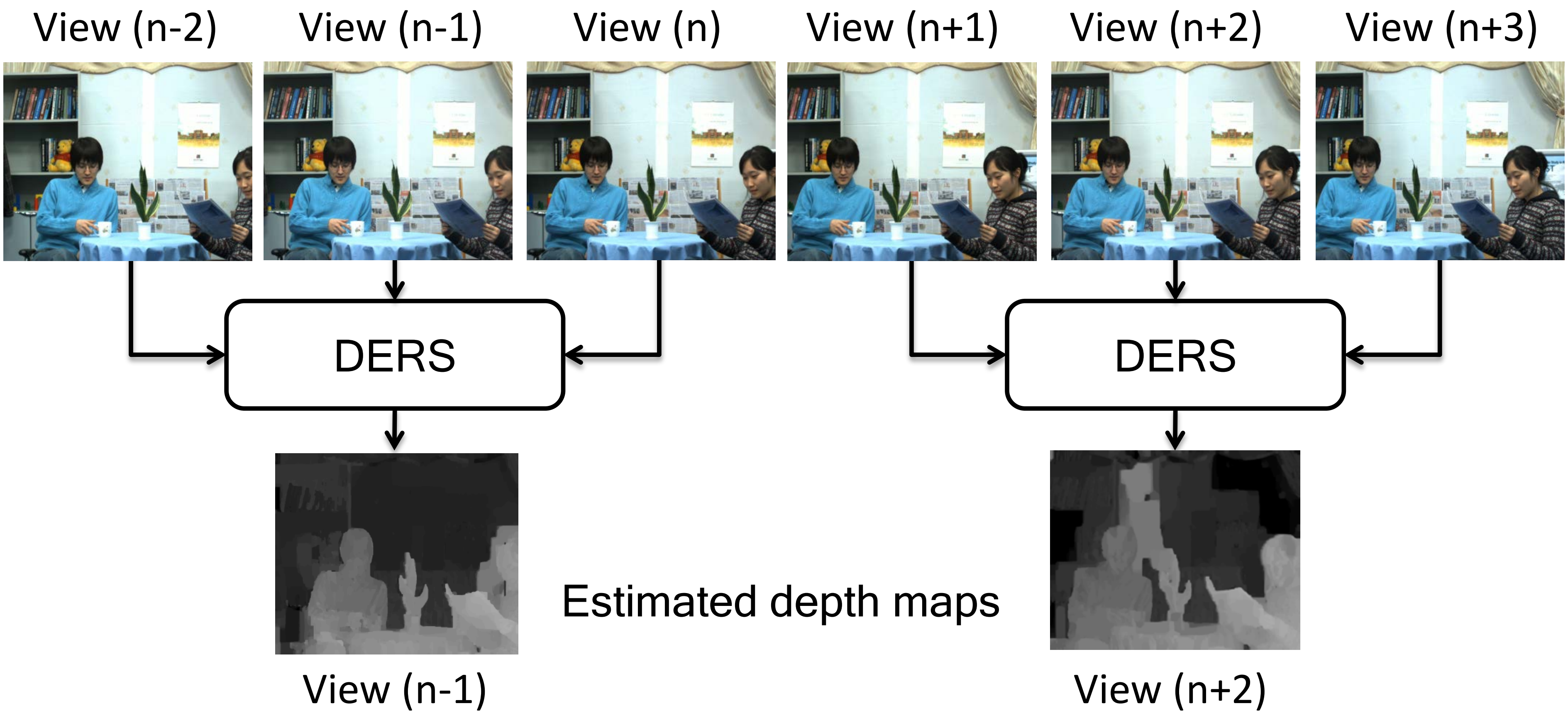
MPEG Depth Estimation Reference Software (DERS)




Note: we assume a 1D-parallel camera arrangement

# Depth estimation

MPEG Depth Estimation Reference Software (DERS)

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# Depth estimation

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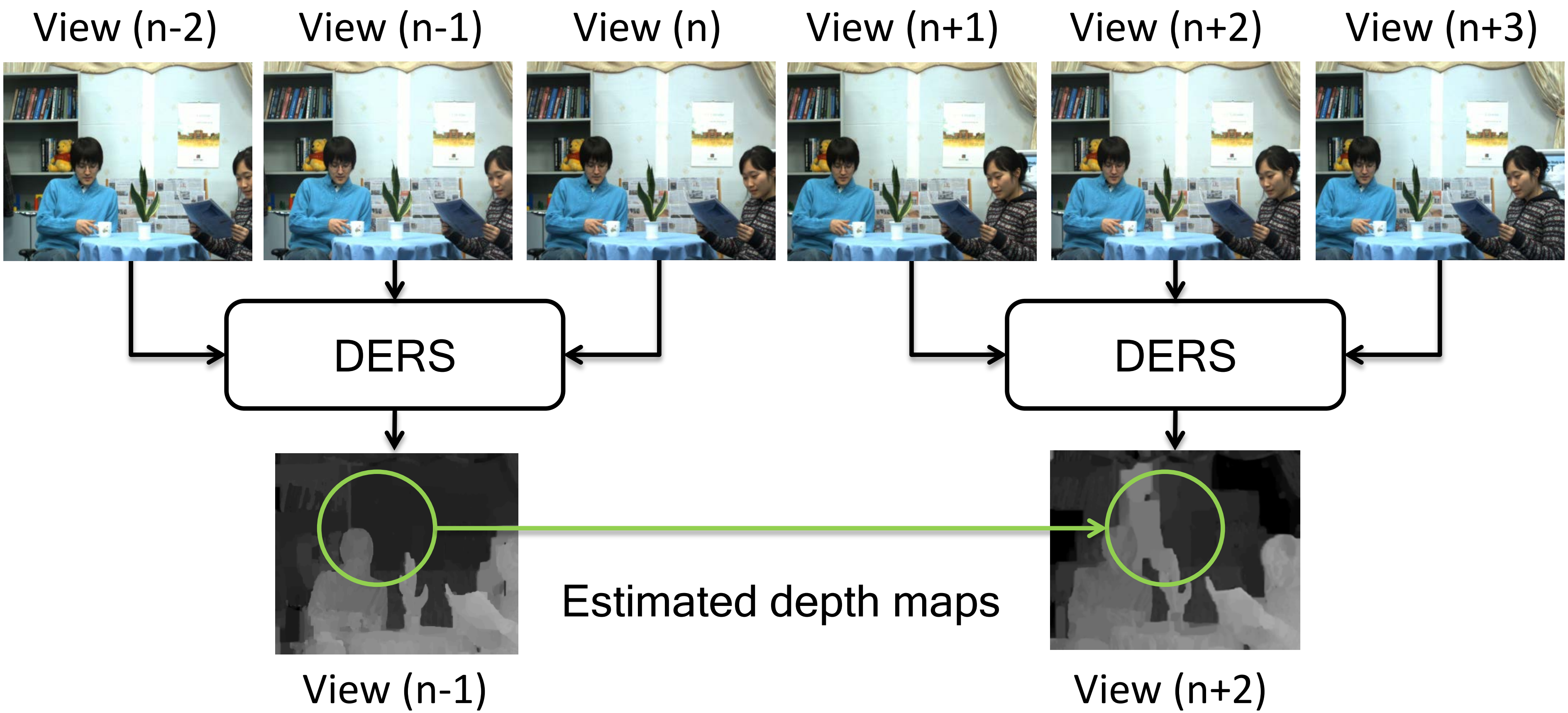


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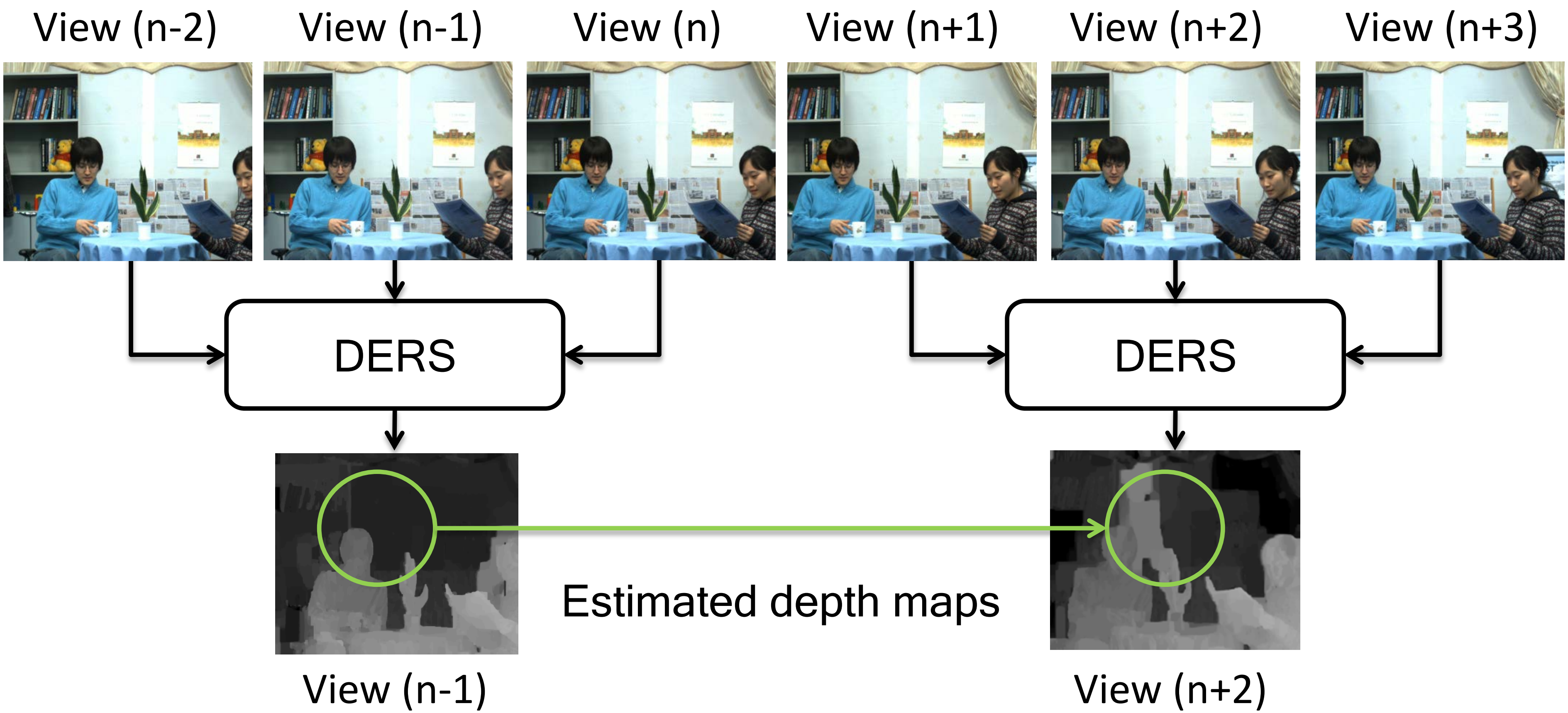
# Depth estimation

## MPEG Depth Estimation Reference Software (DERS)




**Problem: Inter-view depth inconsistency**

Note: we assume a 1D-parallel camera arrangement

# Depth enhancement framework

# Overview of our prior work

Multiview imagery

↓

Concatenation of view imagery

↓

Multiview color classification

↓

Multiview depth classification

↓

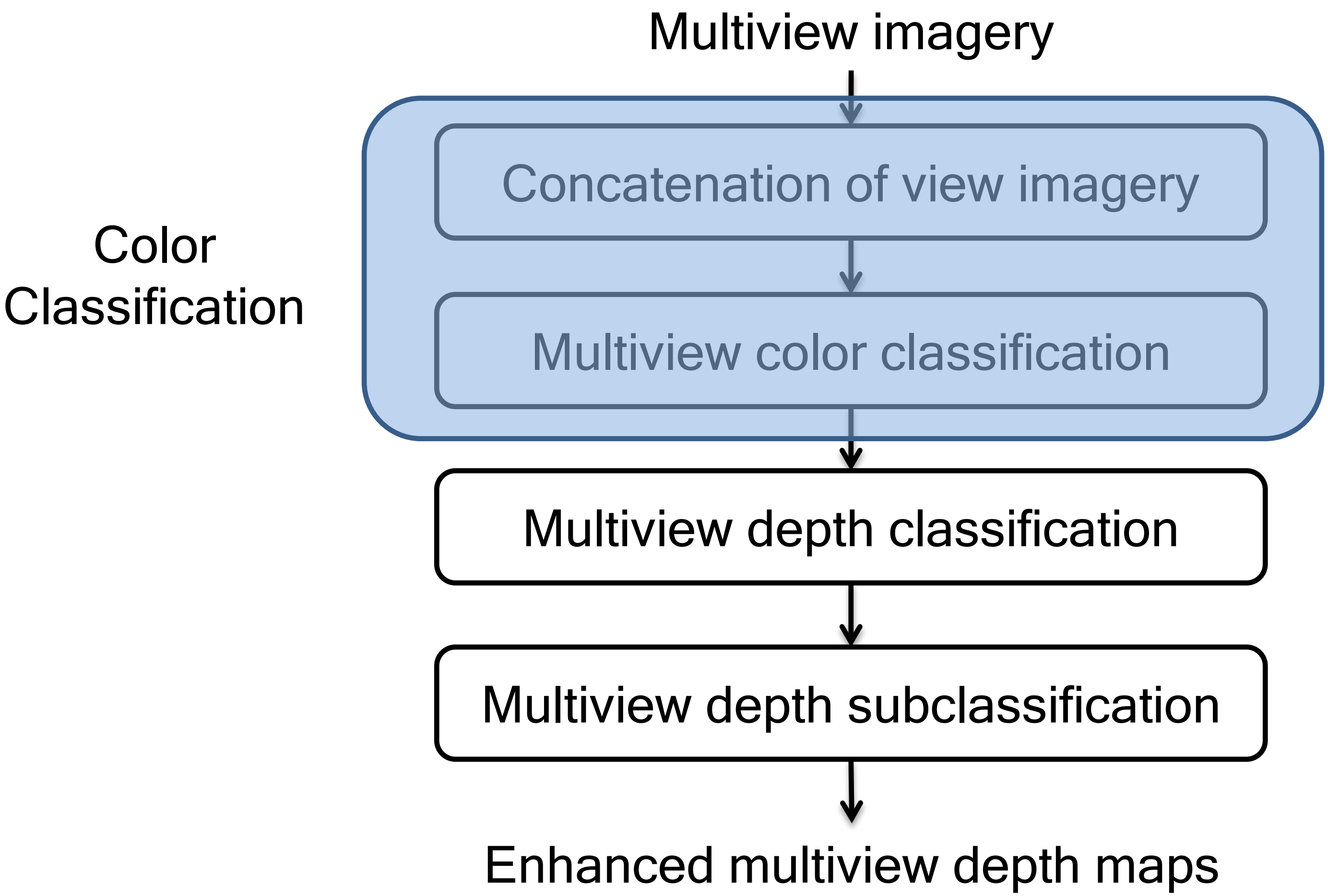
Multiview depth subclassification

↓

Enhanced multiview depth maps

[1] P. K. Rana, J. Taghia, and M. Flierl, "A variational Bayesian inference framework for multiview depth image enhancement," IEEE Int. Symp. Multimedia (ISM), 2012

# Overview of our prior work

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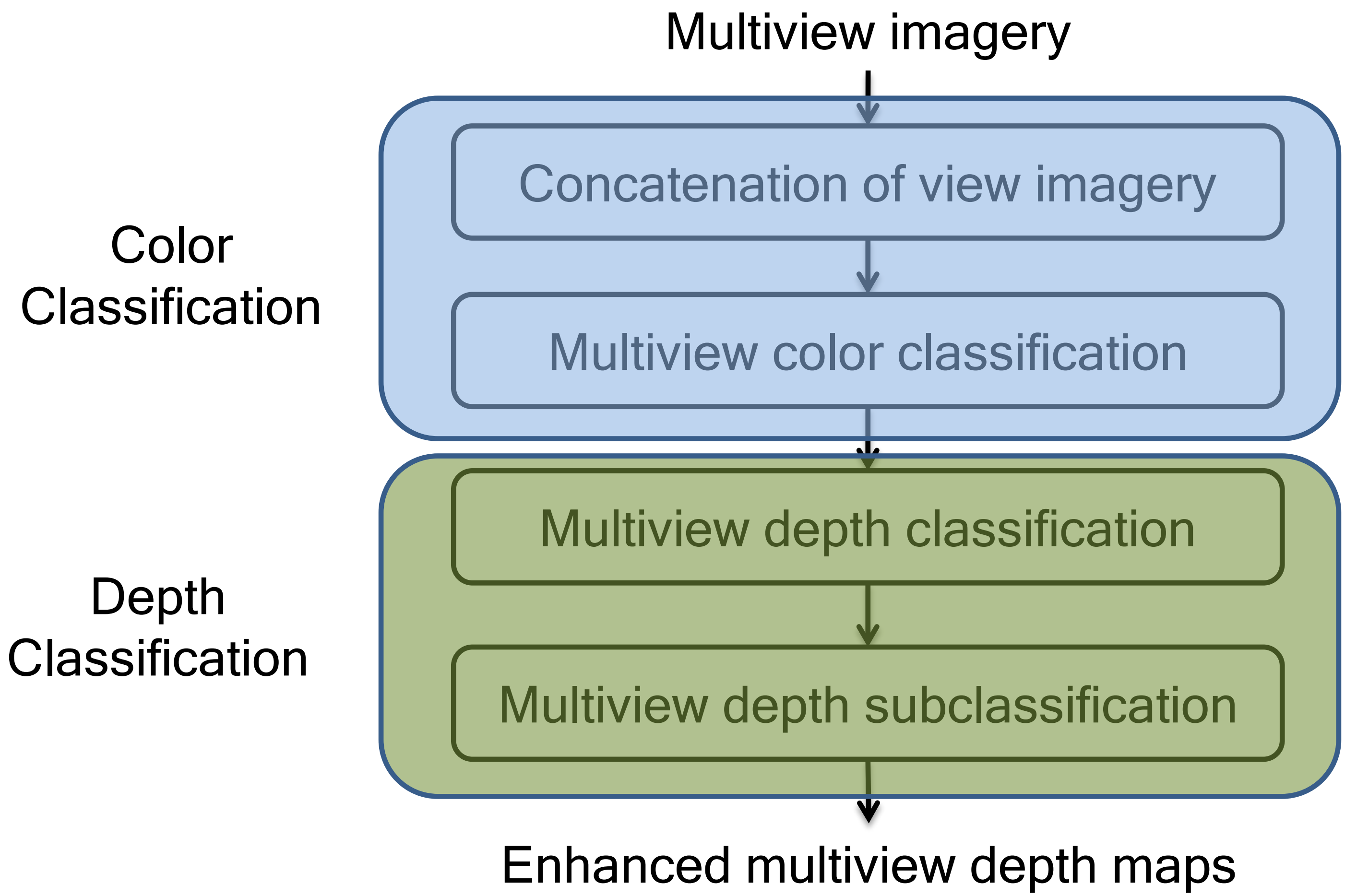


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# Improved depth enhancement framework

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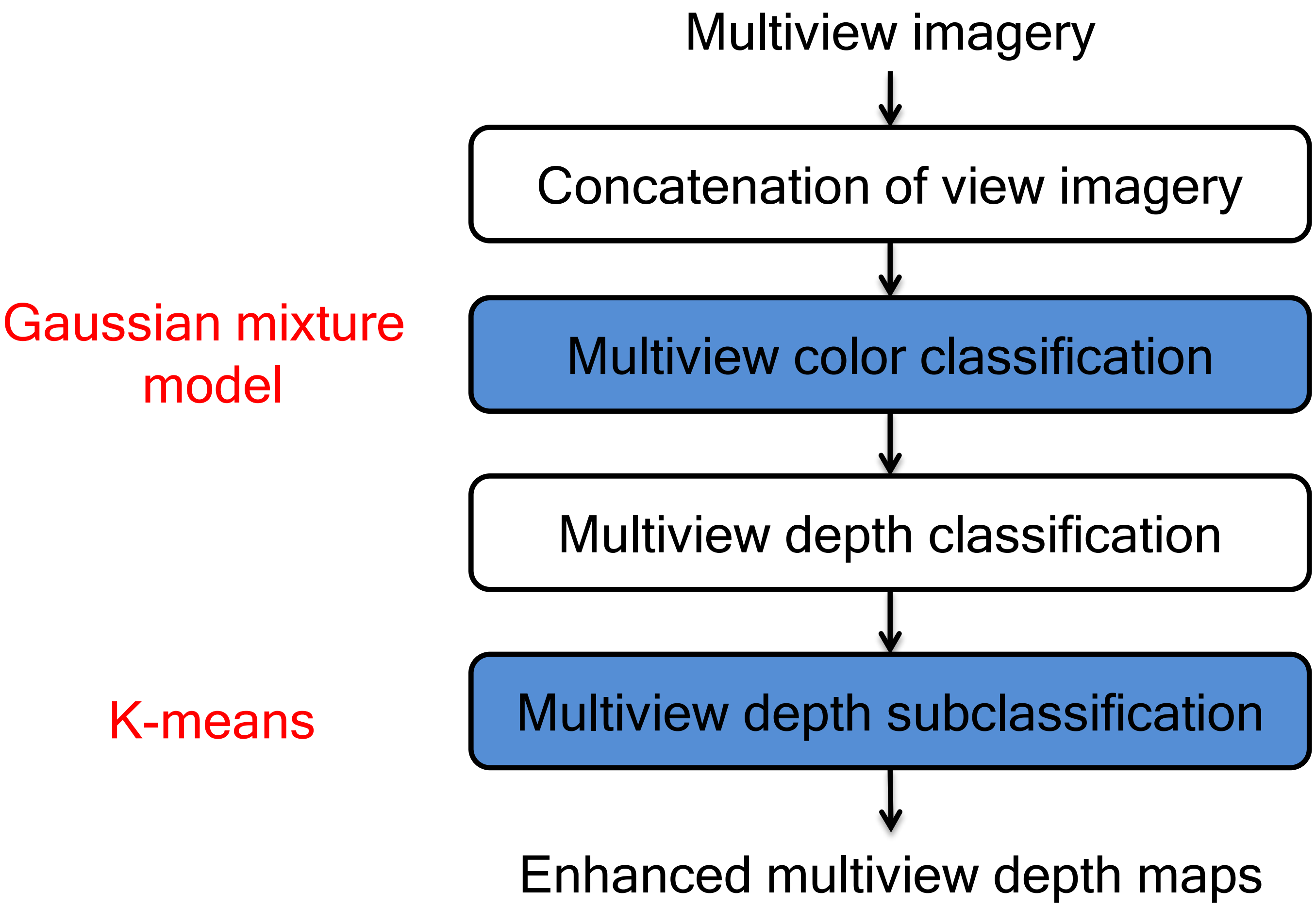


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# Improved depth enhancement framework

Multiview imagery

↓

Concatenation of view imagery

↓

Gaussian mixture model | **Multiview color classification** | Dirichlet mixture model

↓

Multiview depth classification

↓

K-means | **Multiview depth subclassification** | Mean-shift

↓

Enhanced multiview depth maps

[1] P. K. Rana, J. Taghia, and M. Flierl, "A variational Bayesian inference framework for multiview depth image enhancement," IEEE Int. Symp. Multimedia (ISM), 2012

# Concatenation of view imagery

- Multiview imagery has inherent inter-view similarity
- To have a unique model for multiview imagery
  - The inherent inter-view similarity is exploited by concatenating views from multiple viewpoints

# Multiview color classification

## Color space

View (n) View (n+1)

...  ...

RGB

[1] P. K. Rana, J. Taghia, and M. Flierl, "A variational Bayesian inference framework for multiview depth image enhancement," IEEE Int. Symp. Multimedia (ISM), 2012

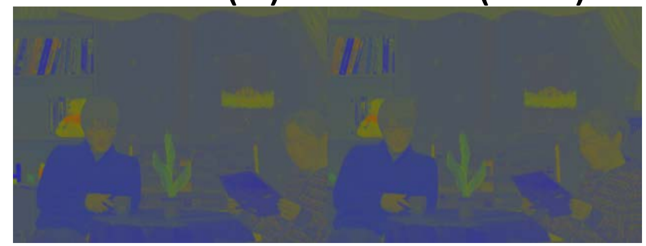
# Multiview color classification

## Color space

View (n) View (n+1)

…  …

RGB

…  …

View (n) View (n+1)

xyz

- Use the chromatic color representation to make the procedure insensitive to the absolut luminance
- The chromaticity of a pixel is described by a vector of three chromaticity coefficients $[x\ y\ z]^T$

$$x+y+z = 1$$

[1] **P. K. Rana, J. Taghia, and M. Flierl, "A variational Bayesian inference framework for multiview depth image enhancement," IEEE Int. Symp. Multimedia (ISM), 2012**

# Multiview color classification

## Why variational Bayes inference (VBI)?

- 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 (EM) suffers from one major drawbacks that the number of clusters has to be known
- Variational Bayes inference automatically select the number of cluster

[2] 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?

- The vector of image pixels has nonnegative elements and is bounded
  - It can be efficiently modeled by utilizing non-Gaussian distributions [3]
- Based on the pixel vector's properties, assume that the pixel vectors of each cluster are Dirichlet distributed
- Use Dirichlet mixture model (DMM) with VBI to capture the all underlying clusters in multiview imagery
- It reduces complexity

**[3] 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.**

# Multiview color classification

Newspaper

Balloons

Kendo

Input multiview data

# Multiview color classification

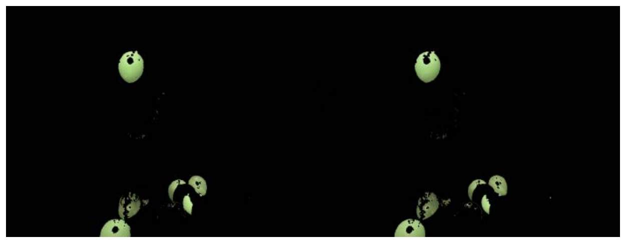
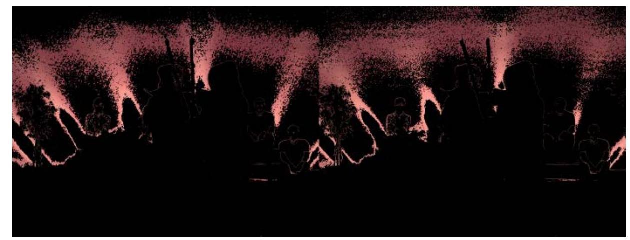
Newspaper

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

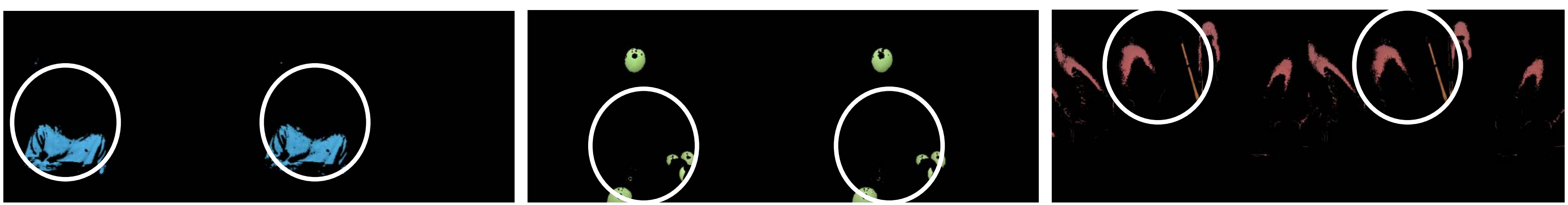
Using Gaussian mixture model with variational Bayes inference

# 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

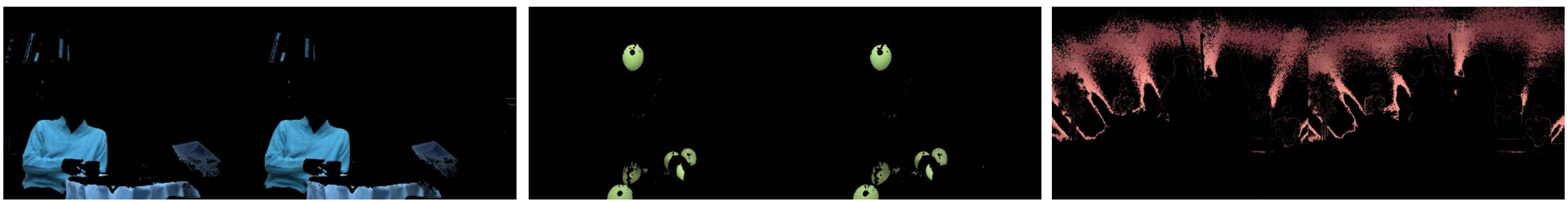
View image Depth image

Concatenated view imagery Concatenated depth imagery

# Multiview depth classification

Newspaper | Balloons | Kendo

Input multiview data



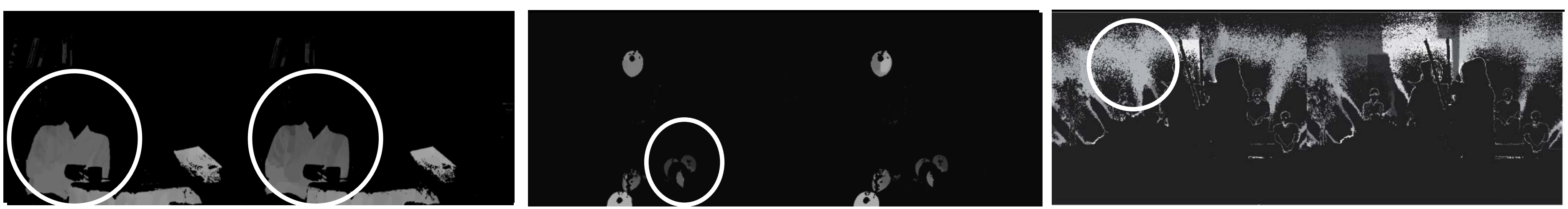
Using Dirichlet mixture model with variational Bayes inference in xyz space

# Multiview depth classification

Newspaper Balloons Kendo

Input multiview data

Using Dirichlet mixture model with variational Bayes inference in xyz space



# 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

## Means-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 setup

## 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)

# Complexity

| Multiview data set | Initial number of mixture components | Active number of mixture components (after convergence) | |
|---|---|---|---|
| | | VBI-GMM | VBI-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

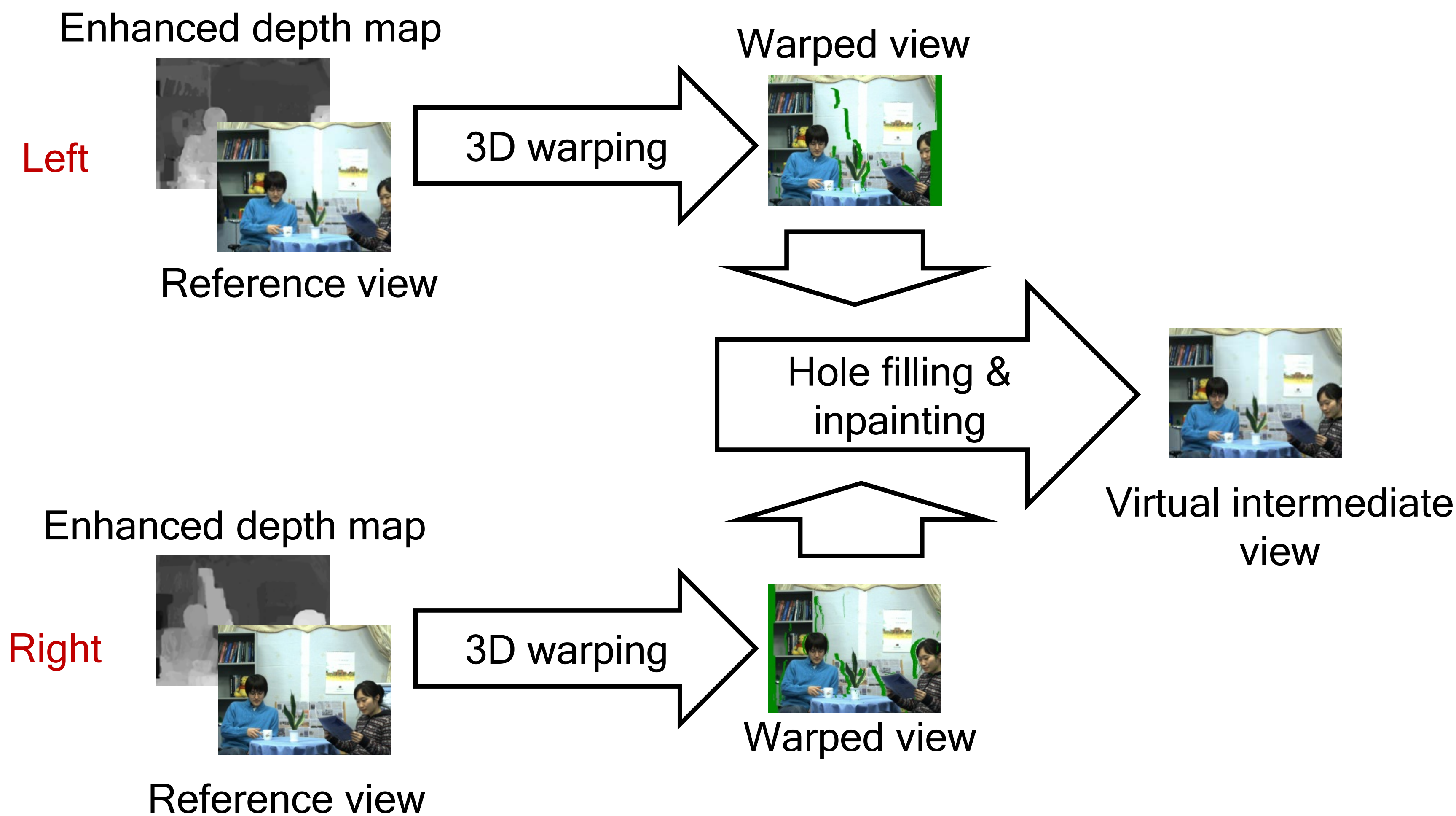
Reference view

3D warping

Warped view

# Depth image based rendering

## MPEG View Synthesis Reference Software (VSRS) 3.5



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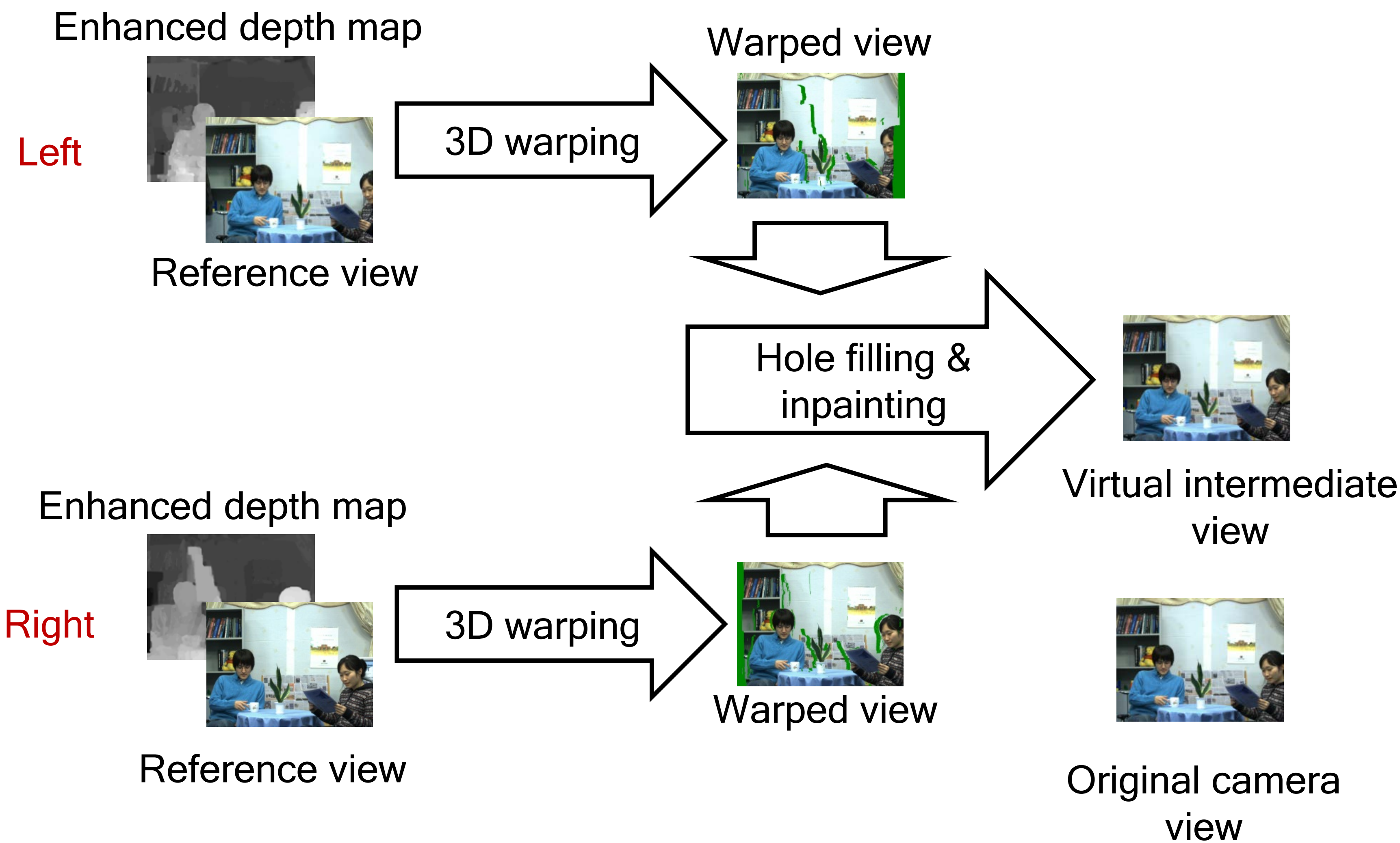

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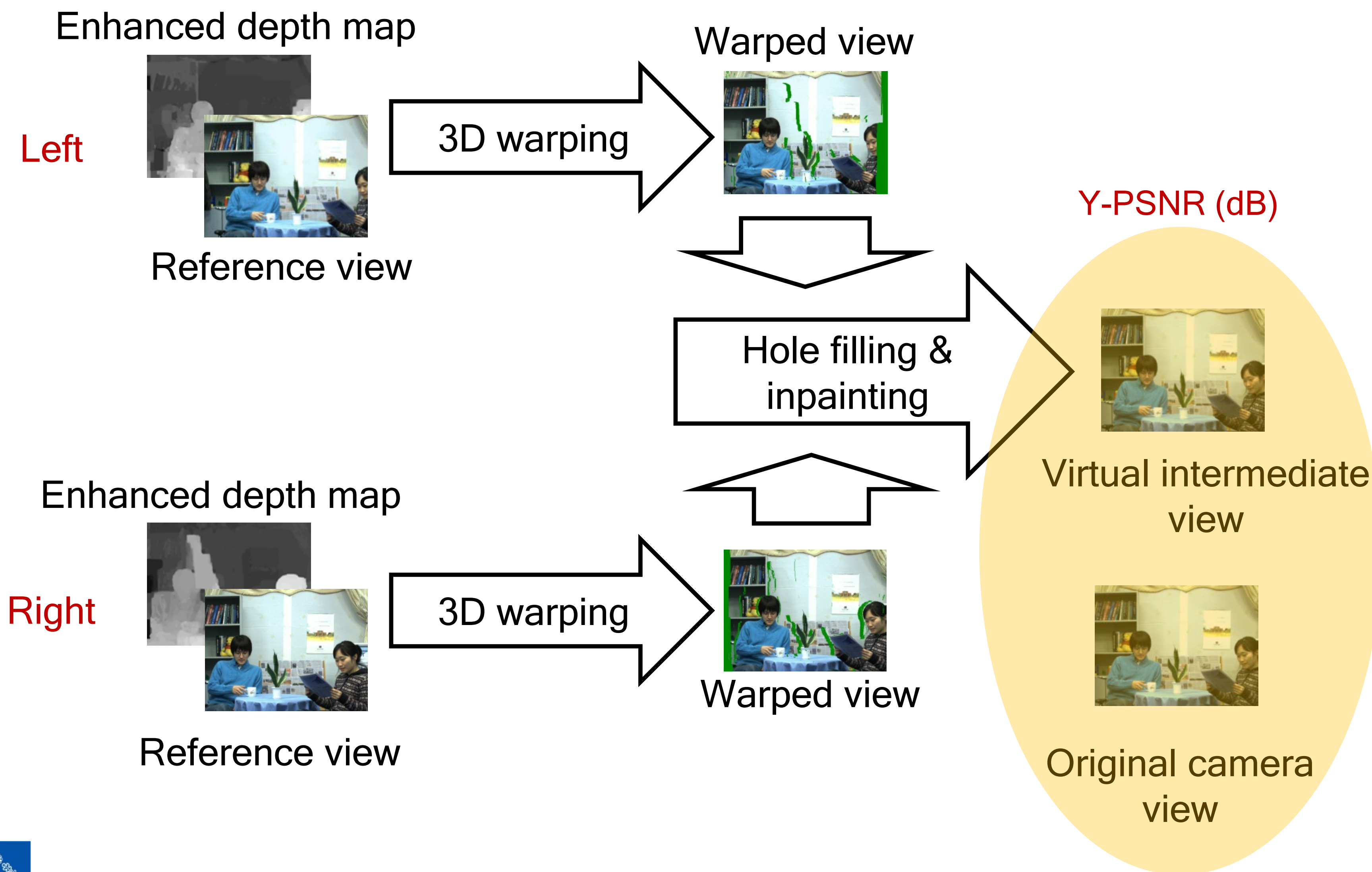

# Objective results

| 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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- K-means sub-clustering
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# Subjective results

## Test sequence: Kendo

With MPEG depth map

With VBDMM Mean-shift depth map

# Subjective results

## Test sequence: Kendo

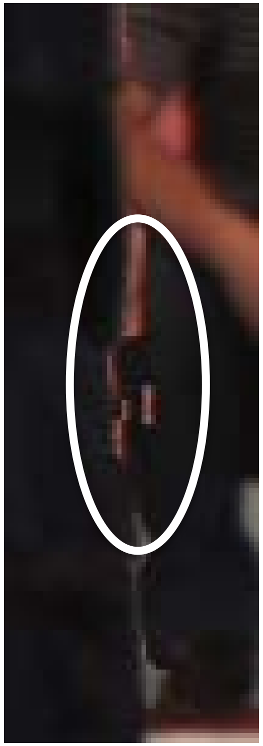
With MPEG depth map

With VBDMM Mean-shift depth map

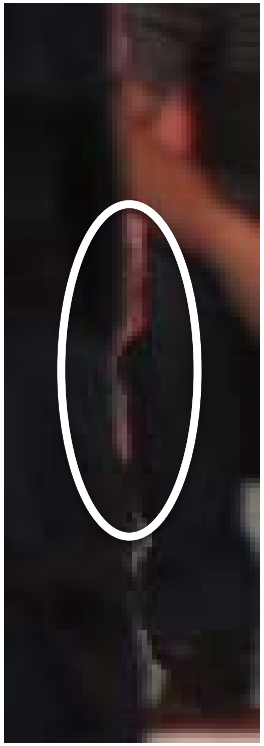
# Subjective results

Test sequence: Kendo

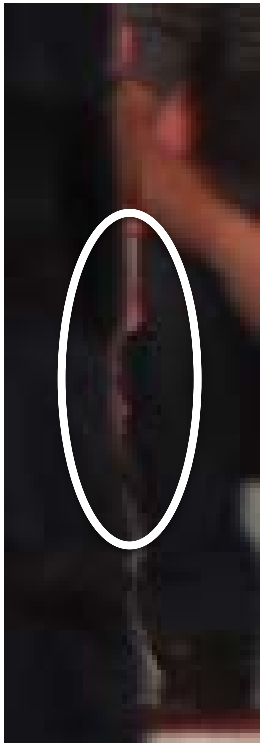
Original



With MPEG depth maps



With VBGMM + K-Means depth maps

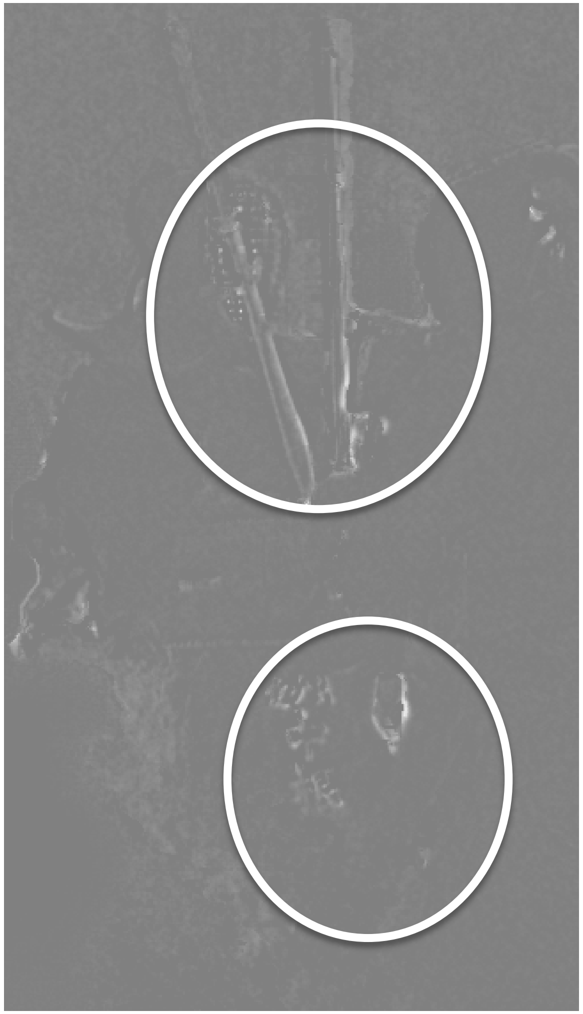


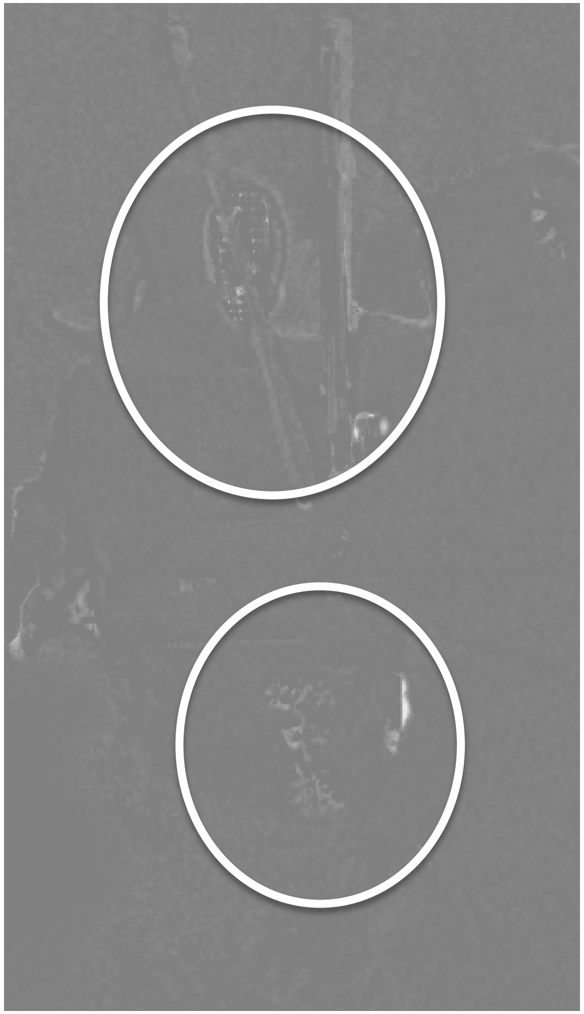
With VBDMM + Mean-Shift depth maps

# 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

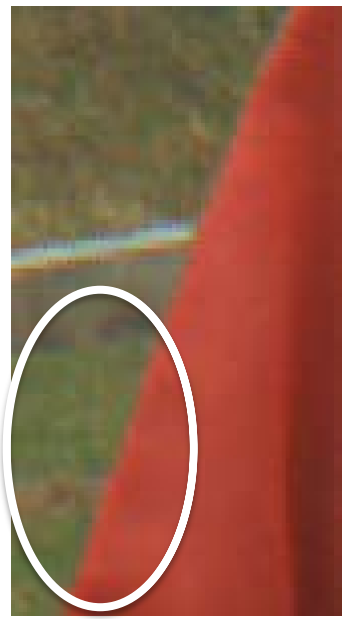
Test sequence: Lovebird 1

With MPEG depth map

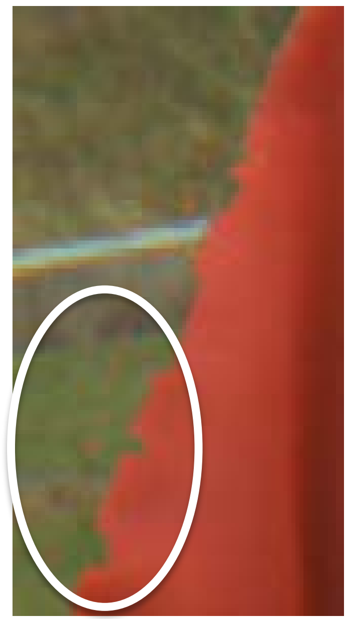
With VBDMM Mean-shift depth map

# Subjective results

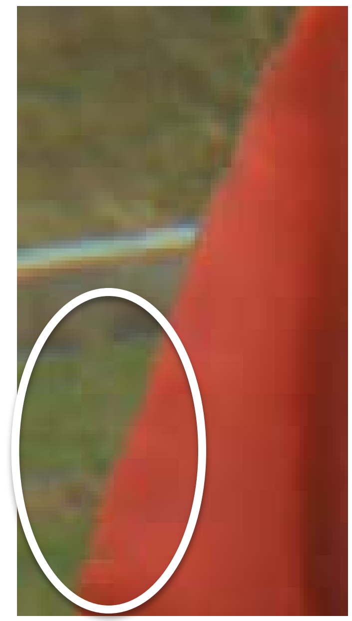
Test sequence: Lovebird 1



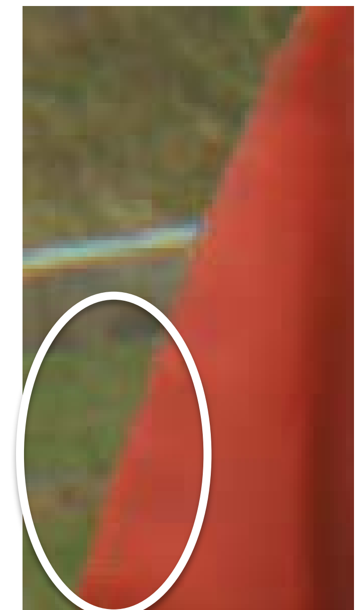
Original



With MPEG depth maps



With VBGMM K-Means depth maps



With VBDMM Mean-Shift depth maps

# Subjective results

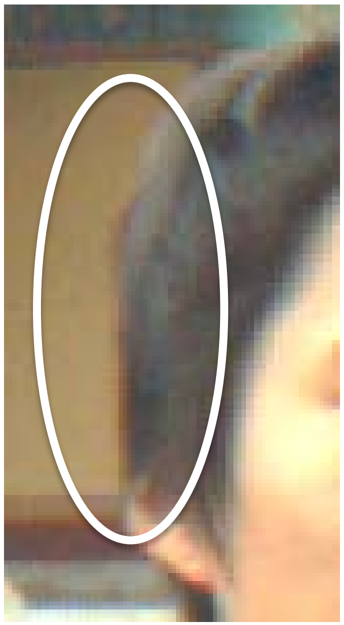
Test sequence: Lovebird 1

With MPEG depth map

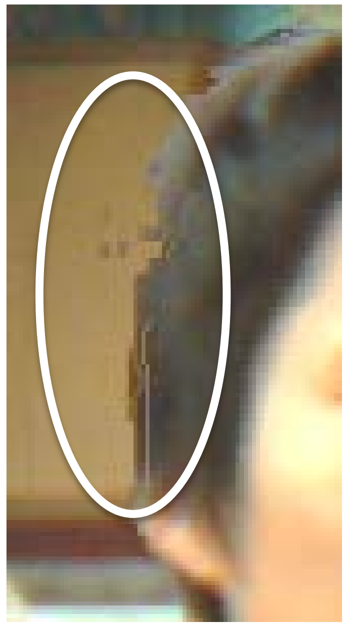
With VBDMM Mean-shift depth map

# Subjective results

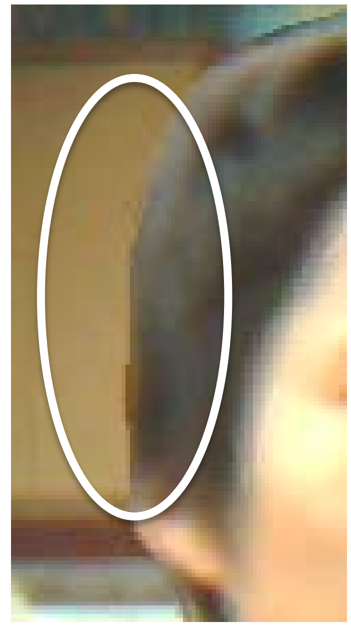
Test sequence: Lovebird 1



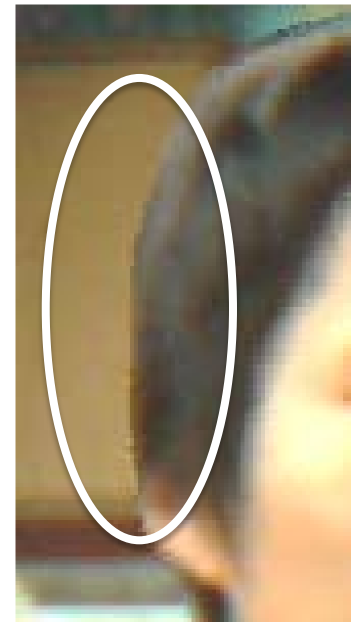
Original



With MPEG
depth maps



With VBGMM
K-Means
depth maps



With VBDMM
Mean-Shift
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

# Thank you