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Temporally Consistent Snow Cover Estimation from Noisy, Irregularly Sampled Measurements

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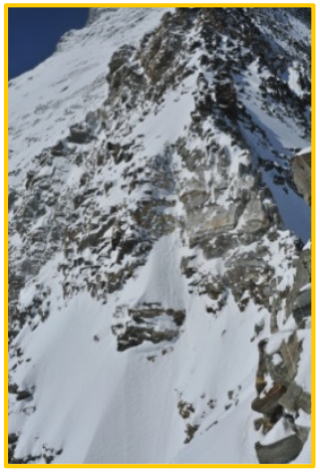
Outline

- Introduction
  - PermaSense Project
- **Single Image Snow Segmentation**
  - GMM of Color
- Temporal Consistency
  - Median
  - Markov Random Field
- Improvement
- Results
- Conclusions

PermaSense Project

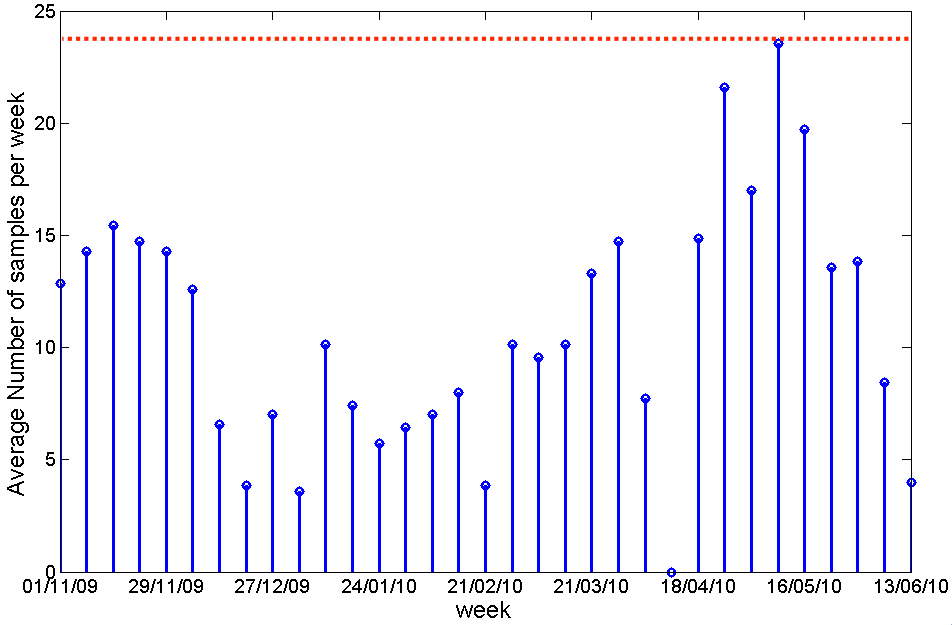


Matterhorn, Switzerland

- Wireless Sensor Network (WSN) to monitor **Permafrost**
  = rock, ground and debris **frozen throughout the year**
- DSLR to **monitor snow coverage**
  - Programmed to take hourly captures
- **Challenges**
  - Camera at **3500 m.a.s.l.**
  - Extremely **harsh weather** conditions
  - **Uninformative** images
  - **Missing** images

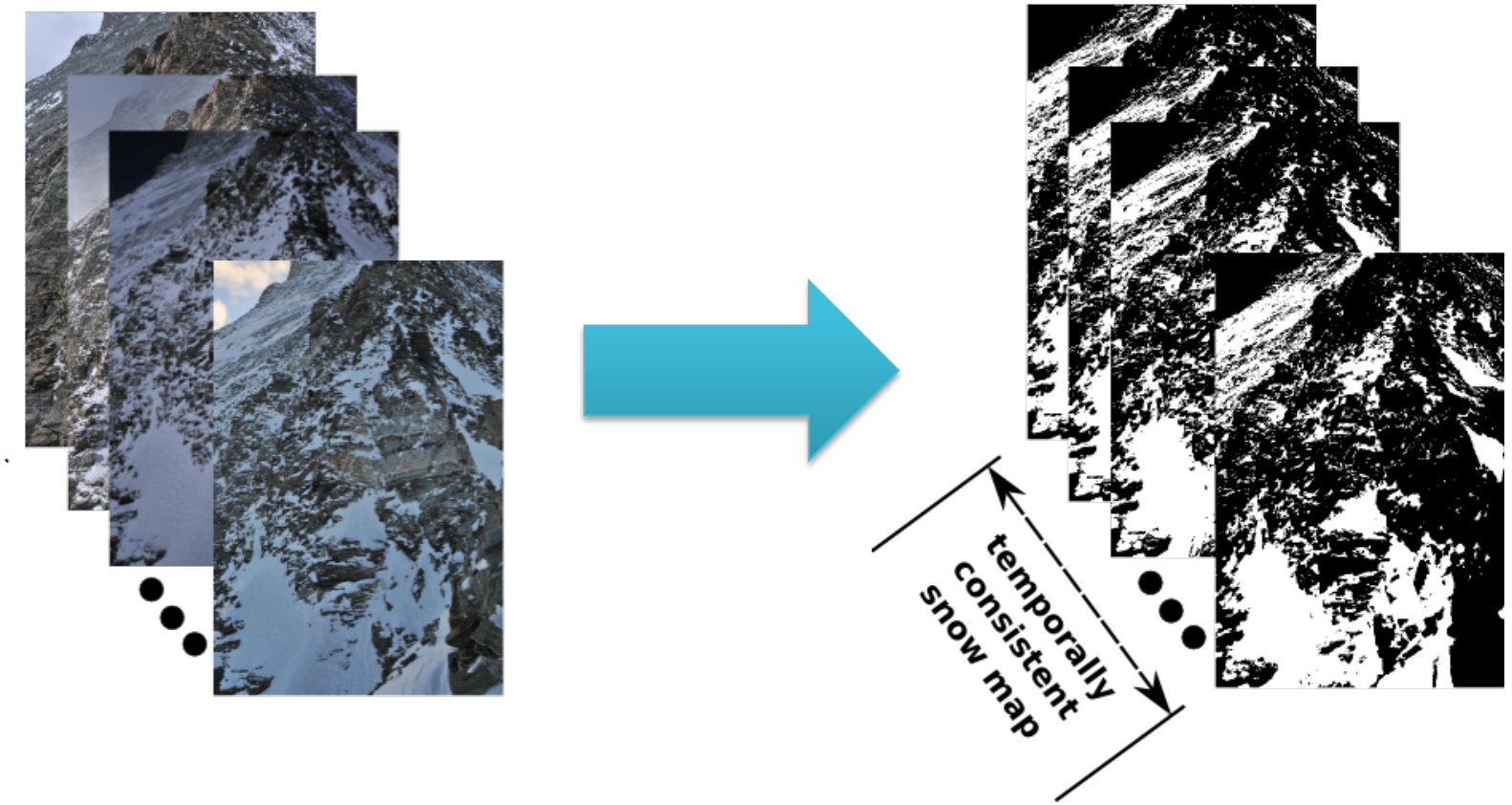
Image Set

- Very **different** image taking conditions
  - Changing illumination
- **Noisy** data
  - Precipitation on lens
  - Fog
  - Ice
- **Irregular** Sampling



Project Aim

- Create a **temporally consistent** snow cover map which is driven by **informative** images, and robust to **uninformative** images where the illumination/visibility is poor.

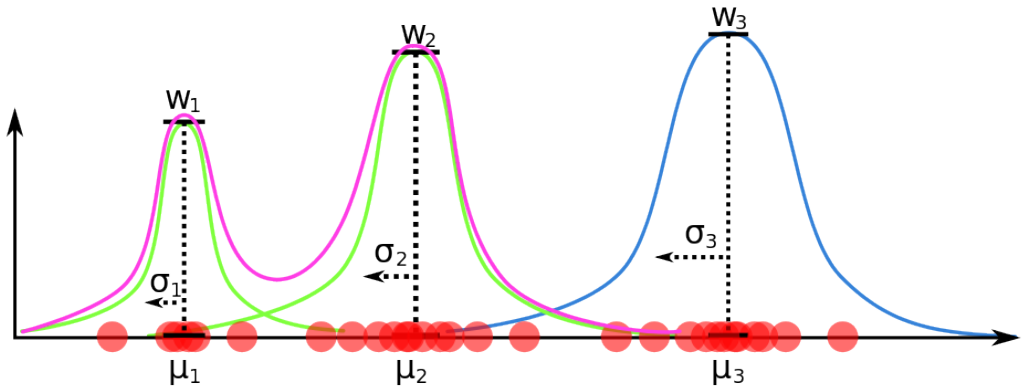


Single Image Snow Segmentation

z = observation
x = snow state

- Gaussian Mixture Model of Color

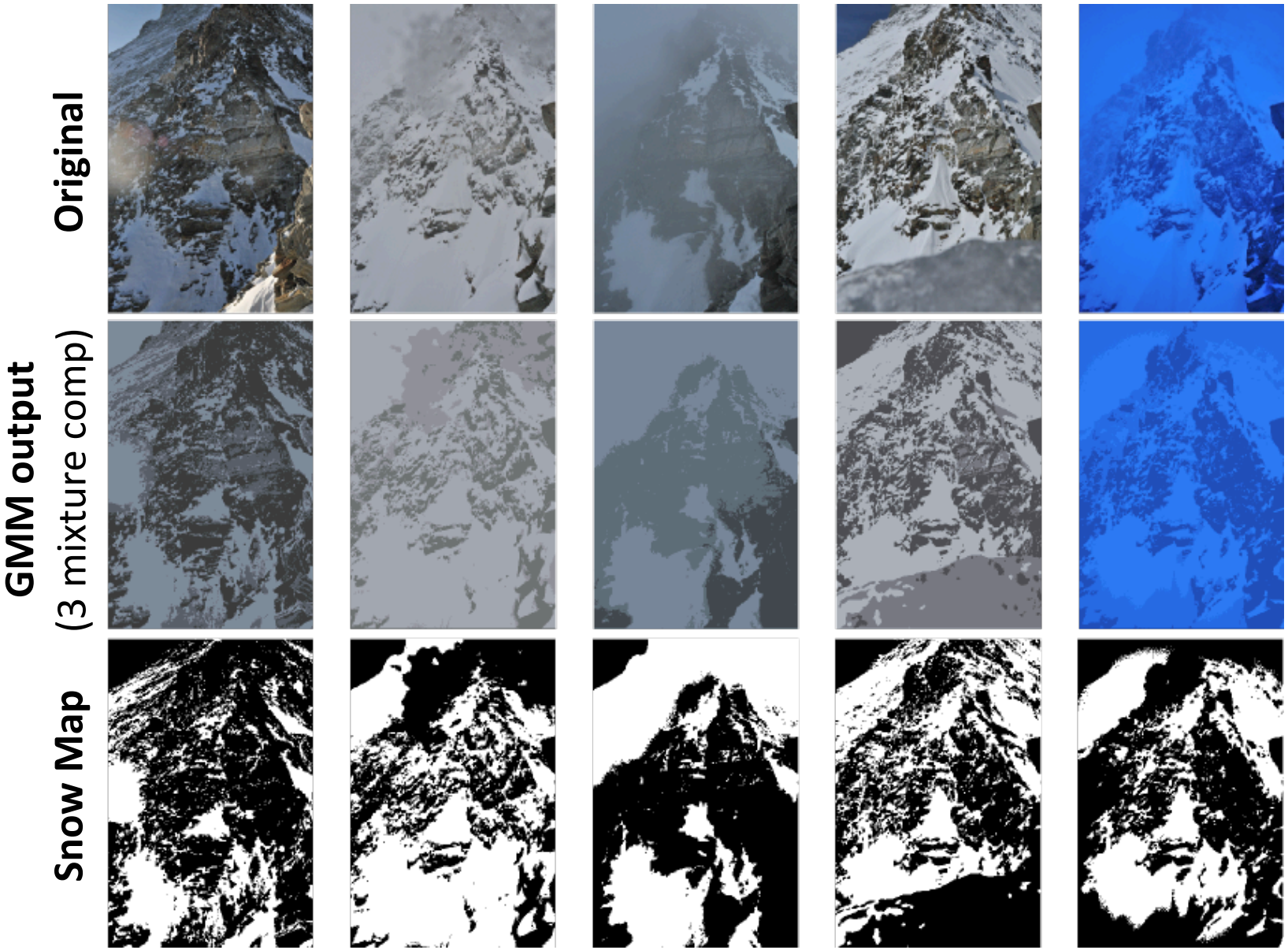
$$p(z) = \underbrace{p_s \cdot \mathcal{N}(z;\mu_s,\Sigma_s)}_{p(z|x=1)} + \underbrace{\sum_c p_c \cdot \mathcal{N}(z;\mu_c,\Sigma_c)}_{p(z|x=0)}$$



- Bayes Formula leads to:

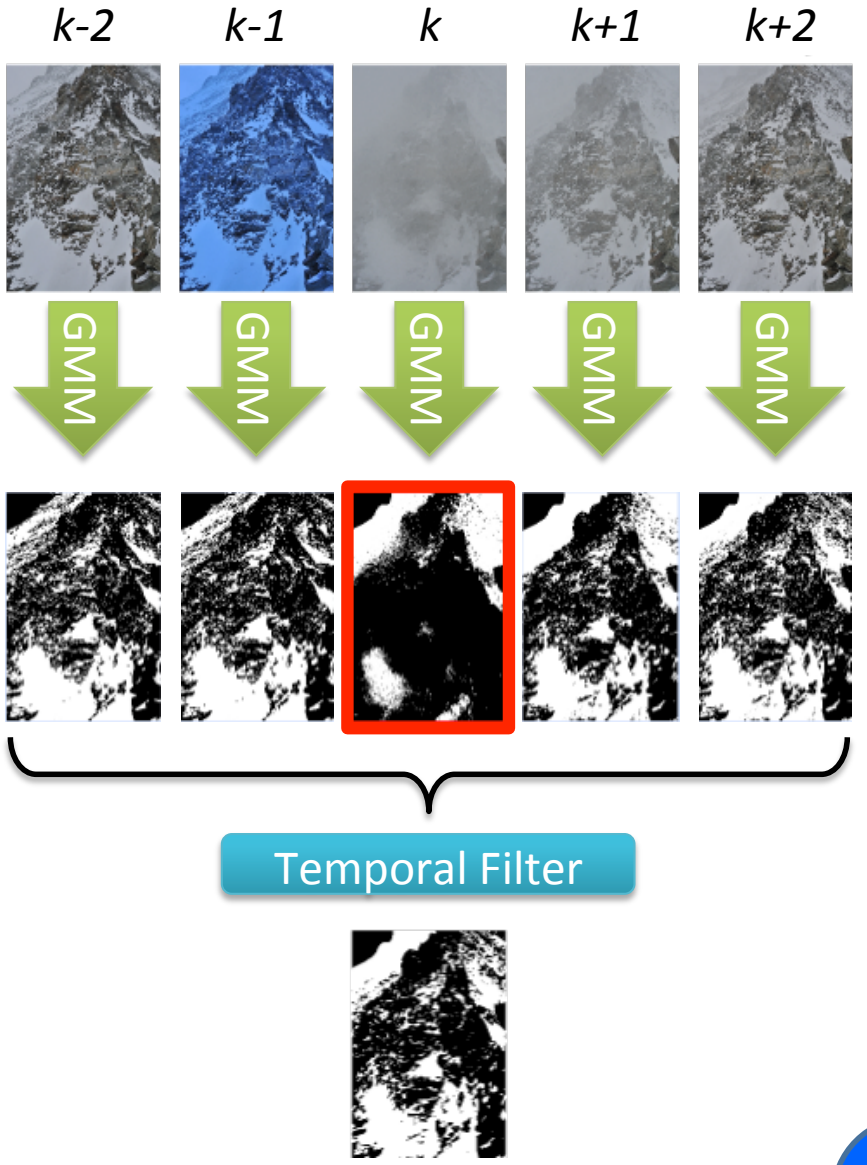
$$p(x=1|z) = \frac{p(z|x=1)\cdot p_s}{p(z|x=1)\cdot p_s + p(z|x=0)}$$

Some Segmentation Results



Temporal Consistency

- Use **temporal dependence** between images to obtain temporally consistent results
- Different Approaches
  - Median Filter
    - In space and time
    - Not sensitive to data
  - Markov Random Field
    - Contains **data** and **prior** term



Markov Random Field (MRF)

- Minimize the following energy function

$$-\log p(z,x) = \sum_i f_1(z_i, x_i) + \sum_i \sum_{j \in N(i)} f_2(x_i, x_j)$$

- Data term: **Negative log likelihood** from GMM

$$f_1(z_i, x_i) = -\log p(z_i | x_i)$$

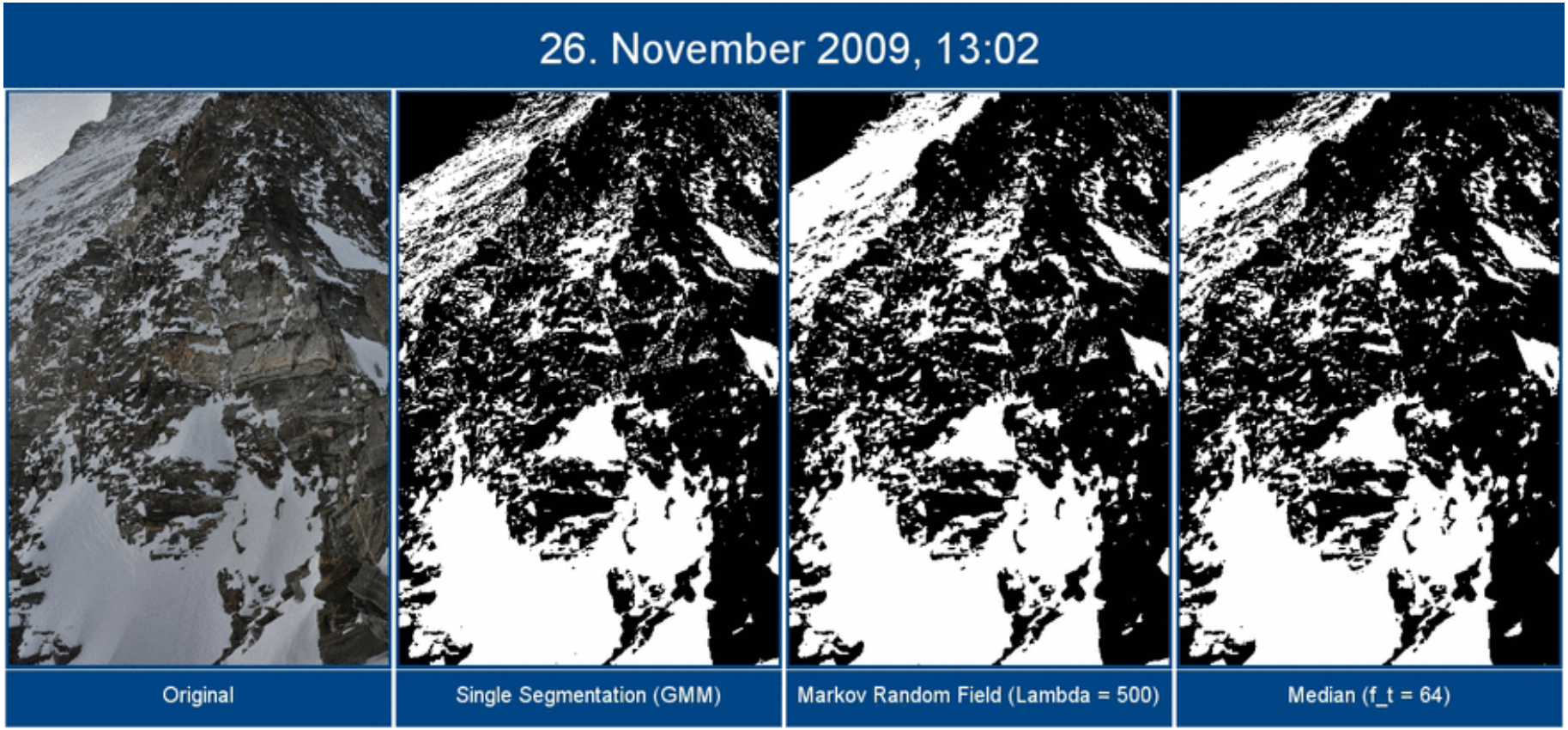
- Prior term: **Potts Model**

$$f_2(x_i, x_j) = \lambda_{i,j} |x_i - x_j|$$

controls the strength of the bond between adjacent pixels

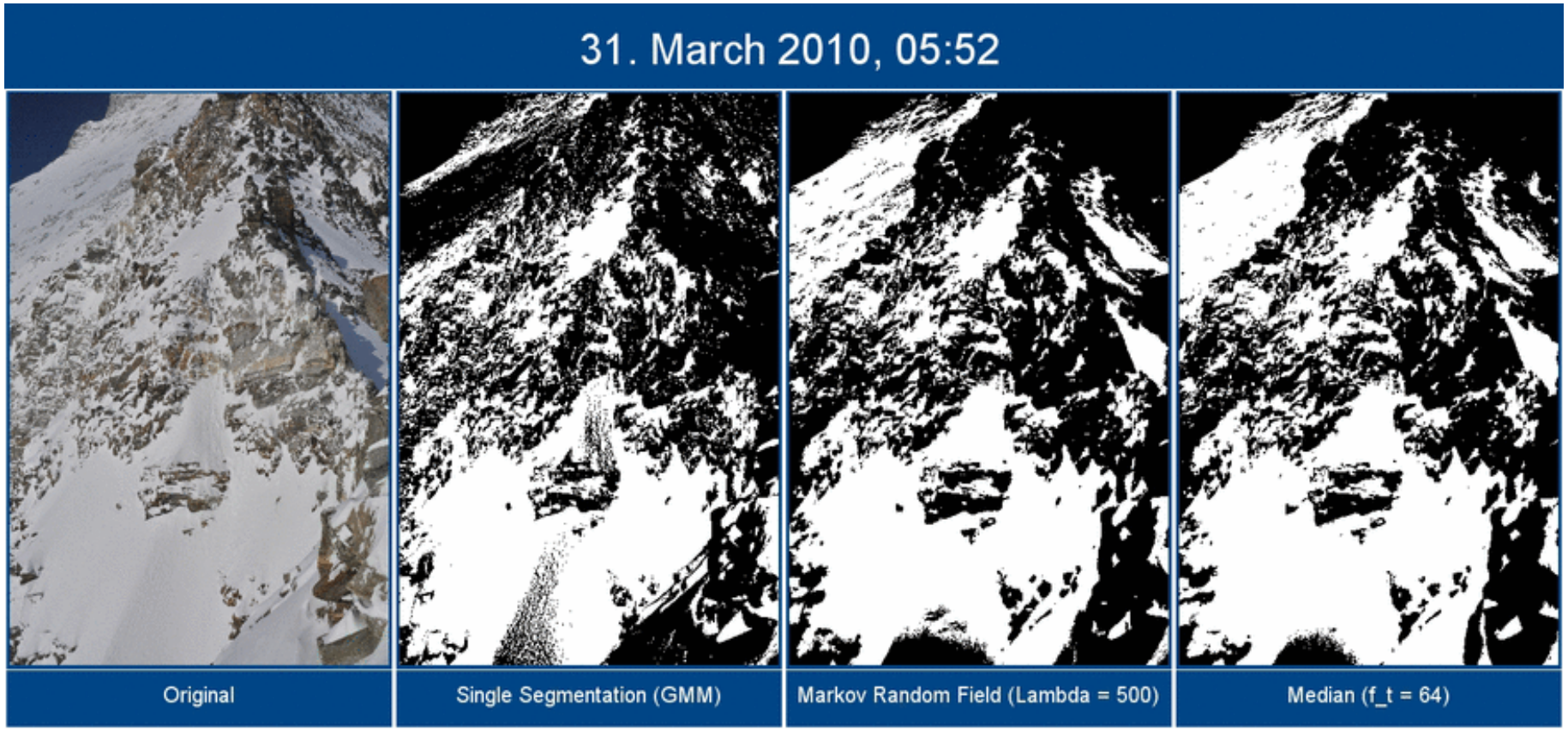
- Only need to connect neighboring pixels **in time** for temporally (and spatially) consistent results

Demo I on *Daytime* Images



- **Long temporal filter** sizes needed to be robust to uninformative images

Demo II on *Daytime* Images



- Problems if **too many consecutive** images are **uninformative**

A Closer Look at the Dataset

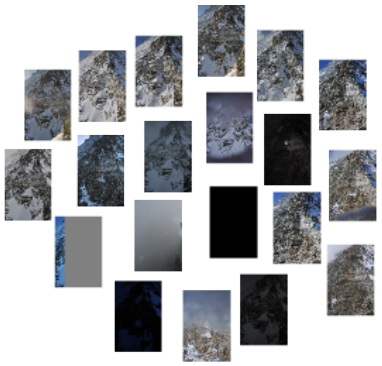
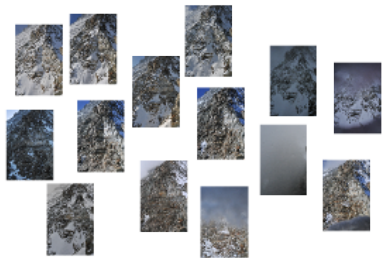
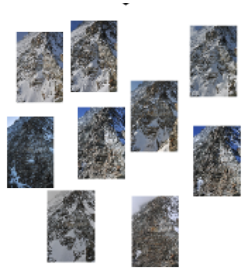


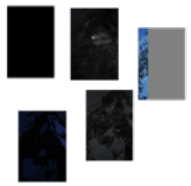
Image Database
(2500 images)



Daytime Images
(1770 images)



Good Images
(650 images)



Dark or Corrupted
(730 images)

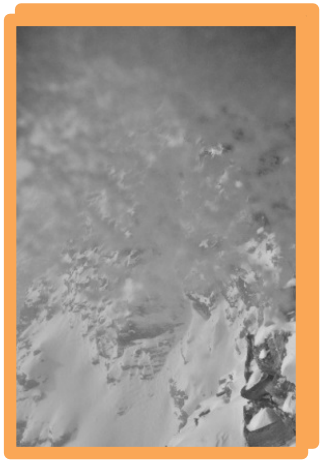
Uninformative
(1120 images)

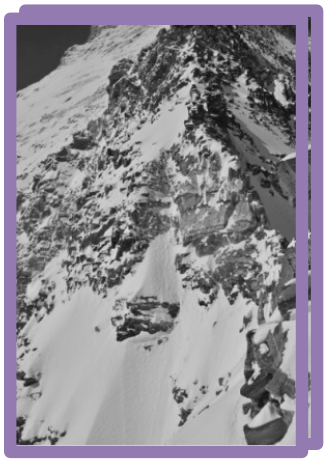
Excluding Uninformative Images

- Manually labelled 250 **informative** and 250 **uninformative** images
  - **Sharpness Index**

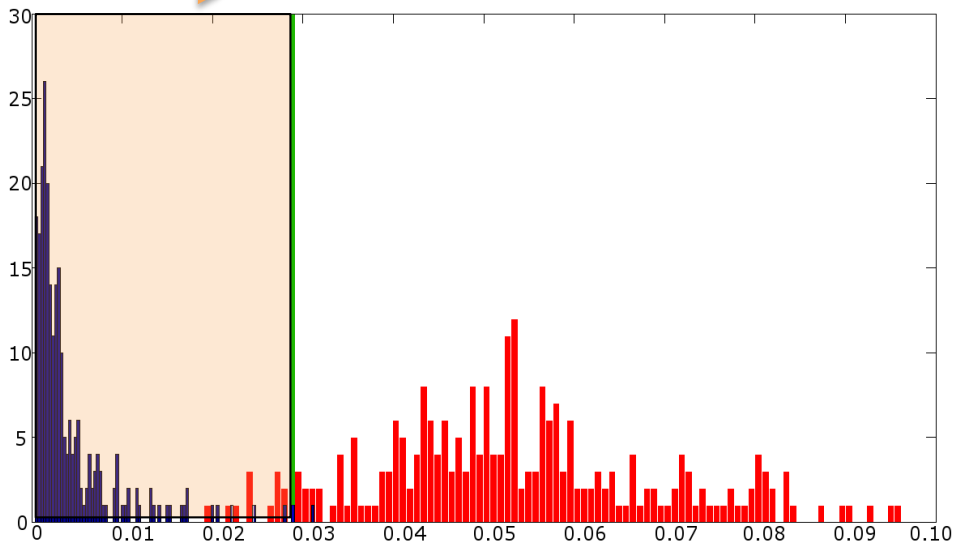
$$s = \frac{\sum_m \sum_n |L_{\text{high}}(m,n)|^2}{\sum_m \sum_n |L_{\text{low}}(m,n)|^2}$$

  - **Threshold** set such that there are less than **1% false positives**





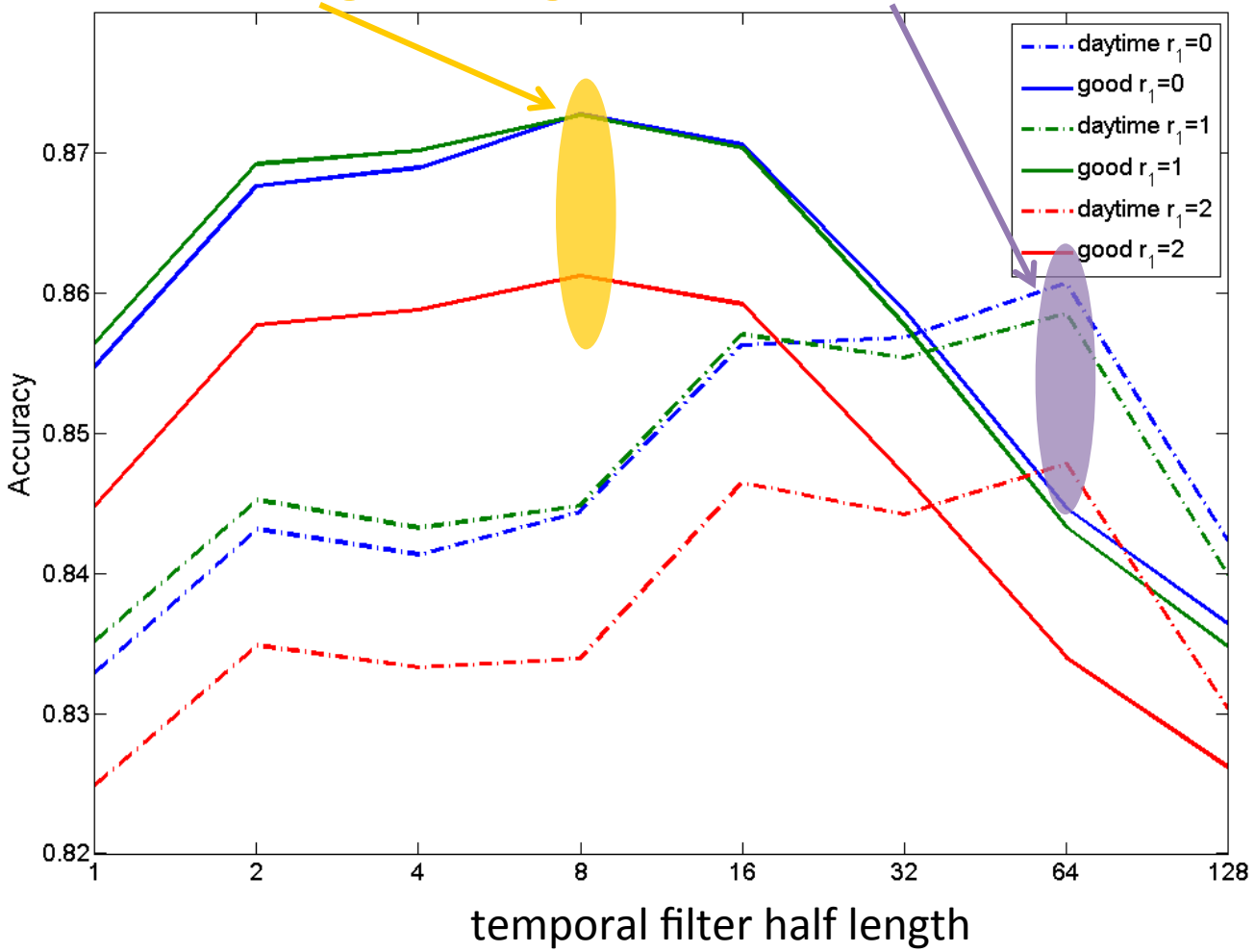
exclude these



Results: Median Filter

Best results on **good** images

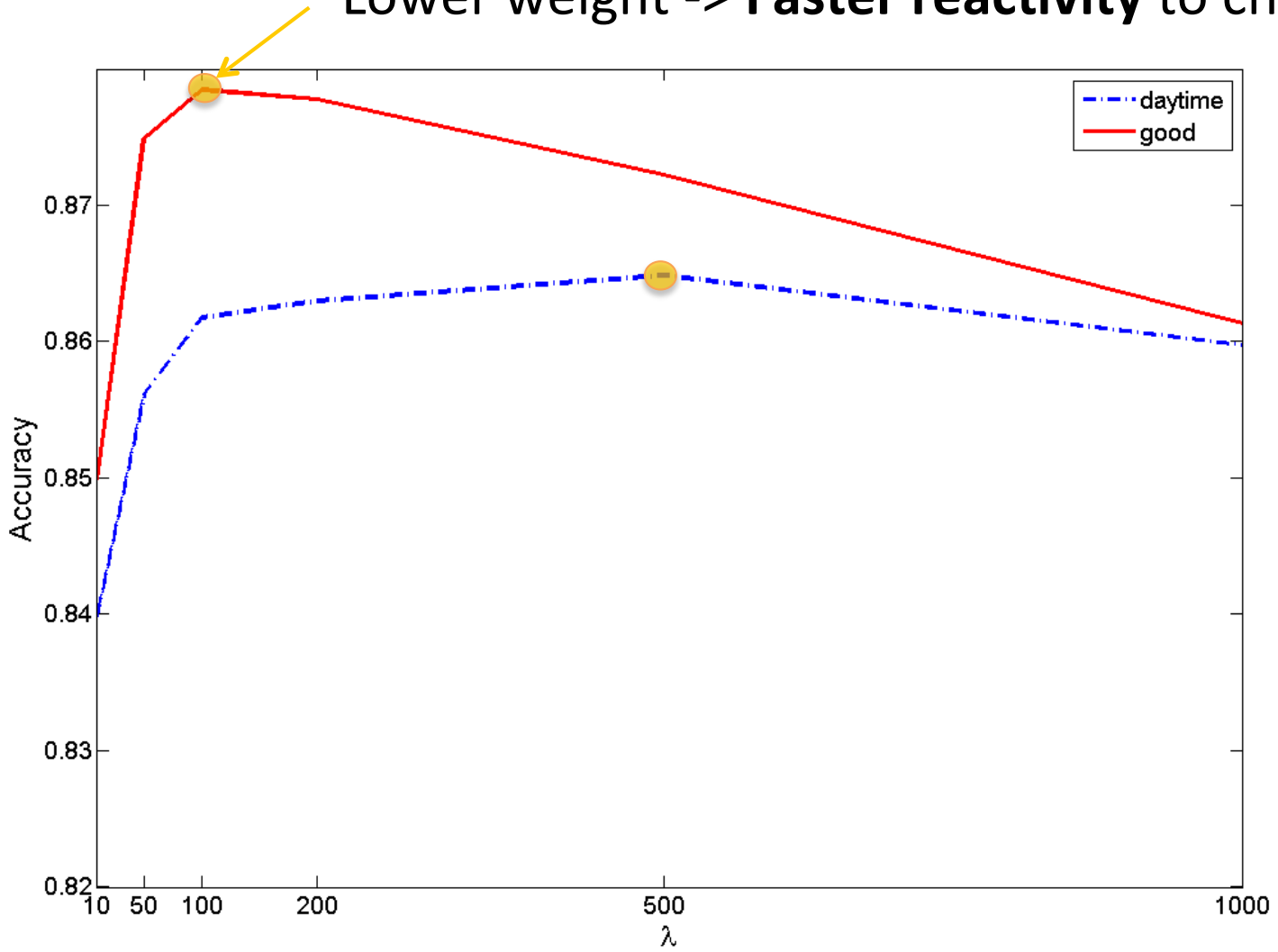
Best results on **daytime** images



→Temporal filter length **reduced** by a **factor of 8**

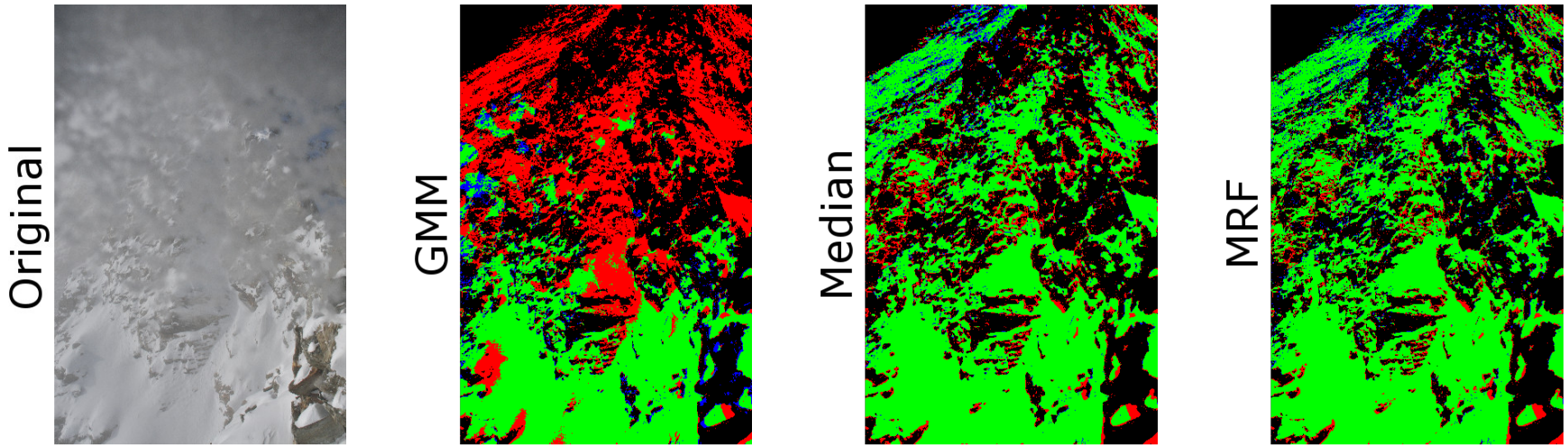
Results: Markov Random Field (MRF)

Lower weight -> **Faster reactivity** to changes

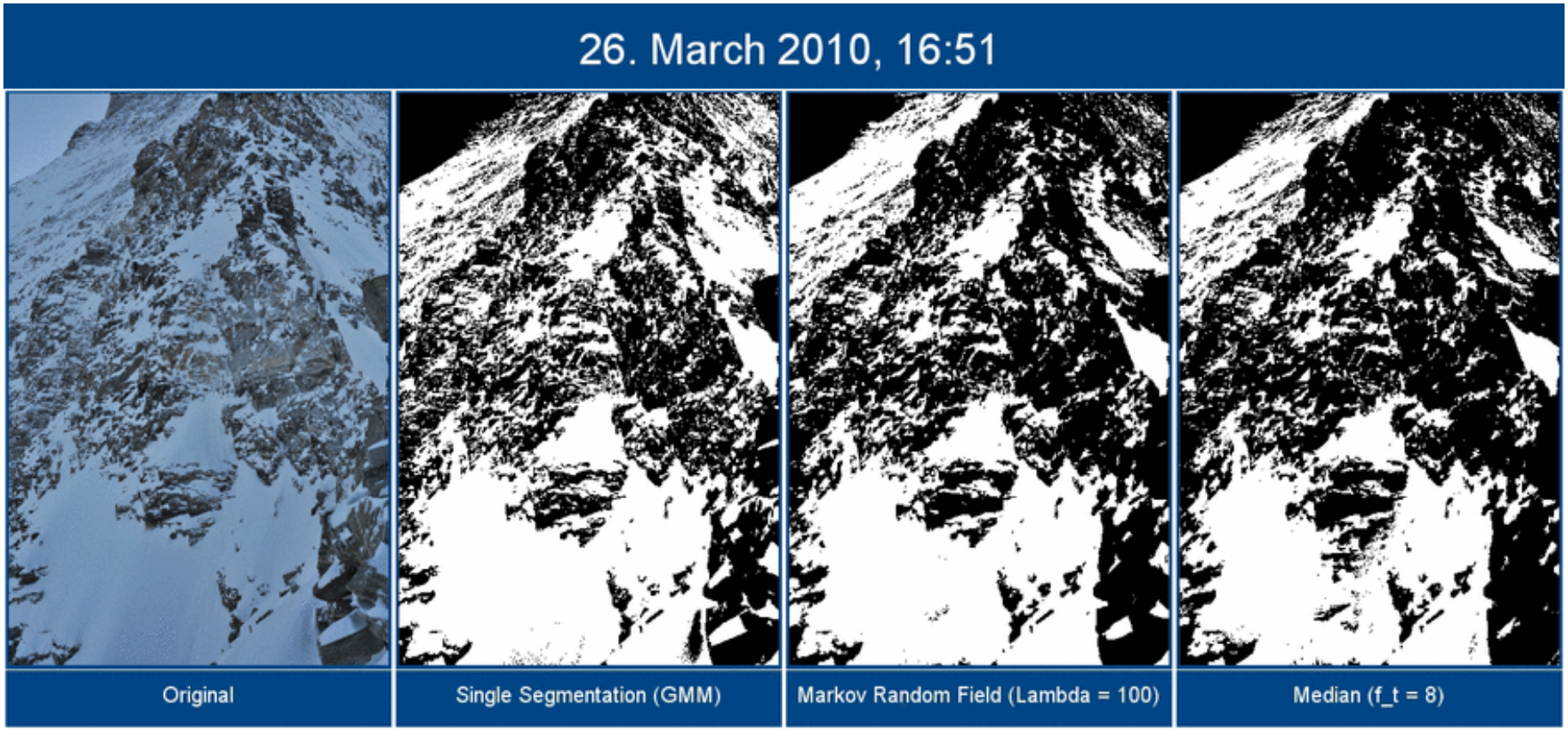


Quantitative Results

Method	Correctness	Std Dev
GMM of Color	83.3%	8.7
Median *Daytime*	86.1%	6.9
MRF *Daytime*	86.5%	6.6
Median *Good*	87.2%	6.8
MRF *Good*	**87.9%**	**6.1**



Demo on *Good* Images



Conclusions & Future Work

- Challenging dataset
  - Single image segmentation insufficient
  - Temporal filtering for more consistent results
- Incorporate **domain knowledge**
  - Discard *uninformative* images to improve results
- **Future work**
  - Implementation of a **snow depositioning** model

    → Smoother transitions
  - Different models for different **weather states**

    → Improve initial snow cover estimates

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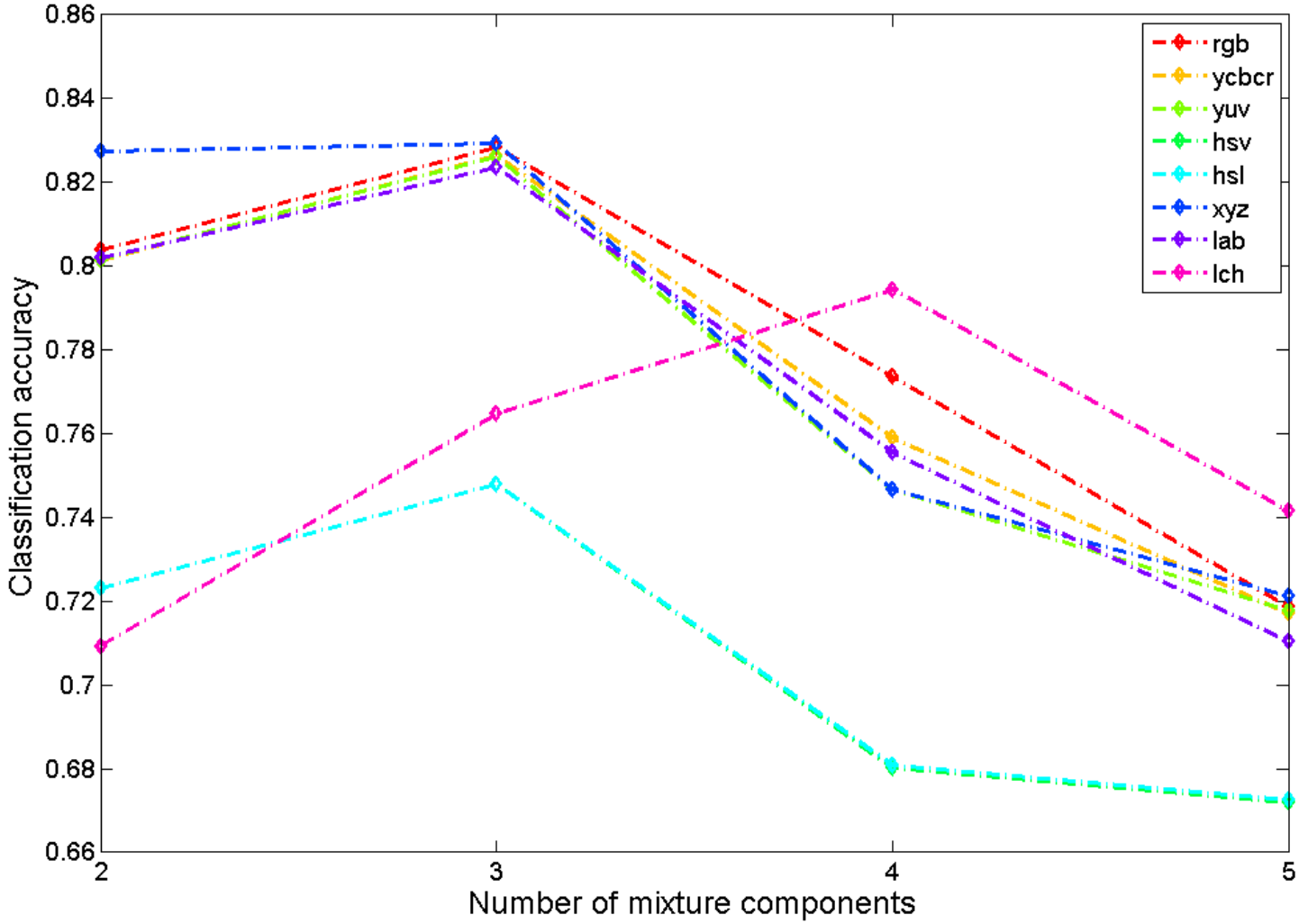
Thank you for your attention

Questions?

More information:
PermaSense project:
http://www.permasense.ch
Time Lapse Videos:
http://ivrg.epfl.ch/research/snow_segmentation

Number of Mixture Components



Three Mixture Components

XYZ Color Space