**Depth-aware Video Magnification**

Julian F. P. Kooij and Jan C. van Gemert

1 Delft University of Technology, 2 Leiden University Medical Center, The Netherlands

---

**1 Contributions**
- Use depth cue to magnify motion of occluded regions
- Depth-Aware Steerable Pyramids
- Generalize the Fast Bilateral Filter to Non-Gaussian bilateral filters
- Application on and RGB+D dataset for tremors measurement

**2 Main motivation**
- Medical application of full body tremor assessment
- Real-world hospital setting (e.g., Parkinson patients)
- Need to discover and measure small motions in arms, body, head, with minimum patient effort
- Should be robust against viewpoint, self-occlusions, and presence of large motions
- Other uses of our novel filter explored in Sup. Mat.

**3 Example magnification task**
- Magnify small motions in body, but large movements in foreground

**4 Magnification comparison to state-of-the-art**
- [1] Wadhwa et al., SIGGRAPH'13
- Phase-based motion magnification:
  - Per frame, build complex steerable pyramid
  - Amplify temporal variations of complex pyramid coefficients
  - Reconstruct video from amplified pyramids
- Problem: magnifies small & large motions equally

**5 Processing pipeline comparison**
- [2] uses fg.mask only at last step; we use it directly in pyramid representation
- **Baseline [2]**
- [Ours] Depth-aware motion magnification

**6 Measuring motion task**
- Steerable Pyramids also used for motion measurement
  - "Leaking" into background affects measurement too
  - Using our bilateral pyramid is therefore more robust

**7 More single frame magnification comparisons**

**8 Building a steerable pyramid**
- Our novel non-Gaussian bilateral filter generalizes the Fast Bilateral Filter [3]
  - Given input image \( I(x) \), depth image \( z(x) \), and let \( x, y, z \) be 2D image locations
  - The **standard bilateral filter** outputs \( O(x) \), using Gaussian kernel \( G(d; \sigma) \)
    \[
    O(x) = \frac{1}{W(x)} \sum_{y \in N(x)} G(d, \sigma) \cdot I(y) \\
    W(d) = \frac{1}{d} \cdot \frac{1}{\sigma} \cdot \frac{1}{\sqrt{2\pi}} \cdot e^{-\frac{d^2}{2\sigma^2}}
    \]
  - Our **non-Gaussian bilateral filter** \( O^\times(x) \) for non-Gaussian kernels \( F(d) \)
    \[
    O^\times(x, \xi) = \frac{1}{W(x, \xi)} \sum_{y \in N(x)} F(|x-y|, \xi) \cdot I(y)
    \]
- Here \( O^\times(x, \xi) \) is a volumetric representation (2D image + 1D depth) that magnifies small & large motions equally

**9 Non-Gaussian bilateral experiments**
- Study non-Gaussian filters on images + binary mask
  - Ideally, filter ignores intensity within masked region
  - Compare our method to using inpainting techniques
  - Tested on steerable filters and ConvNet filters
- **Result:** Inpainting yields large responses; Our method is fast, has minimum response

**10 References, acknowledgements, and code**
- [2] Elgharib et al., CVPR’15

Acknowledgments: This work is part of the research programme Technology in Motion (TIM [628.004.001]), financed by the Netherlands Organisation for Scientific Research (NWO)

Code: [github.com/jkooij/depthaware-momag](https://github.com/jkooij/depthaware-momag)

Project page: tim.lumc.nl