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Supplementary material for the manuscript 'Motion deblurring of faces'

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1 Introduction

This is the supplementary material accompanying the paper 'Motion deblurring of faces'. In the supplementary material, we provide auxiliary experiments and visualizations in order not to clutter the main results in the manuscript.

In Fig. 1 the drawbacks of predefined number averaging are depicted. Namely, in two videos, four different blur levels are illustrated. As it can be noticed, this predefined averaging is an oversimplification even in a single video, since it does not account for the motion in the current frames.

Fig. 1: Four cases from the same clip with a predefined (constant) number of averaging frames (here 15). The frames are put in chronological order from left to right. All four cases vary a lot depending on the movement of the person in each temporal neighborhood. All figures are best viewed in color.

2 Experiment with landmark localization

The complete CED plots with all methods visualized for the landmark localization experiment of the manuscript are depicted in Fig. 2 and 3. Similarly, the cumulative distribution for the cosine distances are illustrated in Fig. 4 and 5.

In addition to the state-of-the-art method used for landmark localization in the manuscript, we have additionally experimented with the robust regression method of CFSS of Zhu et al (2015). The rest conventions remain the same as in the manuscript and are not repeated here. The experiments with i) predefined averaging of 11 frames, ii) VLA blurring method were conducted. The results are visualized in table 1 and Fig. 6.

Method	PrAvg 11		VLA	
	AUC	*Failure Rate (%)*	*AUC*	*Failure Rate (%)*
Pan et al (2016)	0.660	17.492	0.735	4.915
Nah et al (2017)	0.663	17.578	0.742	5.584
ours	**0.679**	**17.818**	**0.770**	**4.738**
blurred	0.655	17.885	0.729	5.848
oracle	0.706	16.350	0.800	3.981

Table 1: Quantitative results for the landmark localization experiment.

Additional visual results in several images are provided in Fig. 7 - 10.

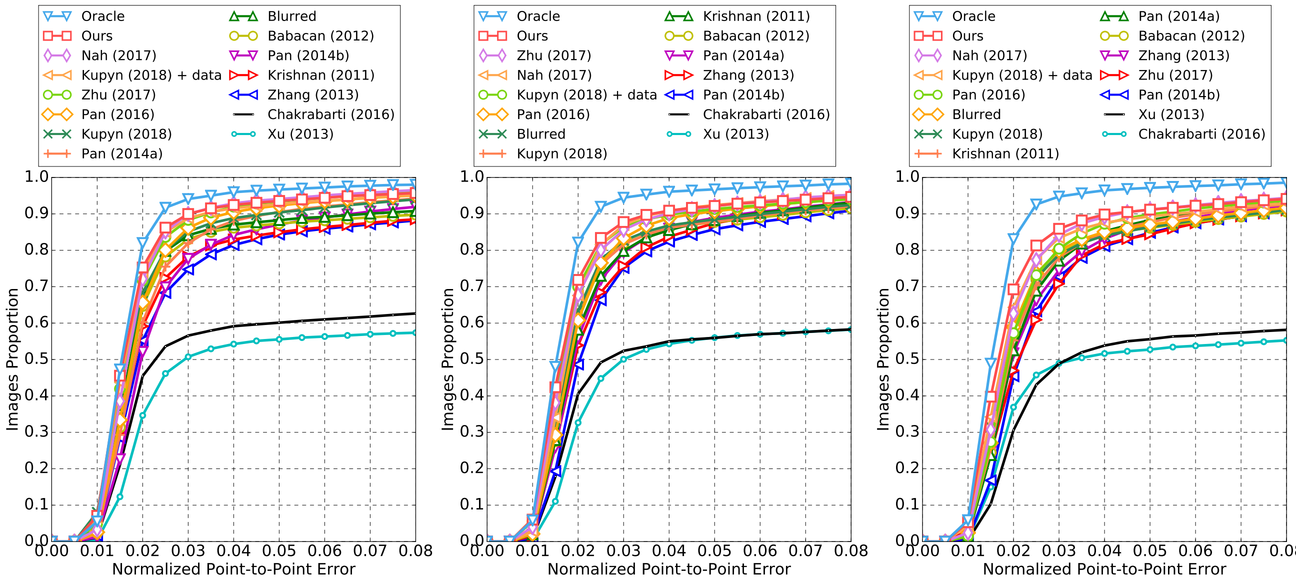

Fig. 2: Auxiliary CED plots for the landmark localization experiment of the manuscript. The legend is ranked based on the AUC. From left to right the plots correspond to the experiments with blurring process: predefined averaging with (a) 7, (b) 11, (c) 15 frames.

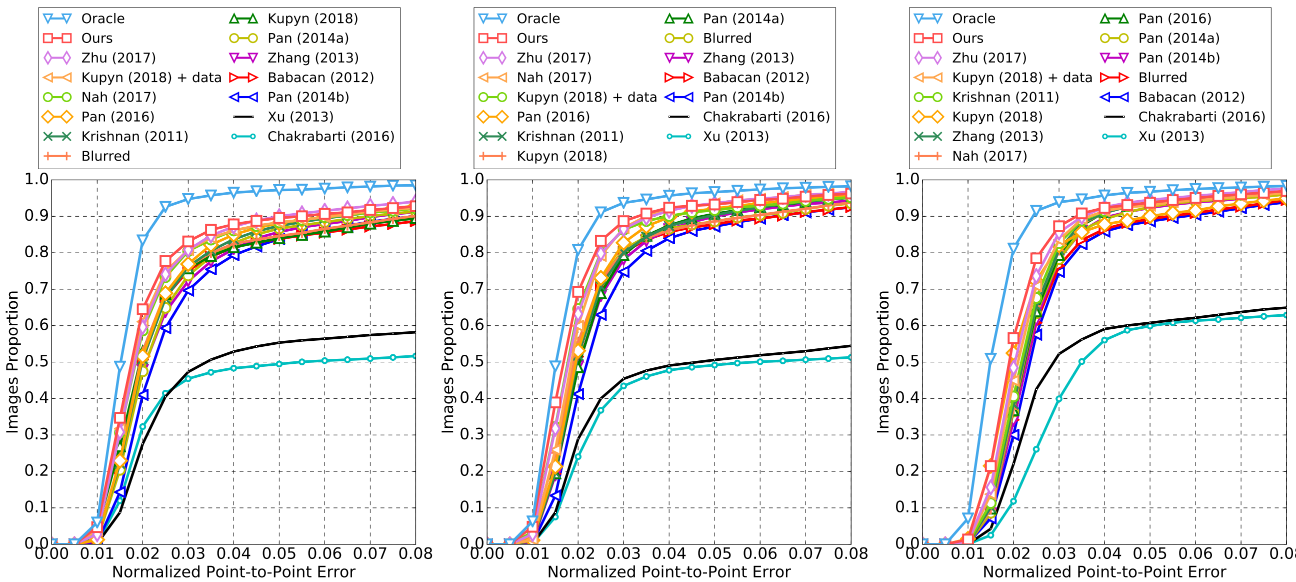

Fig. 3: Auxiliary CED plots for the landmark localization experiment of the manuscript. From left to right the plots correspond to the experiments with blurring process: (a) predefined averaging with 21 frames, (b) VLA, (c) synthetic blur.

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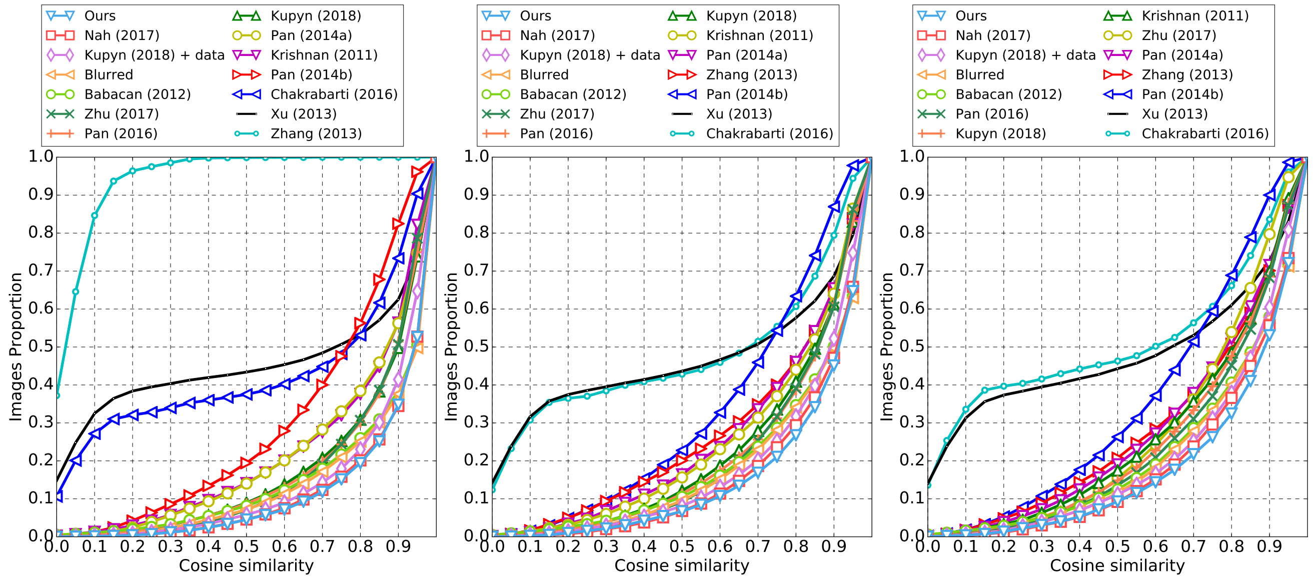

Fig. 4: Auxiliary cumulative cosine distance distributions plots for the landmark localization experiment of the manuscript. The legend is ranked based on the AUC (ascending order). From left to right the plots correspond to the experiments with blurring process: predefined averaging with (a) 7, (b) 11, (c) 15 frames.

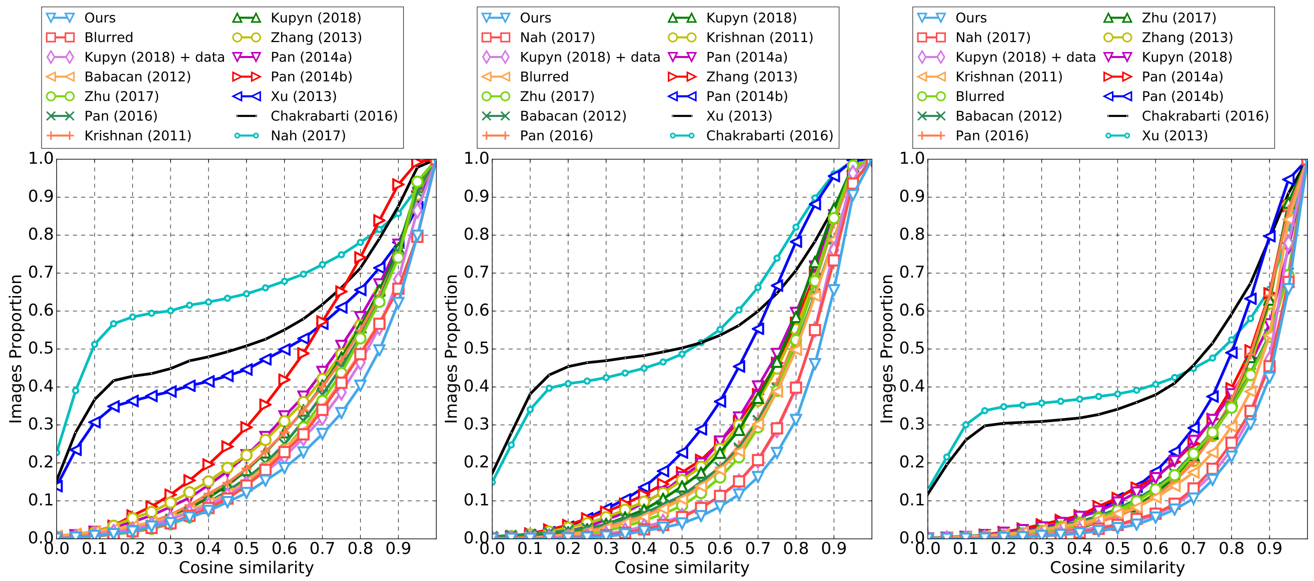

Fig. 5: Part 2 of the auxiliary cumulative cosine distance distributions plots for the landmark localization experiment of the manuscript. From left to right the plots correspond to the experiments with blurring process: (a) predefined averaging with 21 frames, (b) VLA, (c) synthetic blur.

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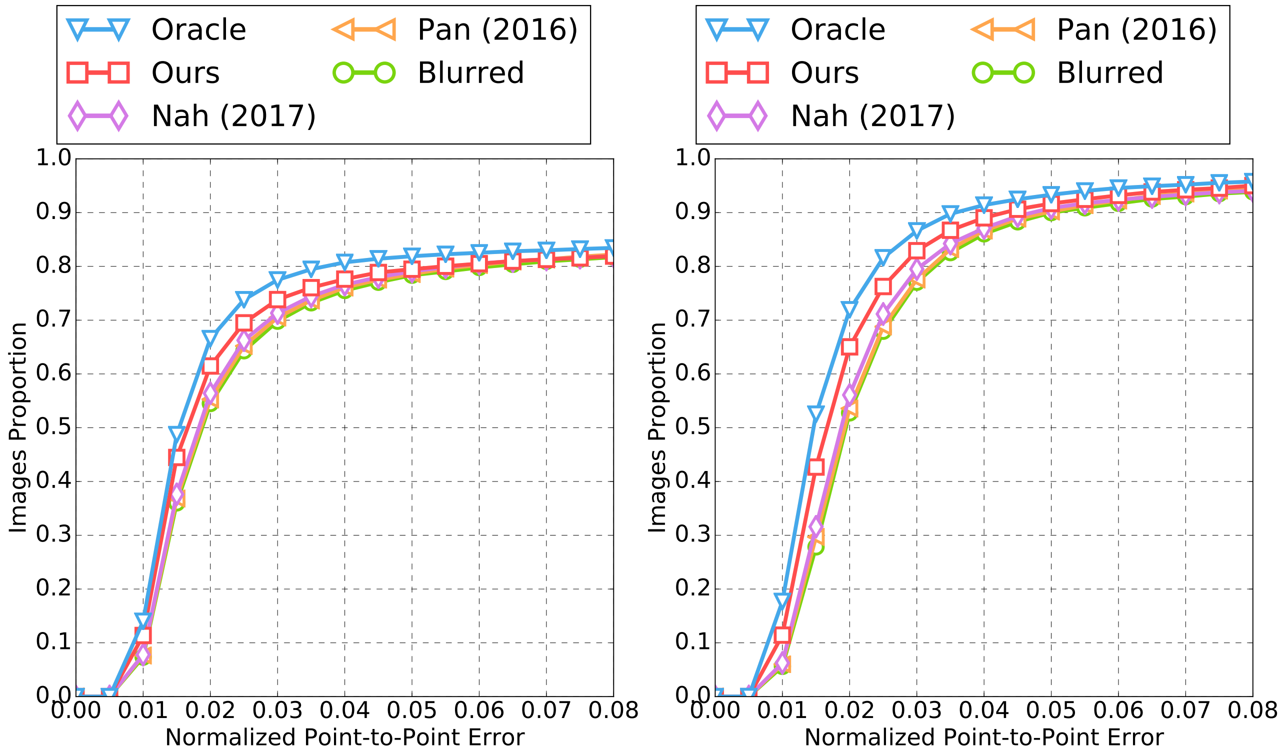
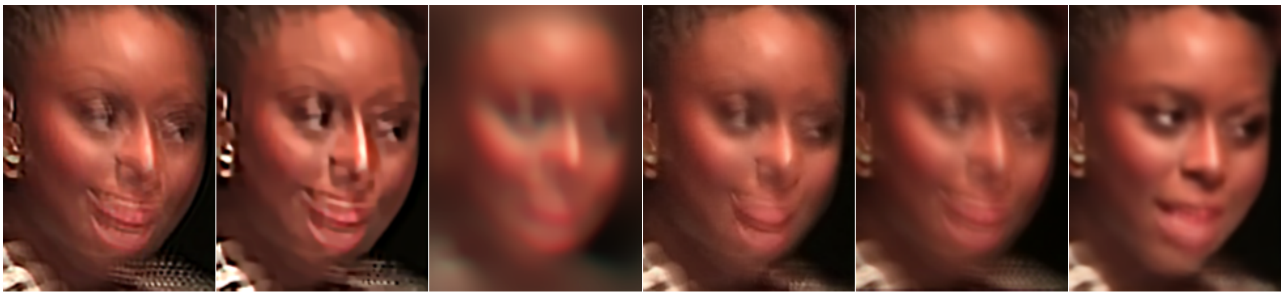


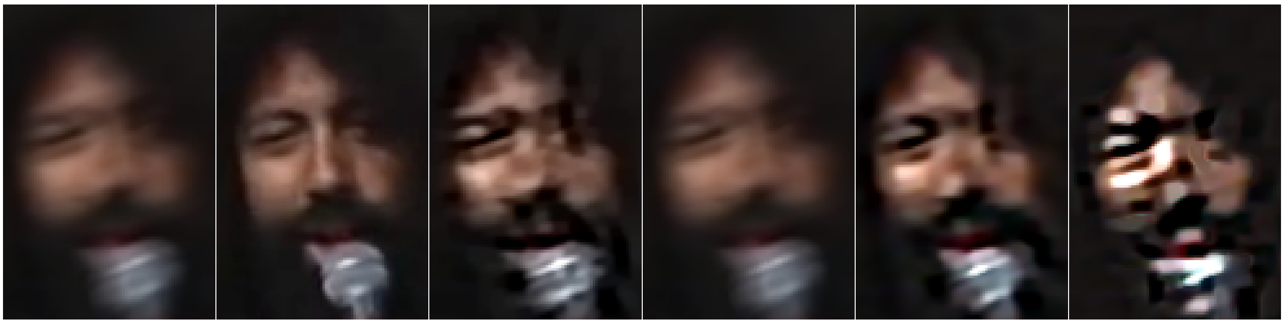
Fig. 6: CED plots for the landmark localization experiment with CFSS localization technique.

(a) blurred (b) gt (c) Krishnan et al (2011) (d) Babacan et al (2012) (e) Zhang et al (2013) (f) Pan et al (2014b)



(g) Pan et al (2014a) (h) Pan et al (2016) (i) Chakrabarti (2016) (j) Nah et al (2017) (k) Kupyn et al (2017) (l) ours

Fig. 7: Qualitative results of deblurring. Despite the severe blur in the mouth region, our method results in a more plausible result than the rest compared methods.



(a) blurred (b) gt (c) Krishnan et al (2011) (d) Babacan et al (2012) (e) Zhang et al (2013) (f) Pan et al (2014b)

(g) Pan et al (2014a) (h) Pan et al (2016) (i) Nah et al (2017) (j) Kupyn et al (2017) (k) ours

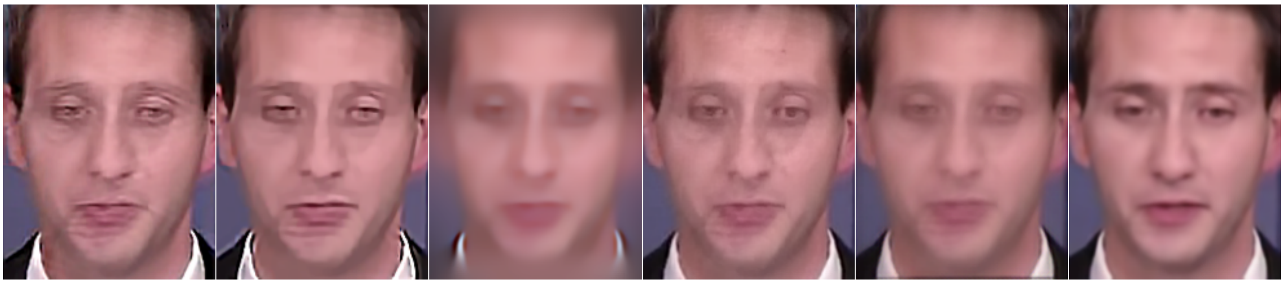
Fig. 8: The strong motion blur is restored by the method of Nah et al (2017) along with ours. However, the method of Nah et al (2017) includes artifacts that our method has avoided.

(a) blurred (b) gt (c) Krishnan et al (2011) (d) Babacan et al (2012) (e) Zhang et al (2013) (f) Pan et al (2014b)

(g) Pan et al (2014a) (h) Pan et al (2016) (i) Chakrabarti (2016) (j) Nah et al (2017) (k) Kupyn et al (2017) (l) ours

Fig. 9: The majority of the deblurred images include artifacts, e.g. in the right cheek; our image avoids them and yields a sharp result.

(a) blurred (b) gt (c) Krishnan et al (2011) (d) Babacan et al (2012) (e) Xu et al (2013) (f) Pan et al (2014b)



(g) Pan et al (2014a) (h) Pan et al (2016) (i) Chakrabarti (2016) (j) Nah et al (2017) (k) Kupyn et al (2017) (l) ours

Fig. 10: The blur in this case is mediocre; nevertheless the compared methods fail or result in artifacts. Conversely, the proposed method returns a sharp image.

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