## Computational Imaging

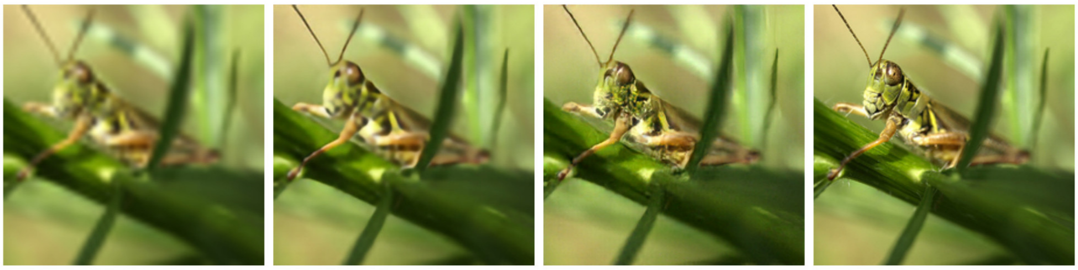

Figure 1.3: Super-resolution aims at estimating a high-resolution image from a single low-resolution input (left). Traditional methods tend to produce over-smoothed images that lack high frequency textures and do not look natural (second picture). One focus of our research was the development of algorithms that are able to create realistic textures (third picture) rather than a pixel-accurate reproduction of ground truth (right picture). This boost in perceived image quality is achieved using neural networks in an adversarial training setting [202].

Handheld video cameras now being available in every smartphone, images and videos have become ubiquitous. The amount of visual content on the internet has been ever increasing and digital images and videos have become the main carrier of information over the last few decades.

In our computational imaging group we are interested in a range of signal and image processing problems both in computational photography and scientific imaging. Our focus is on digital image restoration that aims at computationally enhancing the quality of images and recovering probable original images by undoing the adverse effects of image degradation such as noise and blur. Advances in convolutional neural networks have revolutionized computer vision and the field of digital image restoration has been no exception to this rule.

An important problem in digital image restoration is super-resolution, aiming at recovering a high-resolution image from low-resolution input. Traditionally, the performance of algorithms for this task is measured using pixel-wise reconstruction measures such as peak signal-to-noise ratio (PSNR) which have been shown to correlate poorly with the human perception of image quality. In addition, super-resolution is ill-posed and usually multiple plausible high-resolution "explanations" are possible for a given input image. Algorithms minimizing these metrics thus tend to produce over-smoothed images that lack high-frequency textures and do not look natural despite yielding high PSNR values. In a 2017 CVPR paper, we proposed a novel method for automated texture synthesis in combination with a perceptual loss focusing on creating realistic textures rather than optimizing for a pixel accurate reproduction of ground truth images [128, 202]. By using feed-forward fully convolutional neural networks in an adversarial training setting, we achieve a significant boost in image quality even at high magnification ratios (see figure above). Enforcing time consistency leads to novel approaches for the challenging problem of video super-resolution [154] and video prediction [198].

Another focus area has been the problem of blind deblurring. Images often exhibit blur due to unwanted camera shake or moving objects in the scene. Removing the blur is hard as neither the sharp image nor the motion blur kernel is known. Propagating information between multiple consecutive blurry observations can help restore the desired sharp image or video. We have developed efficient recurrent network architectures to deblur frames taking into account temporal information, which can efficiently handle both ego and object motion for arbitrary spatial and temporal input sizes [134, 183, 184, 205].

In addition to work applying image processing to MR images [35, 175], we have recently also tackled the problem of MTF (modulation transfer function) estimation directly from natural images [146], thus avoiding the need to use expensive equipment to characterize the quality of photographic equipment.

More information: https://ei.is.mpg.de/project/computational-imaging