Single-shot 3D endoscopic imaging exploiting a diffuser and neural networks

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Abstract. Lens-based endoscopes offer high lateral resolution, but suffer from rigid imaging properties, such as a fixed focal plane. We present a miniaturized 0.5 mm diameter endoscope in which the objective lens is replaced by an optical diffuser. The intensity information of the object space is scattered and passed to a camera via a coherent fibre bundle. The image is reconstructed by a neural network. The field of view and resolution depend on the object distance. 3D-single-shot imaging up to video rate can be enabled. The approach shows great potential for applications like robust 3D fluorescence imaging.

1 Introduction

Endoscopic imaging is an effective and efficient tool for in vivo diagnostics of diseases, such as cancer, and during surgical interventions. Regions that are difficult to reach out, like brain tissue and blood vessels, require ultrathin endoscopes for minimal invasiveness. In combination with the inherently compromised endoscope positioning, applications like brain cancer diagnostics or blood flow measurements require high imaging robustness and resolution at video rate, preferably in 3D.

The smallest endoscope diameters can be achieved with single mode (SMF) and multimode (MMF) fibres. However, necessary scanning movements for SMF [1] and the sensitivity of the MMF transmission matrix towards bending [2] require complex in situ correction to maintain robustness. While coherent fibre bundles (CFB) suffer from deterministic phase noise [3], they offer diameters below 0.5 mm and enable robust and spatially resolved light intensity transmission. Commercially available lens based CFB systems offer high lateral resolution, but the field of view (FoV) is limited to a fixed focal plane. Diffuser-based imaging offers the potential of high lateral resolution [4] as well as single shot 3D-imaging [5]. In contrast to lens-based imaging, diffuser-based imaging requires computational image reconstruction. While iterative convolution algorithms result in high reconstruction times [5], neural networks combine high image reconstruction performance at video rate [6,7].

We present a diffuser-based CFB endoscope in combination with a neural network for 2D image reconstruction at video rate. The setup is also capable of 3D reconstruction [8]. The reconstruction performance of different network architectures is compared regarding correlation coefficient (CC), peak signal-to-noise-ratio (PSNR) and structural similarity (SSIM). An in situ validation with a microscope, is shown for demonstration.

2 Setup and Image Processing

The training data is an augmented version of the Digits MNIST dataset. Up to five digits where randomly rotated, translated and put into one 104x104 ground truth image (example in Fig. 2a, top row). The ground truth is projected from a DLP® LightCrafter Display 4710 EVM-G2, containing a 1920x1080 digital micromirror device and high-power RGB LEDs (see Fig. 1, top right). A validation camera is placed into the virtual image plane of the projection optics. The light field is scattered by the diffuser and propagates through an integrated 0.5 mm glass spacer to the distal facet of the CFB. The CFB is a Fujikura FIGH10-3505 with 10,000 cores and 0.325 mm diameter. The proximal facet of the CFB is imaged onto a Thorlabs Quantalux acquisition camera. The camera image is resized to 104x104 and used as input of a single layer perceptron (SLP) for image reconstruction. Eventually, the SLP reconstruction is denoised by a U-Net.

3 Results

To demonstrate the effectiveness of the combined SLP+U-Net approach, reconstructions are also done with a U-Net and an SLP, individually. The results can be seen in Fig. 2a. The U-Net delivers moderate CC on image data similar to the training data, which however decreases rapidly on other data sets due to overfitting. The SLP reconstructions maintain a higher CC over all datasets but suffer from systematic noise, which keeps the PSNR and especially the SSIM low, as can be seen in Fig. 2b. The SLP+U-Net approach outperforms both individual SLP and U-Net regarding all shown quality parameters. The reconstruction rate is 10 Hz on an office PC (Intel® Core™ i5-4590).

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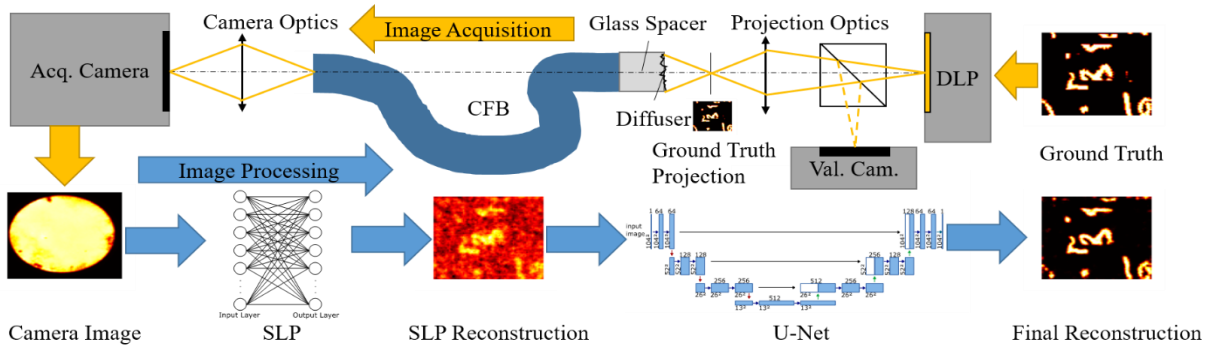

Fig. 1. Sketch of training setup, diffuser endoscope and image reconstruction.

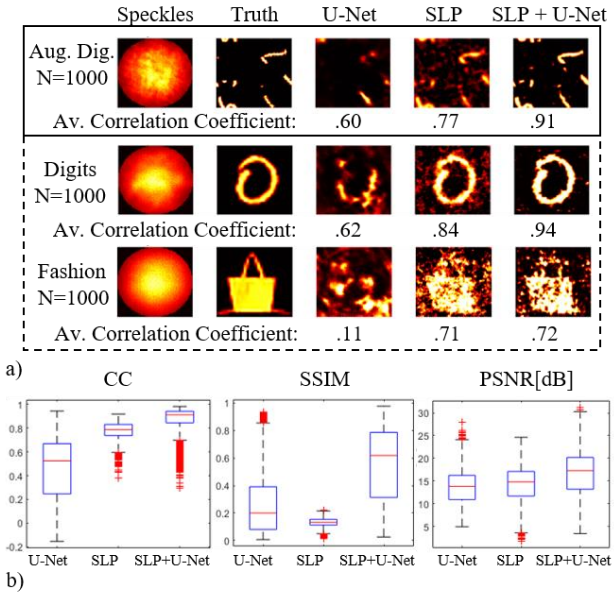

Fig. 2. Comparison between U-Net, SLP and SLP+U-Net after training with Augmented Digits data. a) Reconstruction examples. The CC data set average over N images is displayed below the reconstructions. b) CC, SSIM & PSNR boxplots of all data sets combined.

To demonstrate the feasibility of the method for real life applications, a physical USAF target is placed into the ground truth projection plane at a distance of 800 µm from the diffuser. A square of 400x400 µm is illuminated by the DLP projector. A comparison between validation camera images (reflection) and reconstruction with diffuser endoscope (transmission) can be seen in Fig. 3. The general object structures can be reconstructed and distances down to around 15 µm can be resolved. However, the non-linearity of the network leads to visible distortions of the stripes and numbers.

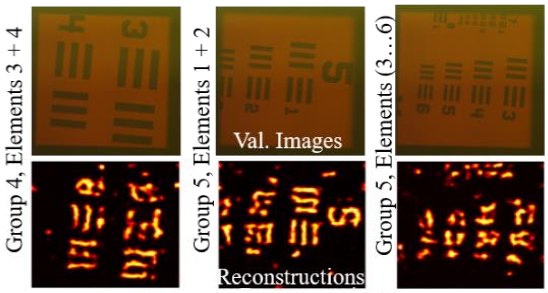

Fig. 3. Reconstruction (bottom) of a physical USAF target and validation images (top).

4 Conclusion

We propose a miniaturized endoscope using an optical diffuser and a neural network for intensity image reconstruction. The reconstruction performance and linearity can be significantly increased by sequentially processing the camera speckle image with a single layer perceptron, followed by a U-Net. Real object 2D imaging is performed on a test target. Video rate reconstruction is possible for 2D reconstruction. The setup can also be used for 3D imaging [8].

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