Supplementary Information

Mapping human tissues with highly multiplexed RNA in situ hybridization



**Supplementary Figure 1. Gel embedding effects and signal stability in DART-FISH. (a)**  Fluorescent signal from RiboSoma (randomly primed cDNA) is stronger when the cDNA is embedded in a polyacrylamide gel immediately after reverse transcription (top) compared to gel embedding after RCA (bottom). The nuclear stain (DRAQ5) shows no difference between the two conditions (left). RT: reverse-transcription, RCA: rolling circle amplification. **(b)** Scatter plot comparing the average gene count per nucleus in the two conditions in (a). Each dot represents a gene. Nuclear segmentation was chosen for counting cells to provide a fair comparison between the two conditions. **(c)** Histogram of the gene expression fold change in (b). 50% of genes show at least a 50% increase in their counts. **(d)** Rolonies are stable after multiple cycles of staining and stripping without background buildup. DART-FISH was performed on a mouse kidney tissue section with a non-combinatorial probe set containing Malat1 and B2m genes on Cy3 and Atto647N channels, respectively. Images show the rolonies of these genes on the 3rd



and 6th cycles as well as the fully cleared signal after stripping. Brightfield images serve as references for image registration. Source data are provided as a Source Data file.

**Supplementary Figure 2. SpD procedure and benchmarking. (a)** Smoothed OLS maps from Fig. 1f. Lasso weight maps (Fig. 1f) undergo pixel-wise elbow filtering to select the top 1 or 2 barcodes per pixel. Unbiased weights are then obtained by fitting an ordinary linear regression (OLS) using the selected barcodes (OLS maps). OLS maps are then smoothed with a Gaussian low pass filter. **(b)** Spot detection on weight maps. For each gene, the local peaks are detected on the respective smoothed OLS map. These peaks then serve as markers for watershed

segmentation. The centroids of the segmented areas are used as spot coordinates. White and red circles are drawn around high quality and rejected spots, respectively. **(c-d)** Scatter plots of two main features extracted from segmented spots with valid barcodes representing genes (c) or empty (unused) barcodes (d). Empty barcodes tend to be smaller in area and have lower weights than valid barcodes. **(e)** Emptiness probabilities inferred from a random forest that was trained to distinguish empty from non-empty spots based on the extracted features (weight max, weight mean, area). A cutoff is later set on the empty probabilities to keep high quality spots. (**f**) Comparison of SpD with StarFish (naive matching), BarDensr and ISTDECO (deconvolution-based methods) on synthetic images with varying degrees of difficulty. Naive matching is only sensitive when the data is sparse. Deconvolution-based methods perform more robustly against dense data.



**Supplementary Figure 3. Probe design and production strategy. (a)** A genome browser view showing the target locations for individual padlock probes. Up to 50 padlock probes are designed to tile the constitutive exons. **(b)** To obtain more probes targeting short genes, we allow overlapping target sequences for padlock probes (*NPY* as an example with 893 nucleotides) **(c)** Enzymatic production of padlock probes from an oligo pool. A probe set is PCR amplified with a pair of probe-set specific amplification primers from an oligo pool. The forward primer carries a 5' phosphorothioate modification to prevent exonuclease digestion and a 3' deoxyuridine modification, while the reverse primer carries a 5' phosphorylation modification to promote digestion by lambda exonuclease. The 5' and 3' ends of the amplicons are cleaved by USER and DpnII, respectively, to obtain single-stranded padlock probes with a 5' phosphate.



**Supplementary Figure 4. RiboSoma, cell segmentation and RNAscope validation. (a)**  Segmentation of cells using only nuclear (DRAQ5) or **(b)** both DRAQ5 and RiboSoma (randomly primed) staining. RiboSoma resolves cell bodies more confidently. **(c)** Assigning decoded rolonies to the closest segmented cell. Transcripts that are too far from cell boundaries are discarded. **(d)** Histogram showing the fraction of spots inside the segmented cells for each gene. *MBP* encoding Myelin basic protein has the lowest fraction of spots inside the cells. **(e)** An

example of *MBP* being expressed outside the soma. Every red dot is a decoded *MBP* transcript on the background of RiboSoma (contrast is increased for clarity). *MBP* spots seem to colocalize with the RiboSoma signal over long threads that resemble axons. **(f)** RNAscope validation of DART-FISH in the human M1C with genes *GAD2*, *PVALB*, *LAMP5*, *AQP4*, *APBB1IP* on parallel sections. Source data are provided as a Source Data file.



**(a)** UMAP embedding of the DART-FISH M1C data colored by transcripts counts for 16 cell type markers. **(b)** Pearson's correlation of DART-FISH subclasses with the snRNA-seq reference subclasses used for annotation<sup>1</sup> (c) Histogram of concordance values for genes in DART-FISH (top) and MERFISH (bottom, sample H18.06.006.MTG.250.expand.rep1<sup>2</sup>). Concordance is defined as the Pearson's correlation of expression levels across subclasses between SNARE-

seq $2<sup>3</sup>$  and the spatial assay. The histogram for DART-FISH is color coded to show the performance of short genes (constitutive exon length <1.5kb). Source data are provided as a Source Data file.



Diagram of the cell types composing the renal corpuscle and the juxtaglomerular apparatus<sup>4</sup>. (b)

Scatter plot comparing average gene counts per bead in Slide-seq (Puck 200903 06 from a healthy patient<sup>5</sup>) with average counts per cell in DART-FISH (r=0.609). Green dots represent canonical cell type markers while red dots are immune markers, suggesting high inflammation in the DART-FISH samples. The orange line indicates equal average counts across the two technologies. The top 150 highly expressed genes in slide-seq had on median 2.2x lower average transcripts per bead than average transcripts per cell in DART-FISH. **(c)** RiboSoma (randomly primed cDNA, middle) resolves tubular morphology better than the nuclear stain (left) and enhances cell segmentation (right). **(d)** Histogram of the number of rolonies per cell in >65,000 cells. There are on average ~30 decoded transcripts per cell. **(e)** Histogram of the number of detected genes per cell in the kidney, averaging at 20 unique genes per cell. **(f)**  Pearson's correlation of average DART-FISH subclasses with the average snRNA-seq reference subclasses used for annotation<sup>5</sup> (g) Bar plot showing the number of cells from each annotated subclass in the human kidney from n=1 section. High numbers of immune cells and fibroblasts are suggestive of inflammation and fibrosis. **(h)** Transmitted light (top) and RiboSoma overlaid with nuclear stain (bottom) of the ROI shown in Fig. 4g. The cells in the sclerosed glomerulus (dashed line) are mostly replaced by scar tissue as shown by the occupied space in the transmitted light view. (i) Plot showing the co-occurrence enrichment<sup>6</sup> of some cell types with MYOF at a range of distances, suggesting an interaction between MYOF with aTAL1 cells whereas there is no apparent co-occurrence enrichment between MYOF and aPT, or healthy PT-S3 and C-TAL. Source data are provided as a Source Data file.



**Supplementary Figure 7. Spatial mapping of cell types in the human kidney.** A whole tissue rendering of all segmented cells colored by all annotated subclasses. Red boxes correspond to ROIs in Fig. 4e-h



## **Supplementary Figure 8. Expression of marker genes in the human kidney.** UMAP

embedding of the DART-FISH data on human kidney colored by different marker genes in Fig. 4e.

## **Supplementary Table 1. The glossary for the abbreviated cell types and the technical terms.**





## **Supplementary Table 2. Comparing DART-FISH with similar methods.**

a Number of used barcodes over the number of valid barcodes. Lower ratios enable better error detection and signal demixing.

**b** Higher magnification is required for smaller and dimmer features. On the other hand, lower magnification objectives can image larger areas faster.

<sup>c</sup> 4-color imaging was used instead of 3-color imaging

<sup>d</sup> Cost of probe sets cannot be accurately compared across technologies for the following reasons: 1) Each technology uses a different number of probes per gene. For example, smFISH-based technologies (e.g., MERFISH) need a minimum number of probes for the signal to be detectable, while padlock-probe based technologies enjoy higher sensitivity with more padlocks per gene. Cost of direct synthesis scales linearly with the number of probes, thus technologies that use direct synthesis tend to keep the number of probes per gene low 3) each technology may use a different mass of probes per experiment which makes it very difficult to estimate cost per experiment. We tried to estimate the cost of purchasing the probe sets with the best knowledge obtained from the cited manuscripts. These values do not include the costs associated with the preparation of these probes for an experiment (e.g., amplification, phosphorylation)

## **Supplementary References**

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