Supplementary Materials

Fast Noninvasive Morphometric Characterization of Free Human Sperms Using Deep Learning

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A. Supplementary Figures

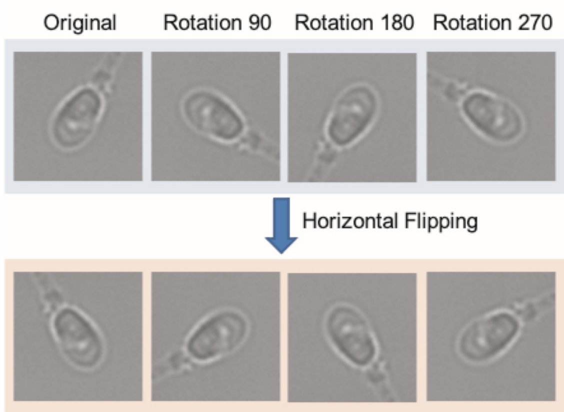

Figure S1. Augmentation of input images for training DNN-based classification models.

B. Supplementary Methods and Materials

Implementation details for the deep learning models used in this study are summarized below.

B.1. Detection and Localization of Sperm Heads

A YOLOv3-tiny model was used to locate single sperm heads. Model training was performed on an Nvidia 2080Ti GPU. Each input image was initialized by zero-mean normalization. Adam was selected as the optimizer for modeling training. Detailed training configuration parameters are listed in Table S1.

Table S1. Training configurations of YOLOv3-tiny model

Name	Values
Batch size	32
Initial learning rate	0.0001
Training epoch	120
λ_{coord} (Weight coefficient of loss component)	1
λ_{obj} (Weight coefficient of loss component)	1
λ_{cls} (Weight coefficient of loss component)	1
λ_{noobj} (Weight coefficient of loss component)	100

B.2. Selection of In-Focus Images

Multiple DNN-based classification models were tested to determine the z-position of sperm heads in input images relative to the microscope focal plane, including AlexNet, VGG-11/12/16, GoogLeNet, ResNet-18/34/50. Input images were initialized by zero-mean normalization. Rotations of 90°, 180°, 270° as well as horizontal flip were used for data augmentation, as shown in Figure S1. Training of all models was performed on an Nvidia 2080Ti GPU. SGD was selected as the optimizer for model training. The initial learning rate was 0.002 and was divided by 10 when the accuracy plateaued. All models used the same hyperparameters. Detailed training configuration parameters are listed in Table S2.

Table S2. Training configurations of classification models for selection of in-focus images

Name	Values
Batch size	32
Initial learning rate	0.002
Training epoch	120
Momentum of the optimizer	0.9
Weight decay of the optimizer	0.001
Monitor of the learning rate scheduler (plateaus)	Top-1 accuracy
Patience of the learning rate scheduler (plateaus)	20

B.3. Segmentation of Sperm Heads

Multiple DNN-based segmentation models, including U-Net, FCN, DeepLabv3 and U-Net++, were tested to segment the substructures in sperm heads. Input images were initialized by zero-mean normalization. Training of all models was performed on an Nvidia 2080Ti GPU. RMSprop was selected as the optimizer. OneCycleLR was selected as the scheduler for the learning rate. For UNet++, a batch size of 8 was used for training. Except for UNet++, all other models used the same hyperparameters. Detailed training configuration parameters are listed in Table S3.

Table S3. Training configurations of segmentation models

Name	Values
Batch size	32
Initial learning rate	0.001
Training epoch	150
Momentum of the optimizer	0.9
Alpha of the optimizer	0.99
Weight decay of the optimizer	1E-8
Anneal strategy of the learning rate scheduler (OneCycleLR)	‘cos’
Pct_start of the learning rate scheduler (OneCycleLR)	0.1
Div_factor of the learning rate scheduler (OneCycleLR)	25