# Deep Learning from Sparse fNIRS Data to Augment High-Density Datasets Improves Decoding Performance

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Keywords: fNIRS · High-density DOT · Sparse-to-dense learning · Deep learning · Image reconstruction
Preferred format: Poster
Category: Analyzed data

## Introduction

Functional near-infrared spectroscopy (fNIRS) is a noninvasive optical neuroimaging technique for measuring hemodynamic responses associated with neural activity in laboratory and real-world settings [1]. Diffuse optical tomography (DOT) extends fNIRS by reconstructing channel-space measurements into spatially resolved cortical or volumetric maps of hemodynamic activity using forward models of light propagation and inverse methods that estimate the distribution of hemoglobin changes [2]. The spatial specificity of fNIRS and DOT depends on the number and arrangement of source–detector pairs: sparse arrays provide limited spatial resolution, whereas high-density (HD) configurations improve lateral and depth resolution, enabling more accurate reconstruction and better separation of cortical and superficial signals [1]. Alongside these advances, the fNIRS/DOT community has increasingly adopted deep learning (DL) methods, which require large annotated datasets. Although DOT provides higher spatial resolution that may benefit DL models, most existing fNIRS studies still rely on sparse sensor configurations [3]. In this study, we investigate whether sparse fNIRS data can be leveraged to improve the performance of DL models designed for high-density acquisitions. To integrate sparse and dense acquisitions, channel-space measurements are reconstructed into cortical image space using DOT methods and aggregated into parcel hemodynamic time series, preserving the spatio-temporal structure of the signals within a common anatomical representation. We hypothesize that reconstruction of sparse and dense measurements into a shared cortical parcellation space preserves sufficient task-relevant information for sparse data to beneficially augment DL models trained on high-density recordings. This representation enables joint learning across acquisition densities within a unified DL framework.

## Methods

Raw fNIRS signals are preprocessed and reconstructed into cortical image space using the Cedalion library [4], then aggregated into parcel time series, yielding a shared representation across sparse and dense acquisition configurations (Fig. 1). These signals serve as input to a convolutional neural network (CNN), which learns spatio-temporal patterns of cortical activation [3]. To leverage sparse data for improving performance on high-density data, we investigate several adaptation strategies based on joint training. These include mixed dense-sparse mini-batch, fine-tuning, and alternating dense and sparse training phases. In addition, generative modeling approaches are being explored to further reduce the domain gap between both densities.

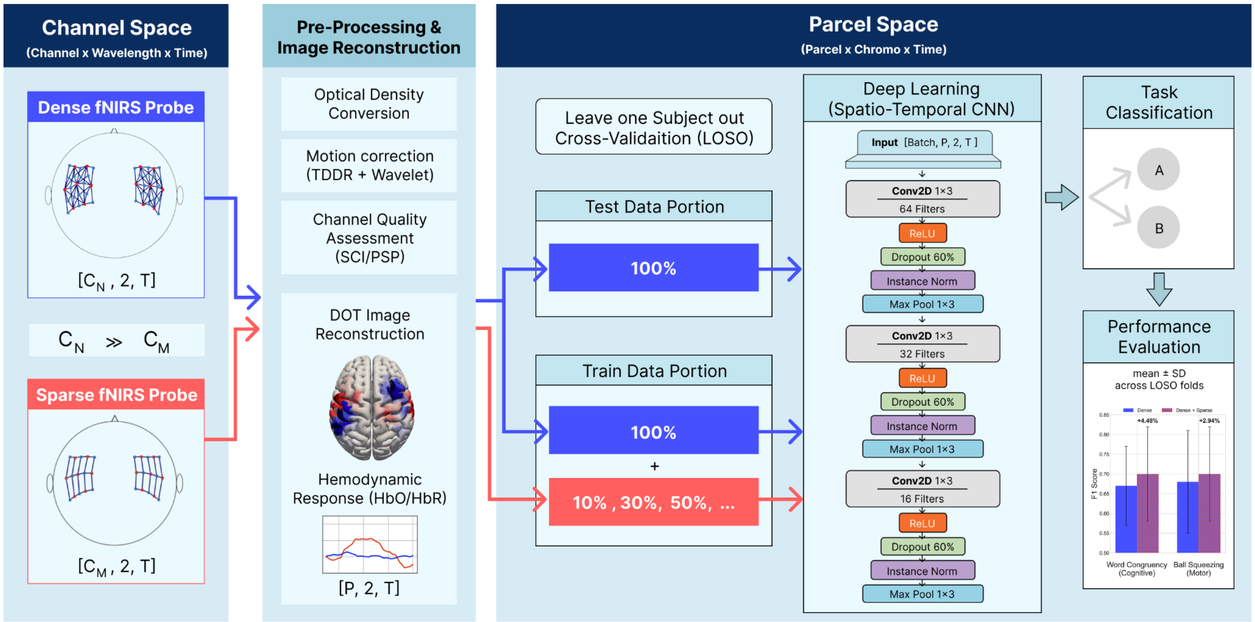

**Fig 1. Cross-density learning framework:** Channel-space measurements from dense and sparse fNIRS probes are preprocessed and reconstructed into cortical image space using diffuse optical tomography (DOT), yielding parcel-wise hemodynamic signals (HbO/HbR). A spatio-temporal CNN is trained on dense data augmented with varying proportions of sparse data and evaluated on dense data using leave-one-subject-out cross-validation (LOSO) to learn patterns of cortical activation for task classification. Performance is reported as the mean F1 score across subjects.

# Results

To leverage sparse data for improving dense-model performance, we established a shared cortical parcel space and implemented DL models for cross-density learning. Preliminary results indicate that incorporating sparse data during training, while keeping evaluation fixed on held-out dense subjects, improves performance by approximately 3-4.5% across both cognitive and motor classification tasks (Fig. 1).

# Discussion

These findings demonstrate the feasibility of integrating sparse and dense fNIRS data within a shared cortical image-space representation to support cross-density learning. The results highlight the potential of collaborative training strategies to leverage widely deployed sparse systems for strengthening models developed for high-density configurations. Ongoing work extends this framework to more complex cognitive paradigms to assess its generalizability beyond motor tasks.

# References

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