

# OPTICAL FLOW COMPONENTS AS AUXILIARY FEATURES FOR 3D PANCREATIC DUCTAL ADENOCARCINOMA TUMOR SEGMENTATION

Soomin Park, Kay C. Igwe, Soroush Arabshahi, Siddhardha Nanda, Samuel Lee, Sree Kuntamukkala, Carmine Palermo, Stephen Sastra, Michael A. Badgley, Yanping Sun, Kenneth P. Olive, Andrew F. Laine

Optical flow, an ultrasound-derived motion feature, provides additional information to improve tumor segmentation accuracy in preclinical PDAC mouse models. We assess the utility of optical flow components ( $u$ ,  $v$ ) by evaluating whether they provide complementary information beyond image intensity alone.

## 1. INTRODUCTION

Three-dimensional (3D) ultrasound is a non-invasive imaging technique for observing pancreatic ductal adenocarcinoma tumors in preclinical models, enabling longitudinal monitoring of tumor response to treatment. However, ultrasound suffers from low resolution, which limits tumor boundary detection and makes longitudinal analysis difficult, especially for deep learning models.

Optical flow fields, which can be estimated from ultrasound images, characterize temporal tissue motion patterns and may serve as a complementary feature for automatic tumor segmentation [1]. While motion has been widely studied for tracking and registration, its utility as an auxiliary signal for segmentation remains less explored [2].

We present a quantitative analysis of pixel-wise optical flow components ( $u$ ,  $v$ ) evaluated with a complementary binary tumor mask to determine whether flow statistics differ systematically between foreground and background regions [3]. Then we evaluate whether these directional components can provide distinct information that could be exploited by deep learning-based segmentation models.

## 2. METHODS

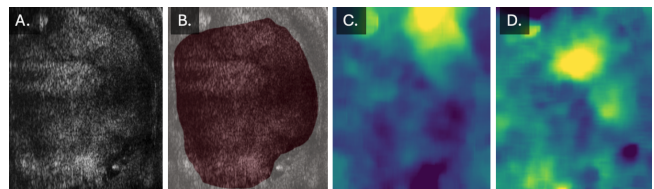
For each scan, we derived  $u$ - and  $v$ -flow masks and computed flow-magnitude summaries ( $|f| = \text{sqr}(u^2 + v^2)$ ) for foreground and background regions, the mean magnitude within each region, and the foreground-to-background ratio. To assess directional anisotropy, we computed per per-volume mean ( $|u|$ ) and ( $|v|$ ) within the foreground and compared

Soomin Park, Kay C. Igwe, Soroush Arabshahi, Siddhardha Nanda, Samuel Lee, Sree Kuntamukkala are with Biomedical Engineering (BME), Columbia University New York, NY, (email: kci2104@columbia.edu). Carmine Palermo, Stephen Sastra, Michael A Badgley, Yanping Sun, and Kenneth P. Olive are with the Department of Medicine, Columbia University Vagelos College of Physicians and Surgeons. Andrew F. Laine is with BME and the Department of Radiology, Columbia University, New York, NY, USA

them using the Wilcoxon signed rank test. All statistics were computed independently for training ( $n = 763$ ), validation ( $n = 157$ ), and test ( $n = 154$ ) splits to assess consistency. Spatial correspondence between images, labels, and flow fields was verified by matching to the ground-truth masks.

## 3. RESULTS AND DISCUSSION

Foreground and background flow magnitudes differed consistently across splits, with median ratios of mean foreground-to-background magnitude of 0.70 (train), 0.73 (val), and 0.72 (test), and 11.6% of volumes exhibited higher foreground motion. Directional components were strongly anisotropic, with a median foreground indicating larger ( $|v|$ ) than ( $|u|$ ) and with overall significant differences ( $p \ll 0.001$ ). This relationship remained significant when evaluated per split train, validation, and test splits ( $p \ll 0.001$ ), including a significant background difference ( $p \ll 0.001$ ), indicating a consistent directional motion bias. These results support integrating optical flow magnitude and directional components ( $u$ ,  $v$ ) as auxiliary channels into deep learning segmentation models to improve tumor boundary localization.



**Fig. 1.** (A) Base ultrasound scan, (B) tumor mask overlay, (C) horizontal flow ( $u$ ), and (D) vertical flow ( $v$ ).

## 4. REFERENCES

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