PREDICTION OF POLARIMETRIC MAPS FROM MUELLER MATRIX IMAGES USING PHYSICS-INFORMED MACHINE LEARNING ALGORITHMS

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Imaging Mueller polarimetry (IMP) shows promise for biomedical diagnosis; however, computational bottlenecks in post-acquisition data processing limit its clinical implementation. Standard Lu-Chipman polar decomposition requires computationally intensive non-linear calculations to extract polarimetric parameters (diattenuation, depolarization, linear retardance, and optical axis azimuth), thereby hindering near real-time applications. We developed physics-informed machine learning approaches to predict these parameters directly from measured Mueller matrices (MMs). Our methodology addresses the inherent challenges of circular nature through circular statistics techniques. Angular parameters (linear retardance and optical axis orientation) are transformed into cosine/sine pairs to eliminate wrap-around discontinuities at $\pm\pi$ boundaries. Additionally, we incorporate established biological properties in Mueller polarimetry as contextual information to enhance neural network performance. We also present a more stable approach utilizing a conditional Variational Autoencoder model that directly incorporates contextual information from polarimetric maps. Training was performed on datasets of human brain tissue images acquired using wide-field reflection geometry at 550 nm. Both models demonstrated excellent performance across all parameters ($R^2 > 0.95$). Robustness testing on Mueller matrix images from completely unseen samples maintained high accuracy. The machine learning models are compatible with both complete 4×4 Mueller matrices and partial 3×4 Mueller matrices. Runtime comparison demonstrates significant acceleration over standard decomposition methods, enabling near real-time polarimetric parameter extraction suitable for clinical applications.

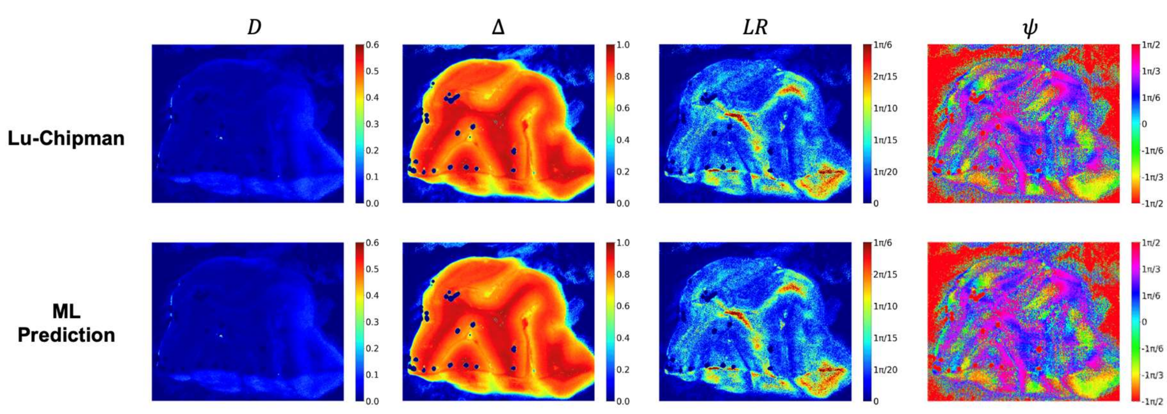

Fig. 1: Polarimetric maps of healthy brain specimen: diattenuation D (first column), depolarization Δ (second column), linear retardance R (third column) and orientation angle of the optical axis Ψ (last column). The first row represents polarimetric maps obtained from MM images by applying Lu-Chipman decomposition pixel-wise and the second row represents predicted polarimetric maps from conditional Variational Auto-encoder (cVAE) model with full 4 x 4 MM as inputs.