Geometric deep learning on graphs and manifolds using mixture model CNNs

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1. Graphs

Table 1. Results obtained with and without hidden layer prior to gaussians. The additional FC layer introduced for computing $\tilde{\mathbf{u}}$ actually helps MoNet at better representing the relationship existing between different vertices, slightly increasing the final performance produced.

Method	Cora	PubMed
MoNet($\mathbf{u}$)	$81.55 \pm 0.50\%$	$78.45 \pm 0.61\%$
MoNet($\tilde{\mathbf{u}}$)	$\mathbf{81.69} \pm 0.48\%$	$\mathbf{78.81} \pm 0.44\%$

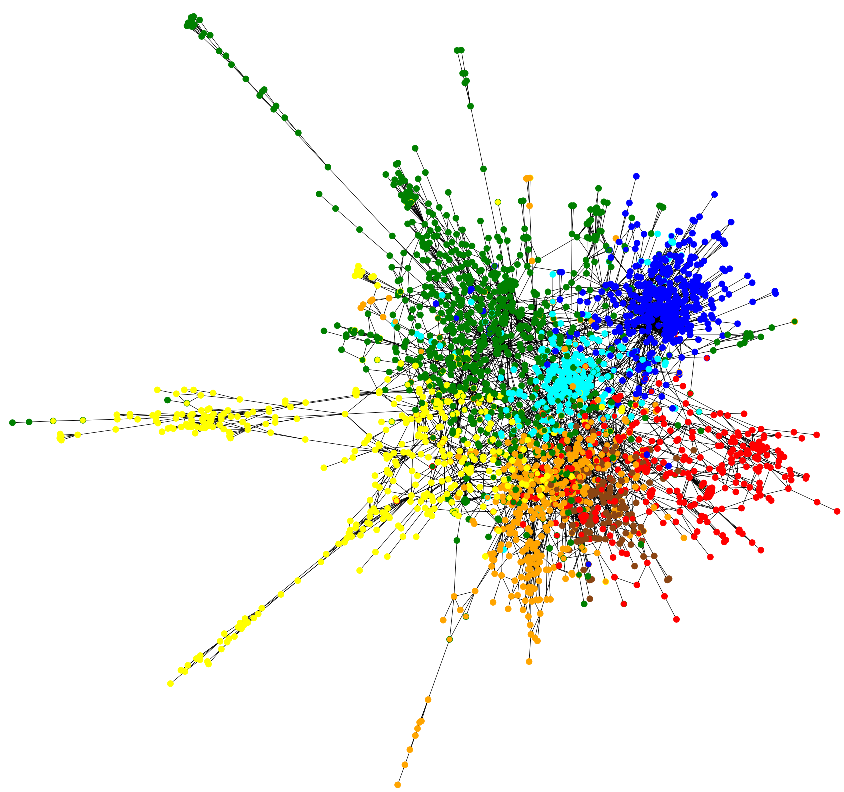

Figure 1. Predictions obtained applying MoNet over the Cora dataset. Marker fill color represents the predicted class; marker outline color represents the groundtruth class.

*Equal contribution

2. Manifolds

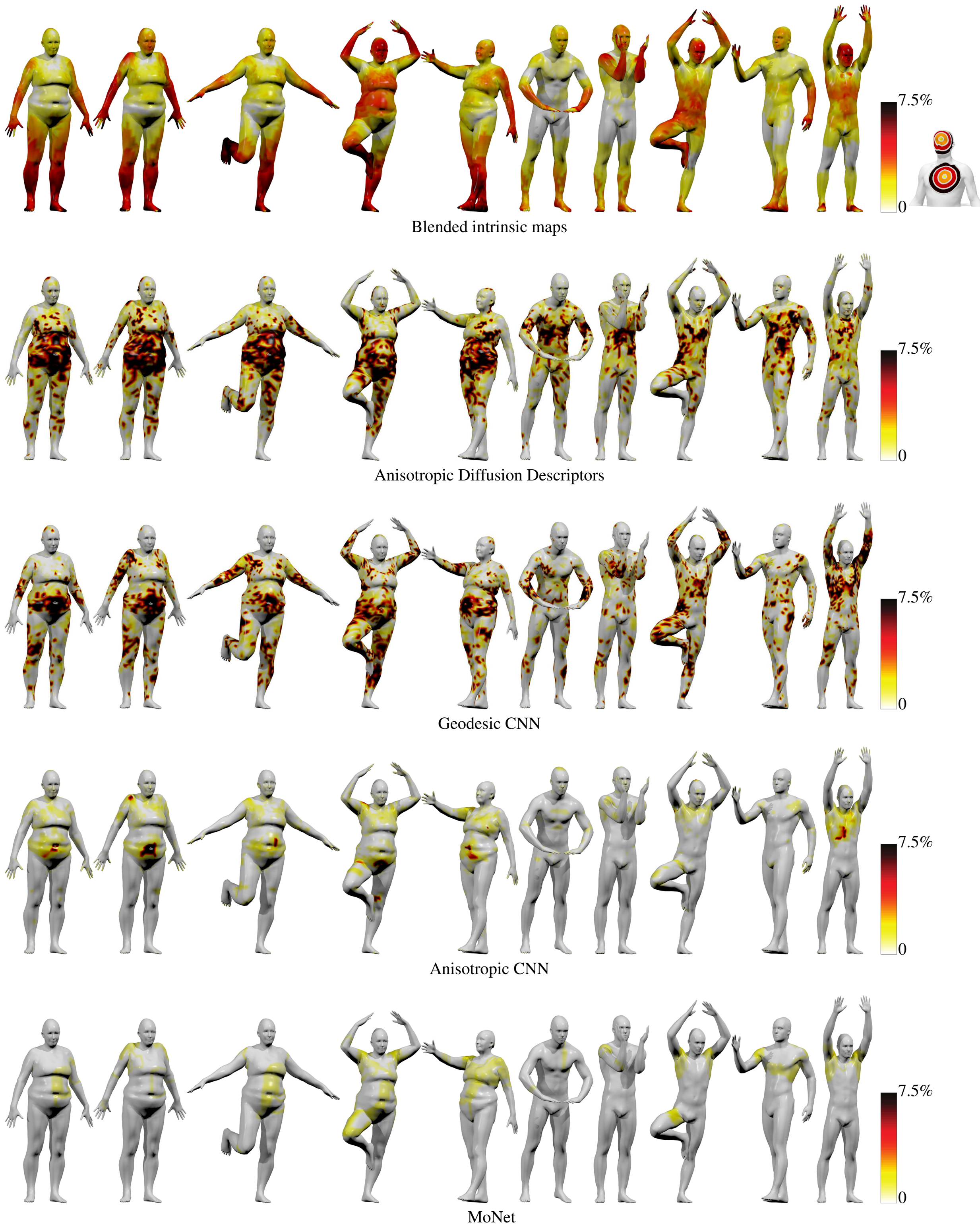

Figure 2. Pointwise error (geodesic distance from groundtruth) of different correspondence methods on the FAUST humans dataset. For visualization clarity, the error values are saturated at 7.5% of the geodesic diameter, which corresponds to approximately 15 cm. Hot colors represent large errors.

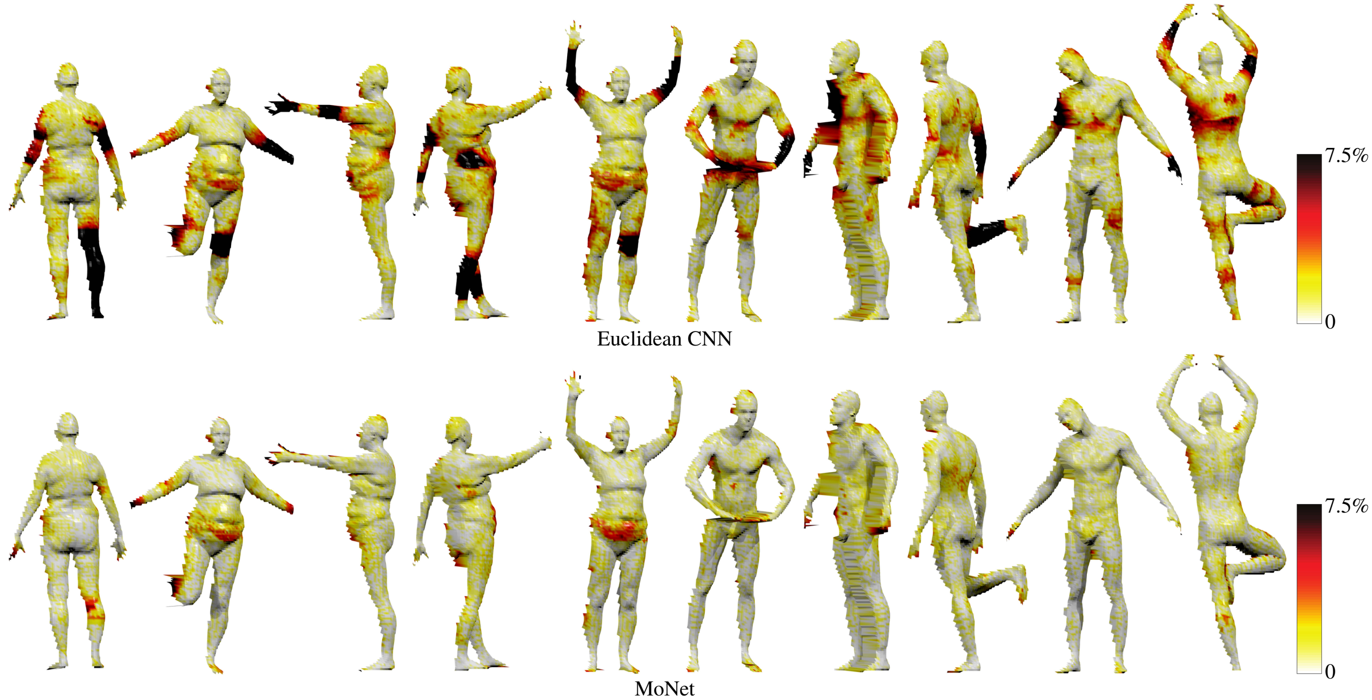

Figure 3. Pointwise error (geodesic distance from groundtruth) of different methods on FAUST range maps. For visualization clarity, the error values are saturated at 7.5% of the geodesic diameter, which corresponds to approximately 15 cm. Hot colors represent large errors.