Neural Intrinsic Embedding for Non-Rigid Point Cloud Matching

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Code available

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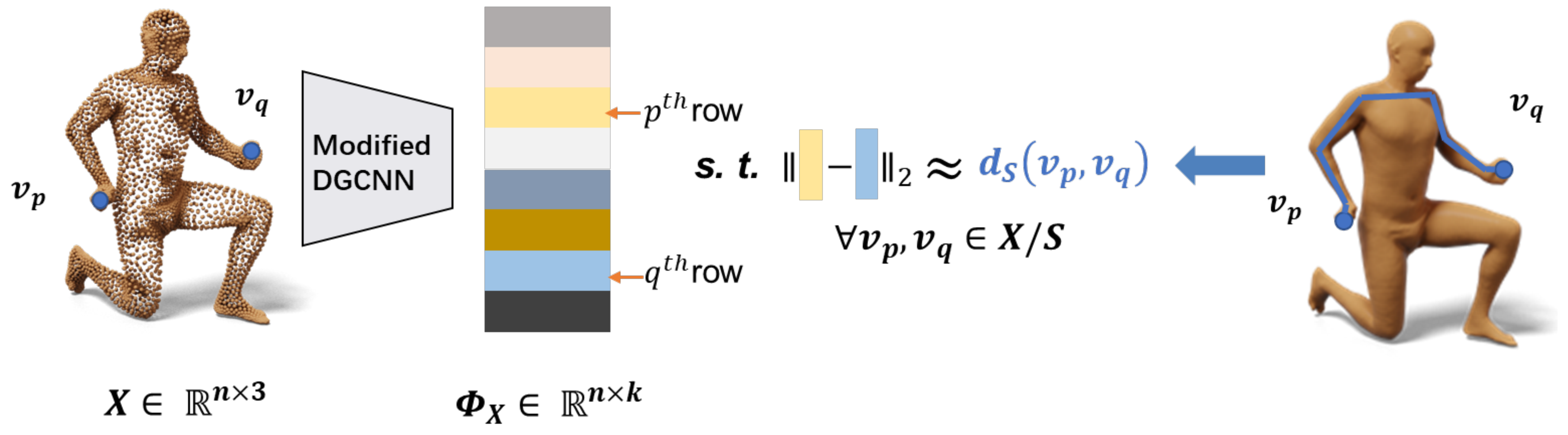
1. Motivation

Goal : Non-rigid point cloud matching

Challenges:	Desiderata :
Lack of intrinsic structure	Intrinsic geometry aware
Varying sampling density	Computationally efficient
Artifacts like noise, partiality…	Robustness
Lack of correspondences labels	Weak supervision

Solution: To develop an intrinsic geometry aware embedding scheme



Contributions:

- **Neural Intrinsic Embedding (NIE):** a learning-based framework to ***efficiently*** embed point cloud in an ***intrinsic geometry aware*** way.
- **Neural Intrinsic Mapping (NIM):** a ***weakly supervised*** deep functional maps framework based on NIE in place of eigenbasis.
- **A modification of DGCNN:** ***robust*** to sampling bias.

2. Method

Neural Intrinsic Embedding (NIE)

We design loss function to maintain the geodesic distance between points in NIE:

$$L_G(\Theta_B) = \sum_i \sum_{(p,q)\in S_i} \frac{\left|d_E^i(v_p, v_q) - d_S(v_p, v_q)\right|^2}{d_S(v_p, v_q)^2}$$

where d_S denotes the geodesic on the surface and d_E is the Euclidean distance between embedding.

Furthermore, we strengthen the short-distance recovery from a statistical point of view as follows :

$$L_{KL}(\Theta_B) = \sum_i \sum_p KL(P_E^p, P_S^p)$$

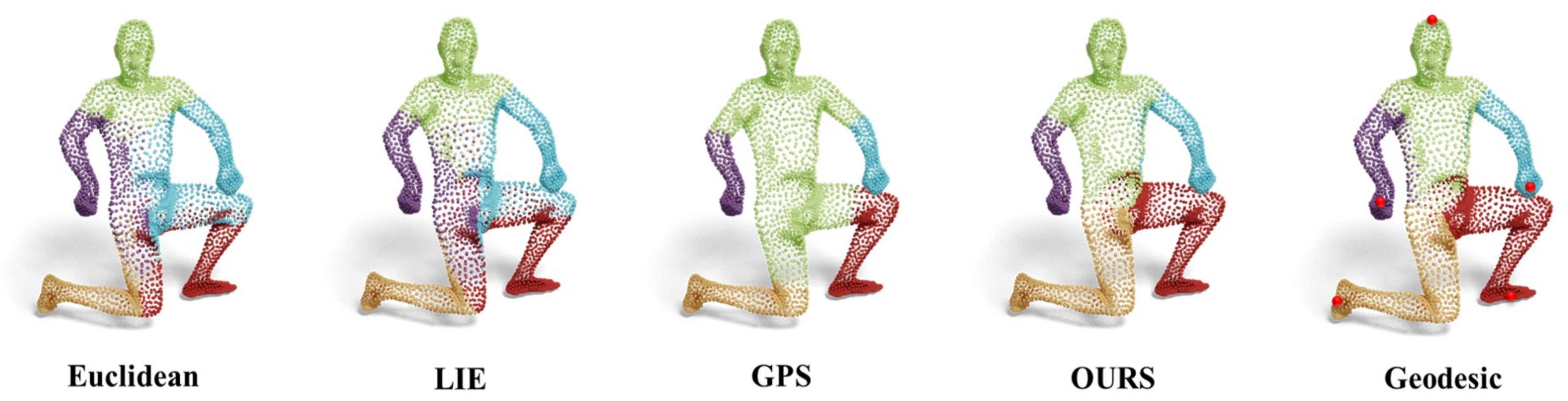
where P_E^p and P_S^p are distance distributions of p.

Finally, we take a self-supervised approach to avoid rank deficiency.

$$C_{ab} = \Phi_i^{b\dagger}\Pi_{ba}\Phi_i^a, C_{ba} = \Phi_i^{a\dagger}\Pi_{ab}\Phi_i^b$$

$$L_B(\Theta_B) = \sum_{a,b,i} \|C_{ab}C_{ba} - I\|_F^2 + \|C_{ba}C_{ab} - I\|_F^2$$

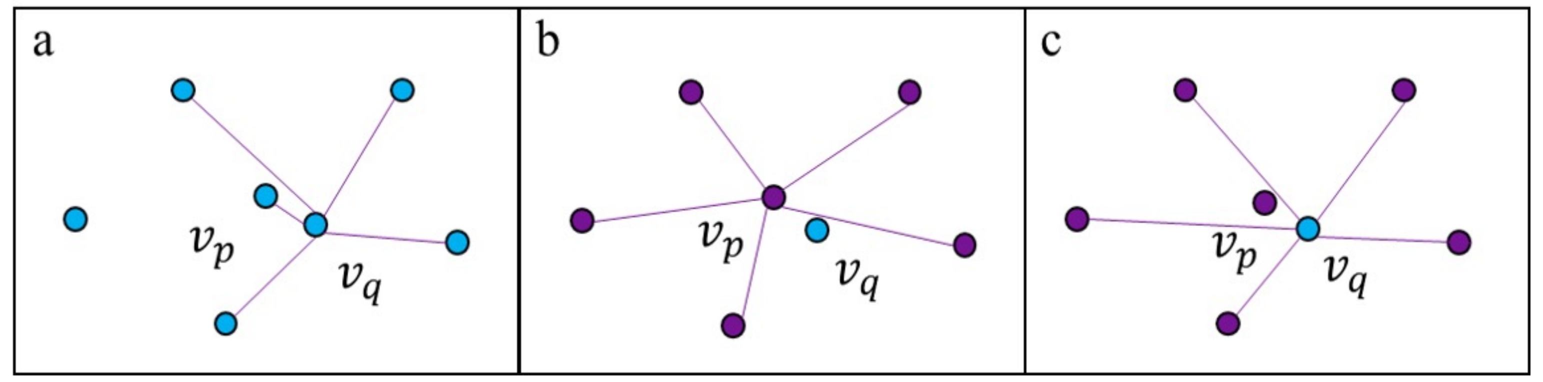
where X_i^a and X_i^b are disjoint subsamples from X_i via FPS, and Φ_i^a and Φ_i^b are the respective embeddings.



Our method takes in a raw point cloud and produces segmentation that is intrinsic geometry-aware.

A modification of DGCNN

DGCNN is sensitive to sampling density. To alleviate this, we propose a simple yet effective modification on DGCNN

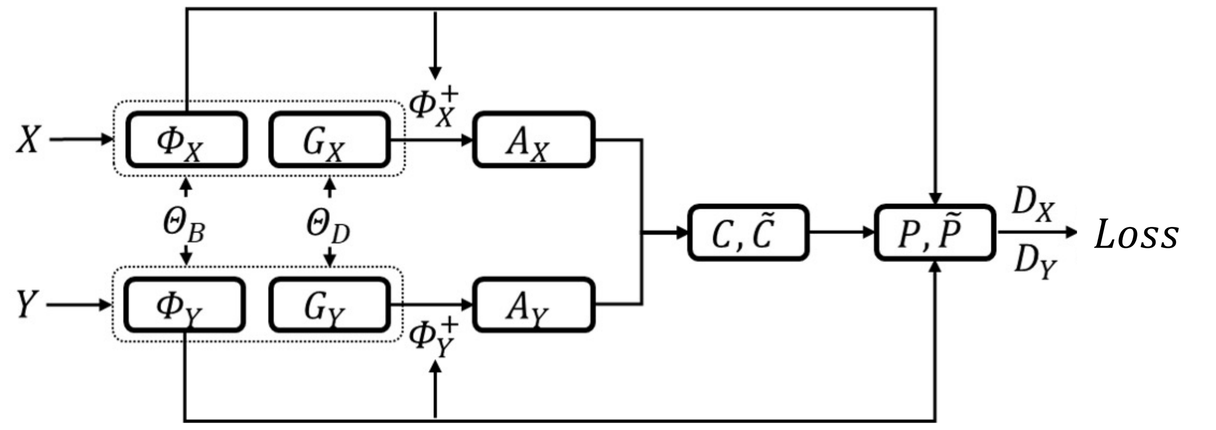


Given a point cloud X, we conduct FPS on X to obtain a evenly distributed subset X_s. Then, for a point v_q, instead of searching directly its k−NN within X, we find its nearest neighbor, v_p, in X_s, and then assign the k−NN of v_p within X_s to v_q.

Neural Intrinsic Mapping (NIM) network

We adopt the framework of **[1,2]** with the following changes:

- Replace the eigenbasis with our trained neural intrinsic embedding(NIE).
- Leverage NIE's intrinsic information to introduce a self-supervised loss.



3. Results

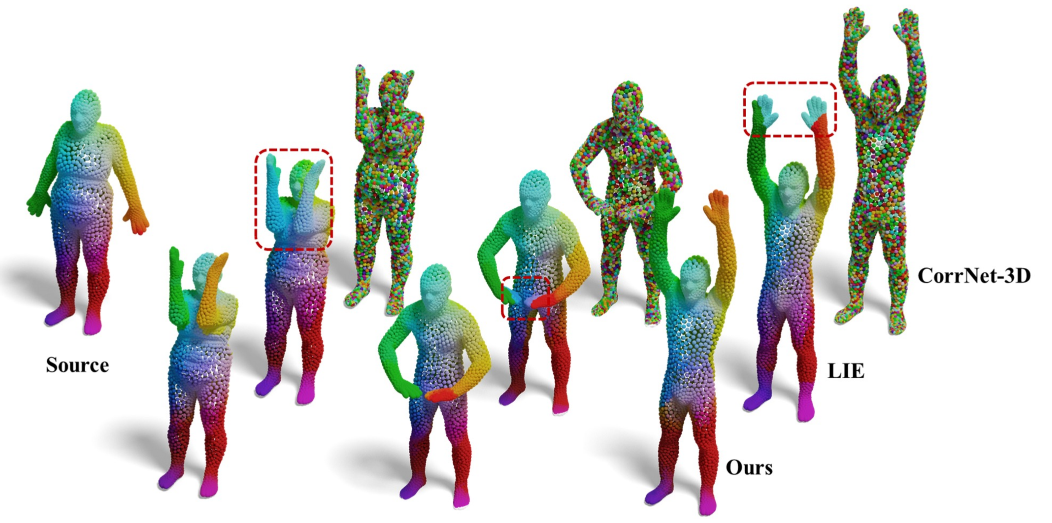
Ablation study of training loss terms

Method	OPT	Geo. Err.	Mat. Err.
L_G	4.4	**8.8**	13.2
$L_G + L_B$	3.5	12.4	11.8
$L_G + L_B + L_{KL}$	3.3	10.6	11.5
Full model with sample	**3.1**	9.5	**11.0**

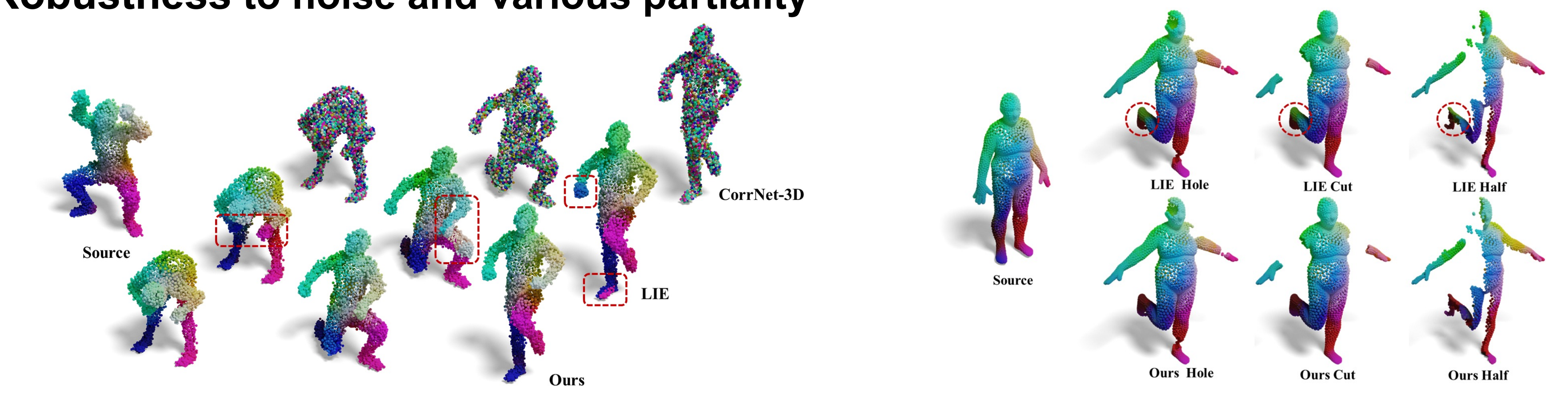
Method	Training: Surreal	
	Testing: S	F
Ours w/o sample	12.	8.1
Ours w sample	**10.**	**6.5**

Quantitative and Qualitative results

Method	F	S	F on S	S on F
3D-CODED(S)	**2.5**	31.	31.	33.
CorrNet-3D(U)	63.	58.	58.	63.
LIE(S)	3.6	12.	19.	12.
Ours(W)	5.5	**11.**	**15.**	**8.7**



Robustness to noise and various partiality



5. References

[1] Or Litany et al. **DeepFMap** ICCV 2017

[2] Dvir et al. **CyclicFMap** ECCV 2020