Supplement: Unsupervised Deep Learning for Structured Shape Matching

1. Supplement

A. Correlation with actual geodesic loss

To support the claim made in the subsection 'Evaluation and Results', we include a plot here to visualize the correlation between our loss and the actual geodesic loss. As evident in Figure 1, there is a strong correlation between our loss value and the quality of correspondence as measured by average geodesic error.

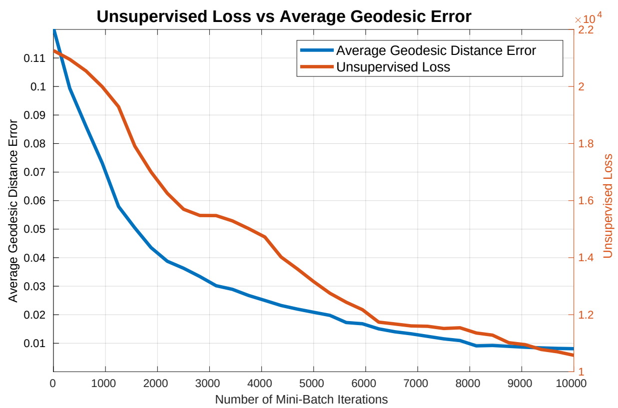


Figure 1: Correlation with average geodesic loss computed from ground truth correspondences.

B. Detailed Tabular Quantitative Comparison

Besides the average geodesic error reported for quantitative comparison in Figures 3 and 4, we provide detailed statistics in Table 1. Note that Table 1 also includes 'Fmap Ours Opt' which is equivalent to "Fmap Basic" but uses the learned descriptors instead of original ones. Its competitive performance across all datasets proves quantitatively the utility of learning descriptors. Figures 7 and 8 illustrate this further. For completeness, in Table 2, we also provide a detailed ablation study with different combinations of penalties.

C. Sensitivity to number of basis functions

Figure 2 shows the sensitivity of our network SURFMNet on the SCAPE remeshed dataset as the number of eigen functions are varied from 20 to 150. We train the network each time with 10000 mini batch steps. As evident, we obtain best result using 120. However, when trained on an individual dataset and tested on a different one, we see over-fitting when using a large eigen-basis. We attribute this phenomenon to the initialization of our descriptors with SHOT which is a very local descriptor and is not robust to very strong mesh variability. However, over-fitting is minimal when we train together on a relatively larger subset of SCAPE and FAUST and test on a different subset of shapes from both datasets, with smaller eigen basis.

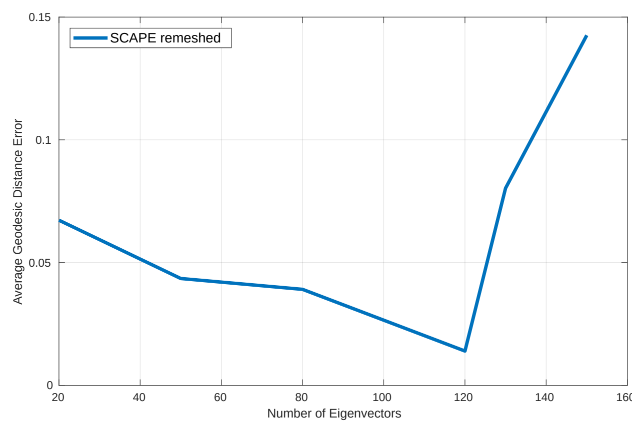


Figure 2: Accuracy of our method on the SCAPE remeshed dataset as the number of eigenfunctions is varied from 20 to 150.

D. More Qualitative Comparison

In Figures 5 and 6, we provide more qualitative comparisons of SURFMNet on the FAUST remeshed datasets whereas Figures 3 and 4 provide a comparison on the SCAPE remeshed dataset. In all cases, our method produces the highest quality maps.

(Results are $\times 10^{-3}$)	FAUST 7k			FAUST 5k			SCAPE 5k		
Supervised Methods	Mean	95th Percentile	Maximum	Mean	95th Percentile	Maximum	Mean	95th Percentile	Maximum
FMNet	25.01	63.11	1207.8	112.8	451.8	1280.6	172.6	543.8	1399.6
SURFMNet Subset	19.83	52.11	1204.0	92.09	493.6	1279.4	60.32	329.8	1068.7
FMNet + PMF	**2.98**	14.10	1222.7	83.61	395.7	1576.4	63.00	159.8	1561.5
SURFMNet-sub + PMF	5.33	22.90	1302.4	74.80	408.5	1619.3	51.03	111.5	1555.6
FMNet + ICP	11.16	27.91	1206.8	47.53	237.3	1348.6	81.76	341.4	1226.5
SURFMNet-sub + ICP	11.79	35.76	1088.4	**30.47**	95.64	1277.3	**23.00**	54.76	73.18
GCNN	-	-	-	50.49	206.3	1578.2	71.85	374.2	1523.7
Unsupervised Methods									
BCICP	15.46	53.27	572.4	31.08	64.51	1149.9	22.28	50.60	107.5
PMF (Gaussian Kernel)	29.42	83.80	1168.1	75.13	236.9	1632.7	54.68	156.9	465.1
PMF (Heat Kernel)	17.26	25.06	1168.1	31.08	64.51	1150.0	47.23	133.4	802.1
Fmap Basic	457.56	1171.4	1568.4	366.2	1159.0	1549.1	383.0	1043.7	1280.3
Fmap Ours Opt	9.75	30.02	420.2	20.19	53.24	1169.5	**13.98**	31.16	86.45
SURFMNet-all	**7.89**	26.01	572.4	**18.56**	50.25	1156.3	17.50	42.50	228.8

Table 1: Quantitative comparison on all three benchmark datasets for shape correspondence problem.

Methods	E1+E2+E3+E4	E3	E1+E2+E3	E1+E3+E4	E1	E2+E3+E4	E1+E2+E4	E2	E4	FMNet	Ours-Sub	Ours-all
Mean Geodesic Error	0.044	0.073	0.081	0.077	0.111	0.079	0.126	0.135	0.330	0.025	0.020	**0.008**

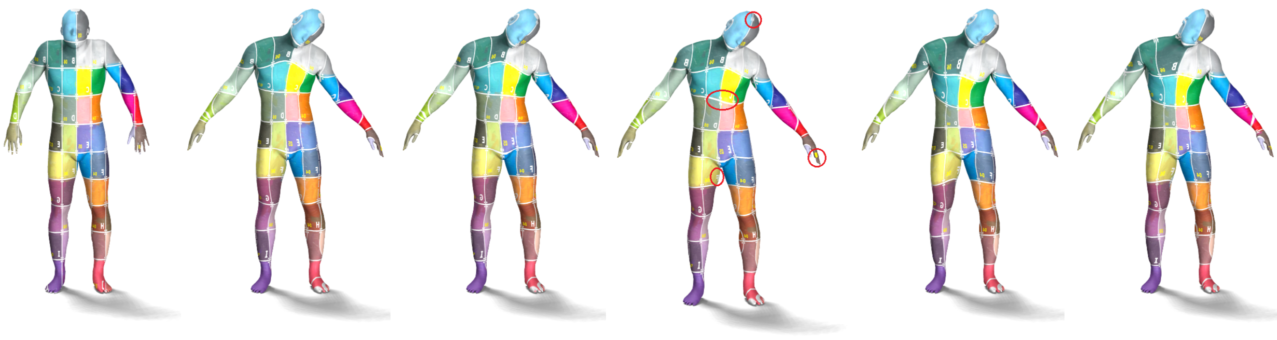
Table 2: Ablation study of penalty terms in our method and comparison with the supervised FMNet on the FAUST benchmark.

Source Ground-Truth SURFMNet-all BCICP PMF (heat) PMF (gauss)

Figure 3: Comparison of our method with *Unsupervised* methods for texture transfer on the SCAPE remeshed dataset.

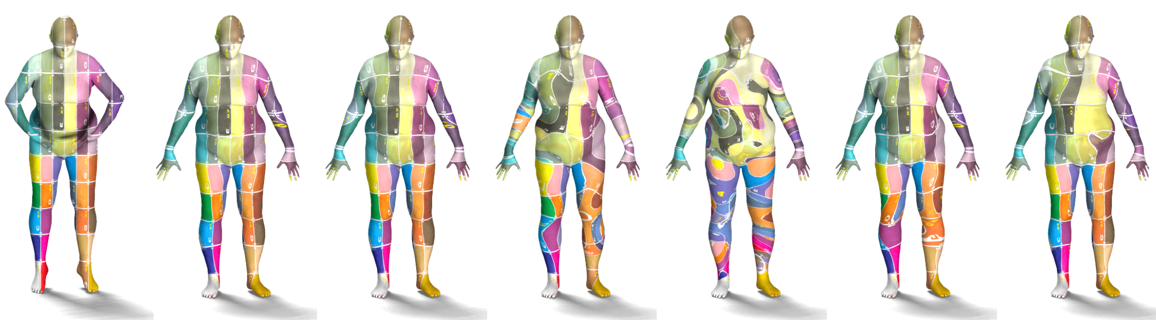
Source Ground-Truth SURFMNet + ICP SURFMNet FMNet FMNet + ICP GCNN

Figure 4: Comparison of our method with *Supervised* methods for texture transfer on the SCAPE remeshed dataset.



Source Ground-Truth SURFMNet BCICP PMF (heat) PMF (gauss)

Figure 5: Comparison of our method with *Unsupervised* methods for texture transfer on the FAUST remeshed dataset. Note that BCICP is roughly 7 times slower when compared to our method. We highlight the shortcomings of BCICP matching with red circles.



Source Ground-Truth SUFMNet + ICP SUFMNet FMNet FMNet + ICP GCNN

Figure 6: Comparison of our method with *Supervised* methods for texture transfer on the FAUST remeshed dataset.

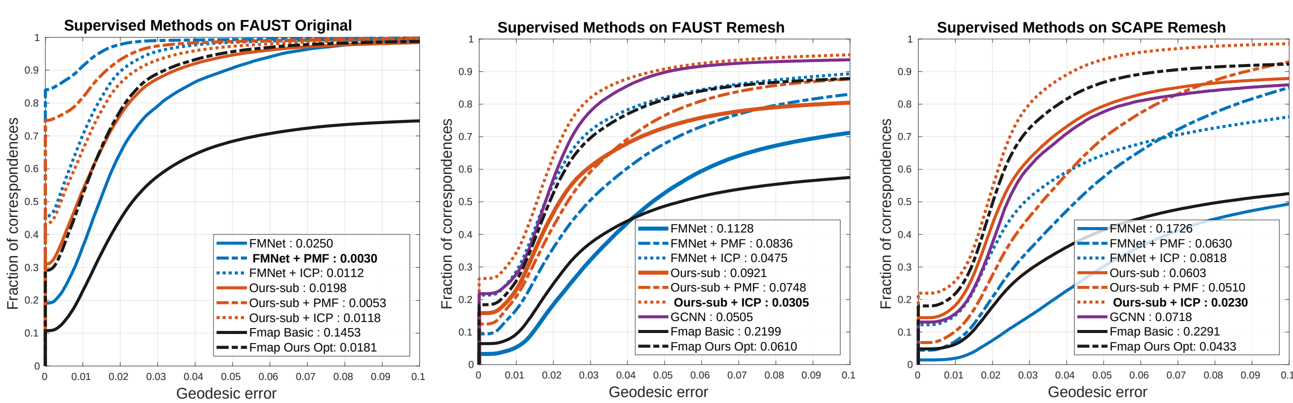


Figure 7: Quantitative evaluation of pointwise correspondences comparing our method with Supervised Methods.

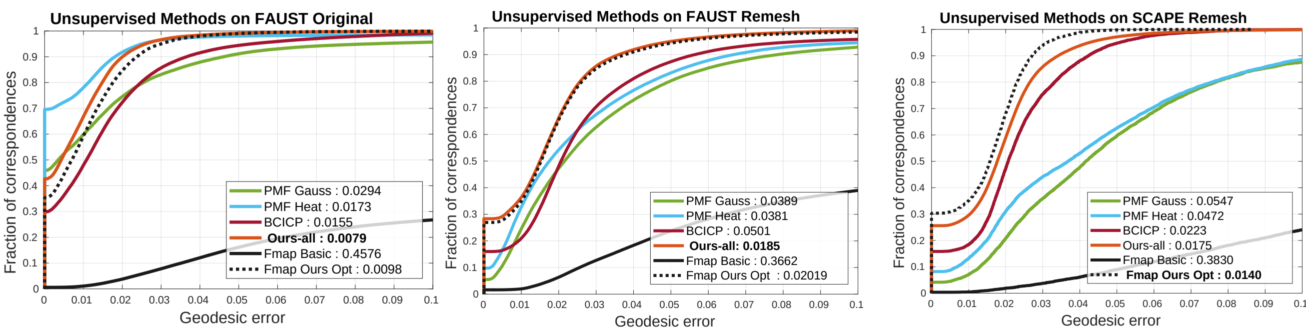


Figure 8: Quantitative evaluation of pointwise correspondences comparing our method with Unsupervised Methods.