THU-AM-120

Self-Supervised Learning for Multimodal Non-Rigid 3D Shape Matching

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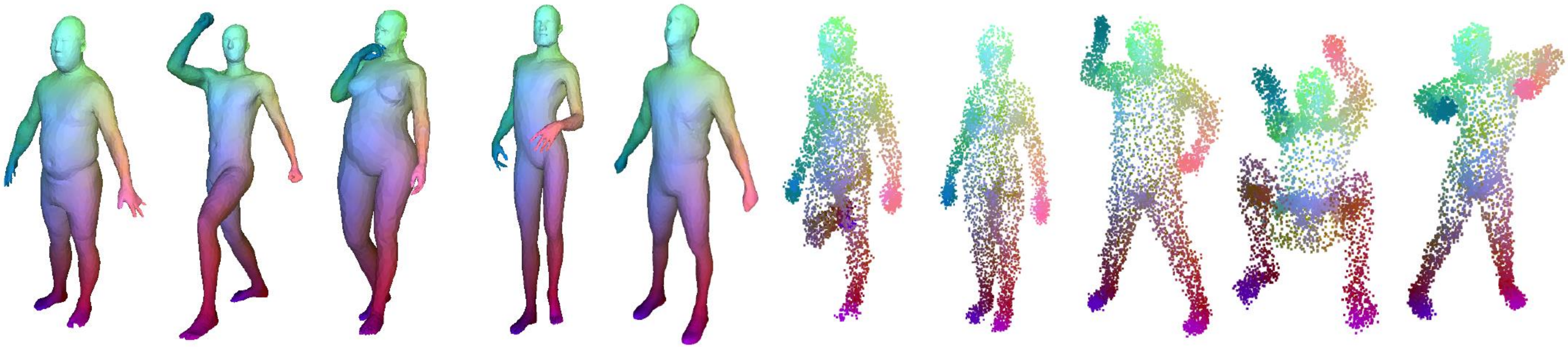
Non-rigid 3D shape matching results of ***partial*** shapes represented by both ***meshes*** and ***point clouds***

Overview

1) Multimodal non-rigid 3D shape matching under a ***self-supervised*** learning framework.
2) Combination of *unsupervised* ***functional map regularisation*** with *self-supervised* ***contrastive loss***.
3) Matching for both ***complete*** and ***partial*** meshes, point clouds, as well as across these data modalities.
4) Our method ***outperforms*** SOTA and shows previously unseen cross-dataset ***generalisation ability***.



Matching results on challenging dataset (trained on synthetic dataset) for both meshes and noisy point clouds

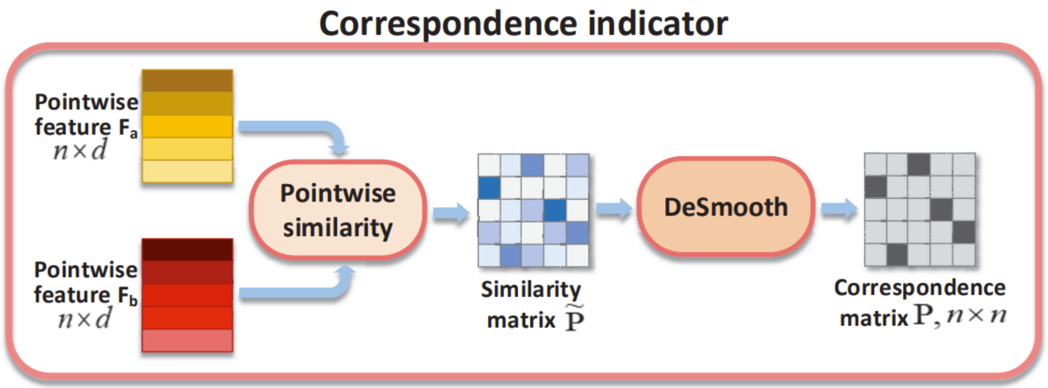
Background

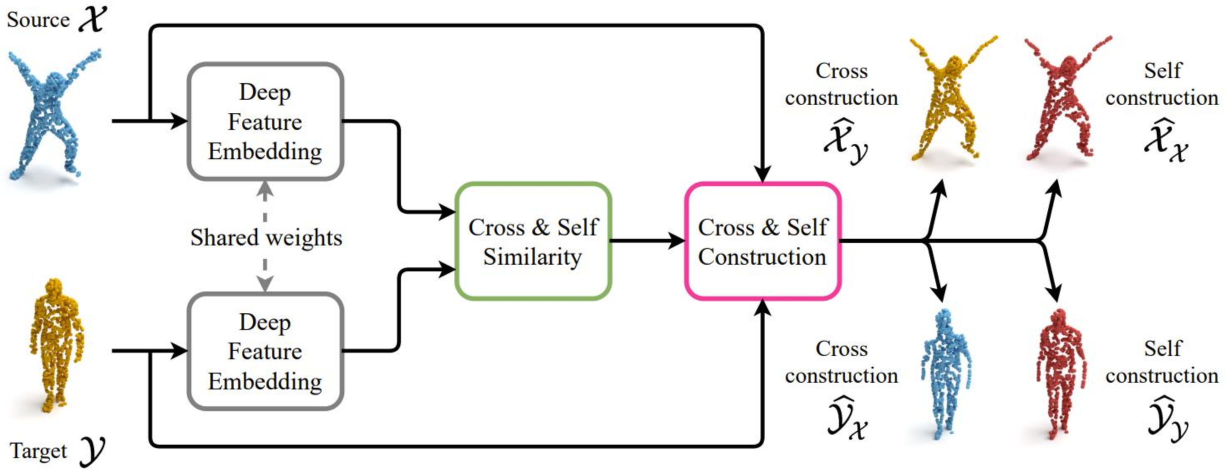
Source | DPC[1] | Deep Shells[2] | Ours | Ground Truth

Unsatisfiable matching results from both **point cloud matching** methods (e.g. DPC[1]) and **mesh-based** methods (e.g. Deep Shells[2]) applied to point cloud

[1] Itai Lang et al. DPC: Unsupervised deep point correspondence via cross and self construction. In 3DV, 2021.
[2] Marvin Eisenberger et al. Deep Shells: Unsupervised shape correspondence with optimal transport. In CVPR, 2021.

Related Work





Unsupervised Point Cloud Matching

Idea:

Unsupervised *point cloud matching methods* typically focus on learning discriminative *point-wise features*

Point-wise correspondences can be obtained using *nearest neighbour search* in the feature space

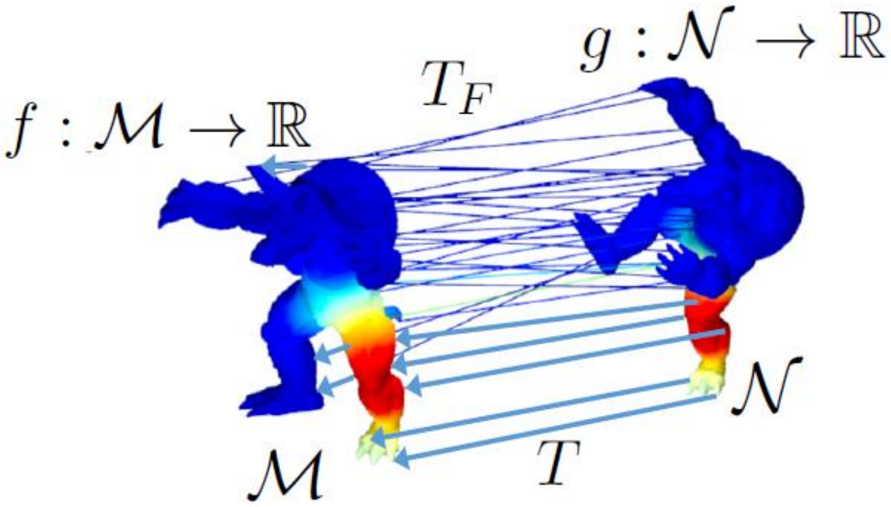
Difficulties:

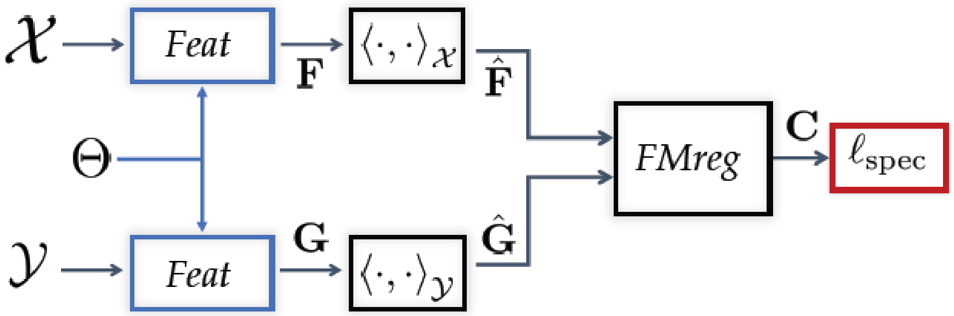
Design of efficient unsupervised loss terms to fully exploit the geometric information in point cloud

How to be robust against noisy and partial point clouds

[1] Y. Zeng et al. CorrNet3D: Unsupervised End-to-end Learning of Dense Correspondence for 3D Point Clouds. In CVPR, 2021.
[2] Itai Lang et al. DPC: Unsupervised deep point correspondence via cross and self construction. In 3DV, 2021.

Related Work





Unsupervised Matching for Meshes

Idea:

Unsupervised *matching methods for meshes* typically utilizes the *functional map framework* that is theoretically well analysed

Point-wise correspondences can be encoded into a small *functional map* that can be *regularized* during training

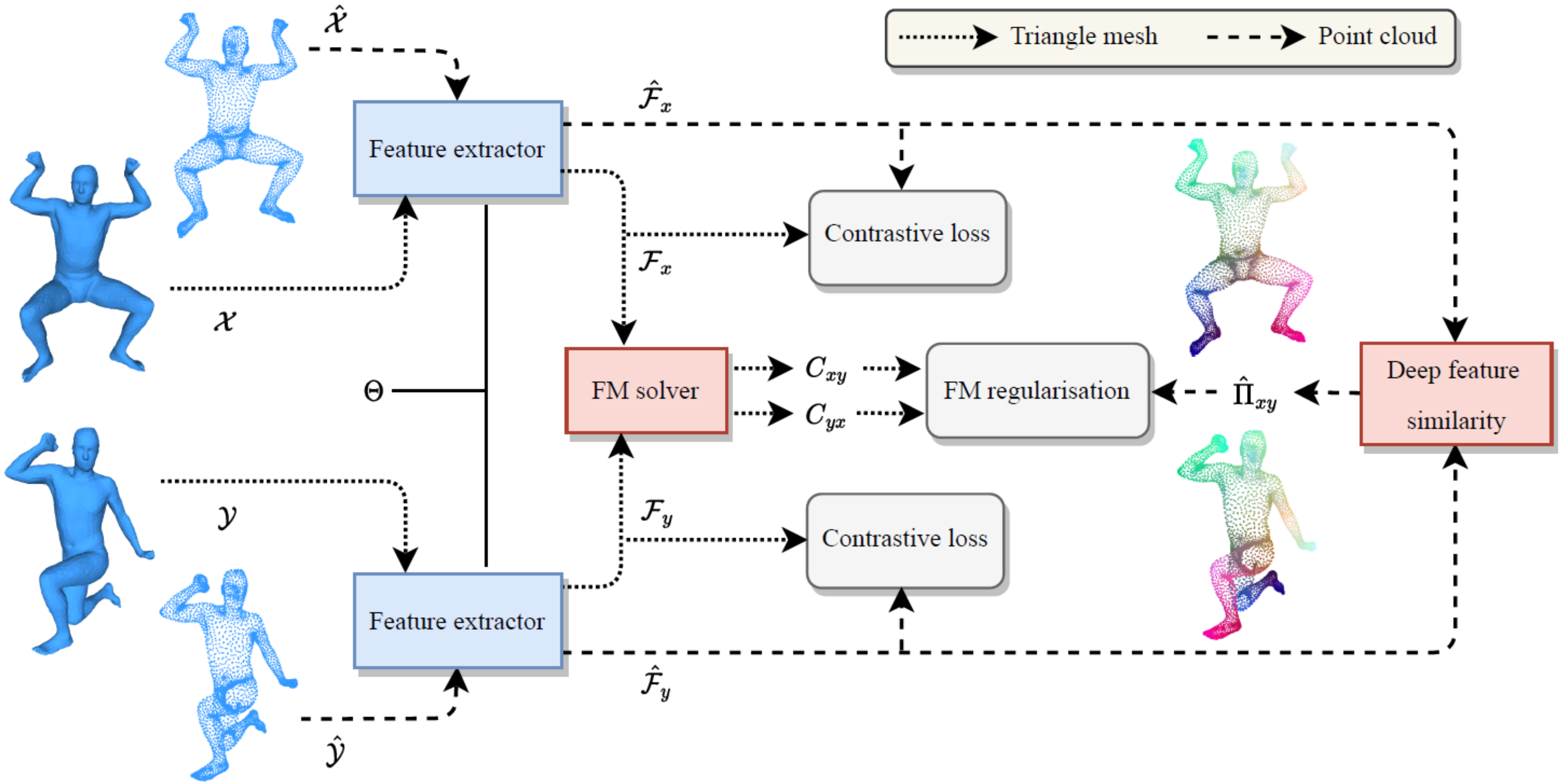
Difficulties:

Functional map computation is *inaccurate* for point clouds

Functional map computation and conversion during inference

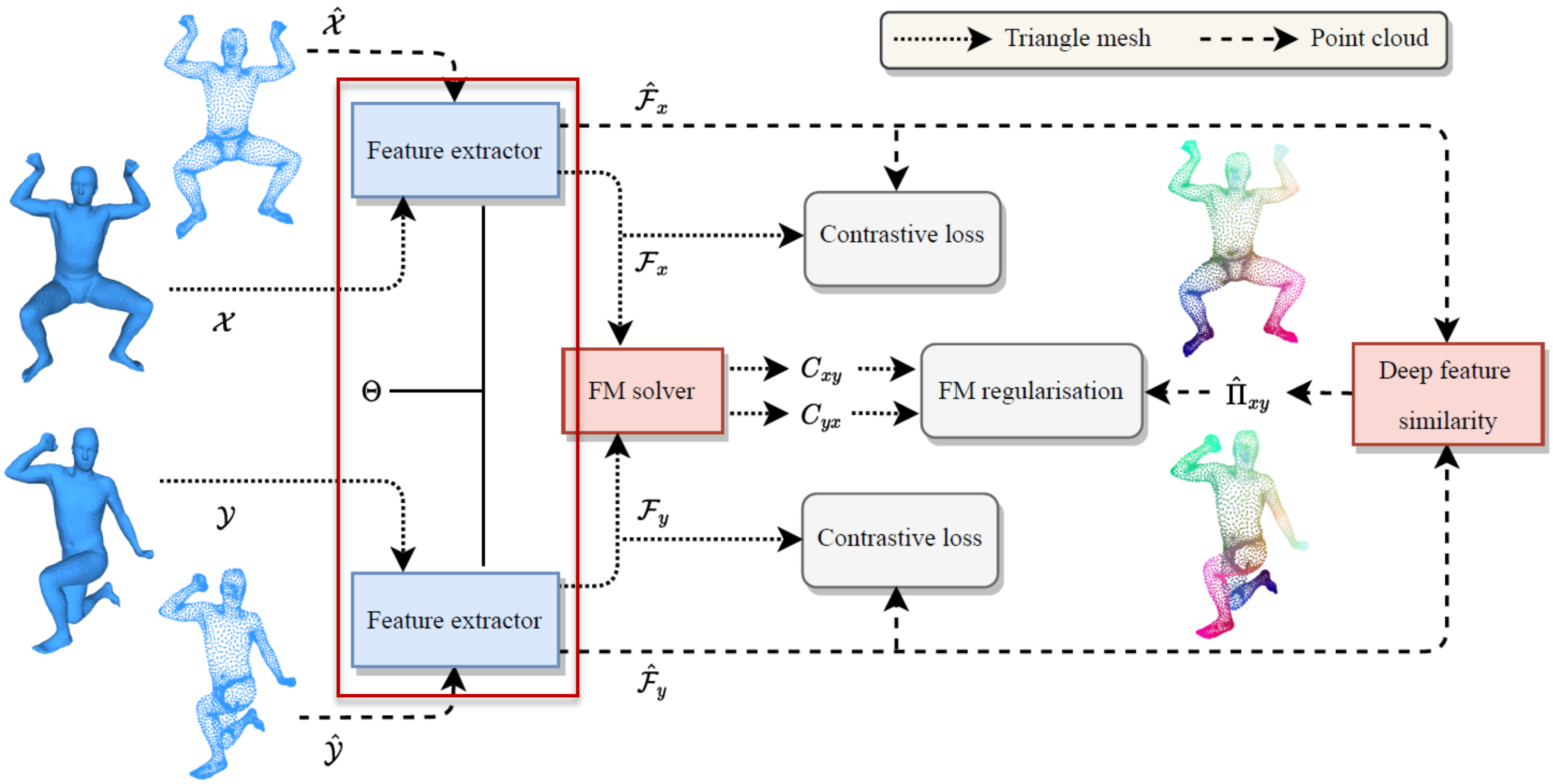
[1] M. Ovsjanikov et al. Functional maps: a flexible representation of maps between shapes. In ToG, 2012.
[2] N. Donati et al. Deep Geometric Functional Maps: Robust Feature Learning for Shape Correspondence. In CVPR, 2020.

Our Method



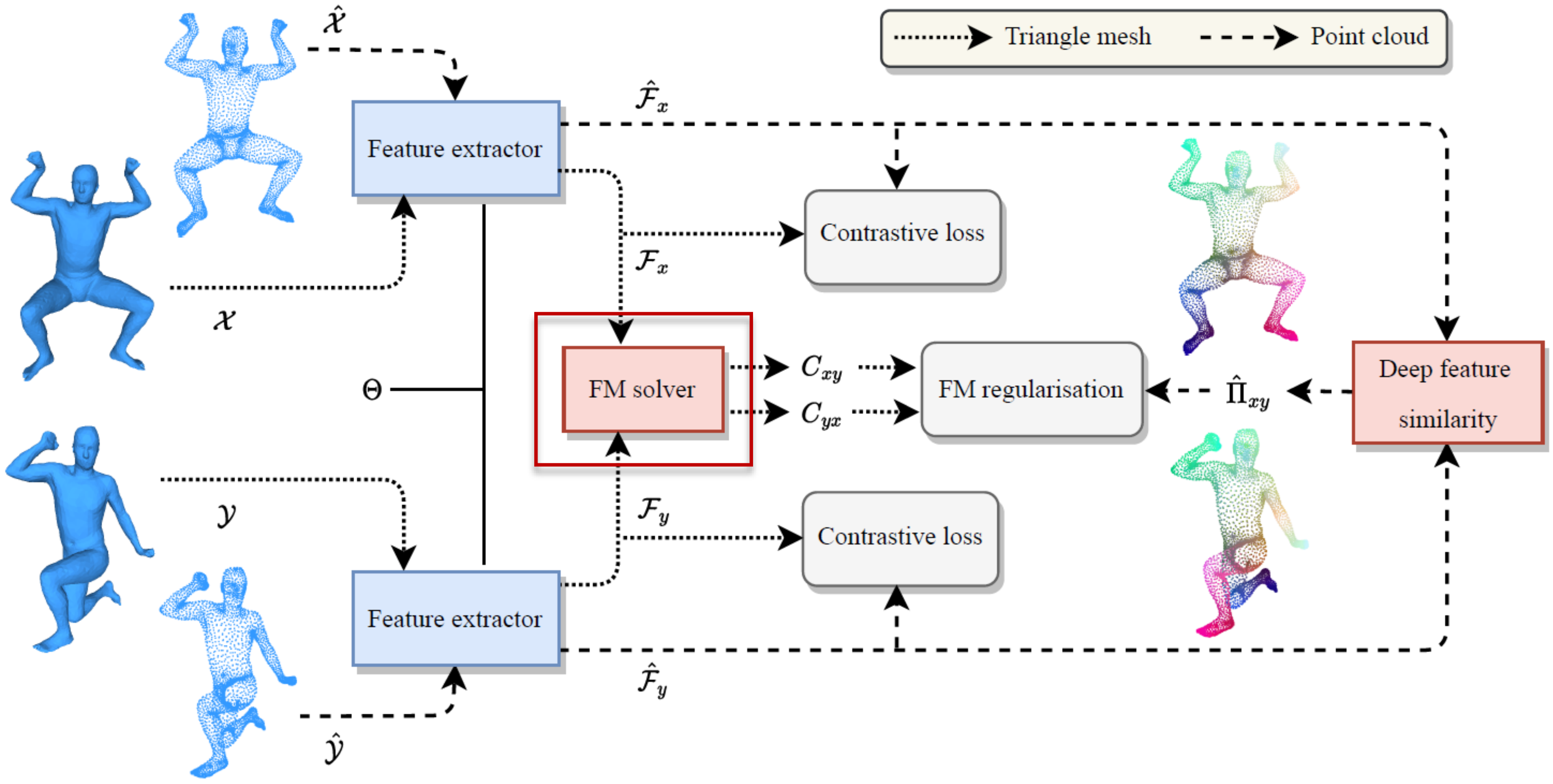
Our method combines *unsupervised functional map regularisation* with *self-supervised contrastive learning* to enable multi-modal non-rigid 3D shape matching

Feature Extractor



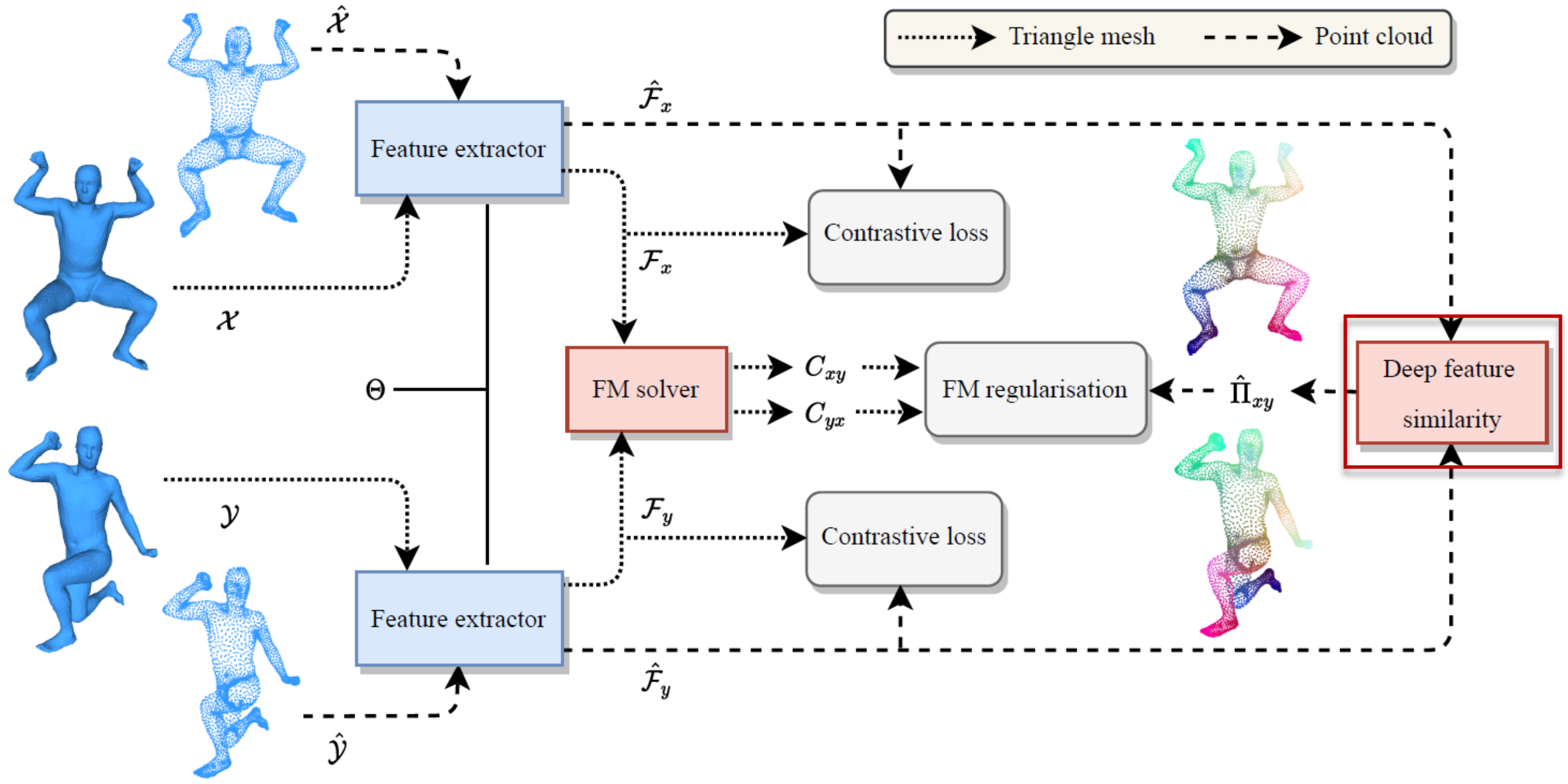
A Siamese network takes *multimodal* input shapes to extract *point-wise features*

FM Solver



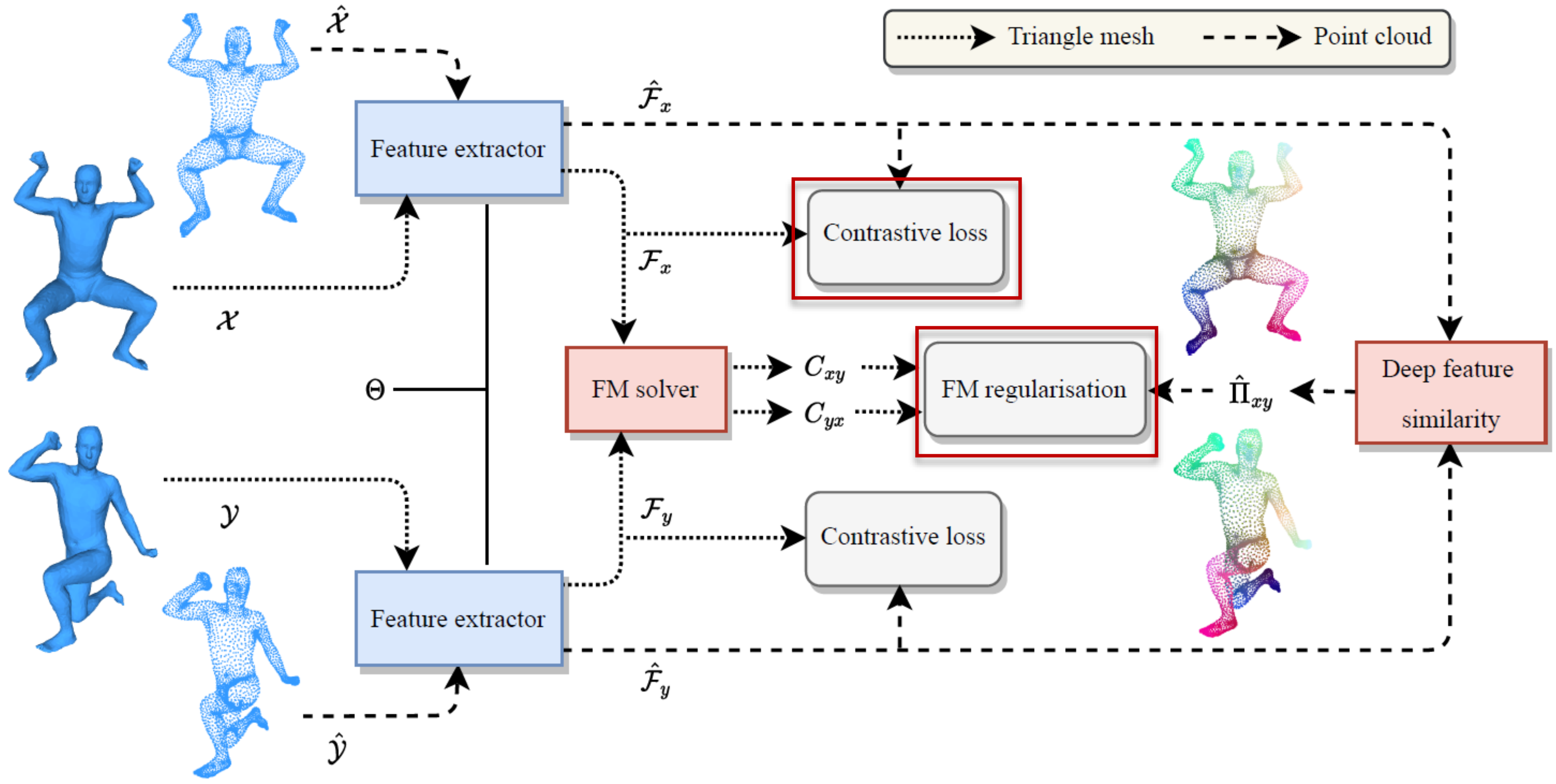
A *differentiable* and *non-learnable* solver to obtain bidirectional *functional maps* for *meshes*

Deep Feature Similarity



Obtain soft *point-wise correspondences* between *point clouds* based on deep feature similarity

Self-Supervised Losses



Combination of *functional map regularisation* and multimodal *contrastive loss*

Experiments

Geo. error (×100)	FAUST Mesh	FAUST PC	FAUST Noisy PC	SCAPE Mesh	SCAPE PC	SCAPE Noisy PC	SHREC'19 Mesh	SHREC'19 PC	SHREC'19 Noisy PC	FM-based
Axiomatic Methods										
BCICP [43]	6.4	-	-	11.0	-	-	8.0	-	-	✓
ZOOMOUT [35]	6.1	-	-	7.5	-	-	7.8	-	-	✓
Smooth Shells [15]	2.5	-	-	4.7	-	-	7.6	-	-	✓
Supervised Methods										
FMNet [28]	3.1	8.5	14.0	9.1	15.0	21.3	10.4	14.3	19.1	✓
3D-CODED [19]	2.5	2.5	2.8	9.8	9.8	10.0	7.7	7.7	7.9	✗
IFMatch [55]	2.6	2.6	2.7	11.0	11.0	11.2	6.5	6.5	6.6	✗
DiffFMaps [32]	10.5	10.5	11.7	23.1	23.1	22.7	18.2	18.2	19.4	✓
GeomFMaps [13]	2.6	6.1	10.2	3.0	7.7	13.3	4.1	10.6	14.6	✓
Unsupervised Methods										
SURFMNet [46, 51]	2.4	6.0	13.5	6.0	11.3	20.1	4.8	13.9	19.1	✓
UnsupFMNet [21]	4.8	9.6	17.8	9.6	11.3	15.5	11.1	17.3	23.8	✓
Deep Shells [17]	**1.7**	6.0	11.2	5.3	7.8	11.1	7.5	11.7	14.4	✓
ConsistFMaps [8]	2.4	11.2	16.9	5.1	12.3	16.4	4.2	13.7	17.2	✓
CorrNet3D [63]	26.5	26.5	27.0	37.3	37.3	36.8	33.7	33.7	34.0	✗
DPC [26]	11.6	11.6	14.6	16.0	16.0	18.6	17.6	17.6	19.4	✗
Ours	2.0	**2.4**	**4.4**	**3.1**	**4.1**	**6.6**	**4.0**	**4.5**	**5.8**	✓

Quantitative results on the FAUST, SCAPE and SHREC'19 datasets in terms of mean geodesic errors.

Experiments

Geo. (×100)	F (PC)	S (PC)	S19 (PC)	|Data|
Supervised Methods				
FMNet [28]	3.8 (12.2)	10.2 (15.3)	13.8 (22.7)	5k
DiffFMaps [32]	26.5 (26.5)	34.8 (34.8)	42.2 (42.2)	230k
GeomFMaps [13]	2.7 (10.4)	3.3 (8.7)	4.7 (14.1)	5k
Unsupervised Methods				
SURFMNet [46, 51]	2.3 (16.0)	3.3 (14.7)	8.3 (27.8)	5k
Deep Shells [17]	8.1 (12.5)	12.2 (14.1)	12.1 (15.9)	5k
ConsistFMaps [8]	3.2 (19.3)	6.7 (17.3)	13.7 (24.2)	5k
CorrNet3D [63]	18.1 (18.1)	18.3 (18.3)	18.8 (18.8)	230k
DPC [26]	13.4 (13.4)	15.8 (15.8)	17.4 (17.4)	230k
Ours	**2.0 (3.5)**	**3.2 (3.8)**	**4.4** (6.6)	5k

Cross-dataset generalisation evaluated on the **F**AUST, **S**CAPE and **S**HREC'**19** datasets and trained on the SURREAL dataset.

Geo. error (×100)	CUTS (PC)	HOLES (PC)
Axiomatic Methods		
PFM [44]	9.7 (-)	23.2 (-)
FSP [29]	16.1 (-)	33.7 (-)
Supervised Methods		
GeomFMaps [13]	8.0 (18.5)	12.9 (18.9)
DPFM sup [2]	3.2 (10.4)	11.8 (17.0)
Unsupervised Methods		
ConsistFMaps [8]	8.4 (26.6)	17.9 (27.0)
DPFM unsup [2]	9.0 (20.9)	20.5 (22.8)
Ours	**7.6** (**12.2**)	**15.9** (**16.7**)

Quantitative results on the CUTS and HOLES subsets of the SHREC'16 dataset

Qualitative Results