# DispVoxNets: Non-Rigid Point Set Alignment with Supervised Learning Proxies


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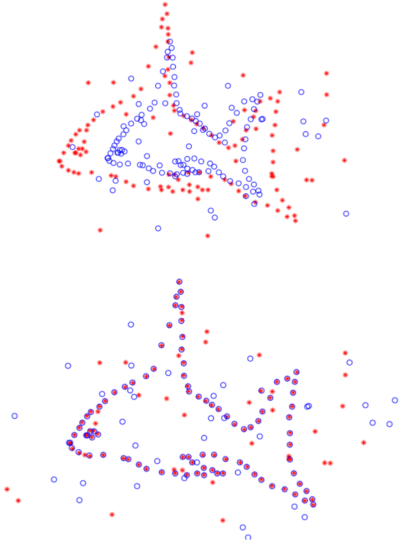
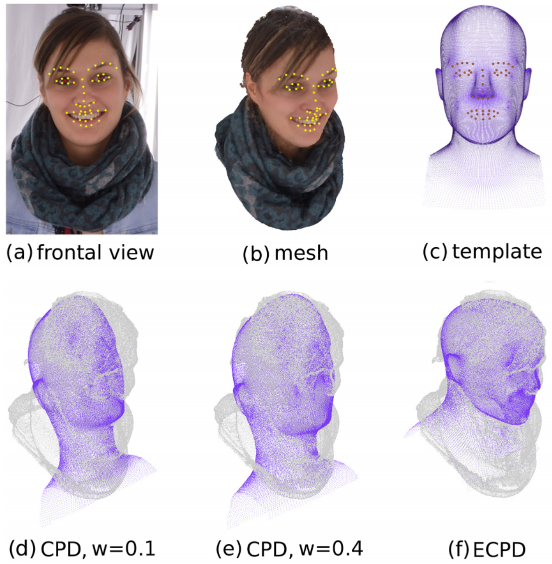
# Non-rigid Point Set Registration (NRPSR)

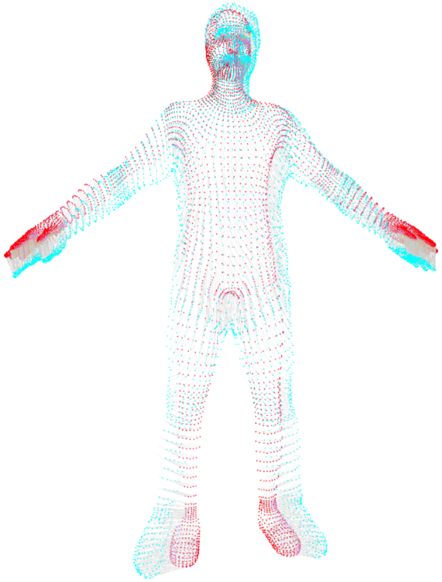
Objective: given two point sets, find displacements (or correspondences) between the point sets.



*2D point set registration*
[Myronenko and Song 2010]




*3D face registration*
[Taetz *et al.* 2016]



*3D pose registration*
[Golyanik *et al.* 2017]

# Related Works,  General-Purpose Methods

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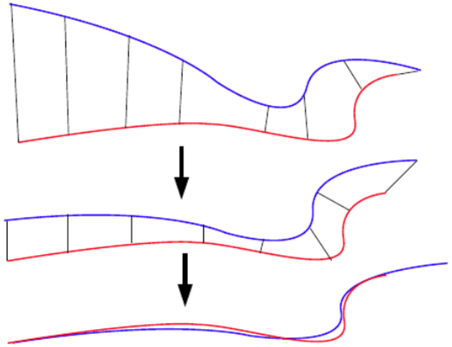
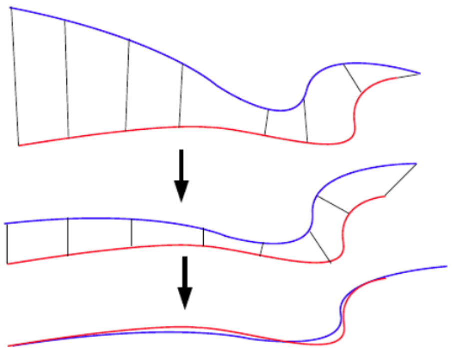


Iterative Closest Point (ICP)

[Besl and McKay 1992]

the image is taken from [Smistad *et al*. 2015]

# Related Works,  General-Purpose Methods



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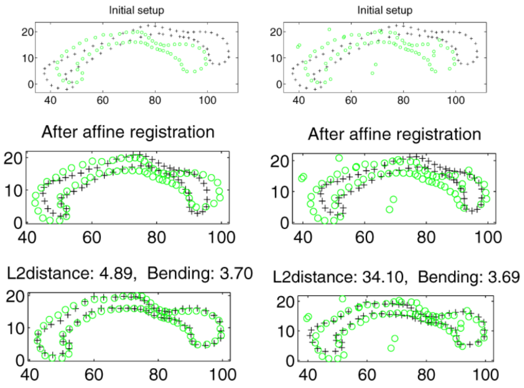
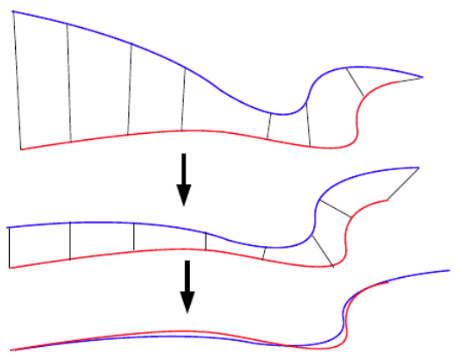



Gaussian Mixture Model Registration (GMR)

[Jian *et al*. 2005 ]

# Related Works, General-Purpose Methods



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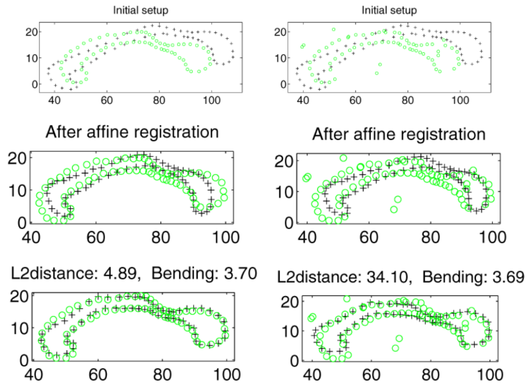
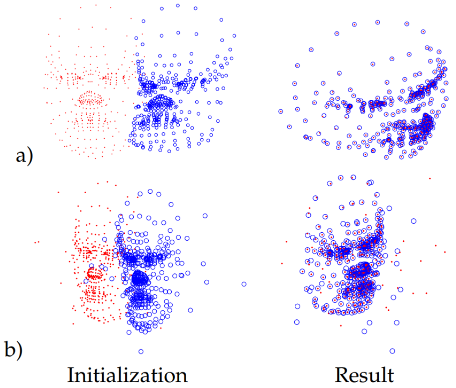


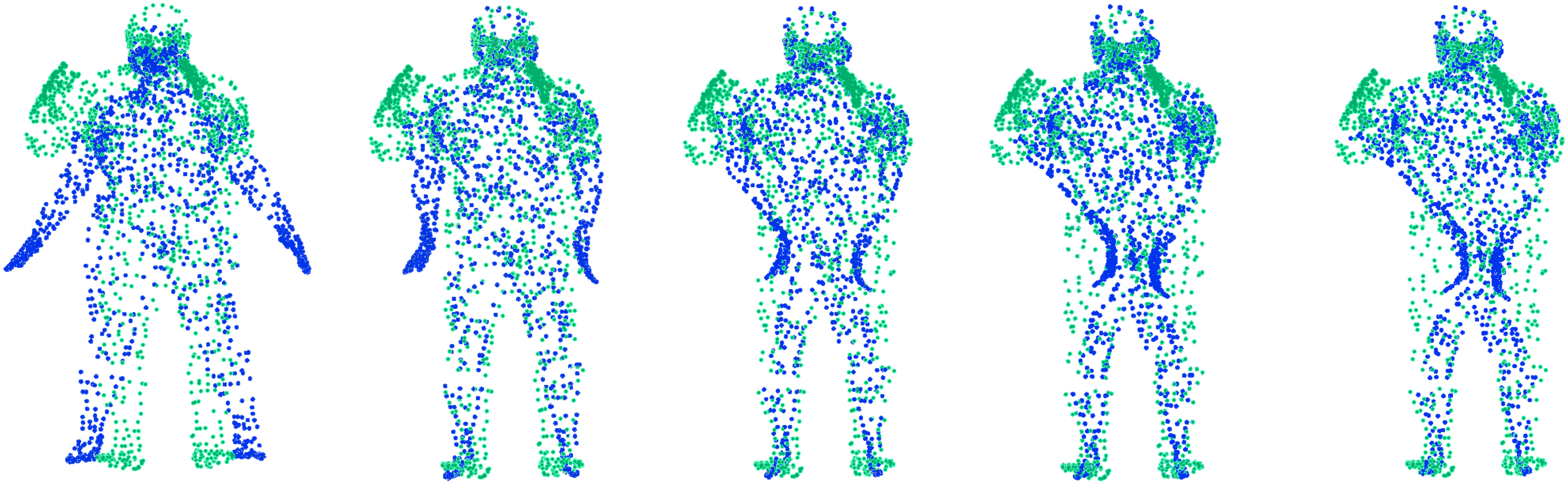

Gaussian Mixture Model Registration (GMR)
[Jian *et al*. 2005 ]




Coherent Point Drift (CPD)
[Myronenko and Song 2010 ]

# Related Works, General-Purpose Methods

Green : reference
Blue : template

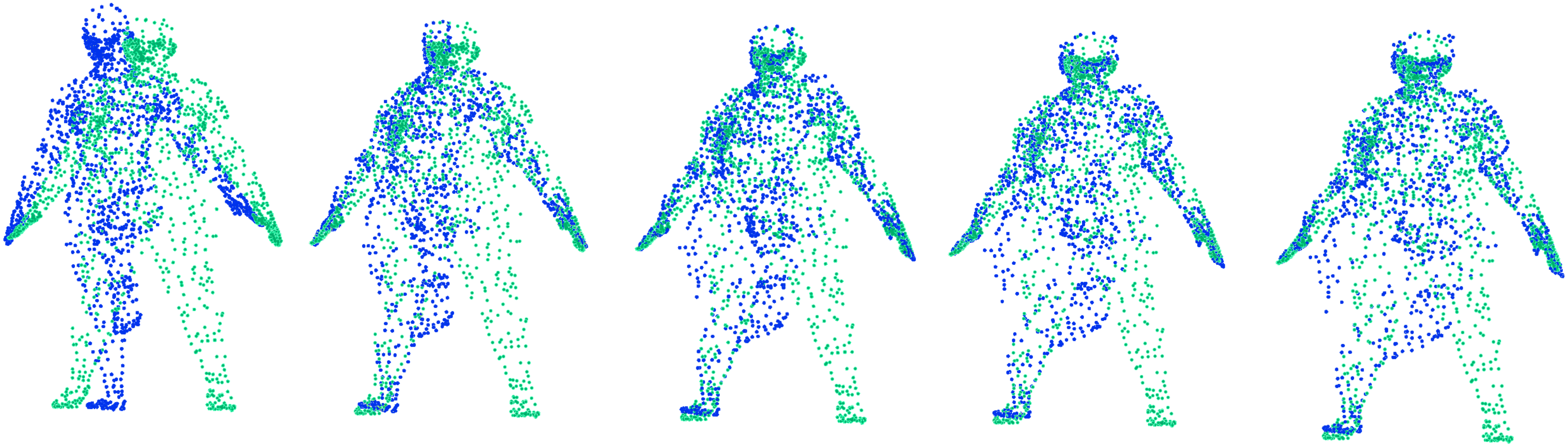


Initialisation Iteration 25 Iteration 50 Iteration 75 Iteration 100

Gravitational Approach for NRPSR
[Ali *et al.* 2018]

# Related Works, General-Purpose Methods

Green : reference
Blue : template

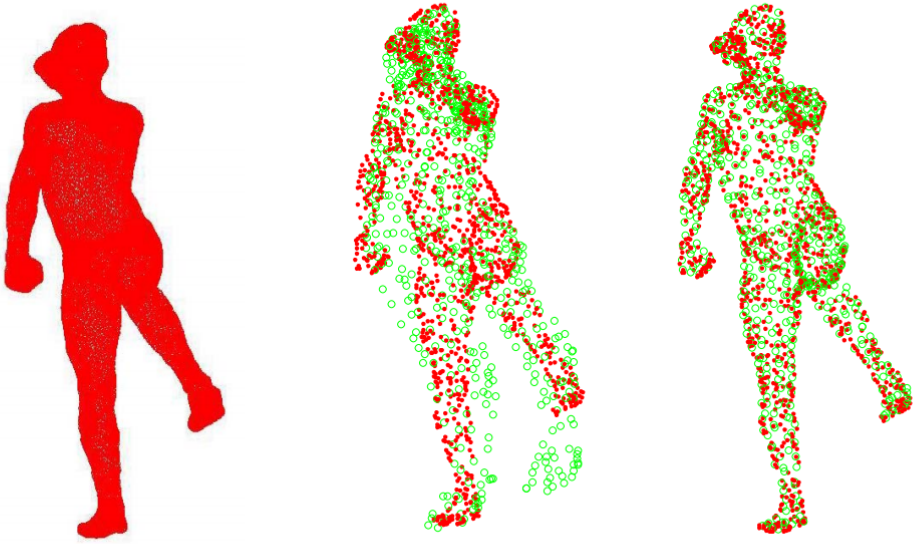


Initialisation Iteration 25 Iteration 50 Iteration 75 Iteration 100

Gravitational Approach for NRPSR
[Ali *et al.* 2018]

➡ Often fails with large deformations and articulated motions between the point sets.

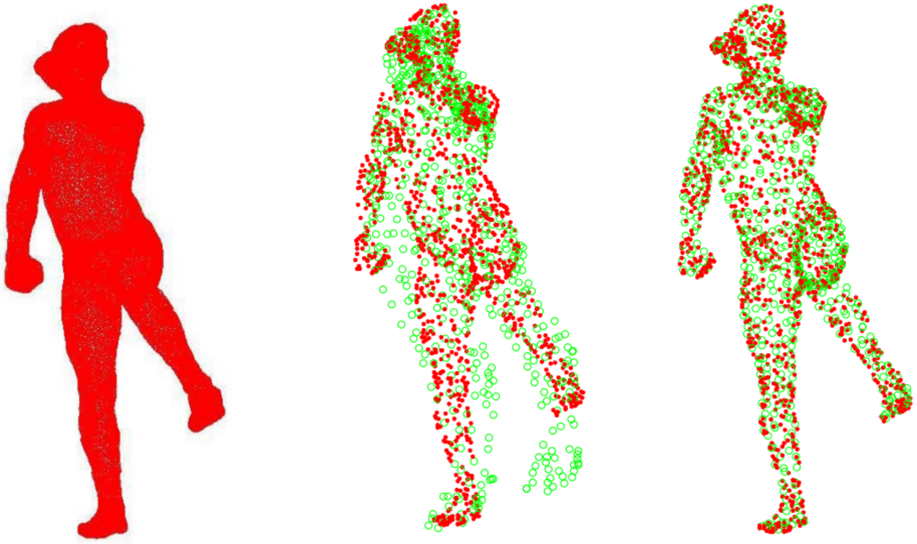
# Related Works, General-Purpose Methods



Target CPD GLTP

[Ge *et al*. 2014 ]

# Related Works, General-Purpose Methods

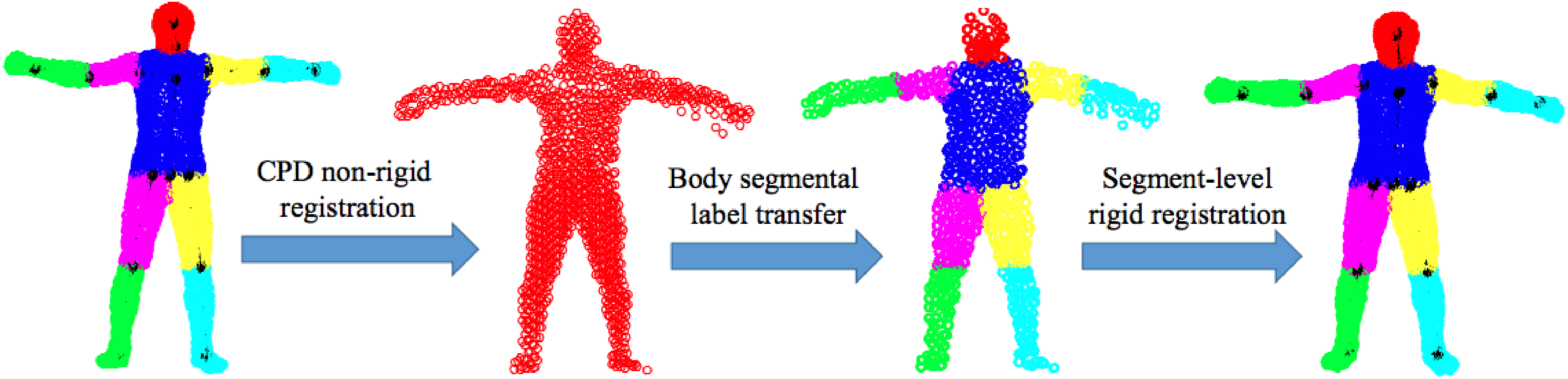


Target CPD GLTP

[Ge *et al.* 2014 ]

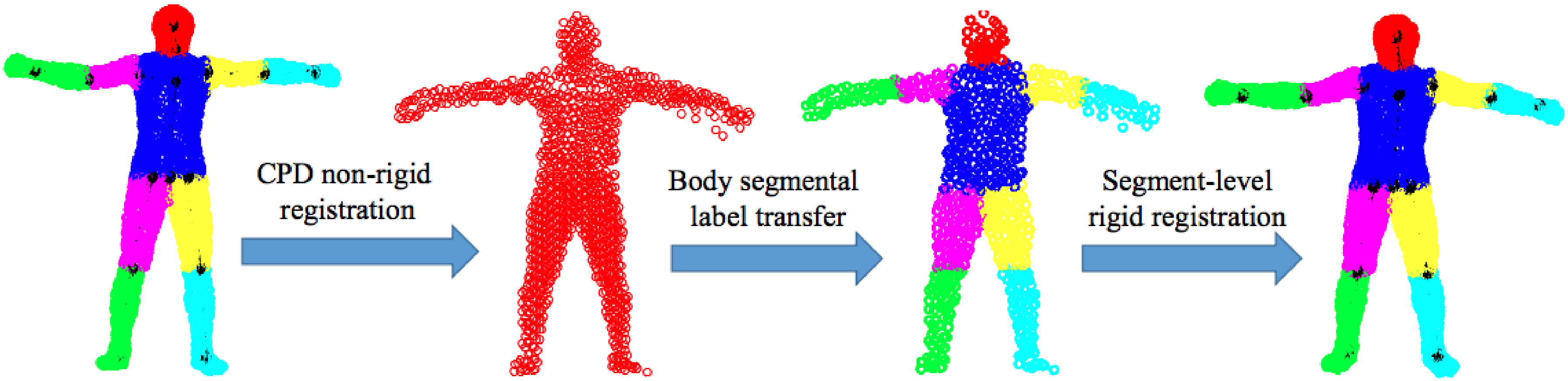
Relatively accurate however sensitive to noises

# Related Works,  Class-Specific Methods




[Ge and Fan 2015 ]

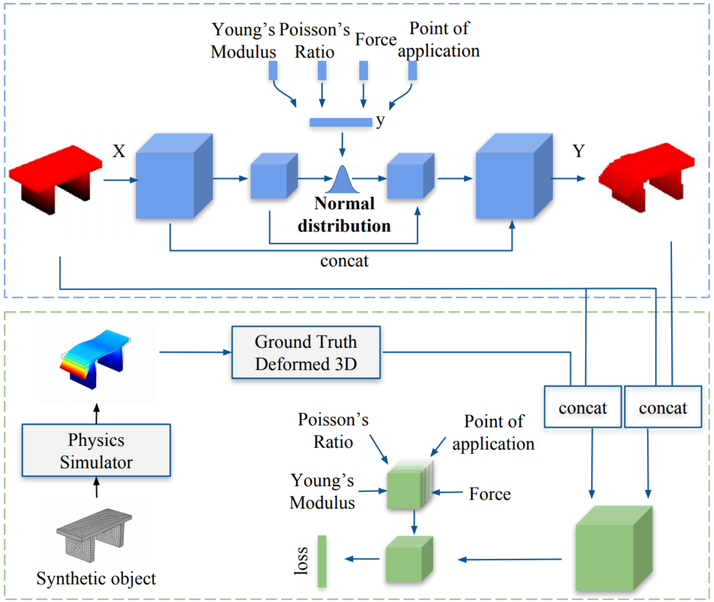
# Related Works, Class-Specific Methods




[Ge and Fan 2015 ]

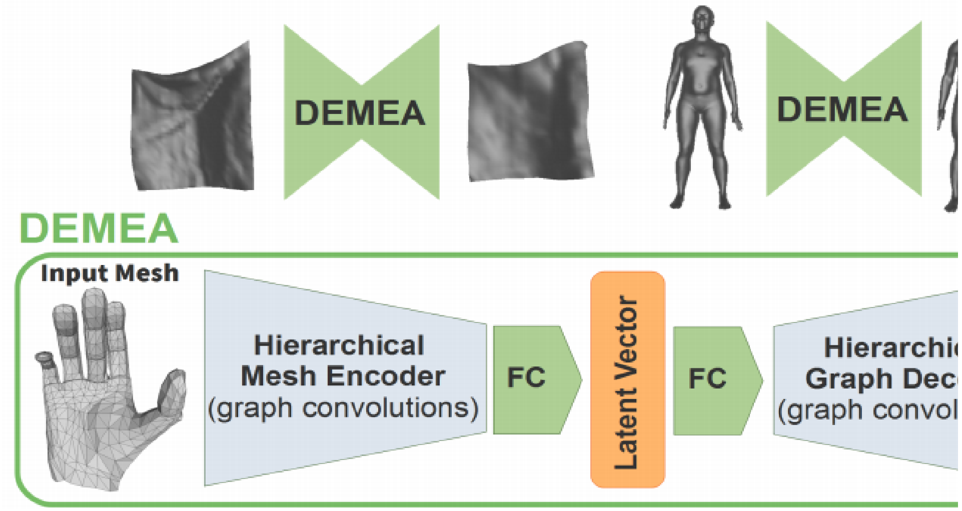
Perform well with large deformations and articulated motions between the point sets. However, the generalisability is limited.

# Related Works,  Neural Network Based Approaches (Other Fields)




3D-PhysNet

[Wang *et al.* 2018 ]



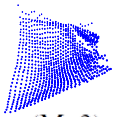

…

DEMEA

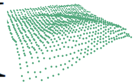
[Tretschk *et al.* 2019 ]

# Pipeline

# Pipeline

Y 

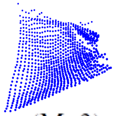
(Mx3)

X 

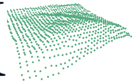
(Nx3)

- Y: template point set,  X: reference point set

# Pipeline

Y 

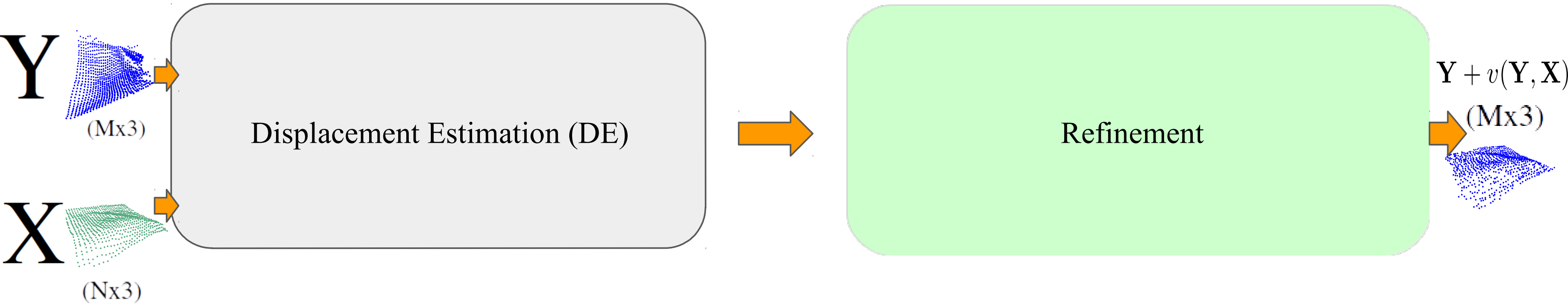
(Mx3)

X 

(Nx3)

- Y: template point set,  X: reference point set
- Assume M is not equal to N in general

# Pipeline




- Y: template point set, X: reference point set
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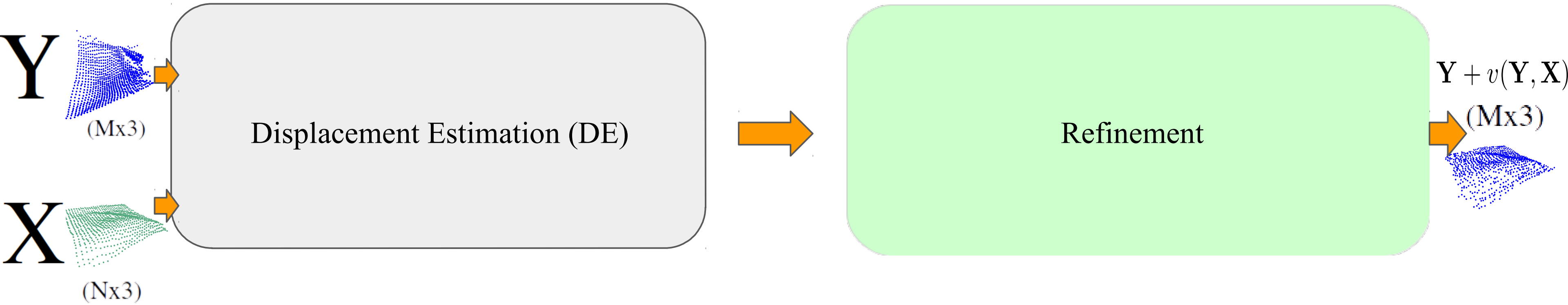
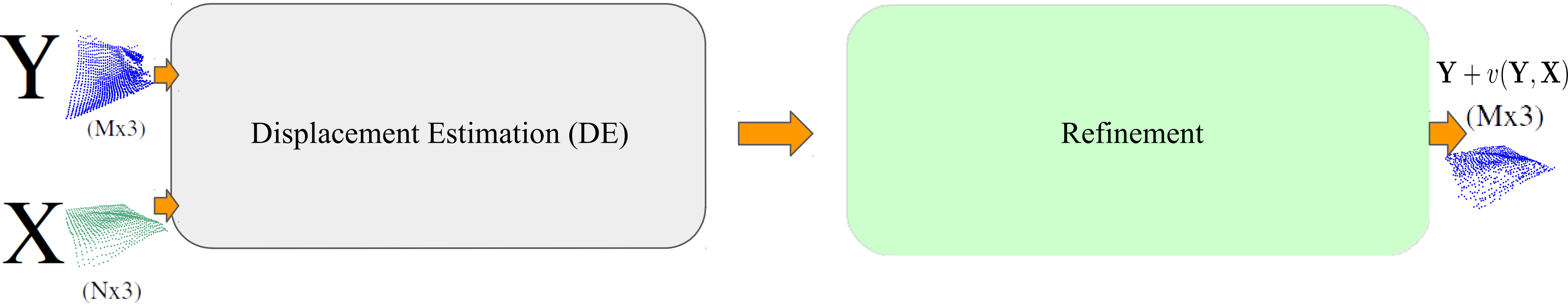
# Pipeline



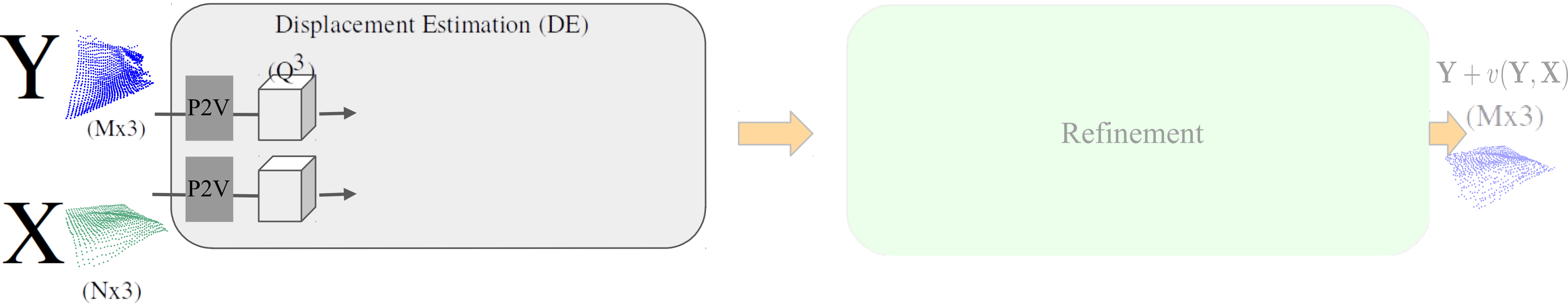

- Y: template point set,  X: reference point set
- Assume M is not equal to N in general
- DE stage regresses global displacements between Y and X

# Pipeline



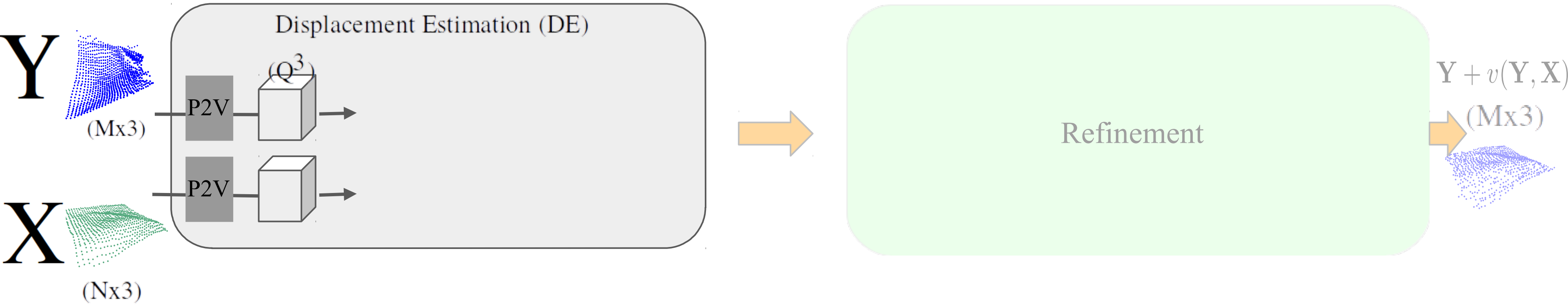

- Y: template point set,  X: reference point set
- Assume M is not equal to N in general
- DE stage regresses global displacements between Y and X
- Refinement stage improves the initial displacements

# Pipeline



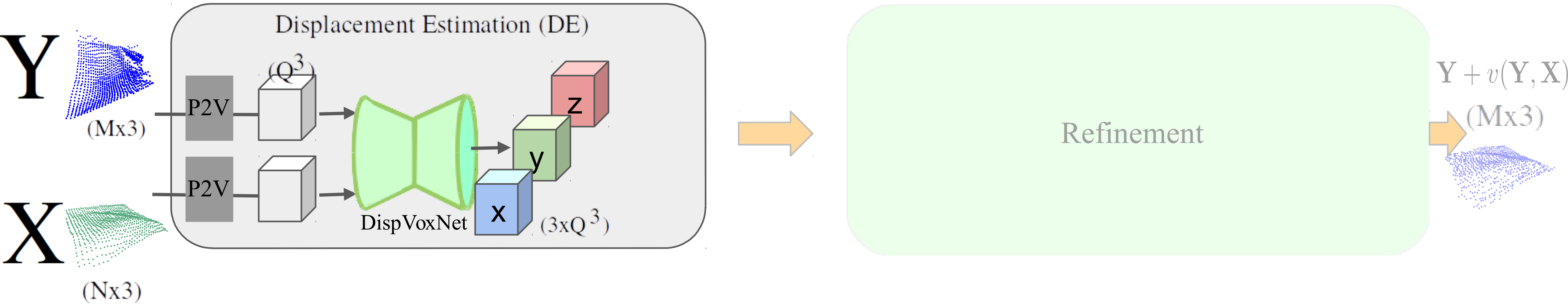

- Y and X are firstly converted into voxel representation (P2V)

# Pipeline




- Y and X are firstly converted into voxel representation (P2V)
- During the conversion, point-voxel correspondence information is stored in an **affinity table**

# Pipeline

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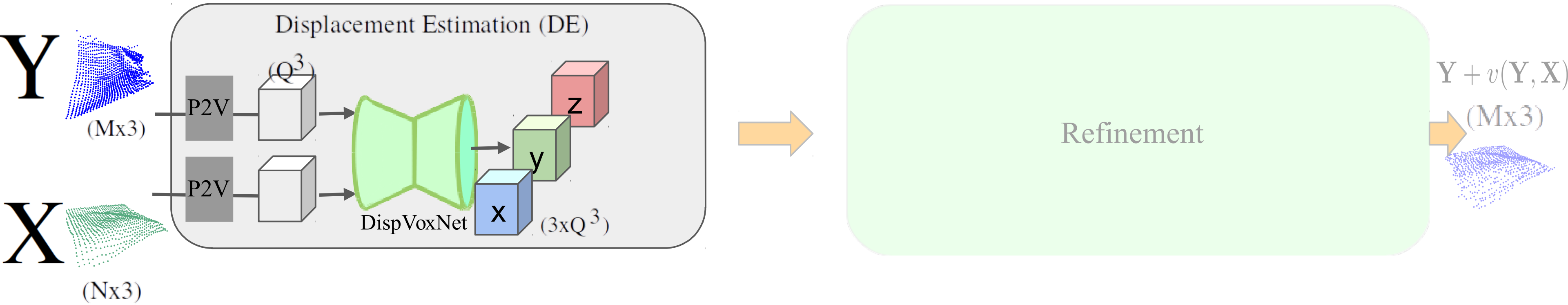
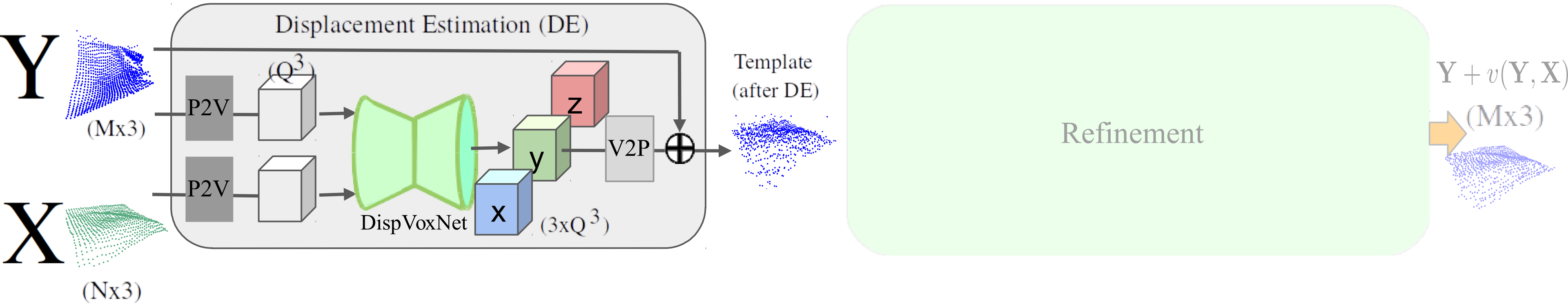


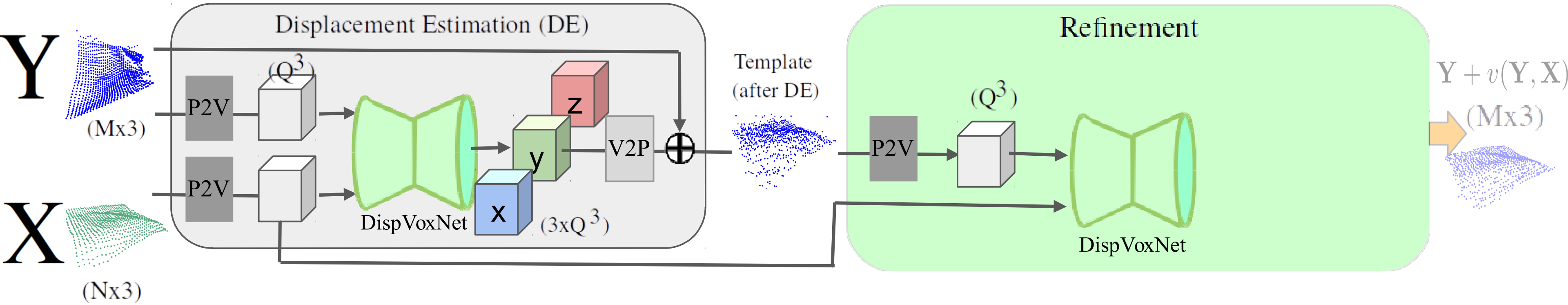

- Y and X are firstly converted into voxel representation (P2V)
- During the conversion, point-voxel correspondence information is stored in an **affinity table**
- DispVoxNet accepts two voxel grids and returns voxel displacements

# Pipeline



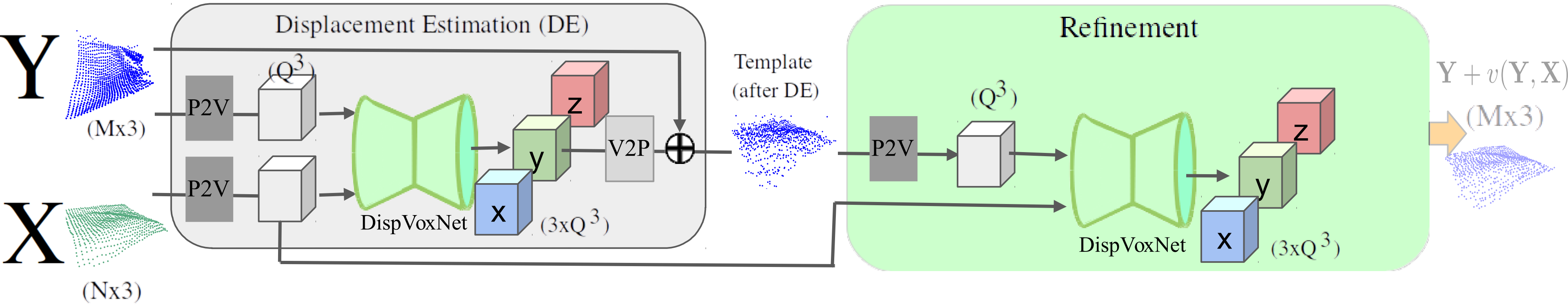

- Y and X are firstly converted into voxel representation (P2V)
- During the conversion, point-voxel correspondence information is stored in an **affinity table**
- DispVoxNet accepts two voxel grids and returns voxel displacements
- The displacements are applied using the affinity table at the end of DE stage

# Pipeline



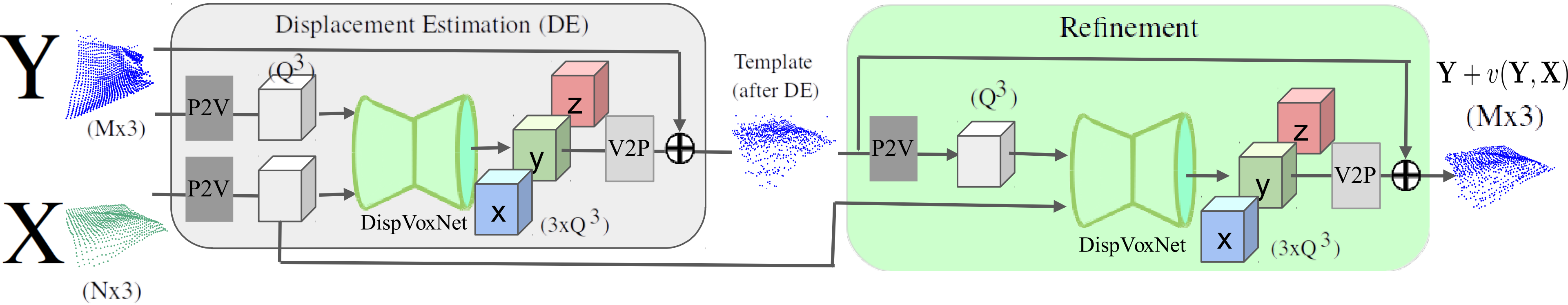

- The outputs from the DE stage are further sent to the Refinement stage after P2V

# Pipeline



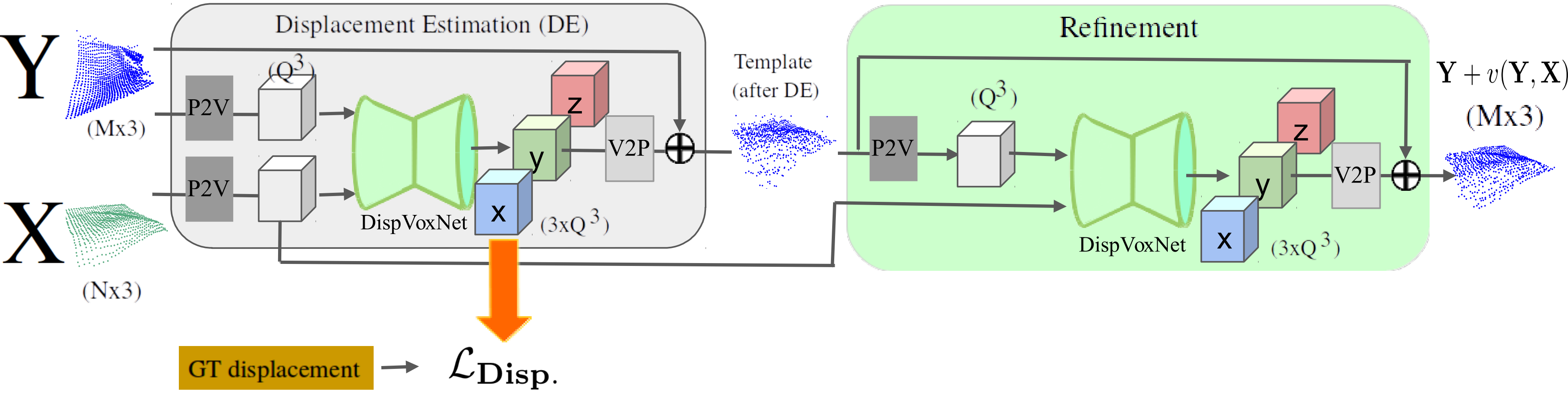

- The outputs from the DE stage are further sent to the Refinement stage after P2V
- The new instance of DispVoxNet returns small displacements for refinement

# Pipeline



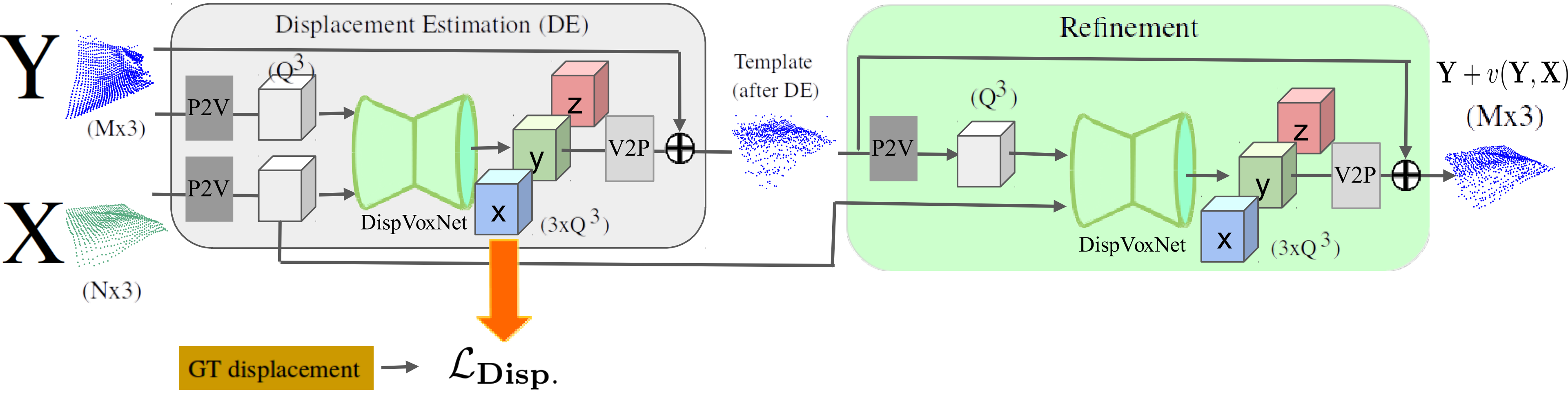

- The outputs from the DE stage are further sent to the Refinement stage after P2V
- The new instance of DispVoxNet returns small displacements for refinement
- The inferred displacements are added to the template points

# Pipeline



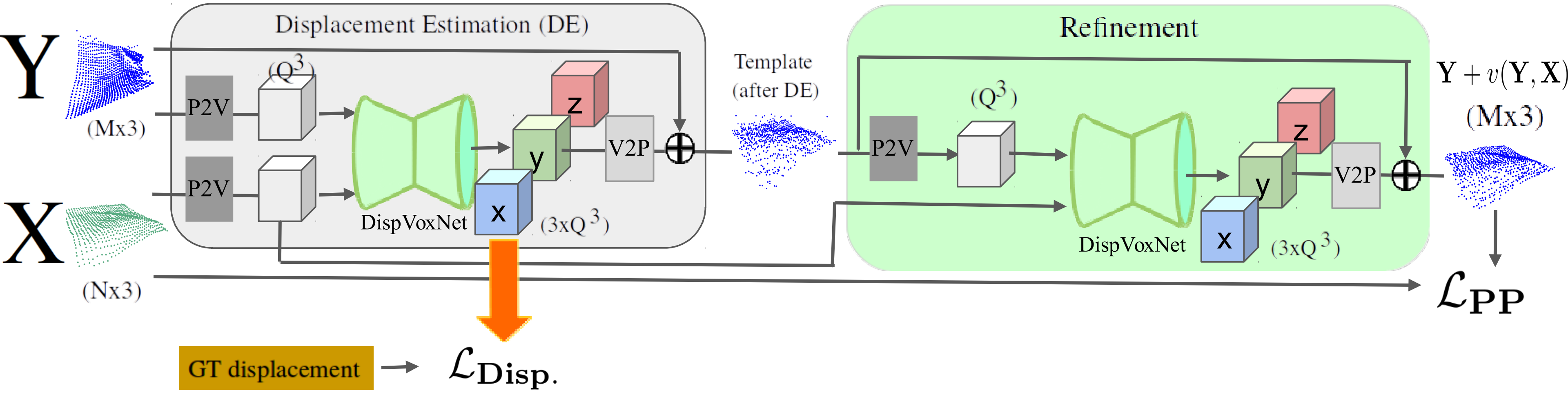
Displacement Estimation (DE)
Y
(Mx3)
X
(Nx3)
P2V
P2V
($Q^3$)
DispVoxNet
z
y
x
($3xQ^3$)
V2P
Template
(after DE)
Refinement
P2V
($Q^3$)
DispVoxNet
z
y
x
($3xQ^3$)
V2P
$\mathbf{Y} + v(\mathbf{Y}, \mathbf{X})$
(Mx3)
GT displacement
$\mathcal{L}_{\mathbf{Disp.}}$

# Pipeline




- The network in the DE stage is trained in a supervised manner (displacement loss)

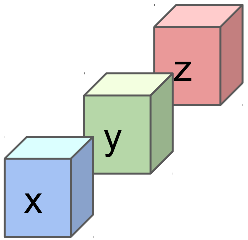
# Pipeline



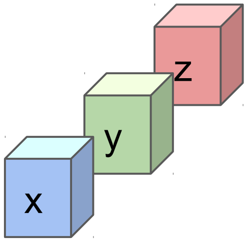

- The network in the DE stage is trained in a supervised manner (displacement loss)
- The network in the Refinement stage is trained in an unsupervised manner (point projection loss)

# Loss Functions - Displacement Loss

$$\mathcal{L}_{\mathbf{Disp.}} = \Bigg\| \quad \text{Network output} \quad - \quad \text{GT displacement} \quad \Bigg\|_2^2$$

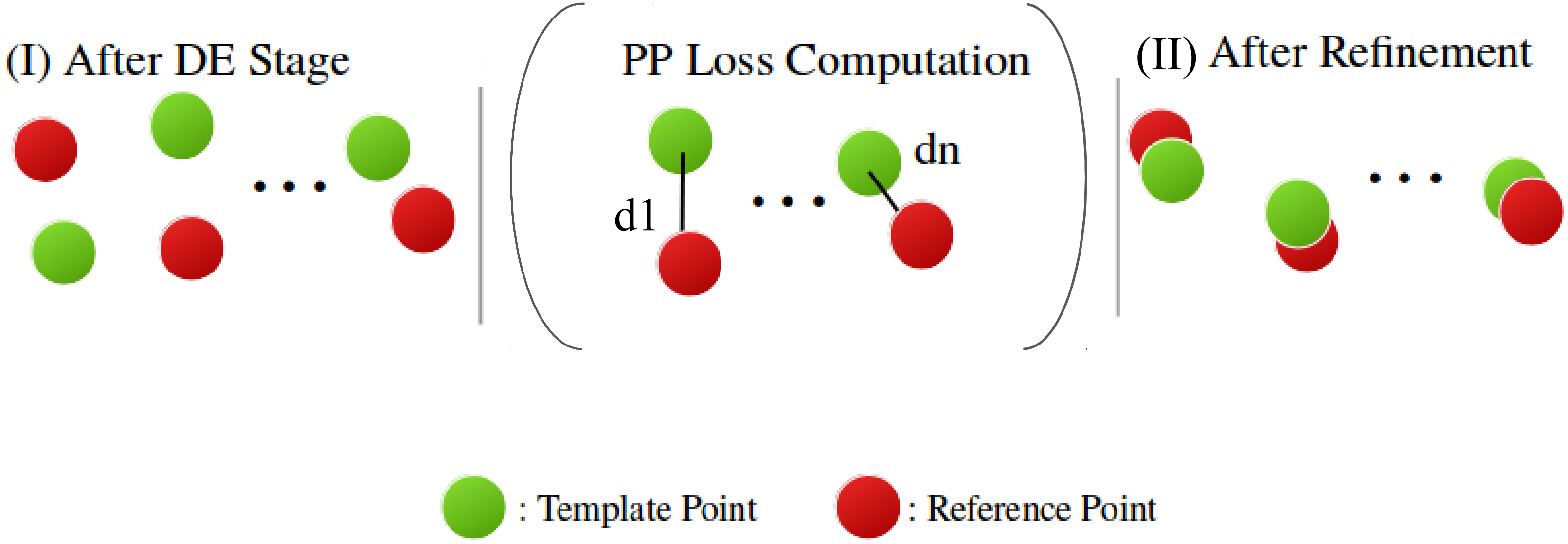



Network output

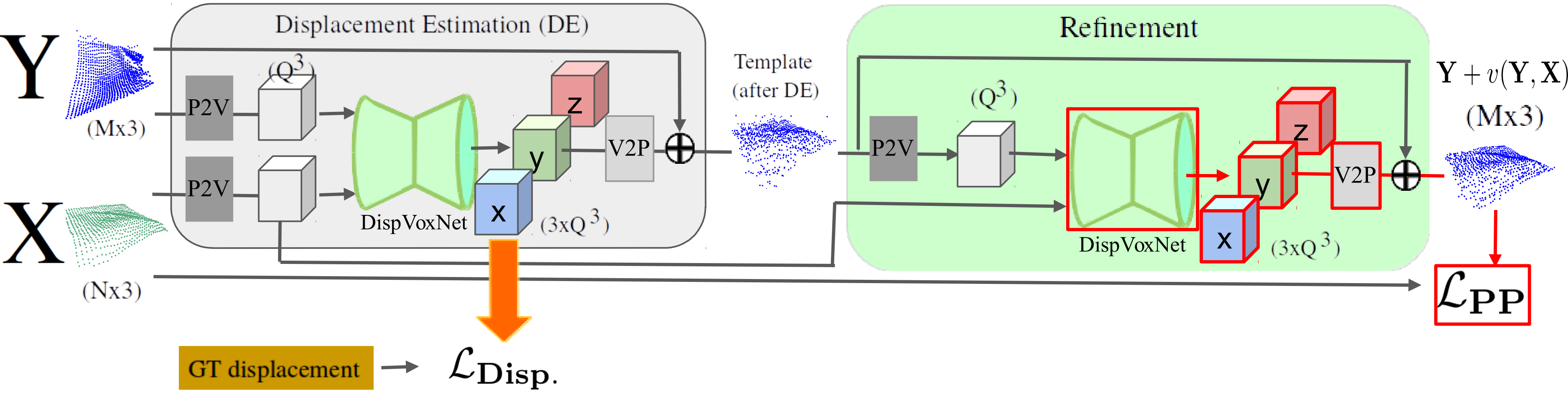



GT displacement

# Loss Functions - Point Projection Loss



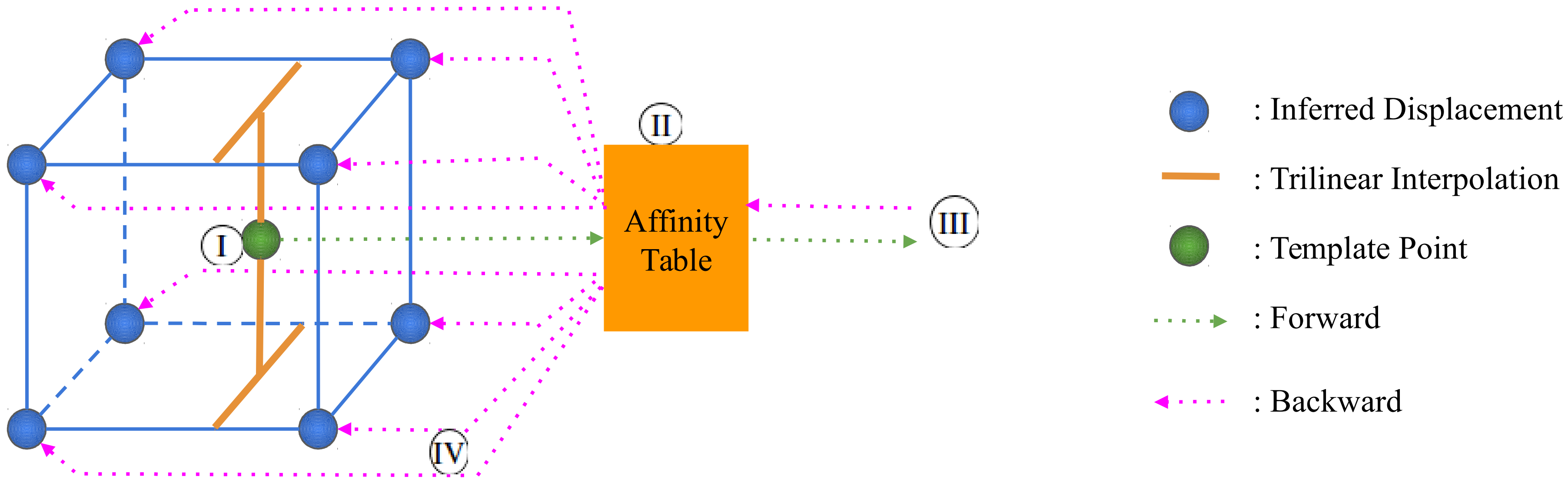
# Pipeline




Problem 1: Discretisation effect due to the nature of voxel grids

Problem 2: Indifferentiability problem

# Solution for Discretisation and Indifferentiability Problems




I. Compute trilinear weights for each template point using its 8 nearest inferred displacements
II. Record the weights and indices of the 8 nearest displacements in the affinity table
III. Compute the point projection loss
IV. Distribute gradients following the IDs and weights information recorded in the affinity table in II.

# Datasets

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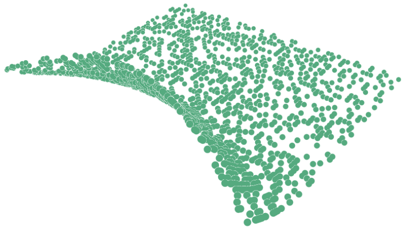
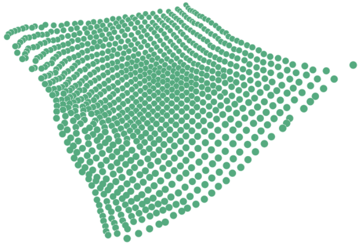


*thin plate*
[Golyanik *et al*. 2018]

*FLAME*
[Li *et al*. 2017]

*DFAUST*
[Bogo *et al*. 2017]



*cloth*
[Bednařík *et al*. 2018]

# Evaluation

# Quantitative Results - Baseline and Outliers

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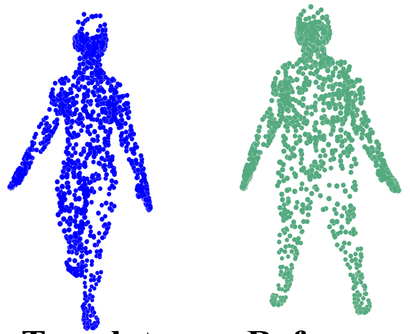

**Template** **Reference**

| | | Ours | NR-ICP [9] | CPD [38] | GMR [29] |
|---|---|---|---|---|---|
| ***thin plate*[17]** | $e$ | 0.0103 | 0.0402 | **0.0083** / 0.0192 | 0.2189 |
| | $\sigma$ | **0.0059** | 0.0273 | 0.0102 / 0.0083 | 1.0121 |
| ***FLAME*[33]** | $e$ | 0.0063 | 0.0588 | **0.0043** / 0.0094 | 0.0056 |
| | $\sigma$ | 0.0009 | 0.0454 | 0.0008 / **0.0005** | 0.0007 |
| ***DFAUST*[5]** | $e$ | **0.0166** | 0.0585 | 0.0683 / 0.0721 | 0.2357 |
| | $\sigma$ | **0.0020** | 0.0215 | 0.0314 / 0.0258 | 0.8944 |
| ***cloth*[2]** | $e$ | **0.0080** | 0.0225 | 0.0149 / 0.0138 | 0.2189 |
| | $\sigma$ | **0.0021** | 0.0075 | 0.0066 / 0.0033 | 1.0121 |

Baseline Comparison

**Template** **Reference**

| | | | Ours | NR-ICP [9] | CPD [38] | GMR [29] |
|---|---|---|---|---|---|---|
| ***thin plate*[17]** | ref. | $e$ | **0.0107** | 0.0668 | 0.0218 / 0.0386 | 0.4415 |
| | | $\sigma$ | **0.0061** | 0.0352 | 0.0148 / 0.0067 | 1.4632 |
| | temp. | $e$ | **0.0108** | 0.0334 | 0.0479 / 0.0471 | 0.4287 |
| | | $\sigma$ | 0.0062 | 0.0281 | 0.0101 / **0.0038** | 1.3832 |
| ***FLAME*[33]** | ref. | $e$ | 0.0084 | 0.0519 | **0.0046** / 0.0140 | 0.0193 |
| | | $\sigma$ | 0.0010 | 0.0451 | 0.0009 / **0.0006** | 0.0008 |
| | temp. | $e$ | 0.0088 | 0.0215 | **0.0076** / 0.0201 | 0.0274 |
| | | $\sigma$ | **0.0010** | 0.0219 | **0.0010** / 0.0016 | 0.0019 |
| ***DFAUST*[5]** | ref. | $e$ | **0.0167** | 0.0463 | 0.0562 / 0.0636 | 0.0714 |
| | | $\sigma$ | **0.0029** | 0.0195 | 0.0308 / 0.0216 | 0.0282 |
| | temp. | $e$ | **0.0169** | 0.0426 | 0.0672 / 0.0710 | 0.0737 |
| | | $\sigma$ | **0.0033** | 0.0194 | 0.0291 / 0.0229 | 0.0243 |
| ***cloth*[2]** | ref. | $e$ | **0.0090** | 0.0455 | 0.0248 / 0.0315 | 0.0288 |
| | | $\sigma$ | **0.0018** | 0.0061 | 0.0056 / 0.0027 | 0.0087 |
| | temp. | $e$ | **0.0132** | 0.0208 | 0.0486 / 0.0347 | 0.0397 |
| | | $\sigma$ | 0.0019 | 0.0087 | 0.0077 / **0.0014** | 0.0092 |

Outlier

# Quantitative Results - Uniform Noises

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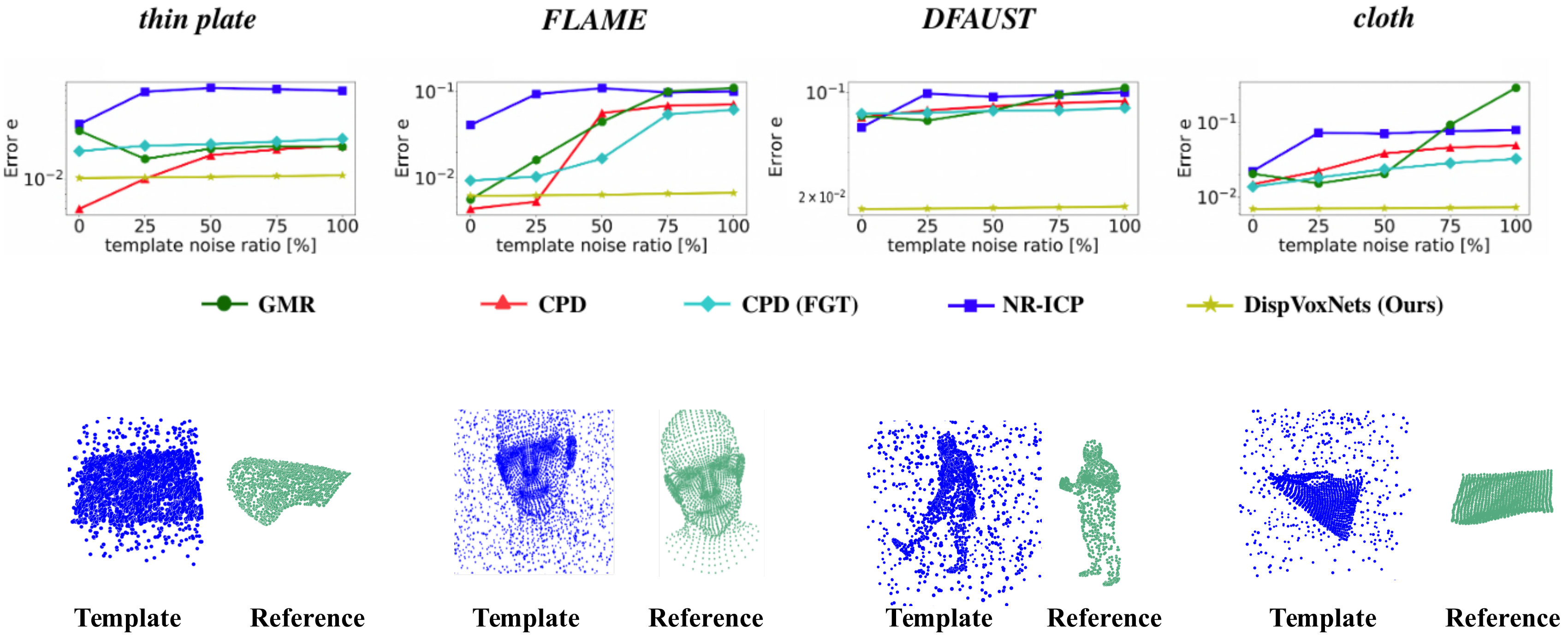

# Quantitative Results - Runtime

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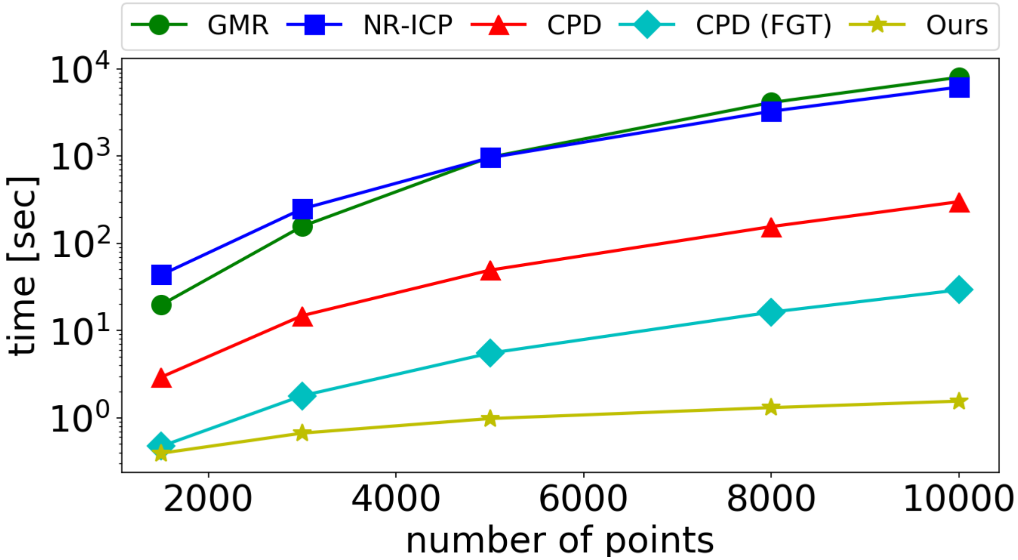
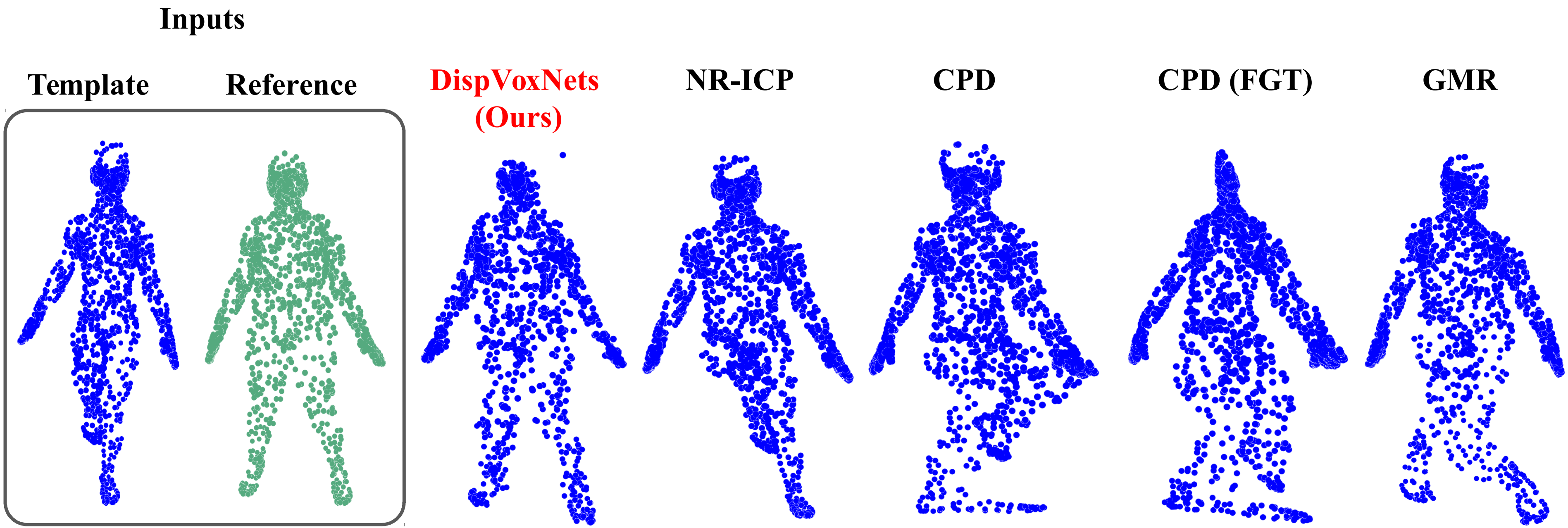



- With 10K points, our approach requires only a second per registration whereas others require around 2 hours - 15 seconds

# Qualitative Results

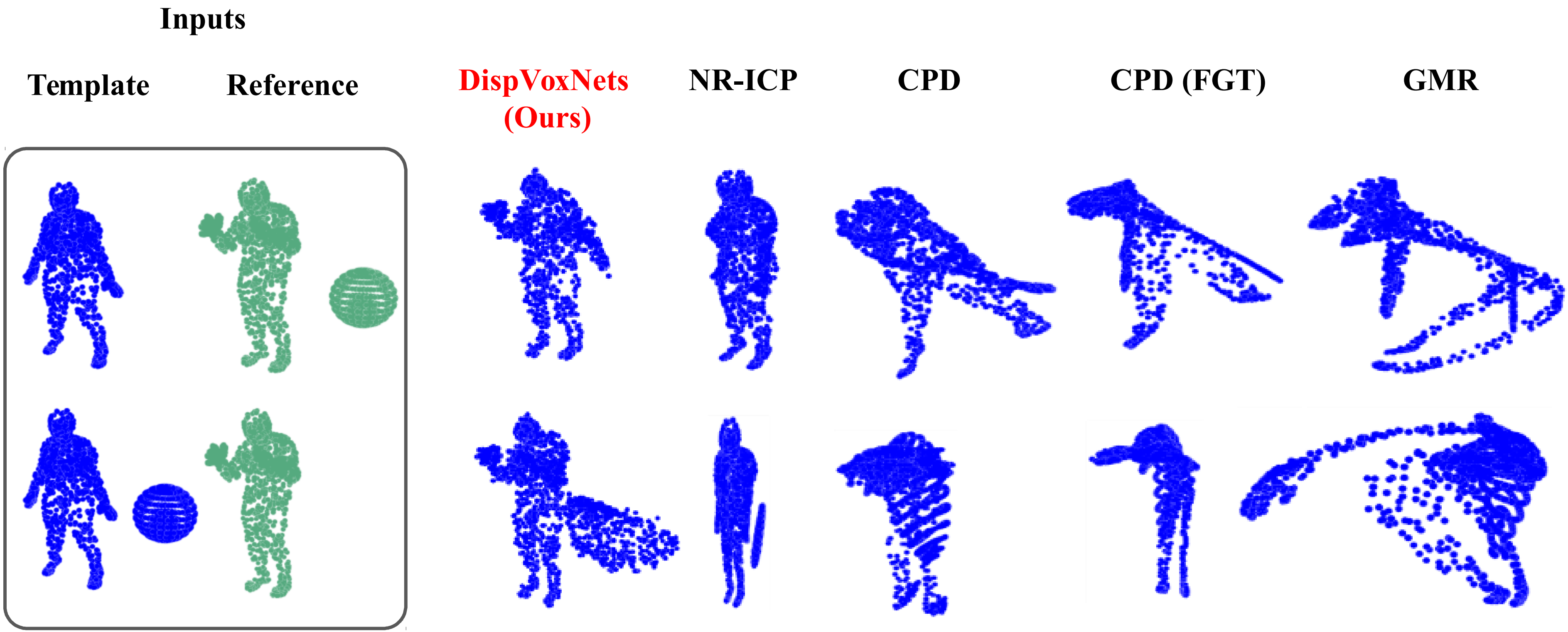
# Baseline Comparison

# Baseline Comparison



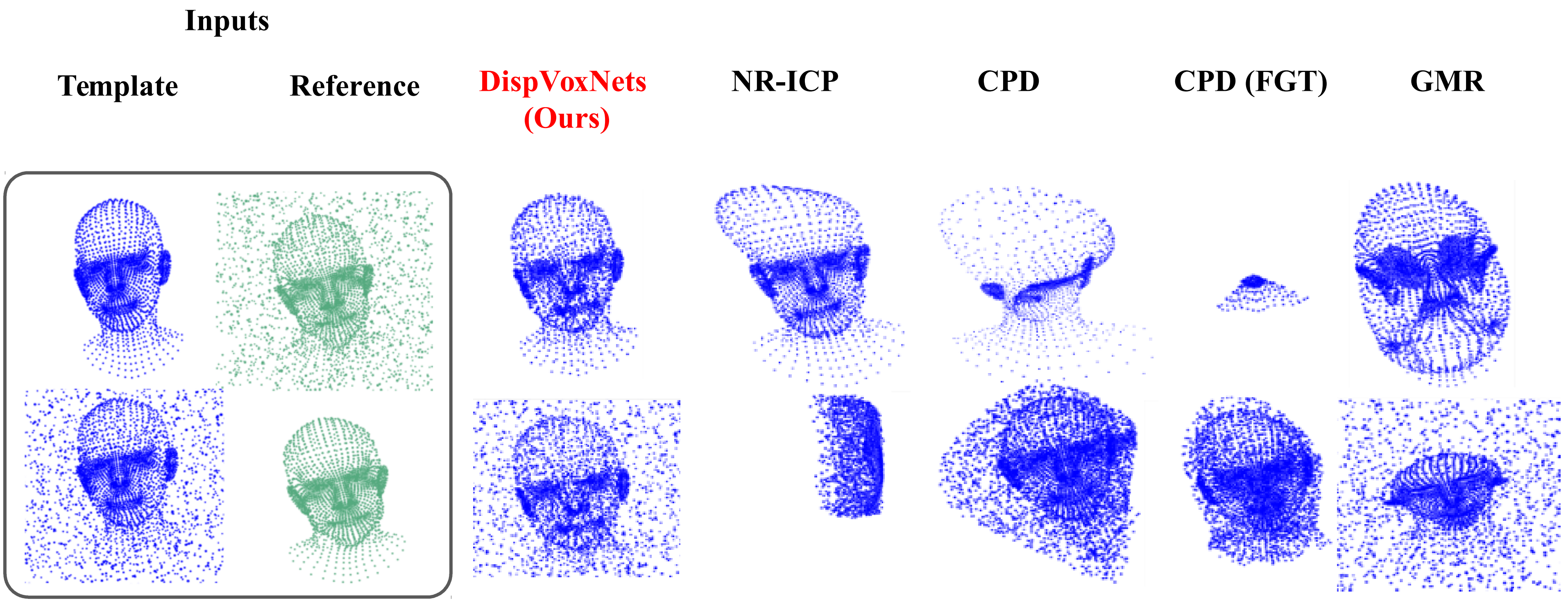
# Outliers

# Outliers


Inputs
Template
Reference
DispVoxNets (Ours)
NR-ICP
CPD
CPD (FGT)
GMR

# Uniform Noises

# Uniform Noises



# Real Face Dataset

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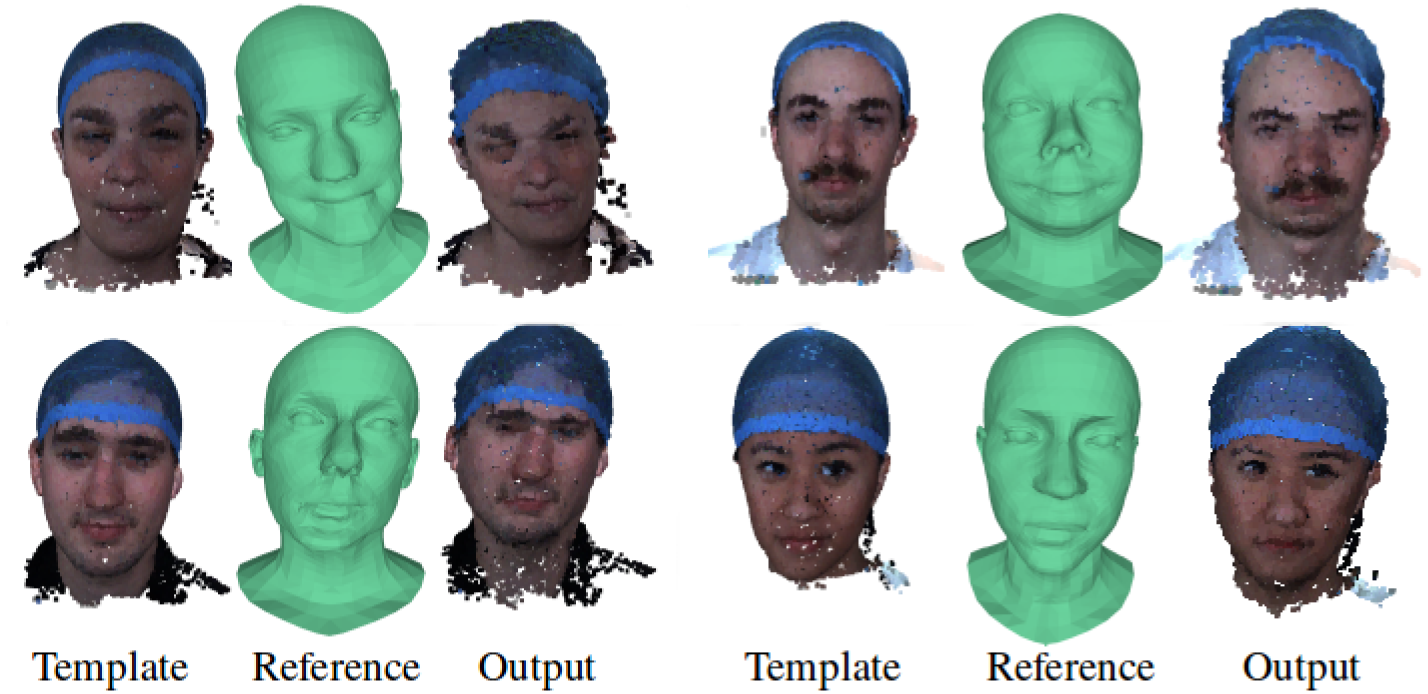


Datasets: [Dai et al. 2017], [Li *et al.* 2017]

# Summary

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Project Page: http://gvv.mpi-inf.mpg.de/projects/DispVoxNets/

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# Questions?

# DispVoxNets: Non-Rigid Point Set Alignment with Supervised Learning Proxies

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# Thank you