Skoltech
Skolkovo Institute of Science and Technology

Data Science

Adversarial point set registration

Student: Sergei Divakov

Scientific Advisor(s): *Ivan Oseledets*

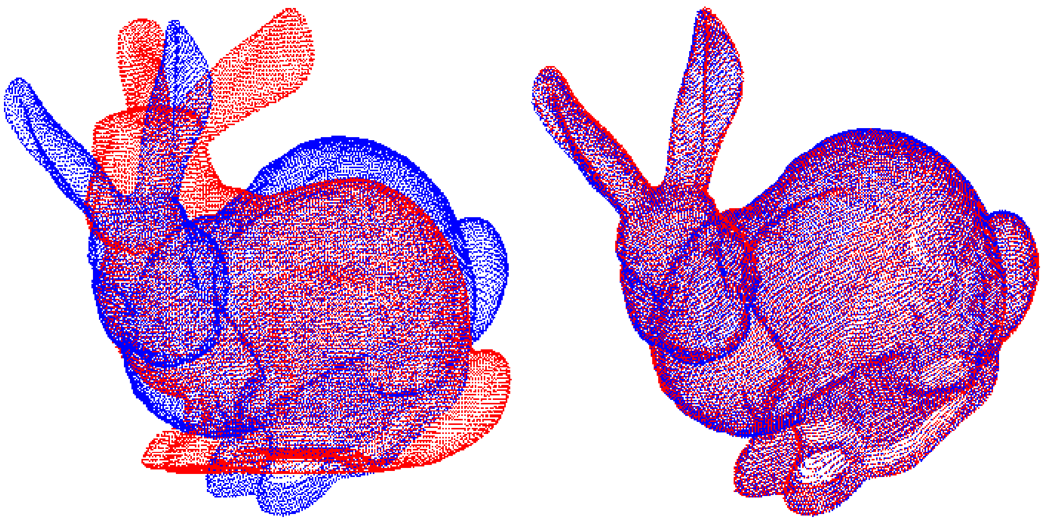
May, 2019

Skoltech

Skolkovo Institute of Science and Technology

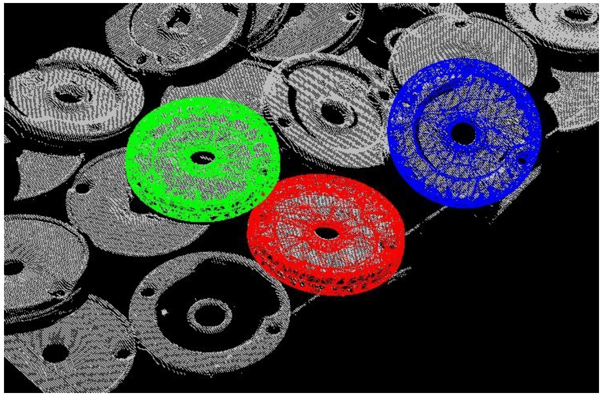
Registration problem

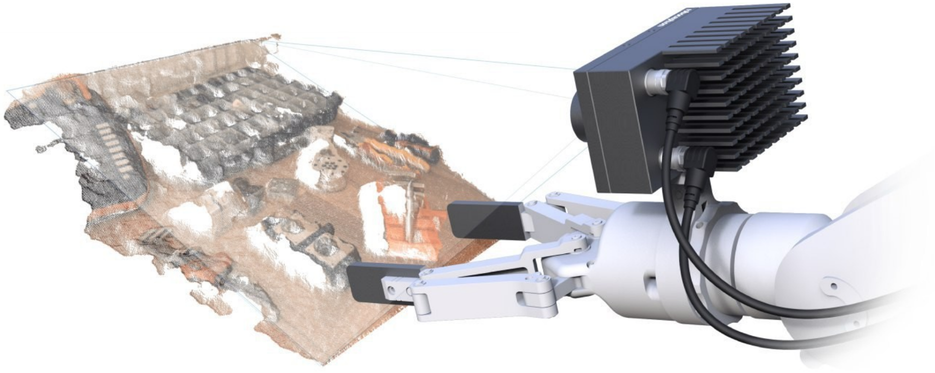
Find a rigid transformation which aligns two point clouds



Applications

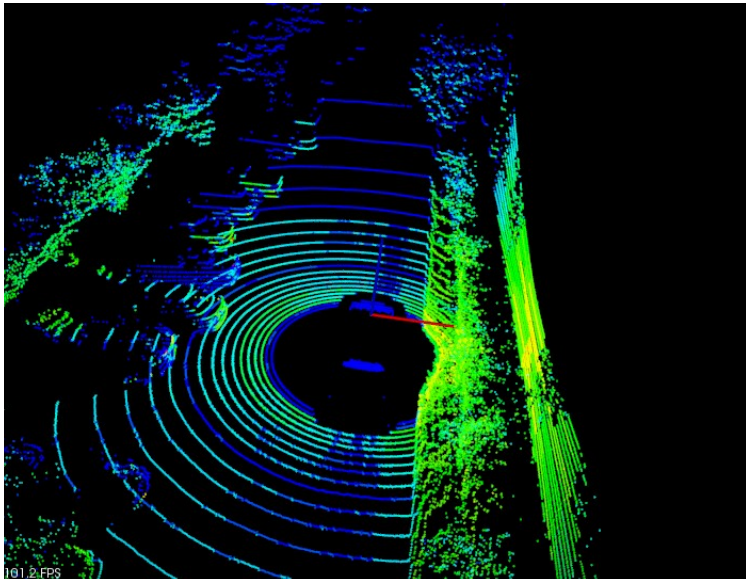
Motion planning in robotics

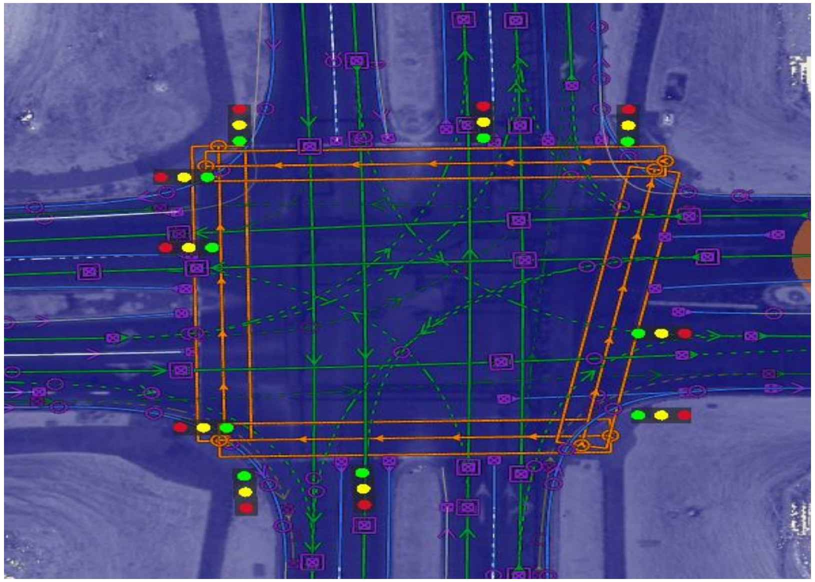




Applications

Localization of autonomous vehicles





Current approaches:
Iterative Closest Point

+ Works well on closely aligned data
+ Robust to noise
+ Fast
- The optimization objective has a lot of local minima

This is typically the method of choice for real time applications, if rough approximation of the transformation is known – (Global registration).

Current approaches: Geometric feature matching

The problem of Global registration is typically solved by computing some features of points of regions in the point clouds and finding a transformation, respecting the correspondence of these features.

A lot of works in these area, both hand-crafted and learnable.

We will consider Fast Point Feature Histograms.

Registration problem

- Becomes increasingly important with wide distribution of 3D sensors.
- Currently solved by matching geometric features and finding the transform which respects the correspondence.
- Local methods match points (ICP, CPD). Global methods match high-level geometric features (PFH, FPFH, Fast Global Matching).
- “Chicken-and-egg” problem

Aim

To develop an end-to-end solution, which does not rely on correspondences, has a quasi-linear complexity and solves the problem regardless of the initial alignment.

Objectives

1. To develop a novel approach for point set registration, which is based on adversarial learning
2. To conduct an experimental study of the approach
3. To measure its’ effectiveness on a number of datasets and compare it to the existing methods

Skoltech
Skolkovo Institute of Science and Technology

General framework

$$X, \tilde{X} \subset \mathbb{R}^3$$

Source and target point sets

$$M \in SE(3)$$

The aligning transformation

$$P_X(x) = \frac{1}{|X|} \sum_{i=1}^{|X|} \delta(x - x_i),$$

$$P_{\tilde{X}}(x) = \frac{1}{|\tilde{X}|} \sum_{i=1}^{|\tilde{X}|} \delta(x - \tilde{x}_i).$$

Atomic distributions naturally associated with source and target point sets

$$\xi \sim P_X,$$

$$\hat{\xi} \sim P_{\tilde{X}},$$

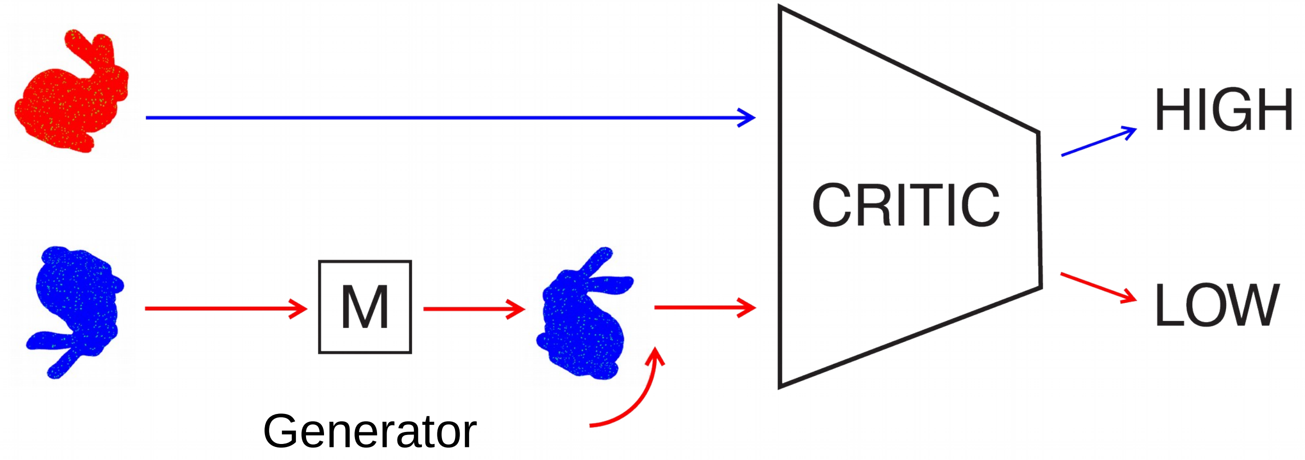
Random variables distributed according to these distributions

$$\min_M \mathbf{D}(\xi, M[\hat{\xi}]).$$

Registration = minimization of divergence

Skoltech
Skolkovo Institute of Science and Technology

Adversarial setting



Wasserstein critic

$$\mathbf{D}_W[\xi, \hat{\xi}] = \inf_{\gamma \in \pi(P, \tilde{P})} \mathbb{E}_{x,y\sim\gamma}\, d(x, y),$$

$$\mathbf{D}_W[\xi, \hat{\xi}] = \sup_{||f||_L \leq 1} \mathbb{E}_{x\sim P} f(x) - \mathbb{E}_{x\sim \tilde{P}} f(x),$$

Wasserstein loss

$$f_{\theta_C} \ : \ \mathbb{R}^3 \ \to \ \mathbb{R}$$

$$L_C(\theta_C) = -[\frac{1}{n}\sum_{i=1}^{n} f_\theta(x_i) - \frac{1}{m}\sum_{j=1}^{m} f_\theta(M(\tilde{x}_j))].$$

$$L_{GP}(\theta_D) = \frac{1}{n}\sum_{i=1}^{n}(|\nabla_{\theta_D} f_{\theta_D}(\hat{x}_i)|_2^2 - 1)^2,$$

$$L_C^{full}(\theta_C) = L_C(\theta_C) + \lambda L_{GP}(\theta_C).$$

$$L_G(\theta_G) = -\frac{1}{m}\sum_{j=1}^{m} f_{\theta_C}(M_{\theta_G}(\tilde{x}_j)).$$

Algorithm

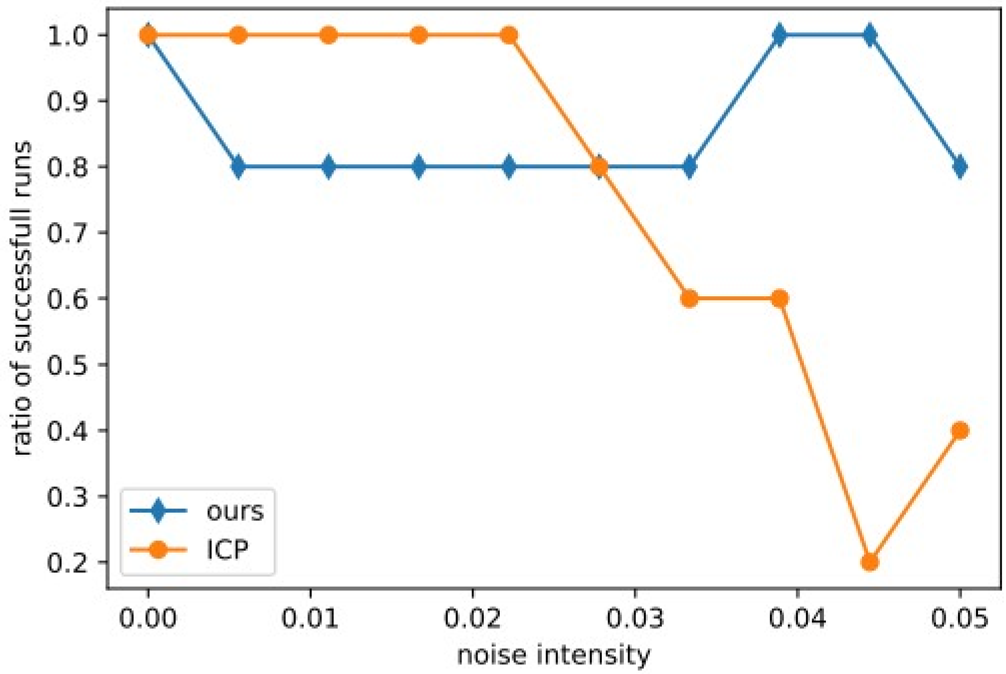
Input: Source and target point clouds $\tilde{X}, X$
Output: θ_G - rotation vector and translation
N_{Epochs} - the number of epochs to train
K_{critic} - the number of steps to train the critic
$K_{generator}$ - the number of steps to train the generator
while *epoch* $< N_{Epochs}$ **do**
  for K_{critic} *steps* **do**
    Sample mini-batch x from X
    Sample mini-batch $\tilde{x}$ from $\tilde{X}$
    Apply transformation M to $\tilde{x}$
    Compute $L_C^{full}(x, M(\tilde{x}))$
    Update parameters of the critic:
    $\theta_C = \theta_C - \nabla_{\theta_C} L_C^{full}(x, M(\tilde{x}))$
  end
  for $K_{generator}$ *steps* **do**
    Sample mini-batch $\tilde{x}$ from $\tilde{X}$
    Apply transformation M to $\tilde{x}$
    Compute $L_G(M(\tilde{x}))$
    Update parameters of the generator:
    $\theta_G = \theta_G - \nabla_{\theta_C} L_G(M(\tilde{x}))$
  end
end

Experimental Setup

- Implementation: PyTorch.
- Baseline algorithms: Vanilla ICP and Fast Global Registration.
- Datasets: Stanford scanning repository and ModelNet10.
- Evaluation metric: angular distance

$$d_{ang}(R_{gt}, R) = 2 \arcsin \left[||R_{gt} - R||_F / \sqrt{8} \right]$$

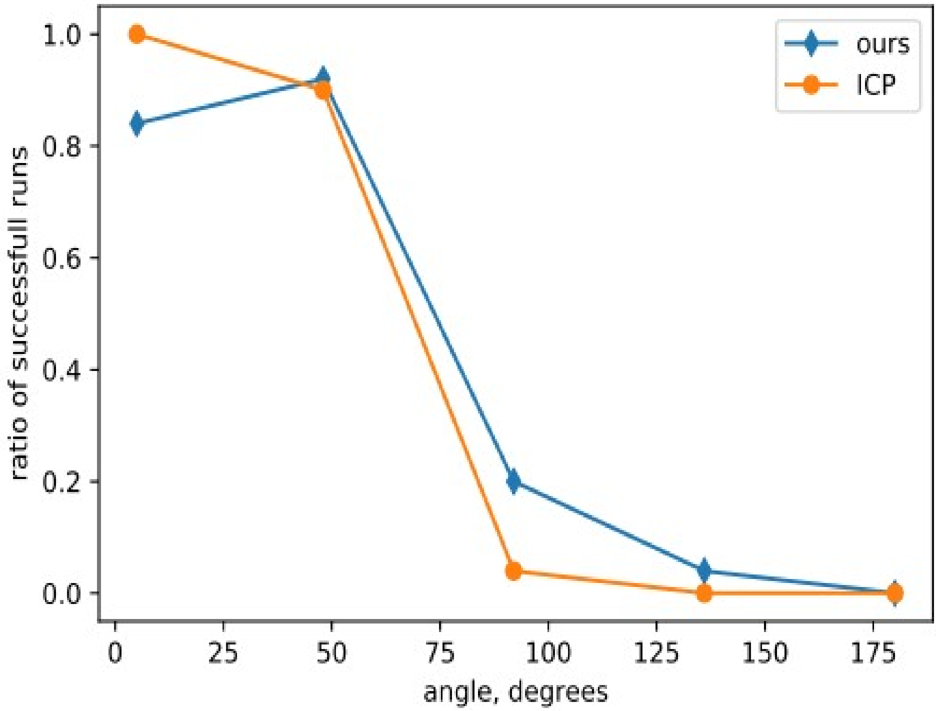
Robustness



Experiment on a Stanford bunny mesh. Measuring the number of successful runs with respect to noise intensity.

An experiment is considered successful if the angular distance is less than 4°

Initial angle



Experiment on a Stanford bunny mesh. Measuring the number of successful runs with respect to initial rotation angle.

ModelNet10

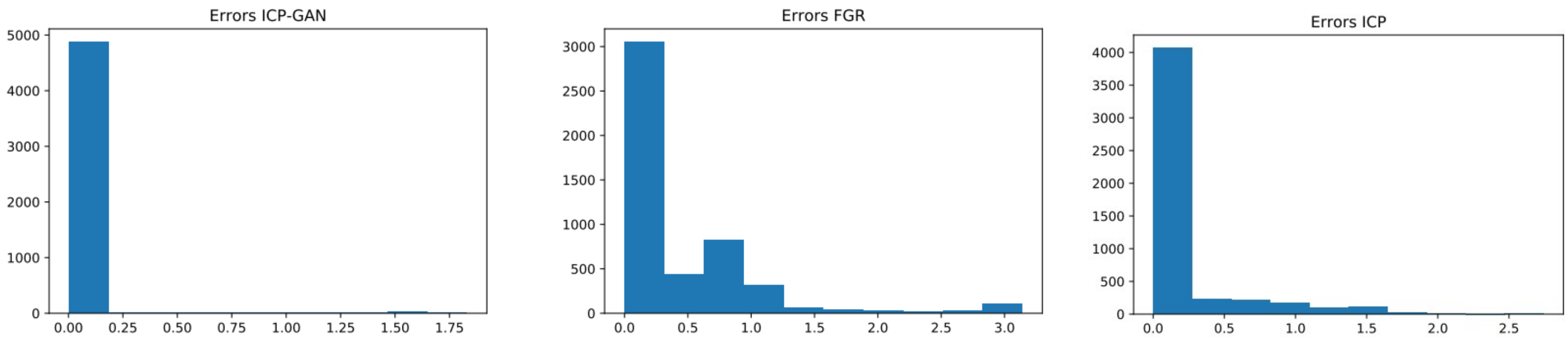
- ~5k models from 10 categories
- All models centered and scaled to [-1, 1] on each dimension
- Random rotation: Euler angles sampled uniformly from [-45°, 45°]
- Normal noise with $\sigma = 0.01$ added to source and target point clouds

Skoltech
Skolkovo Institute of Science and Technology

ModelNet10

Model	Mean error	0.9 Quantile
ICP	0.162	0.704
FGR	0.416	0.985
ICP-GAN	**0.023**	**0.006**

Error analysis of three models on ModelNet10

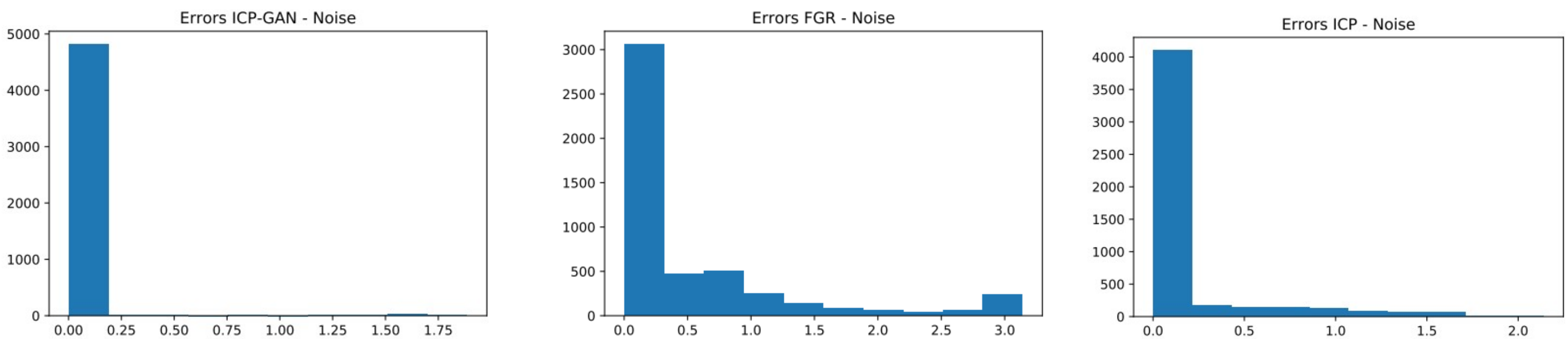


Error distributions

ModelNet10 + Noise

Model	Mean error	0.9 Quantile
ICP	0.156	0.659
FGR	0.534	1.566
ICP-GAN	**0.0171**	**0.0069**

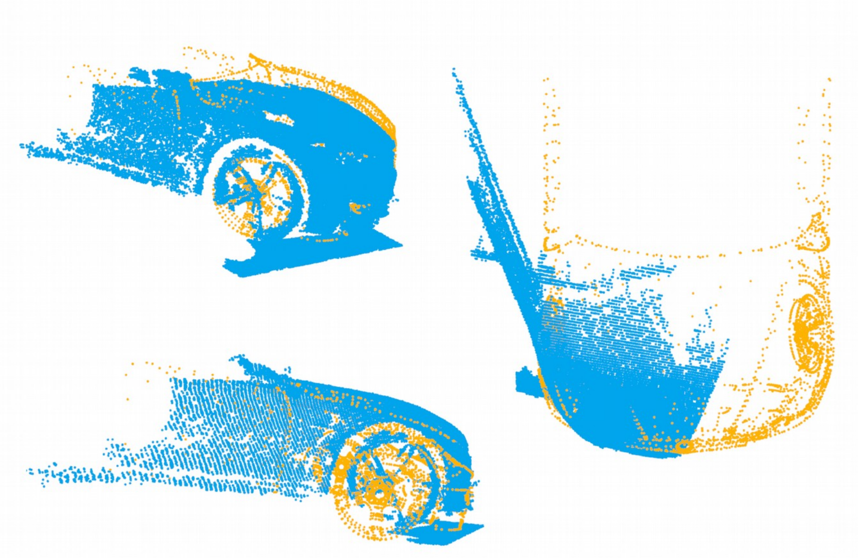
Error analysis of three models on ModelNet10 with added Gaussian noise



Error distributions

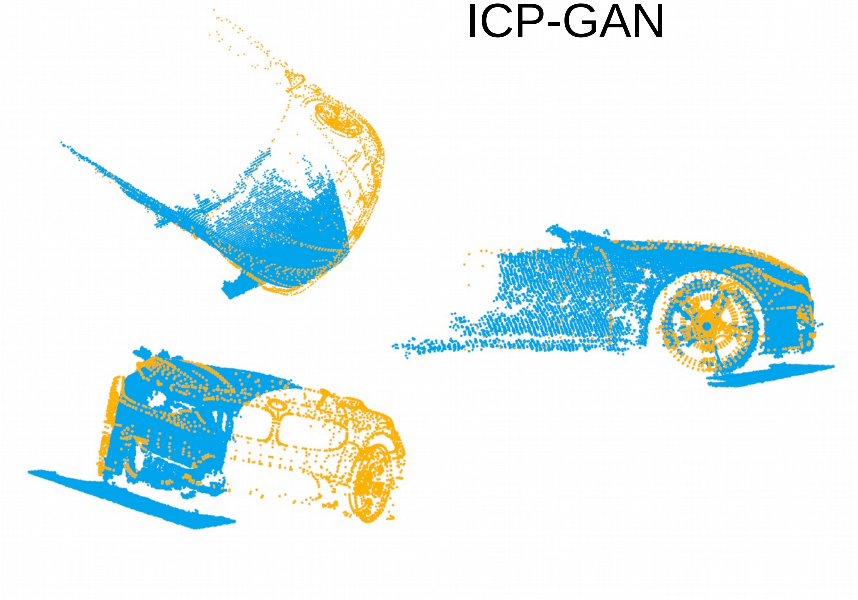
Practical example

Registering raw depth point cloud against a CAD model of a car



Fast global registration

ICP-GAN



Skoltech
Skolkovo Institute of Science and Technology

Conclusions

1. We have developed a novel approach for point set registration, which does not rely on matching geometric features.
2. It highlights yet another interesting application of adversarial learning setups, showing that in certain scenarios training GANs can be very robust and predictable.
3. Rapid development of GANs might quite soon make the algorithm viable in real-time applications.

Skolkovo Institute of Science and Technology

Acknowledgments

This work was supported by the Ministry of Science and Education of Russian Federation as a part of Mega “Grant” Research Project 14.756.31.0001.

Appendix – Running Time