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# SJB INSTITUTE OF TECHNOLOGY

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Seminar

on

# “Pose Estimation and a study of Iterative Closest Point Algorithm”

**By**


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# Agenda

- Introduction
  - Autonomous Vehicles
  - Pose Estimation
  - Point Cloud data
  - LiDAR and other devices for Pose Estimation
  - ICP
- Problem Statement
- Literature Survey
- Design and Implementation
  - Working of ICP
- Conclusion and Future Enhancement
- References

# Autonomous Vehicles

Sense environment and navigate without human input

# Pose Estimation

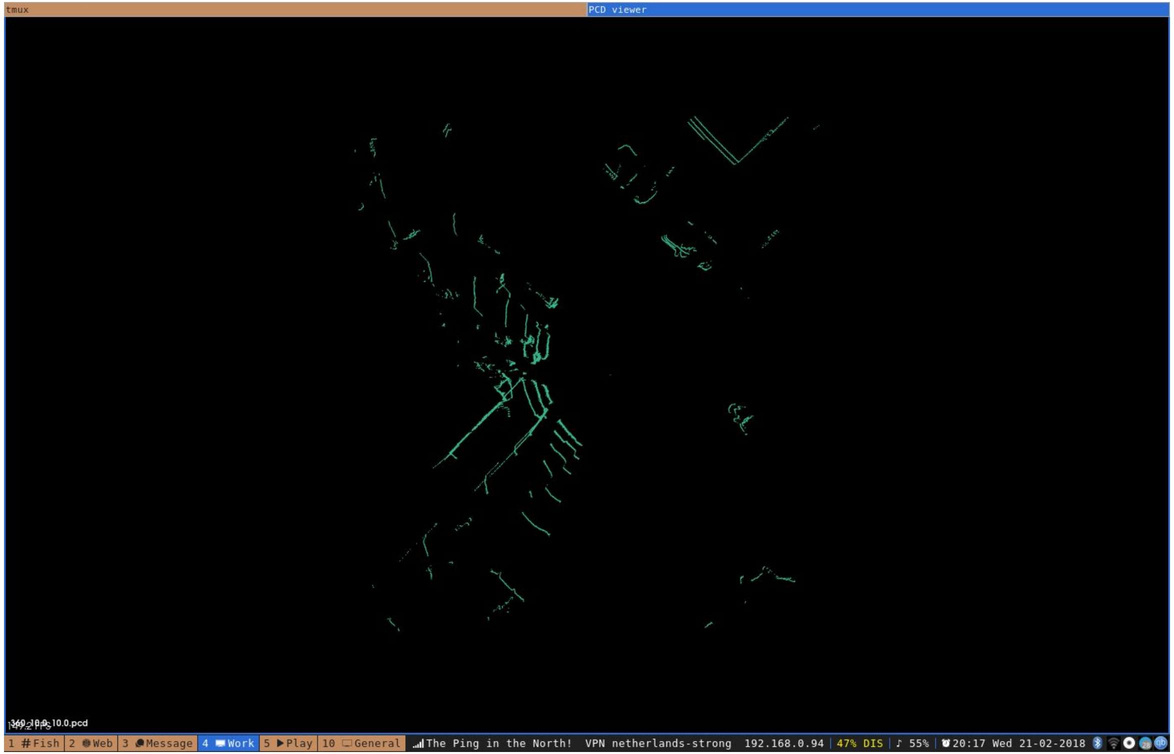
- Orientation of the subject
- Perspective the subject has
- Pose is the orientation of the autonomous vehicle

Two primary transformations:

- Rotations (when the vehicle turns)
- Translation (when there is linear motion which can be mapped to x, y, and z ordinates)

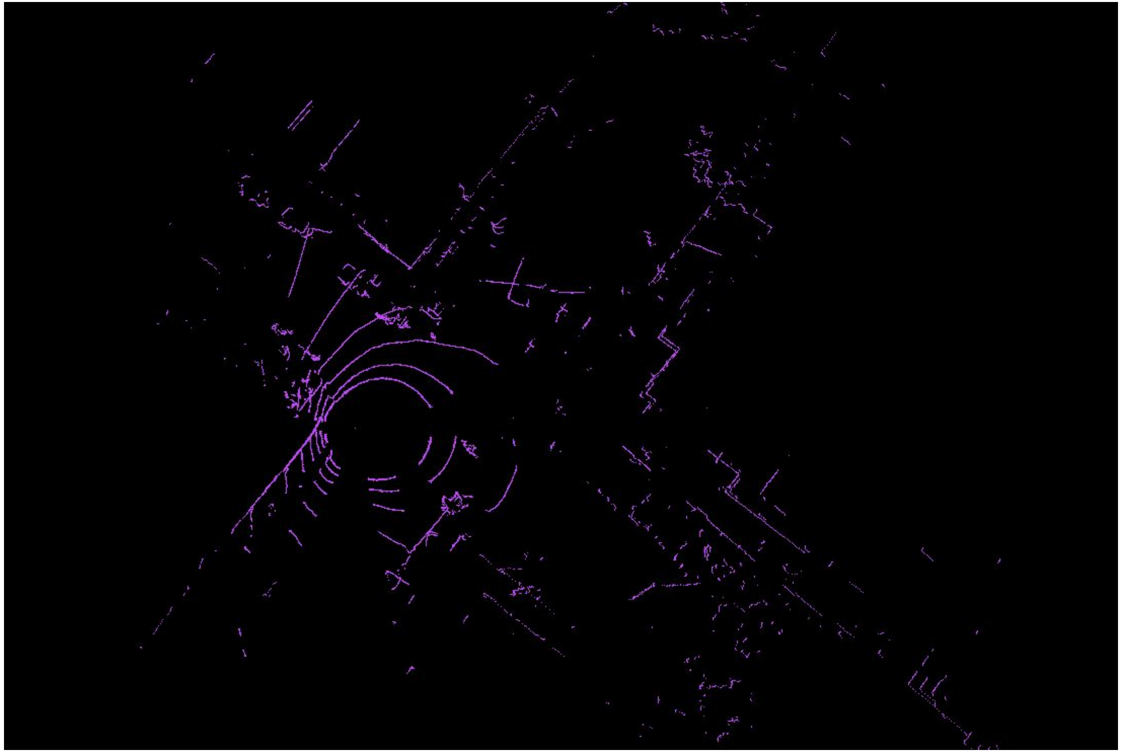
We compare current pose and previous pose and identify the transformations that have occured between the two states

# Point Cloud

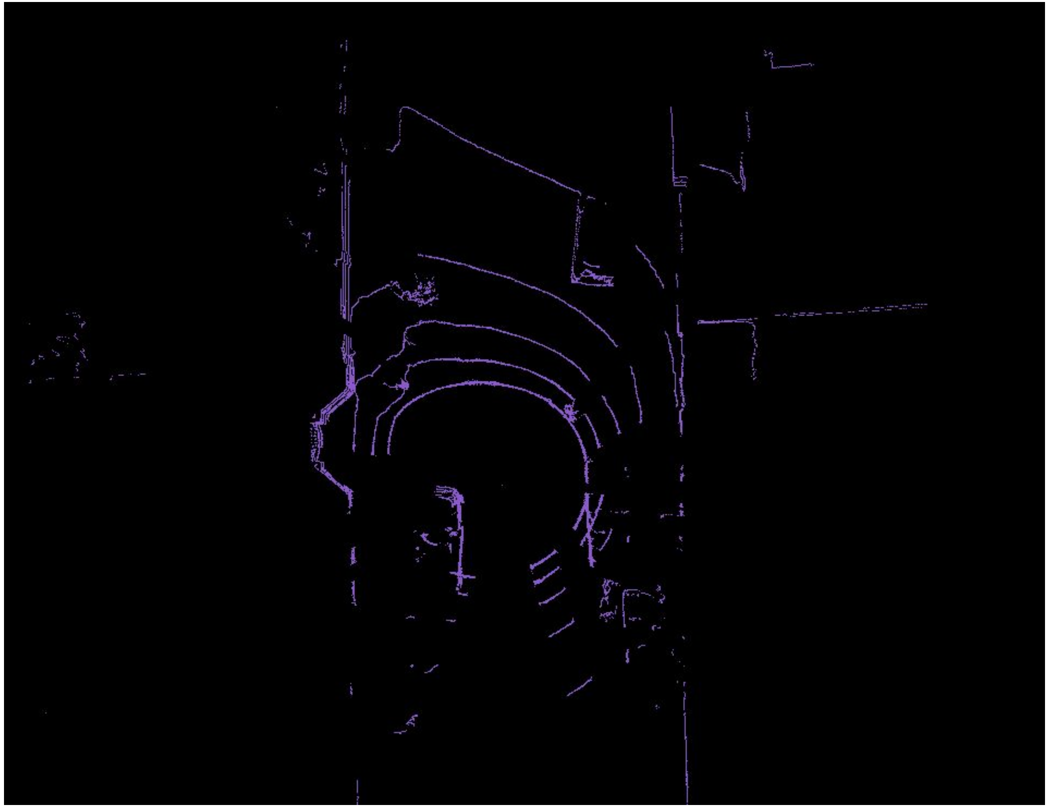



- Depth pixel
- A point cloud is the output of a LiDAR. It maps out everything in its environment within a range in the form of three dimensional coordinates.
- PCL - open source library

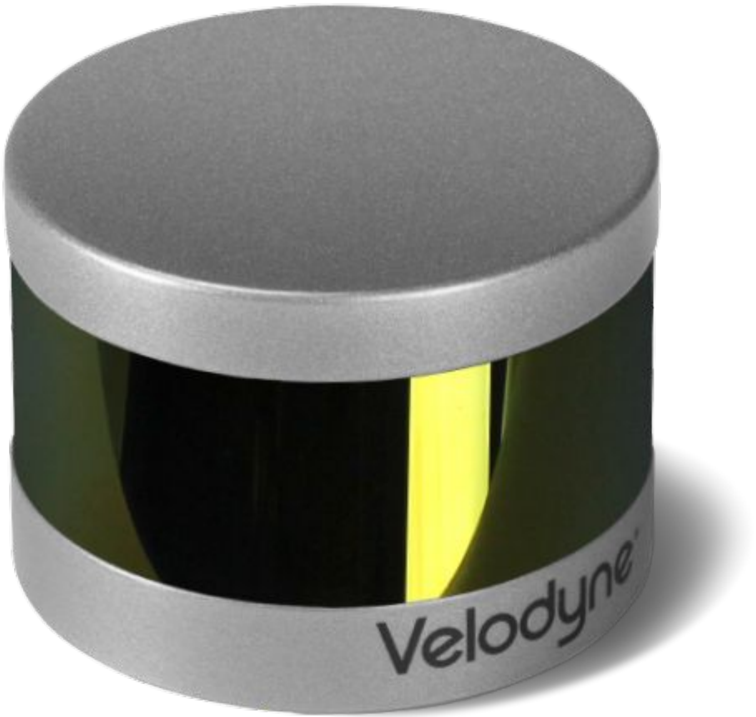
# Point Cloud



# Point Cloud



# Methods to obtain point cloud data




- Light Detection and Ranging.
- Uses light in the form of a pulsed laser to measure ranges and distances

Contains:

- Laser
- Scanner
- GPS

Other devices that can be used:

- Camera
- 3D scanner

# Methods to Estimate Pose

- Analytical approach - point set registration algorithms
- Genetic approach
  - Genetic representation
  - Fitness function
- Learning-based approach - AI models
  - Learning phase
  - Estimation

# An introduction to Iterative Closest Point (ICP)

**Iterative Closest Point**

**The Problem:**
Two point clouds are chosen:

- Reference point cloud
- Source point cloud

These are mapped onto each other to determine the relative transformation.

**Constraints** using this approach:

- Time efficiency - about 70-100ms for about 3000 points
- Accuracy - single mistake can skew entire result

# Problem Statement

# A Method for Registration of 3-D Shapes

Objective: Registration of 3-D shapes using six degrees of freedom

Advantage: Can handle pose estimation of complex models in less time

Applications:

- Registering unfixtured shapes
- Deciding congruence of geometric shapes

# Literarute Survey

| **Name** | **Objective** | **Methodology** | **Advantage** | **Disadvantage** |
|---|---|---|---|---|
| A Method for registering 3-D shapes - Paul J Besl | Registering 3D shapes accurately and computationally | ICP Algorithm | Handles 6 degrees of freedom | Not time efficient |
| Pose Estimation of Autonomous Vehicles using Visual Information: A Minimum - Energy Estimator Approach - Antonio Pedro Aguiar | Estimate pose of a vehicle using a monocular charged-coupled-device (CCD) | Minimum-energy estimator with Kalman filter | Inertial sensors used | There may be delayed calculation of pose |

| | | | | |
|---|---|---|---|---|
| PoseCNN: A Convolutional Neural Network for 6D Object Pose Estimation in Cluttered Scenes - Yu Xiang | Pose Estimation | CNN for 6D object pose estimation performing 3 tasks:<br>1) Labelling<br>2) 3D translation<br>3) 3D rotation regression | Quick estimation of pose because of the presence of a CNN model | Training of model takes a long time |
| Pose Estimation from Corresponding Point Data - Robert A Haralick | Pose Estimation for 2D and 3D point data | Least squares fitting in combination with Robust algorithm | Quicker to estimate pose vs Iterative algorithms | Cannot eliminate least squares estimation |
| Uncertainty-Driven 6D Pose Estimation of Objects and Scenes from a Single RGB Image | Pose estimation in uncertain conditions in 6 degrees of freedom | Neural Network model and RANSAC hypothesis | Quick computation of pose because of use of neural networks, system is broadly applicable | The data fed in was not robust |

| | | | | |
|---|---|---|---|---|
| Real-time 3-D Pose Estimation Using a High-speed Range Sensor - David A Simon | Pose Estimation | ICP and triangular mesh | High speed acquisition of 3D data<br>High speed pose estimation | Feature extraction not prominent |
| Autonomous vehicles: from paradigms to Technology - Silviu Ionita | Autonomous vehicle management | Modular classification of tasks and classes of ADAS | Clarity in the operation and management of autonomous vehicles using deep learning | Issues not dealt with:<br>● Sensors<br>● Optimal model to use |
| Sparse Iterative Closest Point - Sofien Bouaziz | Face construction and shape matching | ICP | Superior registration results | Sensitivity to outliers and missing data |

| | | | | |
|---|---|---|---|---|
| Artificial Neural Networks - John J Hopfield | Give a clear overview about artificial neural networks | Evaluation of artificial neural networks based on available knowledge | Concepts are explained distinctly | Applications not explained explicitly. |
| An ICP variant using a point-to-line metric - Andrea Censi | Implementation of ICP using point to point metric | PlICP | Less robust, requires less iterations, more precise, open source | Quicker than general ICP but slower than when Neural Network models are used |

# Design and Implementation

How the algorithm works:

1. For each point in the source point cloud, match the closest point in the reference point cloud.
2. Estimate transformation using an RMS point to point distance metric minimization technique.
3. Transform the source points using the obtained transformation.
4. Iterate (re-associate the points, and so on).

# Mathematical overview of ICP

Source Point Cloud: S0(...)

Destination Point Cloud: S1(...)

$$d = | p_{position} - q_{position} | = \sqrt{}(p_x - q_x)^2 - (p_y - q_y)^2 - (p_z - q_z)^2$$

# Conclusion and Future Enhancement

- Pose Estimation - Important aspect in Robotics
- ICP:
  - Too many iterations and computations
  - More vulnerable to errors - precision
- In depth analysis of ICP

# References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[3] https://docs.opencv.org/3.3.0/d7/d53/tutorial_py_pose.html

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Thank You