정윤석 / Yunsuk Jeung

Profile

- 서울대학교 김호영 교수님 지도하에 있는 마이크로 유체역학 및 소프트 메터 연구실 소속 석사과정 생이며, 반도체 공정 및 메타모핑 기계시스템 연구단 소속으로 연구하고 있습니다.

Project Experience

- Nano/bio-mechanical system technology using micro/nanoscale porous flow control(2018)
- 2018-2019 SEMES-SNU Research project(2018-2019)
- Research Center for Metamorphing Mechanical Systems(2019-2020)

Main Research Theme

- Line/plane extraction based LiDAR Odometry

Interests/Knowledge

- Microfluidics
- Flow visualize with highspeed camera
- Line/plane extraction from LiDAR pointcloud and odometry calculation
- Project Management

Skills

- C++, MATLAB, Solidworks, ROS(C++), LiDAR Data Processing Using PCL Library

Education

- 2013-2018 B.S. in Mechanical Engineering, SNU
- 2018-2019 M.S. in Mechanical Engineering, SNU
- 2019-2020 Ph.D. candidate in Mechanical Engineering, SNU

목차

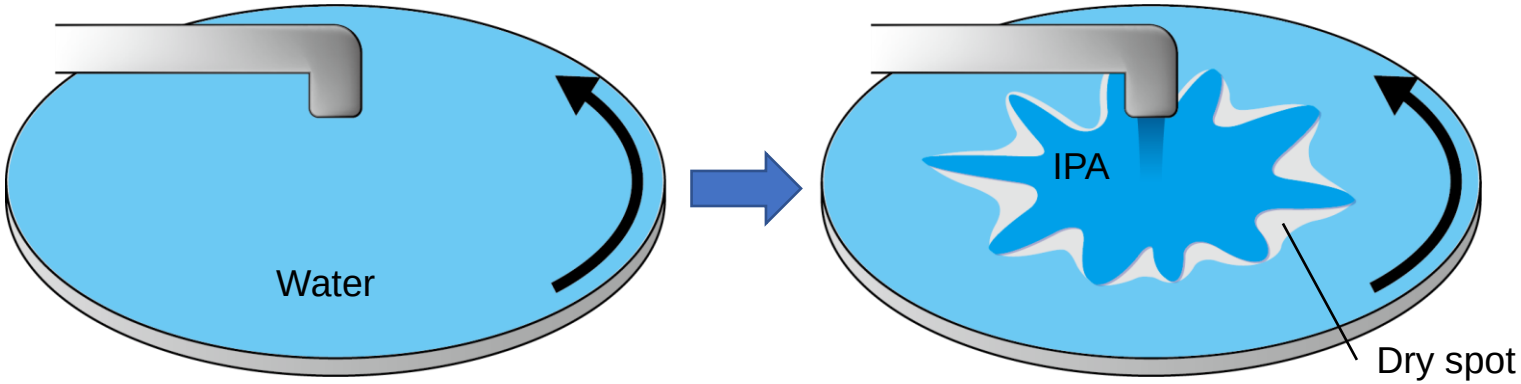
SEMES-SNU Research Project

Fingering instability during a semiconductor cleaning process

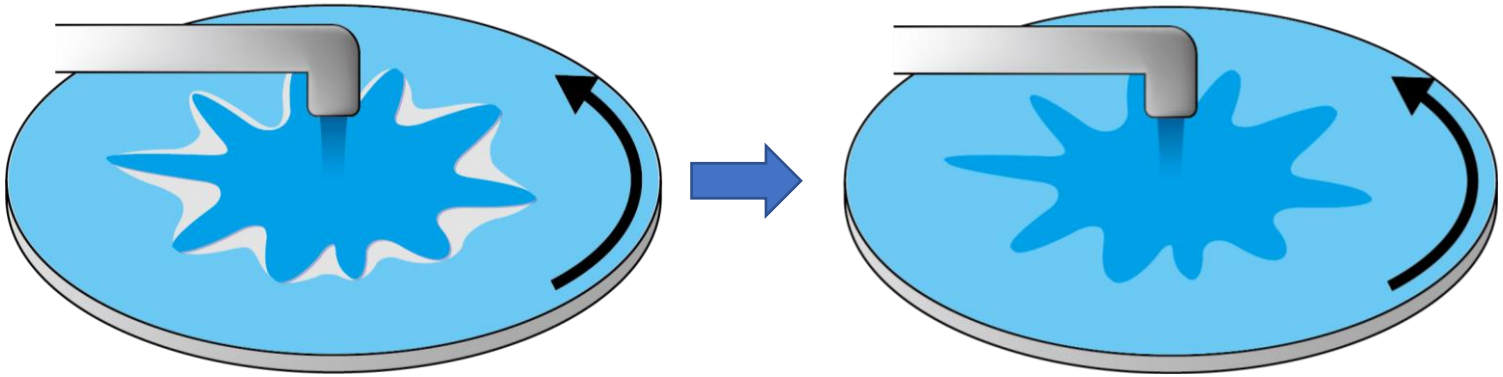
: Analyzing physics of cleaning process, project management

300 mm wafer에서의 fingering 메커니즘 및 개선안 도출

- 연구 개요 : 반도체 세정 공정에서 물이 덮여진 웨이퍼에 IPA를 분사 시 finger 모양의 dry spot이 생성되어 공정의 효율이 떨어지는 문제 발생



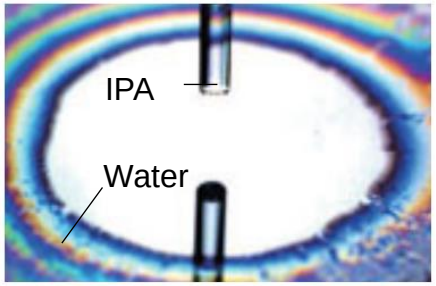
- 연구 목표 : Dry spot의 생성 원인을 파악하고 해결 방안 제시

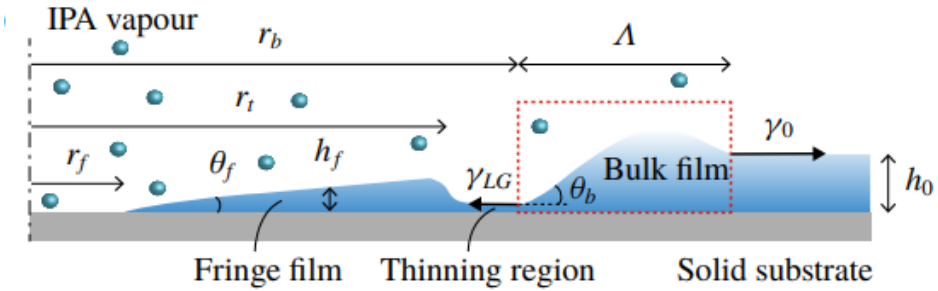


300 mm wafer에서의 fingering 메커니즘 및 개선안 도출

- 연구 방향 설정
  - 주어진 예산 내에서 실제 세정 공정을 재현할 수 있도록 장비 선정
  - 선행 연구를 바탕으로 가설 설정

S. Kim et al., *J. Fluid Mech., 2019*





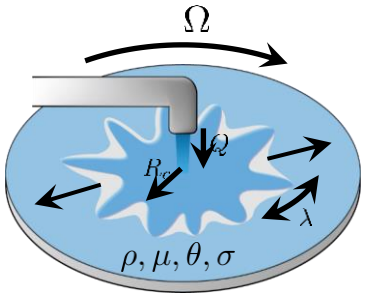
IPA 증기가 물 표면에 달라붙어 표면장력 감소 → Dry spot 발생

  - 선생 연구를 바탕으로 주요 parameter 선정

Liquid property: 표면장력, 밀도, 점도

Controllable parameter: 접촉각, 유량, 회전속도

→ R_c 를 최대화 하여 dry spot 제거



$$R_c = f(Q, \rho, \mu, \theta, \sigma, \Omega)$$

R_c : Dry spot이 생성되는 위치

Q : 액체 유량 θ : 접촉각

ρ : 밀도 σ : 표면장력

μ : 점도 Ω : 회전 속도

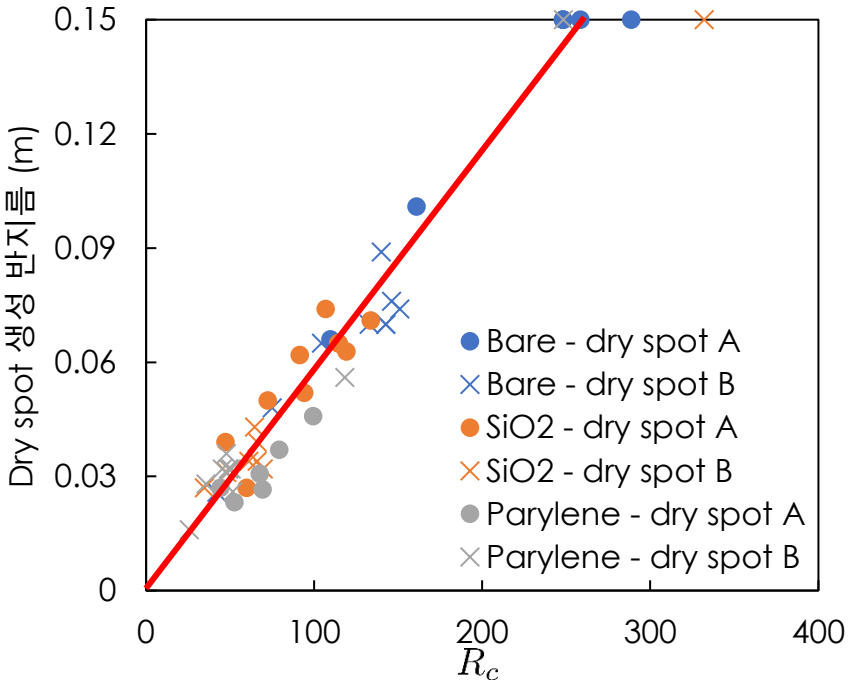
300 mm wafer에서의 fingering 메커니즘 및 개선안 도출

- 이론 모델 검증
  - 주요 parameter를 이용한 이론 모델 생성

$$R_c \sim \rho_d^{\frac{1}{4}} \left(\frac{1}{\mu_d}\right)^{\frac{1}{4}} \mu_{cv}^{\frac{3}{4}} Q_g^{\frac{1}{2}} \Omega^{\frac{1}{2}} \left(\frac{1}{\Delta\sigma}\right)^{\frac{3}{4}} \left(\frac{1}{h_c} - \frac{1}{h_0}\right)^{\frac{3}{4}}$$

$$h_0 = \left(\frac{3}{2\pi} \frac{Q_d \mu_d}{\rho_d \Omega^2 r_0^2}\right)^{\frac{1}{3}}, \quad h_c = \left(\frac{3}{2\pi} \frac{Q_d \mu_d}{\rho_d \Omega^2 r_f^2}\right)^{\frac{1}{3}}, \quad r_f = 0.13 \frac{\rho_d \Omega^{\frac{1}{2}} Q_d^{\frac{5}{4}}}{\mu_d^{\frac{1}{4}} \sigma_d^{\frac{3}{4}} (1 - \cos\theta)^{\frac{3}{4}}}$$

  - 실험과 비교



정확한 이론 모델을 통해 변수를 조절하여 dry post 제거 가능

Main Research Theme:

Feature extraction from LiDAR pointcloud and Odometry estimation

: Feature extraction from Lidar pointcloud & LiDAR Odometry

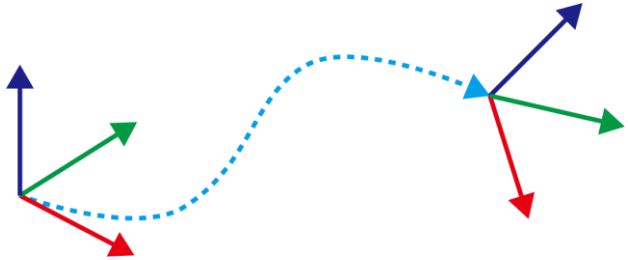
Keyword: Feature(line, plane) extraction / LiDAR odometry

Research Motivation

- **연구 동기 및 개요 : 실내 3D LiDAR Odometry**

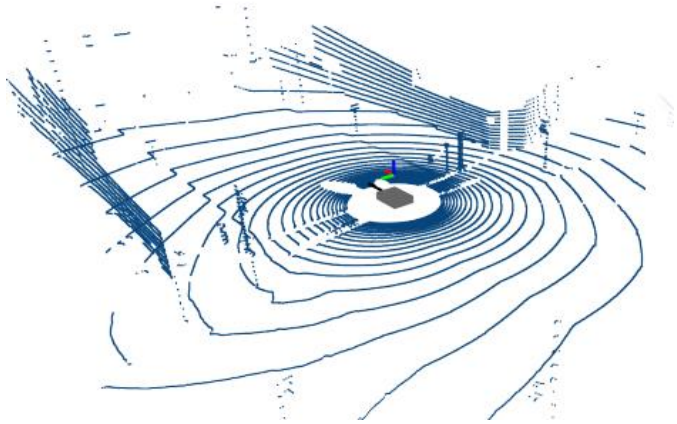
– **연구 동기 :** LiDAR를 이용한 실내 Odometry algorithm 구현

Velodyne VLP-16



$$Z_{Lidar,\,1:t} \longrightarrow \hat{x}_{1:t}$$

– **연구 개요 :** 실내 환경의 주요 구성 요소인 Line-plane feature extraction algorithm을 이용하여 Odometry 계산



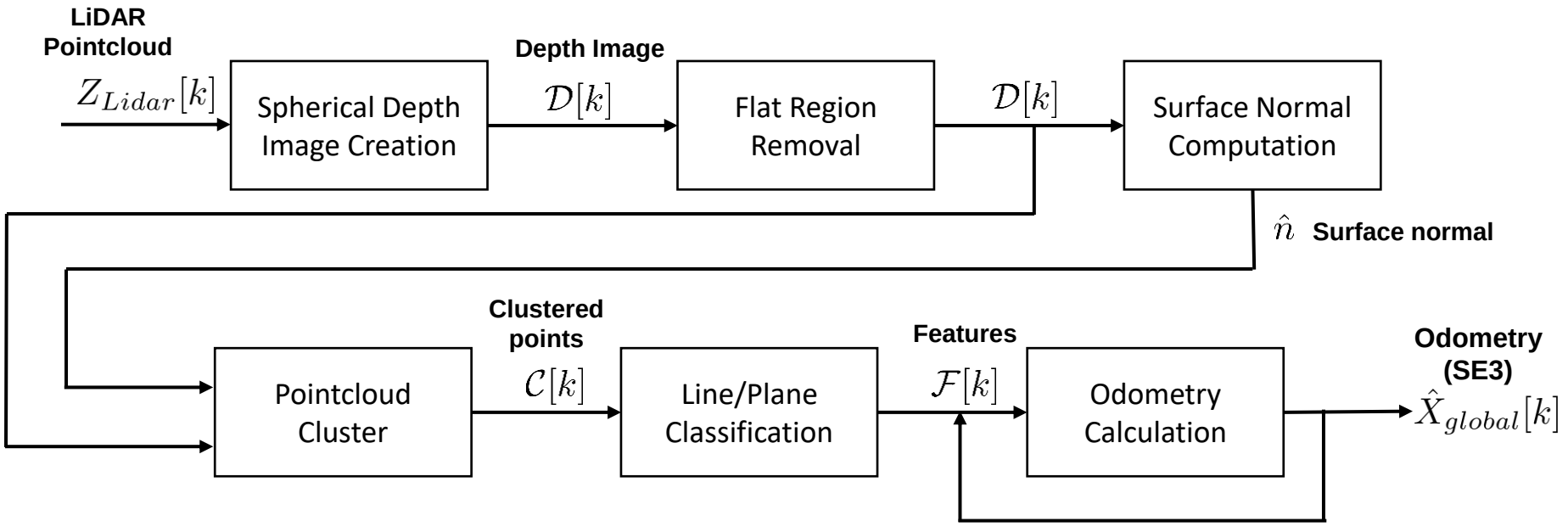
J. Serafin et al., “Fast and Robust 3D Feature Extraction from Sparse Point Clouds,” *IROS*, 2016

LiDAR Odometry Algorithm Block Diagram

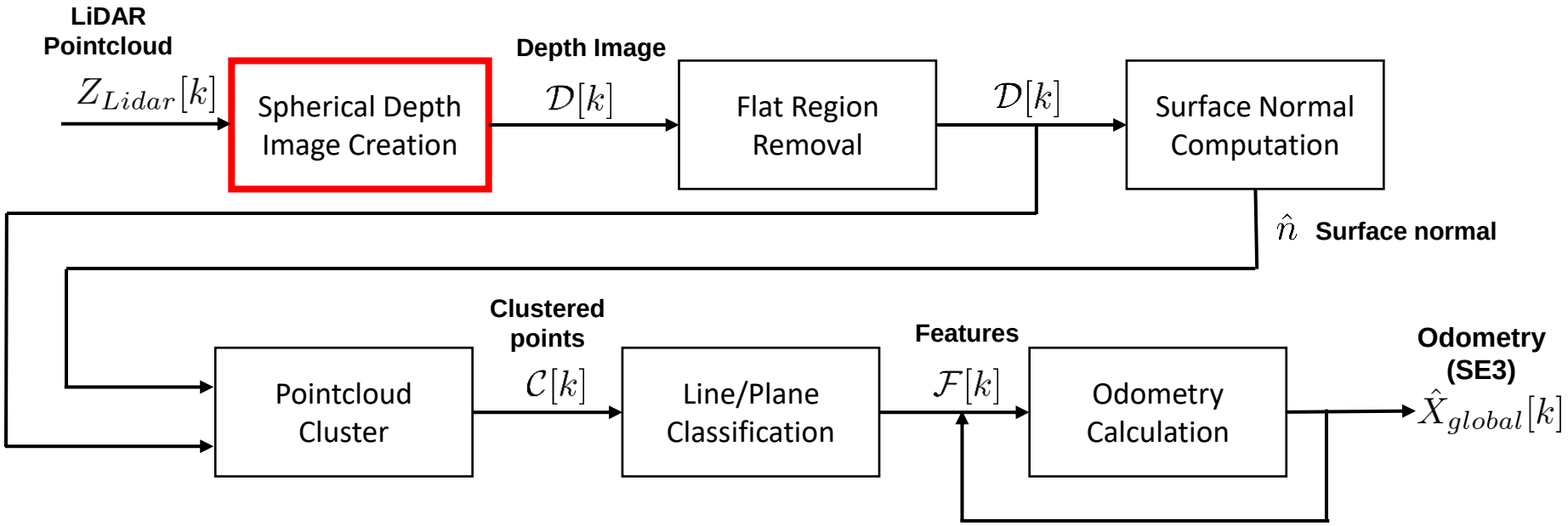
- **Lidar Odometry Algorithm : Line & plane matching**

– **알고리즘 개요 :**

1) LiDAR로 수집된 Pointcloud를 spherical depth image로 변환 후 flat region 제거
2) Covariance matrix와 Adaptive window size를 이용한 surface normal 계산
3) Extract line and plane
4) Find odometry with matching features

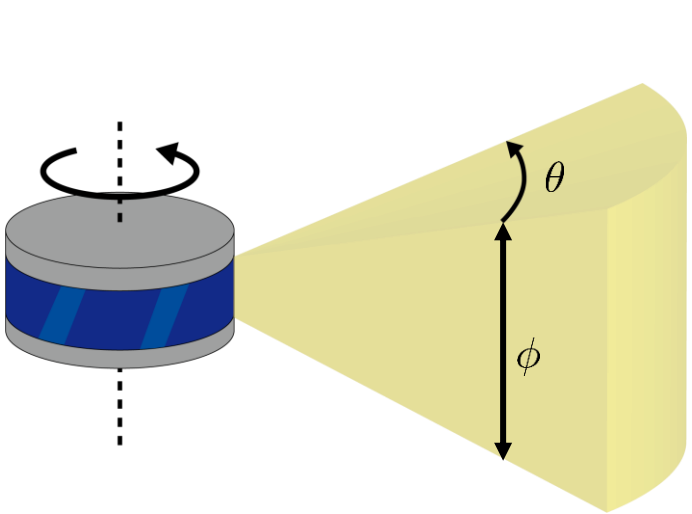


Spherical Depth Image Creation

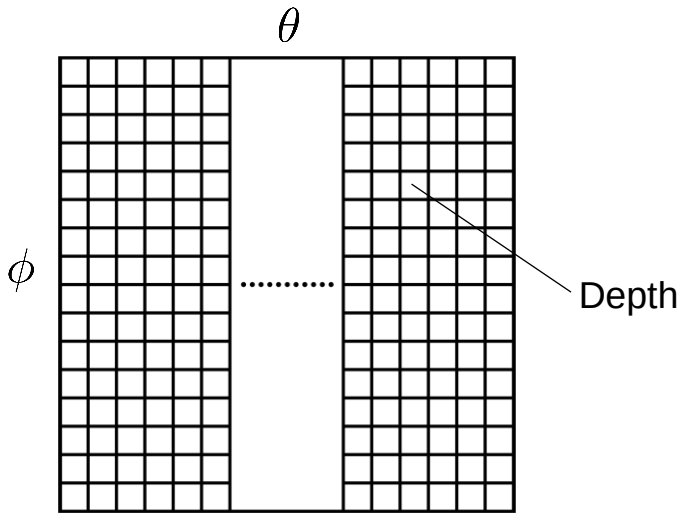


Spherical Depth Image Creation

- **Spherical Depth image**
  - Velodyne LiDAR의 scan 방식을 반영하여 polar coordinate 사용



Velodyne VLP-16 scanning

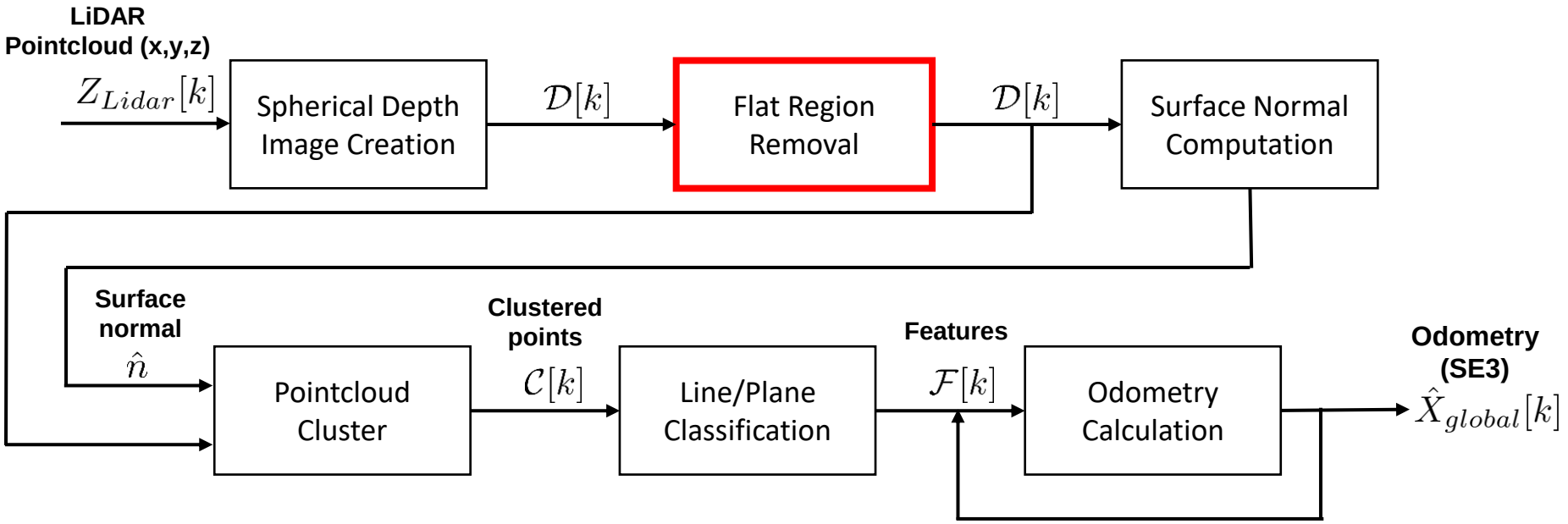


Spherical Depth Image

$$p = (x, y, z) \rightarrow \Phi(p) = s \rightarrow s = (\theta, \phi, d)$$

  - Spherical depth image를 이용함으로써 LiDAR로 스캔한 3차원 데이터를 2차원 배열과 depth로 표현 가능
  - VLP-16: 16채널 0.2 deg의 분해능으로 16 x 1800 의 image 사용

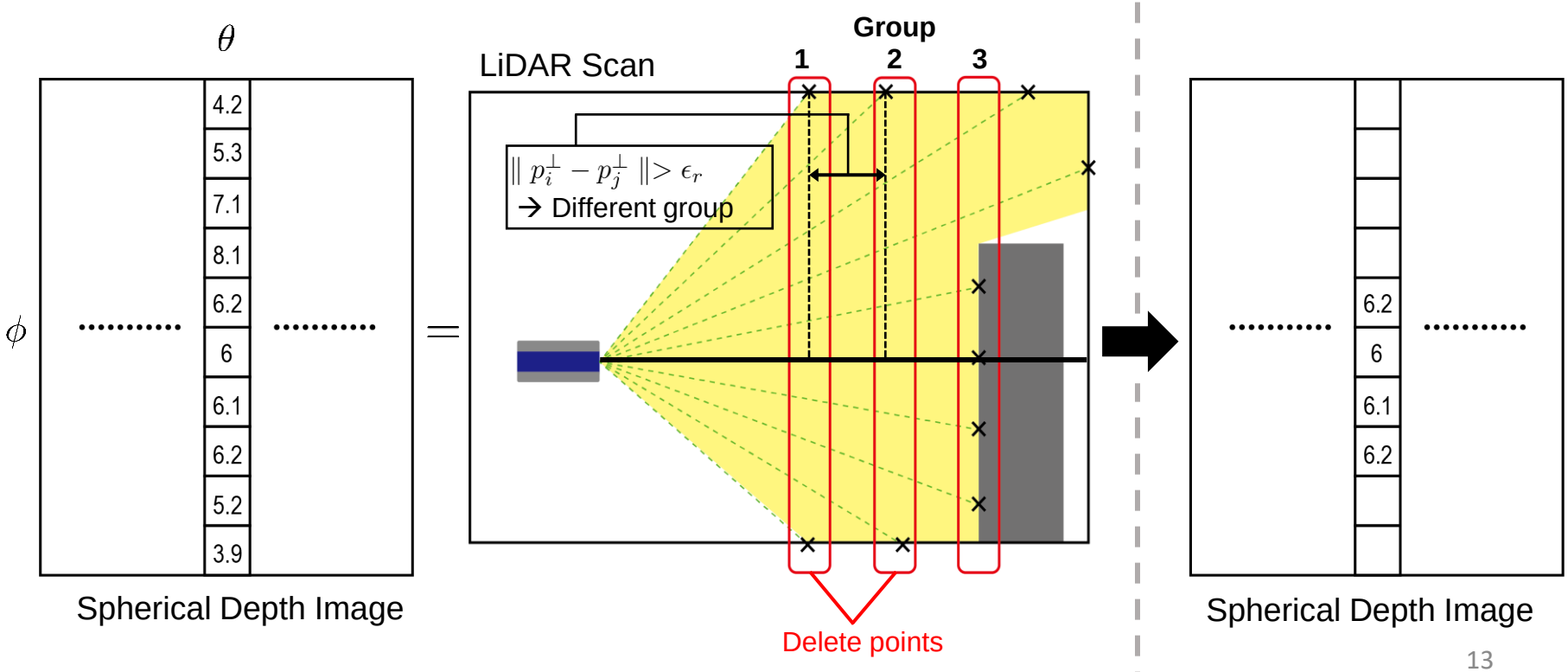
Flat region removal



Flat region removal

- **Flat region removal**
  - 중요하지 않은 ground를 제거함으로써 계산 속도 향상 및 odometry 정확도 향상
  - Points를 LiDAR Local Coordinated XY평면에 정사영 시킨 후 vertical points 판단
    1) $\| p_i^{\perp} - p_j^{\perp} \| < \epsilon_r$ → Group points ($p^{\perp}$: xy 평면에 정사영 된 좌표)
    2) Number of points in group > ϵ_t → Label vertical points

ϵ_r	0.5 m
ϵ_t	3

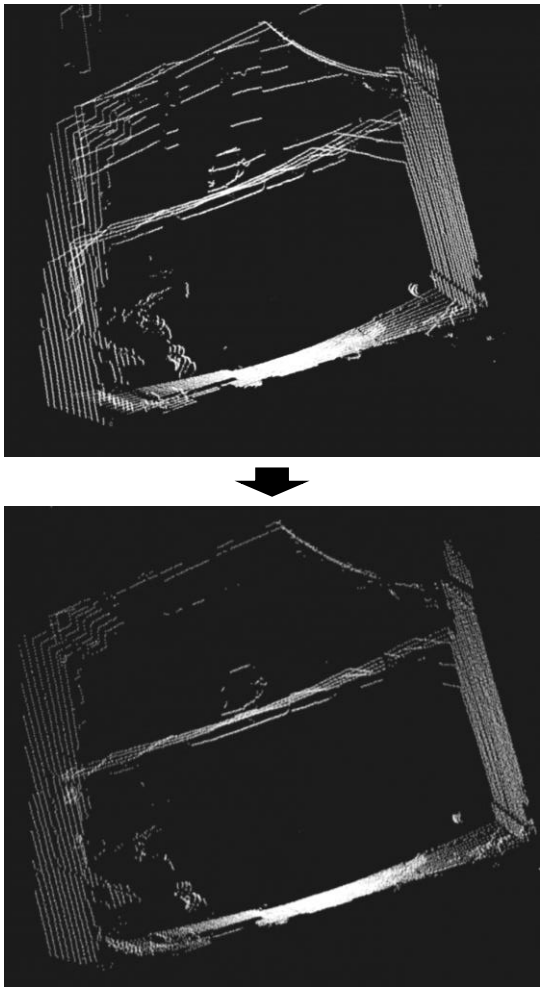


Flat region removal

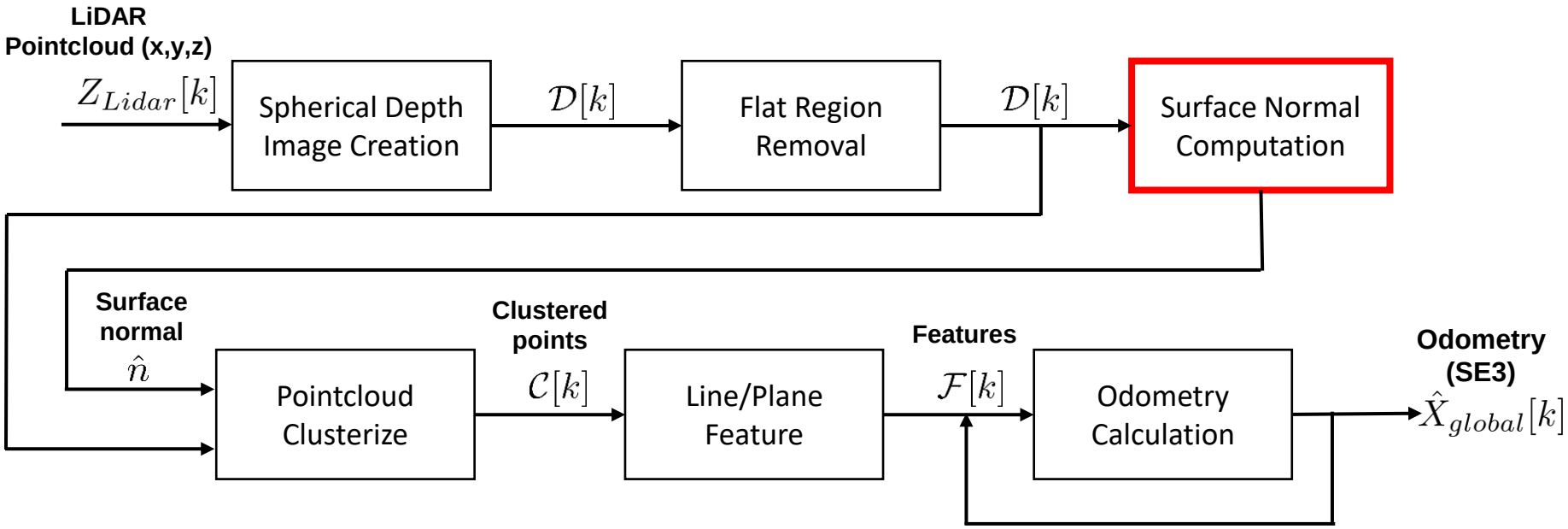
- **Algorithm & Result**

foreach *column* u *in* D^p *do*
  foreach *row* v *in* D^p *do*
    if $D^P_{uv} \neq 0$ && p_{uv} *not labeled vertical* **then**
      $n \leftarrow 0$
      $p \leftarrow p_{uv}$
      foreach *row* w *in* D^p *greater than* v *do*
        If $\| p^{\perp}_{uv} - p^{\perp}_{uw} \| < \epsilon_r$ **then**
          $n \leftarrow n + 1$
          $p \leftarrow p \cup p_{uw}$
        end
      end
      If $n > \epsilon_t$ **then**
        label all points in p as vertical
      else
        delete p_{uv} from P
        $D^P_{uv} = 0$
      end
    end
  end
end

P : Pointcloud
D^p : Spherical depth image
$p^{\perp}$: 2D projection on the ground



Surface Normal computation



Surface Normal computation

- **Feature 분류를 위한 surface normal 계산**
  - Integral Image를 이용한 Covariance matrix 계산
  - Covariance matrix → eigenvalue decomposition → surface normal
  - Feature를 구분하기 위하여 depth change를 바탕으로 adaptive window size 결정

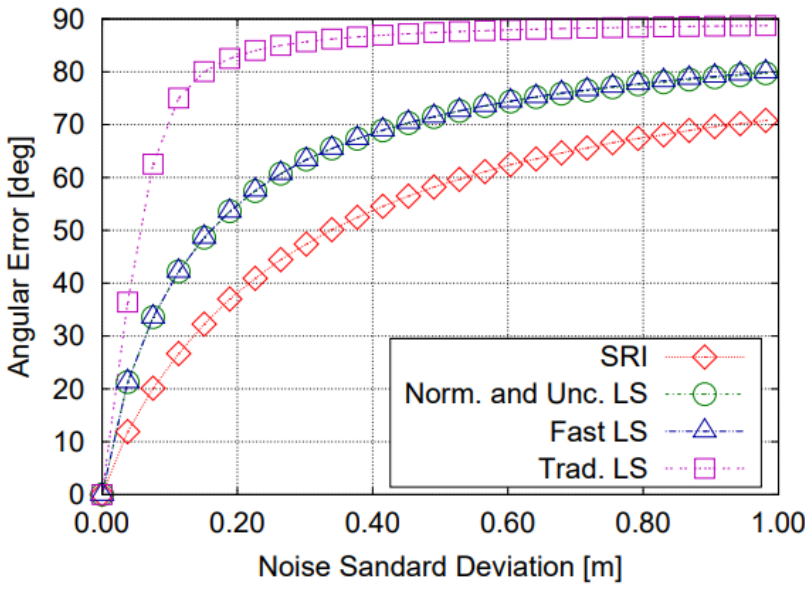
- **Covariance Matrix (SRI) vs Least Square (LS) for surface normal**

M. Size	Methods	Time (ms) $\pm \sigma$	SUF
3×3	Trad. LS	192.25 ± 5.92	1
	Norm. LS	227.52 ± 4.04	0.85
	Unc. LS	18.87 ± 0.18	10.19
	Fast LS	7.02 ± 0.05	27.39
	SRI	3.66 ± 0.01	52.53
5×5	Trad. LS	195.00 ± 3.04	1
	Norm. LS	237.2 ± 4.04	0.82
	Unc. LS	19.14 ± 0.16	10.18
	Fast LS	7.04 ± 0.03	27.70
	SRI	$3.71 \pm < 0.01$	52.56
7×7	Trad. LS	436.12 ± 7.2	1
	Norm. LS	483.5 ± 3.1	0.9
	Unc. LS	19.14 ± 0.14	15.57
	Fast LS	7.07 ± 0.03	42.14
	SRI	4.33 ± 0.01	68.81
9×9	Trad. LS	436.12 ± 2.58	1
	Norm. LS	489.96 ± 4.8	0.89
	Unc. LS	19.35 ± 0.16	22.54
	Fast LS	7.18 ± 0.12	60.74
	SRI	4.40 ± 0.01	99.12

TABLE II

ACTUAL COMPUTATION TIMES WITH SPEED UP FACTORS (SUF) OVER THE

H. Badino et al., *ICRA*, 2011



→ Covariance Matrix shows faster and more accurate performance

Surface Normal computation

- **Feature 분류를 위한 surface normal 계산**
  - *Integral Image를 이용한 Covariance matrix 계산
  - Covariance matrix → eigenvalue decomposition → surface normal
  - Feature를 구분하기 위하여 depth change를 바탕으로 adaptive window size 결정

- **Integral image**
  - $\mathcal{I}_o(m,n) = \sum_{i}^{m}\sum_{j}^{n}\mathcal{O}(i,j)$ ($\mathcal{I}_o$: integral image, $\mathcal{O}$: original image)
  - 특정 영역 픽셀 값의 합을 4개의 픽셀로 계산 가능 → 계산 속도 향상

*Integral image

10	15	7	9	5	6
9	32	65	45	12	7
7	24	66	65	41	34
9	11	70	89	44	37
32	78	91	78	48	65
64	12	89	58	65	45

Original image of x

89+44+37+78+48
+65+58+65+45 = 529

10	25	32	41	46	52
19	66	138	192	209	222
26	97	235	354	412	459
35	117	325	533	635	719
67	227	526	812	962	1111
131	303	691	1035	1250	1444

Integral image of x

1444-459-691+235 = 529

Faster computation

1. Depth image와 같은 크기의 integral image 생성
2. Point의 좌표 (x, y, z) 를 바탕으로 9개의 integral image 생성

$$\mathcal{I}_x,\ \mathcal{I}_y,\ \mathcal{I}_z,\ \mathcal{I}_{xx},\ \mathcal{I}_{xy},\ \mathcal{I}_{xz},\ \mathcal{I}_{yy},\ \mathcal{I}_{yz},\ \mathcal{I}_{zz}$$

3. Covariance matrix 계산

$$C = \begin{bmatrix} c_{xx} & c_{xy} & c_{xz} \\ c_{xy} & c_{yy} & c_{yz} \\ c_{xz} & c_{yz} & c_{zz} \end{bmatrix} - \begin{bmatrix} c_x \\ c_y \\ c_z \end{bmatrix} \begin{bmatrix} c_x \\ c_y \\ c_z \end{bmatrix}^T$$

c_k : 관심 영역 내 k의 평균

ex) $c_x = 529/9 \approx 59$

S. Holzer et al., *IROS*, 2012

*APPENDIX 참조

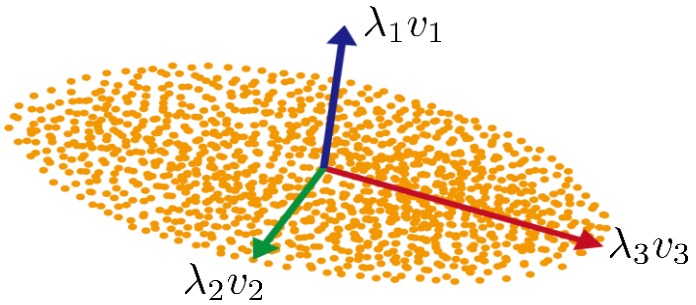
Surface Normal computation

- **Covariance matrix eigenvalue decomposition**

$$C = \begin{bmatrix} cov(x,x) & cov(x,y) & cov(x,z) \\ cov(y,z) & cov(y,y) & cov(y,z) \\ cov(z,x) & cov(z,y) & cov(z,z) \end{bmatrix}$$

Eigenvalue decomposition $(\lambda_3 \geq \lambda_2 \geq \lambda_1)$

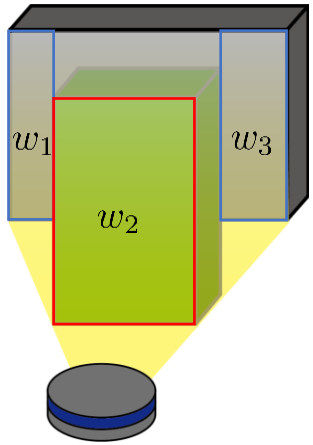
$$C = \begin{bmatrix} v_1 & v_2 & v_3 \end{bmatrix} \begin{bmatrix} \lambda_1 & 0 & 0 \\ 0 & \lambda_2 & 0 \\ 0 & 0 & \lambda_3 \end{bmatrix} \begin{bmatrix} v_1^{\mathrm{T}} \\ v_2^{\mathrm{T}} \\ v_3^{\mathrm{T}} \end{bmatrix}$$



- v_3: 가장 분산이 큰 방향
- v_2: v_3과 수직이면서 가장 분산이 큰 방향
- v_1: v_3 과 v_2와 수직 → surface normal

- **Adaptive window size**
  - Depth image에서 depth 변화를 감지하여 window size 결정
  - $|d_i - d_j| > \epsilon_w$ → change window

    d : Depth of image pixel
  - ϵ_w = 0.6



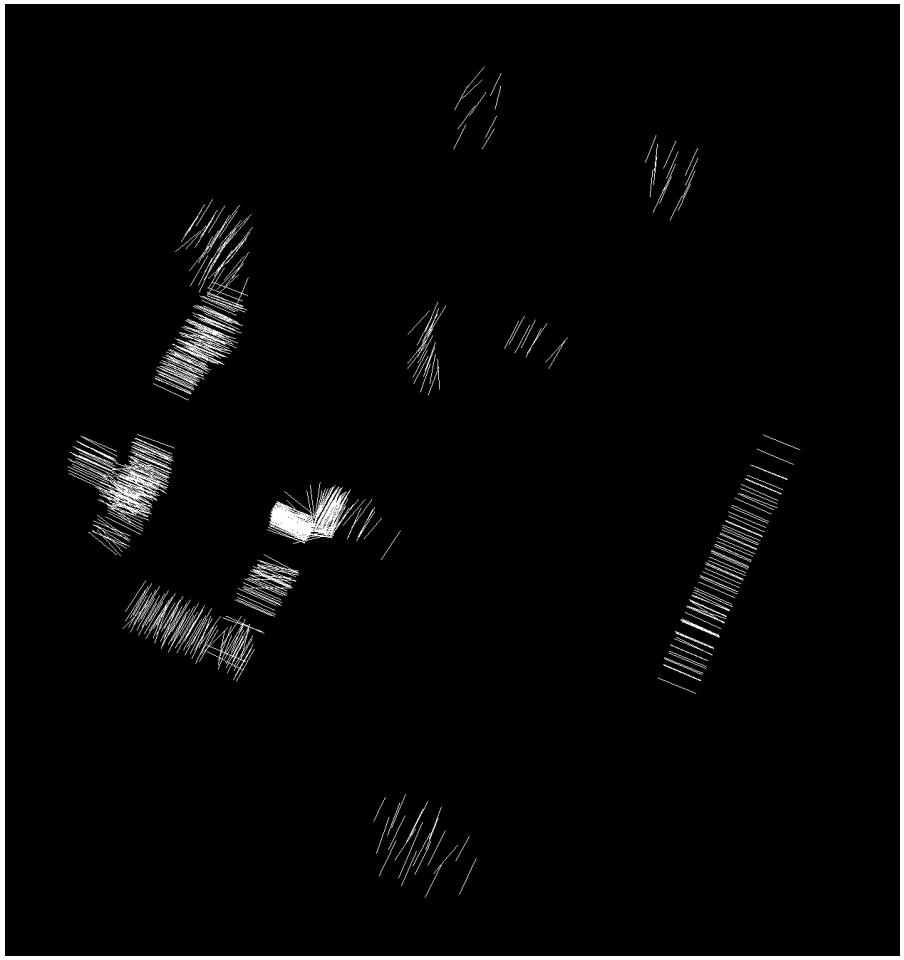
Depth image

3	3	1	1	1	3	3
3	3	1	1	1	3	3
3	3	1	1	1	3	3
3	3	1	1	1	3	3
3	3	1	1	1	3	3
		w_1		w_2		w_3

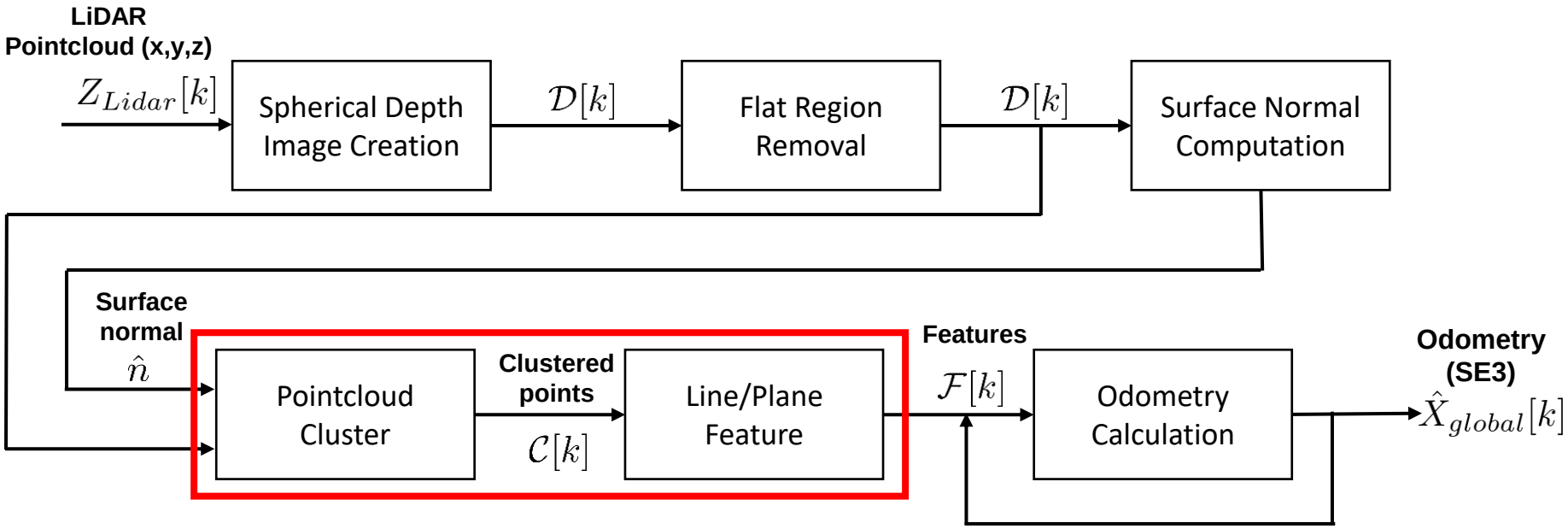
- 각 window 에서의 covariance matrix를 eigenvalue decomposition하여 surface normal 계산

Surface Normal computation

- **Result**



Feature extraction



Feature extraction

- **Cluster pointcloud**
  - Neighbor points (p)간의 거리 및 surface normal(n) 의 각도 확인 후 point cluster

$$\| p_s - p_i \| = d$$

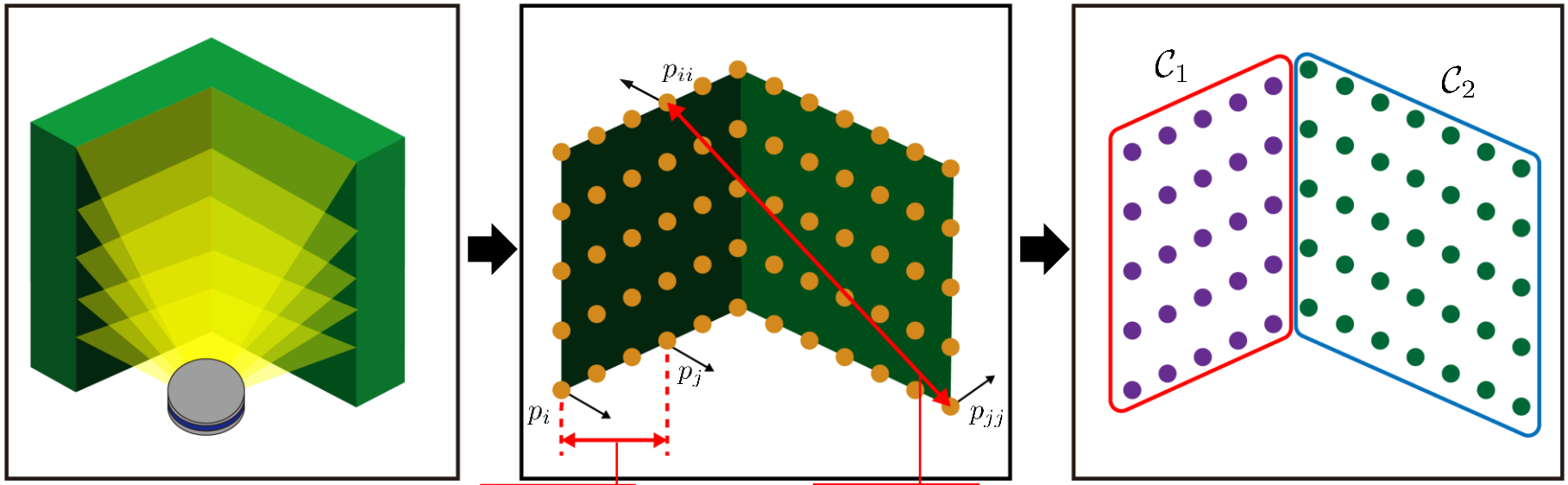
If $d < \epsilon_d$ && $n_s \cdot n_i > \epsilon_n$ **then**

$C_s \leftarrow C_s \cup p_i$

end

Seed point: p_s, n_s
Neighbor point: p_i, n_i
Clustered pointcloud: $\mathcal{C}$

ϵ_d	1.0 m
ϵ_n	0.9



p_i, p_j → Same cluster

p_{ii}, p_{jj} → Different cluster

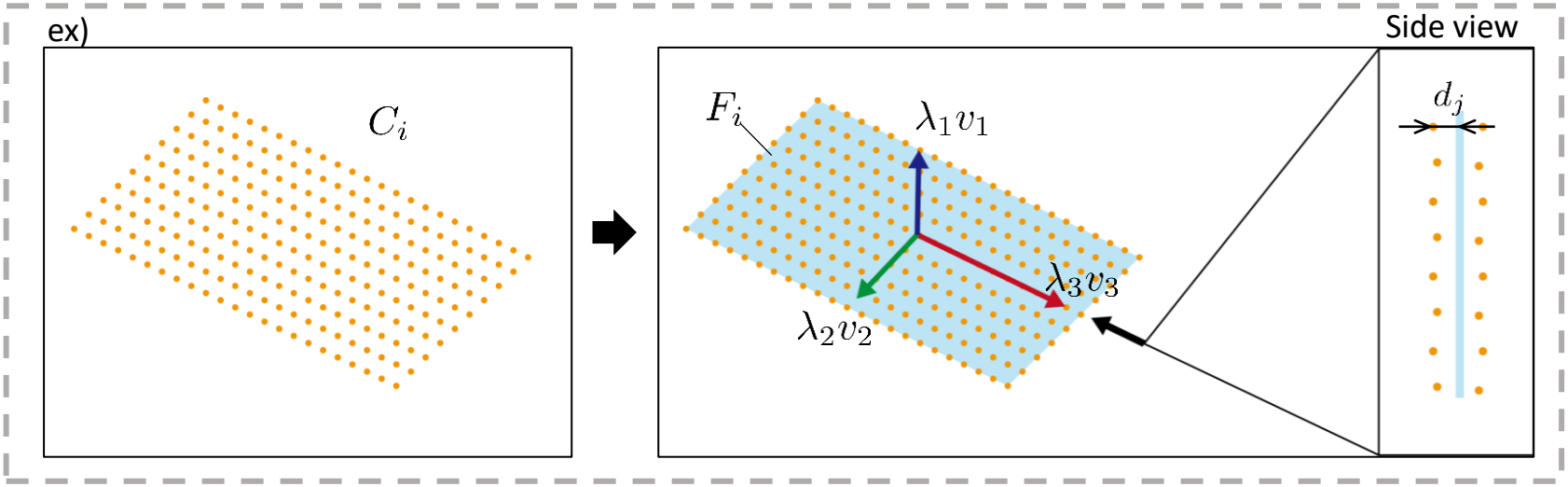
Feature extraction

- **Line/Plane 분류**
  - C_i의 Gaussian distribution $\mathcal{N}_i^c(\mu_i^c, \Sigma_i^c)$ 계산 후 covariance matrix(CM)의 eigenvalue deposition
  - Feature 생성 (F_i)

$$\frac{\lambda_1^c + \lambda_2^c}{\lambda_1^c + \lambda_2^c + \lambda_3^c} < \epsilon_l \Rightarrow F_i\text{: Line with origin } \mu_i^c\text{, direction with } v_3^c$$

$$\frac{\lambda_1^c}{\lambda_1^c + \lambda_2^c + \lambda_3^c} < \epsilon_p \Rightarrow F_i\text{: Plane with origin } \mu_i^c\text{, normal with } v_1^c$$

ϵ_l	0.02
ϵ_p	0.03



  - Valid feature 확인

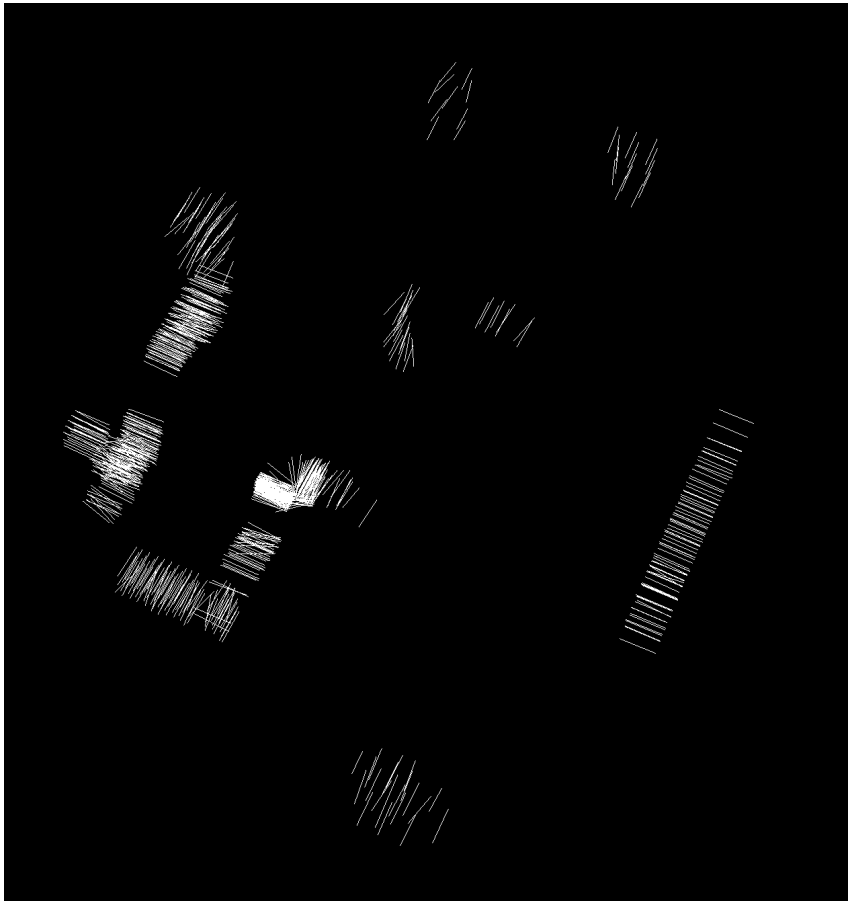
$$e_i = \frac{1}{N_i}\Sigma d_j, (N_i : \text{\# of points in } C_i) \quad e_i < \epsilon_f \rightarrow C_i, F_i \text{ 저장}$$

$$\epsilon_f = 0.1\,\mathrm{m}$$

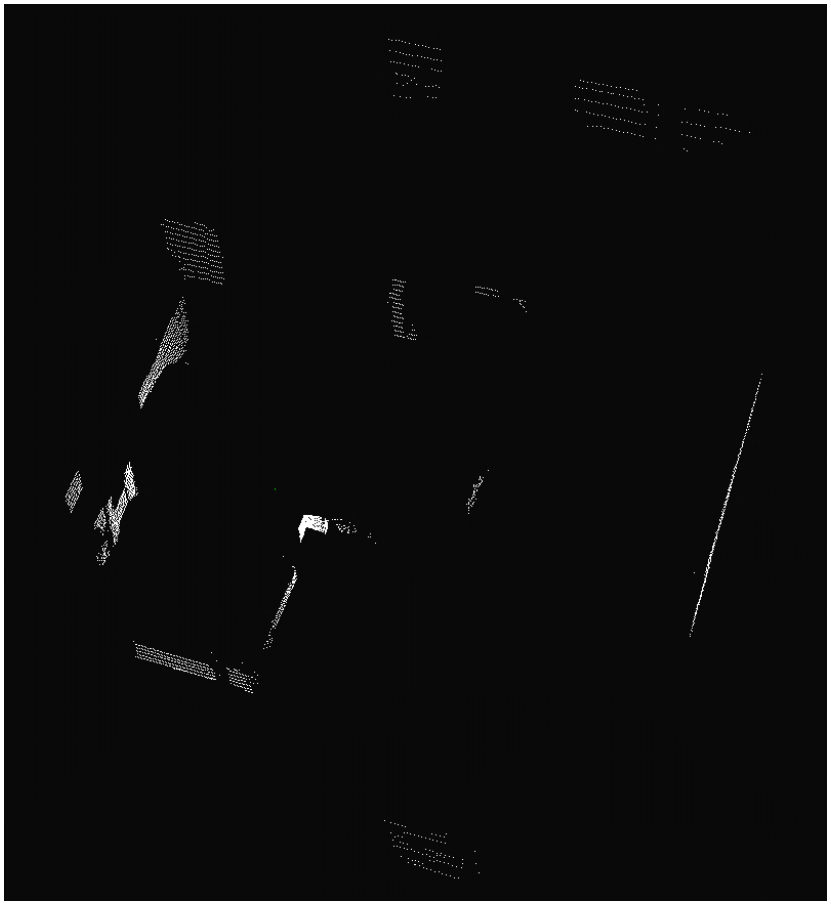
Feature extraction

- **Result**

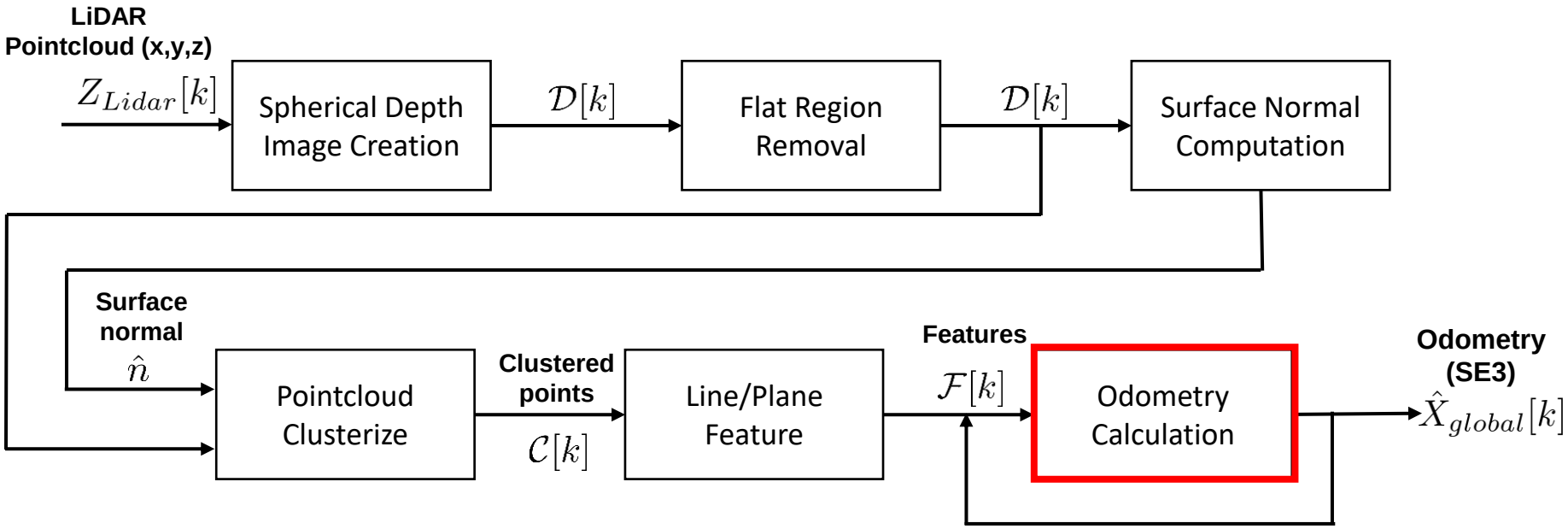
Points & Surface normal



Clustered points to features



LiDAR Odometry computation



LiDAR Odometry computation

- **Existing Odometry algorithm**

1. $\mathcal{F}^k$ 와 $\mathcal{F}^{k+n}$사이의 matching features 찾기

$\mathcal{F}^k$: k 번째 input pointcloud $\mathcal{P}_k$ 에서 추출한 feature (F_i^k) 의 집합 → $F_i^k \in \mathcal{F}^k$

o_i^k : F_i^k 의 중심 좌표

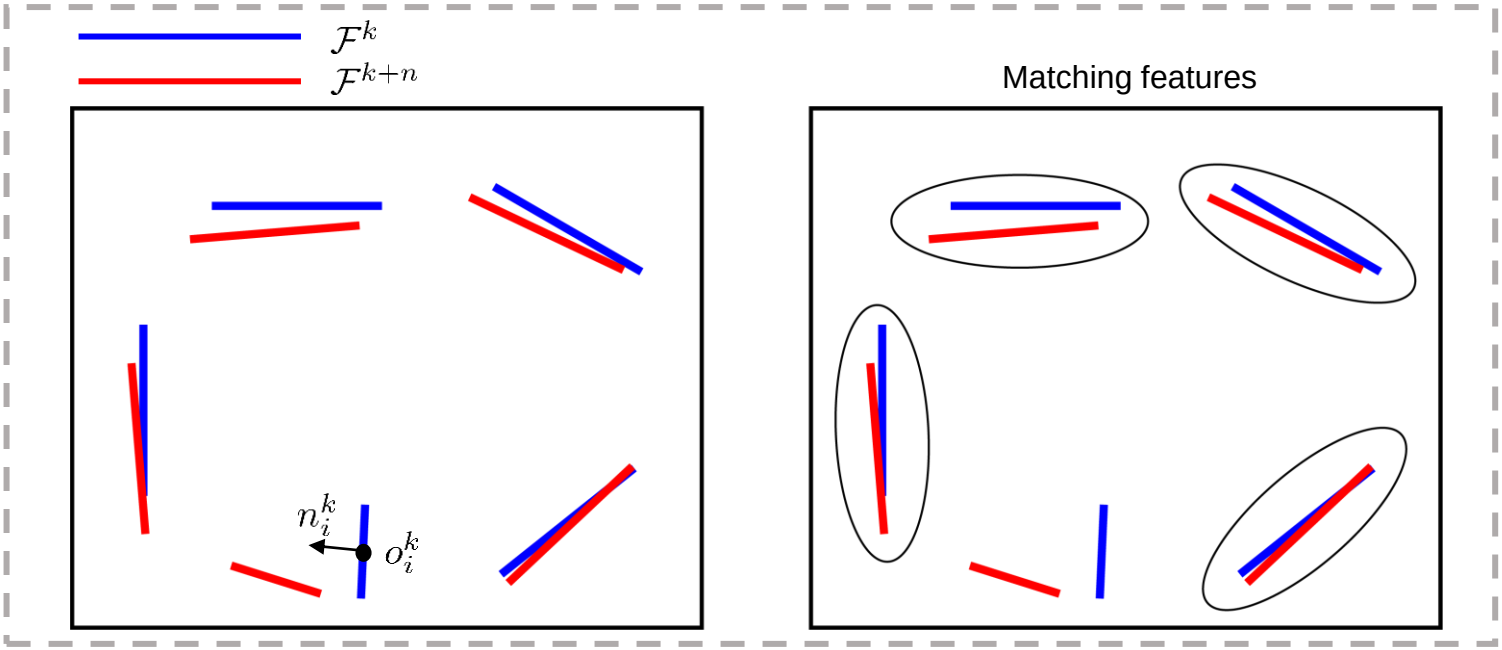
n_i^k : F_i^k 의 normal vector (feature 가 line 경우 direction vector)

If $\| o_i^k - o_j^{k+n} \| < \epsilon_{df}$ && $n_i^k \cdot n_j^{k+n} > \epsilon_{nf}$ **then**

  $F_{(k,i)}, F_{(k+n,j)} \rightarrow$ Matching features

end

ϵ_{df}	0.5 m
ϵ_{nf}	0.85



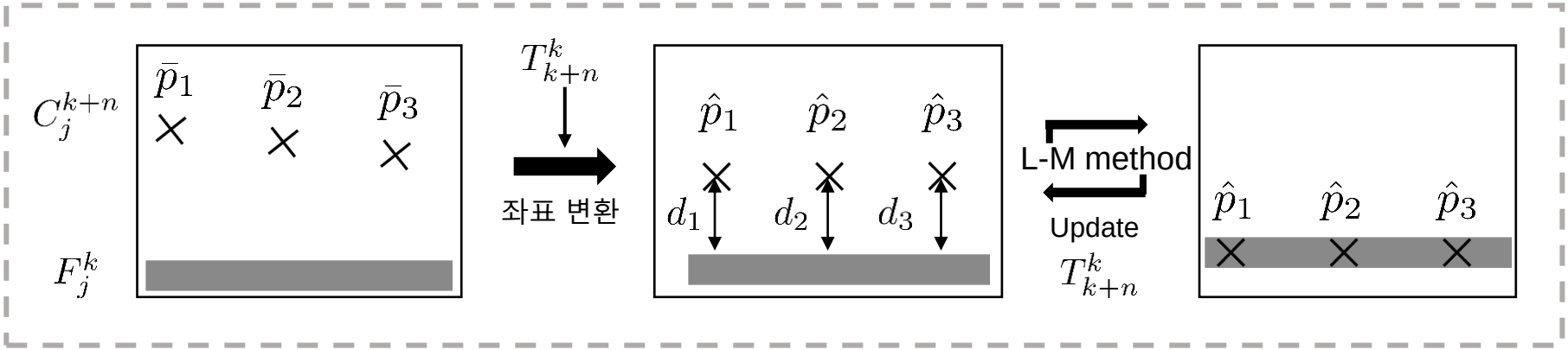
LiDAR Odometry computation

- **Existing Odometry algorithm**

  2. *L-M method를 이용한 T_{k+n}^{k} 최적화

     - T : 6-DOF motion LiDAR, $T = [\ \tau^T\ \theta^T\ ]$, $\tau = [\ t_x\ t_y\ t_z\ ]^T$, $\theta = [\ \theta_x\ \theta_y\ \theta_z\ ]^T$
     - k_{th} frame 과 $(k+n)_{th}$ frame 의 6-DOF motion : T_{k+n}^{k}
     - $(k+n)_{th}$ time step의 pointcloud 를 T_{k+n}^{k}이용해 좌표를 변화시켰을 때 k_{th} time step의 point cloud와 일치시킬 수 있도록 T_{k+n}^{k}를 최적화

       C_j^{k+n} 내의 points들과 F_j^k 와의 거리 사용, $C_j^{k+n} : F_j^{k+n}$ 에 대응하는 cluster



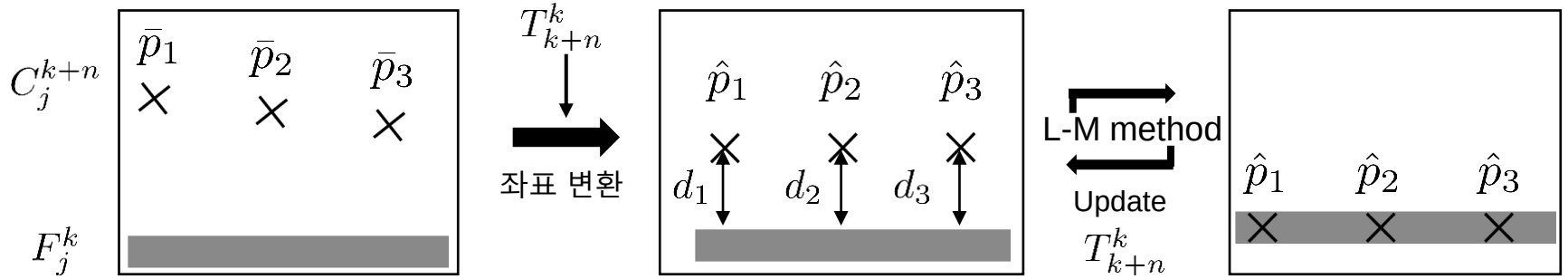
LiDAR Odometry computation

- **Existing Odometry algorithm**

  2. *L-M method를 이용한 T_{k+n}^{k} 최적화

  - T : 6-DOF motion LiDAR, $T = [\ \tau^T\ \theta^T\ ]$, $\tau = [\ t_x\ t_y\ t_z\ ]^T$, $\theta = [\ \theta_x\ \theta_y\ \theta_z\ ]^T$
  - k_{th} frame 과 $(k+n)_{th}$ frame 의 6-DOF motion : T_{k+n}^{k}
  - T_{k+n}^{k} 를 이용하여 C_j^{k+n} 의 좌표 변환 ($\bar{p} \rightarrow \hat{p}$), C_j^{k+n} : F_j^{k+n} 에 대응하는 cluster

    $\bar{p}_m \in C_j^{k+n}$, $R = e^{\hat{\theta}_{k+n}^{k}}$, $t = \tau_{k+n}^{k}$ $\longrightarrow$ $\hat{p}_m = R\bar{p}_m + t$
  - Matching feature 와의 거리 $f(\bar{p}_m, T_k) = d$, for each m, stack f → $\boldsymbol{f}(T_{k+n}^{k}) = \boldsymbol{d}$
  - $T^* = \arg\min_T F(T)$, $F(x) = \frac{1}{2} \parallel \boldsymbol{f}(T) \parallel^2$ ➡ $T \leftarrow T - (J^T J + \lambda diag(J^T J))^{-1} J^T \boldsymbol{d}$



LiDAR Odometry computation

- **Modified algorithm**

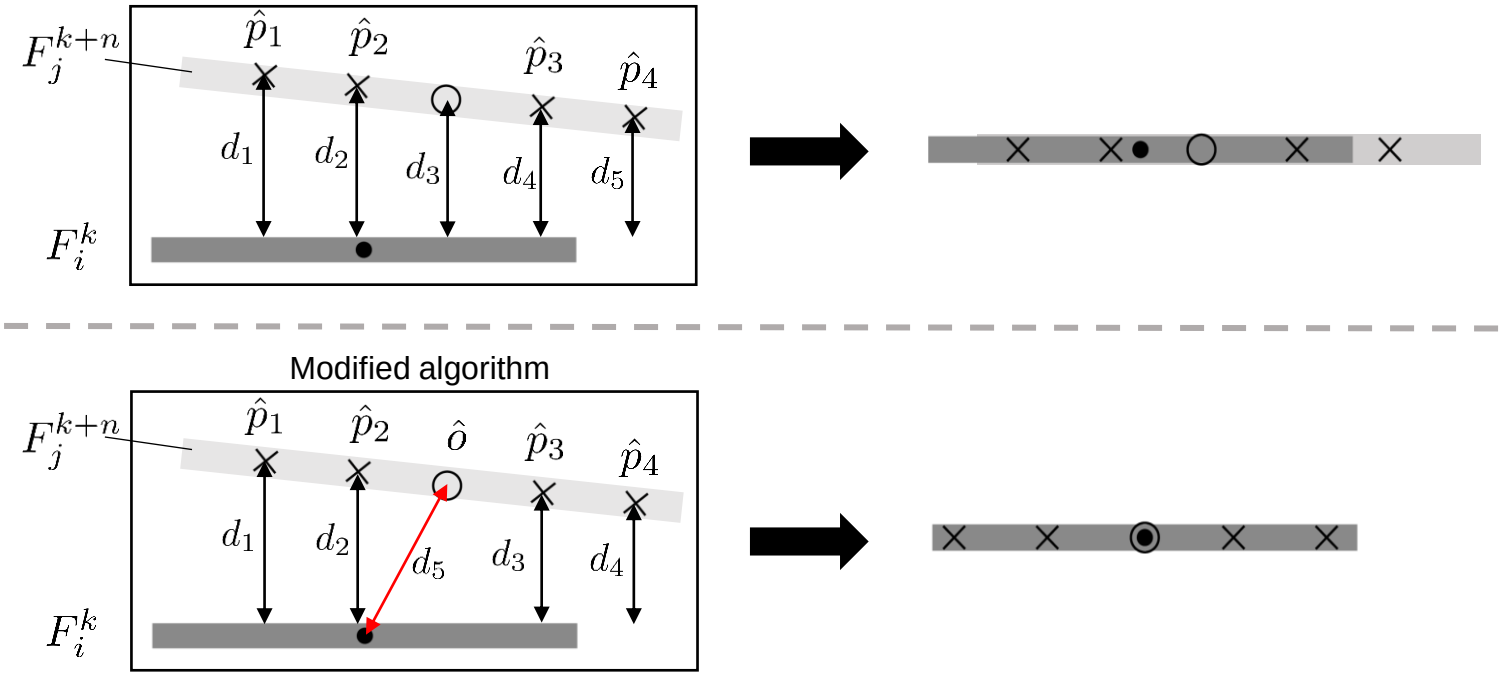
  2. *L-M method를 이용한 T_{k+n}^{k} 최적화 중

  *APPENDIX 참조

  - Matching feature 와의 거리 $f(\bar{p}_m, T_k) = d$, for each m, stack f → $\boldsymbol{f}(T_{k+n}^{k}) = \boldsymbol{d}$
  - Cost 감소를 위해 C_j^{k+n} 대신 F_j^{k+n} 위의 좌표 5개 사용

    → Feature 수가 적을 시 정확한 Odometry를 찾을 수 없는 문제 발생 · · · ①
  - Matching feature의 중심간 거리 함수 추가 · · · ②

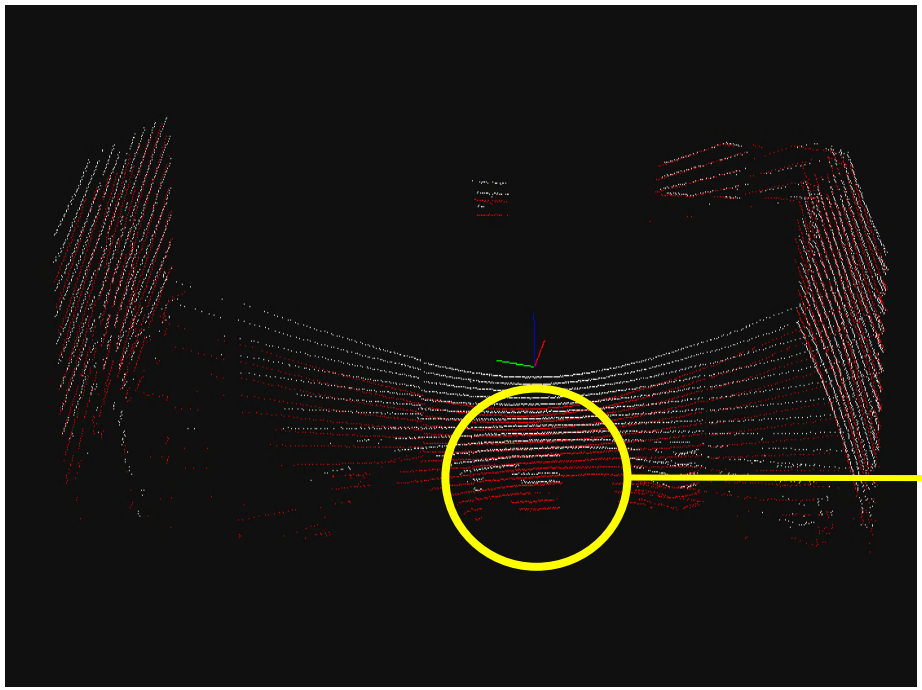
① ② Modified algorithm



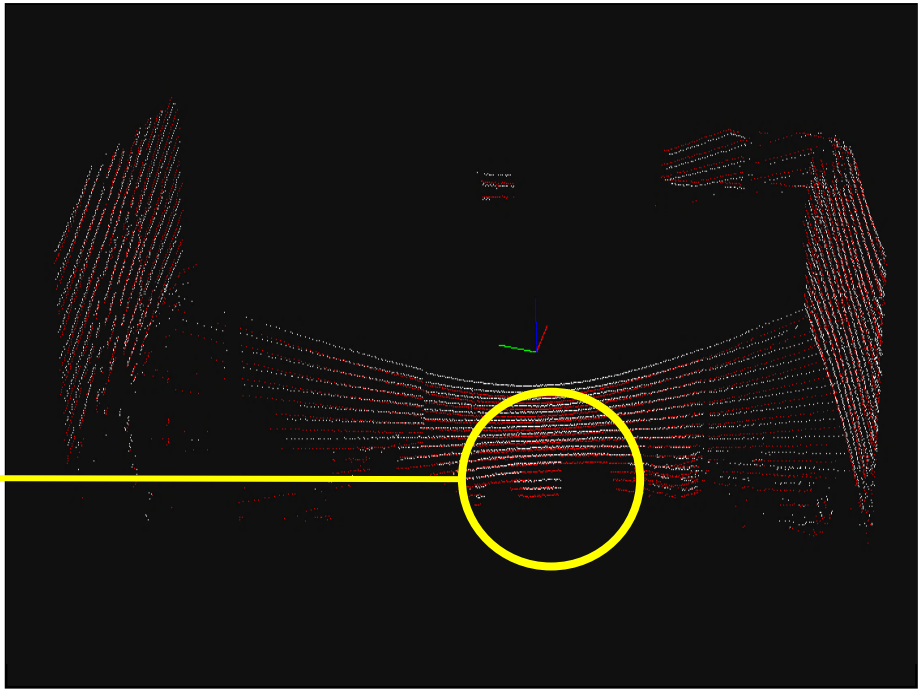
LiDAR Odometry computation

- **Result**

중심간의 거리 함수 추가 전

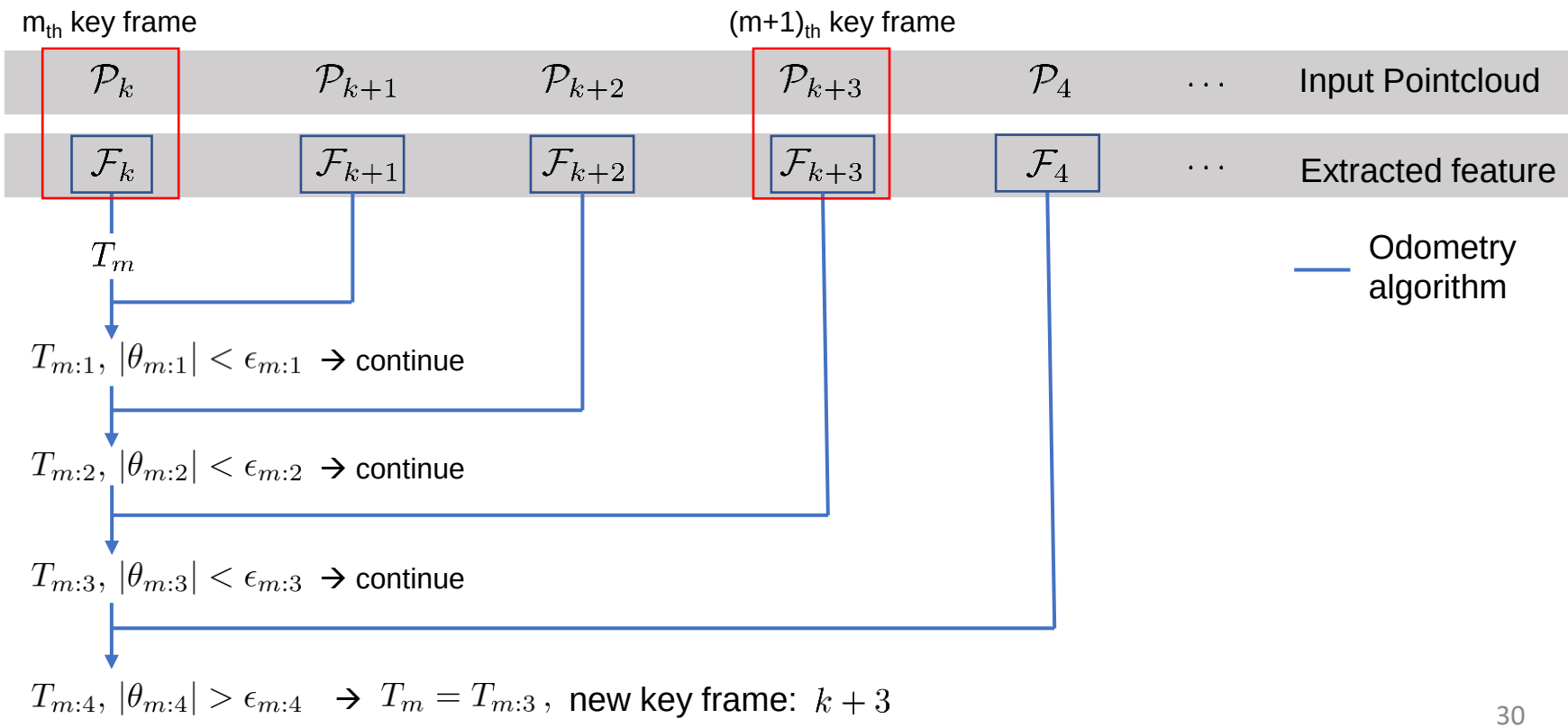


중심간의 거리 함수 추가 후



LiDAR Odometry computation

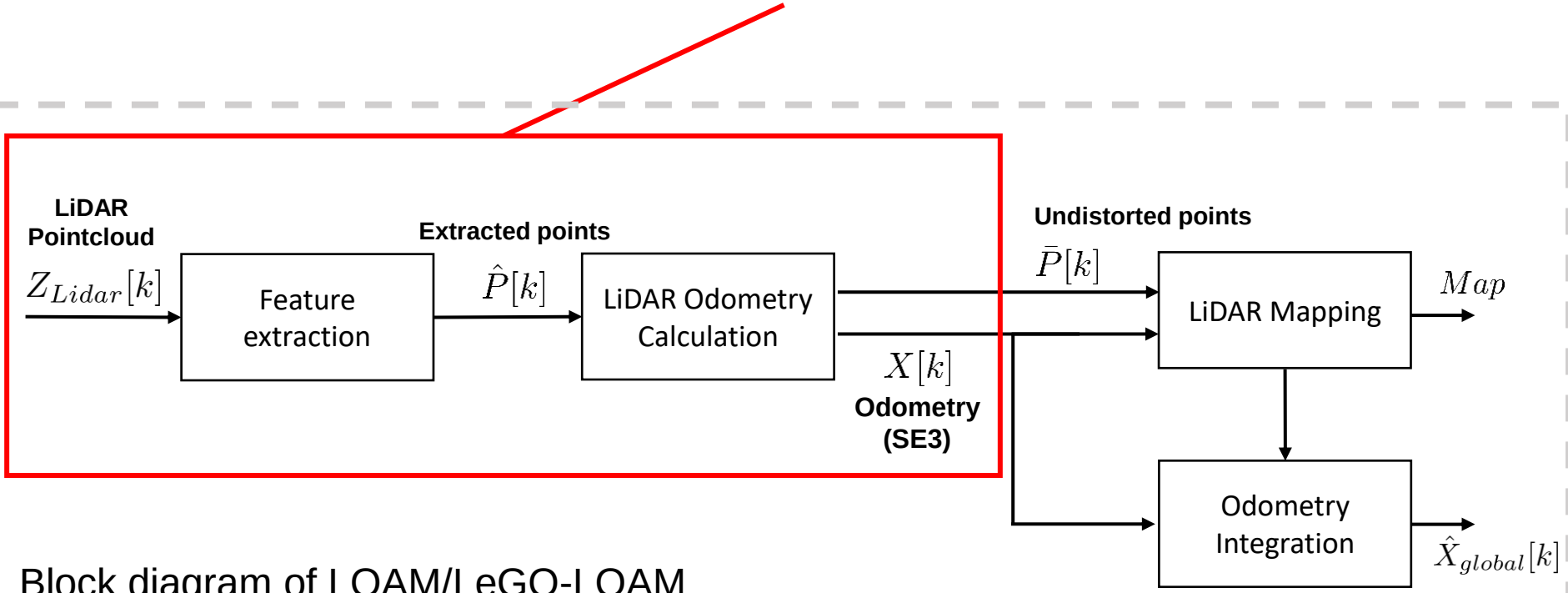
- **Key frame selection**
  - Frame 간 Odometry 계산 시 drift가 누적되는 현상 발생 → Key frame 이용
  - 초기값 $T_m = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}^T$ 으로 시작, Odometry & initial guess update with subframes
  - $|\theta_m| > \epsilon_f$ → key frame 변경, $\epsilon_f = 0.06$



Odometry Result

- **Experimental process**
  - Velodyne VLP-16 datasets in indoor environments 사용하여 Odometry 계산
  - General한 성능 지표로 쓰이는 LiDAR SLAM 알고리즘과의 비교 (거리 오차)

    LOAM/LeGO-LOAM의 frame-frame odometry algorithm과 비교

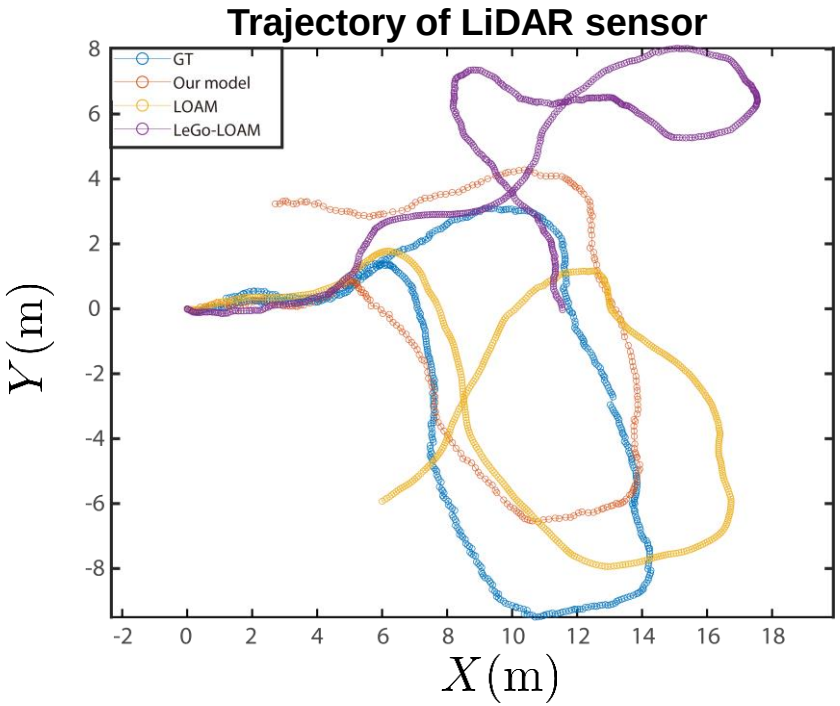


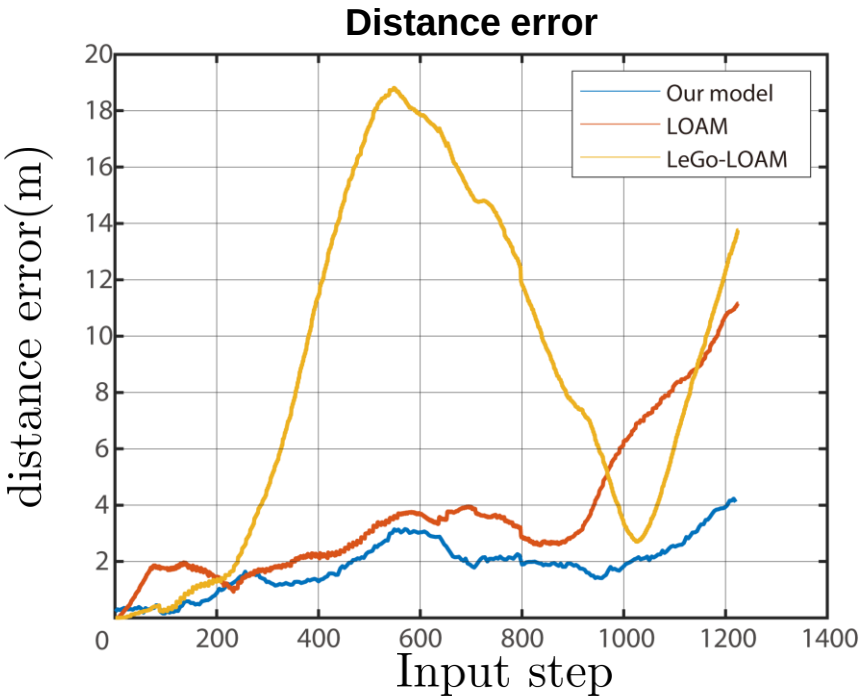
Block diagram of LOAM/LeGO-LOAM

Odometry Result

- Velodyne VLP-16 datasets in indoor environments 사용 결과
  - vs LOAM/LeGO-LOAM의 frame-frame odometry algorithm

    Ground truth와의 거리 오차 비교





→ Our model shows higher accuracy

Conclusion

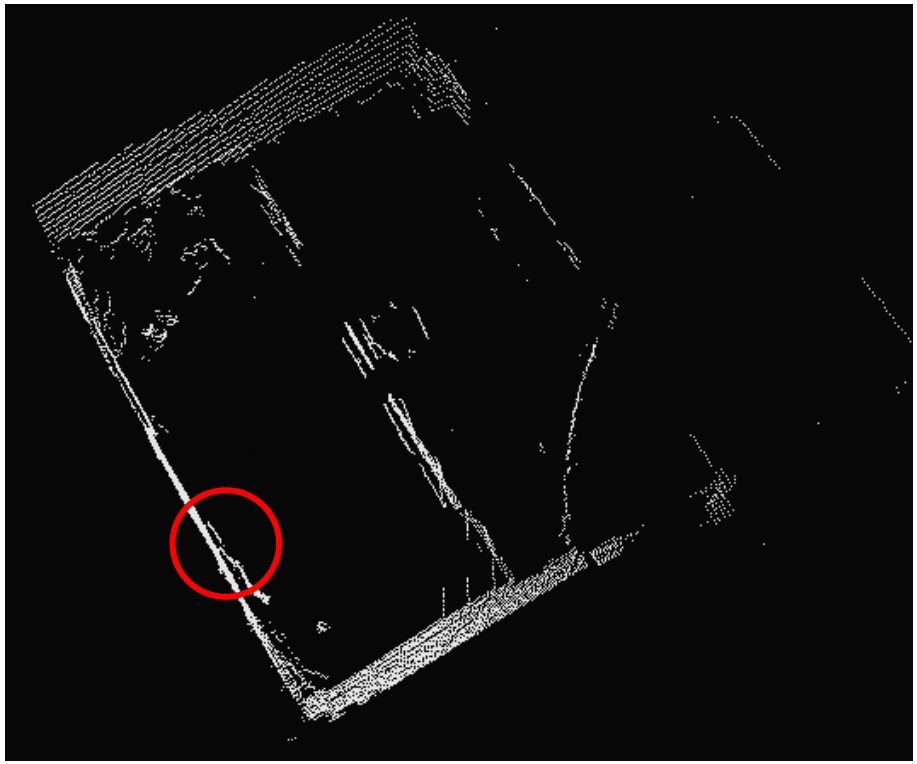
- **Summary**
  - 실내 환경에 적합한 3D LiDAR odometry algorithm 을 선정하여 구현
  - Velodyne VLP-16 datasets in indoor environments 사용하여 성능평가
  - LOAM/LeGO-LOAM의 frame-frame odometry와 비교 (거리 오차)

    정확도가 높은 Odometry 알고리즘 구현에 성공

- **Future works**
  - Odometry algorithm의 속도 향상
  - loop closer, back-end 추가
  - Real-time 3D LiDAR Odometry algorithm 구현

Appendix

Surface Normal



Integral Image to Covariance Matrix

For a given rectangular region R (본 연구에서 adaptive window, $R \subset \mathcal{D}$)

D : Depth image

$$C_R = \frac{1}{n}\sum_{k=1}^{n}(\boldsymbol{f}_k - \boldsymbol{\mu})(\boldsymbol{f}_k - \boldsymbol{\mu})^T \qquad \boldsymbol{f}_k : \text{Features (본 연구에서 x, y, z 좌표)}$$

$$C_R(i,j) = \frac{1}{n}\sum_{k=1}^{n}(f_k(i) - \mu(i))(f_k(j) - \mu(j)) = \frac{1}{n}\left[\sum_{k=1}^{n} f_k(i)f_k(j) - \frac{1}{n}\sum_{k=1}^{n} f_k(i)\sum_{k=1}^{n} f_k(j)\right]$$

$$\Rightarrow \quad C_R = \begin{bmatrix} c_{xx} & c_{xy} & c_{xz} \\ c_{xy} & c_{yy} & c_{yz} \\ c_{xz} & c_{yz} & c_{zz} \end{bmatrix} - \begin{bmatrix} c_x \\ c_y \\ c_z \end{bmatrix} \begin{bmatrix} c_x \\ c_y \\ c_z \end{bmatrix}^T$$

10	15	7	9	5	6
9	32	65	45	12	7
7	24	66	65	41	34
9	11	70	89	44	37
32	78	91	78	48	65
64	12	89	58	65	45

Original image of x

89+44+37+78+48
+65+58+65+45 = 529

10	25	32	41	46	52
19	66	138	192	209	222
26	97	235	354	412	459
35	117	325	533	635	719
67	227	526	812	962	1111
131	303	691	1035	1250	1444

Integral image of x

1444-459-691+235 = 529

Faster computation

1. Depth image와 같은 크기의 integral image 생성
2. Point의 좌표 (x, y, z) 를 바탕으로 9개의 integral image 생성

$$\mathcal{I}_x,\ \mathcal{I}_y,\ \mathcal{I}_z,\ \mathcal{I}_{xx},\ \mathcal{I}_{xy},\ \mathcal{I}_{xz},\ \mathcal{I}_{yy},\ \mathcal{I}_{yz},\ \mathcal{I}_{zz}$$

3. Covariance matrix 계산

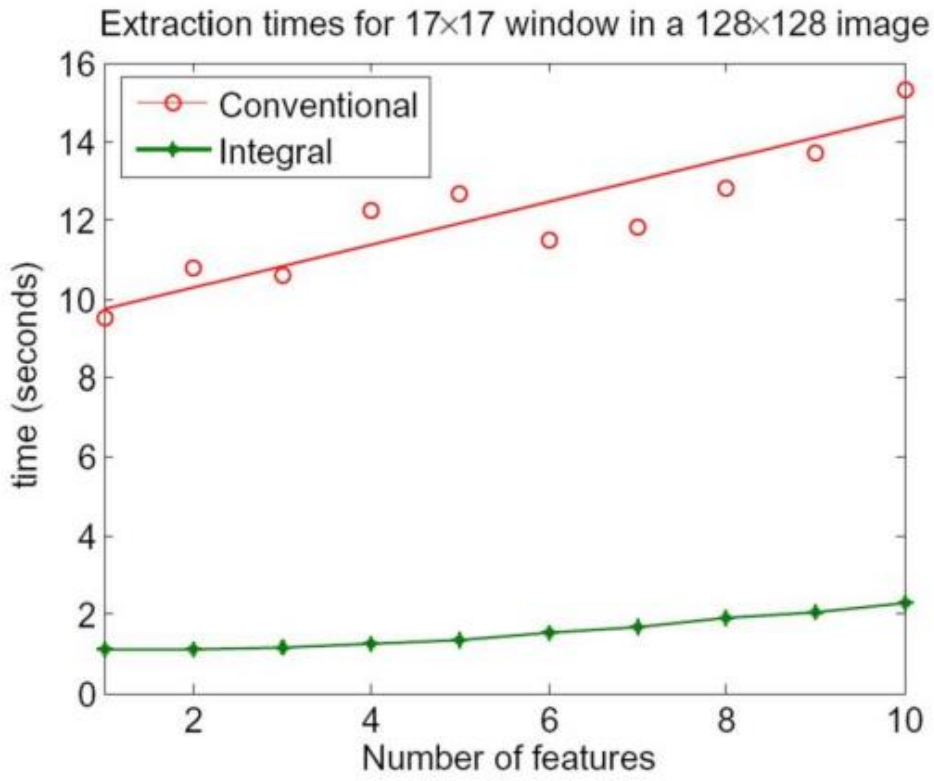
$$C_R = \begin{bmatrix} c_{xx} & c_{xy} & c_{xz} \\ c_{xy} & c_{yy} & c_{yz} \\ c_{xz} & c_{yz} & c_{zz} \end{bmatrix} - \begin{bmatrix} c_x \\ c_y \\ c_z \end{bmatrix} \begin{bmatrix} c_x \\ c_y \\ c_z \end{bmatrix}^T$$

c_k : 관심 영역 내 k의 평균

ex) $c_x = 529/9 \approx 59$

Integral Image to Covariance Matrix

- Integral Image 사용 여부에 따른 Covariance Matrix 계산 시간 비교



F. Porikli and O. Tuzel, Fast Construction of Covariance Matrices for Arbitrary Size Image Windows, IEEE International Conference on Image Processing, 2006

L-M method

Problem: for given a set of m empirical pairs (x_i, y_i)

$$\hat{\boldsymbol{\beta}} \in \operatorname{argmin}_{\boldsymbol{\beta}} S(\boldsymbol{\beta}) \equiv \operatorname{argmin}_{\boldsymbol{\beta}} \sum_{i=1}^{m} [y_i - f(x_i, \boldsymbol{\beta})]^2$$

$\hat{\boldsymbol{\beta}} : T$ (LiDAR 6-DOF motion)

x_i : Odometry 계산에 쓰이는 point p

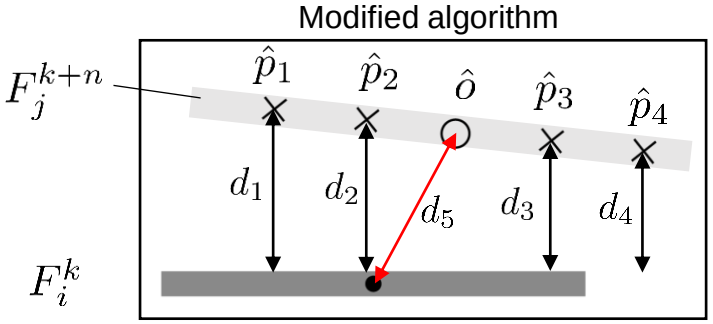
$y_i = 0$ (두 feature 간 거리가 0이 되는 T를 찾는게 목적)

$f(x_i, \boldsymbol{\beta})$: Given point x_i와 matching feature와의 거리

$$\left[\mathbf{J}^{\mathrm{T}}\mathbf{J} + \lambda\,\mathrm{diag}\left(\mathbf{J}^{\mathrm{T}}\mathbf{J}\right)\right]\boldsymbol{\delta} = \mathbf{J}^{\mathrm{T}}\left[\mathbf{y} - \mathbf{f}(\boldsymbol{\beta})\right] \quad \Rightarrow \quad T \leftarrow T - (J^T J + \lambda diag(J^T J))^{-1} J^T \boldsymbol{d}$$

- $T^* = \arg\min_T F(T),\ F(x) = \frac{1}{2} \parallel \boldsymbol{f}(T) \parallel^2$ → $T \leftarrow T - (J^T J + \lambda diag(J^T J))^{-1} J^T \boldsymbol{d}$

한 세트의 matching feature 간의 자코비안 계산 $\boldsymbol{J}_i = \dfrac{\partial f_l(x_i, T)}{\partial T}$



$f_l\ (l = 1, 2, 3, 4) : p_j$ 와 F_i^k 의 거리

$f_l\ (l = 5) : F_j^{k+n}$ 의 중심과 F_i^k의 중심 사이 거리

Publication

American physical society March Meeting 2018 Los Angeles
Elastic hoops jumping on water: A model system for fishing spiders
Han Bi Jung, Yunsuk Jeung, Ho-Young Kim

ASME-JSME-KSME Joint Fluids Engineering Conference 2019
Liquid jet impingement on a rotating substrate
Yunsuk Jeung, Jae Hong Lee, Ho-Young Kim

제 11회 한국유체공학학술대회
회전하는 고체표면과 액체 젯(jet)의 충돌 현상 연구
정윤석, 이재홍, 김호영

Patent

액막의 종류와 Wafer 소수성 정도에 따른 Fingering 제어 방법 (1020200105261)

액적 포집 시스템 및 제어 방법 (1020190155451)

기판 처리 방법 및 기판 처리 장치 (1020190056565)
해외특허 출원 : 일본 (2020-084408), 중국 (202010406079.3), 미국 (15/931,911)