## 3D data processing 1

## Geometric modeling

• Modeling real objects in 3D manner using cameras and laser range sensors









## Modeling procedures



## **1. DATA ACQUISITION**



## Range image example





#### Range image (2.5D) Reconstructed partial 3D model

# Measurement method (non-contact)



- Active
  - Structured light
  - Laser range sensor

## Grey code structured lighting

#### [Inokuchi ICPR'84]



integer row/column index -> binary code -> Gray code

## Structured light



Gray code -> binary code -> integer row/column index [Lanman et al.]



• Depth from ray-plane triangulation

### Measurement result





[Lanman et al.]

Real-time full-field 3-D surface-shape measurement using off-the-shelf components and a single processor

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## Time-Coded Light Patterns

• Assign each stripe a unique illumination code over time [Posdamer 82]



Space

## Proposed method

- Real-time Structured Light
  - Triangular-pattern & phase-shifting
  - Software synchronization (projector & camera)



## Intensity ratio



## Intensity ratio unwrapping



*R* is the region number

## Intensity ratio unwrapping



## Measurement Pipeline

- Image acquisition
- Intensity-ratio wrapping
- Intensity-ratio unwrapping
- 3D data reconstruction

### Multi-thread Programming



## Measurement of a human face



Photo Fringe image 3D model

## Results 1: 2-step pattern



Measurement speed : 5.6 fps

## Results 2: 6-step pattern



Measurement speed : 4.2 fps

## Summary

- Triangular-pattern & phase-shifting
- Software synchronization (projector & camera)
- Measurement speed: 5.6 fps (2-step)
  4.2 fps (6-step)

A Sensor for Simultaneously Capturing Texture and Shape by Projecting Structured Infrared Light

> K. Akasaka, R. Sagawa, Y. Yagi Osaka University

# Color coded pattern [Zhang 3DPVT2002]



## Capturing texture and shape

• Color patterns method requires two shots for capturing both texture and shape



- Texture: Visible light
- Shape: Infrared structured light

## Distribution of wavelengths



## System overview



## Structured light patterns

- De Bruijn sequence
  - n=8, q=2 (2colors: 880nm, 940nm)
  - The number of symbols=150



• Matching: DP matching



## Multi-band camera



## Experimental overview



## Captured images



Texture image



#### IR filtered image
#### Detected lines



#### Generated 3D mesh model



Measurement time: 60 ms (16.7fps) with Intel Pentium 4 3.0GHz

# Summary

- Simultaneously capturing texture and shape
  - Texture: Visible light
  - Shape: Infrared structured light (880nm, 940nm)
  - De Bruijn sequence (n=8, q=2)
  - DP matching

#### Dense 3D reconstruction

[Sagawa et al. ICCV'09]



#### Demo video



# Codes for moving scenes

- Assign time codes to stripe boundaries
- Perform frame-to-frame tracking of corresponding boundaries

- Propagate illumination history



[Hall-Holt & Rusinkiewicz, ICCV 2001]

# Kinect (Microsoft)

- Near-infrared laser
- Dot patterns





#### LASER RANGE SENSOR





### VIVID910 (Konica Minolta)

- Range : 0.6-1.0m
- Accuracy : 0.05-0.4mm
- Time : 2.5 sec
- Resolution :  $640 \times 480$
- Laser class : 2





#### Measured Data







# Time to travel Distance

#### Scanning mechanism



Scan Station C10 (Leica geosystems)

- Range: 0.1-300m
  360 x 270 degrees
- Accuracy: 6mm (Depth: 4mm)
- Speed: 5,0000 pt / sec
- Laser class: 3R



### Measured data (Cyrax)



#### Phase shift method



# Imager5003(Z+F)

- Range : 187.3m
  - :  $310^{\circ}$  (v)  $\times 360^{\circ}$  (h)
- Accuracy: 0.4 1.6mm
- Speed : 1,000,000 pt/sec
- Phase shift method (Amplitude modulation)



#### Measured data (Imager)



# Velodyne LiDAR



#### Climbing Sensor -- Narrow Corridors – [Ono et al.]



# Balloon sensor [Banno et al.]



2. ALIGNMENT (REGISTRATION)

#### Modeling procedures



#### Alignment of range images

• Estimation of relative positions



### Self positioning



#### GPS measurement



3D laser measurement system for large scale architectures using multiple mobile robots

R. Kurazume, Y. Tobata, Y. Iwashita, and T. Hasegawa Kyushu University

# 3D measurement of large scale architectures



#### Alignment of multiple range images

- Post-processing
  - ICP algorithm etc.
    - Requires initial positions: Laborious & time consuming
- Directly measuring positions
  - GPS (RTK, VRS)
    - Limited to outdoor environment & low accuracy

# Proposed method

- Cooperative Positioning System (CPS)
   Multiple mobile robots
  - Measurement devices of mutual positions



# Positioning method

- Odometry (Wheel encoder, Acceleration sensor)
  - low accuracy
- Landmarks (Camera, Range sensor)
  - require prior knowledge
- GPS
  - outdoor only

# **Cooperative Positioning System**



(1) Robot 1 and 2 move.



(2) Robot 0 measures the position of robot 1.



(3) Robot 0 measures the position of robot 2.



(4) Robot 0 moves and measures the position of robots 1 and 2.

### Measurement system with CPS V



# Parent robot (P-cle)

- 3D measurement: Rotating table + 2D laser range sensor
- Position: Total station
- Measurement time: 37.8 sec


#### Child robot



# Experimental result



# Experimental result



#### Experimental result



- Total distance: 86.21m
- Number of scans: 23
- Positioning error: 1.17m (1.36%)

# Alignment

• Estimation of relative positions using overlapping areas





# Category of alignment method

- With and without features
  - Global features (EGI, SAI), Local features (Spin image)
  - ICP (Iterative Closest Point), many extensions of ICP
- Pair-wise vs. Simultaneous
  - In order to avoid error accumulation, errors have to be globally minimized

#### **Global features**



• 3D model is transformed to low dimension and rotation-scale invariant vectors



## Spherical Attribute Image (SAI)







# SAI matching



# Local features

• Relative pose of two range images can be estimated from 3 or more matching points



 $\alpha$ : the radial distance to the surface normal line L  $\beta$ : the axial distance above the tangent plane P Rotation invariant

#### Spin image examples



#### Matching result by Spin image





Range image





Recognition result

#### **ITERATIVE METHOD**

# Alignment method without features

• Iterative Closest Point (ICP) [Besl et al. '92]



#### Procedures of ICP

- 1. Find corresponding (nearest neighbor) points between 2 range images
- 2. Take sum of the errors between correspondences
- 3. Compute transformations so as to minimize the error
- Iterate the processes until termination criteria is fulfilled

# **ICP** variants

#### [Rusinkiewicz et al. '01]

- 1. Selecting source points
- 2. Finding corresponding points
- 3. Weighting the correspondences
- 4. Rejecting certain (outlier) point pairs
- 5. Assigning an error metric to the current transform
- 6. Minimizing the error metric

# 1. SELECTION OF SOURCE POINTS

# Selection of source points

- All points [Besl et al. '92]
- Uniformly sampled points[Turk '94]
- Randomly sampled points [Masuda '96]
- Normal vectors are uniformly distributed [Rusinkiewicz '01]

## Normal space sampling





Uniform sampling

Normal space sampling



# 2. CORRESPONDENCE SEARCH

# Matching method

• Closest point (Nearest Neighbor)

• Normal shooting

• Projection

# Closest point

#### [Besl and McKay '92]

- Advantages
  - Correspondences are given independently to the initial positions
  - Robust to noises
- Disadvantages
  - Computational cost is high
  - Weak to sliding

#### Nearest neighbor search

• *k*-d tree (Binary search tree)



#### **Approximate Nearest Neighbor** search [Arya et al. 94] • $(1+\varepsilon)$ -approximate nearest neighbor p $||\mathbf{p} - \mathbf{p}_q|| \le (1 + \varepsilon) ||\mathbf{p}^* - \mathbf{p}_q||$ $\left\| \mathbf{p}_{q} - \mathbf{p} \right\| / (1 + \varepsilon)$ $\varepsilon > 0$ pq

#### Cached k-d tree search for ICP [A. Nüchter et al. 3DIM'07] cached kd-tree edges · data points traditional kd-tree search • query point proposed kd-tree search ٠. • • .

vector of point pairs v

#### Evaluation

• 3D laser range sensor based on SICK



Cluttered indoor environment

Outdoor environment

#### Search time / iteration



#### Overall comparison

cached kd-tree vs. kd-tree





#### Normal shooting [Chen and Medioni '91]

- Advantages
  - Fast convergence

- Disadvantages
  - High computational cost
  - Correspondences depend on initial estimation
  - Weak to noises

## 3. WEIGHTING CORRESPONDENCES

# Weighting method

- Constant weight
- Inner product of normals  $Weight = n_x \bullet n_y$
- Accuracy of sensors
- Confidence obtained from other modalities (color, reflectance, etc.)
- Distance between correspondences

Weight = 
$$f\left(1 - \frac{Dist(x, y)}{Dist_{max}}\right)$$
#### Weight functions





#### Using photometric properties [Nishino & Ikeuchi '02]

• Reflectance obtained by laser range sensors

– Robust to illumination changes





Robust Range Image Registration Using Local Distribution of Albedo

Diego Thomas, Akihiro Sugimoto

#### Issues

• Range images of symmetrical objects





# Approach

- Similarity evaluation using albedo
- Region-based approach using Level Set method

# Albedo (True Color)



# Region growing



#### Level set method

$$\frac{d}{dt}\psi = -P(x)\|\nabla\psi\|$$





[Fast level set method Kurazume et al. 03]

# Correspondence search

Searching for the corresponding point of *m* n(m)m Region of point p Region of point q

#### Similarity evaluation using Albedo

$$\begin{split} & \text{Size of the regions} \\ & L(p,q) = \frac{size(R(p)) + size(R(q))}{(\sum_{m \in R(p)} \omega_{(m,q)} + \sum_{m \in R(q)} \omega_{(m,p)})^2} \\ & \times \Big\{ \sum_{m \in R(p)} \omega_{(m,q)} \| \overrightarrow{alb(m)} - \overrightarrow{alb(n(m)_q)} \|_2^2 \\ & + \sum_{m \in R(q)} \omega_{(m,p)} \| \overrightarrow{alb(m)} - \overrightarrow{alb(n(m)_p)} \|_2^2 \Big\}, \end{split}$$
 Weight by distance

# Rigidity constraint



# Pairs satisfying rigidity constraint Pairs violating rigidity constraint

# Evaluation with synthetic data



Restance of the Constant



(a) First image.

(b) Second image.

(c) Albedo image.

#### Comparison with previous method



# Evaluation with real data

• Range images captured from differenct viewpoints



(a) First image.



(b) Second image.



(c) Superimposed.

# Albedo and Speed image

• Illumination conditions and region generation



(a) Albedo image.



(b) Gradient map.



(c) Speed map.

# Experimental result 1



Proposed method



ICPA



ICP-CG

# Experimental result 2



# Summary

- Robust range images registration method
- Similarity evaluation using albedo
- Region-based approach by Level Set method

#### **4. OUTLIER REJECTION**

# Outlier rejection

- Point to point distance is more than a threshold
- N % of pairs that have large distances
- Point to point distance is larger than the median (Lmeds) [Masuda et al. '96]
- Point to point distance is inconsistent with the neighboring pairs [Drai '98]
- Pairs include points on boundaries [Zhang '94] (Nearest neighbor search)

# Threshold values

- Given by users
  - Generally used because ICP-based method is sensitive to initial positions

# Consistency with neighbors

• Point to point distance is inconsistent with the neighboring pairs





#### Points on boundary [Zhang '94]

• A point on boundaries is matched with many points on non-overlapped areas



Outlier Robust ICP for Minimizing Fractional RMSD

J. M. Phillips, R. Liu and C. Tomasi Duke University

# Registration with outliers

• New data



• Deformation

Registration is often skewed by outliersOutlier detection depends on registration

# Proposed method

• Register point sets and find outliers in one algorithm



• Using FRMSD (Fractional Root Mean Squared Distance)

### Distance function

• RMSD (Root Mean Squared Distance)

$$\min_{T \in \mathcal{T}} \sqrt{\frac{1}{|D|} \sum_{p \in D} ||T(p) - \mu(p)||^2}$$

Align data point set *D* to model point set *M* T = rotations, translations, scale, ...  $\mu$  = matching from *D* to *M* 

Hard to optimize over both  ${\cal T}$  and  $\mu$  susceptible to outliers

#### Fractional RMSD

Let  $D_f$  be f|D| points  $p \in D$  with smallest residuals  $||p - \mu(p)||$ .

$$\min_{\substack{T \in \mathcal{T} \\ f \in [0,1]}} \frac{1}{f^{\lambda}} \sqrt{\frac{1}{|D_f|}} \sum_{p \in D_f} ||T(p) - \mu(p)||^2$$

 $\lambda$  is empirically given

# Algorithm

- 1: Compute  $\mu_0 = \arg \min_{\mu_0: D \to M} \operatorname{RMSD}(D, M, \mu_0).$
- 2: Compute  $f_0 \in [0, 1]$  minning FRMSD $(D, M, f_0, \mu_0)$ .
- 3:  $i \leftarrow 0$ .

#### 4: repeat

- 5: Compute  $D_{f_i}$  minimizing  $\text{RMSD}(D_{f_i}, M, \mu_i)$  such that  $D_{f_i} \subseteq D$  and  $|D_{f_i}| = \lfloor f_i |D| \rfloor$ .
- 6: Compute  $T \in \mathcal{T}$  minimizing  $\text{RMSD}(D_{f_i}, M, \mu_i)$ .  $D \leftarrow T(D)$ .
- 7:  $i \leftarrow i+1$ .
- 8: Compute  $\mu_i : D \to M$  minning  $\text{RMSD}(D, M, \mu_i)$ .
- 9: Compute  $f_i \in [0, 1]$  minning FRMSD $(D, M, f_i, \mu_i)$ .
- 10: **until**  $(u_i = u_{i-1} \text{ and } f_i = f_{i-1})$

# Optimal value of $\lambda$

Alg.	$\lambda$	time (s)	# iter.	RMSD	FRMSD	f
FICP	1	0.142	10.38	0.158	0.225	0.701
FICP	1.3	0.069	3.81	0.170	0.248	0.749
FICP	2	0.059	3.06	0.170	0.303	0.750
FICP	3	0.061	3.17	0.170	0.404	0.750
FICP	4	0.062	3.21	0.171	0.538	0.751
FICP	5	0.063	3.30	0.172	0.717	0.751

#### FRMSD is robust for $\lambda \in [1, 5]$

# Experiments

- Stanford bunny
  - 25% deformation, 5° rotation





# Experimental result



# Comparison

time (s)	60.1	
# iter.	78.8	
RMSD	0.6668	
FRMSD	0.6668	
f	1.0	

time (s)	16.5
# iter.	17.3
RMSD	0.0052
FRMSD	0.0124
f	0.750






#### **5. ERROR METRIC**

#### Error metric

• Point-to-Point [Besl & Mackey '92]  $\hat{\varepsilon} = \min_{R,t} \sum_{i \neq j,k} (\vec{y}_{ijk} - (R_i \vec{x}_{ik} + \vec{t}_i))^2$ 

• Point-to-Plane [Chen & Medioni '91]  $\hat{\varepsilon} = \min_{R,t} \sum_{i \neq j,k} \left( R_i \vec{n}_{ik} \cdot \{ (R_j \vec{y}_{ijk} + \vec{t}_j) - (R_i \vec{x}_{ik} + \vec{t}_i) \} \right)^2$ 

#### Point-to-Point [Besl & Mackey '92]

- Guaranteed to converge to local minima
- Low convergence-speed
- Weak to horizontal movement



#### Point-to-Plane

[Chen & Medioni '91]

- Sensitive initial positions, noises, threshold
- Convergence speed is high





6. OPTIMIZATION

# Optimization method

- Non-linear: Levenberg-Marquat method etc.
- Linear:
  - Point-to-Point: Closed form solution [Horn][Umeyama]
  - Point-to-Plane: Linealization by assumption of small angles[Neugebauer]

### Closed form solution

$$e^{2}(R, \mathbf{t}, c) = \frac{1}{3} \sum_{j=1}^{3} ||\mathbf{y}_{ji} - (cR\mathbf{x}_{j} + \mathbf{t})||^{2}$$
  
Rotation  $R = USV^{T}$   
Translation  $\mathbf{t} = \mu_{y} - cR\mu_{x}$   
Scaling  $c = \frac{1}{\sigma_{x}^{2}} \operatorname{tr}(DS)$ 



# Linealization

Neugebauer '97]Assumption: rotation angles are enough small

$$\overline{\varepsilon} = \arg\min_{\vec{\delta}} \sum_{i \neq j,k} \left\| A_{ijk} \vec{\delta} - s_{ijk} \right\|^{2}$$

$$\begin{pmatrix} \vec{\delta} = (m_{0} \cdots m_{n-1}) \\ m_{i} = (c_{1i} \quad c_{2i} \quad c_{3i} \quad t_{xi} \quad t_{yi} \quad t_{zi}) \\ s_{ijk} = \vec{n}_{ik} \cdot (\vec{x}_{ik} - \vec{y}_{ijk}) \\ A_{ijk} = \left( \underbrace{0...0}_{6i \times 1} \underbrace{C_{ijk}}_{6 \times 1} \underbrace{0...0}_{6i \times 1} \right) + \left( \underbrace{0...0}_{6j \times 1} \underbrace{-C_{ijk}}_{6 \times 1} \underbrace{0...0}_{6i \times 1} \underbrace{-C_{ijk}}_{6i \times 1} \underbrace{0...0}_{6i \times 1} \underbrace{-C_{ijk}}_{-n_{ik}} \underbrace{0...0}_{-n_{ik}} \right)$$



# Alignment result (Nara Great Buddha)





# Alignment result (Bayon)



### Modeling procedures

