E-CNN: Accurate Spherical Camera Rotation Estimation via Uniformization of Distorted Optical Flow Fields

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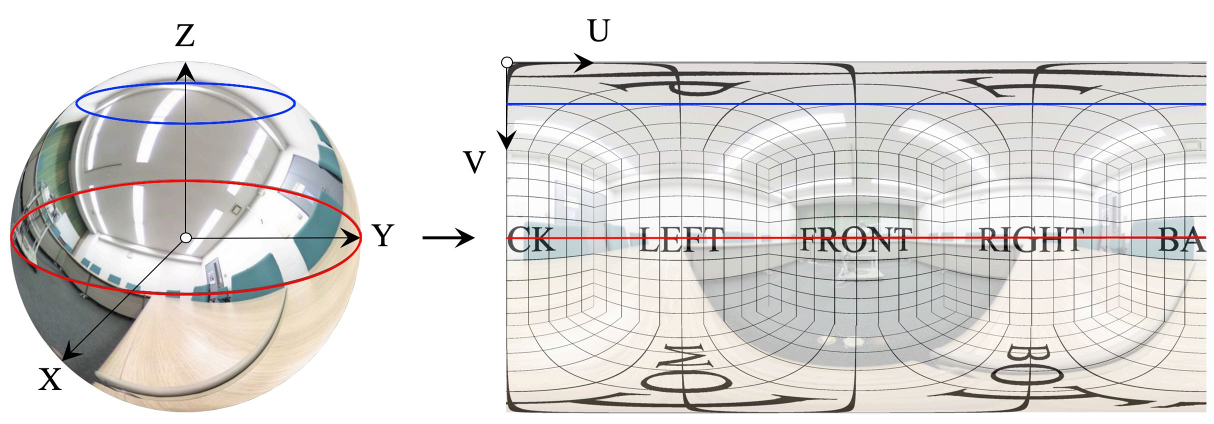
① Introduction

Spherical Camera (Ricoh Theta S)



Spherical and Equirectangular Images with distortion

- Rotation estimation is an important task for camera-equipped robots (Visual Odometry, Structure from Motion, Visual SLAM)
- **Spherical cameras** are effective for this due to their 360-degree FoV
- **CNNs** estimate robustly against environment variations
- Applying CNNs to spherical images is difficult

→ equirectangular images, which are a distorted planar projection can be used

Distortion remains in equirectangular images → low accuracy

② Motion Estimation by Optical Flow

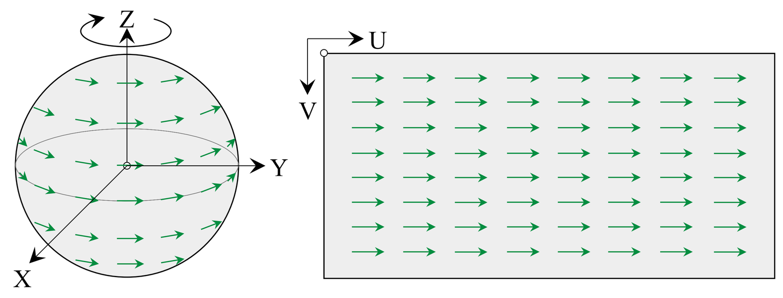
- **Optical Flow**

: Scene-independent vector representation of pixels movement

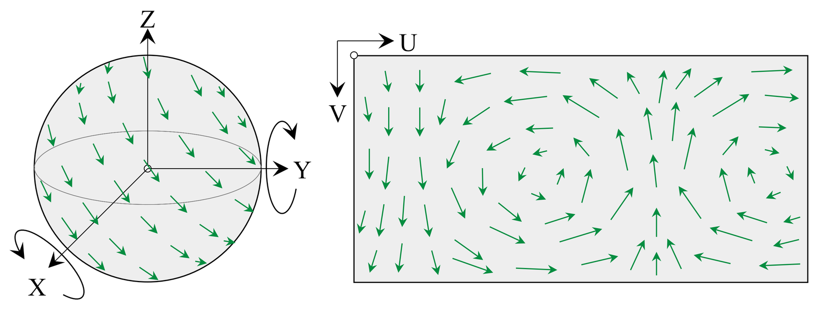
- Different lined/curved patterns appear on equirectangular images even if cameras rotate same quantity around a different axis

→ rotation estimation becomes axis dependent

→ this leads difficulty to learning and interrupt accurate estimation



Lined Optical Flow Patterns



Curved Optical Flow Patterns

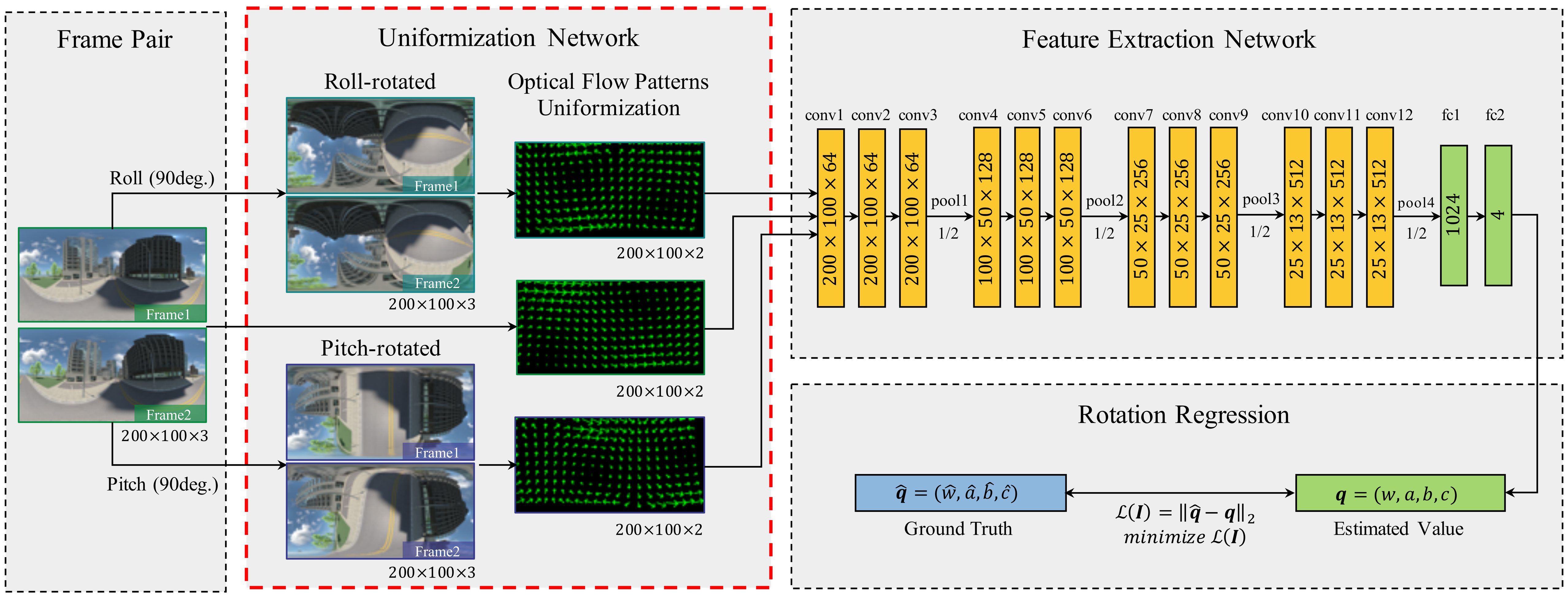
Objective

Accurate spherical camera rotation estimation considering non-uniformity of equirectangular projection

- **E-CNN**: uniformizes non-uniform rotation around all axes

③ Equirectangular-Convolutional Neural Network Structure

- **Uniformization Network**: distorted optical flow patterns uniformization network by spherical image rotation
- **Feature Extraction Network**: feature extraction network by CNN, and rotation regressor



Equirectangular-Convolutional Neural Network (E-CNN) Structure

- **E-CNN process**

(1) takes two image frames as input

(2) rotates them in the directions of roll and pitch by 90 [deg.]

(3) calculates three non-rotated, roll-rotated, and pitch-rotated optical flow

(4) stacks three optical flow as 200×100×6

(5) extracts features by CNN

(6) regresses euclidean distance between ground truth and estimated quaternion

$$\mathcal{L}(\boldsymbol{I}) = \|\hat{\boldsymbol{q}} - \boldsymbol{q}\|_2$$

④ Experimental Verification

- **Datasets**

- different 20 indoor/outdoor real world scenes for training, validation, test datasets
- training data (9,261): 0.5 [deg.] increments in every axis limited to 0~10 [deg.]
- validation (1,000), test data (1,000): randomly chosen limited to 0~10 [deg.]

- **Networks**

- case1(*4lyrs.*), case2(*6lyrs.*), case3(*8lyrs.*) case4(*10lyrs.*), case5(*12lyrs.*)

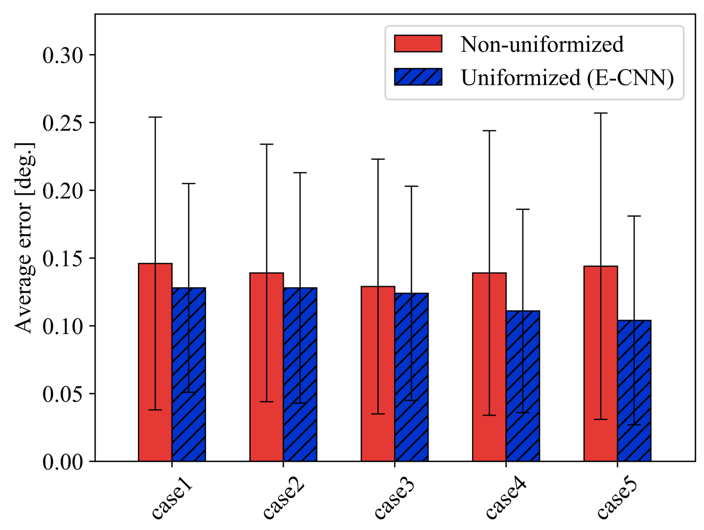
Indoor/Outdoor real world scenes (Ricoh Theta S)

- **Method**

- experiments to verify the effectiveness of uniformization
- same input data size (200×100×6) for a fair comparison

- **Results**

- E-CNN increased the accuracy of estimation by 27.8%
- Higher precision by the lower standard deviation
- E-CNN performed better with increasing network depth whereas the naïve approach did not



Results for Various Network Depths

⑤ Conclusion

- **Conclusion**

- 360 degree FoV property of spherical cameras enables uniformization of distortion
- The effectiveness of our proposed E-CNN was verified in various indoor/outdoor scenes

- **Future works**

- Handling the large angle rotation
- Scale independent rotation estimation
- Simultaneous estimation of rotation and translation