Glidar3DJ: A VIEW-INVARIANT GAIT IDENTIFICATION VIA FLASH LIDAR DATA CORRECTION

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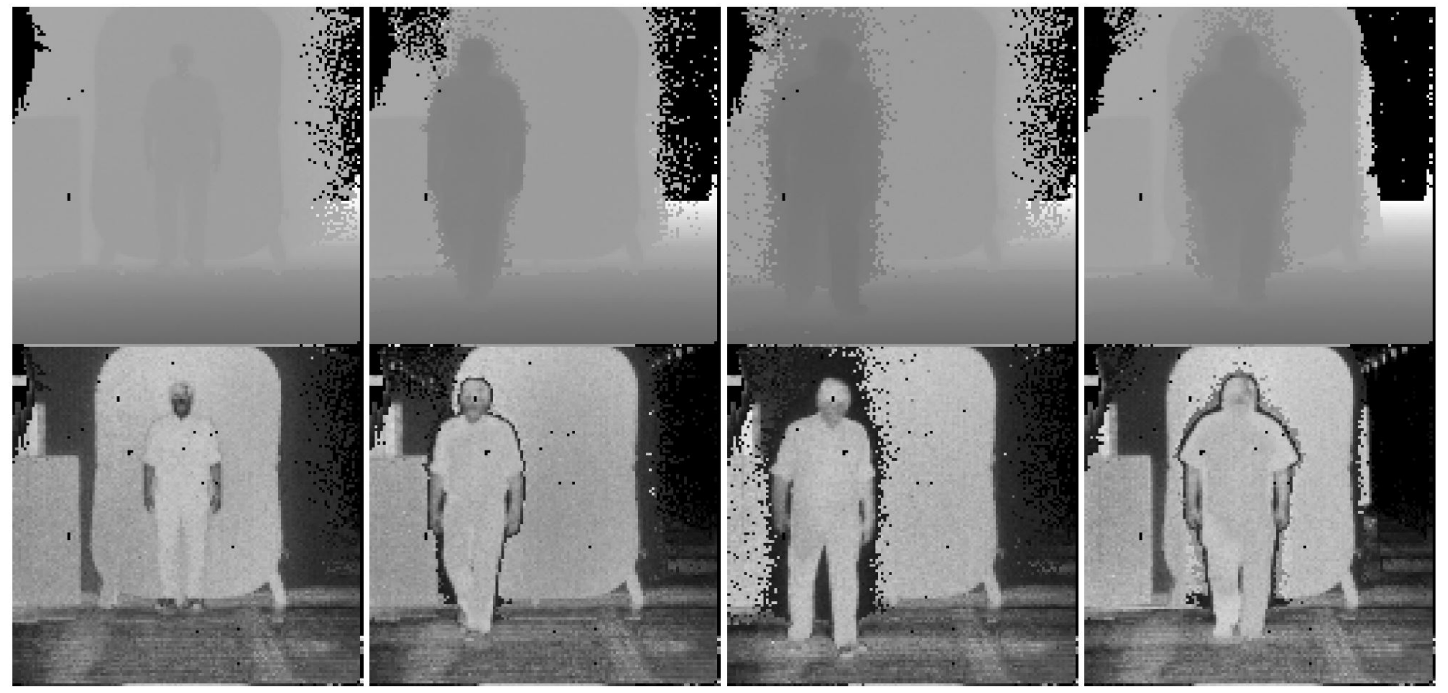
Introduction

Gait recognition is a leading remote-based identification method, suitable for applications in forensic cases, surveillance, and medical studies. We present Glidar3DJ, a model-based gait recognition methodology, using a skeleton model extracted from sequences generated by a single flash lidar camera. Compared with Kinect, a flash lidar camera has a drastically extended range (> 1000 meters) and its performance is not affected in outdoor. However, the low resolution and noisy imaging process of lidar negatively affects the performance of state-of-the-art skeleton-based systems, generating a significant number of outlier skeletons. We propose a rule-based filtering mechanism that adopts robust statistics to correct for erroneous skeleton joint measurements.

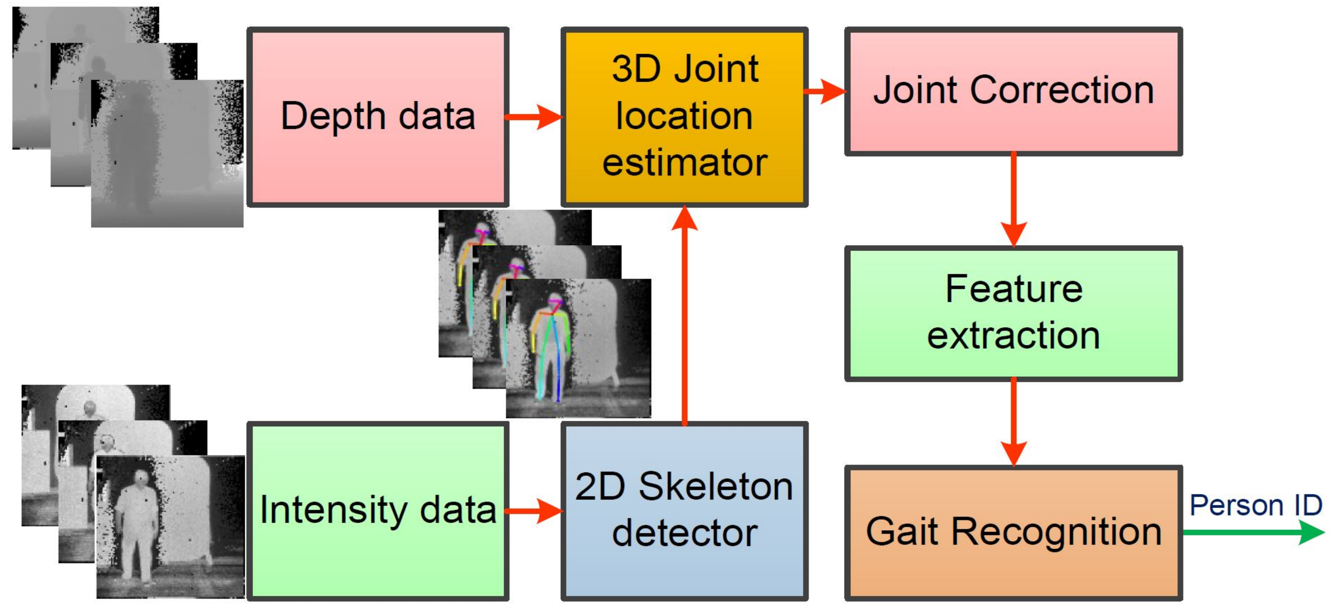


Sample range (top), and intensity (bottom) frames

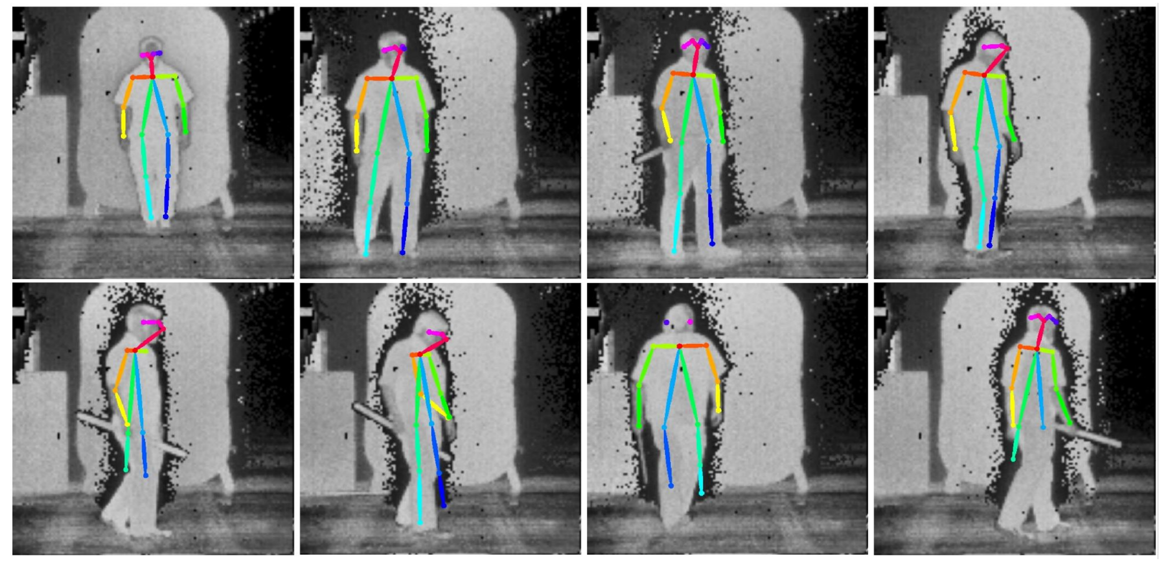
Highlights

- Existing state-of-the-art model-based methods avoid the challenge of erroneous features by adopting high-quality skeleton data provided by Kinect or Mocap. However, they are limited to controlled lab environments.
- We employ a pre-trained skeleton detector (OpenPose), and model the joint locations as time sequences for faulty skeleton correction.

Glidar3DJ



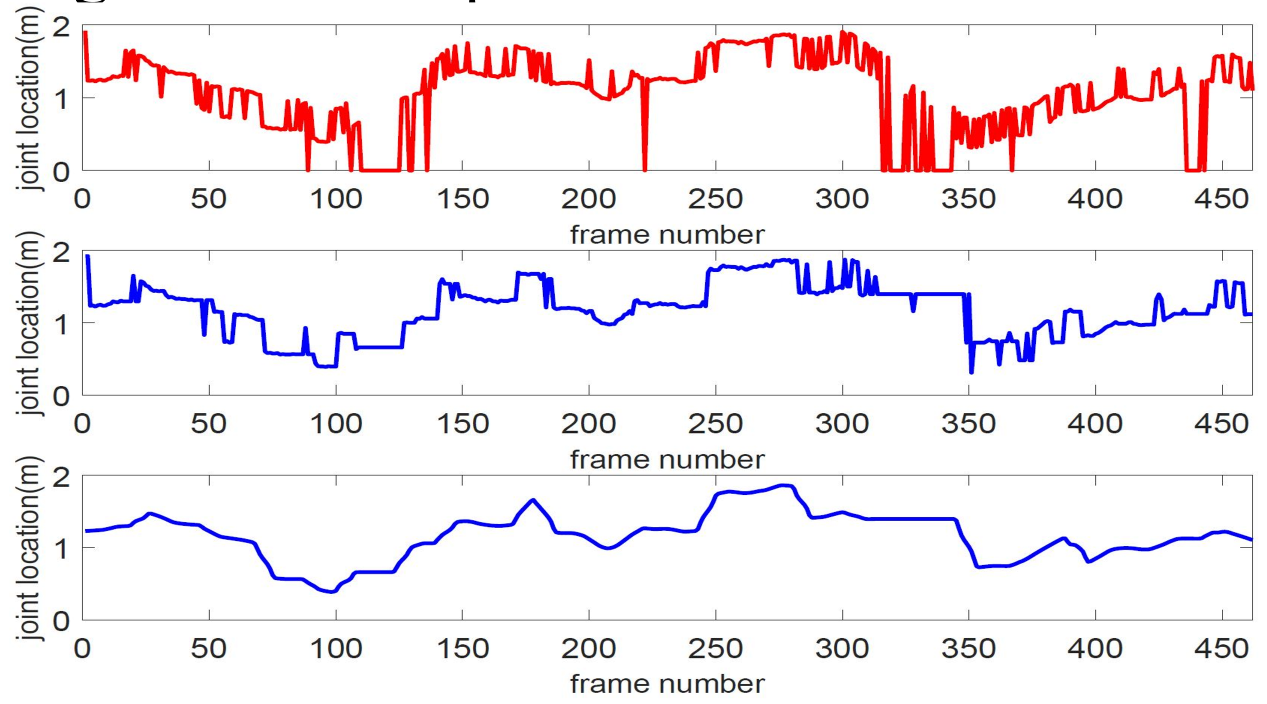
- ***Skeleton detection***



Correctly (top) and faulty (bottom) detected skeletons by OpenPose

- ***Joint location correction***

A rule-based median filter, followed by Rlowess (robust locally weighted scatterplot smoothing) to alleviate the effect of signal flattening and low-amplitude outliers



Joint time sequence before (top), after joint correction by rule-based median (middle), and RLowess (bottom)

Rule-based median filter

$L_x(t) = median(W(t))$

$W(t) = [L_x(i) | L_x(i) \neq 0]_{i=t-F}^{t-1}$

$\mathbf{Card}(W(t)) = P_{nz}$, $F \geq P_{nz}$

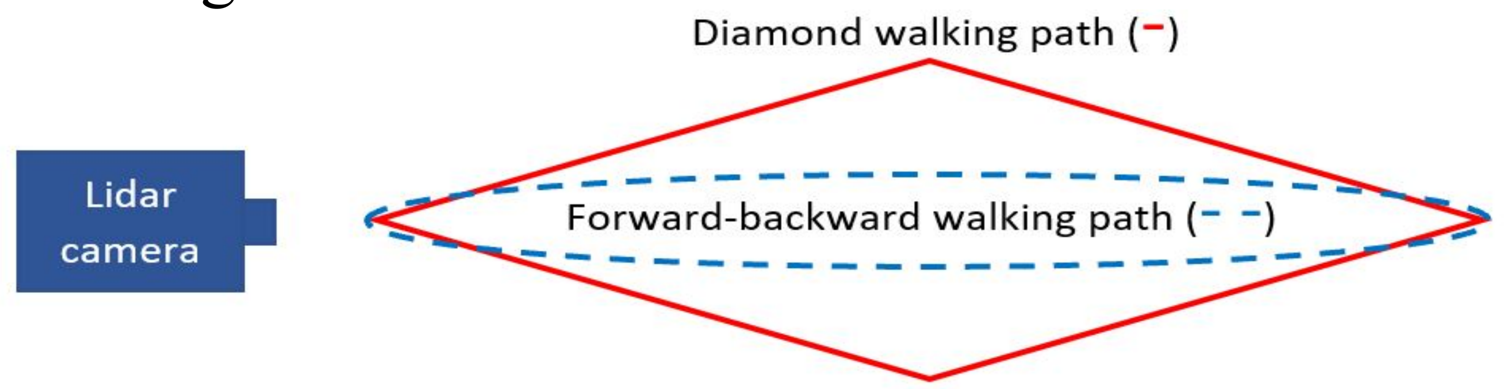
P_{nz} : the number of previous closest non-zero neighbors of $L_x(t)$

Features

- A set of 3D limb vectors capture angle and distance between joints.
- Feature concatenation in successive frames captures temporal information

Data description

34 sequences of 10 subjects with 3different types of walking: walking toward and away from the camera, diamond walking, and diamond walking with stick in hand.



Results

	Sinha	Yang	Ours
Accuracy	43.07%	45.67%	<u>56.26%</u>
F-score	42.41%	43.72%	<u>57.24%</u>

	Sinha	Yang	Glidar3DJ	Glidar3DJ + F-C
Accuracy	61.20%	70.59%	81.24%	<u>85.11%</u>
F-score	57.41%	65.15%	80.30%	<u>84.33%</u>

Classification scores with KNN before (top) and after joint correction (bottom). F-C: feature concatenation

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