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Human Gait Recognition using LiDAR and Deep Learning Technologies

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Contents

1.

Motivation and Goals

- Motivation
- Goals

Motivation

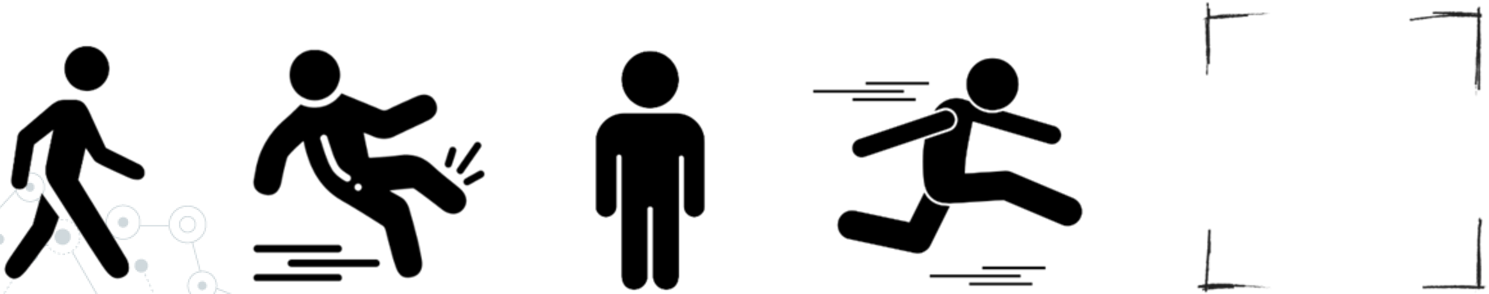
Home security care

- unable to move freely
- fall down
- Monitor at any time without violating privacy

Goals

Using Light Detection and Ranging (LiDAR) to sense the human gait

- Collect information from the environment through 3D-LiDAR
- Combined with deep learning to identify human gait
- Five categories



2.

Related research

- Human Activity Recognition
- Deep Learning

Human Activity Recognition

- Human activity recognition has a wide range of applications, such as health care and smart homes.
- Sensors for HAR
  - Wearable device
  - Camera
  - Wi-Fi
  - Radar
  - LiDAR

Human Activity Recognition

- Wearable device
  - Pressure sensors are used to detect human muscle activity for gesture recognition.
  - Sensors are deployed on the body to recognize behavior.

- Advantage : Accurate results
- Disadvantage : Uncomfortable

Human Activity Recognition

- Camera
  - Convert the collected data into human skeleton for activity recognition and gesture recognition.

- Advantage : Non-contact, Accurate results.
- Disadvantage : Affected by light, Privacy problem.

Human Activity Recognition

- Wi-Fi
  - Wi-Fi’s CSI signals are used to detect fall.
  - Convert Wi-Fi signals into visual images to identify human activity.

- Advantage : Have privacy, Non-contact.
- Disadvantage : Disturbed by the environment.

Human Activity Recognition

- Radar
  - Radar Echo is used to gesture and human activity recognition.

- Advantage : Have privacy, Non-contact.
- Disadvantage : Disturbed by the environment.

Human Activity Recognition

- LiDAR
  - Collect human movement trajectories for multi-object classification.
  - Human Recognition and Tracking.

- Advantage : Have privacy, Non-contact, High precision, Not easily disturbed by the environment.

Deep Learning

- Deep Learning models for time-series data.
  - Recurrent Neural Network (RNN)
  - Long Short-Term Memory (LSTM)
  - Temporal Convolutional Network (TCN)

- Integrate with other Deep Learning models.

3.

Methodology

- Data Collection and Processing
- Deep Learning architecture

Data Collection and Processing

- The horizontal and vertical axes are the 3D-LiDAR recognition area (divided into 8*8), and the value is the distance from the 3D-LiDAR in millimeters.

2885	2790	2990	2980	2925	2925	2935	2870
3035	3090	2850	3065	2985	2985	2860	3010
2835	2855	2875	2960	2930	2930	3010	2970
2895	3005	2985	2890	2940	2940	3015	2905
3095	3005	2945	2945	2910	3175	3180	2970
2965	3060	3100	3040	2985	2935	3065	2910
3025	3070	3060	2960	3055	3015	2980	2945
3320	3000	3060	3155	3000	2995	3035	3085

Data Collection and Processing

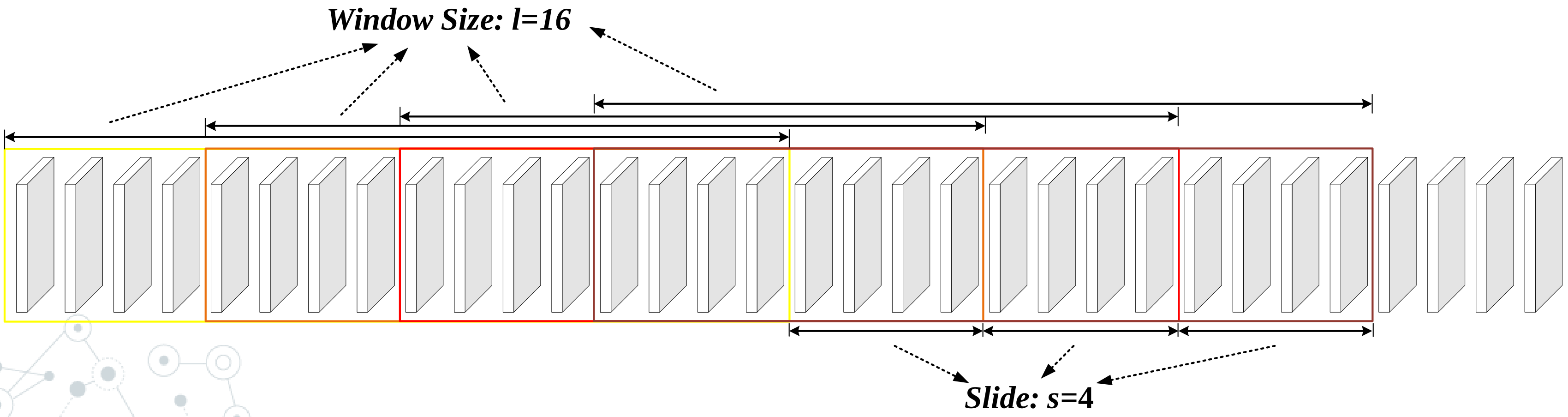
- Two 3D-LiDARs are used for data collection at the same time, collected data as (1) shows.
- $$F = \left\{ \left[\begin{bmatrix} f_{11} & f_{12} & \cdots & f_{1j} \\ f_{21} & f_{22} & & f_{2j} \\ & \vdots & \ddots & \vdots \\ f_{i1} & f_{i2} & \cdots & f_{ij} \end{bmatrix} \right] 1 \le i \le 8, 1 \le j \le 16 \right\} \qquad (1)$$

Data Collection and Processing

- To reduce the influence of bias, the data is normalized to the interval of 0 and 1, normalization formula as (2) shows.
- $$\hat{f}_{ij} = \left\{ \begin{matrix} \frac{f_{ij}}{distance}, \text{if } 0 \le f_{ij} \le distance \\ 1, \text{ if } f_{ij} > distance \end{matrix} \middle| 1 \le i \le 8,\ 1 \le j \le 16 \right\} \qquad (2)$$
- f_{ij} is raw data, $\hat{f}_{ij}$ is normalized data
- $distance = 3000$

Data Collection and Processing

- A series of time-series data are segmented by the sliding window method as figure shows.

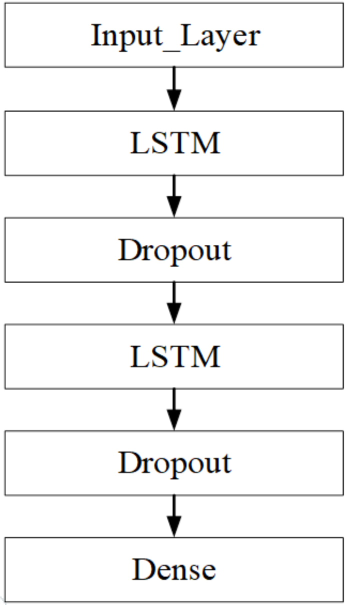


Deep Learning Architecture

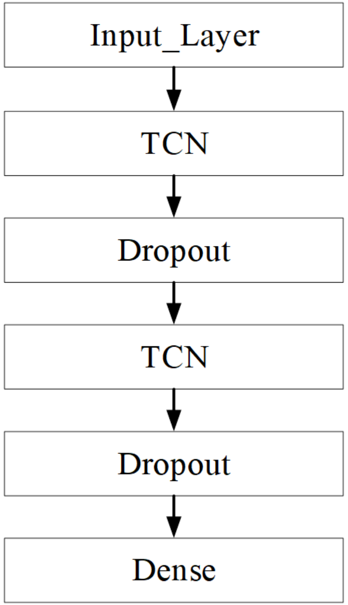
- Six deep learning architectures
  - LSTM
  - TCN
  - CNN-LSTM
  - CNN-TCN
  - AutoEncoder-LSTM (AE-LSTM)
  - AutoEncoder-TCN (AE-TCN)

Deep Learning Architecture

- LSTM

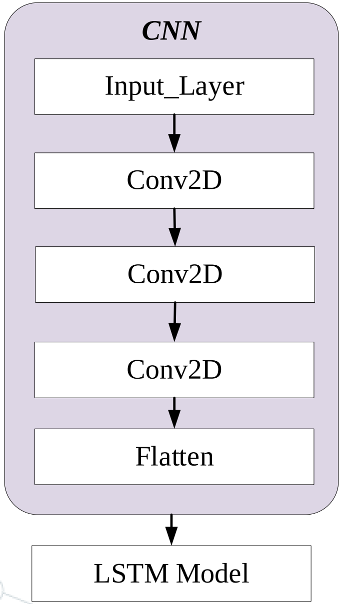


- TCN

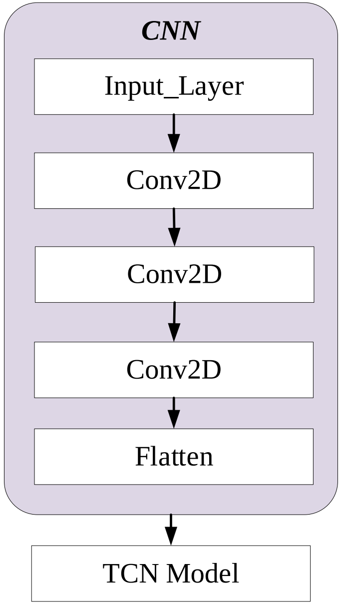


Deep Learning Architecture

- CNN-LSTM

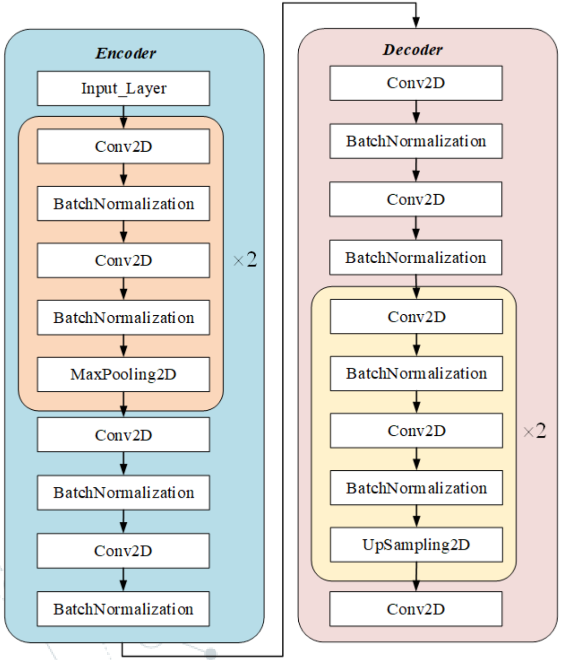


- CNN-TCN

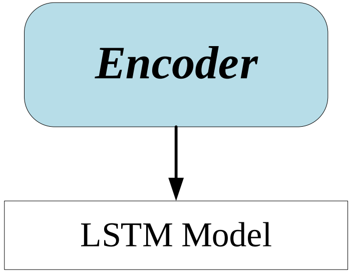


Deep Learning Architecture

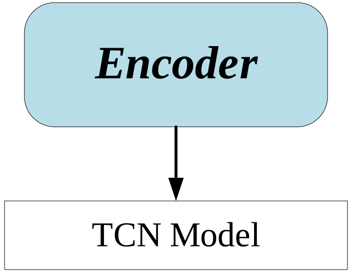
- AutoEncoder



- AE-LSTM



- AE-TCN



4.

Experiment and Result

- Experiment
- Result

Experiment

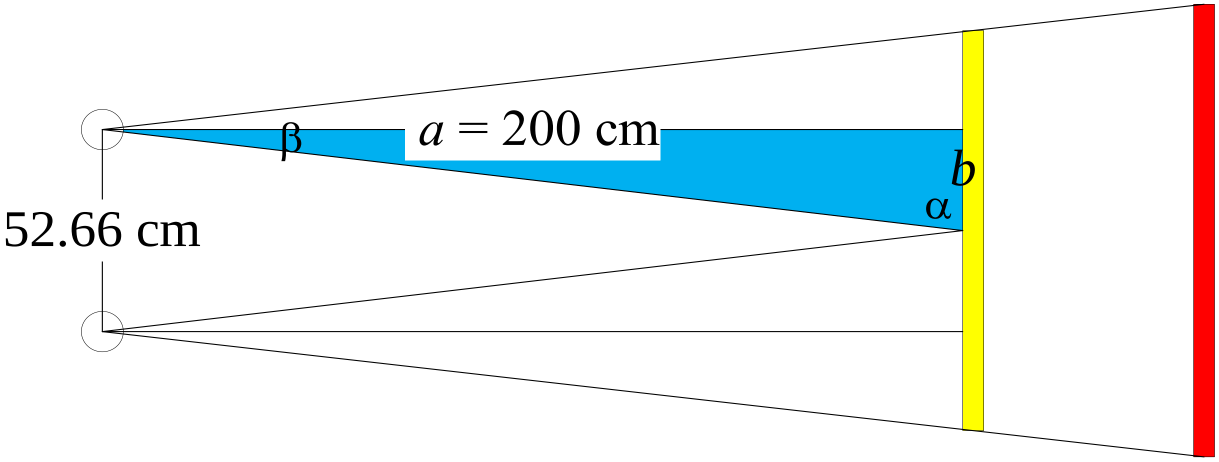
- 3D-LiDAR : TERABEE's TeraRanger-EVO-64PX
- LiDAR layout : (1) LiDAR is placed 3 meters in front of the wall (2) The distance between the two LiDARs needs to be 52.66 cm
- Hardware Specifications : Intel i7-8700 3.2GHz, DDR4 32GB, GeForce GTX 1070Ti 8GB
- 100 pieces of data were collected in each of the 5 categories.
- 80% of the collected data is used to train the model and 20% is used to test the model.

Experiment

- Deep Learning parameters
  - Epoch : 200
  - Batch Size : 128
  - Loss : Cross-Entropy
  - Optimizer : Adam

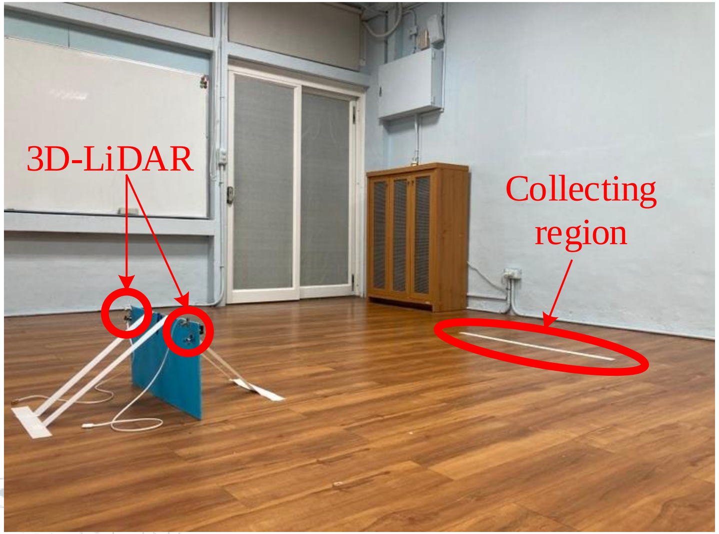
Experiment

- The experiment environment as figure shows.

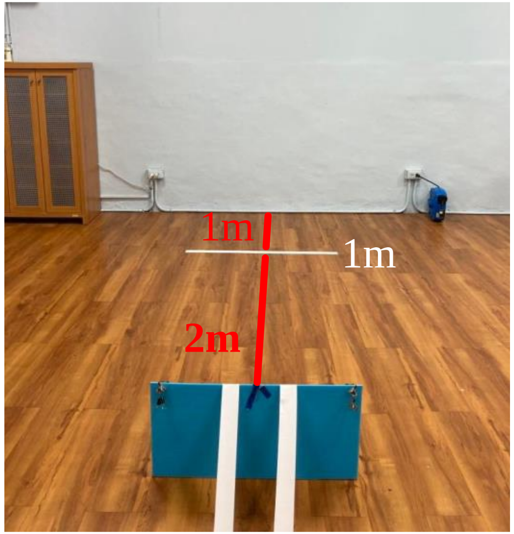


Experiment

◎ Experimental scenario



◎ Equipment layout



Experiment

◎ 3D-LiDAR sensing schematic

Experiment

0.965	0.928	0.936	0.951	0.865	0.713	0.651	0.675	0.736	0.998	1	1	1	1	1	1
0.975	1	0.92	0.955	0.85	0.715	0.623	0.64	0.743	0.95	1	1	1	1	1	1
0.998	0.958	0.99	0.966	0.78	0.678	0.62	0.553	0.755	0.955	1	1	1	1	1	1
1	1	1	0.963	0.821	0.67	0.595	0.655	0.711	0.941	1	1	1	1	1	1
1	1	1	0.901	0.751	0.595	0.605	0.57	0.751	0.901	1	1	1	1	1	1
1	0.96	1	0.965	0.773	0.605	0.555	0.573	0.718	0.961	1	1	1	1	1	1
1	1	0.97	0.9	0.755	0.585	0.523	0.533	0.79	0.998	1	1	1	1	1	1
1	0.998	0.996	0.958	0.741	0.593	0.518	0.571	0.823	1	1	1	1	1	1	1

Experiment

- nobody

Experiment

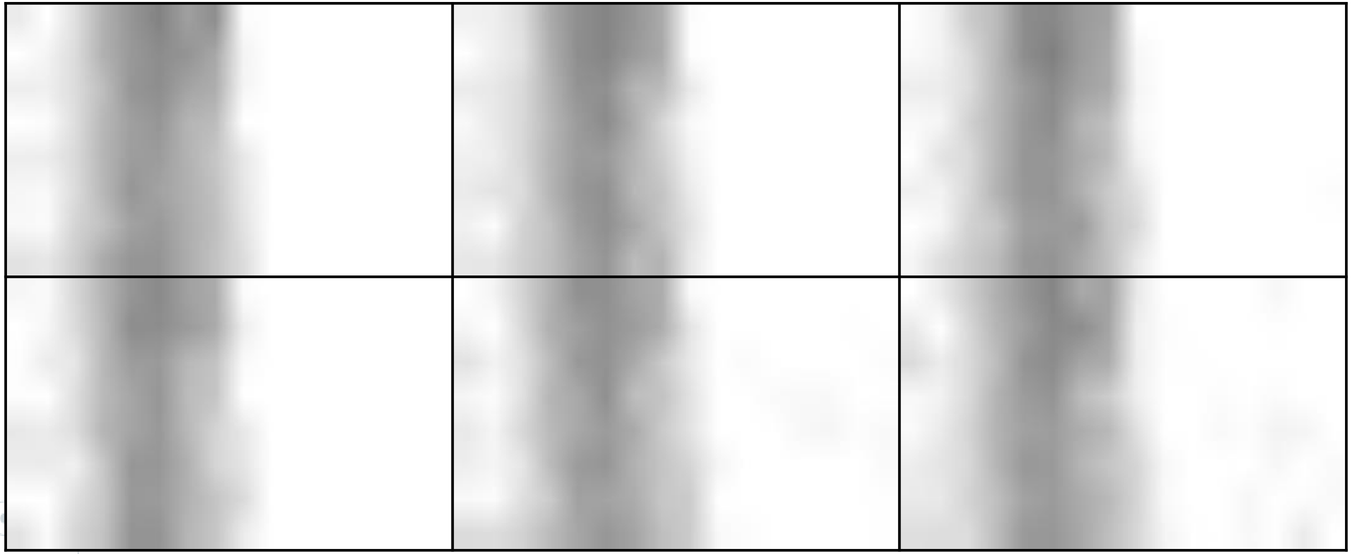
- nobody

Experiment

- nobody

Experiment

- stand



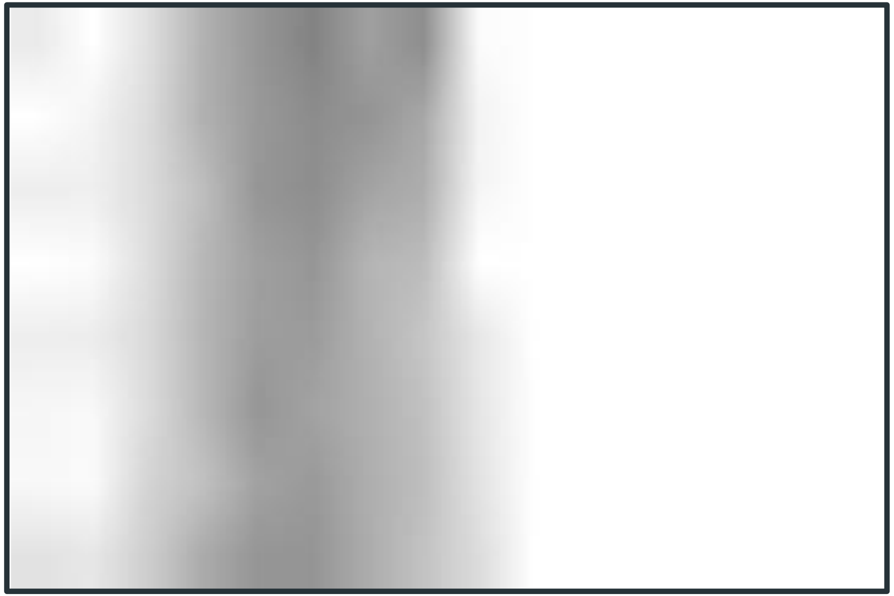
Experiment

- stand

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0	2775	3000	2640	2100	1770	1550	1885	1680	2960	3000	3000	3000	3000	3000	3000	3000
1	3000	2880	2590	2090	1800	1670	1750	1985	2870	3000	3000	3000	3000	3000	3000	3000
2	2800	2820	2590	2240	1770	1675	1940	2055	2885	3000	3000	3000	3000	3000	3000	3000
3	3000	2970	2620	2160	1885	1770	2135	2220	3000	3000	3000	3000	3000	3000	3000	3000
4	2800	2790	2565	2145	1855	1845	2100	2335	2725	3000	3000	3000	3000	3000	3000	3000
5	2895	2935	2595	2170	1765	1920	2075	2280	2710	3000	3000	3000	3000	3000	3000	3000
6	2920	2955	2495	2280	1910	1815	2050	2240	2675	3000	3000	3000	3000	3000	3000	3000
7	2660	2720	2425	2015	1760	1760	2045	2295	2590	3000	3000	3000	3000	3000	3000	3000

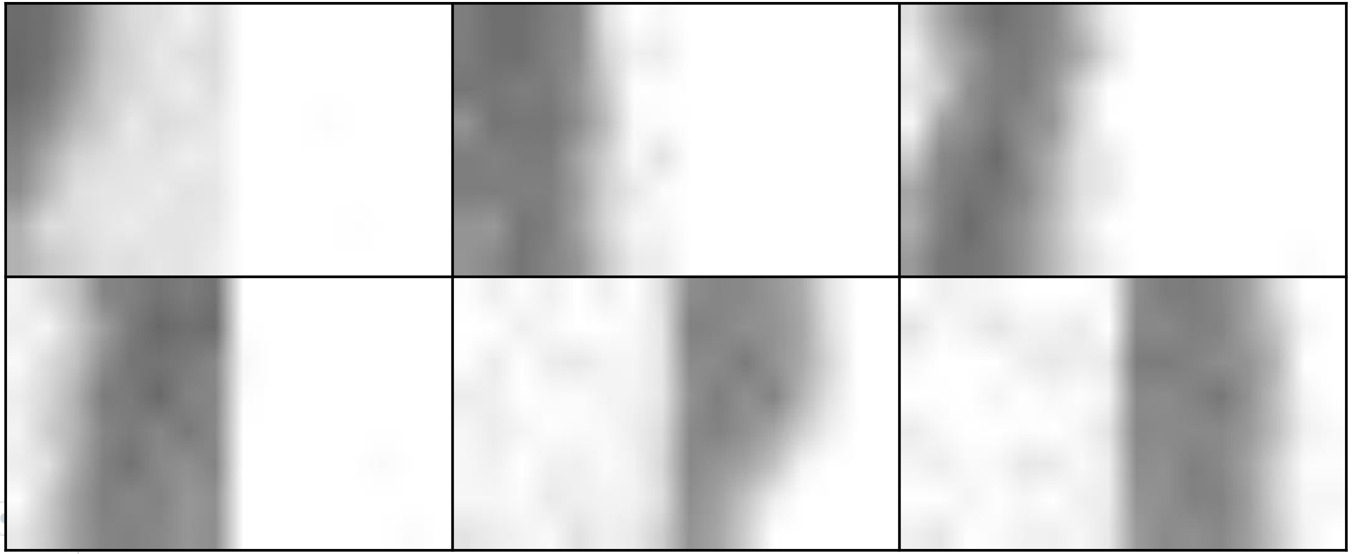
Experiment

- stand



Experiment

- walk



Experiment

- walk

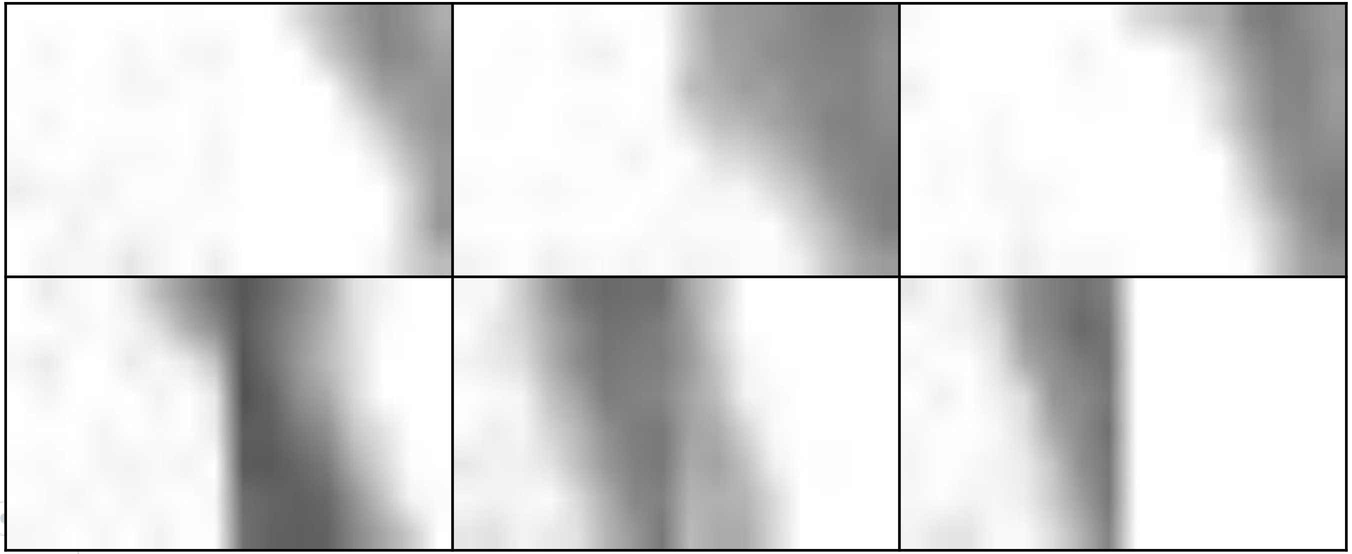
	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0	2980	2995	2880	2895	2965	2910	3000	2355	1705	2020	2415	3000	3000	3000	3000	3000
1	2905	3000	2820	2825	2950	2870	2980	2335	1645	1970	2535	2850	3000	3000	3000	3000
2	3000	3000	3000	3000	2870	2910	2835	2570	1605	1795	2360	3000	3000	3000	3000	3000
3	3000	2840	2860	2805	3000	2900	2760	2295	1640	2020	2560	2955	3000	3000	3000	3000
4	2780	3000	2785	3000	3000	2935	2665	2520	1815	2280	2755	3000	3000	3000	3000	3000
5	2765	2805	2920	2950	2810	2820	2685	2335	1855	2340	2905	3000	3000	3000	3000	2965
6	2905	2970	2855	2985	2890	2870	2505	2115	2120	2620	3000	2990	3000	3000	3000	2995
7	2795	2840	2720	2915	2730	2610	2250	1905	2100	2825	3000	3000	3000	3000	3000	3000

Experiment

- walk

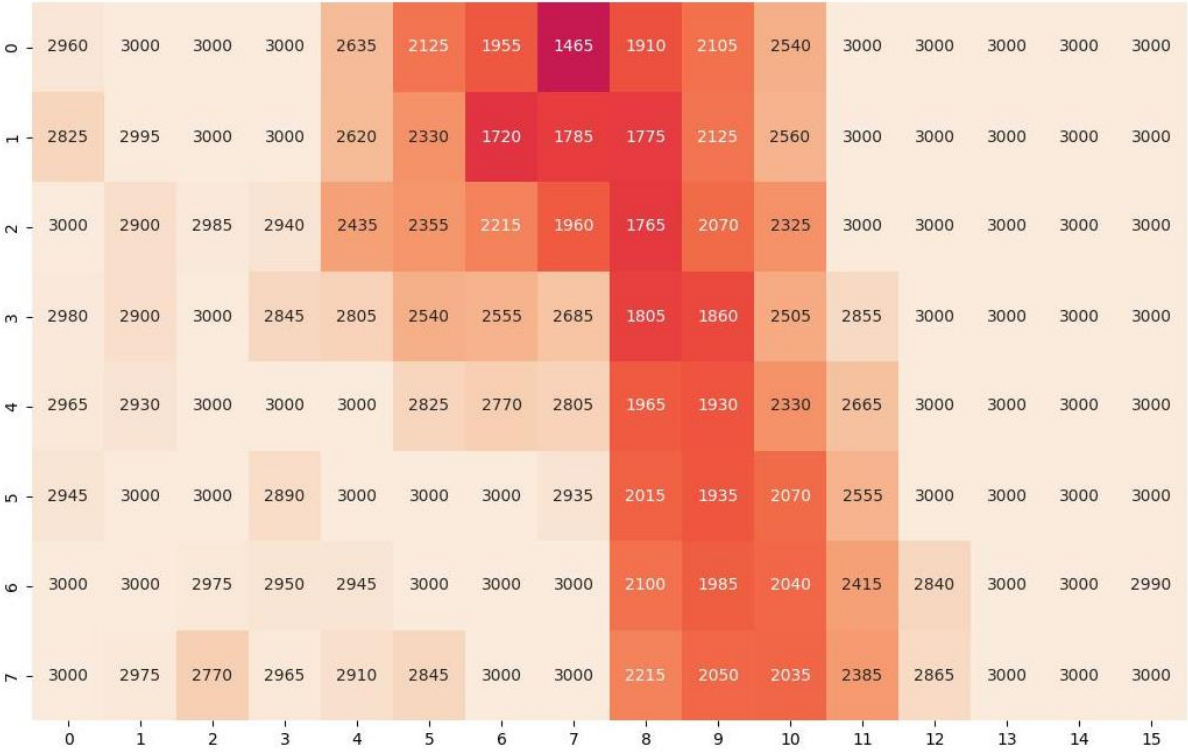
Experiment

- run



Experiment

- run

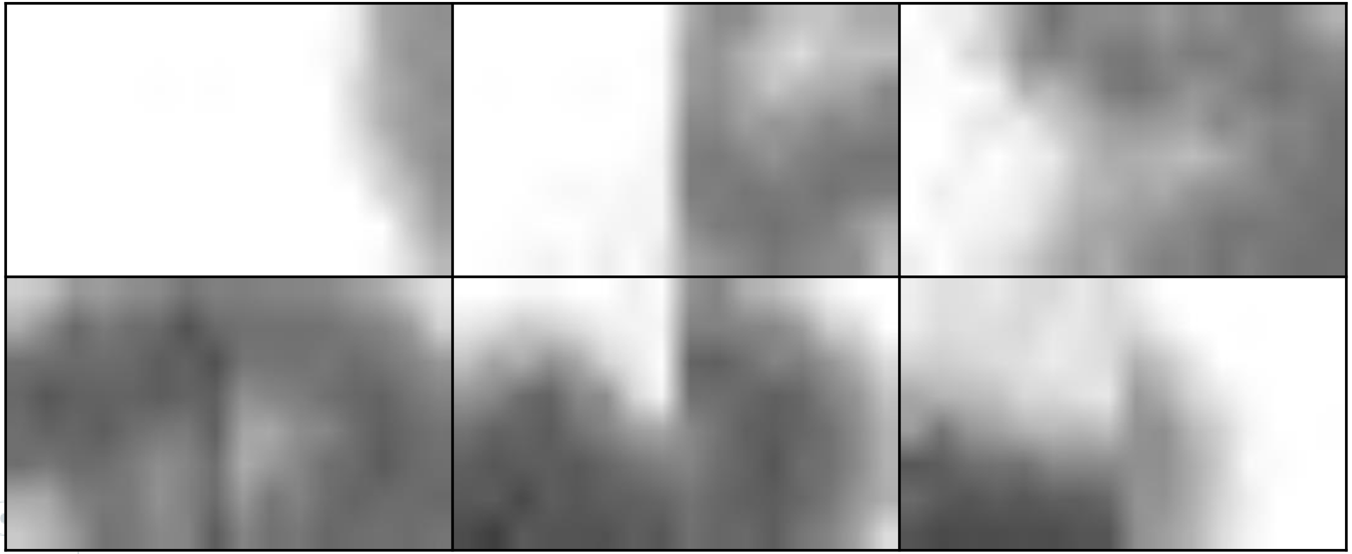


Experiment

- run

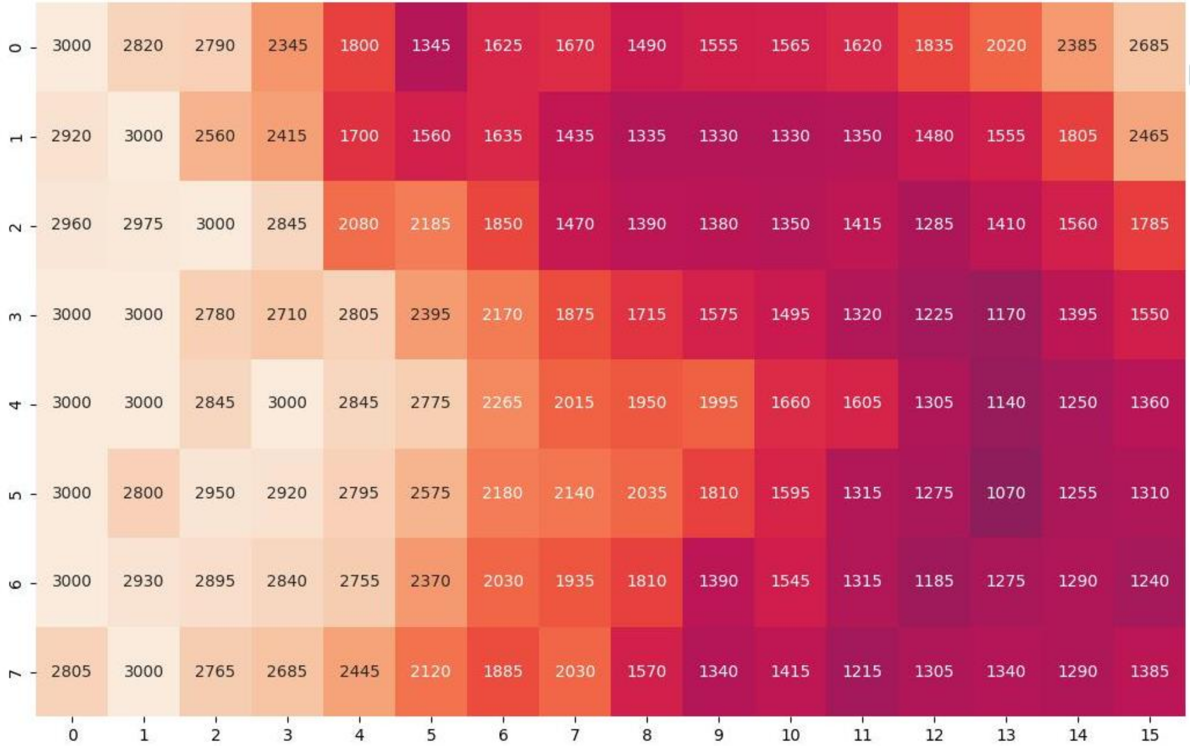
Experiment

- fall



Experiment

- fall

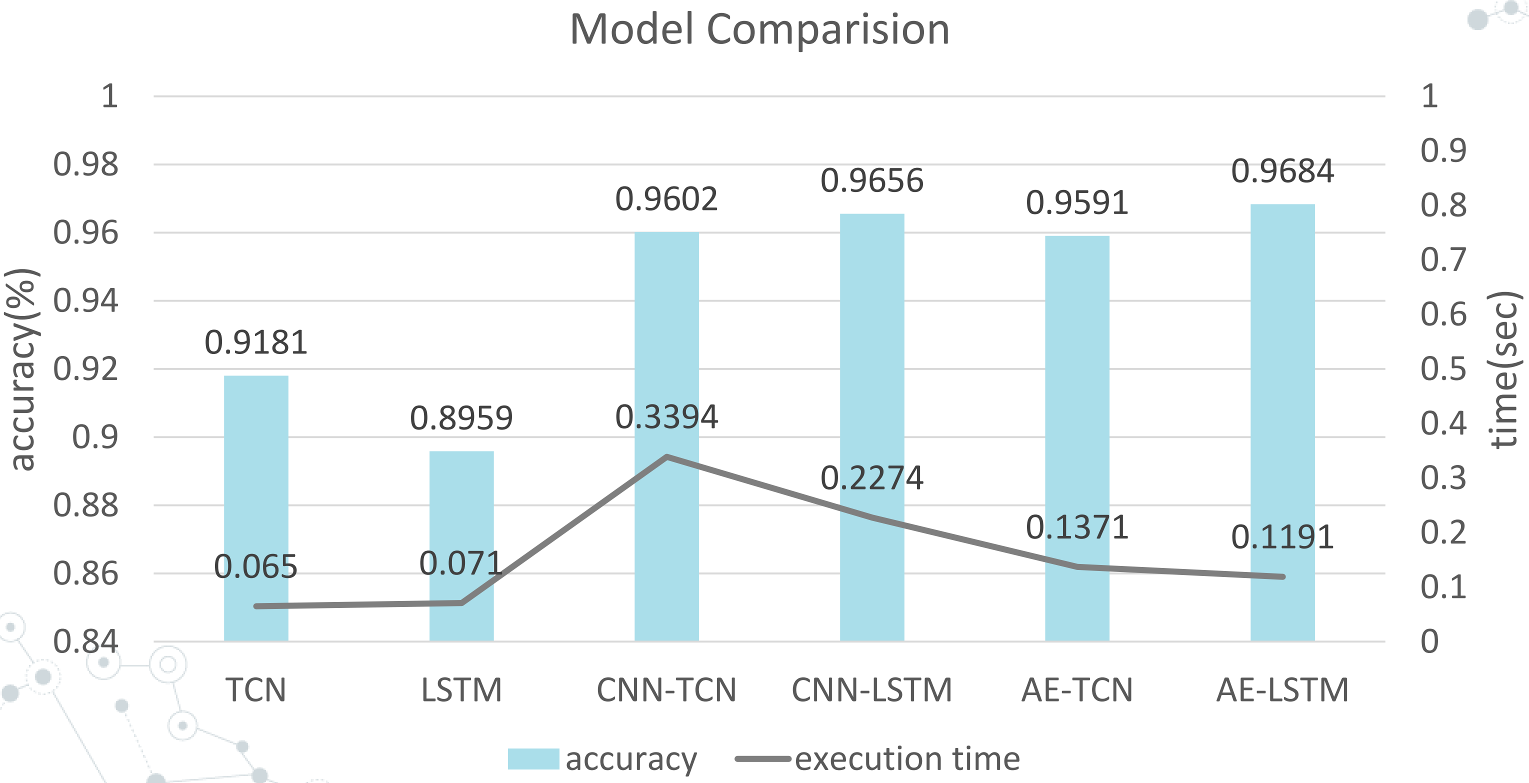


	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0	3000	2820	2790	2345	1800	1345	1625	1670	1490	1555	1565	1620	1835	2020	2385	2685
1	2920	3000	2560	2415	1700	1560	1635	1435	1335	1330	1330	1350	1480	1555	1805	2465
2	2960	2975	3000	2845	2080	2185	1850	1470	1390	1380	1350	1415	1285	1410	1560	1785
3	3000	3000	2780	2710	2805	2395	2170	1875	1715	1575	1495	1320	1225	1170	1395	1550
4	3000	3000	2845	3000	2845	2775	2265	2015	1950	1995	1660	1605	1305	1140	1250	1360
5	3000	2800	2950	2920	2795	2575	2180	2140	2035	1810	1595	1315	1275	1070	1255	1310
6	3000	2930	2895	2840	2755	2370	2030	1935	1810	1390	1545	1315	1185	1275	1290	1240
7	2805	3000	2765	2685	2445	2120	1885	2030	1570	1340	1415	1215	1305	1340	1290	1385

Experiment

- fall

Result


Model Comparision
accuracy(%)
time(sec)
1
0.98
0.96
0.94
0.92
0.9
0.88
0.86
0.84
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0.9181
0.8959
0.9602
0.9656
0.9591
0.9684
0.065
0.071
0.3394
0.2274
0.1371
0.1191
TCN
LSTM
CNN-TCN
CNN-LSTM
AE-TCN
AE-LSTM
accuracy
execution time

Result

LSTM Confusion Matrix					
Predict / True	walk	nobody	fall	stand	run
walk	83%	3%	4%	2%	8%
nobody	0	99%	1%	0	0
fall	6%	6%	86%	0	2%
stand	0	0	0	99%	1%
run	12%	0	3%	4%	81%

Result

AE-LSTM Confusion Matrix					
Predict / True	walk	nobody	fall	stand	run
walk	95%	1%	2%	0	2%
nobody	0	100%	0	0	0
fall	3%	2%	93%	0	2%
stand	0	0	0	100%	0
run	2%	0	1%	1%	96%

5.

System Display

System Display

◎ 3D-LiDAR Information

2465.0	2215.0	1780.0	1430.0	1220.0	1340.0	1540.0	1400.0	1770.0	2075.0	2505.0	3000.0	3000.0	3000.0	3000.0	3000.0
2270.0	1900.0	1640.0	1525.0	1440.0	1445.0	1385.0	1505.0	1735.0	2035.0	2490.0	2925.0	3000.0	3000.0	3000.0	3000.0
1705.0	1670.0	1575.0	1355.0	1290.0	1375.0	1550.0	1505.0	1805.0	2240.0	2620.0	2885.0	3000.0	3000.0	3000.0	3000.0
1550.0	1370.0	1360.0	1320.0	1390.0	1435.0	1460.0	1610.0	2100.0	2340.0	2850.0	3000.0	3000.0	3000.0	3000.0	3000.0
1525.0	1365.0	1450.0	1405.0	1455.0	1410.0	1640.0	1815.0	2275.0	2735.0	2950.0	3000.0	3000.0	3000.0	3000.0	3000.0
1340.0	1325.0	1470.0	1395.0	1505.0	1580.0	1790.0	2025.0	2540.0	2895.0	3000.0	3000.0	3000.0	3000.0	3000.0	3000.0
1345.0	1420.0	1345.0	1510.0	1530.0	1815.0	2005.0	2295.0	2995.0	3000.0	3000.0	3000.0	3000.0	3000.0	3000.0	3000.0
1485.0	1345.0	1405.0	1660.0	1875.0	2255.0	2795.0	2930.0	3000.0	3000.0	3000.0	3000.0	3000.0	3000.0	3000.0	3000.0

fall : 99.9987244606018%

◎ Fall Detection

6. Conclusion and Future Outlook

Conclusion

- LiDAR are combined with deep learning for gait recognition.
- In order to improve the accuracy of gait recognition, models are established through combining CNN, AutoEncoder and LSTM / TCN respectively.
- Among them, AE-LSTM has the best achievement in gait recognition.

Future Outlook

- Multi-object Trajectory Recognition
- Expand the scope of 3D-LiDAR collection

Thanks