Part-based Collaborative Spatio-temporal Feature Learning for Cloth-changing Gait Recognition

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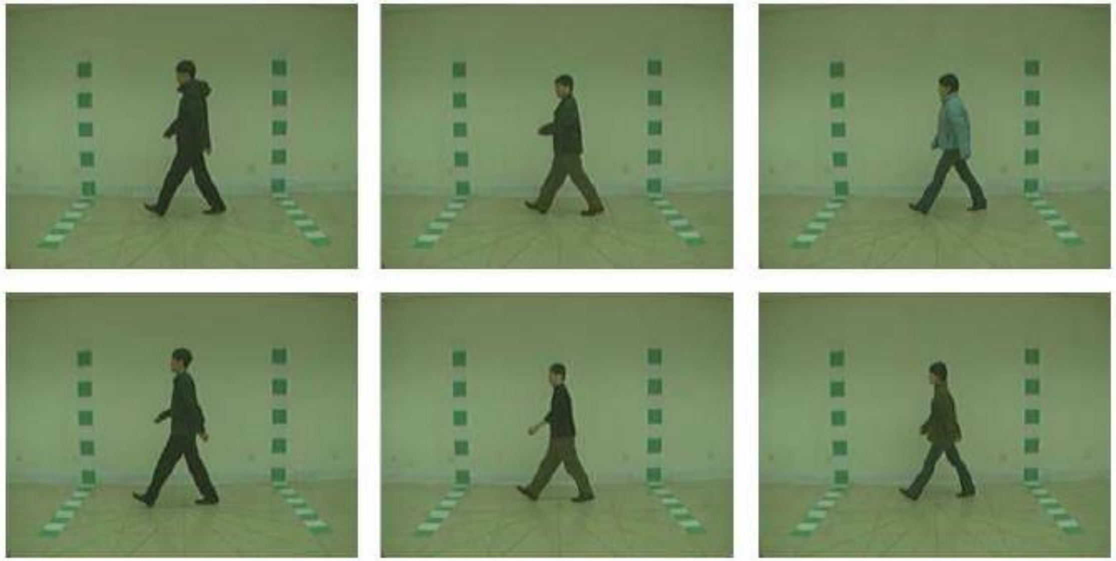
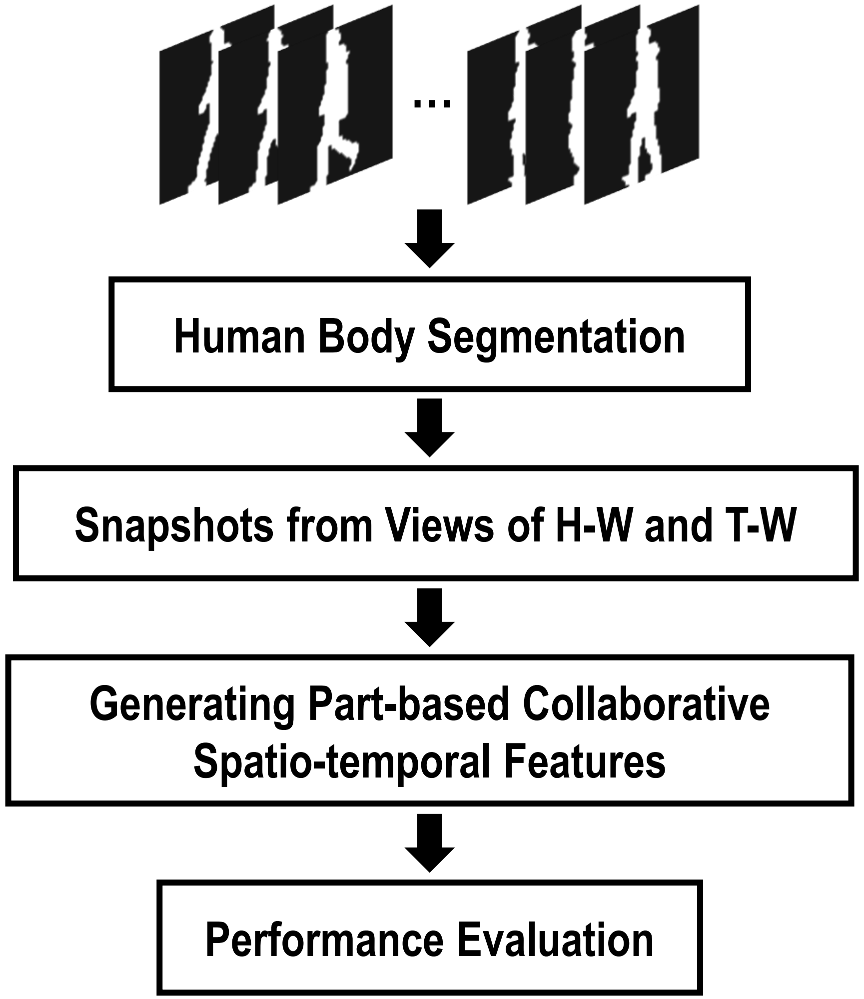
Introduction

- Gait provides a non-contact way of identifying a target person in a distance without his/her co-operation, which enables gait to be used in security surveillance and forensic authentication.
- The result of image/video-based gait recognition is influenced by exterior factors. Among these factors, clothing changes can be treated as one of the most challenging factors for gait recognition.



Proposed Method



Motivations:

- Although human gaits vary in different dressing patterns, they are still related to some extent, depending on the degree of clothing changes.
- For each person, gaits in different dressing patterns can be divided into two parts: the parts unaffected or less affected by clothing variations and the parts largely affected.
- It is reasonable to generate a robust feature representation for cloth-changing gait recognition from the non/less affected body parts.

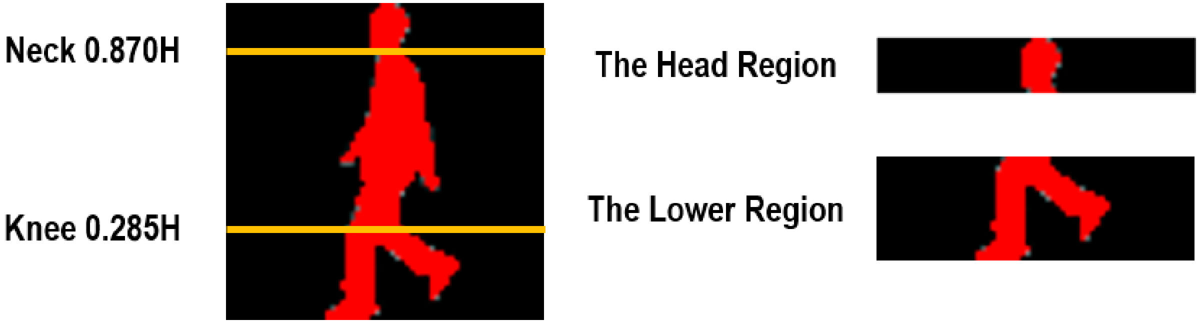
Proposed Method: Human Body Segmentation

Human Body Segmentation

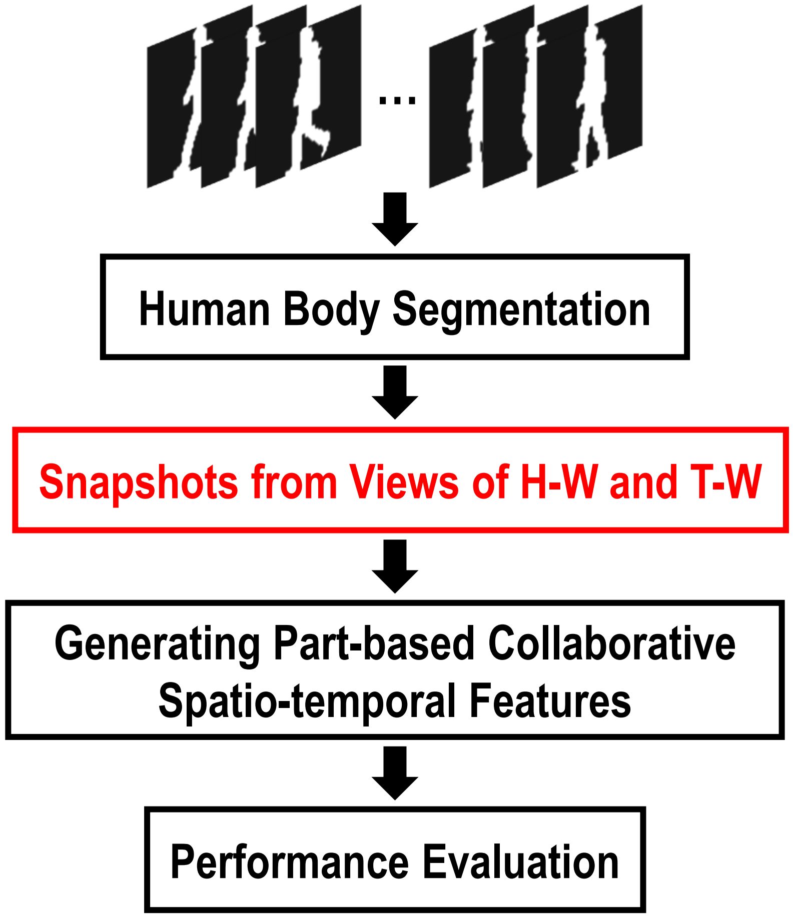
Snapshots from Views of H-W and T-W

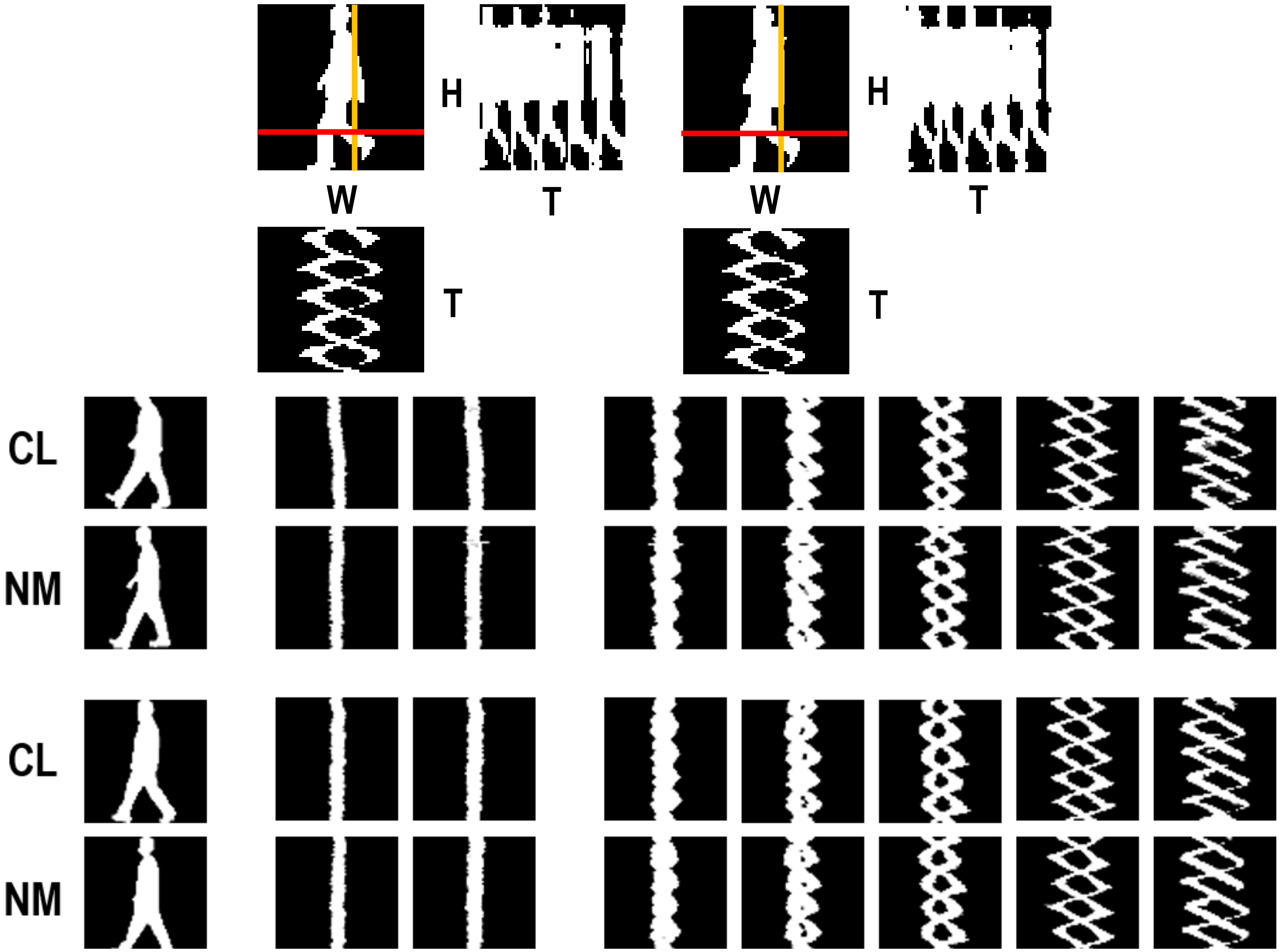
Generating Part-based Collaborative Spatio-temporal Features

Performance Evaluation



Proposed Method: Snapshots from View of $T - W$





Proposed Method: Part-Based Collaborative Feature Learning

Human Body Segmentation

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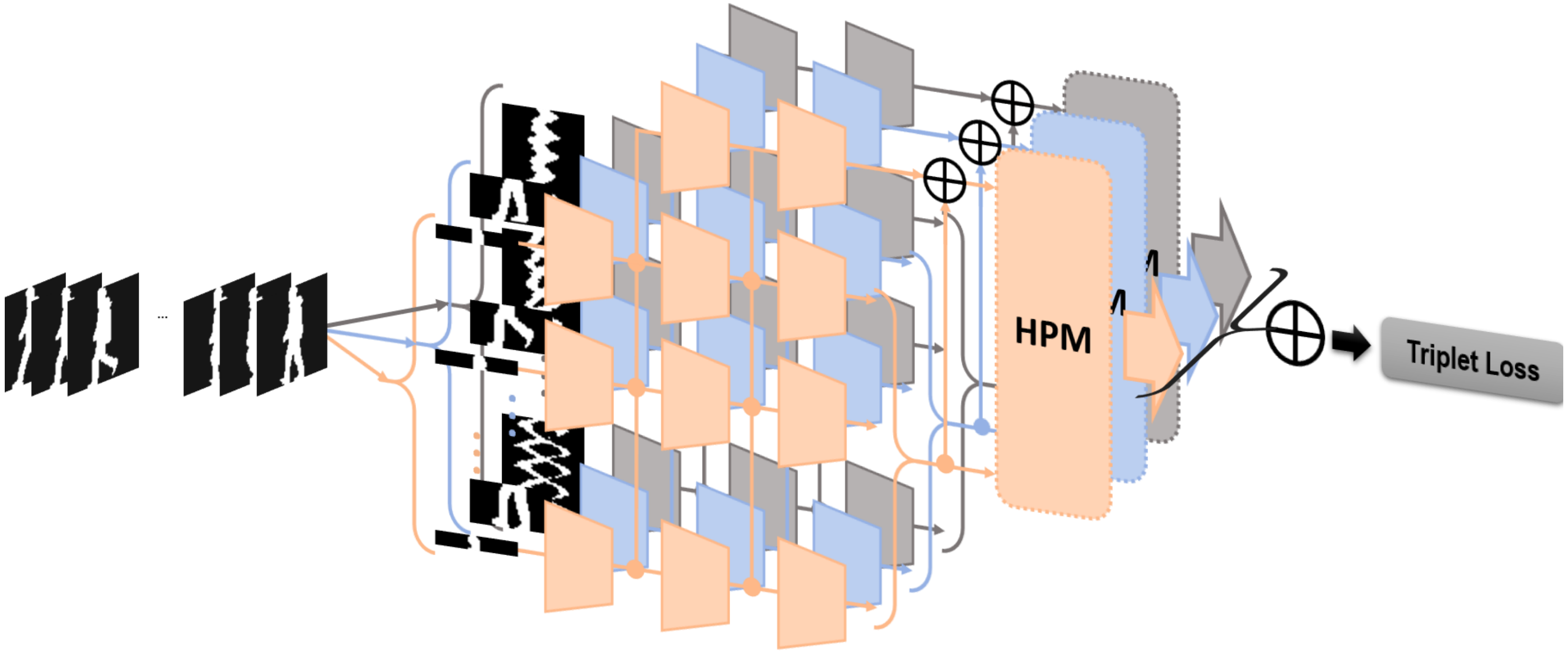
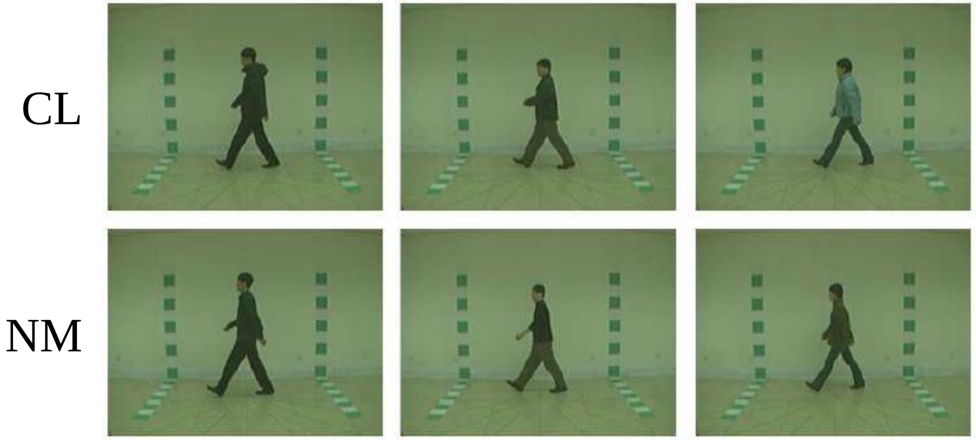
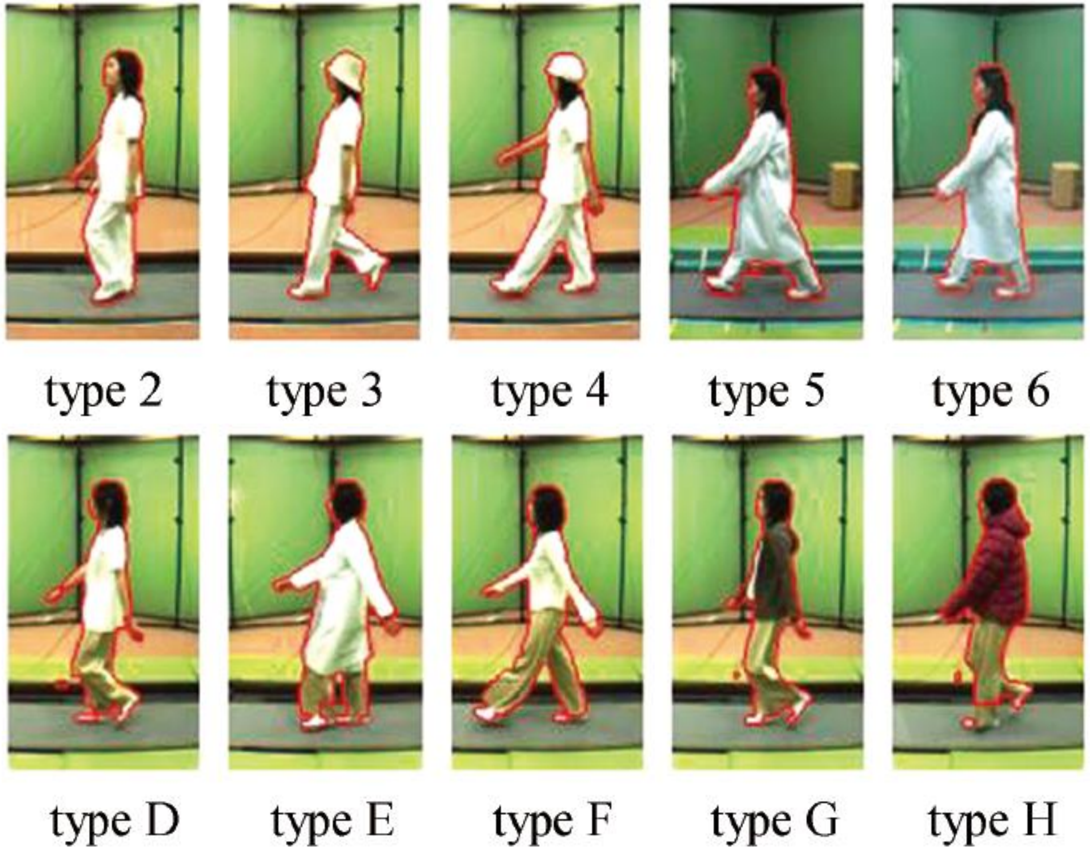


Experiments

- The proposed method has been verified on two gait datasets,
  - CASIA Gait Dataset B, one of the most widely-used gait datasets.
  - OU-ISIR Treadmill Dataset B, the maximum number of clothing conditions.





Experiments On CASIA-B

Gallery NM#1-4		0°-180°											
Probe CL#1-2		0°	18°	36°	54°	72°	90°	108°	126°	144°	162°	180°	Mean
ST(24)	GaitSet[1] (30frames)	29.4	43.1	49.5	48.7	42.3	40.3	44.9	47.4	43.0	35.7	25.6	40.9
	Ours (30frames)	**34.0**	**47.1**	**51.0**	**54.0**	**52.9**	**48.9**	**49.8**	**50.3**	**48.2**	**41.4**	**30.5**	**46.2**
	GaitSet[1] (64frames)	37.4	50.1	54.2	52.0	49.6	44.9	47.9	48.6	46.6	40.0	29.3	45.5
	Ours (64frames)	**38.1**	**52.3**	**57.9**	**59.1**	**56.2**	**51.3**	**53.8**	**56.6**	**56.3**	**48.0**	**31.2**	**51.0**
MT(62)	AE [2]	18.7	21.0	25.0	25.1	25.0	26.3	28.7	30.0	23.6	23.4	19.0	24.2
	MGAN [3]	23.1	34.5	36.3	33.3	32.9	32.7	34.2	37.6	33.7	26.7	21.0	31.5
	GaitSet[1] (30frames)	**52.0**	**66.0**	**72.8**	**69.3**	**63.1**	**61.2**	**63.5**	**66.5**	**67.5**	**60.0**	**45.9**	**62.5**
	Ours (30frames)	59.2	74.7	77.4	74.5	69.5	66.3	69.8	74.4	73.6	69.2	52.5	69.2
	GaitSet[1] (64frames)	63.8	72.5	78.0	76.8	67.3	64.4	67.1	71.2	71.7	68.3	52.7	68.5
	Ours (64frames)	**61.8**	**77.6**	**83.1**	**80.4**	**74.3**	**70.5**	**75.7**	**80.8**	**81.1**	**74.9**	**54.9**	**73.4**
LT(74)	CNN-LB [4]	37.7	57.2	66.6	61.1	55.2	54.6	55.2	59.1	58.9	48.8	39.4	54.0
	GaitNet [5]	42.1	-	-	70.7	-	**70.6**	-	69.4	-	-	-	63.2
	GaitSet[1] (30frames)	61.4	75.4	80.7	77.3	72.1	70.1	71.5	73.5	73.5	68.4	50.0	70.4
	Ours (30frames)	**64.2**	**80.9**	**83.0**	**79.5**	**74.3**	69.1	**74.8**	**78.5**	**81.0**	**77.0**	**60.3**	**74.8**
	GaitSet[1] (64frames)	69.3	82.4	83.3	78.7	74.3	70.5	74.9	78.0	77.6	74.7	60.8	75.0
	Ours (64frames)	**71.8**	**86.6**	**87.7**	**83.2**	**78.3**	**75.4**	**81.0**	**85.2**	**84.9**	**82.0**	**64.1**	**80.0**

Experiments On OU-ISIR Treadmill B

Probe Set	Ours	Anusha and Jaidhar [6]	Deng et al. [7]
Type 0	99.7	94.0	**100.0**
Type 2	**100.0**	93.5	**100.0**
Type 3	**100.0**	91.6	**100.0**
Type 4	**100.0**	94.1	98.5
Type 5	**100.0**	94.5	94.1
Type 6	**100.0**	92.0	91.2
Type 7	**100.0**	94.2	94.1
Type 8	**100.0**	94.5	94.1
Type 9	**100.0**	92.0	97.1
Type A	**100.0**	91.6	91.2
Type B	**99.9**	88.2	95.6
Type C	**100.0**	94.5	94.1
Type D	**100.0**	92.0	**100.0**
Type E	**100.0**	91.5	91.2
Type F	**100.0**	93.1	**100.0**
Type G	**99.8**	89.1	98.5

Probe Set	Ours	Anusha and Jaidhar [6]	Deng et al. [7]
Type H	**100.0**	95.0	94.1
Type I	**100.0**	98.5	98.5
Type J	**100.0**	91.5	91.2
Type K	**100.0**	87.5	98.5
Type L	**100.0**	90.0	**100.0**
Type M	**100.0**	97.5	97.1
Type N	**100.0**	85.5	**100.0**
Type P	**100.0**	91.1	**100.0**
Type R	**100.0**	86.2	88.2
Type S	**100.0**	89.1	95.6
Type T	**100.0**	95.0	94.1
Type U	**100.0**	95.5	94.1
Type V	**100.0**	91.6	91.2
Type X	**100.0**	90.1	**100.0**
Type Y	**100.0**	89.0	**100.0**
Type Z	**100.0**	87.2	98.5

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Thank you!