Gait Recognition using Multi-Scale Partial Representation Transformation with Capsules

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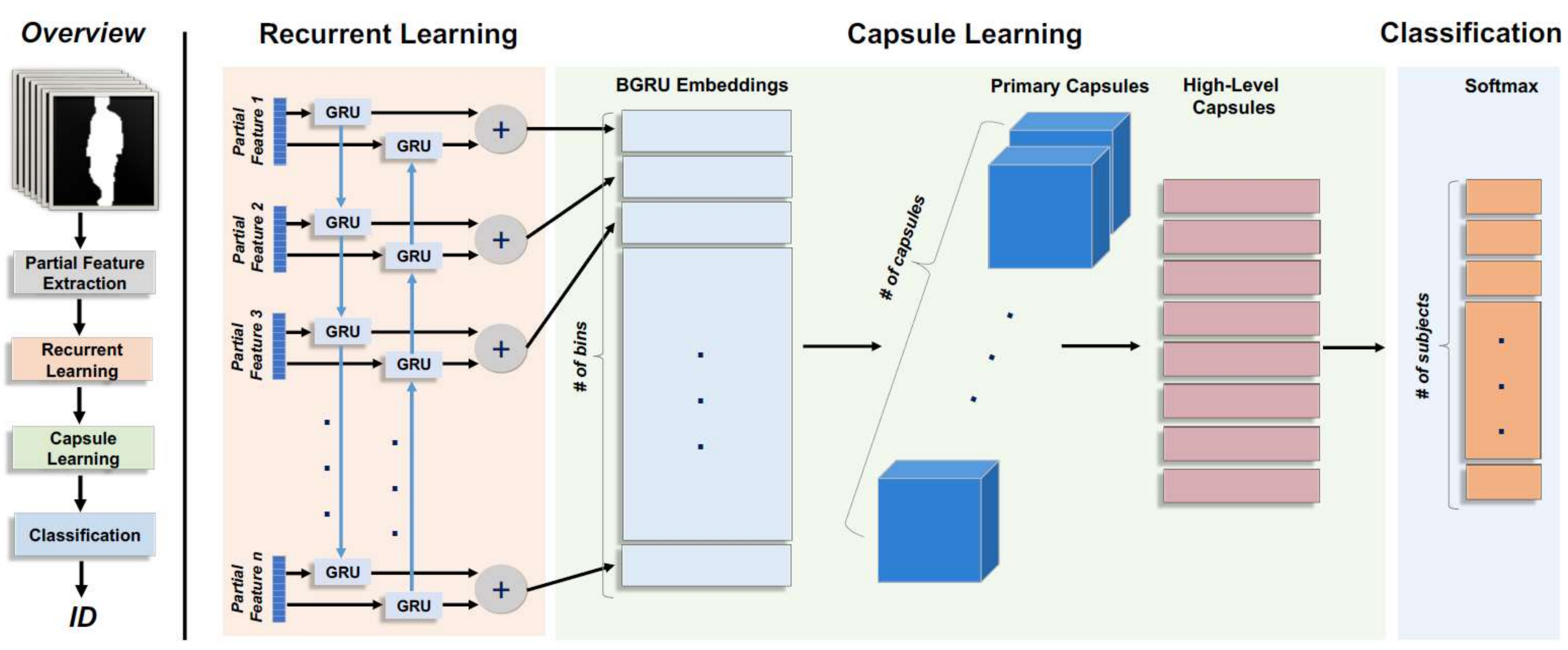
1. Gait Recognition

Gait data, acquired from an individual's body movement during walking, can provide important identity information.

- Due to the unconstrained nature of gait recognition, gait data can be captured from different viewpoints, so some parts of the body can be hidden from one view to another.
- The appearance of individuals can also be different due to variations in clothing, for instance wearing a coat or hat, or carrying a handbag or backpack.

2. Proposed Solution

we propose a novel deep network, learning to transfer partial gait representations using capsules to obtain more discriminative gait features robust to both viewing and appearance changes.



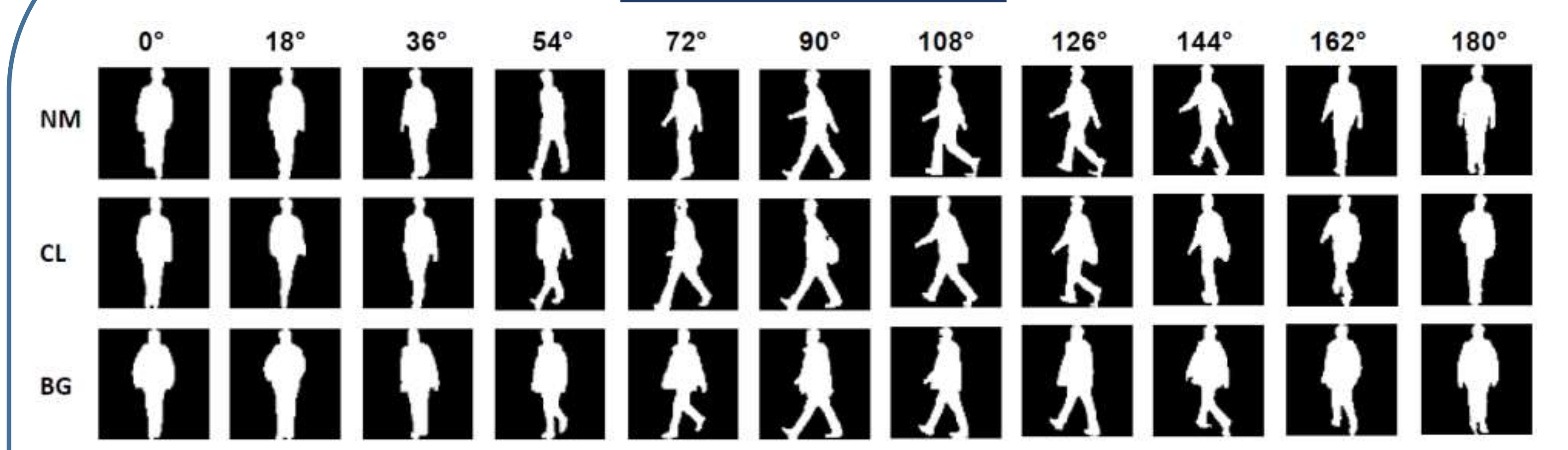
1- Partial feature extraction: We first extract partial features of gait-maps using GaitSet[1] method involving multiple convolutional, pooling, and fully connected layers.

2- Recurrent learning: We then transform the features extracted by the previous layer using Bi-GRU to a more discriminating manifold by exploring the spatial correlations between the horizontal strips in the feature maps.

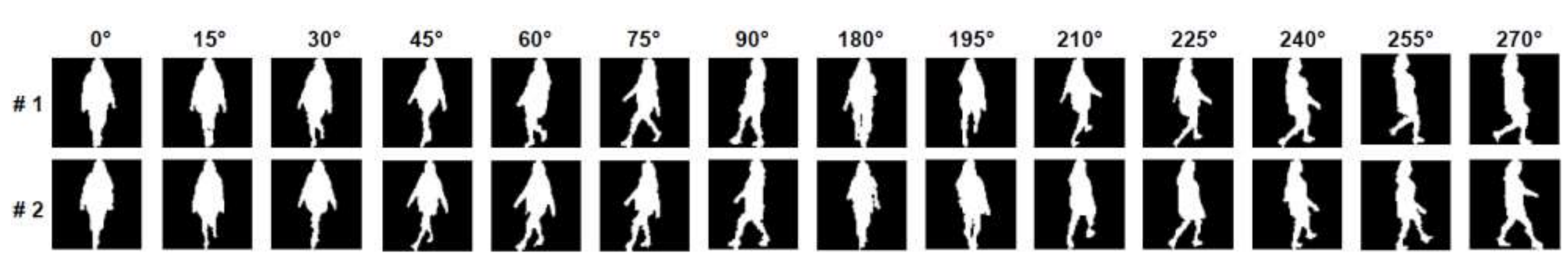
3- Capsule attention: We learn deeper part-whole relationships between the strips and then selectively assign more weights to the more discriminative features and explains away misleading factors.

4- Classification: We performs classification using a softmax activation function.

3. Datasets



CASIA-B dataset:
124 subjects in 3 different walking conditions and 11 different view angles



CASIA-B dataset:
10,307 subjects in 2 different sessions and 14 different view angles

4. Results

TABLE I
CASIA-B GAIT RECOGNITION RESULTS UNDER NORMAL (NM) WALKING CONDITIONS.

Method			View											
Name	**Year**	**Venue**	**0°**	**18°**	**36°**	**54°**	**72°**	**90°**	**108°**	**126°**	**144°**	**162°**	**180°**	**Mean**
CNN-3D [2]	2017	*T-PAMI*	87.1	93.2	97.0	94.6	90.2	88.3	91.1	93.8	96.5	96.0	85.7	92.1
CNN-Ens. [2]	2017	*T-PAMI*	88.7	95.1	98.2	96.4	94.1	91.5	93.9	97.5	98.4	95.8	85.6	94.1
MGAN [3]	2019	*T-IFS*	-	-	-	84.2	-	72.3	-	83.0	-	-	-	79.8
EV-Gait [4]	2019	*CVPR*	77.3	89.3	94.0	91.8	92.3	96.2	91.8	91.8	91.4	87.8	85.7	89.9
Gait-Joint [5]	2019	*PR*	75.6	91.3	91.2	92.9	92.5	91.0	91.8	93.8	92.9	94.1	81.9	89.9
GaitSet [1]	2019	*AAAI*	90.8	97.9	**99.4**	96.9	93.6	91.7	95.0	97.8	**98.9**	**96.8**	85.8	95.0
GaitNet-1 [6]	2019	*CVPR*	91.2	-	-	95.6	-	92.6	-	96.0	-	-	-	93.9
GaitNet-2 [7]	2019	*arXiv*	**93.1**	92.6	90.8	92.4	87.6	**95.1**	94.2	95.8	92.6	90.4	**90.2**	92.3
Ours	-	-	91.8	**98.3**	99.0	**98.0**	**94.1**	92.8	**96.3**	**98.1**	98.4	96.2	89.2	**95.7**

TABLE II
CASIA-B GAIT RECOGNITION RESULTS UNDER CARRIED BAGS (BG) CONDITIONS.

Method			View											
Name	**Year**	**Venue**	**0°**	**18°**	**36°**	**54°**	**72°**	**90°**	**108°**	**126°**	**144°**	**162°**	**180°**	**Mean**
CNN-LB [2]	2017	*T-PAMI*	64.2	80.6	82.7	76.9	64.8	63.1	68	76.9	82.2	75.4	61.3	72.4
MGAN [3]	2019	*T-IFS*	48.5	58.5	59.7	58	53.7	49.8	54	61.3	59.5	55.9	43.1	54.7
GaitSet [1]	2019	*AAAI*	83.8	91.2	91.8	88.8	83.3	81.0	84.1	90.0	92.2	**94.4**	79	87.2
GaitNet-1 [6]	2019	*CVPR*	83.0	-	-	86.0	-	74.8	-	85.8	-	-	-	82.6
GaitNet-2 [7]	2019	*arXiv*	**88.8**	88.7	88.7	**94.3**	85.4	**92.7**	**91.1**	92.6	84.9	84.4	**86.7**	88.9
Ours	-	-	87.3	**93.7**	**94.8**	93.1	**88.1**	84.5	88.8	**93.5**	**96.3**	93.3	83.9	**90.7**

TABLE III
CASIA-B GAIT RECOGNITION RESULTS UNDER DIFFERENT CLOTHING (CL) CONDITIONS.

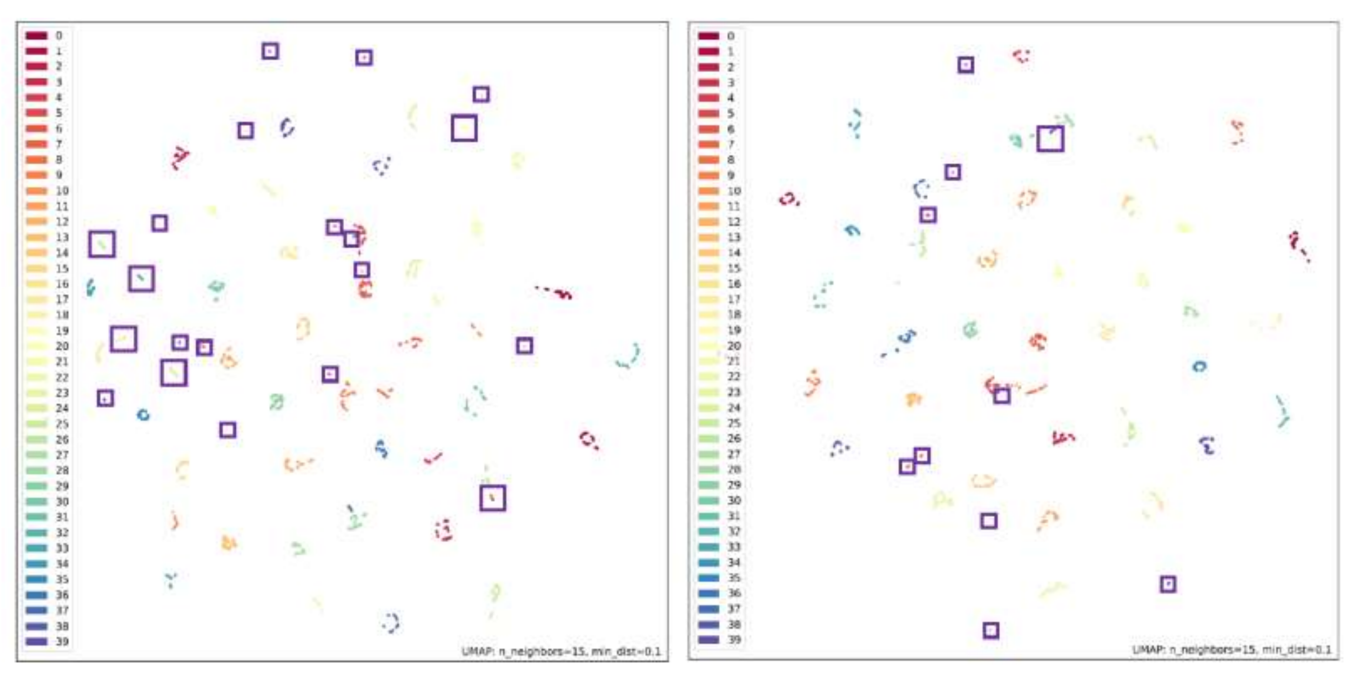
Method			View											
Name	**Year**	**Venue**	**0°**	**18°**	**36°**	**54°**	**72°**	**90°**	**108°**	**126°**	**144°**	**162°**	**180°**	**Mean**
CNN-LB [2]	2017	*T-PAMI*	37.7	57.2	66.6	61.1	55.2	54.6	55.2	59.1	58.9	48.8	39.4	54.0
MGAN [3]	2019	*T-IFS*	23.1	34.5	36.3	33.3	32.9	32.7	34.2	37.6	33.7	26.7	21.0	31.5
GaitSet [1]	2019	*AAAI*	61.4	75.4	80.7	77.3	72.1	70.1	**71.5**	73.5	73.5	68.4	50	70.4
GaitNet-1 [6]	2019	*CVPR*	42.1	-	-	70.7	-	70.6	-	69.4	-	-	-	63.2
GaitNet-2 [7]	2019	*arXiv*	50.1	60.7	72.4	72.1	**74.6**	**78.4**	70.3	68.2	53.5	44.1	40.8	62.3
Ours	-	-	**63.4**	**77.3**	**80.1**	**79.4**	72.4	69.8	71.2	**73.8**	**75.5**	**71.7**	**62.0**	**72.4**

TABLE IV
OU-MVLP GAIT RECOGNITION RESULTS.

Method			View				
Name	**Year**	**Venue**	**0°**	**30°**	**60°**	**90°**	**Mean**
GEI NET [8]	2016	*ICB*	15.7	41	39.7	39.5	34.0
CNN-LB [2]	2017	*T-PAMI*	14.2	32.7	32.3	34.6	28.5
DigGAN [9]	2018	*arXiv*	30.8	43.6	41.3	42.5	39.6
Gait-Set [1]	2019	*AAAI*	77.7	86.9	85.3	83.5	83.4
Ours	-	-	**78.3**	**88.8**	**85.7**	**85.1**	**84.5**

- Our model obtains state-of-the-art values for gait recognition on two gait datasets.

5. Feature Space Exploration



- our solution (left) creates denser clusters, thus the subjects are more easily separable in our feature spaces, compared to global feature representation (right).

6. References

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