Learning Joint Gait Representation via Quintuplet Loss Minimization

Kaihao Zhang[1*] Wenhan Luo[2] Lin Ma[2] Wei Liu[2] Hongdong Li[1]
[1]Australian National University [2]Tencent AI Lab
{kaihao.zhang, hongdong.li}@anu.edu.au
{whluo.china, forest.linma}@gmail.com wl2223@columbia.edu

Abstract

Gait recognition is an important biometric technique relevant to video surveillance, where the task is to identify people at a distance by their walking patterns captured in the video. Most of the current approaches for gait recognition either use a pair of gait images to form a cross-gait representation or rely on a single gait image for unique-gait representation. These two types of representations empirically complement one another. In this paper, we propose a new Joint Unique-gait and Cross-gait Network (JUCNet) *representation, to combine the advantages of both schemes, leading to significantly improved performance. A second contribution of this work is a tailored* quintuplet *loss function, which simultaneously boosts inter-class differences by pushing different subjects further apart and contracts intra-class variations by pulling same subjects closer. Extensive tests demonstrate that our method achieves the best performance tested on multiple standard benchmarks, compared with other state-of-the-art methods.*

1. Introduction

Gait recognition is the task of identifying people at a distance using videos of their walking patterns [47]. This is an active research topic in the field of computer vision, due to its importance in real-world applications such as video surveillance, forensic identification, and evidence collection [6, 22]. As a behavioral biometric, gait exhibits unique advantages over other biometrics like fingerprint, iris and face [46], because gait based methods can identify subjects from low-resolution video sequences [33] without subject's cooperation.

In real-world scenarios, variations such as clothing [35], walking speed [30, 43], carrying condition [42], and camera viewpoints [24] result in remarkable changes in gait appearance, which may further degrade the performance of gait recognition. Previous methods [18, 20, 48] have been proposed to alleviate these issues. Most of them focus on *cross-gait* representation, which is the concatenation of a pair of gait images and labeled to *"Same"* or *"Different"* like the input of Fig. 1. While being effective in capturing the relationship between a pair of gaits (gallery and probe [23]), these methods ignore the label (*e.g.*, "$X1$", "$X2$", "$Z1$", and "$K2$" in Fig. 1) of each single gait image. The potential of *unique-gait/single-gait* representation is ignored, which makes these methods confused in discriminating different subjects with similar clothing, illumination, and carrying conditions. For example, X_1 and Y_1 in Fig. 2 (a) may be predicted to be an identical subject as they are close in the feature space. Nowadays, some deep learning methods (*e.g.*, [37]) tackle this problem based on unique-gait representation solely. They extract unique-gait features enclosed in a single image and then match them to predict the relationship. While these methods ignore the cross-gait representation.

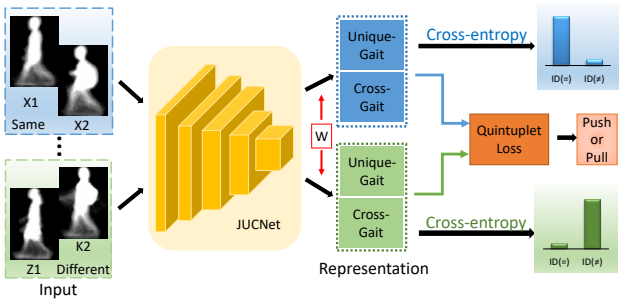


Figure 1. An illustration of our feature learning process. The JUCNet structure synchronously learns unique-gait and cross-gait representations, and the Quintuplet loss is proposed to increase the inter-class differences and meanwhile reduce the intra-class variations.

To this end, we develop a deep network called *JUCNet* to jointly learn the unique-gait and cross-gait representations. Different from existing gait recognition methods, there are three output branches in our network, of which two branches learn unique-gait representation and one branch

*This work was primarily done while Kaihao Zhang was a research intern with Tencent AI Lab.

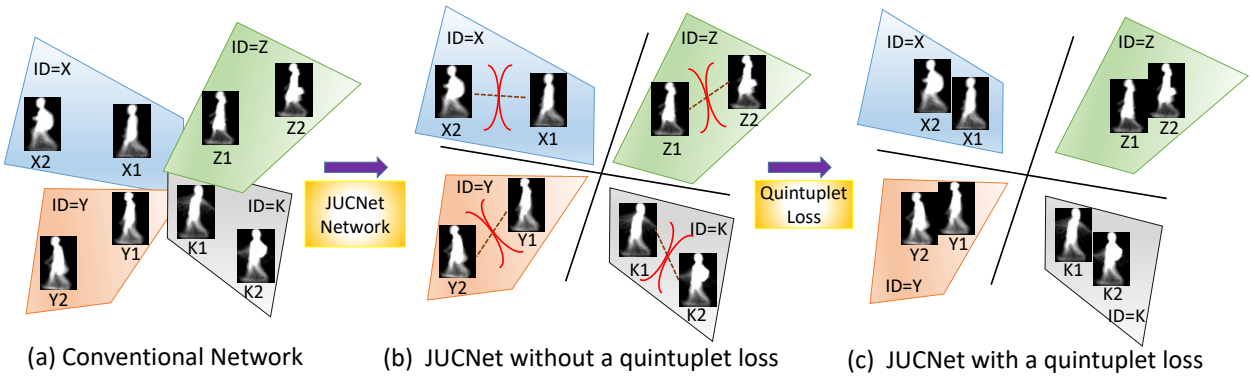


Figure 2. A conventional network, our JUCNet without and with the quintuplet loss are shown in (a), (b), and (c), respectively. From (a) to (b), JUCNet additionally learns the identical unique-gait representation, which enlarges inter-class differences among subjects. From (b) to (c), not only the inter-class variations increases, but also the intra-class discrepancy is decreased, with the help of the proposed quintuplet loss. Red arch lines of each subject domain in (b) indicate the significant intra-class discrepancy, which is reduced as shown by the red circles in (c).

learns concatenated cross-gait representation. Fig. 2 (b) shows the effectiveness of JUCNet. Additionally considering the identity uniqueness, our model can extract discriminative features, which enlarges the inter-class variations due to the uniqueness information. This could improve the performance in the case that gaits are difficult to recognize based on sole cross-gait information.

When conducting recognition, conventional models rank the affinity scores of a given probe against all gallery gaits. To achieve this, these models are usually trained by combining a pair of gaits as a whole, and predicting their relationship via a binary classifier supervised by recognition signals. By doing so, they can obtain correct classification on the training set. However, models trained in this way extract features of relatively large intra-class variations and small inter-class differences, leading to inferior performance in the testing stage. Though JUCNet is designed to enlarge inter-class differences to some extent, the intra-class variations are still large. For instance, JUCNet increases the distance between inter-class subjects (*e.g.*, X_1 and Y_1 in Fig. 2 (b)), while the intra-class subjects (*e.g.*, X_1 and X_2) are not sufficiently tight.

In order to address this issue, we propose a quintuplet loss function which is a joint of both recognition and verification signals as the supervision. The basic JUCNet described above is therefore extended to be Multi-Pair JUCNet. This Multi-Pair JUCNet, trained effectively with the proposed quintuplet loss, learns to enlarge the inter-class differences by separating the cross-gait representation from different classes and reduces the intra-class variations by grouping the representation in the same class together. Fig. 2 (c) shows the effect. The distance between gait features from different subjects (*e.g.*, X_1 and Y_1) becomes larger, while the discrepancy of gait features from an identical subject (*e.g.*, X_1 and X_2) becomes smaller.

Our main contributions are as follows. 1) We develop a neural network called JUCNet, which jointly learns unique-gait representation and cross-gait representation. The two kinds of representations complement each other and boost the performance of gait recognition. 2) An effective loss function for gait recognition, termed as quintuplet loss, is proposed to guide an extension of JUCNet, named as Multi-Pair JUCNet, to extract powerful features with small intra-class variations and large inter-class differences. 3) Our proposed model outperforms the state-of-the-art models on public challenging gait datasets, showing its superiority.

2. Related Work

Model based methods. These methods aim to model the underlying structure of human body and extract motion features for recognition [2, 5, 18]. They have the advantage of recognizing gaits under various situations like different clothing, carrying conditions, *etc*. It is difficult for these methods to model body structures from relatively low-resolution images, so they can merely work under uncontrolled conditions.

Appearance based methods. Appearance based methods [11, 19, 20, 27, 29, 34, 44, 45] directly extract gait features from videos without modeling the underlying structure of human body. Therefore these methods can work in low-resolution conditions. They usually consist of three steps: 1) obtaining human silhouettes, 2) computing silhouette based representations such as Gait Energy Images (GEIs) [29], chrono-gait images [17], and gait flow [21], and 3) evaluating similarities between gaits.

Deep neural network based methods. Deep learning methods have achieved a great success in the field of computer vision [13, 38, 40, 41, 51, 25, 10]. Recent methods for gait recognition have also adopted CNNs [1, 7, 48, 49].

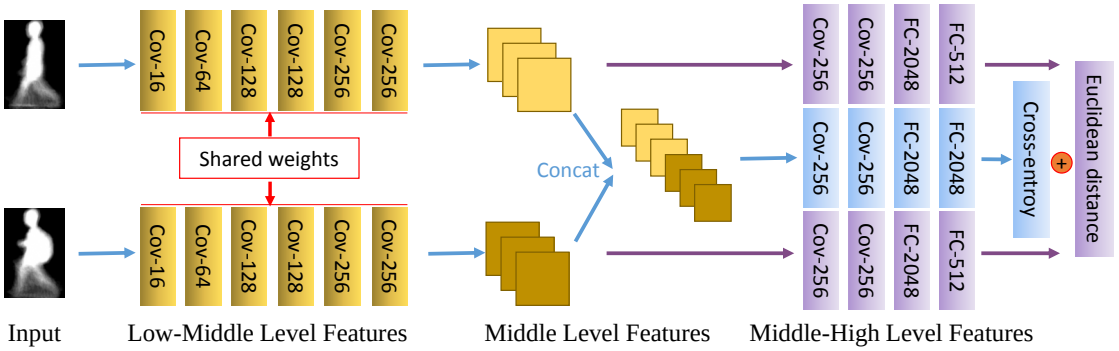


Figure 3. The architecture of the basic JUCNet model for gait recognition. Its input is a pair of gaits. There are three output branches, with two corresponding to unique-gait representations (purple part) and one for cross-gait representation (blue part). The unique-gait and cross-gait representations complement each other to update our model.

These methods learn features from pair GEIs in low-level [48, 49], middle-level, or high-level layers [1, 7, 9, 36, 48] and then forward features to a binary classifier for prediction. Wu *et al.* [48] conducted comprehensive experiments to evaluate these models. However, in these methods, models are trained by merely learning the cross-gait representation, ignoring the identical uniqueness. On the other hand, representative works like [7] train models based on unique-gait representations, without considering useful cross-gait representations. On the contrary, the proposed JUCNet learns both unique-gait and cross-gait representations. Meanwhile, we design a quintuplet loss to guide the model to extract features with smaller intra-class variations and larger inter-class differences.

3. Joint Learning with a Quintuplet Loss

Our method jointly learns unique-gait and cross-gait representations based on a proposed quintuplet loss. Before introducing JUCNet, we represent the method of joint learning and the quintuplet loss in the following.

3.1. Joint Learning

Cross-gait Learning. Methods based on cross-gait representation concatenate probe and gallery gait features and input them to a binary classifier to obtain the correct order via their ranking scores. In this work, we denote an instance of pair gaits as $\{(\mathbf{x}_p, \mathbf{x}_g), \theta_{pg}\}$, where $\mathbf{x}_p$ is the p-th probe, $\mathbf{x}_g$ is the g-th gallery gait, and θ_{pg} is the relationship between them. $\theta_{pg} = 0$ means that $\mathbf{x}_p$ and $\mathbf{x}_g$ come from an identical subject, and $\theta_{pg} = 1$ indicates that they are from different subjects. The cross-gait representation should satisfy the following conditions,

$$\begin{aligned} d(\mathbf{x}_p, \mathbf{x}_g) &\leq \mathrm{b}_c - 1 + \delta_{pg}, \quad if\ \theta_{pg} = 0, \\ d(\mathbf{x}_p, \mathbf{x}_g) &\geq \mathrm{b}_c - 1 + \delta_{pg}, \quad if\ \theta_{pg} = 1, \end{aligned} \tag{1}$$

where δ_{pg} is a nonnegative slack variable, b_c is a distance threshold, and $d(\cdot, \cdot)$ is a predefined or learned metric measuring discrepancy between a pair of gaits. We minimize the cross-entropy loss which is formulated as,

$$\mathcal{L}_c(\mathbf{x}_p, \mathbf{x}_g) = -\sum_{p,g} P(\mathbf{x}_{pg}) \log Q(\mathbf{x}_{pg}), \tag{2}$$

where $\mathbf{x}_{pg}$ is the cross-gait feature vector, $P(\mathbf{x}_{pg})$ is the true distribution, and $Q(\mathbf{x}_{pg})$ is the predicted distribution.

Unique-gait Learning. Similar to the learning of cross-gait representation, the unique-gait representation should satisfy the constraints as,

$$\begin{aligned} ||U(\mathbf{x}_p) - U(\mathbf{x}_g)||_2^2 &\leq \mathrm{b}_u - 1 + \delta_{pg}, \quad if\ \theta_{pg} = 0, \\ ||U(\mathbf{x}_p) - U(\mathbf{x}_g)||_2^2 &\geq \mathrm{b}_u - 1 + \delta_{pg}, \quad if\ \theta_{pg} = 1, \end{aligned} \tag{3}$$

where $U(\mathbf{x}_p)$ and $U(\mathbf{x}_g)$ are unique-gait representations and b_u is a distance threshold between them. In this formulation, the discrepancy between unique-gait representations from identical subjects in terms of Euclidean distance is expected to be smaller than b_u, while that of unique-gait representations from different subjects is expected to be greater than b_u.

In our model, we consider multiple pairs of gaits as input, so the above constraints should be modified as follows,

$$||U(\mathbf{x}_{\hat{p}}) - U(\mathbf{x}_{g'})||_2^2 - ||U(\mathbf{x}_p) - U(\mathbf{x}_g)||_2^2 \geq 1 - \delta_{pg}, \tag{4}$$

where $\{\mathbf{x}_p, \mathbf{x}_g\}$ come from an identical subject, while $\{\mathbf{x}_{\hat{p}}, \mathbf{x}_{g'}\}$ are from different subjects. Our aim is to make the distinction between $\mathbf{x}_{\hat{p}}$ and $\mathbf{x}_{g'}$ greater than the distance between $\mathbf{x}_p$ and $\mathbf{x}_g$. The above constraint should be satisfied no matter $\mathbf{x}_p$ and $\mathbf{x}_{\hat{p}}$ are identical or not. Thus, the loss function of learning unique-gait representation is composed of two terms,

$$\begin{aligned} \mathcal{L}_u(\mathbf{x}_p, \mathbf{x}_g, \mathbf{x}_{p'}, \mathbf{x}_{g'}) = \sum_{p,g,g',p'} \{[1 + ||U(\mathbf{x}_p) - U(\mathbf{x}_g)||_2^2 - ||U(\mathbf{x}_p) - \\ U(\mathbf{x}_{g'})||_2^2]_+ + \eta_i \cdot [1 + ||U(\mathbf{x}_p) - U(\mathbf{x}_g)||_2^2 - ||U(\mathbf{x}_{p'}) - U(\mathbf{x}_{g'})||_2^2]_+\}, \end{aligned} \tag{5}$$

where $[z]_+ = max(z, 0)$. The first term corresponds to the case that $\mathbf{x}_p$ and $\mathbf{x}_{\hat{p}}$ are identical ($\hat{p} = p$), the second term corresponds to the case that $\mathbf{x}_p$ and $\mathbf{x}_{\hat{p}}$ are different ($\hat{p} \neq p$ thus we employ p' for clarity). We note that, in both cases, $\{\mathbf{x}_p, \mathbf{x}_{g'}\}$ and $\{\mathbf{x}_{p'}, \mathbf{x}_{g'}\}$ are from different subjects, individually.

Joint Learning Function. Finally, JUCNet is updated based on both unique-gait and cross-gait representations, so the overall loss function is the combination of $\mathcal{L}_c$ and $\mathcal{L}_u$,

$$\mathcal{L}_o = \mathcal{L}_c + \eta_u \cdot \mathcal{L}_u, \tag{6}$$

where η_u is a hyperparameter to balance cross-gait and unique-gait.

3.2. Quintuplet Loss

The popular methods for learning the cross-gait representation summarized in Wu *et al.* [48] are based on recognition signals in Eq. (2), which aims to classify concatenated cross-gait representation. Namely, one class is "identical subject", and the other class is "different subjects". In order to obtain more powerful cross-gait representation, we adopt both recognition and verification signals as our supervision and propose a quintuplet loss, targeting at simultaneously enlarging the inter-class differences and reducing the intra-class variations. Different from the traditional recognition-verification loss [32, 39, 8], we define a novel quintuplet loss associated with quintuplet gaits. This loss function considers not only discriminating gait *instances*, but also differentiating gait *pairs*.

The Euclidean distance can be employed to measure the similarity between two gaits in the quintuplet loss. While in this work, we replace the Euclidean distance with a *learned metric* $C(\cdot, \cdot)$, which represents the distance between two gaits. Specially, the concatenated cross-gait features are forwarded to a fully-connected layer with two neurons. The output value of one neuron is set to be the metric. Considering multiple pairs, constraints in Eq. (1) are reformulated as,

$$C(\mathbf{x}_{\hat{p}}, \mathbf{x}_{g'}) - C(\mathbf{x}_p, \mathbf{x}_g) \geq 1 - \delta_{pg\hat{p}g'}, \tag{7}$$

where $\{\mathbf{x}_p, \mathbf{x}_g\}$ are from an identical subject, while $\{\mathbf{x}_{\hat{p}}, \mathbf{x}_{g'}\}$ are from different subjects. $\delta_{pg\hat{p}g'}$ is a nonnegative slack variable. Different from the loss function Eq. (2) utilized in [48], the loss with the learned metric $C(\cdot, \cdot)$ can be denoted as

$$\mathcal{L}_c(\mathbf{x}_p, \mathbf{x}_g, \mathbf{x}_{\hat{p}}, \mathbf{x}_{g'}) = \sum_{p,g,\hat{p},g'} [C(\mathbf{x}_p, \mathbf{x}_g) - C(\mathbf{x}_{\hat{p}}, \mathbf{x}_{g'}) + \delta_1]_+, \tag{8}$$

where δ_1 is the value of margin. The last fully-connected layer is followed by a softmax layer, which normalizes the learned metric into the range of [0, 1].

Due to the normalization operation, the parameter δ_1 is set to 1 in our model. The purpose of the above loss can be concluded as two aspects: 1) Gaits from the same subject $\{\mathbf{x}_p, \mathbf{x}_g\}$ are predicted to the class with label 0 and gaits from different subjects $\{\mathbf{x}_{\hat{p}}, \mathbf{x}_{g'}\}$ are predicted to the other class (label = 1). 2) The distance between $C(\mathbf{x}_p, \mathbf{x}_g)$ and $C(\mathbf{x}_{\hat{p}}, \mathbf{x}_{g'})$ is enlarged as far as possible. The first aspect can be regarded as a binary classification problem, which is to classify the concatenated cross-gait representation with recognition signals. The second aspect can be treated as a verification problem, which aims to make a distinction between the cross-gait representation from an identical subject and the cross-gait representation from different subjects.

To employ both recognition and verification signals for more powerful cross-gait features with smaller intra-class variations and larger inter-class differences, the loss function of cross-gait is reformulated as

$$\begin{aligned}
&\mathcal{L}_c\left(\mathbf{x}_p, \mathbf{x}_g, \mathbf{x}_{\hat{p}}, \mathbf{x}_{g'}, \mathbf{x}_{p''}\right) = \\
&- \sum_{p,g,\hat{p},g'} \left[P(\mathbf{x}_{pg}) \log Q(\mathbf{x}_{pg}) + P(\mathbf{x}_{\hat{p}g'}) \log Q(\mathbf{x}_{\hat{p}g'})\right] \\
&+ \eta_c \cdot \sum_{\substack{p,g \\ \hat{p},g',p''}} \left[\delta_2 - D(C(\mathbf{x}_p, \mathbf{x}_g), C(\mathbf{x}_{\hat{p}}, \mathbf{x}_{g'})) + D(C(\mathbf{x}_{\hat{p}}, \mathbf{x}_{g'}), C(\mathbf{x}_{p''}, \mathbf{x}_{g'}))\right]_+,
\end{aligned} \tag{9}$$

where $D(x, y) = ||x - y||_2^2$. The pair gaits $\{\mathbf{x}_p, \mathbf{x}_g\}$ come from an identical subject, while $\{\mathbf{x}_{\hat{p}}, \mathbf{x}_{g'}\}$ and $\{\mathbf{x}_{p''}, \mathbf{x}_{g'}\}$ are from different subjects. The first term in the right hand is based on the recognition signal, which denotes the classification of gait-cross representation. The second term is based on the verification signal, denoting whether two pairs of gait-cross representations are of the same pair-wise class label (both pairs from identical subjects or both pairs from different subjects, which is the case in Fig. 4) or not (one pair from an identical subject and the other pair from different subjects).

Similar to the extension from Eq. (4) to Eq. (5), the constraint in Eq. (7) should be satisfied no matter $\mathbf{x}_p$ and $\mathbf{x}_{\hat{p}}$ are identical or not. Therefore, the two terms in the right hand of Eq. (9) for learning cross-gait representation are respectively extended to cover both cases ($p = \hat{p}$ and $p \neq \hat{p}$) as

$$\begin{aligned}
&\mathcal{L}_c(\mathbf{x}_p, \mathbf{x}_g, \mathbf{x}_{p'}, \mathbf{x}_{g'}, \mathbf{x}_{p''}) = - \sum_{\substack{p,g \\ p',g'}} [(P(\mathbf{x}_{pg}) \log Q(\mathbf{x}_{pg}) \\
&+ P(\mathbf{x}_{pg'}) \log Q(\mathbf{x}_{pg'})) + \eta_i \cdot (P(\mathbf{x}_{pg}) \log Q(\mathbf{x}_{pg}) + P(\mathbf{x}_{p'g'}) \log Q(\mathbf{x}_{p'g'}))] \\
&+ \eta_c \cdot \sum_{\substack{p,g \\ g',p' \\ p''}} [||\delta_2 - D(C(\mathbf{x}_p, \mathbf{x}_g), C(\mathbf{x}_p, \mathbf{x}_{g'})) + D(C(\mathbf{x}_p, \mathbf{x}_{g'}), C(\mathbf{x}_{p''}, \mathbf{x}_{g'}))||_+ \\
&+ \eta_i \cdot ||\delta_2 - D(C(\mathbf{x}_p, \mathbf{x}_g), C(\mathbf{x}_{p'}, \mathbf{x}_{g'})) + D(C(\mathbf{x}_{p'}, \mathbf{x}_{g'}), C(\mathbf{x}_{p''}, \mathbf{x}_{g'}))||_+],
\end{aligned} \tag{10}$$

where $\{\mathbf{x}_p, \mathbf{x}_g\}$ are from an identical subject, while $\{\mathbf{x}_p, \mathbf{x}_{g'}\}$, $\{\mathbf{x}_{p'}, \mathbf{x}_{g'}\}$, and $\{\mathbf{x}_{p''}, \mathbf{x}_{g'}\}$ come from different subjects, respectively. The hyperparameters η_c and η_i are used to balance different terms. We replace $\mathcal{L}_c$ in Eq. (6) with the above formulation in the training stage. As it may be noticed, there are quintuplet gait instances

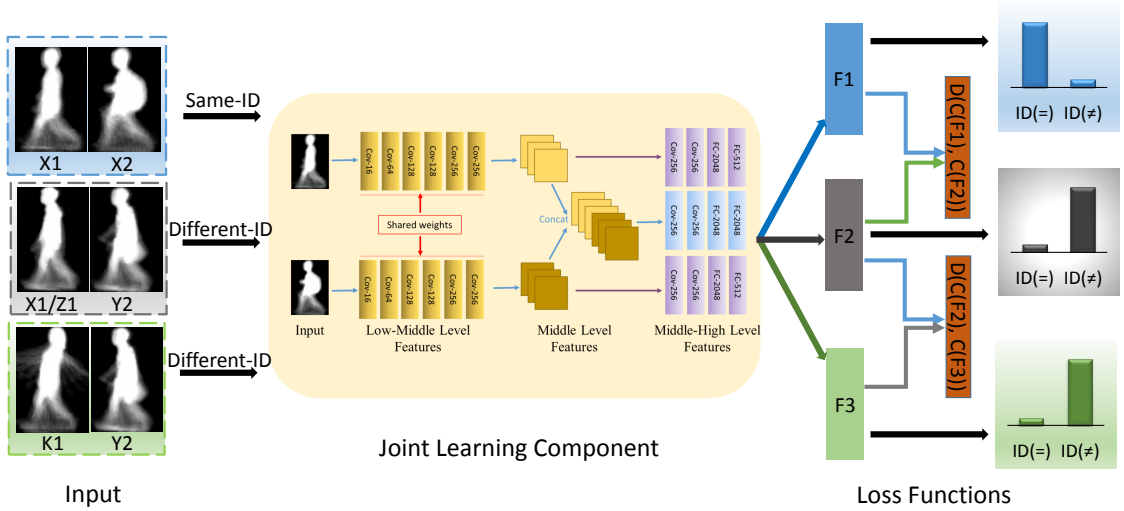


Figure 4. The Multi-Pair JUCNet structure based on the Quintuplet loss in the training stage. The input to our network is several pairs of gaits. Features are extracted from each pair individually, and are processed based on the quintuplet loss. Here, the quintuplet associated with our quintuplet loss can be regarded as X1, X2, Y2, Z1, and K1.

($\mathbf{x}_p, \mathbf{x}_g, \mathbf{x}_{p'}, \mathbf{x}_{g'}$ and $\mathbf{x}_{p''}$) in Eq. (10), which are the proposed quintuplet loss named after.

4. JUCNet

In this section, we introduce the architecture of the JUCNet, then present a Multi-Pair JUCNet model and the training procedure based on the quintuplet loss.

4.1. Basic JUCNet

As shown in Fig. 3, given a pair of gray-scale gait images, our JUCNet model jointly learns the unique-gait and cross-gait representations, in both low-middle and middle-high levels. The components for learning unique-gait and cross-gait representations are presented in the **purple** and **blue** parts, respectively.

Middle-level features. The component for capturing middle-level features is shown as the yellow part in Fig. 3, consisting of six convolutional layers. The numbers of kernels in each convolutional layer are sequentially 16, 64, 128, 128, 256, and 256, respectively. The activation function of convolutional layers is Rectified Linear Unit (ReLU). The size of all filters in this stage is 3×3 with stride 1. Each of the convolutional layers is followed by a max-pooling layer of size 2×2 and stride 2.

High-level features. The part learning high-level features is composed of three branches, of which two learn unique-gait representation and one learns cross-gait representation. Each branch of learning unique-gait representation includes two convolutional layers and two fully-connected layers. Middle-level feature maps with 256 channels are forwarded to the first convolutional layer with 256 kernels of size 3×3 and stride 1. The second convolutional layer also contains 256 kernels of size 3×3 and stride 1. Both of them are followed by a max-pooling layer with pooling size 2×2 and stride 2. After the convolutional layers, two fully-connected layers project feature maps extracted from previous layers into a subspace by 2048 and 512 neurons, respectively.

The component for learning cross-gait representation is also comprised of two convolutional layers and two fully-connected layers. Middle-level features are concatenated as cross-gait feature vectors, which are input into a convolutional layer with 256 kernels of size 3×3 and stride 1. The difference from the first layer of learning the unique-gait representation is that the number of kernels is doubled due to concatenation. The second convolutional layer and the first fully-connected layer are the same as those learning unique-gait representation. The second fully-connected layer contains 2048 neurons.

4.2. Multi-Pair JUCNet

As described above, JUCNet learns both unique-gait and cross-gait representations. The proposed quintuplet loss can enlarge inter-class differences and reduce intra-class variations simultaneously. To this end, we extend the basic JUCNet as a Multi-Pair JUCNet, which serves as the final framework during training, and train it with the quintuplet loss.

Fig. 4 shows the overview of the Multi-Pair JUCNet. A pair of gaits can be combined as a whole, with the label of *Same-ID* or *Different-ID*. The basic JUCNet model extracts both unique-gait and cross-gait representations. For Multi-Pair JUCNet, three pairs of gaits are input to extract features. Two pairs of gaits are from different subjects, while one pair of gaits is from an identical subject. Our model learns unique-gait representation based on the loss in Eq. (5), and learns cross-gait representation based on the

quintuplet loss in Eq. (10).

4.3. Training

We choose the popular GEIs [29] as the input of Multi-Pair JUCNet because of its robustness to noise and its simplicity for computation [16]. GEIs images are resized to the size of $256 \times 372 \times 1$. In order to augment training samples, we crop a set of $224 \times 326 \times 1$ patches from GEIs images and flip them horizontally at random. It is worth noting that a pair of GEIs are flipped at the same time to ensure the same walking direction. It is trained based on stochastic gradient descent. Weights are initialized as a Gaussian distribution with mean 0 and standard deviation 0.01. The momentum is set as 0.9. The model is updated every time after learning one mini-batch of size 32.

5. Experiments

To verify our model, we test it on three public datasets, which are at first introduced in this section. These datasets cover challenges like clothing variation, cross view, *etc.* in the task of the gait recognition. Based on the datasets, we then investigate effectiveness of JUCNet and the quintuplet loss. Meanwhile, comparison with the state-of-the-art methods is also reported. Finally, we study the performance of our method with the protocol of cross view.

5.1. Datasets

The OUTD-B dataset. The OU-ISIR Gait Database, Treadmill Dataset B (OUTD-B) [26], is challenging due to its considerable clothing diversities, such as wearing hat, regular pants, and half shirt. It is composed of 68 subjects with up to 32 clothing conditions. There are three subsets in this dataset, a training set, a gallery set, and a probe set. The training set includes 20 subjects with 446 sequences. The gallery set and probe set are employed in the testing stage. There are 48 subjects with standard clothing types in the gallery set. The probe set contains 856 sequences of subjects with other clothing types. Note that subjects in the gallery set and probe set are disjoint from those in the training set.

The OU-LP-Bag β dataset. The OU-LP-Bag β database [28] is built to alleviate the problem of too small variations in existing datasets. There are one training set, one gallery set, and one probe set in this dataset. The training set includes $1,034$ subjects. For each subject, there are two sequences, one carrying objects while the other one not. The gallery and probe sets contain $1,036$ subjects which are disjoint from the subjects in the training set. Subjects in the gallery set carry objects while subjects in the probe set carry nothing. This dataset provides GEIs of all sequences, so we directly use these GEIs to carry out our experiments.

The CASIA-B gait dataset. The CASIA-B gait database [50] is composed of 124 subjects, with 110 sequences per subject. It contains eleven views and there are ten sequences per view. Among the ten sequences, six are taken under normal walking conditions (NM), two are taken when subjects are with coats (CL), and two are taken when subjects are with bags (BG).

5.2. Effectiveness of JUCNet and Quintuplet Loss

To demonstrate the effectiveness of the JUCNet and quintuplet loss, we develop three third-party baseline networks, *MT*, *Deeper MT*, and *CNet*. MT and Deeper MT are representative methods from [48] for learning sole cross-gait representation to predict the relationship between a pair of gaits. CNet is a simplified version of JUCNet without the component of learning unique-gait representation. We also conduct ablation analysis by comparing our full method *JUCNet (Metric & Quintuplet)* with two versions of self baseline networks, *JUCNet* and *JUCNet (Metric)*. All these networks are illustrated in the following.

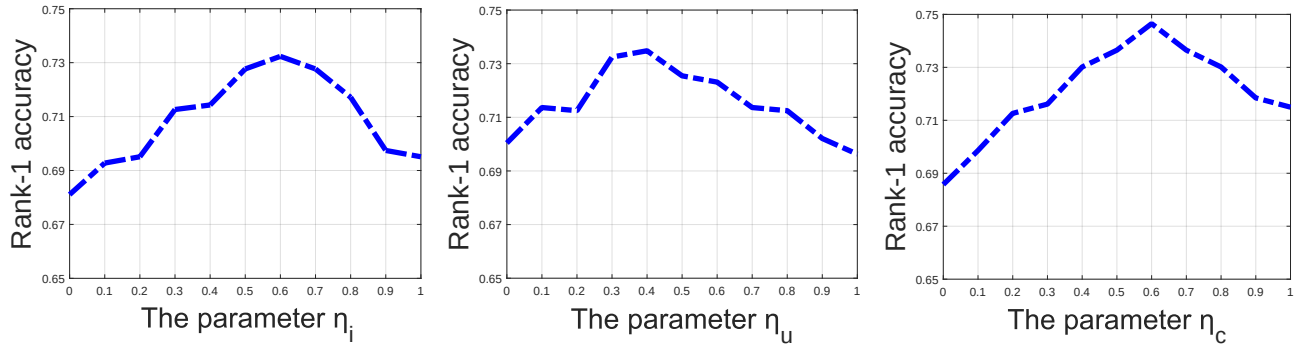
- **MT** is a CNN consisting of two convolutional layers, two pooling layers, and one fully-connected layer. The input of this model is a pair of GEIs. The MT extracts features by the convolutional layers and concatenates features as the cross-gait representation by the fully-connected layer. Finally, the cross-gait representation will be input to a binary classifier to predict their relationship.

- **Deeper MT** is a deeper version of MT. It contains two additional fully-connected layers. Two convolutional layers and two fully-connected layers are utilized to learn two feature sets from the input GEIs. Then they will be concatenated as a whole to learn cross-gait representation by the third fully-connected layer. MT and Deeper MT have achieved state-of-the-art performance on some datasets [48].

- **CNet** is a network which excludes the unique-gait part from our JUCNet. It contains eight convolutional layers and two fully-connected layers. As shown in the yellow and blue parts of Fig. 3, CNet shares a similar structure with both MT and Deeper MT. The major difference from them is that when the feature maps are concatenated as a whole, more layers are built in order to learn powerful cross-gait representation.

- **JUCNet** is our proposed network that jointly learns unique-gait and cross-gait representation. This JUCNet model is updated based on the loss functions in Eq. (2), (4), and (6).

- **JUCNet (Metric)** is our JUCNet model plus metric learning. It learns the metric $C(\cdot, \cdot)$ to represent the distance between a pair of gaits. The loss functions employed to train this model are Eqs. (4), (6), and (8) .



(a) (b) (c)

Figure 5. The Rank-1 accuracy by varying the weighting parameters η_i, η_u, and η_c investigated on the validation set of OU-LP-Bag β. When varying one hyperparameter, the other two are fixed.

- **JUCNet (M & Quintuplet)** is our JUCNet model plus both metric learning and our proposed quintuplet loss. Fig. 4 and the section of Quintuplet Loss present the details of this model and the quintuplet loss. The model is trained based on the loss functions in Eqs. (4), (6) and (10).

Parameter analysis. Different loss terms are weighted by hyperparameters in our loss functions. In order to set them appropriately, we utilize a part of the training set as a validation set and investigate the effect of hyperparameters by varying η_i, η_u, and η_c in Eqs. (5), (6), and (10) from 0 to 1. When hyperparameters are equal to 0, only the first term in the above equations works. With the increase of hyperparameters, the binding term plays a more and more important role in our model. When varying one hyperparameter, the other two hyperparameters are set to be fixed. According to the results shown in Fig. 5, in general the accuracies become higher with the increase of hyperparameters until becoming lower with increased values. The best performance is achieved when $\eta_i = 0.6$, $\eta_u = 0.4$, and $\eta_c = 0.6$, which are set in our following experiments.

Results in terms of rank-n accuracy. We report the results of rank-1, rank-3, rank-5, and rank-10 accuracies of the aforementioned six models on both OU-LP-Bag β and OUTD-B, shown in Table 1 and Table 2, respectively.

In both tables, we observe that: 1) JUCNet achieves higher accuracies than MT, Deeper MT and CNet. This verifies the effectiveness of the proposed JUCNet by jointly learning unique-gait and cross-gait representations. As shown in Fig. 3 , the unique-gait representation and cross-gait representation complement each other to update the shared-weight layers, leading to more powerful high-level features. 2) The improvement from JUCNet to JUCNet (Metric) reveals the advantage of metric $C(\cdot, \cdot)$, which learns to measure discrepancy between gaits driven by data automatically, in contrast to pre-defined metric like the Euclidean distance. 3) The JUCNet (Metric & Quintuplet) achieves better performance than both JUCNet and JUCNet (Metric), which additionally suggests the effectiveness of our proposed quintuplet loss. 4) The improvement from other models to JUCNet (Metric & Quintuplet) in terms of rand-1 accuracy is more evident than that in terms of rank-3, rank-5, and rank-10 accuracies. We that suspect the following reason justifies. Given a probe gait, other models may determine more than one gallery gait as from an identical subject, because they are trained with only classification loss. To the contrast, the quintuplet loss guides our model to not only obtain correct *classification* results, but also learn more powerful features ensuring enlarged inter-class differences and decreased intra-class variations, leading to correct *ranking orders*.

Table 1. The rank-1, rank-3, rank-5, and rank-10 accuracies [%] of different models on the OU-LP-Bag β dataset. The best results are shown in bold, which also applies to the following tables.

Models	rank-1	rank-3	rank-5	rank-10
MT [48]	59.9	75.2	80.1	86.8
Deeper MT [48]	68.1	81.8	86.0	90.8
CNet	71.0	86.9	91.5	95.2
JUCNet	74.3	87.4	90.8	95.3
JUCNet (Metric)	74.8	88.9	92.3	95.6
JUCNet (M & Quintuplet)	**78.2**	**89.6**	**92.8**	**95.8**

Table 2. The rank-1, rank-3, rank-5, and rank-10 accuracies [%] of different models on the OUTD-B dataset.

Models	rank-1	rank-3	rank-5	rank-10
MT [48]	70.7	87.7	91.9	97.9
Deeper MT [48]	72.4	90.3	95.8	98.4
CNet	71.1	88.2	94.3	97.9
JUCNet	73.2	88.9	94.2	98.0
JUCNet (Metric)	73.8	88.4	93.9	97.9
JUCNet (M & Quintuplet)	**76.4**	**91.4**	**95.2**	**98.7**

5.3. Comparison with State-of-the-art Methods

We have verified that the proposed JUCNet with the quintuplet loss outperforms the conventional CNN mod-

Table 3. The rank-1 accuracies [%] of different methods on testing sets of OU-LP-Bag β and OUTD-B."-" indicates not provided.

Methods	OU-LP-Bag β	OUTD-B
FDF (Part-based)	-	66.3
EnDFT (Part-based)	-	72.8
GEnI	29.5	59.0
Masked GEI	-	28.0
Gabor GEI	46.4	62.3
GEI w/o ML	24.6	55.3
GEI w/ Ranking SVM	28.3	58.4
JISML	57.4	74.5
JUCNet	74.1	73.2
JUCNet (Metric)	74.7	74.9
JUCNet (M & Quintuplet)	**79.3**	**77.6**

els which are solely based on cross-gait representation. In this section, we compare our method with other state-of-the-art methods, including part-based FDF [14], part-based Entropy of the Discrete Fourier Transform (EnDFT) [35], GEnI [3], Masked-GEI [4], Gabor GEI [42] and spatial metric learning methods using GEI like ranking SVM [31], and a Joint Intensity and Spatial Metric Learning method (JISML) [28].

The results in Table 3 show that JUCNet plus metric learning outperforms the previous best method on both OU-LP-Bag β and OUTD-B databases, which reveals its effectiveness. JUCNet based on metric learning and quintuplet loss achieves better performance than JUCNet with metric, justifying the advantage of our proposed quintuplet loss again. The JISML method introduces joint learning of intensity and spatial metric in order to mitigate the large intra-class differences and leverage the subtle inter-class differences, while in our method the quintuplet loss accomplishes this task. A method proposed by Guan *et al.* [12] achieves better rank-1 accuracy on the OUTD-B dataset than ours. While their results are achieved under a different training/testing protocol. Meanwhile, their method requires a regular within-class matrix for the gallery set, so it cannot be applied on datasets including only a single probe and a single gallery per subject like the OU-LP-Bag β dataset.

In addition, Table 3 reveals that the improvement over existing methods achieved by our method on the OU-LP-Bag β dataset is greater than that on the OUTD-B dataset with regard to the rank-1 accuracy. This is because that there are more subjects $(1,034)$ in the training set of the OU-LP-Bag β dataset, while there are only 20 subjects in the training set of OUTD-B. Larger scale of the training set benefits our model in gaining greater learning capacity. On the other hand, though there are more samples in the OU-LP-Bag β dataset, the final results regarding the rank-1 accuracy on both datasets are at the same level. We believe that, it is more difficult for models to recognize the correct subjects from the OU-LP-Bag β dataset than the OUTD-B dataset because the OUTD-B dataset includes only 48 subjects in the testing set, while there are $1,036$ subjects in the testing set of the OU-LP-Bag β dataset.

Table 4. The rank-1 accuracies [%] of different methods under the cross-view condition on the BG subset of the CASIA-B gait dataset.

Probe	Gallery	RLTDA	MT	JUCNet
54°	36°	80.8	**92.7**	91.8
54°	72°	71.5	90.4	**93.9**
90°	72°	75.3	93.3	**95.9**
90°	108°	76.5	88.9	**95.9**
126°	108°	66.5	93.3	**93.9**
126°	144°	72.3	86.0	**87.8**
Average		73.8	90.8	**93.2**

It may be observed that the results of OU-LP-Bag β and OUTD-B in Table 3 are better than those in Tables 1 and 2. As mentioned above, we utilize a part of the training set in these two datasets as a validation set to tune weight parameters. Thus results in Tables 1 and 2 are reported by models trained without the validation set. While comparing with other methods in Table 3, we put the validation set back to the training set to re-train the model for a fair comparison, because the validation set belongs to the training set in other methods.

5.4. Cross-view Study

The issue of cross view is crucial for gait recognition, so we evaluate our method under the condition of cross view on the BG subset of the CASIA-B gait dataset. We evaluate our method on the more challenging BG set (the accuracy is between 86.0% and 93.3%), rather than the NM set (the accuracy is between 97.0% and 99.5%). As shown in Table 4, subjects in the probe and gallery sets are of different views. The comparison with Wu *et al.* [48] and Hu *et al.* [15] indicates that our method achieves satisfactory performance under the cross-view protocol.

6. Conclusion

We have proposed a JUCNet model to jointly learn unique-gait and cross-gait representations for gait recognition. The two kinds of representations complement each other to boost the performance of gait recognition. Moreover, a quintuplet loss for gait recognition was proposed to increase the inter-class differences by pushing the cross-gait representation learned from different classes apart and reduce the intra-class variations by pulling the representations learned from an identical class together. The experimental results on public datasets suggest that the JUCNet model outperforms existing CNN models based on sole cross-gait representation, demonstrating the effectiveness of the JUCNet model. JUCNet with the quintuplet loss further improves the performance, validating its superiority over the state-of-the-art methods.

References

[1] Munif Alotaibi and Ausif Mahmood. Improved gait recognition based on specialized deep convolutional neural network. *CVIU*, 2017. 2, 3

[2] Gunawan Ariyanto and Mark S Nixon. Model-based 3d gait biometrics. In *IJCB*, 2011. 2

[3] Khalid Bashir, Tao Xiang, and Shaogang Gong. Gait recognition using gait entropy image. 2009. 8

[4] Khalid Bashir, Tao Xiang, and Shaogang Gong. Gait recognition without subject cooperation. *PRL*, 2010. 8

[5] Robert Bodor, Andrew Drenner, Duc Fehr, Osama Masoud, and Nikolaos Papanikolopoulos. View-independent human motion classification using image-based reconstruction. *Image and Vision Computing*, 2009. 2

[6] Imed Bouchrika, Michaela Goffredo, John Carter, and Mark Nixon. On using gait in forensic biometrics. *JFS*, 2011. 1

[7] Francisco Manuel Castro, Manuel J Marín-Jiménez, Nicolás Guil, and Nicolás Pérez de la Blanca. Automatic learning of gait signatures for people identification. In *IWANN*, 2017. 2, 3

[8] Weihua Chen, Xiaotang Chen, Jianguo Zhang, and Kaiqi Huang. Beyond triplet loss: a deep quadruplet network for person re-identification. In *CVPR*, 2017. 4

[9] Yang Feng, Yuncheng Li, and Jiebo Luo. Learning effective gait features using lstm. In *ICPR*, 2016. 3

[10] Yang Feng, Lin Ma, Wei Liu, Tong Zhang, and Jiebo Luo. Video re-localization. In *ECCV*, 2018. 2

[11] Michela Goffredo, Imed Bouchrika, John N Carter, and Mark S Nixon. Self-calibrating view-invariant gait biometrics. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, 2010. 2

[12] Yu Guan, Chang-Tsun Li, and Fabio Roli. On reducing the effect of covariate factors in gait recognition: a classifier ensemble method. *TPAMI*, 2015. 8

[13] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *CVPR*, 2016. 2

[14] Md Altab Hossain, Yasushi Makihara, Junqiu Wang, and Yasushi Yagi. Clothing-invariant gait identification using part-based clothing categorization and adaptive weight control. *PR*, 2010. 8

[15] Haifeng Hu. Enhanced gabor feature based classification using a regularized locally tensor discriminant model for multiview gait recognition. *TCSVT*, 2013. 8

[16] Haruyuki Iwama, Mayu Okumura, Yasushi Makihara, and Yasushi Yagi. The ou-isir gait database comprising the large population dataset and performance evaluation of gait recognition. *TIFS*, 2012. 6

[17] Worapan Kusakunniran. Attribute-based learning for gait recognition using spatio-temporal interest points. *IVC*, 2014. 2

[18] Worapan Kusakunniran, Qiang Wu, Hongdong Li, and Jian Zhang. Multiple views gait recognition using view transformation model based on optimized gait energy image. In *ICCV Workshops*, 2009. 1, 2

[19] Worapan Kusakunniran, Qiang Wu, Jian Zhang, Hongdong Li, and Liang Wang. Recognizing gaits across views through correlated motion co-clustering. *TIP*, 2014. 2

[20] Worapan Kusakunniran, Qiang Wu, Jian Zhang, Yi Ma, and Hongdong Li. A new view-invariant feature for cross-view gait recognition. *TIFS*, 2013. 1, 2

[21] Toby HW Lam, King Hong Cheung, and James NK Liu. Gait flow image: A silhouette-based gait representation for human identification. *PR*, 2011. 2

[22] Peter K Larsen, Erik B Simonsen, and Niels Lynnerup. Gait analysis in forensic medicine. *JFS*, 2008. 1

[23] Stan Z Li and Anil Jain. *Encyclopedia of biometrics*. Springer Publishing Company, Incorporated, 2015. 1

[24] Jiwen Lu and Yap-Peng Tan. Uncorrelated discriminant simplex analysis for view-invariant gait signal computing. *PRL*, 2010. 1

[25] Wenhan Luo, Peng Sun, Fangwei Zhong, Wei Liu, Tong Zhang, and Yizhou Wang. End-to-end active object tracking and its real-world deployment via reinforcement learning. *TPAMI*, 2019. 2

[26] Yasushi Makihara, Hidetoshi Mannami, Akira Tsuji, Md Altab Hossain, Kazushige Sugiura, Atsushi Mori, and Yasushi Yagi. The ou-isir gait database comprising the treadmill dataset. *CVA*, 2012. 6

[27] Yasushi Makihara, Ryusuke Sagawa, Yasuhiro Mukaigawa, Tomio Echigo, and Yasushi Yagi. Gait recognition using a view transformation model in the frequency domain. *ECCV*, 2006. 2

[28] Yasushi Makihara, Atsuyuki Suzuki, Daigo Muramatsu, Xiang Li, and Yasushi Yagi. Joint intensity and spatial metric learning for robust gait recognition. In *CVPR*, 2017. 6, 8

[29] Ju Man and Bir Bhanu. Individual recognition using gait energy image. *TPAMI*, 2006. 2, 6

[30] Al Mansur, Yasushi Makihara, Rasyid Aqmar, and Yasushi Yagi. Gait recognition under speed transition. In *CVPR*, 2014. 1

[31] Raúl Martín-Félez and Tao Xiang. Uncooperative gait recognition by learning to rank. *PR*, 2014. 8

[32] Hossein Mobahi, Ronan Collobert, and Jason Weston. Deep learning from temporal coherence in video. In *ICML*, 2009. 4

[33] Atsushi Mori, Yasushi Makihara, and Yasushi Yagi. Gait recognition using period-based phase synchronization for low frame-rate videos. In *ICPR*. 1

[34] Hiroshi Murase and Rie Sakai. Moving object recognition in eigenspace representation: gait analysis and lip reading. *PRL*, 1996. 2

[35] Md Rokanujjaman, Md Shariful Islam, Md Altab Hossain, Md Rezaul Islam, Yashushi Makihara, and Yasushi Yagi. Effective part-based gait identification using frequency-domain gait entropy features. *Multimedia Tools and Applications*, 2015. 1, 8

[36] Gregory Shakhnarovich and Trevor Darrell. On probabilistic combination of face and gait cues for identification. In *FG*, 2002. 3

[37] Kohei Shiraga, Yasushi Makihara, Daigo Muramatsu, Tomio Echigo, and Yasushi Yagi. Geinet: View-invariant gait recog-

nition using a convolutional neural network. In *ICB*, 2016. 1

[38] Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition. *ICLR*, 2015. 2

[39] Yi Sun, Yuheng Chen, Xiaogang Wang, and Xiaoou Tang. Deep learning face representation by joint identification-verification. In *NIPS*, 2014. 4

[40] Peng Tang, Xinggang Wang, Xiang Bai, and Wenyu Liu. Multiple instance detection network with online instance classifier refinement. In *CVPR*, 2017. 2

[41] Peng Tang, Xinggang Wang, Angtian Wang, Yongluan Yan, Wenyu Liu, Junzhou Huang, and Alan Yuille. Weakly supervised region proposal network and object detection. In *ECCV*, 2018. 2

[42] Dacheng Tao, Xuelong Li, Xindong Wu, and Stephen J Maybank. General tensor discriminant analysis and gabor features for gait recognition. *TPAMI*, 2007. 1, 8

[43] Akira Tsuji, Yasushi Makihara, and Yasushi Yagi. Silhouette transformation based on walking speed for gait identification. In *CVPR*, 2010. 1

[44] David Kenneth Wagg and Mark S Nixon. On automated model-based extraction and analysis of gait. In *FG*, 2004. 2

[45] Chen Wang, Junping Zhang, Liang Wang, Jian Pu, and Xiaoru Yuan. Human identification using temporal information preserving gait template. *TPAMI*, 2012. 2

[46] Hao Wang, Yitong Wang, Zheng Zhou, Xing Ji, Dihong Gong, Jingchao Zhou, Zhifeng Li, and Wei Liu. Cosface: Large margin cosine loss for deep face recognition. In *CVPR*, 2018. 1

[47] Liang Wang, Tieniu Tan, Huazhong Ning, and Weiming Hu. Silhouette analysis-based gait recognition for human identification. *TPAMI*, 2003. 1

[48] Zifeng Wu, Yongzhen Huang, Liang Wang, Xiaogang Wang, and Tieniu Tan. A comprehensive study on cross-view gait based human identification with deep cnns. *TPAMI*, 2017. 1, 2, 3, 4, 6, 7, 8

[49] Shiqi Yu, Haifeng Chen, Edel B Garcıa Reyes, and P Norman. Gaitgan: invariant gait feature extraction using generative adversarial networks. In *CVPR Workshops*, 2017. 2, 3

[50] Shiqi Yu, Daoliang Tan, and Tieniu Tan. A framework for evaluating the effect of view angle, clothing and carrying condition on gait recognition. In *ICPR*, 2006. 6

[51] Kaihao Zhang, Yongzhen Huang, Yong Du, and Liang Wang. Facial expression recognition based on deep evolutional spatial-temporal networks. *TIP*, 2017. 2