Pose-based Deep Gait Recognition

Anna Sokolova¹, Anton Konushin¹,²
1. National Research University Higher School of Economics, 20 Myasnitskaya str., Moscow 101000, Russia
2. Lomonosov Moscow State University, GSP-1, Leninskie Gory, Moscow, 119991, Russia

Abstract

Human gait or the walking manner is a biometric feature that allows to identify a person when other biometric features such as face or iris are not visible. In this paper we present a new pose-based convolutional neural network model for gait recognition. Unlike many methods considering the full-height silhouettes of a moving person, we consider motion of points in the areas around the human joints. To extract the motion information we estimate the optical flow between current and subsequent frames. We propose the deep convolutional model which computes pose-based gait descriptors. We compare different network architectures and aggregation methods. Besides, we experiment with different sets of body parts and learn which of them are the most important for gait recognition. In addition, we investigate the generalization ability of the algorithms transferring them from one dataset to another. The results of the experiments show that our approach outperforms the state-of-the-art methods.

1. Introduction

Gait recognition is a computer vision problem that consists in the identification of the person in a video using the motion of the body as the only source of information. Unlike the face recognition or re-identification problems, the appearance of the human is not used and it makes the task more complex. Physiological studies show that each person has his own unique manner of walk which is really difficult to be forged, so, the human can be identified by his gait.

There are several advantages that make gait recognition methods usable in many applied problems. First of all, unlike face, iris or fingerprints, gait representation can be recorded without cooperation with the subject. The second advantage is that even if a video has low resolution, the motion still can be captured and the person can be recognized. These features are very significant for video surveillance, thus, gait recognition has become a really important problem recently, especially in the security field. The main goals of this problem are control of the access to restricted areas and detection of the people who have already been captured by any camera (for example, criminals).

Despite the uniqueness of the gait, there are a lot of factors which can affect the gait representation and make the problem more complicated. The gait can look different depending on the view angle and the clothing of the subject. Besides, wearing different shoes or carrying heavy bags changes the gait itself and the recognition algorithm should be stable to such changes.

The problem of gait recognition is close to several computer vision problems. On the one hand, it is identification problem similar to face recognition. The difference is that we evaluate the motion of the body, but not the appearance. On the other hand, since it is video classification problem, we can solve it using action recognition methods. The third problem close to this one is re-identification problem, but as well as face recognition re-id deals with the appearance of the person rather than the motion.

Due to the similarity of these problems, we can use the approaches from adjacent fields for gait recognition. Most of the modern computer vision methods are based on convolutional neural networks (CNN) and they can be transformed for gait recognition. Despite the development of such algorithms, the most successful gait recognition approaches are still not deep and use handcrafted features. In this work, we propose the CNN-based algorithm for recognition people by their walking manner that turns out to be more stable to transfer learning than the previous deep gait models and achieves higher classification accuracy. Since we investigate the motion of the body the person’s appearance should not be taken into the account. Thus we consider the optical flow as the main source of information and do not use raw images. The experiments show that such approach really obtains enough data and gets success.

2. Related Work

Nowadays there are two leading approaches to gait recognition. The first one is more traditional and is based on hand-crafted features extracted from the frames. Most of the investigations following these approaches use silhouette masks as the main source of information and extract
features that show how these masks change. The most popular descriptor of the gait used in such investigations is Gait Energy Image (GEI) [8], the averaged over the gait cycle binary mask of a human figure. This approach developed a lot during recent years. A lot of different descriptors are proposed to be applied to GEI (for example, HOG [12] and HOF descriptors) or to the whole silhouette sequence (frame difference energy image in [4]) to get another aggregation to get better gait representation.

Another approach which can be used for gait recognition is neural networks. Deep models get the best results in most of the computer vision problems, so, recently some new investigations of gait based on CNN have appeared. Due to the similarity of gait recognition and action recognition problems, many approaches applied to the latter can be used for the first one. The first and the most classical method was proposed in [16]. To recognize human actions they train the network with architecture consisting of two similar branches: image and flow streams. The first one processes raw frames of video and the second one deals with the maps of optical flow (OF) computed from the pairs of consecutive frames. To consider long actions they stack several consecutive flow maps to block and use such blocks as network inputs. Many action recognition algorithms are based on this one and consider different top architectures (including recurrent ones in [14]) and ways of fusion several streams [7]. Another method based on optical flow is proposed in [19] where the temporal information is considered by using 3-dimensional convolutions.

The most applicable for gait recognition approach appeared in [5]. As well as in previous methods there are two streams, but each stream gets not the maps with full body, but the patches where different body parts are cropped. Thus, some of the joints are considered more precisely which helps to notice small but important motions of the body.

The OF approach was then applied to gait recognition problem in [2] and [18]. The deep model was proposed that takes the blocks of OF maps containing full body as input and predicts the recorded person. One more deep solution of gait recognition problem from [15] unites neural and GEI approaches. Gait energy images are computed for different view angles and used as network input. Despite the success of neural networks the non-deep methods still achieve the higher quality of gait recognition.

3. Proposed Method

Let us describe the pipeline of the method we propose. Although the algorithm is based on neural networks there are two important stages of preprocessing the data: computing the motion maps and evaluating the pose of the human on each frame. After these steps are done we can train the network and classify video sequences.

Let us discuss all the stages of the algorithm.

3.1. Preprocessing the data

Since our goal is to train the feature extractor that does not depend on the hue of clothes and person’s appearance, we want to get rid of any color information and use only motion. To do this we compute the maps of optical flow between each pair of consecutive frames and deal with these maps as the inputs. We consider 3-channel OF maps: the first two channels are horizontal and vertical components of flow vectors and the third one is its magnitude. Before the further processing, we linearly transform all the maps to the interval $[0, 255]$ similarly to RGB channels.

In addition, we suppose that the motion of some parts of human’s body is more informative than of the others, so we evaluate the human pose and look at the optical flow maps in the neighborhood of the key points. We expect that the bottom part of the body carries more gait information so we pay more attention to the legs than to the hands and head. Having the OF maps we crop 5 patches from them: right foot, left foot, upper body, lower body, and full body. The bounding boxes of the considered body parts are shown in Fig. 2.

In more detail, the patches for legs are the squares with the leg key points in their centers, the upper body patch contains all the joints from the head to the hips (including the hands) and the lower body patch contains all the joints from...
the hips to the foots (excluding hands). Thus we get five patches from each pair of consecutive frames and use these patches as network inputs. Right before putting the data into the network we decrease the resolution of each patch to $48 \times 48$ pixels.

### 3.2. Data augmentation

The main part of the proposed algorithm is extracting neural features. As every deep neural network has a large amount of parameters, we need to augment the data to get stable not overfitted algorithm.

The data is augmented using classic spatial changes. While training we take the bounding square box for each of five considered body parts and uniformly sample four numbers to construct the bounds of input patch. The first two numbers are left and right extensions and are chosen from the interval $[0, w/3]$, where $w$ is the width of the initial bounding box, and the last two ones are upper and lower extensions and lie in $[0, h/3]$ where $h$ is the height of the box. When the patches with these bounds are cropped from the OF maps they all are resized to $48 \times 48$.

Such an augmentation allows us to get patches containing the body parts with both spatial shifts and zoom. If the sum of sampled numbers is close to zero we get a large image of the body part almost without excess background, otherwise, the image is smaller and we get more background. On the other hand, if we fix the sums of the first and the second pair of bounds we will get the same size of the body parts but their location inside the patch will change.

### 3.3. Training the neural network

The network is trained using the augmented data and then used as a feature extractor. We use the outputs of the last convolutional layer as gait descriptors. On the testing stage we do not sample any random bounds for the patches but take the mean value for them ($w/6$ and $h/6$ respectively), so the image of the body part turns out to be in the center of the patch.

### CNN architectures and training methods

We considered two network architectures and compared them. The first architecture is based on VGG-19 network [17] but has one convolutional block less. The details of this architecture are shown in Table 1.

| B1      | B2      | B3      | B4      | F5     | F6     | SM |
|---------|---------|---------|---------|--------|--------|----|
| 3x3,64  | 3x3,128 | 3x3,256 | 3x3,512 | 4096   | 4096   | soft-max |
| pool 2  | pool 2  | pool 2  | pool 2  | d/o    | d/o    | max |

Each column of this table corresponds to the block of layers. The first four blocks are convolutions, every row denotes the layer in the block: the size of its filters ($3 \times 3$ for all the layers) and their number: each layer in the next block has twice as many filters as in the previous one. Additionally, there are four max-pooling layers of the size $2 \times 2$ after each convolutional block.

The next two blocks are fully connected. They consist of one linear dense layer of size 4096 and dropout with probability parameter $p = 0.5$. As well as convolutions the dense layers are followed by ReLU non-linearities. The last column denotes the top block consisting of the dense layer and softmax non-linearity. The number of units in this block equals the number of training subjects to be able to train network for the classification task.

While training we add $L_2$ norm of weights of dense layers to loss function for more regularization against overfitting.

Such a network has given the best result in the experiments from [18] when the blocks of several consecutive maps of OF were used as network inputs. That approach did not take into account the key points of the human pose, only the full body was used. We will compare it with our approach in Section 4.

Similarly to [18], we trained this network step by step. We started from 1024 units in two hidden dense layers and trained the network doubling their size each time the accuracy stopped increasing. When the sizes of these layers reached 4096 units we stop. Each widening of the network is made by random initializing of new parameters. Such approach adds extra regularization and prevents overfitting while training.

After such deep CNN with both convolutional and dense layers, we considered a fully convolutional network. One of the most successful architectures in computer vision that is used for image classification task is ResNet architecture. Residual connections allow to provide the information from low to high levels and the addition of each new block to such network increases the accuracy of classification. Besides, the absence of the fully connected layers makes the number
of parameters of the model smaller. These features make ResNet architectures very popular and we investigate them as well. Although residual networks achieve great results, we need a lot of layers to get a significant improvement of the performance and each new block makes the training process much longer. Another problem of such deep networks is exploding or vanishing gradients due to the very long path from the last layer to the first one during the backpropagation. To avoid these problems we use Wide Residual Network proposed in [21] with decreased depth and increased width of residual blocks. The reduction of layer number makes the training process much faster and lets the network be optimized with less regularization. Table 2 shows the details of the Wide ResNet architecture we use.

Table 2. The Wide Residual Network architecture

| B1      | B2           | B3           | B4           |
|---------|--------------|--------------|--------------|
| 3x3,16  | BN           | BN           | BN           |
| 3x3,64  | BN           | 3x3,128      | 3x3,256      |
| BN      | 3x3,128      | BN           | 3x3,256      |
| 3x3,64  | BN           | 3x3,256      |              |
| stride 1| stride 2     | stride 2     |              |
|         |              |              |              |

Each column of the table defines blocks of convolutions with the same number of filters. As well as in VGG-like architecture all the convolutions have kernels of size $3 	imes 3$. The first layer has 16 filters and is followed by Batch Normalization (BN). Then there are three residual blocks, each consisting of two convolutional layers with 64 filters and Normalization between. Such construction of blocks is classical for Wide ResNet architectures and all our blocks have similar structure. Blocks in every group have twice as many filters as in the previous one. Each first convolutional layer in groups B3-B4 has stride with parameter 2, so starting with $48 \times 48$ pixels the tensor size turns to $24 \times 24$ and then $12 \times 12$ in B3 and B4 groups, respectively.

The detailed construction of residual blocks is shown in Fig. 3. The left scheme corresponds to common block without strides when the input and output shapes coincide. The right one defines the structure of the first block of the group (B3 and B4 columns) when the number of filters doubles and the size of the map decreases. In this case, we add one auxiliary convolutional layer with $1 \times 1$ kernel, stride, and doubled number of filters to make all the shapes equal before the summation.

After all the residual blocks there is the last part needed to be able to use the network for classification. This part consists of one more batch normalization layer, average pooling that "flattens" the sequence of maps $12 \times 12$ obtained after convolutions to one vector and one dense layer with softmax on the top. The number of units in this dense layer equals the number of subjects in the training set. All the activations except the last softmax are rectified linear units and follow the batch normalization layers.

3.4. Final classification

The network is trained to predict one of the subjects from the training set having a patch cropped from the OF map. As our goal is to construct a feature extractor that can be used without retraining and fine-tuning for any testing set we use the outputs of the last hidden layer as the gait descriptors and construct the new classifier for them. We suppose that gait descriptors of the same person are spatially close to each other, so we use one of the simplest methods, Nearest Neighbour (NN) classifier. We additionally make $L_2$ normalization of all the gait feature vectors before fitting and classifying as it is shown in many investigations that the uniform length of all the vectors improves the accuracy of NN classification.

Although the most classical measure of distance between two vectors is the Euclidean one we consider not only this metric but also Manhattan distance. Despite the fact that the normalization is always made relative to $L_2$ distance, it turns out that finding the closest descriptor with respect to $L_1$ metrics gives higher and more stable result in most of the experiments.

To make the classification better and faster we reduce the dimensionality of feature vectors using principal analysis (PCA) algorithm. It helps us to get rid of the noise in the data and accelerates the fitting of classifier.

Fusion of feature vectors

The trained neural network and fitted NN classifier let us predict the subject having a patch with the optical flow around one of the body parts. But initially we have the video sequence, so since we consider $j$ body parts we get $j$ patches for each pair of consecutive frames and thus $(N - 1)j$ descriptors for one video where $N$ is the number of frames in sequence. If we consider them separately we can get $(N - 1)j$ answers for one video while we need only one. We investigate two ways of making one feature
vector from all network outputs. The first "naive" way is averaging of all the descriptors. We calculate the mean feature vector over all the frames and all the body parts. This approach is naive as the descriptors corresponding to different body parts have different nature even considering that we compute them using one network with the same weights. Hence, the averaging of the vectors should have mixed everything into a mess. Surprisingly, the accuracy achieved using this approach is very high, it will be shown and compared with another approach in the next section.

The second and more self-consistent approach is averaging of the descriptors only over the time. After such procedure, we get \( j \) mean descriptors corresponding to each of \( j \) body parts that are concatenated to get one final feature vector.

4. Data and experiments

4.1. Datasets

We have evaluated the described methods on three popular gait databases: "TUM Gait from Audio, Image and Depth" (TUM-GAID) dataset [9], CASIA Gait Dataset B [20] and the OU-ISIR Gait Database, Large Population Dataset [10].

The TUM-GAID dataset is sufficiently large database for gait recognition problem, consisting of videos for 305 subjects. The videos have length 2-3 seconds with the frame rate 30 fps and we use them all in our experiments. All the videos are the recordings of people full height walk captured from the side view. Although each person is recorded only from one viewpoint there are several video sequences per subject with various conditions: different shoes and carried things. So, there are 10 videos for each subject: six normal walks, two walks in coating shoes and two walks with the backpack. The examples of the frames are shown in Fig. 4 (the first column). As well as most of the gait databases TUM-GAID contains records with one person per video without any intersections of figures. It is a naive approach as in real life people often walk together and their bodies intersect, but such structure allows to train a model and to check if the problem of gait recognition can theoretically be solved. Since the size of this database is relatively big it is the main base in our experiments.

The second database we investigate is CASIA Gait Dataset B. This dataset contains only 124 subjects, but it is multiview: the records are captured from 11 different viewpoints with angles from 0 to 180 degrees. As well as TUM-GAID dataset there are 10 videos for each person captured in different conditions: normal walk, carrying a bag and wearing a coat. Despite the fact there are several sequences for each subject and for each viewpoint, the dataset is very small for deep models as every neural network contains too many parameters, especially for multiview mode. Thus, we use only side view videos captured from the same angle as in TUM-GAID and solve only side-view problem. Containing 124 subjects this database is small even for side-view mode, so it is additional database used in some of the experiments. The frames from CASIA database are shown in the second column of Fig. 3.

The third dataset is OU-ISIR Gait Database. It is the largest gait database containing over 4000 subjects captured by two cameras at 4 different angles (55, 65, 75, and 85 degrees). The dataset is distributed in a form of silhouette sequences, which makes the data different from other sets. The examples of silhouettes from this database are shown in the third and fourth columns of Fig. 3. We apply our algorithm to such data as well to learn if the silhouette masks are enough for gait recognition. Since the algorithm we use for pose estimation needs full images, we do not crop the patches of body parts and extract only full body features. In the experiments, we use the subset of this database consisting of 2 walks for 1912 subjects to meet protocols of benchmarks [13].

4.2. Performance evaluation

All the experiments are made the following way. The feature extractor is trained on the training set containing all the data for about a half of subjects of the database (155 for TUM-GAID, 64 for CASIA, and 956 for OU-ISIR). The rest of the subjects is used for fitting the final classifier and testing the whole algorithm. The fitting part consists of four normal walks for each person and the testing one contains other six walks (including two pairs of walks with different additional conditions). We sample 64 training subjects in CASIA base randomly and the split for TUM-GAID dataset is provided by its authors.

For each of the testing videos, the algorithm returns the vector of probability distribution over all subjects from testing set. We evaluate the quality of classification computing \( \text{Rank-1} \) and \( \text{Rank-5} \) metrics that defines the ratio of videos for which the correct label is among the top-5 classifiers answers.
4.3. Experiments and results

All our experiments aimed to explore the influence of different conditions on the gait performance:

- The network architecture;
- Aggregation methods;
- Joints used for training and testing the algorithms;
- The length of the captured walk.

In addition, we investigated the generality of the algorithm training them on one dataset and transferring to another one. The algorithm that depends only on body motion should work equally well on different databases.

We compare our results with two similar neural approaches ([18] and [2]) and one approach based on Fisher vectors [3] that showed the state-of-the-art result.

The first set of the experiments aims to evaluate the approach itself and to compare different technical methods, such as network architectures, ways of aggregation and similarity measure. All the algorithms were trained from scratch. The results of the experiments are shown in Table 3. The accuracy of our approach is the highest one and outperforms the state-of-the-art methods.

In the experiments with OU-ISIR database, we trained the network using all the maps and all the view angles for training subjects. While testing we consider gallery and prob views: the gallery view is fixed and equals 85 degrees, and the probe views are all the others. The NN classifier is fitted on gallery frames from the first walk and tested on the probe frames of the second one. The results and comparison with other techniques are shown in Table 5.

Table 3. Results on TUM-GAID dataset

| Method | Evaluation | Rank1 | Rank5 |
|--------|------------|-------|-------|
| Architecture, Aggregation and Metrics | | | |
| VGG (PCA 1000), avg, \( L_2 \) | 96.44 | 100.00 |
| VGG (PCA 1000), avg, \( L_1 \) | 97.84 | 100.00 |
| VGG (PCA 500), concat, \( L_2 \) | 97.41 | 99.89 |
| VGG (PCA 500), concat, \( L_1 \) | 98.81 | 100.00 |
| Wide ResNet (PCA 230), avg, \( L_2 \) | 98.27 | 99.89 |
| Wide ResNet (PCA 230), avg, \( L_1 \) | 99.24 | 99.89 |
| Wide ResNet (PCA 150), concat, \( L_2 \) | 98.81 | 99.78 |
| Wide ResNet (PCA 150), concat, \( L_1 \) | 99.78 | 99.89 |
| [13] VGG+blocks, \( L_1 \) | 97.52 | 99.89 |
| [2] CNN+SVM, \( L_2 \) | 98.00 | 99.60 |
| [3] PFM | 99.20 | 99.50 |

‘Avg’ in Table 3 defines a naive approach for feature aggregation when we compute the mean descriptor over all body parts, while ‘concat’ defines concatenation of descriptors and really gives better result.

It is worth noting that in PFM approach [3] the input frames had the initial size \( 640 \times 480 \) and the resolution was not changed. We have reduced the inputs and not only kept the quality of the algorithm but even improved it. Although Rank-5 metric is higher when we use VGG-like network the difference is very small and WideResNet architecture has much fewer parameters. It makes us suppose that this architecture is more appropriate for gait recognition problem.

It is also interesting to note that \( L_1 \) metric always gives higher accuracy of classification and, thus, is more suitable for measuring similarity of gait feature vectors.

Since Wide ResNet architecture is the most successful all further experiments were made using such network structure.

Table 4 shows the performance on CASIA dataset comparing to results from [13]. The accuracy is quite high despite rather poor training set. It can be due to the relatively small number of parameters in Wide ResNet architecture and, hence, lack of overfitting that could appear in [13].

Table 4. Results on CASIA dataset

| Method | Evaluation |
|--------|------------|
| Architecture, Aggregation and Metrics | Rank1 |
| Wide ResNet (PCA 150), avg, \( L_2 \) | 85,11 |
| Wide ResNet (PCA 130), avg, \( L_1 \) | 86,68 |
| Wide ResNet (PCA 170), concat, \( L_2 \) | 84,85 |
| Wide ResNet (PCA 170), concat, \( L_1 \) | 92,95 |
| [13] VGG+blocks, \( L_1 \) | 74,93 |

In the experiments with OU-ISIR database, we trained the network using all the maps and all the view angles for training subjects. The gallery view is fixed and equals 85 degrees, and the probe views are all the others. The NN classifier is fitted on gallery frames from the first walk and tested on the probe frames of the second one. The results and comparison with other techniques are shown in Table 5.

Table 5. Comparison of the classification accuracy on OU-ISIR dataset obtained from silhouette masks

| Method | Probe view |
|--------|------------|
| Architecture and Metrics | 55 | 65 | 75 |
| [13] GEINet | 92.8 | 96.2 | 97.8 |
| [15] MvDA | 81.4 | 91.2 | 94.6 |
| [11] Joint Bayesian | 88.0 | 96.0 | 97.0 |
| [13] Joint Bayesian | 94.9 | 97.6 | 98.6 |

The experiments show that the proposed algorithm can be generalized to multiview and get high accuracy even in case of partial information.

After the experiments with different training techniques, we investigated which body parts are really important for gait recognition. Results on OU-ISIR database show that full-body features are quite informative, thus, we compare different sets of body parts. We trained the network in three modes: on all 5 parts (two legs, upper and lower body and full body), then on 3 lower parts (two legs and lower body) and finally using only full body as input. The results for TUM-GAID are shown in Table 6.

We see that the legs turn out to be the least informative joints: the network trained on the lower parts of the body...
Table 6. Comparison of the results on TUM-GAID dataset obtained using different parts of the body

| Body parts                             | Rank1 | Rank5 |
|----------------------------------------|-------|-------|
| legs, lower body, upper body, full body| 99.78 | 99.89 |
| legs, lower body                       | 96.22 | 98.70 |
| full body                              | 98.92 | 100.00|

gives the worst result. Instead, the algorithm built only on full body shows high accuracy close to the best one.

The third thing we were interested in is the length of video needed for good gait recognition. In all the previous experiments we used the whole video sequence containing up to 90 frames and did not reduce it. In Table 7 the results of the algorithms tested on shortened parts of TUM-GAID sequences are presented.

Table 7. Comparison of the results for different lengths of videos.

| Length of video | Rank1   | Rank5   |
|-----------------|---------|---------|
| 50 frames       | 94.28   | 94.93   |
| 60 frames       | 97.52   | 97.84   |
| 70 frames       | 99.35   | 99.46   |
| full length     | 99.78   | 99.89   |

Although the length of gait cycle is about 1 second or 30 – 35 frames, such short sequences are not enough for good person recognition. The more consecutive frames we use for classification the better result we get. It happens because the movements of body points are similar but not the same during every human’s step and taking long sequences makes the recognition more stable to small changes in walking style.

The last thing we experimented with was stability and transferability of the algorithm. If the feature extractor is really general and does not depend on the background and the appearance of the person it should be able to extract features from videos even if they were recorded under the conditions different from the initial ones. In order to check such generality, we used both of available datasets in our experiment. We tried to train the algorithm on one of the databases and evaluate its quality on the other one without any fine-tuning. Table 8 shows the accuracy of transferring the algorithm between datasets.

Table 8. Quality of transfer learning

| Training Set | Testing Set | CASIA | TUM  |
|--------------|-------------|-------|------|
| CASIA        | 92.68       | 66.48 |
| TUM          | 76.76       | 99.78 |

Note that even the algorithm trained on the other dataset works on CASIA dataset B better than the method trained on CASIA from [18]. Nevertheless, the accuracy of recognition gets much worse while transferring the algorithm from one database to another, the error becomes three times greater. The situation with TUM-GAID turns out to be even worse. The classifier trained on CASIA recognizes only 66.5% of TUM testing videos which is 1.5 times less than the algorithm trained on TUM. It means that the algorithm overfits and the amount of training data (especially in CASIA dataset) is not enough for constructing general algorithm.

5. Implementation details

Some of the auxiliary methods were implemented using public libraries. The bounding boxes for human figures were computed using the silhouette masks found by background subtraction. It is quite a rough method but since every frame of the databases contains only one moving person, it works well. The maps of optical flow were calculated through OpenCV library using Farneback [6] algorithm. The pose was evaluated using [1] method that finds the key points of the body. For the main part of the algorithm, we used Lasagne with Theano backend and trained the networks on NVIDIA GTX 1070 GPU. The main wide residual network which uses five body parts was trained on TUM-GAID dataset in 10 hours. The model was optimized by Nesterov Momentum gradient descent method with learning rate reducing from 0.1 by a factor of 10 each time the training quality stopped increasing.

6. Conclusions and further work

In this paper we have proposed a pose-based convolutional neural model for gait recognition. Our experiments demonstrate that despite reaching sufficiently high accuracy only with optical flow maps for full-height region, collecting additional information from regions around joints improve the results, surpassing state-of-the-art on TUM-GAID. Our model can also be successfully applied to the moving silhouettes in OU-ISIR, which shows that the most important information for gait recognition is the movement of external edges, and that our method can be straightforwardly applied to multiview gait recognition.

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