A. Attention

A.1. Self and Cross-Attention

The goal of the attention layer is to discover relationships between a given query \( Q \) (e.g. an image) and pre-exist key data \( K \) (e.g. a set of images) and to represent these relationships using \( V \). It is stated as follows:

\[
\text{Attention}(Q, K, V) = \text{Softmax} \left( \frac{QK^T}{\sqrt{d_k}} \right)V, \quad (1)
\]

where \( d_k \) is a scaling factor [3].

Denote \( A(Q, K, V) \) as the attention block (Eq. 1, see [3] for additional details) and denote \( F_S \) and \( F_T \) as the feature encoders of the source and target domains, respectively. The self attention of the Transformers encoders \( E_S \) and \( E_T \) and decoders \( D_S \) and \( D_T \) is:

\[
E_S \left( K^t \right) = A \left( F_T \left( K^t \right), F_T \left( K^t \right), F_T \left( K^t \right) \right),
D_S \left( P^s \right) = A \left( F_S \left( P^s \right), F_S \left( P^s \right), F_S \left( P^s \right) \right),
\]

\[
E_T \left( K^s \right) = A \left( F_T \left( K^s \right), F_T \left( K^s \right), F_T \left( K^s \right) \right),
D_T \left( P^t \right) = A \left( F_S \left( P^t \right), F_S \left( P^t \right), F_S \left( P^t \right) \right).
\]

Note that the target’s Keys \( K^t \) Transformer encoders \( E_S \) remain unchanged throughout the training process whereas the source’s keys \( K^s \) (at \( E_T \)) are updated with accordance of the specific source that is currently being used for the cyclic training.

The generator of the source and target are cross attention operations:

\[
G_{s\rightarrow t} \left( K^t, P^s \right) = H_S \left( A \left( D_S \left( P^s \right), E_S \left( K^t \right), E_S \left( K^t \right) \right) \right),
(2)
\]

\[
G_{t\rightarrow s} \left( K^s, P^t \right) = H_T \left( A \left( D_T \left( P^t \right), E_T \left( K^s \right), E_T \left( K^s \right) \right) \right),
(3)
\]

where \( H_S \) and \( H_T \) are the features decoders of \( G_{s\rightarrow t} \) and \( G_{t\rightarrow s} \), respectively.

Figure 1: Attention Layers. Left side - Transformer encoder. Right side - Transformer decoder. The encoder performs self-attention while the decoder performs self-attention followed by cross attention with the encoder’s outputs.

Figure 1 illustrates the process of attention between the Transformer encoder and decoder. In order to reduce processing power, we use linear attention [1, 2] instead of Transformer’s original attention. Keys in the Transformer encoder undergo a process of attention among themselves and the output is served as the Keys and Values with the decoder’s queries. A self-attention process takes place between the decoder queries \( Q \) and themselves, which reveals temporal relationships between consecutive images. In our model, the Transformer decoder includes both self- and cross- attention blocks. We tested our model with and without using self-attention in the decoder and reported the results for both.
A.2. Attention histograms

Figure 2 shows a series of cross-attention histograms. The graphs show the value of attention between each key and the current image over time. The mean value of the attention of each key was subtracted separately. The attention shown corresponds to the first cross-attention block between the encoder and decoder.

It is feasible to gain some insight into the attention mechanism’s functioning. For example, we can see how Key 0 and Key 1’s cross-attention evolved over time in relation to the position of the legs. In Figure 2.a, where the right leg is forward, and the left leg is backward, Key 0 makes a considerable contribution, whereas Key 1 makes a much smaller contribution. As the legs swap positions, with the left leg moving forward and the right leg moving backward (Figure 2.b,c,d), Key 0 and Key 1 switch roles as well, with Key 1 now contributing substantially and Key 0 contributing much less.
Figure 2: Attention histograms.
B. Ablation study

We evaluate the impact of the different components of the CTrGAN architecture on recognition accuracy (Table 1,2) and appearance quality (Table 3). V2V is the pose to appearance model.

- **Cycle Only** - refers to using only CycleGAN model.
- **Attention** - adds encoder self-attention and cross-attention between the image sequence and the keys using the decoder.
- **Time-Attention** - adds decoder self-attention which takes advantage of the temporal relations between the three frames within the sequence.
- **Time-Attention-5** - same as Time-Attention but increases the length of the temporal relation to five.
- **Target-Training** - same as Time-Attention but include the target in the training set.
### Table 1: Target recognition accuracy.

| Model            | Attention mechanism | Encoder self-attention | Decoder self-attention | GaitPart | GaitSet | GaitGL |
|------------------|---------------------|------------------------|------------------------|----------|--------|--------|
| Cycle Only       | ✗                   | ✗                      | ✗                      | 5.56     | 5.00   | 5.28   |
| + Attention      | ✓                   | ✓                      | ✗                      | 78.06    | 51.39  | 69.17  |
| + Time-Attention  | ✓                   | ✓                      | ✓                      | 84.72    | 56.67  | 68.06  |
| Time-Attention-5 | ✓                   | ✓                      | ✓                      | 79.17    | 55.83  | 66.11  |
| Target-Training  | ✓                   | ✓                      | ✓                      | 87.78    | 73.89  | 77.50  |

### Table 2: Source recognition accuracy.

| Model            | Attention mechanism | Encoder self-attention | Decoder self-attention | GaitPart | GaitSet | GaitGL |
|------------------|---------------------|------------------------|------------------------|----------|--------|--------|
| Cycle Only       | ✗                   | ✗                      | ✗                      | 97.22    | 86.11  | 95.83  |
| + Attention      | ✓                   | ✓                      | ✗                      | 13.06    | 15.56  | 25.00  |
| + Time-Attention  | ✓                   | ✓                      | ✓                      | 10.56    | 13.89  | 21.67  |
| Time-Attention-5 | ✓                   | ✓                      | ✓                      | 12.50    | 12.78  | 23.61  |
| Target-Training  | ✓                   | ✓                      | ✓                      | 8.89     | 10.00  | 15.83  |

### Table 3: Appearance quality.

| Model            | Attention mechanism | Encoder self-attention | Decoder self-attention | SSIM† | LPIPS‡ | FID‡ | IS‡ |
|------------------|---------------------|------------------------|------------------------|-------|-------|------|-----|
| Cycle Only       | ✗                   | ✗                      | ✗                      | 0.9030| 0.0593| 47.30| 0.0011|
| + Attention      | ✓                   | ✓                      | ✗                      | 0.9084| 0.0554| 58.07| 0.0009|
| + Time-Attention  | ✓                   | ✓                      | ✓                      | 0.9093| 0.0549| 52.89| 0.0009|
| Time-Attention-5 | ✓                   | ✓                      | ✓                      | 0.9093| 0.0554| 58.03| 0.0013|
| Target-Training  | ✓                   | ✓                      | ✓                      | 0.9096| 0.0538| 51.72| 0.0011|
C. Sample results

Figure 3: One of the sources is shown in the first line from the top. On the second line are the poses of the source. On the third line are the corresponding generated poses by CTrGAN. On the fourth line are the generated appearances of the target using V2V. The fifth line shows the differences between the source pose image (left image) and the target pose image (right image).
D. Motion transfer mimics the gait of the source.

Here, we examine the extent to which existing motion transfer methods retain the gait pattern of the source. Table 4 presents the source-accuracy. It is defined as the percentage of times the gait recognition model has identified the generated gait as the source’s gait. The top of the table shows that the models correctly identified the sources after generating the target’s appearance in about 87 percent of the test cases, illustrating the challenge of existing motion transfer methods to generate gait distinguishable from the source. The bottom of the table shows that, with CTrGAN, the gait recognition models’ success rate drops significantly to approximately 15 percent of cases.

| Method | Model | GaitPart | GaitSet | GaitGL |
|--------|-------|----------|---------|--------|
|        | EDN   | 17.22    | 20.28   | 47.78  |
|        | V2V   | 93.06    | 76.94   | 93.33  |
| ours   | EDN   | 7.78     | 7.22    | 12.78  |
|        | V2V   | 9.44     | 15.00   | 20.56  |

Table 4: The source-accuracy ↓. 
E. Detailed Implementation

E.1. CTrGAN internals

Both $G_{t \rightarrow s}$ and $G_{t \rightarrow s}$ have the exact same architecture. The input is a 256x256x4 image, the output of encoders $F_T$ and $F_S$ is a 16x16x256 tensor, and the output of the decoders $H_T$ and $H_S$ is an image of the same size (256x256x4).

The Transformers inputs from $F_T$ and $F_S$ are of size 16x16x256. We use spatial max pooling to reduce the tensor size to 4x4x256, which results in a flattened feature vector of 4096. The base dimension for the vectors in our Transformers is 1024. Therefore, the fully connected FC modules for Q, K, and V embed from 4096 to 1024 and vice versa. The Transformer encoders $T E_S$ and $T E_T$ receive 18 fixed key images (used as Q, K, and V) and is composed of two blocks of self-attention, while the Transformer decoders $T D_S$ and $T D_T$ consist of two blocks of one self-attention followed by one cross-attention block.

E.2. Discriminators structure

In this section, we describe (Table 5) the structure of the model that served as a discriminator block in CTrGAN.

| Type   | In  | Out | Kernel | Stride | Activation                  |
|--------|-----|-----|--------|--------|-----------------------------|
| Conv   | 4   | 16  | 3      | 2      | norm + relu                 |
| Conv   | 64  | 128 | 4      | 2      | instance relu(0.2)          |
| Conv   | 128 | 256 | 4      | 2      | instance relu(0.2)          |
| Conv   | 256 | 512 | 4      | 1      | instance relu(0.2)          |
| Conv   | 512 | 1   | 4      | 1      | -                           |

Table 5: Basic discriminator

E.3. Features encoder structure

In this section, we describe (Table 6) the structure of the model that served as the features encoder blocks ($F_T$ and $F_S$) in CTrGAN. The $H_T$ and $H_S$ decoders are identical to the $F_T$ encoder, except that they operate in the other direction.

| Type   | In   | Out  | Kernel | Stride | Activation                  |
|--------|------|------|--------|--------|-----------------------------|
| Conv   | 4    | 16   | 3      | 1      | norm + relu                 |
| Conv   | 16   | 32   | 3      | 2      | norm + relu                 |
| Conv   | 32   | 64   | 3      | 2      | norm + relu                 |
| Conv   | 64   | 128  | 3      | 2      | norm + relu                 |
| Conv   | 128  | 256  | 3      | 2      | norm + relu                 |
| ResBlock | 256  | 256  | 3      | 1      | norm + relu + norm          |
| ResBlock | 256  | 256  | 3      | 1      | norm + relu + norm          |
| ResBlock | 256  | 256  | 3      | 1      | norm + relu + norm          |

Table 6: Feature encoders $F_T$ and $F_S$ structure
References

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