RGait-NET: An Effective Network for Recovering Missing Information from Occluded Gait Cycles

Ayush Agarwal\textsuperscript{1}
Motilal Nehru National Institute of Technology
Allahabad
ayushagarwal@mnnit.ac.in

Dhritimaan Das\textsuperscript{1}, Pratik Chattopadhyay\textsuperscript{2}
Indian Institute of Technology (Banaras Hindu University)
Varanasi
\{dhritimaanand.cd.eee17,pratik.cse\}@itbhu.ac.in

Lipo Wang\textsuperscript{3}
Nanyang Technological University
Singapore
ELPWang@ntu.edu.sg

\textbf{Abstract}—Gait of a person refers to his/her walking pattern, and according to medical studies gait of every individual is unique. Over the past decade, several computer vision-based gait recognition approaches have been proposed in which walking information corresponding to a complete gait cycle has been used to construct gait features for person identification. These methods compute gait features with the inherent assumption that a complete gait cycle is always available. However, in most public places occlusion is an inevitable occurrence, and due to this, only a fraction of a gait cycle gets captured by the monitoring camera. Unavailability of complete gait cycle information drastically affects the accuracy of the extracted features, and till date, only a few occlusion handling strategies to gait recognition have been proposed. But none of these performs reliably and robustly in the presence of a single cycle with incomplete information, and because of this practical application of gait recognition is quite limited. In this work, we develop deep learning-based algorithm to accurately identify the affected frames as well as predict the missing frames to reconstruct a complete gait cycle. While occlusion detection has been carried out by employing a VGG-16 model, the model for frame reconstruction is based on Long-Short Term Memory network that has been trained to optimize a multi-objective function based on dice coefficient and cross-entropy loss. The effectiveness of the proposed occlusion reconstruction algorithm is evaluated by computing the accuracy of the popular Gait Energy Feature on the reconstructed sequence. Experimental evaluation on public data sets and comparative analysis with other occlusion handling methods verify the effectiveness of our approach.

\section{I. INTRODUCTION}

Gait refers to the walking pattern of an individual, and over the past decade, a number of research articles on computer vision-based gait recognition has shown that a gait-based biometric identification system will have immense potential to identify suspects reliably if deployed in surveillance sites to strengthen public security. The main advantage of gait over any other biometric is that it can be captured from a distance, and the videos/images captured by surveillance camera may not be of very high resolution.

Previous studies on gait recognition \cite{1, 2, 3} has already established the fact that accurate gait recognition can be done only if a complete cycle of gait is made available. However, in most practical situations, availability of a complete cycle is not guaranteed, since occlusion can occur anytime during the video capturing phase. Occlusion can be of two types: static and dynamic. In static occlusion, the occluding object (or, the occluder) remains stationary, e.g., a pillar, whereas in case of dynamic occlusion, the occluders are moving objects, e.g., walking persons. Traditional gait recognition approaches are not suitably equipped to handle occlusion reliably, and their accuracy is likely to suffer in the presence of occluded sequences. Till date, only a few techniques \cite{4, 5, 6} have attempted to provide solutions to this very challenging issue. However, the reported results are not significantly accurate, and this limits potential deployment of a gait recognition system in all practical situations.

We propose effective algorithms for detecting frames in a gait cycle that are either corrupted or went missing due to the occurrence of static/dynamic occlusion. A VGG-16 network is initially employed to detect occluded frames present in an input sequence. Next, reconstruction of missing silhouettes in these occluded frames is carried out by employing a recurrent deep learning model that has been seen to perform robustly against varying degrees of occlusion. The only existing gait data set featuring occlusion, namely the TUM-IITKGP data set \cite{7}, consists of only a small set of subjects. Hence, we consider another popular extensive gait data set of non-occluded sequences, namely the CASIA data \cite{8, 9}, and incorporate varying degrees of synthetic occlusion in this data to prepare the data for training the model. The trained model is termed as \textit{Reconstruct Gait Net} (abbreviated as \textit{RGait-Net}, and can be downloaded by clicking \textit{here}). To the best of our knowledge, ours is the first-ever work on occlusion reconstruction in gait sequences by exploiting the generalization capability of neural networks.

The gait recognition scenario considered in this paper can be explained with the help of Figure \ref{fig:1}.

\section{II. RELATED WORK}

Early work on gait recognition \cite{2, 10, 11} work on videos captured by RGB cameras and focus on the fronto-parallel view of gait. Later, with the introduction of depth cameras, a few frontal-view gait recognition techniques \cite{3, 12} have also been developed. In \cite{13}, a methodology to classify human pose based on 3D position of human joints is proposed. Classification based on position of human joints make the frames time independent. But in case of occlusion
where complete human body is not possible, it is not plausible to predict joints positions.

Occlusion while recording walking sequences of a human is inevitable unless and until the walking sequence is recorded in suitable environment due to crowding in areas like railway station, airports, shopping malls, etc. Occlusion can be of distinguished into mainly types that is self-occlusion [14], [15] which refers to the situation when a part of the body is occluded by another part, and occlusion that are caused by other/external objects [6], [16]. Occlusion can be further subdivided into static occlusion i.e. occlusion caused due to static objects in the path of camera and the subject whose gait is being recorded and dynamic occlusion which refers to occlusion due to dynamic objects in the path of camera and subject. The problem statement that we address includes addressing all kinds of occlusion particularly static and dynamic occlusion. It is due to occlusion in videos recorded that brings noise to the feature vector generated to be used for identification, and it Is due to this noise that the identification accuracy decreases. Initially approaches directly extracted features from Gait Energy Image and Colour Histograms and used them for human identification. Also there exist proposed approaches that uses Gaussian process dynamic model to reconstruct the occluded frames [6], [7] uses regression using Support Vector Machine is used and [14] uses genetic algorithm to address the problem of occlusion. In [18] three procedures are explained for reconstruction of missing data, first of which uses interpolation of polynomials, second method uses autoregressive prediction, and last one uses a method involving projection onto a convex set. In [19] an algorithm focusing on tracking of pedestrian is proposed, whose results are evaluated on a synthetic dataset which contains sequences of partially occluded pedestrian. A number of approaches involving methods of human tracking [20], [21] and activity recognition techniques [22], [23] focus on handling occlusion. Work has also been done the field of modelling and characterisation of occlusion as done in [24]. The only data set involving real life occlusion situations is the TUM IITKGP data set. Some work done in the domain of occlusion are address the problem of presence of incomplete gait sequence. In [25] a pose energy image based human identification approach from incomplete gait sequence of a subject has been defined. Also focus on frontal gait recognition In presence of Occlusion is addressed in [4]. Recent approaches like [5], [26] involving deep learning addresses the problem conditioned to presence of incomplete gait cycle of any subject. However, these approaches do not address the problem of occlusion directly that leads to poor performance in the retrieval results.

III. PROPOSED APPROACH

As explained before, we propose a two stage method, mainly occlusion detection and then occluded frame reconstruction. A schematic diagram explaining the steps of the approach is shown in Figure 1. These steps are explained in further details in the following two sub-sections.

A. Occlusion Detection

Occlusion detection is carried out in an automated manner by employing a deep Convolutional Neural Network (more specifically, a VGG-16 network). We use a large data set consisting of 1000 unoccluded silhouettes of gait sequences and 1000 noisy silhouettes consisting of some frames generated by adding synthetic noise to frames and some black frames are created to fine tune the VGG Network for proper occlusion detection. The network is trained by optimizing a binary cross-entropy loss function. If the $i^{th}$ frame of an input gait cycle is denoted by $F_i$ and the occlusion detection model learns an invertible function $G$, then $G(F_i)$ represents the probability of the frame $F_i$ to be occluded. If $y_i$ is the ground-truth class label for the $i^{th}$ frame and $G(F_i)$ is the predicted probability by the occlusion detection
model, then the cross-entropy loss function $L_{occ}$ with trainable parameters is computed as:

$$L_{occ} = -y_i \log(G(F_i)) - (1 - y_i) \log(1 - G(F_i)).$$  \hspace{1cm} (1)

The network is trained in multiple epochs till the loss function attains a saturation level, i.e., the loss value between two successive epochs is less than a small threshold $\epsilon$. Here we choose the value of $\epsilon$ to be $2e - 4$.

On completion of the training phase, the model learns to accurately differentiate between occluded and non occluded frames. Hence, for a test sequence we find all the occluded frames and their index and proceed to the occlusion reconstruction part. The initial 13 layers of VGG-16 network were freezeed and rest of the layers were made trainable followed by a Global Average Pooling layers and 128 neurons dense layers with BatchNormalization and dropout (with dropout rate = 0.5). The last layer was single neuron with sigmoid activation function.

### B. Occlusion Reconstruction

Since we know the missing or occluded frames from the occlusion detection model, we can now reconstruct them. Each pose in a gait cycle is dependent on previous frames. So knowing the previous frames one can predict the upcoming or next frame. In other words, gait cycle is a time series data. So, the accumulated prior knowledge of previous frames can help in reconstructing the occluded frames with high precision instead of using only just one previous frame. Although Fully-Connected LSTMs have proven powerful in handling temporal correlation, it contains too much redundancy for spatial data. Since FC-LSTMs have shown good results in prediction of temporal data and Convolutional Neural Networks have performed well with images, hence we chose to use the Convolutional LSTMs as proposed in [27] which uses Convolutional layers in place of dense layers.

We propose a deep auto-encoder network which consists of 7 Convolutional layers, 4 Time Distributed pooling layers stacked on top of each other and for regularization as we have used Dropout layers with dropout probability of 0.2 and Batch Normalization after each Convolutional Layer. To further improve robustness of our model we add zero centered Gaussian noise to the input silhouette. We have also made the use of skip connection in our model for better gradient flow throughout all the nodes of the graph. The occlusion reconstruction model represents a invertible function $T$ that takes as input a sequence of gait frames represented by $F = \{F_1, F_2, ..., F_K\}$ and outputs the $F_{k+1}$ frame. Mathematically, it can be represented as:

$$T(F_{0:k}) = F_{k+1}$$  \hspace{1cm} (2)

### C. Objective Function

We propose a novel multi-objective loss function which is optimized by the occlusion reconstruction model. Our loss function enables the network to predict proper representation of silhouette frames. The objective function consists of two components, namely binary-cross-entropy loss and dice loss functions.

Since we work with silhouette images which have pixel values between 0 and 1 hence we incorporate the binary cross entropy loss in the form of reconstruction loss function in our model. We apply the pixel wise cross-entropy loss to the reconstructed image with respect to the ground truth image, hence improving the reconstruction ability of the network.

Secondly we propose to use dice loss in our loss function whose main aim is to increases the amount of overlap between the reconstructed frame and the original frame. Hence we use dice loss which enhances the reconstruction ability of the reconstruction model. It is represented as a coefficient that gives the measure of overlap between the original and reconstructed silhouette by giving values between 0 and 1. That is if both the reconstructed and original frame show high overlap then the value of the dice coefficient is near to 1 else its near to 0. If $x$ is represented as the actual frame and $\hat{x}$ as the reconstructed frame then the dice loss coefficient is given by:

$$L_{Dice} = \frac{2\hat{x}x}{\hat{x}^2 + x^2}$$  \hspace{1cm} (3)

$$L_{total} = \lambda_1 L_{BCE} + \lambda_2 L_{Dice}$$  \hspace{1cm} (4)

where $\lambda_1$ and $\lambda_2$ are non-trainable parameters.

### IV. Experimental Evaluation

The proposed algorithm has been implemented on a system having 64 GB RAM, one i9-18 core processor, along with three GPUs: one Titan Xp with 12 GB RAM, 12 GB frame-buffer memory and 256 MB BAR1 memory and, two GeForce GTX 1080 Ti with 11 GB RAM, 11 GB frame-buffer memory and 256 MB of BAR1 memory.

![Fig. 2: (a) Ground truth frames, (b) Reconstruction results](image)

### A. Training

1) **Frame Prediction Model**: The frame prediction model is trained on the publicly available CASIA-B gait data set. This data set consists of a total of 106 subjects with six walking sequences corresponding to each person. Out of these, four walking sequences of each person have been used to train the frame prediction model. The model has been trained for 62
epochs after which the training loss has been seen to attain saturation. The model uses RMSprop (Root Mean Square Propagation) as the optimizer with learning rate as 0.001 and $\lambda_1$ and $\lambda_2$ as 1 and -1 respectively as mentioned in eq(4). During each epoch the initial number of non-occluded frames is selected randomly.

2) Occlusion detection model: The model is trained on synthetically generated occluded images from CASIA-B dataset by random cropping of images and occluded poses present in TUM-KGP dataset. A small dataset of 1524 images are made with 664 non occluded images and 860 occluded images. We train this model for 50 epochs with RMSprop as the optimizer and learning rate as 0.0001. The model achieved a training accuracy of 97.03%.

B. Experimentation

Our approach assumes some number of initial non-occluded frames. The model is validated over two unseen datasets, namely nm05, nm06 and TUM-KGP. The first experiment was done on nm05 and nm06 in which % of occlusion is varied from 5% to 50% with initial non occluded frames as 5 and 10 respectively. As evident from table II and table III increasing the number of initial non-occluded frames increases the rank 1 accuracy which can be justified by the fact that more number of initial non-occluded frames gives extra amount of information to frame prediction model.

| Algorithm | Accuracy | Time |
|-----------|----------|------|
|           |          |      |
| [1]       | 10.25    | 3.65 |
| [2]       | 20       | 0.61 |
| [3]       | 75.86    | 1.09 |
| Proposed  | 91.42    | 0.44 |

TABLE I: Test Accuracy of Various algorithms on TUM-KGP dataset

| % occlusion | Rank1 Accuracy |
|-------------|----------------|
|             |                |
| <10%        | 93.39          |
| 10%-20%     | 86.66          |
| 20%-30%     | 76.66          |
| 30%-40%     | 63.80          |
| 40%-50%     | 47.37          |

TABLE II: Rank1 accuracy with different levels of synthetic occlusion in CASIA-B test dataset using 10 previous non occluded frames for prediction

| % occlusion | Rank1 Accuracy |
|-------------|----------------|
|             |                |
| <10%        | 92.375         |
| 10%-20%     | 85.71          |
| 20%-30%     | 73.33          |
| 30%-40%     | 62.85          |
| 40%-50%     | 40.75          |

TABLE III: Rank1 accuracy with different levels of synthetic occlusion in CASIA B test dataset using 5 previous non occluded frames for prediction
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