CHAPTER 6

Conclusions and Future Work

This chapter recalls the summary of the dissertation's main contributions and provides outlines of future research directions in gait recognition. In this thesis, we have proposed effective solutions to the problem of pose-based gait feature extraction and improve the state-of-the-art by proposing three new methods that use the features termed *Pose-based Binary Energy Image*, *Generalized Active Energy Image*, and *Dynamic Gait Energy Image*. Each of these methods is suitable for application in surveillance sites to identify suspects as they pass through the surveillance area one by one if a few samples of the gait sequences of these suspects are available beforehand.

Chapter 1 introduces the problem and its categorization based on viewpoint, and also highlights the motivation and contributions of the thesis, whereas Chapter 2 presents a thorough literature survey on gait recognition starting from the primitive hand-crafted feature-based methods to the modern Deep Learning-based approaches. Next, Chapter 3 presents a gait feature, namely Pose-based *BEI*, that encodes the static and dynamic information of gait in a set of key pose frames using the contours extracted from the binary silhouette images. In this work, we follow a similar pose-based gait analysis technique as also used in the previous pose-based gait recognition techniques [1, 34]. However, we have made an attempt to improve the gait template by considering the contour information of the silhouettes which preserves more kinematic information compared to the entire silhouettes. Experimental results using CASIA B and TUM-GAID datasets also show that our approach performs robustly and with high accuracy for the different training-test scenarios. However, its prediction is dependent on a fixed set of key poses determined prior to gait feature construction.

Chapter 4 introduces the GAEI feature that captures the periodic walking information through multiple key pose sets instead of a single key pose set as done in Chapter 3 and other existing pose-based gait recognition approaches. The pose-based Active Energy (AEI) Feature is computed corresponding to each pose of a dictionary element. Similar pose-based AEI features are computed for all the other key pose sets present in the dictionary. Basically, for each key pose set, we compute the differences between the adjacent frames in a sequence to form difference images and next aggregate the difference images corresponding to the individual key poses in the set. Experimental results reported in Tables 5.7 and 5.8 indicate that the GAEI feature combined with GAN-based silhouette refinement can handle the differences in the co-variate conditions as well as walking speeds between the training and test sets better than both BEI and Pose-based BEI. However, its response time is very high due to computing features corresponding to each set of key poses in the dictionary.

In Chapter 5, a more time-efficient approach has been proposed to identify an individual from his/her walking sequence. Here, instead of considering a dictionary of key poses we consider a maximal set of unique walking poses in a gait cycle, and next map an input sequence of a subject (with/without co-variate objects) to the appropriate key poses by preserving the temporal order of walking. Unlike the existing pose-based gait features in which transitions are allowed from a given key pose state to the same state or to the next state, here we consider skip connections by allowing additional transitions from a given state to its next to next state. Next, appearance-based gait features are extracted at the granularity of the pre-determined set of maximal unique walking poses. A pix2pix conditional GAN model is next employed to automatically translate the input features with co-variate objects such as clothing and carrying bag into those without co-variate objects. Next, PCA-based dimension reduction is performed and classification is done in the reduced space. Experimental results reported in Tables 5.7 and 5.8

show that our DGEI feature combined with GAN helps in performing accurate gait recognition in the presence of co-variate objects and performs better than each of the other proposed approaches in the thesis for varying training-test scenarios.

6.1 Future Work

Our proposed approaches in the thesis have been evaluated and compared with the existing approaches using standard publicly available gait data sets. More extensive evaluation needs to be done using real-life data sets captured in surveillance sites. Occlusion handling in gait recognition is an important future scope for work since the presence of occlusion in real-life surveillance sites is inevitable. Occlusion is caused due to multiple persons crossing each other in the field-of-view of the camera and the existing approaches to occlusion handling in gait recognition are mostly non-Deep Learning-based and are dependent on several assumptions such as: (i) gait features over a cycle follow a Gaussian, (ii) multiple occluded cycles are available in a sequence from which a complete cycle of gait can be reconstructed. Plausible solutions to occlusion detection and reconstruction from gait sequences using automated Deep Learning techniques need to be developed to enhance the applicability of gait recognition in real-life surveillance.

In recent years, several GAN-based view-invariant gait recognition approaches have been developed [50, 89, 101]. However, the accuracy given by these methods on most data sets, as reported in the above-cited works, is not appreciably high and needs further improvement. Multi-modal recognition using gait and face biometric features in surveillance sites, recognition at night from videos captured by infrared sensors, cross-speed recognition, open set recognition, etc., are some other interesting areas of research.