

VISION BASED GAIT RECOGNITION ROBUST TO VIEW AND APPEARANCE VARIANCE



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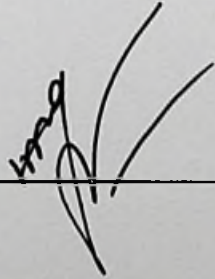
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ABSTRACT

Vision-based gait recognition has excellent potential for biometric person identification due to its non-intrusive, non-invasive and remote access data collection. Gait recognition has diverse applications for visual surveillance due to its adaptability for person identification and making predictions about age, gender, and ethnic background. The vision-based gait recognition is adaptable on low-resolution video as it only requires the visibility of the human body for feature extraction. The vision-based gait recognition-based person identification is highly affected by the factors altering the perceivable shape of the human body, including variance in the subject's appearance and viewing angle. These factors reduce the adaptability of conventional gait feature extraction techniques, including Gait Energy Image and Gait Silhouette. The problem of gait recognition robust to appearance variance is twofold complex as it introduces higher intra class variance and lower inter-class variance. These two problems require developing gait features that strongly correlate within the same class and discriminant enough for multi-class classification. This thesis proposes gait feature extraction technique named "Dynamic Gait Feature", by estimating the relative motion between key poses of the gait cycle and encoding it as feature vectors. The Dynamic Gait Features are evaluated on dual criteria of the problem and are established to be strongly correlated within class and adaptable with Support Vector Machine classifier-based gait recognition. These Dynamic Gait Features are further transformed into Spatio Temporal Power Spectral (STPS) gait features. The robustness of STPS gait features towards different appearances and views is established by adapting machine learning classifiers. The Dynamic Gait Feature based gait recognition has achieved 97.53% accuracy despite significant appearance variance. The STPS

based gait recognition has achieved 99.87% accuracy despite view and appearance variance. This thesis also addressed the effects of south Asian clothing on the subject's appearance. A local dataset has been developed to address the effects of south Asian clothing on the subject's appearance. We expect this research to set a new dimension for the adaptation of vision-based gait recognition for automated visual surveillance that is adaptable in a real-time environment.

ABBREVIATIONS

C

- Convolutional Neural Network
(CNN), 47
- Cross-correlation Strength Analysis
(CCS), 10

D

- Deep Learning
DL, 80

F

- frequency domain gait entropy image EnDFT
EnDFT, 104

G

- Gait Silhouette, 25
- Gait Energy Image
(GEI), 4
GEI, 4
- Gait Entropy Image
(GEI), 32
- Gaussian Mixture Model
(GMM), 45

H

- Histogram of Gradient
(HOG), 101

L

Long Short Term Memory
(LSTM), 47

P

Pose Temporal spatial Network.
(PSTN), 47

S

Spatio-Temporal Power Spectral (SPTS)
(STPS), 11

Support Vector Machine
SVM, 10

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