

UNIVERSITY OF TECHNOLOGY SYDNEY  
Faculty of Engineering and Information Technology

**Person ReID in Different Environment Settings  
Using Deep Learning Methods**

by

**Ziyue Zhang**

A THESIS SUBMITTED  
IN PARTIAL FULFILLMENT OF THE  
REQUIREMENTS FOR THE DEGREE

**Doctor of Philosophy**

Sydney, Australia

2022

## Certificate of Original Authorship

I, Ziyue Zhang declare that this thesis, is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the Faculty of Engineering and IT at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This document has not been submitted for qualifications at any other academic institution.

This research is supported by the Australian Government Research Training Program.

Signature:      Production Note:  
                         Signature removed prior to publication.

Date: 20/05/2022

# ABSTRACT

## **Person ReID in Different Environment Settings Using Deep Learning Methods**

by

Ziyue Zhang

Person Re-identification (Person ReID) is an essential research area in vision-based human image retrieval. It is a technology where the system can automatically identify the same person appearing in different camera views. Most existing works in this area focus on settings where the environment is either kept the same or has tiny fluctuation. However, it is well-known that no matter how small, the degree of environment changes may affect the robustness of a ReID algorithm significantly. Many real-world applications are required to detect the same person at a drastically different place and time, making large environment changes an unavoidable yet under-addressed problem.

Hence, we want to address the problem where environment settings are different, such as illuminations, resolutions, modalities and clothing. Specifically, this thesis proposes a series of methods for environment change person ReID, summarized as follows:

1. We proposed a Two-Stream Model which can solve the illumination adaptive person ReID problem. It can separate ReID features from lighting features to enhance ReID performance. We construct two augmented datasets by synthetically changing a set of predefined lighting conditions in two of the most popular ReID benchmarks: Market1501 and DukeMTMC-ReID. Experiments demonstrate that our algorithm outperforms other state-of-the-art works and is particularly potent in handling images under extremely low light.

2. We proposed a Teacher-Student GAN model to solve the cross-modality person ReID problem. It adopts different domains and guides the ReID backbone. Unlike other GAN-based models, the proposed model only needs the backbone module at the test stage, making it more efficient and resource-saving. To showcase our model’s capability, we did extensive experiments on the newly-released SYSU-MM01 and RegDB ReID benchmark and achieved superior performance to the state-of-the-art methods.
3. We propose a novel two-stream network that can solve the cross-resolution person ReID problem. It contains a lightweight resolution association ReID feature transformation (RAFT) module and a self-weighted attention (SWA) ReID module to evaluate features under different resolutions. Comprehensive experiments on five benchmarks show the validity of our method.
4. We design a novel unsupervised model, Syn-Person-Cluster ReID, to solve the unlabeled clothing change person ReID problem. We develop a purely unsupervised pipeline equipped with synthetic augmentation on person images and feature restriction for the same person. Extensive experiments on clothing change ReID datasets show the out-performance of our methods.

## Acknowledgements

First and most sincerely, I would like to thank my supervisor, Professor Richard Yi Da Xu. As a Ph.D. student, it was my most fantastic luck to meet Richard. Richard is very hardworking, kind and striving for excellence, which has led me to learn from him continuously. In the past few years, he not only taught me knowledge and skills for academic research but also gave me great care and guidance in life. There is a famous saying in ancient China, "In ancient times those who wanted to learn would seek out a teacher, one who could propagate the doctrine, impart professional knowledge, and resolve doubts." I think Richard fits that quote perfectly. Thank you, professor.

I also want to thank my fellow labmates: Congzhentao Huang, Yang Li, Chen Deng, Wei Huang, Shuai Jiang, Haodong Chang, Xuan Liang, Ximeng Zhao, Caoyuan Li, Jason Traish, etc. We discussed the experiment details and innovations of each paper. We work together before conference deadlines sleeplessly. We also enjoyed the hotpot and movies on the weekend. We shared joys and pains from life and research. It is my pleasure to have such good friends in my past few years and future.

I would also like to thank the officers from GRS and SEDE of UTS. During the past years, they have helped me a lot with the admin and research progress. Thanks so much for their patience and kindness.

Sincerely, I must thank my parents, Feng Zhang and Jie Yin. When I was young, you taught me to be a hardworking and sincere person. This belief has permeated my life growing up to this day. I could not have gotten through those struggling times without you by my side. Your continuous encouragement and support are my magic bullets over those difficult problems. I also want to thank my lovely girlfriend, Yige Liu. We've known each other since high school. During the Ph.D.,

your continuous support and understanding is the indispensable reason for me to move forward.

Ziyue Zhang

# List of Publications

## Journal Papers

- J-1. **Zhang Z.**, Jiang S., Huang C., Li Y., Xu R. Y. D. (2021). RGB-IR cross-modality person ReID based on teacher-student GAN model, Pattern Recognition Letters, 150, 155-161.
- J-2. **Zhang Z.**, Jiang S., Huang C., Xu R. Y. D., Unsupervised clothing change adaptive person ReID, IEEE Signal Processing Letters

## Conference Papers

- C-1. **Zhang Z.**, Xu, R. Y. D., Jiang S., **Li Y.**, Huang C., Deng C., Illumination Adaptive Person ReID based on Teacher-Student Model and Adversarial Training, accepted by ICIP, 2020.
- C-2. **Zhang Z.**, Jiang S., Huang C., Xu R. Y. D., Resolution-Invariant Person Reid Based On Feature Transformation And Self-Weighted Attention, 2021 IEEE International Conference on Image Processing (ICIP), 2021.
- C-3. Huang C., Jiang S., Li Y., **Zhang Z.**, Traish J., Deng C., Ferguson S., Xu R. Y. D., End-to-end Dynamic Matching Network for Multi-view Multi-person 3d Pose Estimation, accepted by ECCV, 2020.
- C-4. Li Y., Li K., Jiang S., **Zhang Z.**, Huang C., Xu R. Y. D., Geometry-driven self-supervised method for 3D human pose estimation, In Proceedings of the AAAI Conference on Artificial Intelligence 2020.

# Contents

Certificate	ii
Abstract	iii
Acknowledgments	v
List of Publications	vii
List of Figures	xiii
List of Tables	xiv
<b>1 Introduction</b>	<b>1</b>
1.1 Aims and Motivations . . . . .	1
1.2 Literature Review . . . . .	4
1.2.1 Overview . . . . .	4
1.2.2 Traditional person ReID . . . . .	5
1.2.3 External changes of person ReID . . . . .	9
1.2.4 Internal changes of person ReID . . . . .	11
1.3 Thesis Structure . . . . .	13
<b>2 Illumination Adaptive Person ReID Based on Teacher- student Model and Adversarial Training</b>	<b>15</b>
2.1 Introduction . . . . .	15
2.2 Related work . . . . .	17
2.2.1 Traditional person ReID . . . . .	17



2.2.2	Illumination related person ReID . . . . .	17
2.2.3	Adversarially training for discrete feature learning . . . . .	18
2.2.4	Teacher-Student model . . . . .	18
2.3	Method . . . . .	18
2.3.1	Backbone . . . . .	20
2.3.2	Teacher-Student model for person ReID . . . . .	21
2.3.3	Teacher-Student model for illumination classification . . . . .	22
2.3.4	Illumination variation adaptive module . . . . .	22
2.3.5	Training and testing . . . . .	23
2.4	Experiments and results . . . . .	25
2.4.1	Reid dataset under different illumination condition . . . . .	25
2.4.2	Implementation details . . . . .	25
2.4.3	Comparison with state-of-the-art methods . . . . .	27
2.4.4	Ablation study . . . . .	28
2.4.5	Results on original illumination datasets . . . . .	30
2.5	Conclusion . . . . .	31
<b>3</b>	<b>RGB-IR Cross-modality Person ReID Based on Teacher- student GAN Model</b>	<b>33</b>
3.1	Introduction . . . . .	33
3.2	Related work . . . . .	36
3.2.1	RGB-RGB Person ReID . . . . .	36
3.2.2	RGB-IR Cross-modality Person ReID . . . . .	36
3.2.3	GAN in Person ReID . . . . .	37
3.2.4	Teacher-Student Model in Cross-modality Tasks . . . . .	37

3.3	Method . . . . .	38
3.3.1	Overview . . . . .	38
3.3.2	RGB-IR Image Generation Module . . . . .	39
3.3.3	ReID Backbone Module . . . . .	40
3.3.4	RGB-IR Teacher-Student Module . . . . .	42
3.3.5	Training and Testing . . . . .	44
3.4	Experiment . . . . .	45
3.4.1	Dataset and Evaluation Protocol . . . . .	45
3.4.2	Implementation Details . . . . .	46
3.4.3	Comparison with State-of-the-art Methods on SYSU-MM01 . . . . .	47
3.4.4	Comparison with State-of-the-art Methods on RegDB . . . . .	47
3.4.5	Ablation Study . . . . .	47
3.4.6	Analysis of TS Loss Parameters . . . . .	50
3.4.7	Analysis of Single Modality Results . . . . .	50
3.4.8	Visualization of Results . . . . .	51
3.4.9	Visualization of Generated Images . . . . .	52
3.5	Conclusion . . . . .	52
<b>4</b>	<b>Resolution-invariant Person ReID Based on Feature Transformation and Self-weighted Attention</b>	<b>53</b>
4.1	Introduction . . . . .	53
4.2	Related work . . . . .	54
4.3	Method . . . . .	56
4.3.1	Backbone . . . . .	57
4.3.2	Resolution association ReID feature transformation module . . . . .	57

4.3.3	Self-weighted attention ReID module . . . . .	59
4.4	Experiments . . . . .	61
4.4.1	Dataset and Evaluation Protocol . . . . .	61
4.4.2	Implementation Details . . . . .	61
4.4.3	Comparison with state-of-the-art methods . . . . .	62
4.4.4	Ablation study . . . . .	63
4.5	Conclusion . . . . .	64
<b>5</b>	<b>Unsupervised Clothing Change Adaptive Person ReID</b>	<b>65</b>
5.1	Introduction . . . . .	65
5.2	Related work . . . . .	67
5.2.1	Conventional Person ReID . . . . .	67
5.2.2	Unsupervised Person ReID . . . . .	67
5.2.3	Clothing Change Person ReID . . . . .	69
5.2.4	Data Augmentation in Person ReID . . . . .	70
5.3	Proposed Method . . . . .	70
5.3.1	Overview of Pipeline . . . . .	70
5.3.2	Clothing Change Person Image Augmentation . . . . .	72
5.3.3	Cluster Contrast and Update Procedure . . . . .	72
5.3.4	Self Identity Constraint . . . . .	74
5.3.5	Whole Train Process . . . . .	74
5.4	Experiments . . . . .	74
5.4.1	Implementation Details . . . . .	74
5.4.2	Datasets and Evaluation Protocols . . . . .	76
5.4.3	Comparison With the State-of-The-Art . . . . .	77

5.4.4 Ablation Study . . . . .	78
5.5 Conclusion . . . . .	81
<b>6 Conclusions and Future Work</b>	<b>83</b>
6.1 Conclusions . . . . .	83
6.2 Future Work . . . . .	84
<b>Bibliography</b>	<b>86</b>

# List of Figures

2.1	The architecture overview of our TS-D model. . . . .	19
2.2	Illumination augmented dataset. . . . .	26
3.1	Example of RGB person images at night. . . . .	33
3.2	The example of RGB-IR cross-modality ReID. . . . .	34
3.3	The whole model structure of TS-GAN model. . . . .	38
3.4	Examples of R10 IR query images. . . . .	51
3.5	Examples of generated images on SYSU-MM01. . . . .	52
4.1	The architecture overview of FTWA Network. . . . .	56
4.2	The structure of RAFT module. . . . .	58
5.1	The whole pipeline of Syn-Person-Cluster. . . . .	71

# List of Tables

2.1	Comparison of SotA illumination ReID methods including extremely low light. . . . .	27
2.2	Comparison of SotA illumination ReID methods excluding extremely low light. . . . .	28
2.3	Different Setting Results on dataset including extremely low light. . .	29
2.4	Different Setting Results on dataset excluding extremely low light. . .	29
2.5	Compare results on original dataset. . . . .	31
3.1	Comparison on SYSU-MM01. . . . .	45
3.2	Comparison on RegDB. . . . .	48
3.3	Results of different settings on SYSU-MM01. . . . .	48
3.4	Performance with different weights for TS loss. . . . .	50
3.5	Performance of pretrained model on single modality dataset. . . . .	51
4.1	Comparison with state-of-the-art MLR ReID methods. . . . .	62
4.2	Ablation study on MLR-CUHK03 dataset. . . . .	63
5.1	Comparison on PRCC and VC-Clothes. . . . .	77
5.2	Self comparison on PRCC dataset. . . . .	78
5.3	Sampling method comparison on PRCC dataset. . . . .	80
5.4	Analysis of $\varepsilon$ and $M$ value on PRCC dataset. . . . .	81