**FYP Proposal**

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Content

[**Objectives** 2](#_Toc509668927)

[**Introduction** 2](#_Toc509668928)

[**Methodogy**  4](#_Toc509668929)

[**Project Schedule** 5](#_Toc509668930)

[**One-year Internship** 6](#_Toc509668930)

# **Objectives**

* To understand the situation of face recognition and the main challenge of Low-resolution face recognition problem.
* To grasp the principle face analysis and image processing methods, like PCA, LDA, SIFT, HoG and so on.
* To implement a conventional method and a learning-based method to solve the low-resolution face recognition problem. Conduct experiment on different benchmark datasets to analyze the performance of each method.
* To learn how to think independently and work effectively.
* To learn how to apply knowledge to achieve the objectives of the project.
* To learn how to manage a project and deliver a high-quality project result.

# **Introduction**

Automatic face recognition has been widely researched by many different researchers in recent years. The non-intrusive nature of human faces can be used to identify subjects in different areas, such as security, law enforcement and surveillance [1]. The current algorithms perform satisfactorily on the standard resolution images with the changes in illumination and pose, this makes a great contribution in the development of face ID and other applications.

Though many previous works make great contribution on face recognition, it remains many unsolved problems uncontrolled scenarios [2]. Due to the increase of the number of surveillance cameras for the application in law enforcement, the motivation on research in the relationship between image resolution and the face recognition accuracy are increasing. As the range of the surveillance camera’s view is wide, the captured faces on it are in a small part of the scene with poor quality [3]. These small and poor-quality images are low-resolution images. As the low-resolution images are attributed to the factors of misalignment, noise affection, lack of effective features and dimensional mismatch [4], the performances of face recognition methods drop significantly. Different studies [ 5, 6, 7, 8, 9] show that the general minimum image resolution requirement of existing face recognitions is 32x32px, the recognition performance degrades strongly when the resolution is lower than this threshold. This is low-resolution face recognition problem.

To address this problem, both conventional method and learning-based method will be designed and implemented. The conventional method will base on Yang’s work [10] to find the relationship between low-resolution image features and high-resolution image feature when projecting these features to a latent subplace. The deep-learning-based method will base on Yang’s work [11], to obtain the mapping from a low-resolution image to corresponding high-resolution image. The evaluation on these methods will base on the experiment result in three benchmark datasets, Yale face dataset [12], AR face dataset [13] and FERET face dataset [14].

# **Methodology**

* 1. Overview

In this project, some essential techniques will be utilized to analyze and solve the low-resolution face recognition (LRFR) problem. A conventional approach focuses on embedding low-resolution (LR) probe images and high-resolution (HR) gallery images to a latent subplace and a learning-based approach focuses on exploiting the complementary information from LR images to HR images. The detailed descriptions on these two methods will be discussed on section 3.2 and section 3.3 respectively. After that, the experimental methodologies will be discussed in session 3.4.

* 1. Discriminative Multidimensional Scaling Method

The HR images and LR images of the same subject have the identity information [4]. A direct method for solving LRFR problem are multidimensional scaling (MDS) [ 20 low review]. It uses PCA coefficients [ ] and LBP codes [] as input features, and embeds the LR probe images and the HR gallery in a latent common space such the distance of same subject are minimized. The two transformation functions are constructed to mapping LR images and HR images to common subspace respectively. The iterative majorization algorithm are used to find by solving the proposed lost function. Yang et.al. [ ] propose a discriminative multidimensional scaling method to improve the original MDS method by adding interclass constraint, which can improve the robustness of the original method. In conclusion, this is a structure-based method focuses on constructing the relationship between LR images and HR images by projecting them to a latent space to solve LRFR problem {review}.

* 1. Super-resolution Method

Super-resolution is a signal processing-based method. It exploits the supplemental information from a set of low-resolution images to recover the high-resolution information [x]. The super-resolution problem has ill-posed nature, which results in the super-resolution result is high dependently on the image prior [ ]. And most of super-resolution algorithms are designed for image visual enhancement, but not face recognition. To address this problem, Huang [xx] proposed a super-resolution method for face recognition by using the nonlinear mappings on coherent features. It trains a radial basis functions model to compute super-resolved coherent features from an input LR image. This method use the canonical correlation analysis [xxx] to project the LR and HR PCA [ ] features as coherent feature. This can maximize the correlation between LR and HR pair [30]. To connect the LR features and HR features directly, PBFs are used to construct the nonlinear mapping between LR and HR feature, so that the coherent super-resolution result can be obtained by a learnt PBFs for recognition. Finally, a NN Classifier [49] are used to recognition the super-resolution features obtained from a single LR image. Consequently, this method uses a learnt super-resolution feature from a LR image based on the mapping between LR features and HR features to solve LRFR problem.

[x] Recovering Realistic Texture in Image Super-resolution by Deep Spatial Feature Transform

[xx] super-resolution method for face recognition using nonlinear mappings on coherent features

* 1. Experiment

**Baseline**

To analyze the performance of the methods discussed in section 3.2 and section 3.3, a baseline method need to be provided. The classic face recognition method proposed in [ ] will be used as the baseline in this project. This method uses Eigenface for face recognition and deliver high performance in standard face resolution.

**Benchmark datasets**

Three benchmark datasets, Yale face dataset, FERET face dataset and AR face dataset will be used for conducting LRFR experiment. The Yale face dataset contains 165 frontal face images of 15 people with different lighting and expressions. The FERET face dataset contains over 14000 face images with different poses, expressions and lighting conditions. While the AR dataset contains 2600 frontal face images of 100 persons with simple background. With these three datasets, the performance of each method can be estimated precisely.

**Image preprocessing**

As the poses of galley images are different. We need to align the images in the same class before training and recognition. The MTCNN [ 21 DMS] will be employed as it can provide the coordinates of face landmark. We will locate the landmarks manually to certain position to make sure the images are aligned with each other in the same class. As the gallery images are HR faces, we need to generate LR images for experiment. The Bicubic interpolation [ ] will be used to down-sampling the gallery images to LR images for training and up-sampling the LR images to HR images for recognition.

**Recognition**

As the LR images are generated in the preprocessing step, the datasets contain the HR gallery images and generated LR images. For each dataset, 50% images will be used for training and the others will be used for testing. The performance of each method will base on the recognition accuracy in each dataset.

The Discriminative Multidimensional Scaling method [10] will sho

# **Project Schedule**

* 1. Working schedule

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| --- | --- | --- |
| **Key time** | **Task** | **Remark** |
| September | Implement classic face recognition approach, PCA [ ] ,to analyze the relationship between image resolution and recognition performance. |  |
| October | Literature review on Low-Resolution Problem, especially for multidimensional scaling approach and super-resolution approach. | Complete the FYP proposal |
| November | Implement the conventional method mentioned in section 3.2. Conduct experiment on Yale face dataset, AR face dataset and FERET dataset. |  |
| December | Prepare interim report and interim presentation | Complete the conventional method |
| 08/01/2019 | Interim project report submission |  |
| 12/01/2019 | Interim project presentation |  |
| February | Implement the deep-learning-based method mentioned in section 3.3. Conduct experiment on Yale face dataset, AR face dataset and FERET dataset | Complete the deep-learning-based method |
| March | Analyze the result of conventional method and deep-learning-based method, focus on solving the limitation of these two methods. |  |
| April | Prepare for the project final report, final presentation and demonstration |  |
|  | Final presentation |  |
|  | Project Demonstration |  |

* 1. Routine work schedule

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| --- | --- |
| Frequency | Routine work |
| Every week | Individual meeting with supervisor, update the process of project, discuss the problem I meet |
| Every week | Group meeting with PhD students and other FYP students, discuss the recent top conference paper |
| Every week | Logbook recording |

# **References**

[1] Evaluation of image resolution and super-resolution on face recognition performance

[2] Face Recognition: A Literature Survey

[3] Semi-supervised intelligent surveillance system for secure environments 2010

[4] Low-resolution face recognition: a review

[5] B. Boom, G. Beumer, L. Spreeuwers, and R. Veldhuis. The effect of image resolution on the performance of a face recognition system. In Proceedings of the Ninth International Conference on Control, Automation, Robotics and Vision, pages 409–414, 2006.

[6] J. Wang, C. Zhang, and H. Shum. Face image resolution versus face recognition performance based on two global methods. In Proceedings of Asia Conference on Computer Vision (ACCV’04), 2004

[7] J. Czyz and L. Vandendorpe. Evaluation of LDA-based face verification with respect to available computational resources. In Int’l Workshop on Pattern Recognition in Information Systems, 2002.

[8] F. W. Wheeler, X. Liu, and P. Tu. Multi-frame super-resolution for face recognition. In BTAS, 2007

[9] M. S. Keil, A. Lapedriza, D. Masip, and J. Vitria. Preferred spatial frequencies for human face processing are associated with optimal class discrimination in the machine. PLoS ONE, 3(7), 2008.

[10] DMS

[11] Super-Resolving Very Low-Resolution Face Images with Supplementary Attributes

[12] Yale

[13] AR

[14] FERET

. A meta-analysis of face recognition covariate