HUMAN RE-IDENTIFICATION USING SIAMESE CONVOLUTIONAL NEURAL NETWORK ON NVIDIA GEFORCE RTX 2060

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DEDICATION

Parents who raised me up

Sister who were raised with me

Friends who shared their shoulders with me

Supervisors who lead me

Humanity

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ABSTRACT

Human reidentification in multiple cameras with disjoint views is to match a pair of humans appearing in different cameras with non-overlapping views. Human reidentification has been extensively studied in recent years because it plays a significant role in many applications such as human tracking and video retrieval. However, human re-identification is a challenging task due to varying factors such as color, pose, viewpoint, lighting conditions, low resolution and partial occlusion. Most of the existing methods in handling human re-identification task are based on various handcrafted features and metric learning. However, hand-crafted features method requires expert knowledge and requires a lot of time to tune the features and metric learning methods are not powerful enough to exploit the nonlinear relationship of samples. The main objective of this thesis is to implement Siamese Convolutional Neural Network (SCNN) for person re-identification task in multiple cameras on the NVIDIA® GeForce RTX™ 2060 platform, including person detection. This continuous with validation of the applicability of SCNN and compare with existing techniques. In this work, global and local features of human images are extracted from SCNN. The proposed SCNN consists of two identical Convolution Neural Networks with common parameters that can automatically learn hierarchical feature representations from image pixels directly which has advantages than the hand-crafted design and metric learning method. Experiments were conducted with CUHK02 offline database with non-overlapping cameras. The proposed technique demonstrated a person re-identification using SCNN on the NVIDIA® GeForce RTX™ 2060 platform.

ABSTRAK

Pengenalpastian manusia dalam beberapa kamera dengan pandangan yang tidak sama adalah untuk memadankan sepasang manusia yang muncul dalam kamera yang berbeza dengan pandangan yang tidak bertindih. Pengenalpastian manusia telah banyak dikaji dalam beberapa tahun kebelakangan ini kerana memainkan peranan penting dalam banyak aplikasi seperti penjejakan manusia dan pengambilan video. Walau bagaimanapun, identifikasi semula manusia adalah tugas yang mencabar kerana pelbagai faktor seperti warna, pose, sudut pandang, keadaan pencahayaan, resolusi rendah dan oklusi separa. Sebilangan besar kaedah yang ada dalam menangani tugas mengenal pasti semula manusia adalah berdasarkan pelbagai ciri handcraft dan pembelajaran metrik. Walau bagaimanapun, kaedah ciri handcraft memerlukan pengetahuan pakar dan memerlukan banyak masa untuk menyesuaikan ciri dan kaedah pembelajaran metrik tidak cukup kuat untuk mengeksploitasi hubungan sampel yang tidak linear. Objektif utama thesis ini adalah untuk melaksanakan Siamese Convolutional Neural Network (SCNN) untuk tugas pengenalan semula orang dalam beberapa kamera pada platform NVIDIA® GeForce RTX ™ 2060, termasuk pengesanan orang. Ini berterusan dengan pengesahan penerapan SCNN dan bandingkan dengan teknik yang ada. Dalam thesis ini, ciri global dan tempatan dari gambar manusia diekstrak dari SCNN. SCNN yang dicadangkan terdiri daripada dua Convolutional Neural Network yang serupa dengan parameter umum yang secara automatik dapat mempelajari perwakilan ciri hierarki dari piksel gambar secara langsung yang mempunyai kelebihan daripada reka bentuk handcraft dan kaedah pembelajaran metrik. Eksperimen dilakukan dengan data CUHK02 secara offline dengan kamera yang tidak bertindih. Teknik yang dicadangkan menunjukkan pengenalan semula seseorang menggunakan SCNN pada platform NVIDIA® GeForce RTX ™ 2060.

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INTRODUCTION

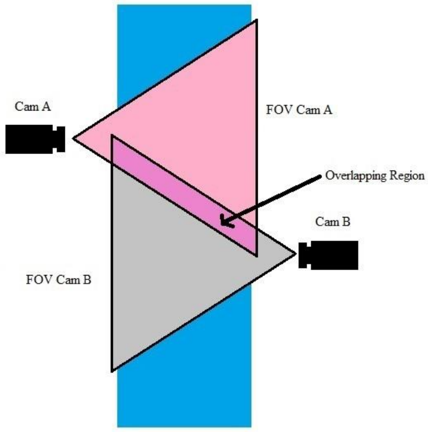
1.1 Overview of Human Re-identification

The demand for the installation of closed-circuit television (or CCTV) camera networks has increased recently to address variety of security issues. CCTV camera networks are being installed at home, office, shopping centers, sport centers and airports. However, it is not an easy task for human operators to continually observe CCTV over multiple cameras especially when tracking human of interest. Hence, a computer vision system is required to assist human operators in recognizing individual humans throughout an entire camera network. The problem of observing a human of interest across multiple camera networks is known as a human reidentification problem [1–6].

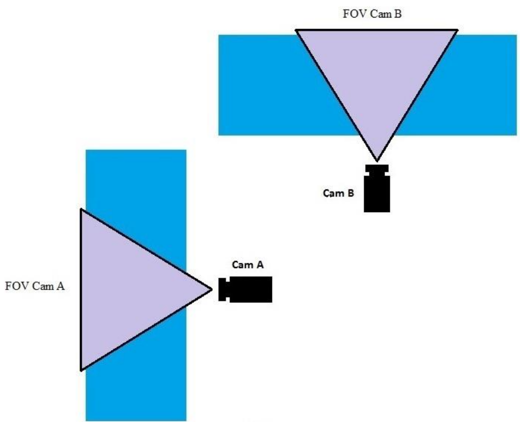
Human reidentification divided into two categories which are appearance-based approach and biometric [7]. Example of biometric approaches for reidentification are face [8], gait [9], iris [10] and fingerprint recognition [11]. However, iris and fingerprint recognition are not suitable for reidentification at wide area video surveillance field of view because recognition of iris and fingerprint requires human cooperation in the monitored environment or high-resolution images, which are not available in common surveillance systems [12]. Compared to iris and fingerprint recognition, gait and face recognition do not require human cooperation and can operate without interrupting or interfering with the human's activity [13]. However, face and gait recognition will only achieve good performance of recognition when some conditions and constraints are achieved. Unfortunately, some of these constraints are not satisfied by most deployed surveillance systems [7].

Biometric approaches are mainly dependent on the camera view and orientation of the human with the camera. Based on the reasons above, biometric approaches are not very suitable for human reidentification in surveillance systems.

Appearance based approaches for human reidentification are more suitable for wide area video surveillance systems because it is less constrained than biometric approaches and more adapted to video surveillance requirements such as does not require human cooperation, low resolution images and no specific conditions and constraint are required [7]. Human reidentification with appearance-based approaches is a central task in surveillance system which is used to match a pair of humans appearing in different cameras with non-overlapping views [14]. The difference between general camera setup with overlapping views and non-overlapping views are shown in Figure 1.1. In most surveillance systems, cameras with nonoverlapping views are applied because it is impossible to cover all the area of interest by using multiple overlapping cameras due to economic and computational reasons. Surveillance over wide-areas such as area of law enforcement, airport and office buildings requires a network of cameras that are sparsely distributed without overlapping field of views. Human reidentification has been extensively studied in recent years due to its various applications such as in surveillance systems with nonoverlapping views.



(a)



(b)

Figure 1.1 Camera network with (a) overlapping views and (b) non-overlapping views.

1.2 Problem Statement

Human reidentification problem is a challenging task and received a great attention of researchers in recent years. In most practical scenarios, the gap between camera views in a surveillance system is quite large due to economic and computational reason. Since images obtained from surveillance cameras have low resolution region of interest (centering humans) which is around 128x48 pixels because taken from long distances, human biometric information such as face and gait are not suitable to be used for reidentification purpose. Therefore, appearance of human becomes an important feature to solve reidentification task. Moreover, appearance of a human varies across multiple cameras due to difference in viewpoint, pose and illumination. Moreover, low resolution image has fewer useful details for classification and especially in non-overlapping views [15–21]. Thus, a better approach is needed for handling the low-resolution issue to increase the accuracy and speed of human reidentification task.

1.3 Objective

Based on the current issues surrounding human reidentification across multiple cameras, the two main objectives of this research can be expressed as follows:

1. To implement SCNN for human reidentification task in multiple cameras, including human detection.

2. To validate the applicability of SCNN in NVIDIA® GeForce RTX™ 2060 and compare with existing techniques.

1.4 Scope

This research focuses on developing a human reidentification system. Hence in this research:

1. The process of human detection is in the scope of this work.

2. The common challenges such as illumination and viewpoint are considered in the proposed human reidentification system.

3. The human reidentification system is prototyped on a NVIDIA® GeForce RTX™ 2060.

4. The proposed work is based on Siamese Convolution Neural Network.

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