

SUPER-RESOLUTION OF CAR PLATE IMAGES USING GENERATIVE
ADVERSARIAL NETWORKS

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To my family and friends.

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ABSTRACT

Car plate recognition is used in traffic monitoring and control systems such as intelligent parking lot management, finding stolen vehicles, and automated highway toll. Car plate recognition consists of several stages of processing namely, car plate localization, extraction, and recognition which consists of Optical Character Recognition (OCR). However, in practice, Low-Resolution (LR) images or videos are widely used in surveillance systems. In low resolution surveillance systems, the car plate text is often illegible. Other than that, small car plate due to the distance and illumination cause the car plate recognition to fail as well. Super-Resolution (SR) techniques can be used to improve the car plate quality by processing a series of LR images into a single High-Resolution (HR) image. Today, the best upscaling algorithms cannot effectively reconstruct data that does not exist. Recovering the HR image from a single LR is still an ill-conditioned problem for SR. Previous methods always minimize the mean square loss in order to improve the peak signal to noise ratio(PSNR). However, minimizing the mean square loss leads to overly smoothed reconstructed image. In this project, Generative Adversarial Networks (GANs) based SR is proposed to reconstruct the LR images into HR images. Besides that, perceptual loss is proposed to solve the smoothing issue. The quality of the GAN based SR generated images will be compared to existing techniques such as bicubic, nearest and Super-Resolution Convolution Neural Network (SRCNN). The results show that the reconstructed images using GANs based SR achieve better results in term of perceptual quality compared to previous methods.

ABSTRAK

Pengenalan plat kereta digunakan secara meluas dalam sistem pengawasan lalu lintas dan kawalan seperti pengurusan tempat letak kereta yang pintar, mencari kenderaan yang dicuri, dan jalan tol automatik. Pengiktirafan plat kereta terdiri daripada beberapa peringkat pemprosesan iaitu penyetempatan, pengekstrakan dan pengenalan plat kereta yang terdiri daripada Pengiktirafan Abjed Optik(OCR). Walau bagaimanapun, secara praktikal, imej atau video resolusi rendah (LR) digunakan secara meluas dalam sistem pengawasan. Dalam sistem pengawasan resolusi rendah, teks plat kereta sering tidak boleh dibaca. Selain itu, plat kereta kecil disebabkan oleh jarak, pencahayaan dan sebagainya akan menyebabkan ujian plat kereta tidak dapat dibaca untuk mengiktiraf juga. Teknik Super-Resolution (SR) digunakan untuk meningkatkan mutu plat kereta dengan memajukan satu siri imej LR kepada satu imej Resolusi Tinggi (HR) tunggal. Hari ini, algoritma upscaling terbaik juga tidak dapat membina semula data yang tidak wujud dengan berkesan. Memulihkan imej HR dari LR tunggal masih merupakan masalah yang tidak berhati-hati untuk SR. Kaedah sebelumnya sentiasa meminimumkan kerugian MSE bagi meningkatkan isyarat puncak kepada nisbah hingar (PSNR). Walau bagaimanapun, meminimumkan kerugian kuantiti MSE membawa kepada imej yang dibina semula dengan lancar. Dalam projek ini, SR berdasarkan Generatif Adversarial Networks (GANs) dicadangkan untuk membina semula imej LR ke dalam imej HR. Di samping itu, kerugian persepsi dicadangkan untuk menyelesaikan isu lancar. Kualiti imej SR yang dihasilkan oleh GAN akan dibandingkan dengan teknik sedia ada seperti bicubic, nearest dan SRCNN. Hasilnya menunjukkan bahawa imej yang dibina semula menggunakan SR berasaskan GAN mencapai hasil yang lebih baik dari segi kualiti persepsi berbanding dengan kaedah terdahulu.

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LIST OF ABBREVIATIONS

CGAN	-	Conditional Generative Adversarial Networks
CNN	-	Convolutional Neural Network
GAN	-	Generative Adversarial Networks
HR	-	High Resolution
LLE	-	Locally Linear Embedding
LR	-	Low Resolution
MAA	-	Malaysia Automotive Association
MISR	-	Multi Images Super Resolution
MRF	-	Markov Random Field
MSE	-	Mean Square Error
OCR	-	Optical Character Recognition
PSNR	-	Peak Signal Noise Ratio
SISR	-	Single Image Super Resolution
SNMF	-	Semi-nonnegative Matrix Factorization
SR	-	Super Resolution
SSIM	-	Structural Similarity

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CHAPTER 1

INTRODUCTION

1.1 Problem Background

Today, the population and economy of Malaysia have grown significantly from year to year. As a result, the number of vehicles registered in Malaysia have shown significant growth as well. In 2017, the Malaysia Automotive Association (MAA) reported that the total number of vehicle registered in Malaysia reached 28.2 million [9]. The complexity of traffic management becomes a challenge from year to year. Many research have been carried on improving the efficiency and accuracy of vehicle car plate recognition. The car plate recognition algorithms are widely used in traffic monitoring and control systems such as intelligent parking lot management, finding stolen vehicles, traffic law enforcement, automated toll management system for highways, bridges, tunnels and other fields.

In general, car plate recognition consists of four sub-stages, which are car plate localization, car plate extraction, character segmentation and character recognition [10]. In practice, car plate is not the only object in an image that is captured by the camera. Road, cars, people and etc. will also be included in the image as well. Car plate localization stage is designed to analyze the input image and locate the region of interest, which is the car plate. Next is the car plate extraction stage. This stage is focused on processing the region of interest to extract the car plate. After extraction stage, the acquired extracted area will be the input to the segmentation stage. In the segmentation stage, the image from the extraction stage will be split into several unique parts, where each part contains only one character. Lastly, in the recognition stage, a classifier will be used to recognize the characters from the segmentation stage. Some common classifiers used are Naïve Bayes algorithm [11, 12], support vector machine [13] and neural networks [14]. The performance of a car plate recognition system relies on the accurateness of the car plate recognition algorithm and the quality of the

images acquisition. However, in practice, Low-Resolution (LR) images or videos are widely used in surveillance systems. In low resolution surveillance systems, the car plate text is often illegible due to the distance, illumination and perspective distortion.

Super-Resolution (SR) techniques can be used to improve car plate image quality by processing a single LR image or a series of LR images into a single High-Resolution (HR) image. Besides that, SR gives an alternative way to solve the limitation of images acquisition from hardware by using software processing. There have two type of SR techniques, which are Single-Image Super-Resolution (SISR) and Multi-Image Super-Resolution (MISR) techniques. SISR techniques can be further categorized into interpolation-based methods [15], reconstruction-based methods [16] and example learning-based methods [17]. For MISR, it can be further categorized into frequency domain method and spatial domain method [18].

1.2 Problem Statement

Existing SISR techniques especially deep learning methods [19, 20] are able to obtain remarkable performance in terms of PSNR. However, the challenge faced by existing SISR techniques is that the reconstructed HR image from single LR image is problematic and it is an ill-conditioned problem [21].

Other than that, at large magnification factors, the finer texture details of the super resolved images is not able to be reconstructed from a single LR image due to the high frequency information loss during large upsampling process which makes the one-to-many mapping becomes more challenging. As a result, the super resolved images with large magnification factor will be fuzzy, overly smooth, and unnatural in appearance [22].

In addition, most of the SR methods today mainly focus on minimizing the mean square loss, in order to achieve better performance in terms of PSNR. However, such methods always lead to overly smooth appearance on the reconstructed images.

1.3 Objective

The objectives of this project are:

- To proposed a GAN based SISR model to reconstruct the LR image into a single HR image.
- To maintain the quality of super resolved images with large upscaling factor.
- To evaluate the performance of the proposed GANs based SR generated images with existing techniques.

1.4 Scope of Work

In this project, the main focus is to generate a realistic car plate image with better perceptual quality at the car plate numbers so that it can improve the accuracy on the recognition. Hence, the focus will be on the perceptual quality of GANs based SR generated images. The computational resources, efficiency and performance will not be part of the work. The image quality metric such as Peak to Noise Ratio (PSNR) and Structural Similarity (SSIM) are used to evaluate the quality of the generated images. In addition, the accuracy or the performance of the car plate recognition on GANs based SR generated images will not be further explored.

The main research will be carried on the SISR techniques while MISR techniques will not be further discussed. Current SISR techniques are analyzed and compared in details in Chapter 2.

Car plate datasets which is adopted from [23] to train the model. 640 images are chosen and downsampled to 96x96 resolution as the training dataset. For evaluation dataset, 10 images are chosen. All the images are evaluated at upscaling factor of 4 only.

Python is the main programing language used to code the GANs based SR model. Besides, Tensorflow platform is used as the deep learning library.

1.5 Organization

The organization of this thesis consists of six chapters.

Chapter one describes the project background, problem statement, objectives, scope of work and the outline of this thesis.

Chapter two describes the literature review on the existing SISR techniques, for example interpolation-based methods, reconstruction-based methods and example learning-based methods. Furthermore, the comparison of the existing SISR techniques will be included in this chapter as well. Next, the overview of the GANs model and its application is discussed as well.

Chapter three discusses the research methodology of this project, especially the overview of the GANs model. The tools used in this project will be discussed as well. In addition, the image quality metric used in this project is further discussed in this chapter as well.

Chapter four illustrates the proposed design. The architecture of the proposed design will be discussed. The training details will be covered as well in this chapter.

Chapter five shows the results of this project. Discussion on the result is carried out in this chapter.

Chapter six, which is the last chapter in this thesis, is the conclusion of this project. Some potential future work is discussed in this chapter.

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