# SUPER-RESOLUTION OF CAR PLATE IMAGES USING GENERATIVE ADVERSARIAL NETWORKS

TAN KEAN LAI

UNIVERSITI TEKNOLOGI MALAYSIA

# SUPER-RESOLUTION OF CAR PLATE IMAGES USING GENERATIVE ADVERSARIAL NETWORKS

TAN KEAN LAI

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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.

# TABLE OF CONTENTS

# LIST OF TABLES

# LIST OF FIGURES

## 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 |

## LIST OF APPENDICES

# 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.

## REFERENCES


1. Bevilacqua, M. *Algorithms for super-resolution of images and videos based on learning methods*. Ph.D. Thesis. Université Rennes 1. 2014.

2. Deng, L.-J., Guo, W. and Huang, T.-Z. Single-image super-resolution via an iterative reproducing kernel hilbert space method. *IEEE Transactions on Circuits and Systems for Video Technology*, 2016. 26(11): 2001–2014.

3. Gong, M., He, K., Zhou, J. and Zhang, J. Single color image super-resolution through neighbor embedding. *Journal of computational information systems*, 2011. 7(1): 49–56.

4. Hardeep, P., Swadas, P. B. and Joshi, M. A survey on techniques and challenges in image super resolution reconstruction. *International Journal of Computer Science and Mobile Computing*, 2013. 2(4): 317–325.

5. Yang, J., Wright, J., Huang, T. and Ma, Y. Image super-resolution as sparse representation of raw image patches. *Computer Vision and Pattern Recognition, 2008. CVPR 2008. IEEE Conference on*. IEEE. 2008. 1–8.

6. Dong, C., Loy, C. C., He, K. and Tang, X. Image super-resolution using deep convolutional networks. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2016. 38(2): 295–307.

7. Reed, S., Akata, Z., Yan, X., Logeswaran, L., Schiele, B. and Lee, H. Generative adversarial text to image synthesis. *arXiv preprint arXiv:1605.05396*, 2016.

8. Isola, P., Zhu, J.-Y., Zhou, T. and Efros, A. A. Image-to-image translation with conditional adversarial networks. *arXiv preprint arXiv:1611.07004*, 2016.

9. Lee, J. Vehicle registrations in Malaysia hit 28.2 million units, 2017. URL `https://paultan.org/2017/10/03/vehicle-registrations-in-malaysia-hit-28-2-million-units`.

10. Hurtik, P. and Vajgl, M. Automatic license plate recognition in difficult conditions - Technical report. *2017 Joint 17th World Congress of International Fuzzy Systems Association and 9th International Conference*

*on Soft Computing and Intelligent Systems (IFSA-SCIS)*. 2017. 1–6. doi: 10.1109/IFSA-SCIS.2017.8023337.

11. Kurzynski, M. and Zolnierek, A. Sequential Pattern Recognition: Naive Bayes Versus Fuzzy Relation Method. *International Conference on Computational Intelligence for Modelling, Control and Automation and International Conference on Intelligent Agents, Web Technologies and Internet Commerce (CIMCA-IAWTIC'06)*. 2005, vol. 1. 1165–1170. doi:10.1109/CIMCA.2005.1631420.

12. Phung, S. L., Bouzerdoum, A., Chai, D. and Watson, A. Naive Bayes face-nonface classifier: a study of preprocessing and feature extraction techniques. *Image Processing, 2004. ICIP'04. 2004 International Conference on*. IEEE. 2004, vol. 2. 1385–1388.

13. Czajkowska, J., Rudzki, M. and Czajkowski, Z. A new fuzzy support vectors machine for biomedical data classification. *Engineering in Medicine and Biology Society, 2008. EMBS 2008. 30th Annual International Conference of the IEEE*. IEEE. 2008. 4676–4679.

14. Ram, R., Palo, H. K. and Mohanty, M. N. Recognition of fear from speech using adaptive algorithm with MLP classifier. *Circuit, Power and Computing Technologies (ICCPCT), 2016 International Conference on*. IEEE. 2016. 1–5.

15. Sarmadi, S. and Shamsa, Z. A new approach in single Image Super Resolution. *2016 6th International Conference on Computer and Knowledge Engineering (ICCKE)*. 2016. 78–81. doi:10.1109/ICCKE.2016.7802119.

16. Zhang, X., Zhou, W. and Duan, Z. Image super-resolution reconstruction based on fusion of K-SVD and semi-coupled dictionary learning. *2016 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA)*. 2016. 1–5. doi:10.1109/APSIPA.2016.7820691.

17. Timofte, R., De, V. and Gool, L. V. Anchored Neighborhood Regression for Fast Example-Based Super-Resolution. *2013 IEEE International Conference on Computer Vision*. 2013. ISSN 1550-5499. 1920–1927. doi:10.1109/ICCV.2013.241.

18. Zhang, H., Zhang, L. and Shen, H. A blind super-resolution reconstruction method considering image registration errors. *International Journal of Fuzzy Systems*, 2015. 17(2): 353–364.

19. Lai, W.-S., Huang, J.-B., Ahuja, N. and Yang, M.-H. Deep Laplacian Pyramid Networks for Fast and Accurate Super-Resolution. *arXiv preprint arXiv:1704.03915*, 2017.

20. Dong, C., Loy, C. C. and Tang, X. Accelerating the super-resolution convolutional neural network. *European Conference on Computer Vision*. Springer. 2016. 391–407.

21. Huang, S., Sun, J., Yang, Y., Fang, Y. and Lin, P. Multi-Frame Super-Resolution Reconstruction Based on Gradient Vector Flow Hybrid Field. *IEEE Access*, 2017. 5: 21669–21683.

22. Sajjadi, M. S., Schölkopf, B. and Hirsch, M. EnhanceNet: Single Image Super-Resolution through Automated Texture Synthesis. *arXiv preprint arXiv:1612.07919*, 2016.

23. Liang, E. Car Plate Dataset, 2017. URL `https://1drv.ms/f/s!AmSINa9nwX9Ch8gI7KQi_chzUyuQlA`.

24. Zhang, X. and Wu, X. Image interpolation by adaptive 2-D autoregressive modeling and soft-decision estimation. *IEEE Transactions on Image Processing*, 2008. 17(6): 887–896.

25. Chopade, P. and Patil, P. Single and Multi Frame Image Super-Resolution and its Performance Analysis: A Comprehensive Survey. *International Journal of Computer Applications*, 2015. 111(15).

26. Lai, C., Li, F., Li, B. and Jin, S. Single Image Super-Resolution via Classified Sparse Representation. *Embedded Software and Systems (ICESS), 2016 13th International Conference on*. IEEE. 2016. 159–163.

27. Yang, J., Wright, J., Huang, T. S. and Ma, Y. Image super-resolution via sparse representation. *IEEE transactions on image processing*, 2010. 19(11): 2861–2873.

28. Goto, T., Kawamoto, Y., Sakuta, Y., Tsutsui, A. and Sakurai, M. Learning-based super-resolution image reconstruction on multi-core processor. *IEEE Transactions on Consumer Electronics*, 2012. 58(3).

29. Rahim, A. N. A., Yaakob, S. N., Ngadiran, R. and Nasruddin, M. W. An analysis of interpolation methods for super resolution images. *2015 IEEE Student Conference on Research and Development (SCOReD)*. 2015. 72–77. doi:10.1109/SCORED.2015.7449432.

30. Dai, S., Han, M., Xu, W., Wu, Y. and Gong, Y. Soft edge smoothness prior for alpha channel super resolution. *Computer Vision and Pattern Recognition, 2007. CVPR'07. IEEE Conference on*. IEEE. 2007. 1–8.

31. Sarmadi, S. and Shamsa, Z. A new approach in single Image Super Resolution. *Computer and Knowledge Engineering (ICCKE), 2016 6th International*

*Conference on*. IEEE. 2016. 78–81.

32. Duanmu, C. and Zhao, D. A new super-resolution algorithm by interpolation in homogeneous areas. *Computer Science and Network Technology (ICCSNT), 2016 5th International Conference on*. IEEE. 2016. 716–719.

33. Zhang, X., Zhou, W. and Duan, Z. Image super-resolution reconstruction based on fusion of K-SVD and semi-coupled dictionary learning. *Signal and Information Processing Association Annual Summit and Conference (APSIPA), 2016 Asia-Pacific*. IEEE. 2016. 1–5.

34. Fattal, R. Image upsampling via imposed edge statistics. *ACM Transactions on Graphics (TOG)*. ACM. 2007, vol. 26. 95.

35. Sen, P. and Darabi, S. Compressive image super-resolution. *Signals, Systems and Computers, 2009 Conference Record of the Forty-Third Asilomar Conference on*. IEEE. 2009. 1235–1242.

36. Dong, W., Zhang, L., Shi, G. and Wu, X. Image deblurring and super-resolution by adaptive sparse domain selection and adaptive regularization. *IEEE Transactions on Image Processing*, 2011. 20(7): 1838–1857.

37. Dong, W., Zhang, L., Lukac, R. and Shi, G. Sparse representation based image interpolation with nonlocal autoregressive modeling. *IEEE Transactions on Image Processing*, 2013. 22(4): 1382–1394.

38. Shan, Q., Li, Z., Jia, J. and Tang, C.-K. Fast image/video upsampling. *ACM Transactions on Graphics (TOG)*, 2008. 27(5): 153.

39. Freeman, W. T., Jones, T. R. and Pasztor, E. C. Example-based super-resolution. *IEEE Computer graphics and Applications*, 2002. 22(2): 56–65.

40. Bevilacqua, M., Roumy, A., Guillemot, C. and Morel, M.-L. A. Neighbor embedding based single-image super-resolution using Semi-Nonnegative Matrix Factorization. *Acoustics, Speech and Signal Processing (ICASSP), 2012 IEEE International Conference on*. IEEE. 2012. 1289–1292.

41. Kim, K. I. and Kwon, Y. Single-image super-resolution using sparse regression and natural image prior. *IEEE transactions on pattern analysis and machine intelligence*, 2010. 32(6): 1127–1133.

42. He, H. and Siu, W.-C. Single image super-resolution using Gaussian process regression. *Computer Vision and Pattern Recognition (CVPR), 2011 IEEE Conference on*. IEEE. 2011. 449–456.

43. Salvador, J. and Pérez-Pellitero, E. Naive bayes super-resolution forest. *Proceedings of the IEEE International Conference on Computer Vision*. 2015.

325–333.

44. Schulter, S., Leistner, C. and Bischof, H. Fast and accurate image upscaling with super-resolution forests. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 2015. 3791–3799.

45. Dai, D., Timofte, R. and Van Gool, L. Jointly Optimized Regressors for Image Super-resolution. *Computer Graphics Forum*. Wiley Online Library. 2015, vol. 34. 95–104.

46. PARKS, C., PARK, M. and KANG, M. Super resolution image reconstruction: a technical review. *IEEE signal processing magazine*, 2003. 5: 21–35.

47. Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A. and Bengio, Y. Generative adversarial nets. *Advances in neural information processing systems*. 2014. 2672–2680.

48. Radford, A., Metz, L. and Chintala, S. Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks. *CoRR*, 2015. abs/1511.06434. URL `http://arxiv.org/abs/1511.06434`.

49. He, K., Zhang, X., Ren, S. and Sun, J. Deep residual learning for image recognition. *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2016. 770–778.

50. Simonyan, K. and Zisserman, A. Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*, 2014.

51. Johnson, J., Alahi, A. and Fei-Fei, L. Perceptual losses for real-time style transfer and super-resolution. *European Conference on Computer Vision*. Springer. 2016. 694–711.

52. Kingma, D. P. and Ba, J. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*, 2014.

53. Hanhart, P., Korshunov, P. and Ebrahimi, T. Benchmarking of quality metrics on ultra-high definition video sequences. *Digital Signal Processing (DSP), 2013 18th International Conference on*. IEEE. 2013. 1–8.

54. Kundu, D. and Evans, B. L. Full-reference visual quality assessment for synthetic images: A subjective study. *Image Processing (ICIP), 2015 IEEE International Conference on*. IEEE. 2015. 2374–2378.