Number Plate Detection in Different Environments using Generative Adversarial Networks

Alden Boby
Supervisor: Dr. Dane Brown
Computer Science Department, Rhodes University

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Abstract

Licence plates are a form of vehicle identification with a unique set of characters that can be used to identify details about a car and its owner. This information can be used by law enforcement to promote adherence to traffic rules. Initially, licence plate recognition was accomplished using clear images taken in favourable and controlled conditions. In real-world licence plate recognition scenarios, images are not as clear as the datasets used as input. Real-world data typically come from mediums such as CCTV, which compromises video quality to reduce storage costs as storing 24-hour high-resolution videos is not economical. Newer machine learning approaches such as applying generative adversarial networks and convolutional neural networks to upscale and reconstruct images, address low-quality input. Training these systems with a suitable data set will enable them to better detect number plates in unfavourable conditions and environments.

1 Context of Research

Licence plate recognition (LPR) is not a new development and has been explored in the past (Chang et al., 2004). There are working systems that can detect number plates on a vehicle, isolate them and successfully deduce the numbers and characters on the plate with either character segmentation or optical character recognition (Anagnostopoulos, 2014). Given an input that is flawless i.e. high-resolution, favourable lighting and no distortion or occlusion, existing systems will work effortlessly (Du et al., 2012). A problem arises when the input is unclear, this is often the case with real-world data such as footage captured from CCTV cameras which is compressed, leading to a loss of image quality decreasing the available data points (pixels) which can be used for character recognition, edge detection and so on (Lee et al., 2018). This specific problem can be addressed by upscaling low-resolution images using machine learning techniques to produce a high-resolution image with more information in it (Lee et al., 2019). The high-resolution image containing more information to extrapolate can then be used to recognise the characters on the number plate through more traditional means. LPR is applicable in a number of areas such as security, traffic regulation and parking (Anagnostopoulos, 2014; Du et al., 2012). Licence plates can be used to identify stolen vehicles and even automatically bill car owners for parking and using toll gates. Reducing the amount of manual work that has to be done.

There is need to create a system that can sustain good accuracy when fed varying quality data. The use of GANs will be investigated to achieve this goal. Related studies will first be explored to narrow down the problem.

2 Related Studies

Chang et al. (2004) offers some insight into how this problem was dealt with historically. gives the basic stages of number plate recognition which involve locating a number plate within an image, isolating it and then afterwards determining the actual data on the number plate. Chang et al. (2004) did not utilise much of the machine learning approach as it was in its infancy during that time, coupled with the relatively high cost of capable machines. Chang et al. (2004) utilised an edge detection technique limited to a small subset of colours related to the plates they were concerned with, followed by the use of fuzzy maps and optical character recognition (OCR) using a neural network.

Anagnostopoulos (2014) provides a condensed paper aimed at researchers looking to explore LPR. Within this paper, the steps of detecting a licence plate overlap with the methods discussed by Chang et al. (2004), with some additional techniques enabled by advances in technology. LPR requires an image as input, which is transformed with the relevant image processing techniques. The resultant image is then used to produce a string of characters as the final output (Anagnostopoulos, 2014). The performance of such systems is measured through two variables; speed and accuracy. This particular project will favour accuracy as speed is of no use if the system cannot produce accurate output. As mentioned previously in the context of research, one of the main factors affecting the performance of such systems is the quality of the data. Images can suffer from occlusion (Anagnostopoulos, 2014) and other issues, resulting in incomplete data, making the detection process more difficult **(Du et al., 2012)**. One of the aims of this research project is to explore how images can be restored before they are used as input to detect characters on a number plate.

Related studies mention the use of convolutional neural networks (CNNs) to automatically detect licence plates within an image **(Masood et al., 2017)**, training the CNN to recognise characters and do character segmentation. The use of CNNs in this area is not limited to detection; they have also been used as a means of upscaling low-resolution images. This is done by mapping low-quality images to high-quality images allowing the CNN to produce high-resolution images using this information **(Dong et al., 2015)**.

The use of generative adversarial networks (GANs) to enhance number plate detection has been explored by **Lee et al. (2018)**. They aimed to use machine learning super-resolution techniques to upscale an image. This was achieved using a GAN as opposed to traditional CNN methods which would create high-resolution images that would be blurry and lack clarity. With the addition of GANs resulting images would be sharper as it would be utilizing adversarial loss rather than mean squared error (MSE) loss in CNNs. Supported by **Lucas et al. (2019)** MSE methods used by existing deep neural networks produce reasonable high-resolution output however do not tap into the full potential of such networks resulting in the said blurry images. Additionally, MSE does not equate to the human perception of image quality and fidelity; an obscure image can have the same MSE as one that is perceptually clearer to the human eye **(Wang and Bovik, 2009)**. Coupling MSE with feature-based losses can provide much more satisfactory results, using a discriminatory network pre-trained with feature spaces to map the l_2 distances between a ground truth image and synthesised image (Lucas et al., 2019).

Lee et al. (2019) touch upon how a GAN can be used to enhance an image. Single image super-resolution and de-blurring are suitable methods to run through a GAN for image enhancement (Lee et al., 2019). Lee et al. (2019) talk of using GANs in conjunction with CNNs in order to produce better results than a CNN alone, which was similarly discussed by Lee et al. (2018). More specifically, applicable to this field of study a super-resolution generative adversarial network (SRGAN) can be used to achieve the desired effect. The GAN which is made up of a discriminator and a generator will be fed low-resolution images and output high-resolution images, the discriminator's job will then be to distinguish whether the image that it has been fed is from the generator or an actual high resolution image (Lee et al., 2019). The discriminator and generator then learn from each other through adversarial loss. Once the training process is complete and the generator is able to create images that the discriminator cannot distinguish, only the generator will be required. The generator will then take in low-resolution images and generate high-resolution ones.

3 Research Statement

Generative adversarial networks (GANs) can improve the accuracy of licence plate recognition by synthesising high-resolution images from low-quality input – sustaining high accuracy across varying quality data.

4 Research Objectives

- Obtain a data set that can be used to train a GAN
- Create or build upon an exisiting GAN
- Train the GAN to be able to recognise and upscale images
- Devise a way of locating a number plate within an image of a vehicle
- Create a system which can then detect number plates within an image
- Feed the number plate recognition system original data (low resolution) and the augmented data (high resolution) and compare the output to measure the effectiveness of generating a high-resolution image.

5 Approach

Additional literature reviews will be done to gain further insight into how licence plate recognition has advanced over time. Furthermore, time will be allocated to the familiarization of image processing techniques relevant to this area of study, such as edge detection, bilateral filtering and character recognition. The majority of this will be done using OpenCV, which is a library tailored explicitly for computer vision. Lastly, resources will be used to better understand GANs and CNNs together with their specific uses and how best to apply them and investigate whether or not certain steps of number plate detection are still relevant or can by bypassed through advancements in machine learning.

6 Limitations

Online resources will be used to obtain data sets to use for training the GAN. This option has been chosen as it is unethical to take pictures of people's number plates without explicit permission. To gain ethical clearance for each number plate would be too time-consuming and severely limit the size of the data set. Suitable data that matches the criteria as closely as possible will be used instead. However, the choice is limited by what data is available for open access. Although most number plates have a general format, there exist vanity plates that do not follow the regular format and can add some complexity when it comes to training the network, so it may be best to exclude this form of licence plate. Moreover, number plates are usually region-specific with varying colour components depending on location.

7 Timeline

Deadline	To Do
6 April 2021	Seminar Series 1: Oral presentations
8 April 2021	Review related literature
	Test an existing LPR program with a few images from a data set (both available online)
15 April 2021	Review more literature
	Test an existing GAN from demo code
22 April 2021	Review related literature
23 April 2021	Final proposal submission
26 April 2021	Ongoing process of learning practical skills needed to create system
21 May 2021	Hand in literature review
18 June 2021	Thesis Design chapter to be handed in to supervisor
23 June 2021	First Semester Exam Period Begins
9 August 2021	Seminar Series 2: Oral presentations
16 August 2021	Having a working version of a number plate detection system
20 September 2021	Progress Report handed to supervisor
4 October 2021	Draft thesis sent to supervisor
11 October 2021	Short ACM paper hand-in
18 October 2021	Seminar Series 3:Final Presentations
29 October 2021	Project submission Deadline
	Website finalised
4 November 2021	Second semester exams begin
17 November 2021	Oral exams
3 December	Corrected ACM short style paper hand in
	Corrected project thesis hand in

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