# low resolution image to high resolution image

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**ABSTRACT**

*Image Super resolution is a widely-studied problem in computer vision, where the objective is to convert a lowresolution image to a high resolution image. Conventional methods for achieving super-resolution such as image priors, interpolation, sparse coding require a lot of pre/post processing and optimization. Recently, deep learning methods such as convolutional neural networks and generative adversarial networks are being used to perform super-resolution with results competitive to the state of the art but none of them have been used on microscopy images. In this thesis, a generative adversarial network, mSRGAN, is proposed for super resolution with a perceptual loss function consisting of a adversarial loss, mean squared error and content loss. The objective of our implementation is to learn an end to end mapping between the low / high resolution images and optimize the upscaled image for quantitative metrics as well as perceptual quality. We then compare our results with the current state of the art methods in super resolution, conduct a proof of concept segmentation study to show that super resolved images can be used as a effective pre processing step before segmentation and validate the findings statistically.In most digital imaging applications, high-resolution images are preferred and often required to accomplish tasks. Image super-resolution (SR) is a widely-studied problem in computer vision, where the objective is to generate one or more highresolution images from one or more low-resolution images. SR algorithm aims to produce details finer than the sampling grid of a given imaging device by increasing the number of pixels per unit area in an image.*

**Keyword : -** *Key word1 Deep Learning, Generative adversarial networks, Super resolution, , Key word2 Generative adversarial networks,, Key word3 Super resolution,, and Key word4 High content screening microscopy etc….*

## Introduction

In this thesis project, we explore the use of Generative adversarial networks for performing single image super resolution on high content screening microscopy images. The project was carried out within the Bioimage Informatics Facility at the Science for Life Laboratory, Sweden.

### 1.1 Image Super-resolution

In most digital imaging applications, high-resolution images are preferred and often required to accomplish tasks. Image super-resolution (SR) is a widely-studied problem in computer vision, where the objective is to generate one or more highresolution images from one or more low-resolution images. SR algorithm aims to produce details finer than the sampling grid of a given imaging device by increasing the number of pixels per unit area in an image. SR is a well known ill-posed inverse problem, where from a lowresolution image (usually corrupted by noise, motion blur, aliasing, optical distortion, etc.) a high-resolution image is restored.

SR techniques can be applied in many scenarios where multiple frames of a single scene can be obtained (e.g., multiple images of the same object by a single camera), various images of a scene are available from numerous sources (numerous cameras capturing a single scene from various locations). SR has its applications in varied fields such as Satellite imaging (eg. remote sensing) where several images of a single area are available, in security and surveillance where it may be required to enlarge a particular point of interest in a scene (such as zooming on the face of a criminal or the numbers of a license plate), in computer vision where it can improve the performance of pattern recognition and other areas such as facial image analysis, text image analysis, biometric identification, fingerprint image enhancement, etc.

**Background**
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## 2. Relevant Theory

*This chapter begins with subchapters 2.1,2.2 aimed at providing the reader sufficient background knowledge to understand the various technical concepts used in the thesis. Then a review of the related work of non-deep deep learning, as well as learning methods for single image super-resolution.*

### 2.1 Background knowledge

#### 2.1.1 Definitions

Image Resolution - The term resolution in image processing corresponds to the amount of information contained in an image that can be used to judge the quality of the image and image acquisition/ processing devices. Resolution can be classified into several categories such as Pixel or Spatial resolution, Spectral Resolution, Temporal resolution, Radiometric resolution. For this project, we will be dealing with spatial resolution, and the term resolution used henceforth will imply spatial resolution. Spatial Resolution is the number of pixels that are used to construct the image and is measured by some pixel columns (width) × number of pixel rows (height), say for, e.g., 800 × 600.

Pixels - They are the smallest addressable parts of an image. Each image can be considered as a matrix consisting of several pixel values. Every pixel stores a value proportional to the light intensity at a particular location, and for an 8-bit grayscale image, the pixel can take values from 0 to 255.

Low resolution - A low-resolution image implies that the pixel density of the image is small thereby giving fewer details.

High resolution - A high-resolution image implies that the pixel density of the image is high leading to more details.

Super-resolution - SR is constructing an HR image from a single/multiple LR images. Super resolution methods can be categorized into two categories based on the number of images involved - a) Multiframe super-resolution b) Single image superresolution.

Multiframe super-resolution - This method utilizes multiple LR images to reconstruct an HR image. These multiple images can come from various cameras at separate locations capturing a scene or several pictures of the same scene. These multiple input LR images more or less contain the same information, however the information of interest is the subpixel shifts that occur due to movement of objects, scene shifts, motion in imaging systems (e.g., satellites) If the different LR image inputs have different subpixel shifts then this unique information contained in each LR image can be leveraged to reconstruct a good HR image [13].

Single image super-resolution (SISR) - In SISR, the super resolving algorithm is applied to only one input image. Since in most cases there is no underlying ground truth, the significant issue is to create an acceptable image. The majority of the SISR algorithms employ some learning algorithms to hallucinate the missing details of the output HR image utilizing the relationship between LR and HR images from a training database. The SR reconstruction problem can be formulated regarding an observation model [1] as shown in Figure 2.2 which relates the HR image with the input LR images. First by continuous signal sampling the desired HR image is produced which is then subjected to translation, rotation leading to blurring due to optical, motion, imaging system motion, etc. Next, LR observation images are achieved by downsampling the blurred image.

**2.1.2 Strategies to increase image resolution**

The resolution of an image can be increased by either increasing the hardware capabilities of imaging devices or using a software/algorithmic approach.

• Hardware Approach - One direct way to increase the spatial resolution is to increase the number of pixels per unit area by reducing the pixel size from sensor manufacturing techniques [14]. But reducing the pixel size beyond a threshold (which is already achieved by current technologies) leads to the generation of shot noise as less amount of light is available for the decreasing number of pixels, degrading the image quality severely. Another way to enhance the spatial resolution is to increase the sensor chip size which leads to an increase in the capacitance and is not sufficient since increasing capacitance adversely affects to speed up a charge transfer rate [1]. Also, the high cost of high precision optics and sensors acts as a hindrance in these approaches adopted to commercial solutions.

• Software Approach- To avoid the disadvantages of the hardware-basedapproaches mentioned above, software and algorithmic methods (i.e., SR algorithms) are preferred. Techniques such as image interpolation, restoration, rendering, etc. are widely used in enhancing spatial resolution. Image interpolation approximates the color and intensity of a pixel based on the neighboring pixels values but fails to reconstruct the high-frequency details as noise is introduced in the HR**.**

**2.1.3 Evaluation metric for Super-Resolution**

Peak signal to noise ratio (psnr) - psnr is a metric used to measure the quality of any image reconstructed/restored concerning its reference or ground truth image. For a given noise-free $m \times n$ monochrome image I and its noisy approximation K,

the Mean squared error is given by - 1 mX−1 nX−1 2 MSE = [I(i,j) − K(i,j)] mn i=0 j=0 and the psnr is given by - (2.1) MAXI psnr = 10log10( ) (2.2) MSE where MAXI is the maximum possible pixel value of the image.

## 3. Motivation

This chapter discusses in detail the motivation behind proposing a GAN utilizing perceptual loss for High content screening (HCS) microscopy images which are -

1. Common problems in HCS causing captured images with artifacts/noise (acquisition errors)
2. Inefficiency of the traditional pixel wise Mean squared error (MSE)
3. Feature transferability issues in CNN’s**.**

## 3.1 HCS microscopy problems in image acquisition

Apart from suffering from the usual challenges in image acquisition as mentioned in section 1.3, microscopy images are prone to a host of domain specific challenges which might further degrade the quality of the images acquired. Through this chapter we attempt to highlight these common problems faced while acquiring microscopic images, which create a need to use denoising, super-resolution approaches.

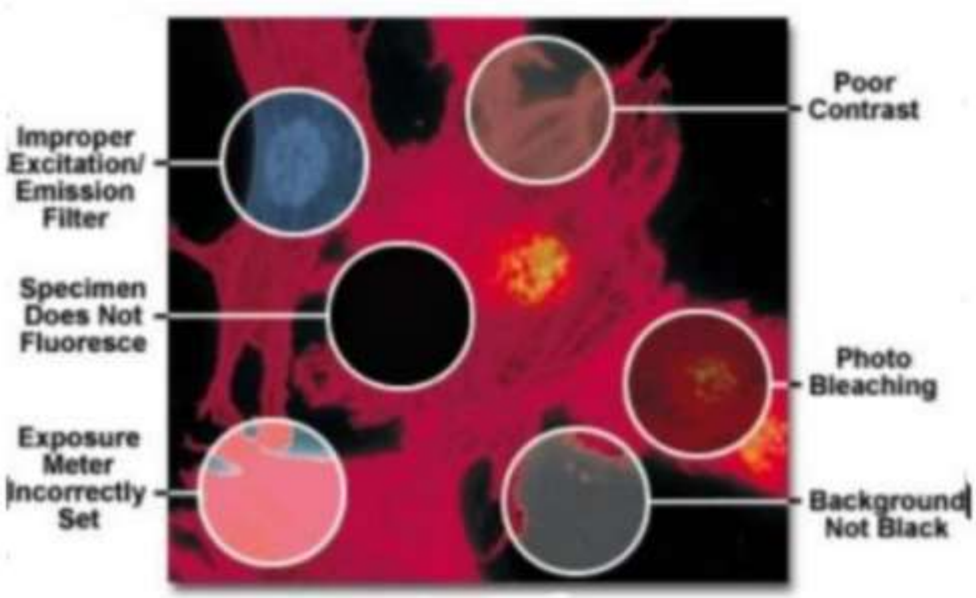


Figure 3.1: An overview of common problems encountered while acquiring microscopy images. Image Source [30]

### 3.1.1 Photo bleaching

Photo bleaching (also called fading) occurs when due to more extended illumination periods, the fluorophores suffer from diminished excitation response thereby losing its ability to fluoresce caused by photon-induced chemical damage and covalent modification. In simple terms when we say a fluorophore is photobleaching it means that it has lost its ability to fluoresce, absorb and emit light. During the photo bleaching process, the imaged sample gradually loses the amount of fluorescence observed thereby ultimately leading to a loss of image quality. Loss of fluorescence caused by photo bleaching is crucial to take into account while performing image quantification studies as it can alter the quantitative data thereby leading to false and misleading results.

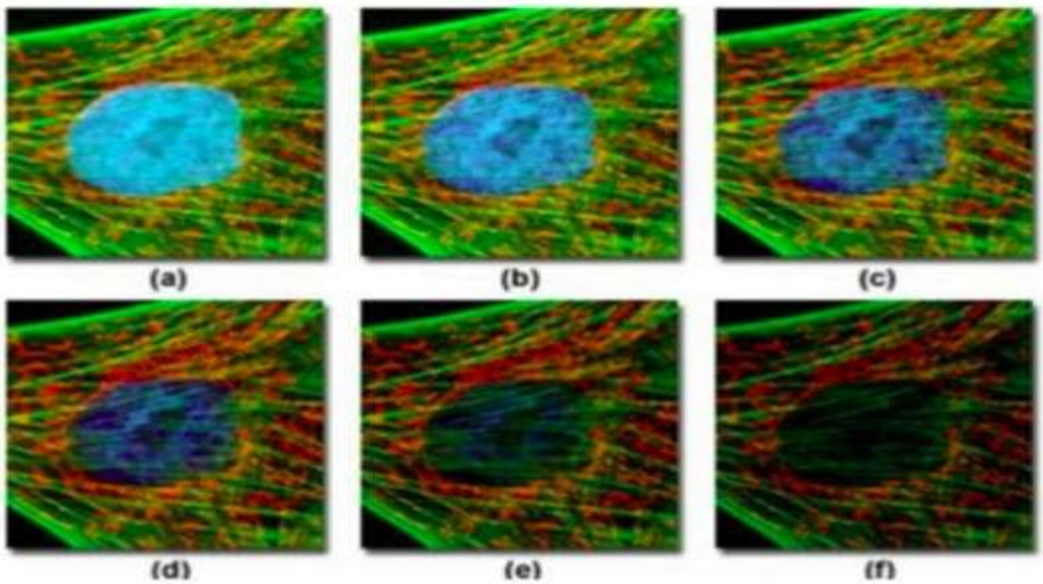


Figure 3.3: Images captured (a-f) at 2 minute intervals for multiply stained specimens. Image Source [32]

### 3.1.2 Bleed through/ Crosstalk

Bleed through/ crosstalk artifacts appear when two or more fluorescent markers are excited simultaneously, and the channel of interest displays fluorescent from the neighboring channel.

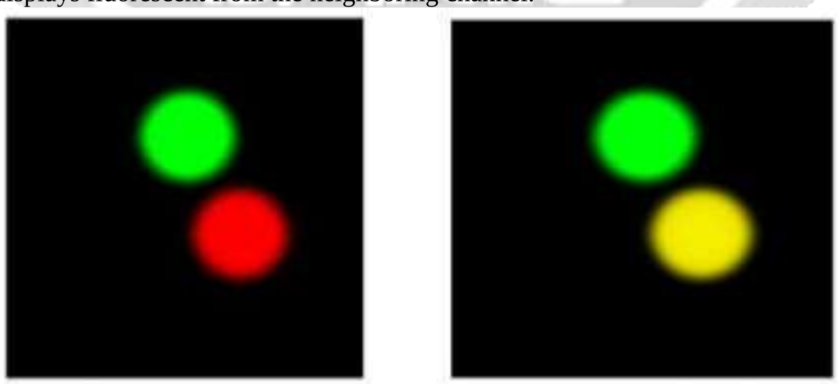

Figure 3.4: In a sample containing two non overlapping objects dyed in red and green and as the crosstalk factor increases the more yellowish the red object looks since its signal is recorded in the green channel apart from just the red channel. Image Source [33]

### 3.1.3 Phototoxicity

in live cell imaging, overexposing the cells to light (both low and high wavelength) for a prolonged time eventually, end up damaging them causing phototoxicity. One of the reasons for phototoxicity is that most cells used in a typical imaging experiment are not used to the sheer number of photons aimed at them. Fig 3.6 illustrates phototoxicity.

### 3.1.4 Uneven illumination

There are instances when a sample is not evenly illuminated by light across the field of view giving rise to uneven illumination in the image regions with darker, unclear and more brightly illuminated areas occurring together.

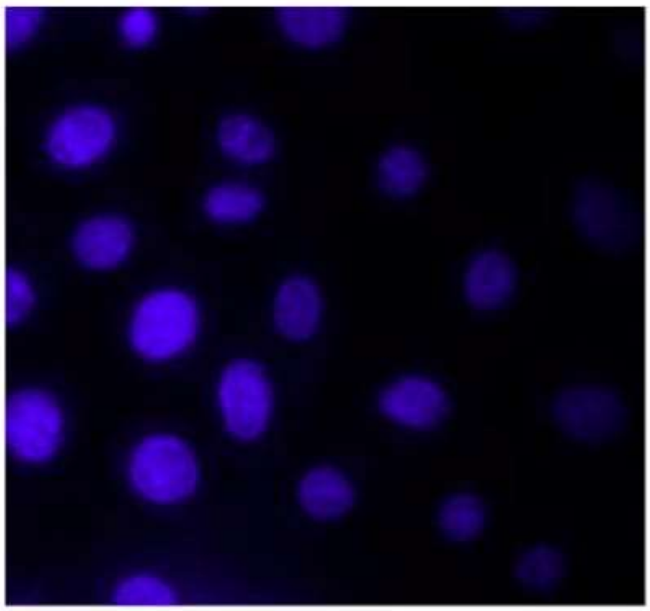

Figure 3.7: In the above figure, cells are stained with nucleic acid dye and uneven illumination is observed. Image Source [36]

### 3.1.5 Color and contrast errors

Color errors occur due to many reasons such as color degradation from auto fluorescence and improper filtration etc. Contrast errors occur due to misconfiguration of the optical train or utilizing wrong filter combinations.

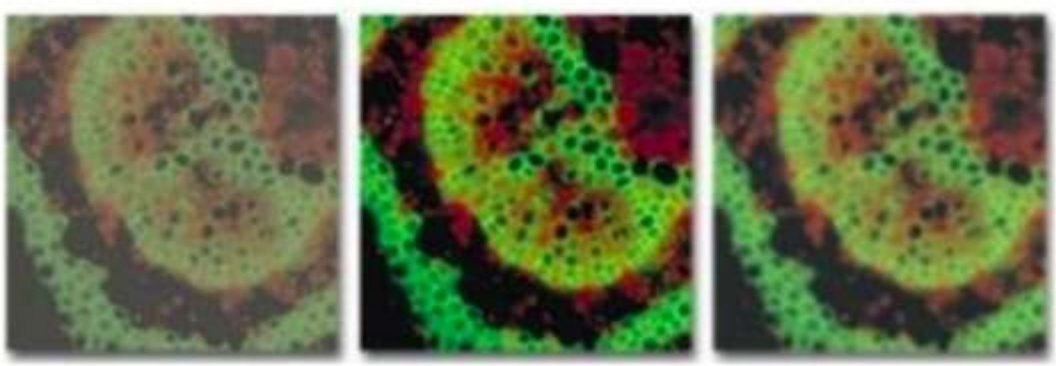

Figure 3.9: Visual demonstration of contrast error across slides. Image Source [30]

### 3.2 Inefficiency of pixel wise M.S.E

L2 loss or mean squared error is widely used in several machine learning applications such as regression, pattern recognition, signal processing, image processing and is the defacto error metric where the pixel-wise distance between generated and ground truth images is measured. M.S.E is used in wide variety of image applications such as super-resolution, segmentation, colorization, depth, and surface normal prediction, etc. Several factors make it a popular choice such as its convexity, symmetry, differentiability (favorable for optimization problems), simplicity (parameter free and inexpensive to compute), it is additive for independent sources of distortions, etc. [37]. Another catalyst for this widespread adoption is that standard software packages such as Caffe, Tensorflow, Keras, etc. facilitate using M.S.E but not many other loss functions for regression discouraging practitioners to experiment with different loss functions. More detailed advantages of M.S.E can be found here [37]

However, M.S.E has a lot of flaws for generating images, and images produced by MSE do not correlate well with the image quality perceived by a human observer. One of the reasons for this is the assumptions made while using M.S.E, such as the impact of noise, does not depend on the local characteristics of an image and M.S.E operates under the Gaussian noise model which isn't the case in many settings. Contrary to the aforementioned assumptions, the factors influencing the sensitivity of the human visual system (HVS) to noise rely on local luminance, contrast, and structure. M.S.E overly penalizes larger errors while is more forgiving to the small errors ignoring the underlying structure of the image. M.S.E tends to have more local minima which make it challenging to reach convergence towards a better local minimum. Consequently, the most common metric to quantitatively measure the image quality, psnr corresponds poorly to a human's perception of an image quality. As can be observed by equation 3.1 below, M.S.E and psnr share an inverse relationship with minimizing M.S.E leading to a high psnr. Thus,psnr itself cannot be an indicator of how well an image looks perceptually and there is need to adopt other loss metrics that capture intricate details affecting the HVS.

metrics that capture intricate details affecting the HVS. L2 psnr = 10log10 l2/MSE

## 4.CONCLUSION

GANs are powerful generative models that are able to model the distribution and manifold over natural images. We leverage these properties to perform manifold regularization by approximating a variant of the Laplacian norm using a Monte Carlo approximation that is easily computed with the GAN. We show that our regularization strategy consistently improves classification performance using unlabeled data on the CIFAR-10 and SVHN benchmarks, on several neural network architectures, and with varying amounts of labelled data. In particular, when incorporated into the feature-matching GAN of [23], we achieve state-of-the-art results for semi-supervised image classification with a method that is significantly easier to implement than competing methods. We explored the interaction between our regularization and the generator in this framework and reveal a potential connection with gradient penalties for stabilizing GAN training. Using an experimental setup where we decoupled the GAN used for estimating the regularizer and the classifier, we further observed a positive correlation between generator image quality and prediction accuracy. Our work uses GANs in a novel way for semi-supervised classification, and we expect that our approach will be applicable to semi-supervised regression [1, 11, 17] as well as unsupervised learning [2].

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