IMAGE RESTORATION

*"A Comprehensive Review on Image Restoration Techniques"*

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Abstract: Image restoration is a process in which computer vision and technology are used to collect information of damaged area in image according to the residual of image information and try to improve it by different techniques. In today’s world, image restoration is one of the vast growing fields. This paper provides classify and summarise and gives an overview of image restoration process and methods or different techniques used in different condition.

INTRODUCTION

Image restoration is a process which is commonly used to improve images which are received from various sources and try to implement certain actions on to it.

Generally, images are formed from components in an exceedingly grid formation called pixels, every pixel holds some information that represents tone. Image restoration states that it retrieves nearly true image information from degraded measurement. The degradation can be caused by many methods. The image can be degraded due to the factors such as noise, blur, motion artifacts, or missing information.

With the progresses in image restoration, high quality images are must for analysis and decision-making. In medical fields, it enhances images such as MRI, CT scans, and X-rays by reducing noise and artifacts, which helps in accurate diagnosis. Fields such as Satellite imagery is also improving due to these techniques. Satellite images which are degraded because of atmospheric conditions, it improves the quality of images which can help in environment monitoring and disaster response. In the fields of security and surveillance it is widely used such as for low resolution CCTV footages to help law enforcement. These are also used in much more fields such as astronomical imaging, underwater surveys, forensic science and to restore historical documents and artwork.

Unlike image enhancement which focuses on improving visual appeal of an image by adjusting its contrast, sharpness, colour or other things, image restoration focuses on recovering the lost part of images using mathematical model.

While image enhancement is useful for making images more visually interpretable, image restoration is essential for critical application which requires accuracy.

Abnormalities in Images: There are many ways image can be degraded. These can be Noise-based, Blur and Distortion, Compression or Structural and geometrical distortion.

Noised based Abnormalities occurs due to unwanted variation in pixels. These include Gaussian noise (Random variation in intensity It appears as grainline structure which occurs due to bad or low lighting). It could be Salt and pepper (random pixels are set on high or low intensity which resembles like scattered black and white dots which could be caused by sensor error). Same as gaussian noise, Poisson noise is also caused by low light intensity. Blur and Distortion Abnormalities is caused by motion or environmental condition such as Motion blur, out of focus and Optical aberrations which can also happen due to poor lens quality.

Compression Artifacts is caused by lousy image compression, these can contain Blocking artifacts (Square-shaped distortion), Ringing Artifacts (Halo effect around sharp edges) and Colour Banding (Smooth gradients appear as bands on image). Structural and geometrical distortion is caused by improper image capture or projection. It can be perspective distortion or rolling shutter effect.

Missing pixels or data corruption occurs when certain region of image is lost, distorted, or degraded due to various factors such as transmission or sensor error. This type of problem is particularly relevant in satellite imagery and medical imaging.

Low resolution images suffer from a lack of details, which makes them blurry or seems more pixelated than normal. This type of problems can be found in surveillance footages, medical scans, astronomical images (telescopic images).

RESTORATION TECHNIQUES

There are many ways to approach images to implement image restoration. Some of the ways are Traditional image restoration techniques and learning based image restoration techniques.

The Traditional restoration techniques involve different approaches such as Filtering-Based techniques, Regularization methods, Inverse and blind Deconvolution. Below there are some Filter-based techniques:

Median filter is widely used and extremely necessary techniques of filtering and renowned for noise reduction (salt and pepper noises).

It is a measurement-based and mathematical technique. By using this filter, it analyses the pixel around the degraded area and take its mean and replaces it.

Mean filter is a simple linear filter which is used for smoothing images and noise reduction. It replaces the degraded pixels with the average of its neighbouring pixel values. It mostly blurs the degraded pixels as it blurs its edges. It includes different approaches which are Arithmetic, Geometric, Harmonic and Contra Harmonic. Each of these are used for removing different types of noises.

Adaptive Filter is also a type of linear filter. It is very different from previous linear filters as it can adapt itself according to the behaviour (noise level and of different type, contrast or texture variation) needed for restoration. It works by analysing the work it needs for each of the noises. Then it modifies its parameters such as kernel size, weights. It also works in a way to preserve as much information it can. It provides higher preserve edges, skinny lines and image details compared to other filters.[4]

Weiner Filter is also a type of linear and math-based filter which is used for denoising and restoration. It minimizes the mean square error (MSE) between the raw original image and the degraded image by estimating and analysing the noise and blur Images. It adapts to each noise and distortion local image variation and also provides better image details and quality. It takes account for the power spectrum of noise and what of original image in its formula.[3]

Regularization methods are also widely use in areas of denoising, deblurring, these include TV (Total variation, Tikhonov regularization and Sparse coding. These types of methods utilise complex mathematical formulas.

The main idea behind Total variation is to preserve the edges in the image while reducing noise. This also ensures the smoothness of image on flat surfaces.

Tikhonov Regularization is a classical technique which is used for reducing noise and blurs in images. It stabilizes the solution by adding smoothness of constraint.[13]

The fundamental assumption of this method is to lay out the image in sparse linear combination. It only needs small number of features to reconstruct an image. It provides high quality image with better texture while it is not cost friendly. It is widely used in denoising, deblurring and to provide super-resolution imaging n medical areas.

Deconvolution is also considered a traditional way of image restoration. It is a process which is used to recover an original image that has been blurred for some reason such as optical distortion. Motion or atmospheric turbulence. When the Point spread Function of an image is known, inverse deconvolution techniques such as Richardson-Lucy and Weiner deconvolution can be used.[14]

Richard-lucy Deconvolution contains an iterative algorithm which is used to restore blurred images. It is more applicable for images in low light, microscopy, and astronomical imaging.

This uses an update formula which assumes that the observed image is the blurred image of original image. It works best for Poisson noise and low light images.

Wiener deconvolution is also used for deblurring images whose PSF (point spread function) is known. It is based on linear filtering; it adapts wiener filter and uses it to solve the problems.

Blind Deconvolution is used when PSF is not known of an image. It uses a much more complex approach because it does not consider original image and PSF of the image.

It often relies on the prior knowledge about the image. It can handle unknown blurring, motion blur, defocus blur and atmospheric distortion.

It includes Maximum likelihood estimation, variation Bayesian methods, deep learning methods.

Learning based Image Restoration techniques

With the advancement of computational power and data availability, these types of methods have become dominant in image restoration fields. These methods use statistical pattern.

It can be broadly categorised in to Machine learning based methods, deep learning methods and hybrid model that combine both. Machine learning methods uses sparse combination of learned basis functions.

Machine learning methods

The K-SVD algorithm (Dictionary Learning) is a widely used approach that iteratively refines a dictionary of images patched to gain better sparse combination. It helps in denoising, deblurring and in inpainting and also preserves fine details and textures.

Sparse representation-based methods assume that the natural image can be represented using only few significant basis function. An image patch is reconstructed using sparse combination of dictionary elements. It is mainly used in denoising and deblurring.[15]

Deep Learning-Based Methods

These methods use neural networks to learn hierarchical features directly from data, it oftens outperforms traditional techniques. It includes CNNs (convolutional Neural Networks). It is used majorly in denoising and deblurring. It contains multiple layer that take out features such as edges and textures from images. It is used to recognize patterns in images and uses this pattern to remove noise, blur and compression artifact.[2]

Generative Adversarial Networks consists two networks, a generator which creates images and a discriminator that checks its realism. It generates high resolution images while removing corrupted parts of image. It is mainly used in medical imaging.

Transformers in image restoration can captures image relationships, which leads to better feature learning. Self-supervised and unsupervised learning techniques are also used to train the model and to remove noise and blurs.

Hybrid Models combine traditional and deep learning approaches to enhance the image.

It uses combination of strengths of both techniques. Techniques methods provide structured priors such as edge preservation, smoothness constraints. It also enhances restoration using learning complex methods from datasets or by being trained. It reduces the chances of limitation which each different types of technique faces. It is mostly used in medical fields for diagnosis, satellite imaging, real time application such as autonomous vehicle.[16]

Performance Metrices for Evaluation

Evaluating the effectiveness of the techniques requires quantitative and qualitative metrices.

This is commonly used to measure performance measures and their significance.

PEAK Signal to Noise Ratio (PSNR), it measures the similarity between the restored image and the original image by calculating the ratio of the intensity of maximum pixels possible to the noise in the image. It means that the higher the PSNR, the better the quality of image is. It is limited to the condition if two distorted images have same PSNR value.

Multi-Channel Blind Image Restoration technique involves recovering an original image from several blurred versions without prior knowledge of the blur function. It utilizes multi-channel data, where images are processed in blocks and filtered to improve signal-to-noise ratio (SNR).[1].

Structural Similarity Index (SSIM), it means the structural similarity between images by considering the brightness, contrast and structural details. The SSIM between 0 to 1 indicates perfect similarities.[5]

Mean Squared Error (MSE), it calculates the average squared difference between neighbouring pixel values of the original images and restored images. It shows that the lower the MSE is, the less error the restored image contains and the better quality it has.[6]

Learned Perceptual Image Patch Similarity (LPIPS), it is a deep learning-based technique that measures the observational similarity between images by comparing its features. It is trained by stock of datasets. It shows that lower LPIPS gives higher similarity in observation.[7]

Human Visual Perception Metrics assess image quality based on human judgement rather than numerical calculation. Human subjects are used to rate the images on scale, it determines that the smallest change in an image that the human eye can detect. It provides reliable assessment but consumes times.[8]

These combination of metrices is essential for a comprehension evaluation.

Challenges and open issue in image restoration

Despite significant advancement in restoration techniques, there are many challenges and open issue that it faces, which limits its effectiveness. Both the types of techniques face each own different challenge. One of the major issues that is faces is cost and accuracy. High performance deep learning techniques and models such as CNNs and transformers, require extensive resources, big data for training it. This also makes it difficult for real-time processing and its usage in autonomous vehicle.

One of the biggest challenges is to cut the computation cost without compromising the quality of image. Another issue is to generalise it across different type of distortion and degradation. Each type of technique is trained to remove a specific type of abnormalities. To achieve all type of degradation patterns is crucial for practical applications. One of the major issues is the lack of high-quality training datasets. Many models rely on huge datasets. The creation of diverse and high-resolution training datasets remains a challenge, which affect the model for performance and real-world applicability.

Real world images suffer from different type of degradation at the same time and existing models struggles to generalise it.

All these type of challenges makes it difficult to apply in real time and real world. These types of techniques often fail in real world images due to their domain gap.

APPLICATIONS:

Image restoration techniques are widely used in different fields, some of these require specific techniques. These fields are:

Medical Imaging technique like MRI, CT scan, X rays are crucial for diagnosis and treatment but they frequently suffer from noise, motion blur, or low contrast, which can affect diagnosis and treatment. Image restoration techniques help to improve the quality of scans.[9]

Noise Reduction: Noise in medical scan refer to unwanted random variation of pixel intensity, which make harder for medical team to detect the important physical structures, organs, anatomical structures. Noise in scan come from various sources like low light level, defect in imaging machine or when the patient moves during the scan.

Edge Enhancement: Edge in an image represent the boundaries between different tissues, muscles or structures. Enhancing these edges makes important diagnose like tumours, fractures more visible, helping the doctors interpret scans more accurately.

Resolution Improvement: It is a technique use to enhance the resolution of medical images and generating high quality images from lower resolution scans.

**Remote Sensing (Satellite Image Enhancement)**

Satellite imagery or remote sensing are crucial for usage such as agriculture, environmental monitoring and urban planning. However, these images often suffer from distortions due to atmospheric conditions, satellite movement, or sensor limitations.[10]

Some image enhancements technique use in remote sensing are:

Cloud/Atmosphere Technique is a used to remove distortion caused by atmospheric condition like haze, clouds. Geometric Correction techniques are used to remove distortion caused by satellite orbits shifts, Earth’s rotation.

**Surveillance and Forensics (Facial Recognition in Low-Light Conditions)**

In forensic investigations and security systems, accurate and clear images are essential for the identification of objects, vehicles, or individuals. Surveillance cameras, however, tend to record degraded images because of low sensor resolution, poor lighting, or motion blur.[11]

Technique use in Surveillance and Forensics are:

Low-Light Enhancement: Surveillance cameras generally install in poor lighting like parking lots, dark alleys, so, this technique use to remove high noise (graininess) and low contrast from images.

Motion Deblurring: Rapidly moving individuals, cars, or sudden camera movements can lead to motion blur, so this technique use to remove blurriness from image.

**Historical Document Restoration**

Restoring ancient manuscripts, paintings, or photographs serves to protect human history so that researchers, historians, and the public can gain access to valuable information. With the passage of time, physical documents become worn by environmental conditions, careless storage, or mere age. Image restoration methods can restore these artifacts electronically, unveiling lost content without causing further damage to the originals.[12]

Historical documents mainly suffer from stains, smudges and paper degradation, making text and illustration hard to read, so this technique use to remove noise and stain. As the time passes ink fades or spreads, causing characters to blur or disappear, through this tool we can boost the contrast between text and background making faded ink more visible.

**Underwater and Astronomical Image Processing**

Images captured in the depth of the ocean or in space are often suffer from scattering, low contrast, and noise due physical and environmental factors. Restoring these images help the scientists, researchers, and explorer to study coral reefs or observing distant galaxies.

Cameras in space or deep ocean environments often operate in low light or near to total darkness leading to high noise, through this tool we can smooth out the noise while preserving edges and details.[17]

**Future Directions**

As image restoration technology advances, new technologies hold the promise of driving the field to new heights. Quantum computing holds the potential to accelerate complex algorithms by orders of magnitude, and Explainable AI (XAI) will provide us with more transparent and reliable models. Real-time restoration is increasingly critical for autonomous systems, allowing them to navigate difficult environments. Multimodal data fusion will merge data from diverse sources to make more complete, precise reconstructions. Together, these technologies will extend applications to medicine, space exploration, security, and more, making image restoration faster, smarter, and more trustworthy.

1.Integration of Quantum Computing in Image Restoration

Quantum Computing has the potential to revolutionize the image restoration by solving complex problems and handle massive amounts of data at massive speed with limited time.

Traditional algorithms or tools for deblurring, denoising, or super-resolution can be very expensive, especially for high-resolution or 3D medical and satellite images. Quantum algorithms could accelerate these processes exponentially.

2. Real-Time Image Restoration for Autonomous Systems

Autonomous systems like self-driving car, drones, and robots, rely heavily on computer vision to navigate and make decisions. Environment are unpredictable cameras may encounter motion blur, low light, or weather effects (like rain, fog). Real time image restoration would help these systems operate reliably in challenges conditions.

3.Fusion of Multimodal Data for Better Reconstruction

Combining multiple data from different sources can provide richer information for image restoration, which help us to get more accurate and detailed reconstructions.

Different imaging technique captures different information. For example, light cameras may struggle to capture image in low light, but thermal camera can detect heat signature. Fusing different and multiple data types can fill in gaps and improve restoration quality.

4. Explainable AI (XAI) for Image Restoration Models

AI models like CNNs and transformer can restore images very well, but it’s often unclear that how they make decisions. This lack of transparency can be a problem, especially in important fields like medicine or self-driving cars. In areas like healthcare, it is crucial to know whether AI-restored details (like a tumour, fractur in a scan) are real or mistakenly added.

LITERATURE REVIEW:

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| --- | --- | --- | --- | --- | --- |
| Paper | Year | Method | Process | Key aspect | Limitation |
| Chen et al.  Diffusion model | 2024 | AI-based image generation for restoration | Uses AI to construct images from bad quality | Handle very extreme damage, produces high quality results | Extremely slow, needs expensive hardware |
| Lee et al.  NAFNet | 2023 | Lightweight CNN Model | A fast and simple method for fixing images | Works in real time and doesn’t use computing power | Not as accurate as other deep learning models |
| Liang et al.  DRUNet | 2023 | U-net for denoising | Uses a popular deep learning model to remove noise | It is good for general noise removal, works on different images | It misses small details and is not the best for High quality restoration. |
| Wang et al. | 2022 | Transformer based model | Uses AI to improve images | Handles multiple types of damages, works well for real world photos | It needs a lot of training data and is quite slow. |
| Zamir et al | 2021 | Multi-stage restoration network | Uses multiple steps to improve image quality. | It has high accuracy and works well for noise and blur. | Needs powerful computers and takes more memory |
| Guo et al | 2019 | Deep CNN | Model for noise removal | Works on different level of noises | It does not work on strong noise. |
| Zhang etal | 2018 | Deep Image prior | Uses deep learning model to fix image without needing training | No need for data training | Very slow, struggles with complex noises |

CONCLUSION:

Over the years, image restoration has been going through many enhancements bridging the gap between theoretical advancement and real-life application. The demand of high-quality images is growing rapidly due to rapid development in cameras and smartphones.

Classical techniques such as Weiner, Median, Mean and many other filters have provided some stable solution while Modern techniques such as Deep learning techniques, machine learning methods has shown remarkable performances compared to traditional ones.

This review gives various image restoration related information. It is significantly growing and advancing with deep learning techniques, surpassing traditional methods. However, challenges like high computational cost, data dependency and generalization to unseen degradation remains. Where lightweight models provide efficiency but lacks in accuracy and on the other side for high accuracy it demands costly hardware and model for computation. Although deep learning can improve quality of images but it needs to be faster. In further time the field of image restoration will broaden as new advancement are invented.

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