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COLOR CORRECTION OF DAMAGED ARCHIVED VIDEOS CONTENT USING SUPERPIXEL TECHNOLOGY

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Master's Thesis

Supervisor

Prof. Dr. Osman Nuri UÇAN

Istanbul, 2022

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The thesis titled COLOR CORRECTION OF DAMAGED ARCHIVED VIDEOS CONTENT USING SUPERPIXEL TECHNOLOGY prepared by MAZIN ABDULRAZZAQ AHMED ALSALMANI and submitted on 21/12/2022 has been **accepted unanimously** for the degree of Master of Science in Information Technologies.

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Mazin Abdulrazzaq Ahmed ALSALMANI

Signature

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This work would have not seen the light without the encouragement and support of many people. To my dear martyred father who is always present with me I dedicate my success. To my adviser Prof. Dr. Osman Nuri UÇAN, thank you for your support and following. To My mother there are no words that conveys my gratitude. And finally, thanks to my wife, my children, my brothers and numerous friends who endured this long process with me, always offering unconditioned support and love.

ABSTRACT

COLOR CORRECTION OF DAMAGED ARCHIVED VIDEOS CONTENT USING SUPERPIXEL TECHNOLOGY

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The study of an image on a pixel-by-pixel basis is not as fruitful as the examination of the image as a whole, despite the fact that the former requires a significant amount of work from the central processing unit of the computer (CPU). Pixels are combined into super pixels; The fundamental objective of this thesis project is to investigate the challenges that have been brought up in connection with the literary canon and to propose solutions that are applicable to these problems in a practical manner. The research of the many different extraction procedures that are based on clustering is going to receive a large amount of focus and attention from us moving forward. In addition, the efficiency of each and every conceivable option will be assessed, and additional suggestions for enhancing efficiency will be provided whenever it will be possible to do so.

Keywords: Super Pixel, AI, GA, Filtering, Video Restoration.

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ABBREVIATIONS

SPs	:	Super Pixels
VR	:	Video Restoration
AI	:	Artificial Intelligence
WMF	:	Weighted Median Filter
DWM	:	Directional Weighted Median
GR	:	Genetic Restoration

1. INTRODUCTION

1.1 BACKGROUND

Pixels, which are frequently referred to as picture components due to their involvement in the storage of information, are in charge of saving data on an image's brightness as well as its spectral content. Pixels are also responsible for storing information on the color content of an image. These individual aspects of the picture are what ultimately come together to form the whole thing. This information is beneficial; however, if you do not know where these pixels are positioned in relation to one another, then the information is substantially less beneficial for you. The study of an image on a pixel-by-pixel basis is not as fruitful as the examination of the image as a whole, despite the fact that the former requires a significant amount of work from the central processing unit of the computer (CPU). Pixels are combined into super pixels, which have the same color quality and spatial distance parameters as their individual counterparts, in order to overcome the challenges that are presented by these concerns. Super pixels have a higher resolution than their individual counterparts. The amount of individual pixels that make up a superpixel is identical to that of its individual counterpart. When pixels are transformed to super pixels (SPs), which are larger copies of ordinary pixels, the number of processing units that are required to execute a picture is substantially reduced. This is because superpixels are larger than standard pixels. In addition, applications such as object recognition and 3D reconstruction, as well as applications such as segmentation and optical flow tracking, receive extra information that is condensed and pertains to the neighborhood. By extracting SPs during the pre-processing step, the computing process may be shortened, which also improves the performance of future applications across a wide variety of use scenarios [1]. [It is essential to keep in mind that only applications that make use of SP extraction are impacted by this.] Over segmentation is a term that refers to any technique for segmentation that produces a significant number of areas with a small number of pixels that have no semantic meaning. This can happen when a person uses a technique for segmentation that produces a large number of areas with a small number of pixels. This might occur when a person applies a technique for segmentation that produces a huge number of areas with a tiny number of pixels. For example, a person might use a technique like this to divide an image into sections. The occurrence of this could take place in any one of a variety of different ways. This is only one of the many potential outcomes that could take place as a result of employing a method of image segmentation. Before being taken into consideration, superpixels need to fulfill a number of other requirements in addition to having an extraordinarily high segment count. This is one of the requirements.

Figure 1.1: Super pixel restored images.

With the use of any one of a vast number of distinct image restoration procedures, it is possible to return images to the quality they possessed when they were first taken. There are many different image restoration processes. The quality of the image may deteriorate for a multitude of different reasons, some of which include, but are not limited to, sensor noises, down sampling, blurring motion, reflection, and various combinations of these challenges. It is necessary, and in many cases absolutely necessary, to return an input image to its optimal condition in a variety of applications that make use of image processing and low-level computer vision [2]. These applications are listed in the following table. This is due to the fact that the quality of an input image is directly tied to its capacity to carry out the function for which it was designed. Denoising, super resolution, deblurring, demosaicing, and decreasing reflections are all steps in the process of recovering images using methods that have been extensively researched and documented [3]. Denoising is the process of removing noise from an image while maintaining its original resolution. The process of reducing noise from an image is referred to as denoising. The procedure of super-resolution involves boosting an image's resolution, whilst the method of denoising an image involves reducing noise from the image. Both of these processes are performed on an image.

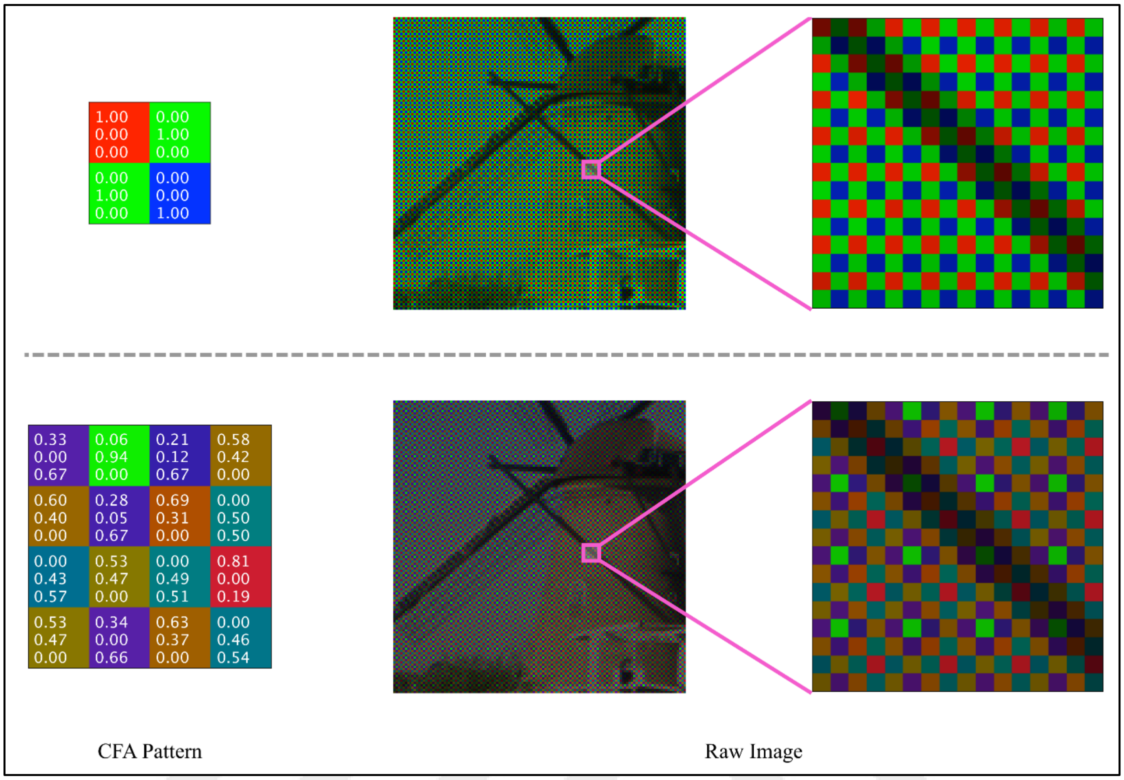


Figure 1.2: Denoising, deblurring and demosaicing using superpixel.

The approach for spectral clustering that was described in is first applied with the intention of detecting and removing any outliers that might have been present in the data. This is the first step in the process. This technique has been shown to be successful by a variety of data collections, one of which is the DrivFace data collection, which was designed specifically for the aim of evaluating it. Other data collections have also demonstrated the strategy's success. Even though every type of data is built from discrete data points, the elimination of data points in accordance with increasingly stringent criteria results in greater challenges for various types of data [4]. This is because all types of data are built from discrete data points. For example, an RGB or hyperspectral image may have a spectral component in addition to a spatial component in its make-up. [Citation needed] It is vital to possess both of these forms of knowledge in order to successfully disassemble an image into its component parts. When data points are removed from an image, the spatial similarity of the image and the consistency of the segmentation are both compromised. This, in turn, leads to a segmentation technique that is less accurate. It is necessary to make use of a big quantity of computer processing power in order to put this strategy into action due to the fact that the average photograph has a very large number of pixels. Our objective is to devise a method that minimizes the susceptibility of path-based distance measurements to path-based noise while at the same time allowing a certain level of path-based noise to be present. This is the challenge that we have set for ourselves. [5].

1.2 PROBLEM STATEMENT

In order to accomplish the work of recovering images, picture degradation models are sometimes used in conjunction with background information describing the primary image frames in a video. This is done in order to successfully complete the task. This is done so that we have the highest possible possibility of being successful. It is difficult to determine the degree to which photographs that were taken in the real world have become less clear over the course of time due to the complexity of the photographs. These photographs were taken in the real world. Due to the fact that a single image frame in a video can consist of a mix of a massive number of different latent image frames in a video, picture restoration is an inverse problem that has been comparatively understudied. One of the many reasons why picture restoration is so crucial is because of this. This is because of the complex nature of the problem that we are attempting to solve. You will need to adhere to several extra limitations in order to solve the inverse issue successfully. Some of these additional constraints include the sparsity and low rank of the visual signal. After that, and only then, will you be able to find a solution to the problem with the inverse. Due to the fact that priors are inherently mathematical in nature and do not have any applications in the real world, the significance of priors is sometimes overstated. This is because priors have no real-world applications. Both the fact that priors are basically mathematical and the fact that they do not have any applicability in the actual world are aspects that contribute to the fact that priors do not have any relevance in the real world. If you try to remedy these issues by employing image restoration methods that are more traditional, you will not be successful [6].

One good illustration of this would be the relatively recent development of deep convolutional neural networks as a powerful and adaptable answer to the problem of picture restoration. When it comes to machine learning, it is possible to make use of a massive sample dataset that is both more accurate and more reliable than the alternative method of deriving statistical inferences from the observations of a single picture. This is made possible by the fact that it is possible to make use of a massive sample dataset. The term for this instructional approach is "ensemble learning."

This is a strategy that is significantly more efficient. It is possible to train deep neural networks to uncover sophisticated nonlinear mappings between the degraded and original versions of visual frames included inside a movie by making use of the vast amounts of data that are currently accessible and by putting those massive amounts of data to good use. Using the data that is now accessible is one way to accomplish this goal. One technique to achieve this objective is to use the data to train deep neural networks, which can be done by putting the data to use. It is not necessary to develop a difficult mathematical model in order to recover an image. This is because image restoration does not require any such thing. In the field of photo restoration, recent years have seen substantial advancements made as a result of deep learning's ability to enable these advancements. When compared to other methods of image processing that are more conventional in character, this is especially true. This has been the experience that a great number of people have had as a result of the use of deep learning. [7].

1.3 OBJECTIVES

The following are some of the objectives that the works seek to accomplish:

a. It is proposed to utilize a SLIC-based segmentation method to automatically determine the optimal amount of superpixels to use.
b. Investigate the feasibility of using superpixel-based representations for hyperspectral unmixing.
c. It will be helpful to compare the new method to past inventive unmixing strategies to see how they compare.
d. Utilize MATLAB to implement the suggested procedure.
e. Evaluate the usefulness of the algorithm in a real-world context.

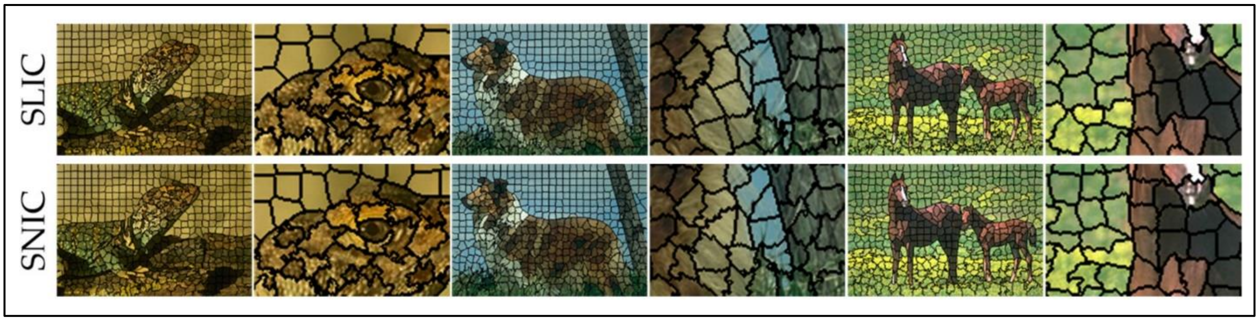


Figure 1.3: SNIC vs SLIC superpixel comparison [8].

1.4 CONTRIBUTION

The fundamental objective of this thesis project is to investigate the challenges that have been brought up in connection with the literary canon and to propose solutions that are applicable to these problems in a practical manner. The research of the many different extraction procedures that are based on clustering is going to receive a large amount of focus and attention from us moving forward. In addition, the efficiency of each and every conceivable option will be assessed, and additional suggestions for enhancing efficiency will be provided whenever it will be possible to do so. It has been proposed that the number of configuration parameters for processes should be kept to a minimum in order to avoid the potential risk of confusion that may be brought on by the utilization of hyper-parameters. This has been recommended for the following reasons: In addition, we will investigate concerns regarding the dependency of benchmark hyper-parameters and present unique techniques in order to develop a core benchmark framework that is universally shared by all parties involved. This will be done in order to achieve our goal of creating a better benchmark. We shall do this in order to realize our objective of developing a superior standard of measurement. This will make it much easier to compare different techniques in an objective manner, and it will provide sufficient information for programs that make use of varied tactics for the extraction of SP. SPs are commonly used as a segmentation tool in graph-based segmentation methods. These methods segment data using graphs. Several research have demonstrated that these methods for segmenting the market are rather effective in achieving their goals. On the other hand, since neural networks do not have a regular grid structure, it is not viable to apply SP techniques to them. This is the case because of the aforementioned limitations. Because of this, it is unable to employ SP strategies. Gathering information is one of the goals of this inquiry, as it will allow us to come up with potential strategies for constructing SPs within a regular grid in the future. In conclusion, during the course of this study, a collection of SP approaches that are centered on clustering were developed. These methods are described below. These methods not only provide an SP grid that is consistent in a shorter amount of time, but they also trace the borders of objects with a greater degree of accuracy. In addition, the user has the ability to manage both the degree of compactness of the SPs as well as the total number of SPs that are produced as a result of the use of these procedures. It is absolutely necessary to conduct research into the effect that various phases of a clustering-based strategy have on the overall effectiveness of the method in order to successfully develop a variety of strategies for SP extraction. Only then will it be possible to successfully develop a wide range of strategies for SP extraction. In order to extract the SP, we are going to make use of these strategies. A benchmark framework will be offered as part of the next research that will include these new approaches. This framework will more correctly analyze the performance of earlier strategies in addition to the newly recommended ones. This examination will take place as part of the future research. As a further contribution to the ongoing research, this framework will also be made available. This assessment is going to be carried out as a component of an upcoming study that is also going to use these unorthodox methods of investigation.

1.5 THESIS STRUCTURE

The framework of the thesis is the following structure: In the 2 portions, we will analyze the historical research and development of smart grids. In the third part, a summary of the various components is provided. In Section 4, we present a comprehensive description of our model. In Section 5, we explain how our model may be used via simulation, and in Section 6, we provide the results of our simulation. Our results are described in Section 6, which also include some potential future scenarios.

2. LITERATURE REVIEW

2.1 CHAPTER INTRODUCTION

The majority of the long-term changes that take place on the surface of the Earth are brought about by factors that are both those that occur naturally and those that have been generated by humans. These changes can be broken down into two categories: natural and human-made. The land cover has altered in a variety of directions as a result of interactions between natural forces and human activities. These interactions have led to these changes. Examples of natural occurrences that can be placed into this category include the movement of continents, the progression and retreat of glaciers, as well as floods and tsunamis. The conversion of previously forested terrain into agricultural land, the rise of metropolitan centers, and the proliferation of new forest planting are all examples of human-induced changes. Over the past few decades, the proportion of land cover that is changed as a result of human activity has significantly increased. This is in contrast to the effects that are produced by natural processes, which have remained relatively constant. This is especially important to keep in mind while considering the contrast between the two. The unprecedented rate of change that is being caused by our species has emerged as a huge threat to the environment on a global scale, and it is having an effect on nearly every ecosystem that exists anywhere in the world. This threat has emerged as a result of the fact that our species is causing these changes. The introduction of innovative technology and the rise in the number of people living in different parts of the world have both contributed significantly to the significant impact that human activities have had on the transformation of the land cover [9]. Changes in the land's cover as well as its utilization have the potential to have either positive or negative effects on human people, depending on the manner in which such changes are put into effect. It is possible that the use of previously wooded land for agricultural purposes will result in an increase in the quantity of food, vegetables, and fruits as well as fibers that can be utilized in the production of textiles that are made available for human use. On the other hand, deforestation is linked to a wide variety of unfavorable impacts, some of which include a reduction in the amount of biodiversity and an increase in the severity of soil erosion, amongst other things. Deforestation also has a direct correlation with climate change, which has the potential to further exacerbate these problems. There is a correlation between deforestation and a variety of adverse effects. Even if there is a chance that these kinds of changes will have a positive impact on the economy and on society as a whole, they almost always have a negative impact on the natural environment. This is true despite the fact that these kinds of changes could have a positive impact on the natural environment. It is possible to determine the various sorts of surface changes as well as the geographic distribution of those changes by combining images that were collected by remote sensing equipment of the same site at different times. These photographs were taken at different points in time. Performing this task is as simple as examining the photographs. This method is utilized in conjunction with images that were obtained via the use of remote sensing equipment in order to facilitate the calculation of the amount of time that has elapsed from the beginning of the process.

2.2 RELATED WORKS

In the research publication that they worked together on [10], Braga and his colleagues developed a speedy level set-based strategy for minimizing the amount of speckle noise that is visible in SAR images. This method is described as being "fast." They were able to do this by employing a nonparametric median filter for the purpose of curvature regularization and morphological processes for the purpose of front propagation. Both of these strategies were successful. In order to achieve the outcomes that were sought after, it was necessary to make use of both of these approaches. There is a possibility that, in the not-too-distant future, this tactic will come to be regarded as the industry standard.

The energy functional that is used in the level set technique to divide high-resolution PolSAR (polarimetric synthetic aperture radar) pictures into homogeneous and heterogeneous areas, respectively, was altered by Jin et al. [13], who did so by making a change to the energy functional that is used in the level set technique. In order to accomplish this goal, the L distribution was utilized on all of the available data.

The approaches of image color correction and restoration were categorized by Ma et al. [12] based on which of three separate sets of fundamental units best represented each method. There are three unique categories that can be used, and they are object-based, region-based, and pixel-based accordingly. Each of these categories has its own set of advantages and disadvantages. Pixels serve as the fundamental processing unit for image color repair and restoration techniques that are pixel-based. These techniques can be used to repair and restore the colors in photographs. Prior to the improvement of the segmentation energy function, a number of different energy function models are utilized in order to determine the probability that a specific pixel is either part of the foreground or the background. This is done so that the improved segmentation energy function can be implemented. This is done so that we can identify which of the two categories the pixel belongs to. This system's strength is in the ease with which it can be put into operation; nevertheless, one of its major flaws is that it requires a significant amount of work to be carried out on a computer.

Merdassi et al. [15] compiled an overview of the many image color correction and restoration processes that are currently in use and divided them into eight categories based on the methodologies that they have utilized in recent years. This was done in order to provide a comprehensive look at the various options that are currently available. This was done so that they could contrast and compare the various approaches in an efficient and effective manner. Image color correction and restoration can be divided into a total of eight distinct categories, which are as follows: MRF-based image color correction and restoration, co-saliency-based image color correction and restoration, image decomposition-based image color correction and restoration, random walker-based image color correction and restoration, map-based image color correction and restoration, active contour-based image color correction and restoration, and clustering-based image color correction and restoration. Graphs are used as the foundation for the vast majority of the solutions that are currently accessible, the MRF framework in particular being one of these. This is done to address concerns with combinatorial optimization and provide a solution to the difficulties associated with such concerns. Image color repair and restoration algorithms are now capable of evaluating photographs that comprise a diverse range of subjects and a significant number of bands. In years gone by, we did not have access to this capability. While the author was explaining how picture color correction and restoration can be utilized to differentiate between roadways, bridges, and rivers in remote sensing photographs, he brought up the point that civilian applications for aerial photography are quite limited. These apps are only relevant to a small portion of the various career paths that are open to people right now.

In addition to change detection, Yuan and his colleagues have developed the remote sensing image techniques of picture color correction and restoration (16). In the course of their research, they made use of a map that illustrated the degree to which the differences had occurred. In order to construct the map that illustrates the shift in intensity, the computation makes use of both geographical and temporal images in tandem. This allows for the creation of the map. The utilization of both of these kinds of pictures brings about the desired results. During the process of generating a network flow diagram, the initial image is utilized, and links are built between the change detection and image segmentation phases. The lowest cut/maximum flow technique is utilized because it improves energy efficiency while also enabling the successful completion of picture segmentation and change detection at the same time. Because of this, the tactic that is utilized is the one that I outlined before in this paragraph. The application of the bitemporal change detection method led to the discovery of two things regarding the image color correction and restoration change detection processes. This is because each picture has its own one-of-a-kind collection of qualities, which is the primary reason why this approach was developed in the first place. As a result of this, the method described here is necessary.

Dinic's method of highest flow/minimum cut was applied by Xie and Zhu et al. [18] after the optimization approach had been modified in order to obtain the energy function with the smallest possible cut. This was done in order to accomplish the task. The energy function could not be attained without doing this first. Reworking the design of the picture feature so that it could accommodate the continuous change in the energy function was one of the key goals of the project.

According to Achanta et al. [17], the process of segmenting superpixels can be broken down into two distinct categories: those that are based on graph theory, and those that are based on gradient descent. Graph theory-based methods are the first category. Gradient descent-based methods are the second category. Both graph theory-based segmentation and gradient descent-based segmentation may be found in the first group. The second category contains segmentation that is based on gradient descent. After being segmented with graph theory-based superpixels, the image is represented as a network flow diagram when it is displayed. When the image is segmented, each pixel acts as a node, the spatial adjacency connections between the pixels work as edges, and the characteristics of the pixels that are adjacent to the divided area act as edge weights. Following the creation of a network flow diagram at the beginning of the process, the succeeding steps involve dividing up the overall picture according to a number of different criteria.

Stutz et al. [33] conducted research in which they compared and contrasted 28 different state-of-the-art superpixel segmentation algorithms by making use of five different datasets and evaluation criteria in their investigation. Methods that are based on border recall, segmentation error, explained variation, and stability are some examples of the kinds of approaches that have been proposed as potential candidates for implementation in real-world scenarios. The six algorithms that were used are ETPS, SEEDS, ERS, CRS, and ERGC. Each of these algorithms is able to maintain the structure of the image while simultaneously reducing the number of superpixels that are contained inside it.

Table 2.1: Summary of related works

Author	year	Findings
Merdassi et.al	2020	Image color correction and restoration techniques are 8 varieties. Active contour, MRF, cosaliency, image decomposition, random walker, and map (DLC). Graph-based MRF. Optimized. Image color correction and restoration examines bands and objects. Image color correction and restoration recognizes highways, bridges, and rivers in remote sensing photographs, although civilian use is limited.
Braga et al	2017	Quick level-set-based approach for decreasing SAR speckle noise. They used a nonparametric median filter for regularizing curvature and morphological processes for front propagation. Future usage of this approach is possible.
Jin et al	2017	Changed the level set energy functional to split high-resolution PolSAR images into homogeneous and heterogeneous zones. The L distribution was used.
Ma et al	2017	Three groups of photo color correction and restoration. Object-, region-, pixel-based. Color repair and restoration use pixels. Before raising the segmentation energy function, many energy function models decide whether a pixel is foreground or background. This method's simplicity is a plus, but it's computer-intensive.

Table 2.2: Summary of related works 'Table Contied'

	2015	Change detection and remote color correction. Change map intensity. This map mixes geographical and temporal images. Creating a network flow diagram from the source picture and change detection. Lowest cut/maximum flow improves picture segmentation/change detection. bitemporal change detection detects color correction and restoration.
Xie and Zhu et al	2017-2019	Dinic's greatest flow/minimum cut technique yielded the least achievable energy reduction. Picture feature design was improved to shift energy function consistently.
Achanta et al	2012	Graph theory or gradient descent segment superpixels. In graph theory-based superpixel segmentation, each pixel is a node, spatial adjacency connections are edges, and surrounding pixel attributes are edge weights. The network flow diagram is split.

2.3 CHAPTER CONCLUSION

The spectral value of a single pixel is the only factor that is taken into account in the method of detection that is known as pixel-based detection. This method of detection was developed by Microsoft. This method of detection pays no attention at all to the spatial link that already exists between the neighboring pixels. As a direct result of this, the reconstructed picture patches have a low degree of precision, a high degree of dispersion, and they are susceptible to the introduction of image noise. The object-based detection method looks for inconsistencies not only in the target object but also in neighboring pixels that have the same level of consistency as the object that is being identified. This is done in order to identify any potential problems. Despite the fact that the recognized picture patches are reliable and that the accuracy has been significantly improved, this method continues to rely on selecting the segmentation scale that is most appropriate for the data that is being examined. This is despite the fact that the accuracy has been significantly improved. However, in order to ensure that the detection accuracy of these techniques is on par with that of the object-based method, improvements have been made to these strategies. When compared to earlier methods, this is a considerable advancement and constitutes a significant step forward in the process. In other words, the object-based method is the detection approach that delivers the maximum level of accuracy. This is because the method focuses on the objects themselves. On the other hand, the operational efficiency of superpixel image color repair and restoration techniques is only slightly different from that of image color correction approaches. This is because superpixel images have a higher number of pixels than traditional images. The size of standard photographs is significantly smaller than that of superpixel photographs, which accounts for this distinction.

3. MATERIALS AND METHODS

3.1 INTRODUCTION

Increasingly, computing has reached high importance in several processes. In particular, image processing becomes indispensable in several areas ranging from entertainment to industrial process control. Along with the capture and transmission of images goes the noise that can be generated by several factors. As an unavoidable feature, it is essential to look for ever better filters that have the ability to remove imperfections, keeping all the information present in the image, as well as its details. The big obstacle is precisely the fact that such different segments have very different needs from each other and even so need efficient filters.

In this context, the proposal for the fusion of two concepts, image processing and Evolutionary Computing, arises. As demonstrated in the work, many studies have been carried out on the subject on several fronts and the results have been very encouraging, which proves to be a promising area. This work proposes the study of filters to remove noise from images and the possibility of using Genetic Algorithms for the fully autonomous synthesis of efficient algorithms from reference images.

3.1.1 Introduction to Noise in Images

In images, noise can be defined as changes in the intensity and color of a pixel from what is being captured or transmitted originally. These deformities can arise from various external factors such as physical-electrical factors in digital capture sensors, grains present in photographic films or even failures in transmission or reading/writing.

As described in Digital Imagen Processing, “Noise from noisy sensors or transmission channel errors usually appears in discrete form and with isolated variations without spatial correlation. Defective pixels are visibly different from their neighbors” Simply put, noises are divided into two basic types, saturation and variation. In the first one, the value of the pixels reached is changed to its maximum or minimum value, without intermediate variations. They are better known as salt-and-pepper noise. This type is very didactically used for its simplicity, but in practice it is rare to happen. The second, commonly found in real cases, can reach a pixel with greater or lesser intensity, making sensitive or drastic changes in its value. It is more difficult to detect in images.

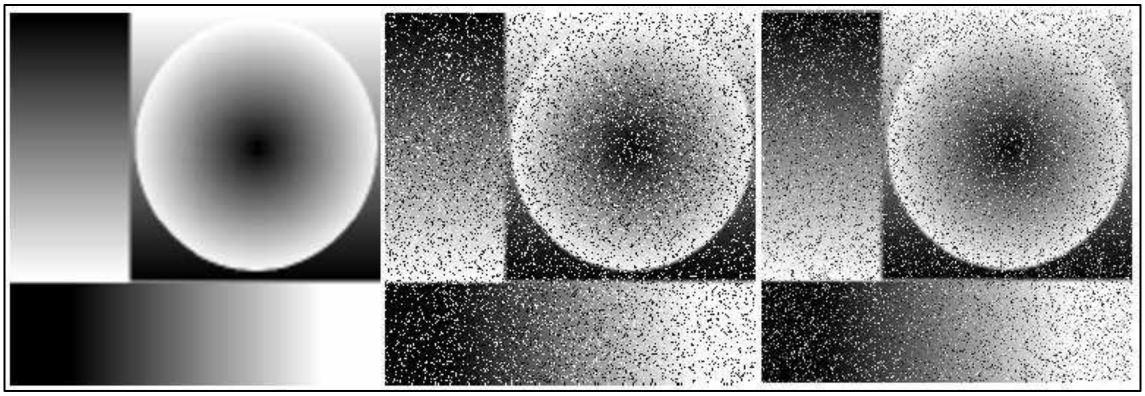


Figure 3.1: Example of salt-and-pepper noise and intensity noise

In addition to visual aspects, where the camera user wants their photos to be consistent with reality and without imperfections, noise is extremely important for applications based on image processing. Segmentation and pattern identification are commonly used in the industry for the automation of production lines using robotics, for example. Filtering images and removing noise is part of a phase called image pre-processing that is crucial for the proper functioning of the system. Without such a process, the algorithms employed in the following phases become much less accurate and may even stop working.

Due to its importance, noise removal has been extensively studied over the years and should be considered when developing real applications. To test the efficiency of filters, it is necessary to have a reference image in addition to the noisy image so that the results can be compared. Normally the process consists of using a clean image as a reference and generating the noisy image artificially through some distribution formula. MATLAB, for example, has several formulas to synthetically create different types of noise with different distribution and intensity in each case, such as uniform, Gaussian and exponential distributions. Figure 3.2 shows a table with several formulations available in MATLAB for generating noise in images:

TABLE 5.1 Generation of random variables.

Name	PDF	Mean and Variance	CDF	Generator†
Uniform	$p_z(z) = \begin{cases} \frac{1}{b-a} & \text{if } a \le z \le b \\ 0 & \text{otherwise} \end{cases}$	$m = \frac{a+b}{2}, \quad \sigma^2 = \frac{(b-a)^2}{12}$	$F_z(z) = \begin{cases} 0 & z < a \\ \frac{z-a}{b-a} & a \le z \le b \\ 1 & z > b \end{cases}$	MATLAB function rand
Gaussian	$p_z(z) = \frac{1}{\sqrt{2\pi}b} e^{-(z-a)^2/2b^2}$ $\quad -\infty < z < \infty$	$m = a, \quad \sigma^2 = b^2$	$F_z(z) = \int_{-\infty}^{z} p_z(v)\,dv$	MATLAB function randn
Salt & Pepper	$p_z(z) = \begin{cases} P_a & \text{for } z = a \\ P_b & \text{for } z = b \\ 0 & \text{otherwise} \end{cases}$ $\quad b > a$	$m = aP_a + bP_b$ $\sigma^2 = (a-m)^2 P_a + (b-m)^2 P_b$	$F_z(z) = \begin{cases} 0 & \text{for } z < a \\ P_a & \text{for } a \le z < b \\ P_a + P_b & \text{for } b \le z \end{cases}$	MATLAB function rand with some additional logic
Lognormal	$p_z(z) = \frac{1}{\sqrt{2\pi}bz} e^{-[\ln(z)-a]^2/2b^2}$ $\quad z > 0$	$m = e^{a+(b^2/2)}, \sigma^2 = [e^{b^2} - 1]e^{2a+b^2}$	$F_z(z) = \int_{0}^{z} p_z(v)\,dv$	$z = ae^{bN(0,1)}$
Rayleigh	$p_z(z) = \begin{cases} \frac{2}{b}(z-a)e^{-(z-a)^2/b} & z \ge a \\ 0 & z < a \end{cases}$	$m = a + \sqrt{\pi b/4}, \sigma^2 = \frac{b(4-\pi)}{4}$	$F_z(z) = \begin{cases} 1 - e^{-(z-a)^2/b} & z \ge a \\ 0 & z < a \end{cases}$	$z = a + \sqrt{-b\ln[1 - U(0,1)]}$
Exponential	$p_z(z) = \begin{cases} ae^{-az} & z \ge 0 \\ 0 & z < 0 \end{cases}$	$m = \frac{1}{a}, \quad \sigma^2 = \frac{1}{a^2}$	$F_z(z) = \begin{cases} 1 - e^{-az} & z \ge 0 \\ 0 & z < 0 \end{cases}$	$z = -\frac{1}{a}\ln[1 - U(0,1)]$
Erlang	$p_z(z) = \frac{a^b z^{b-1}}{(b-1)!} e^{-az}$ $\quad z \ge 0$	$m = \frac{b}{a}, \quad \sigma^2 = \frac{b}{a^2}$	$F_z(z) = \left[1 - e^{-az} \sum_{n=0}^{b-1} \frac{(az)^n}{n!}\right]$ $\quad z \ge 0$	$z = E_1 + E_2 + \cdots + E_b$ (The E's are exponential random numbers with parameter a.)

† $N(0, 1)$ denotes normal (Gaussian) random numbers with mean 0 and a variance of 1. $U(0, 1)$ denotes uniform random numbers in the range $(0, 1)$.

Figure 3.2: MATLAB functions used for noise generation

In addition, certain scenarios make it possible to implement other alternatives that are much closer to reality. Not necessarily noisy images must be synthetic to have a clean image. There are techniques that make it possible to generate a very well filtered image from the superposition of several noisy images of the same subject. In this way, it is not necessary to apply statistical filters, keeping a large amount of details preserved.

3.1.2 Introduction to Filtration Techniques in Images

To remove noise from images, several filters were developed over time with very different approaches and techniques. Each of these has advantages and disadvantages with respect to different analysis parameters. Some are extremely efficient for a certain type of noise while presenting poor results for other types. Amount of memory used in the process and processing time can also be crucial factors in certain

applications. There are currently two major families of filters, linear and non-linear. Linear Filters

Widely used for noise removal as they are extremely simple. They are basically composed of a matrix in which the original image is convoluted to generate a new filtered image. In practice, it is nothing more than a low-pass filter, removing completely isolated pixels that generate high frequencies. The system's disadvantage is that it generates image blurring, regardless of the type of noise and its intensity. The advantages are the speed of application and the possibility of highly robust mathematical modeling in its development.

a. Non-linear filters

Precisely because the noise signal, in practice, does not have a linear behavior, non-linear methods present better results.

Means and medians filters

Currently, they are the most used filters because they present satisfactory results without the need for a large amount of memory and processing power. Instead of performing convolution from a matrix on a given pixel and its neighbors, it calculates the mean or median of this neighborhood and determines its final value. Some methods still use a larger context analysis, making a statistical survey of the entire image to be used in the local calculation. In this context, the best known filters are Common Media Filter (MF), Center Weighted Median Filter (CWMF), Weighted Median Filter (WMF).

b. noise detection

Even though the blurring effect is much less noticeable in this type of filter, it still occurs and important details are lost as they are applied to every pixel in the image. To solve this problem, a new filtering concept has emerged in which the process is divided into two phases. First, the objective is to identify which image pixels are affected by noise and then apply some known method to replace the wrong value with an approximation. Unlike other methods, the detection phase uses filters of statistical order that gradually increase your mask in the search for the best result. This approach greatly increases the filter's ability to retain image detail. This is the concept used by the Adaptive Median Filter (AMF) method.

c. iterative methods

In the search for better results, iterative methods emerged, which try to determine with better precision whether or not the pixels are noise and how to calculate their value with better precision.

For this, among other techniques, it looks for edges and other forms of contextualization. Among the algorithms that use these techniques are Pixel-Wise Median of the Absolute Deviations from de median (PWMAD) and Directional Wighted Median filter (DWM). The disadvantage is clear, as these are iterative methods, the amount of memory and processing power is extremely higher than the other methods. Even so, they are considered the state of the art for presenting the best results to date.

3.1.3 Initial Project Definitions

From the study carried out and before any implementation study, it is necessary to determine which design criteria will be used so that a modeling of the intended system can be determined.

As mentioned in the initial chapter, industrial applications are a great example of the need to apply filters in the pre-processing of captured images to control the production line. Real applications like these need extremely efficient calculations in terms of speed, reliability, etc., as the performance of control mechanisms depends on it. Another example is the case of the photographer who wants to see the result of his capture right after the camera clicks. In this case, in addition to speed, the size of the hardware is limited. These factors mean that in many cases the filtering circuit is not simply software, but can be implemented in hardware so that it respects the design decisions of each application. Regardless of the case, the focus of the work is to scale algorithms that can be implemented in simple hardware,

From the first item, we can make a new analysis of the filtering techniques studied. Iterative methods are extremely efficient but go against the first definition. Among the remaining methods, the concept that made great progress in noise removal was to separate the process into two steps – noise detection and calculation of the new value of each pixel. Therefore, a circuit that represents such a problem must have as input a certain amount of pixels and two output values, one indicating whether the analyzed pixel is noise and the other determining a value calculated by a filter. If the detection value is false, the input base pixel is simply output. Otherwise, the pixel calculated by the filter must be used.

Combining this information, we can make a schematic model of how the circuit responsible for applying the filter on the images should look like. In Figure 4.1 we can see a diagram representing this:

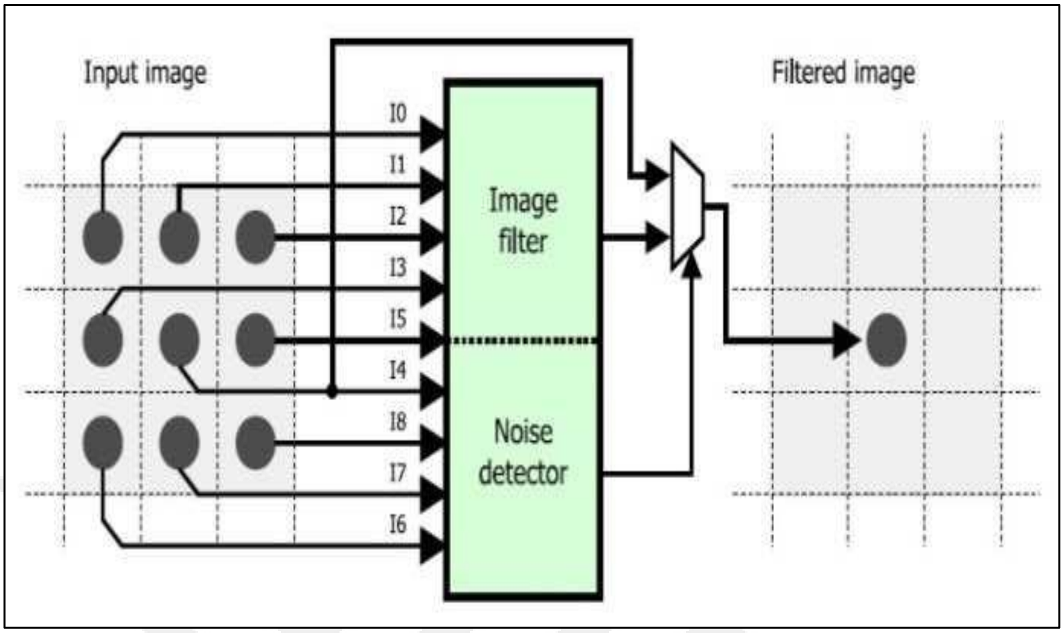


Figure 3.3: Circuit proposal for removing noise in images.

Noise can appear in images presenting different types of patterns depending on where it comes from. Photo camera sensors show deformations different from those presented in transmission errors, which, in turn, can be different from the noise present in digital X-ray images or computed tomography. This makes each segment have different needs and consequently an implementation with its own characteristics. For this to be put into practice, it is necessary to carry out a study of each case, find the best existing solution for the case or implement a new one. Clearly this is an expensive process, as it will be necessary for each case to study, implement and test phases. In many cases the solution is to use known tools even if they do not provide optimal results.

In the search for a filter suitable for each situation, two approaches are possible. In the first one a known filter is chosen. From there, development comes down to getting the parameters right so that it adjusts in the best way to produce the best results. The other alternative is to start the development process from the beginning and produce an entirely new filter.

3.2 SUPPRESSION OF NOISE IN IMAGES

Several times a digital image undergoes a degradation process that can be caused by several factors such as movement at the time of image capture, camera lens imperfections, limitation in the size of the sensors, etc. In addition, problems also occur during image compression and transmission. All of these situations can produce an out-of-focus or noisy image as illustrated in Figure1.

Figure 3.4: The figure shows an image in which there was movement at the time of capture, making it blurry

The degradation that occurs in an image can be described in the spatial domain by the equation model, where F(x,and)is the undegraded image, h(x,and)is the degradation function, η(x,and)the noise added to the image and represents the convolution operation. In the end, the degraded image is represented by the function g(x,and)

Impulsive Noise: Defined by Equation2.8. Also called salt-and-pepper noise; case b>The, the intensity b will be a bright point on the image and a dark point, as long as Pa and Pb are not equal to zero. An example of the effect that each of these different noises causes, when applied to the image in Figuretwo, can be seen in Fig.3.4.

In this work, we used additive white Gaussian noise for most of the experiments performed. This type of noise — which follows a normal distribution and affects frequency bands uniformly — is the most used in several cases in the literature, this is due to the ease of mathematical manipulation that it provides both in the spatial domain and in the frequency domain.

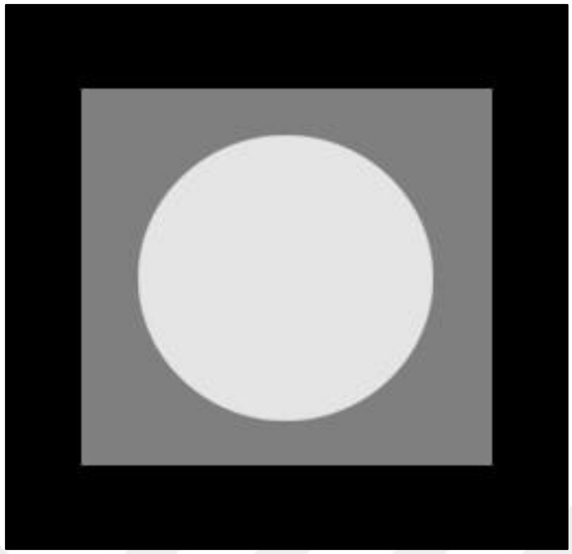


Figure 3.5: Original image

All the PDFs presented so far give us an estimate for the calculation of η (x, and) and do not solve the problem completely, but they serve as a guide-to-guide studies regarding noise attenuation in images.

3.2.1 Noise Attenuation as an Optimization Problem

A. Attenuation through MRF

The approach taken by Ishikawa uses the Bayesian Framework in conjunction with MRF to treat noise attenuation as an optimization problem. In this problem, a model divided into two parts is created, the Prior Model, which is an expectation of what the original image would look like, and the Image Formation Model, which is the noisy image as it is formed, that is, the noise added to the original image.

An MRF can be described as a set of random variables (vertices) that are represented by an undirected graph. The vertices are associated with a set of possible values L and a probability function P(X), where X is a state of the graph. A value of L is associated with each vertex and each edge has a weight representing the conditional probability between two adjacent vertices. When there is no edge between vertices, they represent independent variables.

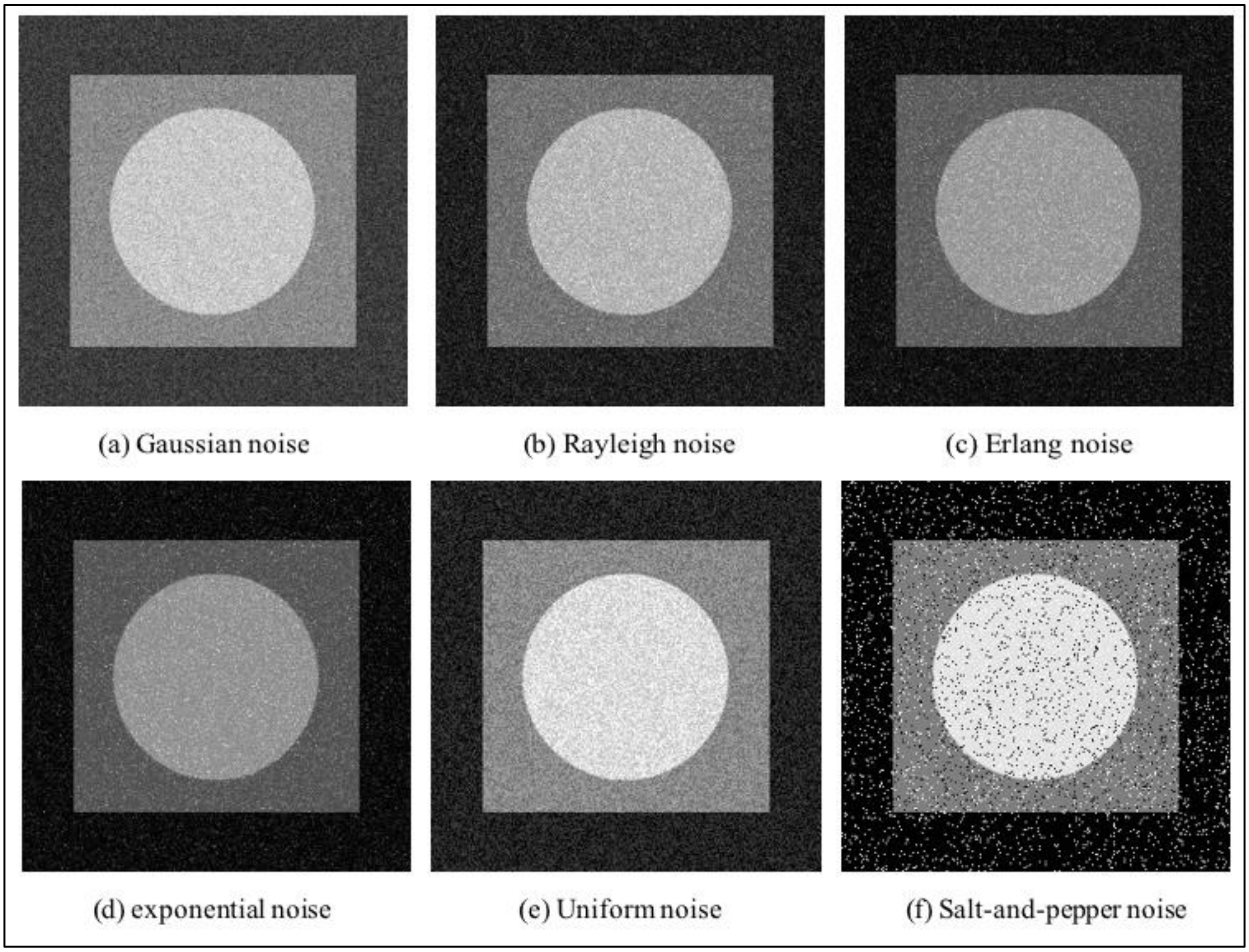


Figure 3.6: The result of different noises applied to the imagetwo

From these assumptions, the problem becomes to estimate the original image from the noisy one. In this case, the Prior Model gives the probability P(X)of the image X to be an original image, while the Image Formation Model gives the probability P(I|X) that the noisy image I was formed from the original X. At this point, we want to look for the image X that is most likely to become the image I after adding the noise, that is, from a mathematical point of view, we want to maximize P(I|X) (equation 3.1).

$$P(X|I) = P(I) \tag{3.1}$$

$$P(I|X) \sim \prod e^{-\left(I(x,y)-X(x,y)\right)^2} \tag{3.2}$$

where μ is a parameter that depends on the noise intensity (x, and) are the pixels of the images and $(x', y')$are its neighboring pixels.

The maximization of P(X|Y) can be treated as a logP minimization problem(X|Y), which can be interpreted as minimizing the energy of the system (where R(X)is the energy of the image.

$$\text{Argmin}\|X-I\|\text{two}+\mu R(X) \tag{3.3}$$

Treating the image as an MRF the problem becomes the minimization of the energy equation

$$\min E(X) = \mu \sum |X_u - X_v| + \sum (I_v - X_v)^2 \tag{3.4}$$

where X is the evaluated individual, I the noisy image, Xv is the vth pixel of X and two pixels(u,v)∈ Noif and only if u belongs to the 4-neighborhood of v. Finally, μ is a constant that aims to balance the smoothing of X.

From the representation of the image as an MRF, the image denoising problem is treated as a minimal cropping problem so that it is possible to obtain a graph whose relationship between its cuts and the configurations of the original MRF is one to one. In this model, the vertices of the graph are arranged in a cube format, where two dimensions represent the location of the pixel and the third one represents the intensity of the pixel, causing there to be one vertex per possible value of intensity. The height of the cube where the cut occurs represents what the intensity will be for the corresponding pixel. In this way, it is expected that the cost of cutting the graph is equal to the value of the energy function of the MRF. That is, when minimizing the energy function of the MRF, the minimum cut of the graph will also be done. This process, illustrated in Fig.4, was solved by Ishikawa with an algorithm called the standard push-relabel method with global relabeling

Attenuation through minimization of total variation

A particularly effective and well-used way of suppressing noise in images is to minimize the total variation present in the same. In this way, a mathematical model that describes this variation can be used as a guide for several optimization methods Based on this, a model in order to minimize this total variation through the following equation:

$$\left\{\int_{\Omega}|\nabla X|+\frac{\lambda}{2}\int_{\Omega}(X-I)^2\right\} \quad 3.5$$

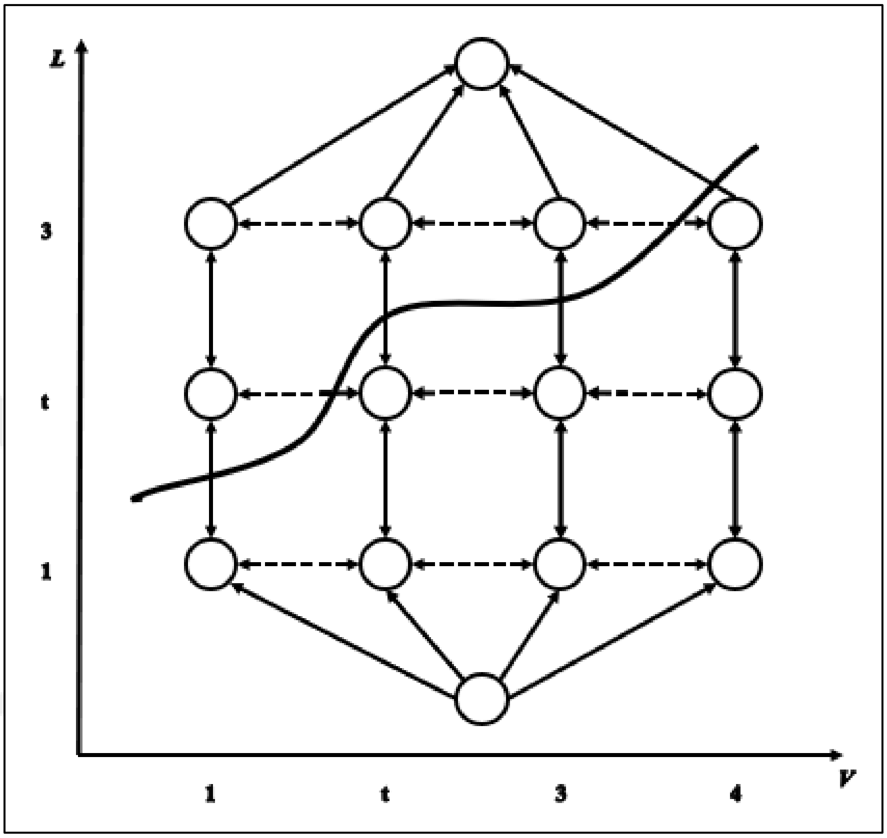


Figure 3.7: Illustration of the minimum cut problem of the Ishikawa proposal.

for a balancing parameter λ>0. In this proposal, X is the evaluated image and I is the noisy image, ∇Xis the gradient of X (total variation norm) and Ω is the set of points in the image.

is based on the concept of Polyakov Action, initially introduced in string theory in the field of physics. The framework consists of two main aspects: first, describing an image as maps between two Riemann manifolds; second, a functional action that allows measurements in the spaces of these maps.

3.3 EVOLUTIONARY COMPUTING

From the possibilities produced by the use of this framework, Zosso and Bustin proposed a formulation in a primal-dual model of the function described in— used in this work, in its discrete form, as a fitness function of the AGH. Through a designed gradient optimization algorithm,

3.3.1 Evolutionary Computing

Evolutionary methods are characterized by creating populations, where each individual is a representation for the solution of the problem addressed. These individuals then start to compete and the population is updated, where those who are more suitable (better fitness) to the problem are more likely to survive and reproduce, making their main characteristics pass on to their children.

An initial population of individuals is constructed randomly or with a certain degree of randomness. Then, some individuals are selected as parents whose characteristics will be recombined to generate new individuals. The elements of the new generation may or may not undergo a mutation process that often brings diversity to the population. An intermediate population is formed from the new individuals and those that already exist in the population. The fittest tend to be chosen to form the population in the next generation. This method is repeated until some stopping criterion is met

From these basic concepts, different trends of development of these techniques emerged:

i. Evolutionary Programming), has some particular characteristics such as the non-existence of recombination and mutation to be carried out through a Gaussian perturbation in the chromosomes.

ii. Evolutionary Strategy Some specific original features are the existence of recombination, Gaussian perturbation mutation and the random selection of parents.

iii. Genetic Programming – The most recent of the four, was proposed by Koza in the early 1990s. In this technique, chromosomes are represented as trees, recombination is done by switching sub-trees, and mutation is done by random changes in trees.

iv. Genetic Algorithms – Proposed by Holland Some of its original features are the encoding of chromosomes as binary strings, recombination of chromosomes using the method

one-point or n-point and defined mutation by inverting the value of bits with a certain probability.

3.3.2 Genetic Algorithms

The problem described in the previous chapter is recurrent and is present in several areas of image processing. From pre-processing phases, such as noise removal filters and contrast adjustments, to post-processing, such as compressing images for transmission. In the search for increasingly specific solutions, several studies have been carried out using Genetic Algorithms to find such solutions. The results found are very encouraging and the scientific community has published several articles proving the effectiveness of such a relationship. Examples are: Application of Image Segmentation Algorithm Based on Particle Swarm Optimization and Rough Entropy Standard, Discrete Cosine Transform Image Compression Based on Genetic Algorithm, Automatic Design of

Image Operators using Evolvable Hardware and Evolutionary Design of Robust NoiseSpecific Image Filters.

In addition to the results presented being comparable to known methods, this approach has the great advantage of finding the best solution from known input data. The solution developer no longer needs to worry about researching and developing new algorithms for each case, it is enough to form a good set of input images so that the GA is properly trained for the context in which it is intended to act. Using any of the techniques described above, you must have a clean image and a defective image. From the comparison between the two, the evolution of the solution occurs with the search for minimization between the result of applying a candidate in the defective image and the reference image.

Until a few years ago, a widely used approach was to generate a tree circuit. In this approach, a series of inputs was consecutively reduced by functions until at the end the number of outputs determined was left. An example of reduction is, for every two inputs, to generate an output using a given function (such as sum, for example). New work has been done using a new technique known as Cartesian Genetic Programming (CGP). This technique has proved to be very efficient because, unlike the concept of a tree, it allows alternative paths to be created over generations and end up adding possibilities of functionality and longer paths to the results. This phenomenon is described by the author of the Cartesian Genetic Programming article as redundancy.

A study that marks the use of this concept is described in the article GateLevel Optimization of Polymorphic Circuits Using Cartesian Genetic Programming. Simply put, the problem described deals with the synthesis of complex digital circuits. These circuits make use of logic gates with behavior dependent on external factors, such as temperature, for example. A certain gate can generate true results as a NAND gate if the component is below a certain temperature. Otherwise it works like a NOR. With this, it is possible to save on components, and consequently on space, so that the circuit has a specific behavior for each temperature range. However, current software has not been efficient to perform the synthesis of such circuits.

In image processing it has also been widely used due to the fact that the processing is still a circuit where some inputs are analyzed, such as a reference pixel and some neighbors, and from that it generates an output that is analyzed with some reference. The objective is to minimize the difference until the results are satisfactory.

The term Cartesian probably arose because the concept is based on a matrix ofmlines bynocolumns that are referenced Cartesian by two-dimensional coordinates. Each position in this matrix represents a cell that can be occupied by one of the pre-defined functions and have the inputs linked to the outputs of other positions or directly to the inputs of the circuit.

Each circuit data source is numbered with an integer value starting from zero. A data source can be the main inputs, which receive the input data from the circuit, and the outputs of each of the cells. Numbering starts at the main entries and continues counting with the cell outputs row by row, from top to bottom, in each of the columns.

A. Definitions

Starting from the general concept of a candidate, the need arises to define and name several parameters that can drastically change the behavior and possibilities of a candidate.

i. the general circuit can have nr rows by nc columns of programmable cells.

ii. the circuit can have pi inputs and po outputs.

iii. each cell can have ni inputs and no outputs.

the inputs of each cell can only be connected with the outputs of cells from previous columns or with the main inputs. the parameter determines the number of previous columns where this connection can be made. In case of l= 1, only neighbouring columns can be connected. On the contrary, ifl=nc, connectivity is total and an output can be directly connected with an input.

B. Genotype

Each candidate solution is represented by a sequence of fixed-length integers, where the input connections of each of theno.xnccells plus the connection of each of the circuit's outputs. Each cell is represented by a tuple withnovalues representing incoming connections plus a number representing the node's role. Therefore, a complete genotype is formed by a sequence of (no+

nc.no. + dust integer values.

To exemplify these concepts, we can see In Figure 3.7 an example of a candidate circuit for a configuration whereno.= 2,nc= 4,pi= 3,dust= 2 andno= 2 andat the= 1:

3.4 EXAMPLE OF A CGP CIRCUIT

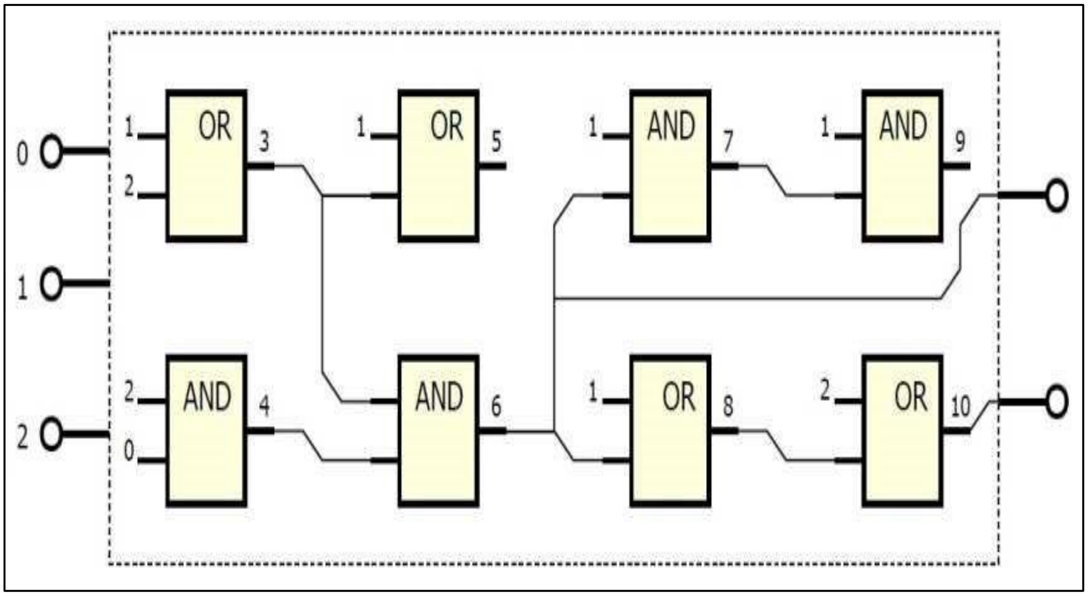


Figure 3.8: CGP circuit for filtering.

In this example, two possible functions were defined: AND, with a value of zero, and OR, with value one. The resulting genotype would be: 1,2,1, 2,0,0, 1,3,1, 3,4,0, 1,6,0, 1,6,1, 1,7,0, 2,8 ,1, 6, 10. Each tuple and output values have been separated by an additional space for easy viewing.

Image processing

Each pixel of an image is represented by eight-bit integer values, that is, they can assume values in the range between 0 and 255. To simplify the project,

only one color layer in image processing (black and white). The improvement to perform the multi-layer treatment becomes quite simple once the first step has been completed.

In this context, the circuit inputs must be the main pixel to be analyzed and a certain number of neighboring pixels. This amount can be nine, in which eight neighbors are used, forming a matrix of three by three pixels; twenty-five, where five by five pixels are selected, and so on. Each entry represents eight bits, and can assume values between zero and two hundred and fifty-five.

In order to maintain full compatibility between all parts of the circuit and the output, it was decided not to use a boolean output to decide whether a given pixel is noise or not. To do so, the value of the most significant bit of the output is used, so values greater than one hundred and twenty-seven represent the true value and values less than that represent the false value. The other output represents the eight bits of the filter output pixel.

The classical or canonical genetic algorithm as proposed by Holland can be described by the algorithm1 Individuals are randomly generated and have their chromosomes encoded as binary strings. From the recombination and mutation operations, new individuals are created and can be inserted into the population. The operators used, as well as the selection of parents, will be explained below.

Algorithm 3.1: Classical Genetic Algorithm.

gen←0;

Generate initial population randomly.

Calculate the fitness of individuals in the population.

while ger<max Genof

Carry out a crossover with the selected parents.

Select parents for breeding;

Apply mutation on the children generated in the previous operation;

calculate the *fitness* of children;

Replace all individuals in the current population with children;

gen ← *gen* + 1;

3.4.1 Parent Selection

The main methods for selecting parents take into account the fitness of each individual in the population. The main ways are selection by ranking, tournament and roulette

a. In ranking selection, all individuals in the population are ordered according to their fitness and the probability of selection of each individual is given by its placement within this ranking.

b. In tournament selection, a number of individuals from the population are randomly selected and the one with the best fitness among them is chosen for reproduction. This process is repeated until the required number of parents is reached.

c. In roulette selection, all individuals in the population have a chance of being selected for reproduction, but the probability of selection varies according to the fitness of each individual.

3.4.2 Crossover

Recombination, also called crossover, is the method in which children are generated from the selected parents that is, information is exchanged to generate a new representation of the solution (individual). There are different ways to carry out the recombination, but the general objective is to generate children that contain a part of their chromosome coming from the first parent and another part from the second parent. Usually, the recombination occurs according to a certain probability rate defined with the need of the problem.

Some well-known crossover methods are the 1-point crossover, where a position is drawn and a child is formed by the starting sequence of the first parent and the ending sequence of the second parent. The second child is formed analogously from the starting sequence of the second parent and ending of the first. The n-point crossover works similarly to the 1-point crossover, but instead of drawing a cut-off point, n cut-off points are drawn. Uniform crossover makes each child element have a 50% chance of belonging to either the first parent or the second parent.

Table 3.1: point crossover.

	1	two	3	4	5	6	7	8	9	10	11	12
father 1	0	1	0	0	1	1	0	1	0	1	1	0
father 2	1	1	1	0	0	1	0	1	0	0	1	1
child 1												
son 2	0	1	0	0	1	1	0	1	0	0	1	1
	1	1	1	0	0	1	0	1	0	1	1	0

New representations were proposed for GAs, where individuals are represented by integer and real numbers with specific recombination operators. For example, in the mean crossover, the value of the child is calculated from the average of the values of the parents. In arithmetic crossover, the value of the child is calculated as a point on the line between the values of the parents.

Table 3.2: point crossover (n=4).

	1	two	3	4	5	6	7	8	9	10	11	12
father 1	0	1	0	0	1	1	0	1	0	1	1	0
father 2	1	1	1	0	0	1	0	1	0	0	1	1
child 1	0	1	1	0	1	1	0	1	0	1	1	0
son 2	1	1	0	0	0	1	0	1	0	0	1	1

	1	two	3	4	5	6	7	8	9	10	11	12
father 1	0	1	0	0	1	1	0	1	0	1	1	0
father 2	1	1	1	0	0	1	0	1	0	0	1	1
child 1	0	1	1	0	0	1	0	1	0	1	1	0
son 2	1	1	0	0	1	1	0	1	0	0	1	1

3.4.3 Mutation

Mutation is a process that makes variations in an individual's chromosome. Its purpose is to help maintain diversity in the population. As in the case of recombination, mutation also occurs according to a certain probability rate. The figure illustrates the use of mutation in the binary representation.

Figure 3.8 – Examples of mutation applied to a binary string.

0 1 0 0 1 ⟶ 0 1 0 1 1

A randomly selected bit is inverted

0 1 0 0 1 ⟶ 0 **0** 0 **1** 1

Two elements of the sequence are exchanged Source:

As with recombination, different representations also bring new possibilities for mutation operators. In uniform mutation, for example, a new value (within the allowed domain) is drawn to replace a chromosome value; another case is the gaussian mutation that draws the new value from a gaussian distribution N(μ,σ)with mean μ and standard deviation σ.

3.5 HYBRID GENETIC ALGORITHM

The Hybrid Genetic Algorithm (HGA) presented in this work is inspired by the Genetic Restoration (GR) method, a genetic algorithm for noise suppression in images proposed in In this approach, we can highlight that each individual in the population is an image in itself, represented by a matrix of pixels whose values are integers within the range. In a similar way to the method in which the AGH is inspired, a noisy image I is used as input to the method and the population is created from the application of mutation operators in I and, in addition, from the three crossover operators used by the AGH

a. Use of an intermediate population — the GR does not use an intermediate population, replacing one of the parents with the new child if he is more fit (better fitness); the AGH creates an intermediate population with all elements of the population together with the new children generated

b. Use of local search — GR applies filters and simple operations such as mutation operators during the evolutionary step of the algorithm, AGH, in turn, uses sophisticated noise suppression methods as local search operators, and applies simple mutations only to ensure population diversity during population initialization and reset processes. This change, in particular, makes a relevant contribution to the work, since known methods for noise suppression serve as ways for the AGH to delve deeper into the search for solutions to the problem.

c. Stopping criterion — the AGH runs for a set time, while the GR runs for a set number of epochs.

In addition to those listed, the AGH has other basic differences from the GR, such as the type of tournament used, the convergence criterion of the evolutionary process, and the algorithm initialization and restart processes. The pseudocode of the method proposed in this work is detailed in Algorithmtwo.

Algorithm 3.2: Hybrid Genetic Algorithm (Img Image)

```
pop←CreatePopulation(Img)
best←pop.best
while time < MaximumTime of
    counter ← 0
    while counter < maximumIterations of
        Intermediary Pop ← pop
        for i ← 1 to SizePopulation of
            ind1, indt ← Select Country(pop)
            ind3 ← crossover(ind1, indtw
            if (λ ∈ [0, 1]) ≤ FeeSearchLocal then
                SearchLocal(ind3)
            Intermediary Pop .he adds (ind3)
        sort( IntermPop )
        pop ← Intermediary Pop [1.. SizePopulation ]
        if best = pop.best then
            counter ← counter + 1
        else
            counter ← 0
    reset( pop )
return pop.best
```

The beginning of the algorithm consists of creating the population in two steps: first, the noisy image is used as input for three methods of noise suppression in images.

These methods were chosen both for their computational speed and for the fact that they are responsible for some of the best results in the literature. The output of these methods is, by default, included in the initial population. Thus, at the end of the first step, the initial population has three individuals. In the second step, one of the outputs of these three methods is chosen at random and subjected to a mutation operator that is also chosen at random. The operators used in this step are as follows:

i. Gaussian Blur: filters the image with a Gaussian filter. The filter size is randomly chosen from 3×3 pixels and 5×5 pixels.

ii. Median Filter: Filters the image with a median filter. The filter size is randomly chosen from 3×3 pixels and 5×5 pixels.

iii. Intensity change: all image pixels are multiplied by the same factor whose value is chosen randomly within the range.

These filters are called mutation operators because they make changes to the image previously retrieved by one of the noise suppression methods. The resulting image is included in the population and the second step of the method is repeated until the population reaches the desired size. At the end of this process, the initial population will be formed by the outputs of the three noise suppression methods and by the images submitted to mutation. This two-step population initialization process is illustrated in Fig.3.9.

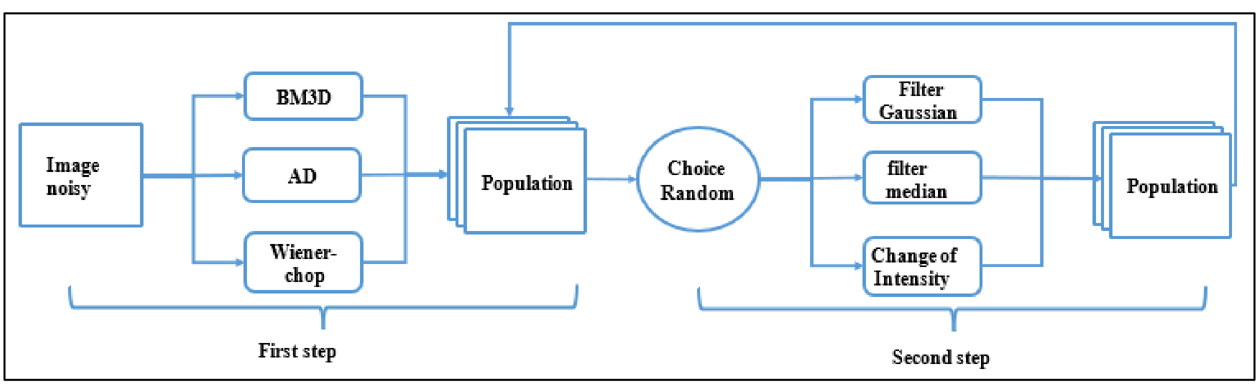


Figure 3.9: Initialization of the AGH population.

Once the initial population is created (line 1, algorithm two), the evolutionary process runs for a defined time interval (lines 3-19). During this run, the population continues to evolve as long as there is no change in the best individuals up to a maximum number of iterations (lines 5-18). When this number is reached, the population is restarted keeping only the best individual found so far (line 19). The remaining individuals in the population are created again by the initialization process mentioned above.

An intermediate population is created during the evolutionary process. This population, whose size is twice as large as the initial population, is initialized with the members of the algorithm's current population and, during the evolutionary process, the new generated individuals are inserted into it (lines 6 and 12).

To reach the number of members needed to complete the intermediate population, new individuals are generated through a sequence of steps:

Parent selection via tournament (line 8) — three individuals are randomly selected from the population and the fittest is chosen as the first parent, then this process is repeated, taking care that the same individual is not chosen again, in choosing the second father.

Crossover (line 9) — a crossover operator is randomly chosen and applied to the previously selected parents and, from this operation, a new individual is created. Possible operators are:

a. Line one-point operator: A line of pixels within the matrix is chosen at random. All pixels above this line will come from one of the parents and all pixels below this line will come from the other parent (see figure10).

b. One-point column operator: Similar to the previous method, but a column is chosen instead of a row (see figure 3.10)

c. Uniform operator: Similar to the classic AG uniform crossover operator each pixel is chosen randomly from one of the parents, with a 50% chance that the chosen value will come from one or the other parent (see figure 3.11).

Local search (lines 10-11) — After creation, the new individual can also undergo a local search operation if a randomly chosen real value within the range [0,1]is less than the algorithm's local fetch rate (lines 10-11). If an individual is chosen for the local search, it will be submitted to an image noise suppression operator randomly chosen from the three methods described above: BM3D, Anisotropic Diffusion and Wiener-chop.

The entire pseudocode execution flow is illustrated in the flowchart of the figure12, where the mentioned evolutionary step refers to lines 7 to 12 of the algorithm.

With the intermediate population complete (size twice as large as the population of the algorithm), it is ordered according to the fitness of its individuals (line 13). From that point on, the PopulationSize, first elements of it start to form the population of the

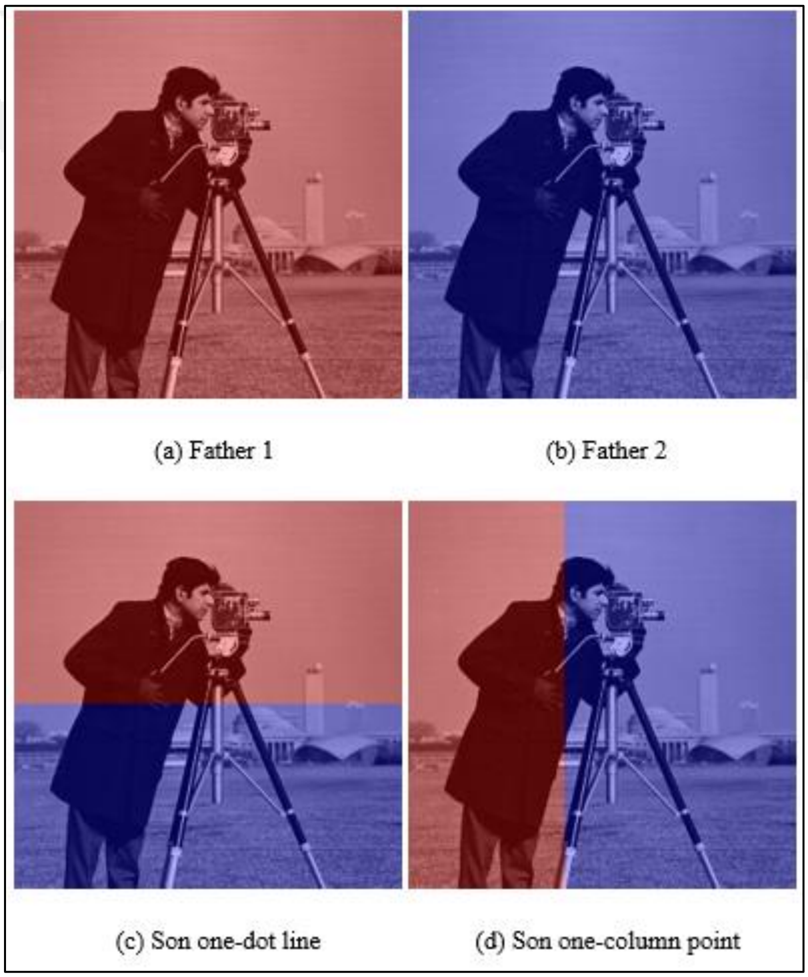
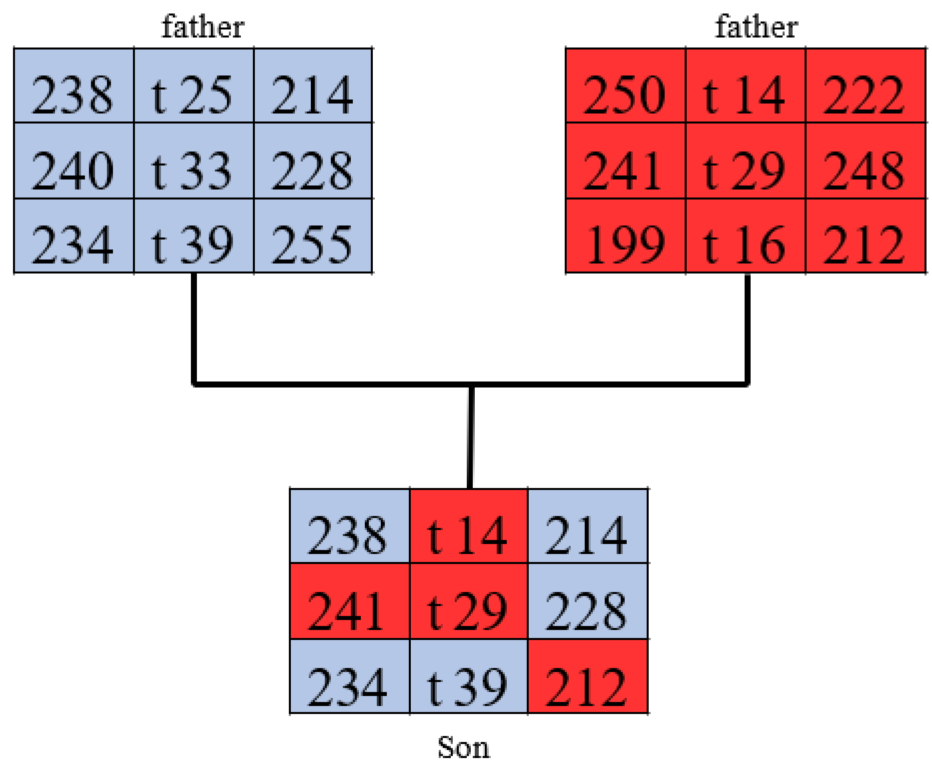


Figure 3.10: Examples of one-point row and column crossover operators.

AGH itself for the next evolutionary step of the algorithm (line 14). To assess whether the population should be restarted, the AGH checks that there are no changes in the best individual in its population for a certain number of runs of its population evolution. If the best individual in the population does not change after MaximoIterations consecutive iterations, then the population is restarted.

In order to guide the AGH, the objective function described In this equation, X and I are, respectively, the currently evaluated images and the noisy image (input of the algorithm), and the term(X−I) two guarantees a certain fidelity between the two. Still within the function, ∇Xis a total variation regularization term (Total Variation - TV), β and λ are balance terms and Ω is the set of all points in the image. By minimizing the objective function, the method seeks,



Source: Prepared by the author.

Figure 3.11: Example of the uniform crossover operator as used by AGH.

basically, to minimize the total variation of the image while trying to preserve the fidelity of the same in relation to the original image fitness.

$$(X) = \left(\sum_{\Omega} \sqrt{1 + \beta^2 |\nabla X|^2}\right) + \frac{\lambda}{2}(X - I)^2 \qquad 3.6$$

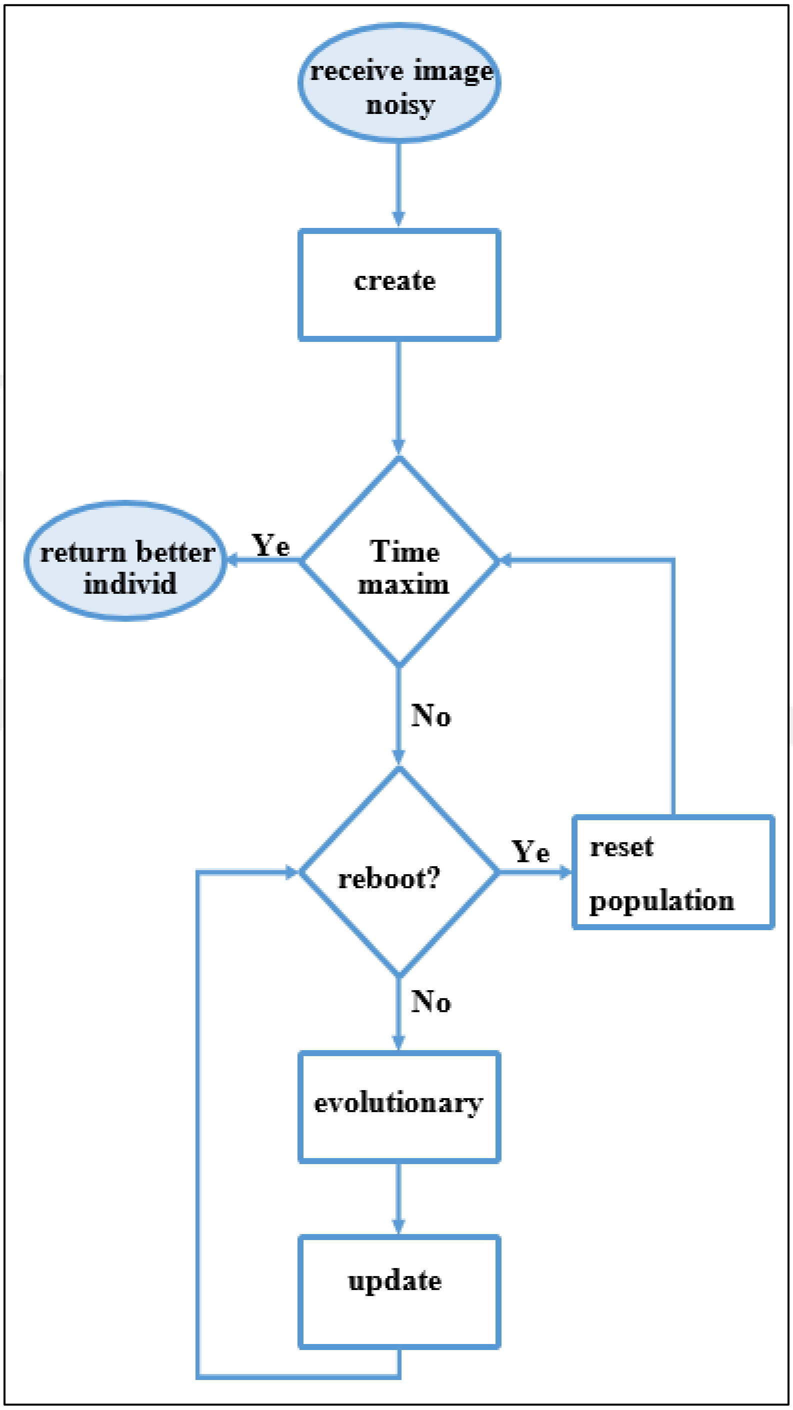


Figure 3.12: Basic flowchart of the AGH operation.

4. PROPOSED METHODOLOGY

4.1 INTRODUCTION

The goal of the project is to learn and comprehend the image super-resolution with the help of mutation neural networks and processing that goes beyond optimization. Using GENETIC ALGORITHM, we have proposed a restoration method that will teach their system to map between low- and high-resolution images from the very beginning to the very end. In addition to this, the study focuses a significant emphasis on picture super resolution that is based on sparse coding. This is accomplished by optimizing all layers with the assistance of a light-weight structured deep genetic algorithm. This establishes a connection that is useful in the process of constructing various network structures. In order to conduct an analysis of the effectiveness of the method for calculating the upscaling factor, I have made use of a training dataset that has a total of six photographs divided into two groups of three pictures each. The first step in the pipeline is referred to as "patch extraction," and it is the procedure that generates high-dimensional vectors representing patches taken from the input image. After that, a non-linear mapping of these vectors to additional vectors of the same kind is performed, and ultimately, aggregation takes place. All of these steps culminate in the production of a high-resolution image that is generated at a faster pace and has a greater quality. In the research, state-of-the-art SR paradigms were applied to assure the achievement of visually pleasant outcomes and the highest possible average PSNR in a period of time that was noticeably less than what would have been required using traditional methods.

Figure 4.1: Super resolution or (super pixel) image enhancement.

4.2 PROPOSED APPROACH

As per the methods proposed, we first extracted the frames by a video sequence shared by Iraqi Media Network IMN archive department and each frame was considered a low-resolution image, that was first up-scaled to a factor either 2 or 3, then the luminance channel 'y' alone was extracted and was input to the GENETIC ALGORITHM. The goal here is to obtained F(Y) from Y that is as similar as possible to the ground truth highresolution image X.

The patches from the low-resolution image Y were extracted in order to form highdimensional vector which was then mapped to another high-dimensional vector nonlinearly which we finally aggregate the final high-resolution image.

Figure 4.2: Original video used for the proposed restoration.

4.2.1 Mutation Layers

First layer for patch extraction is represented as follows:

$F_1(Y) = \max(0, W_1 * Y + B_1);$

where W1, B1 □ the filters and biases respectively, * □ denotes the convolution operation. Here, W_1 support c*f1*f1, where c □ number of channels in the input image, f_1 is the spatial size of a filter.

Second layer for non-liner mapping:

$F_2(Y) = \max(0, W_2 * F_1(Y) + B_2);$

Increasing the layers will eventually require more training time and would also make our GENETIC ALGORITHM complex.

The third layer is used for reconstruction and is represented as:

$F_3(Y) = \max(0, W_3 * F_2(Y) + B_3);$

The operation of these layers are combined to form a GENETIC ALGORITHM.

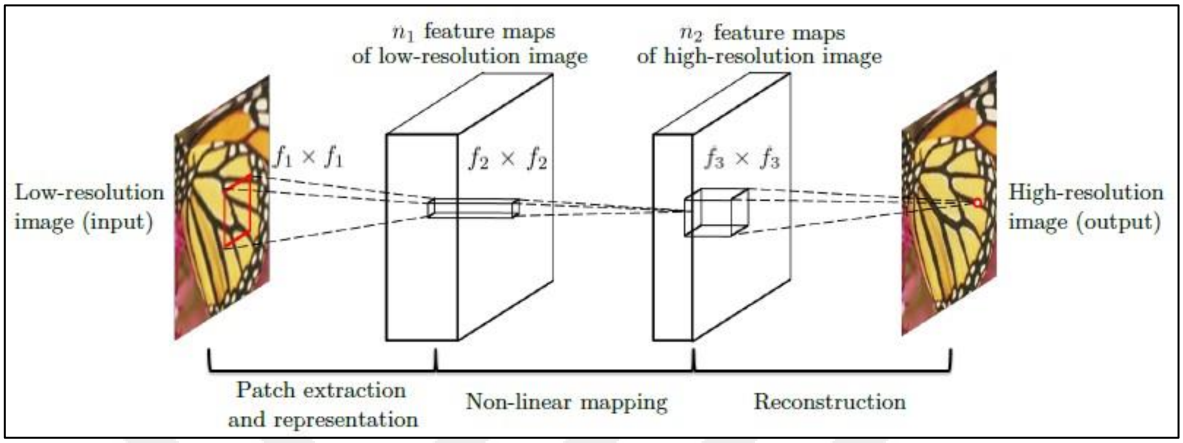


Figure 4.3: Representation of Mutation layers in RGENETIC ALGORITHM.

4.2.2 Experimental Setup

Operating system: Dell

Framework: Caffe by BVLC

Matlab: 2021a

No GPUs were used all the experiments were done on CPU mode. Intel core-i7 processor with 16GB of RAM was used.

4.2.3 Training

Given a set of high-resolution images X and its corresponding low-resolution images Y, we use Mean Squared Error (MSE) as the loss function:

$$L(\Theta) = \frac{1}{n}\sum_{i=1}^{n} \|F(\mathbf{Y}_i;\Theta) - \mathbf{X}_i\|^2 \qquad 4.1$$

function favours high PSNR.

Mutation neural networks do not preclude the usage of other kinds of loss functions, if only the loss functions are derivable. The filter weights of each layer are initialized by drawing randomly from a Gaussian distribution with zero mean and standard deviation 0.001 (and 0 for biases). The learning rate is 10^{-4} for the first two layers, and 10^{-5} for the last layer.

4.3 EXPERIMENTS

4.3.1 Dataset

The 4K data with K=3 that was obtained from the given video and shuffled was then split into three parts. 2K of the frames were used as the training data, another K frames of them as the validation data, and the remaining K frames as the test data. K=3 was chosen due to insufficient computation resources.

4.3.2 Training

The following parameters for training were used:

Size of sub images = 33

Stride = 14

Momentum = 0.9

Base learning rate = 0.0001

Weight decay = 0 CPU
mode Network Setting:

f1 = 9, f2 = 1, f3 = 5, n1 = 8, and n2 = 2. Tried for n1 = 6, and n2 = 2 and n1 = 8, and n2 = 2.

The learning rate was reduced to 0.00001 at the ending 10% of the training phase. About 5 million iterations were done.

4.3.3 Results

we have reported the results on 3 test images that were randomly extracted from the given video and an upscale factor of 3.

Figure 4.4: Resulting images with scale 3**.**

The same images were also tested for up-scaling factor and the output images have been displayed below.

Figure 4.5: Parts of results images with scale 2.

From the comparison of the above images, it can be said that the images with scale 2 have better clarity than the former.

The output images on the intermediate backpropagations for both the scaling factors and both the paradigms (SR-GENETIC ALGORITHM and bi-cubic interpolation) have been shared here for reference.

The below section shows comparison of the performance of the models on both the upscaling factors 2 and 3:

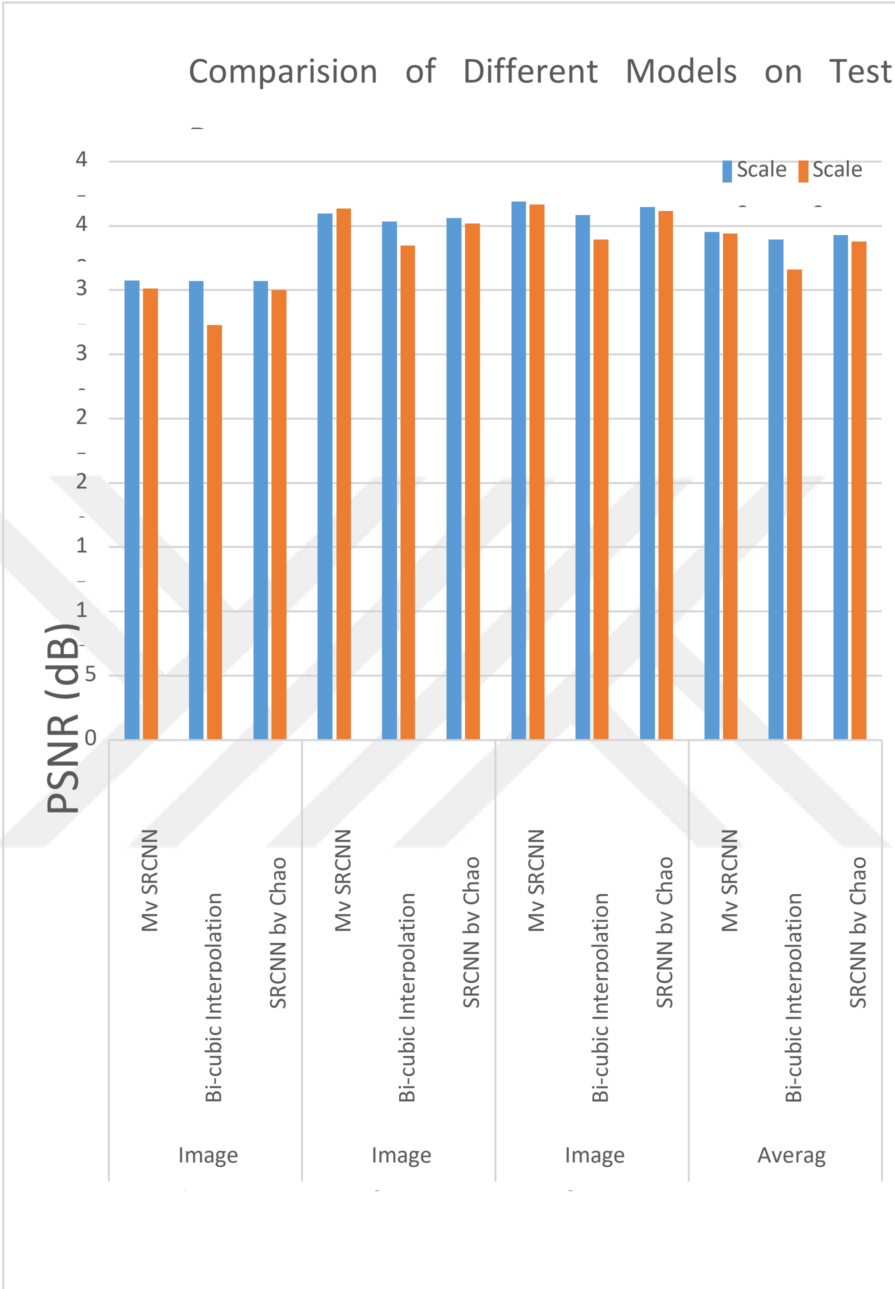


Figure 4.6: Comparison of different model performances on both scales.

Table 4.1: Comparison of different model performances on both scales.

			PSNR		
Model	Scale	Image 1	Image 2	Image 3	Average
My SRGENETIC ALGORITHM	2	35.717118	40.93817	41.850726	39.502005
	3	35.097445	41.329571	41.678445	39.368487
Bi-cubic Interpolation	2	35.678135	40.360482	40.844449	38.961022
	3	32.272841	38.473112	38.943847	36.563267
SRGENETIC ALGORITHM by Chao	2	35.70215	40.587621	41.463722	39.251164
	3	35.032932	40.165723	41.153286	38.78398

The convergence curve for each image and then the average of all the test images have been reported below:

It can be seen in the curve that after 4.5 million back props, the PSNR value was either constant or decreased very slightly. In order to further improve the performance of the system, I reduced the learning rate by $1/10^{th}$ as mentioned in the section above. As shown, the performance started increasing slightly, only 0.5 million iterations were continued from this point but with more iterations, the performance could have been increased further.

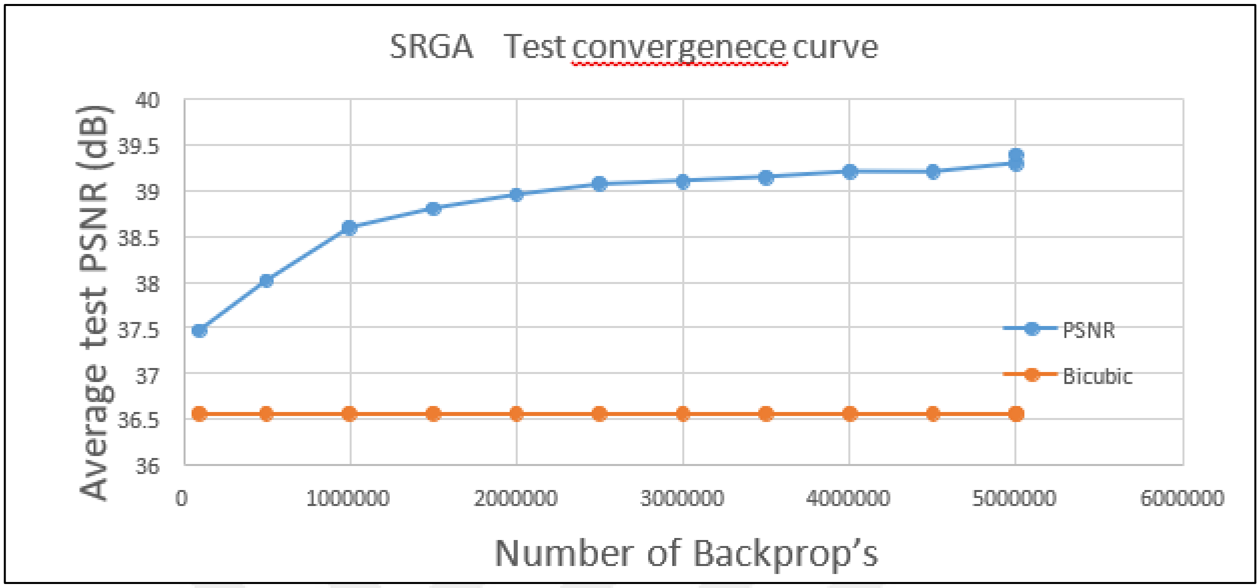


Figure 4.7: PNSR according to the backpropagation.

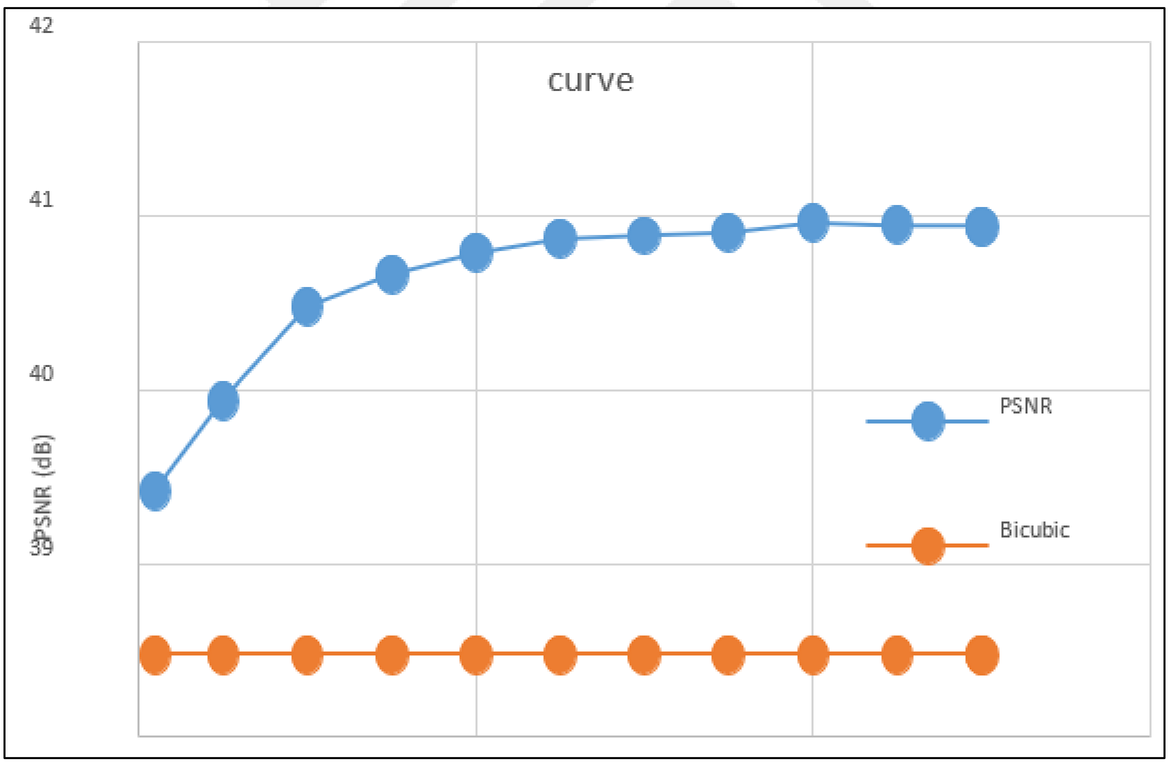


Figure 4.8: The test convergence curve of SRGENETIC ALGORITHM and bi-cubic interpolation paradigms on test dataset.

Different filter numbers were also tried out to check the restoration speed and the results have been shown below:

Table 4.2: Qualitative results of using different filter numbers in SRGENETIC ALGORITHM

n1 = 8 n2 = 2 back props = 5 million	PSNR: 39.28 Time: 137 secs
n1 = 4 n2 = 2 back props = 3 million	PSNR:39.03 Time: 96 secs

Experiments on RGB channels*:*

The system was then trained on the same dataset but with the following network architecture:

Results: c = 3, f1 = 9, f2 = 1, f3 = 5, n1 = 8 , 6 , and n2 = 2.

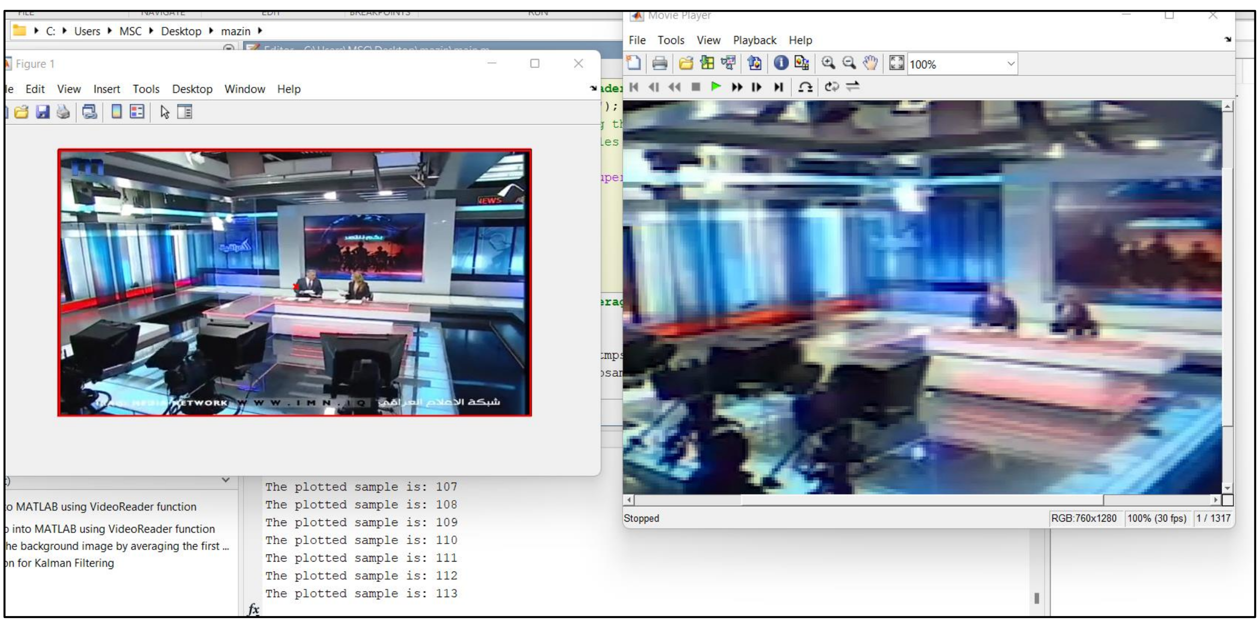


Figure 4.9: Resulting images with scale 3 and RGB channels.

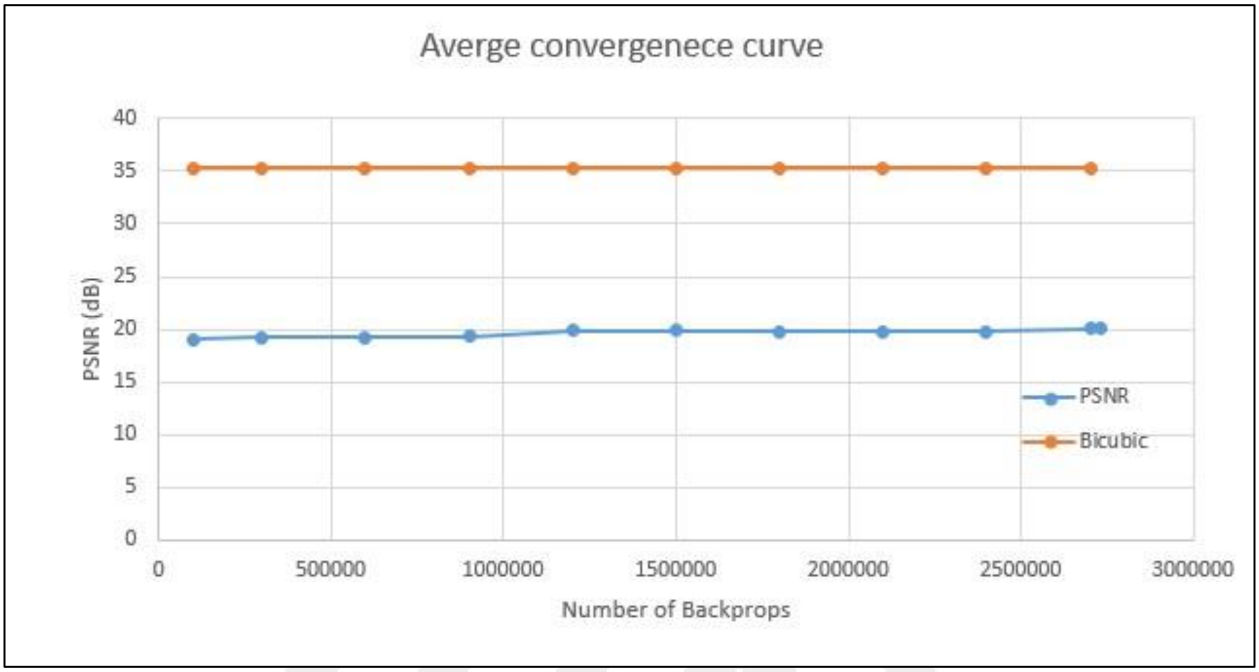


Figure 4.10: The test convergence curve of SRGENETIC ALGORITHM and bi-cubic interpolation paradigms on test dataset on RGB Channels.

Only 2.7 million iterations were done on RGB and it was noticed that the system was learning very slowly, I tried to optimize the system but any change in the learning rate, decay, momentum was resulting in the fall of the network into bad local minimum.

Figure 4.11: ROI box covering the filtering area.

5. CONCLUSION AND FUTURE WORKS

The model can be grasped quickly, can be relied on, and putting it into practice does not require a lot of effort. The SR-GENETIC ALGORITHM was able to reach a higher level of performance than the ways that are currently regarded as state-of-the-art, despite the fact that its architecture was much simpler than those other approaches. This was the case even though it had a more straightforward design. It is probable that it will be essential to carry out tests with a broader variety of training methods and filters in order to achieve even higher levels of performance. This could mean that it will be necessary to do so. At the end of the training period, it is possible to get greater performance by slowing down the rate of learning and reducing the amount of effort put into it.

Even though it is a necessary phase in the process of reconstructing the image, scaling the image takes a significant amount of time. This is despite the fact that it is a necessary step.

When compared to a system that was trained with a somewhat smaller filter scale, there is no discernible improvement in performance. This is due to the fact that both the level of difficulty of the training process and the length of time it takes to complete it increase in direct proportion to the number of filters contained within the network. Because of this, determining the appropriate value for this parameter requires striking a balance between the level of performance that is needed and the amount of time that is now available. As a result of this, this parameter is of the utmost importance.

All that is needed for the system to learn and produce meaningful results is a little amount of input data, so long as it has that, it will be able to function properly. In spite of the adjustments that were made to the rate of weight loss that occurred during the training phase, there was no discernible improvement found.

This method of reconstruction is simply transferrable to the realm of moving pictures, and it is very conceivable that super resolution will be applied to the process of frame reconstruction in video format. This could happen in the near future. Instead of reconstructing one image at a time, we could use methods that are analogous to theirs in order to work on multiple images at the same time. This would be feasible due to the fact that their approach produces superior results while simultaneously enhancing performance. A third significant piece of work that can be seen here is the proof that deep learning is capable of solving the SR problems. This is a really important piece of work. Because it demonstrates how deep learning may be used to address SR problems, this piece of work is quite significant. This is a very significant part of the work that has been done at this location, and it has been completed successfully. Additionally demonstrates that GENETIC ALGORITHMs do not prevent the use of loss functions and alters the measure that is utilized while the individual is in the process of being trained. In the event that this fact is taken into consideration, it has the potential to serve as motivation for additional investigation and development of this flexibility. One of the motivations for doing so is to make use of additional filters and improved training procedures in order to generate even better results for the SR challenges in computer vision, such as noise reduction and other problems of a similar kind. This is one of the reasons why doing so is one of the motivations for doing so.

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