

A NOVEL METHOD FOR
HUMAN FACE ENHANCEMENT
OF VIDEO IMAGES

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A Novel Method for Human Face Enhancement of Video Images

by

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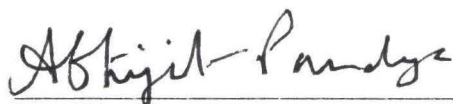
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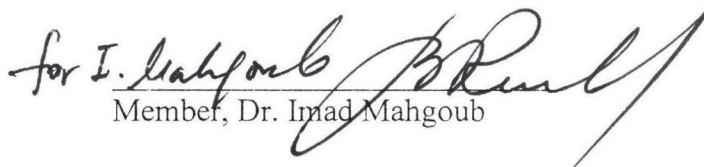
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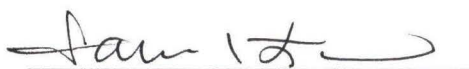
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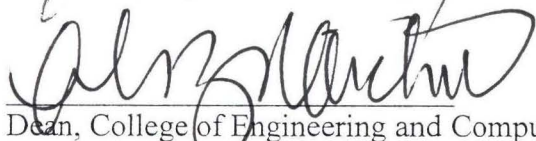
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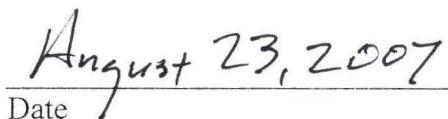
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Abstract

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The focus of this research is on images extracted from surveillance videos that have a low resolution and are taken under low illumination. In recent years, great advances have been made in face recognition and many studies mention results of 80% and 90% of recognition efficiency, however, most of these studies reported results using face images under controlled conditions. Current surveillance systems are equipped with low resolution cameras and are located in places with changing illumination, as opposed to a controlled environment. To be used in face recognition, images extracted from videos need to be normalized, enlarged and preprocessed. There is a multitude of processing algorithms for image enhancement, and each algorithm faces its advantages and disadvantages. This thesis presents a novel method for image enlargement of human faces applied to low quality video recordings. Results and comparison to traditional methods are also presented.

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Chapter 1

Introduction

1.1. Background

In the past, images were typically analog and image enhancement depended highly on the quality of the film used. Digital images which are presented nowadays require a different approach to image management. Mathematics plays an important role in the field of digital image processing since a picture is composed of pixels which have a numeric value. Mathematical formulas are used by both, image software vendors and integrated circuit vendors for features like adaptive de-interlacing, dynamic directional interpolation, removal of unwanted noise, 10 bit image processing for natural color and other previously unknown applications.

The September 11 attacks, the bombing of the London subway and other terrorist attacks have created a growing interest in face images recorded from surveillance videos. Since video surveillance cameras are installed in many businesses for security, they serve as evidence that a subject was there at a particular time (Singh and Partridge, 2006). The challenge though, is that these surveillance videos are of low quality, subject to low illumination, and also images captured are commonly of subjects in poses that make face recognition difficult (Shan and Ward, 2006). Surveillance videos have usually a resolution of 720x240, and are usually installed at distances up to 10 feet of the subjects. These cameras record at a very fast rate with low quality in order to allow recordings for

longer time periods. Therefore, these constraints make it difficult for typical face recognition applications to obtain successful results.

Face recognition has been developed for several years, and studies keep improving current technologies at faster rates (Turk and Pentland, 1991; Shan and Ward., 2006; Zhen and Huang, 2005). In recent years, great advances have been made in face recognition and many studies mention results of 80% and 90% of recognition efficiency. But most of these studies can only be measured using face images under control conditions and not from images extracted from surveillance videos (Wang, 2006). Images from surveillance videos require a process called interpolation or zooming in order to make them adequate for face recognition. Some of the recent studies have approached the problem by example-based learning (Park et al., 2006) and Motion compensation (Tom and Katsaggelos, 2001) but the challenge of obtaining correspondence between the reference face and a given facial image still persists.

Image interpolation, also known as image zooming, where images are enlarged retaining all the initial characteristics is currently a field with a broad scope, and several studies are available about its different applications. Hybrid zooming algorithms use mathematical theorems such as Jensen for edge detection, and Xin Li for interpolation but the results obtained might not be practical as input for a face recognition application (Ruzisnky, 2007). The selection of an enlargement technique should not be done by commonly used measurement methods, since in low quality images sometimes imperfections are amplified resulting in a worst image (Jin, et al., 2004). This makes it

necessary to develop a study that analyzes interpolation algorithms applied to face images from video sources.

1.2. Related Work

With today's security situation, all around the world governments and business demand reliable methods that will allow them to precisely identify individuals. Human faces generally have the same structure, but at the same time they are very different from each other due to race, gender and individual variation (Tsalakanidou, Malassiotis, and Strintzis, 2005). "Face recognition plays an important role in a wide range of application, such as mug-shot database matching, credit card verification, security system, and scene surveillance" (Shan and Ward, 2006).

Due to a growing demand for improved face enhancement, much progress has been made. We shall report work of several researchers that have made an impact on currently used algorithms. In 1998 Xiaomeng and Robinson were interested in enhancement by employing "warping to bring frames of video into correspondence before frame averaging" (Xiaomeng and Robinson, 1998). They found that simplified and efficient way to enhance faces in videos is proposed supervised object-based temporal filtering strategy.

Later, Muresan and Parks (2004) presented a novel interpolation method based on optimal recovery and adaptively determining the quadratic signal class from the local image behavior. Muresan and Parks (2004) found that this interpolation is mathematically

optimal with respect to the image model and is also very efficient at reducing jagged edges.

Furthermore, Zhen and Huang (2005) proposed 3D geometric-model-based face tracking which utilizes 3D geometric face model and extract facial motion information from video. Zhen and Huang (2005) found that 3D geometric-model-based face tracking improves the robustness of the model in low resolution.

In addition, Ngo, Teoh, and Goh (2006) described a biometric hash algorithm for robust extraction of bits from face images. They provided that the enhanced methods outperformed the corresponding raw methods where the number of extracted bit reached 100.

Also in 2006 Jia-Zhong He et al proposed another image enhancement method called Principal Component Analysis (PCA). “The method combines the original training image is with its reconstructed image using only a few low-frequency Discrete Cosine Transform (DCT) coefficients and then performs PCA on the enhanced training images set” (Jia-Zhong et al., 2006). They concluded that PCA performs on average 6% better in recognition accuracy than the standard eigenface algorithm.

Another study in 2006 by Ou, Li and Wang involving face recognition was performed by image enhancement wavelets transformation. This particular study was performed through various lighting conditions. They achieved 94.4% recognition accuracy using 160 features of a face images.

The most recent study of Keun-Chang and Pedrycz (2007) is related to face recognition which uses enhanced independent component analysis approach. They developed an enhancement of the generic independent component through Fisher linear

discriminate analysis called FICA. The FICA approach “leads to the formation of well-separated classes in low-dimension subspace and is endowed with a great deal of insensitivity to large variation in illumination and facial expression” (Keun-Chang and Pedrycz, 2007).

Several enhancement algorithms are now used for face recognition which rely on this body of work. We discuss these traditional algorithms in Chapter 3 and compare results of our novel method to those obtained using the traditional methods in Chapter 5.

1.3. Problem Statement

There are a number of studies reporting results of interpolation algorithms applied in a variety of fields. In addition, face recognition has improved and keeps improving, but a relevant study combining image interpolation of faces, and low quality image from video surveillance systems is necessary. The goal of this thesis is to present a novel method for processing face images from low video sources.

1.4. Proposed Scope and Contribution

The contribution of this study is a new method for enlarging face images obtained from low quality video sources. To reach this objective an analysis of the most commonly used interpolation algorithms is performed. The interpolation algorithms are applied to face images from still images, face images from video and separate face parts. The same methodology is applied to color images as well as to black and white images. To measure the results, PSNR calculations are performed on each enlarged image

facilitating the comparison of the algorithms. The PSNR results are then used to match the optimal enlargement method with its respective face part.

Using the results of the above mentioned study, a selection is performed of the algorithms that perform best in the different face parts to use them together in a single picture. Initially the face is divided into eyes, nose and mouth then, the algorithm that performed better on the noses is used to enlarge the nose, the same for the eyes, mouth and finally to the total face. The resulting image is put together carefully to retain the ratios of eyes nose ears and mouth used by many face recognition applications that use eigenfaces and similar algorithms.

1.5. Thesis Organization

This thesis is organized as follows:

Chapter 1 introduces the problem of the thesis with a background explanation and the motivation of the work. The problem is stated and also a description of recent related studies, and the Chapter is closed with the thesis organization.

Chapter 2 gives an up to date definition of image interpolation and its different types and finalizes with the challenges video images carry when a face enlargement is necessary.

Chapter 3 analyzes the evaluation techniques used to compare enlargement algorithms and Chapter 4 presents the analysis and results of the different available interpolation methods compared by peak signal to noise ratios.

Chapter 5 presents a proposed algorithm to enlarge faces of video images and presents results of using the algorithm.

Chapter 6 describes the conclusions and the future work proposed.

Chapter 2

Image Interpolation and its Application to Video Images

2.1. Introduction to Image Interpolation

To understand the image interpolation concept, one may try to imagine enlarging a 2 by 2 pixel image to a 4 by 4 pixel image. A 2 by 2 pixel image has have a size of 4 pixels and enlarging that picture to 4 by 4 pixels means that twelve new pixels have to be added. The color and brightness intensity of those new pixels should closely resemble the values of the adjacent pixels. If seen the values of the existing pixels as a mathematical equation, then interpolation algorithms can be applied to determine the new pixels (Kidner, et al., 1999).

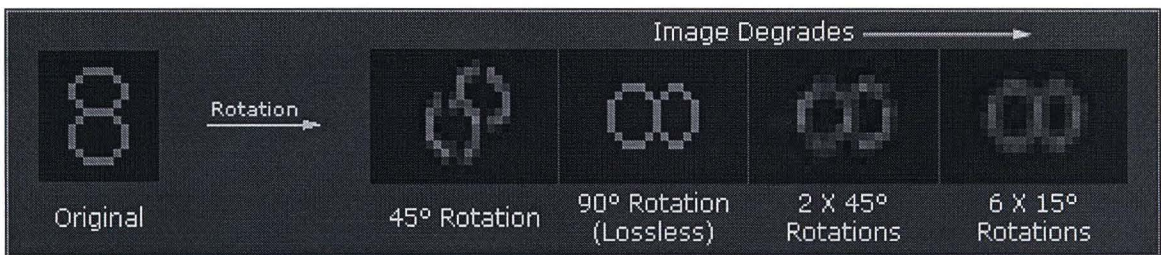


Figure 2.1: Rotation where pixel quality is lost.

Image interpolation is being used in several applications that range in complexity. Most image editor software usually relies on interpolation to rotate pictures to non square angles. Rotating an image 90 degrees is considered a lossless rotation since the quality of

the image is not changed but rotating an image to a 45 degree angle yields to loss of quality. The following example shows the problem more clearly:

“The 90 degrees rotation is lossless because no pixel ever has to be repositioned onto the border between two pixels (and therefore divided). Note how most of the detail is lost in just the first rotation, although the image continues to deteriorate with successive rotations. One should therefore **avoid rotating your photos when possible**; if an unveled photo requires it, rotate no more than once” (Ruzisnky, 2007).

The film industry has adopted many forms of image interpolation as for example, in an effect called morphing used notably in the movie The Matrix.

Image interpolation has a broad coverage and it is applied differently for every field it is used in and each of those fields faces different challenges. This research, concerns only to face recognition enhancements used on low quality video, mainly low resolution short circuit” videos which are being widely used by the private sector and by government agencies. These recordings have resulted essential in the conviction of many delinquents and as seen for example in the London subway terrorist attack, how several of the suicidal bombers were captured by surveillance cameras.

2.2. Types of Images Interpolation

Interpolation algorithms can be cataloged into hybrid, adaptive and non adaptive. Combined methods are called hybrid, and methods that perform different based on the detection of image properties are called adaptive: “Adaptive methods change depending on what they are interpolating (sharp edges vs. smooth texture), whereas non-adaptive methods treat all pixels equally” (Ruzisnky, 2007).

Although all interpolation methods are based on known mathematical algorithms, private companies have licensed proprietary versions adapting small changes to commonly known techniques. It would not be feasible to analyze all commercially available enlargement methods, therefore our study concentrates on interpolation algorithms based on the most widely used mathematical interpolation techniques.

The following is a list of the most commonly used interpolation algorithms applied to image enhancement:

2.2.1. Non adaptive Interpolation Methods

1. Box / Nearest Neighbor: Each pixel is magnified by selecting the nearest neighbor and copying it without considering other surrounding pixels.
2. Bicubic: Each pixel is duplicated as a result of averaging the nearest sixteen samples in a rectangular grid.

$$\sum_{i=0}^3 \sum_{j=0}^3 a_{ij} x^i y^j \quad (2.1)$$

3. Bilinear: Pixels are duplicated by first performing a linear interpolation vertically and then a linear interpolation horizontally.
4. Triangulation: Delaunay triangulation is done between each pixel and its surroundings to create planes were to interpolate the new pixels.
5. Step Interpolation (SI): The image is enlarged multiple times in small increments.
6. Xin Li: Edge directed interpolation that first estimates the edges in order to interpolate the pixels. After the edges are detected Xin Li proposed hybrid approach using bilinear interpolation and covariance based adaptive interpolation.

7. Lanczos: The image is resampled using a function for a convolution kernel.
8. Modified B-Spline: Spline polynomials are used to calculate the values of the interpolated pixels.
9. Data Dependent Lanczos 3 (DDL3): A variation of the Lanczos algorithm privately developed by (Ruzisnky, 2007).
10. Jensen Hybrids: “The Jensen algorithm overwrites edge areas in images interpolated by other methods, thereby producing sharp edges. There is some blending between edge and non edge areas, but, essentially all edge areas appear the same between the different hybrids” (Ruzisnky, 2007).
11. LAD Deconvolution: Least Absolute Deviation is used iteratively in an attempt to acquire Point Spread Functions (PSF) to use deconvolution to recreate missing pixels, hence enlarging the image.

2.3. Challenges of Image Interpolation Applied to Video Images

To enlarge an image obtained from a low quality video source one may face the following challenges.

First, video images are commonly obtained under low illumination. Therefore, the lack of visibility reduces the amount of details in the face of the subject.

Second, once you enlarge a video which has many irregularities, the new image is less recognizable. For example it may happen that poor quality face images once enlarged do not look like faces at all. The intricate details of nose, mouth and eyes are diffused. When these blurry subjects are enlarged without considering the different characteristics of the mouth, eyes and nose, the resulting images are simply unusable.

Third, the distances of eyes, nose and mouth has to be maintained. A problem arises when the distance between the main face parts are miscalculated. Once the picture is enlarged, the distances must be taken into consideration to maintain the usability of the image on a face recognitions system since distance between ears and eyes is sometimes an important factor used by face recognition algorithms.

Fourth, to enlarge an image, the pose or view angle of the image should be considered. For example images taken of a face looking to the side is sometimes feed into 3D interpolation programs which generates the rest of the face therefore, when enlarging an image, the edges of the face have to be closely kept and handled.

Last, all other issues that are common to image enlargement, apply to face recognition enlargement as well:

- A. Jagged edges
- B. Removal of jagged edges that were in input image
- C. Structuring of noise and textures
- D. Halos and/or ringing around edges
- E. Blurred edges
- F. Falsely detected and sharpened edges
- G. Rounded or fuzzy corners

Some of these challenges have been addressed by other researchers and without focusing on interpolation (Guoqiang, 2006). There are several image interpolation techniques and new ones are rapidly being created, many times by combining commonly known techniques. Next is a list of the interpolation algorithms most commonly used for

image enhancement. These are fundamental blocks in image enlargement and many times are used with small proprietary variations in order to achieve slightly better results

Chapter 3

Performance Evaluation Metrics for Digital Images

3.1. Image Evaluation Metrics

Before the advent of digital images, quality was judged only by the human eye. Although with digital images invariably the best method still is the human eye, many other mathematical algorithms can be used to measure image quality. These methods facilitate the gathering of results since experiments require quantitative measures for statistical analysis and base lining. Therefore this chapter studies different methods commonly applied to the quality of an image copy when compared to its original.

3.1.1. PSNR / RMSE

“The phrase peak signal-to-noise ratio, often abbreviated PSNR, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale. The PSNR is most commonly used as a measure of quality of reconstruction in image compression etc. It is most easily defined via the mean squared error (MSE) which for two $m \times n$ monochrome images I and K where one of the images is considered a noisy approximation of the other is defined as:

$$\text{PSNR: } 20 \log_{10} \left(\frac{255}{\text{RMSE}} \right) \quad (3.1)$$

”(Ruzinsky, 2007).

RMSE: “The mean squared error or MSE of an estimator is the expected value of the square of the "error." The error is the amount by which the estimator differs from the quantity to be estimated. The difference occurs because of randomness or because the estimator doesn't account for information that could produce a more accurate estimate” (Ruzinsky, 2007).

$$\text{RMSE} = \sqrt{\text{MSE}} \quad (3.2)$$

Where:

- $\text{MSE} = \frac{1}{N} \sum_0^N [\text{dif}]^2$ (3.3)
- N = the number of pixels in the image
- dif = the difference in the color value on each channel (red, yellow, blue)

Average Absolute Error (AAE): The summation of the difference of each pixel divided by the number of pixels

$$\text{AAE} = \frac{\sum [\text{dif}]}{N} \quad (3.3)$$

3.1.2. MAE / AAE

MAE is the greatest value obtained when calculating dif for every pixel in the image.

3.2. Verification of SAR Image Processor for PSNR Calculation

SAR Image Processor is an image editing program for the PC. This application was selected because of its capability to calculate the Peak Signal to Noise Ratio of two images when they are of the same size. The results of this thesis depend mostly on the PSNR calculations, so a simple experiment was devised to ensure the correctness of the values obtained by SAR. First, two identical black images were created with a size of 2 by 2 pixels. One of the images was changed in one pixel increments and PSNR calculations were performed. The experiment was repeated using red, green and blue, to cover all the three channels. Based on the formula PSNR is calculated and later compared to the results given by SAR. When the images are identical, this is how the PSNR should be calculated:

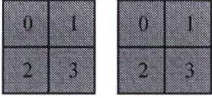
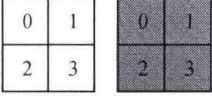
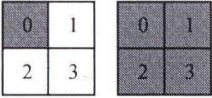
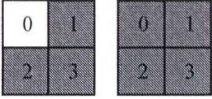




$$\text{RMSE} = \sqrt{\frac{1}{2} \sum_0^2 [0]^2} = \sqrt{\frac{0}{2}} = 0 \quad (3.4)$$


(3.5)

$$\text{PSNR} = 20 \log_{10} \left(\frac{255}{0} \right) = \text{undefined}$$

The complete verification is graphically explained in the following table:

Table 3.1: Verification of PSNR values calculated in the three channels: red, green and blue.

2 x 2 pixel image	Channel	PSNR	RMSE	AAE	MAE
 <p>Identical images</p>	X Y Z	PSNR $\rightarrow \infty$ The value grows beyond any assigned value.	0 0 0	0 0 0	0 0 0
 <p>Completely different images</p>	X Y Z	0 0 0	255 255 255	255 255 255	255 255 255
	X Y Z	249,388 249,388 249,388	220,836 220,836 220,836	191,25 191,25 191,25	255,0 255,0 255,0
	X Y Z	6,0206 6,0206 6,0206	127,5 127,5 127,5	63,75 63,75 63,75	255 255 255
	X Y Z	3,0103 3,0103 3,0103	180,312 180,312 180,312	127,5 127,5 127,5	255 255 255
	X Y Z	3,0103 3,0103 3,0103	180,212 180,212 180,212	127,5 127,5 127,5	255 255 255
 <p>Using only the red channel</p>	X Y Z	10,969 Und Und	72,125 0 0	51 0 0	102 0 0
 <p>Using only the red</p>	X Y Z	Und 10,969 Und	0 72,125 0	0 51 0	0 102 0

channel					
 <p>Using only the blue channel.</p>	X Y Z	Und Und 10.969	0 0 72,125	0 0 51	0 0 102

Chapter 4

Results of Interpolation Algorithms Applied to Face Images

This chapter presents a description of the experiments performed on each image from the database to determine the interpolation methods that best apply to human faces. Section 4.1 describes the baseline tests on still images dividing the results into methodology, color, black/white, and separate face parts. The methodology section details the pre-processing steps that images have to go through before they are of value for the study. Closing the chapter, Section 4.4 analyzes the PSNR results which subsequently delineate the proposed algorithm in Chapter 5. SAR Image Processor is used to calculate the PSNR.

4.1. Results of Tests Applied to Still Images

This section presents PSNR results from subjects facing directly to the camera in a pre-arranged position. The experiments are under controlled light and pose and the results are used as a base for comparison throughout the thesis. Some of the images used in the thesis were taken from a free database provided by Perdue University others images used are from pictures taken with a 5 mega pixel camera. The image database is shown in Figure 4.1. The images that are not from the Perdue database are taken from volunteer subjects and the protocol for selection and process of volunteer subjects was

approved by the Institutional Review Board (IRB) for Research Involving Human
Subject of Florida Atlantic University (Martinez and Benavente, 1998).



Figure 4.1(a): Database of human subject faces.



Figure 4.1(b): Database of human subject faces.

4.1.1. Methodology

The pre-processing operations carried out on each image have slight variations according to the source image but the process for calculating the PSNR is the same all around. The nose, individual eyes, and the mouth were separated from the image and treated as an image by itself. The steps were as follows:

1. Images from the database are left unchanged.

The section of the head from the camera image is cropped leaving a canvas of 768 by 576 pixels, to ensure that the face occupies approximately 70% of the complete picture. See Figure 4.2.



Figure 4.2: Comparison of original image and processed image.

To obtain black and white images the color images are modified with the use of a channel mixer. The channel mixer tool is configured to mix, 25% of the red and 50% of green and blue to create a black and white image with similar brightness conditions as the original color picture.



Figure 4.3: Example of the transformation from color to black and white.


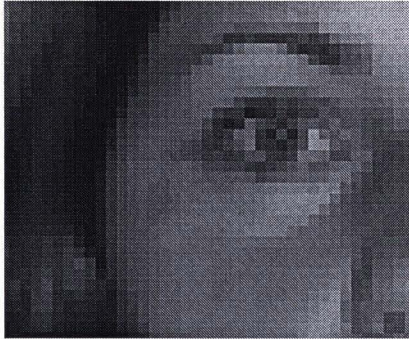

2. The image from step 1 is scaled down four times using box interpolation.











Figure 4.4: Scaled down image to calculate PSNR.




3. The reduced image is then magnified with the 14 mentioned methods and the parameters for each method are described in Table 4.1.


Table 4.1: Parameters used for testing interpolation methods.

#	Interpolation Method		SAR Image Processor Parameter Settings
	Common for all methods		Output Width: 768, Output Height: 576, Horizontal Scale, Factor: 4, Vertical Scale Factor: 4, Horizontal Offset: 0, Vertical Offset: 0, Precedence: Horizontal Scale, Kernel Expansion For Reductions: True
	Original		
1	Box		None Required
2	Lanczos Order 3		Order: 3

3	Triangulation		None Required
4	Stair Interpolation		Approximate Scale For Increment: 1.1 Bicubic Or Lanczos: Bicubic Bicubic Sharpening Factor: -0.5
5	Modified Spline B		Scale Factor: 5 Then Reduce .80 scale factor With Box Interpolation
6	Data Dependent Lanczos (DDL)		Size Iters: 2, Shortcut: YCbCr, DDL order: 3 Pre sharpen: false, Back Projected Iterations: 0, Reduction Method: Lanczos3, Inverse Sharpening Amount: 0, Inverse Sharpening Radius: 0, Super Rez Iter: 0 Base On Enlargement By Lanczos 3, Jaggy Removal Parameter: 0, Edge Sharpening: Off, Edge Sharpening Param 1: 0.2, Edge Sharpening Param 2: 20, Test Reduction Param: 1,2,3: False

7	Xin Li (XL)		<p>Window Size: 6, Bias: 1.0, Tapered Window Weight: 0, Normalization Weight: ∞, Zhao Modified 12th Order: False, Antialias Parameter For Zhao: 1.5</p> <p>Number of Iterations: 2, 0-Automatic Arbitrary Scaling: 4, Center to Half Pixel: true, BP Iterations 1st Pass: 0, BP Order: 0, Backprojection Mode: Box, shortcut YCbCr, Exit Tolerance: 0.5, Regularization Amount: 0, Edge Sharpening Iters. 0, Edge Sharpening Amount: 0.2, Edge Rejection: 0.1, BP Iterations 2nd pass: 0, Backprojection Mode 2nd pass: Box, Presharpen Amount: 0</p>
8	Jensen DDL		<p>Window Size: 5, Edge Detection Parameter 1: 0.45, Edge Detection Parameter 2: 0.04, Edge Blurring Parameter 10.0, Special Mode: True. Repeat parameters for DDL</p>
9	Jensen XL		<p>Window Size: 5, Edge Detection Parameter 1: 0.45, Edge Detection Parameter 2: 0.04, Edge Blurring Parameter 10.0, Special Mode: True. Repeat parameters for XL</p>
10	Back Projected Data Dependent Lanczos 3		<p>Size Iters: 2, Shortcut: YCbCr, DDL order: 3, Presharpen: True, Back Projected Iterations: 5, Reduction Method: Box, Inverse Sharpening Amount: 0, Inverse Sharpening Radius: 0, Super Rez Iter: 0 Base On Enlargement By Lanczos 5, Jaggy Removal Parameter: 0, Edge Sharpening: Medium, Edge Sharpening Param 1: 0.2, Edge Sharpening Param 2: 20, Test Reduction Param: 1,2,3: False</p> <p>Number of Iterations: 1, 0-Automatic Arbitrary Scaling: 5, Center to Half</p>

			Pixel: true, BP Iterations 1 st Pass: 5, BP Order: 3, Backprojection Mode: Box, shortcut YCbCr, Exit Tolerance: 0.5, Regularization Amount: 0, Edge Sharpening Iters. 0, Edge Sharpening Amount: 0.2, Edge Rejection: 0.1, BP Iterations 2 nd pass: 0, Backprojection Mode 2 nd pass: Box, Presharpen Amount: 0
11	Back Projected XL		Window Size: 6, Bias: 1.0, Tapered Window Weight: 0, Normalization Weight: ∞ , Zhao Modified 12 th Order: False, Antialias Parameter For Zhao: 1.5, Number of Iterations: 1, 0-Automatic Arbitrary Scaling: 0, Center to Half Pixel: true, BP Iterations 1 st Pass: 5, BP Order: 3, Backprojection Mode: Box, shortcut YCbCr, Exit Tolerance: 0.5, Regularization Amount: 0, Edge Sharpening Iters. 0, Edge Sharpening Amount: 0.2, Edge Rejection: 0.1, BP Iterations 2 nd pass: 2, Backprojection Mode 2 nd pass: Box, Presharpen Amount: 0
12	Back Projected J DDL		Window Size: 5, Edge Detection Parameter 1: 0.45, Edge Detection Parameter 2: 0.04, Edge Blurring Parameter 10.0, Special Mode: True. Repeat parameters for BPDDL3
13	Back Projected Jensen XL		Window Size: 5, Edge Detection Parameter 1: 0.45, Edge Detection Parameter 2: 0.04, Edge Blurring Parameter 10.0, Special Mode: True. Repeat parameters for DDL Window Size: 6, Bias: 1.0, Tapered Window Weight: 0, Normalization Weight: ∞ , Zhao Modified 12 th Order: False, Antialias Parameter For Zhao: 1.5, Number of Iterations: 1, 0-Automatic Arbitrary Scaling: 0, Center to Half Pixel: true, BP Iterations 1 st Pass: 0, BP Order: 3, Backprojection Mode: Lanczos3, shortcut YCbCr, Exit Tolerance: 0.5, Regularization Amount: 0, Edge Sharpening Iters. 0, Edge Sharpening Amount: 0.2, Edge Rejection: 0.1, BP Iterations 2 nd pass: 2, Backprojection Mode 2 nd pass: Lanczos3,

			Presharpen Amount: 0
14	LADD Deconvolution		LS or LADD Decon. Or Convolve: LADD, Point Spread Function: Decimate, Lens Blur Radius: 10, Gaussian STD. Dev., H: 1, Gaussian Std. Dev., V: 1, Uniform Width 3, Uniform height:3 ,Bicubic Factor: -1, Use Scratch Disk: true, Enlargement Shortcut YCbCr, Max. Iterations LS 750, Min Iterations LS: 50, Exit Tolerance LS 1.0e-09,Max Iterations LADD: 31, Exit Tolerance LADD: 0.0001, Integer Scale Factor: 4

4. Using SAR, the PSNR is calculated between the result of step 1 and the result of step 3.

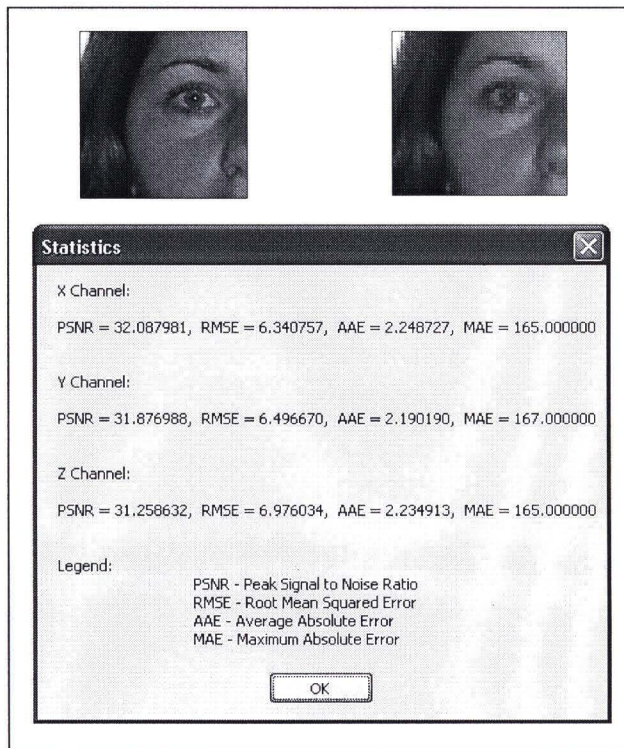


Figure 4.5: PSNR comparison from the original image and an image enlarged by LADD

5. Algorithm ranking is done by assigning values for the top 4 performing algorithms on each face. For instance, in the example above, the best method is LADD, followed by BPXL, Lanczos3 and BPJXL. A value of 4 is given to LADD, 3 to BPXL, 2 to Lanczos3 and 1 to BPJXL. These rankings are then added to the results on each of the test subjects and plotted into a pie chart.

4.1.2. Results on Color Still Images

In this thesis a group of 142 images are analyzed. 61 of them are of females and the remaining 81 are of male subjects. The performance of the algorithms is compared using the RSSI results obtained. At first glance it can be seen that many algorithms generated jagged lines and shadows particularly in the areas where edges exist. Regions like the eyes, mouse, nose and hair obtained noticeably objectionable results.

Among the different methods, box interpolation performed bellow acceptable as expected, but it is used in the tests for completeness. The following table shows an average of the results of the entire dataset of color face images.

Table 4.2: Average PSNR for each interpolation method applied to color images.

Interpolation Method	PSNR R	PSNR G	PSNR B
Box	30.093815	30.386491	30.742512
Triangulation	31.410316	31.902636	32.005679
JZXL	31.528533	32.125387	31.99403
zhao-Xinli	31.613211	32.158908	32.004577
lanczos3 Step	31.813817	32.292447	32.342505
JDDL3	31.87084	32.411081	32.342356
Modified B-Spline	31.88274	32.364252	32.40469
data dep lanczos	32.016455	32.517604	32.419038
BPJDDL	32.089966	32.620301	32.426064
lanczos3	32.116553	32.583283	32.620755
BPDDL3	32.143716	32.693706	32.473177
BPXL	32.21412	32.786532	32.501724
BPJXL	32.21412	32.786532	32.501724
LADD	32.637748	33.092218	32.930649

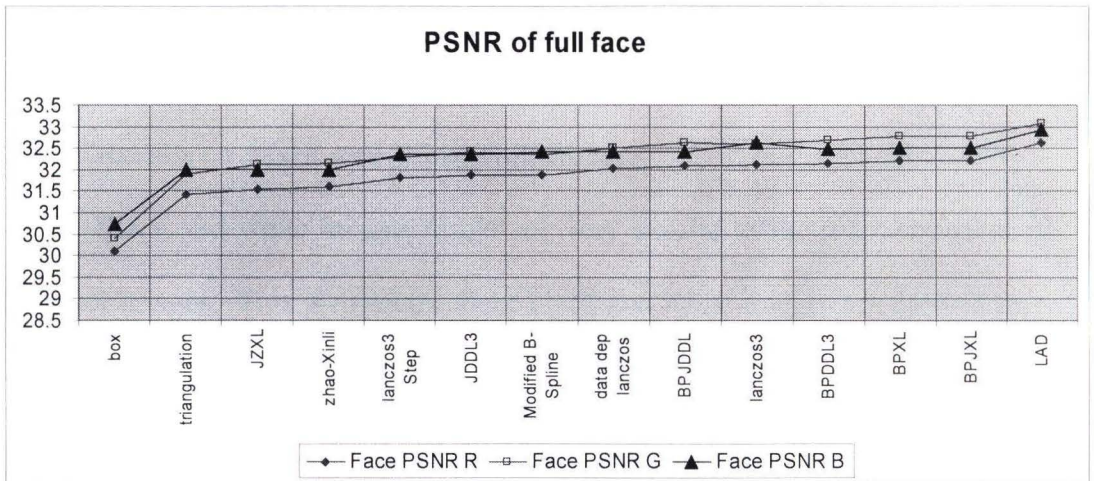


Figure 4.6: Interpolation methods applied to color images.

LADD interpolation results exceeded all other methods in two measures: it performed better than the average and also it finished as the best method more than any other. LADD images are not blurred and incorporate clear edges. It is also noticeable that most back projected edge detection methods performed above average.

Best Performing algorithms in color images

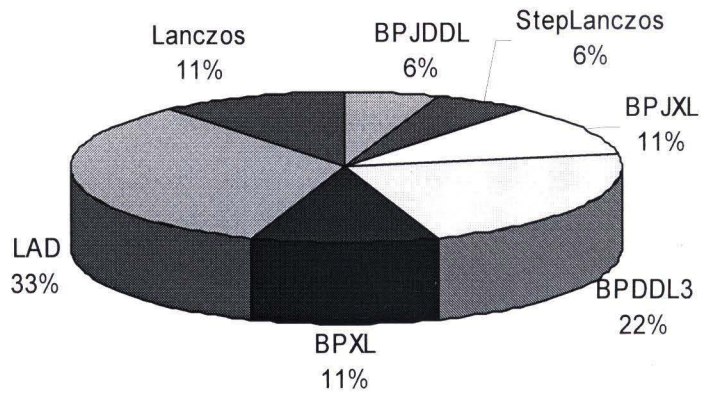


Figure 4.7: Best Performing algorithms in color images. Chart of how many times an algorithm finished with the lowest PSNR when applied to the complete set of pictures.

4.1.3. Results on Black and White Still Images

Black and white images results are very similar to the red component on the color images. This is expected since black and white images are derived from color images.

Table 4.3: PSNR results for B/W images

Interpolation Method	PSNR
box	29.034996
Triangulation	30.793816
Jensen Xli	30.887015
Xin li	30.900725
StepLanczos	31.109642
Jensen DDL	31.175918
data dep lanczos	31.239176
Modified B Spline	31.339874
Lanczos	31.430111
BPXL	31.539964
BPJXL	31.54026
BPDDL3	31.542932
BPJDDL	31.542932

LADD	31.758932
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Similarly to the color images LADD deconvolution outperformed all the methods in average and also in the ranking. Also back projected methods performed better than the total average of methods.

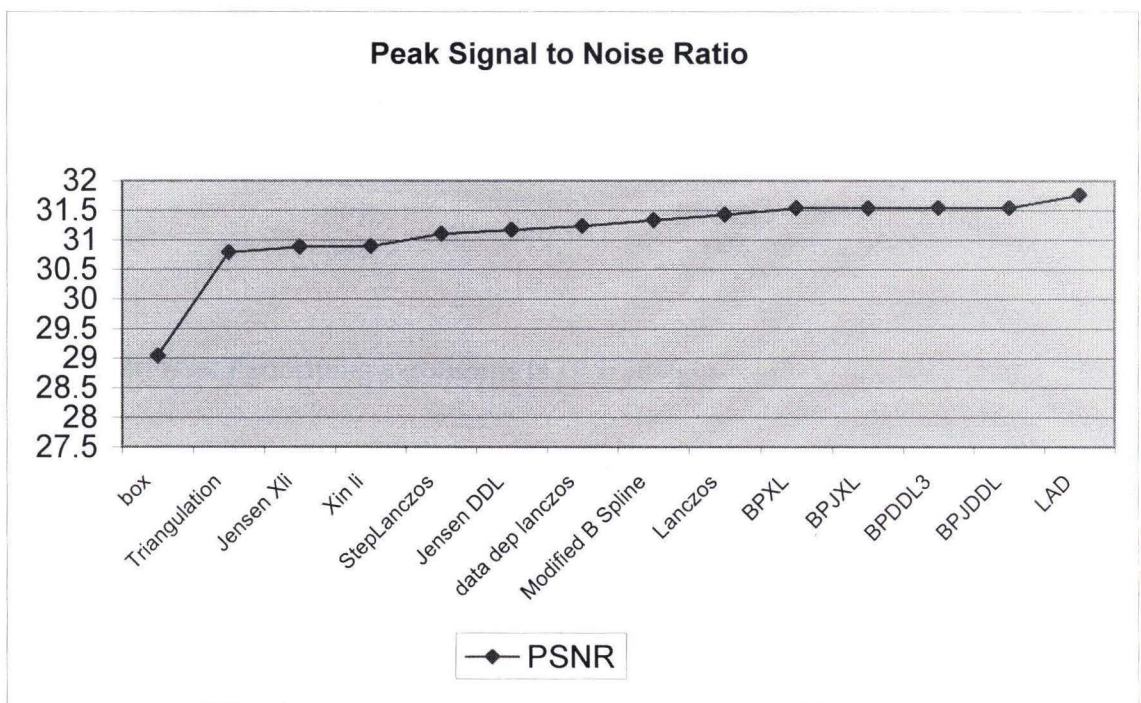


Figure 4.8: Graph of PSNR for B/W images.

As seen in Figure 4.8, LADD and the Back projection hybrid methods obtained the best results on black and white images.

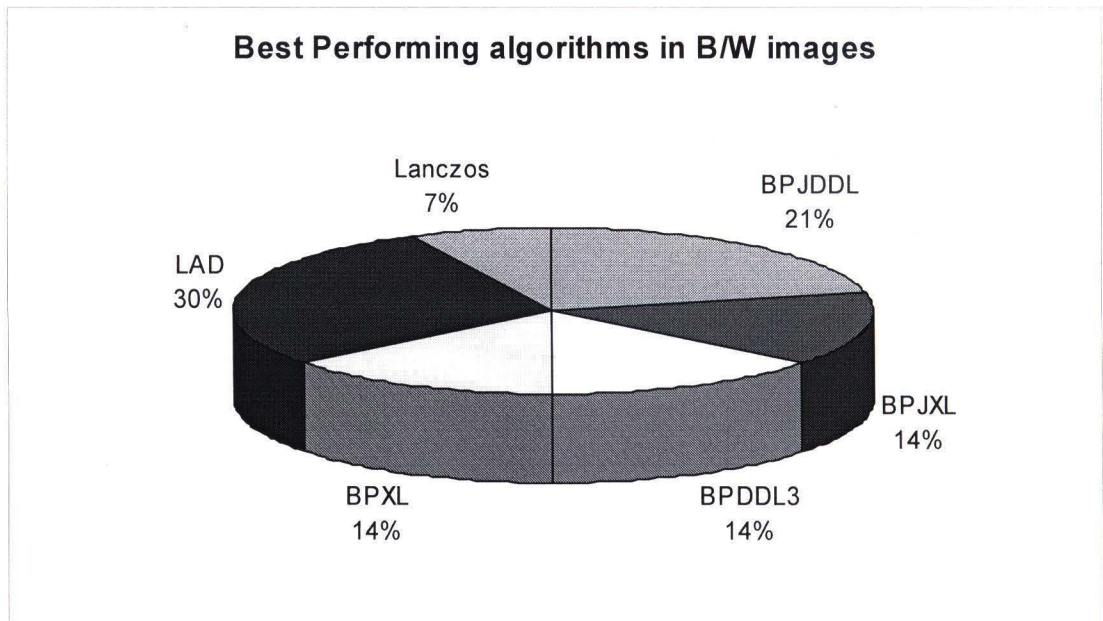


Figure 4.9: Best Performing algorithms in B/W images.

4.1.4. Results on Separate Face Parts from Color Still Images

Each face on the database was edited by removing the eyes, nose and mouth using “Paint Shop Pro 7.04”. In general results on separate face parts yield 10% higher PSNR values in each color channel as well as in black and white. The results show a relation between interpolation algorithms and face parts. When a method is applied to only the mouth, results of as high as 36 for PSNR are obtained, a value never reached on full face interpolation.

4.1.4.1. Results for Mouth

The PSNR calculated of only mouth images brought up BPDDL3 as the top averaging method. LADD finished bellows the top tier. Also best results are in a very close range from each other.

Table 4.4: Mouth PSNR results.

	MOUTH PSNR RED	MOUTH PSNR GREEN	MOUTH PSNR BLUE
Box	30.945973	29.490032	30.88499
JZXL	34.036037	33.433559	33.448176
triangulation	34.434208	33.816142	34.01236
zhao-Xinli	34.443062	33.5417	33.537118
JDDL3	35.464536	35.101347	34.825351
Modified B-Spline	35.516651	34.905618	34.8716
LADD	35.617515	36.056499	35.727746
lanczos3 Step	35.685609	35.325913	35.379752
lanczos3	35.989525	35.340883	35.654644
BPXL	36.157673	35.55661	35.131926
BPJDDL	36.164329	35.698706	35.09611
data dep lanczos	36.223525	35.505822	35.062287
BPJXL	36.311519	35.602047	35.236712
BPDDL3	36.460845	35.785377	35.213086

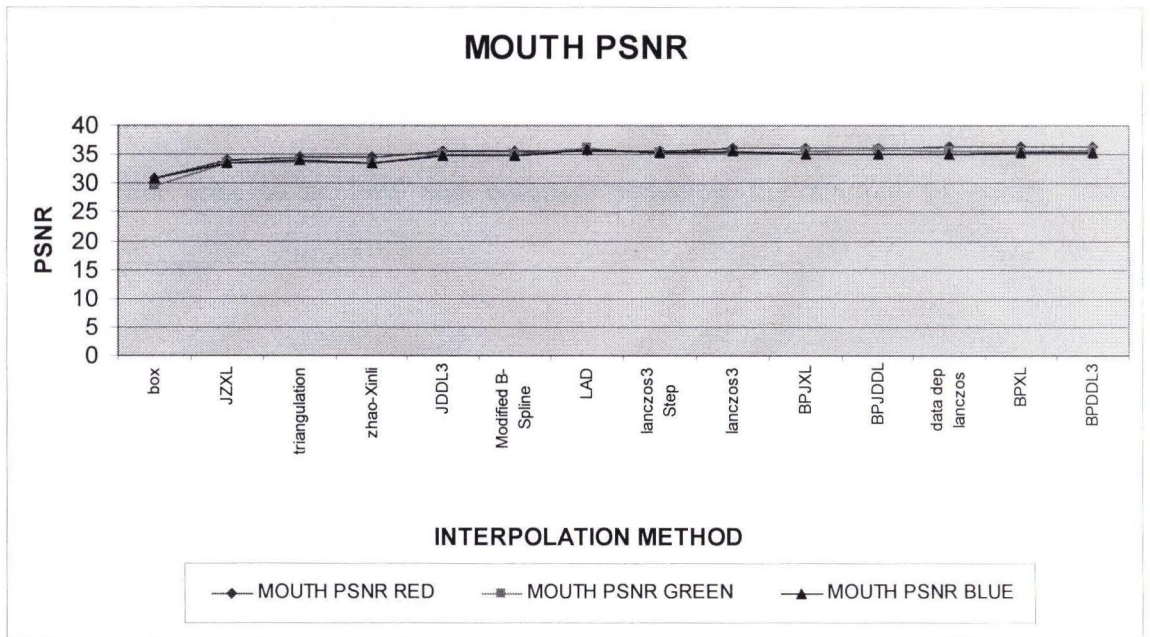


Figure 4.10: Graph of PSNR for color images of the mouth.

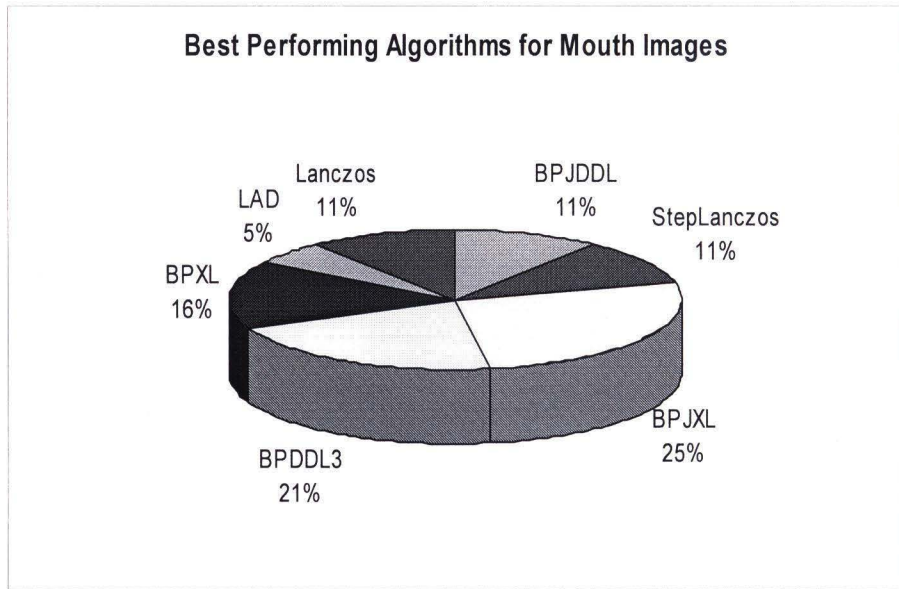


Figure 4.11: Best Performing Algorithms for Mouth Images.

The noticeable improved performance of all the methods in general, guides us to the conclusion that in smaller areas the methods perform better. This is due to the fact that adaptive algorithms have a smaller area to analyze and compare reducing the amount of color variations.

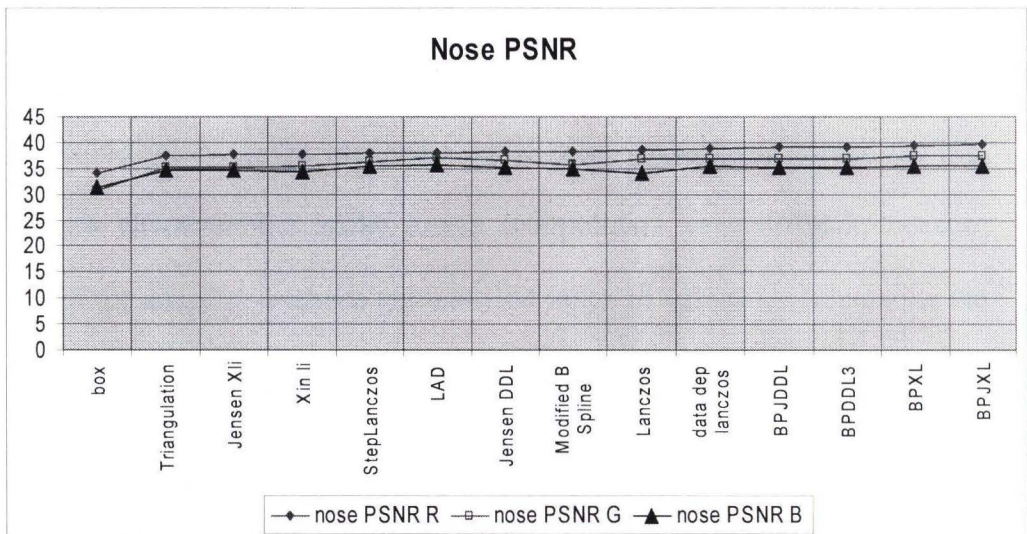
4.1.4.2. Results for Nose

The pixel composition of the nose is very homogenous. Besides the edges on the tip of the nose, and the two nostrils, the pixel colors are similar. Because of this, even Box interpolation returned PSNR values in the range of 34 for the red component. Surprisingly, LADD deconvolution gave average results.

Table 4.5: PSNR of nose color images.

	nose PSNR R	nose PSNR G	nose PSNR B
box	34.218664	30.809389	31.413079
Triangulation	37.41204	35.296423	34.563951
Jensen Xli	37.635043	35.305006	34.55092
Xin li	37.65816	35.392428	34.483846
StepLanczos	37.920594	36.297519	35.456976
LADD	38.03524	37.049811	35.875104
Jensen DDL	38.269156	36.486588	35.326847
Modified B Spline	38.276485	35.778913	34.881588
Lanczos	38.630797	36.894962	34.045089
data dep lanczos	38.826389	36.799219	35.473445
BPJDDL	39.011441	36.995198	35.305158
BPDDL3	39.086018	37.02883	35.192501
BPXL	39.461334	37.421016	35.568533
BPJXL	39.59299	37.37129	35.612153

Since the nose is composed mainly of skin colors, the red component, as shown in the PSNR graph, presents better results compared to the blue and the green components. The graphic depicts that the difference among methods is very thin, with back projected methods outperforming all other methods.

**Figure 4.12:** Graph of PSNR for color images of the nose.

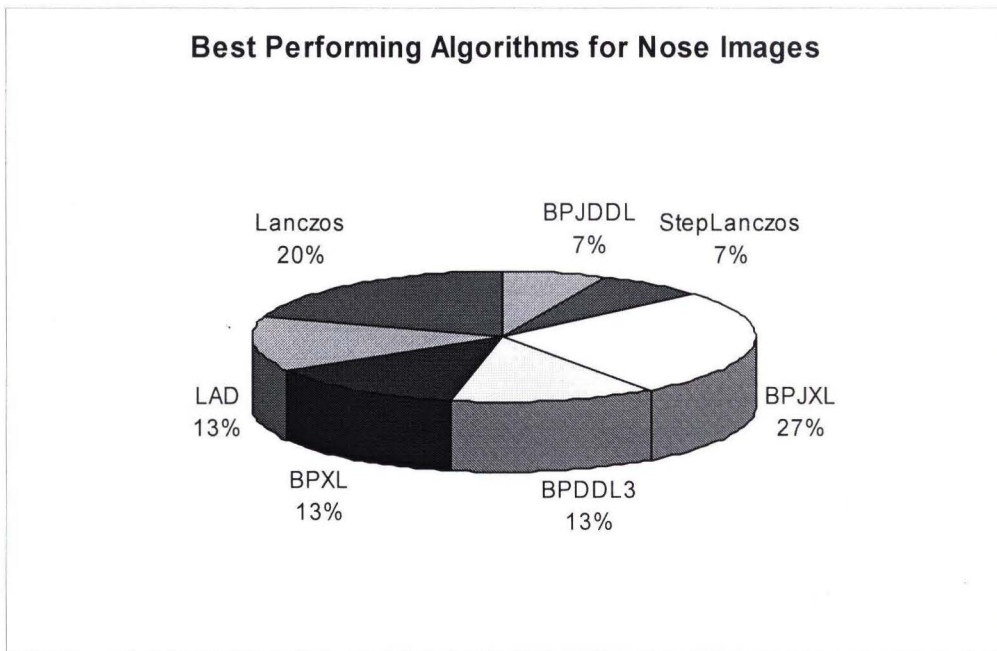


Figure 4.13: Best Performing Algorithms for Nose Images.

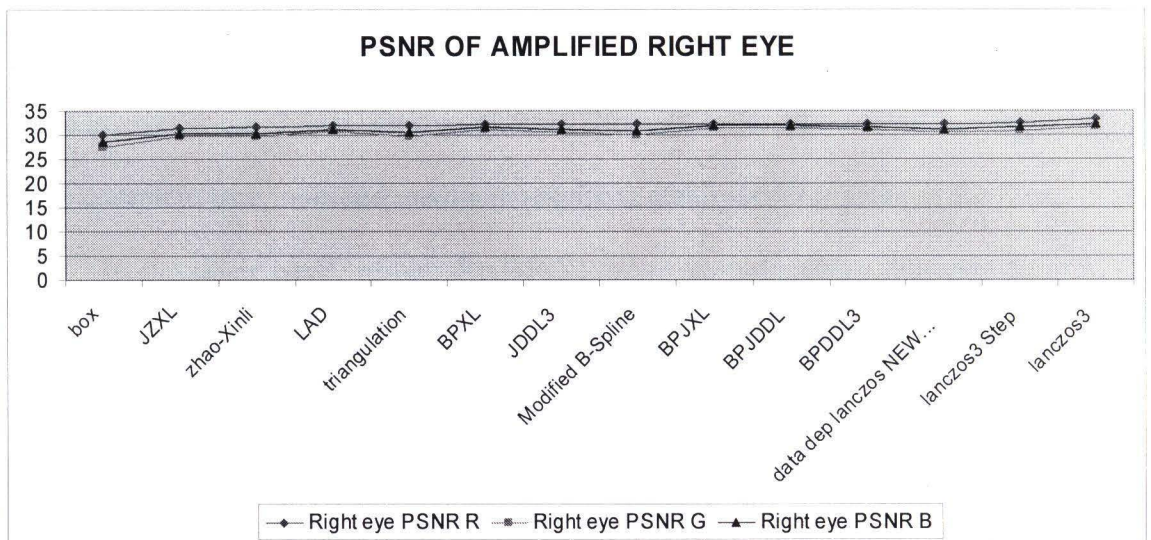
4.1.4.3. Results for Eyes

The eye is composed of the most diverse pixel colors in the face. It comprises different colors for eyebrows, skin, and eye tones. Even within the eye balls humans have a black color on the pupil, a range of possible colors on the iris, and a white color in the areas around the iris. These characteristics make image interpolation very difficult, because even the adaptive methods get scattered range of values for calculating the new pixels. Regardless the obstacles, the best results for enlarging the eye separately are better than the best results for a complete face.

Table 4.6: PSNR values of color images of the right eye

	Right eye PSNR R	Right eye PSNR G	Right eye PSNR B
Box	29.913582	27.424486	28.530529
JZXL	31.436814	29.730741	30.295853
zhao-Xinli	31.610185	29.799797	30.3349
LADD	31.948182	30.852716	31.1664
Triangulation	32.009403	29.848828	30.587809
BPXL	32.206709	31.176685	31.592431
JDDL3	32.217216	30.560996	31.166239
Modified B-Spline	32.223826	30.031544	30.802407
Lanczos3	32.22798	31.26349	31.833862
BPJDDL	32.22798	31.264349	31.833862
BPDDL3	32.332424	31.069485	31.574075
data dep lanczos	32.358672	30.639058	31.232007
lanczos3 Step	32.495857	30.921978	31.663603
BPJXL	33.21556	31.65521	32.360269

As with the previews face parts, the line graph shows the difference among methods is small, but this time Lanczos outperformed the others.

**Figure 4.14:** Graph of PSNR for color Eye Images.

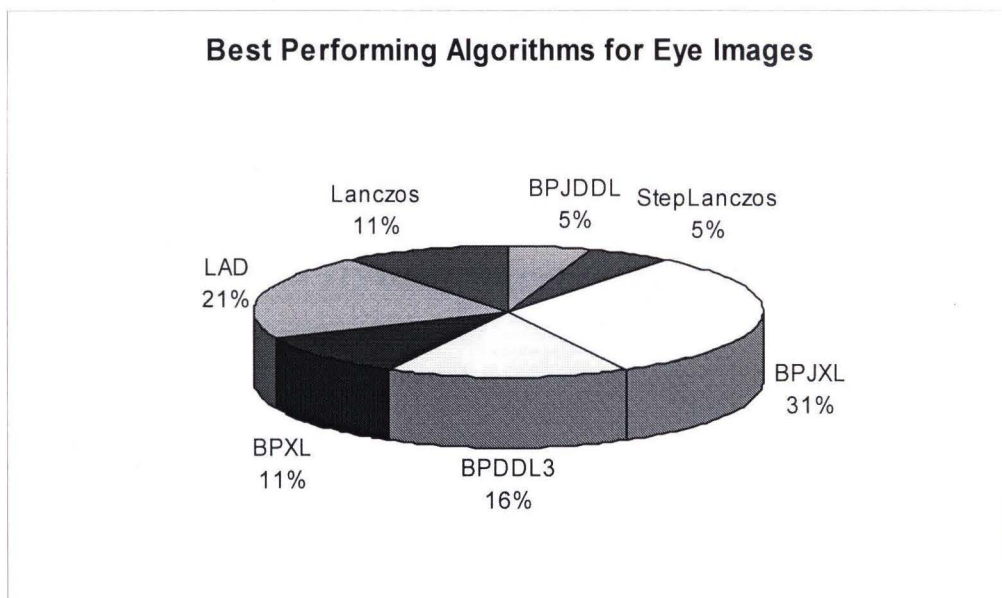


Figure 4.15: Best Performing Algorithms for Eye Images.

4.2. Effects of Face Separation

Interpolation algorithms behave differently depending on the type of image they are applied to. It was discovered in our study that separating the face into parts increases the quality of interpolation. LADD Deconvolution, although returned outstanding results enlarging the complete face, returned mediocre results in small intricate areas of the face, as the eyes. On the other hand, results for BPJXL were remarkable on intricate face parts, and fair on the complete face. This leads us to believe that a combination of the two methods would yield a better overall result.

Chapter 5

Proposed Method of Hybrid Interpolation Using Face Parts

Separation and Results

5.1 Hybrid Interpolation Using Face Parts Separation (HIUFPS)

Image interpolation algorithms recreate pixels based on the surrounding area. Therefore, areas with similar colors within an image, obtain better quality results when interpolated. For example, the cheeks and nose do not have many tone variations but, the eye region have a considerable amount of edges and colors hence, cheeks and nose regions provide better results.

To improve current state of the art methodologies, a technique called (HIUFPS) was devised based on the results of Chapter 4.

As other hybrid interpolation techniques HIUFPS uses different algorithms to enlarge an image, but what makes this hybrid method different is that the algorithms are selected based on the different parts on the human face.

In this chapter we first test HIUFPS by calculating the PSNR of still images from our database of faces. Since the faces of the database are in a pre arranged pose and under control lighting, the study uses PSNR calculations to determine the improvement added by HIUFPS.

The last part of this chapter then presents HIUFPS applied to video images taken from video sources. PSNR cannot be calculated reliably with video images because PSNR requires a reduction of the original image. Since the original image is of low quality in video images, a reduction creates an unusable picture.

5.2 Proposed Algorithm

Based on Chapter 4 we can see that Back Projected Jensen Xin Li and LADD are the best performing methods in our tests. The study shows that BPJXL performs better on the eyes and small intricate areas where LADD deconvolution performs better on the complete face. These results indicate that the algorithms behave differently in intricate areas with many edges than in areas with less variance of colors. We assumed in our tests the feasibility of separating the eyes, mouth and nose, but many images do not have the desired resolution or illumination for this separation. The proposed algorithm (HIUFPS) shown in Figure 5.1 performs differently depending on how viable face separation is. If is not possible, the proposed algorithm first divides the image in a grid and calculates the variance of the pixel colors within each segment, and based on this variance, it executes enlargement with LADD Deconvolution or with BPJXL. If face separation is possible, the eyes, nose and mouth are separated and enlarged with BPJXL, then the rest of the face is enlarged with LADD and at last the image is reassembled.

Hybrid Interpolation Using Face Parts Separation Flow chart

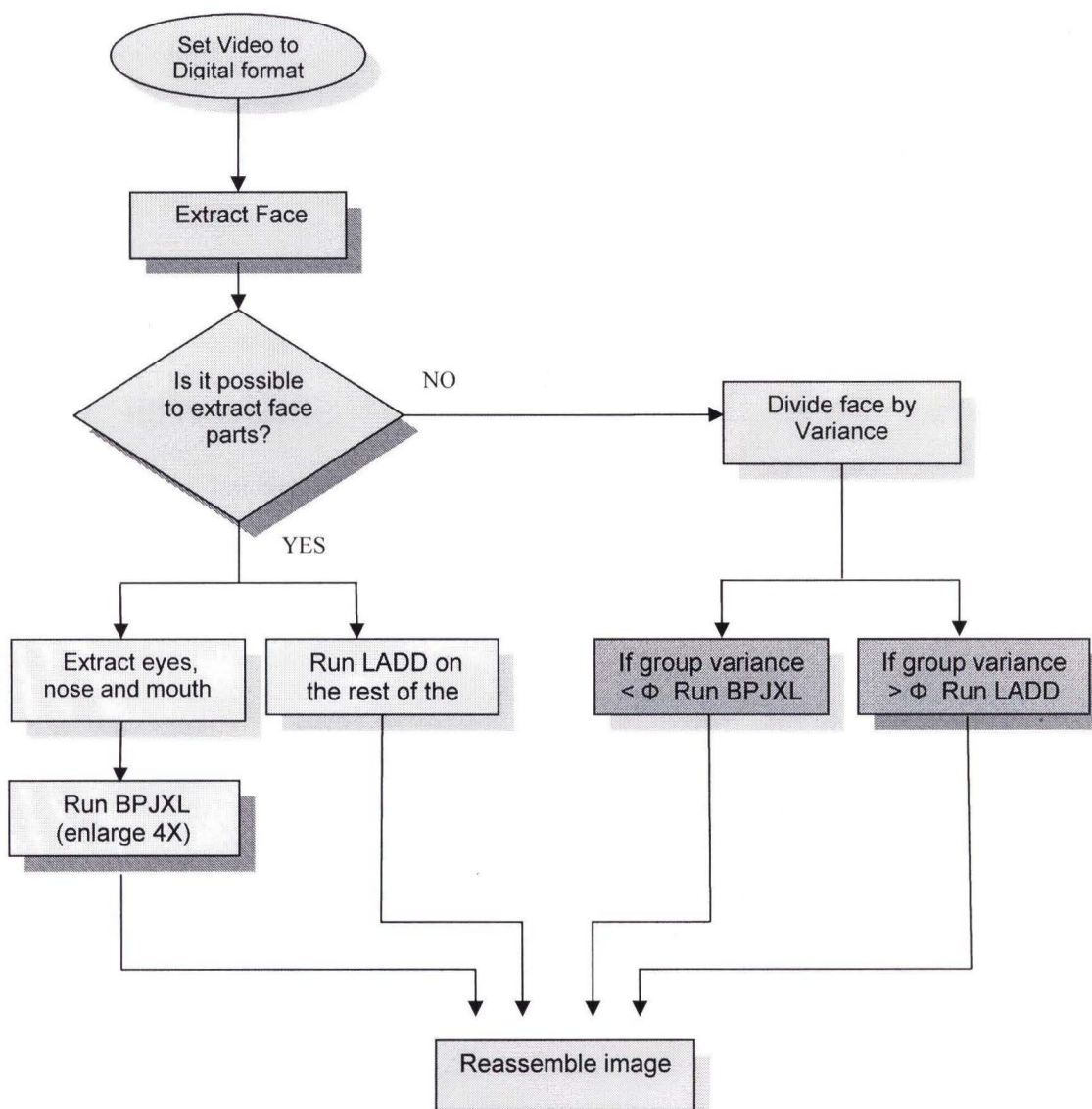


Figure 5.1: Flow diagram of the proposed algorithm.

The study in Chapter 4 proved necessary that to reach better results separating the face into regions with similar color, tones, shades and edges was required.

5.3 Methodology

The necessary steps to verify the improvement obtained with HIUSFP is explained as follows:

1. Videos are captured with a video camera at the entrance of an office. The subjects were not looking at the camera and there was no pre-defined pose.
2. HIFPS is applied to the face images obtained from the video source as well as to the database of face images.
3. PSNR is calculated only on the resulting images taken from the database since images from video are too small. PSNR can only be calculated reliably when the original image is reduced first and then enlarged. In other words, if we reduced the video images the result would be a highly deteriorated image than can point to incorrect results.

This process has been applied to 15 different video images and to the complete set of images from the database (61 female and 81 male).

5.4 Results Obtained from Still Images

Interpolation of still images using HIUFPS returned better results than any other method combined. Table 5.1 shows the average PSNR calculated from complete set of pictures in the database of still images. This average shows improved results when compared to the interpolation algorithms tested in Chapter 3.

Table 5.1: Average PSNR from HIUSFP

Interpolation Method	PSNR R	PSNR G	PSNR B
HIUFPS	32.973682	34.349875	32.735684

Figure 5.2 shows one of the images tested. When the face parts are super imposed, special detail needs to be considered to maintain the eyes mouth and nose in the correct position proportionate to the face.

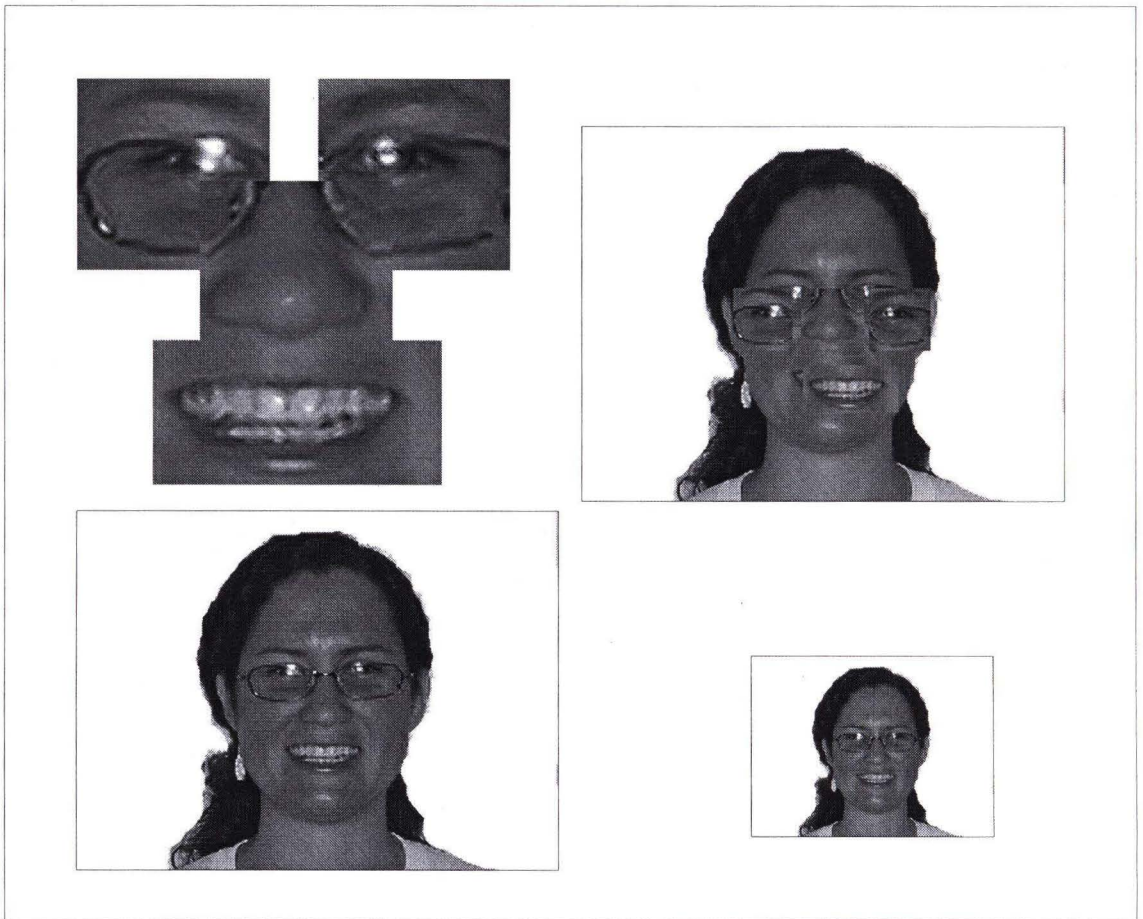


Figure 5.2: The images show process of putting the separate face parts together. The image in the bottom left is the enlarged picture using HIUFPS and the image in the bottom right is the original image.

5.5 Results on Video Images

Video images cannot be compared using PSNR because this value requires a reduction of the original image, and due to the low quality of video sources, a reduced image would be unusable. Validation of the method using metrics is performed in the previews Section (5.4). This section show the resulting images enlarged with HIUFPS compared to the same images enlarged with LADD interpolation. We chose to compare the results with LADD because this was the best performing method out of the 13 original methods tested in Chapter 3.

In Figure 5.3, a picture was taken in an office and the face is separated from the video image. The resulting image is then treated using HIUSFP.



Figure 5.3: HIUFPS applied to a video image. The image in the bottom left was enlarged using HIUFPS, the image on the right uses LADD interpolation.

The image on the right was enlarged using LADD deconvolution, and it shows how the low video source is amplified but enlarging mostly defects. The area of the nose in the original image is not clear. Although the enlarged image resembles an eigenfaces vector map, and probably can be recognize, it is clear that the proposed method is more clear. With the image enlarged with HIUFPS, we can see that the eyes are considerable darker than the cheeks. This is one of the characteristics of HIUFPS, which enlarges small parts of the face, (eyes, nose and mouth) separately. We can see that the nose is

very clear in contrast to the eyes and mouth but still the image is more clearly identifiable.

It can be seen that the image enlarged with HIUSFP has more detail and seems clearer. It can also be observed that face separation changes the general tone of the face. The nose seems to be brighter and the eyes seem darker than the rest of the skin, but this not very important compared to the improved results obtained.

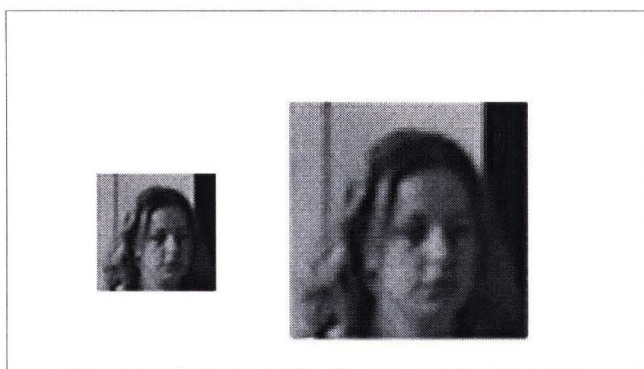


Figure 5.4: Example of HIUFPS applied to a video image.

Figure 5.4 shows an example where the enlarged faces using HIUFPS where there is a background that creates a dark contrast with the face. HIUFPS though, only enlarges the eyes based on the pixels composing each eye, so the darker side of the face is not affected by the dark background shown.

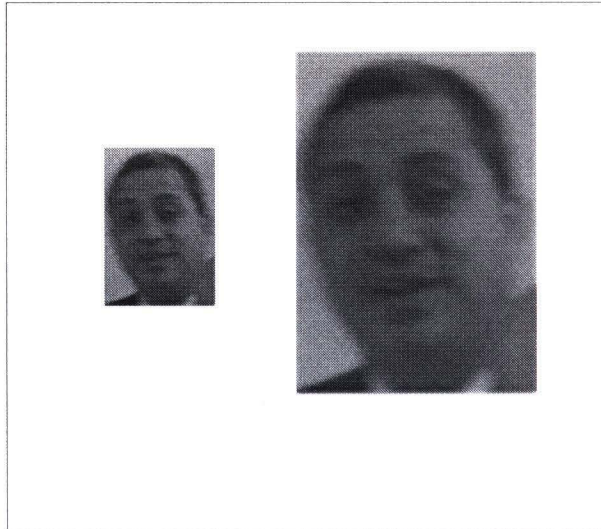


Figure 5.5: Example of HIUFPS applied to a blurry video image.

Figure 5.5 shows a blurry image enlarged with HIUFPS. The enlarged result is still blurred and the left eye looks considerably darker than in the original image.



Figure 5.6: Example of HIUFPS applied to a video image.

The subject in Figure 5.6 is wearing a cap that darkens the eyes. It was very difficult to separate the eyes in this image, and for automatable purposes the separation of the eyes would not be feasible.

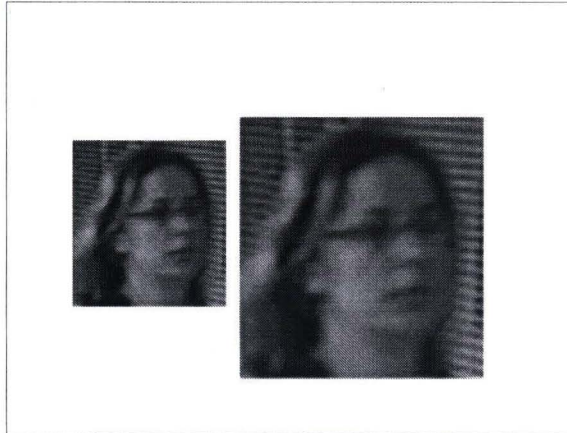


Figure 5.7: Example of HIUFPS applied to an image with a subject with glasses.

The image enlarged in Figure 5.7 shows the movement of the subject. Because of the position, the right eye is not clear and when enlarged using HIUFPS there is not a big improvement on the right side. When looking at the eye area with the glasses we can see that if the original image is not crisp the result is not clear.

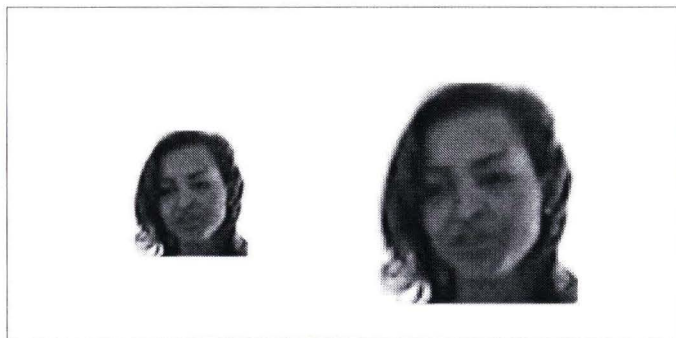


Figure 5.8: Example of HIUFPS applied to a blurry image.

As seen before, Figure 5.8 and Figure 5.9 blurriness cannot be improved using HIUFPS but the resulting blurred images are bigger and clear which is the purpose of the study.



Figure 5.9: Example of HIUFPS applied to a clear image.

Chapter 6

Conclusions and Future Work

6.1 Conclusion

A study was carried out to determine the best interpolation algorithms for face images from video sources. The study of 14 algorithms determined that Least Absolute Deviation (LADD) deconvolution interpolation returns the best quality images when applied to a complete face. Also the study concludes that Back Projected Jensen Xin Li interpolation returns the best quality images when applied only to separate face parts (i.e. eyes, nose and mouth). We can also conclude that the application of interpolation algorithms to separate face parts yields better results than interpolation applied to a complete face. Based on this, an algorithm named Hybrid Interpolation Using Separate Face Parts (HIUSFP) was devised. It employs Back Projected Jensen Xin Li interpolation for the eyes, nose and mouth and LADD deconvolution interpolation for the rest of the face.

The proposed interpolation algorithm successfully creates results superior to all the studied methods. This was validated by applying HIUSFP to a database of 142 images, 61 of them are of females and 81 are of male subjects. The average of the Peak Signal to Noise Ratios calculated applying HIUSFP to the 142 images was lower than the

average of Peak Signal to Noise Ratios of the best performing algorithms applied to the same 142 images.

When applied to images obtained from video, the resulting faces appear more clear and recognizable. The following characteristics are observed when using HIUFPS:

- The proposed method adapts different algorithms based specifically on the human face, and not on ephemeral edges
- Since edges are part of smaller more uniform section (nose, mouth or eyes) the edge detection process is more precise
- Colors and shadows are retained more closely to the surrounding areas.
- Eye, nose and mouse ratio is maintained

A study of interpolation methods applied to human faces was not published before and this research confirms that utilizing different interpolations algorithms in different areas of the face is necessary to obtain optimal results. As discussed in Chapter 2 all of the commercially available algorithms are based on image properties that are universal. HIUFBS on the other hand focuses on special characteristics of the human face, like eyes, nose, lips, etc. and applies enhancements so as to retain their features as best as possible.

6.2 Future Work

Our study relies on several manual processes that can be automated if a future research study is performed. The detection of the eyes, nose and mouth, is already being used commercially and open source technologies are freely available on the internet that perform this task. One commercial application is used by Sony where face detection

algorithm in all its newest cameras is used to help determine how to focus each picture. These technologies were not applied in our project because they require a study on there own, but some were tested as shown in Figure 6.1.

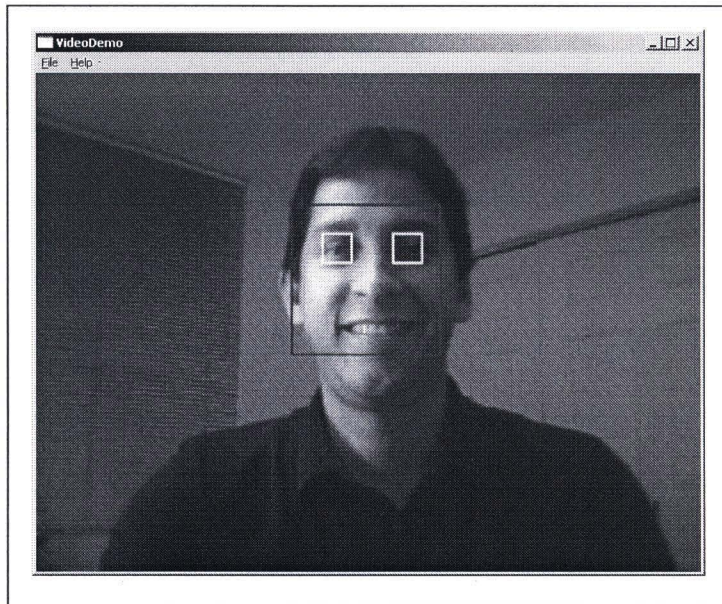


Figure 6.1: Test of an open source eye detection software.

In addition to eye and face detection, the complete automation of our algorithm can be developed. This requires the usage of libraries for the different interpolation algorithms together with the face recognition software. Our study can also be commercialized in order to help the detection of humans from video surveillance systems wherever necessary.

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