# Effect of Temporal Filters on Face Images 

Rasheed Rebar Ihsan

Submitted to the<br>Institute of Graduate Studies and Research in partial fulfillment of the requirements for the degree of

Master of Science<br>in<br>Computer Engineering

Eastern Mediterranean University
January 2017
Gazimağusa, North Cyprus

Approval of the Institute of Graduate Studies and Research

Prof. Dr. Mustafa Tümer
Director

I certify that this thesis satisfies the requirements as thesis for the degree of Master of Science in Computer Engineering.

Prof. Dr. Işık Aybay
Chair, Department of Computer Engineering

We certify that we have read this thesis and that in our opinion it is fully adequate in scope and quality as a thesis for the degree of Master of Science in Computer Engineering.

# Assoc. Prof. Dr. Mehmet Bodur <br> Supervisor 

Examining Committee

\author{

1. Assoc. Prof. Dr. Mehmet Bodur <br> 2. Asst. Prof. Dr. Adnan Acan <br> 3. Asst. Prof. Dr. Ahmet Ünveren
}


#### Abstract

Face detection from low-resolution videos is a challenging research area. This thesis explores the effect of a temporal filtering method by Dr. Bodur on face images. The temporal mean and median filters calculate the intensity of pixels using the intensities of surrounding neighbour pixels, and temporal neighbour pixels in consecutive images. The effect of the proposed technique on the image is measured by the mean square error (MSE) and the peak signal noise ratio (PSNR) values using the pixels of the original high resolution image as reference values to measure the error and noise figures of the pixels of filtered low resolution images. Results demonstrate a significant effect of the proposed filters on the consecutive frames of face video record. In the tests, the median filter is found more effective compared to mean filter.


Keywords: Temporal Mean Filter, Temporal Median Filter, Image Resolution, Effectiveness of Image Filter.

## öZ

Düşük çözünürlüklü videolardan yüz tanıma zorlu bir araştırma alanıdır. Bu tezde, Dr. M. Bodur'un önerisi olan zaman boyutlu filtreleme yönteminin yüz görüntüleri üzerindeki etkisi incelenmektedir. Zamansal ortalama, medyan ve maksimum filtrelerde her pikselin parlaklığı, çevreleyen komşu piksellerin yanısıra ardışık görüntülerdeki zamansal komşu piksellerin yoğunlukları da kullanarak hesaplanır. Önerilen tekniğin görüntü üzerindeki etkisi, düşük çözünürlüklü görüntülerin piksellerini referans amaçlı kullanılan orijinal yüksek çözünürlüklü görüntünün pikselleriyle karşılaştırarak ortalama karesel hata (MSE) ve tepe sinyal gürültü oranı (PSNR) olarak elde edilmiştir. Testlerde, ortalama filtre ile karşılaştırıldığında medyan filtrenin daha etkin olduğu görülmüştür.

Anahtar Kelimeler: Zamanda Ortalama Filtre, Zamanda Medyan Filtre, Görüntü Çözünürlüğü, Görüntü Filtre Etkinliği.

## DEDICATION

# To my parents who helped me to be stronger and better person 

To my lovely sisters and brothers

To everyone who encouraged me

## ACKNOWLEDGMENT

In the present world of competition there is a race of existence in which those are having will to come forward succeed. Project is like a bridge between theoretical and practical working. With this willing I joined this particular project.

First of all, I would like to thank the supreme power the Almighty God who is obviously the one has always guided me to work on the one has always guided me to work on the right path of life. Without his grace this project could not become a reality. Next to him are my parents, whom I am greatly indebted for me, brought up with love and encouragement to this stage.

I sincerely thank to my supervisor Assoc. Prof. Dr. Mehmet Bodur, for his patience, motivation, enthusiasm, and knowledge. His guidance helped me in all the time of research and writing of this thesis. I thank my external jury members, Assist. Prof. Dr. Adnan Acan, and Assist. Prof. Dr. Ahmet Ünveren for their reviews and guidance. And special thanks to my worthy teacher of English, Assist. Prof. Dr. Nilgun Hancioglu for her helping and encouraging. Moreover, I sincerely thank to all the staff members of computer engineering department for their generous attitude and friendly behaviour. At last but not the least I am thankful to all my teachers and friends especially Pawan and Diler who have been always helping and encouraging me though out the year. I have no valuable words to express my thanks, but my heart is still full of the favours received from every person.

## TABLE OF CONTENTS

ABSTRACT ..... iii
ÖZ ..... iv
DEDICATION .....
ACKNOWLEDGMENT. ..... vi
LIST OF TABLES ..... ix
LIST OF FIGURES ..... x
1 INTRODUCTION ..... 1
1.1 Fundamental Information. ..... 1
1.2 Evaluation of Effects of Filters on Pixels of Image ..... 4
1.3 Spatial filters for Improving the Face Image ..... 4
1.4 Surveillance Application for Face Detection ..... 5
1.4 Problem Statement ..... 6
2 LITERATURE SURVEY ON FACE DETECTION ..... 8
2.1 Categories of Face Detection Strategies ..... 8
2.2 Common Approaches of Face Detection Methods ..... 8
2.3 Common Image Representation Methods ..... 9
2.4 Mean Filter ..... 11
2.5 Median Filter ..... 12
2.6 Resizing of an Image by Interpolation. ..... 13
2.7 Face Detection ..... 13
2.8 AdaBoost Algorithm for Feature Selection ..... 16
2.9 Face Detector Implementation Using Matlab ..... 18
2.10 Evaluation of the Effect of Filters on Pixels ..... 19
2.11 Summary ..... 21
3 METHODOLOGY ..... 22
3.1 Introduction ..... 22
3.2 Video Dataset ..... 23
3.3 Determination of Face Frame $k$ ..... 23
3.4 Mean (average) for Frame $k$ ..... 24
3.5 Applying Mean and Median Filter ..... 24
3.6 Interpolation Method ..... 26
3.7 Evaluating and Performance ..... 26
4 IMPLEMENTATION AND RESULTS ..... 28
4.1 Implementation ..... 28
4.2 Description of Data ..... 28
4.3 Effectiveness of Filters Based on Metrics ..... 29
4.4 Test Results ..... 29
4.5 Temporal Filtering with 5-Consecutive Frames ..... 30
4.6 Temporal Filtering with 7-Consecutive Frames ..... 34
5 CONCLUSION ..... 38
REFERENCES ..... 40
APPENDICES ..... 43
Appendix A: Results of 2-Frames Before and 2-After Frame k ..... 44
Appendix B: Results of 3-Frames Before and 3-After Frame k ..... 50
Appendix C: Code ..... 56

## LIST OF TABLES

Table 3.1: Properties of Video Record Dataset ..... 23
Table 4.1: MSE for 5-consecutive frames around $k$ ..... 31
Table 4.2 : PSNR for 5-Consecutive Frames around $k$ ..... 31
Table 4.3: MSE for temporal filters with 7 consecutive frames around $k$ ..... 35
Table 4.4: PSNR for temporal filters with 7 consecutive frames around $k$ ..... 36

## LIST OF FIGURES

Figure 1.1: Example of variation in illumination with permission by Ali Tarhini, 2010 [14].................................................................................................................. 2

Figure 1.2: Example of pose variation with permission by F.Tarrés "GTAV Face
$\qquad$Figure 1.3: Variation in appearance of an individual due to expression [16] .............. 3Figure 1.4: Example of partially occluded faces with permission by A.M. Martinez,the AR Face Database [17] ........................................................................................ 3Figure 1.5: Set of frames from videos surveillance with permission by Cisco Physical
$\qquad$
Figure 2.1: $3 \times 3$ Averaging kernel used in mean filtering ..... 11
Figure 2.2: Intensity calculation of $3 \times 3$ mean filter ..... 12
Figure 2.3: Demonstration of $3 \times 3$ median filter ..... 12
Figure 2.4: Types of features Haar-masks ..... 15
Figure 2.5: Haar Feature, the intensity of pixels difference between eyes region and cheek region ..... 15
Figure 2.6: Sample of taking the values of integral image ..... 16
Figure 2.7: Attentional Cascade ..... 17
Figure 3.1: Determination of Effectiveness of Temporal Filters ..... 22
Figure 3.2: Mean filters between the pixels of frame ..... 24
Figure 3.3: Mean / median filters between the pixels of consecutive frames ..... 25
Figure 4.1: MSE for 2-frames before and 2- frames after the frame k ..... 31
Figure 4.2: PSNR for 2-frames before and 2-frames after the frame k ..... 32
Figure 4.3: Remaining Frames Before and After Filtering ..... 34

Figure 4.4: MSE for 3-frames before and 3- frames after the frame k 35

Figure 4.5: PSNR for 3-frames before and 3-frames after the frame k .................... 36

## Chapter 1

## INTRODUCTION

### 1.1 Fundamental Information

Face detection technology is extensively used in our daily life, especially in the area of real-time monitor, video tracking, criminal inspection, and etc. It is an easy work for humans to detect and recognize human faces by eyes; however, it is not an easy case for computers to do that. Face detection technology has been significantly developed, but a number of challenges waiting for solution. 1) A wide diversity of face models make the limited sample set very difficult to cover all the faces, and establish accurate distribution model in the high-dimensional space. 2) Human faces and optical conditions the background areas that are similar to human face. 3) The present face detection algorithms cannot cover arbitrary pose, lighting condition or faces with invisible parts. 4) Real-time detection system. Face detection in video has the requirement of real-time detection [1].

Recently face detection and face recognition had gotten significant attention from scholars in biometrics, computer vision communities, and pattern recognition. As should be obvious, both methods frameworks are essential in our day by day life [3].

The followings are challenges related with to face detection systems [7]:

- Variations in illumination: When the picture is shaped, factors such as lighting (intensity, source distribution and spectra) and camera features (lenses and sensor response) affect to some degree the appearance of the human face. Figure 1.2 shows the Illumination variations.


Figure 1.1: Example of variation in illumination with permission by Ali Tarhini, 2010 [14]

- Pose variations: The pictures of a face differ as a result of the relative camera face pose (frontal, $45^{\circ}, 90^{\circ}$, topsy-turvy, and some features of face for example the nose or eyes may become partially or completely occluded. Figure 1.3 illustrates the changes appearance due to pose variation.


Figure 1.2: Example of pose variation with permission by F.Tarrés "GTAV Face Database" [15]

- Expressions variation/facial style: The presence of faces is straightforwardly influenced by an individual's facial expression as illustrated in Figure 1.4. Facial hair, for example, moustache and beard can change facial appearance and characteristics in the lower half of the face, particularly close to the mouth and bottom areas.


Figure 1.3: Variation in appearance of an individual due to expression [16]

- Occlusion: Faces might be partially blocked by other objects. In a picture with a set of individuals, a few of the faces or other items may partly occlude other faces, which thus brings about just a little part of the face are accessible in several situations. Examples of partially occluded faces are illustrated in Figure 1.5.


Figure 1.4: Example of partially occluded faces with permission by A.M. Martinez, the AR Face Database [17]

### 1.2 Evaluation of Effects of Filters on Pixels of Image

The following are used as measure of effect of image filters on face images:
Mean Square Error (MSE) is considered to be an important criterion for evaluating the differences of between the filtered and non-filtered images. It is used as part of the digital image processing technique to measure the differences between the predicted and target images. It is well known that the main difference between estimators and predictors is constants are estimated and random variables are predicted. Additionally, MSE can also be used for passing on the concepts of bias, accuracy and precision in statistical estimation. MSE can be examined by knowing the target of prediction or estimation, and an estimator or predictor which is a data function [2].The formula and method of computation are described in more details in chapter 2.

The peak signal-to-noise ratio, sometimes shortened as PSNR, is one of the engineering terms which show the ratio among the signal's noise power and maximum power of a signal's. PNSR is widely used by Engineers for measuring the performance of reconstructed pictures which have been compressed. There is a colour value for each of the image element (pixel). When a picture is compressed and then uncompressed, the colour of the picture changes. PSNR is found to be expressed in terms of the logarithmic decibel scale since signals might have an extensive dynamic range [4]. The formula and method of computation are described in more details in chapter 2.

### 1.3 Spatial filters for Improving the Face Image

Median Filter is a nonlinear smoothing approach that decreases the edges blurring and the current point in the image to be replaced by the median of the brightness in
its neighbourhood is the idea behind it. As for personal noise spikes, these do not influence the median of the radiance in the neighbourhood and so median smoothing eliminates impulse noise in an outstanding manner [19]. Mean Filter the mean filter's function is to replace every pixel by the mean value of the intensities in its region. It can locally decrease the variation and can be implemented easily. It has the ability to smooth and blur the image and for additive Gaussian noise in the meaning of mean square error is excellent. Dappled image is that image in which multiplicative model is added with non-Gaussian noise and subsequently, the simple mean filter does not function well in this situation [18].

### 1.4 Surveillance Application for Face Detection

Surveillance is oversight of behaviours to obtain information. This definition contains a huge number of methods and mechanisms which can be deemed a format of surveillance. Several of these are identifiable out of public knowledge generated by popular civilization. The well known strategies for fixed surveillance systems are (a) technical monitoring (commonly secret video recording or voice recording), and (b) electronic monitoring (digital surveillance, counting of keystroke), and several more [8]. Surveillance is a valuable tool for the governments to observe and identify the people, threats, and criminal action [9].

Face detection surveillance is a part of surveillance which relies on features face for locating and recognition of human by artificial intelligence methods [10]. With increasing demands for protection and security of regions and belongings, nowadays biometric surveillance is a crucial system. Face is one of the most widely use of biometric feature. Observation pictures and recordings caught utilizing different sensors are principle hotspots for reporting and documenting the checked exercises
of concern [3]. In many environs observation video systems are shared and widespread. Video observation has been a key component to accomplish safety at banks, correctional institutions, airports, and gaming club [11]. Some of the frames illustrated in Figure 1.6 that shows humans recorded by surveillance video.


Figure 1.5: Set of frames from videos surveillance with permission by Cisco Physical Security, 2014 [12]

### 1.4 Problem Statement

In many applications related to security a low quality video shall be processed to determine the features of faces in the video. The accuracy of extracting the facial features is a critical step of identification of the persons in the captured videos.

For a poor quality video with $n$ frames $\left\{f_{1}, \mathrm{f}_{2}, \mathrm{f}_{3}, \ldots, \mathrm{f}_{\mathrm{n}}\right\}$ using each frame to find the face features brings considerable loss of information, and high errors of face features. A sequence of frames is expected to have additional facial information for accurate detection of faces. This thesis tests the effectiveness of a set of temporal filters developed by the Supervisor of this thesis, Dr. Mehmet Bodur. Temporary filters combine the information of the consequent image frames into a single image to decrease the error in determination of face images.

To get the effect of filtering, an experimental procedure is developed based on the measured difference of the filtered and the raw images for 50 facial videos. The proposed experimentation starts with high quality images which is expected to provide best face recognition results. HD videos were processed to reduce their size in $10 \%$ steps so that a set of lower and lower quality images are obtained from the initial HD images. The filtered and non-filtered low quality images are compared to determine the effect of the filters on the image pixels.

Detecting human face in video is a hard issue due to the existence of large differences in facial pose and lights, and poor quality of image. Many image processing methods were proposed in literature but non of them measures the effect of the filters on the pixels of the images. This thesis compares the effects of standard mean and median filters to the effects of temporal mean and median filters.

## Chapter 2

## LITERATURE SURVEY ON FACE DETECTION

### 2.1 Categories of Face Detection Strategies

Face detection is one of the main problems in the field image processing and computer vision. Many security applications recently used face detection, and collected intensive attention. In the literature, face detection strategies can be separated in three categories, based on the data acquisition methodology of face images: (a) the approaches that work on the intensity of the images, (b) those which need some sensory data like $3 D$ information or infra-red metaphors and (c) with video sequences [22]. Detecting face in the image is accomplished by the method called Viola-jons, which calculates the features to detect the exact region of the face.

In this chapter an overview is presented on different approaches by several researchers, common features of video recording, and image filtering methods with two spatial filters, interpolation, face detection, performance evaluation and the chapter concludes with a summary.

### 2.2 Common Approaches of Face Detection Methods

There are a number of methods available for the identification of a person face. This section covers the discussion on a number of approaches for facial detection, such as face localization, facial feature detection, face tracking and colour segmentation techniques.

Face localization: means to decide the picture location of a solitary face; this is an abridged detection issue with the supposition that an input image contains one and only one face.

Facial feature detection: The objective of facial characteristic detection is to detect the presence and position of characteristic, for example nose, eyes, lips, eyebrow, nostrils, ears, mouth, etc., with the supposition that there is a single face in a picture.

Face tracking: the technique of continuously guessing the position and possibly the direction of a face in a picture series in real time [5].

Colour segmentation techniques: This method utilizes the skin colour to separate the face. The areas which comprise non-skin colour regions on the face are viewed as candidates for eyes and/or mouth. Therefore, such techniques' performances on facial image databases are to a certain degree inadequate. This is because of ethnical backgrounds of different people [20].

### 2.3 Common Image Representation Methods

Video is the term used for the recording, reproducing, or broadcasting of moving visual image. Just as other media extensions differ in terms of resolution, so does video systems. For development of algorithms on a video record, it is essential to understand the formats of a video. The present study used MP4 as the standard format for the target face videos. A video is made of a set of consequent images, which are reflected on a display at periodic time instants.

Number of frames per second: The number of the still images per the unit of video's duration is known as frame rate and it generally ranges from six to eight
frames per second for traditional cameras and for new cameras it reaches up to more than 120 frames per second. The minimum number of frames that can produce the stimulation of a moving picture is around sixteen frames per second. Each frame consists of the pixels of an image. The video used in this thesis has been recorded at 29 frames per second.

Format of an image: A two dimensional function is known as an image in which $f$ is $(x, y), \mathrm{x}$ in this case and y are spatial coordinates, the intensity is described as the amplitude of coordinate pairs $(x, y)$ of the points on an image. Pixel is the smallest piece of an image. Each pixel corresponds to any one value. The value of a pixel at any point corresponds to the intensity of the light photons striking at that point. Each pixel stores a value proportional to the light intensity at that particular location. In each picture, there may be thousands of pixels that together make up an image. There are many types of images with the colour distribution in them: (a) The binary image: The binary, or monochrome image, as suggested by the name, possesses solely two pixels in which the both pixels refer to white and black colour; (b) $\mathbf{8}$ bit colour format: Also called grayscale image, each pixel is represented by 8 bit, which corresponds to 256 varying shades of colours; (c) $\mathbf{2 4}$ bit colour format: The true colour format, also known as 24 bit, is allocated in three extensions, i.e. red, green and blue extensions. This is because 24 can be equally divided on 8 and into three different channels of colours.

For the purpose of object detection, the colours used in the image provide the basis. It also helps for image tracking and recognition and so on. For this reason, the 24 bit RGB colour was used in this research.

The image files that are most commonly used in cameras, printers, scanners, internets and so on are the JPG, TIF, PNG, and GIF.

### 2.4 Mean Filter

Mean filter is described as a simple method which can be implemented easily for smoothing out images and to suppress the noise by reducing the intensity variation among the pixels. The whole notion works on replacing the values of pixels in different images with those of its neighbours. Consequently it reduces the effect of pixels which are extremely different than their neighbours. The mean filter is also considered as a form convolution filter. A kernel surrounds the target pixel indicating the effect of the neighbouring pixels. Mean filters mostly use a $3 \times 3$ square kernel, as seen in Figure 2.2. Other sizes of square kernels such as $5 \times 5$ are used especially for extreme smoothing. Reducing noise of an image is one of the advantages of a mean filter. And, it has the disadvantage of losing details and turning the image blurry [19].

| $1 / 9$ | $1 / 9$ | $1 / 9$ |
| :--- | :--- | :--- |
| $1 / 9$ | $1 / 9$ | $1 / 9$ |
| $1 / 9$ | $1 / 9$ | $1 / 9$ |

Figure 2.1: $3 \times 3$ Averaging kernel used in mean filtering

The average (mean) is defined as:
$\hat{f}(\mathrm{x}, \mathrm{y})=\frac{1}{m \times n} \quad \sum_{(s, t) \in S x y} g(s, t)$,

Where $g(x, y)$ is the original image, on the other hand $g(s, t)$ is the sub-image whose dimension are $m x n, \hat{f}(\mathrm{x}, \mathrm{y})$ is the image that is filtered. As for the sub-images, they are, after being summed up, divided by $m x n$, and the $x, y$ stand for the dimensions
of the image, and therefore, $s_{x y}$ is the sum of all the pixels in a $3 \times 3$ region $(m=n=3)$ and $(s, t)$ is a pixel which belongs to the $s_{x y}$ set.

| 5 | 3 | 6 |
| :--- | :--- | :--- |
| 2 | 1 | 9 |
| 8 | 4 | 7 |

$$
\begin{gathered}
\text { Mean Filter } \\
\text { mean }=(5+3+6+2+1+9+8+4+7) / 9=5 \\
45 / 9
\end{gathered}
$$

| $*$ | $*$ | $*$ |
| :---: | :---: | :---: |
| $*$ | 5 | $*$ |
| $*$ | $*$ | $*$ |

Figure 2.2: Intensity calculation of $3 \times 3$ mean filter

The value of the centre at the beginning (1) by applying mean replaces to (5).

### 2.5 Median Filter

Similar to the mean filter, the median filter is commonly used for reducing image noise. The median filter is far better than the mean filter for keeping the details in an image.

Similar to the mean filter, the median filter operates on each pixel in a picture, to replace the pixel value by a better representative, the median value, of the surrounding pixels.

The median value is defined the value at the mid of the sorted list of all entries. It is calculated by sorting out the values of the kernel pixels including the surrounding neighbourhood, and selecting the value at the middle of the sorted list to replace the target pixel.

| 5 | 10 | 2 |
| :---: | :---: | :---: |
| 2 | 1 | 3 |
| 8 | 4 | 7 |

## Median Filter

sorted to $1,2,2,3,4,5,7,8,9$. Take the number at the middle: 4

| $*$ | $*$ | $*$ |
| :---: | :---: | :---: |
| $*$ | 4 | $*$ |
| $*$ | $*$ | $*$ |

Figure 2.3: Demonstration of $3 \times 3$ median filter

The median filter has two main advantages over the mean filter over mean filter: (1) Unrepresentative neighbouring pixels will not affect the median value because of the median's average while it influence the mean. (2) The median filter does not produce unrealistic pixel values since the median value is one of the neighbouring pixels. This is especially important at the edges of the image when half of the kernel is empty [18].

### 2.6 Resizing of an Image by Interpolation

Interpolation is the estimation of intensities of pixel when we enlarge an image or reduce the size of image the output image contains more pixels or fewer pixels than the original image. A survey of interpolation systems in the medical image processing domain is presented in [6] it shows in detail how the interpolation work. Mainly interpolation is carried by non-adaptive, and adaptive techniques. Some of the non-adaptive systems are: bi-cubic interpolation, bi-linear and nearest neighbour. Non-adaptive techniques are attractive and are widely used due to their ease of computation. Adaptive techniques rely on the intrinsic features of an image such hue, edge information, etc. Alternatively, non-adaptive techniques do not utilize any intrinsic feature of an image and apply a specific computational logic on the intensities of image pixel to interpolate an image.

### 2.7 Face Detection

The face detection in an image is a material that has always been surveyed in computer literature vision. The face detection algorithm is accorded to the diversities in illumination, visual angle, background and facial expressions and the executing are not easy. Face detection can be utilized in lots applications such as video surveillance; face recognition, driver face observation and or human computer interface, image database management; human face detection is essential and hard
process. Face detection algorithms are either based on (i) features or (ii) learning methods.

Viola - Jones algorithm is purposed for real - time faces detection from an image. Haar type features, computed rapidly by using integral images, feature selection using the AdaBoost algorithm (Adaptive Boost) and face detection with attentional cascade can be used by obtaining its real-time performance.

Viola-jones algorithm detects face robustly, having a very high rate of detection (true-positive rate) and with a very low rate of false-positive; in real time, approximately 2 frames per second providing only face detection, which means to differentiate faces from non-faces. Detection is mostly the first operation in the process of face recognition [4].

Integral image is a concept developed by Frank Crow. A part of the image bounded by corner points $\{\mathrm{a}, \mathrm{b}, \mathrm{c}, \mathrm{d}\}$ is called integral image when it is subject to generate the sum of values in that grid [4].

Haar-masks are mostly used for calculating features. Starting from the mutual features of the faces such as the area around the eyes is much darker than the cheeks or the nose zone is brighter than the area of the eyes. Five Haar-masks (Figure 2.5) have been chosen for defining the features as calculated at various positions and sizes. Haar features are figured as the variation between the sum of the pixels from the white and black zones. In this way, it is somehow hard to expose contrast differences [4].


Figure 2.4: Types of features Haar-masks


Figure 2.5: Haar Feature, the intensity of pixels difference between eyes region and cheek region.

If we consider the mask M from Figure 2.6, the image is associated with the Haar-feature-I behind the mask is being defined by:
$\sum_{1 \leq i \leq N} \sum_{1 \leq j \leq N} I(i, j)_{\text {white }}-I(i, j)_{\text {black }}$

The Haar-feature-I behind the mask is defined by the integral image concept as the difference of pixel values in the white and black regions of the mask.

The features are taken out for windows with their dimensions of $24 * 24$ pixels that have moved on the image where we like to detect faces. For such a window, Haarmasks are scaled and moved performing 162,336 of features. To decrease the Haar-
features computation time, which are vary relying on the type and the size of the feature, the integral image was being used.

II $(\mathrm{i}, \mathrm{j})=\sum_{1 \leq s \leq i} \sum_{1 \leq t \leq j} \mathrm{I}(\mathrm{s}, \mathrm{t}), 1 \leq \mathrm{i} \leq \mathrm{N}, 1 \leq j \leq N$

Let $A, B, C$ and $D$ take the values of the integral image at the rectangle corners as seen in Figure 2.7. Then the total original image values in rectangle can be calculated: sum $=A-B-C+D$. Just 3 additions are necessary for any rectangle size. It is utilized in many areas of computer vision [4].


Figure 2.6: Sample of taking the values of integral image

### 2.8 AdaBoost Algorithm for Feature Selection

According to Haar-features for an image by $24 * 24$ pixels can be as $d=162336$, and most of them are excessive; AdaBoost algorithm had been used for a selection of a minimal number of features. The main idea is just to make an intricate classifier (decision rule) by utilizing a weighted linear by integrating of weak classifiers. Each feature is considered a weak classifier, as known by:
$h(\mathrm{x}, \mathrm{f}, \mathrm{p}, \theta)=\left\{\begin{array}{l}1, \text { if } p f(x)<p \theta \\ 0, \text { otherwise }\end{array}\right.$

Where x is a 24 x 24 pixel image, $\theta$ is a threshold and $p$ is a parity. AdaBoost algorithm is founded on a set of training that includes n pairs $\left(x_{\mathrm{i}}, y_{\mathrm{i}}\right)$, where $x_{i}$ can be considered as positive or negative image. And $y_{i}$ can be a label allocated to every
single image and is equal to 1 for an image of positive and to -1 for an image of negative.

Attentional Cascade: After AdaBoost algorithm, a strong classifier will result that classifies the windows of $N x N$ size well enough. Since, on average, only $0.01 \%$ of the windows are positive images, meaning faces, only potentially positive windows must be examined. Instead, to achieve a higher detection rate and a smaller misclassified images detection rate, we should use another strong classifier that classifies correctly the before misclassified images. This creates the attentional cascade, as showed in Figure 2.7. At the first layer of the attentional cascade, a strong classifier with few features is used, which will filter/reject most negative windows. A cascade of classifiers that are becoming more and more complex (with more features) will follow and they will allow to achieve a better detection rate. At each layer of the cascade, the negative images classified correctly will be eliminated and the new strong classifier will have a more difficult task than the previous step classifier


Figure 2.7: Attentional Cascade

Eventually, the cascade of classifiers will work as below:
The image will be divided into doubled windows; each window is an input inside the attentional cascade; at each layer, the window is being checked as it includes a face or not - due to the powerful classifier; if it is negative, the window is being declined and the step will be reiterated for another window; if it is positive, which means that window is a potential face and will go to the next layer of the cascade; the window includes of a face if it passes all attentional cascade layers [4].

### 2.9 Face Detector Implementation Using Matlab

Computer vision toolbox in Matlab contains cascade object detector (vision.CascadeObjectDetector) that makes a system object detector that is capable of detecting objects by using Viola - Jones algorithm. By default, the detector is a set to detect faces in an image, but it can also detect the mouth, nose, eyes or the upper part of the body known by the input string MODEL (ClassificationModel).

System object (detector) that detects faces from the image, by utilizing the ViolaJones algorithm, the following common is used as such:
detector=vision.CascadeObjectDetector ('attentionalCascade.xml'), where the parameter is only performed under the name of xml file in which the attentional cascade was saved. After making of detector, the method pace is so-called by the next syntax: BBOX = pace (detector, I) that returns BBOX, an M- by - 4 matrix determining M bounding box including the detected objects. Each row includes of 4 components [x y width height] that assigns in pixels, the bounding box size and upper-left corner. By utilizing a detector acquired from training, the next paces are finished: (1) open the proper image; (2) make the detector object; (3) distinguish
faces from the images; (4) add notes to the faces; (5) display image with adding notes to the faces [4].

### 2.10 Evaluation of the Effect of Filters on Pixels

The visual quality of an image can be improved or enhanced; nevertheless, the whole process is a subjective one. This is because no two persons can agree on the same image enhancement method. It, therefore, necessitates the use of empirical data to identify the effect of algorithms which are used for image quality enhancement.

There are two measures for evaluating in this thesis:
Mean square error (MSE) scores the difference for the pixels between two images, the original image and the produced image. MSE is calculated by:

MSE $=\frac{1}{m n} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1}\|f(i, j)-\mathrm{g}(i, j)\|^{2}$

Where $f$ stands for the matrix data of the original image; $g$ stands for the matrix data of the degraded image to be investigated; $m$ stands for the number of rows of pixels of the images and $i$ stands for the index of that row; $n$ stands for the number of columns of pixels of the image and $j$ stands for the index of that column [2].

For the processing of digital images to see if there are any errors, the mean square error is used. For determining the accuracy of an image, the two MSEs are measured and afterwards compared. In addition, the values are closer to zero are the better ones and are always non-negative.

Peak-Signal-to-Noise Ratio (PSNR) describes the ratio that falls between the power of a signal and the maximum possible value of the distortion noise which may affect
the representation quality of the image. Due to the significant wideness of the image dynamic range, logarithmic decibel scale is used to express the PSNR.

PSNR's mathematical equation is as follows:
$\operatorname{PSNR}=20 \log _{10}\left(\frac{\mathrm{MAX}_{\mathrm{f}}}{\sqrt{\mathrm{MSE}}}\right)$

Where $f$ stands for the original image's matrix data and $M A X_{f}$ signifies the quality present in the "supposed to be good" image.

Applying a filter on a test image changes the pixels of the image. The measurement of change of the pixels can be used for comparison in a systematic manner to see whether or not a certain algorithm is more effective than other ones. The peak-signal-to-noise-ratio is the metric system which is to be investigated. If there is a sort of algorithm that can degrade the image to be investigated to resemble the original image, in this case the algorithm used is determined to be the better one [2].

For the simplicity of implementation, images are considered as a $2 D$ array of data, or a matrix in describing the algorithms. To compare two images, their matrix dimensions should be identical.

If PSNR of a filter is high, that indicates more pixels are corrected in the filtered image. Similarly, if MSE between the filtered and non-filtered pictures are high, it shows the filter changed more pixels, and the intensity levels of the pixels are corrected more heavily.

### 2.11 Summary

One of the most common biometric techniques is face detection. Over recent years, several analysts have proposed distinctive face detection strategies, demanding the recognition of human faces, motivated by the expanded number of real life applications. This thesis compares the effectiveness of mean and median filters against the temporal mean, and temporal median filters, which are proposed by Dr. Bodur. So as to evaluate the effectiveness of filters on test image and the image in a dataset, mean square error (MSE) and pick signal (PSNR) were utilized in this thesis.

## Chapter 3

## METHODOLOGY

### 3.1 Introduction

This chapter will describe the research methodology. To improve face image in a video, it will depend on two filters mean and median. Then, by apply these two filters on consecutive frames in a video, in order to obtain better quality face image. Also, assessment for image quality is a traditional need. The conventional methods for measuring quality of image prior to and after improving are MSE and PSNR. In this thesis we compared different face image with different resolutions by using their quality parameters (MSE and PSNR).


Figure 3.1: Determination of Effectiveness of Temporal Filters

### 3.2 Video Dataset

All of the video records used in the tests were taken in same environment with a camera at the fixed location. However, the background and the time of the day the video records were different from each other. The videos were recorded by using a camera with a resolution $1920 \times 1080$ p. After recording the videos, they were edited, and resized into an eight different resolutions.

Table 3.1: Properties of Video Record Dataset

| Total Size of Dataset | 347 MB |
| :---: | :---: |
| No. of Original <br> Video Records | 50 |
| Frame rate | 29 (per/second) |
| Video type | . mp 4 |
| Video format | RGB24 |
|  | $1920 \times 1080$ |
|  | $480 \times 640$ |
|  | $320 \times 480$ |
| Resolutions | $288 \times 352$ |
| of Videos | $120 \times 320$ |
|  | $100 \times 180$ |
|  | $80 \times 150$ |
|  | $70 \times 120$ |
| Total Number | 450 |
| of Videos |  |

### 3.3 Determination of Face Frame $\boldsymbol{k}$

Assume $V$ is a low resolution video sequence and $F=\left\{f_{1}, f_{2} \ldots, f_{n}\right\}$, n represents the number of frame in $V$. Firstly, the Viola-jons Algorithm has been used for detecting face by using Haar type features. Haar features are calculated at equation 2.2 as the difference between the summations of the pixels from the white region with the summation of the pixels from the black region. There are several types of Haar features. For this thesis the Haar feature that contains left eye, right eye, mouth and
nose is used for detecting the full face, as described in details in the previous chapter in section 2.6. If we found the exact face, then the frame that contains a face was used for improving. Otherwise there was no face to improve. So the frame that we are selecting is our interest frame.

### 3.4 Mean (average) for Frame $\boldsymbol{k}$

To obtain a better image of the $i^{\text {th }}$, $\mathrm{fi}^{\prime}$, a $3 \times 3$ square kernel for calculating averaging (mean) was used between pixels of frame $\mathrm{f}_{\mathrm{i}}$, also for the rest of frames that we selected for improving the interest frame we had to apply $3 \times 3$ square kernel. In this process $3 \times 3$, we had to calculate average for the centre pixel relies on the neighbour's pixels. We had to apply this procedure for all the pixels in the frame $(f i)$, also apply it for the rest of frames $\left(f_{i-1}, f_{i-2}, f_{i+1}, f_{i+2}\right)$ that had selected.


Figure 3.2: Mean filters between the pixels of frame

### 3.5 Applying Mean and Median Filter

After applying mean technique between the pixels of each frame, again averaging (mean) and median filters were utilizes between pixels of a sequence of frames $f_{i-1}, f_{i-2}, f_{i+1}$ and $f_{i+2}$.


Figure 3.3: Mean / median filters between the pixels of consecutive frames

The proposed technique was calculates the mean and median for all the pixels of consequent images (frames). Therefore, all of the pixels that we are calculating with each other, from the sequence of frames, they should in the same location and putting the result to the exact position in the output image as illustrated in figure 3.3.

For this process we can easily calculate using the following formulas:
$d n(\mathrm{i}, \mathrm{j})=\frac{\sum_{r=m-t, \ldots, m+t} d_{i, j, r}}{k}$
$d n(\mathrm{i}, \mathrm{j})=$ median $\{\mathrm{d} i, j, m-t, \ldots ., \mathrm{d} i, j, m+t\}$

Where, $m$ is face frame, d is the intensity value of pixel in location $i$ and $j$ in frame $r$, $k$ is the number of frames, $t=(\mathrm{k}-1) / 2, d n$ is the output image. The mean (average) between pixels of the different frames is calculated using (3.1). The median of consecutive neighbour pixels were calculated using (3.2).

### 3.6 Interpolation Method

For evaluating the difference between the images with different sizes image interpolation was used in this thesis. Image resize is a Matlab function used for changing the size of images similar to the each other; this is for measuring the difference between images before and after improving. In this thesis for measuring the performance of each low resolution with the original image we resized the original image similar to the size of low resolution image for all videos. "imresize" uses interpolation to determine the values of these pixels, computing a weighted average of some set of pixels in the vicinity of the pixel location." imresize" bases the weightings on the distance each pixel is from the point. By default, "imresize" uses bicubic interpolation.
$W$ = imresize(I, scale) returns image $W$ that is scale times the size of $I$. An input image $I$ can be a binary, grayscale or RGB image. If scale is from 0 through $1.0, W$ is smaller than $I$. If scale is greater than $1.0, W$ is larger than $I$. Therefore in all comparisons we reduced the size of original image similar to the size of low quality image.

### 3.7 Evaluating and Performance

For evaluating the rate between the low resolution image prior to and after improving with the original frame, two measures were established to determine the closeness of two frames: mean square error (MSE) and peak signal to noise ratio (PSNR). These two evaluations were described in detail in chapter two.

In this thesis the mean square error (MSE) was used for knowing the difference between the actual image and the produced image after applying our method. Also,
the proposal is that the higher the PSNR, the better degraded image has been reconstructed to match the original image and the better the reconstructive algorithm. This would occur because we wish to minimize the MSE between images with respect the maximum signal value of the image.

In this thesis, there are two limitations, first one for detecting face. Correct face detection below the size $100 \times 180$ is not possible because the size is not sufficient and resizing noise makes the detection of face impossible. The effect of pixels on MSE and PSNR figures indicate that for this low resolution images the filters does not provide effective filtering.

## Chapter 4

## IMPLEMENTATION AND RESULTS

### 4.1 Implementation

In the tests, a personal computer is used with 64-bit CPU 2.10 GHz processor, 8 GB RAM, and Windows 10 operating system. The coding is implemented in Matlab 2016 because of its wide range of toolbox opportunities.

### 4.2 Description of Data

In this thesis 50 face videos of different persons are recorded as HD video sources. Videos are recorded by a camera with a resolution $1920 \times 1080$ and hold 29 frames/seconds. Each HD video is resized to generate nine different resolutions, some of them giving no face detection because resolution is extremely low. Each video is about 4 to 6 seconds. This video record database consists of brief, low resolution video clips of fifty individuals, each showing the face of a person standing in front of a camera. Each individual has an original high definition video and eight low resolution copies obtained from it by reducing the resolution as shown in Table 3.1.

As explained in previous chapters, the filter is applied on a selected frame, $k$, and its neighbour frames. At the beginning of the process all the videos are converted to sequences of frames. The image pixels of all fifty original high definition videos ( $1920 \times 1080$ ) of the dataset were compared to the image pixels of the rest of fifty videos in each of the low resolution dataset, they are $480 \times 640,320 \times 480,288 \times$
$352,240 \times 320,120 \times 240,100 \times 180,80 \times 150$ and $70 \times 120$. Then two ordinary filters, the mean and the median filters, were applied on the low resolution frames. Then, the temporal mean and median filters were accomplished all of the neighbour frames were fused by mean and median of pixel intensities. For evaluating the performance of techniques two evaluation schemes were used Mean Square Error (MSE) and Peak Signal to Noise Ratio (PSNR). After each of the mean and median operations those evaluation schemes have been used. In section 4.3 these evaluation schemes are clarified in details respectively.

### 4.3 Effectiveness of Filters Based on Metrics

Pixel-change effectiveness of the filters are compared using two different methods which are mostly used in scoring the quantity of pixel errors for the images after contaminated with a noise, as well as the amount of pixel corrections for an image after filtering: Mean square error (MES), and, peak signal to noise ratio (PSNR).

Especially at low resolution frames, the face images extracted from the videos needs to be improved using image filters, for an accurate biometric determination of identities. The measure of effectiveness of the filters by MSE and PSNR is assumed to provide an important indication on the quality improvement of the images.

### 4.4 Test Results

As described in a previous chapter, temporal filtering relies on a sequence of frames in improving the face image. We evaluate the filtered images by methods of MSE and PSNR to determine the amount of the pixel intensity changes after selecting the centre frame, $k$, and applying mean and median filters on consecutive frames.

The experiments are repeated using 3-consecutive frames, 5-consecutive frames, and 7-consecutive frames in the filtering operations. With 3-consecutive frames, after we select centre frame $k$, we use frames $k-1$ and $k+1$ as temporal neighbours of the frame k. Similarly, for 7 -consecutive frames, we used frames $\{k-3, \ldots, k, \ldots, k+3\}$ in the temporal filter.

### 4.5 Temporal Filtering with 5-Consecutive Frames

The following figures and tables show the results of average for all the 50 videos with different six resolutions that depend on 2-frames before and 2-frames after the interested frame.

Tables 4.1, 4.2 and figures 4.1, 4.2 compares HD resolution frame against a) raw low resolution frames, b) low resolution frames after applying mean filter, and c) low resolution frames after applying median filter technique, this is by using two performance measurements mean square error (MSE) and peck signal to noise ratio (PSNR). Compared to the differences between the original and raw image, both temporal mean, and temporal median filtered images have less changes with respect to original. Although the percent difference of MSE is around $2 \%$, the reduction of the difference between the original and the filtered image implies that filter has corrective effect on the image to reduce the information loss due to size reduction of the images.

Table 4.1: MSE for 5-consecutive frames around $k$

| Resolutions | Original vs <br> Raw Im. | $\%$ change | Original vs <br> Mean | $\%$ change | Original vs <br> Median | $\%$ change |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $480 \times 640$ | 6663.02 | $66.6 \%$ | 6558.383 | $65.6 \%$ | 6561.513 | $65.6 \%$ |
| $320 \times 480$ | 4541.364 | $45.4 \%$ | 4417.609 | $44.2 \%$ | 4419.871 | $44.2 \%$ |
| $288 \times 352$ | 7710.921 | $77.1 \%$ | 7589.517 | $75.9 \%$ | 7590.628 | $75.9 \%$ |
| $240 \times 320$ | 6510.971 | $65.1 \%$ | 6366.844 | $63.7 \%$ | 6367.923 | $63.7 \%$ |
| $120 \times 240$ | 103.9682 | $1.04 \%$ | 199.2697 | $2 \%$ | 199.3926 | $2 \%$ |
| $100 \times 180$ | 138.1957 | $1.38 \%$ | 240.0958 | $2.4 \%$ | 240.377 | $2.4 \%$ |



Figure 4.1: MSE for 5-Consecutive Frames around $k$

Table 4.2 :PSNR for 5-Consecutive Frames around $k$

| Resolutions | Original vs Raw <br> Image | Original vs Mean | Original vs Median |
| :---: | :---: | :---: | :---: |
| $480 \times 640$ | 10.236 | 10.307 | 10.305 |
| $320 \times 480$ | 11.920 | 12.045 | 12.043 |
| $288 \times 352$ | 9.593 | 9.665 | 9.665 |
| $240 \times 320$ | 10.342 | 10.444 | 10.444 |
| $120 \times 240$ | 28.486 | 25.476 | 25.476 |
| $100 \times 180$ | 27.071 | 24.554 | 24.547 |



Figure 4.2: PSNR for 5 consequent frame filters

As seen by the plots of first four resolutions 480x640, 320x480, $288 \times 352$ and $240 \times 320$ improvement occurred, mean square error decreased and the peak signal-tonoise ratio increased. In contrast, in two last resolutions $120 \times 240$ and 100x180 the MSE increased and PSNR decreased probably because of extreme information loss by heavy size reduction.

Figure 4.3 shows face images that extracted from high quality video with a set of similar face images, these images were in different resolutions from higher to lower resolution, and also the images after applying mean and median techniques.

| High Quality $\begin{gathered} 1920 \\ \text { X } \\ 1080 \end{gathered}$ |  |  |  |
| :---: | :---: | :---: | :---: |
| $\begin{gathered} 480 \\ x \\ 640 \end{gathered}$ |  |  |  |
| $\begin{gathered} 320 \\ \mathrm{X} \\ 480 \end{gathered}$ |  |  |  |
| $\begin{gathered} 288 \\ x \\ 352 \end{gathered}$ | Frame from low video (288x 352 ) |  |  |
| $\begin{gathered} 240 \\ \mathrm{x} \\ 320 \end{gathered}$ | Frame from low video ( $240 \times 320$ ) |  | Median |



Figure 4.3: Remaining Frames Before and After Filtering

In general, only small differences occur between the values of mean and median filters. In case, mean filter had better improve than the median filter for 2-frames before and 2-frames after the selected frame (k).

### 4.6 Temporal Filtering with 7-Consecutive Frames

The test procedure for 5-consecutive frames is repeated to get the average for all the 50 videos for six different resolutions using 3 previous frames, 3 post frames starting from the centre frame $k$, thus processing 7-consecutive frames of the video records.

Tables 4.3, 4.4 and figures 4.3, 4.4 consists of the test results of comparisons for a) the difference of original frames to the raw low resolution frames, b) the difference of original frames to the filtered low resolution frames by temporal mean, c) similar to (b) but using temporal median filter. The differences are evaluated by two methods, MSE and PSNR.

Table 4.3: MSE for temporal filters with 7 consecutive frames around $k$

| Resolutions | Original <br> vs Low | by \% | Original vs <br> Mean | By \% | Original vs <br> Median | By \% |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $480 \times 640$ | 6663.02 | $66.63 \%$ | 6555.49 | $65.55 \%$ | 6559.45 | $65.59 \%$ |
| $320 \times 480$ | 4541.36 | $45.41 \%$ | 4415.24 | $44.14 \%$ | 4418.24 | $44.18 \%$ |
| $288 \times 352$ | 7710.92 | $77.11 \%$ | 7588.29 | $75.88 \%$ | 7589.86 | $75.9 \%$ |
| $240 \times 320$ | 6510.97 | $65.11 \%$ | 6494.21 | $64.94 \%$ | 6495.86 | $64.96 \%$ |
| $120 \times 240$ | 103.968 | $1.4 \%$ | 201.20 | $2.01 \%$ | 201.28 | $2.01 \%$ |
| $100 \times 180$ | 138.2 | $1.38 \%$ | 240.93 | $2.04 \%$ | 241.02 | $2.41 \%$ |



Figure 4.4: MSE for temporal filters with 7 consecutive frames around $k$

Table 4.4: PSNR for temporal filters with 7 consecutive frames around $k$

| Resolutions | Original vs Low | Original vs Mean | Original vs Median |
| :---: | :---: | :---: | :---: |
| $480 \times 640$ | 10.235861 | 10.3095 | 10.3066519 |
| $320 \times 480$ | 11.92019 | 12.04815 | 12.04482 |
| $288 \times 352$ | 9.592557 | 9.666018 | 9.665083 |
| $240 \times 320$ | 10.2838 | 10.38566 | 10.38449 |
| $120 \times 240$ | 28.48555 | 25.42783 | 25.42564 |
| $100 \times 180$ | 27.0707 | 24.53569 | 24.53305 |



Figure 4.5: PSNR for temporal filters with 7 consecutive frames around $k$

As seen on the graph, bars for 5 consequent frame filters of first four qualities $480 \times 640,320 \times 480,288 \times 352$ and $240 \times 320$ has almost same the bar of raw filter PSNR, mean square error decreased and the peak signal-to-noise-ratio increased, in contrast, in last two resolutions 120x240 and 100x180 the MSE increased and PSNR decreased.

Generally, small differences occur for the values of MSE between mean and median filters, also same differences in PSNR values between the two techniques. In general, mean filter had more effect than the median filter for 5 consecutive frame temporal filters.

The results show that for the first three resolutions 7 consecutive frames had more effect compared to 5 consecutive frame filters. On the other hand, for the last improved resolution ( $240 \times 320$ ), 5 consecutive frame filtering had higher effect than the other filter. This is illustrates, for the very low resolution frames, fusing the less number of frames will obtain better improvement.

In this thesis, temporal mean and median filters with 5 and 7 consecutive frames were applied on the pixels of each selected frame separately, and then mean (average) and median filters were applied between the pixels of sequence frames. The results illustrate that positive effect of the applied mean and median filters were observed for the images with higher first four resolutions. Although the difference between the temporal mean and median filters are not significant, mean filter had slightly higher effect on the tested face images.

## Chapter 5

## CONCLUSION

Improving of face image is necessary to use low resolution image in face detection and recognition. This thesis tested the effects of two temporal image improving techniques for filtering face images in a large range of resolutions.

The temporal filters are a good candidate for improving images for the face images even near the lower bound of resolution. The temporal mean and the median filters are an expansion of ordinary mean and median filters to temporal domain to be used on consecutive images captured from a video record. In the tests for fifty faces, they both decreased the error rate of biometrics obtained from low resolution videos using the consecutive images around a certain image frame.

The thesis indicates that intensity level change of pixels of the non filtered low resolution images with respect to original image is more than the temporal filtered low resolution images with respect to original image. This shows that the temporal filtering recovers some information from the consequent frames, and improves the quality of the face image. Simplicity of the filter, and its computationally inexpensive algorithm can be listed as some of the important advantages of applying temporal mean and temporal median filtering on a sequence of frames.

Tests indicate that the quality of the output image through temporal mean filtering on a consecutive set of frames is better than that of the temporal median filtering technique.

Future studies may be recommended on testing the success rate improvement of face detection using temporal filters against using the raw and ordinary filters. The MSE and PSNR values in the tests indicate that an improvement of successful face detection rate is expectable.

## REFERENCES

[1] Huang, T., \& Wang, Z. Face Detection Using Improved AdaBoost. New York University, USA.
[2] Measures of image quality (2016, December, 10). Retrieved From. http://homepages.inf.ed.ac.uk/rbf/CVonline/LOCAL_COPIES/VELDHUIZEN/n ode18.html.
[3] Jillela, R. R., Ross, A., Li, X., \& Adjeroh, D. (2008). Adaptive Frame Selection for Enhanced Face Recognition in Low-Resolution Videos. West Virginia University Libraries.
[4] Alionte, E., \& Lazar, C. (2015, October). A practical implementation of face detection by using Matlab cascade object detector. In System Theory, Control and Computing (ICSTCC), 2015 19th International Conference on (pp. 785790). IEEE.
[5] Yang, M. H., Kriegman, D. J., \& Ahuja, N. (2002). Detecting faces in images: A survey. IEEE Transactions on pattern analysis and machine intelligence, 24(1), 34-58.
[6] Lehmann, T. M., Gonner, C., \& Spitzer, K. (1999). Survey: Interpolation methods in medical image processing. IEEE transactions on medical imaging, 18(11), 1049-1075.
[7] Hassaballah, M., \& Aly, S. (2015). Face recognition: challenges, achievements and future directions. IET Computer Vision, 9(4), 614-626.
[8] Baker, B. D., \& Gunter, W. D. (2005). Surveillance: concepts and practices for fraud, security and crime investigation. Int. Found. Prot. Off, 2, 1-17.
[9] Types of Survelillance: Camera, Telephones etc. (2016, Nov, 3). Retrieved From. http://www.wsystems.com/news/surveillance-cameras-types.html
[10]Biometric surveillance: searching for identity. (2016, Nov. 1). Retrieved From. https://business.highbeam.com/127/article-1G1-81471034/biometric-surveillance-searching-identity
[11]Ovsenik, L., Kolesárová, A. K., \& Turán, J. (2010). Video surveillance systems. Acta Electrotechnica et Informatica, 10(4), 46-53.
[12]Cisco Video Surveillance operations Manager. (2014, Jan, 17). Retrieved From. $\underline{\text { http://www.cisco.com/c/en/us/td/docs/solutions/Enterprise/Education/SchoolsSR }}$ A_DG/SchoolsSRA-DG/SchoolsSRA_chap8.html.
[13]Jillela, R. R., \& Ross, A. (2009, June). Adaptive frame selection for improved face recognition in low-resolution videos. In 2009 International Joint Conference on Neural Networks (pp. 1439-1445). IEEE.
[14]Face Recognition: An Introducion. (2016, October, 5). Retrieved From. https://alitarhini.wordpress.com/tag/face-recognition/.
[15]GTAV Face Database. (2016, October, 20). Retrieved From. https://francesctarres.wordpress.com/gtav-face-database/.
[16]Expressions (2016, October, 19). Retrieved From. http://www.quizz.biz/quizz-430184.html.
[17]Naseem, I., Togneri, R., \& Bennamoun, M. (2010). Linear regression for face recognition. IEEE Transactions on Pattern Analysis and Machine Intelligence, 32(11), 2106-2112.
[18]Islam, M. M., Asari, V. K., Islam, M. N., \& Karim, M. A. (2010). Superresolution enhancement technique for low resolution video. IEEE Transactions on Consumer Electronics, 56(2), 919-924.
[19]Sundaram, D. K. M., Sasikala, D., \& Rani, P. A. (2014). A study on preprocessing a mammogram image using Adaptive Median Filter. International Journal of Innovative Research in Science, Engineering and Technology, 3(3), 10333-10337.
[20]Khadhraoui, T., Benzarti, F., \& Amiri, H. Robust Facial Feature Detection for Registration.
[21]Biometric. (2016, December, 15). Retrieved From. http://www.globalsecurity.org/security/systems/biometrics.htm.
[22]Chao, W. L. (2007). Face Recognition. GICE, National Taiwan University.

APPENDICES

## Appendix A: Results of 2-Frames Before and 2-After Frame k

| No. of video | MSE Original VS $480 * 640$ | MSE Original VS $480 * 640$ mean Filter | MSE Original VS $480 * 640$ median Filter | $\begin{gathered} \text { PSNR } \\ \text { Original VS } \\ 480 * 640 \end{gathered}$ | PSNR Original VS $480 * 640$ mean Filter | PSNR Original VS $480 * 640$ median Filter |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | 7023.435 | 6917.709 | 6921.103 | 9.665308 | 9.73118 | 9.72905 |
| 2 | 3975.383 | 3925.681 | 3927.977 | 12.13701 | 12.19165 | 12.18911 |
| 3 | 3810.412 | 3734.672 | 3746.622 | 12.32108 | 12.40828 | 12.39441 |
| 4 | 6984.566 | 6916.712 | 6919.669 | 9.689409 | 9.731807 | 9.72995 |
| 5 | 6215.686 | 6119.868 | 6125.097 | 10.19591 | 10.26338 | 10.25967 |
| 6 | 7510.514 | 7396.148 | 7406.467 | 9.374107 | 9.440748 | 9.434693 |
| 7 | 7053.742 | 6916.719 | 6929.263 | 9.646608 | 9.731802 | 9.723933 |
| 8 | 8155.101 | 7979.403 | 7980.923 | 9.01651 | 9.1111 | 9.110272 |
| 9 | 6290.807 | 6242.401 | 6243.321 | 10.14374 | 10.17729 | 10.17665 |
| 10 | 2916.644 | 2878.106 | 2881.83 | 13.48197 | 13.53974 | 13.53412 |
| 11 | 6482.258 | 6423.425 | 6425.61 | 10.01354 | 10.05314 | 10.05166 |
| 12 | 2472.176 | 2439.867 | 2441.054 | 14.20001 | 14.25714 | 14.25503 |
| 13 | 9398.735 | 9310.277 | 9315.914 | 8.400109 | 8.441178 | 8.438549 |
| 14 | 2336.322 | 2294.244 | 2295.344 | 14.44548 | 14.52441 | 14.52233 |
| 15 | 6620.621 | 6542.308 | 6544.757 | 9.921817 | 9.973494 | 9.971868 |
| 16 | 1184.733 | 1157.583 | 1158.635 | 17.3946 | 17.49528 | 17.49134 |
| 17 | 9625.02 | 9538.495 | 9538.805 | 8.296787 | 8.336005 | 8.335864 |
| 18 | 10119.99 | 9769.348 | 9772.19 | 8.079002 | 8.232148 | 8.230884 |
| 19 | 9350.03 | 9239.255 | 9239.565 | 8.422674 | 8.474434 | 8.474288 |
| 20 | 6177.567 | 6077.729 | 6078.723 | 10.22263 | 10.29339 | 10.29268 |
| 21 | 10287.72 | 10204.28 | 10206.69 | 8.007614 | 8.042981 | 8.041955 |
| 22 | 11092.26 | 11005.55 | 11007.56 | 7.680605 | 7.714685 | 7.713892 |
| 23 | 11218.23 | 11097.86 | 11102.55 | 7.631561 | 7.678413 | 7.676578 |
| 24 | 10755.84 | 10661.53 | 10663.77 | 7.814362 | 7.852607 | 7.851697 |
| 25 | 6614.862 | 6509.985 | 6510.344 | 9.925596 | 9.995004 | 9.994764 |
| 26 | 7685.289 | 7298.761 | 7313.63 | 9.274201 | 9.498312 | 9.489474 |
| 27 | 5413.015 | 5233.662 | 5234.246 | 10.79641 | 10.94275 | 10.94226 |
| 28 | 6314.218 | 6203.826 | 6202.149 | 10.12761 | 10.20421 | 10.20538 |
| 29 | 9678.944 | 9575.384 | 9576.652 | 8.272524 | 8.319242 | 8.318667 |
| 30 | 3672.576 | 3569.025 | 3570.91 | 12.4811 | 12.60531 | 12.60301 |
| 31 | 5814.744 | 5754.082 | 5757.418 | 10.4855 | 10.53104 | 10.52853 |
| 32 | 6421.594 | 6371.066 | 6372.188 | 10.05438 | 10.08868 | 10.08792 |
| 33 | 6390.468 | 6114.283 | 6117.55 | 10.07548 | 10.26735 | 10.26503 |
| 34 | 8852.171 | 8753.458 | 8756.673 | 8.660306 | 8.709007 | 8.707412 |
| 35 | 5110.768 | 5084.259 | 5086.309 | 11.04594 | 11.06853 | 11.06678 |
| 36 | 7125.451 | 6953.347 | 6964.293 | 9.60268 | 9.708864 | 9.702034 |
| 37 | 5602.914 | 5536.17 | 5538.614 | 10.64666 | 10.69871 | 10.69679 |
| 38 | 9751.748 | 9633.738 | 9633.375 | 8.239979 | 8.292855 | 8.293019 |
| 39 | 3487.18 | 3411.428 | 3413.129 | 12.70606 | 12.80144 | 12.79928 |
| 40 | 7755.767 | 7693.632 | 7695.999 | 9.234556 | 9.26949 | 9.268154 |
| 41 | 6965.886 | 6869.269 | 6875.708 | 9.70104 | 9.761698 | 9.757629 |
| 42 | 4365.726 | 4228.021 | 4239.685 | 11.73024 | 11.86943 | 11.85747 |
| 43 | 6232.423 | 6083.696 | 6086.914 | 10.18423 | 10.28913 | 10.28683 |
| 44 | 4419.999 | 4369.374 | 4369.943 | 11.67658 | 11.72661 | 11.72605 |
| 45 | 5666.324 | 5567.315 | 5571.796 | 10.59779 | 10.67435 | 10.67085 |
| 46 | 7271.799 | 7112.592 | 7115.335 | 9.514385 | 9.610525 | 9.60885 |
| 47 | 5776.753 | 5721.515 | 5719.122 | 10.51397 | 10.55569 | 10.55751 |
| 48 | 5186.04 | 5146.882 | 5148.399 | 10.98244 | 11.01536 | 11.01408 |
| 49 | 7698.83 | 7606.35 | 7601.486 | 9.266556 | 9.31904 | 9.321818 |
| 50 | 6817.749 | 6728.856 | 6730.361 | 9.794394 | 9.851391 | 9.85042 |

$\left.\left.\begin{array}{|c|c|c|c|c|c|c|}\hline \begin{array}{c}\text { No. of } \\ \text { video }\end{array} & \begin{array}{c}\text { MSE } \\ \text { Original VS } \\ 320^{*} 480\end{array} & \begin{array}{c}\text { MSE } \\ \text { Original VS } \\ 320^{*} 480 \\ \text { mean Filter }\end{array} & \begin{array}{c}\text { MSE } \\ \text { Original VS } \\ 320 * 480 \\ \text { median Filter }\end{array} & \begin{array}{c}\text { PSNR Original } \\ \text { VS }\end{array} & \begin{array}{c}\text { PSNR } \\ \text { Original VS } \\ 320 * 480\end{array} & \begin{array}{c}\text { PSNR } \\ \text { Original VS } \\ 320 * 480\end{array} \\ \text { mean Filter }\end{array}\right] \begin{array}{c}\text { median Filter }\end{array}\right]$

| No. of video | $\begin{gathered} \text { MSE } \\ \text { Original VS } \\ 288 * 352 \end{gathered}$ | $\begin{gathered} \text { MSE } \\ \text { Original VS } \\ 288 * 352 \\ \text { mean Filter } \end{gathered}$ | $\begin{gathered} \text { MSE } \\ \text { Original VS } \\ 288^{* 352} \\ \text { median Filter } \end{gathered}$ | $\begin{gathered} \text { PSNR } \\ \text { Original VS } \\ 288 * 352 \end{gathered}$ | PSNR Original VS $288 * 352$ mean Filter | PSNR <br> Original VS 288*352 median Filter |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | 8329.208 | 8170.987 | 8170.679 | 8.924766 | 9.008058 | 9.008222 |
| 2 | 4626.298 | 4561.696 | 4562.176 | 11.47847 | 11.53954 | 11.53908 |
| 3 | 4468.057 | 4400.16 | 4405.839 | 11.62962 | 11.69612 | 11.69052 |
| 4 | 8286.931 | 8186.302 | 8185.814 | 8.946866 | 8.999926 | 9.000185 |
| 5 | 7522.795 | 7400.383 | 7398.415 | 9.367011 | 9.438262 | 9.439417 |
| 6 | 8627.618 | 8478.226 | 8483.316 | 8.771894 | 8.847754 | 8.845147 |
| 7 | 8207.745 | 8062.746 | 8067.15 | 8.988565 | 9.065974 | 9.063602 |
| 8 | 9253.037 | 9037.928 | 9037.718 | 8.46796 | 8.570115 | 8.570216 |
| 9 | 7420.335 | 7347.268 | 7348.244 | 9.426569 | 9.469545 | 9.468968 |
| 10 | 3543.019 | 3491.817 | 3493.102 | 12.63707 | 12.70029 | 12.69869 |
| 11 | 7637.179 | 7553.342 | 7553.781 | 9.301474 | 9.349412 | 9.349159 |
| 12 | 2952.308 | 2909.128 | 2909.539 | 13.42919 | 13.49318 | 13.49256 |
| 13 | 10909.67 | 10776.92 | 10783.27 | 7.752688 | 7.805856 | 7.803298 |
| 14 | 2787.723 | 2744.837 | 2744.349 | 13.67831 | 13.74564 | 13.74641 |
| 15 | 7675.131 | 7560.8 | 7563.416 | 9.279945 | 9.345126 | 9.343624 |
| 16 | 1392.018 | 1355.759 | 1354.926 | 16.69436 | 16.80898 | 16.81165 |
| 17 | 10670.08 | 10543.41 | 10545.34 | 7.849125 | 7.900994 | 7.900196 |
| 18 | 11123.51 | 10945.17 | 10947.21 | 7.668385 | 7.738578 | 7.73777 |
| 19 | 10720.95 | 10570.73 | 10571.85 | 7.828471 | 7.889752 | 7.889295 |
| 20 | 7374.524 | 7242.124 | 7242.906 | 9.453464 | 9.532144 | 9.531675 |
| 21 | 12013.1 | 11884.75 | 11885.35 | 7.334252 | 7.380904 | 7.380682 |
| 22 | 12984.3 | 12861.95 | 12863.97 | 6.996619 | 7.037735 | 7.037055 |
| 23 | 12903 | 12765.18 | 12765.6 | 7.023896 | 7.070535 | 7.070391 |
| 24 | 12533.17 | 12397.34 | 12400.22 | 7.150193 | 7.19752 | 7.196509 |
| 25 | 7998.666 | 7892.701 | 7890.883 | 9.100628 | 9.158547 | 9.159547 |
| 26 | 8443.88 | 8218.844 | 8222.349 | 8.865383 | 8.982696 | 8.980845 |
| 27 | 5997.386 | 5793.704 | 5794.152 | 10.35118 | 10.50124 | 10.5009 |
| 28 | 7333.661 | 7177.517 | 7179.293 | 9.477596 | 9.571061 | 9.569987 |
| 29 | 11262.83 | 11121.32 | 11122.35 | 7.614328 | 7.669239 | 7.668837 |
| 30 | 4306.249 | 4180.147 | 4179.878 | 11.78981 | 11.91889 | 11.91917 |
| 31 | 6874.998 | 6796.23 | 6800.293 | 9.758078 | 9.808123 | 9.805528 |
| 32 | 7850.089 | 7777.62 | 7777.726 | 9.182058 | 9.222336 | 9.222277 |
| 33 | 7268.558 | 7038.41 | 7039.366 | 9.516321 | 9.656058 | 9.655468 |
| 34 | 10325.1 | 10193.38 | 10194.54 | 7.991859 | 8.04762 | 8.047127 |
| 35 | 6161.737 | 6120.222 | 6120.708 | 10.23377 | 10.26313 | 10.26279 |
| 36 | 8197.01 | 8013.979 | 8016.538 | 8.994249 | 9.092322 | 9.090935 |
| 37 | 6428.286 | 6344.138 | 6344.156 | 10.04985 | 10.10708 | 10.10707 |
| 38 | 11326.88 | 11167.36 | 11166.43 | 7.589699 | 7.651297 | 7.65166 |
| 39 | 3953.946 | 3845.972 | 3845.589 | 12.1605 | 12.28074 | 12.28118 |
| 40 | 9276.902 | 9190.558 | 9190.055 | 8.456774 | 8.497385 | 8.497622 |
| 41 | 7858.219 | 7750.586 | 7756.213 | 9.177562 | 9.237458 | 9.234306 |
| 42 | 4991.504 | 4852.382 | 4854.894 | 11.14849 | 11.27125 | 11.26901 |
| 43 | 6856.455 | 6677.679 | 6678.556 | 9.769807 | 9.884548 | 9.883978 |
| 44 | 5173.071 | 5112.303 | 5112.4 | 10.99332 | 11.04464 | 11.04456 |
| 45 | 6114.044 | 5987.783 | 5988.154 | 10.26752 | 10.35814 | 10.35787 |
| 46 | 8041.628 | 7805.192 | 7805.344 | 9.077364 | 9.206968 | 9.206883 |
| 47 | 6843.203 | 6763.546 | 6761.686 | 9.778209 | 9.829059 | 9.830254 |
| 48 | 5970.969 | 5920.371 | 5920.999 | 10.37036 | 10.40731 | 10.40685 |
| 49 | 8948.566 | 8833.854 | 8832.116 | 8.613269 | 8.669301 | 8.670156 |
| 50 | 7780.501 | 7651.085 | 7652.569 | 9.220728 | 9.293574 | 9.292731 |


| No. of video | $\begin{gathered} \text { MSE } \\ \text { Original VS } \\ 240 * 320 \end{gathered}$ | MSE <br> Original VS $240 * 320$ mean Filter | MSE <br> Original VS $240 * 320$ median Filter | $\begin{gathered} \text { PSNR } \\ \text { Original VS } \\ 240 * 320 \end{gathered}$ | PSNR <br> Original VS 240*320 mean Filter | PSNR <br> Original VS 240*320 median Filter |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | 6818.437 | 6642.006 | 6642.409 | 9.793955 | 9.907811 | 9.907547 |
| 2 | 3916.266 | 3833.081 | 3833.667 | 12.20208 | 12.29532 | 12.29466 |
| 3 | 3734.524 | 3641.996 | 3647.381 | 12.40845 | 12.51741 | 12.51099 |
| 4 | 6927.967 | 6807.632 | 6807.429 | 9.724745 | 9.800843 | 9.800973 |
| 5 | 6096.723 | 5954.425 | 5953.231 | 10.27984 | 10.38241 | 10.38328 |
| 6 | 7373.943 | 7199.559 | 7204.784 | 9.453806 | 9.557745 | 9.554594 |
| 7 | 6860.671 | 6700.081 | 6706.279 | 9.767138 | 9.870003 | 9.865988 |
| 8 | 7917.428 | 7657.368 | 7659.903 | 9.144962 | 9.290009 | 9.288571 |
| 9 | 6241.192 | 6148.328 | 6149.153 | 10.17813 | 10.24323 | 10.24265 |
| 10 | 2859.524 | 2800.849 | 2801.943 | 13.56787 | 13.65791 | 13.65621 |
| 11 | 6411.285 | 6305.63 | 6305.542 | 10.06135 | 10.13352 | 10.13358 |
| 12 | 2402.557 | 2349.216 | 2349.979 | 14.32407 | 14.42157 | 14.42016 |
| 13 | 9301.332 | 9140.836 | 9145.367 | 8.445352 | 8.520945 | 8.518792 |
| 14 | 2265.262 | 2221.386 | 2221.344 | 14.57962 | 14.66456 | 14.66465 |
| 15 | 6556.874 | 6418.024 | 6419.214 | 9.963836 | 10.05679 | 10.05598 |
| 16 | 1145.332 | 1103.679 | 1102.736 | 17.54149 | 17.70238 | 17.70609 |
| 17 | 9523.253 | 9353.442 | 9353.616 | 8.342951 | 8.421089 | 8.421008 |
| 18 | 9525.107 | 9304.565 | 9305.904 | 8.342105 | 8.443843 | 8.443218 |
| 19 | 9248.697 | 9057.756 | 9057.913 | 8.469998 | 8.560597 | 8.560522 |
| 20 | 6085.222 | 5934.393 | 5934.231 | 10.28804 | 10.39704 | 10.39716 |
| 21 | 10188.09 | 10027.75 | 10028.26 | 8.049877 | 8.118768 | 8.118546 |
| 22 | 10970.79 | 10820.63 | 10823.08 | 7.728424 | 7.788277 | 7.787296 |
| 23 | 11034.95 | 10873.09 | 10876.08 | 7.703102 | 7.767274 | 7.766078 |
| 24 | 10645.23 | 10476.34 | 10478.61 | 7.859253 | 7.928709 | 7.927767 |
| 25 | 6401.2 | 6271.638 | 6270.696 | 10.06819 | 10.15699 | 10.15765 |
| 26 | 7013.365 | 6795.846 | 6799.824 | 9.671539 | 9.808368 | 9.805827 |
| 27 | 5145.25 | 4922.806 | 4922.841 | 11.01674 | 11.20868 | 11.20865 |
| 28 | 6179.726 | 6003.964 | 6005.318 | 10.22111 | 10.34642 | 10.34544 |
| 29 | 9508.663 | 9330.362 | 9332.261 | 8.349609 | 8.431818 | 8.430935 |
| 30 | 3528.757 | 3394.05 | 3392.779 | 12.65459 | 12.82362 | 12.82525 |
| 31 | 5719.999 | 5620.946 | 5622.705 | 10.55684 | 10.63271 | 10.63135 |
| 32 | 6351.835 | 6265.393 | 6265.76 | 10.10181 | 10.16132 | 10.16107 |
| 33 | 6035.879 | 5806.895 | 5807.727 | 10.3234 | 10.49136 | 10.49074 |
| 34 | 8765.07 | 8599.734 | 8600.765 | 8.70325 | 8.785953 | 8.785433 |
| 35 | 5017.623 | 4959.906 | 4960.333 | 11.12582 | 11.17607 | 11.1757 |
| 36 | 6854.841 | 6644.083 | 6648.053 | 9.77083 | 9.906453 | 9.903859 |
| 37 | 5420.544 | 5314.501 | 5313.557 | 10.79037 | 10.87618 | 10.87695 |
| 38 | 9578.438 | 9384.749 | 9386.075 | 8.317857 | 8.406577 | 8.405963 |
| 39 | 3387.271 | 3256.954 | 3255.835 | 12.8323 | 13.00269 | 13.00418 |
| 40 | 7673.105 | 7559.824 | 7561.929 | 9.281092 | 9.345687 | 9.344478 |
| 41 | 6862.212 | 6719.548 | 6720.494 | 9.766163 | 9.857403 | 9.856791 |
| 42 | 4117.621 | 3968.25 | 3969.448 | 11.98434 | 12.14481 | 12.1435 |
| 43 | 5982.123 | 5787.175 | 5788.641 | 10.36225 | 10.50614 | 10.50504 |
| 44 | 4315.366 | 4237.418 | 4236.933 | 11.78063 | 11.85979 | 11.86029 |
| 45 | 5526.394 | 5365.138 | 5365.15 | 10.70639 | 10.83499 | 10.83499 |
| 46 | 7091.484 | 6823.274 | 6823.598 | 9.623432 | 9.790876 | 9.790669 |
| 47 | 5667.773 | 5566.585 | 5565.308 | 10.59668 | 10.67491 | 10.67591 |
| 48 | 5074.007 | 5004.671 | 5005.201 | 11.07729 | 11.13705 | 11.13659 |
| 49 | 7622.152 | 7470.684 | 7470.593 | 9.310028 | 9.3972 | 9.397253 |
| 50 | 6657.199 | 6495.722 | 6496.259 | 9.897888 | 10.00453 | 10.00417 |


| No. of video | MSE Original VS $120 * 240$ | MSE <br> Original VS $120 * 240$ mean Filter | MSE Original VS $120 * 240$ median Filter | PSNR Original VS $120 * 240$ | $\begin{gathered} \text { PSNR } \\ \text { Original VS } \\ 120 * 240 \\ \text { mean Filter } \end{gathered}$ | PSNR Original VS $120 * 240$ median Filter |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | 110.3409 | 190.7996 | 190.4287 | 27.70344 | 25.32503 | 25.33348 |
| 2 | 50.92693 | 104.5933 | 104.5766 | 31.06133 | 27.93576 | 27.93646 |
| 3 | 54.90789 | 127.7123 | 123.047 | 30.73446 | 27.06848 | 27.23009 |
| 4 | 54.20314 | 131.6684 | 132.4316 | 30.79056 | 26.93599 | 26.91089 |
| 5 | 123.6192 | 219.5291 | 219.7427 | 27.20995 | 24.71588 | 24.71166 |
| 6 | 81.87874 | 193.5309 | 193.7507 | 28.99909 | 25.2633 | 25.25837 |
| 7 | 121.3944 | 215.0902 | 216.9489 | 27.28882 | 24.8046 | 24.76723 |
| 8 | 120.6526 | 279.3742 | 279.9215 | 27.31544 | 23.66894 | 23.66044 |
| 9 | 40.4589 | 110.1318 | 110.2137 | 32.06066 | 27.71167 | 27.70845 |
| 10 | 61.40105 | 95.69013 | 95.69198 | 30.24905 | 28.32213 | 28.32205 |
| 11 | 69.63684 | 131.701 | 131.4643 | 29.70241 | 26.93491 | 26.94273 |
| 12 | 105.2392 | 142.8067 | 142.4537 | 27.90903 | 26.58332 | 26.59406 |
| 13 | 55.66336 | 165.0047 | 164.5029 | 30.67511 | 25.95584 | 25.96907 |
| 14 | 58.92306 | 85.80472 | 85.96101 | 30.42795 | 28.79569 | 28.78779 |
| 15 | 62.67817 | 145.6037 | 145.5634 | 30.15964 | 26.49908 | 26.50028 |
| 16 | 54.38493 | 73.93294 | 73.8457 | 30.77602 | 29.44242 | 29.44755 |
| 17 | 60.9612 | 166.8836 | 166.8781 | 30.28027 | 25.90667 | 25.90681 |
| 18 | 228.4366 | 355.7537 | 355.5483 | 24.54315 | 22.61931 | 22.62182 |
| 19 | 78.7151 | 187.6314 | 188.0007 | 29.17022 | 25.39775 | 25.38921 |
| 20 | 175.6349 | 249.0423 | 249.1725 | 25.68469 | 24.16807 | 24.1658 |
| 21 | 84.18807 | 199.1498 | 198.5354 | 28.8783 | 25.139 | 25.15242 |
| 22 | 63.19544 | 166.3121 | 166.3735 | 30.12395 | 25.92157 | 25.91996 |
| 23 | 67.18953 | 178.8404 | 178.7526 | 29.85779 | 25.60615 | 25.60828 |
| 24 | 142.682 | 252.0873 | 252.3828 | 26.58711 | 24.11529 | 24.11021 |
| 25 | 147.9987 | 247.2492 | 246.825 | 26.42823 | 24.19945 | 24.20691 |
| 26 | 318.0552 | 489.8382 | 495.0252 | 23.10578 | 21.23028 | 21.18453 |
| 27 | 135.8505 | 286.3431 | 286.3669 | 26.80019 | 23.56194 | 23.56157 |
| 28 | 101.858 | 204.8172 | 204.8718 | 28.05085 | 25.01714 | 25.01598 |
| 29 | 73.28317 | 192.9617 | 192.9438 | 29.48076 | 25.27609 | 25.2765 |
| 30 | 98.32815 | 152.2795 | 152.7724 | 28.20403 | 26.30439 | 26.29036 |
| 31 | 58.72855 | 132.4016 | 132.2138 | 30.44231 | 26.91187 | 26.91804 |
| 32 | 62.77095 | 137.3378 | 137.5209 | 30.15322 | 26.7529 | 26.74712 |
| 33 | 291.6337 | 441.7182 | 442.208 | 23.48243 | 21.67935 | 21.67454 |
| 34 | 62.35424 | 167.6949 | 167.5182 | 30.18214 | 25.8856 | 25.89018 |
| 35 | 65.71288 | 125.1083 | 125.351 | 29.9543 | 27.15794 | 27.14953 |
| 36 | 181.2225 | 326.4336 | 328.0766 | 25.54868 | 22.99286 | 22.97105 |
| 37 | 124.2567 | 213.9519 | 213.4182 | 27.1876 | 24.82764 | 24.83849 |
| 38 | 78.68741 | 223.5373 | 223.5846 | 29.17175 | 24.6373 | 24.63638 |
| 39 | 100.5336 | 195.6347 | 195.5531 | 28.10769 | 25.21635 | 25.21816 |
| 40 | 59.66878 | 151.7028 | 151.7071 | 30.37333 | 26.32087 | 26.32074 |
| 41 | 110.9965 | 197.7368 | 198.1534 | 27.67771 | 25.16993 | 25.16079 |
| 42 | 124.0266 | 232.5749 | 231.9014 | 27.19565 | 24.46517 | 24.47777 |
| 43 | 100.5894 | 192.8235 | 192.2882 | 28.10528 | 25.2792 | 25.29128 |
| 44 | 90.78376 | 136.9231 | 136.965 | 28.55072 | 26.76604 | 26.76471 |
| 45 | 138.3309 | 224.859 | 224.7548 | 26.72161 | 24.6117 | 24.61371 |
| 46 | 197.6829 | 398.68 | 398.7705 | 25.17111 | 22.12456 | 22.12357 |
| 47 | 91.93579 | 173.2187 | 173.1147 | 28.49596 | 25.74486 | 25.74746 |
| 48 | 82.98608 | 148.0156 | 147.6673 | 28.94075 | 26.42773 | 26.43796 |
| 49 | 46.75583 | 157.8231 | 161.1141 | 31.43245 | 26.1491 | 26.05947 |
| 50 | 126.0693 | 243.146 | 242.7542 | 27.12471 | 24.27213 | 24.27914 |


| No. of video | MSE Original VS $100 * 180$ | MSE Original VS $100 * 180$ mean Filter | MSE Original VS $100 * 180$ median Filter | PSNR Original VS $100 * 180$ | $\begin{gathered} \hline \text { PSNR } \\ \text { Original VS } \\ 100 * 180 \\ \text { mean Filter } \\ \hline \end{gathered}$ | PSNR Original VS $100 * 180$ median Filter |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | 169.5264 | 267.332 | 267.3942 | 25.83843 | 23.86029 | 23.85928 |
| 2 | 72.48956 | 135.7239 | 135.6718 | 29.52805 | 26.80424 | 26.80591 |
| 3 | 73.38513 | 153.2847 | 157.6964 | 29.47472 | 26.27582 | 26.15258 |
| 4 | 77.62631 | 166.7135 | 166.9623 | 29.23071 | 25.9111 | 25.90462 |
| 5 | 185.2211 | 278.6952 | 278.703 | 25.4539 | 23.67951 | 23.67939 |
| 6 | 128.2671 | 244.2173 | 243.6925 | 27.04965 | 24.25304 | 24.26238 |
| 7 | 165.7835 | 262.8873 | 264.252 | 25.93539 | 23.93311 | 23.91062 |
| 8 | 175.0817 | 342.2518 | 342.3649 | 25.6984 | 22.78735 | 22.78591 |
| 9 | 57.34861 | 143.8285 | 143.6437 | 30.54557 | 26.55236 | 26.55794 |
| 10 | 88.28781 | 126.9019 | 127.1779 | 28.6718 | 27.09612 | 27.08669 |
| 11 | 101.0426 | 168.3989 | 168.7324 | 28.08576 | 25.86741 | 25.85882 |
| 12 | 132.291 | 172.9094 | 173.1609 | 26.9155 | 25.75262 | 25.74631 |
| 13 | 83.41328 | 212.2644 | 211.753 | 28.91845 | 24.86203 | 24.87251 |
| 14 | 72.84743 | 102.7733 | 102.6634 | 29.50666 | 28.012 | 28.01665 |
| 15 | 93.34913 | 185.2492 | 185.0643 | 28.4297 | 25.45324 | 25.45758 |
| 16 | 83.02619 | 102.1585 | 102.1808 | 28.93865 | 28.03806 | 28.03711 |
| 17 | 96.09224 | 218.4435 | 218.4956 | 28.30392 | 24.73741 | 24.73638 |
| 18 | 169.4533 | 311.362 | 311.3682 | 25.8403 | 23.19815 | 23.19806 |
| 19 | 116.1016 | 238.852 | 238.9453 | 27.48242 | 24.34952 | 24.34782 |
| 20 | 224.2645 | 307.5992 | 308.8081 | 24.6232 | 23.25095 | 23.23392 |
| 21 | 126.5063 | 255.6856 | 255.9945 | 27.10968 | 24.05374 | 24.0485 |
| 22 | 102.5178 | 225.8156 | 226.6609 | 28.02281 | 24.59326 | 24.57704 |
| 23 | 92.24726 | 219.9852 | 220.3039 | 28.48127 | 24.70687 | 24.70058 |
| 24 | 196.8314 | 319.3788 | 319.5032 | 25.18986 | 23.08774 | 23.08605 |
| 25 | 184.8292 | 295.297 | 294.9846 | 25.4631 | 23.42821 | 23.43281 |
| 26 | 311.2747 | 412.1395 | 411.9821 | 23.19936 | 21.98036 | 21.98202 |
| 27 | 166.3901 | 300.413 | 300.3327 | 25.91953 | 23.35362 | 23.35478 |
| 28 | 152.1501 | 264.381 | 264.35 | 26.30808 | 23.9085 | 23.90901 |
| 29 | 120.4875 | 253.0508 | 253.0763 | 27.32138 | 24.09873 | 24.09829 |
| 30 | 152.4803 | 204.1365 | 204.2177 | 26.29867 | 25.0316 | 25.02987 |
| 31 | 88.12681 | 171.0812 | 170.9138 | 28.67972 | 25.79878 | 25.80303 |
| 32 | 89.36478 | 172.605 | 173.0158 | 28.61914 | 25.76027 | 25.74994 |
| 33 | 283.5354 | 358.749 | 358.8625 | 23.60473 | 22.5829 | 22.58152 |
| 34 | 92.70709 | 217.6018 | 217.643 | 28.45967 | 24.75418 | 24.75336 |
| 35 | 96.54204 | 164.3309 | 165.7723 | 28.28364 | 25.97361 | 25.93568 |
| 36 | 240.0366 | 389.3853 | 390.039 | 24.32803 | 22.22701 | 22.21972 |
| 37 | 158.3439 | 264.6765 | 264.855 | 26.13479 | 23.90365 | 23.90072 |
| 38 | 119.4391 | 277.8071 | 277.6731 | 27.35934 | 23.69337 | 23.69547 |
| 39 | 146.0179 | 248.2702 | 248.438 | 26.48674 | 24.18156 | 24.17862 |
| 40 | 91.269 | 199.1005 | 199.7746 | 28.52757 | 25.14008 | 25.1254 |
| 41 | 145.2585 | 244.5836 | 244.8928 | 26.50939 | 24.24653 | 24.24104 |
| 42 | 180.9114 | 293.5978 | 292.9156 | 25.55615 | 23.45328 | 23.46338 |
| 43 | 153.5281 | 249.9095 | 249.1605 | 26.26893 | 24.15298 | 24.16601 |
| 44 | 128.1993 | 182.054 | 182.0445 | 27.05195 | 25.5288 | 25.52903 |
| 45 | 182.8213 | 279.989 | 279.979 | 25.51054 | 23.65939 | 23.65955 |
| 46 | 265.7172 | 478.753 | 478.4235 | 23.88661 | 21.32969 | 21.33268 |
| 47 | 131.4914 | 222.1935 | 221.7999 | 26.94183 | 24.66349 | 24.67119 |
| 48 | 104.7841 | 183.9062 | 183.8531 | 27.92785 | 25.48484 | 25.48609 |
| 49 | 66.49611 | 206.0045 | 210.0261 | 29.90284 | 24.99204 | 24.90807 |
| 50 | 174.5821 | 308.0604 | 308.6294 | 25.71081 | 23.24444 | 23.23643 |

## Appendix B: Results of 3-Frames Before and 3-After Frame k

| No. of video | MSE Original VS $480 * 640$ | MSE Original VS $480 * 640$ mean Filter | MSE Original VS $480 * 640$ median Filter | PSNR Original VS $480 * 640$ | PSNR Original VS $480 * 640$ mean Filter | PSNR Original VS $480 * 640$ median Filter |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | 7023.4350 | 6919.39583 | 6925.141468 | 9.665307900 | 9.730121 | 9.726517 |
| 2 | 3975.3833 | 3927.27169 | 3927.956267 | 12.13701350 | 12.18989 | 12.18913 |
| 3 | 3810.4123 | 3720.35851 | 3730.871811 | 12.32108386 | 12.42495 | 12.41270 |
| 4 | 6984.5663 | 6915.09695 | 6919.352792 | 9.689409109 | 9.732820 | 9.730148 |
| 5 | 6215.6855 | 6115.30021 | 6122.681010 | 10.19591322 | 10.26662 | 10.26138 |
| 6 | 7510.5136 | 7384.95271 | 7397.462642 | 9.374107189 | 9.447326 | 9.439975 |
| 7 | 7053.7424 | 6916.17225 | 6929.732414 | 9.646607602 | 9.732145 | 9.723638 |
| 8 | 8155.1014 | 7977.25575 | 7978.988181 | 9.016509943 | 9.112268 | 9.111325 |
| 9 | 6290.8068 | 6242.47672 | 6243.477561 | 10.14374013 | 10.17723 | 10.17653 |
| 10 | 2916.6442 | 2877.80766 | 2879.626643 | 13.48196896 | 13.54018 | 13.53744 |
| 11 | 6482.2576 | 6411.08116 | 6422.437177 | 10.01354074 | 10.06149 | 10.05380 |
| 12 | 2472.1763 | 2440.48716 | 2441.999930 | 14.20000912 | 14.25603 | 14.25334 |
| 13 | 9398.7353 | 9294.48770 | 9304.386666 | 8.400109421 | 8.448549 | 8.443926 |
| 14 | 2336.3219 | 2292.11418 | 2293.485998 | 14.44547666 | 14.52844 | 14.52584 |
| 15 | 6620.6206 | 6535.45857 | 6538.950127 | 9.921816585 | 9.978042 | 9.975723 |
| 16 | 1184.7333 | 1156.31600 | 1156.598978 | 17.39459731 | 17.50003 | 17.49897 |
| 17 | 9625.0203 | 9537.70179 | 9538.034323 | 8.296787057 | 8.336366 | 8.336214 |
| 18 | 10119.991 | 9765.48599 | 9768.370796 | 8.079002205 | 8.233864 | 8.232582 |
| 19 | 9350.0295 | 9231.83391 | 9235.766457 | 8.422673795 | 8.477923 | 8.476074 |
| 20 | 6177.5673 | 6073.36726 | 6076.776232 | 10.22262871 | 10.29650 | 10.29407 |
| 21 | 10287.716 | 10207.5605 | 10209.82137 | 8.007613611 | 8.041583 | 8.040622 |
| 22 | 11092.255 | 11008.0190 | 11009.29063 | 7.680605024 | 7.713711 | 7.713210 |
| 23 | 11218.228 | 11096.6424 | 11100.13621 | 7.631560733 | 7.678887 | 7.677520 |
| 24 | 10755.836 | 10659.1637 | 10662.05357 | 7.814361581 | 7.853572 | 7.852395 |
| 25 | 6614.8622 | 6507.80180 | 6508.024109 | 9.925595567 | 9.996460 | 9.996312 |
| 26 | 7685.2892 | 7276.36841 | 7289.993297 | 9.274201423 | 9.511656 | 9.503532 |
| 27 | 5413.0152 | 5234.61596 | 5235.199986 | 10.79641106 | 10.94195 | 10.94147 |
| 28 | 6314.2175 | 6201.83187 | 6202.089042 | 10.12760823 | 10.20560 | 10.20542 |
| 29 | 9678.9436 | 9571.43459 | 9572.714367 | 8.272524001 | 8.321033 | 8.320452 |
| 30 | 3672.5764 | 3566.33706 | 3568.654794 | 12.48109512 | 12.60857 | 12.60575 |
| 31 | 5814.7439 | 5753.46705 | 5755.464902 | 10.48549765 | 10.53150 | 10.52999 |
| 32 | 6421.5941 | 6370.03981 | 6371.989671 | 10.05437504 | 10.08938 | 10.08805 |
| 33 | 6390.4681 | 6107.124966 | 6116.410922 | 10.07547687 | 10.272435 | 10.265837 |
| 34 | 8852.1706 | 8745.747444 | 8750.613356 | 8.660305855 | 8.7128342 | 8.7104186 |
| 35 | 5110.7682 | 5086.520218 | 5090.446161 | 11.04594174 | 11.066595 | 11.063245 |
| 36 | 7125.4506 | 6940.856655 | 6950.620084 | 9.602680231 | 9.7166728 | 9.7105680 |
| 37 | 5602.9135 | 5536.000357 | 5539.282195 | 10.64666441 | 10.698842 | 10.69626 |
| 38 | 9751.7484 | 9637.652941 | 9637.159813 | 8.23997871 | 8.2910907 | 8.2913129 |
| 39 | 3487.1802 | 3405.343433 | 3409.427772 | 12.70605963 | 12.809194 | 12.803988 |
| 40 | 7755.7666 | 7697.79141 | 7700.499187 | 9.234556264 | 9.2671422 | 9.2656148 |
| 41 | 6965.8859 | 6870.205955 | 6876.438202 | 9.701040034 | 9.7611060 | 9.7571681 |
| 42 | 4365.7261 | 4223.818903 | 4237.384545 | 11.7302387 | 11.873750 | 11.859824 |
| 43 | 6232.4233 | 6079.641865 | 6083.14043 | 10.18423417 | 10.292023 | 10.289525 |
| 44 | 4419.9993 | 4368.474978 | 4368.678416 | 11.67658151 | 11.727505 | 11.727302 |
| 45 | 5666.3237 | 5564.65135 | 5569.965168 | 10.59778978 | 10.676424 | 10.672278 |
| 46 | 7271.7987 | 7113.484527 | 7115.801843 | 9.514385121 | 9.6099796 | 9.6085651 |
| 47 | 5776.7533 | 5724.244792 | 5723.728523 | 10.51396533 | 10.553621 | 10.554013 |
| 48 | 5186.0400 | 5149.410391 | 5150.548343 | 10.98244497 | 11.013228 | 11.012268 |
| 49 | 7698.8304 | 7604.803648 | 7601.385224 | 9.266556064 | 9.3199235 | 9.3218761 |
| 50 | 6817.7487 | 6730.863532 | 6733.498952 | 9.794393702 | 9.8500957 | 9.848395 |


| No. of video | MSE Original VS $320 * 480$ | MSE <br> Original VS 320*480 mean Filter | MSE Original VS $320 * 480$ median Filter | PSNR Original VS $320 * 480$ | PSNR Original VS $320 * 480$ mean Filter | PSNR Original VS $320 * 480$ median Filter |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | 4515.144 | 4394.907 | 4401.1838 | 11.58409 | 11.70131 | 11.69511 |
| 2 | 2852.288 | 2789.462 | 2789.6499 | 13.57887 | 13.6756 | 13.67531 |
| 3 | 2565.699 | 2461.931 | 2473.2945 | 14.03875 | 14.21804 | 14.19805 |
| 4 | 4589.271 | 4497.113 | 4500.38 | 11.51337 | 11.60147 | 11.59831 |
| 5 | 4037.522 | 3909.007 | 3915.9469 | 12.06965 | 12.21014 | 12.20244 |
| 6 | 5102.599 | 4948.953 | 4958.724 | 11.05289 | 11.18567 | 11.1771 |
| 7 | 4742.565 | 4579.037 | 4589.916 | 11.37067 | 11.52306 | 11.51276 |
| 8 | 5792.73 | 5572.269 | 5572.1043 | 10.50197 | 10.67048 | 10.67061 |
| 9 | 4323.011 | 4254.877 | 4255.2386 | 11.77294 | 11.84193 | 11.84156 |
| 10 | 1772.325 | 1725.349 | 1726.2897 | 15.64537 | 15.76203 | 15.75967 |
| 11 | 4152.98 | 4063.208 | 4074.9534 | 11.94721 | 12.04211 | 12.02958 |
| 12 | 1595.359 | 1552.849 | 1554.2596 | 16.10222 | 16.21951 | 16.21557 |
| 13 | 6441.485 | 6307.078 | 6316.5538 | 10.04094 | 10.13252 | 10.126 |
| 14 | 1550.104 | 1502.017 | 1503.0284 | 16.2272 | 16.36406 | 16.36113 |
| 15 | 4691.428 | 4575.045 | 4578.6367 | 11.41775 | 11.52685 | 11.52344 |
| 16 | 747.2317 | 714.2511 | 713.93022 | 19.39625 | 19.59229 | 19.59425 |
| 17 | 6728.97 | 6602.601 | 6602.9902 | 9.851318 | 9.933653 | 9.933397 |
| 18 | 7104.386 | 6824.634 | 6826.5295 | 9.615538 | 9.79001 | 9.788804 |
| 19 | 6528.531 | 6364.712 | 6366.034 | 9.982649 | 10.09302 | 10.09211 |
| 20 | 4099.319 | 3974.525 | 3976.8571 | 12.00369 | 12.13795 | 12.1354 |
| 21 | 6886.926 | 6774.01 | 6775.367 | 9.750549 | 9.822345 | 9.821475 |
| 22 | 7075.439 | 6967.804 | 6967.0522 | 9.63327 | 9.699845 | 9.700313 |
| 23 | 7567.645 | 7431.534 | 7433.5341 | 9.341196 | 9.420019 | 9.41885 |
| 24 | 7215.038 | 7082.481 | 7083.9195 | 9.548417 | 9.628949 | 9.628067 |
| 25 | 4521.411 | 4406.452 | 4406.6841 | 11.57806 | 11.68991 | 11.68968 |
| 26 | 5231.601 | 4886.939 | 4894.7552 | 10.94446 | 11.24043 | 11.23349 |
| 27 | 3956.953 | 3738.654 | 3738.9954 | 12.15719 | 12.40365 | 12.40325 |
| 28 | 4384.482 | 4237.596 | 4237.8509 | 11.71162 | 11.85961 | 11.85935 |
| 29 | 6470.402 | 6330.749 | 6331.4321 | 10.02149 | 10.11625 | 10.11578 |
| 30 | 2407.348 | 2280.193 | 2281.7952 | 14.31542 | 14.55109 | 14.54804 |
| 31 | 3847.039 | 3769.218 | 3770.5672 | 12.27954 | 12.36829 | 12.36674 |
| 32 | 4191.242 | 4131.233 | 4133.6673 | 11.90738 | 11.97001 | 11.96745 |
| 33 | 4414.639 | 4071.552 | 4075.1814 | 11.68185 | 12.0332 | 12.02933 |
| 34 | 6003.563 | 5868.954 | 5872.9035 | 10.34671 | 10.4452 | 10.44227 |
| 35 | 3266.606 | 3234.099 | 3238.0496 | 12.98984 | 13.03327 | 13.02797 |
| 36 | 4909.242 | 4711.152 | 4717.7839 | 11.22066 | 11.39953 | 11.39342 |
| 37 | 3890.032 | 3813.929 | 3815.2438 | 12.23127 | 12.31708 | 12.31558 |
| 38 | 6726.935 | 6584.18 | 6583.6843 | 9.852631 | 9.945787 | 9.946114 |
| 39 | 2382.149 | 2276.207 | 2279.9905 | 14.36111 | 14.55869 | 14.55147 |
| 40 | 5177.124 | 5098.262 | 5100.4979 | 10.98992 | 11.05658 | 11.05468 |
| 41 | 4842.627 | 4717.356 | 4721.4469 | 11.27999 | 11.39382 | 11.39005 |
| 42 | 2943.078 | 2805.022 | 2813.9764 | 13.44279 | 13.65144 | 13.6376 |
| 43 | 4451.675 | 4278.554 | 4280.3149 | 11.64557 | 11.81783 | 11.81605 |
| 44 | 2861.052 | 2802.43 | 2803.356 | 13.56555 | 13.65546 | 13.65402 |
| 45 | 4227.671 | 4107.519 | 4110.9051 | 11.86979 | 11.99501 | 11.99143 |
| 46 | 5728.694 | 5520.214 | 5523.2848 | 10.55025 | 10.71124 | 10.70883 |
| 47 | 3777.721 | 3713.661 | 3713.1803 | 12.3585 | 12.43278 | 12.43334 |
| 48 | 3572.161 | 3531.147 | 3532.2923 | 12.60149 | 12.65165 | 12.65024 |
| 49 | 5388.768 | 5276.312 | 5275.5012 | 10.81591 | 10.9075 | 10.90817 |
| 50 | 4815.997 | 4700.699 | 4702.4354 | 11.30394 | 11.40918 | 11.40758 |


| No. of video | MSE Original VS $288 * 352$ | MSE Original VS $288 * 352$ mean Filter | MSE Original VS $288 * 352$ median Filter | PSNR Original VS $288 * 352$ | $\begin{gathered} \text { PSNR } \\ \text { Original VS } \\ 288 * 352 \\ \text { mean Filter } \\ \hline \end{gathered}$ | PSNR Original VS $288 * 352$ median Filter |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | 8329.208 | 8173.024 | 8174.656 | 8.924766 | 9.006976 | 9.006109 |
| 2 | 4626.298 | 4563.365 | 4563.153 | 11.47847 | 11.53795 | 11.53815 |
| 3 | 4468.057 | 4398.157 | 4403.444 | 11.62962 | 11.6981 | 11.69288 |
| 4 | 8286.931 | 8184.566 | 8186.042 | 8.946866 | 9.000847 | 9.000064 |
| 5 | 7522.795 | 7396.795 | 7399.306 | 9.367011 | 9.440368 | 9.438894 |
| 6 | 8627.618 | 8473.805 | 8478.964 | 8.771894 | 8.850019 | 8.847376 |
| 7 | 8207.745 | 8066.485 | 8072.161 | 8.988565 | 9.06396 | 9.060906 |
| 8 | 9253.037 | 9035.886 | 9036.746 | 8.46796 | 8.571096 | 8.570683 |
| 9 | 7420.335 | 7347.5 | 7348.829 | 9.426569 | 9.469408 | 9.468622 |
| 10 | 3543.019 | 3490.471 | 3490.641 | 12.63707 | 12.70196 | 12.70175 |
| 11 | 7637.179 | 7545.573 | 7552.365 | 9.301474 | 9.353881 | 9.349974 |
| 12 | 2952.308 | 2909.92 | 2910.506 | 13.42919 | 13.49199 | 13.49112 |
| 13 | 10909.67 | 10766.53 | 10774.51 | 7.752688 | 7.810045 | 7.806828 |
| 14 | 2787.723 | 2743.071 | 2743.366 | 13.67831 | 13.74843 | 13.74797 |
| 15 | 7675.131 | 7554.75 | 7557.488 | 9.279945 | 9.348603 | 9.347029 |
| 16 | 1392.018 | 1355.007 | 1354.48 | 16.69436 | 16.81139 | 16.81308 |
| 17 | 10670.08 | 10544 | 10545.6 | 7.849125 | 7.90075 | 7.900093 |
| 18 | 11123.51 | 10943.3 | 10943.46 | 7.668385 | 7.739319 | 7.739258 |
| 19 | 10720.95 | 10565.07 | 10566.9 | 7.828471 | 7.892078 | 7.891326 |
| 20 | 7374.524 | 7238.917 | 7240.334 | 9.453464 | 9.534068 | 9.533217 |
| 21 | 12013.1 | 11887.19 | 11887.7 | 7.334252 | 7.380012 | 7.379826 |
| 22 | 12984.3 | 12864.07 | 12864.7 | 6.996619 | 7.037019 | 7.036806 |
| 23 | 12903 | 12764.41 | 12764.63 | 7.023896 | 7.070795 | 7.07072 |
| 24 | 12533.17 | 12395.54 | 12397.79 | 7.150193 | 7.198148 | 7.19736 |
| 25 | 7998.666 | 7890.709 | 7889.778 | 9.100628 | 9.159643 | 9.160156 |
| 26 | 8443.88 | 8216.197 | 8216.12 | 8.865383 | 8.984095 | 8.984136 |
| 27 | 5997.386 | 5793.704 | 5793.777 | 10.35118 | 10.50124 | 10.50119 |
| 28 | 7333.661 | 7175.513 | 7176.309 | 9.477596 | 9.572274 | 9.571792 |
| 29 | 11262.83 | 11117.36 | 11117.98 | 7.614328 | 7.670787 | 7.670547 |
| 30 | 4306.249 | 4178.816 | 4178.823 | 11.78981 | 11.92027 | 11.92026 |
| 31 | 6874.998 | 6796.56 | 6799.082 | 9.758078 | 9.807912 | 9.806301 |
| 32 | 7850.089 | 7776.316 | 7776.951 | 9.182058 | 9.223065 | 9.22271 |
| 33 | 7268.558 | 7039.202 | 7038.247 | 9.516321 | 9.655569 | 9.656159 |
| 34 | 10325.1 | 10187.98 | 10190.04 | 7.991859 | 8.049921 | 8.049045 |
| 35 | 6161.737 | 6122.404 | 6124.916 | 10.23377 | 10.26158 | 10.2598 |
| 36 | 8197.01 | 8006.849 | 8010.475 | 8.994249 | 9.096187 | 9.094221 |
| 37 | 6428.286 | 6343.791 | 6345.002 | 10.04985 | 10.10732 | 10.10649 |
| 38 | 11326.88 | 11169.76 | 11169.72 | 7.589699 | 7.650365 | 7.650379 |
| 39 | 3953.946 | 3842.439 | 3844.694 | 12.1605 | 12.28473 | 12.28219 |
| 40 | 9276.902 | 9193.973 | 9194.096 | 8.456774 | 8.495771 | 8.495713 |
| 41 | 7858.219 | 7753.509 | 7759.111 | 9.177562 | 9.23582 | 9.232684 |
| 42 | 4991.504 | 4849.48 | 4853.997 | 11.14849 | 11.27385 | 11.26981 |
| 43 | 6856.455 | 6674.989 | 6676.065 | 9.769807 | 9.886298 | 9.885598 |
| 44 | 5173.071 | 5111.175 | 5111.507 | 10.99332 | 11.0456 | 11.04531 |
| 45 | 6114.044 | 5987.139 | 5989.661 | 10.26752 | 10.35861 | 10.35678 |
| 46 | 8041.628 | 7807.399 | 7807.881 | 9.077364 | 9.20574 | 9.205472 |
| 47 | 6843.203 | 6764.639 | 6763.729 | 9.778209 | 9.828357 | 9.828942 |
| 48 | 5970.969 | 5922.146 | 5922.607 | 10.37036 | 10.40601 | 10.40567 |
| 49 | 8948.566 | 8832.281 | 8830.568 | 8.613269 | 8.670075 | 8.670917 |
| 50 | 7780.501 | 7652.833 | 7654.155 | 9.220728 | 9.292581 | 9.291831 |


| No. of video | MSE Original VS $240 * 320$ | MSE Original VS $240 * 320$ mean Filter | MSE <br> Original VS $240 * 320$ median Filter | PSNR Original VS $240 * 320$ | $\begin{gathered} \text { PSNR } \\ \text { Original VS } \\ 240 * 320 \\ \text { mean Filter } \end{gathered}$ | $\begin{gathered} \text { PSNR } \\ \text { Original VS } \\ 240 * 320 \\ \text { median Filter } \end{gathered}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | 6818.437 | 6640.985 | 6645.417 | 9.793955 | 9.908478 | 9.905581 |
| 2 | 3916.266 | 3834.398 | 3833.971 | 12.20208 | 12.29383 | 12.29432 |
| 3 | 3734.524 | 3632.988 | 3640.733 | 12.40845 | 12.52816 | 12.51892 |
| 4 | 6927.967 | 6807.934 | 6808.842 | 9.724745 | 9.80065 | 9.800071 |
| 5 | 6096.723 | 5951.133 | 5954.147 | 10.27984 | 10.38481 | 10.38261 |
| 6 | 7373.943 | 7196.144 | 7200.666 | 9.453806 | 9.559805 | 9.557077 |
| 7 | 6860.671 | 6704.529 | 6711.555 | 9.767138 | 9.867121 | 9.862572 |
| 8 | 7917.428 | 7654.433 | 7656.152 | 9.144962 | 9.291673 | 9.290698 |
| 9 | 6241.192 | 6148.624 | 6149.207 | 10.17813 | 10.24302 | 10.24261 |
| 10 | 2859.524 | 2799.555 | 2799.68 | 13.56787 | 13.65991 | 13.65972 |
| 11 | 6411.285 | 6298.348 | 6303.9 | 10.06135 | 10.13854 | 10.13471 |
| 12 | 2402.557 | 2350.396 | 2351.396 | 14.32407 | 14.41939 | 14.41754 |
| 13 | 9301.332 | 9129.481 | 9136.235 | 8.445352 | 8.526343 | 8.523131 |
| 14 | 2265.262 | 2219.636 | 2220.649 | 14.57962 | 14.66799 | 14.666 |
| 15 | 6556.874 | 6411.532 | 6413.896 | 9.963836 | 10.06119 | 10.05958 |
| 16 | 1145.332 | 1102.342 | 1102.041 | 17.54149 | 17.70764 | 17.70883 |
| 17 | 9523.253 | 9352.902 | 9352.972 | 8.342951 | 8.42134 | 8.421307 |
| 18 | 9525.107 | 9302.138 | 9302.755 | 8.342105 | 8.444976 | 8.444688 |
| 19 | 9248.697 | 9050.551 | 9052.465 | 8.469998 | 8.564053 | 8.563135 |
| 20 | 6085.222 | 5932.354 | 5933.177 | 10.28804 | 10.39853 | 10.39793 |
| 21 | 10188.09 | 10030.46 | 10030.27 | 8.049877 | 8.117594 | 8.117679 |
| 22 | 10970.79 | 10822.58 | 10823.24 | 7.728424 | 7.787495 | 7.787232 |
| 23 | 11034.95 | 10872.66 | 10876.9 | 7.703102 | 7.767447 | 7.76575 |
| 24 | 10645.23 | 10474.36 | 10475.83 | 7.859253 | 7.929529 | 7.92892 |
| 25 | 6401.2 | 6269.624 | 6269.31 | 10.06819 | 10.15839 | 10.15861 |
| 26 | 7013.365 | 6792.638 | 6793.996 | 9.671539 | 9.810419 | 9.809551 |
| 27 | 5145.25 | 4922.886 | 4922.919 | 11.01674 | 11.20861 | 11.20858 |
| 28 | 6179.726 | 6002.527 | 6002.906 | 10.22111 | 10.34746 | 10.34719 |
| 29 | 9508.663 | 9327.904 | 9328.358 | 8.349609 | 8.432963 | 8.432751 |
| 30 | 3528.757 | 3392.767 | 3392.335 | 12.65459 | 12.82526 | 12.82582 |
| 31 | 5719.999 | 5621.266 | 5622.112 | 10.55684 | 10.63246 | 10.63181 |
| 32 | 6351.835 | 6264.569 | 6265.811 | 10.10181 | 10.16189 | 10.16103 |
| 33 | 6035.879 | 12934.68 | 12935.31 | 6.977245 | 7.013248 | 7.013034 |
| 34 | 8765.07 | 5807.11 | 5807.138 | 10.3234 | 10.4912 | 10.49118 |
| 35 | 5017.623 | 8593.318 | 8595.438 | 8.70325 | 8.789195 | 8.788124 |
| 36 | 6854.841 | 4963.218 | 4965.915 | 11.12582 | 11.17317 | 11.17081 |
| 37 | 5420.544 | 6635.68 | 6640.177 | 9.77083 | 9.911949 | 9.909007 |
| 38 | 9578.438 | 5314.992 | 5315.413 | 10.79037 | 10.87578 | 10.87543 |
| 39 | 3387.271 | 9388.236 | 9387.864 | 8.317857 | 8.404964 | 8.405136 |
| 40 | 7673.105 | 3252.796 | 3254.712 | 12.8323 | 13.00824 | 13.00568 |
| 41 | 6862.212 | 7563.682 | 7565.926 | 9.281092 | 9.343471 | 9.342183 |
| 42 | 4117.621 | 6722.365 | 6723.546 | 9.766163 | 9.855583 | 9.85482 |
| 43 | 5982.123 | 3965.167 | 3969.201 | 11.98434 | 12.14819 | 12.14377 |
| 44 | 4315.366 | 5784.822 | 5785.911 | 10.36225 | 10.5079 | 10.50709 |
| 45 | 5526.394 | 4236.448 | 4236.555 | 11.78063 | 11.86078 | 11.86068 |
| 46 | 7091.484 | 5364.317 | 5365.793 | 10.70639 | 10.83566 | 10.83446 |
| 47 | 5667.773 | 6824.913 | 6824.837 | 9.623432 | 9.789832 | 9.789881 |
| 48 | 5074.007 | 5568.073 | 5567.739 | 10.59668 | 10.67375 | 10.67402 |
| 49 | 7622.152 | 5006.753 | 5007.374 | 11.07729 | 11.13524 | 11.1347 |
| 50 | 6657.199 | 7469.269 | 7468.044 | 9.310028 | 9.398023 | 9.398735 |


| No. of video | MSE <br> Original VS $120 * 240$ | MSE <br> Original VS $120 * 240$ <br> mean Filter | MSE <br> Original VS $120 * 240$ <br> median Filter | PSNR Original VS $120 * 240$ | PSNR <br> Original VS 120*240 mean Filter | PSNR <br> Original VS <br> 120*240 <br> median Filter |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | 110.3409 | 191.6731 | 191.1359 | 27.70344 | 25.30519 | 25.31738 |
| 2 | 50.92693 | 104.9375 | 104.7277 | 31.06133 | 27.92149 | 27.93019 |
| 3 | 54.90789 | 142.0816 | 143.5107 | 30.73446 | 26.60542 | 26.56196 |
| 4 | 54.20314 | 132.3213 | 132.5973 | 30.79056 | 26.91451 | 26.90546 |
| 5 | 123.6192 | 223.3678 | 226.0203 | 27.20995 | 24.6406 | 24.58933 |
| 6 | 81.87874 | 204.0186 | 201.4686 | 28.99909 | 25.03411 | 25.08873 |
| 7 | 121.3944 | 221.5484 | 222.4082 | 27.28882 | 24.67612 | 24.6593 |
| 8 | 120.6526 | 280.5763 | 280.2707 | 27.31544 | 23.65029 | 23.65503 |
| 9 | 40.4589 | 110.776 | 111.2366 | 32.06066 | 27.68635 | 27.66833 |
| 10 | 61.40105 | 95.7301 | 95.77236 | 30.24905 | 28.32032 | 28.3184 |
| 11 | 69.63684 | 136.0893 | 133.8252 | 29.70241 | 26.79257 | 26.86543 |
| 12 | 105.2392 | 143.9962 | 145.0279 | 27.90903 | 26.54729 | 26.51629 |
| 13 | 55.66336 | 168.8647 | 167.5641 | 30.67511 | 25.85541 | 25.88899 |
| 14 | 58.92306 | 86.90698 | 87.4449 | 30.42795 | 28.74026 | 28.71346 |
| 15 | 62.67817 | 148.1684 | 148.3558 | 30.15964 | 26.42325 | 26.41776 |
| 16 | 54.38493 | 74.62355 | 75.22448 | 30.77602 | 29.40204 | 29.36721 |
| 17 | 60.9612 | 166.8585 | 166.8671 | 30.28027 | 25.90732 | 25.9071 |
| 18 | 228.4366 | 356.936 | 356.3327 | 24.54315 | 22.6049 | 22.61225 |
| 19 | 78.7151 | 189.8777 | 190.4551 | 29.17022 | 25.34606 | 25.33288 |
| 20 | 175.6349 | 249.6886 | 249.7113 | 25.68469 | 24.15682 | 24.15642 |
| 21 | 84.18807 | 199.8281 | 199.6484 | 28.8783 | 25.12424 | 25.12815 |
| 22 | 63.19544 | 166.9075 | 166.5186 | 30.12395 | 25.90604 | 25.91618 |
| 23 | 67.18953 | 179.6451 | 179.6169 | 29.85779 | 25.58665 | 25.58733 |
| 24 | 142.682 | 252.4213 | 252.6151 | 26.58711 | 24.10954 | 24.10621 |
| 25 | 147.9987 | 248.254 | 247.6477 | 26.42823 | 24.18184 | 24.19246 |
| 26 | 318.0552 | 485.8954 | 488.7731 | 23.10578 | 21.26538 | 21.23973 |
| 27 | 135.8505 | 286.3741 | 286.3547 | 26.80019 | 23.56147 | 23.56176 |
| 28 | 101.858 | 204.9128 | 204.905 | 28.05085 | 25.01511 | 25.01528 |
| 29 | 73.28317 | 193.5445 | 193.0314 | 29.48076 | 25.26299 | 25.27452 |
| 30 | 98.32815 | 154.0189 | 153.6322 | 28.20403 | 26.25506 | 26.26598 |
| 31 | 58.72855 | 133.2897 | 133.1987 | 30.44231 | 26.88284 | 26.8858 |
| 32 | 62.77095 | 139.3974 | 140.147 | 30.15322 | 26.68826 | 26.66497 |
| 33 | 291.6337 | 440.7041 | 441.4074 | 23.48243 | 21.68933 | 21.68241 |
| 34 | 62.35424 | 169.0404 | 168.7173 | 30.18214 | 25.8509 | 25.85921 |
| 35 | 65.71288 | 126.6493 | 128.1805 | 29.9543 | 27.10478 | 27.05259 |
| 36 | 181.2225 | 333.3065 | 334.2281 | 25.54868 | 22.90237 | 22.89037 |
| 37 | 124.2567 | 215.677 | 216.1499 | 27.1876 | 24.79277 | 24.78325 |
| 38 | 78.68741 | 224.7469 | 225.1399 | 29.17175 | 24.61387 | 24.60628 |
| 39 | 100.5336 | 196.351 | 195.985 | 28.10769 | 25.20047 | 25.20858 |
| 40 | 59.66878 | 153.4605 | 153.6718 | 30.37333 | 26.27084 | 26.26486 |
| 41 | 110.9965 | 200.4689 | 201.1906 | 27.67771 | 25.11033 | 25.09473 |
| 42 | 124.0266 | 242.2535 | 240.2579 | 27.19565 | 24.2881 | 24.32403 |
| 43 | 100.5894 | 195.1501 | 193.439 | 28.10528 | 25.22712 | 25.26536 |
| 44 | 90.78376 | 136.9898 | 137.0355 | 28.55072 | 26.76392 | 26.76247 |
| 45 | 138.3309 | 228.056 | 225.9578 | 26.72161 | 24.55039 | 24.59053 |
| 46 | 197.6829 | 398.8681 | 398.7112 | 25.17111 | 22.12251 | 22.12422 |
| 47 | 91.93579 | 173.5671 | 173.6556 | 28.49596 | 25.73613 | 25.73392 |
| 48 | 82.98608 | 147.9403 | 147.7177 | 28.94075 | 26.42994 | 26.43648 |
| 49 | 46.75583 | 158.7022 | 161.2461 | 31.43245 | 26.12497 | 26.05591 |
| 50 | 126.0693 | 244.7824 | 245.1535 | 27.12471 | 24.243 | 24.23642 |


| No. of video | $\begin{gathered} \text { MSE } \\ \text { Original VS } \\ 100 * 180 \end{gathered}$ | MSE <br> Original VS 100*180 mean Filter | MSE <br> Original VS 100*180 median Filter | $\begin{gathered} \text { PSNR } \\ \text { Original VS } \\ 100 * 180 \end{gathered}$ | PSNR <br> Original VS 100*180 mean Filter | PSNR <br> Original VS 100*180 median Filter |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | 169.5264 | 267.735 | 267.4074 | 25.83843 | 23.85375 | 23.85907 |
| 2 | 72.48956 | 136.2326 | 135.9718 | 29.52805 | 26.78799 | 26.79631 |
| 3 | 73.38513 | 163.5028 | 163.0899 | 29.47472 | 25.99555 | 26.00653 |
| 4 | 77.62631 | 166.5946 | 166.6144 | 29.23071 | 25.91419 | 25.91368 |
| 5 | 185.2211 | 282.2412 | 279.2141 | 25.4539 | 23.6246 | 23.67143 |
| 6 | 128.2671 | 249.5539 | 251.0107 | 27.04965 | 24.15916 | 24.13388 |
| 7 | 165.7835 | 266.07 | 265.8577 | 25.93539 | 23.88084 | 23.88431 |
| 8 | 175.0817 | 342.7049 | 342.4493 | 25.6984 | 22.7816 | 22.78484 |
| 9 | 57.34861 | 144.1361 | 144.3061 | 30.54557 | 26.54308 | 26.53796 |
| 10 | 88.28781 | 126.9612 | 127.0629 | 28.6718 | 27.09409 | 27.09062 |
| 11 | 101.0426 | 171.3355 | 170.9855 | 28.08576 | 25.79233 | 25.80121 |
| 12 | 132.291 | 173.9691 | 174.9959 | 26.9155 | 25.72608 | 25.70052 |
| 13 | 83.41328 | 216.2879 | 215.1966 | 28.91845 | 24.78048 | 24.80245 |
| 14 | 72.84743 | 103.29 | 103.5183 | 29.50666 | 27.99022 | 27.98063 |
| 15 | 93.34913 | 187.4668 | 187.5536 | 28.4297 | 25.40156 | 25.39955 |
| 16 | 83.02619 | 102.3802 | 102.6194 | 28.93865 | 28.02864 | 28.01851 |
| 17 | 96.09224 | 218.4454 | 218.4992 | 28.30392 | 24.73737 | 24.7363 |
| 18 | 169.4533 | 311.2811 | 311.1744 | 25.8403 | 23.19928 | 23.20076 |
| 19 | 116.1016 | 239.5776 | 239.2944 | 27.48242 | 24.33634 | 24.34148 |
| 20 | 224.2645 | 307.8402 | 308.5489 | 24.6232 | 23.24755 | 23.23756 |
| 21 | 126.5063 | 255.9886 | 255.6213 | 27.10968 | 24.0486 | 24.05483 |
| 22 | 102.5178 | 225.4288 | 225.741 | 28.02281 | 24.60071 | 24.5947 |
| 23 | 92.24726 | 220.9057 | 219.8844 | 28.48127 | 24.68874 | 24.70886 |
| 24 | 196.8314 | 319.7212 | 319.717 | 25.18986 | 23.08309 | 23.08315 |
| 25 | 184.8292 | 295.8136 | 295.3853 | 25.4631 | 23.42062 | 23.42692 |
| 26 | 311.2747 | 413.98 | 414.7075 | 23.19936 | 21.96101 | 21.95338 |
| 27 | 166.3901 | 300.345 | 300.2944 | 25.91953 | 23.3546 | 23.35533 |
| 28 | 152.1501 | 264.3771 | 264.3542 | 26.30808 | 23.90856 | 23.90894 |
| 29 | 120.4875 | 253.2856 | 253.3074 | 27.32138 | 24.0947 | 24.09432 |
| 30 | 152.4803 | 204.793 | 205.3007 | 26.29867 | 25.01765 | 25.0069 |
| 31 | 88.12681 | 171.2838 | 171.3469 | 28.67972 | 25.79364 | 25.79204 |
| 32 | 89.36478 | 173.9676 | 175.3518 | 28.61914 | 25.72612 | 25.6917 |
| 33 | 283.5354 | 358.749 | 358.8625 | 23.60473 | 22.5829 | 22.58152 |
| 34 | 92.70709 | 217.6018 | 217.643 | 28.45967 | 24.75418 | 24.75336 |
| 35 | 96.54204 | 164.3309 | 165.7723 | 28.28364 | 25.97361 | 25.93568 |
| 36 | 240.0366 | 389.3853 | 390.039 | 24.32803 | 22.22701 | 22.21972 |
| 37 | 158.3439 | 264.6765 | 264.855 | 26.13479 | 23.90365 | 23.90072 |
| 38 | 119.4391 | 277.8071 | 277.6731 | 27.35934 | 23.69337 | 23.69547 |
| 39 | 146.0179 | 248.2702 | 248.438 | 26.48674 | 24.18156 | 24.17862 |
| 40 | 91.269 | 199.1005 | 199.7746 | 28.52757 | 25.14008 | 25.1254 |
| 41 | 145.2585 | 244.5836 | 244.8928 | 26.50939 | 24.24653 | 24.24104 |
| 42 | 180.9114 | 293.5978 | 292.9156 | 25.55615 | 23.45328 | 23.46338 |
| 43 | 153.5281 | 249.9095 | 249.1605 | 26.26893 | 24.15298 | 24.16601 |
| 44 | 128.1993 | 182.054 | 182.0445 | 27.05195 | 25.5288 | 25.52903 |
| 45 | 182.8213 | 279.989 | 279.979 | 25.51054 | 23.65939 | 23.65955 |
| 46 | 265.7172 | 478.753 | 478.4235 | 23.88661 | 21.32969 | 21.33268 |
| 47 | 131.4914 | 222.1935 | 221.7999 | 26.94183 | 24.66349 | 24.67119 |
| 48 | 104.7841 | 183.9062 | 183.8531 | 27.92785 | 25.48484 | 25.48609 |
| 49 | 66.49611 | 206.0045 | 210.0261 | 29.90284 | 24.99204 | 24.90807 |
| 50 | 174.5821 | 308.0604 | 308.6294 | 25.71081 | 23.24444 | 23.23643 |

## Appendix C: Code

```
%% Main Function
clc
clear
close all
fol1='HQ\';
fol2='480v640\';
fol3='320v480\',
fol4='288v352\'';
fol5='240v320\';
fol6='120v240\';
fol7='100v180\';
fol8='C:\Users\Rasheed Sarky\Desktop\25_11_code\code_\80v150\';
fol9='C:\Users\Rasheed Sarky\Desktop\25_11_code\code_\70v120\';
```

path_orig=fol1;
if $i==1$
path diffres=fol2;
elseif $i==2$
path_diffres=fol3;
elseif $i==3$
path_diffres=fol4;
elseif $i==4$
path diffres=fol5;
elseif $i==5$
path_diffres=fol6;
elseif $i==6$
path diffres=fol7;
elseif $i==7$
path_diffres=fol8;
elseif $i==8$
path_diffres=fol9;
end
filename_orig=[path_orig num2str(1) '.MP4'];
filename_diffres=[ path_diffres num2str(1) '.MP4'];
orig_vdo=filename_orig;
low_vdo=filename_diffres
\% convert video into frames
disp([' video ' num2str(1) ' is working'])
disp('convert $H Q$ video into frames')
orig_frames=vdo_to_frame (orig_vdo);
disp('convert low res video into frames')
lowres_frames=vdo_to_frame (low_vdo) ;
disp(['Selected video has ' num2str(size(orig frames,4)) ' frames'])
frame_count=2; \%input('Enter the number of frames you will use before and after : ');
for $i=1: s i z e(o r i g$ frames, 4)
[im,flag]=demo(orig frames(:,:,:,i)); \% function to detect the full face
if $\mathrm{flag}=0$
F=i;
break
end
end
if $\mathrm{F}>=(\mathrm{frame}$ count+1) \&\& $\mathrm{F}<($ size(orig_frames, 4)-frame_count)
frames_selected_orig=orig_frames(:,:, f (F-frame_count:F+frame_count);
frames selected lowres=lowres frames(:,:, $:$ F-frame count: F+frame count).
elseif $\mathrm{F}<(\overline{\mathrm{f}}$ rame_count+1)
frames_selēcted_orig=orig_frames(:, :, :, 1:F+frame_count);
frames_selected_lowres=lowres_frames(:, :, :1:F+frame_count);
elseif $\mathrm{F}>($ size (orig_frames,4)-frame_count)
frames_selected_orig=orig_frames (:, :, :, F-frame_count:end);
frames_selected_lowres=lowres_frames(:,:,:,F-frame_count:end);
end
frames_selected_lowres_N=mean_filter(frames_selected_lowres);
\% frames_selected_lowres_N2=median_filter(frames_selected_lowres);
disp('Comparíson betwēen orī̄inal $H Q$ vīdeo frame and low resolution video frame')
[peak_sig_to_noise_ratio, mean_squared_error, max_squared_error, ratio_of_squared_norms]=..


disp('MEAN OPERATION')
\% newframe_from_orig=mean_of_frames(frames_selected_orig, size(frames_selected_orig, 4)),
newframe_from_lowres=mean_of_frames(frames_selected_lowres_N,size(frames_selected_lowres_N, 4));
\%\%here

```
    orig_frame=orig_frames(:,:,:,F);
```

    figure
    imshow(uint8(newframe_from_orig))
    title('Frame from orig frames')
    saveas(gcf,'Original frames''s super resolution frame.jpg')
    figure
    imshow (uint8(newframe_from_lowres))
    title('Frame from low res frames')
    saveas(gcf,'Low res frames''s super resolution frame.jpg')
    disp('Comparison between newframe_from_orig and orig_frame')
    [peak_sig_to_noise_ratio_1, mean_squared_error_1, max_squared_error_1,
    ratio_of_squared_norms_1]=...
measer $\bar{r}\left(i m r e \overline{\left.s i z e(n e w f r a m e ~ f r o m ~ o r i g, ~[100 ~ 100]), ~ i m r e s i z e\left(o r i g \_f r a m e, ~[100 ~ 100]\right)\right) ; ~}\right.$
\%
\% ['peak_sig_to_noise_ratio_1 ' 'mean_squared_error_1 ' 'max_squared_error_1 '
'ratio_of_squared_norms_1']
[peak sig to noise ratio 1, mean squared error 1, max squared error 1,
ratio of squarē nōrms 1]
$\div$
disp('Comparison between newframe_from_lowres and orig_frame'
[peak sig_to_noise_ratio_2, mean_squared_error_2, max_squared_error_2,
ratio_of_squared_norms_2]=...
measerr(imresiz̄e(newframe from lowres,[320 480]), imresize(orig frame, [320 480]));
['peak_sig_to_noise_ratio_2 ' 'mean_squared_error_2 ' 'max_squared_error_2 '
'ratio of squared norms 2']
[peak sig to noise ratio 2, mean squared error 2, max squared error 2 ,
ratio_of_squared_norms_2]

disp('MEDIAN OPERATION')
\% newframe_from_orig=median_of_frames(frames_selected_orig,size(frames_selected_orig, 4));
newframe_from_lowres=median_of_frames(frames_selected_lowres_N,size(frames_selected_lowres_N,4));
\%here

```
% figure
    imshow(uint8(newframe_from_orig))
    title('Frame from orig frames')
    saveas(gcf,'Original frames''s super resolution frame.jpg')
    figure
    imshow(uint8(newframe_from_lowres)
    title('Frame from low res frames')
    saveas(gcf,'Low res frames''s super resolution frame.jpg')
    disp('Comparison between newframe_from_orig and orig_frame')
    [peak_sig_to_noise_ratio_1, mean_squared_error_1, max_squared_error_1,
ratio_of_squared_norms_1]=...
            measerr(imresize(newframe_from_orig,[100 100]),imresize(orig_frame,[100 100]))
    ['peak_sig_to_noise_ratio_1 ' 'mean_squared_error_1 ' 'max_squared_error_1 '
ratio_of_squared_norms_1']
[peak sig to noise ratio 1, mean squared error 1, max squared error 1,
ratio_of_square\overline{d_nōrms_1]}
%
    disp('Comparison between newframe_from_lowres and orig_frame')
    [peak_sig_to_noise_ratio_2, mean_squared_error_2, max_squared_error_2,
ratio_of_squared_norms_2]=...
            measerr(imresize(newframe_from_lowres,[320 480]),imresize(orig_frame,[320 480])) ;
    ['peak_sig_to_noise_ratio_2 ' 'mean_squared_error_2 ' 'max_squared_error_2 '
'ratio of squared norms 2']
    [pēak_sig_to_noise_r.ratio_2, mean_squared_error_2, max_squared_error_2,
ratio_of_squared_norms_2]
%%%
    function frames=vdo to frame(filename)
%reading a video file
mov = VideoReader(filename);
%getting no of frames
numFrames = mov.NumberOfFrames
% number of frames to be used
% numFrames=10;
% creating a data of frames
for t = 1 : numFrames
    currFrame = read(mov, t);
```

```
    frames(:,:,:,t)=currFrame
end
end
%%%
function [im,flag]=demo(img)
flag=0; % if flag=0, that means a full face is detected
detector = buildDetector();
[bbox bbimg faces bbfaces] = detectFaceParts(detector,img,2);
if size(bbfaces,1)==0
    flag=1 ; % if flag=1, that means a full face is not detected, current frame will be dismissed
    im=0;
else
    im=bbfaces{1};
end
%%%
function filtered_frames=mean_filter(frames)
sz=size(frames);
f=sz (end);
for i=1:f
    currframe=frames(:,:,:,i); % one frame from the video
    % resolving the frame in different channels
    currframe1=currframe(:,:,1); % channel 1
    currframe2=currframe(:,:,2); % channel 2
    currframe3=currframe(:,:,3); % channel 3
    % create mean filter
    h = 1/3*ones (3,1);
    H}=h*h'
    imfilt frame1 = filter2(H,currframe1); % apply mean filter on channel 1
    imfilt_frame2 = filter2(H,currframe2); % apply mean filter on channel 2
    imfilt_frame3 = filter2(H,currframe3); % apply mean filter on channel 3
    % saving the filtered variable back to a new variable
    filtered_frames(:,:,1,i)=imfilt_frame1;
    filtered_frames(:,:,2,i)=imfilt_frame2;
    filtered_frames(:,:,3,i)=imfilt_frame3;
end
end
%%%
function filtered_frames=median_filter(frames)
sz=size(frames);
f=sz (end);
for i=1:f
    currframe=frames(:,:,:,i); % one frame from the video
    % resolving the frame in different channels
    currframe1=currframe(:,:,1); % channel 1
    currframe2=currframe(:,:,2); % channel 2
    currframe3=currframe(:,:,3); % channel 3
    imfilt_frame1 = medfilt2(currframe1); % applying median filter on channel 1
    imfilt_frame2 = medfilt2(currframe2); % applying median filter on channel 2
    imfilt_frame3 = medfilt2(currframe3); % applying median filter on channel 3
    % saving the filtered frame into a new variable
    filtered frames(:,:,1,i)=imfilt frame1;
    filtered_frames(:,:,2,i)=imfilt_frame2;
    filtered_frames(:,:,3,i)=imfilt_frame3;
end
%%%
% clc
% clear
% close all
% reading the video
[file,path]=uigetfile('*.mp4','Select the original HQ video file');
% vdo=strcat(path,file);
% for vdocount=5
        disp('-----------------------------------------------------------------------------------
        disp(['Working on video : ' num2str(vdocount)])
    % select a video
        filename = [ num2str(vdocount) '.mp4']
        filename = vdo,
    disp('convert video into frames')
```

```
    frames=vdo_to_frame(filename);
    disp(['Selected video has ' num2str(size(frames,4)) ' frames'])
    vertical=input('Enter the vertical height of the image: ')
    horizontal=input('Enter the horizontal width of the image: ');
    disp('reduce resolution of these frames')
    for i=1:size(frames,4)
    lowres_frames(:,:,:,i)=imresize(frames(:,:,:,i),[vertical horizontal]); % restricting
    frame to vertical X horizontal resolution
    end
    disp('detect frame which have a full face (i.e. 2 eyes, 1 nose and 1 mouth)')
    for i=1:size(frames,4)
    [im,flag]=demo(frames(:,:,:,i)); % function to detect the full face
    if flag==0
            F=i;
            break
        end
    end
    frame_count=input('Enter the number of frames you will use before and after: ');
    disp('getting a super resolution frame using the detected faces')
    if F>=(frame_count+1) && F<(size(frames,4)-frame_count)
        frames_se\overline{lected_orig=frames(:,:,:,F-5:F+frame_count);}
        frames_selected_lowres=lowres_frames(:,:,:,F-\overline{5}:F+frame_count);
    elseif F<(frame_count+1)
    frames selected orig=frames(:,:,:,1:F+frame count);
    frames_selected_lowres=lowres_frames(:,:,:,\overline{1}:F+frame_count);
    elseif F>(\overline{size(framés,4)-frame_coünt)}
    frames_selected_orig=frames (:,:,:,F-frame_count:end);
    frames_selected_lowres=lowres_frames(:,:,:,F-frame_count:end);
    end
    disp('
    disp('MEAN OPERATION')
    newframe_from_orig=mean_of_frames(frames_selected_orig,size(frames_selected_orig,4));
    newframe_from_lowres=mean_of_frames(frames_selected_lowres,size(frames_selected_lowres,4));
    orig_frame=frames(:,:,:,F);
    figure
    imshow(uint8(newframe_from_orig)
    title('Frame from orig frames')
    saveas(gcf,'Original frames''s super resolution frame.jpg')
    figure
    imshow(uint8(newframe_from_lowres))
    title('Frame from low res frames')
    saveas(gcf,'Low res frames''s super resolution frame.jpg')
    [peak_sig_to_noise_ratio_1, mean_squared_error_1, max_squared_error_1,
io_of_square\overline{d_norms_1]=. . .}
        measerr(imresize(newframe_from_orig,[100 100]),imresize(orig_frame,[100 100]));
    ['peak_sig_to_noise_ratio_1 ' 'mean_squared_error_1 ' 'max_squared_error_1 '
ratio_of_square\overline{d_nōrms_1']}]
```



```
io_of_square\overline{d_nōrms_1]}
    [peak_sig_to_noise_ratio_2, mean_squared_error_2, max_squared_error_2,
ratio_of_square\overline{d_norms_2]}=...
            measer\overline{r}(imresize(newframe_from_lowres,[100 100]),imresize(orig_frame,[100 100]));
    ['peak_sig_to_noise_ratio_2 ' 'mean_squared_error_2 ' 'max_squared_error_2 '
ratio_of_square\overline{d_norms_2']}
    [peakk_sig_to_noise__ratio_2, mean_squared_error_2, max_squared_error_2,
ratio_of_square\overline{d_norrms_2]}
    disp('
            ''-------------------------------------------------------------------------------------
    disp('MEDIAN OPERATION')
    newframe_from_orig=median_of_frames(frames_selected_orig,size(frames_selected_orig,4));
newframe_from_lowres=median_of_frames(frames_selected_lowres,size(frames_selected_lowres,4));
    figure
    imshow(uint8(newframe_from_orig))
    title('Frame from orig frames')
    saveas(gcf,'Original frames''s super resolution frame.jpg')
    figure
    imshow(uint8(newframe_from_lowres))
    title('Frame from low res \overline{frames')}
    saveas(gcf,'Low res frames''s super resolution frame.jpg')
    [peak_sig_to_noise_ratio_1, mean_squared_error_1, max_squared_error_1,
ratio_of_square\overline{d_norms_1]=...}
```

$\%$
\%
\%

```
    measerr(imresize(newframe_from_orig,[100 100]),imresize(orig_frame,[100 100]));
    ['peak_sig_to_noise_ratio_1 ' 'mean_squared_error_1 ' 'max_squared_error_1 '
'ratio_of_square\overline{d_nōrms_1'']}
% [pe\overline{a}_sig_to_noise__ratio_1, mean_squared_error_1, max_squared_error_1,
ratio_of_squared_norms_1]
%
% [peak_sig_to_noise_ratio_2, mean_squared_error_2, max_squared_error_2,
ratio_of_square\overline{d_nōrms_2]}=...
            measerr(imresize(newframe_from_lowres,[100 100]),imresize(orig_frame,[100 100])) ;
        ['peak_sig_to_noise_ratio_2 ' 'mean_squared_error_2 ' 'max_squared_error_2 '
'ratio_of_square\overline{d_norms_2'']}
    [pe\overline{ak_sig_to__noise__ratio_2, mean_squared_error_2, max_squared_error_2,}
ratio_of_square\overline{d_norms_2]}
lat
% end
function [bbox,bbX,faces,bbfaces] = detectFaceParts(detector,X,thick)
if( nargin < 3 )
thick = 1;
end
%%%%%%%%%%%%%%%%%%%%%%% detect face %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Detect faces
bbox = step(detector.detector{5}, X);
bbsize = size(bbox);
partsNum = zeros(size(bbox,1),1)
%%%%%%%%%%%%%%%%%%%%%%%%%%% detect parts %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
nameDetector = {'LeftEye'; 'RightEye'; 'Mouth'; 'Nose'; };
mins = [[12 18]; [12 18]; [15 25]; [15 18]; ];
stdsize = detector.stdsize;
for k=1:4
if( k == 1 )
    region = [1,int32(stdsize*2/3); 1, int32(stdsize*2/3)];
elseif( k == 2 )
    region = [int 32(stdsize/3),stdsize; 1, int32(stdsize*2/3)];
elseif( k == 3)
    region = [1,stdsize; int32(stdsize/3), stdsize];
elseif( k == 4 )
    region = [int32(stdsize/5),int32(stdsize*4/5); int32(stdsize/3),stdsize];
else
    region = [1,stdsize;1,stdsize];
end
bb = zeros(bbsize);
for i=1:size(bbox,1)
    XX = X(bbox(i,2):bbox(i,2) +bbox(i,4)-1,bbox(i,1):bbox(i,1)+bbox(i,3)-1,:);
    XX = imresize(XX,[stdsize, stdsize]);
    XX = XX(region(2,1):region (2,2),region(1,1):region(1,2),:);
    b = step(detector.detector{k},XX);
    if( size(b,1) > 0 )
    partsNum(i) = partsNum(i) + 1;
    if( k == 1 )
        b = sortrows (b,1);
    elseif( k == 2 )
    b = flipud(sortrows(b,1));
    elseif( k == 3)
    b = flipud(sortrows(b,2));
    elseif( k == 4 )
        b = flipud(sortrows(b,3));
    end
    ratio = double(bbox(i,3)) / double(stdsize);
    b(1,1) = int32( ( b(1,1)-1 + region(1,1)-1 ) * ratio + 0.5 ) + bbox(i,1);
    b}(1,2)=\operatorname{int32( ( b (1,2)-1 + region(2,1)-1 ) * ratio + 0.5 ) + bbox(i,2);
    b}(1,3)=\operatorname{int32( b (1,3) * ratio + 0.5 );
    b}(1,4)=\operatorname{int32( b (1,4) * ratio + 0.5);
    bb(i,:) = b(1,:)
    end
end
bbox = [bbox,bb];
p = ( sum(bb') == 0 );
bb(p,:) = [];
end
```

$\% \% \% \% \frac{2}{\sigma} \% \% \% \% \% \% \% \% \% \% \% \% \%$ draw faces $\% \% \% \% \% \% \% \% \% \% \% \% \% \% \% \% \% \% \% \% \% \% \% \% \%$
bbox = [bbox,partsNum];
bbox (partsNum<=2, : ) = [];

```
if ( thick >= 0 )
    \(t=(\) thick-1)/2
    t0 \(=\)-int32 (ceil(t))
    t1 \(=\) int32(floor(t));
else
    t0 \(=0\);
    t1 \(=0\);
end
\(b b x=X\)
```


if ( nargout > 2 )
faces $=\operatorname{cell}(\operatorname{size}($ bbox,1),1).
bbfaces $=$ cell $($ size $(\mathrm{bbox}, 1), 1)$;
for $i=1: s i z e(b b o x, 1)$
faces $\{i, 1\}=X(b b o x(i, 2): b b o x(i, 2)+b b o x(i, 4)-1, b b o x(i, 1): b b o x(i, 1)+b b o x(i, 3)-1,:) ;$
bbfaces $\{i, 1\}=\operatorname{bbx}(\operatorname{bbox}(i, 2): \operatorname{bbox}(i, 2)+b b o x(i, 4)-1, \operatorname{bbox}(i, 1): b b o x(i, 1)+b b o x(i, 3)-1,:)$;
end
end
$\% \%$

