

# **Temporal Ultrasound Image Enhancement for Kidney Diagnosis**

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## ABSTRACT

Ultrasound imaging enables the physician to view the tissues and organs in abdominal region of the body without hazards of ionization compared to the other radiation based internal organ inspection devices. It provides highly accurate imaging of a kidney on suspected acute renal diseases. This thesis proposes temporal filtering methods to enhance the ultrasound images from ultrasound kidney video for the purposes of identification and diagnosis of kidney diseases by processing consecutive images of the acquired kidney video extending the spatial mean, median and weighted mean image filters to temporal dimension after cropping and aligning the image frames manually in MATLAB by Image Processing Toolbox to suppress speckle noise, and improve information content for a diagnosis by a medical doctor. The assessment of the filtered images by 10 medical experts indicates that the proposed temporal mean, median, and weighted mean filters improve the images better than the common spatial mean, median and weighted mean filters. The evaluators ranked the temporal weighted mean filtered images as the least preferable, while they scored the temporal median filtered images as the best preferable ultrasound images for the purpose of renal diagnosis.

**Keywords:** Ultrasound Kidney Image, Image Enhancement by Video, Temporal Mean filter, Temporal Median Filter, Temporal Weighted Mean Filter.

## ÖZ

Bu tez böbrek hastalıklarının tanımlanması ve tıp doktorlarınca teşhisi amacıyla böbrek videosunda ardışık görüntüleri elle kırpma ve hizalama sonrasında işlemek üzere 2-boyutlu ortalama, medyan ve ağırlıklı-ortalama görüntü filtrelerini temporal boyuta genişleterek leke gürültüsünü bastıran zamansal filtreleme yöntemleri önermektedir. Matlab kullanılarak filtrelenmiş görüntülerin 10 tıbbi uzman tarafından değerlendirilmesi sonucu, önerilen temporal ortalama, medyan ve ağırlıklı ortalama filtrelerin, görüntüleri ortak mekânsal ortalama, medyan ve ağırlıklı ortalamalı filtrelerden daha fazla iyileştirdiğini gösteriyor. Filtrelenmiş görüntüleri böbrek teşhisi amacıyla değerlendiren uzman doktorlar, sıralamalarında temporal ağırlıklı ortalama filtrelenmiş görüntüleri en az tercih edilen olarak seçerken, temporal medyan filtrelenmiş görüntüleri en iyi tercih olarak seçtiler.

**Anahtar Kelimeler:** Ultrason Böbrek Görüntüsü, Videodan Görüntü Geliştirme, Temporal Ortalama filtre, Temporal Medyan Filtre, Temporal Ağırlıklı Ortalama Filtre.

## **DEDICATION**

To my precious Family,  
*a continuous acoustic source of song and laughter, wisdom and understanding.*

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# Chapter 1

## INTRODUCTION

### 1.1 Properties of Medical Ultrasound (US)

In physics sound is a propagation of energy in the form of mechanical vibrations. Ultrasound (US) is a term specifying the frequency of the sound, which is above human perception. In medical technology the term “Ultrasound” utilizes high-frequency sound waves to examine the structures and organs inside of the body. Health care specialist use it to view internal organs such as the kidneys, blood vessels, liver, heart, for the diagnosis of the reason for pain, swelling and infections [7][8].

In the imaging systems, the short wavelengths of diagnostic ultrasonic waves are convenient to carry the information about the body by their reflection or attenuation because of tissues inside the body [1]. Figure 1.1 shows the types of mechanical energy propagation by waves. Waves produced by ultrasound machine and probes cannot be heard by the human ear. Figure 1.2 shows the medical ultrasound probes. They generate ultrasound waves, which move through the skin of the patient. Waves reflected to the probe when they come across a mass with different density. The brightness of the image on the screen shows the intensity of the returning echo.

A strongly reflected signal is displayed white, and called hyperechoic point, which means that there is a reflecting surface of an organ at that point. The weakly reflected signals are called hypoechoic, and appear as black on the ultrasound screen. Surfaces of tissues which are reflecting partially appear as shades of gray.

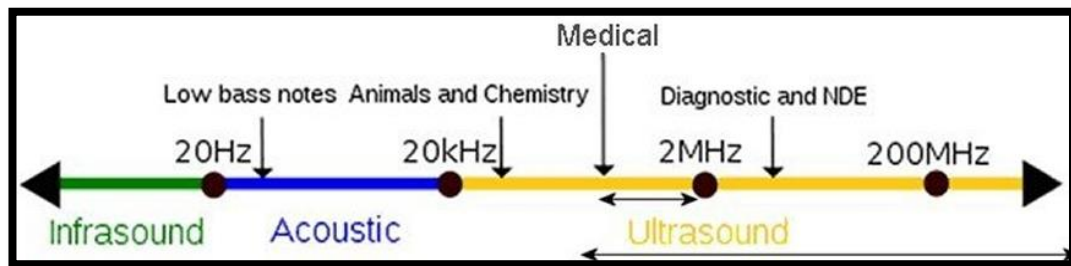
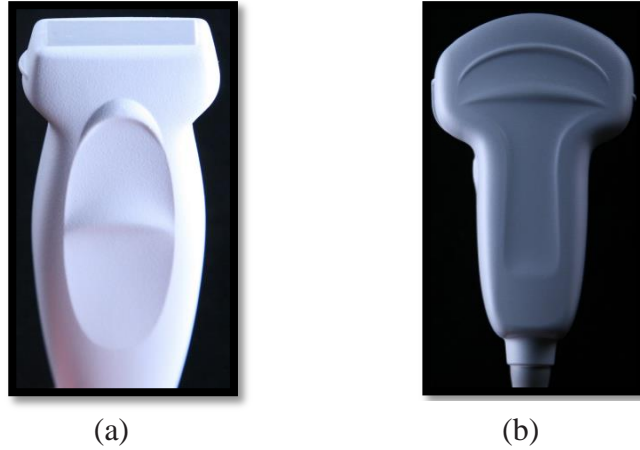


Figure 1.1: Types of Mechanical Energy Propagation as Waves by the permission from, Ken Marx, 2014

**Frequency of sound wave** is the number of vibrations per second the wave is repeated at a stationary point. Analytic ultrasound employ waves that are in the range of 2 to 15 MHz frequency because US waves at that range of frequency accomplish to picture finest formations in highest detail by generating high resolution excellent-quality images. On the other hand, lower frequency ultrasound waves are capable of searching the skin better to visualize deeper forms.

**US probes/transducers** vary according to the target tissues in the body mainly with their depth inside the body. A *linear probe* seen in figure 1.2, (a) can be used for forms near skin. Figure 1.2, (b) shows conversely a *curved probe* of lower frequency which can provide images of deep structures such as the aorta [2].



(a) (b)  
Figure 1.2: Probe Types (a) Linear (b) Curved.  
With permission by Thomas Ptak MD, 2011

**Image processing methods** are required in order to improve the quality of the kidney ultrasound image. There are many image processing techniques developed to enhance ultrasound image to get clearer and higher quality image by reducing the noise in the image [6]. The following subsection contains a brief discussion description of the three enhancement techniques:

**I. Mean or Average filter** is a windowed linear filter to smooth the target image. The filter operates as low-pass, which modifies the pixel values of the image to approach to the average of the neighbour pixels [9].

**II. Median Filter** is a nonlinear windowed filter, which may remove destructive noise while preserving edges. This filter sorts the pixel values in the neighbourhood of the target pixel, and decides the value at the middle of the sorted list for pixel value of the centre element [10].

**III. Weighted-mean Filter** detects the weighted average value of the neighbourhood window to exchange the centre pixel of the neighbourhood with a view to obtain the noise filtering [11].

## 1.2 Improving Image Quality

In figure 1.3, the marks on the right side show the depth of the ultrasound screen in centimetres. As seen in figure 1.4, in a scan the weak hypoechoic tissues like blood or urine appears black in colour, while the strong hyperechoic tissues such as bone appears white in the ultrasound screen [2].



Figure 1.3: Depth Markings on the Ultrasound Screen Correspond to Actual Tissue Depth

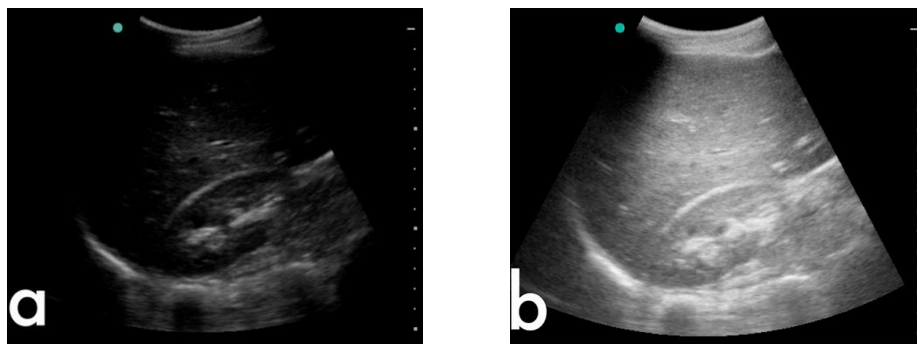


Figure 1.4: Increases are Used to Alter the Brightness of the Monitor.  
(a)The gain is excessively little or hypoechoic. In (b), the gain is excessively lofty or hyperechoic, with permission by Thomas Ptak MD, 2011

### **1.3 The Usage of Ultrasound**

Diagnostic ultrasound is an imaging tool that is helpful in a broad range of clinical applications, and in particular, prenatal diagnosis. The use of ultrasound is not limited to medical diagnosis. It is also used in screening for diseases and to aid in the treatment of diseases or health conditions. There is no health hazard in using medical doses of ultrasound waves even for extended periods of time.

The Ultrasonography system was modified for therapeutic purposes since thirty years, along with getting the image of tumours, internal organs, tendons and muscles. Especially it is widely used for prenatal care, with its capability to capture and monitor the fetal stages during pregnancy weeks.

Ultrasonography provides various important advantages, including its transportable structure, inexpensive investment and running costs, which has been harmless to body tissues. With these benefits, ultrasound becomes more commonly used in emergency.

Ultrasound is verified to be handy in several areas consisting medical imaging, which is also known as sonography. The operation is carried out with medical practitioners and veterinarians and provides an approach to check for organ parts. This will help in measuring intervals in the existing bodies as its shown in figure 1.5. The notion of using high frequency sound waves for medical optical imaging was first proposed by Sokolov at 1939. The image quality of those first images was low in regards to sensitivity and contrast.



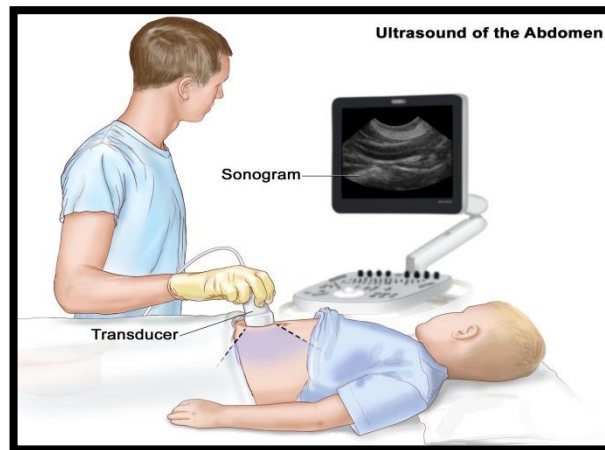


Figure 1.5: Ultrasound Machine in Medical Diagnosing  
by the permission from, The National Cancer Institute's, USA

Along with medical uses, there are several places of application of ultrasound in various industries including accelerating and purifying chemical reactions. Ultrasonic effect treatment concerns ultrasonic energy towards metals to change the properties of these metals, like in grain size and refinement.

Ultra-sonication is a type of slurry or liquid procession that improves the assimilation of materials of chemical reactions on manufacturing stages to penetrate cavitation's, and collapse tiny vacuum bubbles, which helps to get smooth and uniform mixtures. Ultrasonic waves are also used in cleaning jewellery, optical lenses, and medical instruments in addition to industrial instruments. The sound waves that are released hit the object's surface causing the object to be cleaned and as such this process creates bubbles by cavitation's and as a consequence it directs small jets in the direction of the surface, accomplishing the removal process. This method may also use to be directed to infected zones, as infected with bacteria, to eliminate joined particles.

## 1.4 Modes of Ultrasound Visualization

A mode is an equipped state that a system has been changed to. An ordinary mode happens when completely parts of a system vibrate with the identical hesitance. For ultrasound visualization, varied modes are utilized to inspect the venous / arterial system, pancreas, joints, heart, spinal cord, ovaries, urinary system, and extra. The operator or tech can manage the various kinds of modes [4].

**B-Mode** is the “brightness” mode, which provides structural information by using shades of greyness or brightness in a two dimensional image. It is the most integral mode of ultrasound-beginner.

**M-mode** stands for ‘Motion Mode’. It measures echoes from all target area simply one line of the “B-mode” axis as brightness along time. Generally both the B-mode and M-mode are shown jointly on the ultrasound monitor, as seen in figure 1.6.

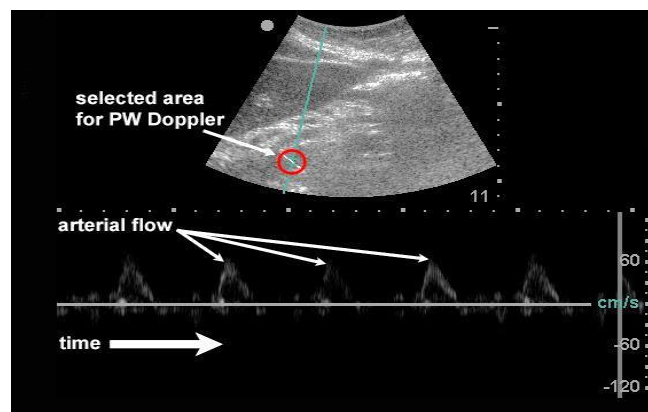


Figure 1.6: M-Mode (Lower Portion of the Image) Shared with B-Mode Image. In this still image the M-Mode captures the motion of a certain part of the heart. With permission by Beatrice Hoffmann, 2008

**Doppler Mode** shows the shift of frequency of the reflected waves in colour. The Doppler effect of a moving object on the reflected wave appears as a change in frequency. This mode monitors the change of frequency of the echo, and indicates the direction and velocity of blood flow and tissue motion in an audible, spectral or colour on the image [5].

## **1.5 Problem Statement**

Very often, doctors use ultrasound images for diagnosis. In many cases these images are not sufficiently clear to identify the particular structures and formations. Raw ultrasound images need operations for correction of acquisition artefacts, and filtering of noise to improve quality of analysis. Such filtering operations may sometimes introduce negative effect in the information carried with the image. In the analysis of ultrasound images, the existence of speckle noise leads to problems in diagnosis, because it disturbs the quality of the images, masking the sight of the weak contrast lesions and increasing the rate of possible misdiagnosis. The enhancement of speckle noised ultrasound image is complicated especially in imaging of the kidney whose underlying structures are quite small to be determined by large wavelength. Speckles also obscure consequent image processing, such as edge detection and image segmentation. Hence removing the speckle noise and improving the image without the loss of valuable image features is a necessity.

This study targets to test the reduction of the speckle noise using the temporal filters proposed by the Supervisor of the Thesis, Dr. Mehmet Bodur, who is the owner of the novel idea to expand the usual spatial mean, median and weighted-mean filters to the temporal domain by including the previous and next frames of the video to into the filtering operation. This thesis implemented the temporal filtering code in

MATLAB and evaluated the enhancement of kidney ultrasound images by using medical doctors to assess the suitability of the images for the diagnosis purpose. The assessment process targets to find the best filtering method for the consecutive frames of a kidney ultrasound video. The study tests the enhancement of the image regarding a diagnosis by extending three common image filtering methods to consequent images of kidney ultrasound videos. These three filtering methods: mean filtering, median filtering, and weighted mean filtering are the most frequently used image filtering tools in reducing image speckle. The filters were extended to time domain, and the proposed temporal filters combine the information content of three consecutive images into one image using the MATLABs image toolbox.

## **1.6 Purpose and Significance of the Study**

There are numerous earlier studies conducted in contrasting various US noise repression and image enhancement tools for US images. However, they are focused only on enhancement of a single image frame. The proposed temporal filtering provides enhancement of an image in a video record, enriching the information contents of a single frame by including extra information from consequent images, while old methods provide only a smoothening effect that leads to information loss. Medical Ultrasound imaging is also known as diagnostic sonography or Ultrasonography and it has become one of the main techniques in today's medical diagnosis. It is inexpensive, widely accessible and comparatively safe to the users as well as the operators. A sonographer's task is to collect reliable sonographic documents under supervision of a physician to diagnose a diversity of circumstances and illnesses. The proposed technique can be adopted into the standard processes of diagnostic sonography for the medical benefits of the human being.

## Chapter 2

# DIAGNOSTIC ULTRASOUND IMAGING TOOLS AND METHODS

### 2.1 Introduction

This chapter contains information about ultrasound image types, and their filtering methods commonly used in medical imaging. Ultrasound is largely utilized in clinical applications because of its intuitive, convenient, safe, non-invasive, and inexpensive nature. The goal of radiologic imaging serves to increase the number of positive diagnosis and reduce the number of negative diagnosis in the analysis of US images [12].

Ultrasound has long been used as diagnostic equipment which helps in diagnosing the internal organs, tendons of human beings to visualize the size and structure of these organs. In particular, this thesis is focused on ultrasound images of the kidneys.

In general, an ultrasonic image depends on the operators practice. The purpose of this study is to develop techniques that may help the ultrasonic operator for taking clear images of kidney, and, to view other soft organs or abnormalities in the human body [13].

Ultrasound scanning is highly open to human error while measuring size of organs and tissues because of noisy US images and inexperienced sonographers. Filtering the noise by mean, median, and weighted mean filters reduce the effect of noise, but it also reduces information content of the images [14]. The proposed filters can help to sonographer to develop better filtered images with higher information contents such as better edges, correct contrast, etc.

The following sections of this chapter introduce necessary information to understand the spatial filtering techniques that is commonly used in enhancing the ultrasound images. These techniques will also be useful to understand the proposed filtering techniques.

## **2.2 Medical Imaging**

Medical image equipment, for instance, US, X-RAY, MRI and so on, shown in figure 2.1, is designed to large extent for the diagnosis of diseases. Medical anatomical imaging allowed medical care to inspect the body with best settings and without the trauma caused by exploratory surgery was the anatomical imaging. However, as described in the following paragraphs, the majority of anatomical imaging technologies are highly modern [15].

**X-Ray imaging:** The patient is exposed to a small quantity of ionizing electromagnetic radiation, produced by an X-Ray tube. A 2D image of the incoming radiation is produced by a detector panel on the other side of the patient. Hence an X-Ray image, or radiograph, is a displayed image of the X-Ray reduction along the lines from the source of the X-Ray through the patient to and back to the detector [17].

**Computed Tomography (CT):** X-Ray physics are used in order to produce a three-dimensional image. For instance, a CT scanner has an X-ray tube attached to it on a rotating gantry; one or more than one line detectors are on the other side [17].

**Positron Emission Tomography (PET):** Positron Emission Tomography is an essential imaging performance which assists the surgeons with knowledge regarding how matters and organs function. PET, sometimes applied in coordination with Computed Tomography scanning, utilizes a minor quantity, and a scanner of radiopharmaceuticals that is injected into the veins of a patient to aid in manufacturing comprehensive, programmed pictures of organs of the body [16]. PET is frequently utilized to assess: Neurological illnesses for instance Alzheimer's and Multiple Sclerosis, Cancer, effectiveness of therapy, and Heart conditions [16].

**Magnetic Resonance Imaging (MRI):** As opposed to the X-Ray based imaging techniques above, MRI does not make use of any ionizing Radiation, and is hence regarded as a non-invasive modality. The magnetic nuclei (mostly protons) of the anatomy are aligned in a powerful consistent magnetic field produced by the scanner. The energy is absorbed by the magnetic nuclei from tuned radiofrequency pulses, and emits radiofrequency signals as their excitation diminishes [17].

**Ultrasound:** Ultrasound is basically different from the tomographic modalities. As opposed to CT or MRI Scanners, an ultrasound system is a portable machine which gives way for interactive real-time Imaging. In its simplest functions, it displays 2D slice images that display the organs of the patient, showing the quantity of ultrasonic reflections. Since this work is centred on the use of ultrasound [17].

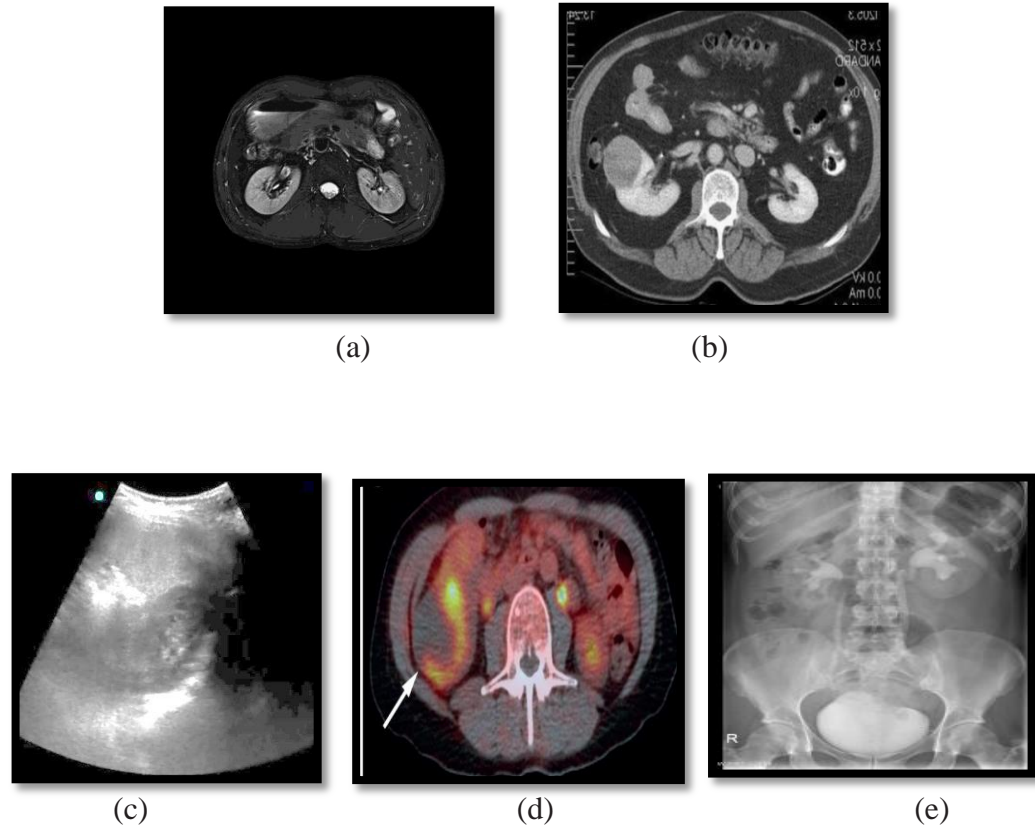


Figure 2.1: Examples of Kidney Images from Different Modalities  
 (a)CT image, with permission by Health wise Staff, 2016, (b) MRI image, with permission by Loerch, Jeff, 2015, (c) Ultrasound image, (d) PET image with permission by Michael Gorin, 2015, and (e) X-ray image, with permission by Dr.Christiane Kulinna, Austria

### 2.3 Contrast Enhanced Ultrasound (CEUS)

Contrast enhancement ultrasound technology is a method to make the intravascular images contrast by injecting lipid bubbles into the blood system. This method enhances the contrast of blood vessels using a material that diverts the ultrasound, resulting very sharp vessel images. However, application of the technique is very complicated and restricted to only certain cases. It shall not be confused to the image enhancement methods by spatial filtering of an ultrasound image.



## 2.4 Common Methods in Medical Image Enhancement

**Image Registration or Alignment** is used to align the images of tissues or organs to overlap exactly on each other. If images are taken at different moments and from different angles, even using different probes or sensors, these images are combined by image registration. This process is called as image registration. Image registration compares a reference image and the secondary images in a geometrical manner. Medically, CT and NMR are combined to combine information of both images and to obtain more detailed images about the tissues. It helps to diagnosis and monitoring of the growth of tumours, realization of a treatment, and the comparison of the data of the patient with anatomical atlases, more so in cartography, and in the vision of the computer, i.e. target localization, automatic quality control amongst others [18].

**Segmentation of Image** uses the colour of a region to isolate it, which may correspond to a tissue or organ in an image. It extracts any abnormal clot/lesion or blood vessels/cells appeared in an image [19]. It is one of the main procedures in medical image processing which is generally carried out after enhancement. The regions in a segmented image own equivalent aspects on features, for instance, the property difference from an area to another on an image and grey scale, structure or colour. It splits the image into groups corresponding to items during range of the view, which are primary in recognizing dissimilar kind of leukocytes otherwise calculating resulting in the magnitude of the tumour or Blood Vessels or some further issues occurring in the human body.

**Boundary Detection** is a substantial operation in medical image processing. It detects the structural information of the image, and thus, hugely decreases the information to be treated [19]. There is a variation in grey scale density, while edge is existent. Edge image possibly labelled as gradient image. The boundaries of image help in specifying the position and the aspect of the items, for example, lesions, tumours, blood cells, or vessels which are unusual in structure. The medical images are not similar because of issues of illumination and contrast. As such, the boundaries, in the beginning, are usually improved by applying the edge detection method.

**Morphology:** Morphology operations are nonlinear image processing methods to reshape the region in an image. They deal with the form of image features such as thinning, thickening, etc. [19]. Very often, it is required to collect a skeleton of an image or to erode/dilate an image or open/close an image to eliminate or plug small gaps or holes on an image form.

## **2.5 Design of Ultrasound Sensors**

The shape and the scene of US image depend on the design of transducer. Basic transducer formats can be as sector, linear array, and curved array as shown in Figure2.2.

**Sector (Phased) transducers** make slice-of-pie shaped images that sound slight in the near-field but own a wide view in the far-field. These transducers seem most favourable for checking bigger organs in among the ribs.

**Linear array transducers** can provide rectangular images with the image width aligned to the physical width of face transducer. Linear array transducers sometimes give the perfect image overall quality and excel for checking anatomy in the near-field only underneath the skin surface.

**Curved (Convex) array transducer** has a wide sensor with the gently curved sensing edge. It is differentiated from linear and sector transducers by a cross mark on the image. They provide a narrow-scene in the near-field while giving wider view of far-field [22].

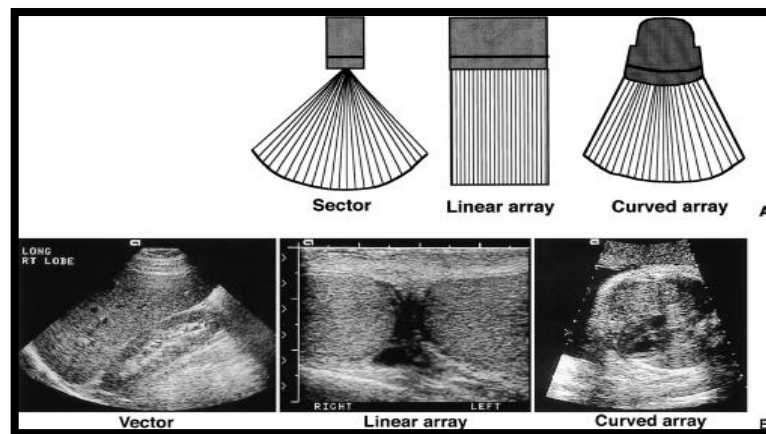


Figure 2.2: Design of the Ultrasound Probes and their Images by the permission from Lacus Ranchaus, 2014

## 2.6 Ultrasound Image Processing Related Research Studies

There are a number of studies conducted in the past, which compare various ultrasound speckle suppression and image enhancement methods for US images.

Donoho presented a soft-thresholding de-noising method in which the image observed is decomposed into wavelet domain. Using Donoho's method, Thakur et al made a comparative study of different wavelet filters that have various thresholding

values of US images and have come to the conclusion that de-noising methods of this kind are effective in that they preserve, besides suppressing the noise, the edge details [20]. Local histogram equalization (LHE) has been widely used. The region of interest in medical ultrasound image is usually surrounded by large areas of dark background, which include modest information but consumes a huge amount of computational resource. Direct use of LHE will not only consumes time but will in addition affect the global visibility due to the distortion of the background.

LHE algorithm is used on the centre pixel of this sub-block. The technique can speed up the pace of processing and decrease the background distortion remarkably. Xiaoying Li, Dong C.Liu used dynamic filtering technique for the particularly enhancement of images. Gajanand Gupta compared improved median filter technique with median and mean filter techniques. The median filter is one of the most commonly used nonlinear spatial domain filters. Wen Chien Yen, Shen-Chun Tai suggested the use of ultrasound enhancement method by employing the dual tree wavelet method [21].

## **2.7 Some Well-Known Filters**

Image pre-processing is applied to raw images in order to reduce image noise. Images with speckle noise, reflection and similar factors are pre-processed to reduce the effects of these factors. Filtering is among the pre-processing techniques which help in enhancing the images by removing the noise of the images [21].

Filtering techniques decrease undesirable signals which are recognized as “noise”. Efficiency of a filter measures the reduction of undesirable signals while keeping desired signal. Image enhancement and filtering methods are applied on the image

before the main operation such as object detection in order to reduce the degrading interference of the impulse noise in the image. Impulse noise was mostly caused when signal is converted from analogue to digital as the analogue-to-digital conversion error. For best efficiency, the type of filter to be applied on an image depends on the noise and intensity of the noise [23]. The following filters are used in this study:

**Mean (“Average”) Filter** smoothens the pixel values in an image making the intensity variation lesser between the pixels. It has an effect to reduce pixel values which does not represent properties of their surroundings. Mean filtering is obtained by applying a convolution mask (also called kernel) that represents sum of pixels in the mask divided by number of pixels in the mask. The dimension of the mask is often (3x3). The sum of mask coefficients shall be unity to provide no change in image brightness. One of the disadvantages of this filter is loss of the sharp details of image. However, easy implementation, and effectiveness of moving certain types of noise, such as impulse noise, are significant advantages of this filter [24].

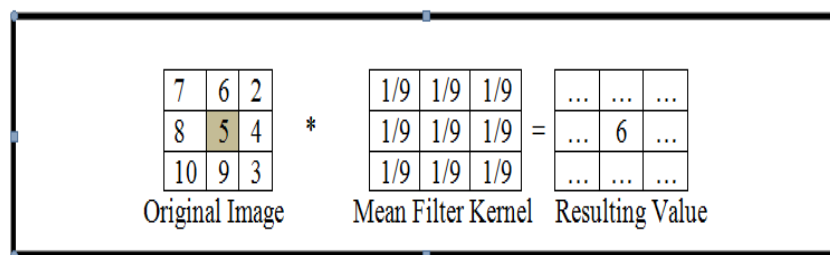


Figure 2.3: (3x3) Kernel Used in Mean Filtering

In Figure 2.3, the mean for the pixel 5 is calculated by the mean of all items in 3x3 matrixes, and “\*” represents convolution operation applied on image. The pixel value of the centre pixel is calculated by:

$$\text{Mean} = (7+6+2+8+5+4+10+9+3)/9=6.$$

If we number all elements in the mask from  $i=1$  to  $K$ , the pixel value  $\bar{g}(x, y)$  of the image after filtering the image  $g$  at coordinates  $(x, y)$  is obtained by equation:

$$\bar{g}(x, y) = \frac{1}{K} \sum_{i=1}^K g_i(x, y)$$

**Weighted Mean Filter** blurs an image by a smoothing process with the centre pixel having the highest effect, and other pixels with diminishing effect depending on distance from the centre pixel. The weights are normalized by a factor to have unity sum to keep the image brightness stable [25]. In other words, a weighted average is performed in the adjacent pixels and the values of the average are replaced. For a mask  $h$  with dimension  $(2L+1)$  by  $(2L+1)$ , each pixel of mask can be addressed by indices  $k= -L \dots L$  and  $l= -L \dots L$  as  $h(k, l)$ , which provides addressing the centre pixel of the image  $h$  by  $h(0,0)$ ; a general mathematical notation, this operation is shown by:

$$g(m, n) = \sum_{l=-L}^L \sum_{k=-L}^L h(k, l) s(m - k, n - l)$$

Where  $(m, n)$  is the pixel coordinate,  $L$  is half-size of the mask,  $g(m, n)$  is output pixel value at coordinate  $(m, n)$ ;  $h(k, l)$  is a weight in the mask,  $s(m - k, n - l)$  is a pixel in input image  $s$ , and  $\sum_{l=-L}^L \sum_{k=-L}^L$  is summation operators.

As an example, in Figure 2.4, the weighted-mean for the pixel 5 is calculate by the weighted mean of all items in 3x3 matrixes.

$$\text{Weighted-Mean} = (1*7+2*6+1*2+2*8+4*5+2*4+1*10+2*9+1*3)/16 = 6.$$

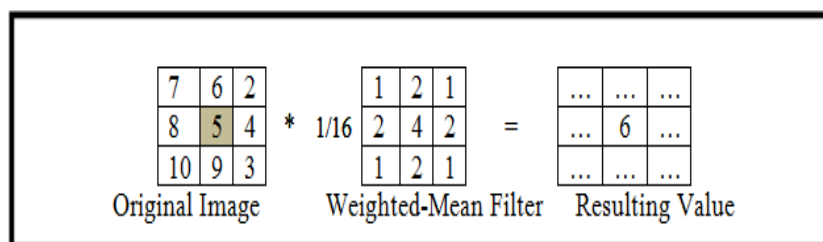


Figure 2.4: (3\*3) Weighted Averaging Filter

Properties of the weighted average filter are: It should be odd ordered, the sum of all the elements must be 1, and the weight of centre element must be more than all of the other elements [26].

**Median filter** is another non-linear digital filtering method that is static in nature. It is often used to decrease the image noise significantly. The idea behind the filter is to select the most representative value in the neighbourhood of the pixel as the filtered pixel value by sorting all neighbour pixels and pick the value at the middle of the sorted list as shown in Figure 2.5. For the preservation of information in the image, the median filter performs better than the other techniques such as mean filtering.

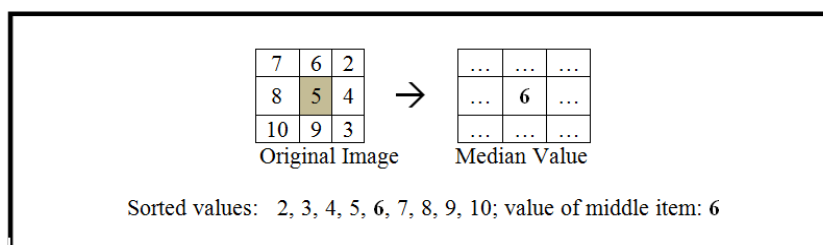


Figure 2.5: Calculating the Median Value of a Pixel Neighbourhood

## Chapter 3

### PROPOSED FILTERS AND TEST METHOD

#### 3.1 Video and Image Formats

This section provides an illustration of filter in proposed this thesis: temporal mean, temporal median and temporal weighted mean filter.

A **video** is made of a sequence of image frames to be displayed for a fraction of seconds. Human eyes integrate the image sequence to a continuous motion. The most common raw format of a video signal is RGB analogue component video, where the images are scanned row wise for all three colour components simultaneously. MATLAB has image processing toolbox to grab frames of any complex multimedia video format (i.e., MPEG, AVI etc.) to RGB images.

An **RGB image** is a representation of a single frame from a video by three matrices. The image  $f$  contains the *red*, *green* and *blue* pixel values  $f(x, y, c)$ , where  $c$  is the index for the colour, and  $x, y$  are pixel coordinates.

A **grayscale image** is representation of a grayscale frame by a single matrix,  $f$ . The pixels  $f(x,y)$  at coordinate  $(x, y)$  in the range  $(0, 1)$ , where 0 corresponds to black, and 1 is white. This thesis is interested only in grayscale images since ultra-sonographic devices provide only a grayscale raw video source.



**A raw video** is the video obtained directly from a video source, such as a video camera, or a radar screen, or, an ultrasonography screen. The noise of the video source requires filtering for suppressing the noise compared to the meaningful image signal.

**An image filter** is a mathematical operation on the pixel values of a raw image to suppress the noise of the image without reducing the meaningful part of the image.

The previous chapter explained three well-known image filtering methods: the mean, the median, and the weighted-mean filters. This section introduces the proposed temporal filters which converts a set of video frames to an enhanced image.

### 3.2 Proposed Temporal Filters

**A temporal image filter** is a mathematical operation that converts a set of video frames to a single image with less noise contents compared to any single frame of the video source.

**Temporal mask filter** converts a set of image frames  $d(i,j,k)$  with  $k=1,\dots,F,\dots, nf$  images into a single frame  $D(i, j)$  by pixel-wise mean between consecutive images around the image frame  $F$  of the video source. The general form of a temporal mask filter is:

$$D(i,j) = \sum_{p,q=-s,\dots,s; r=-t,\dots,t} h(p,q,r) d(p+i,q+j,r+F) / [(1+2s)^2 (1+2t)]$$

Where:  $D(i, j)$  is the intensity of the pixel at coordinate  $i,j$  of the filter output;  $d_{i,j,r}$  is the pixel intensity of the pixel at coordinate  $i, j$  of the  $r^{\text{th}}$  raw image in the video;  $S$  is the spatial half-depth,  $T$  is the temporal half-depth of the filter;  $h(p,q,r)$  is the three dimensional mask or kernel of the filter, which contains the weights of each raw

pixel at the neighbourhood of  $s$  and  $t$  around its centre pixel  $h(0,0,0)$  which overlaps on  $d(i,j,F)$ .

**Temporal mean filter** of any spatial and temporal depth is obtained by using unity mask coefficients by setting  $s$  and  $t$  for the required half-depths. It finds the average of the intensities at the neighbourhood of  $s$  and  $t$  around each pixel  $d(i,j,F)$  as the output pixel  $D(i,j)$ . For example, a  $0 \times 0 \times 1$  purely temporal (non-spatial) mean filter is obtained by pixel-wise mean of the frames  $r = F - 1$ ,  $r = F$ , and  $r = F + 1$ , which calculates:

$$D(i,j) = (d(i,j,F-1) + d(i,j,F) + d(i,j,F+1))/3.$$

**A temporal weighted mean filter** requires a three dimensional matrix of convolution mask,  $h(p,q,r)$ , shall have coefficients with overall average exactly unity. For example, a purely temporal  $0 \times 0 \times 3$  weighted mean filter with the centre weight three times higher than the previous and next frame weights shall be:

$h = [3/5, 9/5, 3/5]$ ; and it calculates the weighted-mean filter output as:

$$\begin{aligned} D(i,j) &= ((3/5) d(i,j,F-1) + (9/5) d(i,j,F) + (3/5) d(i,j,F+1))/3 \\ &= d(i,j,F-1)/5 + 3d(i,j,F)/5 + d(i,j,F+1)/5. \end{aligned}$$

**A temporal median filter** is calculated by the median operation along the pixels in the neighbourhood of  $s$  and  $t$  around the centre pixel  $(i, j)$ :

$$D(i,j) = \underset{\substack{p=i-s, \dots, i+s \\ q=j-s, \dots, j+s \\ r=k-t, \dots, k+t}}{\text{median}} \{d(p,q,r)\}$$

It is possible to have only spatial filtering effect by setting  $t=0$ , as well as, it is possible to obtain a purely temporal median filter by setting  $s=0$ , but  $t \neq 0$ .

The proposed temporal filters have both spatial and temporal smoothing effects since they convert the pixel intensity to the values between the maximum and minimum intensities in the spatial and temporal neighbourhood of the pixel, which makes them good candidates for suppressing the impulse noise in the images. As an example, figure 3.5 shows a raw centre image and the corresponding purely temporal median filtered image for the half-depth  $s = 0$ ,  $t = 9$ . It is clearly less noisy, and rich of details, which makes it preferable to the medical experts for the diagnosis purposes.

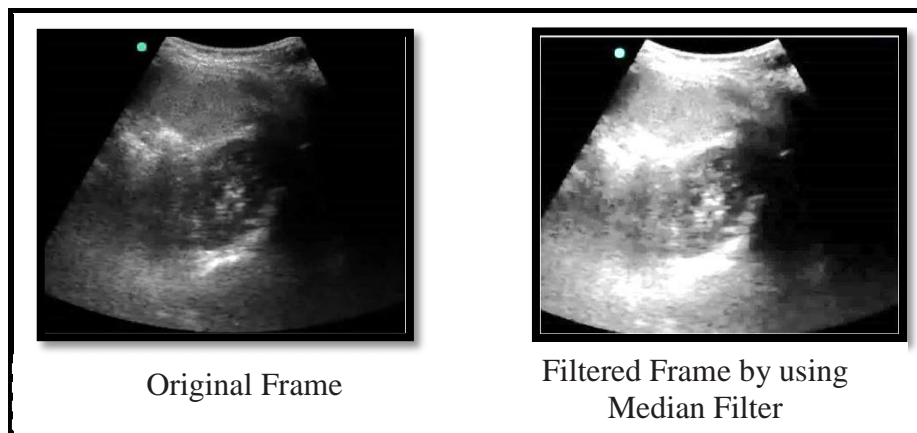


Figure 3.1: Pre-Processed and Filtered Image of Kidney

### 3.3 Determination of the Best Temporal Filter for Kidney US

The flow diagram of the assessment process to determine the best temporal filter and its parameters are demonstrated in figure 3.1. In this research, a set of kidney ultrasound video avi format had been captured and saved in MPEG format. The image frames of the videos were captured by the step function of image processing toolbox in MATLAB. The images were cropped and registered to overlap the kidney images on each image to the same coordinates.

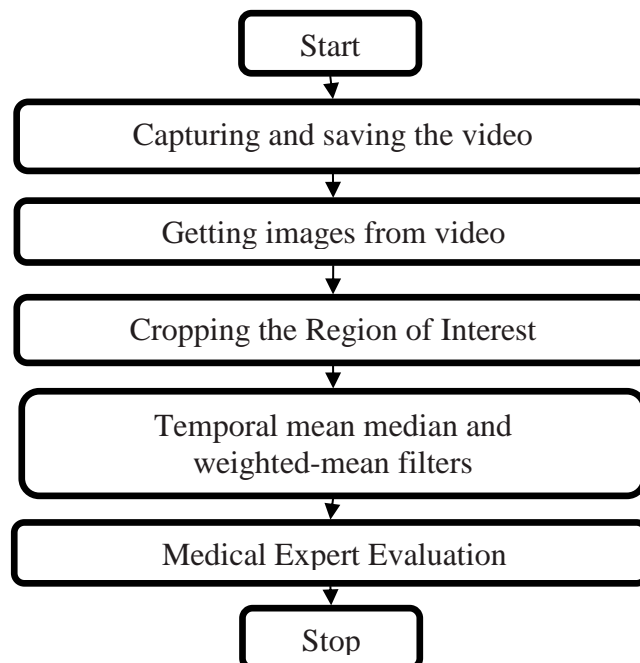


Figure 3.2: Overview of Assessment Process

In the evaluation process, total 11 videos are processed by three purely temporal filters at various temporal half-depths from 0 to 5, where 0 corresponds to using only a single image input, and 5 corresponds to using 11 frames to produce one filtered image output. For example, for temporal depth 5 frames, it uses previous 2 frames, plus the third frame as the centre frame, plus the next two frames in temporal mask filter operation.

**Capturing videos** is carried by medical doctors and expert technicians using an ultrasound device during the examination of patients. All 12 videos are captured by the same ultrasound device, but from different patients, which is decided by the medical doctor considering the significance of US images in diagnosis. However, it is naturally expected to observe similar benefits of the temporal filtering on other brands of US devices including 2D, 3D, 4D and Doppler Ultrasound.

These 12 video samples consists of 6 normal renal videos, 6 renal calculi (kidney stones, and complex cysts) videos. They are clips of around 20 seconds in avi file type with 25 frames per second. Consecutively, 25 frames can be captured per their seconds. One of them was marked later as not suitable for diagnosis, and remaining 11 videos are processed for the selection of the best filter in enhancing video captures to an image subject to kidney disease diagnosis.

**Getting Consecutive Images of a Video** is carried after a medical expert decides the significant frame of each video to determine the centre frame  $F$  for the temporal filtering. An original centre image of a kidney video is shown in figure 3.3.



Figure 3.3: The Centre Image of a Kidney Ultrasound Video

Thereafter, previous five, and next five frames starting from Fth frame is captured in grayscale image format, which is saved by MATLAB in a two dimensional matrix.

**Cropping the Region of Interest** is necessary to register the frames for the position and orientation of the kidney images. This step is carried manually using an image editor. Cropping removes most of the black areas around the kidney, and only the part for diagnosis remains in the cropped image.

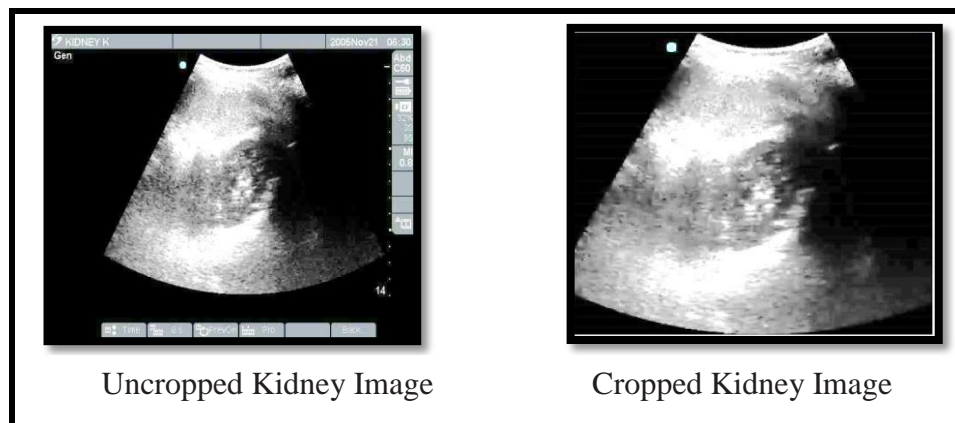


Figure 3.4: Cropping and Aligning the Image Frames

**Temporal mean median and weighted-mean filters** are applied to the manually cropped and aligned set of images to produce a set of filtered kidney images as described in Section 3.3. The filters are applied on all 11 frames are individually applied by this process.

**Medical Expert Evaluation** is the last step to determine the best filtering method among the three proposed temporal filters. All images generated from a single video capture are directed to one US expert, so that total 11 medical experts evaluated one series of filtered images blindly after an interview to inform them about the filtering method used in producing the images.

The evaluation is carried by assigning a score for each image without knowing which image is produced by which filter, and finally they are asked to fill comments about the best and the worst of the images for the purpose of diagnosis.

Kidney screening is used by US medical doctors to measure the size of the kidney in length and width. For this operation clear edges of the kidney image are basically necessary to have a more accurate measurement. Finally, the performance of different filters is compared based on the doctor's assessment.

## Chapter 4

### RESULTS OF PERFORMANCE EVALUATION

#### 4.1 Image Processing System for Proposed Filters

The filtering of medical ultrasound videos of kidney requires an image processing environment that can open a video file, capture images from the video frames, crop the images manually to align the target tissue to the same coordinates, access the intensities of each pixel by their coordinate, carry out processing on the intensities of the pixels, save and print the output images on disk in jpeg or pdf formats. Matlab R2016a is a convenient general purpose matrix operation software package with many toolbox sets to perform a very large set of operations on almost any scientific and technical field. It is set up on a personal computer with an Intel core i3 processor with 4GB RAM, with CPU 1.80 GHz 64-bit CPU and Windows 10 operating system.

The captured kidney ultrasound videos were saved in .avi format, and the filtered images were pro after that, the videos were copied into the laptop and separated into frames for image processing step. The image processing methods were applied to all frames images.



## 4.2 Implementation of Temporal Image Filtering

As explained in Chapter 3 on figure 3.1, the most significant image of the videos has been selected by the experts to determine the value of  $K$ . Next, videos were stripped off from all unnecessary frames to contain only 11 frames, from five frames before  $K^{\text{th}}$  frame to five frames after the  $K^{\text{th}}$ . A sample of the selected image, and its purely spatial mean, median and weighted mean filtered images are shown in figure 4.1.

The developed MATLAB script loads a video to memory by its file name. the *pre-processing section* of MATLAB script manages capturing 11 frames from the loaded video. After manual entry of the cropping box corners, the images become ready for temporal filtering.

Next section of the MATLAB script contains the temporal filters, which are applied on the required images in a for-loop increasing the depth of the temporal mean, median and weighted mean filters. The filtered images are printed in 2x2 subplot matrix as shown in figure 4.2, where (1) the top-left cell contains original frame, (2) the top-right cell has (3x3)-mean-filtered image, (3) the bottom-left cell has (3x3)-median-filtered image, and (4) the bottom-right cell keeps (3x3)-weighted-mean filtered image; for the spatial half-depths from 0 (raw image, labelled by Frame=1) to 5 (labelled by Frame=6).

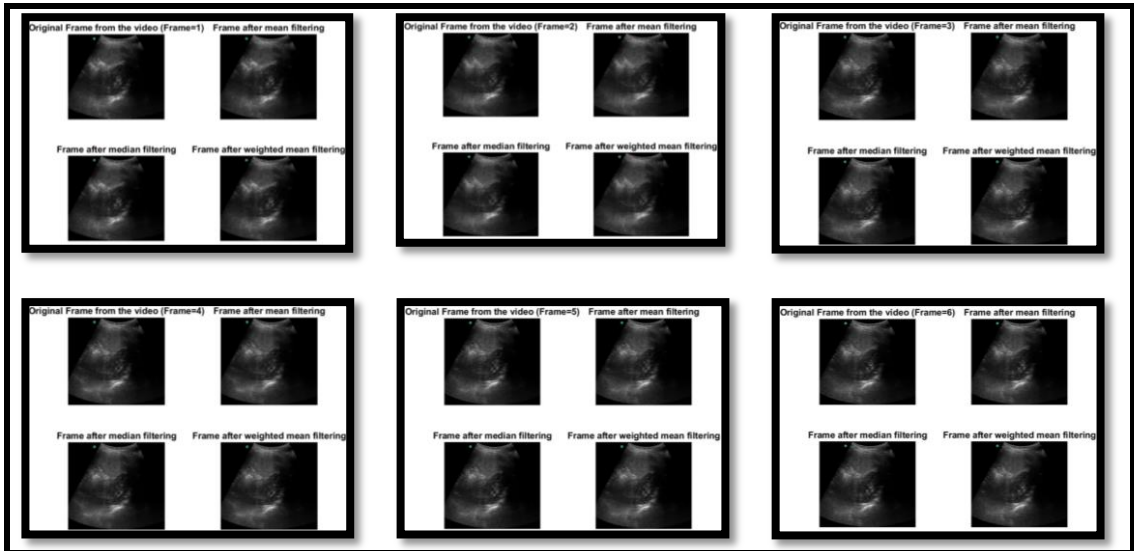


Figure 4.1: A Sample of Diagnostically Significant Image, and its 3x3 Mean, Median and Weighted-mean Images

For example when index is 3, mean filtered output is obtained by spatial mean filter using 3 frames. Similarly, for index 11, mean filtered output contains temporal filtration of 11 frames. The spatial and temporal filter outputs of a sample video are shown in figure 4.2, where the first box contains (3x3) spatial mean, median, and weighted-mean images; and remaining boxes contain temporal filtered images for the depths {3,5,7,9,11}. Each box is organized to contain (1 top-left) Mean, (2 top-right) median, and (3 bottom-left) weighted mean filtered images. These images are delivered to the experts to select the best image for the diagnosis of kidney disease and anomalies.

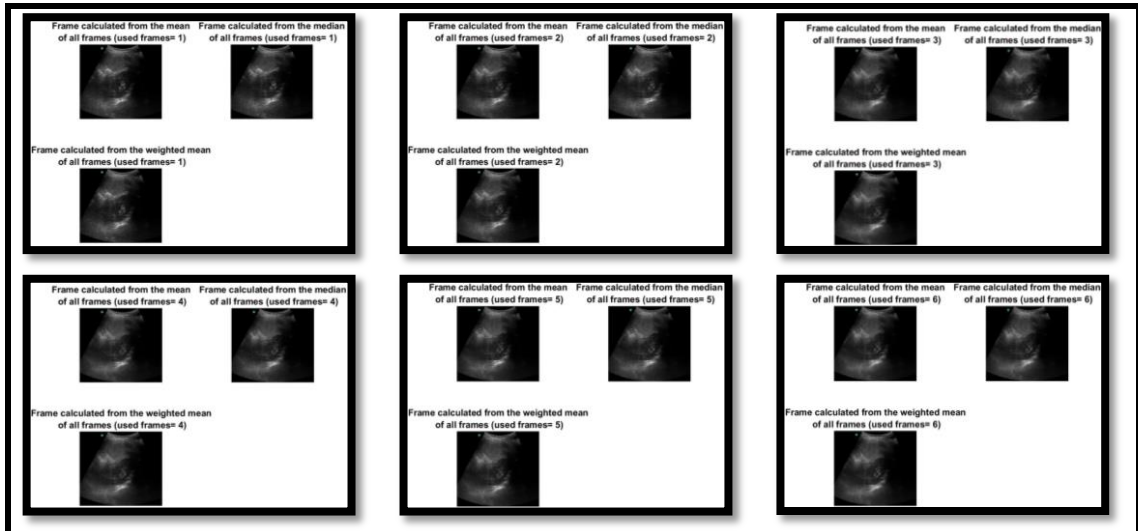


Figure 4.2: Temporal Filtered Image Results, Mean, Median, and Weighted mean

All images generated from a single video source are directed to the same expert, so that both the load of medical experts is reduced to minimum, as well as the fairness of the comparison between the filters is increased to maximum level. Each medical expert filled a questioner to score each filter type at 5 different temporal half-depth values against the raw image {1, 2, 3, 4, and 5}.

That means they scored 3x3- spatially filtered mean, median, weighted-mean total 3 images, plus, for 3 filters each at 5 temporal depth, total 18 images checking a score in the range of 0-10. One of the samples which is preferred by the expert with highest score is shown in figure 4.3.

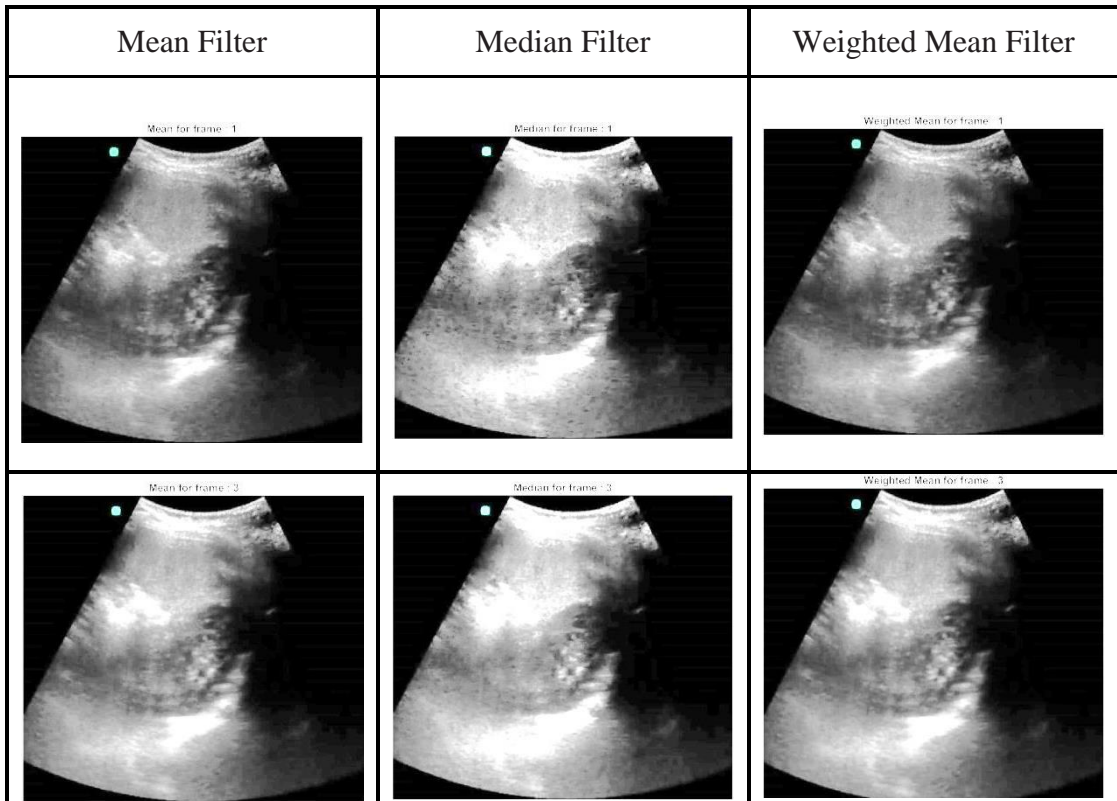


Figure 4.3: The Result of Selected Frames

On top of the evaluation for these 3-type times 5 depth image set, for the depth of images that collected the highest scores, mean, median, and weighted mean images are directed to the experts again, to verify their score, and to distinguish the best filter. A sample of these triplet image sets is shown in figure 4.4.

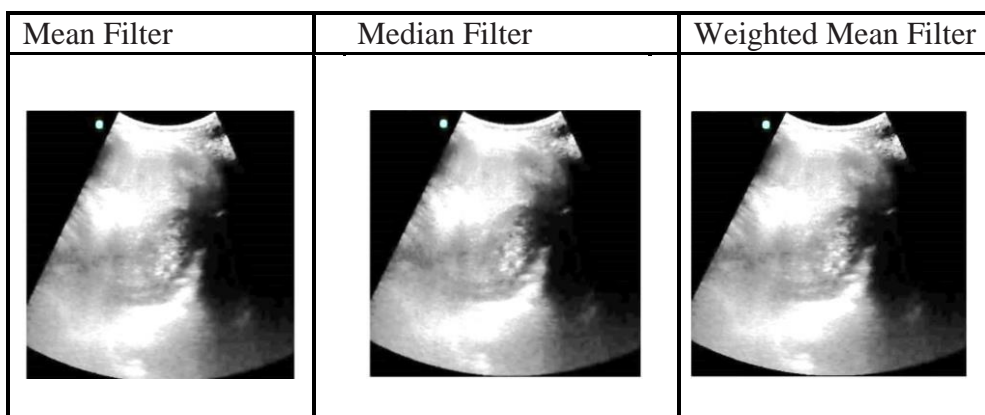


Figure 4.4: The Result of Collection All 11 Frames

### 4.3 Evaluation Process of Temporal Filters

In the evaluation phase, 18 filtered images from each video were evaluated by a single medical expert. The score is requested to rank the significance of each image in a scale from 1 to 10. Together with a score, experts were asked to fill in comments for the images. These comments are listed in Table 4.1.

Table 4.1: Doctors Comments on Mean Filter

NAMES OF DOCTORS	COMMENTS TO MEAN FILTER
Dr. Shirwan S. Atroshy	Regarding the mean filtration, we can depend on the first three one, otherwise the rest cannot be depend on it for diagnosis due to bad resolution.
Dr. Zhivan F. Amidy	Mean filter shows good resolution acceptable homogeneity texture.
Dr. Jalal J. Zanganna	The mean filtering is shows some flurring of the picture in the frame one through five but better in last frames.
Dr. Shilan M. Karkuki	The resolution of the images after mean filtering are becoming much better than the images before filtering
Dr. Hero O. Sindy	This kidney looks normal size, shapes, echogencity, and normal condition and corticomedullary differentiation cortical thickness, no stones and no hydronephrosis, no mass, and no cyst.
Dr. Süreyya Vudali Doğruyol	Latest Frames are more acceptable.

Table 4.2: Doctors Comments on Median Filter

NAMES OF DOCTORS	COMMENTS TO MEDIAN FILTER
Dr.Shirwan S. Atroshy	Regarding the second filtration, which is the median filtration, regarded the best between the three and we can depend even till the first sixth. However even this; the last three are terrible in resolution and it's difficult to depend on it.
Dr.Zhivan F. Amidy	Median filter shows good contrast of tissue and clear edges.
Dr.Jalal J. Zanganna	The median filter is better showing the details of the calyceal system of the kidney.
Dr.Shilan M. Karkuki	After using median filter, the noise in the pictures are much reduced, becoming much better quality and good resolution without effecting the fine details.
Dr.Hero O. Sindy	In this type of filter ("Median filter") the resolutions of the Kidney clearer than the previous filter ("Mean Filter").
Dr. Süreyya Vudali Doğruyol	Above all of the filters median filter has best resolution in my opinion.

Table 4.3: Doctors Comments on Weighted Mean Filter

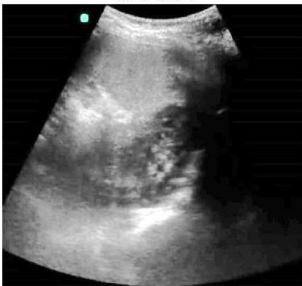

NAMES OF DOCTORS	COMMENTS TO WEIGHTED MEAN FILTER
Dr.Shirwan S. Atroshy	Concerning this filtration, really this filtration has awful resolution and much fog covering the image than the Mean, Median filter, all the subgroup belongs to this filtration apart from the first and second subgroup filtration, the all other subgroup are in adequate for diagnosis.
Dr.Zhivan F. Amidy	Not bad at all.
Dr.Jalal J. Zanganna	The weighted mean shows details like picture superior instruments like computed scan and better filtering of the tissue of the abdomen is better shows system of the kidney.
Dr.Shilan M. Karkuki	After using this type of filtering images are of a fine improved resolution and quality for us as Radiologist.
Dr.Hero O. Sindy	In this type of filter the resolution of the kidney is worse than that is in the previous filters
Dr. Süreyya Vudali Doğruyol	Again the latest frames are more satisfactory.


#### 4.4 Questioner Format of Expert Assessment

Samples of expert scores of video-4 and video-11 are listed in Tables from 4.4 to 4.9. They also give hint on the organization of evaluation forms. The experts scored each image freely according to single criteria: the sufficiency of the image for the diagnosis of kidney diseases, and for the accurate measurements of tissues and any formations.

For example, although the images are very similar to each other, in Table 4.4., the expert found all of them highly suitable for the diagnosis purpose, but, he distinguished a small difference among the temporal mean images between depth 3 and depth 5.

Table 4.4: Expert Scores for Video Clip 4 with Mean Filter

Frame count	Images	Score Evaluation
1		0 1 2 3 4 5 6 7 8 <u>9</u> 10
3		0 1 2 3 4 5 6 7 <u>8</u> 9 10

5		0 1 2 3 4 5 6 7 8 <u>9</u> 10
---	---	-------------------------------

At Table 4.5, again expert found temporal median filtering with depth 5 better than depth 3 cases. The scores higher than 7 means actually all images are highly suitable for the diagnosis, but, temporal median filtering at depth 5 made the image more preferable compared to the other two cases.

Table 4.5: Expert Scores for Video Clip 4 with Median Filter

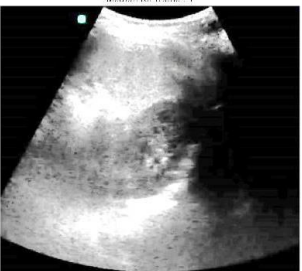

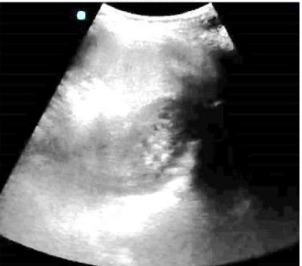
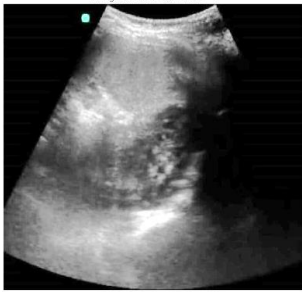

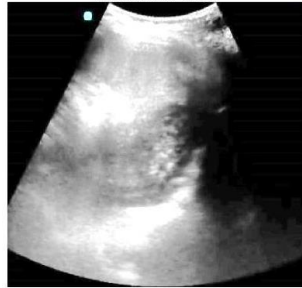
Frame count	images	Score Evaluation
1		0 1 2 3 4 5 6 7 8 <u>9</u> 10
3		0 1 2 3 4 5 6 7 <u>8</u> 9 10
5		0 1 2 3 4 5 6 7 8 <u>9</u> 10



Table 4.6 indicates that temporal filtering at depth 5 is useful also for weighted mean filtering case. At temporal depth 5, the filter reduces the shadow around the renal tissue, and makes it appear much clear compared to the filters of less depth.

Table 4.6: Expert Scores for Video Clip 4 with Weighted Mean Filter

Frame count	Images	Score Evaluation
1		0 1 2 3 4 5 6 7 8 <u>9</u> 10
3		0 1 2 3 4 5 6 7 <u>8</u> 9 10
5		0 1 2 3 4 5 6 7 8 9 <u>10</u>

At Tables 4.7, 4.8, and 4.9, the improvement of image quality again increases with the temporal depth of the filtering.

Table 4.7: Expert Scores for Video Clip 11 with Mean Filter




Frame count	Images	Score Evaluation
1	 <p>Mean for frame 1</p>	0 1 <u>2</u> 3 4 5 6 7 8 9 10
3	 <p>Mean for frame 3</p>	0 1 2 <u>3</u> 4 5 6 7 8 9 10
5	 <p>Mean for frame 5</p>	0 1 2 3 <u>4</u> 5 6 7 8 9 10

Table 4.8: Expert Scores for Video Clip 11 with Median Filter




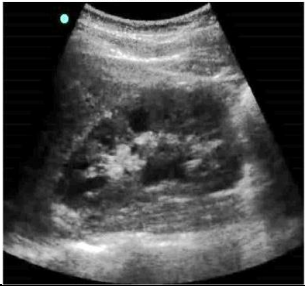
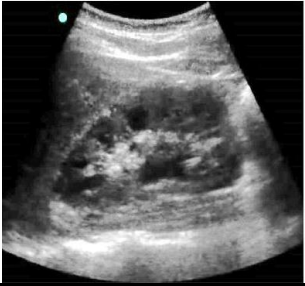

Frame count	Images	Score Evaluation
<b>1</b>	<p style="text-align: center; font-size: small;">Median for frame 1</p> 	0 1 2 3 4 <u>5</u> 7 8 9 10
<b>3</b>	<p style="text-align: center; font-size: small;">Median for frame 3</p> 	0 1 2 3 5 <u>6</u> 7 8 9 10
<b>5</b>	<p style="text-align: center; font-size: small;">Median for frame 5</p> 	0 1 2 3 4 5 6 <u>7</u> 8 9 10

Table 4.9: Expert Scores for Video Clip 11 with Weighted Mean Filter

Frame count	Images	Score Evaluation
1		0 1 2 <u>3</u> 4 5 6 7 8 9 10
3		0 1 2 3 <u>4</u> 6 7 8 9 10
5		0 1 2 3 <u>4</u> 5 6 7 8 9 10

## 4.5 Discussion of the Results

Following the expert evaluations for the 18 images of each of the 12 video sources, the scores decided by experts for each image is filled in table 4.10, and the cells of the table are filled with conditionally bar graphed for easy recognition of the successful clusters. In the table, video 12 is collected very low scores as expected before because the quality of the video was not found suitable for any diagnosis or measurement purpose according to the experts' opinion.

In the table, the sum of all images for the same type and both the same type and the same depth has been evaluated to determine the best filter type, and the best temporal depth of the filters. The overall sum for all depths of the same type over 12 video sources indicate that the temporal weighted mean filter worked better than the other two filters for this test set of the video sources in sufficiency of US images for the kidney disease and/or measurement purposes. It improved the expert scores maximum at temporal depth=11, from 33 to 77, at a rate of  $(77-33)/33= 133 \%$ . However, the other two temporal filters cannot be called useless since their benefit in improving the expert scores are  $(78-33)/33= 136 \%$  for mean, and  $(78-28)/28= 1.78\%$  for the median filter when temporal depth is set to 11 frames.

As a result of these evaluations, it is decided that the temporal filtering is extremely useful in enhancing the ultrasound images. Filtering of raw image with a temporal mean, median or weighted mean filter of a temporal depth 11 frames provide almost three times cleaner US image compared to the spatial filtered images.

Table 4.10: Expert Assessment Scores for Images of All Tested Filters

Filters:	<u>Temporal Mean</u>						<u>Temporal Median</u>						<u>Temporal Weighted-Mean</u>					
Depth: Videos	1	3	5	7	9	11	1	3	5	7	9	11	1	3	5	7	9	11
Video1	5	6	7	7	8	9	2	3	4	5	7	8	3	4	4	5	7	8
Video2	7	5	4	7	6	4	8	7	6	6	4	4	7	6	4	7	5	4
Video3	1	2	4	6	8	10	1	2	3	6	8	9	1	2	3	4	7	9
Video4	9	8	9	6	5	3	9	8	9	7	5	3	9	8	10	6	5	3
Video5	2	3	3	2	3	3	1	1	1	3	4	5	2	2	3	3	4	4
Video6	2	2	3	3	4	4	2	3	3	3	4	4	2	3	3	3	4	6
Video7	0	0	4	4	5	7	2	3	5	6	8	8	2	4	5	5	6	6
Video8	0	0	3	4	6	8	0	1	3	5	6	8	1	3	4	6	7	6
Video9	0	0	4	6	8	9	0	2	3	5	7	9	1	3	6	8	9	10
Video10	0	0	2	4	6	8	0	3	4	6	7	9	1	4	6	8	9	10
Video11	5	6	7	7	8	9	2	3	4	5	7	8	3	4	4	5	7	8
Video12	2	2	2	3	3	4	1	2	3	2	3	3	1	1	1	2	2	3
sum:	33	34	52	59	70	78	28	38	48	59	70	78	33	44	53	62	72	77
overall sum:				326						321						341		

## Chapter 5

### CONCLUSION

In this thesis, a new image enhancement technique on medical ultrasound kidney imaging has been proposed based on mean, median and weighted median image filters. The approach enhances the image by processing the consecutive frames of a video by expanding the filtration techniques to temporal domain. The proposed methods are examined on twelve kidney diagnosis video clips by doctor's assessment. The images are split between total 6 radiology doctors to score them over 10, higher score indicating the image is more useful for the purpose of diagnosis. They also marked the best among a series of the filtered images.

From this evaluation it is deduced that the temporal mean filter with depth of 11 frames provides highest improvement for diagnosis, keeping the details of image apparent and remarkable, while removing noise considering the purpose of diagnosis. However, the results also shows that the weighted-mean filter gives more robust improvement on the images for diagnosis in an average for all range of temporal depths. Also, the experts assigned highest scores to the temporal weighted-mean filtered images with depth=11 compared to the other two filters. The proposed methods may be integrated in US devices to provide higher quality medical ultrasound images to obtain better images for the diagnosis and identify, locate and determine the size of a renal calculi.

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## **APPENDIX**

# Appendix A: Main Code

```
clc
clear
close all

% select a video
% you can use any .avi video here. just write complete name with the extension
filename=input('Please enter a video number (1-12): ');
filename = '1.avi';
% filename = '2.avi';
% filename = '3.avi';
% filename = '4.avi';
% filename = '5.avi';
% filename = '6.avi';
% filename = '7.avi';
% filename = '8.avi';
% filename = '9.avi';
% filename = '10.avi';
% filename='11.avi';
% filename='12.avi';

% convert video into frame
% this user defined function will break the selected video into multiple
% frames. each frame can then be used as an individual image for further
% image processing
frames=vdo_to_frame(filename);

% pause

%-----
% PART 1
%-----
% in part 1, we are taking the first 11 frames from the selected video file
% we are then applying mean, median and weighted mean filter on each of these frames
% below code will make a subplot with 4 images in 1 figure window.
% these 4 images will be:
% 1- original frame
% 2- frame after mean filter
% 3- frame after median filter
% 4- frame after weighted mean filter
%-----
% apply mean filter on all the frames
mean_filtered_frames=mean_filter(frames);
% apply median filter on all the frames
median_filtered_frames=median_filter(frames);
% apply weighted mean filter on all the frames
weighted_filtered_frames=weighted_mean_filter(frames);

% display 11 frames
for i=1:11
    figure % this figure window will show 4 different frames as described below

    % show the original frame from video
    subplot(2,2,1)
    imshow(uint8(frames(:,:,i)))
    title(['Original Frame from the video (Frame= ' num2str(i) ' )'])

    % show the result of mean filtering on the original frame
    subplot(2,2,2)
    imshow(uint8(mean_filtered_frames(:,:,i)))
    title('Frame after mean filtering')

    % show the result of median filtering on the original frame
    subplot(2,2,3)
    imshow(uint8(median_filtered_frames(:,:,i)))
    title('Frame after median filtering')

    % show the result of weighted mean filtering on the original frame
    subplot(2,2,4)
    imshow(uint8(weighted_filtered_frames(:,:,i)))
    title('Frame after weighted mean filtering')

    saveas(gcf,['PART 1--Frame count ' num2str(i) '.jpg'])
end
close all
%-----
% PART 2
%-----
% here we work on making super resolution frames using mean, median and weighted mean
% this is again done for first 11 frames
% as we gradually increase the count for the loop, we gradually increase the data to process
% for example: for idx=3 mean super resolution frame will be mean of first 3 frames
% for idx=11 mean super resolution frame will be mean of first 11 frames
%-----
% making super resolution frames using:
% 1- mean and median and weighted mean statistics
% 2- 1 to 11 frames
for idx=1:11
    mean_superframe(:,:,idx)=mean_of_frames(frames,idx); % superframe matrix for mean statistics
    median_superframe(:,:,idx)=median_of_frames(frames,idx); % superframe matrix for median statistics
    weighted_mean_superframe(:,:,idx)=weighted_mean_of_frames(frames,idx); % superframe matrix for weighted mean statistics

    figure
    subplot(2,2,1)
    imshow(uint8(mean_superframe(:,:,idx))) % display the super resolution frame
    title(['Frame calculated from the mean'];[' of all frames (used frames= ' num2str(idx) ')'])
    % saveas(gcf,['PART 2--Super resolution mean frame, used frames= ' num2str(idx) '.jpg'])

    subplot(2,2,2)
    imshow(uint8(median_superframe(:,:,idx)))% display the super resolution frame
    title(['Frame calculated from the median'];[' of all frames (used frames= ' num2str(idx) ')'])
    % saveas(gcf,['PART 2--Super resolution median frame, used frames= ' num2str(idx) '.jpg'])

    subplot(2,2,3)
    imshow(uint8(weighted_mean_superframe(:,:,idx)))% display the super resolution frame
    title(['Frame calculated from the weighted mean'];[' of all frames (used frames= ' num2str(idx) ')'])

    saveas(gcf,['PART 2--Super resolution mean, median and weighted mean frame, used frames= ' num2str(idx) '.jpg'])
end

%-----
% PART 3
%-----
% here we again work on finding super resolution frames, but with a new technique
% we make use of previous and after frames this time
% here we compute mean-1,3,5,7,9,11. same goes for median and weighted mean
% the number indicates the total number of frames involved in making a super resolution frame
% more description can be seen in each figure's name
%-----
for i=[1 3 5 7 9 11]
    newframe_mean1=selective_mean(1,frames,i);
    imwrite(uint8(newframe_mean1),['Frame ' num2str(i) '--Mean 1 super resolution frame using the same frame only.jpg'])
    newframe_median1=selective_median(1,frames,i);
    imwrite(uint8(newframe_median1),['Frame ' num2str(i) '--Median 1 super resolution frame using the same frame only.jpg'])

    newframe_weighted_mean1=selective_weighted_mean(1,frames,i);
    imwrite(uint8(newframe_weighted_mean1),['Frame ' num2str(i) '--weighted Mean 1 super resolution frame using the same frame only.jpg'])

    newframe_mean3=selective_mean(3,frames,i);
    imwrite(uint8(newframe_mean3),['Frame ' num2str(i) '--Mean 3 super resolution frame using 1 before and 1 after frame.jpg'])
    newframe_median3=selective_median(3,frames,i);
    imwrite(uint8(newframe_median3),['Frame ' num2str(i) '--Median 3 super resolution frame using 1 before and 1 after frame.jpg'])
end
```

```

newframe_weighted_mean3=selective_weighted_mean(3,frames,i);
imshow(uint8(newframe_weighted_mean3),['Frame ' num2str(i) '--Weighted Mean 3 super resolution frame using 1 before and 1 after frame.jpg'])

newframe_mean5=selective_mean(5,frames,i);
imshow(uint8(newframe_mean5),['Frame ' num2str(i) '--Mean 5 super resolution frame using 2 before and 2 after frame.jpg'])
newframe_median5=selective_median(5,frames,i);
imshow(uint8(newframe_median5),['Frame ' num2str(i) '--Median 5 super resolution frame using 2 before and 2 after frame.jpg'])
newframe_weighted_mean5=selective_weighted_mean(5,frames,i);
imshow(uint8(newframe_weighted_mean5),['Frame ' num2str(i) '--Weighted Mean 5 super resolution frame using 2 before and 2 after frame.jpg'])

newframe_mean7=selective_mean(7,frames,i);
imshow(uint8(newframe_mean7),['Frame ' num2str(i) '--Mean 7 super resolution frame using 3 before and 3 after frame.jpg'])
newframe_median7=selective_median(7,frames,i);
imshow(uint8(newframe_median7),['Frame ' num2str(i) '--Median 7 super resolution frame using 3 before and 3 after frame.jpg'])
newframe_weighted_mean7=selective_weighted_mean(7,frames,i);
imshow(uint8(newframe_weighted_mean7),['Frame ' num2str(i) '--Weighted Mean 7 super resolution frame using 3 before and 3 after frame.jpg'])

newframe_mean9=selective_mean(9,frames,i);
imshow(uint8(newframe_mean9),['Frame ' num2str(i) '--Mean 9 super resolution frame using 4 before and 4 after frame.jpg'])
newframe_median9=selective_median(9,frames,i);
imshow(uint8(newframe_median9),['Frame ' num2str(i) '--Median 9 super resolution frame using 4 before and 4 after frame.jpg'])
newframe_weighted_mean9=selective_weighted_mean(9,frames,i);
imshow(uint8(newframe_weighted_mean9),['Frame ' num2str(i) '--Weighted Mean 9 super resolution frame using 4 before and 4 after frame.jpg'])

newframe_mean11=selective_mean(11,frames,i);
imshow(uint8(newframe_mean11),['Frame ' num2str(i) '--Mean 11 super resolution frame using 5 before and 5 after frame.jpg'])
newframe_median11=selective_median(11,frames,i);
imshow(uint8(newframe_median11),['Frame ' num2str(i) '--Median 11 super resolution frame using 5 before and 5 after frame.jpg'])
newframe_weighted_mean11=selective_weighted_mean(11,frames,i);
imshow(uint8(newframe_weighted_mean11),['Frame ' num2str(i) '--Weighted Mean 11 super resolution frame using 5 before and 5 after frame.jpg'])

figure('units','normalized','outerposition',[0 0 1 1])

subplot(2,3,1)
imshow(uint8(newframe_mean1))
title(['Mean 1 for frame : ' num2str(i)])
subplot(2,3,2)
imshow(uint8(newframe_mean3))
title(['Mean 3 for frame : ' num2str(i)])
subplot(2,3,3)
imshow(uint8(newframe_mean5))
title(['Mean 5 for frame : ' num2str(i)])
subplot(2,3,4)
imshow(uint8(newframe_mean7))
title(['Mean 7 for frame : ' num2str(i)])
subplot(2,3,5)
imshow(uint8(newframe_mean9))
title(['Mean 9 for frame : ' num2str(i)])
subplot(2,3,6)
imshow(uint8(newframe_mean11))
title(['Mean for frame : ' num2str(i)])

saveas(gcf,['PART 3--Super resolution Mean frames for frame= ' num2str(i) '.jpg'])

figure('units','normalized','outerposition',[0 0 1 1])

subplot(2,3,1)
imshow(uint8(newframe_median1))
title(['Median 1 for frame : ' num2str(i)])
subplot(2,3,2)
imshow(uint8(newframe_median3))
title(['Median 3 for frame : ' num2str(i)])
subplot(2,3,3)
imshow(uint8(newframe_median5))
title(['Median 5 for frame : ' num2str(i)])
subplot(2,3,4)
imshow(uint8(newframe_median7))
title(['Median 7 for frame : ' num2str(i)])
subplot(2,3,5)
imshow(uint8(newframe_median9))
title(['Median 9 for frame : ' num2str(i)])
subplot(2,3,6)
imshow(uint8(newframe_median11))
title(['Median for frame : ' num2str(i)])

saveas(gcf,['PART 3--Super resolution Median frames for frame= ' num2str(i) '.jpg'])

figure('units','normalized','outerposition',[0 0 1 1])

subplot(2,3,1)
imshow(uint8(newframe_weighted_mean1))
title(['Weighted Mean 1 for frame : ' num2str(i)])
subplot(2,3,2)
imshow(uint8(newframe_weighted_mean3))
title(['Weighted Mean 3 for frame : ' num2str(i)])
subplot(2,3,3)
imshow(uint8(newframe_weighted_mean5))
title(['Weighted Mean 5 for frame : ' num2str(i)])
subplot(2,3,4)
imshow(uint8(newframe_weighted_mean7))
title(['Weighted Mean 7 for frame : ' num2str(i)])
subplot(2,3,5)
imshow(uint8(newframe_weighted_mean9))
title(['Weighted Mean 9 for frame : ' num2str(i)])
subplot(2,3,6)
imshow(uint8(newframe_weighted_mean11))
title(['Weighted Mean for frame : ' num2str(i)])

saveas(gcf,['PART 3--Super resolution Weighted Mean frames for frame= ' num2str(i) '.jpg'])
pause
end

%-----
% PART 4
%-----
% this is method 3 for calculating a super resolution frame
% here we are directly taking mean, median and weighted mean
% of first 11 frames
%-----

superframe1_mean=mean_of_frames(frames,11); % superframe matrix for mean statistics
superframe2_median=median_of_frames(frames,11); % superframe matrix for median statistics
superframe3_weightedmean=weighted_mean_of_frames(frames,11); % superframe matrix for weighted mean statistics

figure
imshow(uint8(superframe1_mean))
title('Super resolution frame from mean of first 11 frames')

figure
imshow(uint8(superframe2_median))
title('Super resolution frame from median of first 11 frames')

figure
imshow(uint8(superframe3_weightedmean))
title('Super resolution frame from weighted mean of first 11 frames')

```