بِسْمِ اللهِ الرَّحْمٰنِ الرَّحِيْمِ

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USING STRAIN ESTIMATION TO IMPROVE DETECTION OF TUMORS IN ULTRASONOGRAPHIC IMAGES

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It is hereby declared that this thesis or any part of it has not been submitted elsewhere for the award of any degree or diploma.

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Abstract

Ultrasound imaging is a diagnostic imaging technique based on the application of ultrasound. It is used to see internal body structures such as tendons, muscles, joints, vessels and internal organs. Its aim is often to find a source of a disease or to exclude any pathology. However, in order to gain more valuable information from the image, more processing needs to be done on the images themselves. One of these is strain calculation from the image. Pressure is applied to the area from which the image is derived and the behavior of the tissues in response to various amounts of pressure is observed. There are various methods to calculate the strain from an image. We propose a new method which makes use of Kalman filter for the strain estimation. From the motion vector of the tissues deformation, estimated using Kalman filter, we can classify whether the tissue exhibits cancerous behavior or it is a normal tissue.

Acknowledgements

First of all we would like to thank Almighty Allah, whose blessings allowed us to complete the thesis within time and up to an expected standard.

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CHAPTER 1: INTRODUCTION

1.1 Overview

Images produced using ultrasound is a versatile technique which has numerous applications in the field of medicine. It is possible to perform both diagnosis and therapeutic procedures, using ultrasound to guide interventional procedures (for instance biopsies or drainage of fluid collections). Sonographers are medical professionals who perform scans which are then typically interpreted by themselves or the radiologists, physicians who specialize in the application and interpretation of a wide variety of medical imaging modalities, or by cardiologists in the case of cardiac ultrasonography (echocardiography). Sonographers typically use a hand-held probe (called a transducer) that is placed directly on and moved over the patient. Increasingly, clinicians (physicians and other healthcare professionals who provide direct patient care) are using ultrasound in their office and hospital practices.However, the purpose of our research does not involve any medical professional, rather it seeks to use image processing techniques as a substitute for the diagnosis. But before delving into the specifics of the purpose and method which we wish to use, an overview of the ultrasound imaging process is required.

Ultrasound is sound waves with frequencies which are higher than those audible to humans (>20,000 Hz). Ultrasonic images also known as sonograms are made by sending pulses of ultrasound into tissue using a probe. The sound echoes off the tissue; with different tissues reflecting varying degrees of sound. These echoes are recorded and displayed as an image to the operator. The image shown helps to detect changes in appearance, size or contour of organs, tissues, and vessels or to detect abnormal masses, such as tumors. A transducer both sends the sound waves into the body and receives the echoing waves. When the transducer is pressed against the skin, it directs small pulses of inaudible, high-frequency sound waves into the body. As the sound waves bounce off internal organs, fluids and tissues, the sensitive receiver in the transducer records tiny changes in the sound's pitch and direction. These signature waves are instantly measured and displayed by a computer, which in turn creates a real-time picture on the monitor. One or more frames of the moving pictures are typically captured as still images. Short video loops of the images may also be saved. [1] A visual diagram of the process is shown below:

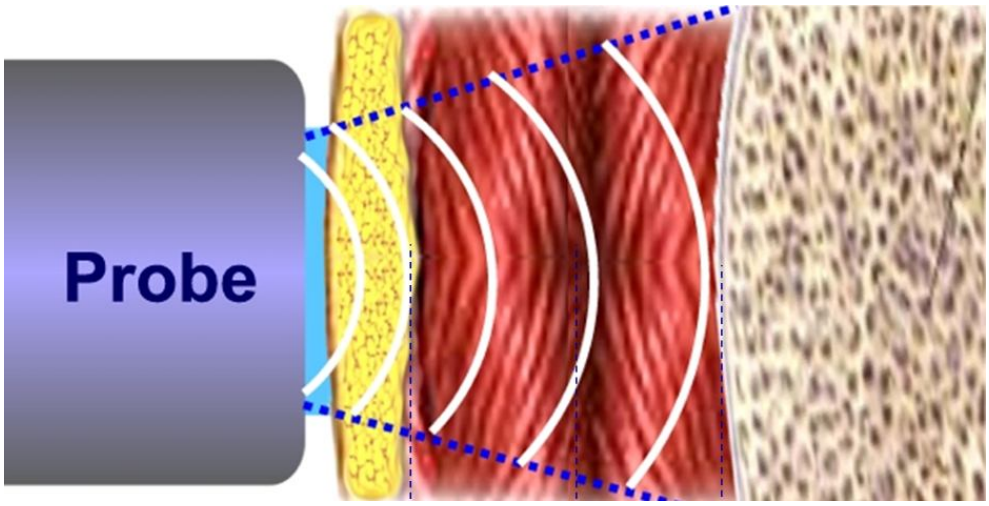


Figure 1: Ultrasound process

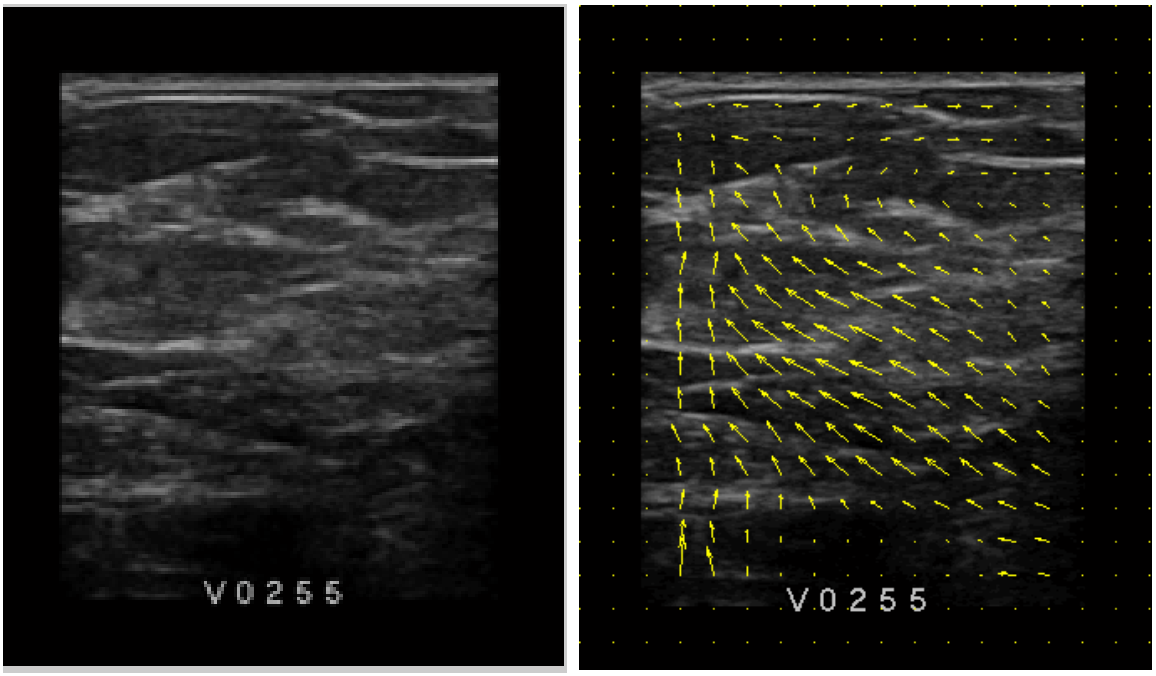


Figure 2: Ultrasound image along with optical flow displacements with another image

1.2Problem Statement

The area of interest for us is an application of ultrasound imaging called elastography. Elastography is a medical imaging modality that maps the elastic properties of soft tissue. The main idea is that whether the tissue is hard or soft will give diagnostic information about the presence or status of disease. For example, cancerous tumors will often be harder than the surrounding tissue, and diseased livers are stiffer than healthy ones. Other uses of elastography include:

- identifying early traumatic changes in muscles and tendons
- aiding in deciding the biopsy site more accurately, reducing negative biopsy rates
- assessing liver fibrosis
- assessing liver steatosis (abnormal retention of lipids within a cell)

The process of elastography is outlined as follows. There are numerous elastographic techniques, in development stages from early research to extensive clinical application. Each of these techniques works in a different way. What all methods have in common is that they create a distortion in the tissue, observe and process the tissue response to infer the mechanical properties of the tissue, and then display the results to the operator, usually as an image. Each elastographic method is characterized by the way it does each of these things.

To image the mechanical properties of tissue, we need to see how it behaves when deformed. There are three main ways of inducing a distortion to observe. These are:

- Pushing/deforming or vibrating the surface of the body (skin) or organ (prostate) with a probe or a tool,
- Using radiation force of focused ultrasound to remotely create a 'push' inside the tissue, and
- Using distortions created by normal physiological processes, e.g. pulse or heartbeat.

The primary way elastographic techniques are categorized is by what imaging modality (type) they use to observe the response. Elastographic techniques use ultrasound, magnetic resonance imaging (MRI) and pressure/stress sensors in tactile imaging (TI). There are a handful of other methods that exist as well.

The observation of the tissue response can take many forms. In terms of the image obtained, it can be 1-D (i.e. a line), 2-D (a plane) or 3-D (a volume), or just a single value, and it can either be a video or a single image. In most cases, the result is displayed to the operator along with a conventional image of the tissue, which shows where in the tissue the different stiffness values occur. Once the response has been observed, the stiffness can be calculated from it. Most

elastography techniques find the stiffness of tissue based on one of two main principles:

- For a given applied force (stress), stiffer tissue deforms (strains) less than does softer tissue.
- Mechanical waves (specifically shear waves) travel faster through stiffer tissue than through softer tissue.

Some techniques will simply display the distortion and/or response, or the wave speed to the operator, while others will compute the stiffness (specifically the Young's modulus or similar shear modulus) and display that instead. Some techniques present results quantitatively, while others only present qualitative (relative) results.

There are mainly two different types of elastography namely strain elastography (also known as static or compression elastography) and shear wave elastography(also known as transient elastography). Strain elastography is our area of interest. Strain elastography assesses tissues' macro structure through the strain modulus. This is different from normal B-mode grayscale ultrasound which characterizes a tissue's elasticity, but at a micro level. Strain elastography relies on Young's modulus to detect strain in the axial dimension. The characteristics of an ultrasound beam through tissue before and after compression are compared. In some systems, the strain of tissues is measured in a semi-quantitative way, relying on Young's modulus, but not directly calculating it.

On the other hand, in case of shear wave elastography, the concept is similar to strain elastography, but instead of using transducer pressure to compare a shift in an ultrasound A-line (thereby measuring changes in strain), a higher intensity pulse is transmitted to produce shear waves, which extend laterally from the insonated(exposed to ultrasonographic waves) structure. The shear waves may then be tracked with low intensity pulses to find the shear velocity and this velocity is related to Young's modulus.

Quasistatic elastography or strain imaging (sometimes called simply 'elastography' for historical reasons) is a pioneering elastography technique. In this technique, an external compression is applied to tissue, and the ultrasound images before and after the compression are compared. The areas of the image that are least deformed are the ones that are the stiffest, while the most deformed areas are the least stiff. Generally, what is displayed to the operator is an image of the relative distortions (strains), which is often of clinical utility. From the relative distortion image, however, making a quantitative stiffness map is often desired. To do this requires that assumptions be made about the nature of the soft tissue being imaged and about tissue outside of the image. Additionally, under compression, objects can move into or out of the image or around in the image, causing problems with interpretation. Another limit of this technique is that like manual palpation, it has difficulty with organs or tissues that are not close to the surface or easily compressed.

The elastic properties of soft tissues depend on theirmolecular building blocks, and on the microscopic andmacroscopic structural organization of these blocks. The standard

medicalpractice of the soft tissue palpation is based on qualitative assessment of the low-frequencystiffness of tissue. Pathological changes are generallyknown to be correlated with changes in tissue stiffnessas well. Many cancers, such as scirrhous carcinoma of the breast, appear as extremely hard nodules. In many cases, despite the difference in stiffness, the small size of a pathological lesion and/or its location deep in the body preclude its detection and evaluation by palpation. In general, the lesion may or may not possessechogenic properties which would make it ultrasonically detectable. For example, tumors of the prostate or thebreast could be invisible or barely visible in standardultrasound examinations, yet be much harder than the embedding tissue. Diffuse diseases such as cirrhosisof the liver are known to significantly increase the stiffness of the liver tissue on the whole, yet they may appear normal in a conventional ultrasound examination. Since the echogenicity and stiffness of the tissue are generally uncorrelated it is expected that imaging tissue stiffness and strain will provide new information that is related to their structure. [3] This is the main purpose of strain elastography.

1.3Research Challenges

While it may seem that strain imaging is infallible for tumor detection in the various areas such as breasts, prostate gland, thyroid gland etc. it too is not without its limitations.

Quasi-static elastography cannot give a quantitative value for the Young's modulus since only the strain can beestimated and the applied stress is unknown. It is thus impossible to recover the Young's modulus using Hooke's law.The main limitations of this technique are still the control of the stress applied, which remains operator dependent,and the absence of a specific quantification. In addition, theuse of a stress applied by the operator limits the techniqueto superficial organs, mainly the breast or the thyroid. Strain elastography in all its forms remains an examiner-dependent method. All SE techniques require a trained and experienced operator to perform valid free-hand cyclic compressions that can yield reliable and reproducible SE readings. The free-hand probe pressure is difficult to standardize among different US operators and strain variations due to changes in the amplitude and velocity of compression that cannot be avoided. Non-uniform compressions produce intra- and inter-observer variability. Therefore, several compression-relaxation cycles are needed to ensure that quality data are obtained. Another important issue is the fact that pre-stress compression can result in misleadingly high stiffness results, especially in superficial tissues like the thyroid or prostate. Therefore, the operator should be trained to maintain just a light contact and pressure before beginning the cycles of palpations because tissues appear stiffer when they are pre-compressed. Another technical limitation is the lack of standardization both in the technique application, the type of measurements obtained, the cut-off values, and the color coding. [4]

Other than that, in contrast to engineering materials, the mechanical properties of biological tissues are not easily definable by closed-form mathematical expressions. When living, tissues are metabolically active and exhibit certain mechanical properties, which change soon after

death. Moreover, these mechanical properties may be dependent on age, strain rate and strain range.

1.4 Thesis Objectives

During the course of this thesis we researched with the aim of finding a way to improve detection of tumors in ultrasonographic images by using strain estimation. Thus the general objectives of the thesis are:

- Improving the Signal-to-noise Ratio (SNR) in measuring displacements between ultrasonographic images
- Measuring large displacements accurately using optical flow
- Providing competitive results to existing methods of strain estimation

1.5 Thesis Organization

The thesis is organized as follows: Chapter 2 provides the literature review of all the papers and sources that were the basis of our research as well as existing methods of strain estimation that are being used in other applications. In chapter 3 we provide our proposed methodology and how we have implemented it. Chapter 4 compares the results of our proposed method against the existing methods of cross correlation and traditional optical flow. Finally in chapter 5 we conclude our thesis and provide some future work possibilities.

CHAPTER 2: LITERATURE REVIEW

2.1 Literature Review

Optical flow is the distribution of apparent velocities of movement of brightness patterns in an image. Optical flow can arise from relative motion of objects and the viewer. Consequently, optical flow can give important information about the spatial arrangement of the objects viewed and the rate of change of this arrangement. Discontinuities in the optical flow can help in segmenting images into regions that correspond to different objects. Optical flow cannot be computed locally, since only one independent measurement is available from the image sequence at a point, while the flow velocity has two components. A second constraint is needed.A method for finding the optical flow pattern is presented which assumes that the apparent velocity of the brightness pattern varies smoothly almost everywhere in the image. An iterative implementation is shown which successfully computes the optical flow for a number of synthetic image sequences. The algorithm is robust in that it can handle image sequences that arequantized rather coarsely in space and time.[11]

Digital Image Correlation (DIC) is a 3D, full-field, non-contact optical technique to measure contour, deformation, vibration and strain on almost any material. The technique can be used for many tests including tensile, torsion, bending and combined loading for both static and dynamics applications. The method can be applied from very small (micro) to large testing areas – and the results are readily comparable with FEA results or strain gauges. Digital Image Correlation (DIC) is a full-field image analysis method, based on grey value digital images, that can determine the contour and the displacements of an object under load in three dimensions.

The correlation algorithm is based on the tracking of the grey value pattern G(x,y) in small local neighborhood facets. Due to a loading of the object this pattern is transformed into

$$G_t(x_t,y_t) = g_0 + g_1 G(x_t,y_t) \quad \text{..... (1)}$$

and

$$x_1 = a_0 + a_1 x + a_2 y + a_3 xy$$
$$y_1 = a_4 + a_5 x + a_6 y + a_7 xy \quad \text{..... (2, 3)}$$

Within the correlation algorithm the difference

$$\sum (G_t(x_t,y_t) - G(x,y))^2 \quad \text{..... (4)}$$

of these patterns is minimized.

By varying the illumination parameters

(g_0 , g_1)

and the parameters of the affine transformation. [7]

The local warping technique used in the two-step OF method requires the prior strain information, which is obtained in the first step. The pre-deformed RF signal is locally deformed according to estimated axial strain and axial shear strain, and then sub-sample displacement and strain tensors are estimated again from the warped pre- and post-deformed signals. This procedure is similar to the local stretching or local companding used in cross-correlation based motion estimator. The local warping technique is helpful to improve the coherence between the pre and post-deformed RF signals, and reduce the de-correlation of signals. Hence, by taking the advantages of local warping, the two-step OF method can reduce the bias and standard deviation of strain estimation, i.e., improve the accuracy and precision of strain estimation. [8]

Traditionally, dense optical flow estimation has been formulated as a continuous optimization problem and many of today's most successful methods leverage elaborate variants of the original formulation, allowing for more robust penalties or improving optimization. As continuous methods typically require linearizing the highly non-convex data term, they only permit the estimation of very small displacements up to a few pixels. Thus, in order to handle large displacements in real world videos, a simple heuristic is often employed: Optical flow is estimated in a coarse-to-fine manner, thereby guaranteeing an upper bound to the maximal displacement at each level of the image pyramid. Unfortunately, this strategy is highly susceptible to local minima as small structures and textural details vanish at coarse image resolutions, leading to over smoothing artifacts in the estimated flow field.In contrast to optical flow, the most successful approaches to stereo matching typically rely on discrete inference in graphical models. While such models are loopy by nature and thus lead to NP-hard optimization problems, good approximate solutions can often be efficiently computed using graph cuts, belief propagation or mean field approximations. Importantly, no image pyramids are required as the full data cost volume is considered at the same time during inference. Unfortunately, the application of discrete methods to the problem of optical flow is not straightforward and hence there exists only relatively little work in this direction. The main reason for this is the huge size of the label space which needs to be considered for the 2D large-displacement optical flow problem as opposed to the 1D stereo problem.

First, they restrict the label set by considering only the L most likely matches per pixel which we obtain via approximate nearest neighbor search in feature space subject to non-maxima suppression constraints. To validate this restriction, we experimentally show that the oraclesolution of the restricted set outperforms all existing optical flow techniques by a significant margin.Second, our inference scheme takes advantage of efficient convergent block

coordinate descent (BCD) and iteratively updates all image rows and columns conditioned on the remaining variables via dynamic programming. Third, they exploit the special form of the pairwise potentials used by our formulation to further decrease computational complexity, thereby making very large unordered label sets with hundreds of labels tractable. Upon convergence, they remove outliers (e.g., in occluded regions) using strategies borrowed from the stereo literature. Finally, theyregress a real-valued dense flow field from our semi-dense integer flow estimate using variational techniques.Unfortunately, the application of discrete methods to the problem of optical flow is not straightforward and hence there exists only relatively little work in this direction. The main reason for this is the huge size of the label space which needs to be considered for the 2D large-displacement optical flow problem as opposed to the 1D stereo problem. [17]Variational methods are among the most successful approaches to calculate the optical flow between two image frames. A particularly appealing formulation is based on total variation (TV) regularization and the robust L1 norm in the data fidelity term. This formulation can preserve discontinuities in the flow field and offers an increased robustness against illumination changes, occlusions and noise. In this work they present a novel approach to solve the TV-L1 formulation. Their method results in a very efficient numerical scheme, which is based on a dual formulation of the TV energy and employs an efficient point-wise thresholding step. Additionally, their approach can be accelerated by modern graphics processing units. They demonstrate the real-time performance (30 fps) of their approach for video inputs at a resolution of 320 × 240 pixels.[10]

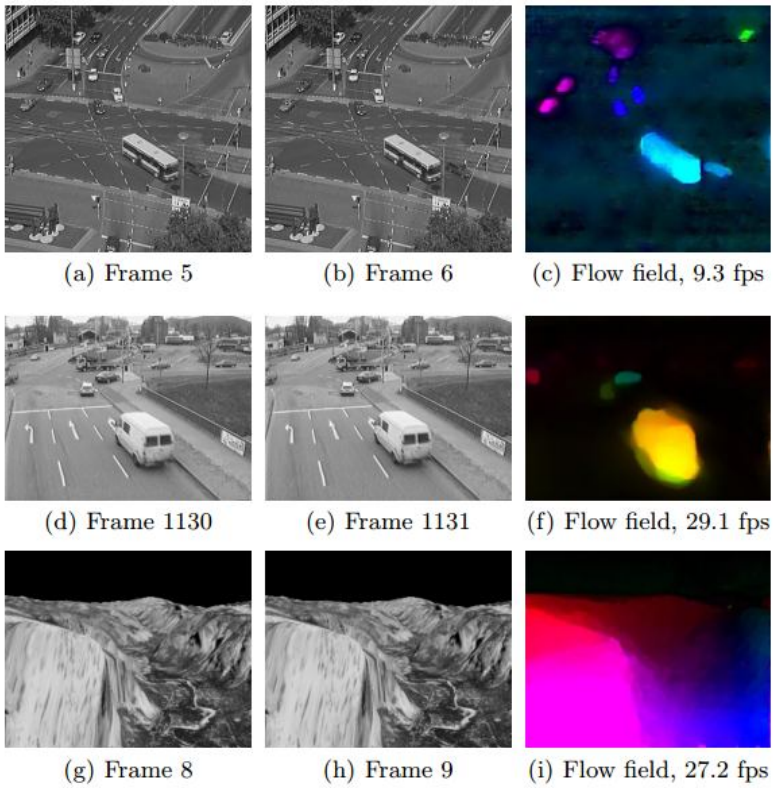


Figure 3: Optical flow field for different images [10]

2.2 Implemented Methods of Strain Estimation

There are a number of methods which already exist for strain estimation. Some of these are used in the medical field and some outside of it in applications such as building strain, structural strain.

Methods for strain estimation:

- Elastographic Process
- Axial Strain Elastography
- Lateral Strain Elastography
- Modulus Elastography
- Vibrational Methods
- Adaptive Stretching
- Correlation Coefficient
- Phase Based Method
- Least Squares Strain Estimator
- Butterfly Search
- Direct, incoherent, spectral strain estimator

2.2.1 Axial Strain Elastography

Tissue axial strains are calculated from the gradient of the estimated axial displacements. The current problem while performing strain elastography is that common differentiation operation which needs to be applied during the estimation amplifies the noise present in the displacement. This is undesirable and will cause problems in the calculation. AS a replacement, low-pass digital differentiator was proposed. Three types were implemented and tested, namely Simple DD, Optimum DD and Smoothed DD The quality of axial strain elastograms improved with increasing applied strain and A-line density but decreased with increasing lateral beamwidth and deteriorated as the number of active transmission elements in the sparse arrays were reduced. Also as filter length increases, the minimum square error and the noise amplification factor decrease.[20]

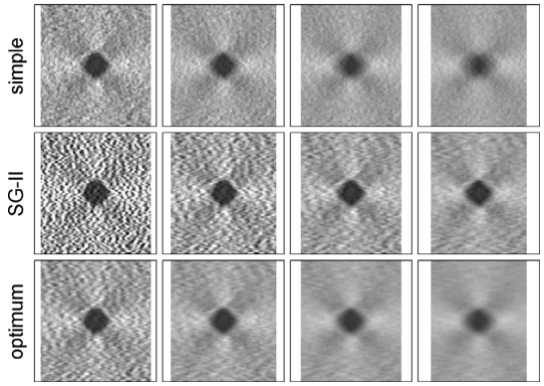


Figure 4: The ideal axial strain image and strain images obtained by various LPDDs in the one-inclusion tissue model [20]

2.2.2 Lateral Elastography:

A major disadvantage of the current practice of elastography is that only the axial component of the strain tensor is used to produce the elastogram, while the lateral and elevational components are basically disregarded. However, all three components are needed to fully characterize the motion of a three dimensional target. Furthermore, the lateral and elevational components can severely corrupt the axial strain estimation by inducing de-correlation noise. A new method has therefore been developed that produces high precision lateral displacements. In reference it is shown that the higher the interpolation scheme, the higher the number of independent displacement estimates and thereby the higher the precision of the estimation. Due to this high precision lateral tracking, quality lateral elastograms can be generated that display the lateral component of the strain tensor.

2.2.3 Modulus Elastography:

Elastography based on quantitative strain imaging suffers from mechanical artefacts (shadowing and target resolution) and from limitations to the contrast transfer efficiency (CTE). To go beyond such presumed limitations, a few groups independently considered elastography as a new, challenging inverse problem. The inverse problem (IP) approach is used extensively in electromagnetics, optics and geophysics research. In the biomedical field it has been extensively studied in bioelectricity to determine the distribution of potentials on the surface of the heart or the brain from a limited number of peripheral potential measurements. However, it is relatively new in the field of continuum mechanics and until recently it was not applied in the field of biomechanics, to which elastography belongs.

2.2.4 Adaptive Stretching:

Temporal stretching significantly improves TDE in elastography. However, the proper temporal stretching factor is dependent on the local strain, an unknown parameter one is trying to estimate. In an elastically inhomogeneous tissue, the strains will vary and thus, ideally, the stretching factor will have to be varied at different window locations. Since temporal stretching by the factor that compensates for the strain maximizes the correlation, an iterative algorithm is indicated. In this algorithm, the local temporal stretching factor is adaptively varied until a maximum in the correlation is reached. The local strain is then computed directly from this temporal stretching factor. Since the axial correlation is maximized at each data window between the pre- and post-compression A-lines, this estimator is an ‘optimal’ (one-dimensional) estimator of strain. It is also well known that the gradient operation amplifies noise in the displacement estimates. Since adaptive stretching involves only intra-window operations and no inter window operation, it does not suffer from this type of degradation.

2.2.5 Correlation Coefficient:

It has been discussed how the correlation between the pre- and post-compression echoes can decrease with applied strain. However, de-correlation itself has been used to estimate delay and/or strain. Various researchers used the correlation coefficient to estimate tissue motion. Bamber and Bush proposed using the de-correlation coefficient for the envelope signal for free zand elasticity imaging. But Varghese and Ophir [Varghese, T. and Ophir, J. Estimating tissue strain from signal de-correlation using the correlation coefficient. signal de-correlation using the correlation coefficient Ultrasound Med. Biol., 1996, 22, 1249–1254.] have demonstrated that the de-correlation coefficient has poor precision as strain estimator. So these this advantage need to be recognized and care should be taken while using this estimator.

2.2.6 Phase Based Method:

It is also possible to use phase to measure small tissue displacements and commercial ultrasound scanner use phase change to estimate motion for Doppler processing. Since the phase is only defined for narrowband systems some bandpass filtering is done prior to computation of the phase, which introduce a loss in the spatial resolution. [21]

2.2.7 Least Squares Strain Estimator:

It was shown that with such an estimator the signal to noise ratio in an elastogram was significantly improved due to the reduction of the displacement noise amplification due to the gradient operation. [2]

2.2.8 Butterfly Search:

Alam and Parker developed the ‘butterfly search’ technique for complex envelope signals from a deterministic analysis, derived using Schwartz’s inequality. Since this method can simultaneously analyze more than two successive A-lines, it is a natural candidate in multi compression elastography. Preliminary results have shown that it may improve the SNR and the dynamic range in elastography. [5]

2.2.9 Direct, incoherent, spectral strain estimators:

Elastography has been shown to be capable of producing quality strain images in vitro and in vivo. Standard elastography uses a coherent cross-correlation technique to estimate tissue displacement and tissue strain using a subsequent gradient operator. While coherent estimation methods generally have the advantage of being highly accurate and precise, even relatively small undesired motions are likely to cause signal de-correlation, and thus significant degradation of the elastogram. For elastography to become more universally practical in

applications such as intravascular and abdominal imaging, limitations associated with coherent strain estimation methods that require tissue and system stability must be overcome. On the other hand, incoherent estimators are moderately less precise but far more robust.

2.2.10 Poission's Ratio Elastography:

Poisson's ratio (n) for a plane strain state under uniaxial stress conditions is defined as

v=-e1/ea

Where e1 and ea are the lateral and axial strains respectively. Poisson's ratio is an important mechanical parameter that describes the degree of material compressibility, or the change in volume following an applied compression. Poisson's ratio equals 0.5 for totally incompressible materials and 0 for totally compressible ones. By measuring and imaging the distribution of Poisson's ratio in tissues, it may be possible to estimate the amount ratio in tissues, it may be possible to estimate the amount regions.

In cases where there is a strain contrast between an inclusion and the background, the Poisson elastogram is able to indicate whether that strain contrast (on the axial and lateral elastograms) is due to a Poisson's ratio contrast, elastic modulus contrast or both.

Poisson elastograms may have interesting applications in assessing the degree of unbound water content in tissues. The Poisson elastogram or the time sequence of Poisson elastograms may be used for quantitative of Poisson elastograms may be used for quantitative of oedema, inflammation or other hydrated poro-elastic tissues. Another interesting and potentially very useful property of the Poisson elastogram is that, as long as the tissue isotropy assumption holds, mechanical stress concentration artefacts due to geometrical boundary conditions should cancel out. This means that unlike earlier methods for quantifying tissue fluid transport that were highly dependent on the geometry, it may be possible to produce images of this basic tissue parameter that are free from geometrical artefacts.

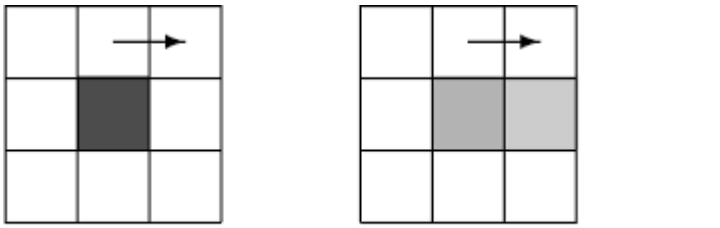
Finally, the knowledge of both lateral strain and Poisson's ratio in addition to the axial strain is in general necessary for reconstruction algorithms this implies that the final modulus elastogram could become more accurate if the lateral and Poisson elastograms are computed first.

CHAPTER 3: METHODOLOGY AND IMPLEMENTATION

3.1 Methodology

3.1.1 Optical Flow Introduction

Optical flow or optic flow is the pattern of apparent motion of objects, surfaces, and edges in a visual scene caused by the relative motion between an observer and a scene. The concept of optical flow was introduced by the American psychologist James J. Gibson in the 1940s to describe the visual stimulus provided to animals moving through the world. Gibson stressed the importance of optic flow for affordance perception, the ability to discern possibilities for action within the environment. Followers of Gibson and his ecological approach to psychology have further demonstrated the role of the optical flow stimulus for the perception of movement by the observer in the world; perception of the shape, distance and movement of objects in the world; and the control of locomotion.



(a) I(x,y,t) (b) I(x+v,y+v,t+1)

Sequences of ordered images allow the estimation of motion as either instantaneous image velocities or discrete image displacements.The optical flow methods try to calculate the motion between two image frames which are taken at times t and t+Δt at every voxel position. These methods are called differential since they are based on local Taylor series approximations of the image signal; that is, they use partial derivatives with respect to the spatial and temporal coordinates.

For a 2D+t dimensional case (3D or n-D cases are similar) a voxel at location (x,y,t) with intensity I(x,y,t) will have moved by Δx,Δy andΔt between the two image frames, and the following brightness constancy constraint can be given:

$$I(x, y, t) = I(x + \Delta x, y + \Delta y, t + \Delta t)$$

Assuming the movement to be small, the image constraint at I(x,y,t) with Taylor series can be developed to get:

$$I(x+\Delta x, y+\Delta y, t+\Delta t) = I(x,y,t) + \frac{\partial I}{\partial x}\Delta x + \frac{\partial I}{\partial y}\Delta y + \frac{\partial I}{\partial t}\Delta t + \text{H.O.T.}$$

Followed by:

$$\frac{\partial I}{\partial x}\Delta x + \frac{\partial I}{\partial y}\Delta y + \frac{\partial I}{\partial t}\Delta t = 0$$

or

$$\frac{\partial I}{\partial x}\frac{\Delta x}{\Delta t} + \frac{\partial I}{\partial y}\frac{\Delta y}{\Delta t} + \frac{\partial I}{\partial t}\frac{\Delta t}{\Delta t} = 0$$

which results in

$$\frac{\partial I}{\partial x}V_x + \frac{\partial I}{\partial y}V_y + \frac{\partial I}{\partial t} = 0$$

And finally resulting in

$$I_x V_x + I_y V_y = -I_t$$

or

$$\nabla I^T \cdot \vec{V} = -I_t$$

where V_x and V_y are the velocity vector components in x and y and I_x, I_y, I_t are derivatives in the respective dimensions. This is an equation in two unknowns and cannot be solved as such. This is known as the aperture problem of the optical flow algorithms. To find the optical flow another set of equations is needed, given by some additional constraint. All optical flow methods introduce additional conditions for estimating the actual flow.

Lucas-Kanade algorithm is one of these methods which attempts to estimate the optical flow in its own way.

3.1.2 Optical Flow using Lucas-Kanade algorithm

In computer vision, the Lucas–Kanade method is a widely used differential method for optical flow estimation developed by Bruce D. Lucas and Takeo Kanade. It assumes that the flow is essentially constant in a local neighborhood of the pixel under consideration, and solves the basic optical flow equations for all the pixels in that neighborhood, by the least squares criterion.

By combining information from several nearby pixels, the Lucas–Kanade method can often resolve the inherent ambiguity of the optical flow equation. It is also less sensitive to image noise than point-wise methods. On the other hand, since it is a purely local method, it cannot provide flow information in the interior of uniform regions of the image.

The local image flow (velocity) vector ($V_xV_{y)}$ must satisfy the following equations:

$$\begin{aligned} I_x(q_1)V_x + I_y(q_1)V_y &= -I_t(q_1) \\ I_x(q_2)V_x + I_y(q_2)V_y &= -I_t(q_2) \\ &\vdots \\ I_x(q_n)V_x + I_y(q_n)V_y &= -I_t(q_n) \end{aligned}$$

where $q_1,q_2,\ldots,q_n$ are the pixels inside the window, and I_x, q_i, I_y, q_i,I_t, $q_i$are the partial derivatives of the image I with respect to position x, y and time t, evaluated at the point qiand at the current time.

These equations can be written in matrix form Av=b, where,

$$A = \begin{bmatrix} I_x(q_1) & I_y(q_1) \\ I_x(q_2) & I_y(q_2) \\ \vdots & \vdots \\ I_x(q_n) & I_y(q_n) \end{bmatrix} \qquad v = \begin{bmatrix} V_x \\ V_y \end{bmatrix} \qquad b = \begin{bmatrix} -I_t(q_1) \\ -I_t(q_2) \\ \vdots \\ -I_t(q_n) \end{bmatrix}$$

The Lucas–Kanade method obtains a compromise solution by the least squares principle. Namely, it solves the 2×2 system

$$A^T Av = A^T b \text{ or}$$
$$\mathrm{v} = (A^T A)^{-1} A^T b$$

Thus,

$$\begin{bmatrix} V_x \\ V_y \end{bmatrix} = \begin{bmatrix} \sum_i I_x(q_i)^2 & \sum_i I_x(q_i) I_y(q_i) \\ \sum_i I_y(q_i) I_x(q_i) & \sum_i I_y(q_i)^2 \end{bmatrix}^{-1} \begin{bmatrix} -\sum_i I_x(q_i) I_t(q_i) \\ -\sum_i I_y(q_i) I_t(q_i) \end{bmatrix}$$

3.2 Implementation: Multistep Optical Flow

For our implementation, we have selected Lucas-Kanade algorithm as the ideal algorithm due to its obvious performance gain over the Horn-Schunck method.[19]

Optical Flow is very reliable when it comes to tracking movement of objects or points of interest from one image to another or in video frames. However, Optical Flow breaks down for large movements because the differentials fail to hold. The Lucas–Kanade method per se can be used only when the image flow vector(V_xV_y) between the two frames is small enough for the differential equation of the optical flow to hold, which is often less than the pixel spacing. When the flow vector may exceed this limit, such as in stereo matching or warped document registration, the Lucas–Kanade method may still be used to refine some coarse estimate of the same, obtained by other means; for example, by extrapolating the flow vectors computed for previous frames, or by running the Lucas-Kanade algorithm on reduced-scale versions of the images. Indeed, the latter method is the basis of the popular Kanade-Lucas-Tomasi (KLT) feature matching algorithm. But that is not related to our application

The workaround for this is to calculate the optical flow as a multistep addition between the initial image and the final image, by calculating the optical flow at regular intervals in between where the movement is small and suited to Lucas-Kanade method constraints and then adding them up for the final optical flow

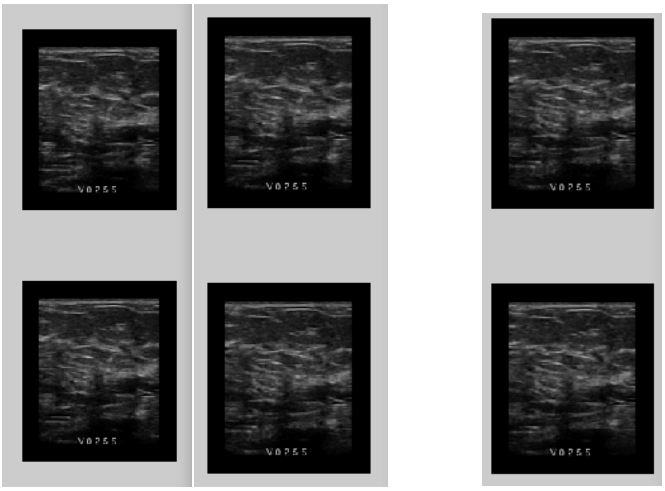


Figure 5: Image set for a particular data sample

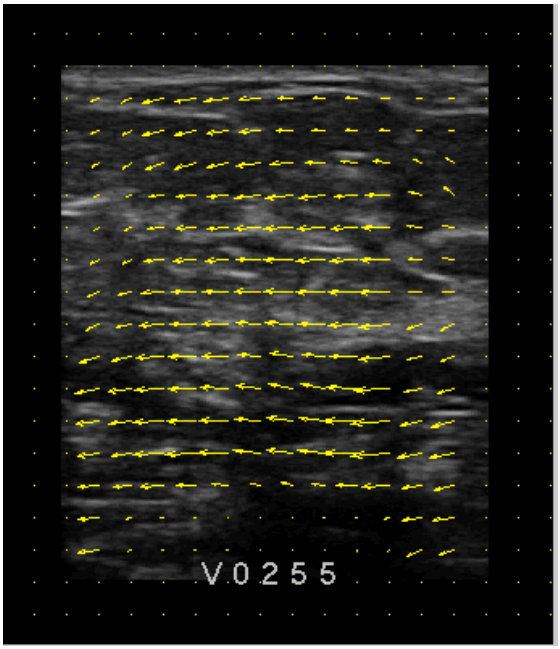


Figure 6: Final displacement from image 1 to image 4

3.2.1 Isolating a uniform region and calculating Signal to Noise Ratio (SNR)

For a good estimation of the strain (displacement matrices) we need to select a uniform region. So first we need to convert the image to a colormap format and subsequently to grayscale and prepare a histogram for the image. AS we know, uniform regions will have the same brightness or intensity and thus we can easily select a threshold for converting the image to a binary form. This will then give a few regions which are uniform. From there the largest connected component will provide us with the uniform area from which we can calculate the SNR.

For calculating the SNR the following formula was used:

$$SNR = \frac{mean\ of\ the\ velocity\ vectors}{standard\ deviation\ of\ the\ vectors} = \frac{\mu}{\sigma}$$

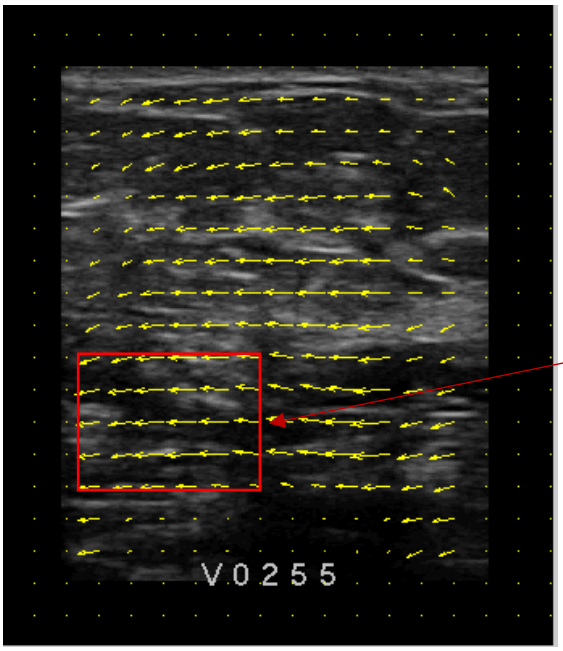


Figure 7: Uniform region identified from image

CHAPTER 4: RESULTS

4.1 Dataset

Dataset collected from Fletcher Allen Health Care, University of Vermont. The ultrasound transducer that was used was a L14-5/38 Linear Array with 38mm Probe. The probe was rotated in Anti-Radial plane. The videos were each 8 seconds long in duration and there were 45 frames per second for each video (360 frames in total). Some sample images:

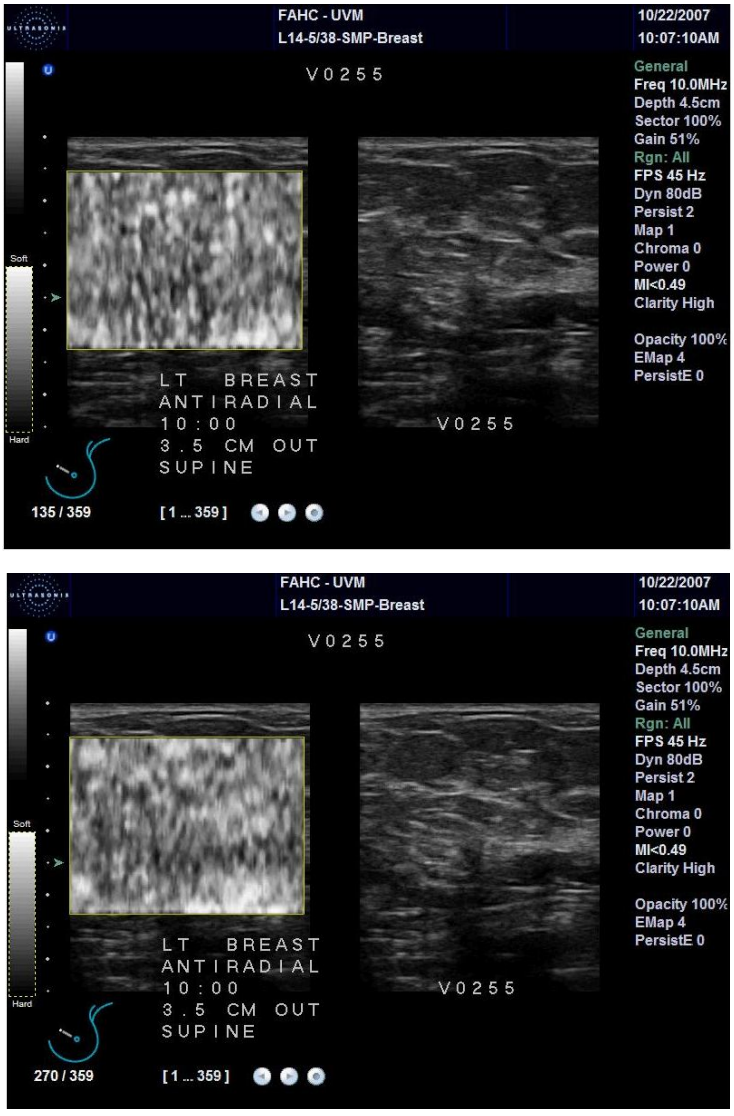


Figure 8:Samples of dataset

Details of the transducer array:

Applications: Abdominal, Musculoskeletal, Pediatric, Small Parts
Frequency Range: 14 - 5 MHz
Focal Range: 2 - 9 cm
Image Field: 16mm

4.2 Results and Comparison

The algorithm was tested against the cross correlation method for finding strain estimates for an image set as well as against traditional optical flow applied on the same set of images. To truly show the performance gain of Multistep Optical Flow, images with fairly considerable displacement between them were chosen

Table Set1: Calculation of SNR from strain applied in the lateral direction

Strain Percentage=1%	Mean	Deviation	SNR
Cross Correlation Method	0.0218	0.001036	21.04
Normal Optical Flow	0.5445	0.0244	22.33
Multistep OF	0.6741	0.0245	*27.48*

Strain Percentage=2%	Mean	Deviation	SNR
Cross Correlation Method	0.0312	0.0026	11.99
Normal Optical Flow	0.4421	0.0279	15.87
Multistep OF	0.4812	0.0278	*17.28*

Strain Percentage=4%	Mean	Deviation	SNR
Cross Correlation Method	0.123	0.014	9.16
Normal Optical Flow	0.5124	0.0280	*18.33*
Multistep OF	0.4678	0.0272	17.21

Strain Percentage=5%	Mean	Deviation	SNR
Cross Correlation Method	0.112	0.019	5.81
Normal Optical Flow	0.5475	0.0452	12.12
Multistep OF	0.5568	0.0360	*15.48*

Table Set 2: Calculation of SNR from strain applied in the axial direction

Strain Percentage=1%	Mean	Deviation	SNR
Cross Correlation Method	0.201	0.0416	11.85
Normal Optical Flow	0.4144	0.0336	*12.74*
Multistep OF	0.3568	0.0294	12.51

Strain Percentage=2%	Mean	Deviation	SNR
Cross Correlation Method	0.4838	0.0408	11.85
Normal Optical Flow	0.5144	0.0236	21.74

Multistep OF	0.4517	0.0204	*22.07*

Strain Percentage=4%	Mean	Deviation	SNR
Cross Correlation Method	0.4512	0.0538	8.39
Normal Optical Flow	0.5865	0.0404	14.52
Multistep OF	0.5912	0.0365	*16.20*

Strain Percentage=5%	Mean	Deviation	SNR
Cross Correlation Method	0.4209	0.0539	7.81
Normal Optical Flow	0.5271	0.0471	11.21
Multistep OF	0.5871	0.0444	*13.20*

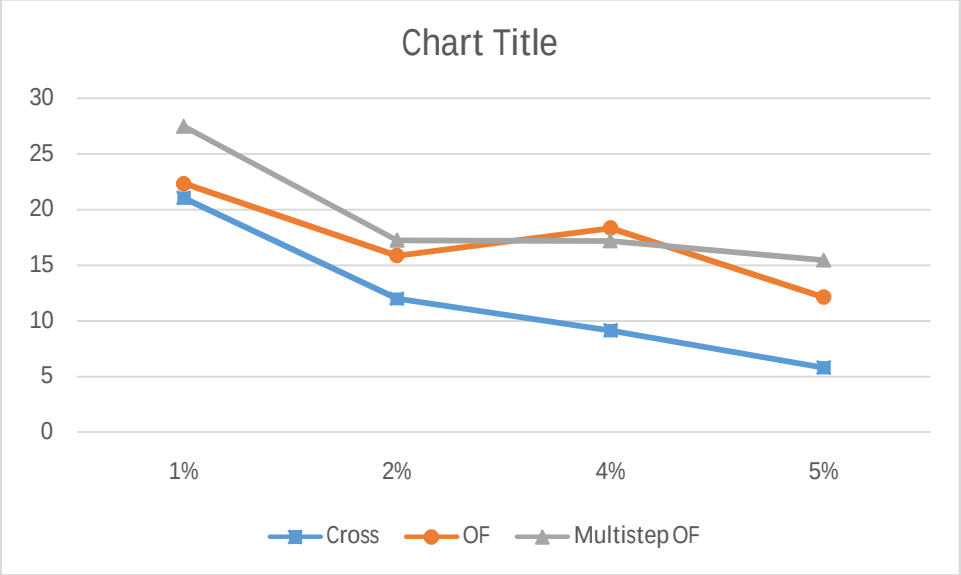


Figure 9: Graph comparing the SNR for lateral direction

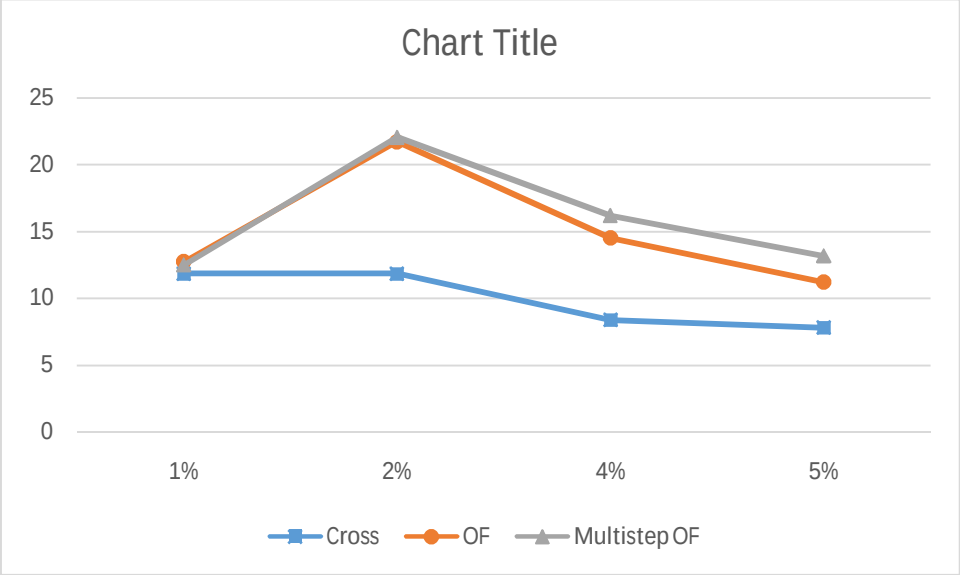


Figure 10: Graph comparing the SNR for axial direction

As we can see from the above results, our implementation performs favorably especially as the strain percentage goes higher. Only in 2 cases out of the 8, tradition OF outperformed the multistep OF.

CHAPTER 5: CONCLUSION

5.1 Summary

In this thesis, an optical flow based strain estimation algorithm is proposed that uses multistep optical flow calculation to estimate displacements over large distances which normally would not yield accurate results meaning there would be a low SNR for those calculations. By adding the individual optical flows between intermediate images we can get an accurate assessment of optical flows between images that normally would have a large displacement between them, hampering calculations. As we have seen in the results section of Chapter 4, our proposed method provides a competitive SNR value at most strain percentages, only falling behind in few occasions, that too by a relatively negligible amount.

5.2 Future Works

Calculation of Signal to Noise Ratio requires an area of uniform displacement along the axial or lateral direction otherwise it offers a very poor result. It is easy to convert the image to binary and then select the largest uniform area for computation. However it requires the observer to select a threshold according to the histogram. It would be useful if this process was converted to dynamic and also provides reliable results, because we could not get both to occur simultaneously in our efforts.

Also we wish to reliably detect the lesions as another feature which we hope to use machine learning or even deep learning with. The area of classification is largely dominated by the use of training classifiers and applying them to the sample data. For the training itself we would need a huge sample dataset which is not possible at the moment.

Finally we wish to see our algorithm be applied in the real world and not as a theoretical approach. Hopefully it can be used to better diagnose patients with tumors and detect them whilst they are still in benign stage before they become malignant.

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