# FAST 4D ULTRASOUND TECHNIQUE IN IMAGE PROCESSING

**M.SIVAGAMI., M.E(CSE).,**
**VEERAMMAL COLLEGE OF ENGINEERING,SINGARAKOTAI,DINDUGAL.**
2 ND AUTHOR: **K.SRIDAR.,M.E.,(Ph.D).,**ASSISTANT PROFESSOR,
**VEERAMMAL COLLEGE OF ENGINEERING,SINGARAKOTAI,DINDUGAL**.
3 RD AUTHOR**: V.KEERTHIKA.,M.E.,**ASSISTANT PROFESSOR,
**VEERAMMAL COLLEGE OF ENGINEERING,SINGARAKOTAI,DINDUGAL.**

**ABSTRACT**

Continuous-domain visual signals are usually captured as discrete images. This operation is not invertible in general, in the sense that the continuous-domain signal cannot be exactly reconstructed based on the discrete image, unless it satisfies certain constraints. Study the problem of recovering shape images with smooth boundaries from a set of samples. Thus, the reconstructed image is constrained to regenerate the same samples, as well as forming a shape image. Initially formulate the reconstruction technique by minimizing the shape perimeter over the set of consistent binary shapes. Next, relax the non-convex shape constraint to transform the problem into minimizing the total variation over consistent non-negative-valued images. This also introduce a requirement that guarantees equivalence between the two problems. Illustrate that the reducibility property effectively sets a requirement on the minimum sampling density. This also evaluate the performance of the relaxed alternative in various numerical experiments.

## I. INTRODUCTION

Replacing classical surgical interventions by minimally invasive alternatives is beneficial for the patient and the health care system, as it has large potential for reducing complication rates, minimizing surgical trauma, and reducing hospital stay. The minimally invasive character, however, makes these interventions challenging for the clinician. There is no direct eyesight on the target region and conventional interventional imaging modalities have limited capabilities. Furthermore the user interfacing and interaction with the equipment involved often is not ergonomically well-designed, and does not match the interventional work flow well. Image guidance is crucial in minimally invasive interventions. Image guidance can be based on preoperative imaging data (mostly magnetic resonance imaging and computed tomography) or intraoperative imaging data (X-ray, ultrasound). Hybrid approaches can also be useful, in which the diagnostic quality of preoperative images can be combined with the real-time nature of intraoperative images (also known as fusion imaging).

Four dimensional (4D) ultrasound (US) is a relatively novel imaging modality that currently is mainly used for diagnosis. Radiofrequency ablation (RFA) and the transjugular intrahepatic portosystemic shunt (TIPS) procedure are examples of percutaneous minimally invasive imageguided interventions which are used more and more as alternative to surgical procedures. 4D US has large potential in assisting the clinicians in these procedures, as it provides real-time three dimensional (3D) vision. During these procedures the clinician often holds the US probe steady to visualize a localized area in the liver US volume. Breathing shifts the region of interest and makes it difficult to constantly focus on a region of interest, more so in the presence of a catheter. The purpose of our work is to develop a technique suited for fast 3Dultrasound registration during image guided minimally invasive intervention to compensate breathing motion. In addition, our approach would help in keeping the registration up to date in US fusion imaging.

segmentation. Section III shows the results of the developed methodology using a MATLAB image. Finally, section IV defines the conclusion and application of the method in diagnostics of various diseases.

### 1.1 Image segmentation

Image segmentation is the process of dividing the individual elements of an image or volume into a set of groups, so that all elements in a group have a common property. In the medical domain, this common property is usually that elements belong to the same tissue type or organ. Medical images contain a lot of information as well as noise and other image artifacts. Usually only one or two structures are of interest. Segmentation allows visualization of the relevant structures, removing unnecessary information as shown in Figure 1.1. Segmentation is also useful for registration and structure analysis such as calculating the volume of a tumor. There are many different segmentation methods from simple intensity-based methods like thresholding and region growing (Adams and Bischof, 1994), to more advanced modelbased approaches such as statistical shape models (Heimann and Meinzer, 2009). No segmentation method is considered to be the best, and the method of choice depends on the application, structure to be segmented, and the type of images.

### 1.2 Image guided surgery

The term open surgery refers to any surgical technique where the incision in itself is enough to enable the procedure. These methods may involve large wounds and unnecessary damage to healthy tissue. Minimal invasive surgery (MIS) is an alternative to open surgery which aims to improve patient treatment. It has been shown in several surgical procedures that MIS reduces the risk of complications, the amount of postoperative pain and shortens recovery time (Darzi and Munz, 2004). In MIS, surgical instruments are placed through small incisions, thus avoiding large surgical scars. Endoscopes equipped with a camera and a light, are often used allowing the surgeon to see inside the body.

Figure 1.1: Example of airway segmentation of a CT scan. The green pixels of the segmentation highlights the airways, while the rest of the pixels are identified as other tissue

The goal of image guided surgery (IGS) is to enhance MIS with computer technology and images acquired by ultrasound, X-ray, computer tomography (CT), magnetic resonance imaging (MRI) and cameras. A typical computer assisted image guided intervention uses the following sequence (Cleary and Peters, 2010). First, preoperative images are acquired and used to plan the procedure. During the procedure, instruments are tracked using an optical or electromagnetic tracking system. Using the tracked instruments, the preoperative images are registered to the patient. This enables the instruments to be displayed in relation to the preoperative images, thus guiding the surgeon during the procedure. Intraoperative images are often acquired during the procedure to provide updated image data of the patient. IGS has been used in several applications. One such application is neurosurgery, in which image and computer guidance has been practiced in more than 30 years, and its success has made it a standard method in most centers (Cleary and Peters, 2010). Many of the neurosurgical procedures require a craniotomy, which results in a brain deformation called brain shift (Nimsky et al., 2001). This is a major challenge in neurosurgery, and the conclusion is that these procedures can only be performed accurately with intraoperative imaging (Cleary and Peters, 2010), using methods such as intraoperative MRI (Hall and Truwit, 2008) and ultrasound (Unsgaard et al., 2002). Another application of IGS is abdominal laparoscopy, which involves insufflation of a gas into the abdominal cavity, and insertion of instruments through small incisions in the abdomen (Perrin and Fletcher, 2004). Procedures such as liver tumor resection and ablation can be performed in this manner. The abdominal organs shift and deform due to respiration, surgical manipulation and pneumoperitoneum making accurate image guidance challenging (Vijayan et al., 2014).

The goal of image guided surgery (IGS) is to enhance MIS with computer technology and images acquired by ultrasound, X-ray, computer tomography (CT), magnetic resonance imaging (MRI) and cameras. A typical computer assisted image guided intervention uses the following sequence (Cleary and Peters, 2010). First, preoperative images are acquired and used to plan the procedure. During the procedure, instruments are tracked using an optical or electromagnetic tracking system. Using the tracked instruments, the preoperative images are registered to the patient. This enables the instruments to be displayed in relation to the preoperative images, thus guiding the surgeon during the procedure. Intraoperative images are often acquired during the procedure to provide updated image data of the patient. IGS has been used in several applications. One such application is neurosurgery, in which image and computer guidance has been practiced in more than 30 years, and its success has made it a standard method in most centers (Cleary and Peters, 2010). Many of the neurosurgical procedures require a craniotomy, which results in a brain deformation called brain shift (Nimsky et al., 2001). This is a major challenge in neurosurgery, and the conclusion is that these procedures can only be performed accurately with intraoperative imaging (Cleary and Peters, 2010), using methods such as intraoperative MRI (Hall and Truwit, 2008) and ultrasound (Unsgaard et al., 2002). Another application of IGS is abdominal laparoscopy, which involves insufflation of a gas into the abdominal cavity, and insertion of instruments through small incisions in the abdomen (Perrin and Fletcher, 2004). Procedures such as liver tumor resection and ablation can be performed in this manner. The abdominal organs shift and deform due to respiration, surgical manipulation and pneumoperitoneum making accurate image guidance challenging (Vijayan et al., 2014).

Bronchoscopy is a minimal invasive technique for diagnosis and treatment of the airways, where a bronchoscope is inserted into the airways. Today, the bronchoscope is usually flexible containing fiberoptic cables and light, which allows the surgeon to see inside the airways through the bronchoscope (Leira, 2012). Due to the breathing motion of the patient and the complex and narrow structure of the airways, it is difficult for the surgeon to navigate to the target site using this procedure. Also, the bronchoscope is too wide to pass through the smallest airways. Anaesthesia is an important step in most surgical procedures. The use of regional anaesthesia (RA) is increasing due to the benefits over general anaesthesia (GA), such as reduced morbidity and mortality (Rodgers et al., 2000; Beattie et al., 2001; Urwin et al., 2000), reduced postoperative pain, earlier mobility, shorter hospital stay, and lower costs (Chan et al., 2001). Despite these clinical benefits, RA remains less popular than GA. One reason for this is that GA is far more successful and reliable than RA. Ultrasound imaging has been employed to increase the success rate of RA (Griffin and Nicholls, 2010; Dolan et al., 2008). In ultrasound-guided RA, the nerve and other important structures, such as blood vessels and fascias, are located using the ultrasound images. After a good view of the target nerve has been achieved, a needle is inserted and used to inject local anaesthesia around the nerve. Several computer technologies are important in IGS, such as image segmentation, registration, tracking and visualization. The role of image segmentation in IGS is to extract the structures of interest from the pre- and intraoperative images. In all of the applications mentioned above, it may be beneficial to use segmentation to extract the important structures, and thereby create a map which can be used to plan and guide the procedure. Segmentation can also be used for structure analysis and feature-based registration which can deal with anatomical shift.

**1.3 Image segmentation challenge**

Segmentation of nontrivial images is one of the most difficult tasks in image processing. In this section, the challenges of segmentation will be discussed.

**1.3.1 Accuracy**

Human experts are in many cases still superior to computer algorithms in terms of accuracy when it comes to image segmentation of nontrivial images. For instance, Lo et al. (2009) evaluated 15 different algorithms for segmentation of airways from CT images, and concluded that none of the methods were able to extract more than 77% of the manually segmented references on average. Sharma and Aggarwal (2010) argued that image segmentation accuracy is affected by the following factors:

• **Partial volume effect** - If the image resolution is lower than the structure of interest, multiple tissue types contribute to the intensity value of the pixel. This results in the structure boundary being either blurred or not visible at all in the image (Pham et al., 2000). This effect can be addressed by allowing segmentation regions to overlap, often called soft-segmentation.

• **Tissue intensity in homogeneity** - Many segmentation methods use the pixel intensity value to identify the tissue type. However, in many cases the same tissue has different intensity values and different tissue have the same intensity. This is especially the case in magnetic resonance and ultrasound images were the intensity of the same tissue varies with the location in the image.

• **Low contrast** - Different tissue may have similar intensity values. This is common for soft-tissue in CT images, which can make it hard to separate different soft tissues based on intensity values alone.

• **Other image artifacts** - Different image modalities may also have other image artifacts. One example is motion during image capture which can introduce blurring or inconsistencies from one image slice to another.

Given the challenges above, one may argue that relying on pixel intensity alone is not suf- ficient for segmentation. To counter these challenges, prior knowledge about the anatomy can be used to make the segmentation more robust, such as the shape and location of the structure of interest. Segmentation methods using prior knowledge are often referred to as model-based segmentation methods. One example is using a circle to model the cross-section of a blood vessel as done by Krissian et al. (2000). Statistical shape models (SSMs) are more complex examples of model-based segmentation. These models are trained to capture the average shape and variation of anatomical structures (Heimann and Meinzer, 2009). Appearance models describe how a structure appears in an image, and can also be used to make segmentation more robust. One example is active appearance models (AAMs) (Cootes et al., 2001), which can generate synthetic images of how a structure should look in an image based on training data.

**1.3.2 Speed**

Segmentation of images acquired just before the operation as well as during the operation, has to be both fast and accurate in order to be useful in image guided surgery. Although machines are generally faster than humans at image segmentation, several segmentation methods are still not fast enough. Ideally, the result should be ready instantly, but many segmentation methods may require several minutes of processing. The amount of data available for each patient is steadily increasing (Scholl et al., 2010), making fast segmentation algorithms even more important. The following are factors affecting the speed of segmentation algorithms.

• **Segmentation algorithm complexity** - The time-complexity of an algorithm quantifies the amount of time an algorithm uses as a function of the input size.

• **Segmentation algorithm implementation** - An algorithm can be implemented and optimized in different ways, for instance by using different data structures, intrinsic functions and parallelization.

• **Computer hardware** - The speed and capacity of the computer hardware on which the segmentation is executed.

• **Image size** - Larger images tend to require more processing time as well as memory. Thus, speed may be increased by cropping the image before segmentation, use image compression, or use a smaller and less accurate data type.

There is usually a trade-off between speed and accuracy, in which accuracy may be reduced for increased speed and vica versa.

**1.3.3 Automation**

Semi-automatic segmentation methods may be used to improve the accuracy over automatic segmentation, while being faster than manual segmentation. Most segmentation algorithms require some sort of initialization. This initialization may be difficult to do automatically, while easy to do manually. For instance, region growing segmentation requires one or more seed pixels, which may be selected by a user with the computer mouse and anatomical domain knowledge. Although semi-automatic segmentation methods can be used to increase accuracy, user interactions during surgical procedures are not desired as it takes time, distracts the surgeons from the actual procedure, require expert knowledge, and is non-repeatable and subjective.

**1.4 Research goals**

The main goal of this thesis is to develop image segmentation methods for image guided surgery that are accurate, fast and automatic, with primary focus on increasing the speed of image segmentation. Two image segmentation domains which are important in image guided surgery have been investigated. These domains are segmentation of tubular structures, and segmentation of ultrasound images. In this section, these domains and the related research goals are presented.

**1.4.1 Accelerating segmentation with parallel and GPU computing**

As discussed previously, speed is one of the main challenges of image segmentation for image guided surgery. There are several ways of increasing the speed of an image segmentation algorithm. One way is to exploit the parallel processing capabilities of modern processors. Interconnected machines and processors were used to run image segmentation in parallel already in the 1980's (Tilton, 1988; Morioka et al., 1990), but it required expensive hardware. Today, consumer computers contain processors capable of running many operations in parallel at a low cost. In addition to the central processing unit (CPU), most modern computers also contain another processor called the graphic processing unit (GPU). The main difference between a CPU and a GPU, is that a GPU has a lot more arithmetic logic units (ALUs) than the CPU (McCool, 2008), allowing the GPU to process many different data elements in parallel. However, many of the ALUs share a control unit and therefore have to run the same instruction for each data element. GPUs were originally created for rendering graphics and are primarily used for computer games. However, in the last ten years, GPUs have become popular for general-purpose high performance computation, including medical image processing (Eklund et al., 2013).

**1.4.2 Segmentation of tubular structures**

Blood vessels, airways, bones, neural pathways and intestines are all examples of important tubular structures in the human body. In addition to segmentation, it can be useful to extract the centerline of these structures. The centerline is a line going through the center of the tubular structures, providing a structural representation of the tubular structures as shown in Figure 1.2.

The extraction of these structures can be essential for planning and guidance of several surgical procedures such as bronchoscopy, laparoscopy, and neurosurgery. Tubular structures extracted from preoperative images can be matched to similar intraoperative structures, such as a set of positions inside the airways generated by a tracked bronchoscope, or brain vessels extracted from ultrasound. It has been shown that registration of blood vessels from pre- and intraoperative image data can also be used to detect and correct organ-shift, such as brain-shift (Reinertsen et al., 2007). There are several methods for extracting tubular structures from medical images. A recent and extensive review on blood vessel extraction was done by Lesage et al. (2009), and an older one was done by Kirbas and Quek (2004).

Two reviews on the segmentation of airways were done by Lo et al. (2009) and Sluimer et al. (2006). A common strategy for extracting tubular structures is to grow the segmentation from an initial point or area, using methods such as region growing (Adams and Bischof, 1994), active contours (Xu and Prince, 1998) and level sets (Sethian, 1999). A centerline can be extracted from a binary segmentation using iterative morphological thinning, also called skeletonization (Palàgyi and Kuba, 1998; Palágyi and Kuba, 1999; Xie et al., 2003). Iterative thinning removes voxels from the segmentation in a particular order until the object can not be thinned anymore.

Another approach is to use a distance transform or gradient vector flow (GVF), as done by Hassouna and Farag (2007). Direct centerline extraction without a prior segmentation is also possible using methods such as shortest path and ridge traversal. The segmentation can be grown afterwards using region growing with the centerline as seeds. Aylward and Bullitt (2002) presented a review of different centerline extraction methods. They proposed an improved ridge traversal algorithm based on a set of ridge criteria, and different ways of handling noise. Bauer and Bischof (2008c) showed that ridge traversal could be used together with GVF. Direct centerline extraction usually needs some initial centerpoints and the direction of the tubular structure. This can be acquired with tube detection filters (TDFs).

TDFs are used to detect tubular structures by calculating a probability of each voxel being inside a tubular structure. Most TDFs use gradient information, often in the form of the eigenanalysis of the Hessian matrix. Frangi et al. (1998) presented an enhancement and detection method for tubular structures based on the eigenvalues of this matrix. Krissian et al. (2000) created a model-based detection filter that fits a circle to the cross-sectional plane of the tubular structure. These TDFs have the potential of detecting different types of tubular structures such as blood vessels and airways. There are several examples of methods claiming to be robust enough to segment and extract centerlines of tubular structures of different types (e.g. vessels and airways), organs and modalities (Bauer, 2010; Bauer and Bischof, 2008b,a,c; Bauer et al., 2009a,b; Krissian et al., 2000; Aylward and Bullitt, 2002; Benmansour and Cohen, 2010; Li and Yezzi, 2007; Behrens et al., 2003; Cohen and Deschamps, 2007; Lorigo et al., 2000; Spuhler et al., 2006). However, most of these present results for only a few datasets of one or two organs/modalities. The PhD thesis of Bauer and related articles (Bauer, 2010; Bauer and Bischof, 2008b,a,c; Bauer et al., 2009a,b) are exceptions that present results for several different organs (e.g. lung, heart and liver), however only from CT scans.

**1.4.3 Segmentation of ultrasound images**

Ultrasound is a key intraoperative imaging modality in image guided surgery, due to its real-time imaging capability, low cost and small footprint in the operating room. It can be used intraoperatively to look inside the patient during the procedure or to update preoperative images and models. Ultrasound has shown significant potential in several procedures, such as neurosurgery (Gronningsaeter et al., 2000) and laparoscopy (Langøet al., 2008).

Segmentation of ultrasound images is challenging due to noise and image artifacts such as tissue inhomogeneity, reverberations and acoustic shadowing. Thus, relying on pixel intensity alone for may not be sufficient for robust and accurate ultrasound segmentation. Noble and Boukerroui (2006) conducted a review of current segmentation methods for ultrasound images, where they concluded that a good ultrasound image segmentation method needs to make use of all task-specific constraints and prior knowledge due to the low image quality.

It is a challenge to segment ultrasound images at the same speed as they are produced, as ultrasound is a real-time imaging modality, delivering several images per second. Several different segmentation methods have been used on ultrasound images including region growing (Abdel-Dayem and El-Sakka, 2005), level sets (Xie et al., 2005; Li et al., 2006), active contours (Mao et al., 2000; Mikic et al. ´ , 1998; Chen et al., 2004), tube detection filters (Hennersperger et al., 2015) and statistical shape models (Bosch et al., 2002). However, most of these do not target real-time ultrasound segmentation.

One way to segment dynamic images, is to apply a segmentation method on each image frame, but this may not satisfy real-time constraints. Another approach, often called tracking, is to use the segmentation of the previous frame as prior knowledge to segment the next frame, and thus reduce the computational cost. The Kalman and particle filters are examples of such tracking methods. The Kalman filter (Kalman, 1960) is an algorithm that estimates a state using a series of noisy measurements over time.

In image segmentation, the state may be a set of parameters describing the shape of the structure of interest and its position in the image. One type of measurement for object tracking, is the offset from each point on the shape to the object's edges in the current image frame. Previous work has shown that the Kalman filter can track structures such as blood vessels (Guerrero et al., 2007) and the left ventricle of the heart (Orderud, 2006; Orderud et al., 2007; Orderud and Rabben, 2008) in real-time.

The Kalman filter algorithm consists mostly of a set of matrix operations. Linear algebra libraries such as ATLAS, Eigen and boost can accelerate these type of operations. The particle filter method (Arulampalam et al., 2002) estimates the posterior density of the state variables given the measurements using Monte Carlo simulations. Generally many samples are required, but each sample can be evaluated in parallel using a GPU (Montemayor et al., 2006; Mateo Lozano and Otsuka, 2008; Lozano and Otsuka, 2008; Murphy-Chutorian and Trivedi, 2008; Lenz et al., 2008; Brown and Capson, 2012). The review of Noble and Boukerroui (2006) showed that most segmentation methods for ultrasound depend on user interaction such as the selection of a seed point or region of interest. As ultrasound is an intraoperative image modality, user interaction may distract the physician from the procedure or require additional personnel, which is why automation of ultrasound segmentation methods is important.

**II LITERATURE SURVEY**

Jyotirmoy Banerjee et al.,(2016)is proposed a method for 4D Ultrasound Tracking of Liver and its Verification for TIPS guidance. In this work to describe a 4D registration method for on the fly stabilization of ultrasound volumes for improving image guidance for transjugular intrahepatic porto systemic shunt (TIPS) interventions. The purpose of the method is to enable a continuous visualization of the relevant anatomical planes (determined in a planning stage) in a free breathing patient during the intervention. This requires registration of the planning information to the interventional images, which is achieved in two steps. In the first step tracking is performed across the streaming input. An approximate transformation between the reference image and the incoming image is estimated by composing the intermediate transformations obtained from the tracking. In the second step a subsequent registration is performed between the reference image and the approximately transformed incoming image to account for the accumulation of error. The two step approach helps in reducing the search range and is robust under rotation. To additionally present an approach to initialize and verify the registration. Verification is required when the reference image (containing planning information) is acquired in the past and is not part of the (interventional) 4D ultrasound sequence. The verification score will help in invalidating the registration outcome, for instance, in the case of insufficient overlap or information between the registering images due to probe motion or loss of contact, respectively. To evaluate the method over thirteen 4D US sequences acquired from eight subjects. A graphics processing unit implementation runs the 4D tracking at 9 Hz with a mean registration error of 1.7 mm. This criterion will additionally help the registration application. switch from the RTR mode in the verification to the RTRT mode in the 4D Tracking.

J.Niessen et al.,(2015) is proposed a method for Fast and Robust 3D Ultrasound Registration - Block and Game Theoretic Matching, *Medical Image Analysis.* Real-time 3D US has potential for image guidance in minimally invasive liver interventions. However, motion caused by patient breathing makes it hard to visualize a localized area, and to maintain alignment with pre-operative information. In this work we develop a fast affine registration framework to compensate in real-time for liver motion/displacement due to breathing. The affine registration of two consecutive ultrasound volumes in time is performed using block-matching. For a set of evenly distributed points in one volume and their correspondences in the other volume, to propose a robust outlier rejection method to reject false matches. The inliers are then used to determine the affine transformation. The approach is evaluated on 13 4D ultrasound sequences acquired from 8 subjects. For 91 pairs of 3D ultrasound volumes selected from these sequences, a mean registration error of 1.8mm is achieved. A graphics processing unit (GPU) implementation runs the 3D US registration at 8 Hz.

E.G.Learned-Miller et al.,(2015)is proposed a method for Data driven image models through continuous joint alignment. The method presents a family of techniques that to call congealing for modeling image classes from data. The idea is to start with a set of images and make them appear as similar as possible by removing variability along the known axes of variation. This technique can be used to eliminate "nuisance" variables such as affine deformations from handwritten digits or unwanted bias fields from magnetic resonance images. In addition to separating and modeling the latent images - i.e., the images without the nuisance variables - to can model the nuisance variables themselves, leading to factorized generative image models. When nuisance variable distributions are shared between classes, one can share the knowledge learned in one task with another task, leading to efficient learning. The demonstrate this process by building a handwritten digit classifier from just a single example of each class. In addition to applications in handwritten character recognition, we describe in detail the application of bias removal from magnetic resonance images. Unlike previous methods, to use a separate, nonparametric model for the intensity values at each pixel. This allows us to leverage the data from the MR images of different patients to remove bias from each other. Only very weak assumptions are made about the distributions of intensity values in the images. In addition to the digit and MR applications. It describe experiments about the robustness and consistency of the method.

Christian Wachinger Munich et al.,(2014) is describes a method for Similarity Metrics and Efficient Optimization. To address the alignment of a group of images with simultaneous registration. Therefore, to provide further insights into a recently introduced framework for multivariate similarity measures, referred to as accumulated pair-wise estimates (APE), and derive efficient optimization methods for it. More specifically, we show a strict mathematical deduction of APE from a maximum-likelihood framework and establish a connection to the congealing framework. This is only possible after an extension of the congealing framework with neighborhood information. Moreover, to address the increased computational complexity of simultaneous registration by deriving efficient gradient-based optimization strategies for APE: Gauss-Newton and the efficient second-order minimization (ESM). The present next to SSD the usage of intrinsically nonsquared similarity measures in this least squares optimization framework. The fundamental assumption of ESM, the approximation of the perfectly aligned moving image through the fixed image, limits its application to monomodal registration. We therefore incorporate recently proposed structural representations of images which allow us to perform multimodal registration with ESM. Finally, to evaluate the performance of the optimization strategies with respect to the similarity measures, leading to very good results for ESM. The extension to multimodal registration is in this context very interesting because it offers further possibilities for evaluations, due to publicly available datasets with ground-truth alignment**.**

Christian Wachinger et al., (2014) is proposed a method for Three-Dimensional Ultrasound Mosaicing. The creation of 2D ultrasound mosaics is becoming a common clinical practice with a high clinical value. The next step coming along with the increasing availability of 2D array transducers is the creation of 3D mosaics. In the literature of ultrasound registration, the alignment of multiple images has not yet been addressed. Therefore, to propose registration strategies, which are able to cope with problems arising by multiple image alignment. The use pair-wise registration with a consecutive Lie normalization and simultaneous registration, which urges the usage of multivariate similarity measures. In which propose alternative multivariate extensions based on a maximum likelihood framework. Due to the higher computational cost of simultaneous registration, to describe possibilities for speeding them up, among others, the usage of a stochastic pyramid. This also present methods to reduce speckle noise and to detect shadow in ultrasonographic volumes, to improve the overall registration performance. For the compounding of the final volume, a variety of approaches are listed, ranging from general to advanced ones. Experimental results, on multiple ultrasound data sets, show the good performance of the proposed registration strategies and similarity measures.

Thomas Langø et al.,(2014) is proposed a method for Validation of a method based on 4D ultrasound using a nonrigid registration technique. Treatments like radiotherapy and focused ultrasound in the abdomen require accurate motion tracking, in order to optimize dosage delivery to the target and minimize damage to critical structures and healthy tissues around the target. 4D ultrasound is a promising modality for motion tracking during such treatments. In the method, the authors evaluate the accuracy of motion tracking in the liver based on deformable registration of 4D ultrasound images. The offline analysis was performed using a non rigid registration algorithm that was specifically designed for motion estimation from dynamic imaging data. The method registers the entire 4D image data sequence in a group wise optimization fashion, thus avoiding a bias toward a specifically chosen reference time point. Three healthy volunteers were scanned over several breathing cycles

(12 s) from three different positions and angles on the abdomen; a total of nine 4D scans for the three volunteers. Well-defined anatomic landmarks were manually annotated in all 96 time frames for assessment of the automatic algorithm. The error of the automatic motion estimation method was compared with interob server variability. The authors also performed experiments to investigate the influence of parameters defining the deformation field flexibility and evaluated how well the method performed with a lower temporal resolution in order to establish the minimum frame rate required for accurate motion estimation.

P.J.Stappers et al.,(2013) describes a Comparing image guidance systems to improve complex navigation in medicine. One of the most technically challenging procedure in interventional radiology is a transjugular intrahepatic portosystemic shunt (TIPS) placement. The main problem is the limited image guidance while navigating. The physician basically punctures blind through the liver into the target portal vein, leading to many unsuccessful punctures and unnecessary risks before access to the portal vein is gained. To be able to improve guidance, developers have to be sure to use the most promising image modality available. This paper compares the available modalities for TIPS to various criteria to find which modality is the most suitable to improve the success of the puncture. Results showed that, even though many user interface improvements are required, real-time three-dimensional ultrasound has the most potential to improve the puncture in the future. The study emphasizes the importance of thorough technology analysis before developing medical devices. Navigation systems using the tracking devices (e.g., electromagnetic, optical) are well advanced and cater to clinical routines of largely rigid anatomical regions e.g. in neurosurgery. For interventions of the soft tissue regions like the abdomen, the support by the navigation systems are limited, because the displacement of the organs caused by factors like the breathing may result in a large misalignment.

In literature a great deal of work has been published dealing with image-based needle or instrument navigation using x-rays, computed tomography, and magnetic resonance imaging [102]. For real-time guidance, x-rays and ultrasound are two frequently used imaging modalities. With its ease of use, improved image quality over the years and nonionizing energy for imaging, ultrasound is an essential part of modern diagnostic and therapeutic navigation.

## III SYSTEM DESCRIPTION

### 3.1 Existing System

Ultrasound image acquisition is known to be affected by various factors, such as acoustic shadowing due to loss of probe contact (inadequate amount of gel) and a gamut of panel settings such as gain, time gain compensation, focus etc. While US images, because of these factors, may be of relatively poor quality, they are highly textured. A texture-based similarity measure was investigated used a combination of texture and edge features. Feature correspondence based methods find correspondences between image features. The concept of attribute vectors has been used to define corresponding voxels in fixed and moving images in.

Information theoretic based feature detection was discussed. Popular 3D Scale Invariant Feature Transform (SIFT) feature descriptors were used for feature extraction. A local phase based method was employed. A hybrid feature-based registration approach using combination of local forces in a variation framework and block-matching correspondences was reported. Knowing the correspondence between a numbers of feature points in images, the transformation can be determined. Efficient algorithms for the correspondence problem have been an active research topic in the computational geometry and pattern recognition communities.

Establishing correspondences between sparse image features in natural images using Markov random fields was discussed. One popular approach to the correspondence problem involves applying the algorithms for the more general graph matching problem. Spectral matching is an eigenvector-based method for graph matching. A game theoretic approach to correspondence estimation formulated as a quadratic assignment problem was presented. Intensity based registration has gained popularity over feature-based approaches in recent years. In feature-based approaches feature images are generated by extracting features from images, which are then used in subsequent analysis. From an information theoretical perspective, there is generally information loss in the process of creating a feature. Any feature constructed from a set of voxel data cannot contain more information than the same set of voxel data. Nevertheless feature based approaches are helpful when the noise in the data is significant or an invariant representation of the data is required (e.g. rotational invariance). Feature based approaches also help in encoding image content in a way that makes it more distinctive to be used in classification or registration algorithms. A rigid registration approach that combines the properties of both intensity based and feature based approaches and is suitable for parallel implementation is the block-matching approach.

There are a few reports on real-time US registration. To address the issue of missing anatomical structures, near real-time image fusion of multiple single-view real time 3D echocardiography using wavelet features. Real-time image based registration of 3D US images from a 4D US sequence is a challenging task. 3D frames from a 4D sequence have much lower resolution than a static 3D US image.

**Demerits**

- It often uses filters and operations that are tailored for a particular type or resolution of image and can require significant modifications to be applied to others.
- This method use intensity features to discriminate between arteries and veins.
- Due to the acquisition process, very often the retinal images are non-uniformly illuminated and exhibit local luminosity and contrast variability, which can affect the performance of intensity-based A/V classification methods.

**3.2 Proposed System**

Our ultrasound registration approach is motivated by methods described in ultrasound speckle tracking literature. A speckle pattern contains densely positioned targets created by the interaction of ultrasonic beams and the tissue. The speckle pattern allows highly accurate (sub millimeter level) tracking of tissue motion. Automatic speckle tracking can be performed using block-matching. In an ultrasound image speckle patterns are found in large collections. The tracking information from multiple such speckle patterns can be used to perform registration. In an ideal scenario, if all the speckle patterns are tracked accurately, the speckle pattern correspondences can be used to estimate the transformation. However in practice not all of the speckle patterns will be tracked well, e.g. because of acoustic shadowing or due to motion decorrelation. To address these issues and to remove false matches, we employ a matching approach, inspired by game theory, to retain only pairs that have been matched correctly. This outlier rejection is formulated in a game theoretic framework. Speed is an important aspect of our application, and a matching strategy reduces over reliance on selecting the speckle patterns.

In the speckle tracking propose a novel, fast solution to the 4D ultrasound liver registration problem. Our contributions are fourfold: first, to integrate a fast outlier rejection approach to improve the result of a block-matching approach, second, to develop a method to use both the geometric consistency and the appearance information from block-matching to reject outliers, third, the (non-homogeneous quadratic) optimization function of the outlier rejection module is mapped to a homogeneous quadratic function to be solved efficiently using replicator dynamics, and fourth process is perform an extensive evaluation on real 4D imaging data. Finally demonstrate that the method is able to perform registrations at 8 Hz. Following steps contains proposed system performance,

- Ultrasound (Us) is a unique medical imaging modality as it is non-invasive, affordable, portable and real-time. Ultrasonography is widely used in diagnosis.
- The purpose of the method is to enable a continuous visualization of the relevant anatomical planes (determined in a planning stage) in a free breathing patient during the intervention.

- In the first step tracking is performed across the streaming input. An approximate transformation between the reference image and the incoming image is estimated by composing the intermediate transformations obtained from the tracking.

- In the second step a subsequent registration is performed between the reference image and the approximately transformed incoming image to account for the accumulation of error.

- The additionally present an approach to initialize and verify the registration. Verification is required when the reference image (containing planning information) is acquired in the past and is not part of the (interventional) 4D ultrasound sequence.

- The verification score will help in invalidating the registration outcome, for instance, in the case of insufficient overlap or information between the registering images due to probe motion or loss of contact, respectively.

- Our proposed solution is to render specific planes (cross-sections) from the US volumes, i.e., by using planes from a planning US volume, in which the relevant vessels have been annotated and the planes are chosen such that they show the anatomy of interest.

In this system architecture Register-to-Reference by Tracking (RTRT). In step-I consecutive images are rigidly aligned using tracked points. The step-I information is propagated to the step-II. However, composition of transforms causes accumulation of error. Hence, in step-II the reference image and the transformed incoming image are realigned. In this work present the following contributions. First, to propose a Register-to-Reference by Tracking (RTRT) strategy for *4D US tracking* to compensate for breathing motion in realtime. The RTRT approach helps in reducing the search range and is robust under rotation.

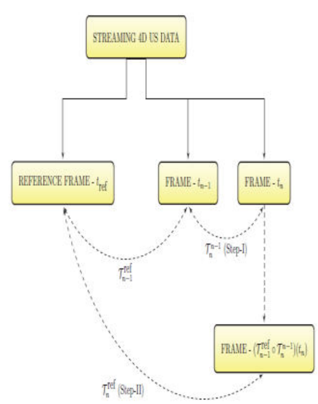



Fig.3.1. System Architecture

Second, in a phantom experiment show that the RTRT approach is robust under external devices such as needles. Third, we present an approach for registration *verification*, that would indicate whether the planning US volume and the interventional 4D US sequence can be adequately registered. This criterion will additionally help the registration application to switch from the RTR mode in the verification to the RTRT mode in the 4D US tracking, whenever required, automatically. Fourth, we thoroughly evaluate the technique on thirteen 4D US sequences. Additionally, a GPU implementation shows that the approach runs in real-time, and to develop demonstrate the application on US datasets. The rest of the paper is structured as follows. In

Section II we discuss the RTRT 4D US tracking approach. In Section III we discuss the registration verification approaches. The experiments and results are presented in Section IV, which are discussed in Section V.

The *dead reckoning* approach from navigation to perform real-time image registration on streaming 4D ultrasound data. Instead of registering the current incoming image to a single reference image, they register to a compound reference volume generated from a collection of images. This approach uses a graphics processing unit (GPU) to achieve real-time performance. Unlike the group-wise methods, real-time approaches use a simple transformation model like rigid or affine. Used a feature-based approach for real-time 4D US registration. They used SIFT-based features followed by RANSAC to establish correspondences between image pairs. To limit accumulation of error they maintained a global set of features and integrate them in their registration framework. Sufficient proximity or overlap between the fixed and the moving images is required for a good registration.

A detection approach may be used to determine if the moving image is well localized/initialized such that it images the same region of interest as the reference image proposed an automatic solution for localizing a fetal abdominal standard plane using an image feature based classification method. Proposed an active appearance model. Which mimics the visual cues for scan plane detection in US fetal head images. In radiation therapy address the problem of tissue deformation caused by a US probe, resulting in a mismatch between planning and delivery, by using robotic probe placement. In proposed system proposed solution to render cross-section technique from the US volumes for example in this technique using implemented in this proposed system. This process is used to implement fast 4D ultrasound of liver. In addition, our approach would help in keeping the registration up to date in US fusion imaging.

**IV METHODOLOGY**

Our registration method consists of three basic steps a) naive point selection, b) block-matching, and c) outliers rejection followed by an affine transformation using the inliers. The block-matching step uses a similarity metric to establish correspondences between the selected points in the fixed image and the moving image. The true displacements are retained and the false displacements are rejected in the outlier rejection step. The inliers are used to estimate the transformation using for the affine case and for the rigid case.

**4.1 Naïve point selection**

We sample the points used in our registration pipeline from a regular 4D grid structure. The grid structure is made up of a series of intersecting axes which are parallel to the $x$, $y$ and $z$ axis. The vertices or the junction location of the axes form the set of points used in the block-matching scheme. Before we sample points from the US volume based on the grid structure, we define a region of interest (ROI) inside the cone of the 4D US image. The region outside the ROI, see Figure 2.1, is not used in the registration process. Instead of a regular grid structure, other choices of sampling schemes are equally applicable.

**4.2 Block-matching**

We employ a straightforward block-matching scheme to find matching homologous points across volumes. This is achieved by taking a block of a certain size around the voxel of interest in the fixed image and finding the homologous pixel within the block in the moving image, while searching in the corresponding neighbourhood in the moving image. The size of the block in both the images is given by $B = (Bx, By, Bz)$. The neighborhood in the moving image is defined by the search window $W = (Wx, Wy, Wz)$. The goal is to find the corresponding (correlated) pixel that maximizes the similarity. The correspondences for all the input points from the fixed image to the points in themoving image form the input to our outlier rejection scheme.

NCC is used as a similarity metric for block-matching. Assuming an affine transformation and small rotation between the two consecutive volumes, no rotation of the block during matching is applied.

**4.3 Outlier rejection**

A game theoretic perspective on the matching problem is popular in literature. These matching approaches are deduced from clustering approaches presented in [125], [100]. In these approaches an adjacency matrix (payoff matrix in game theory) is built from a graph, the vertices of the graph represent the potential correspondences and the edges embed the pairwise constraints between candidate assignments. A function of this adjacency matrix is optimized to find the cluster.

The concept of dominant set as discussed in [100], is a game theoretic way of partitioning the graph. The optimization function of a dominant set formulation consists of a homogeneous quadratic term. Similar formulations are also found in spectral clustering literature, see [74]. In our work, we discuss the application of game theory in establishing potential correspondences based on (pairwise) geometric constraints and appearance information.

**4.3.1 Geometric constraint**

Let $P = \{ph\}$ and $Q = \{qh\}$ where $0 < h \leq m$, be the set of locations from fixed volume and moving volume, respectively, having the highest degree of similarity. We have a one to one correspondence between the points in the point set $P$ and $Q$. As both the points are from volumes representing the same anatomical structure, the geometric distance between the points ought to be preserved. A point $qh$ in the moving volume that preserves the geometric distances with most of the other points in the same set $Q$ has a higher chance of being an inlier, and vice versa. This criterion of preserving the geometric distances forms the core of our outlier rejection scheme, similar. This information is embedded in a graph structure and is represented as an *adjacency matrix*. An adjacency matrix (**A**) represents a fully-connected undirected graph whose edges express the relative relationships, or affinities, between each pair of points in the point set, and is defined as follows:

$$f^{geo}(\mathbf{x}) = \sum_{u,v \in O} A_{u,v} x_u x_v \,,$$

Where

$$A_{u,v} = e^{-\delta_{u,v}^2/2\sigma_A{}^2} \text{ and } \delta_{u,v} = \frac{\left| \|q_u - q_v\| - \|p_u - p_v\| \right|}{\|q_u - q_v\| + \|p_u - p_v\|} \,.$$

$O = \{1, \cdots, m\}$ is a set of elements enumerating the bijective association between the point sets $P$ and $Q$. For $h \in O$, $xh$ is the probability of $qh$ being an inlier. The disparity between the pairwise distances is normalized by dividing the pairwise distance by the sum of the distance between the points. The parameter $\sigma A$ moderates the strength of the term $\delta u,v$. It is apparent from the pairwise distances that the inliers have high similarity with each other and poor similarity with the outliers.

**4.3.2 Appearance constraint**

The appearance constraint is derived from the block-matching scores. This constraint favours locations that have high block-matching scores. The appearance term is defined for each point as follows:

$$f^{app}(\mathbf{x}) = \sum B_u x_u \,,$$

$$B_u = e^{-\gamma_u^2/2\sigma_B{}^2} \,,$$

$\gamma u$ is the appearance term from the $u$th block, $\gamma u = |1 - \mathrm{BM}u|$, where $\mathrm{BM}u$ is the block-matching score of the $u$th block. The parameter $\sigma B$ moderates the strength of the term $\gamma u$. Appearance and geometric constraints are combined to remove the false matches and retain true matches.

**4D US tracking**

The outline of the RTRT approach is described in Figure 4.3. In our approach every incoming image is aligned with the reference image. The reference image is the US volume containing the planning information, and could be a US volume that has been acquired before the intervention. The approach consists of two steps. In the *tracking step* (step-I), the most recent consecutive images, i.e. the $tn-1$ image and the current incoming image $tn$ are rigidly aligned. The transformation from this step is combined with the previously estimated transformation between the reference image $t$ref and the $tn-1$ image to approximate the transformation between the reference image $t$ref and the current incoming image $tn$. In the subsequent *refine step* (step-II), a registration between the reference image $t$ref and the current incoming image $tn$ is performed to estimate the final transformation motivation for this two-step registration is two-fold. First, compared to a direct registration of the incoming image to the reference image, which needs a large search range to be able to deal with liver and transducer motion, we can apply two registrations that only require a small search range. This reduces computation time and the registration is more likely to succeed. Second, compared to a concatenation of the transforms as in a tracking approach, our approach accumulates minimal error.

**Block-matching and outlier rejection**

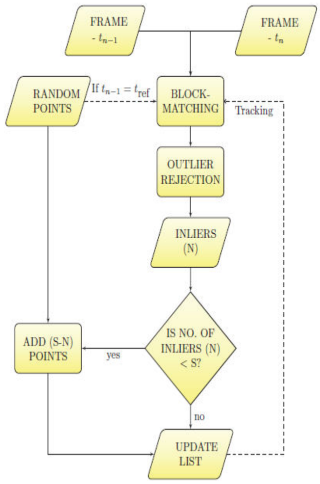
We briefly summarize the block-matching and outlier rejection which are important components of our 4D tracking process and which were presented earlier; for complete review and details refer to the Chapter 2 [6]. Given a set of input points X := $\{xi\}m-1$ $i$=0 in the fixed image, we employ a block-matching strategy to determine the corresponding target points Y := $\{yi\}m-1$ $i$=0 in the moving image, and find the best (rigid or affine) transform that matches the displacements from X to Y. As block-matching in general, and in ultrasound in particular, is bound to fail in some cases (i.e. for some points), we need to first estimate the true correspondences, and discriminate those from erroneous block-matching results. For this, we employ a graph-based clustering approach, based on geometric consistency of the

transformation: we use the fact that the distance between two points in X should not change after block-matching. Therefore, we fill an adjacency matrix A, where each element $aij$ encodes this geometric consistency ($aij$ is small when the distance between point $i$ and $j$ before block-matching differs much from the distance between point $i$ and $j$ after block-matching, and $aij$ is large if the distances are equal). We also add the appearance information derived from the block-matching scores in to the adjacency matrix. Subsequently, to find the inliers and outliers of the block matching,

**Estimate transform by tracking**

In step-I we track points across the streaming 4D US data. overview of the tracking based registration approach. The inputs are two successive images $tn-1$ and $tn$. Block-matching is used to find correspondences between $S$ points randomly selected in image $tn-1$ and image $tn$. The block-matching may not always result in true correspondences. The outlier rejection scheme from the previous section is applied to retain the true matches and remove the false matches. The inliers are used to determine the rigid transformation between the images using the method described by Arun et al. [4]. Inliers also forminput to the block-matching in the next cycle, i.e. registration between images $tn$ and $tn+1$. If the number of inliers, say $N$, is less than $S$, the minimum number of points required for robust tracking,

then $(S - N)$ random points are added. Thus there are always $S$ number of points used for block-matching. By reusing inliers, the fraction of inliers in the total number of points is larger than when not reusing inliers. As a certain number of inliers are required to obtain a good registration, this allows us to reduce the total number of points to track while keeping a good registration.




**Tracking landmarks**

The anatomical landmark tracking approach, see Figure 5.1, consists of the following two rigid registration steps. First, in the *global* 4D registration/tracking step, the RTRT strategy is used track the whole (liver) US volume ($T(re\,f\,,n)$). Second, in the *local* 3D registration step, we refine the tracking result by performing registration using the neigh or hood region close to the anatomical landmark ($T'(re\,f\,,n)$). 0Both the RTR and RTRT strategies use block-matching followed by an outlier rejection scheme to find correspondences between the US volumes. Input to the block-matching module is a point set. The portion/region of the image used for the registration/tracking is determined by the locations of the points in the US volume. As shown in the block diagram in Figure 5.1, a combination of a global and a local

point set is used to Performa global 4D tracking/registration and only a local point set is used to Performa local 3D registration. The global point set is generated using a grid structure spread over the entire US volume, the local point set is a collection of points in the neigh or hood of the anatomical landmark

**Conclusion**

We perform the task of tracking anatomical landmarks using a combination of previous methods . A mean tracking error of 1.62 ± 0.94 mm is achieved on the test set. In the first step, the point set used for the global 4D tracking step is a combination of a global point set generated from a grid structure and the local point set generated randomly in the neighbourhood of the anatomical landmark. This combination of point set ensures a high percentage of points close to the landmark position during the global 4D tracking step. The local point set is intended to track a specific landmark well, whereas the global point set helps in increasing robustness in tracking. In the second step, the local point set is again used in the local 3D registration step. This step is designed to track the landmark in the presence of local deformations. The mean tracking error for the training set is 3.26 ± 2.62 mm. Two of the datasets (EMC-03_1, SMT-04_1) from the training set have large tracking errors, see To conclude, we extended our current registration approaches for 3D and 4D US volumes such that it enables tracking of anatomical landmarks in 4D US sequences. The method is evaluated using CLUST 2015 challenge datasets. For a test set of eight 4D US sequences, an accuracy of 1.62 ± 0.94 mm is achieved. After the challenge, accuracy of 1.80 ± 1.64 mm was reported by the challenge organizer on the entire test set.

**REFERENCES**

[1] AJ, E., PW, G.,MO, H., F, Y., D, P.; Impact of minimally invasive surgery on medical spending and employee absenteeism. JAMA Surgery 2013;148(7):641–647.

[2] Albarelli, A., Bulo, S.R., Torsello, A., Pelillo, M.; Matching as a non-cooperative game. In: ICCV. 2009. p. 1319–1326.

[3] Albarelli, A., Rodola, E., Torsello, A.; Imposing semi-local geometric constraints for accurate correspondences selection

in structure from motion: A game-theoretic perspective. International Journal of Computer Vision 2012;97(1):36–53.

[4] Arun, K.S., Huang, T.S., Blostein, S.D.; Least-squares fitting of two 3-D point sets. IEEE Trans Pattern Anal Mach Intell 1987;9(5):698–700.

[5] Banerjee, J., Klink, C., Niessen, W.J., Moelker, A., van Walsum, T.; 4d ultrasound tracking of liver and its verification for TIPS guidance. IEEE Trans Med Imaging 2016;35(1):52–62.

[6] Banerjee, J., Klink, C., Peters, E.D., Niessen, W.J.,Moelker, A., vanWalsum, T.; Fast and robust 3D ultrasound registration - block and game theoretic matching. Medical Image Analysis 2015;20(1):173–183.

[7] Bell, M.A.L., Byram, B.C., Harris, E.J., Evans, P.M., Bamber, J.C.; In vivo liver tracking with a high volume rate 4D ultrasound scanner and a 2D matrix array probe. Physics inMedicine and Biology 2012;57(5):1359.

[8] Bhatia, K.K., Hajnal, J.V., Hammers, A., Rueckert, D.; Similarity metrics for groupwise non-rigid registration. In: MICCAI (2). 2007. p. 544–552.

[9] Blachier, M., Leleu, H., Peck-Radosavljevic, M.,Valla, D.C., Roudot-Thoraval, F.; The burden of liver disease in europe: A review of available epidemiological data. Journal of Hepatology 2013;58(3):593 – 608.

[10] Bomze, I.M., Locatelli, M., Tardella, F.; New and old bounds for standard quadratic optimization: dominance, equivalence and incomparability. Math Program 2008;115(1):31–64.

[11] Brattain, L.J., Howe, R.D.; Real-time 4D ultrasound mosaicing and visualization. In: MICCAI (1). 2011. p. 105–112.

[12] Brox, T., Bruhn, A., Papenberg, N., Weickert, J.; High accuracy optical flow estimation based on a theory for warping. In: Computer Vision - ECCV 2004, 8th European Conference on Computer Vision, Prague, Czech Republic, May 11-14, 2004. Proceedings, Part IV. 2004. p. 25–36. 122 References

[13] Buades, A., Coll, B., Morel, J.; A non-local algorithm for image denoising. In: 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR 2005), 20-26 June 2005, San Diego, CA, USA. 2005. p. 60–65.

[14] Buades, A., Coll, B., Morel, J.; Non-local means denoising. IPOL Journal 2011;1.

[15] Buades, A., Coll, B.,Morel, J.; Self-similarity-based image denoising. Commun ACM 2011;54(5):109–117.