Registration of 2D Ultrasound Images in Preparation for 3D Reconstruction

by

Rachel J. Dowell

S.B. Computer Science and Engineering (1996)
Massachusetts Institute of Technology

Submitted to the Department of Electrical Engineering and Computer Science in Partial Fulfillment of the Requirements for the Degree of Master of Engineering in Electrical Engineering and Computer Science at the Massachusetts Institute of Technology

June 1997

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Abstract

Ultrasound images display relative acoustic densities of the objects being imaged. 2D ultrasound images are routinely used in medical cardiac diagnosis. A set of 2D acquisitions obtained by rotation around an axis can be used to create a 3D image of the heart. However, movements that occur during the collection of consecutive images often produce poor reconstructions. While gating is performed on heartbeat and respiration to reduce the apparent movement between consecutive images, it does not eliminate all movement. This thesis investigates the ability of registration, using correlation as the similarity metric, to detect movement between consecutive images. Both single frame and localized correlation are investigated. Thirty-nine data pairs of tissue phantom images are used in comparing the various methods. This investigation finds that the best method uses localized correlation. The best method has a median error of 0.7 pixels and has only one case of failure in the 39 data pairs.

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Title: Professor, Electrical Engineering and Computer Science

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Chapter 1

Introduction

Ultrasound images display relative acoustic densities of the objects being imaged. 2D ultrasound images are routinely used in medical cardiac diagnosis. A set of 2D acquisitions obtained by rotation around an axis can be used to create a 3D image of the heart. It is easier to gauge the structure of the heart from a 3D reconstruction than to determine it from viewing the 2D cross-sectional images. However, movements that occur during the collection of consecutive images often produce poor reconstructions. Current techniques for 3D reconstruction of cardiac ultrasound images do not correct for motion during the image gathering process caused by breathing or other sources. As a result, artifacts in the form of jagged edges appear in the reconstructions. While the technique of gating is performed on heartbeat and respiration to reduce the apparent movement between consecutive images, it does not eliminate all movement. This thesis investigates the ability of registration, using correlation as the similarity metric, to detect movement between consecutive images. Both single frame and localized correlation are investigated. Thirty-nine data pairs of tissue-phantom images are used to compare the various methods. The investigation has found that the best method uses localized correlation. The best method has a median error of 0.7 pixels for finding displacements of between 5.5 and 23.7 pixels and has only one case of failure, error greater than five pixels, in the 39 data pairs. See table 1.1 for a summary of the results.
### Table 1.1: Summary of Results

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This thesis opens with an overview of the problem. Chapter 2 then discusses the methods used. Chapter 3 analyzes and evaluates the results of these methods applied to phantom data. Chapter 3 also shows the development of the localized correlation algorithm. Though the investigation used only phantom data throughout, the potential application of the results to actual heart data is discussed in Chapter 4 along with other areas for future investigations.

### 1.1 Background

Ultrasound images are acquired using a transducer which converts electrical impulses into sound waves at the transducer patient boundary. The sound waves enter the patients body and are reflected back to the transducer at different distances. These reflected waves are selectively converted back to electrical energy to be used in production of an ultrasound
image (Journal of ASE, 1995). More sound waves are reflected off of dense objects making the dense objects appear bright in the ultrasound image.

Since two-dimensional echocardiography was introduced in the mid-1970s, there have been many advances in echocardiography, making the use of ultrasound of greater and greater importance in the diagnosis and monitoring of cardiovascular disease (Journal of ASE, 1995). Three-dimensional echocardiography, however, is still a new field. Most 3D displays are currently too slow or of too low quality to be used widely. The primary advantage gained by 3D echocardiography over 2D is that it is much easier to recognize the structure of the heart with the 3D image. One difficulty, which creates artifacts in the final 3D image, is movement between the acquisition of consecutive 2D images from which the 3D image is built.

1.1.1 Data Acquisition

This investigation will be restricted to one of several possible 3D acquisition methods - the rotational method. The rotational acquisition method involves obtaining a conical set of image planes in which images are taken at different rotations about the central axis of the cone. See figure 1.1. The rotational acquisition method uses a transducer with a rotating imaging element to acquire images at a set integer degree increment from 0 to 180 degrees. The acquisition begins at 0 degrees, at which a set number of temporally sequential acoustic frames spanning the heart cycle is acquired. Next, the transducer is rotated a set increment of a few degrees and another heart cycle is recorded. This sequence is repeated until the entire 180 degrees has been spanned.
**Figure 1.1:** Acquisition of 2D images.

a. A typical ultrasound image, contains a sector of ultrasound data and an area of background data.

b. A set of 2D images are acquired at increments of 3 degrees of rotation around a central axis. From these images a 3D reconstruction can be created.

c. Ideally, there would be no movement between the acquisition of consecutive images other than the 3 degrees of rotation.

d. In actuality, other movement occurs between consecutive acquisitions; such as, the transducer movement shown in the above figure. The movement causes poor 3D reconstructions. Detection and correction of this movement is the goal of this thesis.

### 1.2 The Fundamental Difficulty

The movement between the ultrasound transducer and the patient’s heart has 6 degrees of freedom: along the x, y, and z axes and by rotation about each of the three axes. During image acquisition in which a transesophageal transducer is used (a transducer lowered through the patient’s mouth and down the esophagus), the swallowing or coughing of the patient may cause the transducer to move. Similarly when a transthoracic transducer is
used (a transducer used on the chest of a patient), misalignment between consecutive images may occur when the patient moves or the position of the transducer being held against the surface of the patient changes. The heart will also move inside of the patient due to breathing and the regular cycle of the heart.

To minimize reconstruction artifacts, the heart cycles are acquired synchronized to the R wave of the heartbeat. This is called R-R interval gating. Acquisition is restricted to times when the R-R interval between consecutive heartbeats is within the bounds set by the physician. This restriction ensures that the heart cycles which are recorded are close to the same temporal length. The image acquisition is also constrained to a particular portion of the respiratory cycle. This is called respiratory gating. While movement can be lessened by only acquiring images during certain portions of the heart and respiratory cycles, there is no way to be certain that the heart and transducer are in the same relative position for each acquisition.

A trade off occurs when the bounds of the gating are tightened. The tighter the bounds for respiratory or R-R interval gating, the longer the duration of the acquisition. The longer the acquisition, the greater the probability misalignment will occur due to sources such as patient or sonographer movement. If movement occurring within the gating limits set by the physician could be corrected, then the resulting reconstructions would be more accurate. If respiration gating could be eliminated completely, then acquisition time would greatly decrease.

1.3 Basic Approach
Registration of images, using correlation as a similarity metric, is investigated as a solution to identifying image misalignment. Both single frame and localized registration methods are examined. Figure 1.2 illustrates single frame registration. Figure 1.3 illustrates
localized correlation. Throughout this thesis the terms correlation, registration, and similarity metric are often used interchangeably in describing the method used - single vs. local.

The actual change between images may not be a pure translation, but the consecutive images will be acquired at a small enough degree increment that most of the major image features should be the same. Thus, the primary motion will be a rigid one in most cases.

**Figure 1.2: Single Frame Registration (or Correlation)**

*a.* Select a template from image 1.

*b.* Select the possible translation range from image 2. The template of image 1 and the translation range of image 2 should have their centers in the same location.

*c.* Take the template and move it around to all of the possible translations within the translation range, calculating the similarity between the template and the portion of the translation range which the template overlaps. In this example there are 9 possible translations.

*d.* Compare the similarity values obtained at each translation. The translation with the greatest similarity value represents the best match found by single frame registration and is the detected movement between the two images.
**Figure 1.3: Localized Registration (or Correlation)**

**Image 1**

**Image 2**

**a.** Select several small templates from image 1.

**b.** For each template in image 1, select the possible translation ranges from image 2. The template translation range pairs should have their centers in the same location.

**c.** Take each template and find the best match for it in its possible translation range. At the end of this stage one should have four arrows representing the best match for each of the template-translation range pairs.

**d.** To derive a value for the overall translation from the local translations, a displacement distribution is created. The center of a displacement distribution represents zero displacement. All of the cells in the displacement distribution are initially set to zero. One by one the tails of the arrows derived at the end of step c, are translated to the center of the displacement distribution. The cell where the head of each arrow lands is incremented by 1. Once all the arrows have been added to the displacement distribution the overall translation can be derived. There are several methods used to derive the overall translation; the simplest being finding the location of the highest value in the displacement distribution.
1.4 Why Registration is Difficult

In ultrasound images there is a significant amount of noise and speckle. Most boundaries between areas of different densities are several pixels wide, and boundaries can vary in gray level. In addition, shadows from objects closer to the sound source result in variations in the gray levels (Sakas, 1995).

Most registration methods are designed for recognizing offsets between images of the same objects from the same perspective. Yet, in the conical acquisition method two consecutive images differ because they are cross-sections taken at different angles. The differences in the images can be due to both change in geometry of the object, as seen by the cross-section, and to the appearance and disappearance of objects in the line of the cross section. See figure 1.4. In figure 1.4, object B appears to have a longer cross-section at 15 degrees than at 0 degrees, yet the object has not moved. Also in figure 1.4, the objects visible in the cross-section change. At 0 degrees objects A and B appear in the image. At 15 degrees object A has disappeared from the cross-section, and a new object C has appeared. Standard full image registration methods are inadequate because they are not designed to handle these differences.

**Figure 1.4:** Cross-sections at nearby angles may contain different objects. For example at 0 degrees object A and B are in the cross-section, but at angle 15 degrees object A has disappeared and a new object C has become visible in the cross-section.
Using correlation to find the translation between images works best when most of the image features are constant. Figures 1.5 and 1.6 display two images taken 3 degrees apart. Notice that there are many similarities between the two images, but also a few differences. If the images are similar enough then standard registration methods may be successful.

**Figure 1.5:** Image from parasternal site; 48 degrees

![Figure 1.5](image1.png)

**Figure 1.6:** Image from parasternal site; 51 degrees

![Figure 1.6](image2.png)
1.5 Methods
Several registration algorithms will be developed and evaluated with the goal of improving 3D reconstruction by correcting for movement between 2D images from consecutive angles in a conical data set. This evaluation will consist of several stages including identifying a registration algorithm, testing its accuracy on phantom data, and applying the algorithm to heart data.

1.5.1 Registration Algorithm
Development of the registration algorithm includes identifying a feature space, similarity metric, search space, and search strategy (Brown 1992). The registration algorithm uses raw pixel values as the feature space. Single frame two dimensional normalized cross-correlation, localized cross-correlation, two dimensional correlation coefficient, and localized correlation coefficient were used as similarity metrics. The search space is restricted to translations within 27 pixels of the center of the template image location, and the search strategy is an exhaustive search. From the results of evenly spaced localized registrations an overall translation is then derived. See figure 1.7 for a sample localized registration display between heart images at 48 and 51 degrees from the parasternal view with respiratory gating.
Figure 1.7: Localized correlation vector display. '+' represents the head of the vector. The vectors begin at evenly spaced locations and end where the translation has the best localized correlation value.
Figure 1.8: A method for deriving an overall displacement from localized displacements

Derive local correlations from localized templates.

From localized correlation arrows derive a displacement distribution.

Apply filter to each location of the displacement distribution padding the edges of the distribution with zeros.

Perform subpixel averaging on the 3x3 area around the highest value of the smoothed displacement distribution.

\[
x = \frac{(2.5+3.5+1.5)\times 0 + (5+7+3)\times 1 + (2.5+3.5+1.5)\times 2}{2.5+3.5+1.5+5+7+3+2.5+3.5+1.5}
\]

\[
y = \frac{(2.5+5+2.5)\times 0 + (3.5+7+3.5)\times 1 + (1.5+3+1.5)\times 2}{2.5+5+2.5+3.5+7+3.5+1.5+3+1.5}
\]

x = 1, y = -13/15
After all the localized displacements are derived, an overall displacement of the image must be derived. See figure 1.8. Several methods were explored for finding this overall displacement. All methods involved creating a displacement vector distribution. This distribution is created by translating the tails of the displacement vectors found in localized correlation to a common origin on a 2D grid. Next, the heads of the vectors are plotted. Each grid location is associated with a value representing the number of vectors with heads at that location. See figure 1.9 for a sample displacement distribution. After the displacement distribution has been created, it is then smoothed by applying a filter. Next, the maximum valued location of the smoothed displacement distribution is found and is used as a displacement estimate. This estimate is then used to derive a sub-pixel location value by performing averaging of the displacement distribution in the area around the estimate.
1.5.2 Data acquisition

All data sets were obtained using a rotational transducer, and an HP SONOS 2500 ultrasound imaging system. First images were acquired using the transducer and the SONOS imaging system. Next the images were saved to an optical disk. From the optical disk the images were loaded onto a HP 700 series UNIX workstation for conversion to Tagged Image File Format (TIFF) and registration.

1.5.3 Phantom Data

To judge the accuracy of the registration algorithm, a set of phantom data was obtained. Image sets of a wire tissue phantom were acquired at various known translations
using a digitally calibrated translation station. The registration algorithm’s ability to correctly identify the movement between phantom images at different locations could then be ascertained.

1.5.4 Summary of Results

A summary of the results is shown in table 1.2. The method which yielded the least number of errors is the localized correlation coefficient method. This method used the correlation coefficient with weighting and smoothing as a similarity metric.

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1.5.5 Future Investigations

Now that the methods have been tested using phantom data, they should be tested on actual heart data. The registration algorithm should be applied consecutively to each pair of adjacent images of a conical acquisition set. A second data set can then be constructed, composed of images from the original data set which were translated to correct for the
offset found by the registration algorithm. Images from the two sets can be compared before and after using several verification methods such as comparing reconstructed images.

1.6 Related Work

Not much is known about what methods, if any, are currently being used to correct for movement of the heart within the chest during 3D ultrasound examinations. 3D ultrasound is still a new area, and companies with 3D ultrasound products are keeping their research proprietary. While the idea of 3D ultrasound has been around for a while (see Ghosh, 1982 and Geiser, 1980), many of the technical problems associated with 3D imaging of the heart have only recently begun to be solved (Vuille, 1996). This has opened the path to making 3D reconstructions a feasible clinical tool and commercial product.

Gating on both respiration and heart beat using the multiplane transducer is relatively new. An article published by Roelandt in 1994 claims, “In the multiplane transesophageal imaging transducer approach, the heart is “fixed” in space by the gating algorithm during the acquisition relative to the fixed stable interrogating transducer. This article reports the first clinical results with this approach (Roelandt, 1994).” With just the first clinical results being published three years ago this is still a young field. In 1993 an article was published in the Video Journal of Cardiology exploring the “feasibility of multidimensional reconstruction in transesophageal echocardiography” (Belohlavek, 1993). Pandian’s 1993 paper “Three-Dimensional Echocardiography: A New Dimension in Cardiac Imaging” provides a good overview of 3D echocardiography (See also Freeman 1994).

The current main focus of research in 3D ultrasound is in improving the 3D visualizations through filtering or different methods of display (Sakas, 1995a; Sakas 1995b; Thune,
1991; Salustri, 1995). Research is also being performed in the segmentation of the 3D images to highlight the object of interest (Sakas, 1995a; Sakas, 1995b; Kubica, 1994).

In the area of image alignment, other methods include correlation in the frequency domain (Hibbard, 1992). Another method for alignment involves matching control points in one image to the corresponding known control points in the next image (Flusser, 1992).

1.7 Conclusions
This investigation will lead to insight into whether registration of consecutive ultrasound images using localized correlation is a feasible approach to improving 3D reconstructions.
Chapter 2

Methods

This chapter provides a technical background and description of the methods used in the investigation. The project was centered around developing a registration algorithm which would correctly identify movement between ultrasound images acquired at consecutive angles during a 3D data set acquisition.

A registration algorithm is an algorithm designed to match an object in one image with an object in another image. There are four major components of a registration algorithm: search space, feature space, similarity metric and search strategy. Of these four variables, it is the similarity metric which differs between the registration methods discussed in this chapter. The four major approaches are as follows: single frame cross-correlation, single frame correlation coefficient, local cross-correlation, and local correlation coefficient.

Of the four major similarity metric approaches, the local correlations can differ further in how the overall translation is derived from the results of the local correlations. This chapter first discusses cross-correlation vs. correlation coefficient and then proceeds to single frame vs. local correlation. Following this, options for deriving an overall translation from the results of local correlations are explored. Then, weighting is added to the similarity metric. The chapter closes with a discussion of how to verify that the registration method is successful.

2.1 Cross-Correlation vs. Correlation Coefficient
Cross-correlation is based on the idea that two images are likely to be well matched if the sum of the product of the individual pixel values is high. Yet if this metric were based on multiplication alone then a template (a section of an image to be matched) would elect to
match to a very bright portion of the corresponding image instead of to the correct match. To reduce this bias, the correlation metric is normalized based on the intensity values of the template and the image portion being matched. The normalization reduces the chance of false matching to a bright portion of the image. The cross-correlation metric formula for a $n \times m$ template from image A and a $n \times m$ portion from image B is given below ($u$ and $v$ represent the offset between the location of template A and the location of the image portion from image B which is being matched).

$$x_{corr} = \frac{\sum_m \sum_n (A(m, n)B(m - u, n - v))}{\sqrt{\sum_m \sum_n A^2(m, n)\sum_m \sum_n B^2(m - u, n - v)}}$$

The correlation coefficient is similar in principle to cross-correlation. However, the correlation coefficient is designed so that values range from -1 to 1, where -1 is a perfect inverse correspondence of the images and 1 is a perfect positive correspondence of the images.

The cross-correlation metric formula for a $n \times m$ template from image A and a $n \times m$ portion from image B is given below ($u$ and $v$ represent the offset between the location of template A and the location of the image portion from image B which is being matched).

$$corrcoeff = \frac{\sum_m \sum_n ((A(m, n) - \mu_A)(B(m - u, n - v) - \mu_B))}{\sqrt{\sum_m \sum_n (A(m, n) - \mu_A)^2}\sum_m \sum_n (B(m - u, n - v) - \mu_B)^2}$$

Mean of an $n \times m$ image portion $x = \mu_x$
The advantage of cross-correlation is that it is faster to compute than the correlation coefficient. Therefore, cross-correlation is a preferred method to find a good match quickly. However, if one needs to compare relative strengths of correlations, the correlation coefficient is the method of choice. A danger or a feature with both of these methods is that, due to the normalization, a low average intensity pattern can match to a high average intensity pattern if the patterns are otherwise similar.

2.2 Local vs. Single Frame Correlation

Single frame registration involves using a single large template from one image to match the second image. Registration using single frame correlation as the similarity metric involves searching the list of allowable translations and calculating the correlation value between the template and the image which it is trying to match to. The translation with the highest correlation value is considered to be the best match. The term “Correlation value” will be used in place of “similarity metric value” throughout this discussion.

Local correlation involves performing many small template matches using the same matching process as single frame correlation. For local correlation small templates from the first image are used to see where different pieces of the first image best match locally to the image being matched. After finding out how the pieces of the first image best match the second, the overall movement which should yield the best match is derived from the results of the local correlations.

One advantage of single frame correlation over local correlation is that it can be faster. Single frame correlation is also less susceptible to the speckle noise which plagues ultrasound. However, local correlation is sometimes more resistant to appearance of new features. Local correlation can also provide information on movement of different families of objects. Is there more than one major movement occurring? Do different objects in the
same image move differently? If local correlation data is accurate, then from the patterns of movement one might be able to derive the rotational movement which occurred.

2.3 Deriving an Overall Translation from Local Correlation Results

After one is presented with the results of localized correlation, there must be a method to derive the overall translation which occurred from the localized translations. Five different methods were explored for deriving this overall translation.

The first method is averaging. Averaging is error prone because incorrect matches which are far from the correct match can have a large effect on the overall average. In general, there are many ambiguous regions that simply contribute noise to the average.

The second through fifth methods are all based on the creation of a displacement distribution. To create a displacement distribution, the results of each local translation are plotted on a displacement distribution graph by translating the tails of the local translation vectors to a common origin at the center of the displacement distribution. Once the vectors have been translated, a count is made of the number of vector heads which map to each box of the distribution. See figure 2.1. The displacement distribution graph is a graph of boxes where the central box represents zero displacement. Each location in the displacement distribution graph maps to an allowable translation. Each box in the graph has a count associated with it which contains the number of local translations which map to that box or translation. Each of the local correlations is plotted on this graph.
Figure 2.1: Displacement Distribution

Y.

X.

After the graph is created, four methods were used to derive the overall translation. The first of these methods is to find the location in the graph with the highest count (i.e. the translation found by the most local correlations). The second method is to then perform subpixel averaging around the maximum in a 5x5 pixel area to get a value which is not limited to whole pixels. The third method is to smooth the displacement distribution graph by applying a 5x5 gaussian filter and then taking the maximum. See figure 2.2. The last method involves performing subpixel averaging on the smoothed displacement distribution.
The advantage of the displacement distribution method over the averaging method is that the displacement distribution is less susceptible to random and non-random noise. The displacement distribution, where only a maximum is taken, could be strongly influenced by one area of the image which has a strong consistent match. The advantage of smoothing and subpixel averaging is that it allows for consideration of other translations with a high density of matches within a small area even if the matches do not map to exactly the same location. There may be many translations in a small area. For example, there could be 27 translation mappings in a 3x3 area with each location within the area having three local translation vectors mapping to it. Whereas there could be another single
isolated box in the displacement distribution with four exact matches. The smoothing method would find the 3x3 area instead of the isolated box, which the maximum method would find.

In summary, the five methods explored for deriving overall translations from local correlations are as follows.

1. Averaging.
2. Creating a displacement distribution and taking the maximum.
3. Creating a displacement distribution and performing sub-pixel averaging around the maximum.
4. Creating a smoothed displacement distribution and finding the location in the displacement distribution with the maximum value.
5. Creating a smoothed displacement distribution and performing sub-pixel averaging around the maximum.

2.4 Weighting the Local Correlation Values
If the methods described in the section above are used, a local correlation match from a small template with no major features has the same influence on the outcome as a match of a small template which contains a major feature. If there are few major features in the image then it is important to reduce the chances of an incorrect match. This can be done by weighting each local translation vector by the correlation value. It can also be done by ignoring local translation with correlation values under a set threshold.

Another problem which occurs is that there may be many good matches within a translation range. Less confidence should be placed in the best match when there are many high correlation matches than should be placed in the best match when there are very few high correlation matches. As a result, a measure called uniqueness was created which could be used for weighting the displacement distribution graph.

2.4.1 Determining Uniqueness of the Best Correlation
As a measure of uniqueness, a histogram of all of the correlation values is created. Each bar of the histogram covers a range of 0.01 of the correlation value. The bar which con-
tains the correlation coefficient value of the peak will be the bar which is the furthest to the right, if 0 is the origin and 1 is to the right of the origin. This bar containing the peak and the four bars to the left of the peak are summed to give a rough measure of how many translations have correlation coefficient values within 0.05 of the peak. After all the localized correlations are performed for a particular image pair, the maximum count of values within 0.05 of the peak is taken. This maximum is used to normalize the uniqueness measure.

This histogram method was chosen over some other common methods for the following reasons. If a variance measure were taken around the correlation maximum to characterize the peak, it would not take into consideration peaks in other areas of the translation range. Also, a variance measure is designed to characterize a gaussian. If there is not one simple peak then the variance measure is not as meaningful. Another method used is to compare the ratio of the average taken in a small box centered around the peak to the peak value. If this ratio is above a set threshold then the peak is too flat and should not be used in calculating the overall displacement. Difficulties with this method include the introduction of two new parameters instead of one. A parameter controlling the size of the area around the peak that should be used to calculate the average must be added. In addition, a parameter controlling the cutoff threshold must be introduced. It is this threshold parameter which can create difficulty. In addition, this method would miss the case of multiple strong separated peaks, which indicate a nonunique match.

2.4.2 Weighting Methods Tested

We tested seven weighting methods on the local correlations.

1. No weighting.
2. Correlation coefficient weighting.
3. Threshold at correlation coefficient value of 0.5.
4. Threshold on the correlation coefficient and then weighting by uniqueness and
correlation coefficient.
5. Threshold on the correlation coefficient and then weighting by uniqueness.
6. Weighting by uniqueness.
7. Correlation coefficient and uniqueness weighting.

2.5 Verification of Registration Methods
Thus far, various methods for registration have been discussed. The question now is how can one determine which of these methods is the best; or whether any of these methods are accurate? Several verification methods are proposed in this section. Some are qualitative, and others are quantitative. Some are designed for use when a translation is known. Others were derived for use when the translation is not known.

Verification Method 1 would be to know the translations which occurred between images and then to test whether the registration algorithm is able to correctly identify the translations. While this is the most accurate method of judgement, it is an impossible task using in vivo heart data because there are no absolute reference points on the heart that can be used for locating the position of the heart in relation to the imaging element. For initial verification, phantom data was used. Both single frame and local correlation as well as the many combinations of weighting and deriving overall correlation from the local correlation, were tested on the phantom data.

Verification method 2 is to compare 3D reconstructions of the corrected and uncorrected data sets to see if improvement was obtained through the registration process. The difficulty with this method is that it is very subjective and only verifies that the resulting image looks smoother and does not verify that the registration algorithm is accurate. Unfortunately, a commercial 3D reconstruction program for ultrasound images was not accessible for this project.

Verification method 3 is to compare visually the $0$ degree and the flipped $180$ degree images of a data set pre and post registration. See figure 2.3. In theory, if there was no
movement these two images should be identical except for noise (neglecting slight variations expected due to the fact that different sensor elements are producing different parts of the two images). The images should be better aligned post registration. Half of the 0 degree image and half of the 180 degree image are displayed to see if the sides line up.

**Figure 2.3:** 0 and 180 degree images pre and post registration.

Verification method 4 is to create a movie which shows the slices of uncorrected vs. corrected images side by side. By viewing the movie, one can compare visually which
data set has the least movement between frames. This is a useful tool. However, it still only allows you to tell if there is a smoother change between the images at different angles. It does not let one determine whether or not the correct translation was found.

Verification method 5 is to view a single row of an image lined up with the same row from images taken at consecutive angles. There should be smoother changes in the corrected data set row picture than in the uncorrected data set row picture.

Verification method 6 is to create a 3D data set from the 2D slices and to take corresponding slices from the corrected and uncorrected data set to compare the smoothness of transitions between consecutive angles.

Verification method 7 is to create a difference graph, plotting the sum of the absolute value of the differences between the intensity values of the images pre and post correction. See figure 2.4. The shortcoming of this method is that it judges whether the correlation method performed as it should have, since the basis for the correlation method is to find the match with the minimum difference between two slices (i.e. validates the algorithm, not whether the algorithm actually solves the problem).
Figure 2.4: Difference graph. x axis = data pairs 1-39. y axis = sum of absolute differences between the images in each pair. - = original image vs. translated image. -- = original image vs. translated image corrected with the actual translation. --- = original image vs. translated image corrected with the translation found by localized correlation.

Verification method 8 involves viewing movies of two images at consecutive angles 3 degrees apart alternating. From viewing such a movie one can visually ascertain the general type of movement which is occurring. Is it primarily rotational, vertical or horizontal? Since one can gather visually an overall impression of movement using this tool, one could painstakingly take each consecutive image pair and adjust the translation
between each pair until the least movement is seen. This is now the value for the absolute movement between the two slices which can be compared to the registration algorithm's results. Before this method can be used it should first be verified on phantom data to test its accuracy.

All of the above methods except method 1 have the disadvantage that they have qualitative aspects. Method 8, once verified, could provide the next most quantitative approach. Method 8 could also provide insight into the types and extent of movement most commonly occurring in the data sets.
Chapter 3

Phantom Data Results

This chapter outlines the results of single frame and local correlation methods applied to the phantom data. The phantom data are images acquired of a tissue phantom in a water tank. The phantom was secured in the water tank. Above the phantom, the imaging transducer was secured on a translation station. This allowed an accurate measurement of the relation between the phantom and the transducer to be taken. With this known, the results of registration algorithms can be compared directly to the actual movement.

Thirty-nine pairs of phantom images with known translations were used to judge the performance of the registration algorithms. Initially, both localized and single frame cross-correlation were tested. The single frame and localized correlation performed well in most cases, yet had some extreme outliers. Time was spent trying to understand the failure in the localized correlation and in trying to improve the method. This was viewed as an important investigation because images of the heart are more complicated than the phantom data and there may be cases in which the localized correlation performs better.

After an investigation into the failed cases of cross-correlation in order to try to eliminate the cases of failure, it was discovered that the correlation coefficient provided a more informative measurement than cross-correlation. This chapter takes the reader through a sequence of results in “historical order” ending with the best method. The results are summarized in table 3.1.
Table 3.1: Summary of Results

<table>
<thead>
<tr>
<th>Method</th>
<th>Mean distance from actual displacement in pixels</th>
<th>Median distance from actual displacement in pixels</th>
<th># of failures out of the 39 phantom image pairs (errors of &gt; 5 pixels)</th>
<th>Maximum error in pixels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single Frame Cross-Correlation</td>
<td>1.5639</td>
<td>0.7716</td>
<td>3</td>
<td>8.0775</td>
</tr>
<tr>
<td>Localized Correlation using cross-correlation with smoothing</td>
<td>1.3634</td>
<td>0.3916</td>
<td>4</td>
<td>8.4323</td>
</tr>
<tr>
<td>Single Frame Correlation Coefficient</td>
<td>1.7499</td>
<td>0.9912</td>
<td>4</td>
<td>8.5564</td>
</tr>
<tr>
<td>Localized Correlation using the correlation coefficient with weighting and smoothing</td>
<td>1.2094</td>
<td>0.6999</td>
<td>1</td>
<td>6.6517</td>
</tr>
</tbody>
</table>

3.1 Collection of Watertank Data
The phantom data was acquired using a digitally calibrated translation station which allowed movement of the probe along the horizontal axis. A tube of +15dB material within a Multipurpose Phantom model 539 from ATS Laboratories was the object used during the phantom acquisitions. The phantom was secured in a water tank in order to allow constant acoustic contact between the probe and imaging surface. However, this did produce an artifact within the images of a bright reflection at the boundary of the phantom surface and the water. A secondary artifact was also often seen at about twice the depth of the primary artifact. See figure 3.1.
The 39 phantom data pairs used were acquired from two different phantom positions. 18 pairs were taken from position 1. Position 1 was close to the smallest cross-section of the tube, resulting in the tube appearing as a circle in the image. In position 2, the probe was positioned at an angle to the tube thus giving the tube cross-section an oval appearance. The size of the images acquired was 216x300 pixels. The maximum displacement was 23.7 pixels and the minimum displacement was 5.49 pixels. The first image of the pair was at 0 degrees and the second image of each pair was acquired at 3 degrees rotation around the central axis of the transducer.

3.2 Cross-Correlation Investigation
Several constraints were placed on the investigations. Each picture is composed of a sector window containing the ultrasound data and background data around the sector. See figure 3.2. Background pixels can corrupt correlation calculations. Precautions were taken to avoid this effect. The single frame correlation was limited so that the entire translation range of the image was within the image sector. For local correlations, local translations containing background pixels in the translation range were not included in the calculation.
of the overall translation. An additional constraint placed on both methods was that the translation search range was limited to a box which allowed a movement of 27 pixels up, down, right, or left, and in combinations. In addition, square templates were used in both methods in order to limit the number of parameters.

**Figure 3.2:** Each image is composed of a sector of ultrasound data and background data. Correlation is restricted to the largest square which will fit within the bounds of the ultrasound data.

### 3.2.1 Results Local vs. Single Frame

The image area used in the single frame correlations was a square area: rows 52-192 and columns 82-222 of the image. The template within this area was 87x87 pixels. The image area used was selected so that all possible translations of the template lay within the bounds of the image sector, and so that the primary artifact was not included in the translation range. Under the above constraints, the results of performing overall correlation on the 39 data sets are displayed in table 3.2. Note that the mean and median distances from the actual displacement is less than 2 pixels, yet there are 3 cases of failure. This 7.69% failure rate is much too high for practical use.
### Table 3.2: Results for Single Frame Cross-Correlation

<table>
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<tr>
<th>Method</th>
<th>Mean distance from actual displacement in pixels</th>
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</table>

Localized correlation was also performed on the phantom images. Correlations were performed on 45x45 pixel boxes, with box centers 9 pixels apart. The local templates, with translation ranges that included background pixels, were discarded. From the local translation results, an overall translation was derived by first creating a displacement distribution of the local translation results. The distribution was then smoothed by a 7x7 gaussian filter, and the peak of the smoothed distribution was found. Next, subpixel averaging was performed in the 5x5 pixel box centered around the peak. The statistics for localized cross-correlation are displayed in table 3.3. There were four outliers, only one of which was common with the single frame correlation outliers. The median and mean are better than the performance with single frame correlation. However, the maximum is slightly worse and there is one more outlier. Localized correlation performs better in the average case, yet fails in some cases. If the cases in which the local correlation fails could be eliminated, it may be able to perform distinctly better than the single frame correlation method.
Table 3.3: Summary of Results from Localized Cross-Correlation compared to Single Frame Cross-Correlation results

<table>
<thead>
<tr>
<th>Method</th>
<th>Mean distance from actual displacement in pixels</th>
<th>Median distance from actual displacement in pixels</th>
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</tr>
<tr>
<td>Localized Correlation using cross-correlation with smoothing</td>
<td>1.3634</td>
<td>0.3916</td>
<td>4</td>
<td>8.4323</td>
</tr>
</tbody>
</table>

3.2.2 Investigation into Failures

By understanding the failures in the local cross-correlation examples, one may be able to improve the overall displacement deriving algorithm and thus improve the performance. What makes localized correlation unappealing are the large errors which occurred, with several errors of more than 5 pixels. The image pair with the maximum distance from the actual displacement was selected to undergo investigation. The two images are shown below. The first image is the 0 degree slice of the data set taken of the phantom at position 2 with the probe at 7.5 mm and 0 degrees. The second image is the 3 degree slice of the data set taken of the phantom at position 2 with the probe at 15 mm and 0 degrees. The net actual pixel displacement is 16.5 pixels.
Figure 3.3: Image 1 with intensities inverted; 0 degree slice of acquisition at phantom position 2 with probe location at 7.5 mm and 0 degrees

Figure 3.4: Image 2 with intensities inverted; 3 degree slice of acquisition at phantom position 2 with probe location at 15 mm and 0 degrees

The localized correlation, of the images shown in figures 3.3 and 3.4 contained three strong families of arrows, which can be viewed in the arrow plot of figure 3.5. The family of arrows at the top have a zero displacement. This artifact is caused by the reflection at the water/tissue phantom boundary. The second family of arrows is seen at the vertical line, which corresponds to the wall of the phantom on the left side of the images. This
family of arrows represent the correct displacement. The last family of arrows corresponds to the oval cross-section of the tube, and represent an incorrect displacement. This incorrect displacement family is being identified as the overall displacement by the method for deriving the overall translation from the local translation results. The question of why correlation is failing to find the actual displacement in this area needs to be addressed.

Figure 3.5: Local correlation results for images 1 and 2

An initial hypothesis of failure was that the change in the geometry due to rotation was too great for a correct match. As a test, the 0 degree images of the 7.5mm and 15 mm data
sets were compared, thus eliminating the 3 degree rotation. The translation again failed to find the correct displacement of 16.5, finding a horizontal displacement of 8. Since it failed just on pure translation, there must be another source besides changing geometry causing the error. A new hypothesis was that the boundary definition was not sharp enough and that speckle patterns were being matched which were stronger than the boundary definition.

In order to further understand the failure of the correlation to find the correct value, a 3D surface plot was created with the axes being correlation value, the template number, and the displacement from the template center. The plot corresponds to a single horizontal line across the image. Every 9 pixels the correlation of the 45x45 pixel template centered at that pixel was recorded along horizontal displacement of up to 27 pixels left and right of the template center. The correlation values in the 55 pixel translation range along this line were plotted against template number.
Cross-correlation value

Displacement from template center

In the surface plot above, there is a trend in the first several templates; the correlations are high where they should be high and low where they should be low. These templates contain the vertical bar in the image. However, in the higher template numbers the correlation values become almost uniform, making the peak hard to discern. Yet in the current overall translation method being used, the local correlations with weak peaks are weighted equally with the local correlations with strong peaks. Finding a way to incorporate the uniqueness of the correlation in the derivation of the overall translation
method could help overcome the flaw in the correlation method which found a shorter family of arrows to be stronger than the family of arrows reflecting the correct translation.

3.3 Weighting Investigation

The weighting investigation began as an investigation into whether the accuracy of localized correlation could be improved through weighting by correlation value and/or uniqueness of the correlation.

How does one measure the uniqueness of a correlation match? Since exploring the 3D case is very difficult, a simpler 2D case was used for this investigation. In this 2D case, the translation range is restricted to horizontal movement: 27 pixels left and 27 pixels right of the starting position. Investigation into cross-correlation and then into correlation coefficient leads to the conclusion that the correlation coefficient is a better measure for judging peak strength.

3.3.1 Investigation of cross-correlation

Since the surface plot in figure 3.6 is difficult to read, a set of 2D plots were created to allow more accurate investigation of the data. See figures 3.7-3.9. Each of the 22 plots corresponds to a different localized correlation template, set up with spacings between them of 9 pixels. The first template is located at 50 pixels. Table 3.4 shows the location of the maximum found for each of the plots. From the table we can conclude that boxes 1-6, 8-10, and 23 found the correct translation of close to 16.5 pixels, whereas boxes 7 and 11-22 did not. Is there a pattern to the failure? To check we can look at what was in the original templates. See figure 3.10 for the templates.
Figure 3.7: 2D plots of cross-correlation movement along row 122; templates 1-8.
Figure 3.8: 2D plots of cross-correlation movement along row 122; templates 9-16.
Figure 3.9: 2D plots of cross-correlation movement along row 122; templates 17-23.
Table 3.4: Maximum locations found for each of the 2D Plots

<table>
<thead>
<tr>
<th>Template number</th>
<th>Pixel-location corresponding to template center</th>
<th>Location of best match</th>
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<tbody>
<tr>
<td>1</td>
<td>50</td>
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<td>3</td>
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Figure 3.10: Image Templates along row 122 of image 1.

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Templates 1-6 of image 1 contain the bar. Templates 7 and 8 contain no features. Templates 9-12 contain the first edge of the tube, and templates 13-20 contain the body of the tube. Templates 21-23 contain the second edge of the tube. How do the cross-correlation values compare? The sharp peaks correspond to templates 1-6. The constant correlation values correspond to templates 7-22. The most unfortunate item is that the correlation strength of the featureless templates 7 and 8 have high correlation values, when there is actually little information in the templates. This shows that weighting by cross-correlation value will not likely improve the results because low information templates can

60
have high correlation values. Yet weighting by uniqueness of the high correlation value does seem likely to improve the results, since templates 1-6, which had sharp correlation peaks, correspond to the area where the correct match was found with the localized correlation.

3.3.2 Investigation of correlation coefficient

Instead of using cross-correlation as a matching metric, more accurate results may be obtainable by using a different correlation metric. We should be able to use the correlation coefficient metric as an absolute measure of correlation strength correspondence in the range of 1 to -1. The surface plot and 2D correlation coefficient plots are shown below, along with the table of maximum value locations for each of the 2D plots.
Figure 3.11: Surface Plot of correlation coefficient values along row 122 of the images.

Correlation coefficient value

Displacement from template center

Template number

displacement right

zero displacement of template

displacement left
Figure 3.12: 2D plots of correlation coefficient movement along row 122; templates 1-8.
Figure 3.13: 2D plots of correlation coefficient movement along row 122; templates 9-16.
Figure 3.14: 2D plots of correlation coefficient movement along row 122: templates 17-23.
Table 3.5: Maximum value locations of the 2D correlation coefficient plots

<table>
<thead>
<tr>
<th>Template number</th>
<th>Pixel-location corresponding to template center</th>
<th>Location of best match</th>
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<td>23</td>
<td>248</td>
<td>-1</td>
</tr>
</tbody>
</table>

The correlation coefficient metric, when used in place of the previous cross-correlation metric, produced results which better matched the expected results. The first 5 templates
had high, well-defined peaks at location 18 which is close to the correct value of 16.5. The 6th template only contains a small portion of the vertical bar, but had a lower yet still well-defined peak at location 15. The 7th template contained none of the bar and none of the edge of the tube. Its peak was very low and was at location -3 which corresponds to just catching all of the bar in the matching box, yet not including much of the water beyond the bar. The 8th template contains a small amount of the edge of the tube and has a low peak at location 21. The 9th, 10th, and 11th templates contain most of the edge. The 9th template has a larger peak than templates 7-8 but a smaller peak than the first 6 templates which contain the strong edge of the bar. The 9th template is also a smoother peak. The 10th template also contains the edge and has a stronger but smoother peak than template 9. The peaks continue to become smoother with the next templates and also become incorrect, matching best at location 6-9 instead of near location 16.5. From analyzing the templates, one may think that the correct answer should also be found at the second edge of the tube. However, this second edge is not sharply defined in image 2 and so there is no distinct best match with the image 1 template.

The 2D graphs of the correlation coefficient followed the rule that high correlation coefficient value and sharp peak corresponds to the best matches, while either low correlation coefficient or smooth peak corresponds to the answers furthest from the actual answer of 16.5 pixels displacement. In the cross-correlation, the peaks were not very sharp and the boxes with few features which had low correlation coefficient values had high cross-correlation values. This fact shows that weighting by cross-correlation value only is not a useful or reliable metric. All of the 2D cross-correlation graphs were considerably flatter than those obtained by the correlation coefficient, which makes identifying the strengths of peaks more difficult. As a result, a new method using the correlation coefficient and an evaluation of sharpness of peak will be investigated.
3.3.3 Horizontal vs. 2Dpeak

In the above sections a simplified 1D translation range has been used. How does it apply to the 2D translation range? One could test movement along the horizontal and vertical only and get a value for the uniqueness in each direction. This, however, would miss well matching correlation along a diagonal. To equally weight high correlations in any direction, a count is made of the number of values close to the highest correlation value. See explanation in Chapter 2 section 2.4.1 Determining Uniqueness of the Best Correlation.

3.4 Correlation Coefficient

Since the correlation coefficient had a more accurate relation between strength and information in the image and it had a greater variance of values, it was elected to be used for all further experiments in this thesis. Weighting by correlation coefficient value, setting a threshold at a correlation coefficient value, weighting by uniqueness of the highest correlation value, and combinations of the above were all explored to determine which method would yield the best results.

3.4.1 Results from Various Weighting Methods

The interference from the artifact at the top of the image disrupted many correlation results and so the portion of the image containing the artifact was ignored. In real life there may be similar artifacts. Seven weighting methods and five methods for deriving the overall translation from local translation results were tried.

The weighting methods are enumerated below:

1. No weighting.
2. Correlation coefficient weighting.
3. Threshold at correlation coefficient value of 0.5.
4. Threshold on the correlation coefficient and then weighting by uniqueness and correlation coefficient.
5. Threshold on the correlation coefficient and then weighting by uniqueness.
6. Weighting by uniqueness.
7. Correlation coefficient and uniqueness weighting.

The overall peak finding methods are enumerated below:

1. Averaging.
2. Creating a displacement distribution and taking the maximum.
3. Creating a displacement distribution and performing sub-pixel averaging around the maximum.
4. Creating a smoothed displacement distribution and finding the location in the displacement distribution with the maximum value.
5. Creating a smoothed displacement distribution and performing sub-pixel averaging around the maximum.

The results of applying these methods are presented in table 3.6. Most of the methods tried yielded a median error of less than one pixel, which means that most of these methods performed well on most images. Two methods stood out by having only one case of failure: methods o4w7 and o5w7. Method o4w7 weighted the displacement distribution by correlation coefficient and uniqueness and derived the overall answer from the maximum of the smoothed displacement distribution. Method o5w7 weighted the displacement distribution by correlation coefficient and uniqueness and derived the overall answer by performing sub-pixel averaging around the maximum of the smoothed displacement distribution. While these two cases had only one case of failure, 19 of the 35 methods investigated had only two cases of failure. With many methods performing similarly and with the small sample size of 39 image pairs, no concrete conclusions can be
made about which method will perform the best. Yet through investigation of trends in the data, one can gauge how components of the methods perform.

**Table 3.6: Results from the various weighting and overall methods**

<table>
<thead>
<tr>
<th>Overall method = O? Weighting method = w?</th>
<th>Mean in pixels</th>
<th>Median in pixels</th>
<th>Maximum in pixels</th>
<th>Number of failures (error &gt; 5 pixels)</th>
</tr>
</thead>
<tbody>
<tr>
<td>o1w1</td>
<td>3.38</td>
<td>2.39</td>
<td>11.40</td>
<td>10</td>
</tr>
<tr>
<td>o1w2</td>
<td>2.25</td>
<td>1.59</td>
<td>8.13</td>
<td>6</td>
</tr>
<tr>
<td>o1w3</td>
<td>1.45</td>
<td>0.76</td>
<td>5.76</td>
<td>2</td>
</tr>
<tr>
<td>o1w4</td>
<td>1.29</td>
<td>0.60</td>
<td>5.30</td>
<td>2</td>
</tr>
<tr>
<td>o1w5</td>
<td>1.32</td>
<td>0.68</td>
<td>5.45</td>
<td>2</td>
</tr>
<tr>
<td>o1w6</td>
<td>3.27</td>
<td>1.85</td>
<td>10.51</td>
<td>10</td>
</tr>
<tr>
<td>o1w7</td>
<td>2.17</td>
<td>1.55</td>
<td>7.42</td>
<td>6</td>
</tr>
<tr>
<td>o2w1</td>
<td>2.51</td>
<td>1.00</td>
<td>25.24</td>
<td>4</td>
</tr>
<tr>
<td>o2w2</td>
<td>1.76</td>
<td>0.99</td>
<td>14.02</td>
<td>2</td>
</tr>
<tr>
<td>o2w3</td>
<td>1.77</td>
<td>0.99</td>
<td>14.02</td>
<td>2</td>
</tr>
<tr>
<td>o2w4</td>
<td>1.74</td>
<td>0.99</td>
<td>14.02</td>
<td>2</td>
</tr>
<tr>
<td>o2w5</td>
<td>1.72</td>
<td>0.99</td>
<td>14.02</td>
<td>2</td>
</tr>
<tr>
<td>o2w6</td>
<td>2.34</td>
<td>1.00</td>
<td>25.24</td>
<td>3</td>
</tr>
<tr>
<td>o2w7</td>
<td>1.74</td>
<td>0.99</td>
<td>14.02</td>
<td>2</td>
</tr>
<tr>
<td>o3w1</td>
<td>2.36</td>
<td>0.74</td>
<td>25.24</td>
<td>4</td>
</tr>
<tr>
<td>o3w2</td>
<td>1.65</td>
<td>0.73</td>
<td>14.33</td>
<td>2</td>
</tr>
<tr>
<td>o3w3</td>
<td>1.67</td>
<td>0.76</td>
<td>14.28</td>
<td>2</td>
</tr>
<tr>
<td>o3w4</td>
<td>1.59</td>
<td>0.72</td>
<td>13.85</td>
<td>2</td>
</tr>
<tr>
<td>o3w5</td>
<td>1.58</td>
<td>0.63</td>
<td>13.84</td>
<td>2</td>
</tr>
<tr>
<td>o3w6</td>
<td>1.16</td>
<td>0.71</td>
<td>25.24</td>
<td>3</td>
</tr>
<tr>
<td>o3w7</td>
<td>1.59</td>
<td>0.65</td>
<td>13.91</td>
<td>2</td>
</tr>
<tr>
<td>o4w1</td>
<td>1.67</td>
<td>0.99</td>
<td>8.51</td>
<td>4</td>
</tr>
</tbody>
</table>
Table 3.6: Results from the various weighting and overall methods

<table>
<thead>
<tr>
<th>overall method =o? weighting method = w?</th>
<th>mean in pixels</th>
<th>median in pixels</th>
<th>maximum in pixels</th>
<th>number of failures (error &gt; 5 pixels)</th>
</tr>
</thead>
<tbody>
<tr>
<td>o4w2</td>
<td>1.72</td>
<td>0.99</td>
<td>8.51</td>
<td>4</td>
</tr>
<tr>
<td>o4w3</td>
<td>1.74</td>
<td>0.99</td>
<td>8.51</td>
<td>4</td>
</tr>
<tr>
<td>o4w4</td>
<td>1.66</td>
<td>0.99</td>
<td>14.02</td>
<td>2</td>
</tr>
<tr>
<td>o4w5</td>
<td>1.66</td>
<td>0.99</td>
<td>14.02</td>
<td>2</td>
</tr>
<tr>
<td>o4w6</td>
<td>1.48</td>
<td>0.99</td>
<td>7.58</td>
<td>2</td>
</tr>
<tr>
<td>o4w7</td>
<td>1.34</td>
<td>0.99</td>
<td>7.07</td>
<td>1</td>
</tr>
<tr>
<td>o5w1</td>
<td>1.56</td>
<td>0.81</td>
<td>8.56</td>
<td>4</td>
</tr>
<tr>
<td>o5w2</td>
<td>1.62</td>
<td>0.71</td>
<td>8.56</td>
<td>4</td>
</tr>
<tr>
<td>o5w3</td>
<td>1.66</td>
<td>0.77</td>
<td>8.55</td>
<td>4</td>
</tr>
<tr>
<td>o5w4</td>
<td>1.56</td>
<td>0.73</td>
<td>13.86</td>
<td>2</td>
</tr>
<tr>
<td>o5w5</td>
<td>1.55</td>
<td>0.75</td>
<td>13.85</td>
<td>2</td>
</tr>
<tr>
<td>o5w6</td>
<td>1.36</td>
<td>0.70</td>
<td>7.82</td>
<td>2</td>
</tr>
<tr>
<td>o5w7</td>
<td>1.21</td>
<td>0.70</td>
<td>6.65</td>
<td>1</td>
</tr>
</tbody>
</table>

The first investigation into data trends was into which overall peak finding method performed the best. The results are in table 3.7. Overall method 1, averaging, performed the worst with 38 cases of failure. The other four overall methods which involved creation of a displacement distribution performed similarly to one another. Overall methods 2 and 3 had 17 failures and overall methods 4 and 5 had 19 failures.

Table 3.7: Failure of results organized by overall peak finding method

<table>
<thead>
<tr>
<th>overall method</th>
<th># of failures (errors &gt; 5 pixels)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>38</td>
</tr>
<tr>
<td>2</td>
<td>17</td>
</tr>
</tbody>
</table>
Table 3.7: Failure of results organized by overall peak finding method

<table>
<thead>
<tr>
<th>overall method</th>
<th># of failures (errors &gt; 5 pixels)</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>17</td>
</tr>
<tr>
<td>4</td>
<td>19</td>
</tr>
<tr>
<td>5</td>
<td>19</td>
</tr>
</tbody>
</table>

The second investigation into data trends was into which weighting method performed the best. The results are shown in table 3.8. Weighting methods 4, 5, and 7 performed the best. Method 4 involves placing a threshold on the correlation coefficient and then weighting by uniqueness and correlation coefficient. Method 5 involves placing a threshold on the correlation coefficient and then weighting by uniqueness. Method 7 involves weighting on correlation coefficient and uniqueness. Note that all three methods used both the correlation coefficient and uniqueness measure for determining the weight. The other methods used one or none of these measures. Method 1, which had no weighting, performed the worst of all the 7 weighting methods.

Table 3.8: Failure of results organized by weighting method

<table>
<thead>
<tr>
<th>weighting method</th>
<th># of failures (errors &gt; 5 pixels)</th>
<th># of failures not including overall method 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>26</td>
<td>16</td>
</tr>
<tr>
<td>2</td>
<td>18</td>
<td>12</td>
</tr>
<tr>
<td>3</td>
<td>14</td>
<td>12</td>
</tr>
<tr>
<td>4</td>
<td>10</td>
<td>8</td>
</tr>
<tr>
<td>5</td>
<td>10</td>
<td>8</td>
</tr>
<tr>
<td>6</td>
<td>20</td>
<td>10</td>
</tr>
<tr>
<td>7</td>
<td>12</td>
<td>6</td>
</tr>
</tbody>
</table>

Now that overall trends in the data have been explored, the failures will be looked at more closely. A closer look at the failures reveals that the failures happened in cases of
large displacement of 16 pixels or more. All of the image pairs which any method failed to match are listed in table 3.9. If only overall methods 2-5 are considered, the data pairs on which a method failed are reduced from 12 out of 39 to 6 out of 39. The number of data pairs on which a method failed are reduced from 6 to 2 by restricting the weighting method to methods 4, 5, or 7. Another trend was noticed during the development of this chart. The overall method 1 with weighting methods 3, 4, or 5, (i.e. those methods which place a threshold on the correlation coefficient), failed on only two data pairs as well. This result was unexpected.

<table>
<thead>
<tr>
<th>index of image pair</th>
<th>approximate actual pixel displacement</th>
<th># of errors &gt; 5 pixels (out of 35)</th>
<th># of errors &gt; 5 pixels not including overall method 1 (out of 28)</th>
<th># of errors &gt; 5 pixels in weighting methods (4,5,7) and overall methods (2-5) (out of 12)</th>
<th># of errors &gt; 5 pixels in weighting methods (3,4,5) and overall method 1 (out of 3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>23.7</td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>23.7</td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>8</td>
<td>23.7</td>
<td>4</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>16</td>
<td>17.8</td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>18</td>
<td>17.8</td>
<td>4</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>20</td>
<td>22.0</td>
<td>25</td>
<td>18</td>
<td>10</td>
<td>3</td>
</tr>
<tr>
<td>24</td>
<td>22.0</td>
<td>32</td>
<td>28</td>
<td>12</td>
<td>0</td>
</tr>
<tr>
<td>27</td>
<td>22</td>
<td>7</td>
<td>0</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>30</td>
<td>22</td>
<td>10</td>
<td>6</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>34</td>
<td>16.5</td>
<td>10</td>
<td>10</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>37</td>
<td>16.5</td>
<td>6</td>
<td>4</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>39</td>
<td>16.5</td>
<td>6</td>
<td>6</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>
In summary, overall methods 2-5 with weighting methods combining uniqueness and correlation value performed well. Overall method 1 with weighting methods containing a threshold on the correlation value also performed well. Failure cases 20, 24, and 27, which are the cases for which the best methods failed, should be investigated further. See future investigations section 4.1. All failure cases occurred at large displacements of 16 pixels or more; the best methods failed at large displacements of 22 pixels.

3.4.2 Results Single Frame vs. Local

Single frame results were as follows: mean of 1.7499 pixels; median of 0.9912 pixels; standard deviation of 2.1626 pixels; maximum of 8.5564 pixels; minimum of 0.0154 pixels. This method had 4 failed cases. The disadvantage with single frame correlation is that if the translation is restricted so that the translation range is within the data sector, more of the image data is lost than in the localized translation method. This could be overcome by redefining the shape of the template to include a maximum amount of the image. Most of the local methods had two cases of failure, which is better than the single frame results; the best local method had only one case of failure at a large displacement of 22 pixels. The table below summarizes the single frame correlation coefficient and the best local correlation statistics.

<table>
<thead>
<tr>
<th></th>
<th>Single Frame Correlation Coefficient</th>
<th>Local Correlation Coefficient Overall Method 5 Weighting Method 7</th>
<th>Localized Correlation Coefficient Overall Method 4 Weighting Method 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>1.7499</td>
<td>1.2094</td>
<td>1.2934</td>
</tr>
<tr>
<td>Median</td>
<td>0.9912</td>
<td>0.6999</td>
<td>0.5999</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>2.1626</td>
<td>1.3624</td>
<td>1.4556</td>
</tr>
</tbody>
</table>
Table 3.10: Single Frame vs. Best Local Correlation Method Statistics

<table>
<thead>
<tr>
<th></th>
<th>Single Frame Correlation Coefficient</th>
<th>Local Correlation Coefficient</th>
<th>Localized Correlation Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Overall Method 5</td>
<td>Overall Method 1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Weighting Method 7</td>
<td>Weighting Method 4</td>
</tr>
<tr>
<td>Maximum</td>
<td>8.5564</td>
<td>6.6517</td>
<td>5.2980</td>
</tr>
<tr>
<td>Minimum</td>
<td>0.0154</td>
<td>0.0390</td>
<td>0.0140</td>
</tr>
<tr>
<td># of errors &gt; 5 pixels</td>
<td>4</td>
<td>1</td>
<td>2</td>
</tr>
</tbody>
</table>

3.5 Conclusions
With the small selection of data pairs, no one particular localized method distinguished itself. However, overall peak finding methods 2-5 with weighting combining both uniqueness and correlation strength (either by weighting or by taking a threshold) performed better than those methods which did not include both. If a single localized method were to be selected for testing on heart data without further investigation, it would be overall method 5 and weighting method 7, which had only one case of failure. A closer look at the data reveals that overall method 1 and weighting methods with thresholds on the correlation coefficient also performed well and should be included in further investigations. Single frame correlation with a larger template should also be investigated further.
Chapter 4

Recommendations for Future Investigations

Much investigation still needs to be performed before automatic registration becomes clinically viable. This section includes suggestions for future investigations to work towards this goal.

4.1 Phantom Data
The cases of failure of the best methods on the phantom data should be explored further in order to identify likely successful conditions and eliminate likely failure conditions. Possible reasons for failure to be explored include: poor object boundary definition, strong speckle pattern, large change in geometry due to position movement, and low information content in the image.

4.2 Heart Data
Prior to clinical use the registration algorithm must be tested and verified on heart data. The difficulty in verification is that there are no absolute reference points in the heart, which will allow the exact movement of the heart to be known. Considering this, verification could be performed in two stages, one with an in vitro heart specimen. The current phantom is not as complex an object as the heart and other insights and difficulties may present themselves through such study. Another verification method which needs to be tested first through trial on phantom data is as follows. A movie is created of images from two consecutive angles. A human observer can then distinguish the general translational motion occurring between the two images. The observer can correct for the movement and then play the movie again. This process is repeated until the observer can no longer distinguish the major movement. This process should be completed for an entire data set. Then
the final 0 degree and flipped 180 degree images should be closer than they were originally. If this process is accurate, much can be learned about what types of movements are most common during the acquisition. This information would be helpful for optimizing and designing a better registration algorithm.

4.3 Single Frame Correlation
In the phantom data, single frame correlation performed well but still had errors. Expanding the template size by changing the shape of the template could improve performance. The template should be extended to include the largest amount of the image sector possible while still adhering to the constraint that all possible translations of the template must lie within the image sector.

4.4 Speed
After a registration method is proven viable, one may consider optimizing it. One way to do this is to decrease the image size by replacing every 4 pixels with one. Correlation speed would greatly increase, but would have to be weighed against the change in accuracy. Another way to speed up the algorithm is to use a more complex search method for finding the highest correlation value.

4.5 Image Quality
By reducing speckle or by increasing the contrast between objects and the background, one is likely to improve the performance of the registration algorithm.

4.6 Localized Correlation
There are many parameters in the local correlation which could be adjusted. One parameter which heavily affects the overall results is the template size. This parameter could be adjusted for optimal performance.
4.7 Confidence Measure
One may want to create a confidence measure which measures, based on image statistics, the confidence with which the registration results should be believed.

4.8 Other Approaches
Other approaches for improving the 3D reconstructions include fitting the slices to a 3D model of the heart and aligning slices so that some total entropy measure is minimized.
Chapter 5

Conclusions

The proper registration was found in most cases in which a localized registration scheme, which weights by correlation coefficient value and uniqueness, was applied to phantom image pairs. This provides reassurance that the registration of consecutive 2D images could prove to be a feasible method for improving 3D reconstructions. However, the cases for which the registration algorithm failed need to be explored further. The registration algorithm should be adapted to handle most of the cases in which it failed. If the likelihood of error can be reduced, then the registration of consecutive 2D slices prior to 3D reconstruction may prove to be a valuable tool. Since registration does not corrupt the original data, reconstructions from both the original data and the registered data can be made. This allows the physician to make a judgement as to whether the registered data set or the original data set is a more accurate representation of the heart.
References


