DISPLACEMENT SCALE BASED ON SPECKLES

by

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ABSTRACT

MAHSA FARSAD. Displacement scale based on speckles. (Under the direction of DR. CHRIS EVANS)

Speckle patterns are complex intensity distributions, which occur when an optically rough surface is illuminated with a coherent light. The speckle phenomenon was known to be troublesome when the laser was first introduced, but later it was discovered to be an opportunity for various measurements. This research investigates the application of speckle pattern correlation to absolute and relative displacement measurement. The goal is to develop a displacement scale that is non-contact, fast, low cost, and can be used on mechanical machinery as the metrology subsystem. For absolute displacement measurement, this research develops a database of speckle patterns over the range of measurement. Each database pattern is associated with a specific sample position. For an unknown sample position, the maximum correlation of the speckle pattern at that position with the database patterns reveals the position of the sample. This research successfully performs a two dimensional displacement measurement with 1 μm resolution over 20 by 20 μm area. The large number of required database patterns for this technique limits the measurement range, especially in two dimensions. The sensitivity of the system to environmental disturbances restricts the application of this method to industrial processes. In order to overcome these shortcomings, this research develops an innovative displacement measurement technique based on speckle pattern correlation. It uses the correlation between a red and a green speckle pattern for relative displacement measurement.

DEDICATION

This research is dedicated to my fiancé, Jeffrey Lyon, my family in Iran, all my friends around the world, and all the teachers that I have had over the years.

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CHAPTER 1: INTRODUCTION

Speckle metrology is one of the important areas of precision measurement and nondestructive testing. It has been the subject of scientific studies for over four decades. Speckle patterns are complex intensity distributions, which occur when an optically rough surface is illuminated with a coherent light. Scattered light waves from illuminated points of the surface interfere and create the speckle pattern. Speckle patterns are unique for any specific illumination condition and under certain conditions, they shift following the displacement of the surface that generates them. Investigating the properties of the speckle patterns and generating a displacement scale based on speckle shift is the main objective of this research. The advantage of this scale is that it is low-cost, non-contact and high resolution.

After a brief introduction to speckle patterns, the related displacement measurement and mathematical techniques in this chapter, the following chapters investigate four methods of displacement measurement using speckles. Chapter 2 introduces an absolute 2D displacement scale based on a large database of speckle patterns. Chapter 3 investigates a robust method for relative displacement measurement based on the correlation between the speckle patterns of two identical overlapping laser beam spots. This method accounts for the shortcomings of the absolute scale introduced in chapter 2. Chapter 4 evaluates relative displacement measurement using the correlation between the speckle patterns of two identical overlapping laser beam spots with different

wavelengths. This method has a significant improvement over the technique that is introduced in chapter 3. Chapter 5 investigates the application of Digital Image Correlation technique to absolute displacement measurement using speckles. Chapter 6 covers the conclusion and the future work. Appendix A explains the design cycle and the engineering model of a displacement scale based on speckles that is capable of absolute and relative measurement. Appendix B gathers the major Matlab codes developed for this research, and Appendix C includes the Labview code developed for the method introduced in chapter 4.

1.1 Speckle Patterns

Speckle patterns occur when an optically rough surface is illuminated with a coherent light. Based on Huygen's principle, all the illuminated points act like point sources and send out spherical wavefronts that interfere and create a speckle pattern. Figure 1 shows this phenomenon.

It is clear from this figure that all the illuminated points of the surface contribute to each point of the speckle pattern. As a result, each speckle pattern is unique, just like a finger print, and it can identify a specific position of the surface. Also, the speckle phenomenon is a three-dimensional interference pattern and fills the whole of space where scattered ray paths cross.

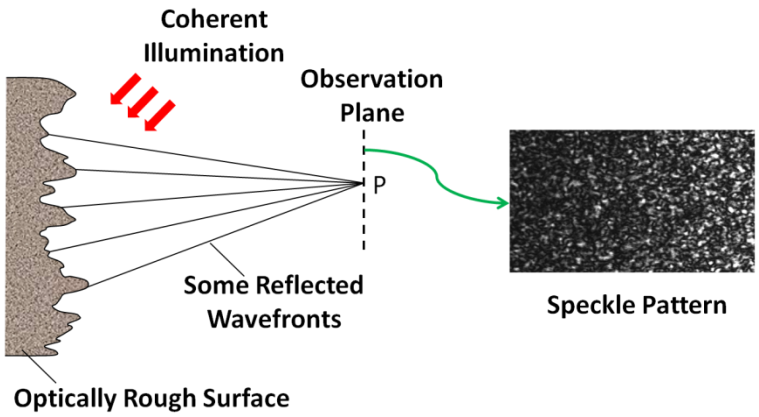

Figure 1: Generation of speckle patterns

One of the important properties of the speckle pattern is the mean diameter of the bright spots of the pattern over a plane that is usually normal to the axis of the optical system generating it. It is a statistical average of the distance between adjacent regions of maximum and minimum brightness and it is about the size of the diffraction limit. For example, if coherent light with wavelength λ scatters from a circular region of diameter D and a screen captures the speckle pattern at a distance L from the scattering surface, the following equation approximates the mean diameter of the objective speckle pattern [1]

$$d_{os} \approx 1.2\,\lambda\,L/D \qquad (1\text{-}1)$$

An objective speckle pattern is the one captured in free space directly on an imaging screen. A subjective speckle pattern, however, is captured in the image plane of a lens, and its mean speckle diameter is related to the numerical aperture of the lens by

$$d_{ss} \approx 0.6\,\lambda\,f/D \qquad (1\text{-}2)$$

in which f is the focal distance of the lens (Figure 2).

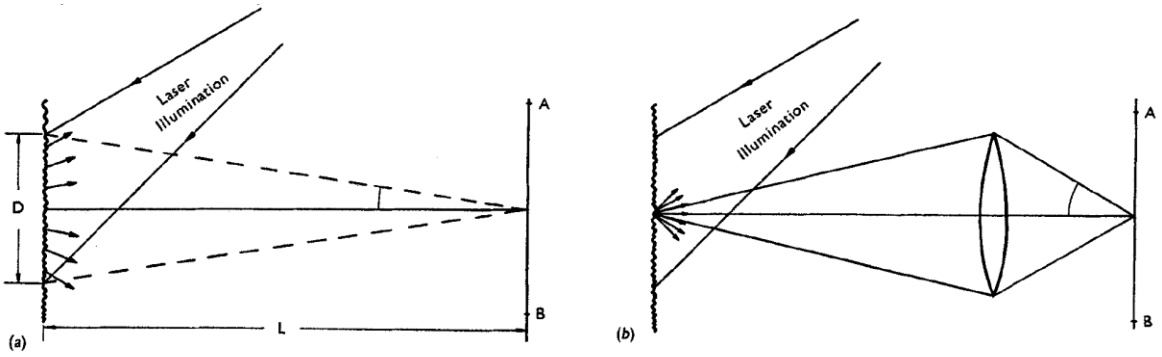

Figure 2: Formation of a speckle pattern. a) Objective speckle pattern. b) Subjective speckle pattern [1]

Another property of the speckle pattern is the speckle shift. When the illuminated surface shifts, some speckles disappear while new speckles appear. If the surface displacement is much smaller than the diameter of the illuminating spot, the speckle pattern will stay approximately stable, but shifts with respect to the surface shift. This is because under this condition, most surface features that participate in generating the speckle pattern will still be illuminated. The wavefront curvature affects the direction of the speckle shift. If the wavefront is convergent, the sample and the speckles move in the same directions and if it's divergent, they move in the opposite directions [2]. It is also possible to reproduce a speckle pattern if the same area of the sample is illuminated under the exact same condition.

Speckle patterns were first observed using candle-light, in 1877 by Exner; In 1919, Lord Rayleigh evaluated the first order statistics of the speckle intensity [3]. Introduction of the laser in 1960 brought deeper investigations for understanding speckle properties [4]; but most studies aimed at speckle reduction techniques.

One of the earliest attempts for measurement using the speckle phenomena goes back to 1970 [5], when Leendertz used speckle pattern correlation to determine in-plane and

out of plane surface displacement. In this technique, two speckle patterns are superimposed; the distribution of intensity in the resultant pattern depends on the relative phases of the component patterns. By measuring the correlation between the resultant patterns at two different positions, a change of relative phase is detected, which leads to measuring either the normal or in-plane components of the surface displacement. Figure 3 shows the proposed setup.

Since then, many investigations have applied speckle techniques to the measurement of position and displacement [6], deformation [7], stress and strain [8], surface roughness [9], and vibration analysis [10]. Two review articles, [4, 11] cover the theoretical and practical characteristics of the technique as well as its development over time.

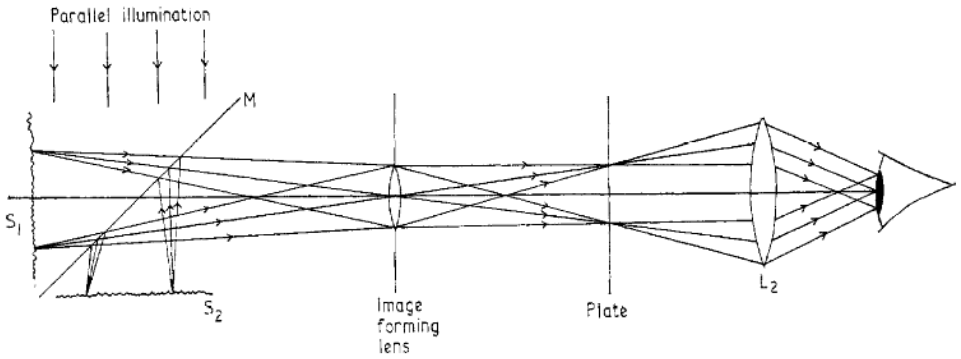

Figure 3: Modified Michelson arrangement to detect normal displacement [5].

1.2 Speckle Photography

Speckle photography is one of the applicable methods for high resolution displacement measurement. It is based on the analysis of speckle shift due to object displacement [4]. Goch et al. have applied this method to enable precise alignment of work pieces with minimum relocation uncertainty of 7.6 μm [2]. Patzelt et al. have used it for absolute position measurement with a lateral resolution of less than ± 20 nm [6]. The main focus of this research is to develop a displacement scale using this technique.

Figure 4 shows a typical speckle photography setup. In this setup, a laser illuminates the sample through a converging lens and a beam splitter. The speckle pattern is captured directly on the screen of a CCD camera.

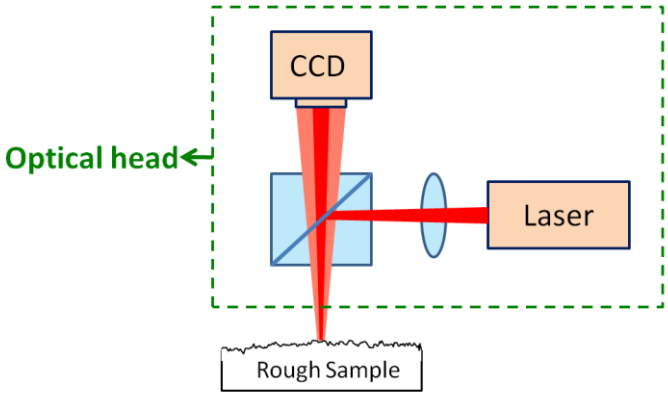

Figure 4: A typical speckle correlation setup

For absolute displacement measurement, it is possible to calibrate the system in Figure 4 by shifting the sample or the read head in incremental steps, capturing and storing the speckle pattern at each position. After that, for absolute position measurement, at any random position in the travel of the machine, the system captures the speckle pattern at that point and compares it with the database patterns. The database pattern that has the highest correlation with the randomly selected pattern, indicates the position of the sample. Figure 5 shows an example of this technique applied to a 10 µm interval [12]. In this example, one database pattern is captured and stored every micron. Figure 5-b demonstrates the correlation coefficient of a speckle pattern captured at an unknown sample position with the database patterns. Because the highest correlation coefficient is at 6 µm sample shift, the random position is at 6 µm. This technique determines the correlation between the intensity of speckle patterns. Sometimes when the phase variations of the speckles are analyzed, the technique is called Speckle Interferometry .

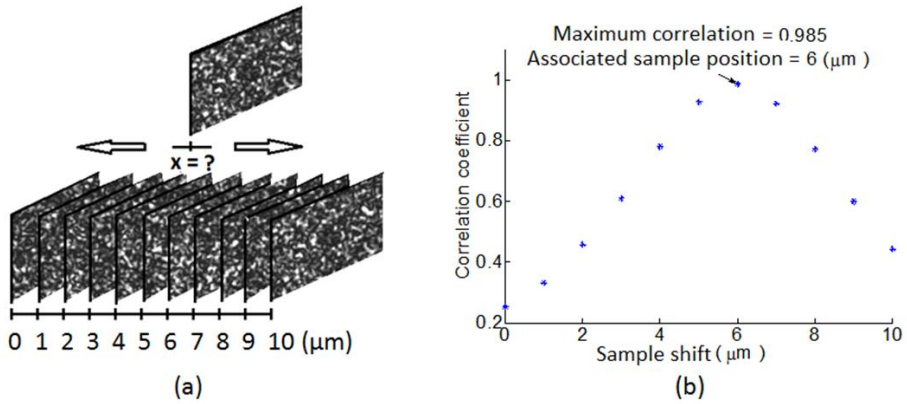

Figure 5: Absolute position measurement using speckle pattern correlation. a) The database of speckle patterns and the corresponding sample positions. b) Correlations between the randomly selected position and the database patterns [12].

1.3 Correlation Techniques

There are different ways to determine the correlation coefficient between two 2D images. Goch et al. [2] use the following formula to determine the correlation coefficient between the two speckle patterns A and B

$$k = \sum_{ij}(a_{ij} - \bar{a}).(b_{ij} - \bar{b}) \quad (1\text{-}3)$$

where a_{ij} and b_{ij} denote the pixel intensities and $\bar{a}$, $\bar{b}$ the mean intensity values of these speckle patterns. This equation is fairly simple, but the resultant correlation coefficient is very sensitive to the lighting conditions of the images.

Lehmann et al. [13] applies the following speckle correlation technique to determine the correlation coefficient between two speckle patterns with different wavelengths

$$\rho_{12} = \frac{<(I_1 - <I_1>)(I_2 - <I_2>)>}{[<(I_1 - <I_1>)^2><(I_2 - <I_2>)^2>]^{1/2}} = \frac{<I_1 I_2> - <I_1><I_2>}{(<I_1{}^2> - <I_1>^2)^{\frac{1}{2}} (<I_2{}^2> - <I_2>^2)^{1/2}} \quad (1\text{-}4)$$

In this formula, I_1 and I_2 are intensities of the illuminating lights for each speckle pattern. The symbol <I> expresses the statistical expectation value of I. For a large number of experimental datapoints, it is possible to replace the expectation values with

arithmetic averages of the independent intensity values, which can be determined experimentally. The correlation coefficient in equation (1-4) is equivalent to the Pearson correlation coefficient as follows [14]

$$r = \frac{\sum(x-x)(y-\bar{y})}{\sqrt{\sum(x-\bar{x})^2 \sum(y-\bar{y})^2}} \qquad (1\text{-}5)$$

In this equation, $\bar{x}$ and $\bar{y}$ denote the means of the two variables x and y. Pearson correlation coefficient is a measure of the linear dependence between two variables. It is a value between +1 and −1 inclusive, where 1 is total positive correlation, 0 is no correlation, and −1 is total negative correlation.

A review article by Pan et. al. [15] summarizes the most common correlation techniques in digital image correlation field. It categorizes the correlation criteria into two groups, Correlation Coefficient (CC) criteria and Sum of Squared Differences (SSD). It also describes how these two criteria are related. The Zero-normalized cross-correlation (ZNCC) based on this reference is as follows

$$C_{ZNCC} = \sum_{i=-M}^{M} \sum_{i=-M}^{M} \left\{ \frac{[f(x_i,y_i)-f_m]\times[g(x_i^{'},y_i^{'})-g_m]}{\Delta f\, \Delta g} \right\} \qquad (1)$$

Where f and g are the pixel intensities of the two images and

$$f_m = \frac{1}{(2M+1)^2} \sum_{i=-M}^{M} \sum_{i=-M}^{M} f(x_i, y_i), \ \Delta f = \sqrt{\sum_{i=-M}^{M} \sum_{i=-M}^{M} [f(x_i, y_i) - f_m]^2}$$

$$g_m = \frac{1}{(2M+1)^2} \sum_{i=-M}^{M} \sum_{i=-M}^{M} g(x_i^{'}, y_i^{'}), \ \Delta g = \sqrt{\sum_{i=-M}^{M} \sum_{i=-M}^{M} [g(x_i^{'}, y_i^{'}) - g_m]^2}$$

A simple calculation shows that ZNCC is the same as equations (1-4) and (1-5). The advantages of this criterion is that it is robust to disturbances and insensitive to offset and scale in illumination lighting. As a result, the correlation criterion used in this research is

based on ZNCC; it is in the form of equation (1-5). Because the image intensity values are always positive, the resultant correlation coefficient is always between 0 and 1.

Another correlation technique used here is the autocorrelation function. In order to determine the speckle size, one way is to determine the autocorrelation function of the speckle pattern. Because calculating this function is computationally intensive, one way is to use the Fourier transform of the autocorrelation function. This function and its Fourier transform are as follows [16]

$$\mathcal{F}\iint_{-\infty}^{\infty} g(\xi,\eta)g^*(\xi-x,\eta-y)d\xi d\eta = \left|G(f_x,f_y)\right|^2 \quad (1\text{-}7)$$

where g is a function of two variables, x and y, $G(f_x,f_y)$ is the Fourier transform of this function, f_x and f_y are independent frequency variables associated with x and y, respectively, ξ and η are used for integration purpose.

In order to determine the speckle size using the autocorrelation function, this research determines the full width half maximum (FWHM) of a profile in the vertical and horizontal directions. For this technique to be effective, the speckle pattern should fill the whole window of the pattern. Cropping the speckle pattern fulfills this purpose.

Figure 6 shows a simulation that summarizes the process of determining the speckle diameter.

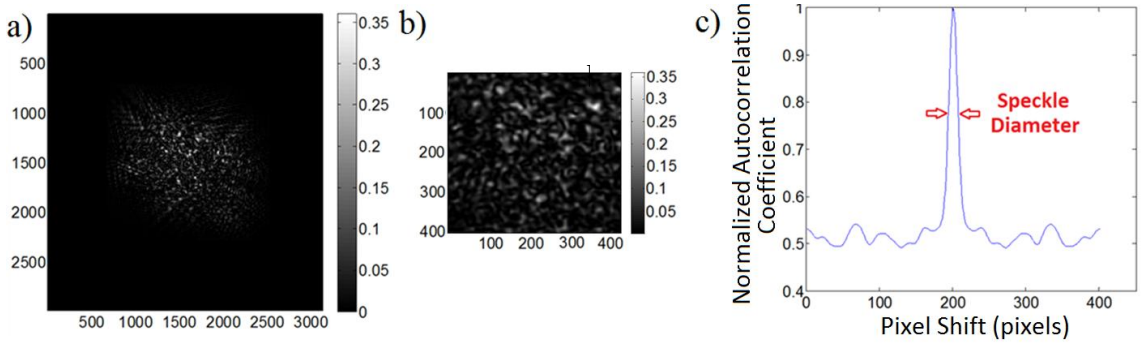

Figure 6: Determining the speckle size. a) A sample speckle pattern. b) The cropped speckle pattern. c)The autocorrelation profile and the speckle diameter

CHAPTER 2: ABSOLUTE SCALE BASED ON SPECKLES

Unique characteristics of speckle photography, including the simple setup, diverse resolution, and capability of non-contact measurement, makes it a strong candidate for developing a non-contact, low cost, high resolution displacement scale. The purpose of this chapter is to design and develop an absolute scale based on speckle photography. It starts with a simple design, evaluates the results, and optimizes the setup in order to achieve the desirable outcome.

2.1 Basic Experimental Speckle Setup and Result

The first experimental setup is composed of a low cost diode laser, which illuminates a steel sample with a ground surface in an angle, and a CCD camera that captures the speckle patterns using an adjustable lens. A mechanical stage controls the displacement of the sample (Figure 7). This setup determines the position of the sample (with 10 μm resolution over the range of the scale) using speckle photography and compares it to the position of the sample that the mechanical scale reads.

As an example, for displacement measurement over 200 μm range, this method requires capturing one database pattern every 10 μm, starting at 0 μm. Then the stage shifts the sample to a random position, where the scale reading for the position of the sample is 150 μm. The camera captures the speckle pattern at this position, and a Matlab code determines the correlation of this pattern with all the database patterns. The maximum correlation shows the position of the sample, which is at 150 μm (Figure 8).

This number matches the scale reading and verifies the validity of the proposed speckle technique. The reason that the maximum correlation coefficient in Figure 8 is not exactly one is mainly due to the relocation uncertainty of the scale.

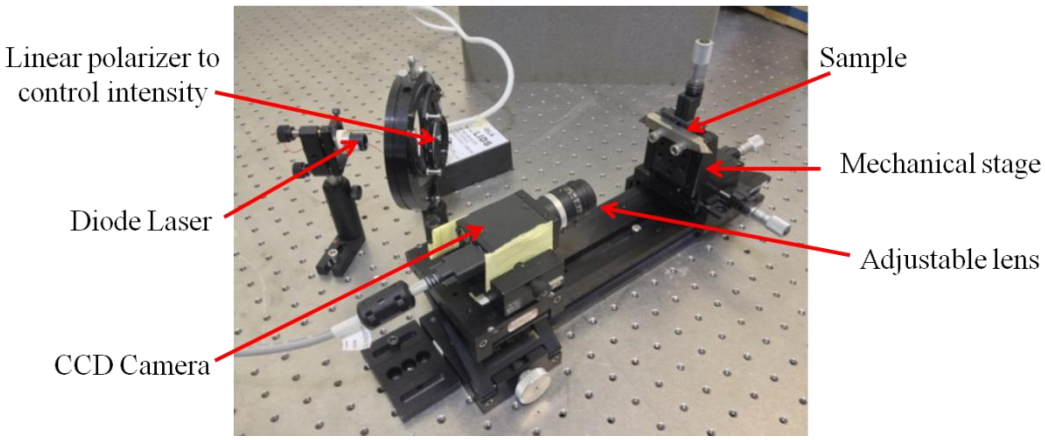

Figure 7: Basic experimental speckle setup

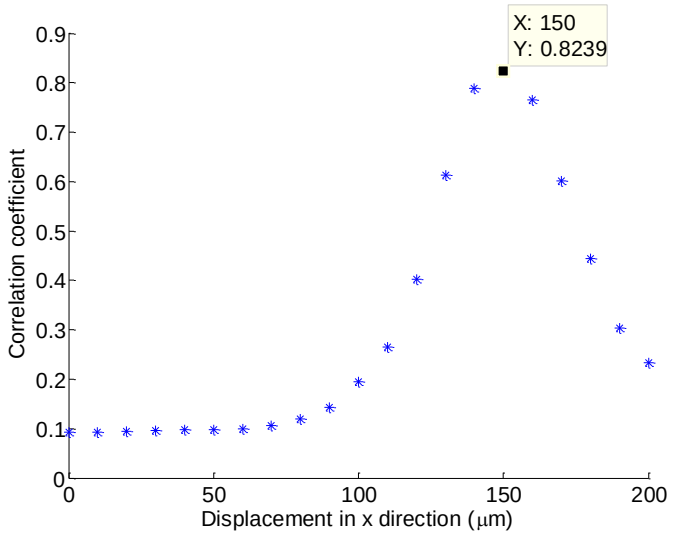

Figure 8: Correlation results of the basic speckle setup

In order to extend the displacement measurement to two dimensions, a circular spot should illuminate the sample perpendicular to its surface. Figure 9 shows a setup inspired by Patzelt et al. [6] that serves this purpose. This setup consists of a 633 nm HeNe laser, a

CCD camera, a pellicle beam splitter (50/50), a plano convex laser lens with 25 mm focal length, and a motorized stage (Thorlabs Nanomax 300). The sample has a ground steel surface characterized by the roughness parameter S_q = 0.5 µm, where S_q is equivalent to the RMS of the roughness over a selected area of the sample. A pellicle beam splitter replaces the normal beam splitter in order to minimize the noise and maximize the intensity of the speckle pattern. The laser lens creates some curvature on the illuminating wavefront to increases the speckle shift. The motorized stage allows precise sample relocation (5 nm resolution over 20 µm range using the piezo and 60 nm resolution over 4 mm range using the stepper motor.

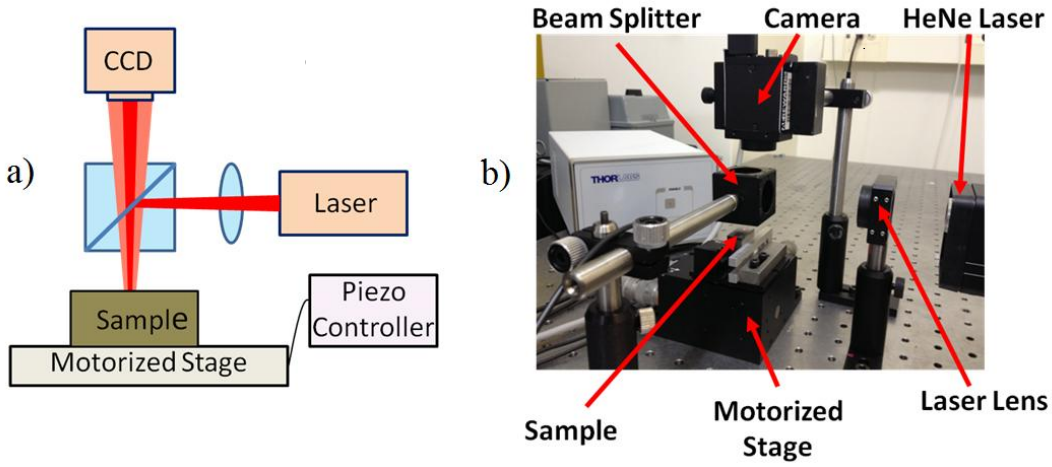

Figure 9: Speckle setup with circular illumination spot. a) Schematic. b) Actual.

The setup of Figure 9 is capable of displacement measurement with 1 µm resolution. Calibrating the system over the range of the piezo actuator (20 µm) requires capturing and storing a database speckle pattern every 1 µm. After that, the stage shifts the sample to a random position, and the result of position measurement using speckle correlation is compared to the stage reading. Figure 10 shows the correlation results for the sample position where the stage reading is 8 µm. The maximum correlation is at 8 µm, which

matches the stage reading. Although the maximum correlation is closer to 1, comparing to the results of Figure 8, the deviation from perfect correlation (correlation coefficient = 1) is investigated in the next section.

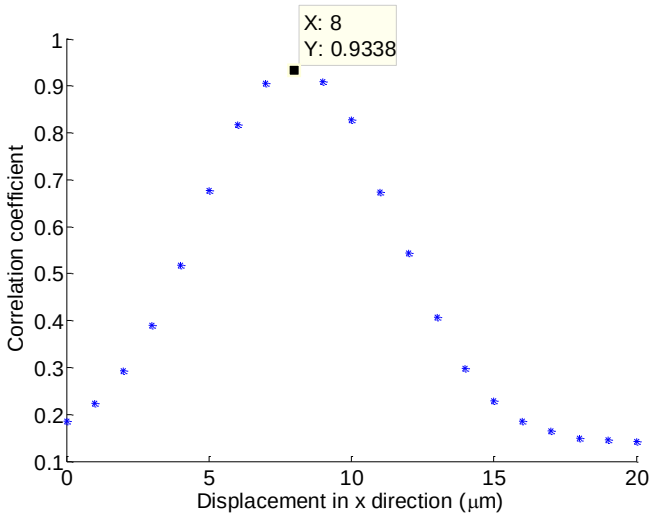

Figure 10: Correlation results for the experimental setup with circular spot (Figure 9)

2.2 Speckle Pattern Stability Analysis

In order to analyze the stability of the setup shown in Figure 9, a Labview code sets the CCD camera to capture the same speckle pattern every hour over 6 days without making any changes to the setup. After collecting all the patterns, a Matlab code determines the correlation of each pattern with the one captured at the beginning of the experiment. Figure 11 shows the results. Although the experiment is performed in the laboratory condition with controlled temperature ($\pm$ 0.5^{o} C), the correlation of the pattern captured after 6 days with the one captured at the beginning of the experiment, under the exact same condition, drops to 0.5.

Investigating the sources of instability leads to the question whether the correlation drop is due to the drift of sample from its initial position, the drift of other system

elements from their initial positions, or changes in the microstructure of surface of the sample. In order to answer this question, first the setup is rearranged to minimize the sources of instability, such as long rods. Figure 12 shows the rearranged system.

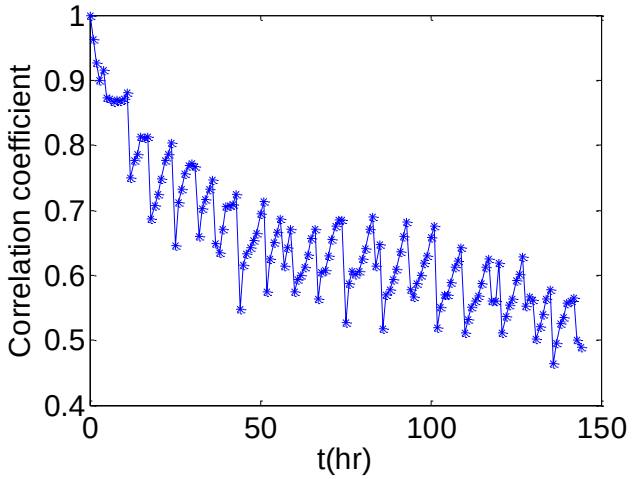

Figure 11: Stability analysis of the same speckle pattern over 6 days

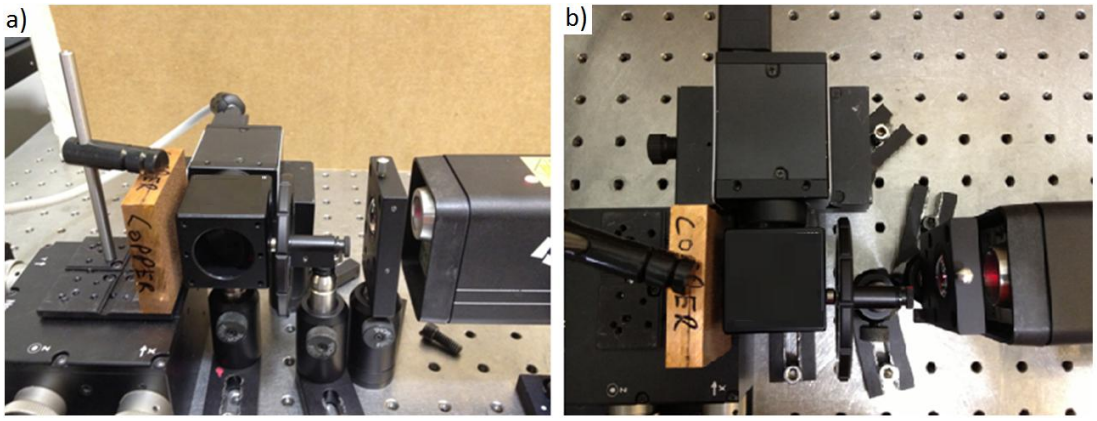

Figure 12: Rearranging the speckle setup to increase the stability. a) Front view. b) Top view.

In order to investigate the possibility of the sample drift, this research determines the sample drift after a specific amount of time using speckle correlation, applies the determined drift to the sample backward in order to shift the sample to the initial position, and observes whether this process retrieves the correlation. For this purpose, a Labview

code sets the camera to capture a speckle pattern every hour for 30 hours without any changes to the system. After 30 hours, the stage creates the database patterns by shifting the sample from -10 to 10 µm with 1 µm steps in x and z directions respectively, while the camera captures the speckle patterns at every step. Note that while shifting the sample in x direction, the z stage reads zero, and while shifting the sample in z direction, the x stage reads zero. After creating the database, a Matlab code determines the correlation of the pattern captured at the beginning of the experiment with all the database patterns. Figure 13 shows the correlation results, which suggest that the sample drifts 1 µm in x and 6 µm in z direction.

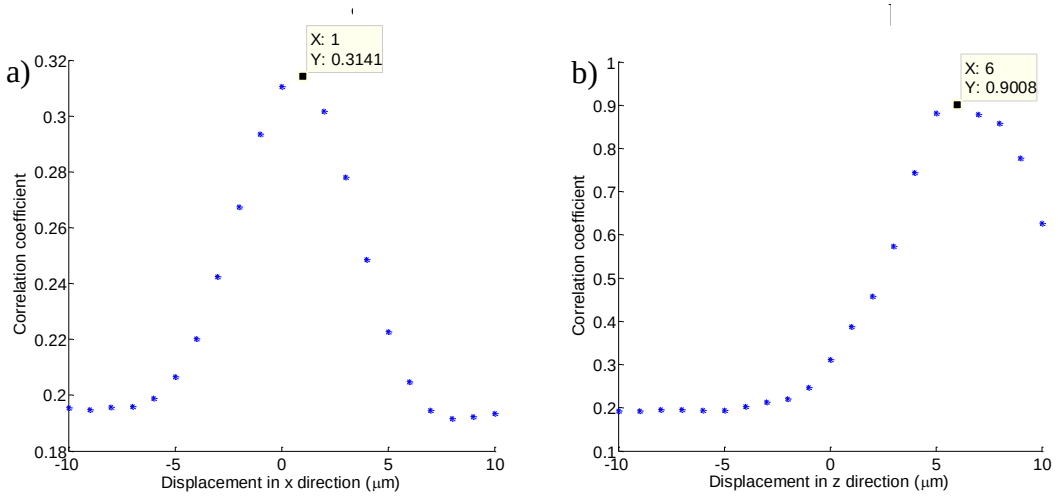

Figure 13: Determining the possibility of sample drift in x and z directions. a) The drift in x direction is 1 µm. b) The drift in z direction is 6 µm.

Next, the stage shifts the sample by (x, z) = (-1, -6) µm, the camera captures the speckle pattern at the new position, and a Matlab code determines the correlation of this pattern with the patterns captured over the 30 hours. Figure 14 shows the stability behavior before and after correcting for the sample drift. The correlation coefficients of the patterns captured every hour with the one captured at the beginning of the experiment

gives the stability behavior before correcting for the sample drift. This data is interpolated linearly for better demonstration of the stability behavior. The correlation coefficients of the patterns captured every hour with the one captured after the sample shift gives the correlation behavior after correcting for the sample drift. Based on Figure 14, the stability behavior before and after correcting for the sample drift are similar, which shows that shifting the sample backwards with the amount of determined drift retrieves the correlation. This confirms that the correlation drop is mainly caused by the sample drift from its initial position. It also explains the exponential decay trend observed in the stability data.

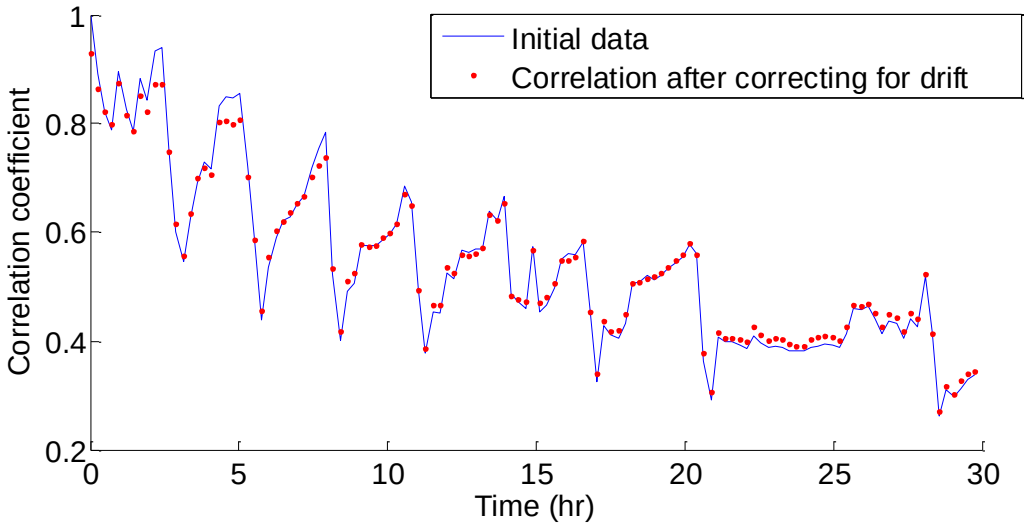

Figure 14: Speckle stability before and after applying the shift due to the sample drift.

Based on Figure 13, because the drift in z direction is much higher than that in x direction, keeping the sample's surface parallel to the table's surface should result in a better stability behavior. Figure 15 shows the rearrangement of the speckle setup in order to achieve this goal and the improved stability results.

Other than the exponential decay trend in the stability behavior, which can be explained by the sample drift, the stability data also shows an oscillatory behavior which can be induced by temperature variations in the lab. In order to investigate this prediction, a sensor measures the temperature of the air in the vicinity of the speckle setup, and compares its variations over time with the correlation behavior. In this experiment, the temperature and the speckle pattern are collected every minute over 30 hours. Figure 16 shows the correlation and the temperature behavior.

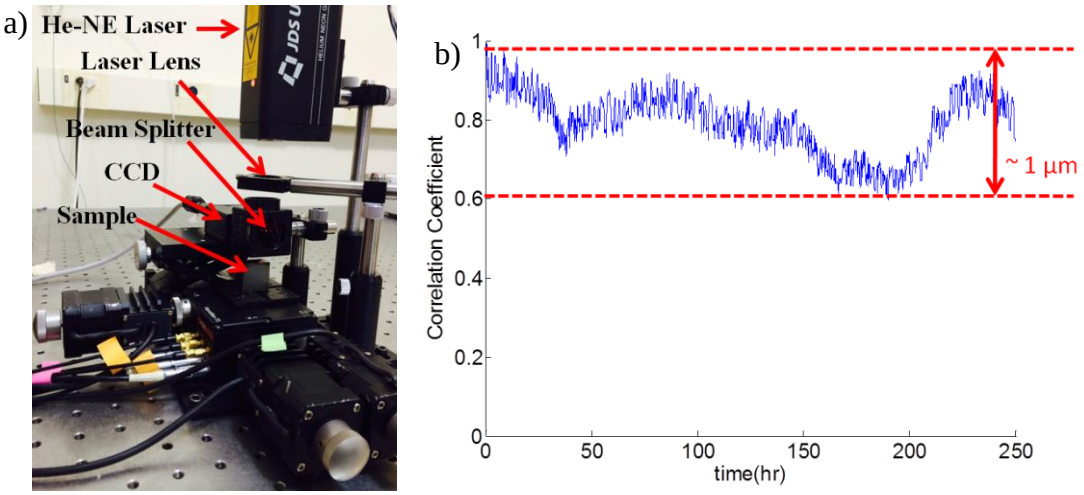

Figure 15: Rearranging for better stability. a) Experimental setup. b) Improved stability results.

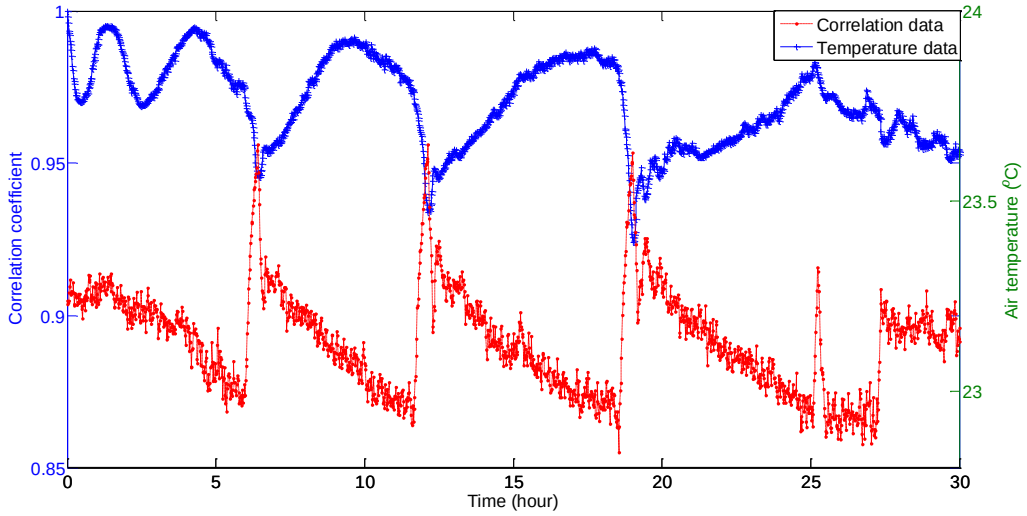

Figure 16: Comparing the correlation and the temperature behavior.

Although there are some similarities between the temperature and correlation behavior, they are not exactly identical. One reason is that the temperature fluctuations not only affect the sample, but they also affect all the other elements of the system. Drift of each element from its initial position can cause some decorrelation. A set of experiments determines the sensitivity of the system to the drift of its major elements and compares them to the drift of sample. In order to determine the sensitivity to the sample drift, the stage shifts the sample 20 μm in 1 μm steps in x and z directions over the center point of the data, (x, z) = (10, 10) μm. In other words, the stage is set to (x, z) = (10, 10) μm, and shifts the sample from 0 to 20 μm in x direction; at each step, the camera captures the speckle pattern. Then the stage is set back to (x, z) = (10, 10) μm, and shifts the sample from 0 to 20 μm in z direction; at each step the camera captures the speckle pattern. A Matlab code determines the correlation of the patterns captured in x and z direction with the one captured at (x, z) = (10, 10) μm respectively. In order to analyze the sensitivity of the system to the deviation of camera from its initial position, first the camera is attached to the motorized stage, while all the other elements including the sample are stationary. The stage shifts the camera in 1 μm steps over 20 μm in x and z direction respectively, while the center point is (x, z) = (10, 10) μm. Figure 17 compares the sensitivity of the system to the sample drift with the sensitivity to the camera drift. The results show that the setup is more sensitive to the sample drift than the camera drift. The sample drift of 1 μm is approximately equivalent to 2.5 μm drift of the camera. One reason that the setup is more sensitive to the sample drift than to the camera drift is that the magnification is not equal to 1.

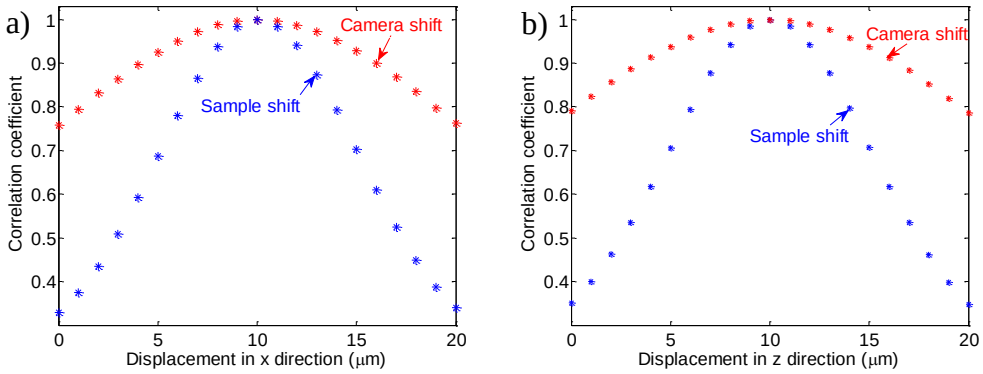

Figure 17: Comparing the sensitivity of the system to sample drift with the sensitivity to the camera drift. a) Sensitivity to the drift in x direction. b) Sensitivity to the drift in z direction

The process of determining the sensitivity of the setup to the laser lens and the beam splitter drift is the same as that for the camera. Figure 18-a shows the results in x direction. For the laser sensitivity, the process is similar, except that the stage shifts the laser 100 μm over the center point (x, z) = (50, 50) μm. This is because the system is much less sensitive to the drift of laser than all the other elements. Thus, the results can be more clearly observed when the drift is monitored over a longer range. Figure 18-b shows the results of sensitivity to the laser drift. Overall, the system is the most sensitive to the drift of sample. The sensitivity to the drift of camera and laser lens are approximately similar, but the system is slightly more sensitive to the drift of beam splitter. The cause of sensitivity to the drift laser lens is that the laser lens controls the position of the laser spot on the sample. The cause of sensitivity to the drift of beam splitter is due to the fact that the beam splitter controls the position of the reflected image on the camera. In z direction, the results are the same as in x direction, except that the system is not sensitive to drift of beam splitter in z direction, showing that there is no beam splitter misalignment in z direction.

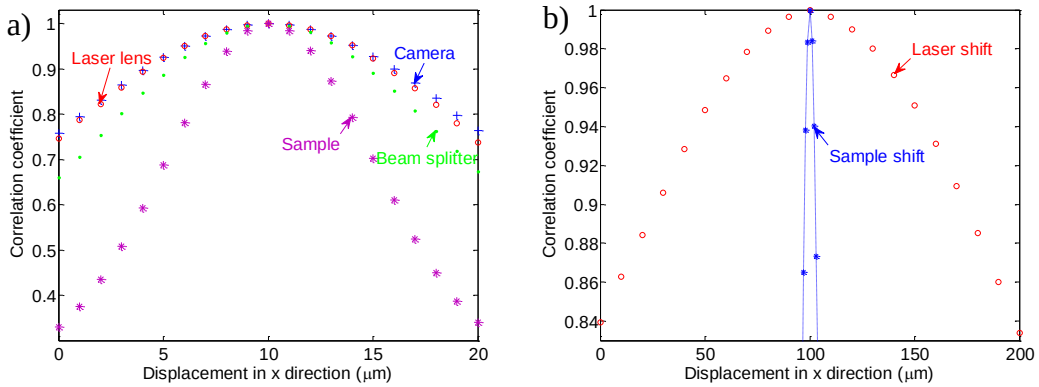

Figure 18: Comparing the sensitivity of the system to the sample drift with other system elements. a) Sensitivity to the drift of the camera, the laser lens, and the beam splitter. b) Sensitivity to the drift of the laser

In order to quantify the sensitivity results Table 1 shows the drift of each element that is equivalent to 3 μm drift of the sample. Obtaining these values is possible by imagining a horizontal line defined by the cc at x = 13 μm in Figure 18 and determining the position where this line crosses each sensitivity curve. It is important to note that the sensitivity curves have different slopes at each position and the quantitative comparison of the sensitivities cannot be linearly applied to other sample shifts.

Table 1: Quantitative comparison of system elements sensitivity to drift

Correlation drop equal to 3 μm sample drift			
Element	Experimental	Theoretical	Reason for deviation from theory
Camera	6.8 μm	3 μm if magnification is 1	Magnification is not 1
Laser	184.7 μm	Not sensitive	No significant deviation
Beam splitter	5.4 μm	Equivalent to the drift of camera	Misalignment
Laser lens	6.5 μm	More sensitive than the drift of laser	No significant deviation

2.3 Analyzing the Effect of Contamination

In order to investigate the limitations of the proposed speckle scale, this section investigates the effect of the sample's surface contamination on the measurement results.

In the literature, difficulty in measuring wet samples using speckles has been reported [17]. The wet surface tends to create fluctuations in the speckles and decorrelate the speckle pattern. Such a pattern is called a “Dynamic Speckle Pattern”. Dynamic speckles are the results of temporal variations of scattering elements that change the intensity and shape of speckles over time. Although the fluctuations of speckle intensities seem to be troublesome for measurements using speckle techniques, there are various applications of speckle techniques to wet samples, called “Dynamic Speckle Interferometry (DSI)”. One example is the application of speckle techniques to studying biological tissues. Water is an essential requirement for many biological samples; their mechanical properties change considerably if they become dry. Therefore, they need be immersed in water while being analyzed. Zaslansky et al. [18] have used the fluctuations of speckle patterns for strain measurements on cortical bone and vascular tissues. Facciaa et al. [19] have applied DSI to analyzing the drying time of different types of paint. For this purpose, they have applied different types of paint with different thicknesses to a surface and monitored the changes in the speckle patterns over time. As the paint dries, the fluctuations of the speckle pattern decrease, until the pattern becomes completely static; this is when the paint is thoroughly dry. Therefore, monitoring the change in speckle patterns over time helps determine the drying time of paint. Because the thickness of the paint layer is related to the drying time, it is also possible to compare the thickness of the paint at different regions by applying this method [20]. DSI has also been used to show qualitatively how two liquids blend under controlled conditions [21], and to analyze the corrosion process of two metallic surfaces immersed in a corrosive liquid [22].

This research performs three experiments to analyze the effect of contamination on the sample surface. In the first experiment, a splash of water makes the sample wet, and the camera captures the speckle pattern every second for 20 seconds without any changes to the system. Figure 19-a shows the correlation of the pattern captured after 10 seconds with all the other patterns. Based on this figure, after one second, the correlation drops to 0.5, and after 4 seconds, there is no correlation between the patterns. This is because the thin layer of water is distributed unevenly on the sample surface and is evaporating quickly. This changes the shape of the scattering elements and decorrelates the speckle patterns captured under the same conditions. For the same reason, the pattern captured when the sample is wet does not correlate with the pattern captured of the dry sample.

In the second experiment, the sample is fully immersed in water, such that the surface of the sample is approximately 2 mm below the water surface. The speckle patterns of the immersed sample are darker that those of the dry sample, because the reflectivity of the surface is a function of the difference between the refractive index of the surface and the environment (Δn). When the sample is immersed in water, Δn decreases. As a result, the reflectivity decreases, and the speckle pattern reflected from the surface becomes darker.

In order to analyze the stability of speckle patterns when the sample is immersed in water, the speckle pattern of the dry surface is obtained, then the sample is immersed in water, and the camera captures the speckle patterns every second over 20 seconds. Figure 19-b shows the correlations of all the patterns of the immersed sample with the one captured after 10 seconds.

In the third experiment, the sample is immersed in acetone such that the surface of the sample is 2 mm below the acetone surface, and the sample is stationary during the

experiment. The camera captures the speckle patterns every second over 17 minutes without any changes to the system. The reason for choosing acetone is that it evaporates quickly, and it is easy to monitor the effect of evaporation on the speckle patterns. Figure 20 shows the correlation of all the patterns with the one captured at the beginning of the experiment. When the surface of the sample is evenly covered with a layer of acetone, the correlation will be lost after approximately 200 seconds. From 480 to 810 seconds, the layer of acetone gets very thin, and the evaporation causes an uneven distribution of acetone on the sample surface that changes very quickly. As a result, the speckle patterns captured over this period do not correlate with each other. After 810 seconds, the sample is getting dry, and while it's getting dried, the correlation drop decreases exponentially. The results show that from 810 to 1020 seconds, the correlation drop is only 0.46. The correlation between the pattern captured before the sample is immersed in acetone and after the acetone completely evaporates from the surface is 0.3. This decorrelation is most likely caused by the change in the temperature of the surface due to the evaporation of acetone and the residues that the acetone leaves on the surface after evaporating. It is important that the sample does not deviate from its initial position after immersion.

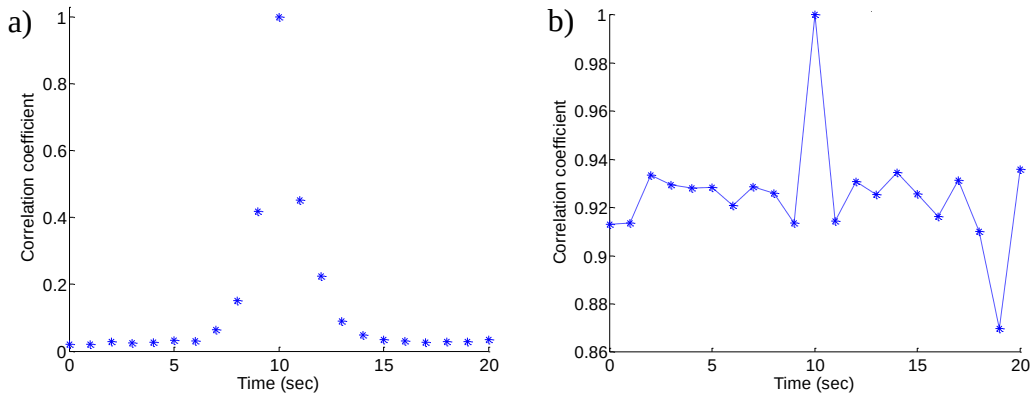

Figure 19: Effect of contamination on speckles. a) Wet sample. b) Sample immersed in water

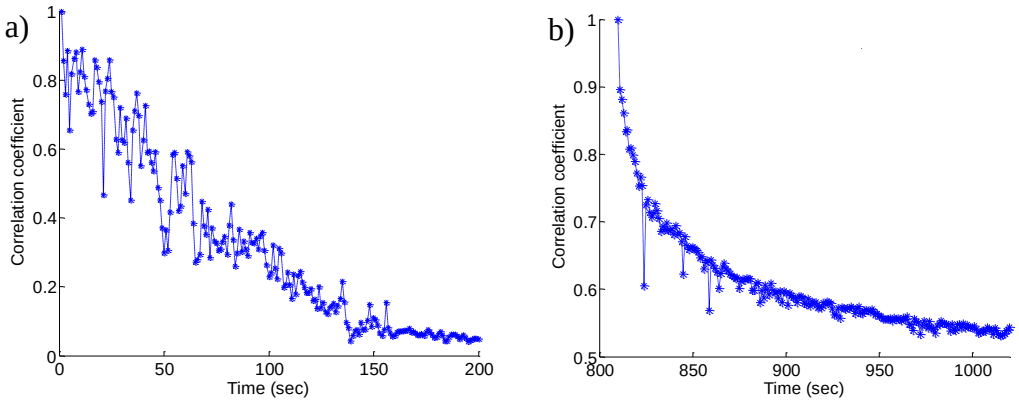

Figure 20: Analyzing speckle stability. a) Sample immersed in acetone. b) The surface getting dried.

2.4 Reducing the Number of Required Database Pattern

The absolute scale based on speckles discussed in this research requires a large number of database patterns. In order to apply this method to longer ranges and two dimensions, this section introduces a curve fitting method that reduces the number of required database patterns by an order of magnitude (comparing to the method introduced in section 2.1 that required one database per micrometer), and compares it to two different methods of fitting a polynomial. For this purpose, one database pattern is created every 10 µm and the sample position in between is determined by fitting a curve to the 10 µm interval. The curve that is used for curve fitting in this chapter is called the "correlation curve" and depends on the characteristics of the measurement system. This curve fitting method is then compared with two different methods of fitting a polynomial.

The curve used here to reduce the number of required database patterns is based on the autocorrelation function of the speckle pattern. Another way to determine this curve is to determine the correlation of one of the database patterns with its neighbors. This gives a set of datapoints. In order to obtain a continuous curve, a cubic spline interpolates

between the two adjacent correlation coefficients. Figure 21 compares a typical correlation curve for the sample position at 10 µm over a 20 µm range with a second order polynomial and a Gaussian distribution over the same range. The polynomial shares three points with the correlation curve at sample positions 0, 10, and 20 µm.

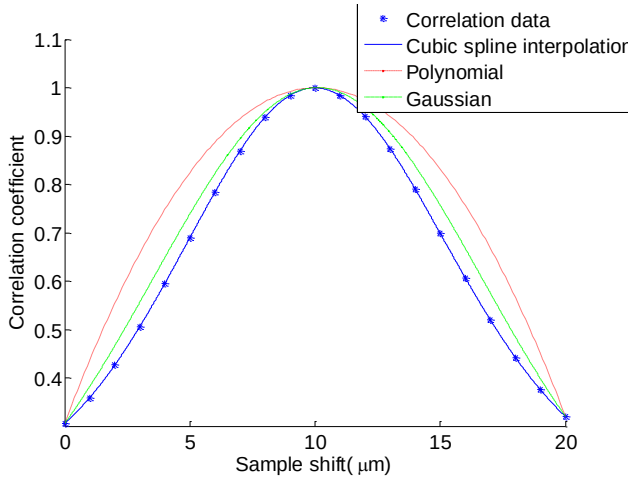

Figure 21: Comparing the speckle correlation curve with a second order polynomial and a Gaussian distribution

The correlation curve depends on the mean speckle size. For an objective speckle pattern, based on equation (1-1), by keeping the wavelength, the sample-camera distance (which also requires no significant form error on the sample surface), and the spot size constant, the correlation curve stays constant over the measurement range. Assuming that the system in Figure 21 has these characteristics, having one database pattern every 10 µm allows estimating the position of the sample. For example, it is possible to determine whether the sample is between 0 and 10 µm, 10 and 20 µm, 20 and 30µm, etc, by having one database pattern every 10 µm. This is feasible only if half width of the correlation curve is larger than 10 µm (which is the length of each interval).

Figure 22-a shows typical correlation curves at sample positions 0 and 10 µm. If the sample is at an unknown position between 0 and 10 µm, its speckle pattern has specific

correlation coefficients with the database patterns at 0 and 10 µm. Hence, by calculating the correlation of the pattern at unknown sample position with these two database patterns, it is possible to determine if the sample is between 0 and 10 µm. If this is true, then the correlation of the speckle pattern captured at the unknown position with the database at 0 µm should be greater than the correlation coefficient at point "b" in Figure 22, which is 0.32, and its correlation with the database at 10 µm should be greater than the correlation coefficient at point "a", which is also 0.32 in this example.

Figure 22-b shows a situation where half width of the correlation curve is smaller than 10 µm. In this case, it is not possible to determine if the sample is between 0 and 10 µm by finding its correlation with the databases at 0 and 10 µm. For example, if the sample is at an unknown position in interval "m", it is not possible to distinguish it from its symmetry about the line "Sample shift = 10 µm", located in interval "n", as both would have zero correlation with the database at 0 µm and the same correlation coefficient with the database at 10 µm.

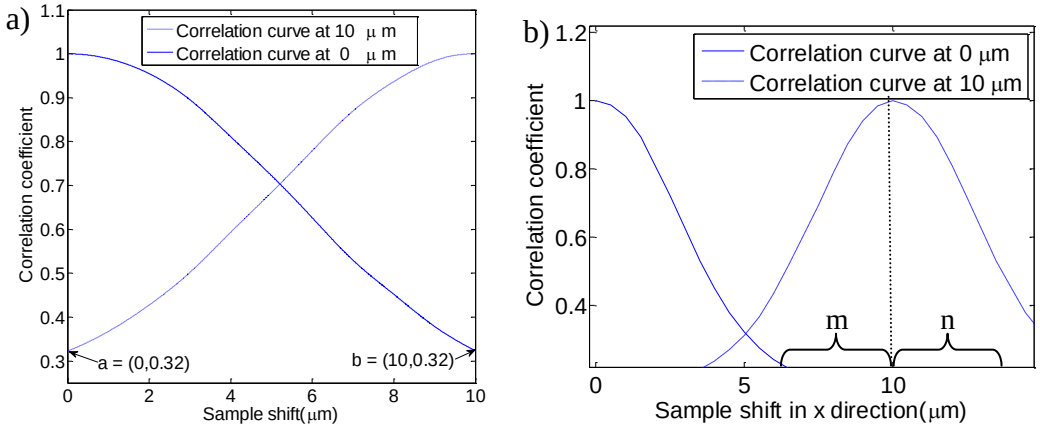

Figure 22: Correlation curves at sample positions 0 and 10 µm. a) The half width of each curve is larger than 10 µm. b) The half width of each curve is smaller than 10 µm.

By designing the correlation curve such that its half width is larger than 10 µm, it is possible to determine the two database patterns between which the sample is located,

over a long range. For a 100 µm range, this research develops a Matlab code that calculates the correlation of the speckle pattern at an unknown sample position with all the database patterns (the patterns at 0, 10, 20, ... , 100 µm). The first and the second correlation maximum are the two patterns between which the sample is located (Figure 23). Based on this figure, the sample is between 60 and 70 µm. Also, because the first maximum is at 70 µm, the sample is closer to this point. By fitting the correlation curve to pass these two points, the peak of the curve reveals the sample position.

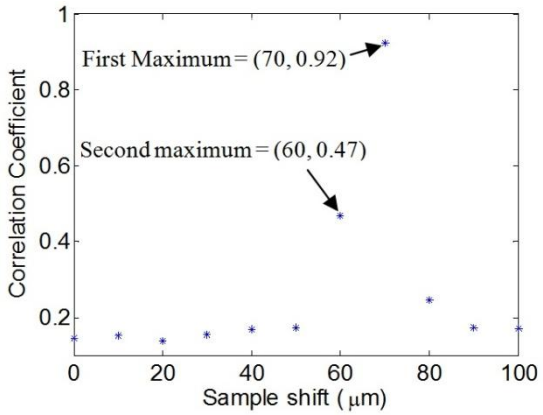

Figure 23: The first and the second correlation maximum observed at 60 and 70 µm showing that the sample is between these two points.

2.4.1 Experimental Setup and Results

Figure 24 shows the experimental setup for absolute position measurement using speckle correlation in this research. A 3 mW HeNe laser illuminates an optically rough sample. A laser lens is used to adjust the spot size and the wavefront curvature. The CCD screen directly captures the speckle patterns. A motorized stage also shifts the sample perpendicular to the beam direction and an attenuator controls the maximum intensity of the speckle pattern.

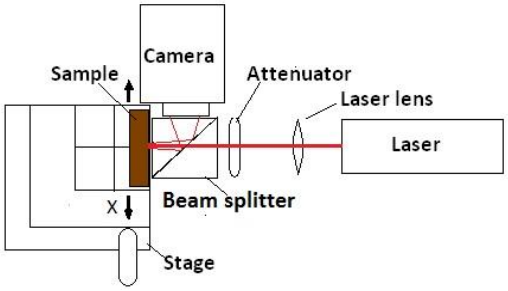

Figure 24: An experimental setup for absolute position measuring using speckle pattern correlation

The motorized stage consists of a piezo actuator for fine displacement and a step motor for coarse displacement. In order to capture the data every 0.1 µm over 100 µm (a total of 1001 data), the piezo shifts the sample in 0.1 µm steps over the first 20 µm range while the camera captures the patterns. Then the step motor shifts the sample to 20 µm in one step, the piezo shifts the sample from 20 to 40 µm in 0.1 µm steps, and the camera captures the patterns. This process repeats up to 100 µm.

In order to analyze the correlation methods discussed in section 2.4, this research compares the sample position that the correlation techniques determine, to the sample position that the stage measures. The purpose of the first experiment is to evaluate the method with one database pattern per 1 µm. The camera captures the database patterns every micron from 0 to 100 µm (the database patterns are at 0, 1, 2, ..., 100 µm). Then a Matlab code selects one data randomly from all the data (captured every 0.1 µm) and calculates its correlation with the database patterns. The highest correlation coefficient shows the sample position (Figure 25). Because the resolution of this method is 1 µm , the position value determined using this method is compared to the stage reading rounded to the nearest integer. Analyzing the system at various data points shows that the position value determined by the correlation method matches the stage reading.

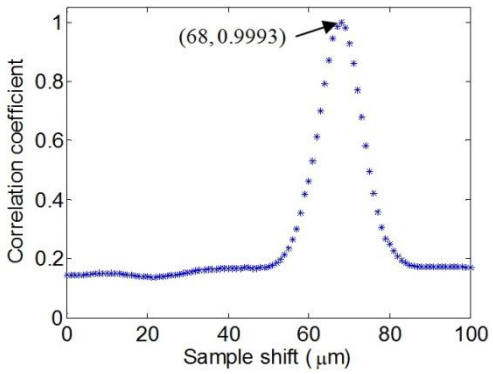

Figure 25: Determining the sample position by finding the correlation peak (determined sample position = 68 μm)

The second experiment evaluates the correlation curve fitting method. For this purpose, the patterns captured every 10 μm over the 100 μm range (the patterns captured at 0, 10, 20, ..., 100 μm) serve as database patterns. A Matlab code selects one position randomly from all the data (captured every 0.1 μm) and it determines between which two database positions the randomly selected position is located. For this purpose, it calculates the correlation of the randomly selected pattern with the database. The first and the second maximum show the two database patterns between which the sample is located (Figure 23). In order to determine the sample position with 1 μm resolution, the first step is to determine the correlation curve and verify that the curve is the same at different sample positions. For this purpose, a Matlab code determines 5 different correlation curves at different sample positions, determines their similarity, and uses the average of them as the reference correlation curve. The selected curves are at 10, 30, 50, 70, and 90 μm. As mentioned earlier, in order to determine the correlation curve at 10 μm between 0 and 20 μm, a Matlab code determines the correlation coefficient of the pattern at 10 μm with the database patterns at every 1 μm and uses a cubic spline to interpolate the distribution. Next, it determines the correlation curve at 30 μm between 20 and 40

μm. It repeats this process to determine the correlation curves at 50, 70 and 90 μm. The maximum possible induced error due to the deviation of each curve from the average curve is 0.04 μm. In order to determine this error, a Matlab code calculates the deviation of each curve from the average curve at the sample positions associated with the database patterns. Then it multiplies the deviations by the derivative of the average curve at each point. Only the deviations at the points located in the -5 to 5 μm interval about the peak of the average curve are important. The maximum of the deviations is 0.04 μm that shows using the average of the correlation curves does not introduce a significant amount of error.

At this point the sample is determined to be between 60 and 70 μm and the correlation curve is estimated. The two points that the correlation curve at the randomly selected position passes are determined, which are 0.47 at 60 μm and 0.92 at 70 μm (Figure 23). Having a higher correlation with 70 μm shows that the sample is closer to 70 μm. In order to find the sample position with 1 μm resolution, a Matlab code fits the correlation curve to these points. The peak of the curve shows the position of the sample (Figure 26). Because the correlation curve might not exactly pass these two points, one way is to shift the curve such that it passes the point with the higher correlation (in this example the correlation is higher at 70 μm). Also, for measurement with 1 μm resolution, the value determined by the peak of the correlation curve should be rounded to nearest integer.

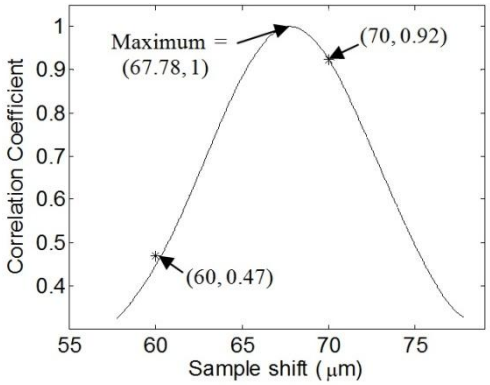

Figure 26: Fitting the correlation curve to the first and the second correlation maximum determined in Figure 23, and rounding the sample shift associated with the peak of the curve to the nearest integer to determine the sample position (68 μm in this example).

The polynomial methods are similar to the correlation curve method. That is, the patterns captured every 10 μm serve as the database patterns. A Matlab code selects one data randomly from all the data captured every 0.1 μm and determines between which two database patterns the randomly selected data is located. However, in the polynomial methods, a second order polynomial (instead of the correlation curve) is fit to the two correlation maxima in Figure 23.

This research investigates two different methods of determining a second order polynomial for fitting to the interval between the two correlation maxima. One way to determine this polynomial is to consider the fact that three points can define a unique polynomial, two of which are the two correlation maxima. The third point is the correlation peak, where the correlation coefficient is one and the associated sample shift is unknown. However, at this specific point, the derivative of the correlation curve is zero. As a result, the sample shift at this point can be expresses using the polynomial coefficients. Assuming that the second order polynomial is $ax^2 + bx + c = y$, at the correlation peak the following equation is valid:

$$2ax + b = 0 \rightarrow x = \frac{-b}{2a} \quad (2\text{-}1)$$

Plugging $(\frac{-b}{2a}, 1)$ into the polynomial equation gives

$$\frac{b^2}{4a} - c + 1 = 0 \quad (2\text{-}2)$$

which is one of the equations to be solved in order to determine the polynomial coefficients (a, b, c). Assuming that the two correlation maxima are (x_1, y_1) and (x_2, y_2) respectively, the two other required equations are $ax_1^2 + bx_1 + c = y_1$ and $ax_2^2 + bx_2 + c = y_2$. Solving these equations gives the polynomial coefficients. In case of multiple solutions, applying the constraint that the sample position should be between the two correlation maxima gives a unique solution. Figure 27 shows the application of this method to the example where the stage reads the sample position to be at 67.9 μm.

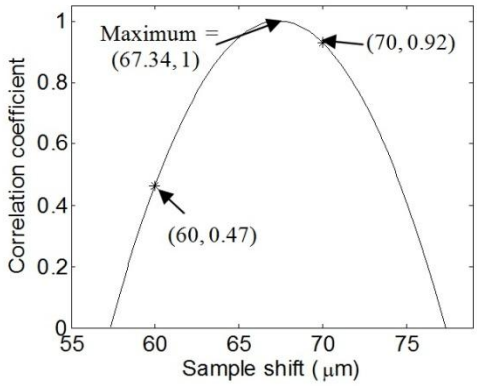

Figure 27: A unique second order polynomial is fit to the first and the second correlation maximum determined in Figure 23. The third point of the polynomial is the correlation peak. Rounding the sample shift associated with the peak of the curve to the nearest integer gives the sample position (68 μm in this example).

An example can explain the second method of determining a polynomial in order to fit to the correlation maxima. For creating a polynomial between 0 and 20 μm, a Matlab code determines the correlation of the pattern at 10 μm with the patterns at 5, 10 and 15

μm. These three points define a unique second order polynomial. In order to determine the polynomial between 20 and 40 μm, the code determines the correlation of the pattern at 30 μm with the patterns at 25, 30 and 35 μm. The code repeats the same process for the remaining intervals (40 to 60 μm, 60 to 80 μm, and 80 to 100 μm). Then it determines the average of the five curves. The maximum induced error due to the deviation of the polynomials from the average polynomial is 0.03 μm, which is not significant. This error is determined using the method explained earlier in this section for the average correlation curve. After determining the average polynomial, the code makes this polynomial pass the first maximum in Figure 23. The peak of the polynomial shows the sample position (Figure 28).

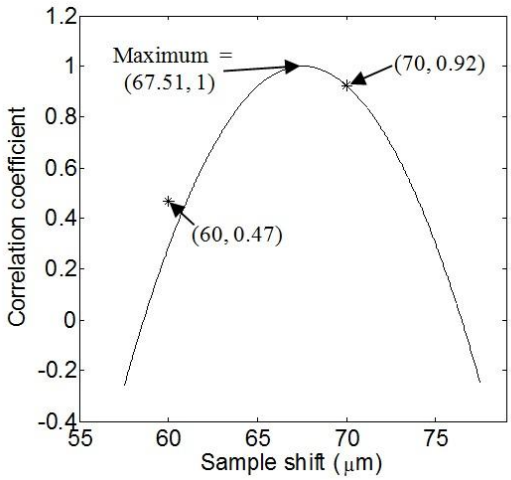

Figure 28: The average second order polynomial is fit to the first and the second correlation maxima determined in Figure 23. Rounding the sample shift associated with the peak of the curve to the nearest integer gives the sample position (68 in this example).

2.4.2 Discussion of Experimental Results

In order to evaluate and compare the results of the four measurement methods discussed in section 2.4, this research compares the stage reading for 1001 data points captured in 0.1 μm steps from 0 to 100 μm, to the sample position that each measurement

method determines. Analyzing the method that has one database pattern per micrometer shows that the position value determined by this correlation method matches the stage reading at all the 1001 data points. Due to the large number of database patterns, this method has the lowest measurement speed. The resolution of this method is limited to 1 μm, unless the database patterns are captured over shorter steps (e.g. one database pattern should be available at least every 0.1 μm step for 0.1 μm resolution). This will increase the number of database patterns and further decrease the speed of the measurement.

In order to analyze the three curve fitting methods, namely the average correlation curve, the unique polynomial, and the average polynomial, a Matlab code determines the deviation of the sample position determined by the curve fitting method from the stage reading at 1001 data points captures every 0.1 μm from 0 to 100 μm. Then it determines the maximum and the standard deviation (std) of these values. It also determines the deviation of the sample position determined by the curve fitting method rounded to the nearest integer from the stage reading rounded to the nearest integer, and estimates the maximum and std of these values. Table 2 shows the results. The purpose of rounding the stage reading and the position determined by the curve fitting method to the nearest integer before determining their deviation is to design all methods for displacement measurement with 1 μm resolution. This makes it feasible to compare the curve fitting methods with the method that has one database pattern per micron and a measurement resolution of 1 μm.

Table 2: Comparing the curve fitting methods. All values are in µm

Curve fitting method	Max deviation	std	Max deviation (rounded values)	std (rounded values)
Average correlation curve	+ 0.6 - 0.5	0.24	+1 - 1	0.43
Unique-polynomial	+ 0.81 - 0.63	0.33	+1 - 1	0.54
Average-polynomial	+ 0.65 - 0.54	0.20	+1 - 1	0.42

Comparing the results of the three curve fitting methods shows that the correlation curve method provides more accurate measurement results than the unique-polynomial method. Although the average-polynomial method has a slightly lower std, it introduces a higher maximum deviation from the stage measurement. This suggests that the correlation curve fitting is preferred to the polynomial fitting techniques. It also requires less number of database patterns (one order of magnitude) comparing to the method with a database patter per 1 µm. In order to compare the speed of measurement of the correlation curve fitting method with the method that has a database per 1 µm, a Matlab code measures the time required to measure one random sample position using each method. It repeats the same process for 4 other random sample positions and determines the average of the five measured values for each method. This value is 0.18 seconds for the correlation curve method and 1.43 second for the method with a database per 1 µm, using a laptop computer. This shows that the correlation curve method is 8 times faster.

2.5 Two Dimensional Absolute Measurement

Although the curve fitting method introduced in section 2.4 increases the speed of measurement, it introduces the curve fitting error to the measurement results. Therefore, it is not applied to the two dimensional measurement that is investigated in this section. Instead, one database pattern is captured per 1 µm in x and z directions for measurement with 1 µm resolution over a 20 by 20 µm resolution, resulting in 421 databases patterns.

Capturing the database patterns is possible by setting the z stage to z = 0 µm and shifting the x stage from 0 to 20 µm in 1 µm steps while the camera captures the patterns at every step. Then the z stage is set to 1 µm, and the x stage shifts from 0 to 20 µm in 1 µm steps, and so on until all the patterns are captured. Then the stage shifts to 1000 random positions in the 20 by 20 µm with 1 µm resolution. At every random position, the speckle pattern and the associated stage reading is stored. Finding the position of the random pattern using speckle correlation is possible by determining the cc of all the database patterns with the random pattern. The position of the database with the highest cc with the randomly captured pattern gives the position of the sample. Table 3 shows the results. The average deviation of about -1 from the stage reading in x and z directions is most likely caused by the homing error introduced to the system after capturing the database patterns and before capturing the patterns at random positions.

Table 3: Two dimensional measurement results using a database of speckle patterns

	Average (µm)	Std (µm)	Average of absolute values (µm)	Maximum of absolute values (µm)
Deviation from stage reading in x	-0.94	0.24	0.94	1
Deviation from stage reading in z	-1	0.71	1.04	2

2.6 Conclusion

Speckle pattern correlation is a one of the non-contact methods for high resolution displacement measurement, even in the order of nanometers [6]. However, the idea of creating an absolute scale using a database of speckle patterns has some shortcomings. The large number of required database patterns limits the measurement range, especially in two dimensions. Moreover, speckle patterns are very sensitive to external disturbances. Changes in temperature, deviation of the system elements from their initial position and

any contamination of the sample can cause the database degradation and its deviation from the designated position. As a result, creating a set of database patterns only once and expecting the measurement system to operate for a long period of time is quite challenging. On the other hand, renewing the database regularly requires a precise stage to be part of the system, which increases the cost of the system significantly and decreases its effectiveness. The next section introduces a method for displacement measurement using speckle correlation that doesn't require a predetermined set of database patterns [23].

CHAPTER 3: DOUBLE BEAM SPECKLE CORRELATION

As mentioned earlier, application of speckle correlation techniques to displacement measurement in industrial processes is limited by the large number of required database speckle patterns and the instability of these patterns. This chapter introduces a displacement measurement method that uses the speckle correlation between two identical parallel overlapping laser beams. This method requires a few database patterns that are updated frequently during the measurement process.

3.1 Theory of Double Beam Speckle Correlation

Speckle patterns are like finger prints for specific positions of the sample. As a result, two speckle patterns created under similar conditions are expected to have a high correlation, especially if the time between capturing the two patterns is too short for any mechanical or environmental disturbances to degrade the correlation. Assume that an optically rough surface is illuminated with two identical parallel overlapping laser beams, which can be created by passing a laser beam through a beam splitter and a mirror. First, the second beam is blocked and the pattern created by the first beam is stored. Then, the first beam is blocked and the pattern created by the second beam is stored. Next, the sample shifts in incremental steps, such that the area of the sample which was initially illuminated by the first beam is now approaching the area that the second beam illuminates at each step

.

As the sample shifts, the speckle pattern created by the second beam is captured at each step and its correlation with the pattern initially created by the first beam is determined. When the sample shifts by the amount equal to the beams' separation, the correlation coefficient between the two patterns reaches its maximum. As a result, if the system is calibrated only once by determining the beams' separation, the relative motion of the sample can be determined by monitoring the correlation between speckle patterns. Figure 29 shows the process of creating required speckle patterns for this technique. In this figure, $B1_0$ is the speckle pattern initially created by beam spot 1, $B2_0$ is the speckle pattern initially created by beam spot 2 and $B2_X$ is the speckle pattern created by beam spot 2 after the sample shifts by X. Figure 29-d shows the speckle patterns generated in the intermediate steps.

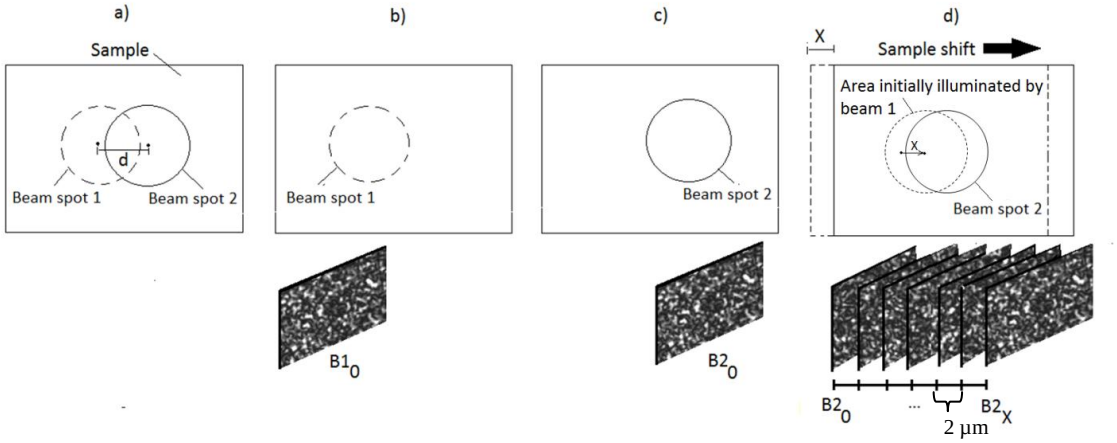

Figure 29: The process of obtaining the speckle patterns for relative displacement measurement. a) Two overlapping beam spot with center to center separation "d". b) The speckle pattern initially created by beam spot 1 while beam spot 2 is blocked. c) The speckle pattern initially created by beam spot 2 while beam spot 1 is blocked. d) The speckle patterns created by beam spot 2 as the sample shifts in 2 µm steps while beam spot 1 is blocked.

Assume that in Figure 29-d, the incremental steps that the sample shifts are 2 µm. Figure 30 shows the correlation distribution corresponding to Figure 29. The circular

markers show the correlation coefficients between $B1_0$ and the patterns that beam 2 creates at each step. As the area of the sample that beam 2 illuminates at each step approaches the area which was initially illuminated by beam 1, the correlation coefficient between the two patterns increases until it reaches the maximum when the sample shift is equal to the beams' separation. The star markers in Figure 30 show the correlation coefficients between $B2_0$ and the patterns that beam 2 creates at each step. As the sample shifts, the area that beam 2 illuminates at each step goes farther from the area that was initially illuminated by beam 2. As a result, the correlation coefficient between $B2_0$ and the patterns that beam 2 creates at each step decreases. In this method, as the sample shifts within the amount equal to the beams' separation, only two reference patterns, $B1_0$ and $B2_0$, need to be stored.

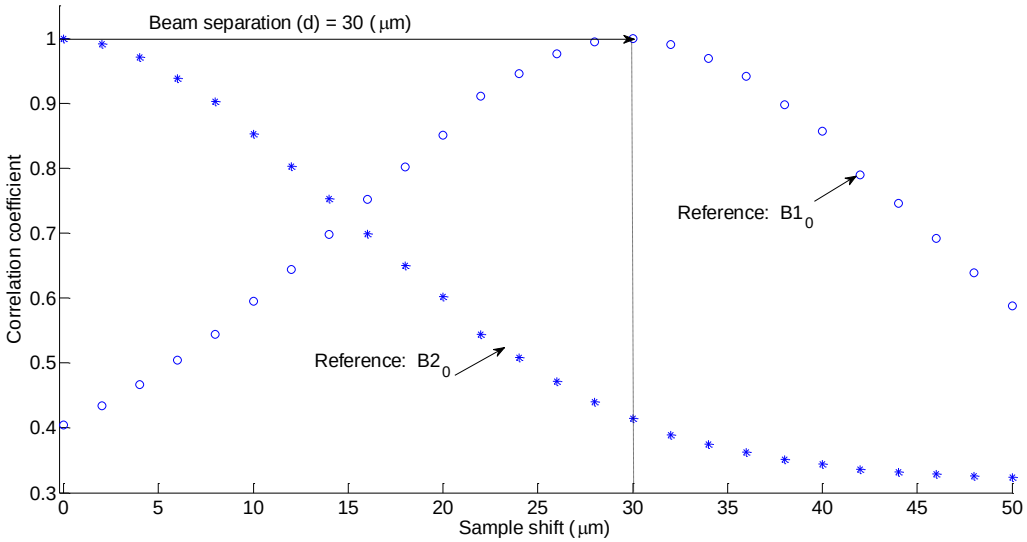

Figure 30: The theoretical correlation coefficients between the speckle patterns created by beam 2 at each step (2 μm sample shift) with $B1_0$ (the circular markers) and with $B2_0$ (the star markers).

3.2 Double Beam Speckle Correlation Experimental Setup and Results

Figure 31 shows the experimental setup for displacement measurement using double beam speckle correlation. The light source block creates two parallel overlapping beams. In Figure 31, this block consists of a 3mW HeNe laser beam and a Mach-Zehnder interferometer that divides the laser beam into two identical overlapping beams. This interferometer consists of two beam splitters (BS1 and BS2) and two mirrors (M1 and M2). Each beam passes through the attenuator, the third beam splitter (BS3), and then illuminates an optically rough sample attached to a motorized stage. The CCD screen directly captures the speckle patterns. The attenuator controls the maximum intensity of speckle patterns.

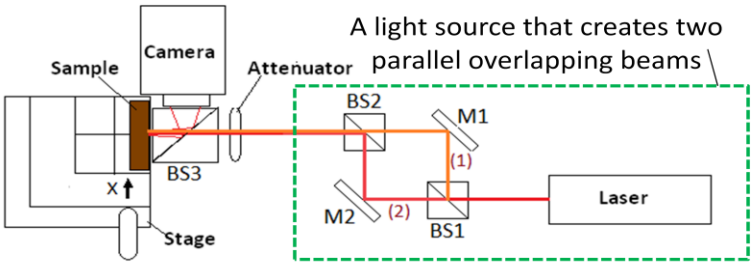

Figure 31: The experimental setup for relative position measurement using speckle correlation with double beam illumination

In order to calibrate the system, the separation between the two beams is determined. For this purpose, the second beam is blocked and the speckle pattern created by the first beam is captured and stored. Then the first beam is blocked and the speckle pattern created by the second beam is captured and stored. Next, the stage shifts the sample 50 µm in 2 µm steps. At each step, the speckle pattern is captured and its correlations with the initial patterns created by beam 1 and 2 are determined. Figure 32 shows the

correlation coefficients between the speckle patterns created by beam 2 at each step, with $B1_0$ and $B2_0$. Based on this figure, the lateral distance between the centers of the two beams is 30 μm. The correlation coefficient difference between the peaks of the two distributions, the one with the reference pattern $B1_0$ and the one with the reference pattern $B2_0$, is due to the beams' separation in z direction (assuming that z is the direction perpendicular to both x direction and the beam's direction).

After calibrating the system, at any moment it is possible to capture the patterns initially created by each beam and store them as reference patterns. Then as the sample shifts in incremental steps, the speckle pattern is captured and its correlation with the two reference patterns is determined. As soon as the correlation coefficient between the pattern captured at each step with the pattern initially created by the first beam reaches the maximum, the sample has shifted 30 μm.

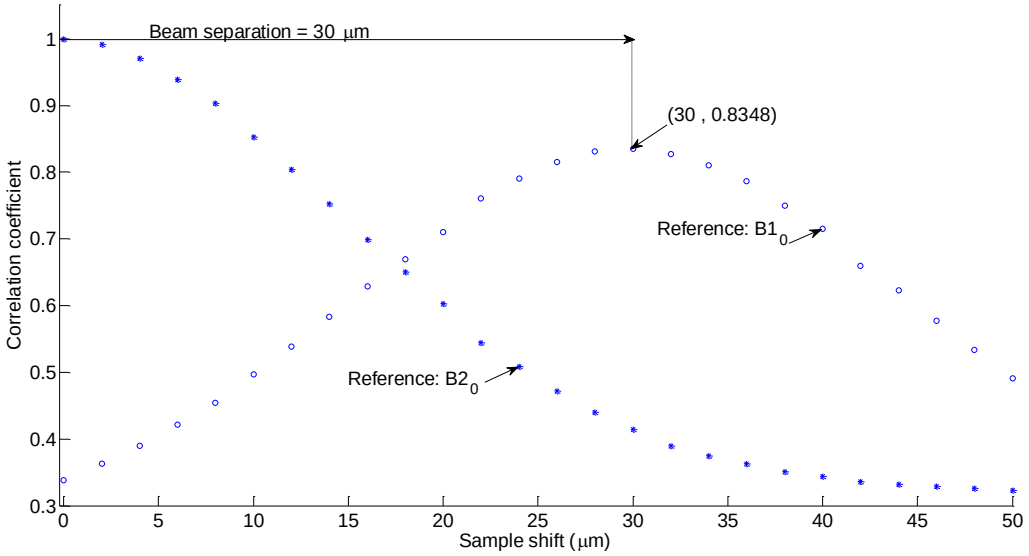

Figure 32: The experimental correlation coefficients between the speckle patterns created by beam 2 at each step (2 μm sample shift) with $B1_0$ (the circular markers) and with $B2_0$ (the star markers).

3.3 Evaluation of the Double Beam Speckle Correlation Technique

Double beam speckle correlation is a method for relative displacement measurement that uses the correlation between the speckle patterns generated by two identical separated beam spots. In this method, the required database patterns are updated frequently and as a result, it does not require a predetermined collection of database patterns. The resolution of this method depends on the separation between the two beams, which is 30 µm for the system introduced in Figure 31.

In this figure, the light source block, which consists of a HeNe laser and a Mach-Zehnder interferometer, can be replaced with a less complex and more cost effective subsystem. Figure 33 shows two possible arrangements for the light source block. One option is to use a laser source and a mirror attached to a stage; the beam makes a 45^{o} angle with the surface of the mirror (Figure 33-a). By shifting the mirror parallel to the beam's direction, two parallel beams can be created with a desired separation. In this method, only one beam is generated at each state of the system. As a result, it does not require blocking one beam at each state.

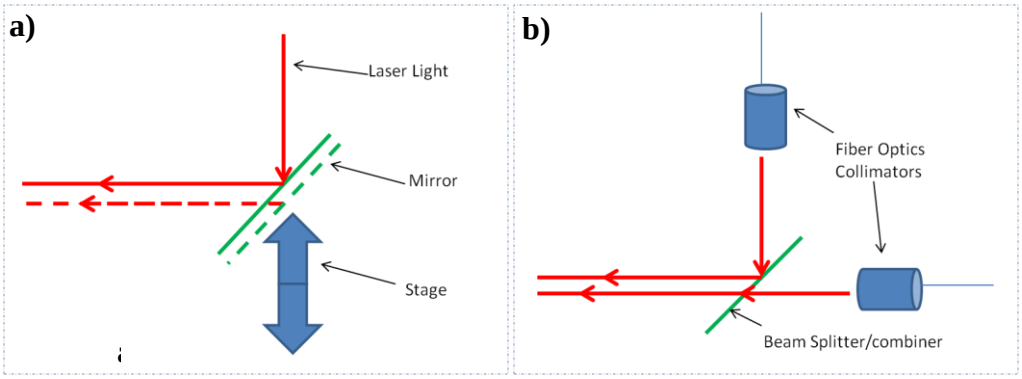

Figure 33: Possible arrangements for double beam light source

Figure 33-b shows another light source option for the double beam speckle correlation method. This light source uses two fiber optics collimators and a beam splitter to generate the overlapping beams. Shifting one collimator perpendicular to its beam direction can tune the beams separation.

One shortcoming of displacement measurement using double beam illumination method is that the beams must go on and off very frequently. In order to estimate this frequency, consider an example where the beams offset is 20 μm. For displacement measurement with 1 μm resolution, the system needs to capture at least one pattern per micrometer. If the speed of the camera is 400 fps and the system works at the maximum speed (400 μm per second), the beams should go on and off 20 times per second. In order to overcome this shortcoming, an optimization to the method is proposed in the next chapter.

CHAPTER 4: DUAL WAVELENGTH SPECKLE CORRELATION

The double beam speckle correlation method introduced in chapter 3, requires turning the beams on and off very frequently, which can downgrade the speed and performance of the system. In order to overcome this problem, this section introduces a method that is similar to the one introduced in chapter 3, but has red color in one branch and green in the second branch of the light source. This method uses a color camera to image the speckle patterns, which allows capturing the red and the green patterns separately but simultaneously. As a result, there is no need to turn the lasers on and off.

4.1 Dual Wavelength Speckle Correlation Theory

As mentioned earlier, it is possible to capture two speckle patterns under similar conditions with a high correlation if the time between capturing two speckle patterns is too short for any mechanical or environmental disturbances to degrade the correlation. Under certain conditions, it is also possible to create two speckle patterns with different wavelengths that still have a high correlation. Lehmann et al. explain these conditions using the principles of speckle elongation [13]. Based on this reference, achieving a high correlation between two speckle patterns of different wavelengths requires small wavelength separation, large speckle size, and precise alignment. In order to generate large speckles, the illuminating beam spot should be small and the imaging lens should have a large focal length (in case of an objective speckle pattern). This reference demonstrates a high correlation between a red and a green pattern using approximately 20

nm wavelength separation, 650 µm spot size, 200 mm imaging lens focal, and samples with RMS roughness (R_q) from 0.1 to 1 µm.

Figure 34 conceptually shows two identical parallel overlapping laser beams with two different wavelengths (red and green) illuminating an optically rough surface, under the conditions that the speckle patterns with different wavelengths correlate. The sample shifts in incremental steps, such that the area of the sample that the red beam initially illuminates, approaches the area that the green beam illuminates at each step. As the sample shifts, the correlation between the green speckle pattern captured at each step with the red pattern captured at the beginning of the experiment (the reference red pattern) increases, until the sample is shifted by the amount equal to the beams' separation. This is when the correlation coefficient (cc) between the two patterns reaches its maximum. At this point, the reference red pattern is replaced by the red pattern captured at the correlation peak position, and the correlation of this pattern with the green patterns is monitored up to the next correlation peak.

Figure 34-a shows the initial position of the sample with a red and a green spot illuminating its surface. Figure 34-b shows how the area initially illuminated by the red beam approaches the area that the green beam illuminates at each step. In this figure, the sample shifts to the left by the amount dx, while the beam spots are stationary. Figure 34-c shows that if the sample shifts to the left by the amount equal to the beams' offset, the area initially illuminated by the red beam will completely overlap the area that the green beam illuminates at that step. This is where the maximum correlation between the reference red and the green patterns captured at each step occurs.

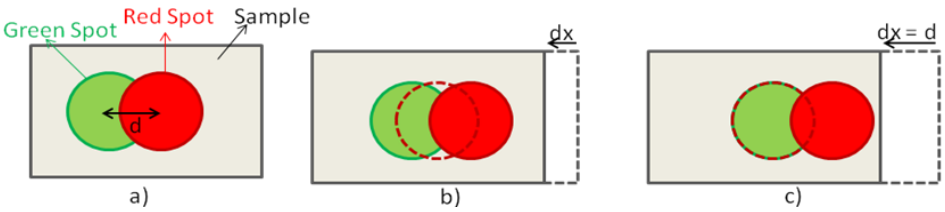

Figure 34: Location of the red and the green spot at different sample positions

Figure 35 shows the correlation behavior assuming that the beams' offset is 30 µm, the sample shifts in 1 µm steps, and the red and the green pattern captured under the exact same condition have a very high correlation. In this figure, the star markers show the cc of the green pattern at every step with the first green pattern captured, and the circle markers show the cc of the green pattern at every step with the first red pattern captured (the reference red pattern). As soon as the cc reaches its maximum, a new red pattern captured at the correlation peak replaces the reference red pattern used so far. The distance between the two correlation peaks is equal to the beams' offset.

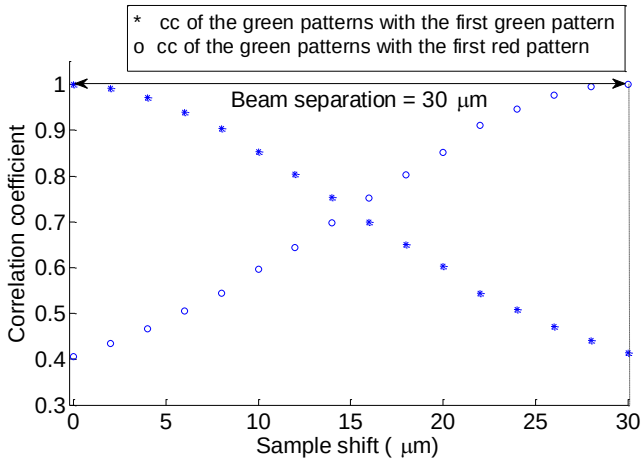

Figure 35: Expected correlation behavior for dual wavelength speckle correlation.

It is important to note that after the sample shifts a distance equal to the beams offset, although the green spot illuminates the exact same area initially illuminated by the red spot, the green pattern has shifted in the image plane with respect to the initial red

pattern. As a result, before determining the correlation between the green pattern and the reference red, the red pattern should be shifted a distance in the image plane with respect to the beams' offset, which is equal to the beams' offset if the magnification is 1. Figure 36-a shows the initial position of the speckle pattern that a specific area of the sample generates, in the image plane of the camera. Figure 36-b shows how that speckle pattern shifts in the image plane of the camera due to the sample shift. In this figure, the sample shift is equal to the offset between the red and the green spot.

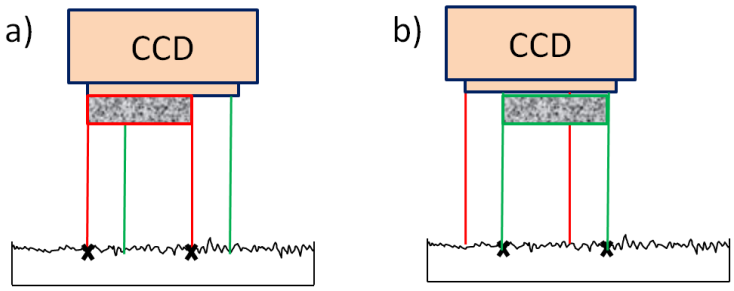

Figure 36 - The shift of the speckle pattern in the image plane of the camera due to the sample shift. a) The position of a specific speckle pattern before the sample shift. b) The position of the same speckle pattern after the sample shift.

Figure 37 shows the expected correlation behavior over 97 µm range for 32 µm beam separation. Calibrating the system only once by determining the beams' separation allows determining the relative motion of the sample by monitoring the correlation behavior.

Displacement measurement in between the correlation peaks is possible using a curve fitting method. The curve used for this purpose can be based on the autocorrelation function of the red or the green speckle pattern, which can be different from one another. One requirement for this purpose is that half width of the curve should be larger than the distance between the two correlation peaks. Otherwise, if the position of the sample is farther than the half width of the curve, the corresponding pattern will have no correlation

with the reference pattern at the correlation peak, which is the only reference pattern available.

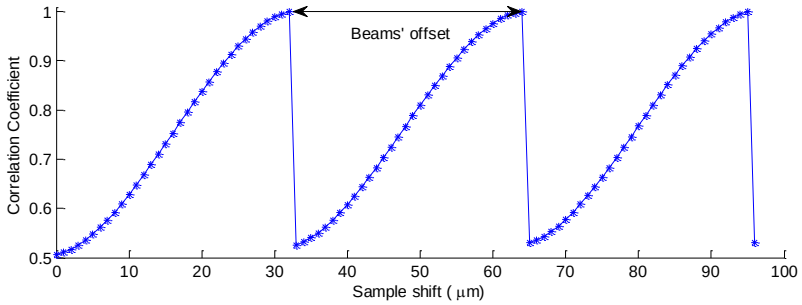

Figure 37: Expected correlation behavior for dual wavelength speckle scale

Using the curve fitting method requires determining the curve while calibrating the measurement system. For displacement measurement, the peak of the curve coincides with the correlation peak. At each sample position, the cc between the pattern at that point and the reference pattern defines a horizontal line (y = cc in an x-y plot). The amount of sample shift from the peak of the curve to the point where the horizontal line crosses the correlation curve, gives the distance of the sample from the reference pattern. Figure 38 shows an example where the reference pattern is at 930 μm. The cc between the pattern captured at the sample position with the reference pattern is 0.6643. The horizontal line, y = 0.6643, crosses the correlation curve at 18.2 μm from the peak of the curve, which shows the sample position determined by the curve fitting is 948.2 μm.

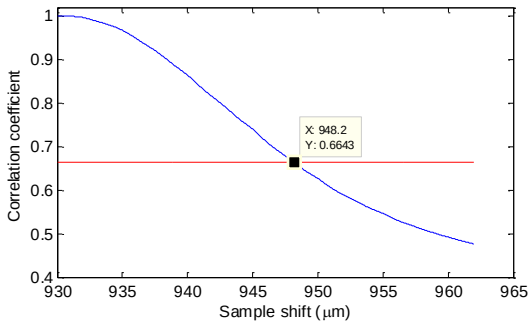

Figure 38: Displacement measurement using curve fitting in between the correlation peaks

4.2 Dual Wavelength Speckle Correlation Experimental Setup

The first experimental setup aims at verifying the correlation between two speckle patterns created with different wavelengths under certain conditions. Figure 39 shows the ideal schematic setup for this purpose. In this figure, a red and a green laser are coupled into a fiber and collimated such that the red and the green spot on the sample are completely overlapping. The color CCD captures the red and the green pattern simultaneously but separately, which allows determining the correlation between the two patterns.

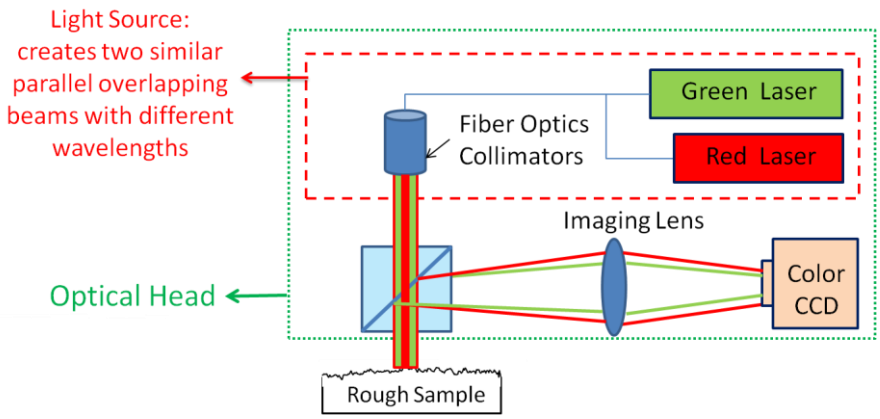

Figure 39: Schematic setup for verifying the correlation between a red and a green speckle pattern

The experimental setup shown in Figure 40 uses a black and white CCD instead of a color camera. As a result, instead of capturing the red and the green pattern simultaneously, the camera captures them in black and white, one after another, while one of the lasers is off at each camera shot. In this setup, a HeNe laser with $\lambda = 543.5$ nm and a diode laser with $\lambda = 657.0$ nm are coupled into a single mode fiber and collimated using a lens. The spot size on the sample is about 1 mm. The sample has a ground silicon surface characterize by the roughness parameter $S_q = 0.75$ µm. A beam splitter reflects

the speckle patterns toward the imaging lens. A black and white CCD captures the patterns in the focal point of a plano-convex lens (f = 200 mm).

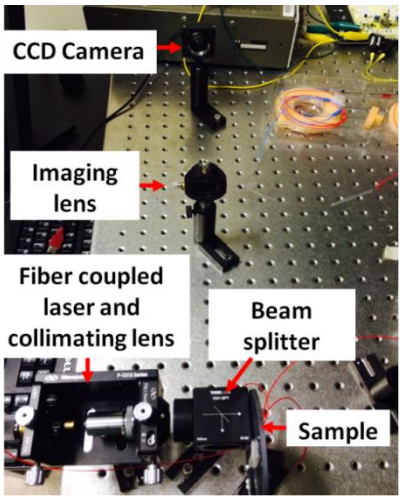

Figure 40: Experimental setup to verify the correlation between a red and a green speckle pattern

Analyzing the speckle patterns shows that the red pattern has larger speckles and higher angular dispersion relative to the green pattern. The cc between the red and the green is approximately 0.42. One way to increase the correlation between the two patterns is to take the effect of dispersion into account, which is possible by scaling the red pattern with a factor of $\lambda_{green}/\lambda_{red}$ using the Matlab "imresize" function. This function reconstructs a continuous signal from the original discrete signal, applies a low-pass anti-aliasing filter to the continuous signal, and then re-samples the resultant signal at the desired new sampling rate to get the output. After scaling the red pattern, the cc between the two patterns increases to 0.78.

The second experiment aims at displacement measurement using the dual wavelength method introduced in section 4.1. Figure 41 shows the schematic setup for this method. A green and a red collimated beam illuminate a beam splitter at 90^{o} angle with respect to each other in order to create two parallel, identical (except the wavelength), overlapping

spots. The beams illuminate the sample, and a second beam splitter reflects the speckle patterns to the imaging lens and the color camera.

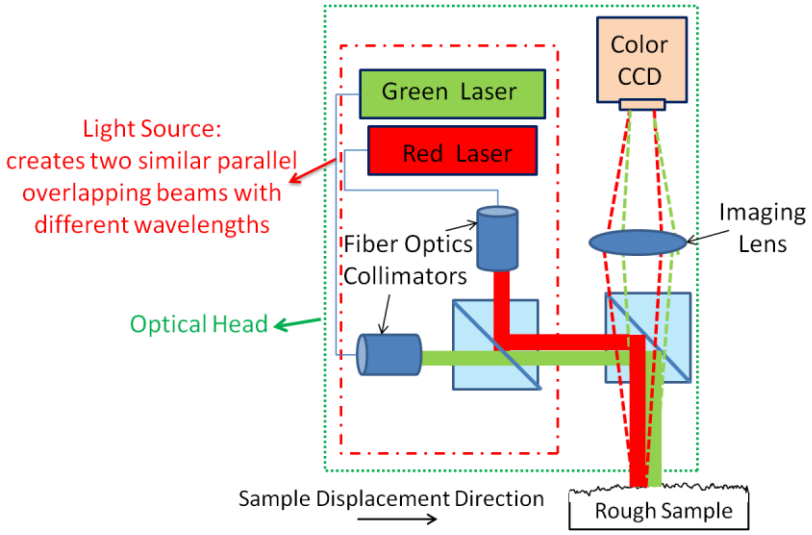

Figure 41: Schematic setup for displacement measurement using dual wavelength speckle correlation

Figure 42 shows the experimental setup for dual wavelength speckle correlation. This setup consists of a red (λ = 635 nm), a green (λ = 520 nm) pigtailed laser diode, and a fiber collimator for each laser. The green laser collimator is attached to a precision translation mount (Thorlabs LM1XY), which allows adjusting the beams' offset by shifting the green collimator in x and in z direction. Here, x direction is parallel to the optical table and perpendicular to the green beam, while z is perpendicular to the optical table. Every full revolution of the control knob of the translation mount is equivalent to 250 µm linear translation. A pellicle beam splitter brings the beams to overlap, and another pellicle beam splitter reflects the beams toward the sample. A plano-convex lens with 100 mm focal length (f) images the speckle pattern on the screen of a color CMOS camera. The sample is ground steel with vibrational finish (surface is characterized by S_q = 0.2 µm), which is attached to a motorized stage with 4 mm range. The distance between

the sample and the imaging lens is 2f. The distance between the imaging lens and the camera is also about 2f.

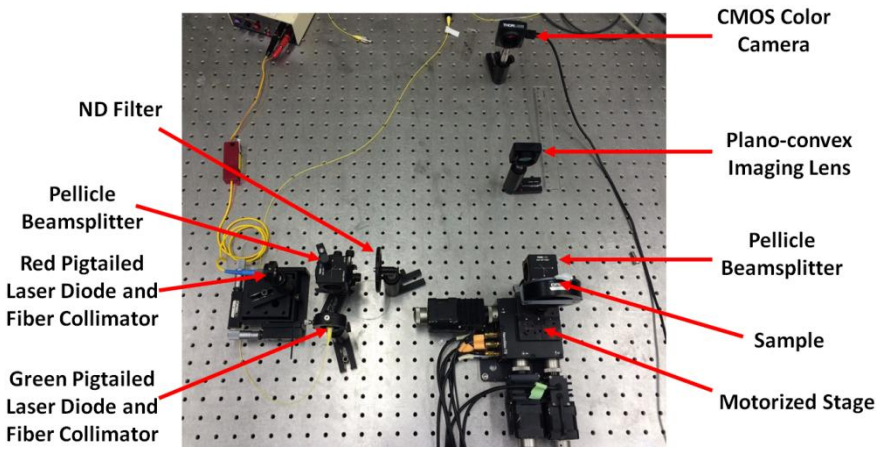

Figure 42: Experimental setup for displacement measurement using dual wavelength speckle correlation

The first step in calibrating the dual wavelength setup is to determine the beams' offset. Although the offset is adjusted using the translation mount, error in adjusting the knob and any misalignment in the setup can introduce error to the beams' offset. A more accurate way to evaluate the beams' offset is to shift the sample in incremental steps, such that the area initially illuminated by the red beam approaches the area that the green beam illuminates at each step, over a range that is about twice the beams' offset adjusted by the translation mount. This assures that the beams' offset is in the range of the sample shift. At every step, the subpixel shift between the red pattern at that step and the red pattern at 0 µm is determined and applied to the red pattern at 0 µm, such that it shifts toward the green pattern. Then, the correlation between the green pattern at each step with the shifted red pattern is determined. The sample shift associated with the maximum correlation shows the beams' offset. Figure 43 shows an example for this process. The

adjustment knob is turned 45^{o} (equivalent to 31.25 µm linear displacement), and the sample shifts from 0 to 80 µm in 1 µm increments. A second degree polynomial is fit to the experimental data in order to determine the position of the peak (32.6 µm), which is a 4.3 % deviation from the stage adjustment. The corresponding required shift for the reference red pattern is -10.14 pixels in x direction and 0.66 pixels in z direction. Repeating the process for the reference red pattern at different positions brings the error due to the surface inhomogeneity into account.

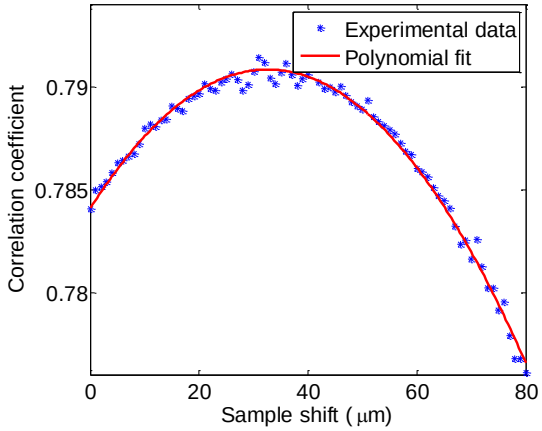

Figure 43: A method to verify the beams' offset

Surface inhomogeneity can introduce a significant error to displacement measurement using dual wavelength speckle correlation. One way to identify a uniform area on the sample in order to evaluate the measurement method is to shift the sample in incremental steps over a long range (2 mm), and determine the correlation of the red pattern with the green pattern at every step. Figure 44 is an example of the cc between the red and the green pattern at every 10 µm step over a 2 mm range. This shows the cc between the red and the green pattern from 930 to 1130 µm is high and the fluctuation (the difference between the maximum and the minimum cc in this range) is only 0.007.

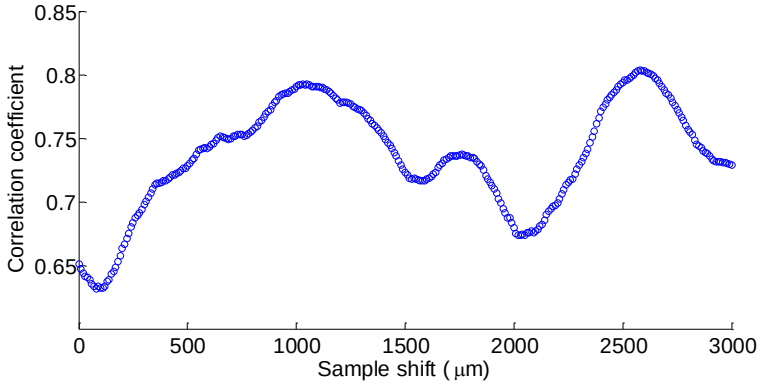

Figure 44: Correlation of the red and the green pattern at different sample positions

Evaluating the uncertainty of the beams' separation requires determining this value, using the method shown in Figure 43, at different positions of the reference red pattern, over the uniform range of the sample. The ten selected reference red patterns are at every 5 μm, ranging from 930 to 975 μm. The average correlation peak over this 200 μm range is at 33.05 μm and the standard deviation (std) from this point is 0.42 μm.

The next step in calibrating the dual wavelength system is to determine the curve to be fit in between the correlation peaks. Figure 45 compares the red and the green correlation distribution at 930 μm over a 32 μm range. The red distribution is the cc of the red part of the patterns captured every 1 μm, with the red pattern at 930 μm. Determining the green distribution is similar to the red. The green speckle size is smaller than the red, because the green distribution drops faster than the red.

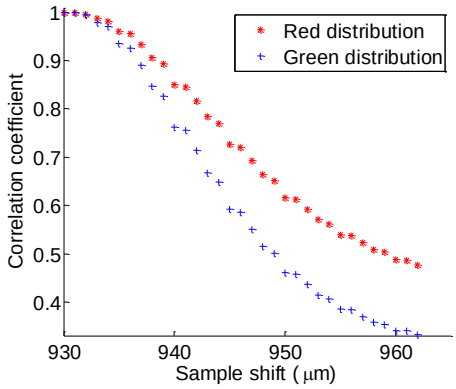

Figure 45: Comparing the red and the green correlation distribution

Approximating the displacement error induced by the changes of the correlation distribution at different sample positions is possible by determining the average of multiple distributions, finding the maximum deviation of the distributions from the average distribution, and estimating the displacement error due to the deviation. As an example, for determining 10 different red distribution over the identified uniform area of the sample, the first distribution is the cc of the red pattern at 930 μm with the red patterns at every 1 μm from 930 to 962 μm. The reference pattern is at 930 μm, the distribution is a vector with 33 elements, and the length of the distribution is 32 μm. The second distribution is the cc of the red pattern at 945 μm with the red patterns at every 1 μm from 945 to 977 μm. The reference pattern is at 945 μm, the number of elements and the length of this distribution are similar to the first one. Repeating this process for the reference patterns at every 15 μm from 960 to 1065 μm creates 8 more distributions, resulting in 10 total distributions. Assuming that each distribution is a row of a 10 by 33 matrix, the average of each column results in a vector with 33 elements, which is the average of the 10 distributions. Subtracting the average distribution from each row of the 10 by 33 matrix, and determining the maximum absolute value of each column of the

resultant matrix, gives a vector with 33 elements that shows the absolute maximum deviation of all the distributions from the average distribution. The next step is to determine the derivative of the average distribution at every 1 μm, which is determined by dividing 2 μm to the difference of the cc values 1 μm after and before each cc except the first and the last cc. Multiplying this vector, element by element, by the maximum cc deviation vector, gives the maximum sample deviation vector. The maximum of the resultant vector gives the maximum possible sample deviation, which is 1.35 μm for the red and 1.56 μm for the green distribution. As a result, the red distribution is more suitable than the green for the curve fitting process. In order to determine the correlation curve, a cubic spline interpolates the red distribution in 0.01 μm steps.

After calibrating the system, the dual wavelength speckle scale is ready for relative displacement measurement. The system is evaluated over a 200 μm uniform range of the sample, from 930 to 1130 μm, by comparing the sample shift determined from the correlation behavior to the stage reading. The first reference red pattern is at 930 μm, and the first cc value is the cc of the shifted reference red with the green pattern at 930 μm. At 931 μm stage position, the cc of the green pattern (at 931 μm) and the shifted reference red pattern (at 930 μm) is larger than the previous cc, showing that the second cc peak has not been reached, and the reference pattern remains at 930 μm.

At 931 μm, the cc of the red pattern (at 931 μm) with the reference red pattern (at 930 μm) crosses the correlation curve at 0.84 μm from its peak, while position of the peak of the curve coincides with position of the reference pattern (at 930 μm). As a results, the position determined by the curve fitting at 931 μm stage reading is 930.84 μm, which

shows a 0.06 µm deviation from the stage reading. This process is the same for the stage position from 931 to 962 µm.

At 963 µm, the cc of the shifted reference red with the green pattern at 963 µm is smaller than the cc of that with the green pattern at 962 µm. This shows that the sample has shifted the amount equal to the beams' separation (about 32 µm), and the first correlation peak, as described in Figure 37, has been reached. At this point, the reference red is replaced with the red pattern at 962 µm. The cc of the red pattern at 963 µm with the reference red (at 962 µm) defines a horizontal line that crosses the correlation curve at 1.94 µm from its peak at 962 µm. This means the position determined by the curve fitting is 963.94 µm, which shows a 0.94 µm deviation from the stage reading. Again, the process is the same up to 964 µm, where the second correlation peak occurs, and at 965 µm, the reference red is replaced with the red pattern at 964 µm. Repeating this process from 930 to 1130 µm at every 1 µm results in 0.5 µm average deviation from the stage reading and 0.8 µm std. Figure 46 shows the correlation results. The correlation curve is scaled to coincide with the peak of the correlation behavior, because the maximum cc in the correlation curve is 1, while here, the maximum correlation between the shifted reference red and a green speckle pattern is less than 0.8.

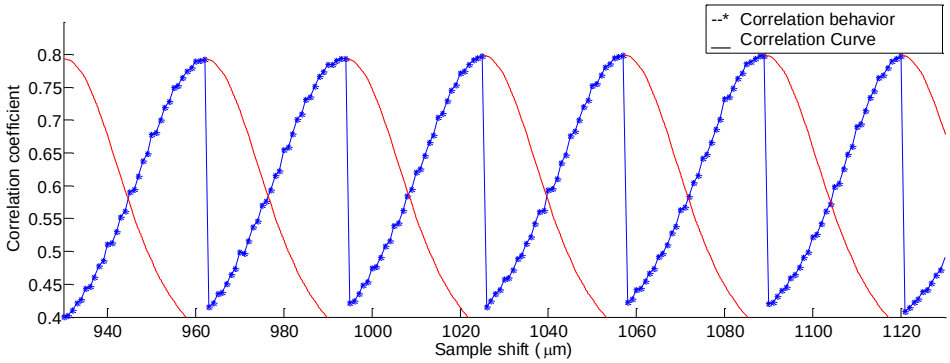

Figure 46: Displacement measurement using dual wavelength speckle correlation.

4.3 Dual Wavelength Speckle Correlation Summary and Future Work

This chapter introduces a robust displacement scale based on speckle pattern correlation. Relative displacement measurement is possible by illuminating the sample with two identical, parallel, overlapping laser beams with different wavelengths (red and green) and monitoring the correlation between the red and the green patterns. The results show that over a 200 µm uniform range of a ground steel sample with 0.2 µm S_q, relative displacement measurement is possible with 1 µm resolution, where the average absolute deviation from the stage reading for 200 data-points is 0.5 µm with 0.8 µm std. This method does not require a database of speckle patterns, which makes it robust to environmental disturbances. Because the speckle patterns are captured under the same conditions, most imaging errors do not affect the results.

Using a sample with a uniform surface roughness over a long range and a reference stage with less positioning error helps improve the evaluation results. The scale is capable of measuring continuous displacement of the sample. Here, the sample shifts in incremental steps to illuminate any possible error that improper timing between capturing the speckle patterns and recording the stage reading might introduce. For continuous displacement, the speed of the scale depends on the resolution of measurement and the speed of the camera. For example, for 1 µm resolution, the camera should capture a pattern at least every 1 µm. If the speed of the camera is 1000 fps, the measurement speed will be 1 mm/s.

The future work aims at expanding this technique to two dimensions, enabling velocity measurement, and increasing the compactness of the setup. This can make the dual wavelength scale a valuable tool for industrial displacement measurement.

One way to identify error accumulation in the dual wavelength speckle correlation scale is to combine Digital Image Correlation (DIC) with the dual wavelength technique. DIC can also be used to increase the resolution of the scale. The next chapter aims at reviewing the DIC technique and evaluating displacement measurement using this method.

CHAPTER 5: DIGITAL IMAGE CORRELATION

Digital image correlation (DIC) is an optical method based on image registration and numerical computing. It compares the changes in the gray intensity image of the surface of the object before and after deformation for precise 2D or 3D deformation or displacement measurement. The pattern of the surface (usually a speckle pattern) can be the natural texture of the surface, artificially made by spraying black and white paint, or generated by illuminating the surface with light. DIC was first introduced in 1980 [24] based on its advantages over interferometric techniques. Since then, it has been a popular research topic, given different names in numerous literature: digital speckle correlation method, texture correlation, computer aided speckle interferometry, and electronic speckle photography [15]. Some of the advantages of this technique are the simple experimental setup, low requirements for the measurement environment, and the wide range of measurement sensitivity and resolution. It can also be coupled with different microscopy methods (e.g. optical microscopy [25], scanning electron microscopy [26], and atomic force microscopy [27]) for micro and nano scale measurements.

This work investigates the application of DIC to displacement measurement of an optically rough surface based on the shift of speckle patterns that are created by illuminating the sample with a laser. Combining DIC method with the dual wavelength scale introduced in chapter 4 can help detect error accumulation associated with the relative scale.

5.1 Brief Description of Displacement Measurement Using DIC

Implementing the DIC method requires recording images of the planar sample surface before and after displacement and processing the acquired images. Different techniques including image registration can determine the pixel or subpixel shift of one pattern with respect to the other. Ideally multiplying the estimated shift of the image by the magnification of the imaging system (in units of length/pixel) equals the actual shift of the sample surface. But factors such as surface form, misalignment, and imaging system aberrations can introduce error to this method. One requirement for using this method is that the sample surface must be flat and remain parallel to the imaging screen. Any out-of-plane displacement of the sample leads to a change in magnification of the recorded images, which further introduces additional in-plane displacements. Another requirement is that the imaging system should not suffer from geometric distortion [15].

For implementing DIC, it is possible to use an entire image or part of it in order to estimate the image shift. There's a tradeoff between using a small or a large subset. Although the subset should be large enough to have a distinctive intensity pattern, a large subset requires more computational effort. A detailed study on selecting subset for DIC for speckle patterns can be found in the literature [28]. Usually for speckle patterns with low contrast, a large subset must be chosen to provide a reliable result, while for speckle patterns with sharp contrast, a very small subset containing sufficiently distinctive intensity pattern yields a satisfactory result [15].

5.2 DIC Method Experimental Setup and Results

In this work, the experimental setup for DIC is identical to the setup shown in Figure 41 and Figure 42, because combining the two techniques (DIC and dual wavelength) can

help determine the error accumulation. Only the red speckle patterns are used for evaluation. The goal is to evaluate absolute position measurement in two dimensions using a database of speckle patterns by applying the DIC method. Determining the required distance between the database patterns is possible by finding the displacement range, over which the subpixel shift of the patterns with respect to the database pattern changes linearly with the displacement of the sample from the position associated with the database pattern.

In order to investigate this behavior, the stage shifts the sample in 10 μm steps over a 500 by 500 μm area, while the camera captures the patterns at every step. The z axis is set to 0 μm and the stage shifts from 0 to 500 μm in 10 μm steps in x direction. Then z is set to 10 μm and the stage shifts from 0 to 500 μm in 10 μm steps in x direction. This process repeats up to z = 500 μm, resulting in 2061 patterns (51 by 51 array of patterns). A suitable algorithm [29] determines the subpixel shift of the patterns captured when z = 250 μm and x changes from 0 to 500 μm in 10 μm steps with respect to the pattern captured at (x, z) = (0, 250) μm. The results show that the linear relationship between the sample shift and the pixel shift is valid up to x = 270 μm. Determining the subpixel shift of the patterns captured when x = 250 μm and z changes from 0 to 500 μm in 10 μm steps with respect to the pattern captured at (x, z) = (250, 0) μm shows that the linear relationship in z direction is valid up to z = 290 μm. As a result, the linear relationship is valid in a 500 by 500 μm with respect to the database pattern at (x, z) = (250, 250) μm, which is the center of this area. Figure 47 shows the linear behavior in x and z directions with respect to the database pattern at (x, z) = (250, 250) μm. In this figure, the x axis shows the stage reading and the y axis shows the pattern shift in the image plane

determined by multiplying the pixel shift by the pixel size (3.6 µm for both x and z direction). The slope of the best fit line shows the magnification.

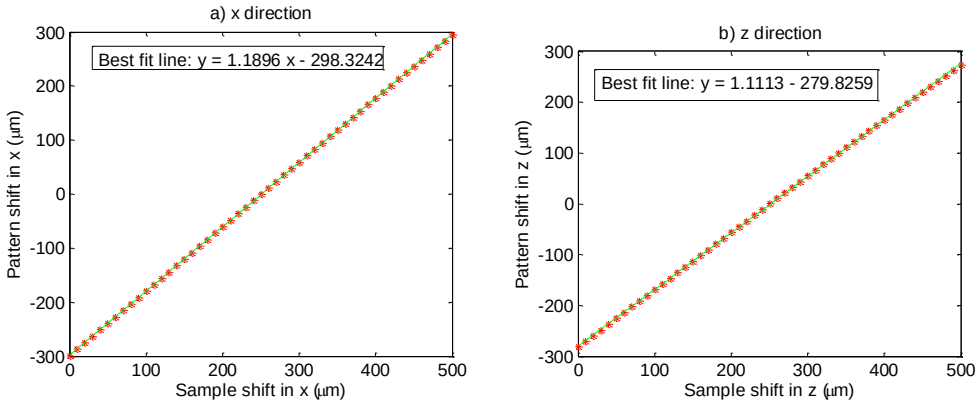

Figure 47: DIC linear range and magnifications. a) magnification in x direction. b) magnification in z direction

Although the sample shift in Figure 47-a is only in x direction, subpixel shift in z directions also exits. A second degree polynomial can approximate this shift. The pattern shift associated with Figure 47-b shows a similar behavior. Figure 48 shows the unexpected drift in the direction perpendicular to the sample shift for x and z directions respectively, which can be a sign of misalignment in the setup and a source of error.

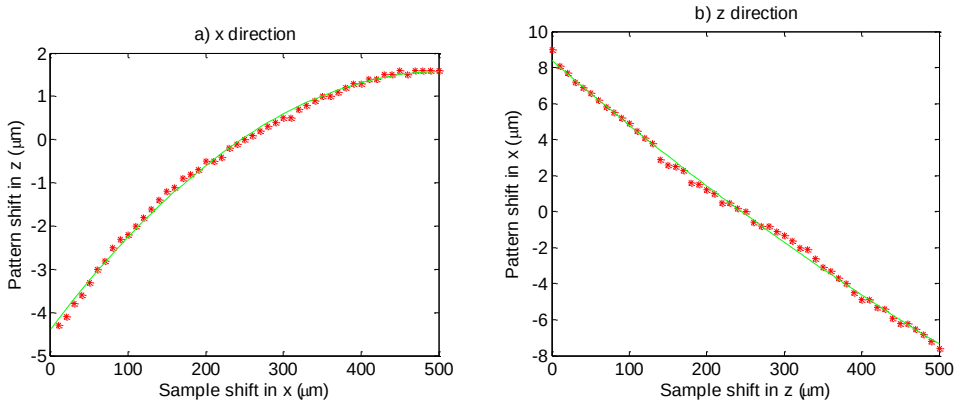

Figure 48: DIC unexpected pattern shift. a) Drift in z direction while shifting thesample in x. b) Drift in x direction while shifting the sample in z direction

After determining the linear range and the magnifications in x and z directions, the next step is to identify the systematic error in the system by determining the deviation of the measurement using DIC from the stage reading over the 500 by 500 μm area at 10 μm steps. This is possible by determining the subpixel shift of all the patterns captured every 10 μm over the 500 by 500 μm area, with respect to the reference point at (x, z) = (250, 250) μm. Multiplying the subpixel shift values by the camera pixel size, and dividing them by the magnification gives the associated sample shift in micrometers. Figure 49 shows the deviation of the displacement measurement using DIC from the stage readings in x and z directions over a 300 by 300 μm area. This is because the deviations are too high (about 300 μm) close to the corners of the 500 by 500 μm. The reference point is still at (x, z) = (250, 250) μm. This figure reveals the tilt error in x and z directions as well as smaller random deviations. Figure 50 shows the total deviation from the stage reading and the deviation from the stage reading in z direction from a different angle (this shows the tilt error in z direction more clearly). Determining the total pattern shift is possible by finding the x and z components of the pattern shift in micrometer and using the Pythagorean theorem to find the total shift. For this purpose, if the shift values in x and z directions are called 'a' and 'b' respectively, $\sqrt{(a^2 + b^2)}$ determines the total shift associated with that point. This value is then subtracted from the total shift that the stage reads. If x and z readings of the stage are called 'm' and 'n' respectively, $\sqrt{(m^2 + n^2)}$ determines the total shift that the stage reads at that point. Figure 50-a is the $\sqrt{(m^2 + n^2)} - \sqrt{(a^2 + b^2)}$ value at each point.

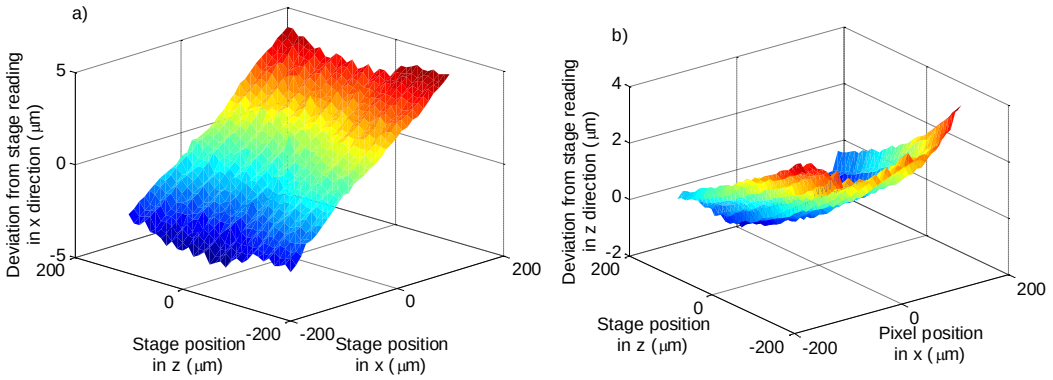

Figure 49: Deviation from stage reading. a) Stage reading in x direction. b) Stage reading in y direction

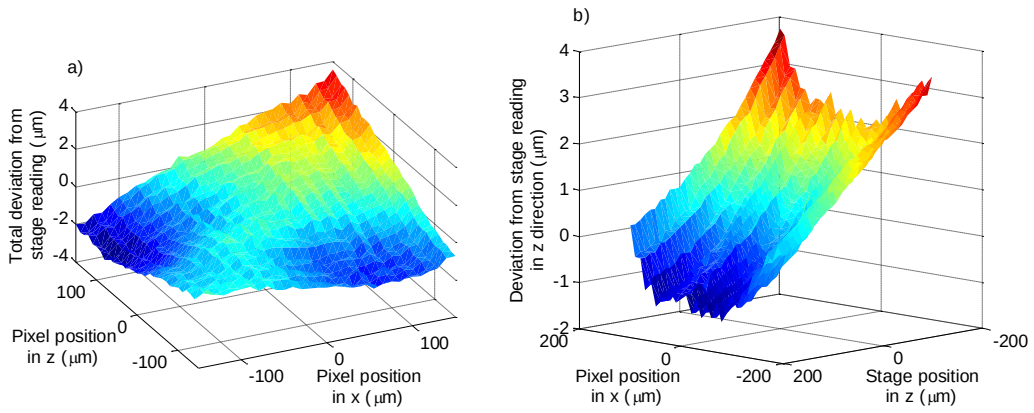

Figure 50: Deviation from stage reading. a) Total deviation. b) Deviation from z reading from a different angle

Repeating this process at four 500 by 500 areas that cover the area from x = 1000 μm to x = 2000 μm, and z = 1000 μm to z = 2000 μm, shows that the deviation from stage reading in x direction is similar for all the four areas, but the deviation from stage reading in z direction is slightly different from one area to another. This can be due to the error induced by the surface form specially in z direction. In x direction, the effect of surface tilt seems to be more dominant. Although these errors are systematic, correcting for them while using the DIC method is quite challenging. The whole surface needs to be

calibrated to account for the effect of surface form. Also, the errors that Figure 49 shows are associated with specific stage readings that are not known while using the DIC method independently.

After evaluating the associated error, the next step is to calibrate and test the DIC method. Because the error over 500 by 500 µm is unacceptable (about 300 µm deviation from the stage reading as mentioned earlier), the distance between the database patterns is set to 300 µm. Calibrating the system over a 3000 by 3000 µm area is possible by capturing the database patterns every 300 µm from 150 to 2850 µm in x and in z direction, resulting in total 100 database patterns. For evaluating absolute displacement measurement using this method, 1000 patterns are captured with 1 µm resolution over the 3000 by 3000 µm area with the associated stage readings. For every random pattern finding the closest database pattern is possible by determining the cross correlation of the random pattern with all the database patterns. For ease of calculation, the Fourier transform of the cross correlation function [30] is used. The highest cross correlation reveals the closest database pattern. It should be noted that the cross correlation of two patterns is a 2D matrix, and the maximum value of this matrix gives the maximum correlation.

After finding the closest database pattern, the subpixel shift registration algorithm determines the subpixel shift of the random pattern with respect to the closest database. Multiplying this value by the pixel size, dividing it by the magnification, and adding it to the position of the database pattern gives the sample position at the pattern captured at a random stage position. There are two ways of determining the error. The error without applying correction is the deviation of the measured values from the stage reading.

Determining the error with correction is possible by subtracting from the stage reading the error value in Figure 49 that is associated to that stage reading. Table 4 shows the evaluation results.

Table 4: Results of DIC method evaluation

	Average (μm)	Std (μm)	Average of absolute values (μm)	Maximum of absolute values (μm)
Corrected error: stage reading in x	2.38	2.64	2.93	11.35
Corrected error: stage reading in z	1.25	8.12	6.38	27.17
Non-corrected error: stage reading in x	2.98	3.23	3.68	13.80
Non-corrected error: stage reading in z	1.92	8.19	6.48	28.06

5.3 Sources of Error in Displacement Measurement Using DIC

Imaging the patterns in the 2f distance from the imaging lens, which is required for making a compact system, makes the magnification very sensitive to the object-camera distance. The distance between the sample surface and the image plane unavoidably changes due to deviation of the sample surface from an ideal plane and misalignment. As a result, these deviations are among the major sources of error in displacement measurement using DIC. Using a telecentric lens or placing the camera far from the specimen to approximate a telecentric imaging system, can reduce the effect of out-of-plane displacements [15]. However, the telecentric lens significantly increases the overall cost of the system, and placing the camera far from the sample surface prevents making a compact system.

Another source of error is the geometric distortion in the imaging system. For most types of camera lenses, such as a fixed length lens, a zoom lens or even for telecentric lenses, image distortions unavoidably exist due to lens aberrations, misalignment of

optical elements and non-parallelism between image plane and sensor plane [31]. It is possible to determine the amount of lens distortion from displacement distributions obtained in a rigid body in-plane translation and then correct for this error to improve the measurement accuracy of DIC for two dimensional displacement measurement [32].

Other than misalignment and distortion errors, the measurement of DIC is closely related to the mean speckle size, speckle contrast, and the selection of the speckle subset size used for correlation. A research by Bornert et al. [33] shows that decreasing the speckle size reduces the shape function mismatch error. This mainly applies to the situation where sample deformation exists. The shape function defines the relationship between the position of the corresponding points in the original and the deformed image. However, when the speckle size is too small (i.e. of the order of one pixel), it might be difficult to distinguish the signal from the noise (e.g. dark current noise, readout noise).

Another source of error in DIC is caused by the correlation and interpolation techniques. The errors associated with a correlation algorithm can be systematic or random. Numerical experiments can identify such errors. The interpolation errors usually occur in subpixel level and can be reduced by using higher order interpolation methods and low pass filtering of the speckle images prior to correlation [34].

Noises that are unavoidably present in digital cameras (e.g. shot noise, thermal noise, cutoff noise) can be sources of random error in displacement measurement using DIC. The use of high-performance hardware such as a cooled CCD and application of robust correlation criterion such as ZNSSD or ZNCC can help to reduce such errors [15]. Deviation of the pixel size from the nominal value can also be a source of error, as the assumption is the pixel size is constant across the image plane.

A study by Sjödahl [35] shows that a high-quality white-light speckle pattern can produce more accurate results than a laser speckle pattern. He also shows that adjusting the speckle size to suit exactly the resolution of the detector, using dense speckle patterns, and choosing large the sub-images, also helps create more accurate results.

CHAPTER 6: CONCLUSION AND FUTURE WORK

The main goal of this work is to develop a displacement scale for machine tools based on speckle patterns that is two dimensional non-contact, fast, low cost, with sub-micrometer resolution. It includes investigating four methods of displacement measurement using speckle correlation. The first method is based on creating a database of speckle patterns over the range of measurement. The position of the database pattern that has the highest cc with the pattern at an unknown sample position gives the position of the sample. Two dimensional displacement measurement over a 20 by 20 μm area is possible with -0.94 μm average deviation and 0.24 μm std from the stage reading in x direction, -1 μm average deviation and 0.71 μm std from the stage reading in z direction. The average deviation of about -1 μm in both directions is mainly due to the homing error of the reference stage. This error is systematic and can be corrected using a more accurate reference scale. The reason that the results shown in Table 2 have lower absolute deviation from the stage readings than the results shown in Table 3 is that the data used to evaluate the former is captured sequentially. The repositioning and homing errors of the stage do not affect these results. The maximum absolute deviation in the former is 0.6 μm, while this values for the latter is 2 μm.

The setup for the method based on a database of speckle patterns is fairly simple. It requires a laser, a beam splitter, and a camera and does not require precise alignment. On the other hand, it is sensitive to environmental disturbances such as temperature

fluctuations and surface contamination, which makes it quite challenging to make a database of speckle patterns and expect it to stay stable for a significant amount of time (e.g. 3 months). It also requires a large number of database patterns (1 database pattern per 1 μm for measurement with 1 μm resolution), which restricts its application to large areas of the sample. This method is suitable for high resolution absolute measurement over short ranges (sub-micrometer measurement over 20 by 20 μm area). Achieving sub-micrometer resolution is possible using curve fitting methods [6].

The double beam and dual wavelength methods use two beam spots for relative displacement measurement using speckle correlation. These methods are robust to disturbances and do not require a database of speckle patterns. Error accumulation over long ranges is a drawback. In double beam method, the two spots have the same wavelength, while in dual wavelength method the two spots have different wavelengths. The double beam method requires turning the beams on and off very frequently (20 times per second for 1 μm resolution, 20 μm beam separation, and 400 fps camera speed). The dual wavelength method does not require turning the beams on and off. As a result, it is a more efficient method. However, it is sensitive to surface irregularity. Performing displacement measurement using dual wavelength method over 200 μm range of the sample (shown to be uniform) with 1 μm resolution results in 0.5 μm average deviation from the stage reading and 0.8 μm std. This method is suitable for robust relative measurement and renewing the database patterns for the absolute scales when necessary.

Displacement measurement using DIC uses image registration for displacement measurement. The setup for this method is simple, it is capable of absolute and relative displacement measurement, and the number of required database patterns is two orders of

magnitude smaller than the first method. However, it requires more computational effort than the first method, it is sensitive to surface irregularities and imaging errors. DIC is suitable for absolute displacement measurement over longer ranges with lower resolution (3 by 3 mm area with 10 µm resolution), and for identifying error accumulation in the relative scale.

A combination of these three techniques can create a scale that is capable of sub-micrometer absolute and relative displacement measurement. The speed of measurement is limited by the camera speed (100 µm/s for 100 fps). The computational effort limits the range of absolute measurements, and error accumulation limits the range of relative measurement.

The aim of the future work is to fully design, develop, and test the engineering model of the speckle scale. It also includes extending the dual wavelength to two dimensions and velocity measurement. Currently, it is possible to add another wavelength to the system that enables displacement measurement in x and z directions independently. Figure 51 shows the suggested arrangement of beam spots on the surface.

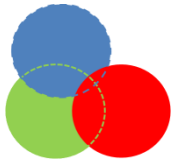

Figure 51: Arrangement of beam spots for two dimensional relative displacement measurement

This means that shifting the sample in x and z direction simultaneously will introduce error to measurement. Designing the system such that it is capable of measuring displacement in x and z directions simultaneously will be a significant achievement. The future work also includes extending the absolute scales to rotation measurement and

investigating speckle interferometry techniques in order to replace the imaging system with a faster sensor.

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APPENDIX A: THE DESIGN CYCLE OF THE SPECKLE SCALE

Defining the right problem to solve and seeking the right solution to that problem requires a systematic, creative process, which is called the design process, or the design cycle due to its iterative nature. The definition and the steps of a design cycle is covered in various literature. This research uses a basic definition for engineering design cycle and follows five simple steps as shown in Figure 52.

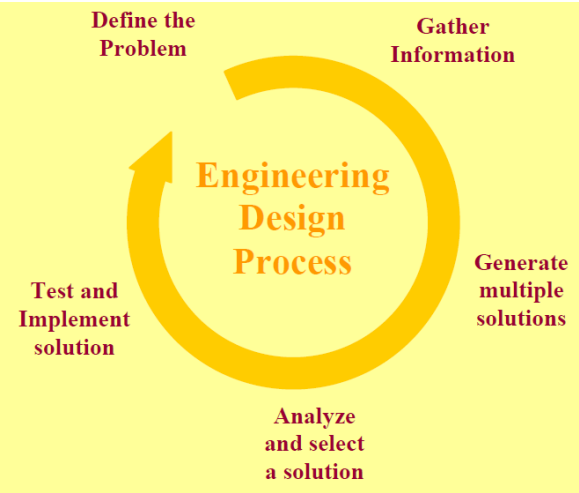

Figure 52: The five steps of a basic engineering design process [36].

It is important to remember that although the design cycle is a set of steps, iteration between the steps is part of this cycle. In practice, deviation from the design process happens, but following this process as closely as possible helps begin with a logical problem that is well defined, generate a structured plan to come to a solution, decrease the number of iterations in the design process, prevent wasting resources, and decrease the cost of the design process. This chapter explains the details of the design cycle and defines the design cycle of the speckle scale under study.

A.1 Defining the Engineering Problem

Identifying the need for a new system is the first step of defining an engineering problem. The customer is usually the one who recognizes the need, but the statement of need provided by the customer can be vague or inaccurate. One of the responsibilities of the design team is to communicate with the customer in order to identify the right problem and develop a clear, unambiguous problem statement. Sometimes, this process requires research, experimentations, and simulations. It is important to note that the problem statement should not preclude any solutions to the problem. A broad definition of the problem allows looking at a wide range of alternative solutions before focusing on a specific solution [36].

Defining the engineering problem results in the definition of a set of requirements that the design solution must meet to be considered successful. For the engineering problem to be well defined, the set of requirements should be complete (none missing), consistent (no contradictions), correct (valid for an acceptable solution), and attainable (an acceptable solution exists) [37].

A.2 Gathering Related Information

After clearly defining the engineering problem, it is important to collect all the information available that relates to the problem. This requires answering to various questions including the following [38]

- What are the existing solutions to the problem?
- Why aren't the existing solutions sufficient?
- What needs to be improved?
- What are the external factors?
- Who are the stakeholders, what are their needs and expectations?

The various sources of information are scientific encyclopedias, technical handbooks, electronic catalogs, and journal papers.

A.3 Investigating Alternative Solutions

After defining the engineering problem and gathering related information, the next step is to investigate alternative solutions to the problem. This requires innovation, creativity, brainstorming, and taking risks. It is possible to start with an existing solution and try to modify it to solve the new problem or to invent a completely innovative system.

A.4 Analyzing the Alternative Design Concepts and Select a Solution

In this step, the design team investigates the feasibility of each concept, lists the pros and cons, and selects one or two concepts for a more detailed design. Applying the detailed design to all of the possible solutions is not efficient considering the time and cost of the project. Selecting the design solution requires considering different aspects. One is the compliance of the design solution with the requirements of the project. Human factors, safety and liability, market analysis, are other important aspects. There are various software and tools that help with the final decision making process. One of them is the Decision Matrix [38], which helps evaluate different alternatives relative to the design requirements and choose the best solution. It can be used at system, subsystem, or component level.

A.5 Test and Implement the Solution

The last step of the design process is implementing the design solution. This includes making a prototype, testing, and documenting the results. Computer-aided design methods and prototyping can reduce the time, cost, and risk of making the final product. The purpose of the prototype is to test the design solution under real conditions, which

also decrease the failure risk of the final product. Implementing the design solution is completed by performing tests and verification.

A.6 Applying the Design Cycle to the Speckle Scale

This section applies the design cycle to the displacement scale based on speckles that is the main topic of this work.

A.6.1 Defining the Problem

The statement of problem for the displacement scale based on speckles is as follows: This project aims at design and development of a two dimensional displacement scale that is non-contact, low cost, compact, high resolution, and applicable in mechanical workshops.

The following are the requirements for the speckle scale under study:

- Non-contact measuring device
- Two-dimensional
- Applicable in mechanical workshops
- Compact (smaller than 30 x 20 x 20 cm^3)
- Light weight (lighter that 5 kg)
- 1 µm resolution
- 30 cm by 30 cm range
- Cost < $5000
- 15^o C to 30^o working temperature with ± 0.5^o C maximum fluctuation

A.6.2 Gathering Related Information

The related information for designing the speckle scale includes investigating the alternative contact and non contact methods.

A.6.2.1 Alternative Contact Methods and Their Shortcomings

A stepping motor is one of the common displacement scales for open-loop control in Computer Numerical Control (CNC) Machining. In an open-loop control there is no feedback and the CNC machine uses a stepping motor for driving the lead screw. A

stepping motor is a device whose output shaft rotates through a fixed angle in response to an input pulse (Figure 53). The accuracy of the system depends on the motor's ability to step through the exact number. The frequency of the stepping motor depends on the load torque. The higher the load torque, the lower would be the frequency. Excessive load torque may occur in motors due to the cutting forces in machine tools. Hence this system is more suitable for cases where the tool force does not exist (Example: laser cutting) [39]. The resolution of this system is also limited.

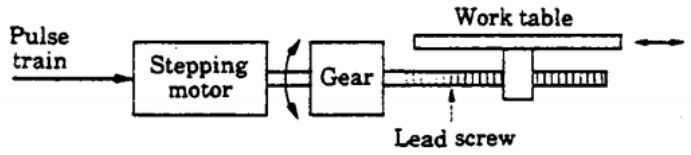

Figure 53: Open loop control stepping motor [39].

Another type of control system is closed-loop. Closed-loop CNC systems are used when there is a force resisting the movement of the tool or the work piece (e.g. milling and turning). In these systems, the DC servomotor and feedback device are used for achieving the desirable position, as shown in Figure 54. The feedback sensor used in this figure is an optical encoder, shown in Figure 55.

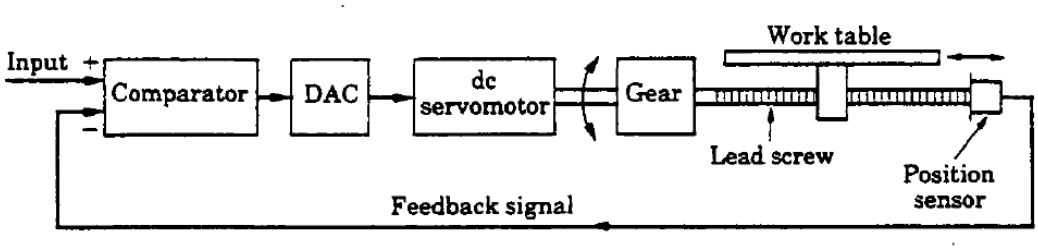

Figure 54: Closed loop control displacement measurement system [39].

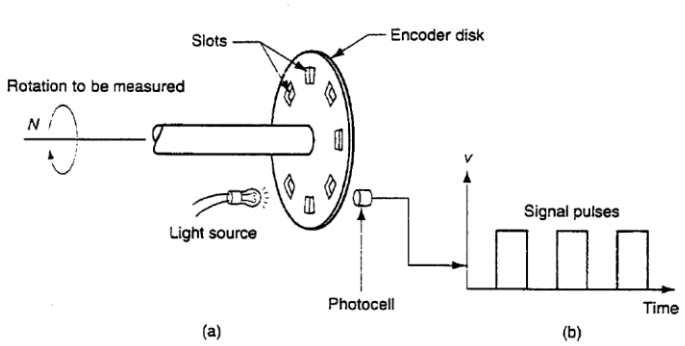

Figure 55: Optical encoder a) Device b) Series of pulses emitted [39]

The encoder consists of a light source, a photo detector, and a disk containing a series of slots. The encoder is connected to the lead screw. As the screw turns, the slots cause the light to be seen by the photo detector as a series of flashes, which are converted into an equivalent series of electrical pulses; they are then used to characterize the position and the speed. In this type of control system, bending of the lead screw or the Abbe error [40] can cause position error that cannot be identified by the positioning system (Figure 56). The shortcomings of these contact scales shows the necessity of the non-contact methods.

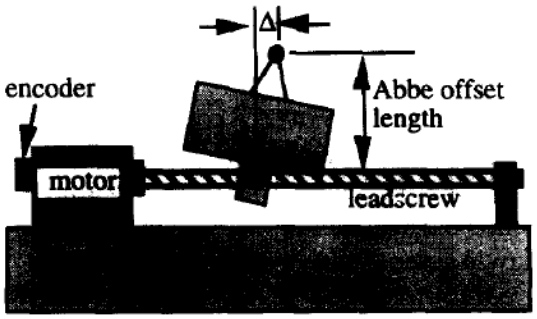

Figure 56: The Abbe offset induced error [40]

A.6.2.2 Alternative Non-Contact Methods and Their Shortcomings

The non-contact displacement measurement methods include optical scales, rotary encoders, inductosyns, magnetic scales, and laser interferometers. Optical scales are

among the most common transducers with a wide application in Coordinate Measuring Machines (CMM). Optical linear scales consist of a scale element and an electro-optical read head, one of the two is fixed to the moving slide of the CMM. The relative motion between these two components generates the positioning signal [41]. There are three general types of optical scales: transmission scale, reflection scale, and interferential scale. These scales can have resolution in the order of nanometers. However, the grating structure in these scales makes them complex and expensive. Also, the two dimensional optical encoders have a very limited range.

Interferometric techniques, such as holographic interferometry, speckle interferometry and Moire interferometry are also among the non-contact measurement methods, normally conducted in a vibration-isolated optical platform in the laboratory. They measure the phase difference of the scattered light wave from the test object surface before and after deformation. The measurement results are often presented in the form of fringe patterns. As a result, further fringe processing and phase analysis techniques may be required [15]. Capacitive gauges are other non-contact scales that are mostly applicable to short ranges.

Speckle photography is another non-contact method for high resolution displacement measurement. The unique characteristics of this method is discussed in section 1.2, chapter 2 and 5; among them is the simple, low cost setup [6], ability to do measurement with various sensitivity and range, large measurement range for in-plane and out of plane displacement, and low requirements for the measurement environment [4].

A.6.2.3 Identifying and Comparing Alternative Design Solutions

The close agreement between the characteristics of speckle photography and the specifications of the displacement scale based on speckles makes this method an ideal candidate for a set of design solutions. The first method is "absolute scale based on speckles" introduced in chapter 2. The setup for this method is fairly simple. As a result, it is compact and low cost. However, it is sensitive to environmental disturbances such as temperature fluctuations and surface contamination. It also requires a large number of database patterns that limits the speed and the range measurement.

The second method is "double beam speckle correlation" introduced in chapter 3. This method requires extra optical elements, comparing to the first method, in order to create two overlapping identical beam spots. It does not require a large number of database patterns; as a result, it is robust to disturbances, it can be designed for long measurement range and possible two dimensions. The problem with this method is that it requires turning the beams on and off very frequently, which can limit the speed of the system.

The third method is "dual wavelength speckle correlation" introduced in chapter 4. The setup for this method can be similar to the second method, but it requires two laser sources with different wavelengths and a higher alignment accuracy. This setup has all the advantages of the second method plus the fact that it does not require turning the beams on and off very frequently.

The fourth method is "digital image correlation" introduced in chapter 5. The setup for this method is fairly simple, similar to the first method, but surface form and factors such as imaging lens aberration and camera distortion can introduce errors to

displacement measurement. Some of these errors are mainly systematic and can be corrected for in advance, but calibrating for surface form can be time consuming. Application of higher quality elements to reduce the random error can increase the cost of the system.

Developing a non-contact scale that is capable of absolute and relative displacement measurement is possible by combing the first, third, and fourth methods. The first method, which requires a large number of database patterns, is suitable for absolute displacement measurement over short ranges with high resolution (e.g. over 20 by 20 µm range with sub-micrometer resolution), DIC is suitable for absolute position measurement over longer ranges with lower resolution (e.g. over 3000 by 3000 µm range with 10 µm resolution) and for identifying error accumulation in the dual wavelength method. The dual wavelength is ideal for relative displacement measurement with sub-micrometer resolution. It can also recalibrate any of the absolute scales in case of decorrelation of the database patterns. The next step of the design cycle is to implement and test these concepts.

A.6.4 Developing and Testing the Engineering Model

Before making the engineering model of the displacement scale based on speckles, simulating it in SolidWorks helps reduce the cost and effort of building the model. Many vendors have SolidWorks files for each component that can be downloaded and manipulated with respect to other parts.

Figure 41 shows the schematic setup for dual wavelength speckle correlation method and Figure 42 shows the experimental setup. The engineering model is more compact as

shown in Figure 57. Creating this engineering model requires importing the SolidWorks model of the following items from Thorlabs website:

1- For the red laser:
- FC/PC connector (30126C3)
- red laser collimator (F230FC-B)
- collimator mount (AD11NT)
- Optical mount for holding the collimator mount (FMP1)

2- For the green laser:
- FC/PC connector (30126C3)
- green laser collimator (F230FC-A)
- precision translation stage (LM1XY)

3- Two pellicle beam splitters (CM1-BP145B2)
4- Imaging lens mount (CP06_M)
5- The CMOS color camera (DCC1645C)

Other that importing some components from Thorlabs website, an enclosure is designed to hold the components.

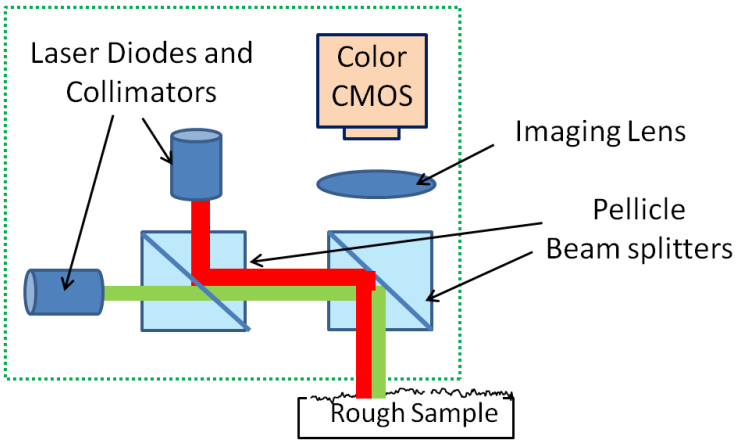

Figure 57: Schematic setup of the engineering model for dual wavelength speckle correlation

The process of assembling the components starts with considering the base of the enclosure as a flat reference surface. The red laser beam determines the optical axis. It is parallel to the reference surface. The optical axis of all the elements should be in a plane parallel to the reference surface, with the same height as the red beam. Comparing the

front view of all the elements helps determine how each element should be attached to the reference surface so that its optical axis is at the same height as the red beam. Figure 58 shows that the camera has the highest optical axis, the second highest optical axis belongs to the green collimator mount, the third is the red collimator mount, the fourth is the lens mount, and the fifth is the beam splitter without the 4.8 mm height convertor.

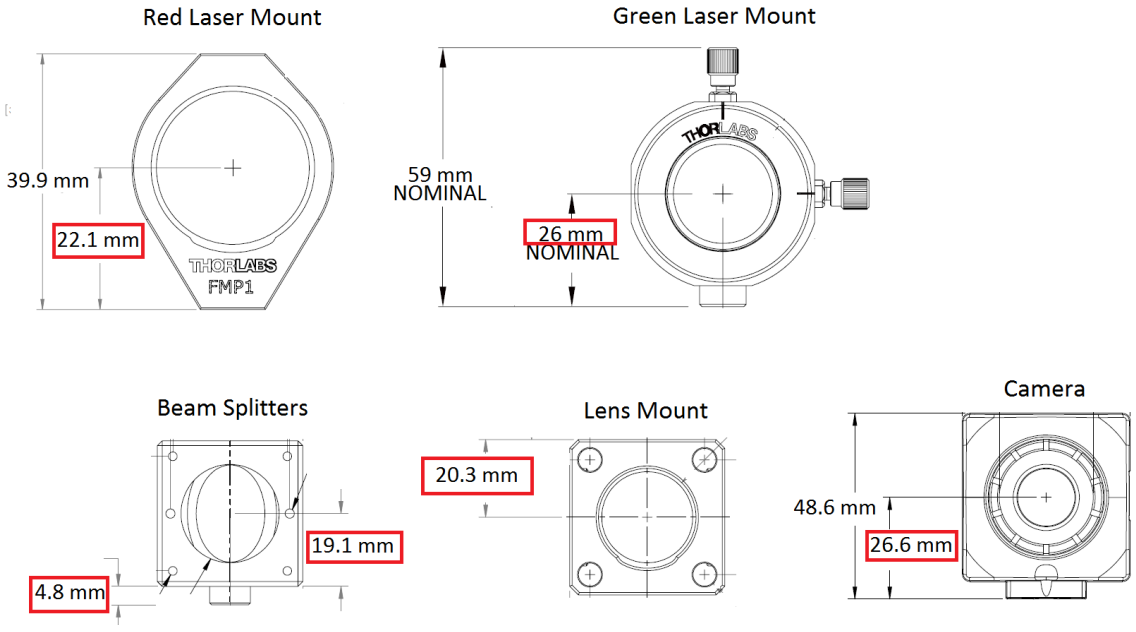

Figure 58: The front view of the main parts [42]

One way to attach the components to the base of the enclosure is to directly glue the part with the highest optical axis (camera) to the base of the enclosure and create platforms for all the other parts such that each of them brings the optical axis of the associated element to the height of the optical axis of the camera. The platforms for other elements are as follows:

- red laser platform: 10.67 x 6.4 x 4.5 mm
- green laser platform: 10 x 10 x 0.6 mm
- beam splitters (2): 38.1 x 38.1 x 7.55 mm
- lens mount: 40.6 x 8.8 x 6.3 mm

The red collimator mount is fixed to its platform assuming that it's parallel to the reference surface, one side of the box, and perpendicular to the other side of the box. The first pellicle beam splitter is set to be concentric with the red collimator. The precision translation that holds the green laser is set to be perpendicular to the red beam and concentric with the side of the pellicle beam splitter that faces the green collimator. The second beam splitter is set to be concentric with the first beam splitter and with the imaging lens mount from the side that faces the mount. The distance between the collimators and the first beam splitter is set to be 5 mm, the distance between the two beam splitters is set to be 10 mm (so that the translation mount does not interfere with the imaging lens mount). The distance between the closest surface of the imaging lens mount to the opening of the box is 45 mm, assuming that the focal length (f) of the lens is 25 mm, the image plane is at 2f, the lens surface that faces the box opening coincides with the surface of the mount, and the sample is 5 mm from the opening of the box. Finally the distance between the screen of the camera is set to be 50 mm from the lens surface that is closer to it. Figure 59 shows the 3D view of this assembly, Figure 60 shows the top view, Figure 61 the left view, and Figure 62 a summary of the design. It is important to note that the power supplies and the laser drivers are designed to be out of the box shown in Figure 59 in order to keep major heat sources away from the sensitive elements.

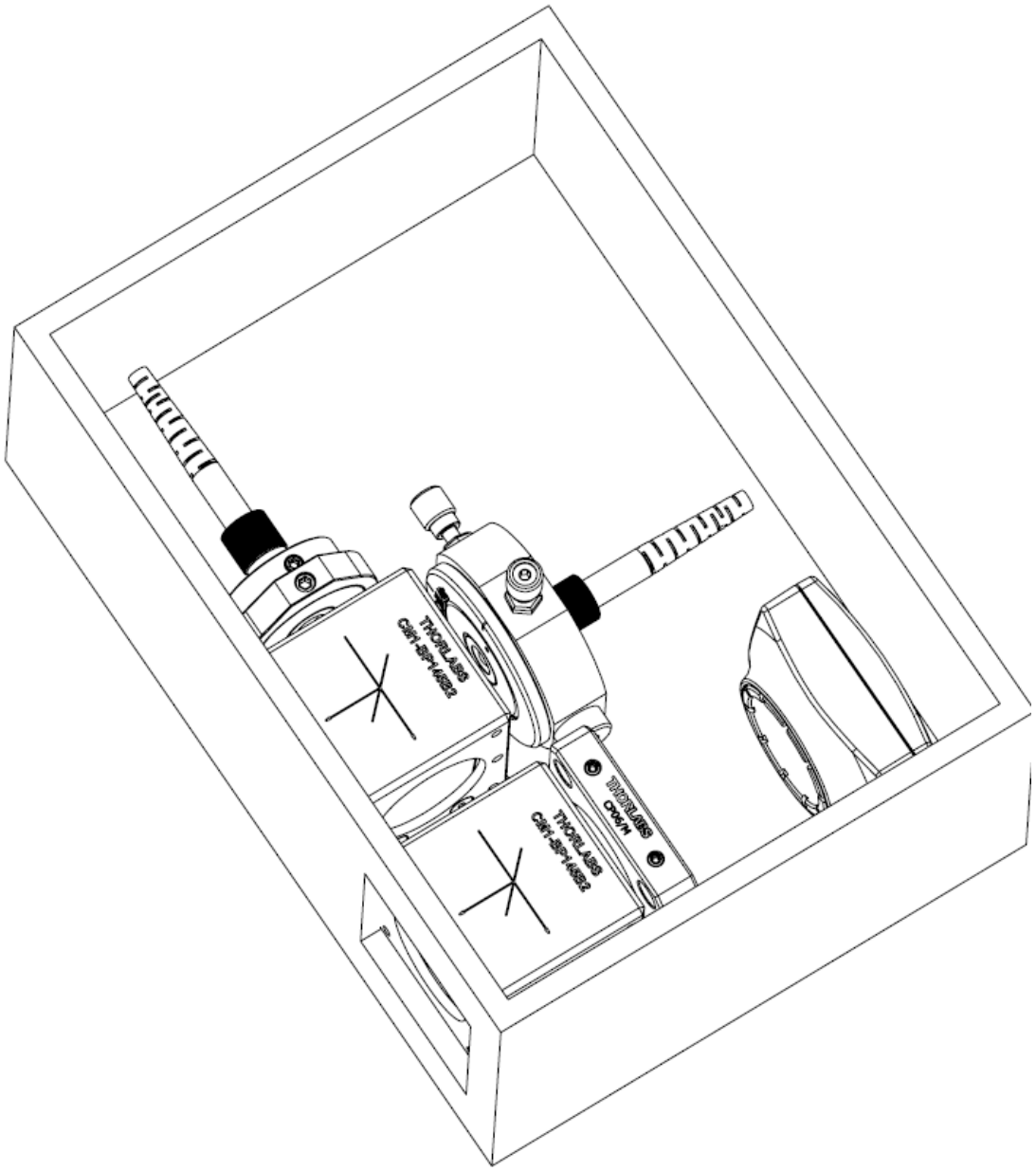

Figure 59: 3D view of the engineering model of the displacement scale based on speckles in SolidWorks

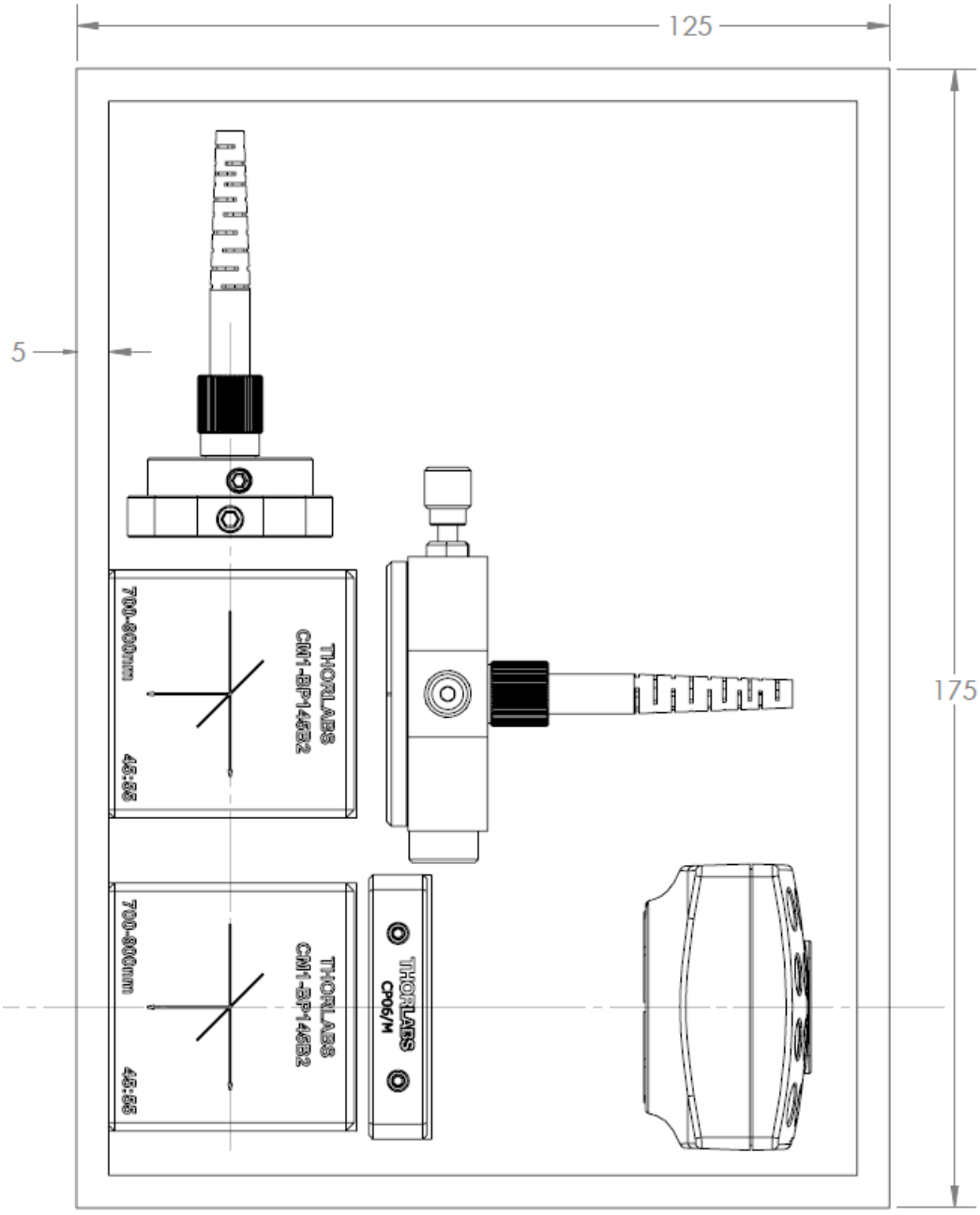

Figure 60: Top view of the engineering model of the displacement scale

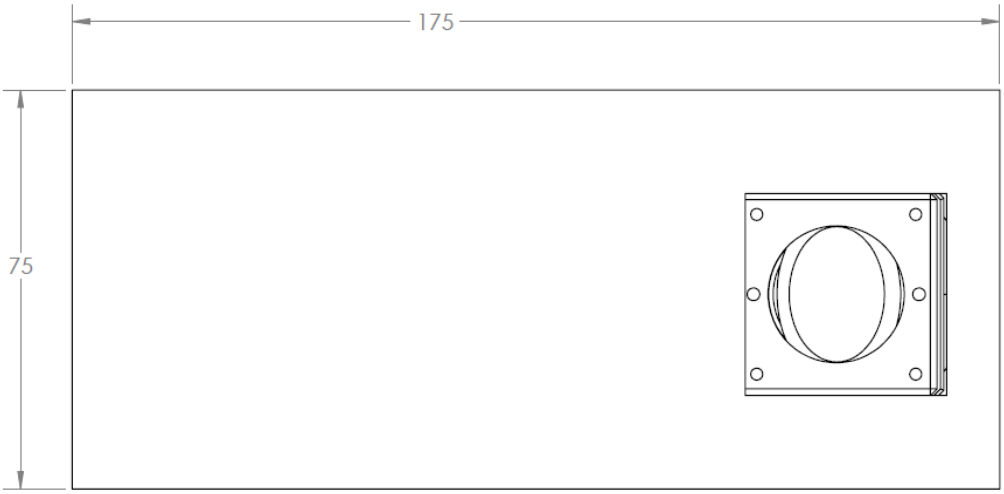

Figure 61 - Left view of the engineering model of the displacement scale

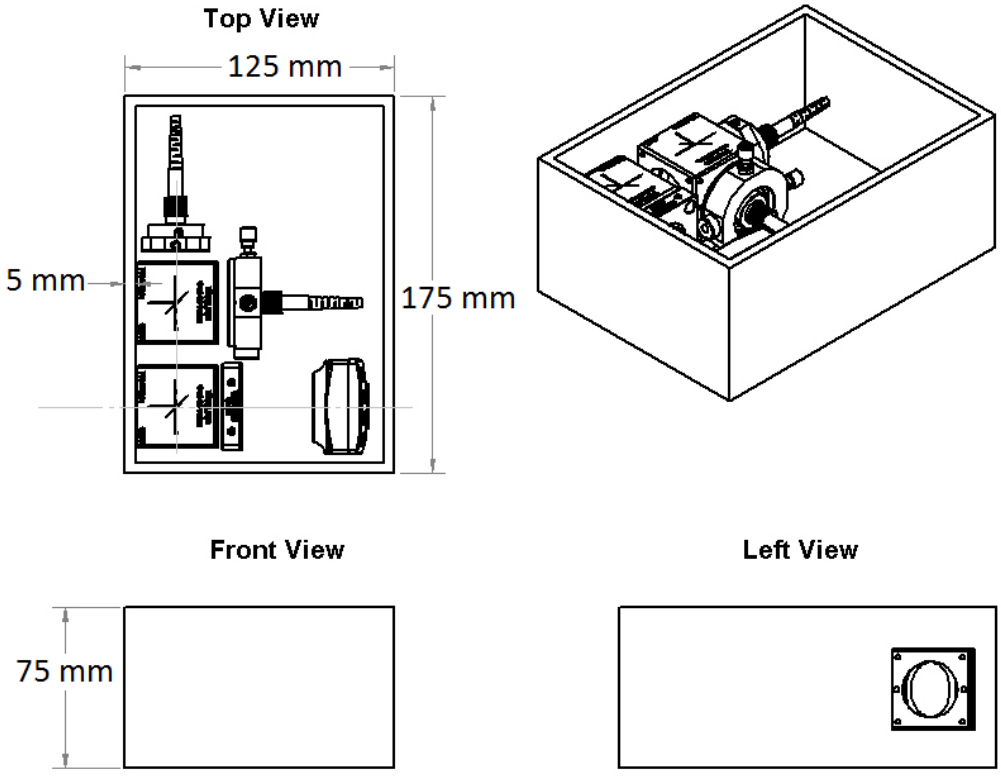

Figure 62: Summary of the engineering model of the displacement scale

Material selection is an important step to insure that the critical distances between the elements stay stable within the tolerance ranges. Usually the off-the-shelf components are made of aluminum with coefficient of thermal expansion (CTE) equal to 22.2 (10^{-6} m/(m K)). The change in each linear dimension of a component can be estimated using the following equation

$$\frac{\Delta L}{L} = \propto_L \Delta T \qquad (6\text{-}1)$$

where ΔL is the change in length of material in the direction being measured, L is the overall length of material, α_L is the CTE, ΔT is the change in temperature over L. The assumption is that the CTE does not change much over the change in temperature. In order to insure maximum 0.5 μm change in the length of an aluminum element under the ΔT = 1 K requirement, the maximum length of the element can be 22.5 mm. Considering the fact that the dimensions of the elements of the scale are comparable to this number, closer analysis of the elements that are sensitive to alignment is important.

Figure 63 shows the position of the coordinate axes in the schematic of the engineering model. It facilitates identifying the directions for each element where the deviation from the designated position is critical.

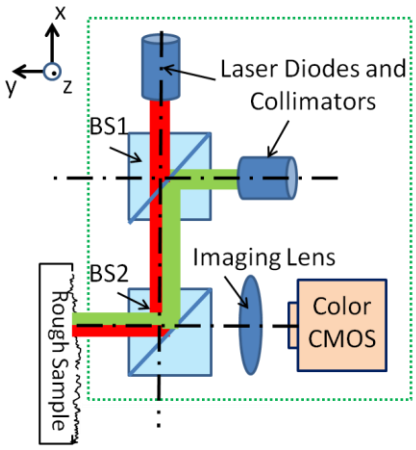

Figure 63: Position of the coordinate axes in the schematic of the engineering model

As mentioned earlier, the red laser is the reference element in the design of the engineering model and defines the optical axis. Deviation of this element in y and z directions should be less than 0.5 µm. Deviation in x direction is not critical for the red laser. Displacement of the green laser in x direction defines the beams' offset. Deviation of this element in x and z directions should be less than 0.5 µm. Deviation in y direction is not critical for the green laser. The position of the first beam splitter (BS1) in the xy plane defines the beams' offset. As a result, deviation of this element in x and y directions should be less than 0.5 µm. Any changes in the beams offset can lead to error accumulation in measurement. Deviation in z direction is not critical for BS1. Based on the alignment sensitivity of the red and the green laser and BS1, simply gluing these elements to the base of the box (in case of an aluminum box) does not provide sufficient stability for generating two identical overlapping beam spots with different wavelengths and a defined offset. Designing a stable structure for these three elements is among the future work.

The position of the second beam splitter (BS2) in the xy plane controls the illuminated area of the sample. The system is not very sensitive to the deviation of the illuminating beam spots as long as their offset doesn't change. As a results, deviation of this element in x and y directions should be less than about 1 µm. Deviation in z direction is not critical for BS2. The drift of the imaging lens in xz plane shifts the pattern in the image plane. The sensitivity of the measurement to the drift of this element is less than other elements mentioned so far. This is shown experimentally in Figure 18-a. Deviation of this element in x and z directions should be approximately less than 1.5 µm (half the

pixel size). Deviation in z direction affects the magnification, but this effect does not introduce a significant error.

The drift of the camera is equal to the drift of the sample for imaging magnification equal to 1. As a result, deviation of this element in x and z directions should be less than 0.5 µm. Deviation in z direction is not critical for the camera. Because the camera is a heat source, the future work aims at isolating the camera from the rest of the elements.

APPENDIX B: MATLAB CODES

```
%-------------------------------------------------------------------------------------------------
%-------------Program 1: 2D measurement using a database of speckles-----------------

% The purpose of this program is to find multiple sample positions using a
% database of speckle patterns. The first step is to read a pattern from
% a folder that contains a set of patterns captured at random sample
% positions. The second step is to determine the correlation coefficient
%(cc) of the pattern at the random position with all the database patterns.
% The position of the database pattern that has the highest cc with the
% pattern captured at a random sample position gives the position of the
% sample. If the stage reading for the sample position is embedded in the
% name of the pattern, it will be possible to determine the deviation of
% the sample position determined by speckle correlation from the stage
% reading
%-------------------------------------------------------------------------------------------
clc; clear all; close all; tic

% Input values
database_n = 441; % Number of database patterns

% Initialize the required variables
fileNamesStr = zeros(numFrames,8); % The stage reading embedded in the files'
names
samplePos = zeros(numFrames,2); % Sample position using speckle correlation
expectedPos = samplePos;  % Stage reading extracted from the files' names
error = samplePos;  %  = samplePos - expectedPos

% Read all the file names of the patterns captured at random sample
% positions from the associated folder
fileFolder = fullfile('C:', 'Users', 'Mahsa', 'Documents', 'Research',...
   'lab results', '150311-F sample piezo-random data-4');
dirOutput = dir(fullfile(fileFolder,'x*.png'));
fileNames = {dirOutput.name}';
numFrames = numel(fileNames); % Number of patterns captured at random
positions

% Assign all the patterns to a sequence
pathImageS ='C:\Users\Mahsa\Documents\Research\lab results\150311-F sample
piezo-random data-5\';
I = double(imread(strcat(pathImageS,fileNames{1})));
I = I(:,:,1);
% Preallocate the array
sequence = zeros([size(I) numFrames],class(I));
```

```
sequence(:,:,1) = I;
% Create image sequence array
for p = 2:numFrames
   Q = double(imread(strcat(pathImageS,fileNames{p})));
   sequence(:,:,p) = Q(:,:,1);
end

for p = 1:numFrames;
% Read the color pattern, separate the red plane, and normalize the pattern
sample = sequence(:,:,p);
sample = sample(:,:,1);
sample = (sample-mean(sample(:)))/std(sample(:));

% Image the sample if desired
figure; imagesc(r_normalized); colormap(gray);title('Normalized Red Pattern');

% Extract the stage reading from the pattern's name
% File name example: x11z5, x_expectedPos = 11 um, z_expectedPos = 5 um
q = size(fileNames{p});
x_expectedPos = str2double(fileNames{p}(2:(strfind(fileNames{p},'z')-1)));
z_expectedPos = str2double(fileNames{p}((strfind(fileNames{p},'z')+1):(q(2)-4)));

% Read the database patterns from the associated folder
pathImage ='C:\Users\Mahsa\Documents\Research\lab results\150311-F sample
piezo-database-4\';
c = zeros(3,database_n); % Save the cc, x and z position for each database
k = 0; % database counter for the cc
for z = 0:20  % database z position in the loop
  for j = 0:20 % database x position in the loop

   k = k+1;

   database =
im2double(imread(strcat(pathImage,'x',num2str(j),'z',num2str(z),'.png')));
   database = database(:,:,1);
   database = (database-mean(database(:)))/std(database(:));

   [m,n]=size(database);

   c(1,k) = dot(database(:),sample(:))./dot(sample(:),sample(:));
   c(2,k) = j;
   c(3,k) = z;
  end
end

% Maximum of cc and the associated position
```

```
[max_cc,max_i]= max(c(1,:));
j = c(2,max_i); % x position of the database at max cc
z = c(3,max_i); % z position of the database at max cc

samplePos(p,:) = [j,z];
expectedPos(p,:) = [x_expectedPos,z_expectedPos];
error(p,:) = expectedPos(p,:) - samplePos(p,:);

end

toc % Determines the time of multiple measurements (here 1000 measurements)

% Determine the average deviation from the stage reading in x and z
% directions
error_Xmean = mean(error(:,1));
error_Zmean = mean(error(:,2));

% Determine the standard deviation from the stage reading in x and z
% directions
error_Xstd = std(error(:,1));
error_Zstd = std(error(:,2));

% Determine the average of absolute deviations from the stage reading in x and z
% directions
error_XabsMean = mean(abs(error(:,1)));
error_ZabsMean = mean(abs(error(:,2)));

% Determine the maximum of absolute deviations from the stage reading in x and z
% directions
error_XabsMax = max(abs(error(:,1)));
error_ZabsMax = max(abs(error(:,2)));

%-------------------------------------End of Program 1---------------------------------------
%-----------------------------------------------------------------------------------------------
                                        *****
%-----------------------------------------------------------------------------------------------
%------------Program 2: Correlation Curve Fitting---------------------------------------

% The purpose of this program is to determine the average curve explained in
section 2.4, determine the position of the patterns captured every 0.1 um from 0 to
100 um, and determine the deviation of measurement from the stage reading
%-----------------------------------------------------------------------------------------
% Step 1 of using the curve fitting method is to determine the average curve
% This code creates 5 correlation curves, at 10,30,50,70,90.
% Each curve is created by determining the correlation of the database
% patterns captured every 1 um with the one in the middle. Example: for the
```

```
% curve at 50, database captured at 40,41,42,...,60
 clc;clear all;close all;
 %Input constants
nCurves = 5; % Number of correlation curves
curveLength = 21; % Number of datapoints that define each curve
cc = zeros ( nCurves , curveLength ); % A matrix to save all the curves
dxx = 0.01; % Interpolation steps
x = 0:(curveLength-1); % Sample position associated to each point of the curve

%---------- Correlation curve at 10 um----------
% The folder where the database patterns are stored:
pathImage ='C:\Users\Mahsa\Documents\Research\lab results\150103-renaming
files in 130704\';

% Read and normalize the reference pattern (gray scale)
reference = im2double( imread(strcat(pathImage,'x10.0.png')));
reference = (reference-mean(reference(:)))/std(reference(:));

% Determine the correlation coefficient of the database patterns from 0 to
% 20 um with the one at 10 um
for j = 1:21
database = im2double(imread(strcat(pathImage,'x',num2str(j-1),'.0.png')));
database = (database-mean(database(:)))/std(database(:));

cc(1,j)=  dot(reference(:),database(:))/dot(reference(:),reference(:));
end
%---------- Correlation curve at 30 um----------
reference = im2double( imread(strcat(pathImage,'x30.0.png')));
reference = (reference-mean(reference(:)))/std(reference(:));
% Determine the correlation coefficient of the database patterns from 20 to
% 40 um with the one at 30 um
for j = 1:21

database = im2double(imread(strcat(pathImage,'x',num2str(20+j-1),'.0.png')));
database = (database-mean(database(:)))/std(database(:));

cc(2,j)=  dot(reference(:),database(:))/dot(reference(:),reference(:));
end
%---------- Correlation curve at 50 um----------
reference = im2double( imread(strcat(pathImage,'x50.0.png')));
reference = (reference-mean(reference(:)))/std(reference(:));
% Determine the correlation coefficient of the database patterns from 40 to
% 60 um with the one at 50 um
for j = 1:21

database = im2double(imread(strcat(pathImage,'x',num2str(40+j-1),'.0.png')));
```

```
database = (database-mean(database(:)))/std(database(:));

cc(3,j)=  dot(reference(:),database(:))/dot(reference(:),reference(:));
end
%-------------- Correlation curve at 70 um-------------------------------
reference = im2double( imread(strcat(pathImage,'x70.0.png')));
reference = (reference-mean(reference(:)))/std(reference(:));
% Determine the correlation coefficient of the database patterns from 60 to
% 80 um with the one at 70 um
for j = 1:21
database = im2double(imread(strcat(pathImage,'x',num2str(60+j-1),'.0.png')));
database = (database-mean(database(:)))/std(database(:));

cc(4,j)=  dot(reference(:),database(:))/dot(reference(:),reference(:));
end
%-------------- Correlation curve at 90 um-------------------------------
reference = im2double( imread(strcat(pathImage,'x90.0.png')));
reference = (reference-mean(reference(:)))/std(reference(:));
% Determine the correlation coefficient of the database patterns from 80 to
% 100 um with the one at 90 um
for j = 1:21

database = im2double(imread(strcat(pathImage,'x',num2str(80+j-1),'.0.png')));
database = (database-mean(database(:)))/std(database(:));

cc(5,j)=  dot(reference(:),database(:))/dot(reference(:),reference(:));
end
%-------------- Determine the average of the five curves-----------------

avgCC = sum(cc)/5;

%----------- Plot curves if desired ------------
% figure(1); hold on
% plot(x,cc(1,:),'*');
% plot(x,cc(2,:),'r*');
% plot(x,cc(3,:),'g*');
% plot(x,cc(4,:),'y*');
% plot(x,cc(5,:),'k*');
% plot(x,avgCC,'*');hold on;
%-----------------------------------------------
% Determine the deviation of each curve from the average curve
ccDeviation = cc - ones(size(cc,1),1)* avgCC;
maxccDeviation = max(ccDeviation);
% Interpolate the average correlation distribution using a spline
x=0:1:curveLength-1;
xx = 0:dxx:curveLength-1;
```

```
y = avgCC;
avgCurve = spline(x,y,xx);

plot(xx,avgCurve(:),'g')
xlabel('Sample shift(mu)')
ylabel ('Normalized correlation coefficient')

% Determine the derivative of the curve at each datapoint
for j = 2:20
   derxxtocc(j) = (xx((j-1)/dxx+1)-xx((j-1)/dxx-1))/(avgCurve((j-1)/dxx+1)-
avgCurve((j-1)/dxx-1));
end
% Determine the induced displacement error due to the error in avg curve
% Remember that only those from 5 um to 15 um are important becaue the
% curve always passes the point with higher correlation
maxInducedDispDev = maxccDeviation .* [derxxtocc,0];
abs(max(maxInducedDispDev(6:16)))

%-------------------------------------------------------------------------------------------
% Step 2 of curve fitting: read all 1001 points available, determine the
% position using the curve fitting method, and determine the error. the
% first step is to determine the two database patterns between which the
% sample is located
tic; clc; clearvars -except avgCurve & dxx; close all;
% The directory where all the database and the patterns at unknown positions are
located
pathImage ='C:\Users\Mahsa\Documents\Research\lab results\150103-renaming
files in 130704\';
%Input constants
sample_n = 1001; % Number of samples
sampleStepSize = 0.1; % The sampling step size (um)
database_n = 11; % Number of database patterns
databaseStepSize = 10; % The distance between two adjacent database patterns
% Initializing variables
samplePos = zeros(1,sample_n); %Sample position determined using curve fitting
roundSamplePos = samplePos;% Round value of the sample position determined
using curve fitting
cc = zeros(1,database_n); % Correlation coefficient of the reference pattern with the
database patterns
x = databaseStepSize*(0:(database_n-1)); % Samples shift at each database position

% First, read and normalize the database patterns and the pattern at an unknown
position (sample)
for k = 1:sample_n
reference = im2double( imread(strcat(pathImage,strcat('x',
num2str(sampleStepSize*(k-1),'%.1f'),'.png'))));
```

```
reference = (reference-mean(reference(:)))/std(reference(:));
% Determine the correlation of the database with the reference
for j = 1:database_n
database = im2double(imread(strcat(pathImage,'x',num2str(databaseStepSize*(j-
1)),'.0.png')));
database = (database-mean(database(:)))/std(database(:));

cc(j)=  dot(reference(:),database(:))/dot(reference(:),reference(:));
end

% Determine the postion and the value of the first and the second maximum
% of the correlation coefficient of the reference with the database
[maxcc,indexMaxcc] = max(cc);
cc(indexMaxcc) = 0;
[max2cc,indexMax2cc] = max(cc);
cc(indexMaxcc) = maxcc;
% Depending on whether the index of the first max is smaller or bigger than
% the second max, the first of second half of the correlation curve can be
% used for curve fitting.
midavgCurve=ceil(size(avgCurve,2)/2); % index(sample shift) of the middle of the
correlation distribution
% Finding the sample position using curve fitting
if indexMaxcc<indexMax2cc
   half1avgCurve = avgCurve(1:midavgCurve)  ;
   [aa,bb] = min(abs( maxcc*ones(size(half1avgCurve))-half1avgCurve));
   bbb = avgCurve(bb:midavgCurve);
   samplePos(k)=x(indexMaxcc)+((size(bbb,2)-1))*dxx;
   roundSamplePos(k) = round(samplePos(k));

   % Draw the fitted cure from -10 to +10 of the detemined sample position
   x_curve = (samplePos(k)-(midavgCurve-
1)*dxx):dxx:(samplePos(k)+(midavgCurve-1)*dxx);

   elseif indexMaxcc>indexMax2cc
   half2avgCurve = avgCurve(midavgCurve:size(avgCurve,2));
   [aa,bb] = min(abs( maxcc*ones(size(half2avgCurve))-half2avgCurve));
   bbb = half2avgCurve(1:bb);
   samplePos(k)=x(indexMaxcc)-((size(bbb,2)-1))*dxx;
   roundSamplePos(k) = round(samplePos(k));
   x_curve = (samplePos(k)-(midavgCurve-
1)*dxx):dxx:(samplePos(k)+(midavgCurve-1)*dxx);
end
end

toc
% Determining the deviation of the determined position from
```

```
stagePos = 0:sampleStepSize:100; %Stage reading at each sample position
roundStagePos = round(stagePos);
deviation = samplePos - stagePos;
% Deviation of measurement using curve fitting from the stage reading
roundDeviation = roundSamplePos - roundStagePos;
%-------------------------------------End of Program 2-----------------------------------------
%--------------------------------------------------------------------------------------------------
```

*****

```
%--------------------------------------------------------------------------------------------------
%------------Program 3: Average Polynomial Fitting---------------------------------------
% The purpose of this program is to determine the average polynomial explained in
section 2.4. The measurement method is identical to Step 2 of Program 2.
%--------------------------------------------------------------------------------------------------
% Step 1 of using the average polynomial fitting method is to determine the
% average polynomial. This code creates 5 polynomial, at 10,30,50,70,90.
% Each polynomial requires three input values, the cc of the pattern in the
% middle with itself and with the patterns at the two ends of the
% polynomial. For example for the polynomial at 10 um, the input values are
% the cc of the pattern at 10 um with the one at 5 um and 15 um. Then a
% second degree polynomial is fit to these points
clc;clear all; close all;
%Input values other than the input values for the polynomial
nCurves = 5; % Number of polynomials
curveLength = 2001;%Number of points that create the polynomial curve after
interpolation
pp = zeros ( nCurves , curveLength ); % A Matix to save all the curves

% Polynomial at 10 um
x = [5,10,15];
dxx = 0.01; % The interpolation steps
xx = 0:dxx:20; % The the associated sample shift with each point of the curve

y = [.6858,1,0.6949];
p = polyfit(x,y,2);
pp(1,:) = polyval(p,xx);

% Polynomial at 30 um
y = [.6841,1,0.6891];
p = polyfit(x,y,2);
pp(2,:) = polyval(p,xx);

% Polynomial at 50 um
y = [.6806,1,0.6884];
p = polyfit(x,y,2);
```

```
pp(3,:) = polyval(p,xx);

% Polynomial at 70 um
y = [.6793,1,0.689];
p = polyfit(x,y,2);
pp(4,:) = polyval(p,xx);

% Polynomial at 90 um
y = [.6867,1,0.6932];
p = polyfit(x,y,2);
pp(5,:) = polyval(p,xx);

avg_poly = sum(pp)/5; % The average polynomial

% Determine the derivative of the curve at every 1 um
for j = 2:20
   derpp(j) = (avg_poly((j-1)/dxx+1)-avg_poly((j-1)/dxx-1))/(xx((j-1)/dxx+1)-xx((j-
1)/dxx-1));
end

%Determine the cc deviation of each curve from the average curve at every 1 um
ppDeviation = pp(:,1:100:2001) - ones(5,1)* avg_poly(1:100:2001);
maxppDeviation = max(ppDeviation); % Maximum cc deviation of all the curves at
every 1 um

maxInducedDispDev = maxppDeviation ./ [derpp,0]; % The induced displacement
error in um
max(maxInducedDispDev(6:16)) % The significant part of the induced
displacement error in um

% Step 2: Displacement measurement using average polynomial fitting is identical
to Step 2 of Program 2. Use avgCurve = avg_poly and run the same code.
%-------------------------------End of Program 3-----------------------------------------
%-----------------------------------------------------------------------------------------------
```

*****

```
%-----------------------------------------------------------------------------------------------
%------------Program 4: Unique Polynomial Fitting-----------------------------------
% The purpose of this program is to determine the unique polynomial explained in
section 2.4 and use this polynomial to determine multiple sample positions

clc; clear all;close all;
% The directory where all the database and the samples are located
pathImage ='C:\Users\Mahsa\Documents\Research\lab results\150103-renaming
files in 130704\';
```

```
% Input constants
sample_n = 1001; % Number of sample positions to be evaluated using a unique
polynomial
sampleStepSize = 0.1; % The sampling step size in um
database_n = 11; % Number of database patterns
databaseStepSize = 10; % The distance between the database patterns in um
x = databaseStepSize*(0:(database_n-1)); % Samples shift at database positions
%Initializing variables
samplePos = zeros(1,sample_n); % Sample position determined using the unique
polynomial fitting
roundSamplePos = samplePos; % The round value of samplePos
cc = zeros(1,database_n); % Correlation coefficient of the reference with the
database

% The fist step of the unique polynomial fit is to determine the correlation
coefficient
% of the pattern at an unknown position with the database patterns at every
% 10 um. Here we have database every 10 um from 0
% to 100 um (0,10,20,30,...,100 um)
for k = 1:sample_n
   xs = 0; %Initialize the sample position value
% Read and normalize the sample pattern whose position is to be determined and
call it the reference pattern
reference = im2double( imread(strcat(pathImage,strcat('x',
num2str(sampleStepSize*(k-1),'%.1f'),'.png'))));
reference = (reference-mean(reference(:)))/std(reference(:));

% Determine the correlation of the database with the reference
for j = 1:database_n

database = im2double(imread(strcat(pathImage,'x',num2str(databaseStepSize*(j-
1)),'.0.png')));
database = (database-mean(database(:)))/std(database(:));

cc(j)=  dot(reference(:),database(:))/dot(reference(:),reference(:));

end
% Determine the postion and the value of the first and the second maximum
% of the correlation coefficient of the reference with the database. These
% values will be plugged in the polynomial equation to setup two of the
% three equations to be solved in order to determine the polynomial
% coefficients
[maxcc,indexMaxcc] = max(cc); cc(indexMaxcc) = 0;
[max2cc,indexMax2cc] = max(cc); cc(indexMaxcc) = maxcc;

x1 = (indexMaxcc-1)*10; y1 = maxcc; x2 = (indexMax2cc-1)*10; y2 = max2cc;
```

```
% Plug (x1,y1) and (x2,y2) into the polynomial equation
syms a1 b1 c1;
eq1= a1*x1^2 + b1*x1 + c1 - y1;
eq2= a1*x2^2 + b1*x2 + c1 - y2;
eq3= b1^2 - 4*a1*c1 + 4*a1; % Equation (2-2) of the dissertation
% Solve the 3 equations for the polynomial coefficients
s = solve(eq1,eq2,eq3,a1,b1,c1); a = double(s.a1); b = double(s.b1); c = double(s.c1);

for l = 1:length(a)
% Determine sample position at the polynomial peak form the derivative of the
polynomial equation
xs(l) = -b(l)/(2*a(l));
end

% In case of multiple answers, make sure the sample position is between the
% two correlation maxima
if indexMaxcc < indexMax2cc
%     xx = x1:0.1:x2;
Z = find (( xs>x1 & xs< x2) | (xs == x1));
samplePos(k) = xs(Z);
else
%     xx = x2:0.1:x1;
Z = find (( xs<x1 & xs> x2) | (xs == x1));
samplePos(k) = xs(Z);
end

roundSamplePos(k) = round(samplePos(k));
end

% Determining the deviation of the determined position from
stagePos = 0:sampleStepSize:100;
roundStagePos = round(stagePos);
deviation = samplePos - stagePos;
roundDeviation = roundSamplePos - roundStagePos;
%----------------------------------End of Program 4---------------------------------------
%-----------------------------------------------------------------------------------------
```

*****

```
%-----------------------------------------------------------------------------------------
%------------Program 5: Dual Wavelength Speckle Correlation-------------------------
% The purpose of this program is to evaluate the dual wavelength speckle
correlation method in Matlab. This requires capturing and storing the speckle
patterns every 1 um over a uniform area of the sample along the measurement
length
%-----------------------------------------------------------------------------------------
```

```
The first step in applying this method is to determine the beams offset which is as
follows:
clc; clear all; close all;
% The folder where the patterns captured every 1 um are saved
pathImage ='G:\Lab results\150203-mullany sample 45 offset\';
% Input constants
imageNo = 80; % The range over which the beams offset is located (um)
peakPosNo = 10; % Number of ranges over which the peak is determined
% Initialize variables
peakPos = zeros(1,peakPosNo); % Peak positions
xshift = zeros(peakPosNo,2); % Pixel shift of each pattern w.r.t the reference
cc = zeros(1,imageNo+1); % Correlation coefficient
required_shift = zeros(peakPosNo,2); % Pattern shift in pixels
k=0; % Pattern counter in each loop
x = 0:imageNo; % Sample position associated with each pattern

% The measurement is done over a smooth area of the sample (from 930 um to
% 975 um). The starting point of the ranges over which the beams offset is
% determined is at every 5 um from 930 um to 975 um
for r = 930:5:975

% Read the reference pattern, which is the starting point of the range,
% separate the red plane, and normalize the red pattern
reference = im2double( imread(strcat(pathImage,'x',num2str(r),'.png')));
reference = reference(:,:,1);
reference = (reference-mean(reference(:)))/std(reference(:));

% From the starting point to the end point of each range, read the patterns
% captured every 1 um, separate and normalize the red and the green planes
for j = 0:(imageNo)

database = im2double(imread(strcat(pathImage,'x',num2str(j+r),'.png')));
database_r = database(:,:,1); % Red plane
database_r = (database_r-mean(database_r(:)))/std(database_r(:));

database = database(:,:,2); % Green plane
database = (database-mean(database(:)))/std(database(:));
% Determine the pixel shift of the reference pattern w.r.t the red plane
[output Greg] = dftregistration(fft2(reference),fft2(database_r),36);
xshift(j+1,:) = output(3:4);
% Detemine the pixel shift required to shift the reference pattern in the
% image plane to the position of the red database pattern
deltar = xshift(j+1,1); deltac = xshift(j+1,2); phase = 0;
% Applying the shift to bring the reference pattern in the
% image plane to the position of the red database pattern
[nr,nc]=size(reference);
```

```
Nr = ifftshift(-fix(nr/2):ceil(nr/2)-1);
Nc = ifftshift(-fix(nc/2):ceil(nc/2)-1);
[Nc,Nr] = meshgrid(Nc,Nr);
reference_shifted =
real(ifft2(fft2(reference).*exp(1i*2*pi*(deltar*Nr/nr+deltac*Nc/nc))).*exp(-
1i*phase));
% Determine the cc of the shifted reference red with the green database
% pattern
cc(j+1) =
dot(database(:),reference_shifted(:))/(dot(reference_shifted(:),reference_shifted(:)));
end
% Plot the correlation behavior
figure;plot(x,cc,'*')

% Fit a second order polynomial to the correlation behavior in order to
% find the peak
coeffs = polyfit(x, cc, 2);
% Get fitted values
fittedX = linspace(min(x), max(x), 200);
fittedY = polyval(coeffs, fittedX);
% Plot the fitted line
hold on; plot(fittedX, fittedY, 'r-', 'LineWidth', 2);
 xlabel('Sample shift ( \mum)'); ylabel('Correlation coefficient')
 legend('Experimental data','Polynomial fit')
% Determine the position of the peak
k=k+1; peakPos(k) = -(coeffs(2))/(2*coeffs(1)); % Peak position at each range

%-------An alternative method for finding the peak of the data
%Using Savitzky-Golay FIR smoothing filter
% smoothCC= sgolayfilt(cc,3,21);
% figure; plot(x,cc,'*',x,smoothCC,'r-', 'LineWidth', 2);
% axis tight;
% xlabel('Sample shift ( \mum)');  ylabel('Correlation coefficient')
% legend('Experimental data','Savitzky-Golay filtered data')
% k=k+1;
% [max_vals,max_locs] = findpeaks(smoothCC);
% [max_val, max_val_i] = max(max_vals);
% TF = isempty(max_val_i);
% if TF == 0
% peakPos(k) = max_locs(max_val_i);
% else
% peakPos(k) = 0;
% end
%-----------------------------------------
% The required pixel shift that brings the reference red pattern to the red
% pattern at the correlation peak position is the shift explained in Figure
```

```
% 36 of the dissertation
required_shift(k,:) =
[xshift(round(peakPos(k))+1,1),xshift(round(peakPos(k))+1,2)];
end
mean(peakPos); %The average peak position
std(peakPos);% Standard deviation of the peak positions
mean(required_shift);%The average required pixel shift
%-----------------------------------------------------------------------------------------------
%The second step of evaluating the dual wavelength method is to determine the
% average curve to fit in between the correlation peaks for displacement
% measurement with 1 um resolution
clc;clear all; close all;
% The folder where the patterns captured every 1 um are stored
pathImage ='G:\Lab results\150203-mullany sample 45 offset\';
%Initialize variables
l = 0; % The cc index counter
% There are 10 curves for determining the average. Each curve is 32 um long
% and it is composed of 33 datapoints
cc = zeros(10,33); % The matrix that stores all the 10 curves
% The starting point of the curves are 15 um from 930 to 1065 um
for i = 930:15:1065
   l = l+1;
 % Read and normalize the red plane of the reference pattern which is the
 % pattern at the starting point of each curve
  reference = im2double( imread(strcat(pathImage,'x',num2str(i),'.png')));
  g_ref = reference(:,:,1);
  g_ref = (g_ref-mean(g_ref(:)))/std(g_ref(:));
  k=0; % Displacement counter for each curve
   % Determine the cc of the pattern captured every 1 um over the length of
   % each curve with the pattern at the starting point of the curve ( the
   % reference pattern)
  for j = i:i+32
   % Read and normalize the red plane of the databse patterns
  database = im2double( imread(strcat(pathImage,'x',num2str(j),'.png')));
  g_db = database(:,:,1);
  g_db = (g_db-mean(g_db(:)))/std(g_db(:));
   % Determine the cc of the database patterns with the reference pattern
  k = k+1;
  cc(l,k)=  dot(g_db(:),g_ref(:))./dot(g_db(:),g_db(:));
   % Assign each curve to each line of the allocated matrix
  plot(cc(l,:),'*')
  end
end
avgRedDist = mean(cc); % The average value of all curves at every 1 um
% Deviation of each curve from the average curve at every 1 um
dev = cc - ones(10,1)*avgRedDist;
```

```
% Maximum deviation of all curves from the average curve at every 1 um
maxDeviation = max(dev);
maxDeviation_derivative = zeros(1,33);
% Determine the derivative of the average curve [(cc(i+1)-cc(i-1))/2um]
for i = 2:32
   maxDeviation_derivative(:,i) = 2/(avgRedDist(i+1)-avgRedDist(i-1));
end
% Maximum displacement error due to the deviation of the 10 curves from the
% average curve
maxDeviation_um = max(abs(maxDeviation.*maxDeviation_derivative));
%Interpolate the average curve Using Savitzky-Golay FIR smoothing filter
dxx = 0.01; % Interpolation stepsize in um
smoothAvgRedDist = sgolayfilt(avgRedDist,3,11);
x=0:1:(length(avgRedDist)-1);
xx = 0:dxx:(length(avgRedDist)-1);
avgRedDist_smooth = [avgRedDist(1:3),smoothAvgRedDist(4:33)];
avgCurve = pchip(x,avgRedDist_smooth,xx); % The average curve
% Plot the average curve
figure;plot(x,avgRedDist,'*',x,avgRedDist_smooth,'+',xx,avgCurve,'r');
% An alternative method for interpolating the curve is to use a spline but
% this method does not work that well for the noisy data
% x=0:1:(length(avgRedDist)-1);
% xx = 0:0.01:(length(avgRedDist)-1);
% avgCurve = spline(x,avgRedDist,xx);
% figure; plot(xx, avgCurve)
%-----------------------------------------------------------------------------------------------------
% After determining the beams offset and the average curve to fit in between the
correlation peaks, the displacement measurement evaluation is as follows:
% Dual wavelength curve fitting: read all 1001 points available, determine the
% position using the curve fitting method, and determine the error.
tic; clc; clearvars -except avgCurve & dxx; close all;
% The folder that stores the patterns captured every 1 um
pathImage ='G:\Lab results\150203-mullany sample 45 offset\';
% Input constants
finalPosition = 200; % The range of measurement in um
stepSize = 1; % The patterns are captured every 1 um
x=930:stepSize:1130; % The sample position changes from 930 to 1130 um
k=1; % cc index counter
% Use the required_shift value from the program that determines the beams
% offset
deltar = 0.66; % Pixel shift in z direction
deltac = -10.14; % Pixel shift in x direction
phase = 0;

% Read the reference pattern, separate and normalize the red plane
pattern = im2double( imread(strcat(pathImage,'x930.png')));
```

```
reference = pattern(:,:,1);
reference = (reference-mean(reference(:)))/std(reference(:));

% Read the database pattern, separate and normalize the green plane
database = pattern(:,:,2);
database = (database-mean(database(:)))/std(database(:));

% Apply the required shift to the reference red pattern
[nr,nc]=size(reference);
Nr = ifftshift(-fix(nr/2):ceil(nr/2)-1);
Nc = ifftshift(-fix(nc/2):ceil(nc/2)-1);
[Nc,Nr] = meshgrid(Nc,Nr);
reference_shifted =
real(ifft2(fft2(reference).*exp(1i*2*pi*(deltar*Nr/nr+deltac*Nc/nc))).*exp(-
1i*phase));

% Determine the first cc value, cc between the shifted refernce red and the
% first green database
cc(k) =
dot(database(:),reference_shifted(:))/(dot(reference_shifted(:),reference_shifted(:)));
reference_n = 930; %Sample position associated with the reference red pattern

% At every 1 um, determine the cc of the normalized green database with the
% shifted reference red
for j = 931:stepSize:1130
 % Plot the cc behavior
figure(1);hold on; plot(x(k),cc(k),'b*');
database = im2double(imread(strcat(pathImage,'x',num2str(j),'.png')));
database_g = database(:,:,2);
database_g = (database_g-mean(database_g(:)))/std(database_g(:));
k = k+1; % cc index counter
cc(k) =
dot(database_g(:),reference_shifted(:))/(dot(reference_shifted(:),reference_shifted(:)
));

% Determine if the correlation peak has been riched,if so, replace the
% reference red pattern with the red pattern captured at the correlation
% peak
if (cc(k)<cc(k-1)) && (cc(k)>0.75)
% Changing the reference red
pattern = im2double(imread(strcat(pathImage,'x',num2str(j-stepSize),'.png')));
reference_n = j-stepSize;
reference = pattern(:,:,1);
reference = (reference-mean(reference(:)))/std(reference(:));
% Apply the required shift to the new reference red pattern
[nr,nc]=size(reference);
```

```
Nr = ifftshift(-fix(nr/2):ceil(nr/2)-1);
Nc = ifftshift(-fix(nc/2):ceil(nc/2)-1);
[Nc,Nr] = meshgrid(Nc,Nr);
reference_shifted =
real(ifft2(fft2(reference).*exp(1i*2*pi*(deltar*Nr/nr+deltac*Nc/nc))).*exp(-
1i*phase));
% Recalculate the cc after the peak cc
cc(k) =
dot(database_g(:),reference_shifted(:))/(dot(reference_shifted(:),reference_shifted(:)
));
end
% Use the average curve to find the position with 1 um resolution
   database_r = database(:,:,1);
   database_r = (database_r-mean(database_r(:)))/std(database_r(:));
   cc_r(k-1) = dot(database_r(:),reference(:))/(dot(reference(:),reference(:)));
   [aa,bb] = min(abs( cc_r(k-1)*ones(size(avgCurve))-avgCurve));
   samplePos(k-1)= reference_n + (bb-1) * dxx;
   roundSamplePos(k-1) = round(samplePos(k-1));
end

%  Determining the deviation of the determined positions from the stage
%  readings
stagePos = 931:stepSize:1130; % The stage reading in um
roundStagePos = round(stagePos); % The round value of the stage reading in um
deviation = samplePos - stagePos; % The deviation from the stage reading in um
roundDeviation = roundSamplePos - roundStagePos;
% The average and the std of the deviations from the stage readings
mean(deviation);std(deviation);
% The average and the std of the absolute values of the deviations from the stage
readings
mean(roundDeviation);std(roundDeviation);
%-----------------------------------End of Program 5--------------------------------------
%-----------------------------------------------------------------------------------------------
```

*****

```
%-----------------------------------------------------------------------------------------------
%------------Program 6: 2D Measurement Using DIC-------------------------------------
% The purpose of this program is to find multiple sample positions using
% DIC. The first step is to calibrate the method by determining the
% magnifications in x and z directions. This also helps identify the
% required spacing between the database patterns. The second step is to
% determine the autocorrelation of the pattern at an unknown sample
% position with all the database patterns. This identifies the closest
% database pattern to the sample pattern. The next step is to determine the
% pixel shift of the sample pattern w.r.t the closest database. This gives
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% the position of the sample
%----------------------------------Calibration-------------------------------------------------
% The purpose of this program is to determine the magnifications of the DIC
% method and estimate the systematic error due to imaging and surface form
% error
tic; clc;clear all; close all;
% Input constants
finalPos = 500; % The size of the area under study (here 500 by 500 um)
stepSize = 10; % The sampling size (here 10 um)
%The folder that stores the data captured every 10 um over the 500 by 500
%um area
pathImage ='G:\Lab results\130506-F sample-2D-error correction\';
%---- find magnification in x-----------------------------------
for z = 2250 % The sample z position at the center of the data set
m=0; % Pattern shift index counter
% Read the reference pattern at the center of the data set and separate the
% red plane
reference = im2double(imread(strcat(pathImage,'x2250z2250.png')));
reference = reference (:,:,1);
% Determine the pixel shift of the patterns captured every 10 um from -250
% um to 250 um of the reference pattern. Here the reference pattern is at
% x = 2250 um, z = 2250 um. The patterns in x direction are from 2000 um to
% 2500 um
for j = 2000:stepSize:2500
   database =
im2double(imread(strcat(pathImage,'x',num2str(j),'z',num2str(z),'.png')));
database = database(:,:,1);

[output Greg] = dftregistration(fft2(database),fft2(reference),36);
m = m+1;
shift(:,m) = output(3:4);
end
% Fit the a line to the data. The slop of the line gives the magnification
% in x
p = polyfit(x,3.6*shift(2,:),1); dx = 0.1; y1 = polyval(p,x);
% Although the sample shift is only in x direction, there is some pattern
% shift in z direction. Fit a second order polynomial to estimate the error
p = polyfit(x,shift(1,:),2); y2 = polyval(p,x);
%--- Plot the deviation from the best fit
end
% ---- find magnification in z-----------------------------------------
for z = 2250 % The sample x position at the center of the data set
m=0;% Pattern shift index counter
% Read the reference pattern at the center of the data set and separate the
% red plane
reference = im2double(imread(strcat(pathImage,'x2250z2250.png')));
```

```
reference = reference (:,:,1);
% Determine the pixel shift of the patterns captured every 10 um from -250
% um to 250 um of the reference pattern. Here the reference pattern is at
% x = 2250 um, z = 2250 um. The patterns in z direction are from 2000 um to
% 2500 um
for j = 2000:10:2500
   database =
im2double(imread(strcat(pathImage,'x',num2str(z),'z',num2str(j),'.png')));
database = database(:,:,1);
[output Greg] = dftregistration(fft2(database),fft2(reference),36);
m = m+1;
shift(:,m) = output(3:4);
end
% Fit the a line to the data. The slop of the line gives the magnification
% in z
p = polyfit(x,3.6*shift(1,:),1); dx = 0.1; y1 = polyval(p,x);
% Although the sample shift is only in x direction, there is some pattern
% shift in z direction. Fit a second order polynomial to estimate the error
p = polyfit(x,shift(2,:),2);
y2 = polyval(p,x);
end

% Note: the shift registration algorithm assumes that the shift is negative
% if the pattern goes up wrt the reference. Consider correct sign for
% maginifications
% Example:
% magnification_x = 1.1896;
% magnification_z = -1.1131;

% The purpose of this part of the program is to determine the deviation
% of displacement measurement using DIC from the stage readings in x and
% z directions. Reference pattern is at x = 2250 um and z = 2250 um, which
% is at the center of a 500 by 500 um area. The evaluation is over the data
% captured every 10 um in x and z directions

n=0;
% The sample position in z changes from 2000 to 2500 um in 10 um steps
for z = 2000:10:2500
n = n+1; m=0; %Pixel shift index counter
%Read the reference pattern and separate the red plane
reference = im2double(imread(strcat(pathImage,'x2250z2250.png')));
reference = reference (:,:,1);
% The sample position in zx changes from 2000 to 2500 um in 10 um steps
for j = 2000:10:2500
% Read the sample patterns in x and z directions and determine the subpixel
% shift of each pattern in x and z directions w.r.t the reference pattern
```

```
database =
im2double(imread(strcat(pathImage,'x',num2str(j),'z',num2str(z),'.png')));
database = database(:,:,1);
[output Greg] = dftregistration(fft2(database),fft2(reference),36);
m = m+1;
shift(m,n,:) = output(3:4);   % moving toward right in the image = +output(4)
moving up in the image = -output(3)
end
end
shift_x = 3.6* shift(:,:,2)/magnification_x; % Pattern shift in um in x direction
shift_y = 3.6* shift(:,:,1)/magnification_z; % Pattern shift in um in z direction
shift_magnitude = sqrt((shift_x.^2)+(shift_y.^2)); % Total shift magnitude in um
% Create a matix of stage reading in x
expected_shift_x = zeros(51,51);
for j = 1:51
expected_shift_x(:,j) = -250:10:250;
end
% Create a matix of stage reading in z
expected_shift_y = zeros(51,51);
for j = 1:51
expected_shift_y(j,:) = -250:10:250;
end
% Deviation from x and z stage readings
error_x = expected_shift_x - shift_x;
error_y = expected_shift_y - shift_y;
% Total displacement value read by the stage
expected_shift_magnitude = sqrt((expected_shift_x.^2)+(expected_shift_y.^2));
% Deviation of the total total shift magnitude determined using DIC from
% the total displacement value determined from the stage readings in x and
% z directions
error_magnitude = expected_shift_magnitude - shift_magnitude;

% Plot the deviaitons from the stage readings in x and z directions
x=-250:10:250; y=x;
figure;surf(x,y,error_x,'EdgeColor','none')
figure;surf(x,y,error_y,'EdgeColor','none')
% Plot the deviaitons from the stage readings in x and z directions
% excluding the large deviation at the corners of the patterns
x=-150:10:150; y=x;
figure;surf(x,y,error_xc,'EdgeColor','none')
figure;surf(x,y,error_yc,'EdgeColor','none')
xlabel({'Stage position'; 'in x ( \mum)'})
ylabel({'Stage position'; 'in z ( \mum)'})
zlabel('Deviation from stage reading ( \mum)')
% Plot the total deviation
x=-150:10:150; y=x;
```

```
figure;surf(x,y,error_magnitude(11:41,11:41),'EdgeColor','none')


%---------------------- Displacement measurement using DIC ----------------------------
clc; clear all; close all; tic
% Input constants
% It is possible to correct for the errors determined from the calibration
% section. Load the error data for this purpose:
ex = load('x2250z2250_1111.mat', 'error_x');
ex = ex.error_x; % Deviations from stage readings in x direction
ey = load('x2250z2250_1111.mat', 'error_y');
ey = ey.error_y;% Deviations from stage readings in z direction
% Enter the dimensionless magnifications in x and z directions from the
% calibraion section
magnification_x = 1.1757;
magnification_z = -1.0669;
% Initialize variables
samplePos = zeros(numFrames,2); % Sample positions determined using DIC
expectedPosWOe = samplePos; % Stage reading without correction for the
systematic errors
expectedPosWe = samplePos;% Stage reading with correction for the systematic
errors
errorWCorrection = samplePos; % Deviation of measurement using DIC from the
stage reading with applying the correction
errorWOCorrection = samplePos;% Deviation of measurement using DIC from the
stage reading without applying the correction
% Read all the file names of the patterns captured at random sample
% positions from the associated folder
fileFolder = fullfile('C:', 'Users', 'Mahsa', 'Documents', 'Research','lab results',
'150307-random data');
dirOutput = dir(fullfile(fileFolder,'x*.png'));
fileNames = {dirOutput.name}';
numFrames = numel(fileNames);
% Assign all the patterns captured at random sample positions to a sequence
pathImageS ='C:\Users\Mahsa\Documents\Research\lab results\150307-random
data\';
I = double(imread(strcat(pathImageS,fileNames{1})));
I = I(:,:,1);
% Preallocate the array
sequence = zeros([size(I) numFrames],class(I));
sequence(:,:,1) = I;
% Create image sequence array
for p = 2:numFrames
   Q = double(imread(strcat(pathImageS,fileNames{p})));
   sequence(:,:,p) = Q(:,:,1);
end
```

```
% Change the file name list to string format = numFrames x length of name
% characters
fileNamesStr = num2str(cell2mat(fileNames));
% Read the sample patterns one after another, separate the red plane, and
% normalize the pattern
for p = 1:1000
sample = sequence(:,:,p);
sample = sample(:,:,1);
sample = (sample-mean(sample(:)))/std(sample(:));
% Determine the stage reading from the files name
 x_expectedPos = str2double(fileNamesStr(p,2:5));
 z_expectedPos = str2double(fileNamesStr(p,7:10));
% The folder that contains the database patterns:
pathImage ='C:\Users\Mahsa\Documents\Research\lab results\150307-database\';

% For each sample pattern a matirx keeps the cc of the sample pattern with
% all the database patterns as well as the stage readings in x and z
% directions:
c = zeros(3,100);
k = 0;
% For each sample pattern, find the closest database pattern.
% The database spacing here is 300 um
% They are captured from sample position 1150 um to 3850 um
for z = 1150:300:3850
  for j = 1150:300:3850
    k = k+1;
    % Read each database pattern, separate and normalize the red plane
    database =
im2double(imread(strcat(pathImage,'x',num2str(j),'z',num2str(z),'.png')));
    database = database(:,:,1);
    database = (database-mean(database(:)))/std(database(:));
   % Determine the cross correlation of the sample pattern with all the database
patterns
    [m,n]=size(database);
    cc = abs(fftshift(ifft2(fft2(database).*conj(fft2(sample))))./(n*m);
% Determine the maximum cc value and the associated stage readings in x and
% z directions for each database
    c(1,k) = max(cc(:));
    c(2,k) = j;
    c(3,k) = z;
  end
end
% Determine the maximum cc value and the associated stage readings in x and
% z directions among all database patterns
[max_cc,max_i]= max(c(1,:));
j = c(2,max_i);
```

```
z = c(3,max_i);
% Read the closest database pattern whose associated stage readings are
% detemrined
database =
im2double(imread(strcat(pathImage,'x',num2str(j),'z',num2str(z),'.png')));
% Separate and normalize the red plane
database = database(:,:,1);
database = (database-mean(database(:)))/std(database(:));
% Determine the pixel shift of the sample pattern w.r.t the closest
% database pattern
[output Greg] = dftregistration(fft2(sample),fft2(database),36);
pixelShift = output(3:4);
% Multiply the determined pixel shift by the camera cell size (3.6 um) to
% obtain the pattern shift in um
sampleShift = 3.6*[output(4)/magnification_x,output(3)/magnification_z];
% Add the determined patern shift to the position of the database pattern
% to get the sample position in um
samplePos(p,:) = [j,z]+sampleShift;
% The deviaitons determined in the calibration section are available every
% 10 um over a 300 um by 300 um are and can be subtracted from the stage
% reading to account for the possible systematic errors
error_i = [26,26] + round([(x_expectedPos-j) (z_expectedPos-z)]/10);
% Stage reading without correcting for the errors:
expectedPosWOe(p,:) = [x_expectedPos,z_expectedPos];
% Stage reading with correcting for the errors:
expectedPosWe(p,:) = [x_expectedPos,z_expectedPos]-
[ex(error_i(1),error_i(2)),ey(error_i(1),error_i(2))];
% Deviation from the stage reading without correcting for the errors:
errorWCorrection(p,:) = expectedPosWe(p,:) - samplePos(p,:);
% Deviation from the stage reading with correcting for the errors:
errorWOCorrection(p,:) = expectedPosWOe(p,:) - samplePos(p,:);
end
% The average value of the deviations from the stage readings in x and z
% directions with correcting for the errors:
errorWCorrection_Xmean = mean(errorWCorrection(:,1));
errorWCorrection_Ymean = mean(errorWCorrection(:,2));
% The standard deviation of the deviations from the stage readings in x and z
% directions with correcting for the errors:
errorWCorrection_Xstd = std(errorWCorrection(:,1));
errorWCorrection_Ystd = std(errorWCorrection(:,2));
% The average value of the absolute values of the deviations from the
% stage readings in x and z directions with correcting for the errors:
errorWCorrection_XabsMean = mean(abs(errorWCorrection(:,1)));
errorWCorrection_YabsMean = mean(abs(errorWCorrection(:,2)));
% The maximum value of the absolute values of the deviations from the
% stage readings in x and z directions with correcting for the errors:
```

```
errorWCorrection_XabsMax = max(abs(errorWCorrection(:,1)));
errorWCorrection_YabsMax = max(abs(errorWCorrection(:,2)));
% The average value of the deviations from the stage readings in x and z
% directions without correcting for the errors:
errorWOCorrection_Xmean = mean(errorWOCorrection(:,1));
errorWOCorrection_Ymean = mean(errorWOCorrection(:,2));
% The standard deviation of the deviations from the stage readings in x and z
% directions without correcting for the errors:
errorWOCorrection_Xstd = std(errorWOCorrection(:,1));
errorWOCorrection_Ystd = std(errorWOCorrection(:,2));
% The average value of the absolute values of the deviations from the
% stage readings in x and z directions without correcting for the errors:
errorWOCorrection_XabsMean = mean(abs(errorWOCorrection(:,1)));
errorWOCorrection_YabsMean = mean(abs(errorWOCorrection(:,2)));
% The maximum value of the absolute values of the deviations from the
% stage readings in x and z directions without correcting for the errors:
errorWOCorrection_XabsMax = max(abs(errorWOCorrection(:,1)));
errorWOCorrection_YabsMax = max(abs(errorWOCorrection(:,2)));
%----------------------------------End of Program 6----------------------------------------
%------------------------------------------------------------------------------------------------------
```

APPENDIX C: DUAL WAVELENGTH METHOD LABVIEW CODE

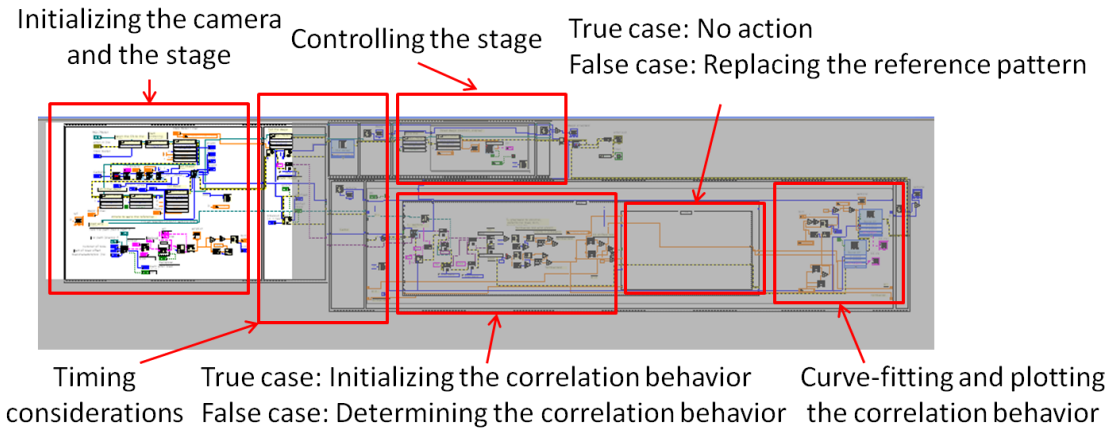

Figure 64: Different sections of the Labview code for relative displacement measurement using dual wavelength speckle correlation

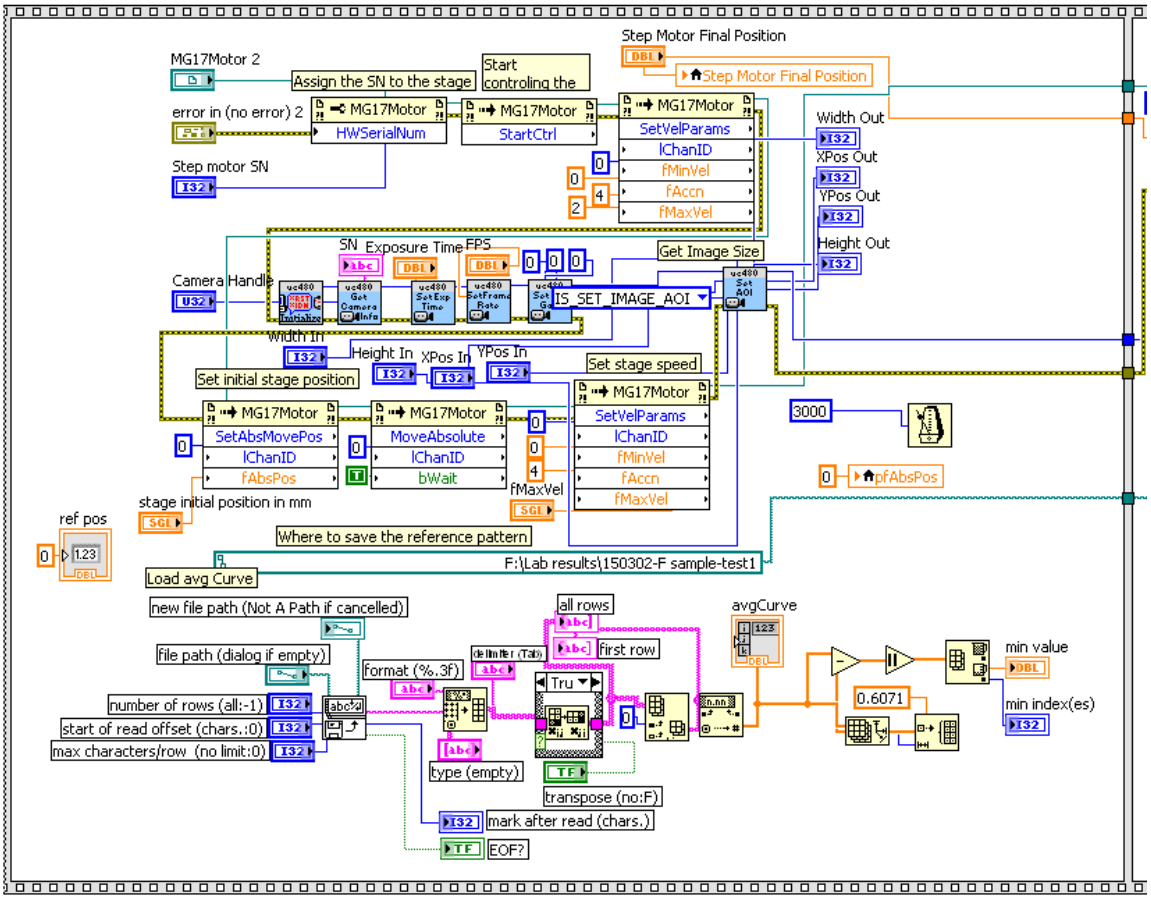

Figure 65: Initializing the camera and the stage

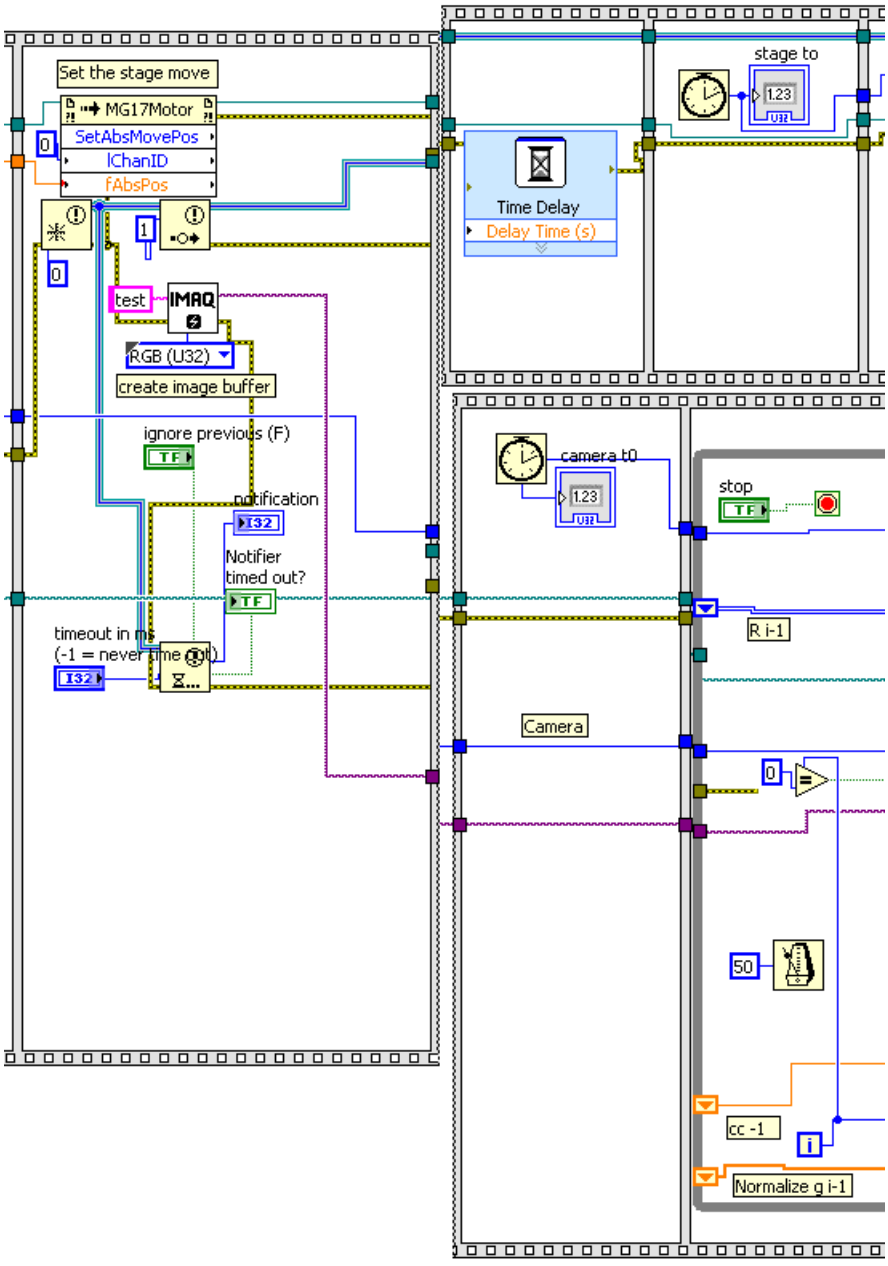

Figure 66: Timing considerations

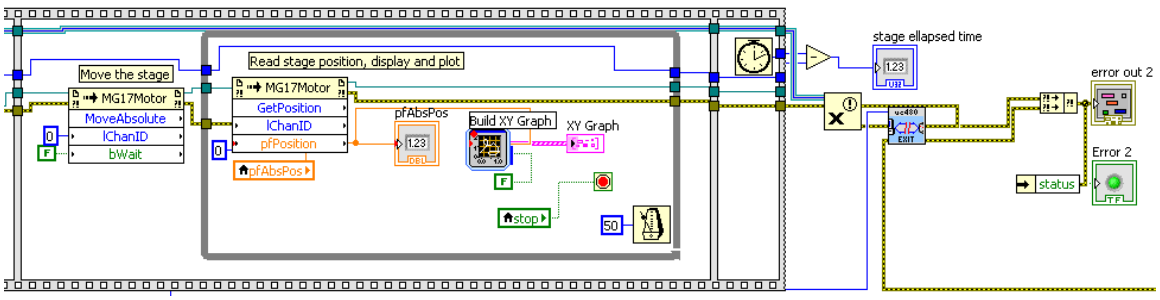

Figure 67: Controlling the stage

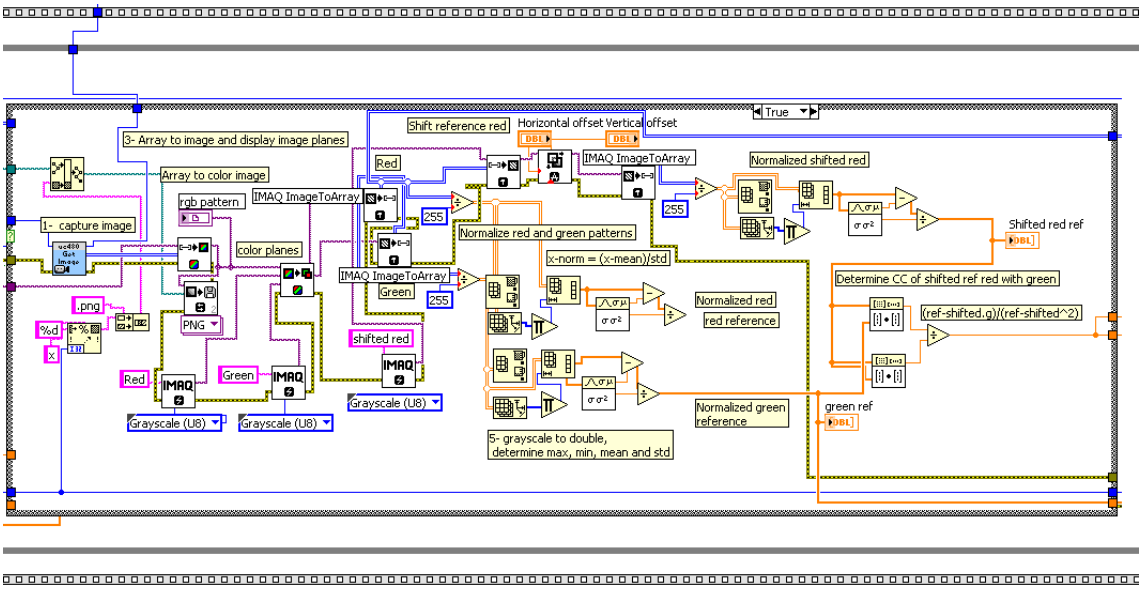

Figure 68: Initializing the correlation behavior

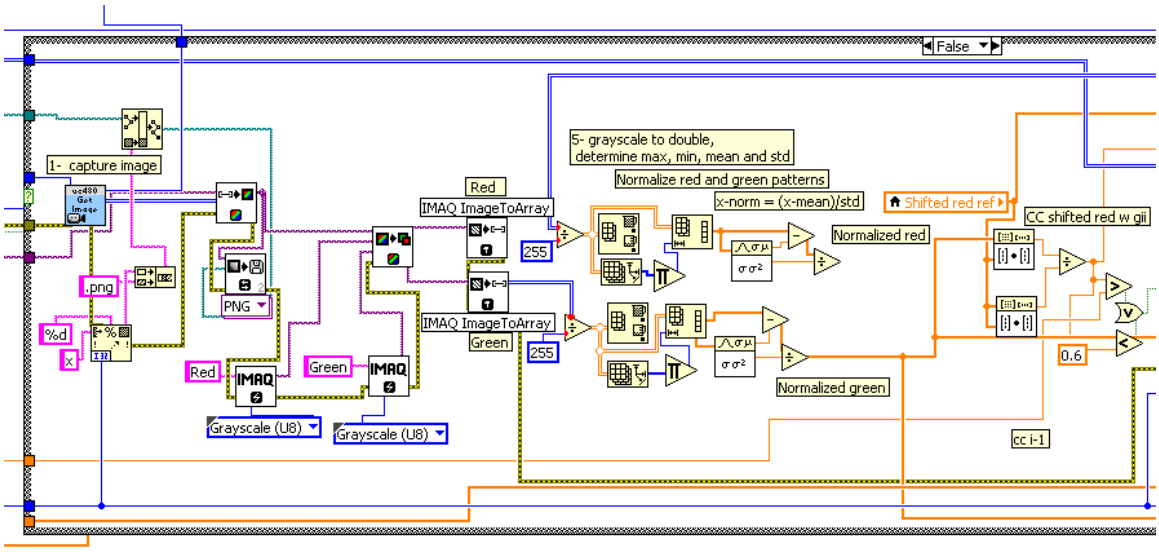

Figure 69: Determining the correlation behavior

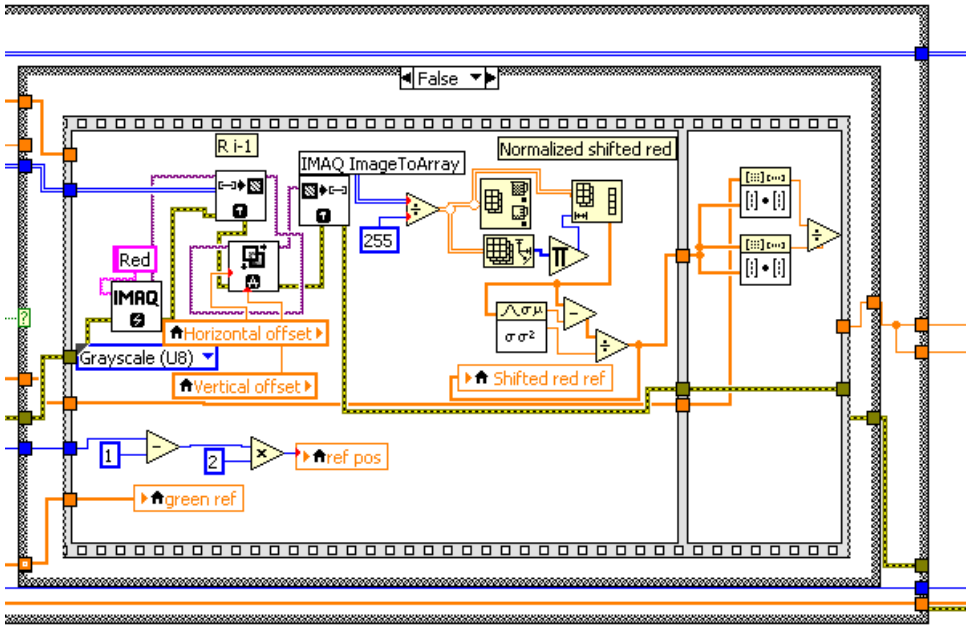

Figure 70: Replace the reference pattern at the correlation peak

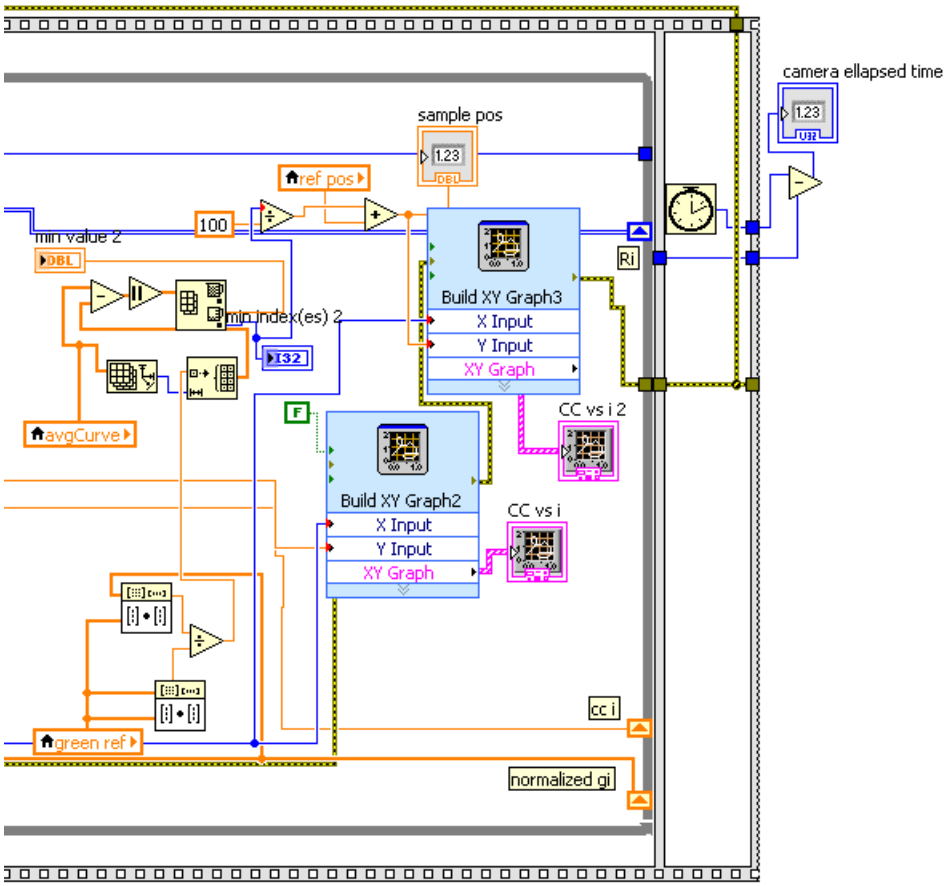

Figure 71: Curve fitting and plotting the correlation behavior