TURNING OF POLYMERS: A NOVEL MULTI-OBJECTIVE APPROACH FOR PARAMETRIC OPTIMIZATION

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By

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Certificate of Approval

This is to certify that the thesis entitled **TURNING OF POLYMERS: A NOVEL MULTI-OBJECTIVE APPROACH FOR PARAMETRIC OPTIMIZATION** submitted by ***Sri Kumar Abhishek*** has been carried out under my supervision in partial fulfillment of the requirements for the Degree of ***Master of Technology*** in ***Production Engineering*** at National Institute of Technology, NIT Rourkela, and this work has not been submitted elsewhere before for any other academic degree/diploma.

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KUMAR ABHISHEK

Abstract

Engineering problems often embodying with multi-response optimization may be confiscatory in nature. Multi-response optimization problems basically correspond to choosing the 'best' alternative from a set of available alternatives (where 'best' can be interpreted as 'the most preferred alternative' from the set of alternative solutions).

Manufacturing process often involves optimization of machining parameters in order to improve product quality as well as to enhance productivity. Quality and productivity are two important but contradictory parameters while performing machining operations. Quality mainly concerns on surface roughness of the machined part whereas productivity is directly related to Material Removal Rate (MRR) during machining. As surface finish (roughness average value) is seemed inversely related to MRR, hence it becomes essential to evaluate the optimal cutting parameters setting in order to satisfy contradicting requirements of quality and productivity.

The aim of this study is to propose an integrated methodology to state the machining characteristics in order that it may be competitive as regards of productivity and quality. Owing to this issue, in the present reporting two integrated multi-response optimization philosophies viz. (i) PCA coupled with TOPSIS and (ii) utility based fuzzy approach combined with Taguchi framework has been adopted for assessing favorable (optimal) machining condition during the machining of polymers (Nylon and Teflon, as case studies).

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CHAPTER 1: Preliminaries

1.1 Background, State of Art and Motivation

Today's economic climate which is characterised by increasing competition and structural turbulence requires an improved level of productivity and high product quality than has been the case in the past. Quality and productivity are being viewed as two important indices of company's performance, especially in manufacturing industries. However, they are always emphasized separately. Quality represents the properties of products and/or services that are valued by the consumer. Quality of a product concerns more valuable as it directly influence the customer's satisfaction during the usage of procured goods. Apart from quality, productivity also pertain an important factor, as it directly associates with profit level of an organisation. After companies determine customer needs, they must concentrate on meeting those needs in an optimized way by yielding high quality products at a faster rate. Here, the term 'optimized' has been introduced to evaluate such a solution which would give the values of the entire objectives acceptable to the decision maker.

In the present growing inflation scenario, it has been observed that optimization of single response proves unbeneficial to manufacturing firm. Optimizing a single response may yield positively in some aspects but it may adversely affects in other aspects, however, the problem can be evoked if multiple objective are optimized simultaneously. The introduction of multi-objective optimization technique provides optimal solution among the confiscatory parameters. Multiple objective functions can be found its application in various fields like products and designing wherever the optimal setting has been required with a motivation of maximizing the strength of machine components and minimizing the production cost.

In any machining process, product quality attributes represents satisfactory yield with surface finish, form stability along with dimensional accuracy whereas productivity can be interpreted in terms of Material Removal Rate (MRR). The main reason that quality and productivity are not emphasized simultaneously is that the objectives of quality management and productivity management are traditionally viewed as contradictory. Increase in productivity results reduction in machining time which may results quality loss. On the contrary, an improvement in quality results in increasing machining time thereby reducing productivity. Since the definitions of quality and productivity are different, it is essential to select a common base through which to correlate them.

Machinability aspects on a wide variety of materials with different cutting tools have been mostly investigated in various machining operations like: turning, drilling, milling etc. Effort has been made to study the influence of process parameters on performance of various aspects of machining like: tool wear, interaction of cutting forces, surface roughness, Material Removal Rate (MRR), tool life, machine tool chatter and vibration etc. Mathematical models have also been developed to understand the functional relationship among process parameters with aforesaid process responses **(Ab Rashid et al., 2009; Kadirgama et al., 2009; Abhang and Hameedullah, 2011, Orhan et al., 2007; Khorasani et al., 2011)**.

Optimization aspects of machining processes have been well documented in literature. In which Taguchi's optimization philosophy **(Taguchi et al., 1989; Antony and Antony, 2001; Antony et al., 2006)** has gained immense popularity. The Japanese management consultant named *Dr. Genichi Taguchi* contributed to the field of quality and manufacturing engineering from both a statistical and an engineering viewpoint. His major contributions are the concepts univariate quality loss functions (QLFs), orthogonal arrays (OAs), robust designs, and Signal-to-Noise (S/N) ratios. The method is often applied by technicians on the manufacturing floor to improve their product and the processes. The goal is not simply to optimize an arbitrary objective function, but rather to reduce the sensitivity of engineering designs to uncontrollable factors or noise. The objective function used is the S/N ratio which is maximized. This moves design targets toward the middle of the design space so that external variation affects behaviour as less as possible. This permits large reductions in both part and assembly tolerances which are major drivers of manufacturing cost **(Taguchi et al. 1989)**. However Taguchi method fails to solve multi-objective optimization problems.

In order to overcome this, desirability function approach **(Trautmann, 2004; Mehnen and Trautmann, 2006; Trautmann and Weihs, 2006; Réthy et al. 2004; Huu et al., 2009; Jeong and Kim 2009)**, utility theory **(Kumar et al., 2000; Walia et al., 2006)**, grey relation theory **(Kao and Hocheng, 2003; Balasubramanian and Ganapathy, 2011; Chakradhar and Venu Gopal, 2011; Lin et al. 2009)** has been applied by previous investigators in combination with Taguchi method. The purpose is to aggregate multiple responses (objective functions) into an equivalent quality index (single objective function) which can easily be optimized using Taguchi method.

These approaches are based on a number of assumptions as well as approximations.

1. In desirability function approach, calculation of desirability value for individual responses is based on the nature of desirability function chosen. There are three types of desirability function viz. Higher-the-Better (HB), Lower-the-Better (LB) and Nominal-the-Best (NB)/ Target-the-Best (TB). The functions may be linear or nonlinear. However, choosing of a function is based on sole discretion of the decision maker.
2. Utility theory is based on logarithmic scale with preference number. This scaling also depends on individuals' discretion. There may be more accurate scale to compute utility values of individual responses.
3. In grey relation theory, computation of grey relational coefficient requires a smoothing constant (varies from 0 to 1). Again selection of smoothing constant depends on decision maker. The grey relational analysis reflects the trend relationship between an alternative

and the ideal alternative, but it cannot reflect the situational relationship between the alternative and the ideal alternative.

4. While computing overall quality index (grey relation grade, overall utility degree), priority weight is assigned to individual responses. Degree of importance of various responses cannot be obtained accurately. Assignment of response weights also affects the optimal process setting.
5. Taguchi's optimization methodology relies on quadratic quality loss function. It is not guaranteed that, in all cases, it should be perfectly parabolic in nature.
6. Many of the quality features assume HB/ LB criteria. But in practice it is not possible to maximize/ minimize it up to infinite value within selected experimental domain.
7. Aforesaid approaches are based on the assumption that response features i.e. quality indices are uncorrelated which seems to be totally infeasible in practical case. Thus assumption of negligible response correlation may create imprecision, uncertainty as well as vagueness in the solution.

It has been found that Principal Component Analysis (PCA) may be a useful statistical technique to solve this kind of inter-correlation problem by examining the relationships within a given data set of multiple-performance-characteristic **(Antony, 2000; Lu et al., 2009; Chen et al., 2011)**. A new set of uncorrelated data, called principal components (PCs) can be derived by PCA in descending order of their ability to explain the variance of the original dataset. Thus, the present work aims to develop an efficient procedural hierarchy for multi-objective optimization by exploring the concept of Principal Component Analysis (PCA) and TOPSIS (*Technique for Order Preference by Similarity to Ideal Solution*) combined with Taguchi method followed by two case studies. Machining of polymers (*Nylon* as well as *Teflon*) has been carried out to optimize productivity and product quality features simultaneously. Appropriate machining process environment (optimal parameters setting) has been identified accordingly.

The *PCA-TOPSIS based Taguchi optimization methodology* proposed here can efficiently tackle the issues of response correlation but it relies on the judgment of decision-maker on assigning response priority weights which may vary depending on individuals' perception. In order to avoid such kind of uncertainty fuzzy logic has come into picture **(Lan, 2010; Gupta et al., 2011)**. Exploring a Fuzzy Inference System (FIS), multiple objectives (responses) can be aggregated logically and meaningfully to compute an Overall Performance Index (OPI) or defined as Multi-Performance Characteristic Index (MPCI). MPCI (or OPI) can further be optimized using Taguchi method. Aforesaid two aspects that cause uncertainty (i) presence of response correlation as well as (ii) response weight assignment can be taken care of by FIS itself in its internal hierarchy. Application feasibility of fuzzy based Taguchi method along combined with utility theory has also been demonstrated in course of the present work.

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CHAPTER 2: Mathematical Background

2.1 Taguchi Method

Robust design method, also called the Taguchi Method, pioneered by *Dr. Genichi Taguchi* in *1940s* greatly improves engineering productivity **(Nalbant et al., 2007; Zhang et al., 2007; Akhyar et al., 2008, Selvaraj and Chandramohan, 2010)**. Robust design focuses on improving the fundamental function of the product or process, thus facilitating flexible designs and concurrent engineering. Indeed, it is the most powerful method available to reduce product cost, improve quality, and simultaneously reduce development interval. The concepts behind the Taguchi methodology are:

1. Quadratic Loss Function (also known as Quality Loss Function, **Fig. 2.1**) is used to quantify the loss incurred by the user due to deviation from target performance.
2. Signal-to-Noise (S/N) Ratio is used for predicting the field quality through laboratory experiments.
3. Orthogonal Arrays (OA) are used for gathering dependable information about control factors (design parameters) with a reduced number of experiments.

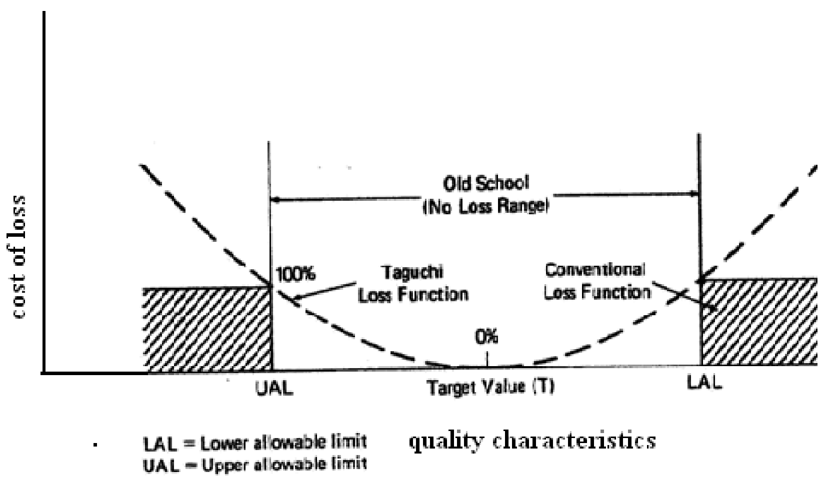


Fig. 2.1: Taguchi loss functions graph

The experiment design theory and quality loss functions have been applied combined together to the robust design of products and process. Taguchi method uses a special design of orthogonal arrays to study the entire parameter space with a reduced number of experiments.

Taguchi technique uses S/N ratio as a performance measure to choose control levels. The S/N ratio considers both the mean and the variability. The change in quality characteristics of a product response to a factor introduced in the experimental design is the signal of the desired effect. The effect of the external factors of the outcome of the quality characteristic under test is termed as noise. To use the loss function as a figure of merit an appropriate loss function with its constant value must first be established which is not always cost effective and easy. The experiment results are then transformed into a Signal-to-Noise (S/N) ratio. Taguchi recommends the use of S/N ratio to measure the quality characteristics deviating from the desired value. The S/N ratio for each level of process parameters is computed based on the S/N analysis and converted into a single metric. The aim in any experiment is to determine the highest possible S/N ratio for the result irrespective of the type of the quality characteristics. A high value of S/N implies that signal is much higher than the random effect of noise factors. In the Taguchi method of optimization, the Signal-to-Noise ratio is used as the quality characteristic of choice.

The different S/N ratio characteristics have been given below.

1. **Nominal-the-Best (NB) or Target-is-Best (TB)**
2. **Lower-the-Better (LB)**
3. **Higher-the-Better (HB)**

Nominal-the-Best (NB) or Target-is-Best (TB)

In this approach, the closer to the target value, the better. It does not matter whether the deviation is above or below the target value (example: diameter of a shaft). Under this approach the deviation is quadratic.

$$\eta_j^i = -10\log_{10}\left[\frac{1}{l}\sum_{k=1}^{l}\frac{\bar{y}_j^{i\,2}}{S_j^{i\,2}}\right] \qquad \textbf{(2.1)}$$

The following graph **(Fig. 2.2)** portrays Nominal-the-Best (NB) characteristics.

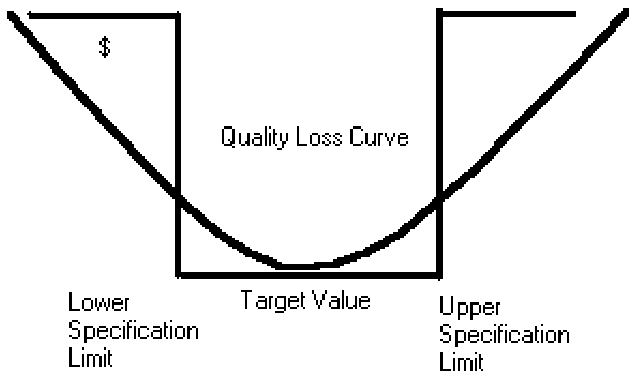


Fig. 2.2: Nominal-the-Best (NB)/ Target-is-Best (TB)

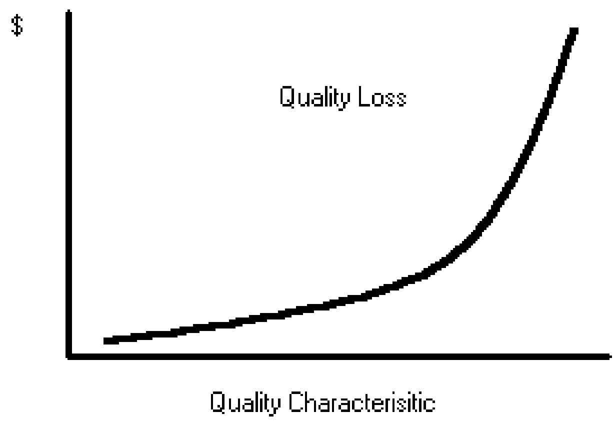


Fig. 2.3: Lower-the-Better (LB)

Lower-the-Better (LB)

Lower-the-Better criteria for S/N ratio always predict values pessimistically. It includes quality characteristic which has the undesired output such as defects in product like surface roughness, pin holes or unwanted by-product. The formula for these characteristics is:

$$\eta_j^i = -10\log_{10}\left[\frac{1}{l}\sum_{k=1}^{l} {y_{jk}^{i}}^{2}\right] \tag{2.2}$$

The following graph **(Fig. 2.3)** portrays Lower-the-Better (LB) characteristics.

Higher-the-Better (HB)

Larger the better characteristic includes the desired output such as bond strength, material removal rate, employee participation and the customer acceptance rate. The formula for these characteristics is:

$$\eta_j^i = -10\log_{10}\left[\frac{1}{l}\sum_{k=1}^{l}\frac{1}{{y_{jk}^{i}}^{2}}\right] \tag{2.3}$$

The following graph **(Fig. 2.4)** portrays Higher-the-Better (HB) characteristics.

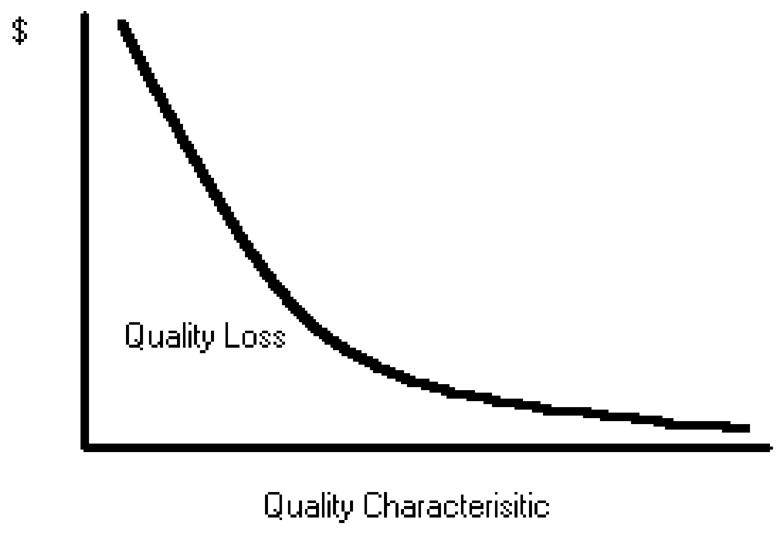


Fig. 2.4: Higher-the-Better (HB)

Here, y_{jk}^{i} =observed data for the j_{th} response at the i_{th} trial, the k_{th} repetition, $\bar{y}_j^i = \frac{1}{l}\sum_{k=1}^{l} y_{jk}^{i}$

(The average observed data for the j_{th} response at the i_{th} trial), $S_j^{i\,2} = \frac{1}{l-1}\sum_{k=1}^{l}\left(y_{jk}^{i} - \bar{y}_j^i\right)^2$ (the variation of observed data for the j_{th} response at the i_{th} trial,) for $i = 1, 2, ..., m$; $j = 1, 2, ..., n$ and $k = 1, 2, ..., l$.

2.2 Principal Component Analysis (PCA)

PCA is a multivariate statistical technique, which explores an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of uncorrelated variables called principal components (PCs) **(Liao, 2006; Routara et al., 2010)**. Each PC has the property of explaining the maximum possible amount of variance obtained in the original dataset. The PCs, which are expressed as linear combinations of the original variables which can be used for effective representation of the system under investigation, with a lower number of variables in the new system of variables being called scores, while the coefficient of linear combination describes each PCs, i.e. the weight of each PCs. Following are the mathematical procedure for evaluating the desired principal components.

(a) Checking for correlation between each pair of quality characteristics

Let, $Q_i = \{X_0^*(i), X_1^*(i), X_2^*(i), ..., X_m^*(i)\}$ where, $i = 1,2,3,............, n.$ **(2.4)**

It is the normalized series of the ith quality characteristic. The correlation coefficient between two quality characteristics is calculated by the following equation:

$$\rho_{jk} = \frac{Cov(Q_j, Q_k)}{\sigma_{Q_j} \times \sigma_{Q_k}}$$ **(2.5)**

here,
$j = 1,2,3,......................,n$
$k = 1,2,3,......................,n$
$j \neq k$

Here, ρ_{jk} is the correlation coefficient, σ_{Q_j} and σ_{Q_k} denotes standard deviation of the quality characteristics j and quality characteristics of k respectively.

(b) Calculation of the principal component score

1) Compute the Eigen value λ_k and the corresponding Eigen vector β_k $(k = 1,2,3,.........n)$ from the correlation matrix formed by all the quality characteristics.
2) Compute the principal component scores of the normalized reference sequence and comparative sequences using the equation shown below:

$$Y_i(k) = \sum_{j=1}^{n} X_i^*(j)\beta_{kj}, i = 0,1,2........,m, k = 1,2,3.............,n \tag{2.6}$$

Here, $Y_i(k)$ is the principal component score of the kth element in the ith series. Let, $X_i^*(j)$ be the normalized value of the jth element in the ith sequence, and β_{kj} is the jth element of the Eigen vector β_k .

(c) Estimation of quality loss $\Delta_{0,i}(k)$

Loss estimate $\Delta_{0,i}(k)$ is defined as the absolute value of the difference between desired (ideal) value and ith experimental value for k_{th} response. If responses are correlated then instead of using [$X_o(k)$ $X_i(k)$]; [$Y_0(k)$ $Y_i(k)$] should be used for computation of $\Delta_{0,i}(k)$.

$$\Delta_{0,i} = \begin{Bmatrix} |X_0(k) - X_i(k)| \\ |Y_0(k) - Y_i(k)| \end{Bmatrix} \tag{2.7}$$

It can be mathematically proved that each principal component has coefficients equal to the Eigen vectors of the correlation or covariance matrix. In the study, the tested sample correlation matrix has been used instead of the covariance matrix, to avoid the units' effects. The PCs are then sorted in descending order by Eigen values (λ_p) which are equal to the variances of the components.

PCs have certain desirable properties. The first is that the sum of the variances of the principal component is equal to the sum of the variances of the original variables i.e.

$$Var(Z_p) = Var(X_1) + Var(X_2) + \dots\dots\dots\dots\dots\dots + Var(X_p) = Var(Z_1) + Var(Z_2) + \dots\dots\dots Var(Z_p)$$

(2.8)

The second is that, unlike the original variables, $Z_p, p = 1, 2, ..., p$ are mutually orthogonal. That is, they are totally uncorrelated, or there is zero multi-co linearity among them.

In most cases in which PCA is used, the first few components contain a large part of the total variance, and the original p- dimensional dataset can, without substantial loss of information, be approximated by a q- dimensional (q < p) dataset, by discarding the p–q highest order PCs.

2.3 TOPSIS

The TOPSIS (*Technique for Order Preference by Similarity to Ideal Solution*) method was initially proposed by **(Hwang and Yoon, 1981)** for evaluating the alternatives before the multiple-attribute decision making. TOPSIS is implemented to measure the proximity to the ideal solution. The basic concept of this method is that the chosen alternative should have the shortest distance from the positive ideal solution and the farthest distance from negative ideal solution **(Tong et al., 2005)**. Positive ideal solution is composition of the best performance values demonstrated (in the decision matrix) by any alternative for each attribute. The negative-ideal solution is the composite of the worst performance values. The steps involved for calculating the TOPSIS values are as follows:

Step 1: This step involves the development of matrix format. The row of this matrix is allocated to one alternative and each column to one attribute. The matrix can be expressed as:

$$D = \begin{array}{c} A_1 \\ A_2 \\ . \\ A_i \\ . \\ A_m \end{array} \begin{bmatrix} x_{11} & x_{12} & . & x_{1j} & x_{1n} \\ x_{21} & x_{22} & . & x_{2j} & x_{2n} \\ . & . & . & . & . \\ x_{i1} & x_{i2} & . & x_{ij} & . \\ . & . & . & . & . \\ x_{m1} & x_{m2} & . & x_{mj} & x_{mn} \end{bmatrix} \quad \textbf{(2.9)}$$

Here, A_i ($(i=1,2,.......,m)$ represents the possible alternatives; x_j $(j=1,2,........,n)$ represents the attributes relating to alternative performance, $j=1,2,..........,n$ and x_{ij} is the performance of A_i with respect to attribute $X_{j.}$

Step 2: Obtain the normalized decision matrix r_{ij} .This can be represented as:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \quad \textbf{(2.10)}$$

Here, r_{ij} represents the normalized performance of A_i with respect to attribute $X_{j.}$

Step 3: obtain the weighted normalized decision matrix, $V = \lfloor v_{ij} \rfloor$ can be found as:

$$V = w_j r_{ij} \quad \textbf{(2.11)}$$

Here, $\sum_{j=1}^{n} w_j = 1$

Step 4: Determine the ideal (best) and negative ideal (worst) solutions in this step. The ideal and negative ideal solution can be expressed as:

a) The ideal solution:

$$A^{+} = \left\{ \left(\max_{i} v_{ij} \mid j \in J \right), \left(\min_{i} v_{ij} \mid j \in J^{'} \middle| i = 1, 2, ..., m \right) \right\} \quad \textbf{(2.12)}$$

$$= \left\{ v_1^{+}, v_2^{+}, ..., v_j^{+}, ...v_n^{+} \right\}$$

b) The negative ideal solution:

$$A^{-} = \left\{ \left(\min_{i} v_{ij} \mid j \in J \right), \left(\max_{i} v_{ij} \mid j \in J^{'} \middle| i = 1, 2, ..., m \right) \right\} \quad \textbf{(2.13)}$$

$$= \left\{ v_1^{-}, v_2^{-}, ..., v_j^{-}, ...v_n^{-} \right\}$$

Here,

$J = \left\{ j = 1,2,......., n \mid j \right\}$: Associated with the beneficial attributes

$J^{'} = \left\{ j = 1,2,......., n \mid j \right\}$: Associated with non beneficial attributes

Step 5: Determine the distance measures. The separation of each alternative from the ideal solution is given by n- dimensional Euclidean distance from the following equations:

$$S_i^{+} = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^{+} \right)^2} \quad i = 1, 2, ..., m \quad \textbf{(2.14)}$$

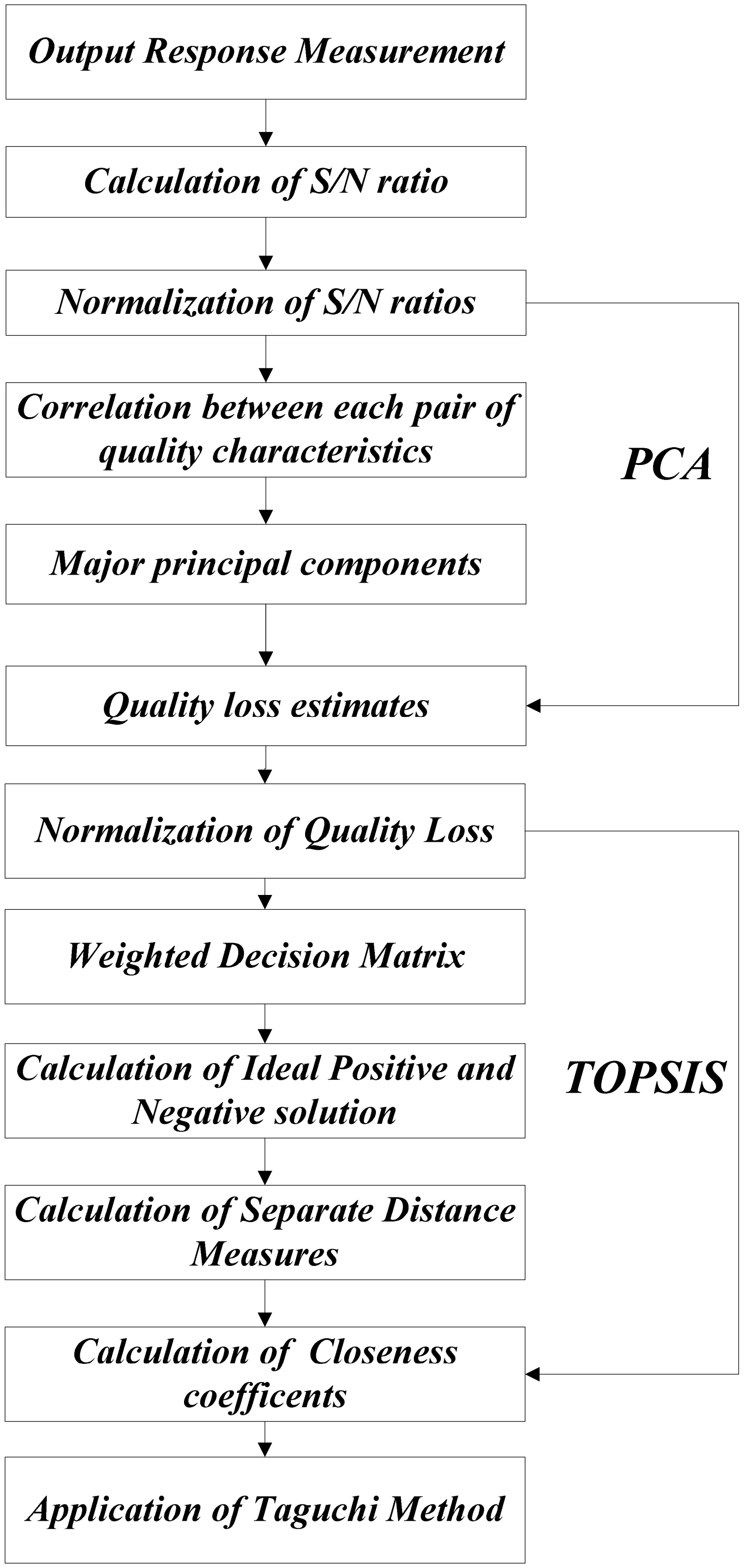
$$S_i^{-} = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^{-} \right)^2} \quad i = 1, 2, ..., m \quad \textbf{(2.15)}$$

Step 6: Calculate the relative closeness (closeness coefficient, CC) to the ideal solution:

$$C_i^{+} = \frac{S_i^{-}}{S_i^{+} + S_i^{-}}, \quad i = 1, 2, ..., m; 0 \le C_i^{+} \le 1 \quad \textbf{(2.16)}$$

Step 7: Rank the preference order: the alternative with the largest relative closeness is the best choice.

2.4 PCA-TOPSIS Integrated with Taguchi's Philosophy



2.5 Utility Theory

Utility function approach provides a methodological framework for the evaluation of alternative attributes made by individuals, firms and organizations. Utility refers to the satisfaction that each attributes provides to the decision maker. Thus, utility theory assumes that any decision is made on the basis of the utility maximization principle, according to which the best choice is the one that provides the highest satisfaction to the decision maker **(Kaladhar et al., 2011)**.

It is the measure of effectiveness of an attribute (or quality characteristics) and there are attributes evaluating the outcome space, then the joint utility function can be expressed as:

$$U(X_{1,}\ X_2,................, X_n) = f\ (U_1(X_1), U_2(X_2),..............., U_n(X_n)) \quad \textbf{(2.17)}$$

The overall utility function is the sum of individual utilities if the attributes are independent, and is given as follows:

$$U(X_{1,}\ X_2,................, X_n) = \sum_{i=1}^{n} U_i(X_i) \quad \textbf{(2.18)}$$

The overall utility function after assigning weights to the attributes can be expressed as:

$$U(X_{1,}\ X_2,................, X_n) = \sum_{i=1}^{n} W_i U_i(X_i) \quad \textbf{(2.19)}$$

The preference number can be expressed on a logarithmic scale as follows:

$$P_i = A \times \log\left(\frac{X_i}{X_i^{'}}\right) \quad \textbf{(2.20)}$$

Here,

X_i is the value of any quality characteristic or attribute i

$X_i^{'}$ is just acceptable value of quality characteristic or attribute i and A is a constant. The value A can be found by the condition that if $X_i = X^*$ (where X^* is the optimal or best value), then $P_i = 9$. Therefore,

$$A = \frac{9}{\log \frac{X^*}{X_i^{'}}} \tag{2.21}$$

The overall utility can be expressed as follows:

$$U = \sum_{i=1}^{n} W_i P_i \tag{2.22}$$

Subject to the condition:

$$\sum_{i=1}^{n} W_i = 1 \tag{2.23}$$

Overall utility index that has been computed treated as a single objective function for optimization. Among various quality characteristics types, viz. Lower-the-Better (LB), Higher-the-Better (HB), and Nominal-the-Best (NB) suggested by Taguchi, the utility function would be Higher-the-Better (HB) type. Therefore, if the quality function is maximized, the quality characteristics considered for its evaluation will automatically be optimized.

2.6 Fuzzy Inference System (FIS)

Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic. The mapping then provides a basis from which decisions can be made, or patterns discerned **(Zadeh, 1976; Cox, 1992; Mendel, 1995; Yager and Filev, 1999)**. The process of fuzzy inference involves the following elements: Membership Functions, Logical Operations, and If-THEN Rules. Most commonly two types of fuzzy inference systems can be implemented: *Mamdani* type and *Sugeno* type. These two types of inference systems vary somewhat in the way outputs are determined.

Fuzzy inference systems have been successfully applied in fields such as automatic control, data classification, decision analysis, expert systems, and computer vision. Because of its multidisciplinary nature, fuzzy inference systems are associated with a number of names, such as fuzzy-rule-based systems, fuzzy expert systems, fuzzy modeling, fuzzy associative memory, fuzzy logic controllers, and simply (and ambiguously) fuzzy systems.

Mamdani's fuzzy inference method is the most commonly viewed fuzzy methodology. Mamdani's method was among the first control systems built using fuzzy set theory. It was proposed in 1975 by Ebrahim Mamdani **(Mamdani, 1976; 1977)** as an attempt to control a steam engine and boiler combination by synthesizing a set of linguistic control rules obtained from experienced human operators.

Fuzzy values are determined by the membership functions, which define the degree of membership of an object in a fuzzy set. However, so far there has been no standard method of choosing the proper shape of the membership functions for the fuzzy set of control variables. Trial and error methods are usually employed. On the basis of fuzzy rules, the Mamdani implication method is employed in this study for fuzzy inference reasoning.

To obtain a rule,

$$R_i : if\ x_1\ is\ A_{i1}, x_2\ is\ A_{i2}, and\ x_s\ is\ A_{iM}$$
$$Then, y_i\ is\ C_i, \qquad \textbf{(2.24)}$$

Here M is the total number of fuzzy rules. $x_j\,(j=1,2,,.........,s)$ are the input variables, y_i are the output variables and $A_{ij}\,and C_i$ are fuzzy sets modeled by the membership functions $\mu_{Aij}(x_j)$ and $\mu_{Ci}(y_i)$, respectively. Based on the Mamdani implication method of inference reasoning for a set of disjunctive rules, the aggregated output for the M rules is

$$\mu_{Ci}(y_j) = \max\{\min[\mu_{Ai1}(x_1), \mu_{Ai2}(x_2), \ldots\ldots, \mu_{Ais}(x_s)]\}, \qquad i = 1,2,\ldots\ldots\ldots, M \qquad \textbf{(2.25)}$$

Basic structures of Fuzzy Inference System (FIS) have been shown in **Fig. 2.5**. Using a defuzzification method, fuzzy values can be combined into one single crisp output value as shown in **Fig.2.6**. The centre of gravity, one of the most popular methods for defuzzifying fuzzy output functions, is employed in this study. The formula to find the centroid of the combined outputs $\hat{y}_i$ is given by:

$$\hat{y}_i = \frac{\int y_i \mu_{ci}(y_i)dy}{\int \mu_{ci}(y_i)dy} \qquad \textbf{(2.26)}$$

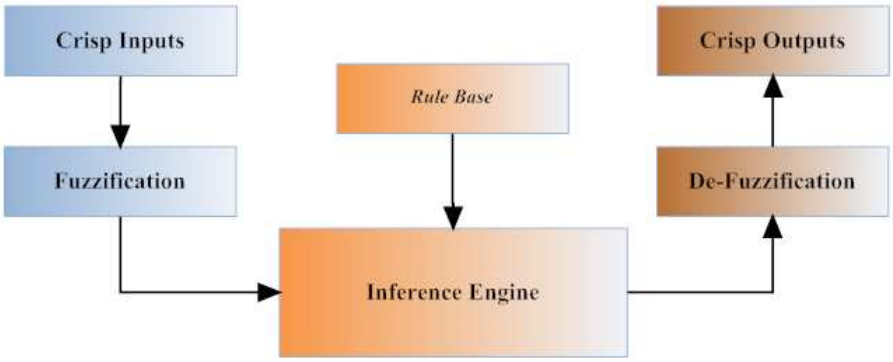


Fig. 2.5 Basic structure of FIS

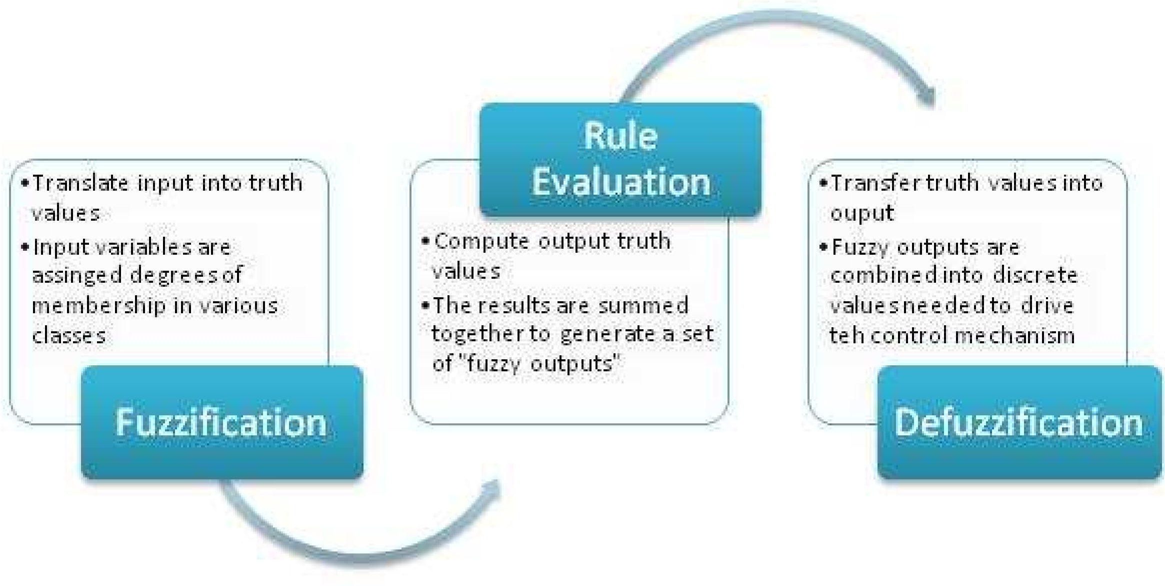
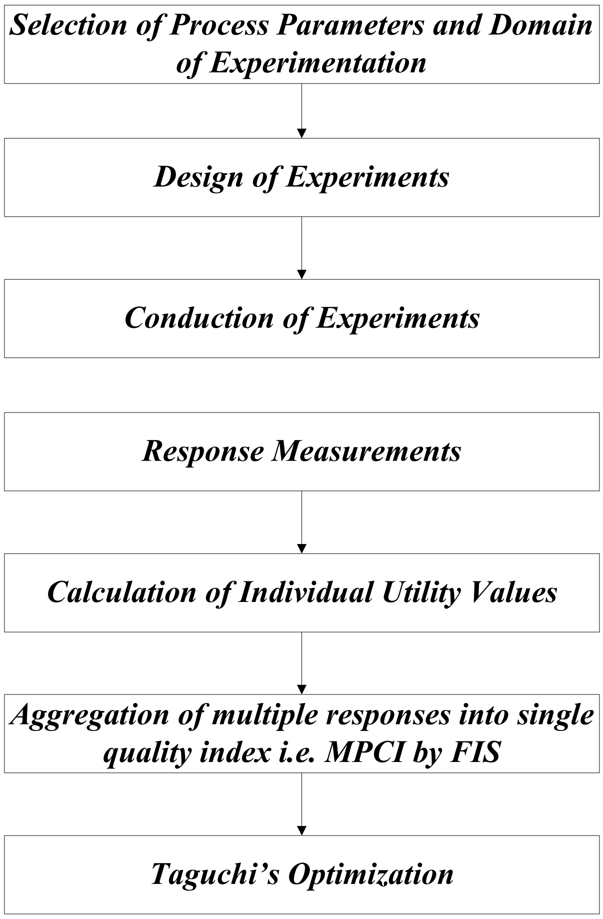


Fig. 2.6 Operation of fuzzy inference system

2.7 Utility-Fuzzy Integrated with Taguchi's Philosophy



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CHAPTER 3: Machining of Nylon 6

In today's competitive corporate world manufacturers should pay more emphasis to maintain overall product quality at an economic cost. Hence it becomes essential to optimizevarious machining parameters. In the present study, Principal Component Analysis (PCA)integrated with TOPSIS has been used in the Taguchi method to assess optimal process environmentin machining of Nylon 6. Multiple surface roughness parameters of statistical importance have been optimized simultaneously.

3.1 Nylon: Structure, Properties, Performance: Issues on Nylon Machining

The term nylon refers to a family of plastics. The two most common grades of nylon are Nylon 6 and Nylon 6/6. The number refers to the number of methyl groups which occur on each side of the nitrogen atoms (amide groups). The term polyamide, another name for nylon, reflects the presence of these amide groups on the polymer chain. The difference in number of methyl groups influences the properties of the nylon.

Unlike polycarbonate, nylon is crystalline in nature; so the molecular chains do not have large substituent groups (such as the phenyl ring in polycarbonate). The crystalline nature of the material is responsible for its wear resistance, chemical resistance, thermal resistance, and higher mold shrinkage.The properties of nylon include:

1. very good heat resistance
2. excellent chemical resistance
3. excellent wear resistance
4. moderate to high price
5. fair to easy processing

As the separation of the amide groups increases (by adding more methyl groups) and the polarity of the amide groups is reduced, moisture absorbance is decreased. Resistance to thermal deformation is lowered due to more flexibility and mobility in the methyl unit sections of the chain. Some common applications of nylon include:

1. electrical connectors
2. gear, slide, cams, and bearings
3. cable ties and film packaging
4. fluid reservoirs
5. fishing line, brush bristles
6. automotive oil pans
7. fabric, carpeting, sportswear
8. sports and recreational equipment

Cast and extruded nylon are used in a wide variety of applications for their outstanding mechanical properties including high wear and abrasion resistance, superior strength and stiffness. Nylon's toughness, low coefficient of friction and wide size range availability make it an ideal replacement for a wide variety of materials from metal to rubber.

Standard nylon offers up to three times better wear than acetal and tops UHMW-PE in applications imposing high loads and stresses. Using nylon reduces lubrication requirements; eliminates galling, corrosion and pilferage problems; and improves wear resistance and sound dampening characteristics. Nylon has a proven record of outstanding service in a multitude of parts for such diverse fields as paper, textiles, electronics, construction, mining, metalworking, aircraft, food and material handling.

Different types of nylon have been developed to satisfy a wide variety of application demands. Nylons with added molybdenum disulfide offer tremendous value in general purpose structural or bearing and wear applications. Heat-stabilized nylons resist degradation at higher temperatures. And for demanding wear applications, an internally lubricated nylon may be specified.The machining and fabrication guidelines are applicable to good quality nylons. The basic properties of nylon are to be clearly understood which may be relevant to machinists and fabricators.

Machining operations can induce internal stress within work material High-quality nylon stock shapes are delivered with very low residual stress. Improper machining or removal of large amounts of material can create large internal stresses that can result in warping, ovality or other dimensional instabilities. Whenever possible, select a stock shape which minimizes the amount of material to be removed to make a finished part. In some cases, it may be advantageous to order custom size stock or consider a near net shape nylon casting. The effects of machined-in stress can be minimized by allowing a part to rest for several hours between machining operations. In rare cases, it may be necessary to post-machine anneal a nylon part if extraordinary dimensional stability is required.

Satisfactory finishes can be easily obtained on nylon over a wide range of surface speeds. Use tools that are honed sharp and have high rake and clearance angles, to minimize cutting force and reduce heat build-up. Chips will be continuous and stringy. They should be directed away from the cut and prevented from winding around the work piece. Coolants are generally not necessary for lathe work unless there is excessive heat build-up.

3.2Modelling-Prediction and Optimization of Surface Roughness in Machining: State of Art and Problem Formulation in context of Nylon Machining

Literature has been found rich enough highlighting various aspects of machining of conventional metals; emphasis made to a lesser extent on machining and machinability of polymeric materials. With the worldwide application of polymeric material; in depth knowledge is highly essential for better understanding of machining process behavior, parametric influence and their interaction etc. in order to produce high quality finished part in terms of dimensional accuracy, material removal rate as well as good surface finish. Part quality can be improved by proper selection and precise control of the adjustable process parameters; the combination of which is called a particular process environment. There exists tremendous need to search the most suitable process environment (optimal) in order to satisfy multi-requirements of part quality simultaneously. This invites multi-objective optimization problem which seeks to determine an optimal solution (optimal process environment) to be determined prior to initiate mass production.

Surface roughness of the finished/ machined part is an important quality characteristic in any machining operation. A number of parameters of statistical importance are defined to describe extent of surface finish. Predictive modeling, optimization of surface roughness has been addressed by pioneer researchers and highlighted in literature.

Lou et al. (1998-99) developed a multiple regression model for predicting surface finish in end milling process. The surface roughness (R_a) predication model was constituted by considering machining parameters viz. spindle speed, feed rate and depth of cut and their interaction. **Lee and Tarng(2001)** proposed a polynomial network model to inspect surface roughness by developing the relationship between the features of the surface image and the actual surface roughness under a variation in machining parameter on turning operation. **Özel and Karpet(2005)** used neural network and regression model analysis for predicating the surface quality and tool flank wear over the machining time for variety of machining conditions in finish hard turning of AISI 52100 steel by using CBN tools. **Aggarwal and Singh (2005)** made a comparative study on the methods for optimizing machining parameters in turning process by comparing conventional and latest method methods of optimization.

Various conventional techniques employed for machining optimization include geometric programming, geometric plus linear programming, goal programming, sequential unconstrained minimization technique, dynamic programming etc. The latest techniques for optimization included fuzzy logic, scatter search technique, genetic algorithm, and Taguchi technique, response surface methodology etc. **Kirby (2006)** discussed on the application of Taguchi framework of experimental design for optimizing the surface roughness during the CNC milling. **Nalbant et al. (2007)** examined the performance characteristics of the cutting parameters viz. insert radius, feed rate and depth of cut during the turning operation of AISI 1030 steel bars by using the TiN coated tools. The performance characteristic comprised the surface roughness which was optimized by using Taguchi's robust design technique.

Özel et al. (2007) investigated the influence of design of nose radius on surface finish and the tool flank wear by developing a neural network model and multiple linear regression models during the turning of AISI D2 steels with the help of ceramic wiper (multi-radii) design inserts. **Zhang et al. (2007)** adopted the Taguchi robust technique combined with the ANOVA to examine the factors influencing the surface quality in a CNC face milling operation.**Routara et al. (2007)** predicted optimal machining parameter condition for multi performance characteristics of the surface finish in CNC turning on AISI 1040 mild steel bar. The machining parameter viz. spindle speed, depth of cut and feed rate were used for assessing the different roughness parameters of statistical significance such as centre line average, root mean square and mean-line peak spacing.**Akhyar et al. (2008)** applied Taguchi technique to optimize the quality of surface finish during the turning of Ti-6%Al-4% with coated and uncoated cemented carbide tools under dry cutting condition and high cutting speed. **Suhail et al. (2010)** optimized machining parameters to increase the degree of machine utilization and to decrease the production cost. The orthogonal array, S/N ratio and ANOVA were applied to study work piece surface temperature and surface roughness.**Singh**

et al. (2010) suggested a comprehensive study for improving the surface quality of the machined product. The study emphasized on the methodology adopted for the optimization of process parameter to improve the surface roughness as it indicates the product appearance, function and reliability.**Kadirgama et al. (2010)** focused on controlling machining parameters during milling of mould aluminium alloys by the aid of Response Ant Colony Optimization (RACO). This approach comprised the both Response surface methodology and Ant colony optimization which were useful for assessing the dominant variables viz. cutting speed, feed rate, axial depth and radial depth. The model predicted that feed rate was found more important factor which affects surface quality.

Jurkovic et al. (2010) made a comparative study on the methods of optimization based on experimental plan in between the conventional rotatable central composite design and orthogonal array for enhancing the surface finish in finish longitudinal turning operations. **Selvraj and Chandramohan(2010)** analyzed the cutting characteristics during the dry turning of AISI 304 austenitic stainless steel (ASS) by using the TiC and TiCN coated carbide tool with the aid of the Taguchi robust technique integrated with the ANOVA.**Dhavamani and Alwarsamy(2011)** reviewed different methods of optimizing techniques including conventional methods like geometric programming, non linear programming etc. and compared to modern methods such as fuzzy logic, scatter search method, genetic algorithm for optimal selection of machining variables in drilling process.**Kaladhar et al., (2011)** presented a multi-characteristics response model for optimizing process parameter in turning on AISI 202 austenitic stainless steel using a CVD coated cemented carbide tool with Taguchi robust design integrated with utility concept.

Ramesh et al. (2011) developed correlation between the process parameters viz. cutting speed, depth of cut and feed rate by using the multiple regression analysis and examined the influence of machining conditions in turning of Duplex stainless steel 2205. **Deep et al.**

(2011) proposed a mathematical model for analyzing the effect of the machining parameters during single and multi-pass turning by using the Real Coded Genetic Algorithm.

In this present reporting, Taguchi's robust technique integrated with PCA and TOPSIS has been used to achieve an optimal machining parameter setting for enhancing surface quality of machined nylon product. PCA has been adopted to convert correlated multiple responses (multiple surface roughness characteristic indices) into uncorrelated quality indices called as principal components. TOPSIS has been applied to combine individual principal components into an Overall Performance Index (OPI). OPI has been optimized (maximized) finally using Taguchi method.

3.3Experimentation

Work material

Sample of Nylon 6 bars having dimension of diameter 50 mm and length of 150 mm (cutting length 50 mm) has been used as work-piece material. Structure of Nylon 6 has been shown in **Fig. 3.1**.

Tool material

Single point HSS tool of INDOLOV SHRIRAM IK-20 has been used during experiments.

Experimental set up

The turning operation has been carried on the manually operated Lathe PINACHO. The surface roughness parameters have been measured inTalysurf.

Design of Experiment (DOE)

For machining of nylon (turning operation), three controllable process parameters: spindle speed, feed and depth of cut have been chosen and these have been allowed to vary in five different levels **(Table 3.1)**. Taguchi's philosophy has been explored for adapting a framework for experimental design and its execution. L_{25} orthogonal array has been adopted for this experimental set up and furnished in **Table 3.2**. Here, only the direct / main effects of machining parameters i.e. spindle speed, feed rate and depth of cut has been considered for assessing the optimal condition. Parametric interaction effect has been assumed insignificant.

Response Measurement

Multiple surface roughness parameters (of the machined Nylon product) have been measured using the stylus-type profilometer, Talysurf (Taylor Hobson, Surtronic 3+). The values of measured roughness parameters: (average of five trials) R_q, R_a, R_t, R_{ku}, R_z, R_{sm} have been shown in **Table 3.3**. Pictorial representation of micro-surface profile has been shown at the end of this thesis in **Appendix 1**.

3.4Proposed Methodology

Thepreceding study highlights on procedural steps for the multi-response optimization based on PCA-TOPSIS combined with Taguchi's philosophy. Multiple responses always contain some extent of correlations; the PCA has been initially performed on the (Signal-to-Noise ratio) S/N values obtained from each response to reduce the dimension of multiple responses to a less number of uncorrelated indices called principal components (PCs). Quality loss estimates has been derived based on the deviation of individual PCs from their ideal value. Based on computed quality loss estimates, TOPSIS has been applied to determine the positive-ideal and negative-ideal solution and thus, closeness coefficient.The closeness coefficient has been treated here as OPI. Optimal factorial combination (parameter setting) has been evaluated finally by optimizing OPI using Taguchi method.

Step 1: calculate the S/N ratio

Taguchi'sformulae have been used to evaluate the S/N ratio for each response. For all surface quality characteristics considered in the present study, the Lower-the-Better (LB) criterion has been imposed on.

In this step, η_j^i (the SN ratio for the j_{th} response at the i_{th} trial, for ($i = 1, 2, ..., m$ and $j = 1, 2, ..., n$) is computed. According to Taguchi, the following three formulae are given:

$$\eta_j^i = -10\log_{10}\left[\frac{1}{l}\sum_{k=1}^{l} y_{jk}^{i\;2}\right],\ 0 \le y_{jk}^i \le \infty \text{ (Lower-the-Better)} \qquad \textbf{(3.1)}$$

$$\eta_j^i = -10\log_{10}\left[\frac{1}{l}\sum_{k=1}^{l} \frac{1}{y_{jk}^{i\;2}}\right],\ 0 \le y_{jk}^i \le \infty \text{ (Higher-the-Better)} \qquad \textbf{(3.2)}$$

$$\eta_j^i = -10\log_{10}\left[\frac{1}{l}\sum_{k=1}^{l} \frac{\bar{y}_j^{i\;2}}{S_j^{i\;2}}\right],\ 0 \le y_{jk}^i \le \infty \text{ ((Nominal-the-Best)} \qquad \textbf{(3.3)}$$

Here, y_{jk}^i =observed data for the j_{th} response at the i_{th} trial, the k_{th} repetition, $\bar{y}_j^i = \frac{1}{l}\sum_{k=1}^{l} y_{jk}^i$

(the average observed data for the j_{th} response at the i_{th} trial), $S_j^{i\;2} = \frac{1}{l-1}\sum_{k=1}^{l}\left(y_{jk}^i - \bar{y}_j^i\right)^2$ (the variation of observed data for the j_{th} response at the i_{th} trial,) for $i = 1, 2, ..., m$; $j = 1, 2, ..., n$ and $k = 1, 2, ..., l$.

Step 2: Normalisation of S/N ratios

After computing S/N ratio of experimentally obtained response data; the requirement of S/N ratio is *as high as possible*. Therefore, Higher-the-Better criterion has been presumed for the normalisation of S/N ratio values (of each response) by using the following equation:

$$S/N_i(k) = \frac{S/N_i - \min S/N_i(k)}{\max_i S/N_i(k) - \min_k S/N_i(k)} \qquad \textbf{(3.4)}$$

Here, S/N_i is the signal-to-noise ratio under the i^{th} experimental run, $\min S/N_i(k)$ minimum value of S/N ratio and $\max S/N_i(k)$ maximum value of S/N ratio of the experimental run.

Step 3: Application of PCA

PCA is a multivariate mathematical procedure which explores an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of uncorrelated indices called principal components (PCs). Each PC has the property of explaining the maximum possible amount of variance obtained in the original dataset. The PCs, which are expressed as linear combinations of the original variables which can be used for effective representation of the system under investigation, with a lower number of variables in the new system of variables being called scores, while the coefficient of linear combination describes each PCs, i.e. the weight of each PCs.

(a) Checking for correlation between each pair of quality characteristics

Let, $Q_i = \{X_0^*(i), X_1^*(i), X_2^*(i), ..., X_m^*(i)\}$ where, $i = 1,2,3,............, n.$ **(3.5)**

It is the normalized series of the *ith* quality characteristic. The correlation coefficient between two quality characteristics is calculated by the following equation:

$$\rho_{jk} = \frac{Cov(Q_j, Q_k)}{\sigma_{Q_j} \times \sigma_{Q_k}}$$ **(3.6)**

here,

$j = 1,2,3,......................, n$

$k = 1,2,3,......................, n$

$j \neq k$

Here, ρ_{jk} is correlation coefficient, σ_{Q_j} and σ_{Q_k} denotes standard deviation of the quality characteristics j and quality characteristics of k respectively.

(b) Calculation of the principal component score

1) Compute the Eigen value λ_k and the corresponding Eigen vector β_k $(k = 1,2,3,.........n)$ from the correlation matrix formed by all the quality characteristics.

2) Compute the principal component scores of the normalized reference sequence and comparative sequences using the equation shown below:

$$Y_i(k) = \sum_{j=1}^{n} X_i^*(j)\beta_{kj}, i = 0,1,2........, m, k = 1,2,3............., n \quad \textbf{(3.7)}$$

Here, $Y_i(k)$ is the principal component score of the kth element in the ith series. Let, $X_i^*(j)$ be the normalized value of the jth element in the ith sequence, and β_{kj} is the jth element of the Eigen vector β_k .

(c) Estimation of quality loss $\Delta_{0,i}(k)$

Loss estimate $\Delta_{0,i}(k)$ is defined as the absolute value of the difference between desired (ideal) value and ith experimental value for k_{th} response. If responses are correlated then instead of using [$X_o(k)$ $X_i(k)$]; [$Y_0(k)$ $Y_i(k)$] should be used for computation of $\Delta_{0,i}(k)$.

$$\Delta_{0,i} = \begin{Bmatrix} \left|X_0(k) - X_i(k)\right| \\ \left|Y_0(k) - Y_i(k)\right| \end{Bmatrix} \textbf{(3.8)}$$

Step 4: Apply TOPSIS to obtain the OPI for multiple responses

(Tong et al., 2005) initially proposed the TOPSIS for evaluating the alternatives before the multiple-attribute decision making. TOPSIS facilitates to assess the propinquity to the ideal solution. The basic fact of this method is that the chosen alternative should have the snippiestspace from the positive ideal solution and the uttermostspace from negative ideal solution. Positive ideal solution compromises of the best execution values to be demonstrated (in the decision matrix) by any alternative for each criteria attribute. The negative-ideal solution is the composite of the worst execution values. The steps involved for calculating the TOPSIS values are as follows:

(a) Development of matrix format

The row of this matrix is allocated to one alternative and each column to one attribute. The matrix can be expressed as:

$$D = \begin{array}{c} A_1 \\ A_2 \\ . \\ A_i \\ . \\ A_m \end{array} \begin{bmatrix} x_{11} & x_{12} & . & x_{1j} & x_{1n} \\ x_{21} & x_{22} & . & x_{2j} & x_{2n} \\ . & . & . & . & . \\ x_{i1} & x_{i2} & . & x_{ij} & . \\ . & . & . & . & . \\ x_{m1} & x_{m2} & . & x_{mj} & x_{mn} \end{bmatrix} \quad \textbf{(3.9)}$$

Here, A_i ($(i = 1, 2, ...,m)$ represents the possible alternatives; x_j $\left(j = 1, 2, ..., n\right)$ represents the attributes relating to alternative performance, $j = 1, 2, ..., n$ and x_{ij} is the performance of A_i with respect to attribute $X_{j.}$

(b) Obtain the normalized decision matrix r_{ij}

The quality loss ($\Delta_{0,i}(k)$) that has been estimated by aforesaid procedure has been normalized by the following equation

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \quad \textbf{(3.10)}$$

Here, r_{ij} represents the normalized performance of A_i with respect to attribute $X_{j.}$

(c) Obtain the weighted normalized decision matrix

$$V = \lfloor v_{ij} \rfloor$$

$$V = w_j r_{ij} \quad \textbf{(3.11)}$$

Here, $\sum_{j=1}^{n} w_j = 1$

(d) Determine the ideal (best) and negative ideal (worst) solutions

The ideal solution is given by:

$$A^+ = \left\{ \left(\max_i v_{ij} \middle| j \in J \right), \left(\min_i v_{ij} \middle| j \in J' \middle| i = 1, 2, \ldots\ldots\ldots, m \right) \right\} \quad \textbf{(3.12)}$$

$$= \left\{ v_1^+, v_2^+, \ldots\ldots\ldots, v_j^+, \ldots\ldots v_n^+ \right\}$$

The negative ideal solution is given by:

$$A^- = \left\{ \left(\min_i v_{ij} \middle| j \in J \right), \left(\max_i v_{ij} \middle| j \in J' \middle| i = 1, 2, \ldots\ldots\ldots, m \right) \right\} \quad \textbf{(3.13)}$$

$$= \left\{ v_1^-, v_2^-, \ldots\ldots\ldots, v_j^-, \ldots\ldots v_n^- \right\}$$

Here,

$J = \left\{ j = 1,2,\ldots\ldots\ldots, n \middle| j \right\}$: Associated with the beneficial attributes

$J' = \left\{ j = 1,2,\ldots\ldots\ldots, n \middle| j \right\}$: Associated with non beneficial attributes

(e) Determine the distance measures

The separation of each alternative from the ideal solution is given by n- dimensional Euclidean distance from the following equations:

$$S_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^+ \right)^2} \quad i = 1, 2, \ldots\ldots\ldots, m \quad \textbf{(3.14)}$$

$$S_i^- = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_j^-\right)^2} \quad i = 1, 2, \ldots\ldots\ldots, m \qquad \textbf{(3.15)}$$

(f) ***Calculate the relative closeness (closeness coefficient) to the ideal solution***

$$C_i^+ = \frac{S_i^-}{S_i^+ + S_i^-}, \quad i = 1, 2, \ldots\ldots\ldots, m; 0 \le C_i^+ \le 1 \qquad \textbf{(3.16)}$$

Step 5: Determine the optimum process variable by optimization OPI using Taguchi method

The optimum process parameter combination ensureshighest OPI value. The closeness coefficient value is optimized using Taguchi method. For calculating S/N ratio (corresponding to the values of closeness coefficient); Higher-the-Better (HB) criterion is to be considered. As larger the value of closeness coefficient, better is the proximity to the ideal solution.

3.5Results

Experimental data have been analyzed by following aforesaid procedure. The S/N ratios for each response evaluated by using Taguchi‘s S/N ratio formula has been furnished in the **Table 3.4**. S/N ratios (of the responses i.e. multiple surface roughness characteristics) have been normalized by using **Eq. 3.4** and these have been shown in **Table 3.5**.

The Pearson’s correlation coefficient between individual responses pairs have been valuated **(Table 3.6)**next. Eigen values, Eigen vectors, accountability proportion (AP) and cumulative accountability proportion (CAP) computed in PCA for the six surface quality indicators (S/N ratios) has been shown in **Table 3.7**. It has been found that, the first four PCs can take care of 68.2%, 28.7%, 1.9% and 0.9% data variability respectively. The contribution of fifth and sixth PCs has been found negligible effect to interpret data variability. Consequently, the effects of these PCs have been snubbed and the first four PCs have been considered for further analysis **(Table 3.8)**. From the aforementioned four major PCs, the quality loss estimates have been assessed **(Eq. 3.8)** and their representing values have been tabulated in **Table 3.9**.

TOPSIS has been applied utilizing these quality loss estimates. Individual experimental runs have been dealt as the alternatives and the normalized decision matrix have been calculated shown in the **Table 3.10**. The weighted normalized matrix has been presented in **Table 3.11**. The positive ideal and negative-ideal solution has been evaluated by using **Eqs. 3.12-3.13** and confronted in **Table 3.12**. The deviation from the ideal solution (distance measures) has been assessed from the Euclidian equation and tabulated in **Table 3.13**. The relative closeness measure (closeness coefficient) has been calculated using**Eq. 3.16**and furnished in **Table 3.14**.

Finally, the Taguchi method has been applied on the closeness coefficient (OPI) to assess the optimal machining parameter by using S/N ratio plot of OPI**(Table 3.15**, **Fig.3.2)**. Higher the value of closeness coefficient, the corresponding parameter combination is said to be close to the optimal solution. The optimal parametric combination has been found as $N_4F_1D_5$. In coded form it is $A_4B_1C_5$. It has been found that at optimal setting predicted value of S/N ratio has become 0.94220 (highest among all entries of corresponding S/N ratio values in **Table 3.14**); whereas in confirmatory test it has reached a value i.e. 1.200. So quality has been improved using this optimal level.

3.6Concluding Remarks

The antecedentresearch has applied PCA and TOPSIS method coupled with Taguchi's parameter design philosophy for optimization of the process variables forproducing good surface finish of the machined nylon product. Correlated multiple responses has been transformed into equal or less number of uncorrelated quality indices with the aid of PCA, whichfacilitates insituation towards optimization of large number of responses. TOPSIS has been found efficient to convert the multiple responses (criteria-attributes) into a single objective function i.e. closeness coefficient. This closeness coefficient has been treated as the Overall Performance Index (OPI) to be optimized (maximized) by Taguchi method. The integrated approach highlighted in this chapter can be efficiently applied for continuous quality improvement and off-line quality control in any production processes which involve multiple response features correlated with each other.

3.7Bibliography

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Table 3.1: Domain of experiments (process control parameters and their limits)

Sl. No.	Factors	Notation	Unit	Level 1	Level 2	Level3	Level 4	Level 5
1	Spindle Speed	N (A)	RPM	260	360	530	860	1400
2	Feed rate	F (B)	mm/rev	0.050	0.052	0.055	0.060	0.063
3	Depth of cut	D (C)	mm	2	3	4	5	6

Table 3.2: L_{25} orthogonal array design of experiment

Sl. No.	Factorial combinations (coded form)		
	N (A)	F (B)	D (C)
1	1	1	1
2	1	2	2
3	1	3	3
4	1	4	4
5	1	5	5
6	2	1	2
7	2	2	3
8	2	3	4
9	2	4	5
10	2	5	1
11	3	1	3
12	3	2	4
13	3	3	5
14	3	4	1
15	3	5	2
16	4	1	4
17	4	2	5
18	4	3	1
19	4	4	2
20	4	5	3
21	5	1	5
22	5	2	1
23	5	3	2
24	5	4	3
25	5	5	4

Table 3.3:Multiple surface roughness estimates of statistical significance

Sl. No.	R_a µm	R_q µm	R_t µm	R_{ku}	R_z µm	R_{sm} mm
1	2.528	2.892	13	2.016	10.634	65.74
2	2.334	2.902	16.22	3.192	13.32	72.88
3	.3836	.5888	8.162	44.22	2.97	338.8
4	3.324	4.156	23.22	2.976	18.62	83.24
5	3.014	3.728	21.38	2.9	17.7	72.88
6	2.878	3.324	18.72	2.63	12.24	69.06
7	2.434	2.972	17.16	2.848	13.68	68.4
8	2.234	2.84	17.8	3.422	14.66	64.04
9	.9452	1.6518	32.88	724.6	8.458	927.4
10	2.1918	2.6962	19.2	39.06	12.326	66.26
11	3.112	3.428	15.2	2.056	12.62	66.92
12	4.628	7.802	184	341.8	41.6	877.8
13	4.548	8.146	184	320.2	44	1294
14	2.592	3.068	32.86	57.8	9.372	289.4
15	2.186	2.624	15.34	2.722	12.14	61.12
16	8.572	15.3	194	45.92	86	796.8
17	8.985	15.6	194	41.82	85.6	752.6
18	19.58	30.42	208	5.348	153.6	593.4
19	2.358	2.882	16.8	2.792	13.22	65.9
20	6.4558	7.438	38.68	4.644	31.408	290.2
21	4.466	7.316	190	412	40	593
22	.826	1.388	18.26	106.12	6.826	412.6
23	5.7698	7.0834	39.8	232.01	30.586	428.44
24	8.888	10.86	60.24	2.892	47.38	120.2
25	5.7216	7.3252	69.934	109.438	31.1956	331.2

Table 3.4: Calculated S/N ratio of each response

Sl. No.	Calculated S/N ratios for:					
	R_a dB	R_q dB	R_t dB	R_{ku} dB	R_z dB	R_{sm} dB
1	-8.0555	-9.2240	-22.2789	-6.0898	-20.5339	-36.3566
2	-7.3620	-9.2539	-24.2010	-10.0813	-22.4901	-37.2522
3	8.3224	4.6006	-18.2359	-32.9124	-9.4551	-50.5989
4	-10.4332	-12.3735	-27.3172	-9.4727	-25.3996	-38.4066
5	-9.5829	-11.4295	-26.6002	-9.2480	-24.9595	-37.2522
6	-9.1818	-10.4332	-25.4461	-8.3991	-21.7556	-36.7845
7	-7.7264	-9.4610	-24.6903	-9.0908	-22.7217	-36.7011
8	-6.9817	-9.0664	-25.0084	-10.6856	-23.3227	-36.1290
9	0.4895	-4.3591	-30.3386	-57.2020	-18.5454	-59.3453
10	-6.8160	-8.6150	-25.6660	-31.8346	-21.8164	-36.4250
11	-9.8608	-10.7008	-23.6369	-6.2605	-22.0212	-36.5111
12	-13.3079	-17.8441	-45.2964	-50.6754	-32.3819	-58.8679
13	-13.1564	-18.2189	-45.2964	-50.1084	-32.8691	-62.2387
14	-8.2727	-9.7371	-30.3334	-35.2386	-19.4366	-49.2300
15	-6.7930	-8.3793	-23.7165	-8.6978	-21.6844	-35.7237
16	-18.6616	-23.6938	-45.7560	-33.2400	-38.6900	-58.0270
17	-19.0704	-23.8625	-45.7560	-32.4277	-38.6495	-57.5313
18	-25.8363	-29.6632	-46.3613	-14.5638	-43.7278	-55.4670
19	-7.4509	-9.1939	-24.5062	-8.9183	-22.4246	-36.3777
20	-16.1990	-17.4291	-31.7497	-13.3378	-29.9408	-49.2539
21	-12.9984	-17.2855	-45.5751	-52.2979	-32.0412	-55.4611
22	1.6604	-2.8478	-25.2300	-40.5159	-16.6833	-52.3106
23	-15.2232	-17.0048	-31.9977	-47.3101	-29.7105	-52.6378
24	-18.9761	-20.7166	-35.5977	-9.2240	-33.5119	-41.5981
25	-15.1503	-17.2964	-36.8938	-40.7834	-29.8819	-50.4018

Table 3.5: Normalized S/N ratio

Sl. No.	Normalized S/N ratios					
	R_a	R_q	R_t	R_{ku}	R_z	R_{sm}
Ideal Situation	1	1	1	1	1	1
1	0.520535	0.596525	0.856251	1	0.676746	0.97613
2	0.540837	0.595652	0.787911	0.921907	0.619668	0.942353
3	1	1	1	0.475221	1	0.438989
4	0.450928	0.504605	0.677114	0.933814	0.534775	0.898816
5	0.47582	0.532156	0.702607	0.93821	0.547617	0.942353
6	0.487562	0.561234	0.743641	0.954819	0.641099	0.959992
7	0.530169	0.589608	0.770513	0.941286	0.612911	0.963138
8	0.551971	0.601124	0.759203	0.910084	0.595375	0.984714
9	0.770691	0.738508	0.569688	0	0.734766	0.109123
10	0.556822	0.614298	0.735822	0.496308	0.639325	0.973551
11	0.467685	0.553424	0.807967	0.99666	0.63335	0.970304
12	0.36677	0.344944	0.037863	0.127692	0.331048	0.127128
13	0.371206	0.334006	0.037863	0.138785	0.316832	0
14	0.514176	0.58155	0.569873	0.42971	0.708762	0.490617
15	0.557495	0.621177	0.805137	0.948975	0.643177	1
16	0.21004	0.174219	0.021521	0.468812	0.146992	0.158842
17	0.198073	0.169295	0.021521	0.484704	0.148173	0.177537
18	0	0	0	0.834208	0	0.255391
19	0.538235	0.597403	0.777059	0.944661	0.621579	0.975335
20	0.282133	0.357056	0.519516	0.858194	0.402274	0.489715
21	0.375831	0.361247	0.027953	0.095948	0.340989	0.255614
22	0.804969	0.782616	0.751324	0.32646	0.789097	0.374433
23	0.3107	0.369439	0.510699	0.193533	0.408993	0.362093
24	0.200833	0.261109	0.3827	0.93868	0.298077	0.77845
25	0.312834	0.360929	0.336617	0.321227	0.403992	0.446423

Table 3.6: Check for correlation among response pairs

Sl. No.	Correlation Between	Pearson's Correlation Coefficient	P-Value
1	R_a, R_q	0.987	0.000*
2	R_a, R_t	0.737	0.000*
3	R_a, R_{ku}	-0.077	0.715
4	R_a, R_z	0.943	0.000*
5	R_a, R_{sm}	0.245	0.238
6	R_q, R_t	0.846	0.000*
7	R_q, R_{ku}	0.066	0.753
8	R_q, R_z	0.987	0.000*
9	R_q, R_{sm}	0.405	0.045*
10	R_t, R_{ku}	0.518	0.008*
11	R_t, R_z	0.884	0.000*
12	R_t, R_{sm}	0.765	0.000*
13	R_{ku}, R_z	0.128	0.541
14	R_{ku}, R_{sm}	0.830	0.000*
15	R_z, R_{sm}	0.466	0.019*

*Significant correlation

Table 3.7: Results of PCA: Eigen values, eigenvectors, accountability proportion (AP) and cumulative accountability proportion (CAP)

	PC1	PC2	PC3	PC4	PC5	PC6
Eigen value	4.0948	1.7228	0.1114	0.0533	0.0171	0.0006
Eigen vector	$\begin{vmatrix} 0.994 \\ 0.990 \\ 0.775 \\ -0.042 \\ 0.969 \\ 0.278 \end{vmatrix}$	$\begin{vmatrix} -0.033 \\ 0.121 \\ 0.570 \\ 0.984 \\ 0.185 \\ 0.910 \end{vmatrix}$	$\begin{vmatrix} -0.008 \\ -0.060 \\ -0.058 \\ 0.174 \\ -0.075 \\ -0.304 \end{vmatrix}$	$\begin{vmatrix} -0.049 \\ 0.026 \\ 0.267 \\ -0.002 \\ 0.082 \\ 0.050 \end{vmatrix}$	$\begin{vmatrix} -0.087 \\ -0.011 \\ 0.015 \\ 0.006 \\ 0.123 \\ 0.012 \end{vmatrix}$	$\begin{vmatrix} -0.015 \\ 0.020 \\ 0.001 \\ 0.001 \\ -0.004 \\ 0.001 \end{vmatrix}$
AP	0.682	0.287	0.019	0.009	0.003	0.000
CAP	0.682	0.970	0.988	0.997	1.000	1.000

Table 3.8: Calculated values of major principal components (PCs)

Sl. No.	PC1	PC2	PC3	PC4
Ideal solution	3.964	2.737	-0.331	0.374
1	2.60272	2.530236	-0.25894	0.316354
2	2.498471	2.362392	-0.25483	0.290087
3	3.832419	1.655294	-0.26146	0.34711
4	2.124005	2.246118	-0.21923	0.252179
5	2.222267	2.31035	-0.23608	0.261884
6	2.404853	2.391274	-0.25068	0.282852
7	2.465602	2.390637	-0.25537	0.286154
8	2.477436	2.366735	-0.2666	0.281828
9	2.641191	0.510994	-0.18684	0.195715
10	2.543227	1.903847	-0.34618	0.280272
11	2.419335	2.480894	-0.24819	0.300476
12	0.978359	0.241372	-0.07455	0.025086
13	0.919933	0.133207	-0.03189	0.016836
14	2.287523	1.309802	-0.20636	0.219877
15	2.595123	2.461768	-0.27188	0.299616
16	0.424772	0.5768	0.010094	0.007101
17	0.413803	0.611166	0.007757	0.008573
18	-0.13028	1.004073	0.077376	-0.00299
19	2.499491	2.411698	-0.2601	0.289145
20	1.427275	1.660678	-0.07842	0.18151
21	1.044312	0.321924	-0.12107	0.02987
22	2.980008	1.227279	-0.22289	0.261446
23	1.464129	0.81809	-0.1686	0.173813
24	1.103607	1.90152	-0.1272	0.150711
25	1.334742	0.932405	-0.15863	0.13046

Table 3.9: Computed quality loss estimates of PC1 to PC4

Sl. No.	Quality loss estimates			
	PC1	PC2	PC3	PC4
1	1.36128	0.206764	0.07206	0.057646
2	2.49847	2.36239	0.25483	0.29009
3	3.83242	1.65529	0.261455	0.34711
4	2.124	2.24612	0.21923	0.25218
5	2.22227	2.31035	0.23608	0.26188
6	2.40485	2.39127	0.250683	0.28285
7	2.4656	2.39064	0.255367	0.28615
8	2.47744	2.36673	0.2666	0.28183
9	2.64119	0.51099	0.186838	0.19572
10	2.54323	1.90385	0.346182	0.28027
11	2.41933	2.48089	0.248187	0.30048
12	0.97836	0.24137	0.074547	0.02509
13	0.91993	0.13321	0.031894	0.01684
14	2.28752	1.3098	0.206362	0.21988
15	2.59512	2.46177	0.271876	0.29962
16	0.42477	0.5768	0.01009	0.0071
17	0.4138	0.61117	0.00776	0.00857
18	0.130278	1.00407	0.07738	0.002994
19	2.49949	2.4117	0.2601	0.28915
20	1.42727	1.66068	0.078424	0.18151
21	1.04431	0.32192	0.121066	0.02987
22	2.98001	1.22728	0.222892	0.26145
23	1.46413	0.81809	0.168603	0.17381
24	1.10361	1.90152	0.127205	0.15071
25	1.33474	0.9324	0.158633	0.13046

Table 3.10: Normalized quality loss coefficients

Sl. NO.	Normalized quality loss coefficients			
	PC1	PC2	PC3	PC4
1	0.131604	0.024586	0.072244	0.052989
2	0.241543	0.280906	0.255482	0.266654
3	0.370505	0.196826	0.262124	0.319067
4	0.205341	0.26708	0.219791	0.231806
5	0.214841	0.274718	0.236684	0.240723
6	0.232492	0.28434	0.251325	0.259998
7	0.238365	0.284265	0.256021	0.263032
8	0.23951	0.281422	0.267282	0.259061
9	0.255341	0.060761	0.187316	0.179908
10	0.24587	0.226382	0.347068	0.257627
11	0.233892	0.294996	0.248822	0.276204
12	0.094584	0.028701	0.074738	0.023063
13	0.088936	0.01584	0.031976	0.015479
14	0.221149	0.155745	0.20689	0.202116
15	0.250887	0.292723	0.272572	0.275414
16	0.041065	0.068586	0.010116	0.006526
17	0.040005	0.072673	0.00778	0.007878
18	0.012595	0.119391	0.077578	0.002752
19	0.241642	0.286769	0.260766	0.265789
20	0.137983	0.197467	0.078625	0.166846
21	0.10096	0.038279	0.121376	0.027457
22	0.288097	0.145933	0.223462	0.240327
23	0.141547	0.097277	0.169035	0.159768
24	0.106693	0.226105	0.127531	0.138534
25	0.129038	0.110869	0.159039	0.11992

Table 3.11: Weighted normalized quality loss coefficients of majors PCs

Sl. No.	Weighted normalized quality loss coefficients			
	PC1	PC2	PC3	PC4
1	0.089754	0.007056	0.001373	0.000477
2	0.164732	0.08062	0.004854	0.0024
3	0.252684	0.056489	0.00498	0.002872
4	0.140042	0.076652	0.004176	0.002086
5	0.146522	0.078844	0.004497	0.002167
6	0.15856	0.081606	0.004775	0.00234
7	0.162565	0.081584	0.004864	0.002367
8	0.163346	0.080768	0.005078	0.002332
9	0.174142	0.017438	0.003559	0.001619
10	0.167684	0.064972	0.006594	0.002319
11	0.159515	0.084664	0.004728	0.002486
12	0.064507	0.008237	0.00142	0.000208
13	0.060654	0.004546	0.000608	0.000139
14	0.150824	0.044699	0.003931	0.001819
15	0.171105	0.084011	0.005179	0.002479
16	0.028007	0.019684	0.000192	.000058734
17	0.027283	0.020857	0.000148	.0000709
18	0.00859	0.034265	0.001474	.0000248
19	0.1648	0.082303	0.004955	0.002392
20	0.094105	0.056673	0.001494	0.001502
21	0.068855	0.010986	0.002306	0.000247
22	0.196482	0.041883	0.004246	0.002163
23	0.096535	0.027919	0.003212	0.001438
24	0.072765	0.064892	0.002423	0.001247
25	0.088004	0.03182	0.003022	0.001079

Table 3.12: Ideal and negative-ideal solutions

Sl. No.	Ideal positive	Ideal negative
1	0.00859	0.252684
2	0.004546	0.084664
3	0.000148	0.006594
4	0.0000248	0.002486

Table 3.13: Separation measures between attributes from ideal and negative ideal solution

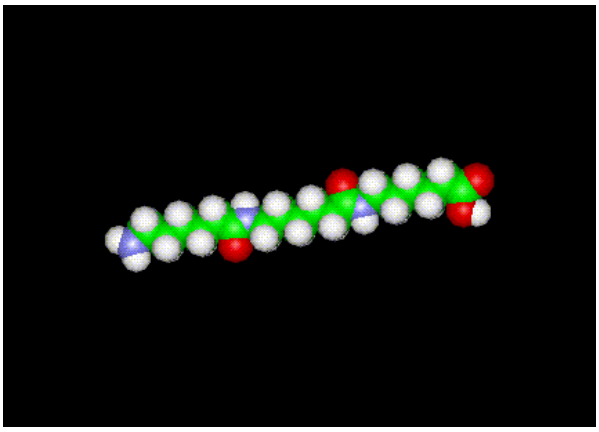
Sl. No.	S^-	S^+
1	0.247769	0.085351
2	0.093821	0.239298
3	0.030174	0.303717
4	0.123471	0.209648
5	0.114399	0.21872
6	0.099147	0.233972
7	0.095047	0.238072
8	0.094904	0.238215
9	0.149669	0.18345
10	0.10486	0.228259
11	0.095036	0.238083
12	0.272057	0.061062
13	0.280481	0.052638
14	0.145155	0.187964
15	0.083654	0.249465
16	0.298486	0.034633
17	0.298069	0.035051
18	0.302074	0.031046
19	0.091979	0.24114
20	0.192655	0.140464
21	0.264034	0.069085
22	0.101655	0.231465
23	0.217325	0.115794
24	0.205101	0.128018
25	0.222504	0.110616

Table 3.14: Closeness coefficient and corresponding S/N ratio

Sl. No.	C_i^+	S/N Ratio
1	0.743783	-2.5711
2	0.281644	-11.0060
3	0.090371	-20.8794
4	0.370651	-8.6207
5	0.343418	-9.2835
6	0.297632	-10.5264
7	0.285324	-10.8932
8	0.284895	-10.9063
9	0.449296	-6.9494
10	0.314782	-10.0398
11	0.285291	-10.8942
12	0.816696	-1.7588
13	0.841984	-1.4939
14	0.435745	-7.2153
15	0.251123	-12.0023
16	0.896034	-0.9535
17	0.894780	-0.9657
18	0.906802	-0.8497
19	0.276115	-11.1782
20	0.578337	-4.7564
21	0.792612	-2.0188
22	0.305160	-10.3094
23	0.652394	-3.7098
24	0.615699	-4.2126
25	0.667939	-3.5053

Table 3.15: Mean response table for S/N ratio of OPI

Level	N	F	D
1	-10.472	-5.393	-6.197
2	-9.863	-6.987	-9.685
3	-6.673	-7.5681	-10.327
4	-3.471	-7.635	-5.149
5	-4.751	-7.917	-4.142
Delta = Max.-Min.	6.731	2.525	6.185
Rank	1	3	2



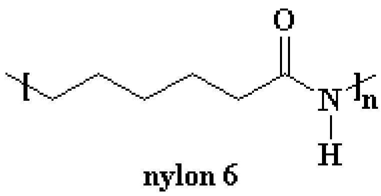


Fig.3.1: Nylon 6 molecule

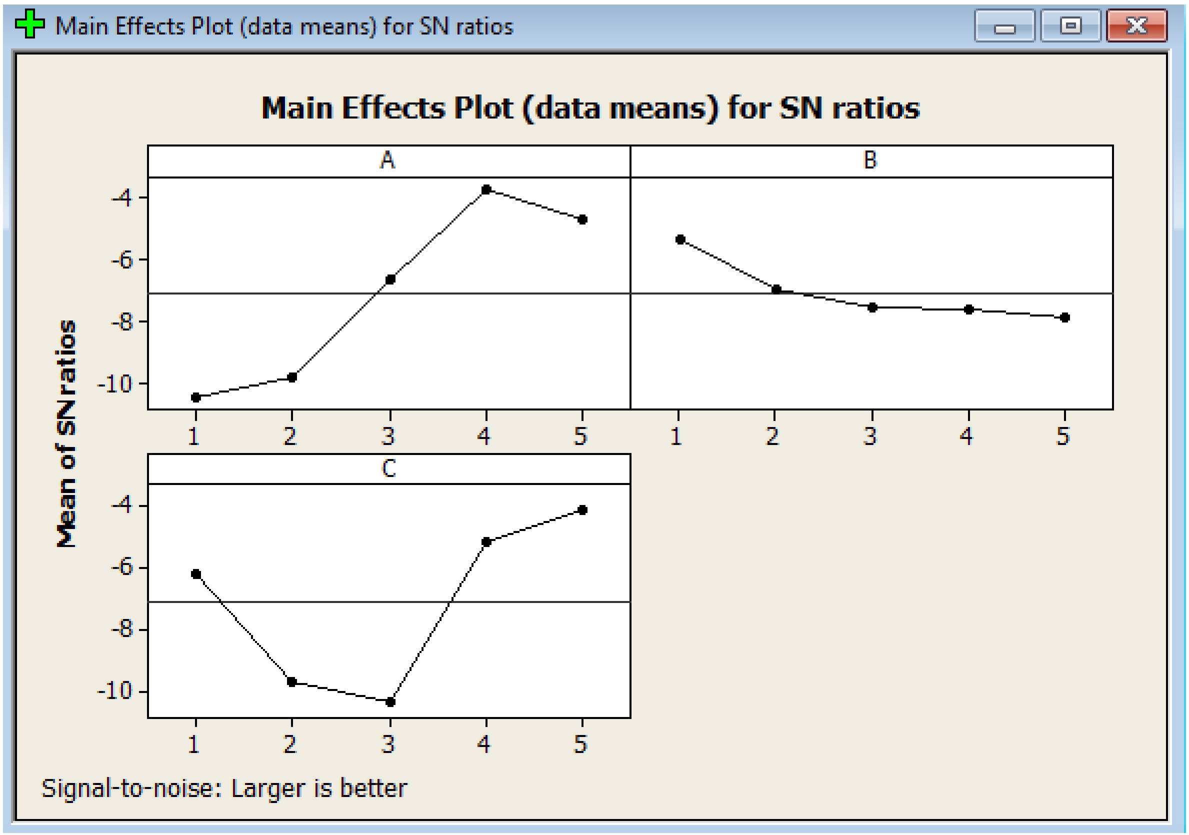


Fig.3.2: S/N ratio plot (of OPI): Evaluation of optimal setting

CHAPTER 4: Machining of Teflon

Machining of polymeric materials has been increasingly carried out and has become necessary when the quantity of precious items does not justify the cost of tooling for moulds or extrusion dies, or when a product needs a costly dimensional accuracy, precision and surface finish. Depending on multi-requirements of overall product quality; machining parameters optimization is indeed essential especially in mass production line. Determining an optimal parameter setting is seemed very difficult due to involvement of multiple product quality characteristics and the extent of correlation associated with them. To address this issue, in the present work, a Taguchi based integrated optimization approach combining Principal Component Analysis (PCA) and TOPSIS has been attempted for optimal machining parameters selection for surface quality improvement in machining of PTFE (Teflon). Various statistical measures (parameters) of surface roughness characteristic (of the machined Teflon product) have been optimized simultaneously. Detailed methodology and effectiveness of the aforesaid approach has been illustrated.

4.1 Introduction to PTFE: Structure, Properties, Application and Machinability

Polytetrafluoroethylene (PTFE) is a synthetic fluoropolymer of tetrafluoroethylene **(Fig. 4.1)**, most widely known by DuPont's trade name of Teflon, was discovered in 1938 by Roy J. Plunkett at DuPont’s laboratories. Teflon was found to be heat resistant and chemically inert and to have very low surface friction. In electrical applications, Teflon exhibits excellent electrical stability over a wide range of frequency and environmental conditions. Teflon is unaffected by outdoor weathering, it is non-flammable and non-adhesive.

PTFE is a fluorocarbon solid, as it is a high-molecular-weight compound consisting of carbon and fluorine. PTFE is hydrophobic i.e. neither water nor water-containing substances wet PTFE, as fluorocarbons demonstrate mitigated dispersion forces (part of the van der Waals forces) due to the high electro-negativity of fluorine. PTFE has one of the lowest coefficients of friction against any solid.

PTFE is widely used as a non-stick coating for cookware. It is very non-reactive, partly because of the strength of carbon–fluorine bonds, and so it is often used in containers and pipe work for reactive and corrosive chemicals. Where used as a lubricant, PTFE reduces friction, wear, and energy consumption of machinery.

PTFE has excellent dielectric properties. This is especially true at high radio frequencies, making it suitable for use as an insulator in cables and connector assemblies and as a material for printed circuit boards used at microwave frequencies. Combined with its high melting temperature, this makes it the material of choice as a high-performance substitute for the weaker and lower melting point polyethylene that is commonly used in low-cost applications.

Because of its chemical inertness, PTFE cannot be cross-linked like an elastomer. Therefore, it has no ‘memory’ and is subject to creep. This is advantageous when used as a seal, because the material creeps a small amount to conform to the mating surface. However, to keep the seal from creeping too much, fillers are used, which can also improve wear resistance and reduce friction. Sometimes, metal springs apply continuous force to PTFE seals to give good contact, while permitting a beneficially low percentage of creep.

Owing to its low friction, it is used for applications where sliding action of parts is needed: plain bearings, gears, slide plates, etc. In these applications, it performs significantly better than nylon and acetal (Polyoxymethylene); it is comparable to ultra-high-molecular-weight polyethylene (UHMWPE), although UHMWPE is more resistant to wear than Teflon. For these applications, versions of Teflon with mineral oil or molybdenum disulfide embedded as additional lubricants in its matrix are being manufactured. It’s extremely high bulk resistivity makes it an ideal material for fabricating long-life electrets, useful devices that are the electrostatic analogues of magnets.

Powdered PTFE is used in pyrotechnic compositions as oxidizers together with powdered metals such as aluminum and magnesium. Upon ignition, these mixtures form carbonaceous soot and the corresponding metal fluoride, and release large amounts of heat. Hence they are used as infrared decoy flares and igniters for solid-fuel rocket propellants.

In optical radiometry, sheets made from PTFE are used as measuring heads in spectroradiometers and broadband radiometers (e.g., illuminance meters and UV radiometers) due to its capability to diffuse a transmitting light nearly perfectly.

PTFE is also used to coat certain types of hardened, armor-piercing bullets, so as to prevent the increased wear on the firearm's rifling that would result from the harder projectile.

High corrosion resistance favors the use of PTFE in laboratory environments as containers, as magnetic stirrer coatings, and as tubing for highly corrosive chemicals such as hydrofluoric acid, which will dissolve glass containers. PTFE is also widely used as a thread seal tape in plumbing applications, largely replacing paste thread dope. PTFE can be used to prevent insects climbing up surfaces painted with the material. PTFE is so slippery that insects cannot get a grip and tend to fall off.

PTFE machining or Teflon machining has a variety of uses as manifolds, insulators, guides, slide blocks, cathode and anode end blocks, arc shields, beads, seals, washers, valve seats and can be found in many industries.

Because of its unique molecular structure, granular PTFE does not melt. It cannot be molded into complex forms like other plastics. However, it is easily machined on all standard equipment, including the most advanced CNC machining equipment. PTFE can be cut, bored, milled and turned using standard tooling. PTFE is very resilient which allows machined parts to conform to most working dimensions. A part can sometimes be press-fitted at lower cost than doing final machining to exact size. When closer tolerances are required, it is essential to use stress-relieved products. A complete machine shop is indeed required to turn out finished parts from prototypes up to production quantities.

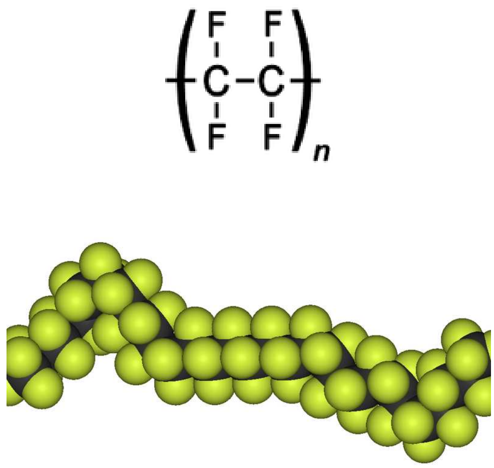


Fig. 4.1: Structure of PTFE

4.2 Literature review on Surface Quality Improvement in Machining

Lee and Tang (2000) developed the polynomial network model to assess the optimum cutting parameters to enhance the production rate. The model itself established the relationship between the machining parameters (cutting speed, feed, and depth of cut) and machined performances (surface finishing and tool life). **Suresh et.al (2002)** proposed the surface roughness predication model by using Response Surface Methodology (RSM) combined with Genetic Algorithms (GA) for machining the mild steel. **Hocheng et al. (2004)** predicated the mathematical model based on the Fourier transform to evaluate the surface roughness on turning the phosphor–bronze lens mould. **Sahin et al. (2004)** derived a surface roughness prediction model in turning of AISI 1040 carbon steel by using RSM and optimized the machining parameters viz. cutting speed, depth of cut and feed rate. **Özel and**

karpat (2005) presented the neural network model to predict cutting tool flank wear and surface roughness and compared with the regression model. **Palanikumar et al. (2006)** developed empirical model for studying the correlation between the machining parameters and surface roughness in machining of GFRP composites by using the carbide tool. The optimal cutting parameters were assessed by using fuzzy logic coupled with Taguchi's robust technique. **Doniavi et al. (2007)** suggested an empirical model for improving surface finish by using RSM methodology based on the full factorial design of experiment. **Raj and Namboothiri (2010)** investigated the influence of the machining parameters to assess the surface finish on the dry turning of stainless steel materials by using the Genetic Algorithm. **Datta and Mahapatra (2010)** adopted the utility theory combined with the PCA and Taguchi robust technique for assessing the optimal condition in straight turning of mild steel.

Literature highlights immense exertions by the pioneers to study the various aspects of the machining operations and output performance measures, especially on conventional metals, composites to a limited extent. Issues of tool life, tool wears and product surface quality have been addressed too. Statistical modelling and parametric appraisal-optimization have also been attempted by previous investigators. But with the upcoming widespread application of polymeric materials, machining and machinability issues have gained immense importance. Surface roughness is the major concern in machining polymeric materials. However, past research highlighted in literature mainly concentrated on average surface roughness of the machined product. Apart from roughness average, there exist a number of statistical measures for describing product surface integrity which need to be taken under consideration. Simultaneously there is an increasing need to optimize process environment for producing desired surface quality. In this context, in the current research, Principal Component Analysis (PCA) and TOPSIS method have been integrated with Taguchi's robust design philosophy in order to select the most suitable machining parameters for producing good surface finish of the machined Teflon product. PCA has been implemented to convert the correlated of response variables (multiple surface roughness parameters) into uncorrelated quality indices called as principal components. TOPSIS has applied to combine multiple uncorrelated responses into an overall performance index (OPI) which has been maximized finally by the Taguchi method.

Lan et al. (2010) presented a study on the multiple-attribute optimization of (cutting depth, feed rate, speed, tool nose runoff) by using the FAHP (Fuzzy Analytic Hierarchy Process) coupled with TOPSIS in turning on an ECOCA-3807 on CNC lathe. **Lee et al. (2005)** proposed a procedure for optimization of multiple responses by using Taguchi robust technique coupled with the principal component analysis (PCA) combined with TOPSIS method. The study on chemical-mechanical polishing of copper (Cu-CMP) thin films demonstrated the effectiveness of the said approach.

4.3 Experimentation

Work Material

Teflon bar $(\phi 30 \times 50)$ has been used as the work-piece material.

Cutting Tool

Single point HSS cutting tool of INDLOV SHRIRAM IK 20 has been used.

Experimental Setup

The machining of Teflon samples has been performed on the PINACHO manually operated lathe.

Design of Experiment (DOE)

Taguchi's L_{25} orthogonal array (OA) design of experiment has been adopted. Here the machining parameters (spindle speed, feed rate and depth of cut) have been varied in five different levels to optimize the machining condition. Interaction effect of process parameters have been assumed negligible. Domain of experiment (process parameters and their levels of variation) has been shown in **Table 4.1**. Selected L_{25} orthogonal array (OA) has been furnished in **Table 4.2** (all factors in coded form).

Response Measurement

Multiple surface roughness parameters (of the machined Teflon product) have been measured using the stylus-type profilometer, Talysurf (Taylor Hobson, Surtronic 3+). The values of measured roughness parameters: (average of two trials) R_q, R_a, R_t, R_{ku}, R_z, R_{sm} have been shown in **Tables 4.3.1-4.3.2** with corresponding S/N ratio values. Pictorial representation of micro-surface profile has been shown in **Appendix 2**, at the end of this thesis.

4.4 Proposed Methodology

The methodology adapted for optimization in the present study has already been discussed in **Chapter 2 (Section 2.4)**. For the convenience of understanding to the readers it has been reproduced below.

This study attempts optimization procedure for multiple responses based on PCA and TOPSIS integrated with Taguchi's parameter design. Because multiple responses always contain some extent of correlations; the PCA has been initially performed on the (Signal to Noise) S/N values obtained from each response to reduce the dimension of multiple responses to a smaller number of uncorrelated indices called principal components (PCs). Quality loss estimates has been derived based on the deviation of individual PCs from their ideal value. Finally, TOPSIS has been applied to determine the ideal and negative-ideal solution and finally to obtain the closeness coefficient which has been treated as OPI. Optimal factorial combination (parameter setting) has been evaluated finally by Taguchi method. The aforesaid procedural hierarchy for optimizing multi-response problems includes the following seven steps:

Step 1: Calculate the SN ratio for each response

In this step, η_j^i (the SN ratio for the j_{th} response at the i_{th} trial, for ($i = 1, 2, ..., m$ and $j = 1, 2, ..., n$) is computed. According to Taguchi, the following three formulae are given:

$$\eta_j^i = -10\log_{10}\left[\frac{1}{l}\sum_{k=1}^{l} {y_{jk}^i}^2\right],\ 0 \le y_{jk}^i \le \infty \text{ (Lower-the-Better)} \qquad \textbf{(4.1)}$$

$$\eta_j^i = -10\log_{10}\left[\frac{1}{l}\sum_{k=1}^{l} \frac{1}{{y_{jk}^i}^2}\right],\ 0 \le y_{jk}^i \le \infty \text{ (Higher-the-Better)} \qquad \textbf{(4.2)}$$

$$\eta_j^i = -10\log_{10}\left[\frac{1}{l}\sum_{k=1}^{l} \frac{{\bar{y}_j^i}^2}{{S_j^i}^2}\right],\ 0 \le y_{jk}^i \le \infty \text{ (Nominal-the-Best)} \qquad \textbf{(4.3)}$$

Here, y_{jk}^i =observed data for the j_{th} response at the i_{th} trial, the k_{th} repetition, $\bar{y}_j^i = \frac{1}{l}\sum_{k=1}^{l} y_{jk}^i$

(The average observed data for the j_{th} response at the i_{th} trial), ${S_j^i}^2 = \frac{1}{l-1}\sum_{k=1}^{l}\left(y_{jk}^i - \bar{y}_j^i\right)^2$ (the variation of observed data for the j_{th} response at the i_{th} trial,) for $i = 1, 2, ..., m$; $j = 1, 2, ..., n$ and $k = 1, 2, ..., l$.

Step 2: Normalization of the S/N ratios of the responses (quality characteristics)

The S/N ratio calculated for each response has been normalized by following equation:

$$S/N_i(k) = \frac{S/N_i - \min S/N_i(k)}{\max_i S/N_i(k) - \min_k S/N_i(k)} \qquad \textbf{(4.4)}$$

For this normalization purpose Higher-the-Better (HB) criteria has been used.

Step 3: Checking for correlation between each pair of quality characteristics

Let, $Q_i = \{X_0^*(i), X_1^*(i), X_2^*(i), \ldots\ldots\ldots\ldots\ldots\ldots, X_m^*(i)\}$ where, $i = 1,2,3,\ldots\ldots\ldots\ldots, n.$

It is the normalized series of the *ith* quality characteristic. The correlation coefficient between two quality characteristics is calculated by the following equation:

$$\rho_{jk} = \frac{Cov(Q_j, Q_k)}{\sigma_{Q_j} \times \sigma_{Q_k}} \tag{4.5}$$

$$\begin{aligned} &here, \\ &j = 1,2,3,\ldots\ldots\ldots\ldots\ldots\ldots, n \\ &k = 1,2,3,\ldots\ldots\ldots\ldots\ldots\ldots, n \\ &j \neq k \end{aligned}$$

Here, ρ_{jk} is correlation coefficient, σ_{Q_j} and σ_{Q_k} denotes standard deviation of the quality characteristics j and quality characteristics of k respectively.

Step 4: Calculation of the principal component score

1) Calculate the Eigen value λ_k and the corresponding Eigen vector β_k $(k = 1,2,3,\ldots\ldots\ldots n)$ from the correlation matrix formed by all the quality characteristics.
2) Calculate the principal component scores of the normalized reference sequence and comparative sequences using the equation shown below:

$$Y_i(k) = \sum_{j=1}^{n} X_i^*(j)\beta_{kj}, i = 0,1,2\ldots\ldots\ldots, m, k = 1,2,3\ldots\ldots\ldots\ldots\ldots, n \tag{4.6}$$

Here, $Y_i(k)$ is the principal component score of the *kth* element in the *ith* series. Let, $X_i^*(j)$ be the normalized value of the *jth* element in the *ith* sequence, and β_{kj} is the *jth* element of the Eigen vector β_k .

Step 5: Estimation of quality loss $\Delta_{0,i}(k)$

$\Delta_{0,i}(k)$ is defined as the absolute value of the difference between desired (ideal) value and *ith* experimental value for k_{th} response. If responses are correlated then instead of using [$X_o(k)$ $X_i(k)$]; [$Y_0(k)$ $Y_i(k)$] should be used for computation of $\Delta_{0,i}(k)$.

$$\Delta_{0,i} = \begin{Bmatrix} |X_0(k) - X_i(k)| \\ |Y_0(k) - Y_i(k)| \end{Bmatrix} \tag{4.7}$$

Step 5: Apply TOPSIS to obtain the OPI for multiple responses

TOPSIS is applied on the quality loss estimates $\Delta_{0,i}(k)$ obtained (in Step 5) to determine the closeness coefficient. According to the optimization direction of the selected principal components obtained; TOPSIS is used to determine the closeness coefficient to be treated as OPI. The closeness coefficient is evaluated by using the **Eq. 2.16** of **Chapter 2**. In this computation, the experimental runs can be treated as alternatives; and the selected quality loss estimates components are treated as attributes and a quality performance matrix is formed. The weighted quality performance matrix can be obtained, where the criteria weights (priority importance) are properly assigned. The ideal and negative-ideal solutions are then obtained by **Eqs. 2.12-2.13** of **Chapter 2**. It is obvious that a smaller value is desired for all quality loss estimates, hence, the ideal and negative ideal solution are selected representing the minimum and maximum quality loss scores in all experimental combinations. Correspondingly, the OPI values (or C_i^+ values for $i = 1, 2, ..., m$ for each experimental run are derived using **Eq. 2.16** of **Chapter 2**.

Step 6: Determine the optimal factor/ level combination

The main factorial effects on OPI are determined based on the C_i^+ values. Thus, the corresponding diagram plots the factor effect on OPI. The optimal factor/level combination produces the maximum OPI value. The closeness value is optimized using Taguchi method. For calculating S/N ratio; Higher-the-Better (HB) criterion is to be selected.

Step 7: Conduct the confirmatory experiment

According to the optimal factor/level combination, confirmation experiments are performed to verify whether the experimental results can be reproduced. The predicted S/N value for each response is compared with the associated actual S/N value obtained from the confirmation experiments. If the predicted S/N values and the actual S/N values differ only slightly then the experiment can be reproduced. If the predicted S/N values and the actual S/N values differ substantially, the experimental result cannot be reproduced. In this case, suitable quality characteristics, control factors, or signal factors must be reselected, and return to Step 1 of the proposed procedure to start all over again.

4.5 Results

Experimental data have been analyzed by aforementioned procedure. The S/N ratios for each response resulting from the Taguchi‘s S/N ratio formula has been furnished in **Tables 4.3.1-4.3.2**. The S/N ratios (of the responses i.e. multiple surface roughness characteristics) have been normalized and then tabulated as shown in the **Table 4.4**.

After normalization, The Pearson’s correlation coefficients between individual responses pairs have been computed **(Table 4.5)**. Eigen values, Eigen vectors, accountability proportion (AP) and cumulative accountability proportion (CAP) computed in PCA for the six surface quality indicators has been shown in **Table 4.6**. It has been found that, the first four PCs can take care of 47.5%, 25.8%, 1.37% and 1.11% data variability respectively. The contribution of fifth and sixth PCs has been found negligible effect to interpret data variability. Consequently, the effects of these PCs have been snubbed and the first four PCs have been considered in further analysis **(Table 4.7)**. From the aforesaid four major PCs, the quality loss estimates have been computed and their corresponding values have been presented in **Table 4.8**.

TOPSIS have been applied utilizing these quality loss estimates. The experimental runs have been treated as the alternatives and the normalized decision matrix have been calculated shown in the **Table 4.9**. The weighted normalized matrix has been presented in **Table 4.10**. From **Table 4.10**, the ideal and negative-ideal solution has been evaluated and presented in **Table 4.11**. The deviation from the ideal solution has been assessed from the Euclidian equation and presented in **Table 4.12**. The relative closeness value (closeness coefficient) has been calculated and furnished in **Table 4.13**.

Finally, the Taguchi method has been applied on the closeness coefficient (OPI) to assess the optimal machining parameter by using S/N ratio plot **(Fig. 4.2)** and **Table 4.14**. Higher the value of closeness factor, the corresponding parameter combination is said to be close to the optimal solution. The optimal parametric combination has been found as $N_1F_1D_5$.

After evaluating the optimal machining condition, it is required to predict and verify improvement of the quality characteristics by using the optimal parametric combination. The predicated value of the S/N ratio of OPI became -0.572677, highest among the entries of all S/N ratios of OPI, except in experiment run no. 1 **(Table 4.13)**. From **Table 4.13** it has been observed that experiment run no. 1 i.e. for setting $N_1F_1D_1$ corresponds to S/N ratio -0.2735; higher than that of predicted at optimal setting $N_1F_1D_5$. As S/N ratio should always be as high as possible so apparently it indicates that setting $N_1F_1D_1$ is better compared to $N_1F_1D_5$. However, unlike conventional metal, high depth of cut is necessary for polymer/ plastic machining in order to achieve good surface finish. At low depth of cut, very fine stringy chips (continuous but in the form of glass wool; chip curl is very high) are generated and due to the heat generated during machining; fibrous chips immediately stick on the machined surface, thereby, deteriorating surface finish. High depth of cut is thus required to ensure formation of comparatively thicker (continuous stringy) chips capable of withstanding elevated temperature (without melting). Therefore, optimal setting having high depth of cut is quite justified. Confirmatory test has been conducted showed good agreement with the prediction.

4.6 Concluding Remarks

The preceding study employs PCA based TOPSIS integrated with Taguchi's robust design philosophy for optimization of multiple surface roughness parameters, thereby determining an optimal machining condition to produce desired surface quality in PTFE machining, as a case study. Detailed methodology and procedural chronology of the aforesaid approach have been illustrated in this reporting. Correlated multiple responses can be transformed into equal or less number of uncorrelated quality indices with the aid of PCA, and it facilitates in situation towards optimization of large number of responses. TOPSIS is efficient to convert the multiple attributes into the single objective function i.e. closeness coefficient. This closeness coefficient can be treated as the Overall Performance Index (OPI) which can be further optimized (maximized) by Taguchi method. The integrated approach highlighted in this paper can be applied for continuous quality improvement and off-line quality control in any production processes which involve multiple response features.

4.7 Bibliography

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Table 4.1: Domain of experiments (process control parameters and their limits)

Sl. No.	Factors	Notation	Unit	Level 1	Level 2	Level3	Level 4	Level 5
1	Spindle Speed	N	RPM	260	360	530	860	1400
2	Feed rate	F	mm/rev	0.050	0.052	0.055	0.060	0.063
3	Depth of cut	D	mm	2	3	4	5	6

Table 4.2: L_{25} orthogonal array design of experiment

Sl. No.	Factorial combinations (coded form)		
	N	F	D
1	1	1	1
2	1	2	2
3	1	3	3
4	1	4	4
5	1	5	5
6	2	1	2
7	2	2	3
8	2	3	4
9	2	4	5
10	2	5	1
11	3	1	3
12	3	2	4
13	3	3	5
14	3	4	1
15	3	5	2
16	4	1	4
17	4	2	5
18	4	3	1
19	4	4	2
20	4	5	3
21	5	1	5
22	5	2	1
23	5	3	2
24	5	4	3
25	5	5	4

Table 4.3.1: Roughness parameters and corresponding S/N ratios

Sl. No.	R_a μm	S/N (R_a) (dB)	R_q μm	S/N (R_q) (dB)	R_t μm	S/N (R_t) (dB)
1	2.01667	-6.0927	2.43333	-7.7240	11.6667	-21.3390
2	2.32667	-7.3347	2.96667	-9.4454	21.2667	-26.5540
3	2.22667	-6.9531	2.75667	-8.8077	19.8667	-25.9625
4	2.26333	-7.0950	2.80000	-8.9432	20.6333	-26.2914
5	2.17000	-6.7292	2.74667	-8.7761	17.1333	-24.6768
6	2.43333	-7.7240	3.38000	-10.5783	22.0000	-26.8485
7	4.46000	-12.9867	7.34333	-17.3179	18.0000	-25.1055
8	2.15667	-6.6757	2.59667	-8.2883	17.5667	-24.8938
9	1.96333	-5.8599	2.4533	-7.7950	16.5333	-24.3672
10	2.93000	-9.3374	3.57000	-11.0534	16.7000	-24.4543
11	2.93000	-9.3374	3.78333	-11.5575	25.0333	-27.9704
12	3.22330	-10.1660	3.94333	-11.9173	23.6333	-27.4705
13	2.21667	-6.9140	2.89667	-9.2380	21.5667	-26.6757
14	1.76333	-4.9267	2.46333	-7.8305	13.3000	-22.4770
15	2.24333	-7.0179	2.78000	-8.8809	18.7000	-25.4368
16	2.85333	-9.1070	3.53000	-10.9555	21.6667	-26.7159
17	2.92667	-9.3275	3.74333	-11.4652	21.0333	-26.4581
18	1.92000	-5.6660	2.53000	-8.0624	18.3667	-25.2806
19	2.94000	-9.3669	3.29667	-10.3615	26.0333	-28.3106
20	2.12667	-6.5540	2.84000	-9.0664	19.1333	-25.6358
21	3.05333	-9.6955	3.79000	-11.5728	21.2667	-26.5540
22	2.26000	-7.0822	3.23000	-10.1841	21.2333	-26.5403
23	2.70666	-8.6487	3.56670	-11.0453	23.9000	-27.5680
24	2.37333	-7.5072	2.93667	-9.3571	23.1667	-27.2973
25	2.63000	-8.3991	3.40000	-10.6296	20.7333	-26.3334

Table 4.3.2: Roughness parameters and corresponding S/N ratios (continued with **Table 4.3.1**)

Sl. No.	R_{ku} μm	S/N (R_{ku}) (dB)	R_z μm	S/N (R_z) (dB)	R_{sm} (mm)	S/N (R_{sm}) (dB)
1	2.58667	-8.2548	9.9867	-19.9884	70.500	-36.9638
2	3.76667	-11.5192	13.9000	-22.8603	89.867	-39.0720
3	4.53000	-13.1220	13.7333	-22.7555	90.467	-39.1298
4	7.19000	-17.1346	11.0667	-20.8804	75.033	-37.5050
5	3.65667	-11.2617	12.7000	-22.0761	98.433	-39.8628
6	3.70233	-11.3695	16.8667	-24.5406	72.433	-37.1987
7	4.08333	-12.2203	12.3333	-21.8216	74.733	-37.4702
8	3.79667	-11.5881	12.8000	-22.1442	70.833	-37.0047
9	3.9333	-11.8951	12.2333	-21.7509	83.83333	-38.4683
10	3.72000	-11.4109	15.6000	-23.8625	145.000	-43.2274
11	3.56333	-11.0371	19.0000	-25.5751	85.567	-38.6461
12	3.41667	-10.6721	19.6333	-25.8599	71.133	-37.0414
13	7.02667	-16.9350	14.4667	-23.2074	73.033	-37.2704
14	3.50000	-10.8814	9.8700	-19.8863	147.000	-43.3463
15	4.85000	-13.7148	12.5000	-21.9382	117.533	-41.4032
16	3.32000	-10.4228	16.0667	-24.1185	72.633	-37.2227
17	3.19000	-10.0758	17.3333	-24.7776	95.367	-39.5880
18	7.63000	-17.6505	12.0667	-21.6318	88.933	-38.9813
19	6.58333	-16.3689	17.0000	-24.6090	153.667	-43.7316
20	3.83000	-11.6640	13.2667	-22.4553	133.667	-42.5205
21	2.87333	-9.1677	17.0000	-24.6090	81.400	-38.2125
22	4.71667	-13.4727	14.6600	-23.3227	102.333	-40.2003
23	9.06667	-19.1490	15.8333	-23.9914	115.667	-41.2642
24	7.38000	-17.3611	13.0000	-22.2789	159.667	-44.0643
25	5.22667	-14.3645	15.4667	-23.7880	154.333	-43.7692

Table 4.4: Normalized S/N ratios

Sl. No.	Normalized data of multiple surface roughness parameters					
	R_a	R_q	R_t	R_{ku}	R_z	R_{sm}
Ideal sequence	1	1	1	1	1	1
1	0.855335	1	1	1	0.978975	1
2	0.701241	0.820573	0.254152	0.700354	0.500133	0.703091
3	0.748586	0.887043	0.339733	0.55323	0.517607	0.694951
4	0.73098	0.872919	0.292147	0.184906	0.830249	0.92378
5	0.776365	0.890337	0.525754	0.723991	0.630886	0.591719
6	0.65294	0.702488	0.211543	0.714096	0.219971	0.966918
7	0	0	0.463728	0.635999	0.673319	0.928681
8	0.783002	0.941181	0.494357	0.69403	0.619531	0.99424
9	0.884218	0.992599	0.570548	0.66585	0.685107	0.788114
10	0.452767	0.652967	0.557946	0.710295	0.333033	0.117865
11	0.452767	0.600423	0.049222	0.744607	0.047486	0.763073
12	0.349963	0.56292	0.121549	0.778111	0	0.989071
13	0.753437	0.842191	0.236544	0.203227	0.44226	0.95682
14	1	0.988899	0.84403	0.758899	1	0.10112
15	0.740546	0.879413	0.415794	0.498816	0.653878	0.374776
16	0.481352	0.663171	0.230728	0.800995	0.290349	0.963538
17	0.453995	0.610044	0.268028	0.832847	0.180456	0.63042
18	0.908275	0.964728	0.438393	0.13755	0.704965	0.715865
19	0.449107	0.725086	0	0.255191	0.208567	0.046856
20	0.798102	0.860078	0.387002	0.687063	0.56766	0.217421
21	0.408337	0.598828	0.254152	0.916203	0.208567	0.824139
22	0.732568	0.743577	0.256135	0.521039	0.423036	0.544187
23	0.538213	0.653811	0.107443	0	0.311541	0.394353
24	0.679839	0.829777	0.146609	0.164115	0.597072	0
25	0.569181	0.697141	0.28607	0.439179	0.345455	0.04156

Table 4.5: Check for correlation among response pairs

Sl. No.	Correlation Between	Pearson's Correlation Coefficient	P-Value
1	R_a, R_q	0.950	0.000*
2	R_a, R_t	0.542	0.004*
3	R_a, R_{ku}	-0.014	0.947
4	R_a, R_z	0.655	0.000*
5	R_a, R_{sm}	-0.029	0.888
6	R_q, R_t	0.428	0.029*
7	R_q, R_{ku}	-0.035	0.866
8	R_q, R_z	0.521	0.006*
9	R_q, R_{sm}	-0.072	0.725
10	R_t, R_{ku}	0.497	0.010*
11	R_t, R_z	0.813	0.000*
12	R_t, R_{sm}	0.155	0.451
13	R_{ku}, R_z	0.044	0.830
14	R_{ku}, R_{sm}	0.361	0.070
15	R_z, R_{sm}	0.050	0.808

*Significant correlation

Table 4.6: Results of PCA: Eigen values, eigenvectors, accountability proportion (AP) and cumulative accountability proportion (CAP)

	PC1	PC2	PC3	PC4	PC5	PC6
Eigen value	2.8150	1.5452	.8250	.6650	.0774	.0365
Eigen vector	$\begin{vmatrix} 0.930 \\ 0.972 \\ 0.229 \\ -0.082 \\ 0.320 \\ -0.063 \end{vmatrix}$	$\begin{vmatrix} -0.328 \\ -0.187 \\ -0.862 \\ -0.078 \\ -0.923 \\ -0.005 \end{vmatrix}$	$\begin{vmatrix} -0.064 \\ -0.037 \\ 0.373 \\ 0.980 \\ -0.120 \\ 0.153 \end{vmatrix}$	$\begin{vmatrix} 0.039 \\ 0.062 \\ -0.009 \\ -0.164 \\ -0.001 \\ -0.986 \end{vmatrix}$	$\begin{vmatrix} 0.009 \\ -0.016 \\ -0.253 \\ -0.017 \\ 0.174 \\ -0.001 \end{vmatrix}$	$\begin{vmatrix} -0.151 \\ 0.123 \\ 0.004 \\ 0.002 \\ -0.010 \\ -0.000 \end{vmatrix}$
AP	.475	.258	.137	.111	.013	.006
CAP	..475	.733	.870	.981	.994	1.000

Table 4.7: Calculated values of major principal components

Sl. No.	Major principal components (PCs)			
	PC1	PC2	PC3	PC4
Ideal Situation	2.306	-2.383	1.285	-1.059
1	2.164734	-2.3181	1.370782	-1.06462
2	1.566271	-1.1233	0.814184	-0.73267
3	1.712677	-1.22968	0.698012	-0.69534
4	1.78751	-1.44185	0.317402	-0.862
5	1.813063	-1.51734	0.903699	-0.62205
6	1.289415	-0.79189	0.884465	-1.0036
7	0.210997	-1.0768	0.857539	-1.02483
8	1.83493	-1.49113	0.927031	-1.01032
9	2.032768	-1.65705	0.883852	-0.79607
10	1.224428	-1.11561	0.877455	-0.17992
11	0.92202	-0.40904	0.852365	-0.82011
12	0.774342	-0.39047	0.957645	-1.05538
13	1.638054	-1.03824	0.363657	-0.89773
14	2.335892	-2.22518	0.926605	-0.13245
15	1.783441	-1.41138	0.60795	-0.37233
16	1.111623	-0.81665	0.977347	-1.02389
17	1.026293	-0.72906	0.98448	-0.70525
18	2.052014	-1.52261	0.300816	-0.63782
19	1.165317	-0.49596	0.230313	-0.02579
20	1.778469	-1.33597	0.763564	-0.24666
21	0.959707	-0.7335	1.089766	-0.9123
22	1.521063	-1.03479	0.619281	-0.55008
23	1.235496	-0.68156	0.052773	-0.32858
24	1.649973	-1.06963	0.131061	0.049128
25	1.344384	-0.91766	0.49137	-0.0505

Table 4.8: Computed quality loss coefficients

Sl. No.	PC1	PC2	PC3	PC4
1	0.141266	0.0649	0.08578	0.00562
2	0.739729	1.2597	0.470816	0.32633
3	0.593323	1.15332	0.586988	0.36366
4	0.51849	0.94115	0.967598	0.197
5	0.492937	0.86566	0.381301	0.43695
6	1.016585	1.59111	0.400535	0.0554
7	2.095003	1.3062	0.427461	0.03417
8	0.47107	0.89187	0.357969	0.04868
9	0.273232	0.72595	0.401148	0.26293
10	1.081572	1.26739	0.407545	0.87908
11	1.38398	1.97396	0.432635	0.23889
12	1.531658	1.99253	0.327355	0.00362
13	0.667946	1.34476	0.921343	0.16127
14	0.02989	0.15782	0.358395	0.92655
15	0.522559	0.97162	0.67705	0.68667
16	1.194377	1.56635	0.307653	0.03511
17	1.279707	1.65394	0.30052	0.35375
18	0.253986	0.86039	0.984184	0.42118
19	1.140683	1.88704	1.054687	1.03321
20	0.527531	1.04703	0.521436	0.81234
21	1.346293	1.6495	0.195234	0.1467
22	0.784937	1.34821	0.665719	0.50892
23	1.070504	1.70144	1.232227	0.73042
24	0.656027	1.31337	1.153939	1.10813
25	0.961616	1.46534	0.79363	1.0085

Table 4.9: Normalized quality loss coefficients

Sl. No.	Normalized quality loss coefficients for major PCs			
	PC1	PC2	PC3	PC4
1	0.029495	0.009755	0.026247	0.00201
2	0.154449	0.189351	0.144062	0.116693
3	0.12388	0.17336	0.179609	0.130041
4	0.108256	0.141468	0.29607	0.070445
5	0.102921	0.130121	0.116672	0.156249
6	0.212254	0.239166	0.122557	0.019811
7	0.437417	0.19634	0.130796	0.012219
8	0.098355	0.134061	0.109533	0.017408
9	0.057048	0.109121	0.122745	0.094021
10	0.225822	0.190507	0.124702	0.314351
11	0.288962	0.296714	0.13238	0.085425
12	0.319796	0.299505	0.100166	0.001294
13	0.139461	0.202136	0.281917	0.057669
14	0.006241	0.023723	0.109663	0.331326
15	0.109105	0.146048	0.207167	0.245547
16	0.249375	0.235445	0.094137	0.012555
17	0.267191	0.248611	0.091954	0.126498
18	0.05303	0.129329	0.301145	0.15061
19	0.238164	0.283649	0.322718	0.369466
20	0.110144	0.157383	0.159551	0.290485
21	0.281093	0.247943	0.059739	0.052459
22	0.163888	0.202655	0.2037	0.181985
23	0.223511	0.25575	0.377042	0.261192
24	0.136972	0.197418	0.353087	0.396257
25	0.200776	0.220261	0.242838	0.36063

Table 4.10: Weighted normalized quality loss coefficients of majors PCs

Sl. No.	Weighted normalized quality loss coefficients of majors PCs			
	PC1	PC2	PC3	PC4
1	0.007374	0.002439	0.006562	0.000502
2	0.038612	0.047338	0.036016	0.029173
3	0.03097	0.04334	0.044902	0.03251
4	0.027064	0.035367	0.074017	0.017611
5	0.02573	0.03253	0.029168	0.039062
6	0.053063	0.059792	0.030639	0.004953
7	0.109354	0.049085	0.032699	0.003055
8	0.024589	0.033515	0.027383	0.004352
9	0.014262	0.02728	0.030686	0.023505
10	0.056456	0.047627	0.031176	0.078588
11	0.072241	0.074179	0.033095	0.021356
12	0.079949	0.074876	0.025041	0.000324
13	0.034865	0.050534	0.070479	0.014417
14	0.00156	0.005931	0.027416	0.082831
15	0.027276	0.036512	0.051792	0.061387
16	0.062344	0.058861	0.023534	0.003139
17	0.066798	0.062153	0.022989	0.031624
18	0.013257	0.032332	0.075286	0.037653
19	0.059541	0.070912	0.080679	0.092367
20	0.027536	0.039346	0.039888	0.072621
21	0.070273	0.061986	0.014935	0.013115
22	0.040972	0.050664	0.050925	0.045496
23	0.055878	0.063938	0.094261	0.065298
24	0.034243	0.049355	0.088272	0.099064
25	0.050194	0.055065	0.06071	0.090158

Table 4.11: Ideal and negative-ideal solutions

Sl. No.	Ideal	Negative Ideal
1	0.00156	0.109354
2	0.002439	0.074876
3	0.006562	0.094261
4	0.000324	0.099064

Table 4.12: Separation measures between attributes from the ideal and negative ideal solution

Sl. No.	S^-	S^+
1	0.181804	0.005817
2	0.118491	0.06851
3	0.11834	0.068827
4	0.124004	0.079513
5	0.128932	0.057055
6	0.127675	0.077338
7	0.116931	0.11521
8	0.149462	0.041388
9	0.145117	0.042241
10	0.089105	0.105761
11	0.10563	0.102494
12	0.124119	0.104214
13	0.117779	0.08576
14	0.145275	0.085369
15	0.106919	0.085632
16	0.129114	0.080653
17	0.107707	0.091381
18	0.123191	0.083935
19	0.052215	0.146215
20	0.10776	0.090042
21	0.123989	0.087978
22	0.100049	0.086402
23	0.064183	0.134353
24	0.079554	0.139108
25	0.071396	0.124932

Table 4.13: Closeness coefficient (OPI) and ranking of alternatives

Sl. No.	C_i^+	S/N Ratio
1	0.9690	-0.2735
2	0.6336	-3.9637
3	0.6323	-3.9815
4	0.6093	-4.3034
5	0.6932	-3.1828
6	0.6228	-4.1130
7	0.5037	-5.9566
8	0.7831	-2.1237
9	0.7745	-2.2196
10	0.4573	-6.7960
11	0.5075	-5.8913
12	0.5436	-5.2944
13	0.5787	-4.7509
14	0.6299	-4.0146
15	0.5553	-5.1094
16	0.6155	-4.2154
17	0.5410	-5.3361
18	0.5948	-4.5126
19	0.2631	-11.5976
20	0.5448	-5.2753
21	0.5849	-4.6584
22	0.5366	-5.4070
23	0.3233	-9.8079
24	0.3638	-8.7827
25	0.3637	-8.7851

Table 4.14: Mean response table for S/N ratio of OPI

Level	N	F	D
1	-13.2020	-12.1464	-11.7279
2	-9.2153	-7.0129	-6.0544
3	-7.2287	-8.1421	-6.3383
4	-6.4800	-7.2631	-8.0962
5	-5.1130	-6.6744	-9.0223
Delta = Max.-Min.	8.0889	5.4720	5.6735
Rank	1	3	2

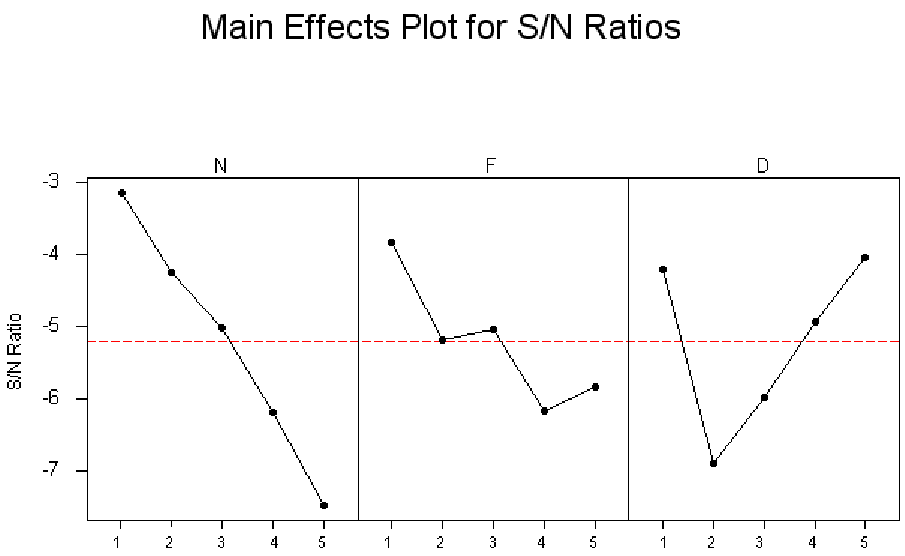

Fig. 4.2: S/N ratio plot of OPI for evaluation of optimal setting

CHAPTER 5: Utility based Fuzzy Approach

This chapter presents a multi response optimization problem for selection of optimal cutting parameter in turning of nylon bar by using fuzzy-integrated utility theory combined with Taguchi's robust design technique. In this study, three cutting parameters: cutting speed, feed, and depth of cut have been considered for optimizing Material Removal Rate (MRR) of the process and centre line roughness average for the machined product based on L_9 orthogonal array experimental design. To avoid the uncertainty, imprecision in application of existing multi-response optimization techniques; a utility theory combined with fuzzy inference system (FIS) has been proposed to compute a Multi-Performance Characteristic Index (MPCI). MPCI has been optimized finally using Taguchi method. The study demonstrates application feasibility of the proposed approach with satisfactory result of confirmatory test.

5.1 Background and State of Art

Nylon is used in a wide variety of applications for their outstanding mechanical properties including high wear and abrasion resistance, superior strength and stiffness. Nylon's toughness, low coefficient of friction and wide size range availability make it an ideal replacement for a wide variety of materials from metal to rubber. Therefore, machining aspects of nylon is an emerging area of research.

Turning operation is the basic machining process to remove the metal from the outer diameter of rotating work piece with the help of single point cutting tool which move parallel to the axis of rotation. Several process parameters like cutting speed, feed, depth of cut, tool geometry etc. are assumed to influence machining performance. Material Removal Rate (MRR), tool life-tool wear, interaction of various cutting forces, quality-dimensional accuracy of the turned product and others are the most important areas of research. Literature depicts substantial amount of work attempted by previous investigators on various aspects of turning on a variety of work materials. In most of the cases surface roughness features have been given immense attention for both prediction as well as its optimization. Because of the fact, thatthe surface finish is related to the product surface quality.

Feng and Wang (2002) reported on the predication of the surface roughness in turning operation by developing the empirical model. Empirical model was developed by using Data mining techniques, non regression analysis with logarithmic data transformation. **Ozel and Karpet(2005)** developed the neural network model in comparison with regression model for the predication of the surface roughness and tool flank wear. **Pal and Chakarborty(2005)** highlighted predication of the surface operation by using the back neural network model. **Mahapatra et al. (2006)** developed a genetic algorithm for the optimization of the cutting parameter as well as for surface roughness predication. **Palanikumar et al. (2006)** used Taguchi method with fuzzy logic to optimize the cutting parameters for machining the GFRP composites. Cutting parameters were optimized by considering the MPCI. **Doniavi et al. (2007)** developed the empirical model for optimizing the cutting parameters and for the predication of the surface roughness by using Response Surface Methodology (RSM). **Srikanth and Kamala (2008)** studied for the predication of surface roughness and optimizing the machining parameters by using RCGA (Real coded genetic Algorithm). **Namboothriet al. (2010)** developed an improved genetic algorithm for the predication of the surface roughness in dry turning of SS 420 materials.

Literature highlights immense effort given by the previous researchers to optimize the various machining parameters during the machining operation. Some researchers highlighted the optimization of surface roughness by developing the several empirical model and network based methodology. Apart from surface quality; there is another important aspect which is called productivity. Material Removal Rate (MRR) is indirectly related to productivity. It is an essential requirement to improve quality as well as productivity simultaneously.

In this context, present work aims to apply utility embedded fuzzy approach coupled with Taguchi philosophy for simultaneous optimization of quality and productivity. The method has been found efficient in overcoming limitations/ assumptions of various existing optimization methodologies available in literature **(Singh et al., 2011)**. In this study, the utility degree has been evaluated for individual responses: MRR and roughness average (R_a) which has been fed to fuzzy inference system to generate the MPCI. MPCI has been finally optimized by Taguchi method. Application feasibility of the aforesaid technique has been highlighted through a case study in turning of nylon.

5.2 Experimental part

Work Material

Samples of nylon 6 bars with dimensions of 50 mm diameter and length of 150 mm with cutting length of 50mm have been used as working material.

Cutting Tool Used

Single point High Speed Steel Tool of Indolov SHRIRAM IK-20 has been used for the machining operation.

Design of Experiment (DOE)

Taguchi method is used to reduce the source of variation on the quality characteristics of the product and to reach the desired value.Taguchi method is used to construct the orthogonal array for minimizing the number of experiments.In the present study, three cutting parameters (speed, feed, depth of cut) varied in three different levels have been used to optimize the machining condition.The most suitable array based on Taguchi's method has been found as

L_9 orthogonal array used for the present study.**Table 5.1** indicates selected process control parameters and their limits.

Equipments used

The manually operated lathe PINACHO has been used for the machining. Corresponding MRR values have also been computed. The surface roughness has been measured by the Talysurf (Taylor Hobson, Surtronic 3+) having a stylus that skids over the surface based on carrier modulating principle.**Table 5.2** represents DOE and measured response parameters.

5.3 Data Analysis

The aim of this study is to maximize the MRR and to minimize the surface roughness. In this study, a multi response optimization methodology based on Taguchi technique with the utility based fuzzy concept has been used for the optimizing multiple responses: MRR and surface roughness. For surface roughness; the Lower-the-Better (LB); whereas for MRR;Higher-the-Better (HB) criterion has been used. Multiple objective responses have been converted into corresponding utility values (also called preference number) **(Table 5.3)**. The individual utility value of each response has been treated as input to the fuzzy inference system**(Fig.5.1)**. The output of the fuzzy inference system has been defined as MPCI**(Table 5.3)**.This Multi-Performance Characteristic Index (MPCI) has been finally optimized by using the Taguchi methodology. Higher- the-Better (HB) criterion has been used for optimizing (maximizing) the MPCI**(Eq.5.1)**.

$$\frac{S}{N}(HigherTheBetter) = -10log\left[\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}\right] \quad \textbf{(5.1)}$$

In calculating MPCI in FIS system, three membership functions **(Fig.5.2)** have been assigned to each of the input variables: (i) individual utility of MRR (ii)individual utility of R_a. The selected membership functions for input variables are: “Low”, “Medium”, and “High”. Five membership functions have been selected for MPCI: “Very Small, “Small”, “Medium”, "Large", and "Very Large" **(Fig.5.3)**. **Fig.5.4** shows fuzzy based rule matrix. Fuzzy logic converts linguistic inputs into linguistic output. Linguistic output is again converted to numeric values (MPCI) by defuzzification method.

Fig.5.5 represents optimal parametric combination (N_3 f_1 d_3). Optimal result has been validated by satisfactory confirmatory test. Predicted value of S/N ratio of MPCI becomes 17.3204 (highest among all entries in **Table 5.3**.

5.4 Concluding Remarks

The present work has beencarried out to achieve the optimum setting of the process parameter under the consideration of the multiple attributes (quality and productivity) during turning of nylon bar. This studycombines the fuzzy linguistic technique, utility theory and Taguchi method for improving the cutting environment for simultaneous optimization of quality as well as productivity. This approach can efficiently bypass limitations of existing optimization approaches in literature. Aspects of response correlation need not to be checked and at the same time individual response priority weights need not to be assigned as well. FIS can take care of these aspects into its internal hierarchy. The technique adapted here can efficiently be applied in any manufacturing/ production processes for continuous quality improvement and off line quality control.

5.5 Bibliography

1. Feng CX and Wang X (2002) ‘Development of Empirical Models for Surface Roughness Prediction in Finish Turning’, International Journal of Advanced Manufacturing Technology, 20, pp. 348-356.
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7. Srikanth T and Kamala V (2008)‘A Real Coded Genetic Algorithm for Optimization of Cutting Parameters in Turning’, International Journal of Computer Science and Network Security, 8 (6), pp. 189-193.

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9. Singh A, DattaS, Mahapatra SS, Singha T andMajumdar G (2011)‘Optimization of Bead Geometry of Submerged Arc Weld using Fuzzy based Desirability Function Approach’, Journal of Intelligent Manufacturing, Springer link.(Published Online 21 April 2011) DOI 10.1007/s10845-011-0535-3

Table 5.1:Domain of Experiments (DOE)

Sl. No.	Factors	Notation	Unit	Level 1	Level 2	Level 3
1	Cutting speed	N	m/min	360	530	860
2	Feed rate	f	mm/rev	0.083	0.166	0.331
3	Depth of cut	d	mm	2	3	4

Table 5.2:DOE and collected response data

Sample no	N	f	d	MRR	Ra1	Ra2	Ra3	R_{avg}
1	1	1	1	1436.839	1.51	1.08	1.46	1.35
2	1	2	2	3992.6746	5.77	2.87	3.93	4.19
3	1	3	3	9909.7919	5.02	4.69	4.57	4.76
4	2	1	2	4290.9832	2.35	1.49	1.52	1.787
5	2	2	3	7693.0652	2.65	2.65	2.62	2.64
6	2	3	1	5298.241	4.81	4.62	4.53	4.653
7	3	1	3	6048.7008	.822	.889	0.863	0.858
8	3	2	1	4762.783	3.08	3.17	2.68	2.977
9	3	3	2	18843.154	4.19	4.24	4.3	4.243

Table 5.3:Individual utility of response parameters and MPCI

Sl. No	Individual utility values of responses		MPCI	S/N Ratio (dB)
	U1 (MRR)	U2 (Ravg)		
1	0	6.618	3.32	10.4228
2	3.5738	0.6699	2.62	8.3660
3	6.752	0	3.38	10.5738
4	3.8258	5.14	4.48	13.0256
5	5.8673	3.096	4.49	13.0449
6	4.563	0.1194	2.41	7.6403
7	5.026	8.9999	6.77	16.6118
8	4.1906	2.465	3.45	10.7564
9	8.9999	0.6039	4.89	13.7862

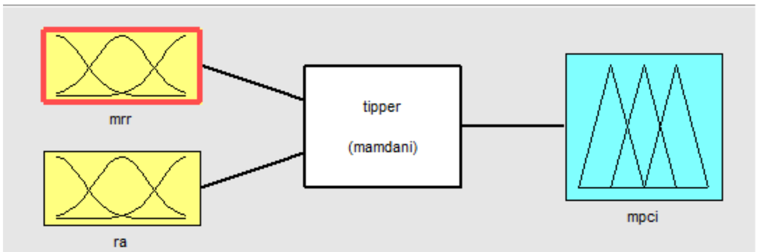


Fig.5.1:Input(s)/Output in FIS

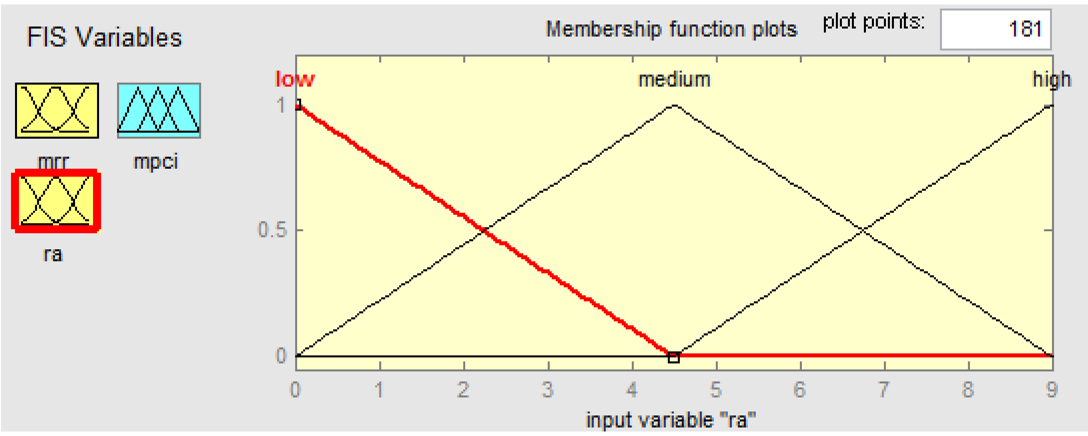


Fig.5.2:Membership Functions for Input Variables

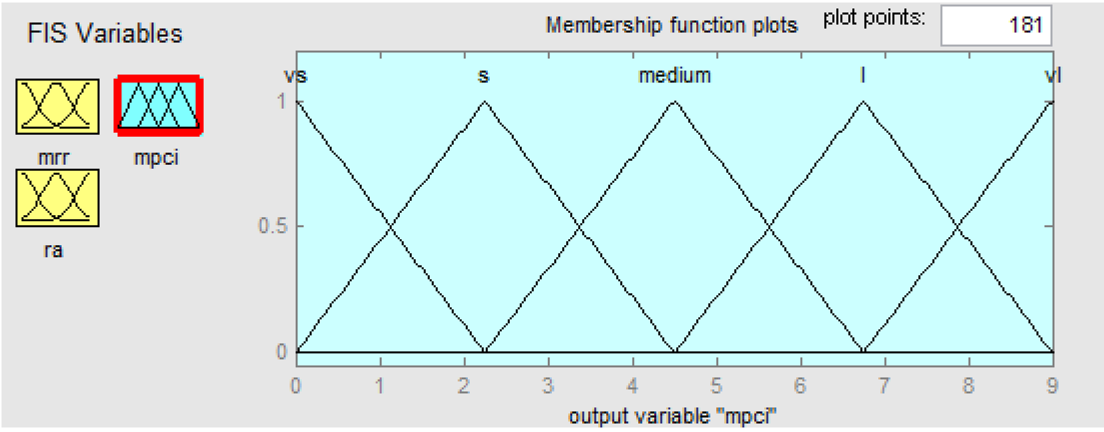


Figure 5.3:Membership Functions for Output Variable

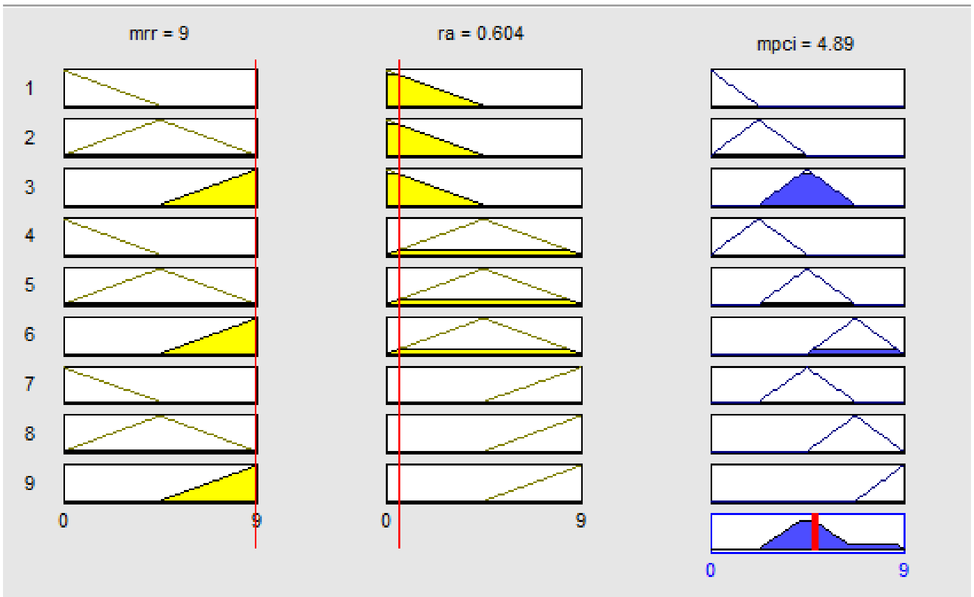


Fig.5.4:Fuzzy Reasoning

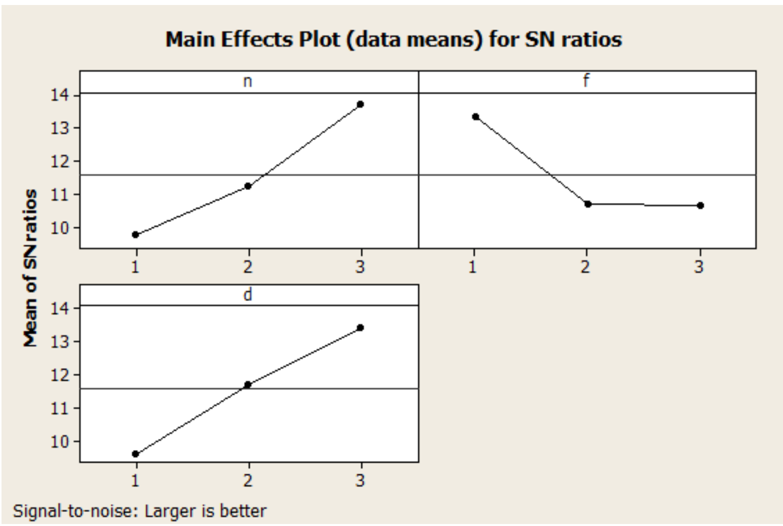
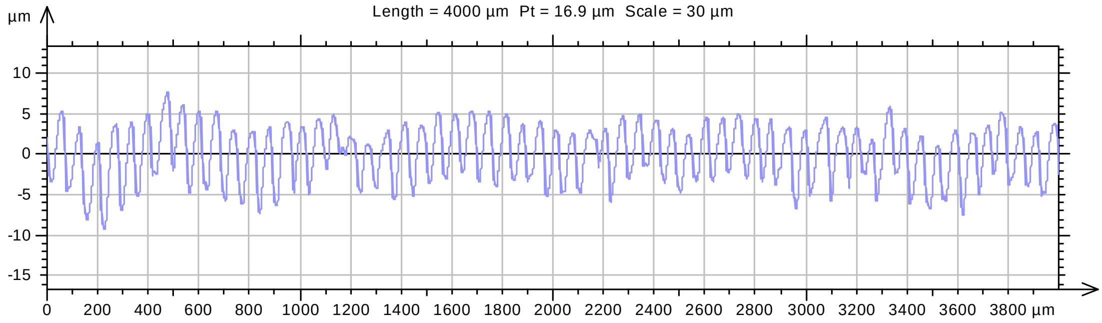


Fig.5.5: Evaluation of Optimal Setting

Appendix 1: Roughness Profile (Machined Nylon 6)



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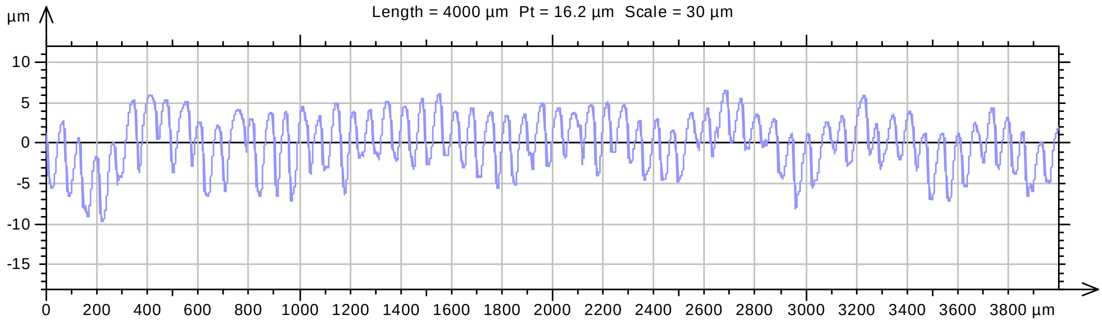

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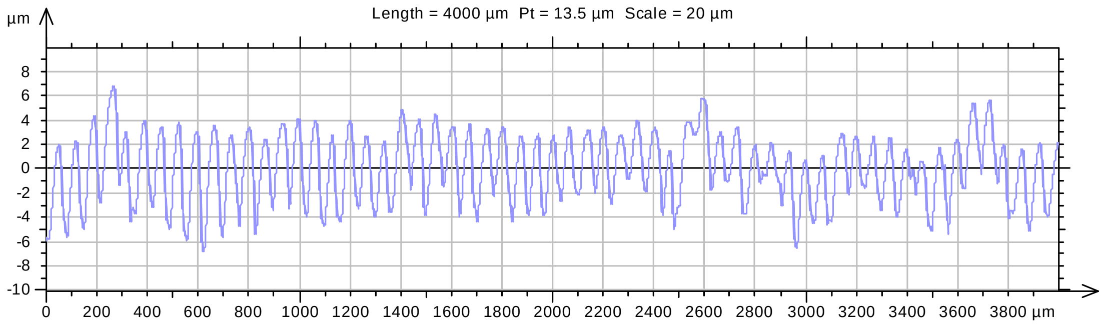

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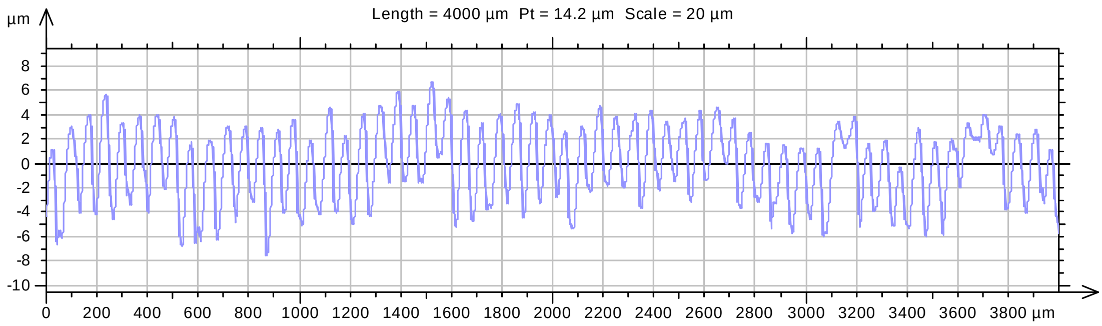

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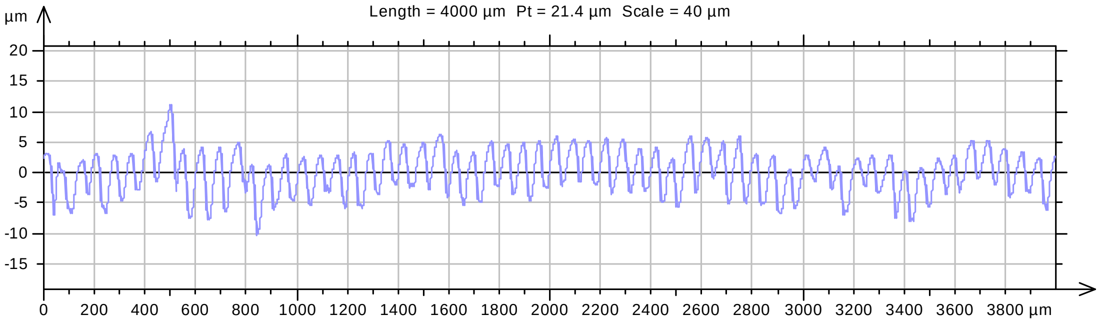
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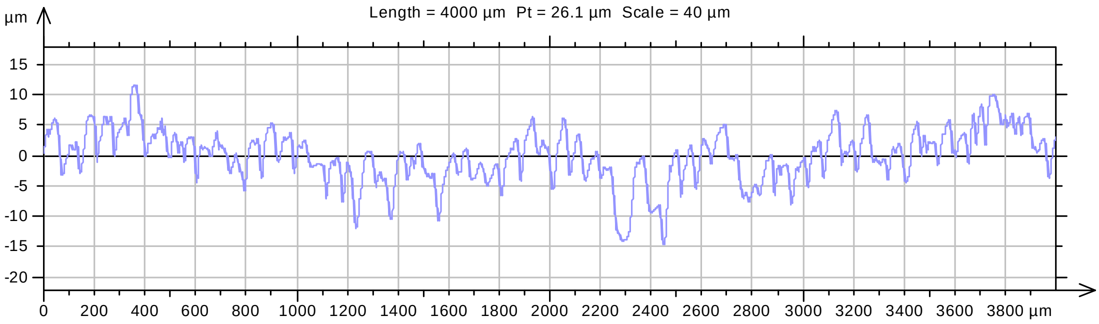
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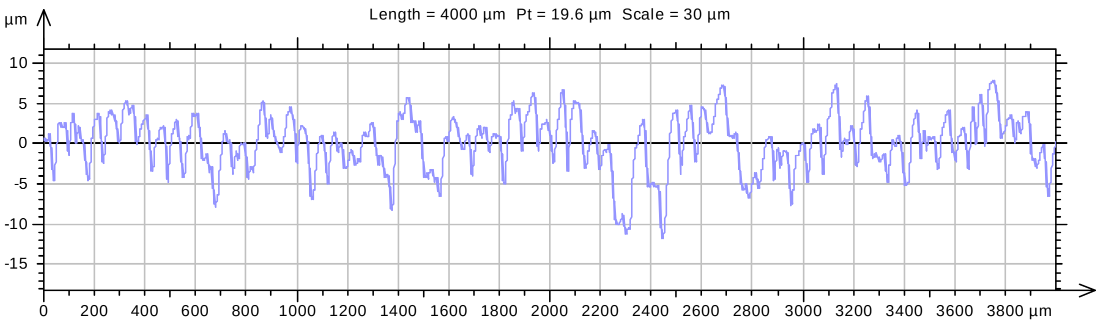
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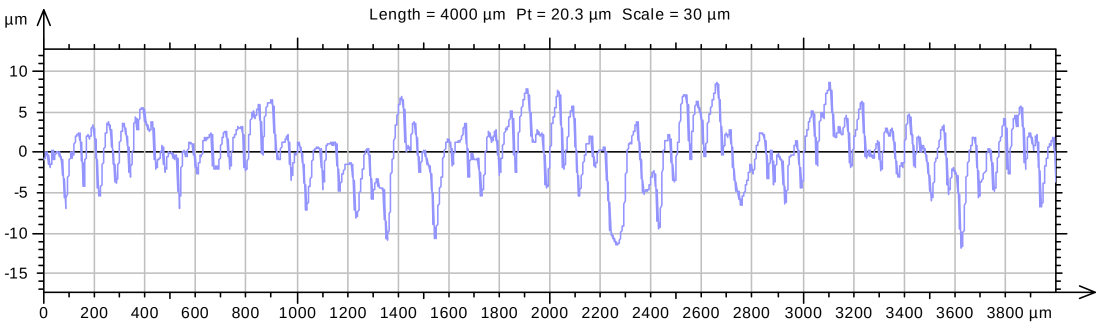
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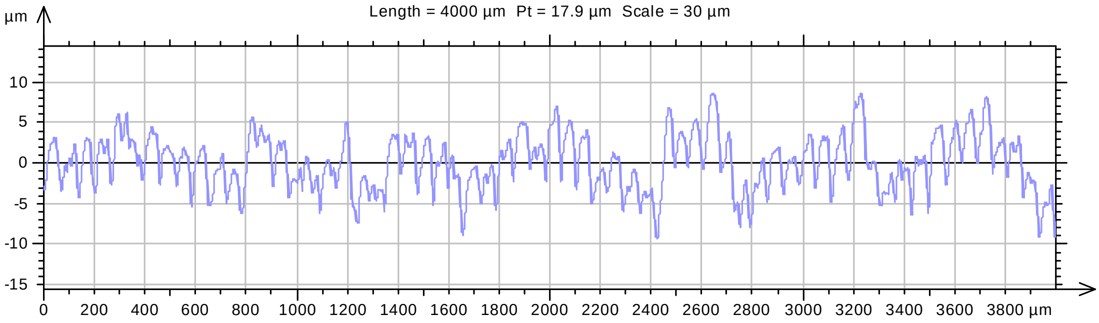
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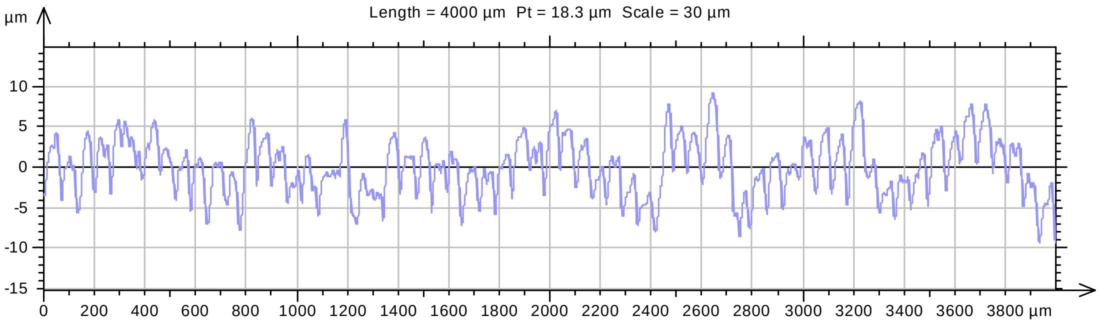
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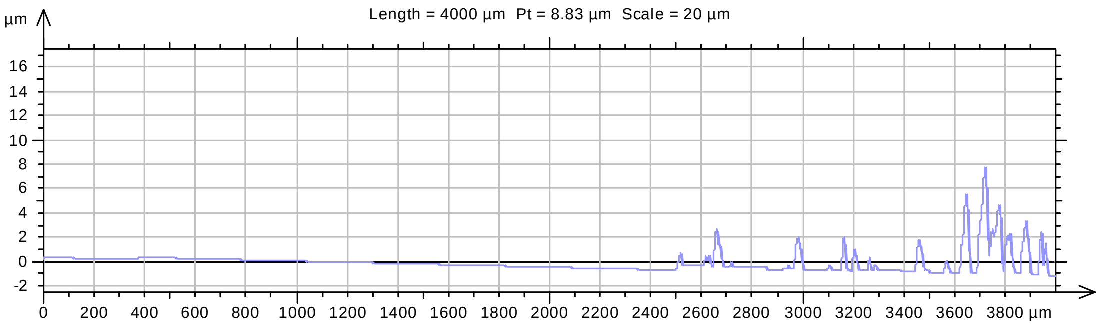
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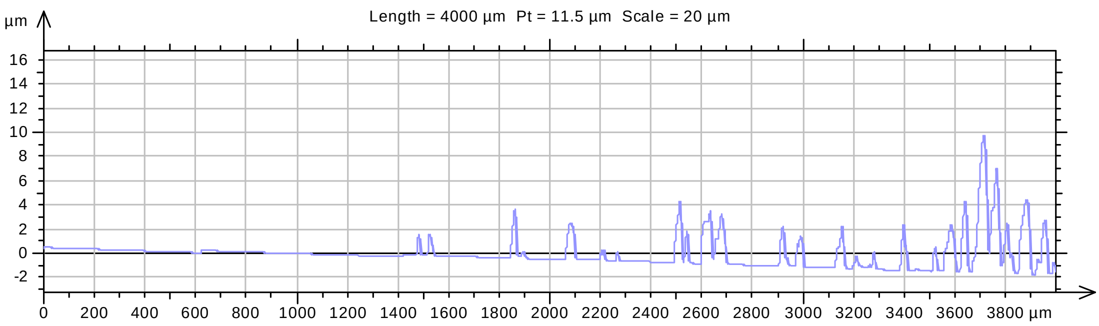
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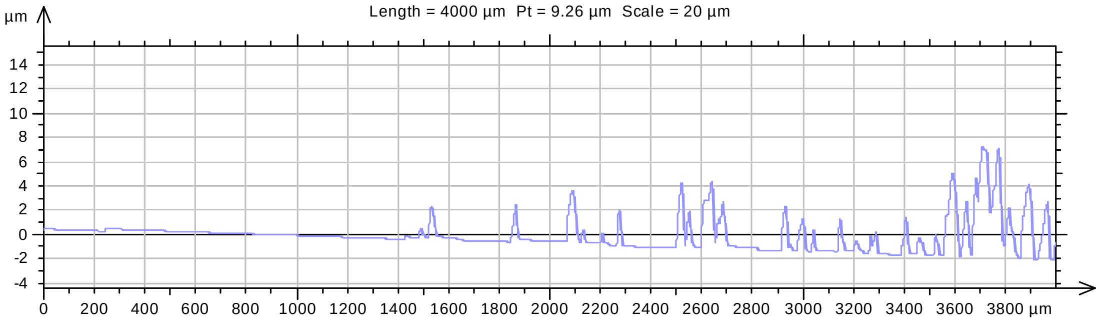
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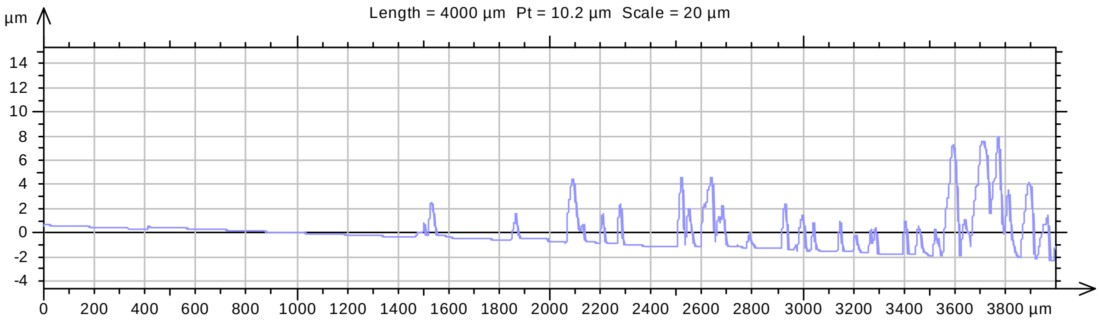
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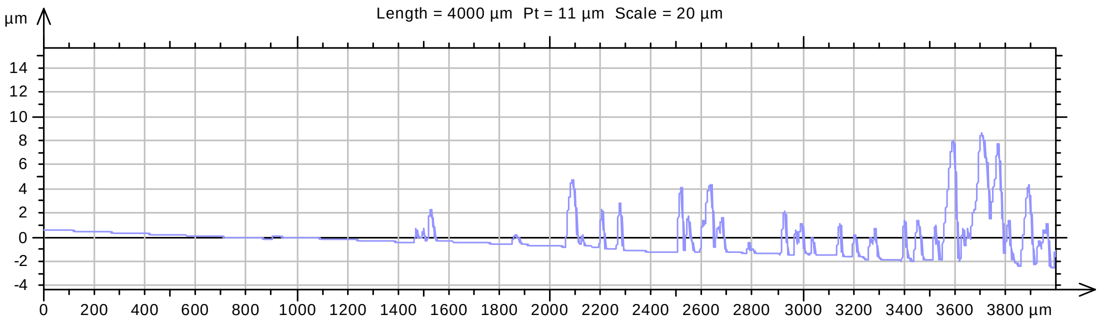
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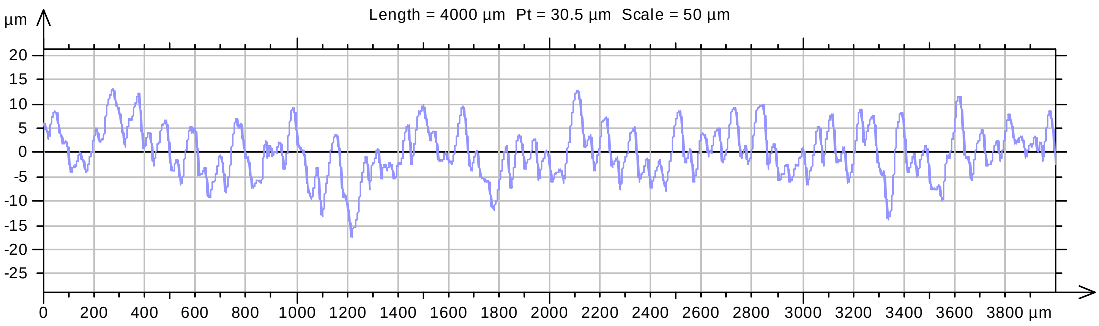
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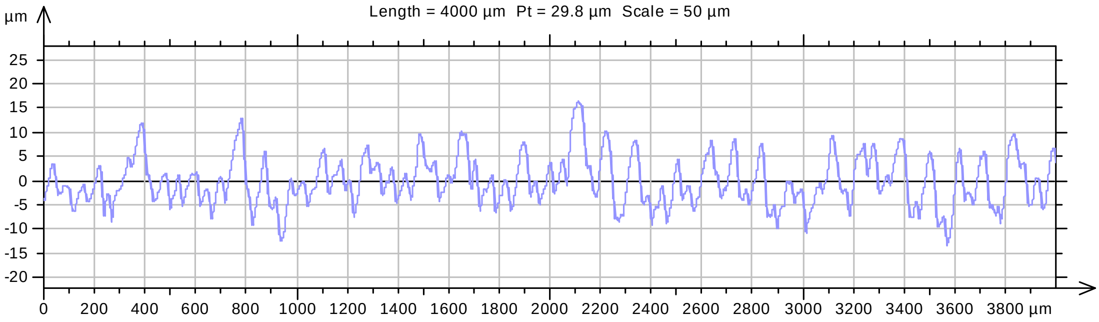
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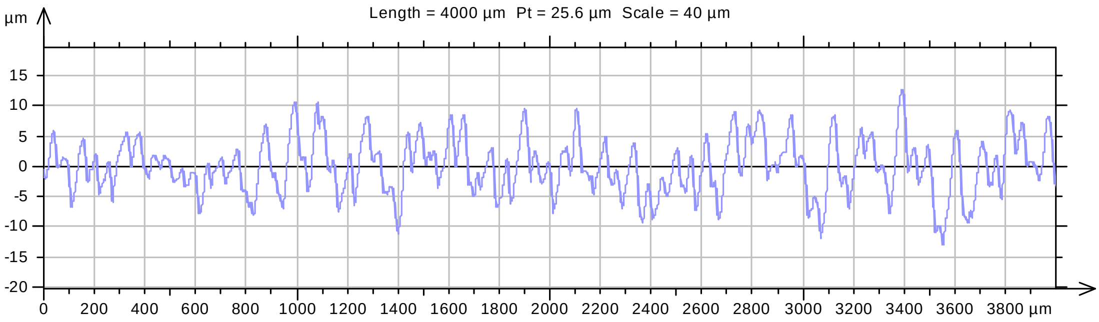
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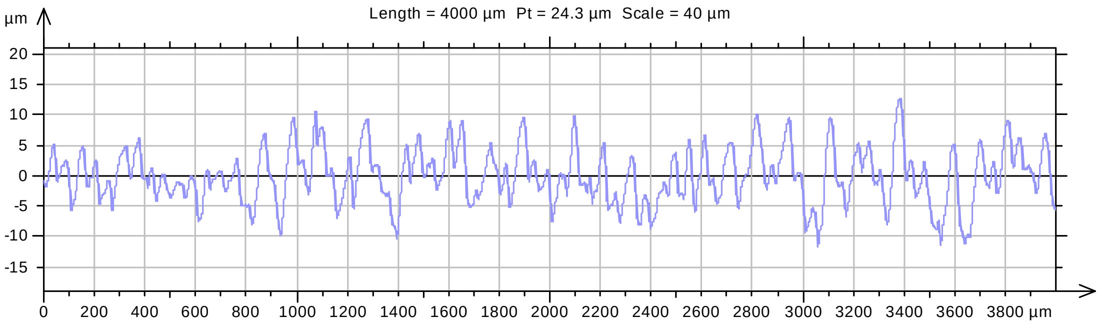
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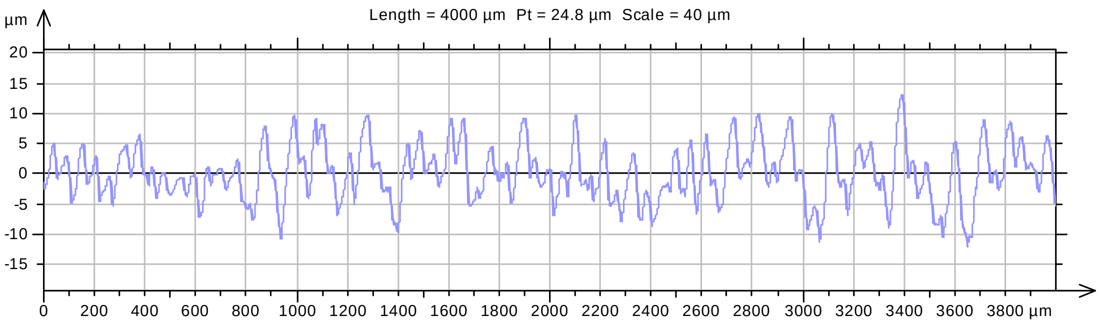
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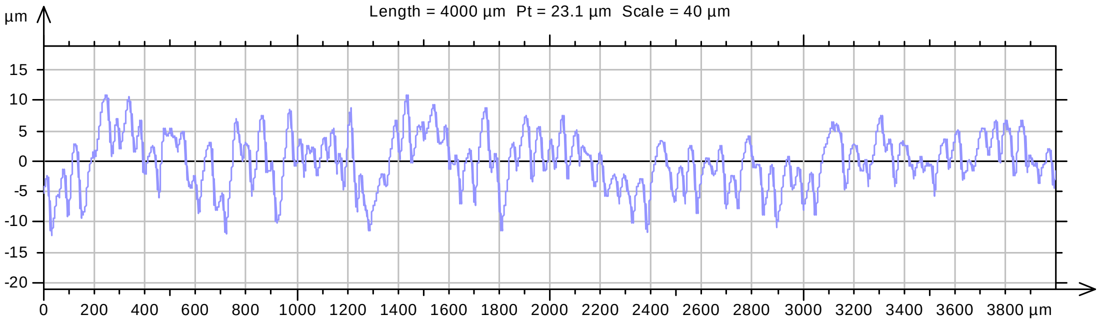
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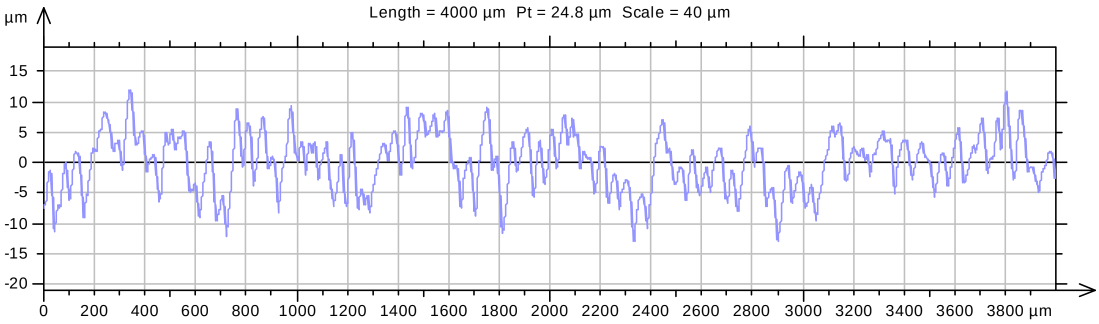
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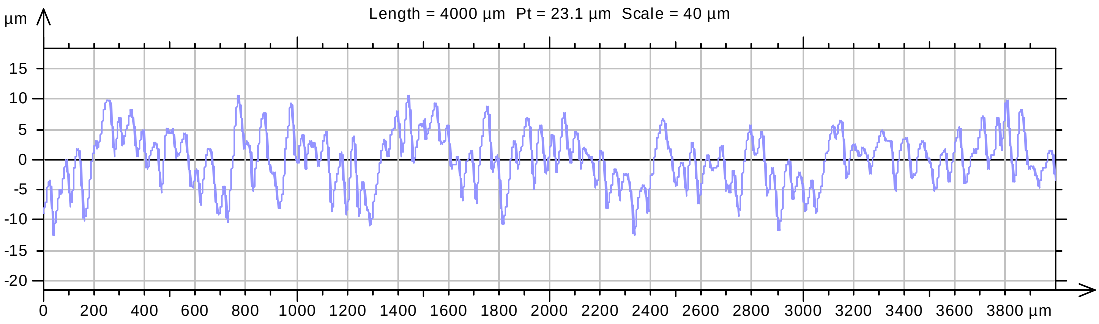
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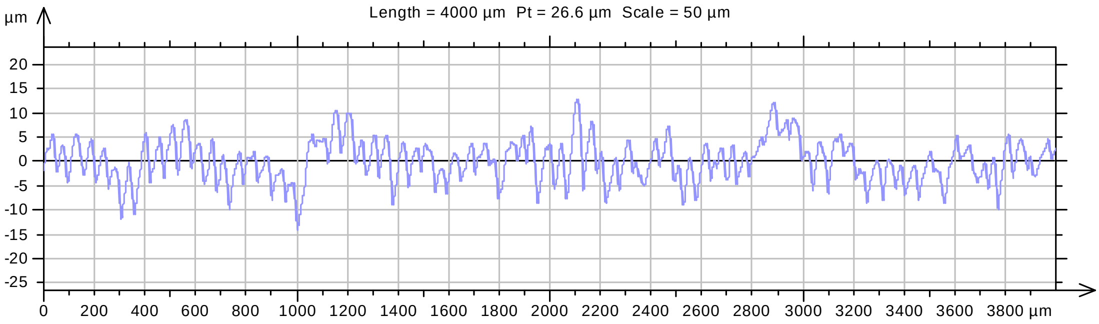
5(c)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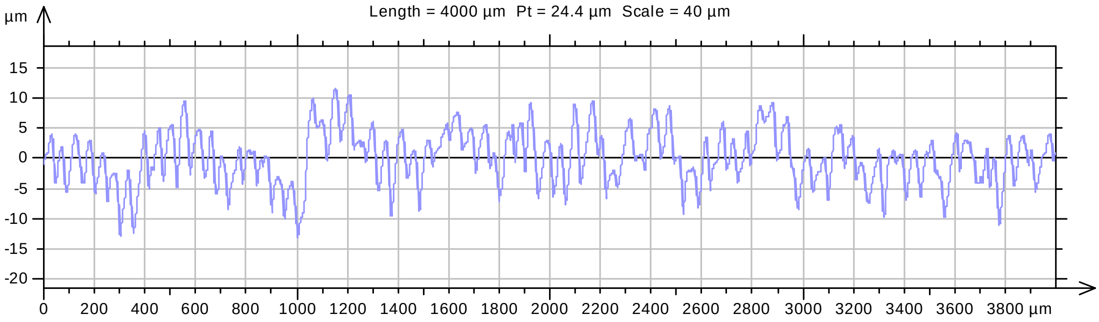
5(d)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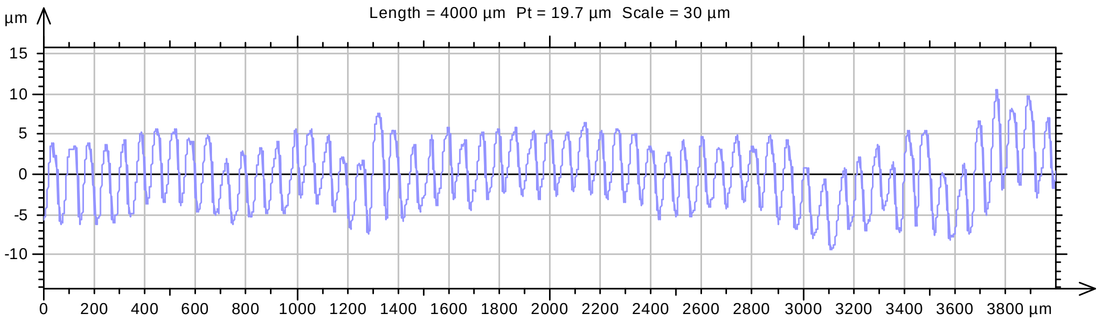
5(e)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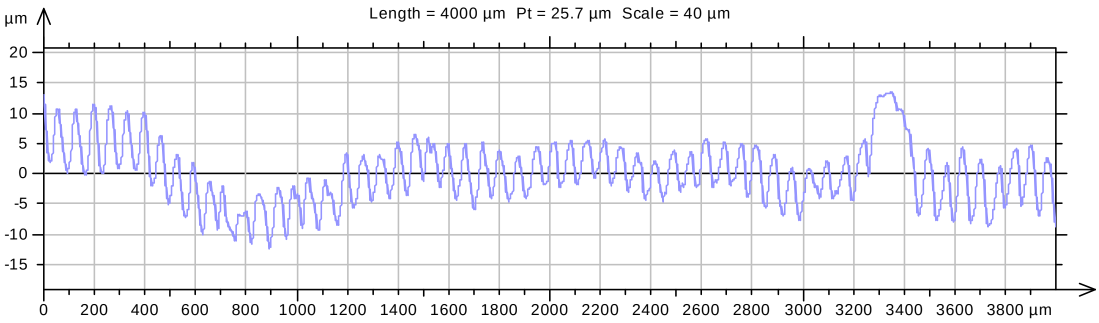
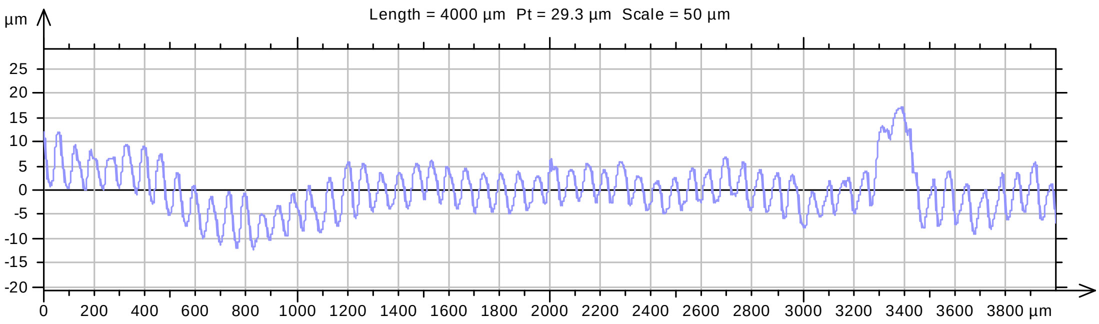
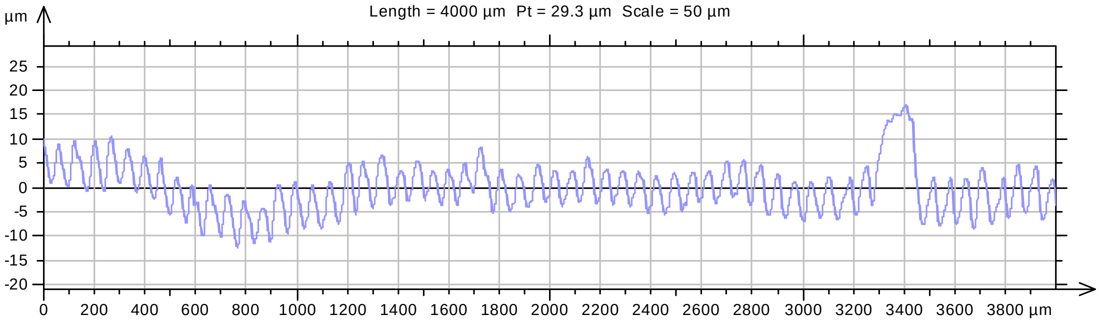
6(a)


Length = 4000 µm Pt = 25.7 µm Scale = 40 µm
µm
20
15
10
5
0
-5
-10
-15
0 200 400 600 800 1000 1200 1400 1600 1800 2000 2200 2400 2600 2800 3000 3200 3400 3600 3800 µm

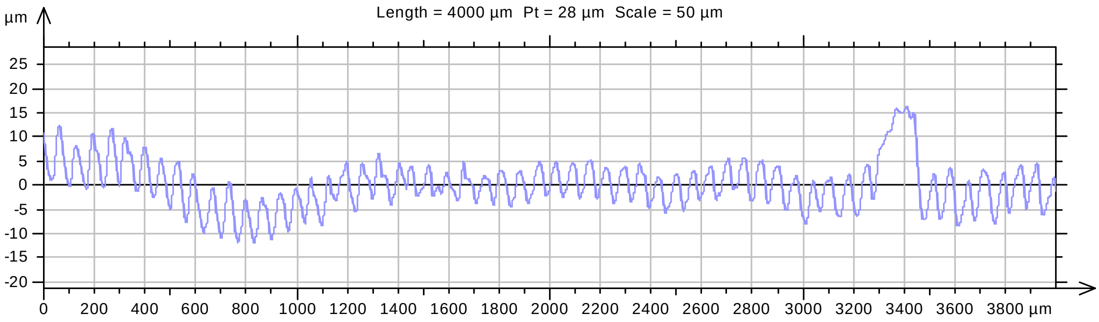
6(b)


Length = 4000 µm Pt = 29.3 µm Scale = 50 µm
µm
25
20
15
10
5
0
-5
-10
-15
-20
0 200 400 600 800 1000 1200 1400 1600 1800 2000 2200 2400 2600 2800 3000 3200 3400 3600 3800 µm

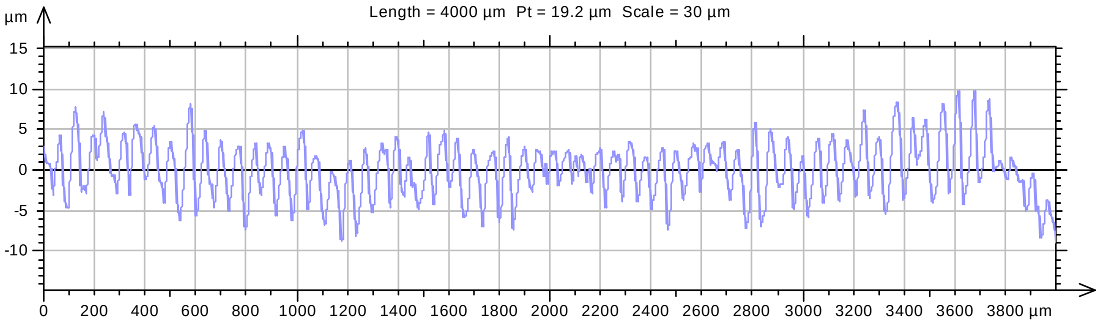
6(c)


µm
Length = 4000 µm Pt = 29.3 µm Scale = 50 µm
25
20
15
10
5
0
-5
-10
-15
-20
0 200 400 600 800 1000 1200 1400 1600 1800 2000 2200 2400 2600 2800 3000 3200 3400 3600 3800 µm

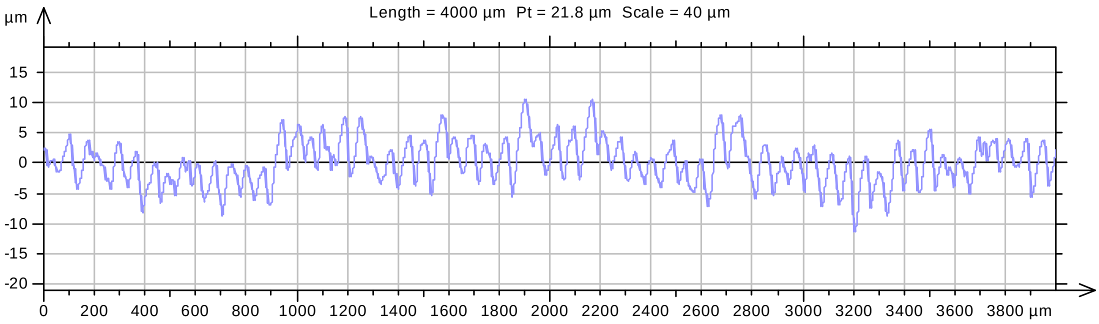
6(d)


µm
Length = 4000 µm Pt = 28 µm Scale = 50 µm
25
20
15
10
5
0
-5
-10
-15
-20
0 200 400 600 800 1000 1200 1400 1600 1800 2000 2200 2400 2600 2800 3000 3200 3400 3600 3800 µm

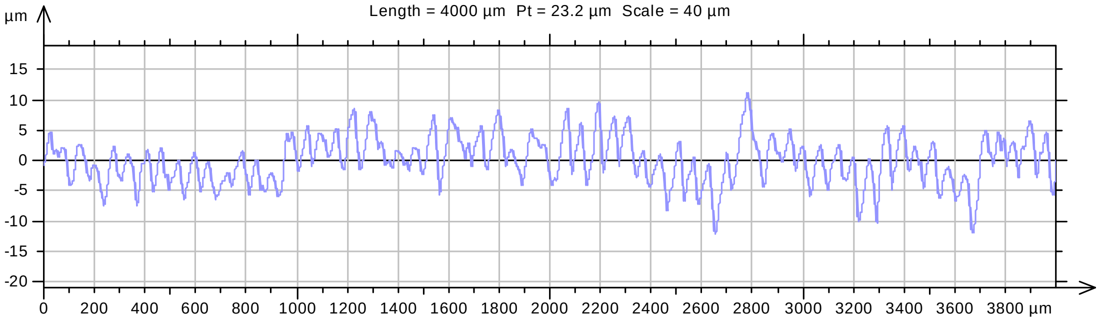
6(e)


µm
Length = 4000 µm Pt = 19.2 µm Scale = 30 µm
15
10
5
0
-5
-10
0 200 400 600 800 1000 1200 1400 1600 1800 2000 2200 2400 2600 2800 3000 3200 3400 3600 3800 µm

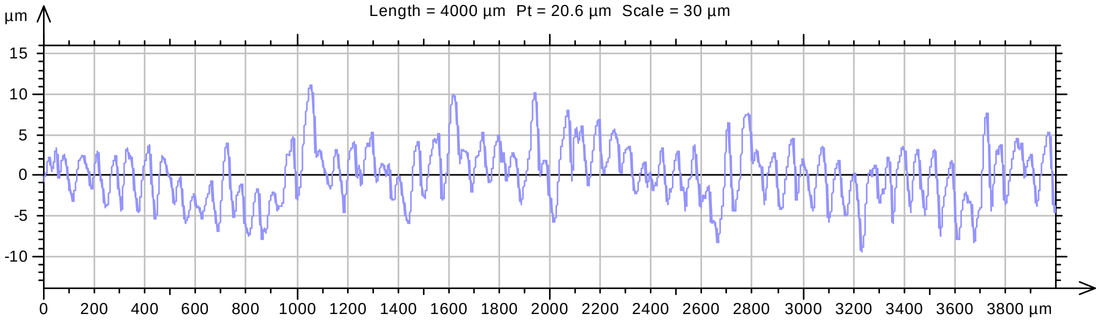
7(a)


µm
Length = 4000 µm Pt = 21.8 µm Scale = 40 µm
15
10
5
0
-5
-10
-15
-20
0 200 400 600 800 1000 1200 1400 1600 1800 2000 2200 2400 2600 2800 3000 3200 3400 3600 3800 µm

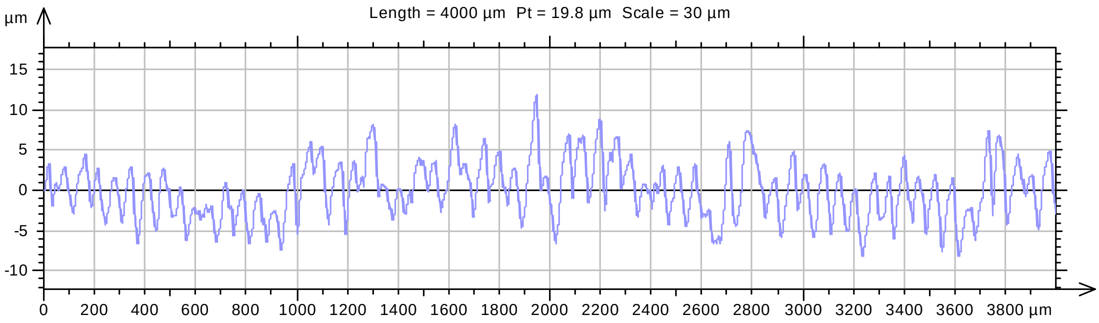
7(b)


Length = 4000 µm Pt = 23.2 µm Scale = 40 µm
µm

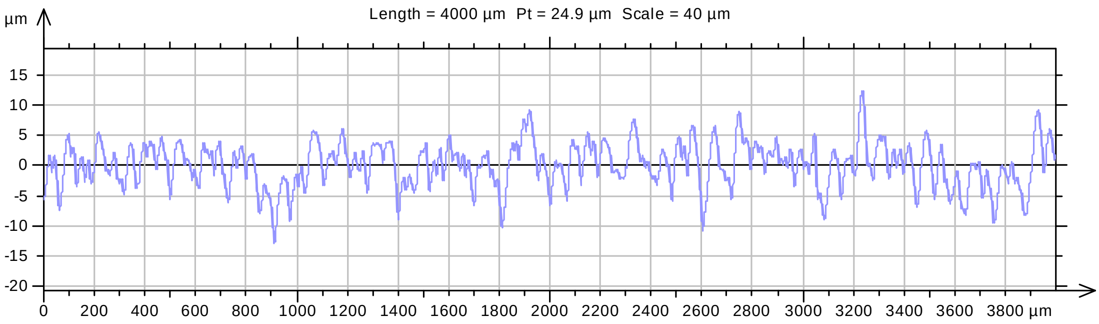
7(c)


Length = 4000 µm Pt = 20.6 µm Scale = 30 µm
µm

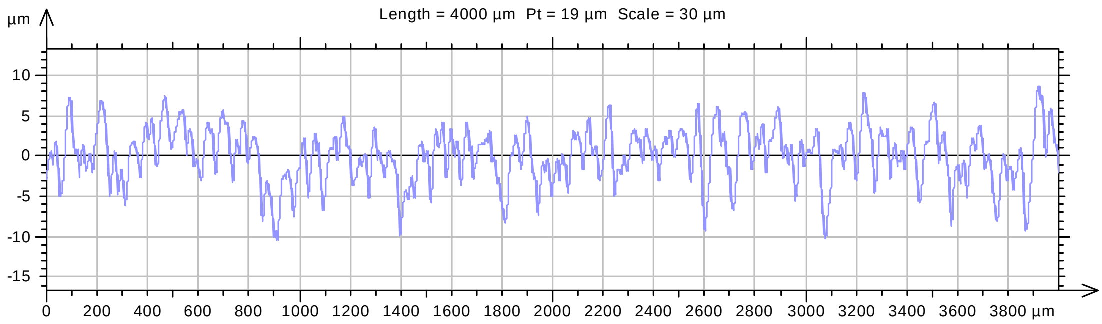
7(d)


Length = 4000 µm Pt = 19.8 µm Scale = 30 µm
µm

7(e)

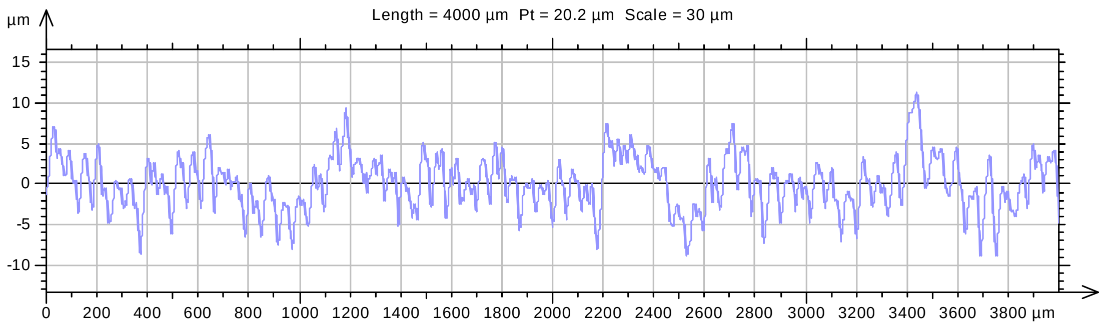

Length = 4000 µm Pt = 24.9 µm Scale = 40 µm
µm

8(a)



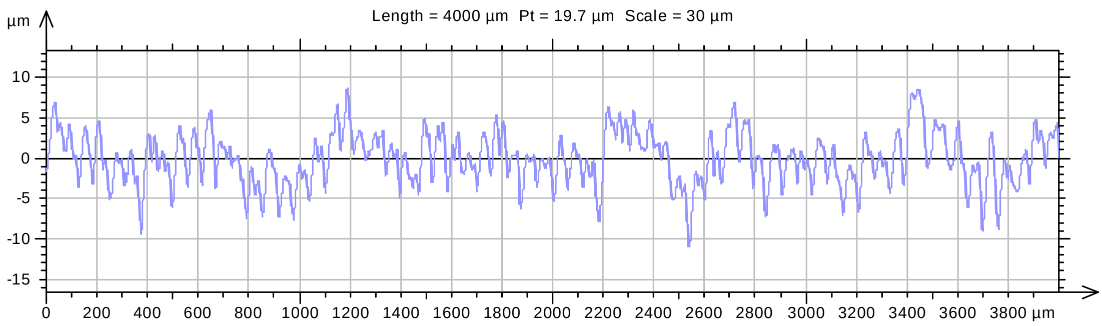
Length = 4000 µm Pt = 19 µm Scale = 30 µm
µm
10
5
0
-5
-10
-15
0 200 400 600 800 1000 1200 1400 1600 1800 2000 2200 2400 2600 2800 3000 3200 3400 3600 3800 µm

8(b)



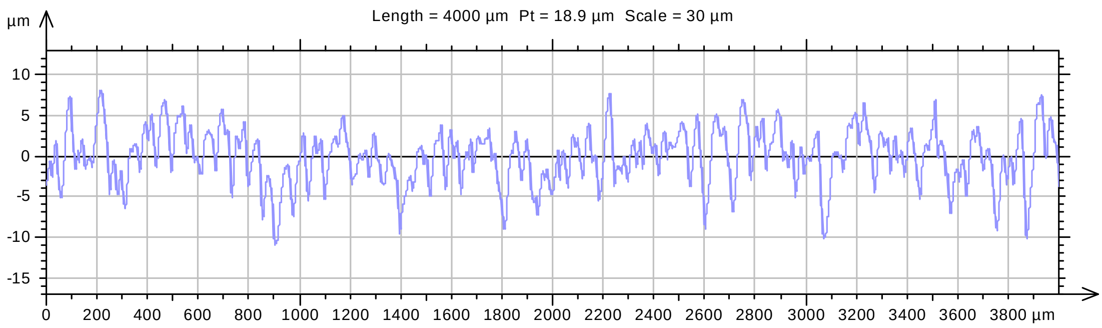
Length = 4000 µm Pt = 20.2 µm Scale = 30 µm
µm
15
10
5
0
-5
-10
0 200 400 600 800 1000 1200 1400 1600 1800 2000 2200 2400 2600 2800 3000 3200 3400 3600 3800 µm

8(c)



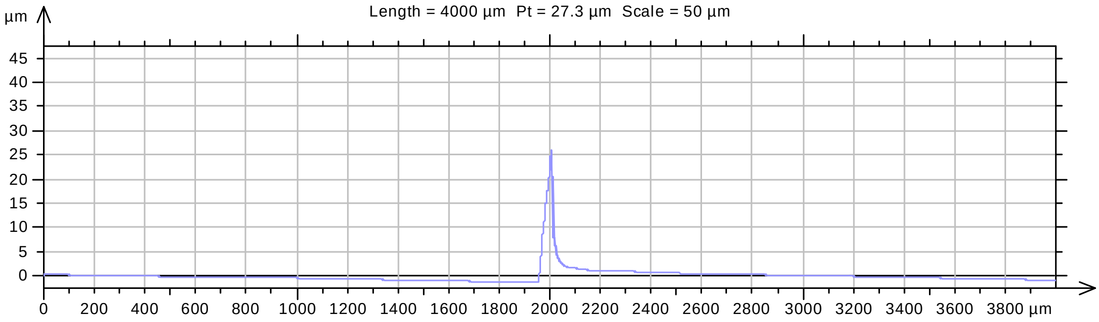
Length = 4000 µm Pt = 19.7 µm Scale = 30 µm
µm
10
5
0
-5
-10
-15
0 200 400 600 800 1000 1200 1400 1600 1800 2000 2200 2400 2600 2800 3000 3200 3400 3600 3800 µm

8(d)

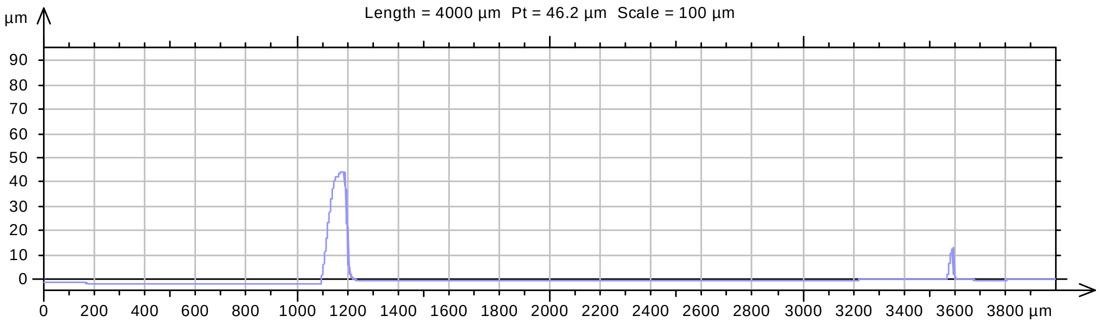


Length = 4000 µm Pt = 18.9 µm Scale = 30 µm
µm
10
5
0
-5
-10
-15
0 200 400 600 800 1000 1200 1400 1600 1800 2000 2200 2400 2600 2800 3000 3200 3400 3600 3800 µm

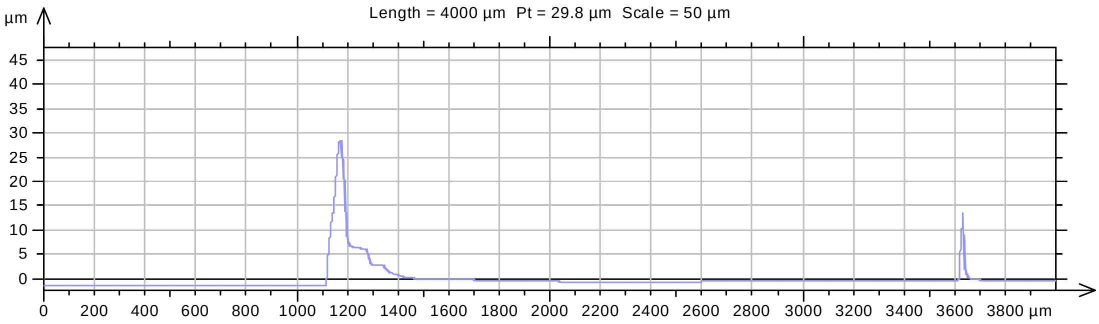
8(e)


Length = 4000 µm Pt = 27.3 µm Scale = 50 µm
µm
µm

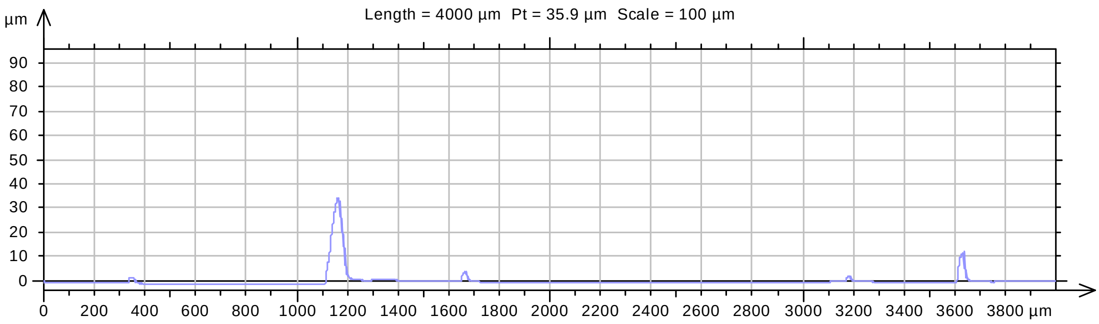
9(a)


Length = 4000 µm Pt = 46.2 µm Scale = 100 µm
µm
µm

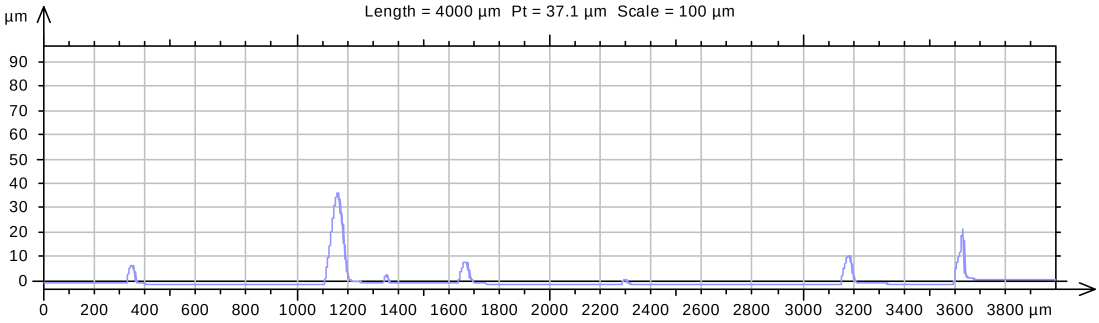
9(b)


Length = 4000 µm Pt = 29.8 µm Scale = 50 µm
µm
µm

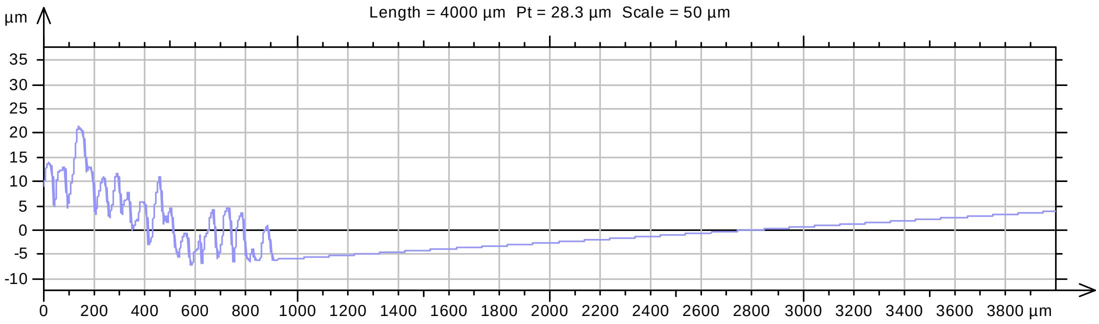
9(c)


Length = 4000 µm Pt = 35.9 µm Scale = 100 µm
µm
µm

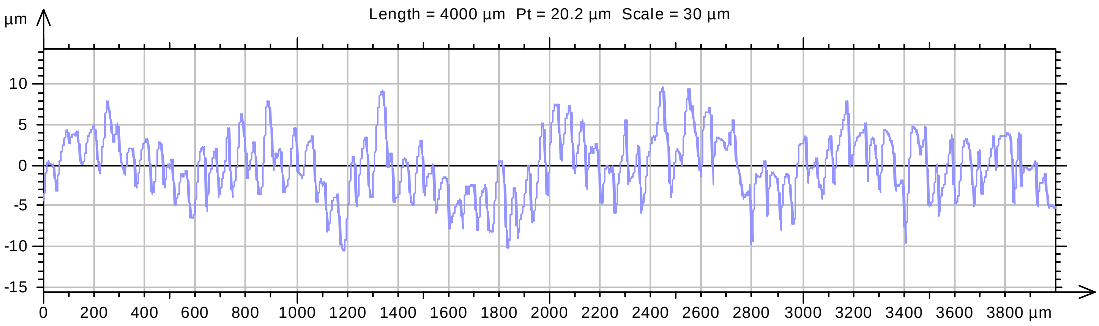
9(d)

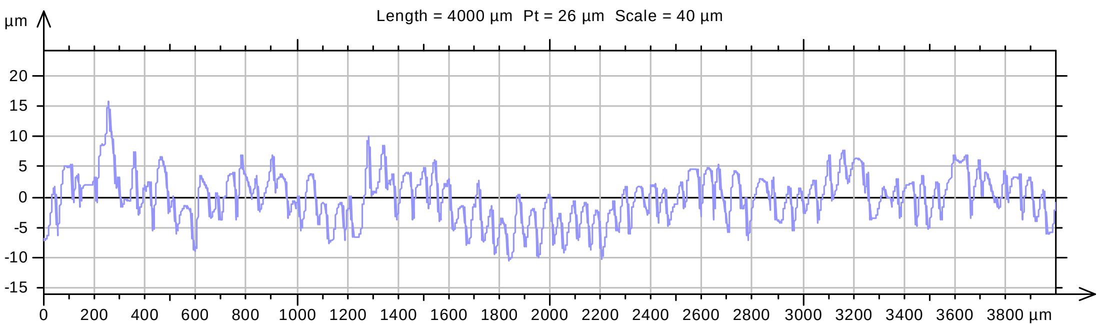

Length = 4000 µm Pt = 37.1 µm Scale = 100 µm
µm
90
80
70
60
50
40
30
20
10
0
0 200 400 600 800 1000 1200 1400 1600 1800 2000 2200 2400 2600 2800 3000 3200 3400 3600 3800 µm

9(e)

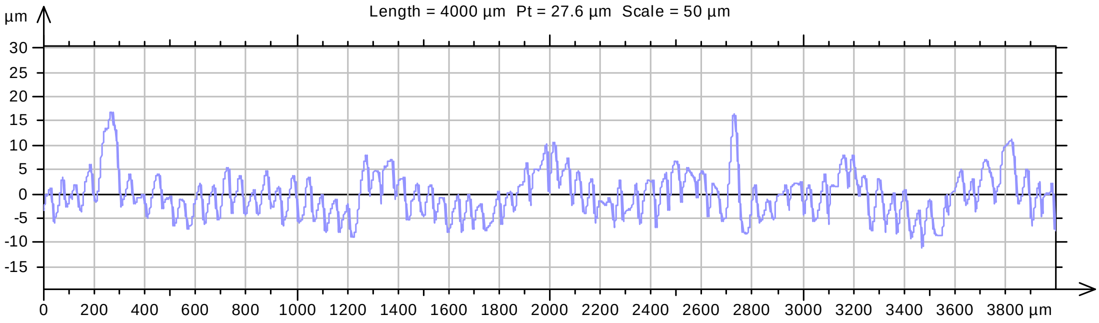

Length = 4000 µm Pt = 28.3 µm Scale = 50 µm
µm
35
30
25
20
15
10
5
0
-5
-10
0 200 400 600 800 1000 1200 1400 1600 1800 2000 2200 2400 2600 2800 3000 3200 3400 3600 3800 µm

10(a)

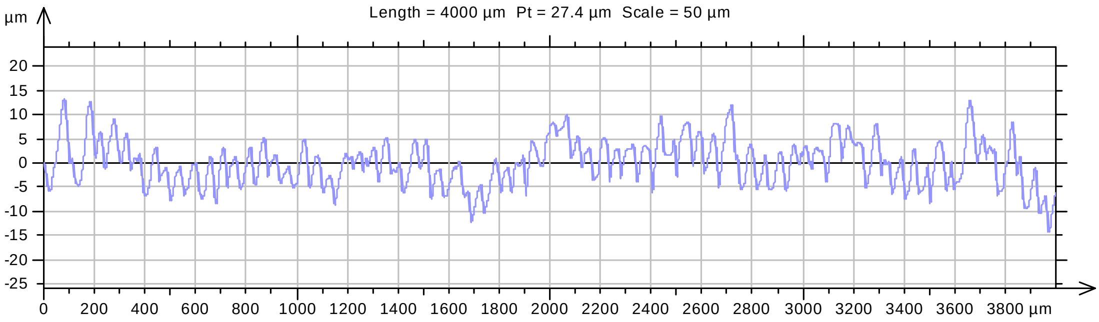

Length = 4000 µm Pt = 20.2 µm Scale = 30 µm
µm
10
5
0
-5
-10
-15
0 200 400 600 800 1000 1200 1400 1600 1800 2000 2200 2400 2600 2800 3000 3200 3400 3600 3800 µm


Length = 4000 µm Pt = 26 µm Scale = 40 µm
µm
20
15
10
5
0
-5
-10
-15
0 200 400 600 800 1000 1200 1400 1600 1800 2000 2200 2400 2600 2800 3000 3200 3400 3600 3800 µm

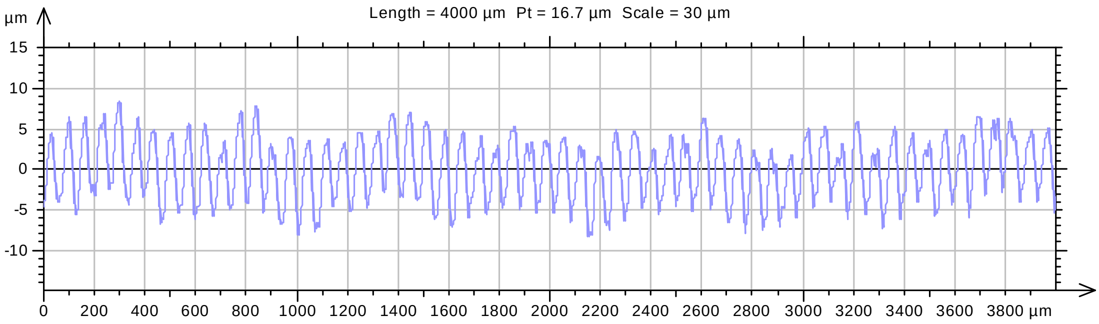
10(c)



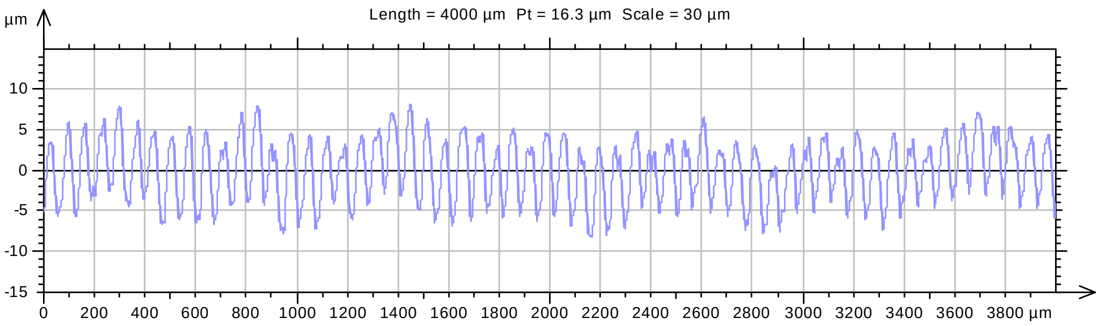
10(d)



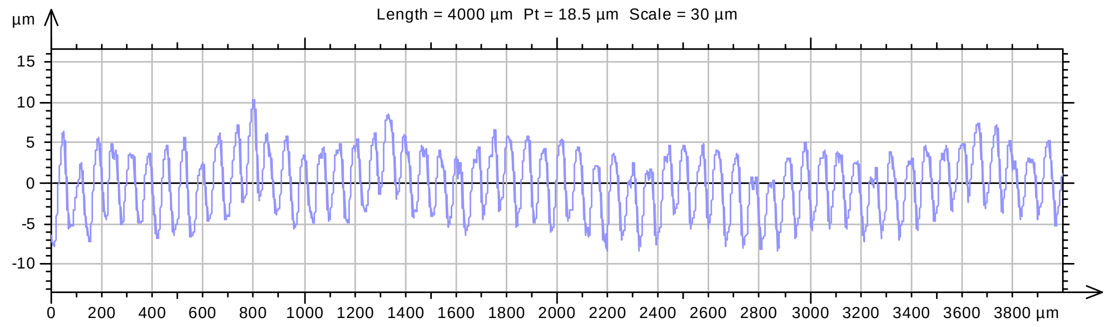
10(e)



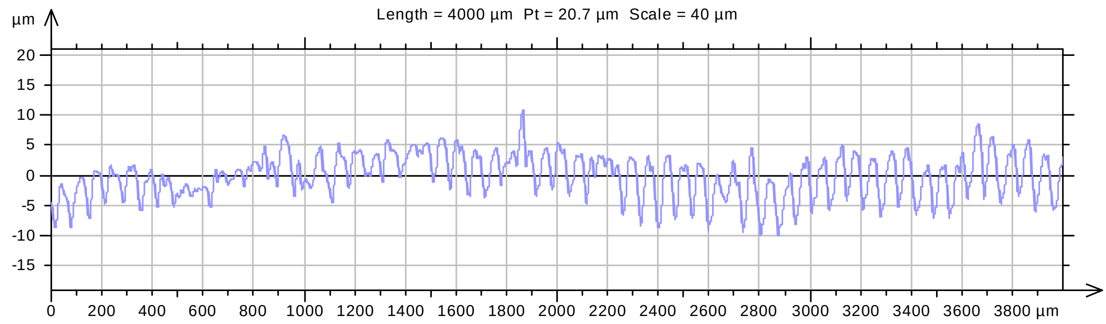
11(a)



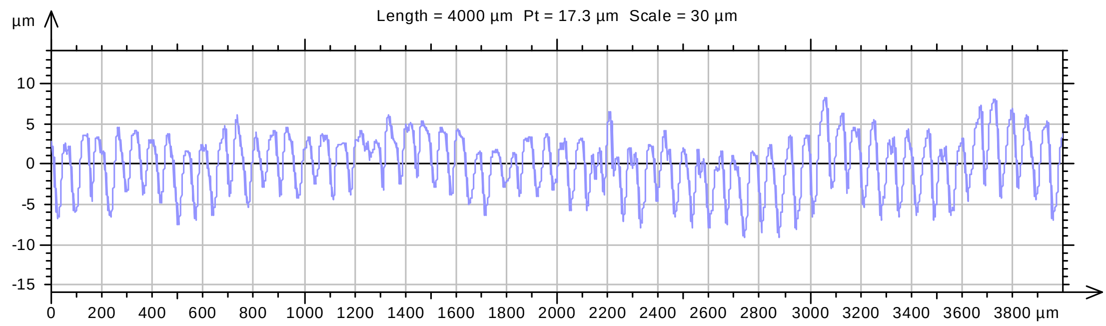
11(b)



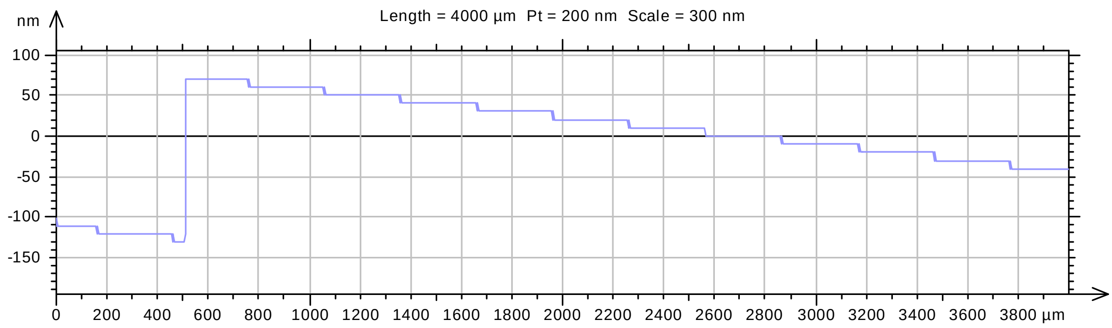
11(c)



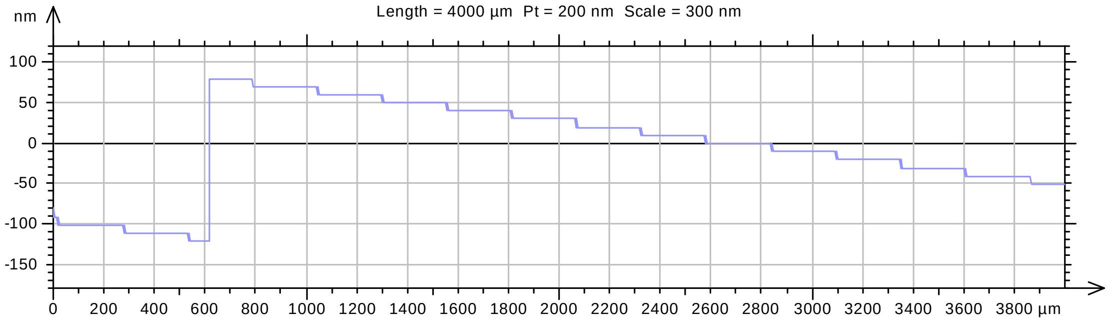
11(d)



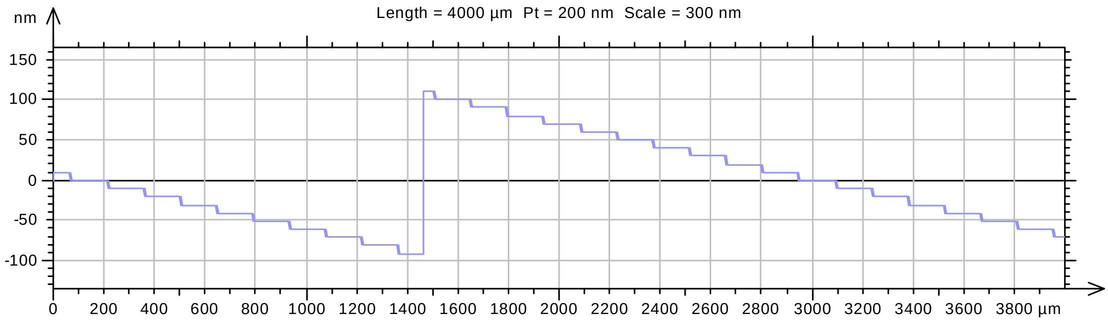
11(e)



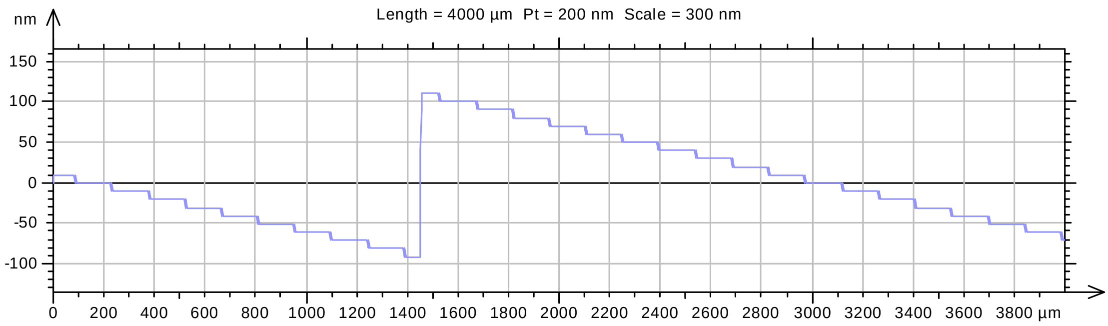
12(a)



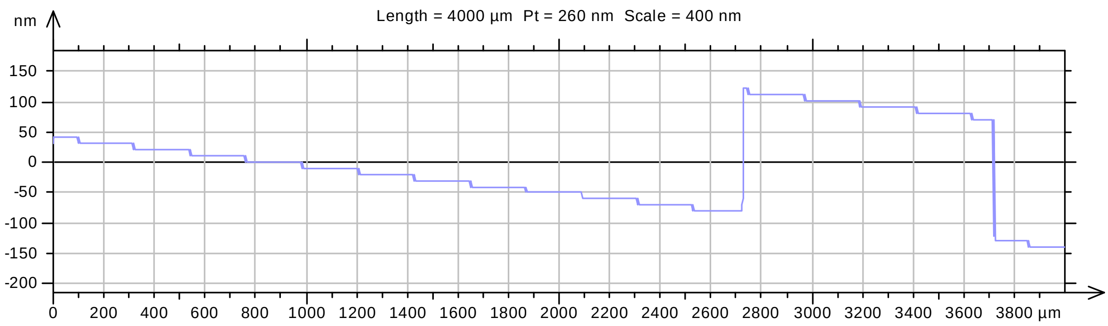
12(b)



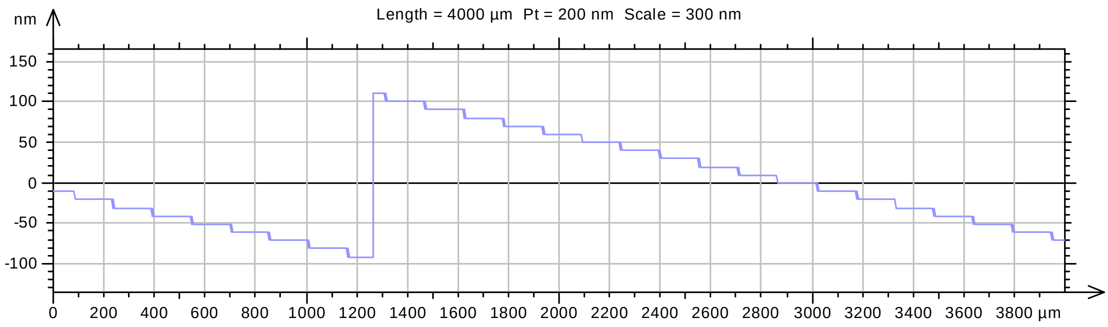
12(c)



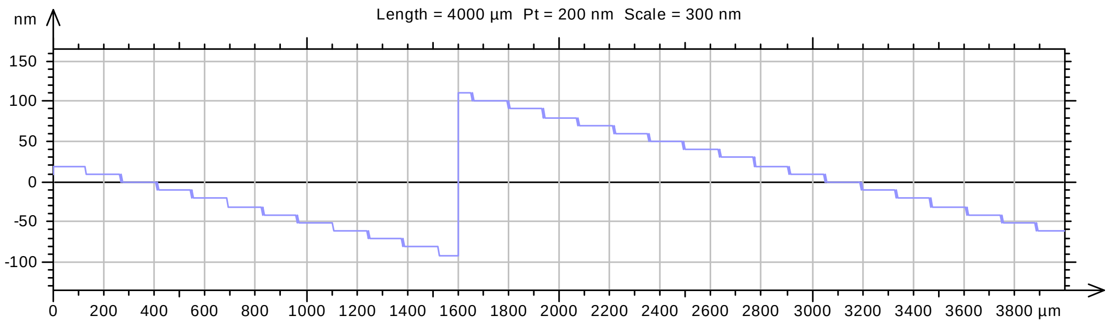
12(d)



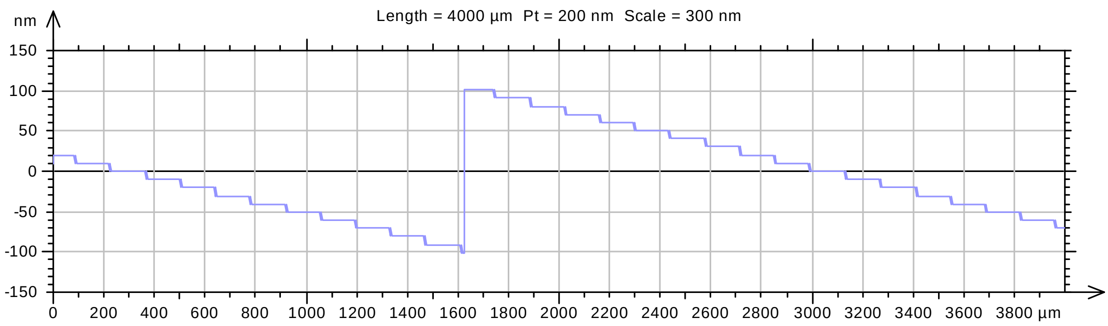
12(e)



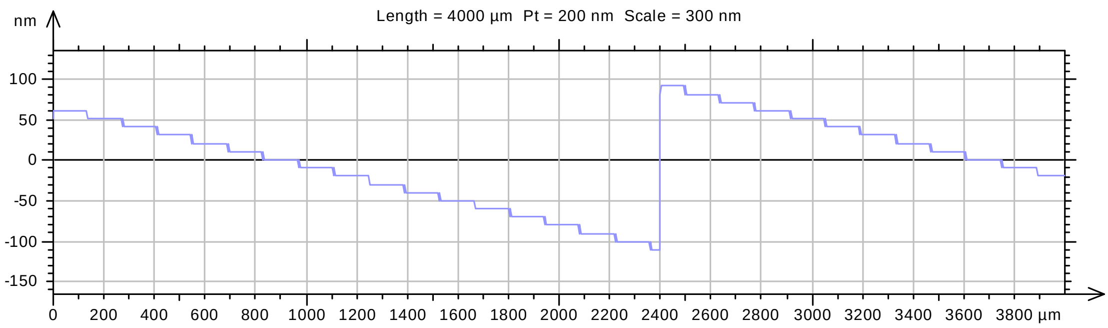
13(a)



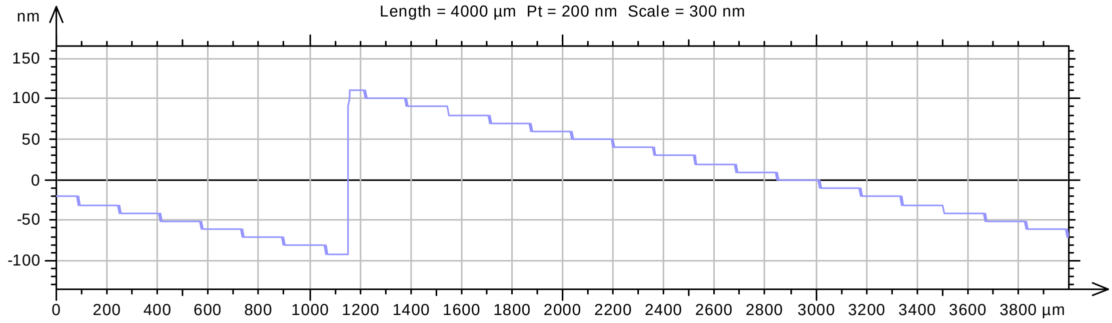
13(b)



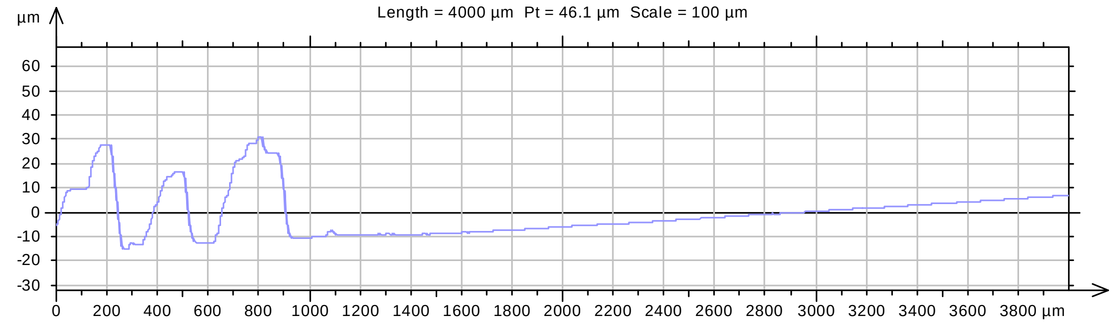
13(c)



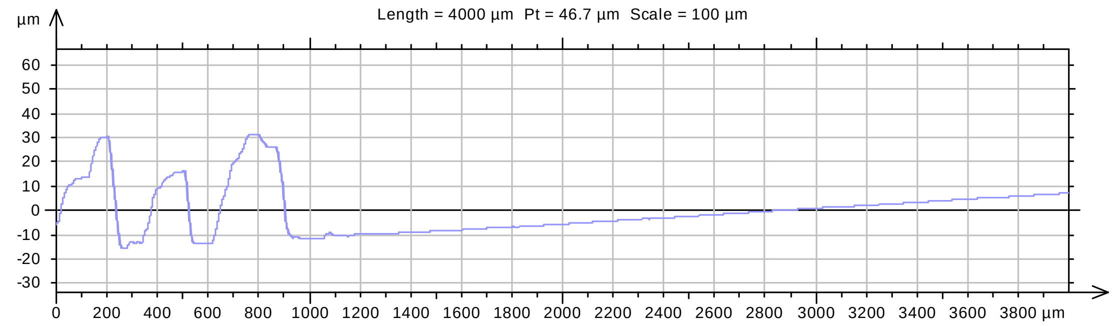
13(d)



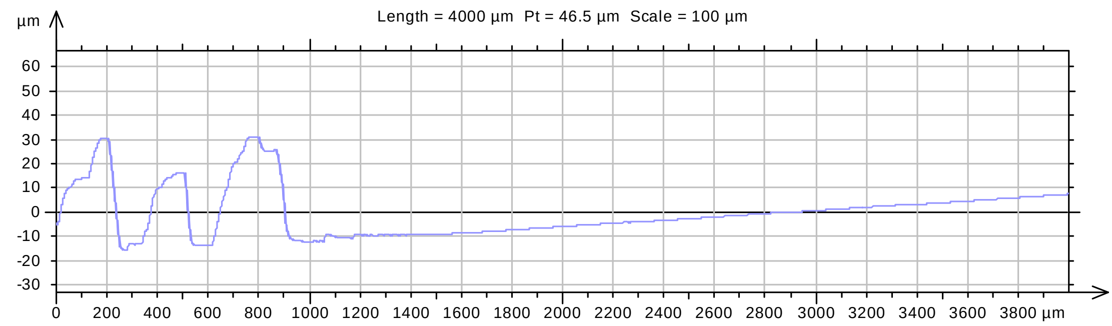
13(e)



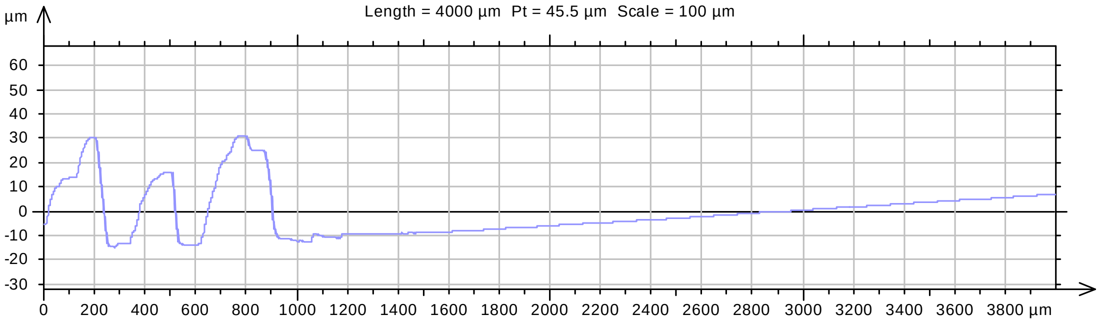
14(a)



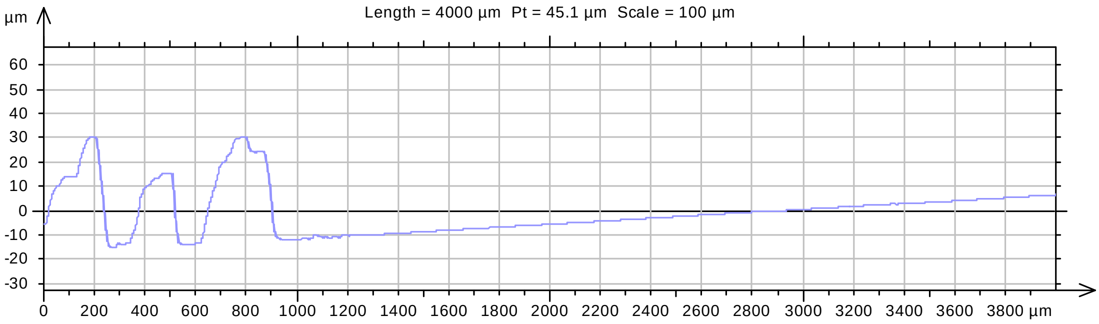
14(b)



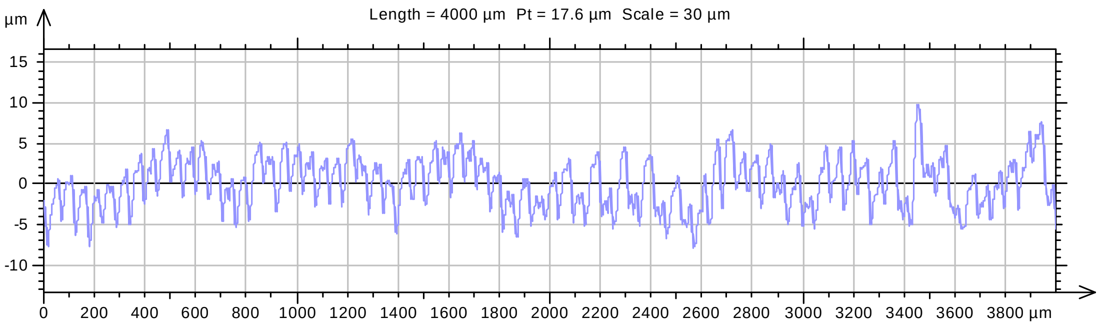
14(c)



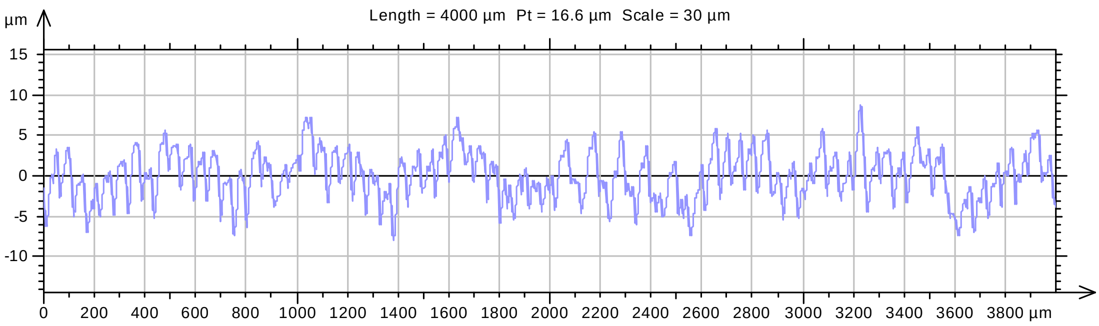
14(d)



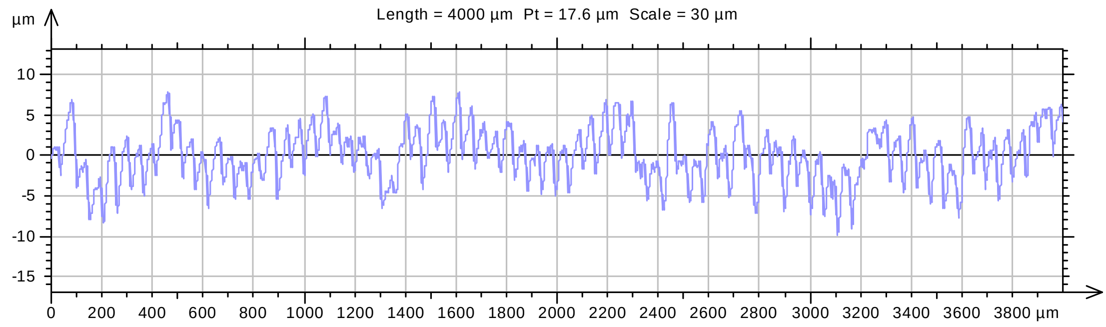
14(e)



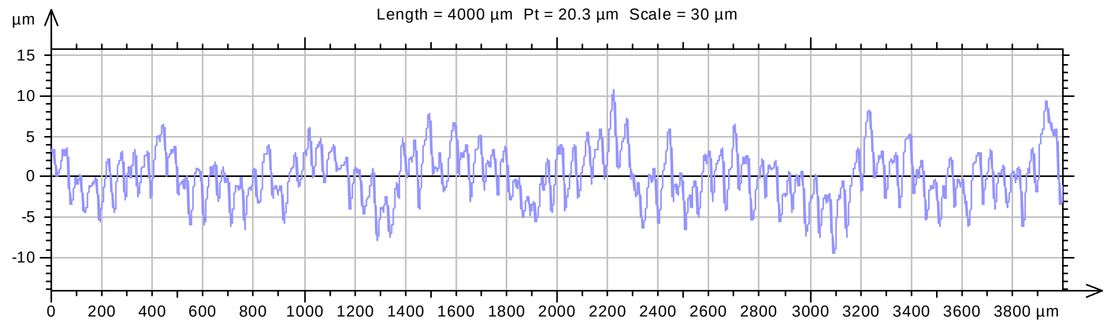
15(a)



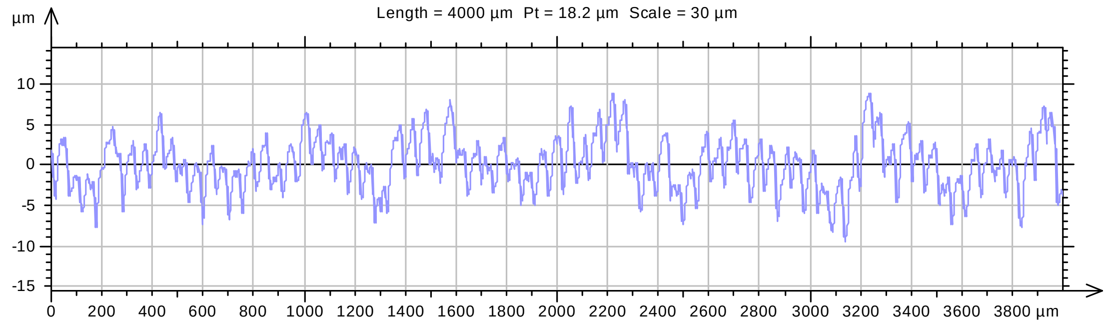
15(b)



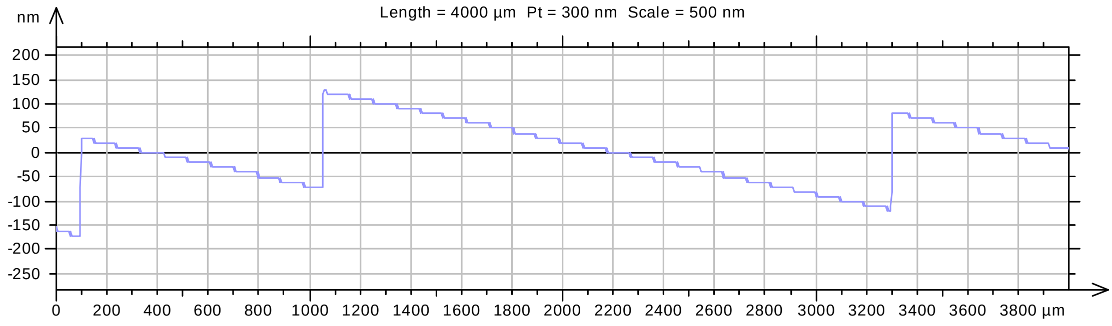
15(c)



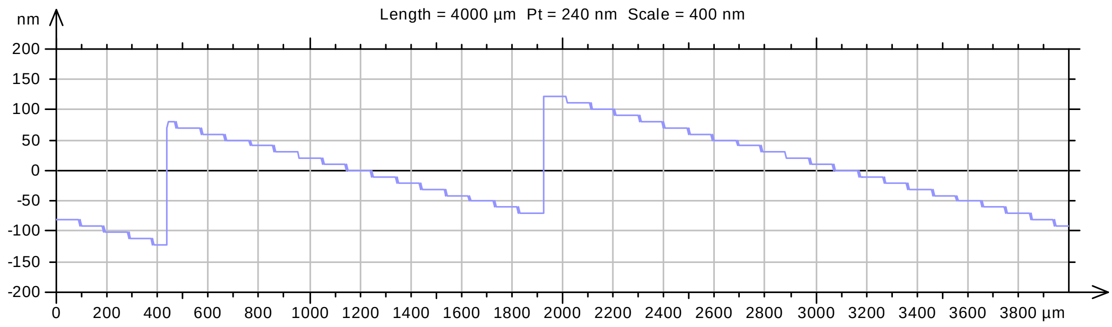
15(d)



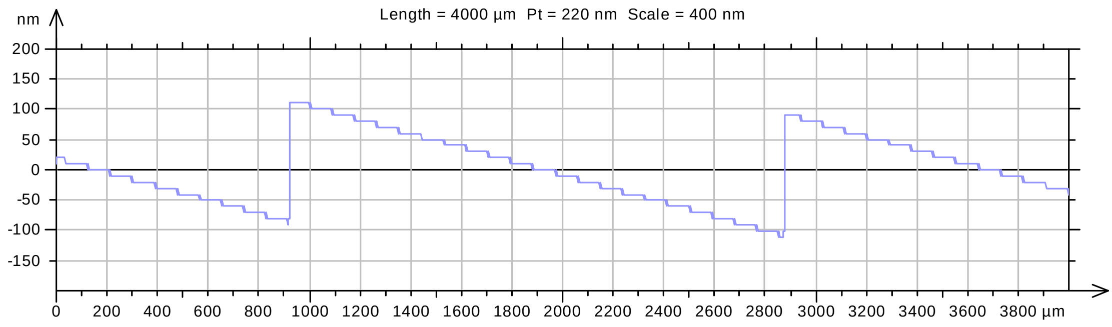
15(e)



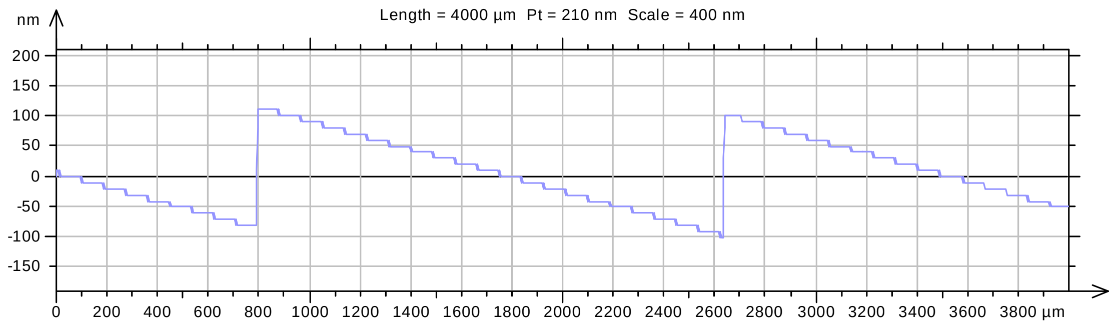
16(a)



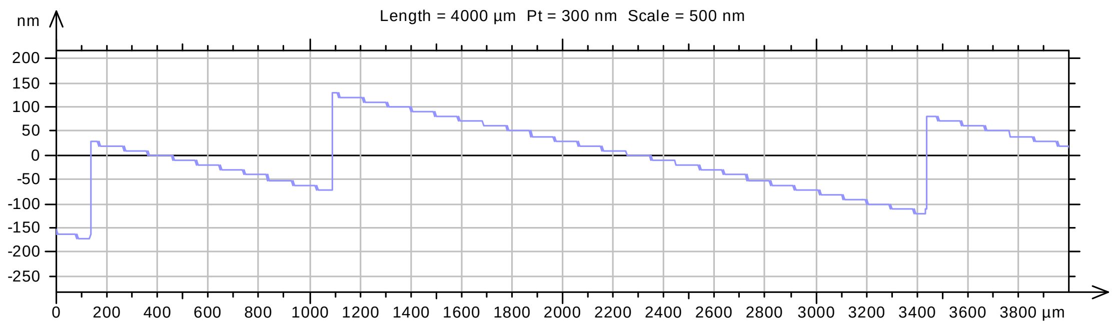
16(b)



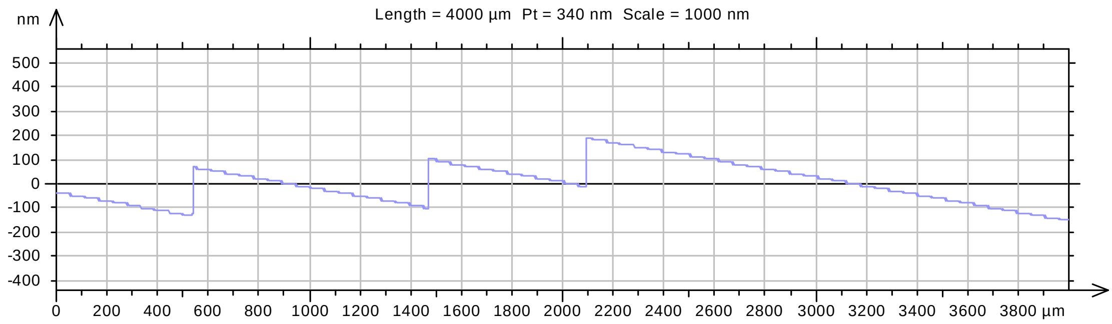
16(c)



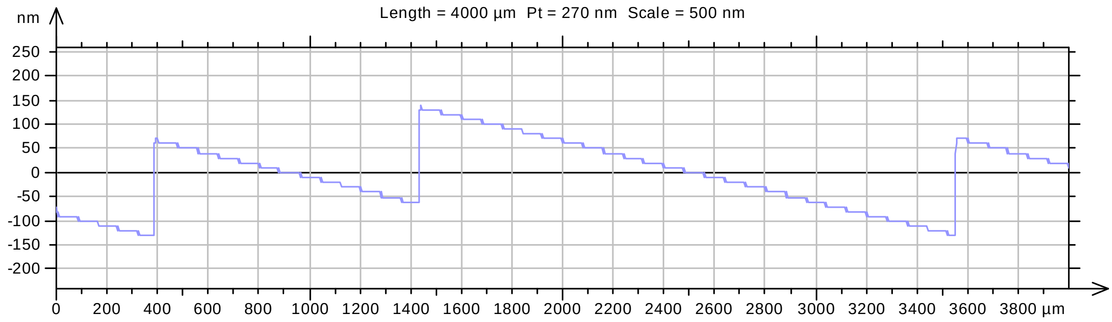
16(d)



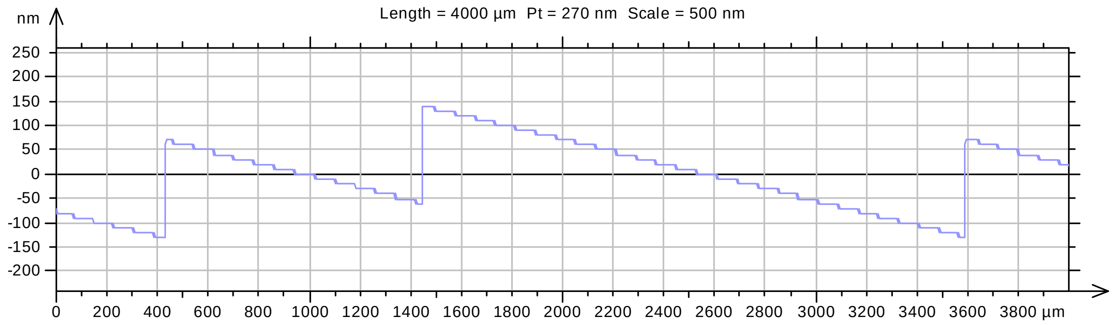
16(e)



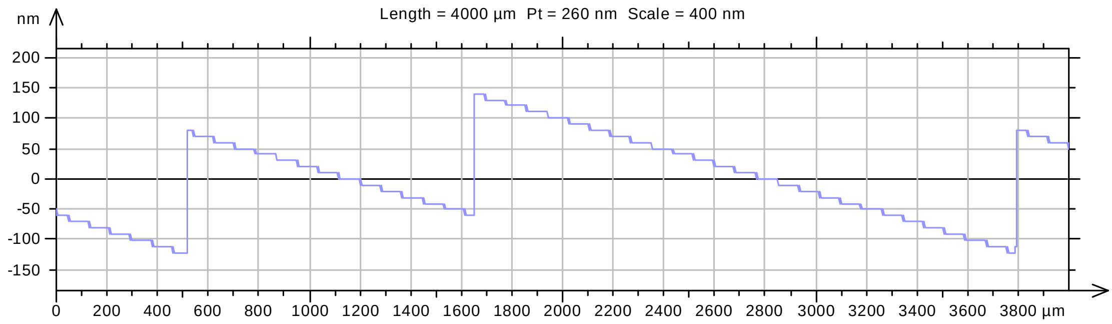
17(a)



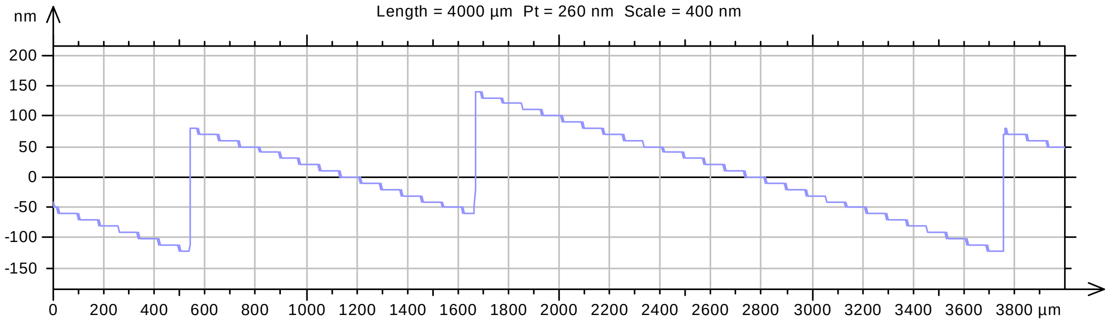
17(b)



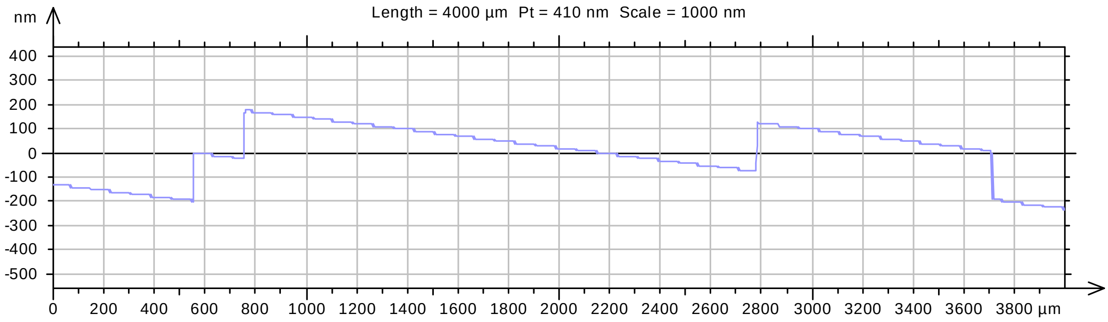
17(c)



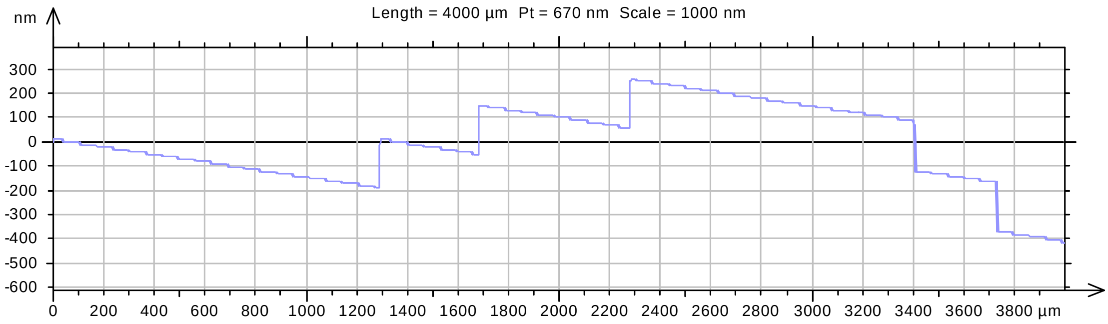
17(d)



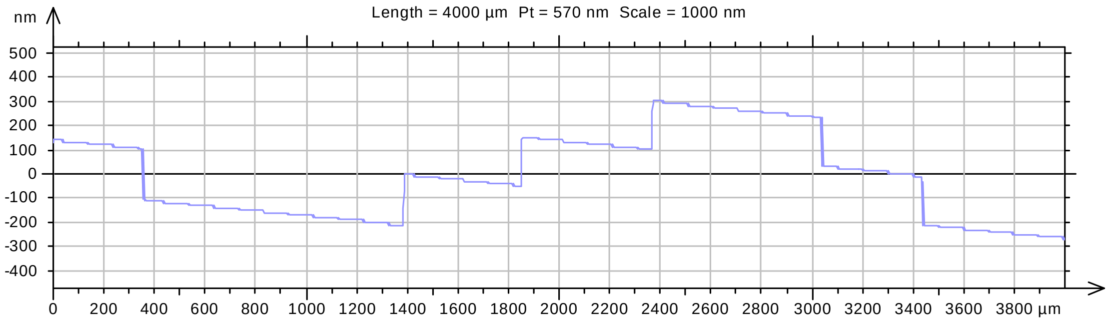
17(e)



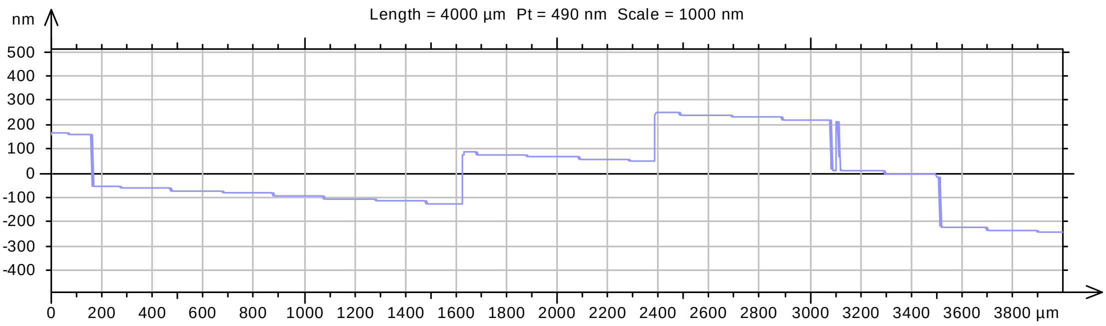
18(a)



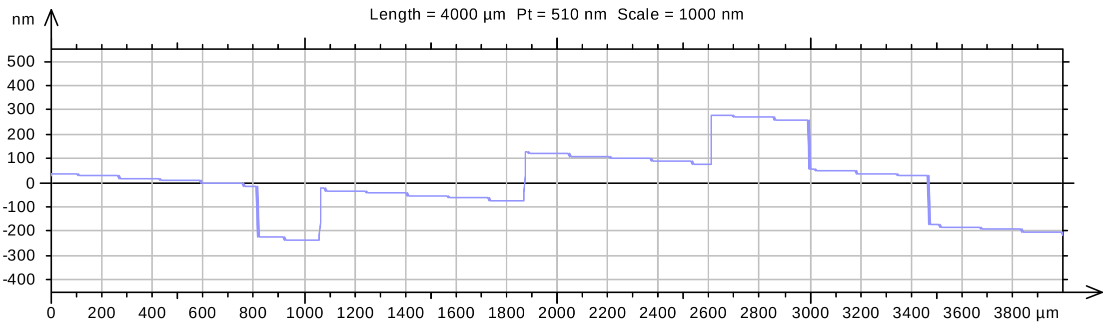
18(b)



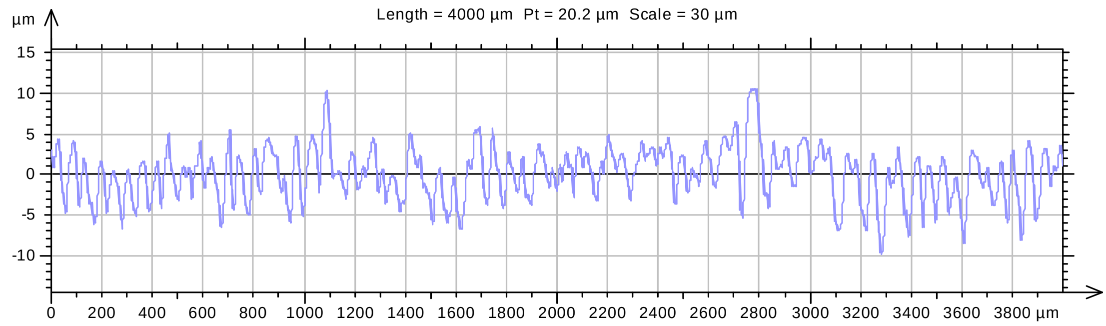
18(c)



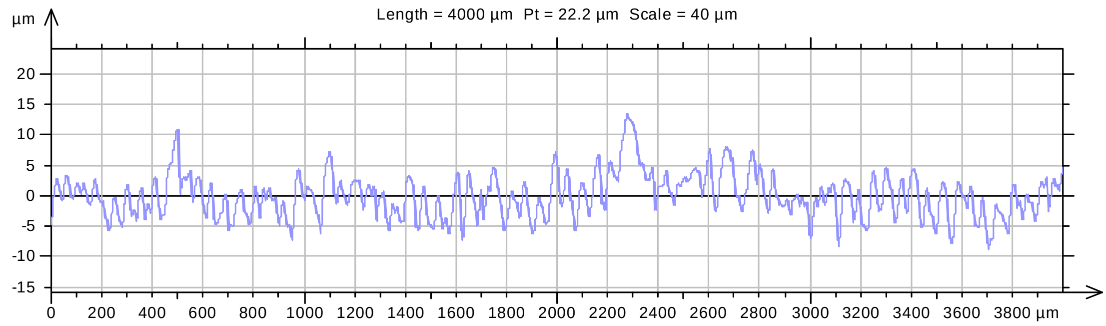
18(d)



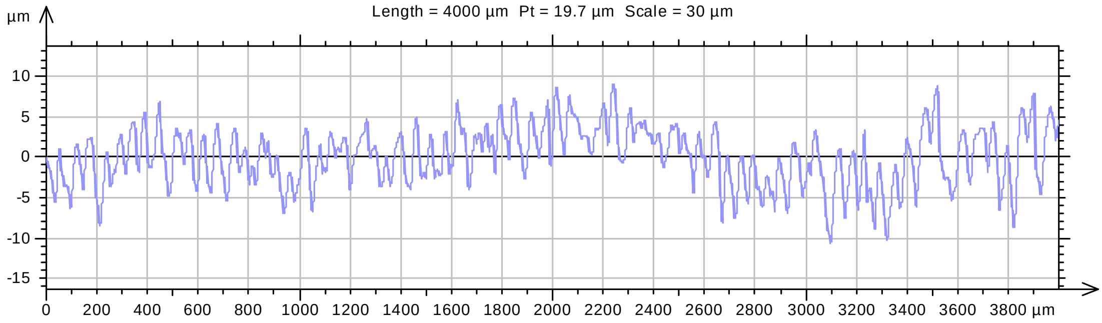
18(e)



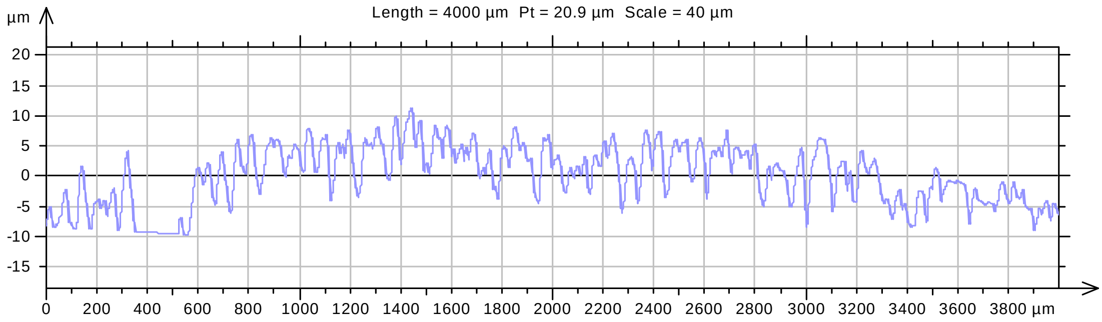
19(a)



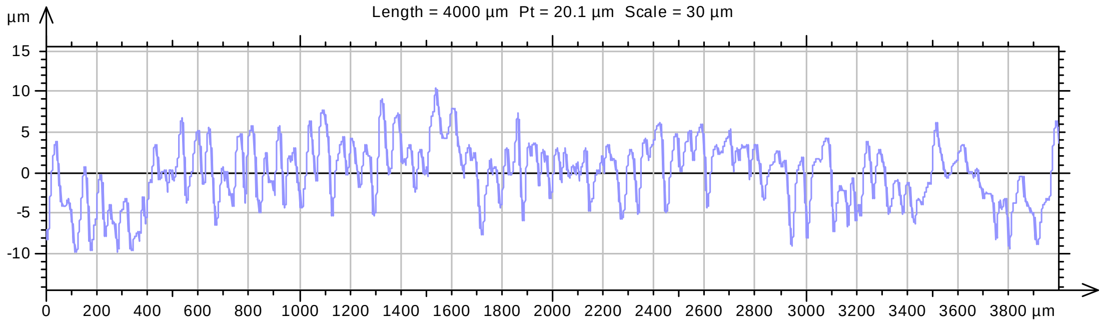
19(b)



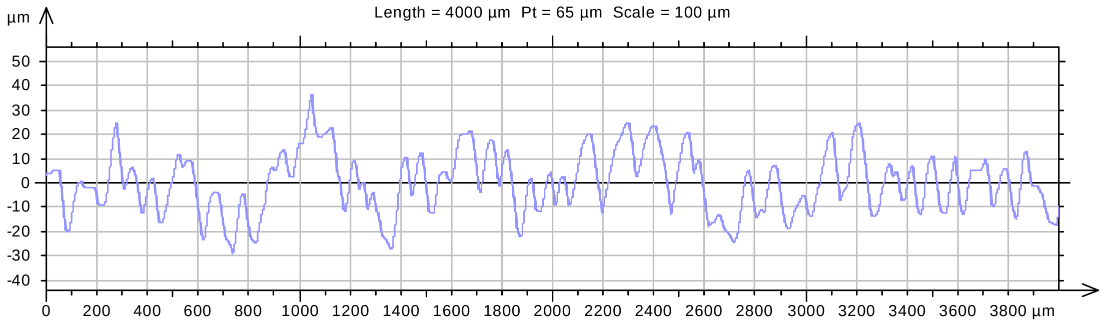
19(c)



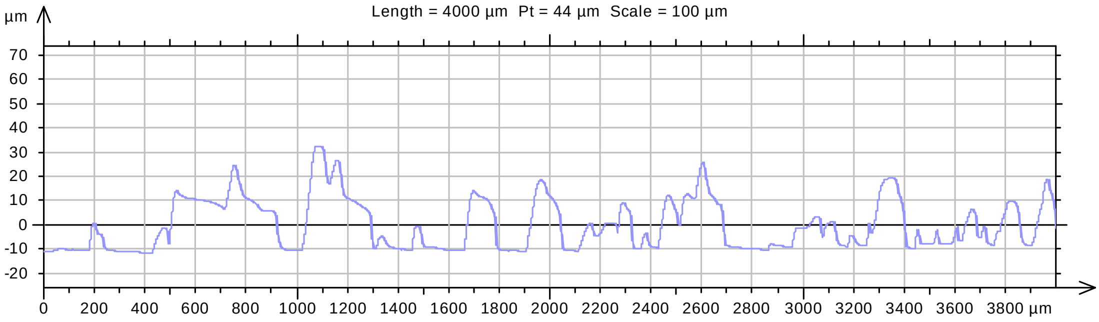
19(d)



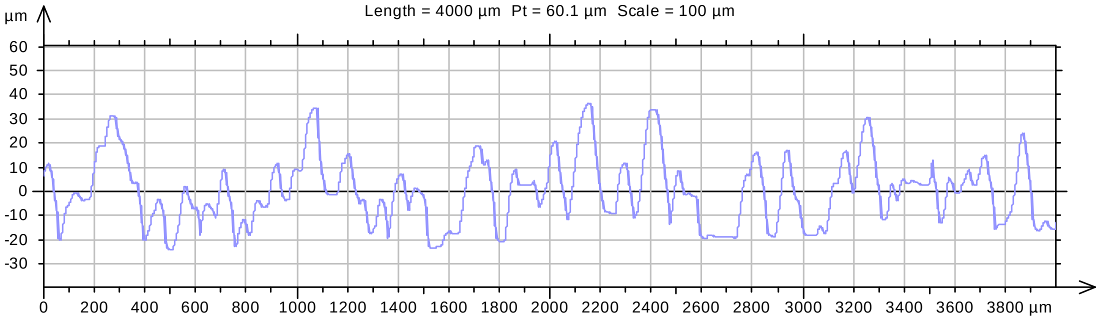
19(e)



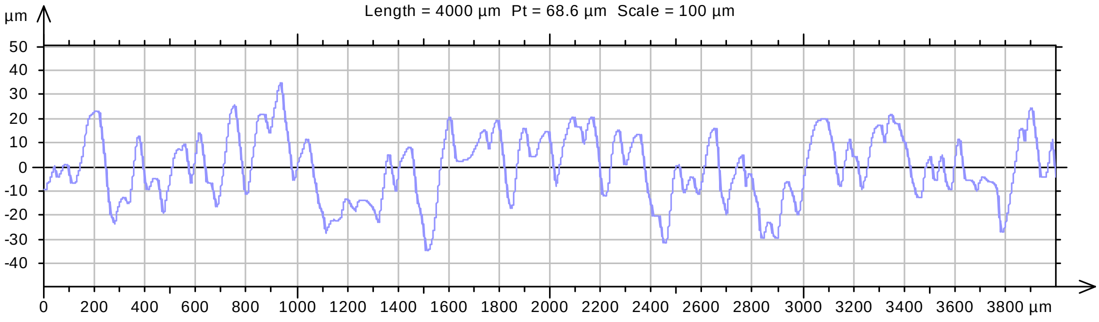
20(a)



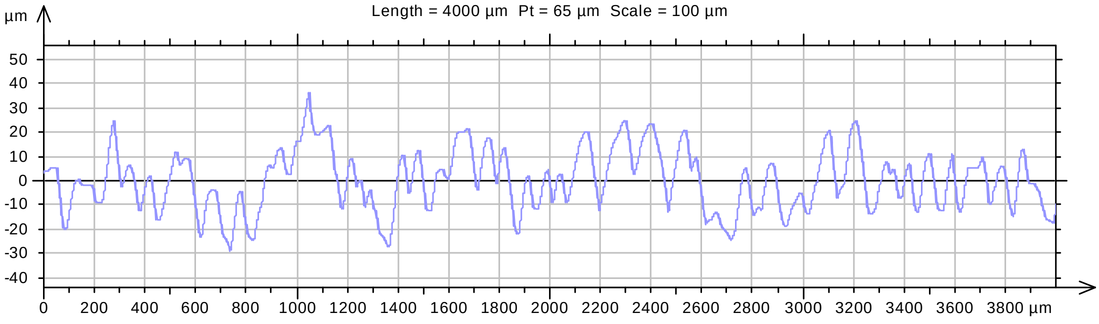
20(b)



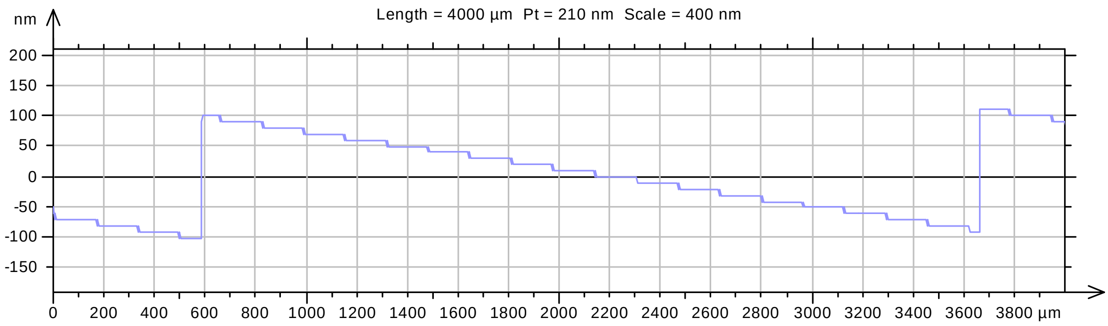
20(c)



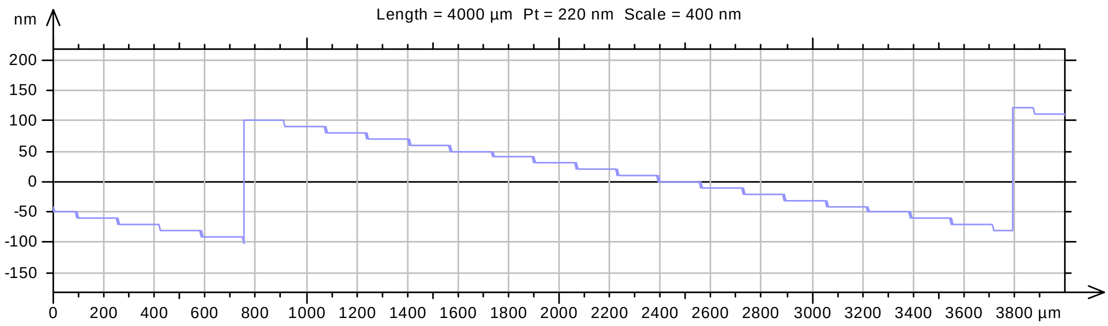
20(d)



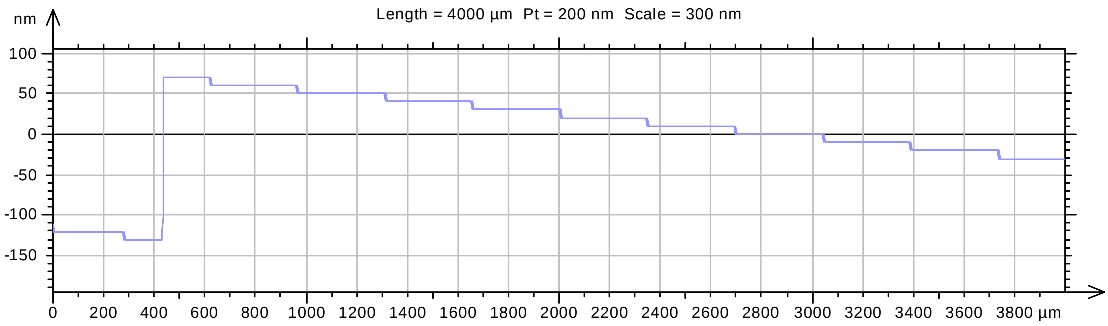
20(e)



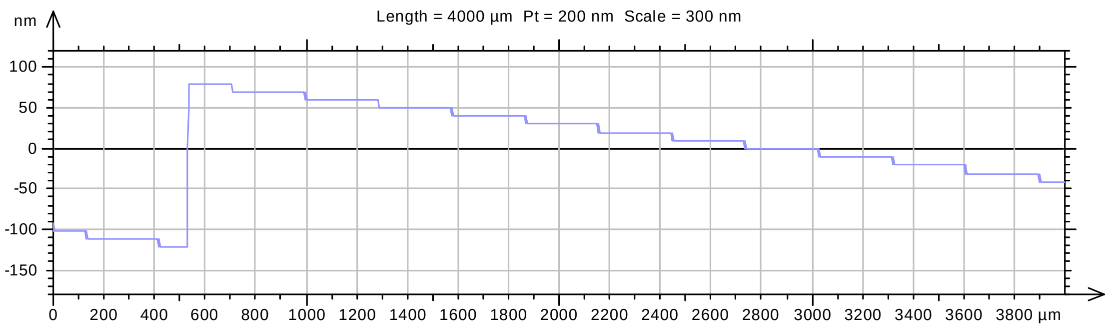
21(a)



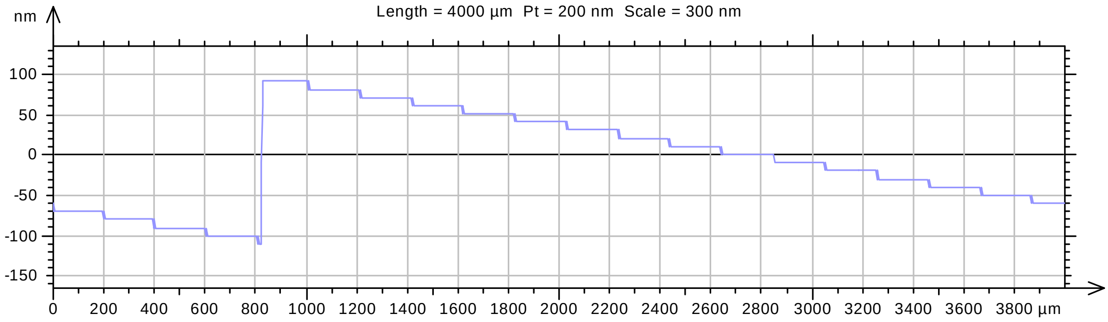
21(b)



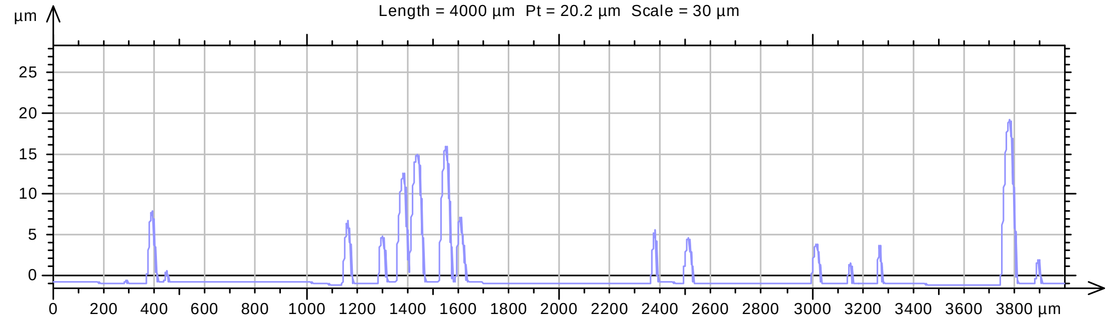
21(c)



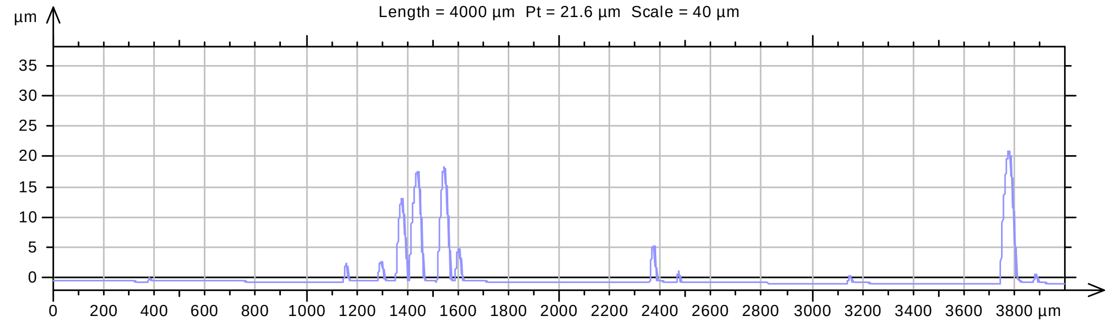
21(d)



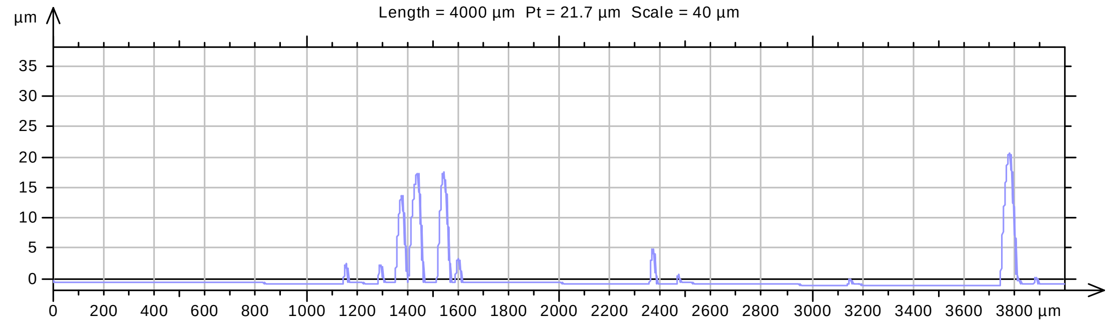
21(e)



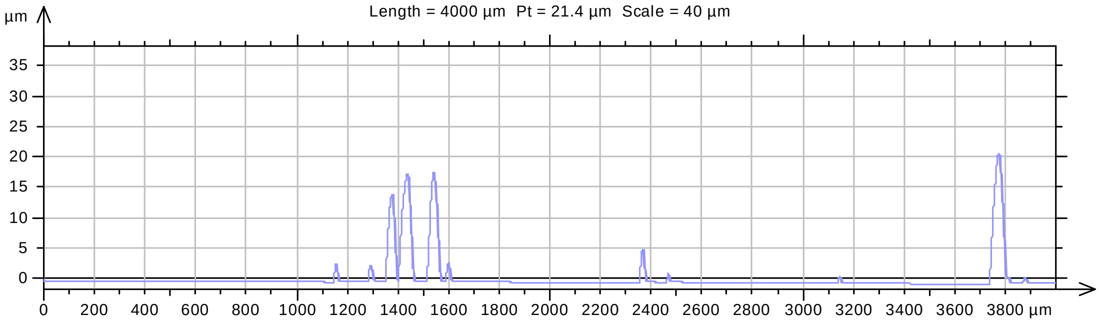
22(a)



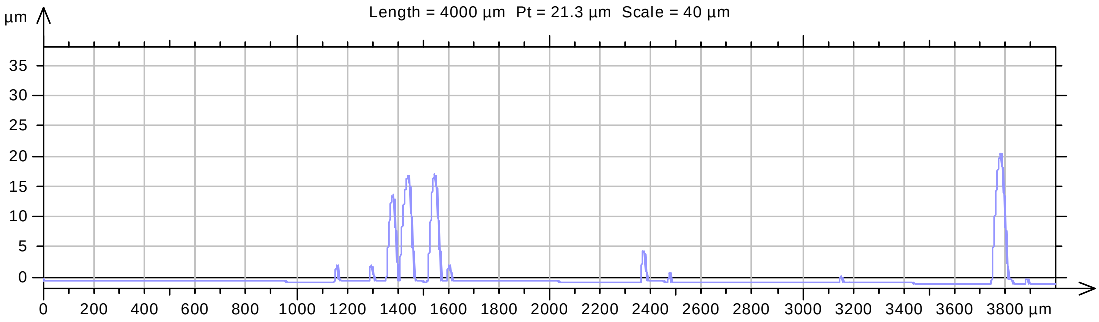
22(b)



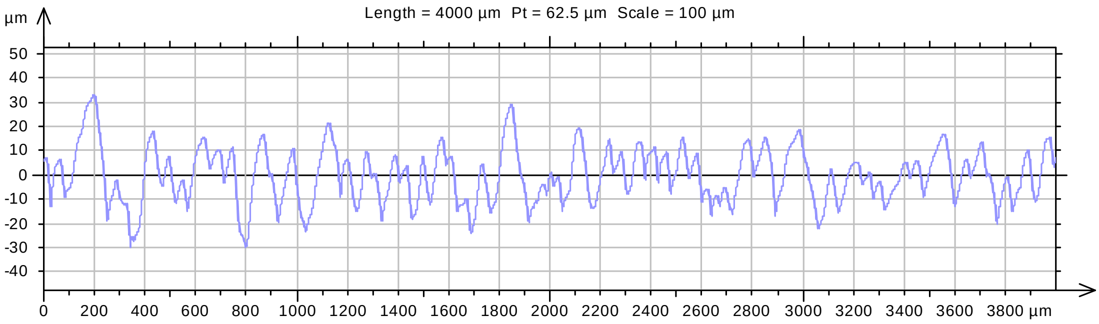
22(c)



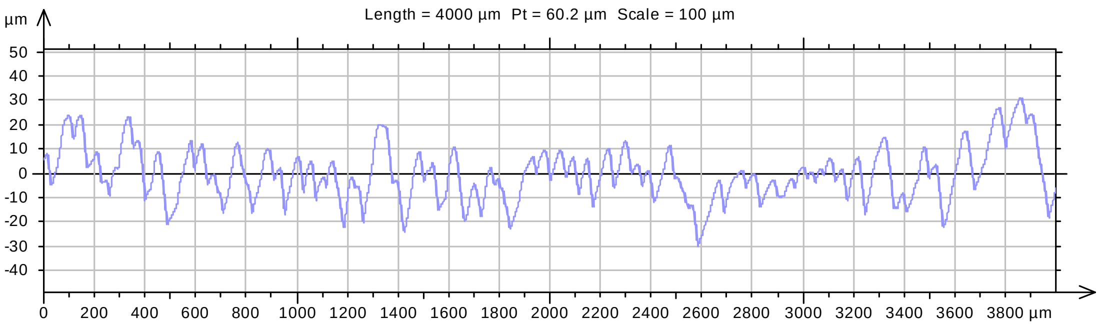
22(d)



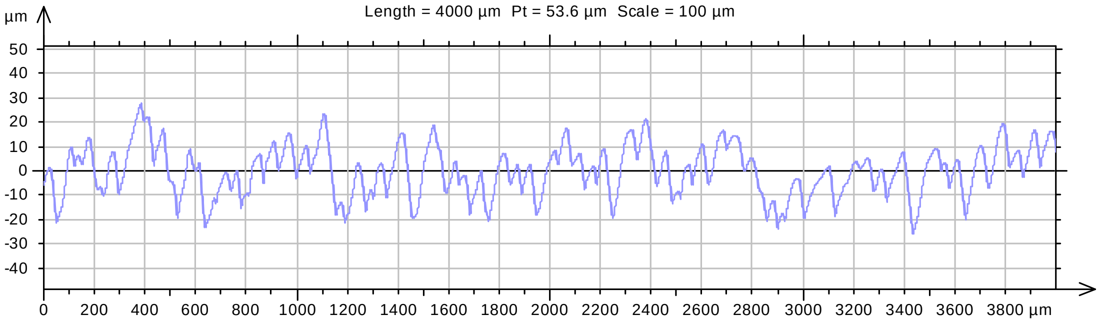
22(e)



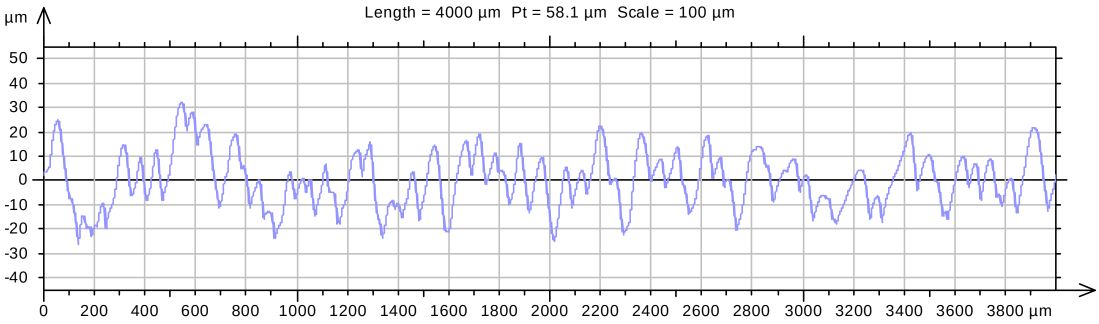
23(a)



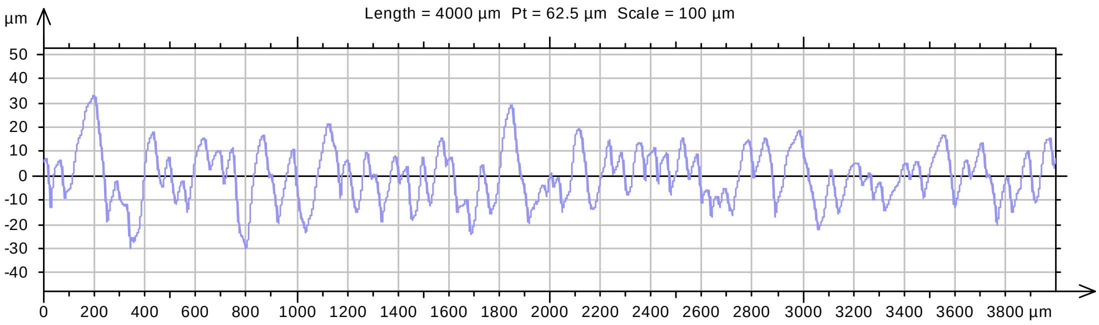
23(b)



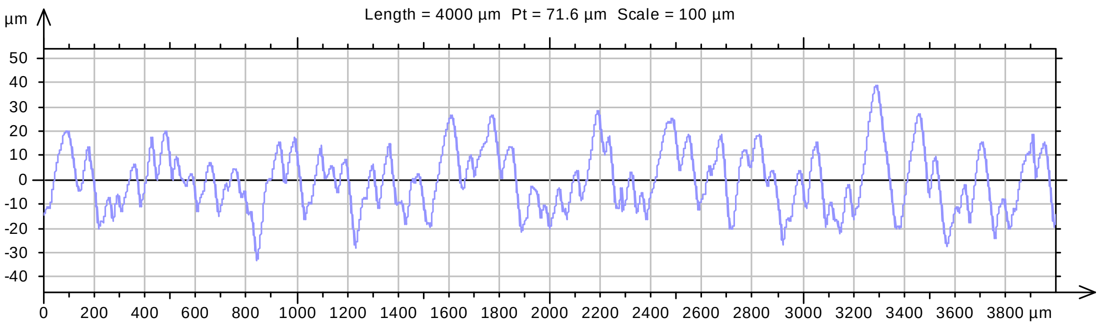
23(c)



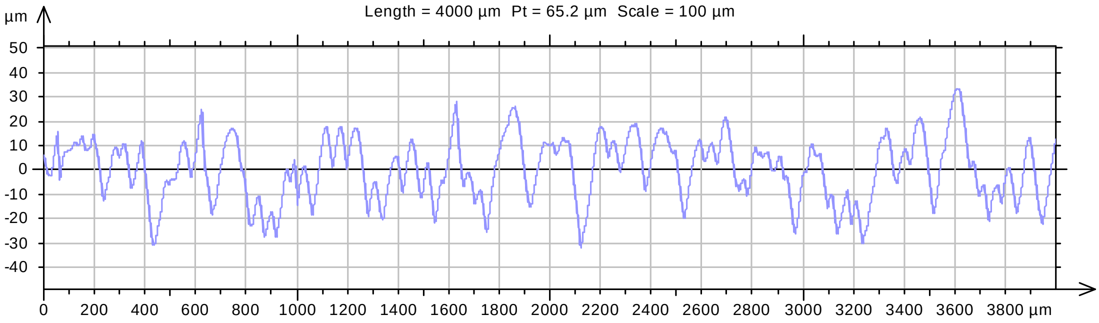
23(d)



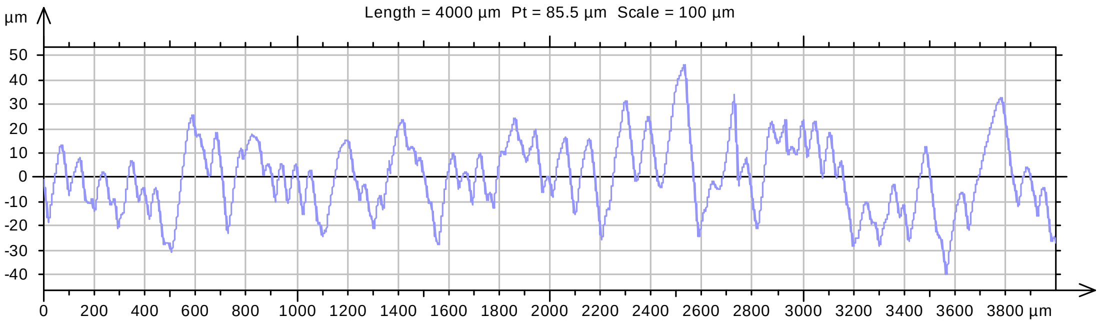
23(e)



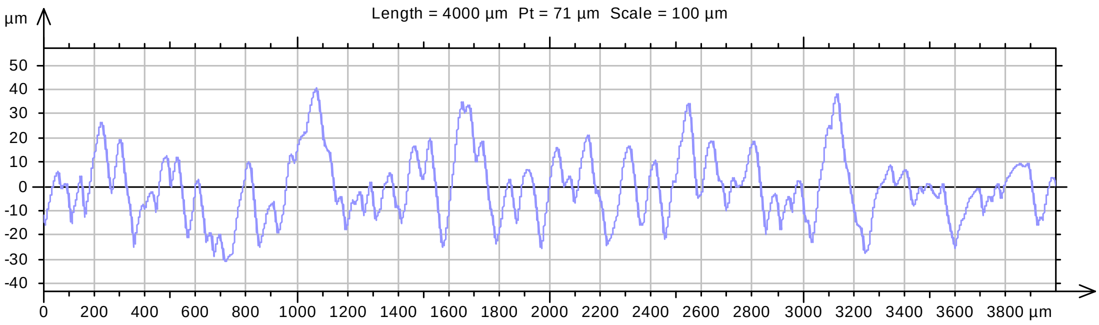
24(a)



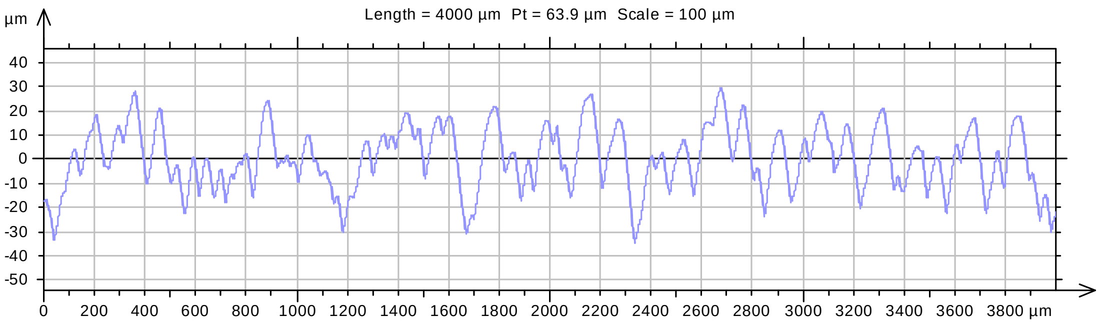
24(b)



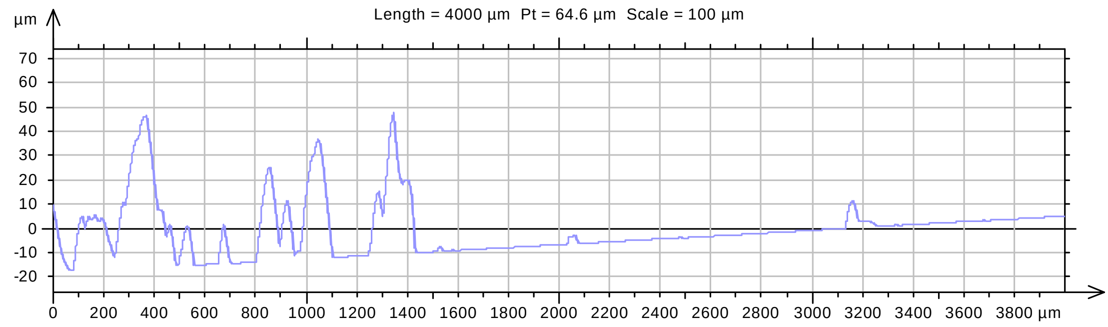
24(c)



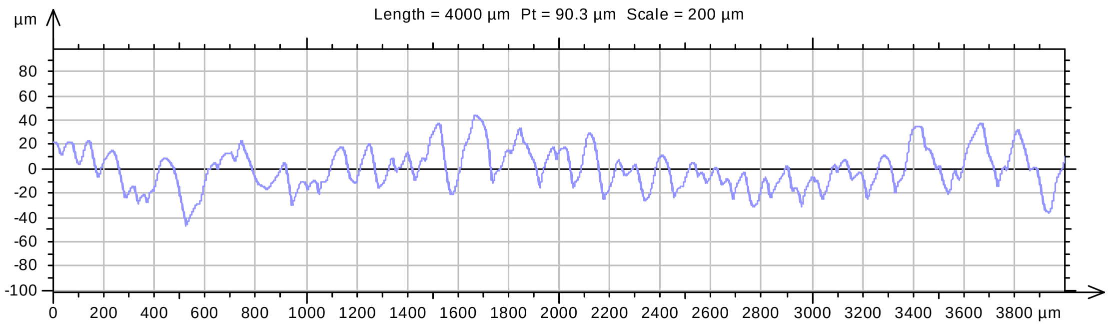
24(d)



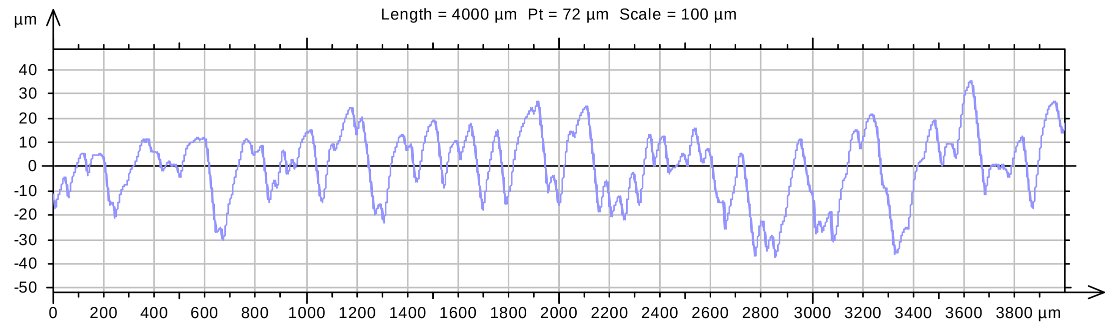
24(e)



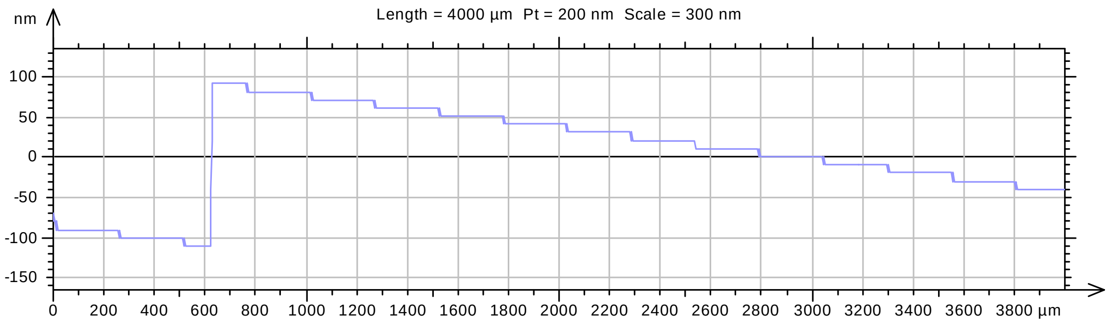
25(a)



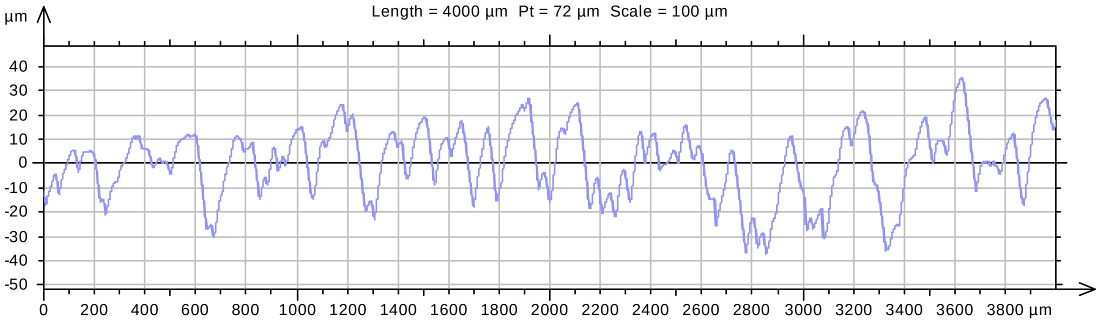
25(b)



25(c)

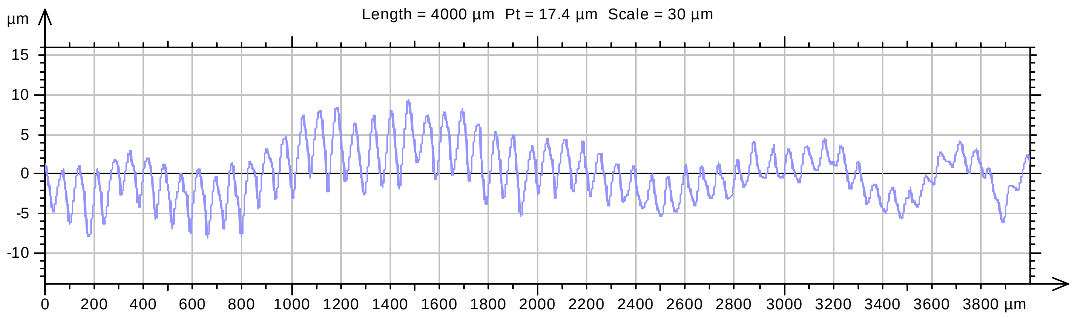


25(d)

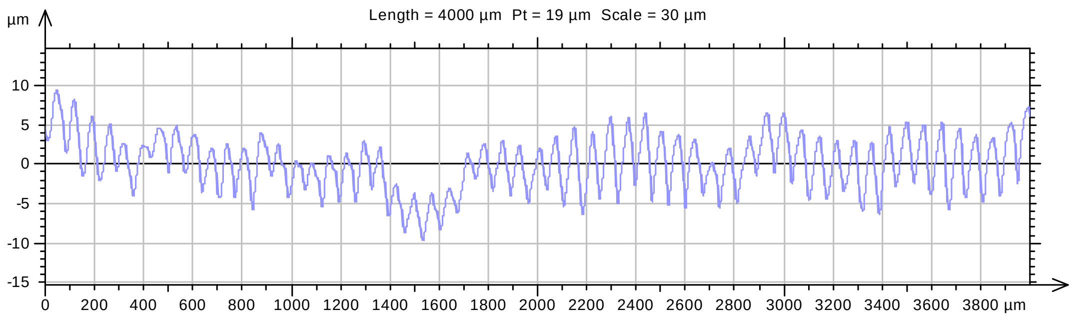

Length = 4000 µm Pt = 72 µm Scale = 100 µm
µm
40
30
20
10
0
-10
-20
-30
-40
-50
0
200
400
600
800
1000
1200
1400
1600
1800
2000
2200
2400
2600
2800
3000
3200
3400
3600
3800 µm

25(e)

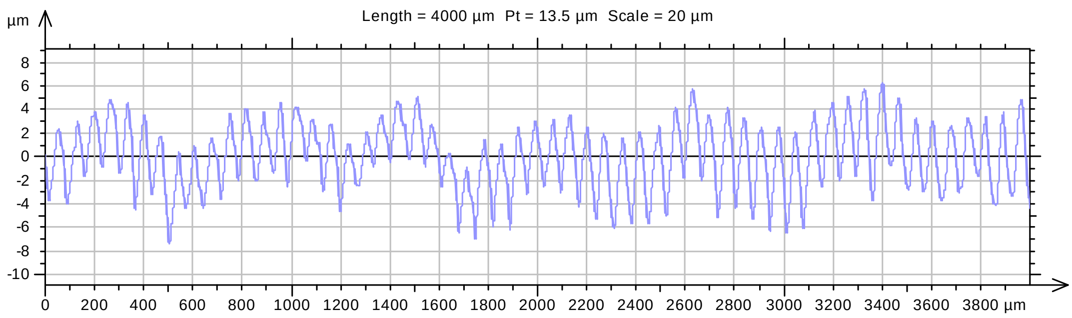
Appendix 2: Roughness Profile (Machined Teflon)



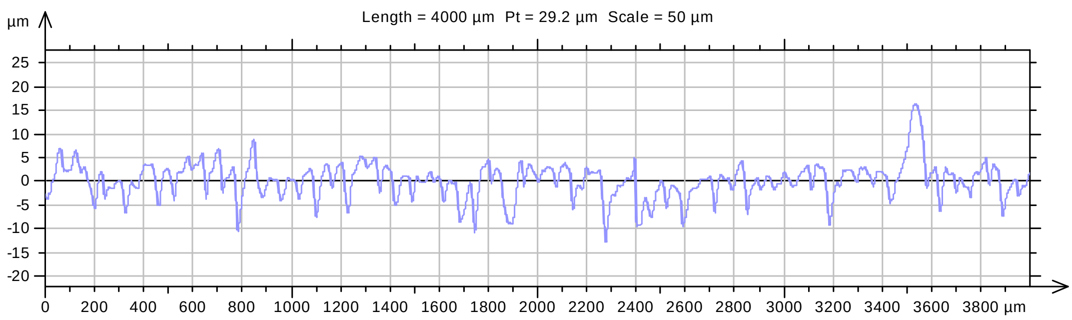
1(a)



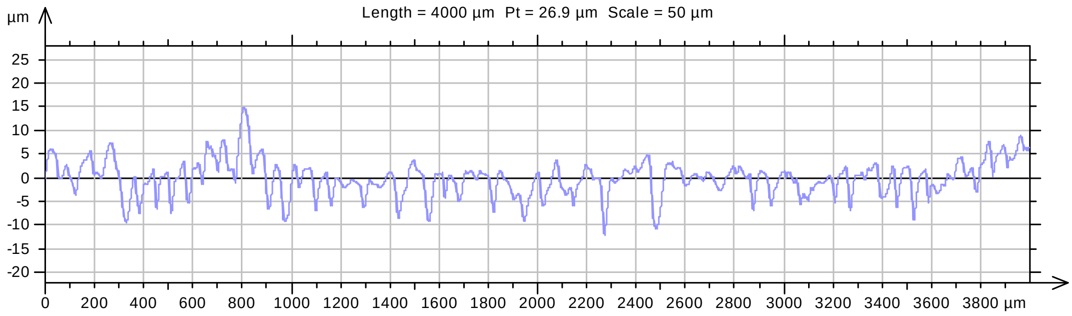
1(b)



1(c)

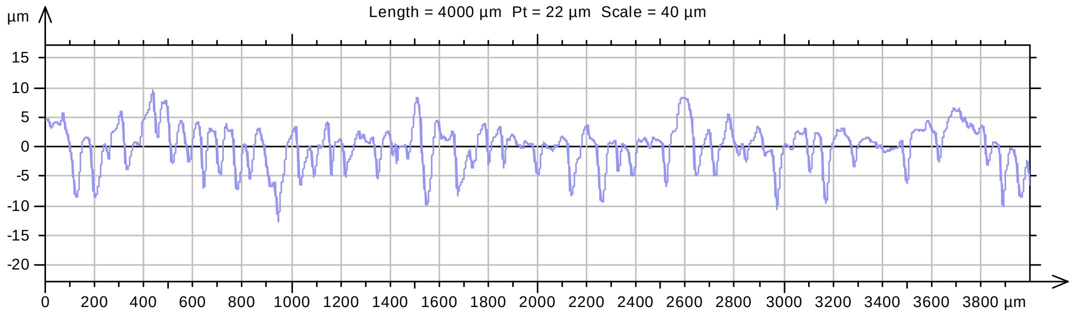


2(a)



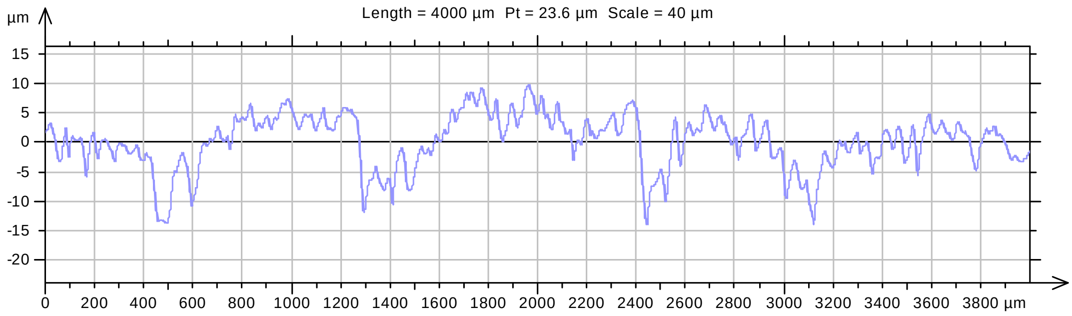
µm
Length = 4000 µm Pt = 26.9 µm Scale = 50 µm
25
20
15
10
5
0
-5
-10
-15
-20
0 200 400 600 800 1000 1200 1400 1600 1800 2000 2200 2400 2600 2800 3000 3200 3400 3600 3800 µm

2(b)



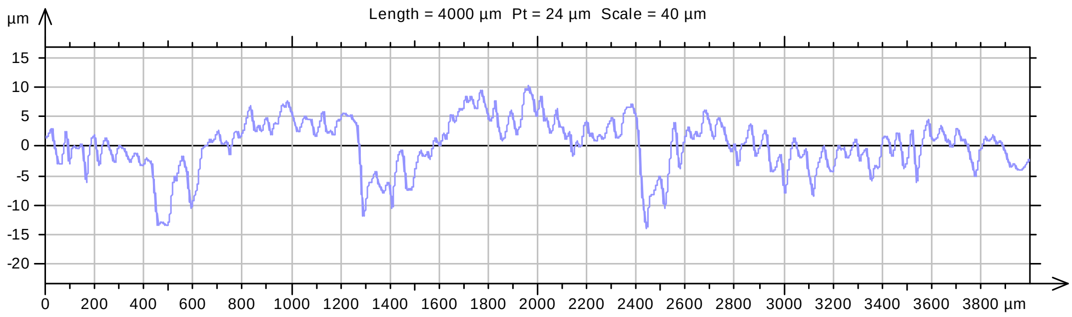
µm
Length = 4000 µm Pt = 22 µm Scale = 40 µm
15
10
5
0
-5
-10
-15
-20
0 200 400 600 800 1000 1200 1400 1600 1800 2000 2200 2400 2600 2800 3000 3200 3400 3600 3800 µm

2(c)



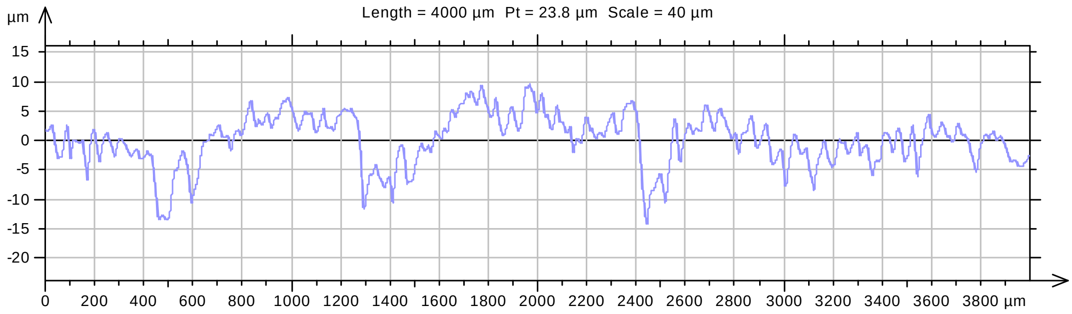
µm
Length = 4000 µm Pt = 23.6 µm Scale = 40 µm
15
10
5
0
-5
-10
-15
-20
0 200 400 600 800 1000 1200 1400 1600 1800 2000 2200 2400 2600 2800 3000 3200 3400 3600 3800 µm

3(a)

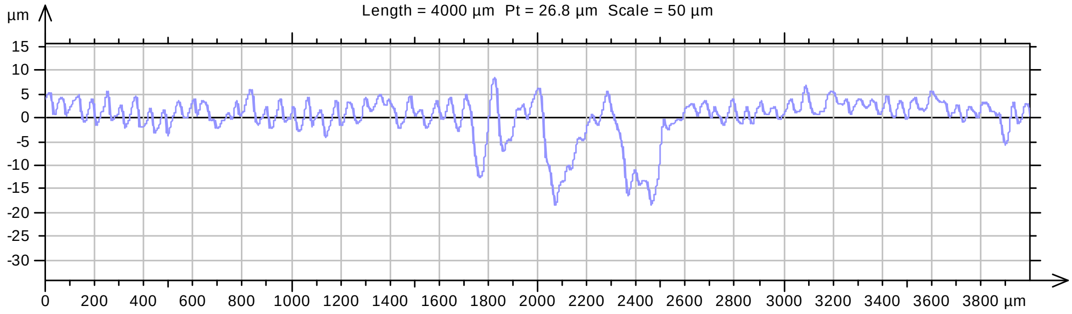


µm
Length = 4000 µm Pt = 24 µm Scale = 40 µm
15
10
5
0
-5
-10
-15
-20
0 200 400 600 800 1000 1200 1400 1600 1800 2000 2200 2400 2600 2800 3000 3200 3400 3600 3800 µm

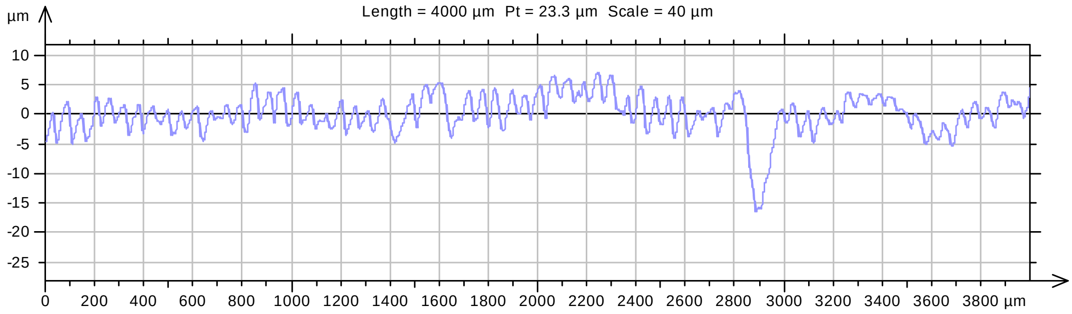
3(b)


µm
Length = 4000 µm Pt = 23.8 µm Scale = 40 µm
15
10
5
0
-5
-10
-15
-20
0 200 400 600 800 1000 1200 1400 1600 1800 2000 2200 2400 2600 2800 3000 3200 3400 3600 3800 µm

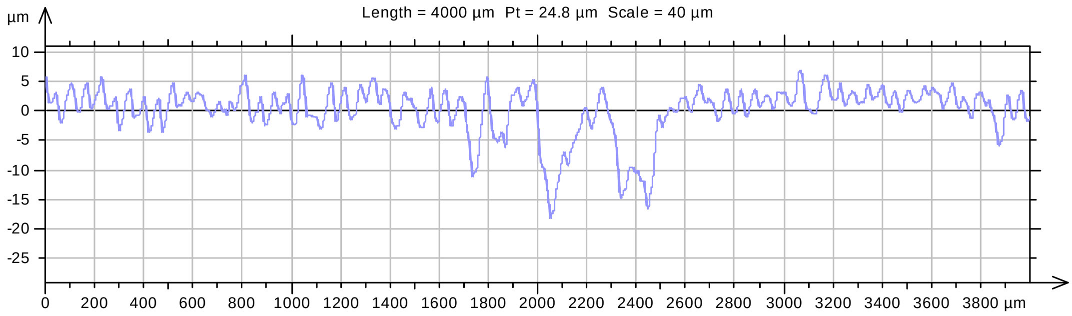
3(c)


µm
Length = 4000 µm Pt = 26.8 µm Scale = 50 µm
15
10
5
0
-5
-10
-15
-20
-25
-30
0 200 400 600 800 1000 1200 1400 1600 1800 2000 2200 2400 2600 2800 3000 3200 3400 3600 3800 µm

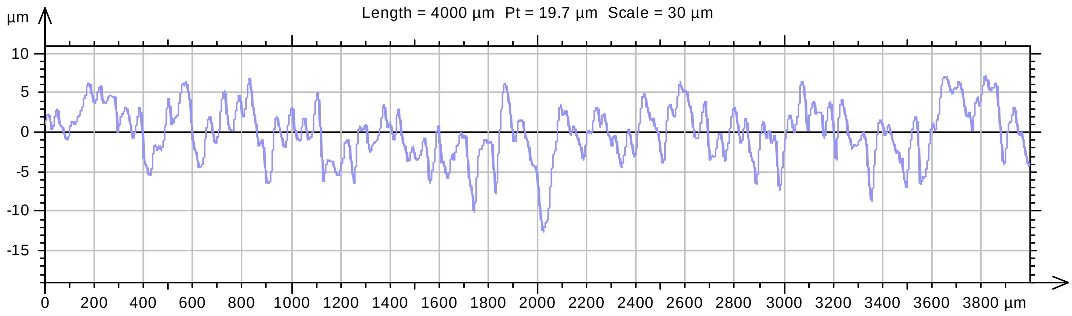
4(a)


µm
Length = 4000 µm Pt = 23.3 µm Scale = 40 µm
10
5
0
-5
-10
-15
-20
-25
0 200 400 600 800 1000 1200 1400 1600 1800 2000 2200 2400 2600 2800 3000 3200 3400 3600 3800 µm

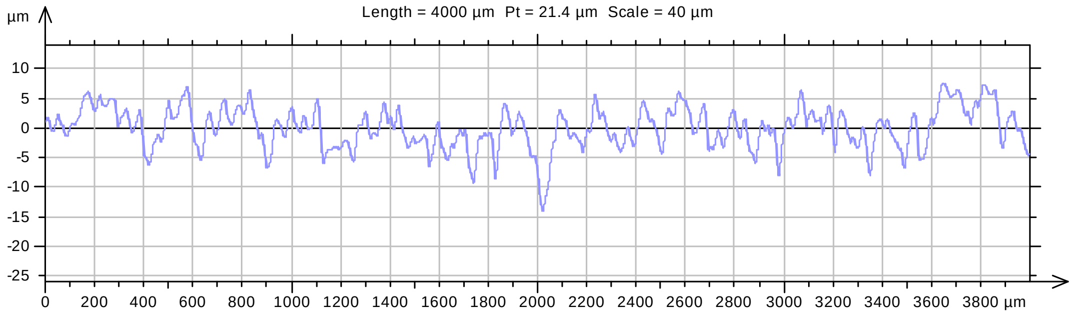
4(b)


µm
Length = 4000 µm Pt = 24.8 µm Scale = 40 µm
10
5
0
-5
-10
-15
-20
-25
0 200 400 600 800 1000 1200 1400 1600 1800 2000 2200 2400 2600 2800 3000 3200 3400 3600 3800 µm

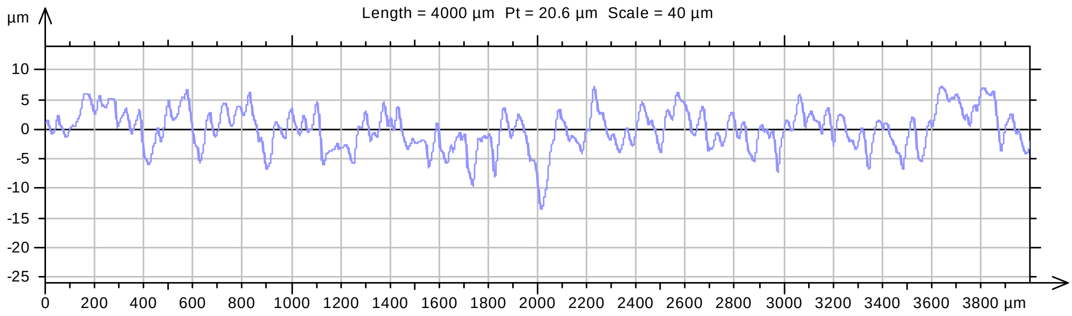
4(c)


Length = 4000 µm Pt = 19.7 µm Scale = 30 µm
µm
0 200 400 600 800 1000 1200 1400 1600 1800 2000 2200 2400 2600 2800 3000 3200 3400 3600 3800 µm

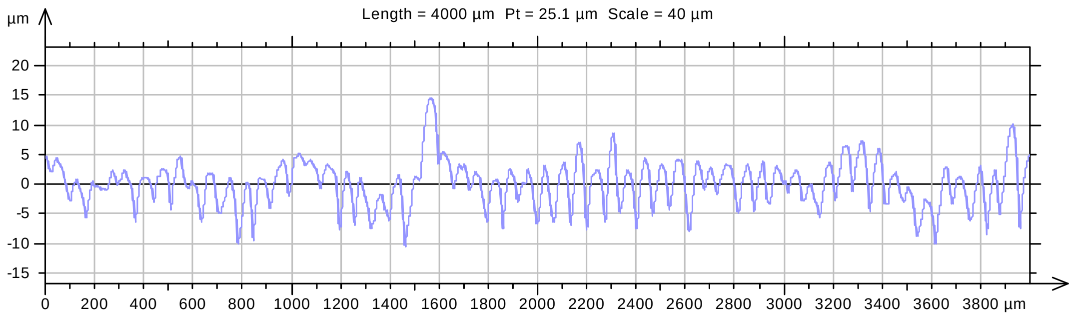
5(a)


Length = 4000 µm Pt = 21.4 µm Scale = 40 µm
µm
0 200 400 600 800 1000 1200 1400 1600 1800 2000 2200 2400 2600 2800 3000 3200 3400 3600 3800 µm

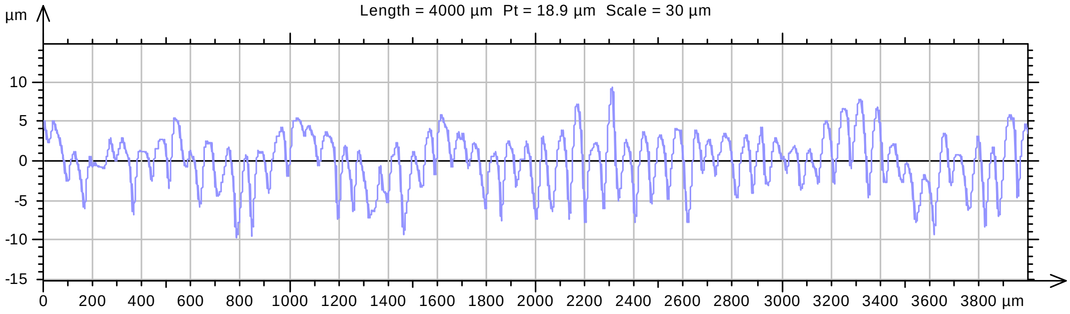
5(b)


Length = 4000 µm Pt = 20.6 µm Scale = 40 µm
µm
0 200 400 600 800 1000 1200 1400 1600 1800 2000 2200 2400 2600 2800 3000 3200 3400 3600 3800 µm

5(c)

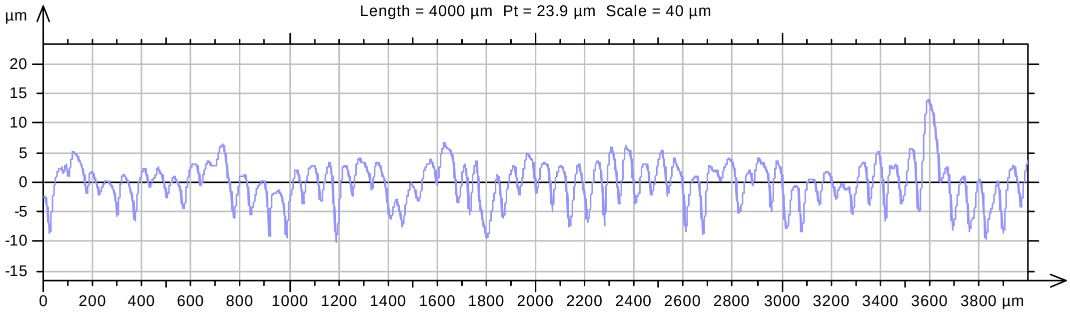

Length = 4000 µm Pt = 25.1 µm Scale = 40 µm
µm
0 200 400 600 800 1000 1200 1400 1600 1800 2000 2200 2400 2600 2800 3000 3200 3400 3600 3800 µm

6(a)



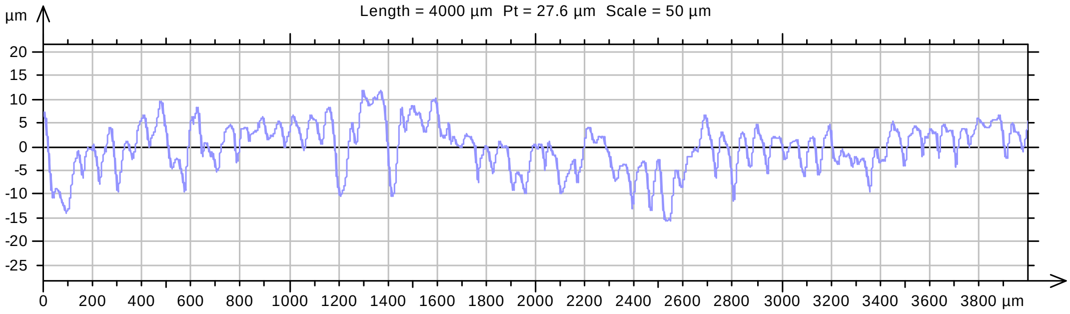
Length = 4000 µm Pt = 18.9 µm Scale = 30 µm
µm
10
5
0
-5
-10
-15
0 200 400 600 800 1000 1200 1400 1600 1800 2000 2200 2400 2600 2800 3000 3200 3400 3600 3800 µm

6(b)



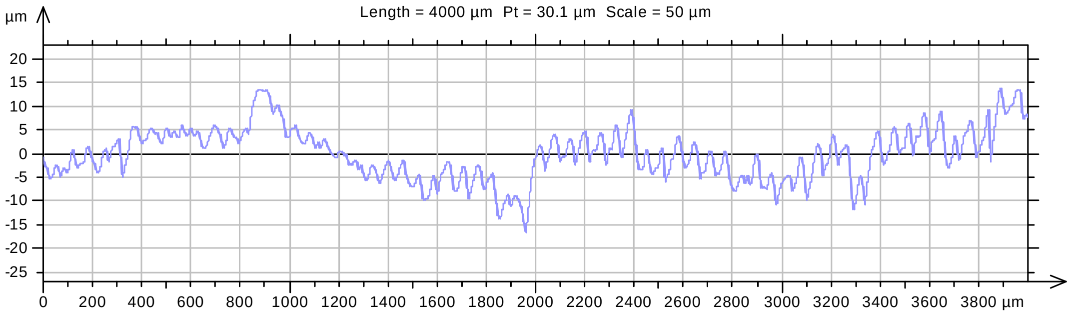
Length = 4000 µm Pt = 23.9 µm Scale = 40 µm
µm
20
15
10
5
0
-5
-10
-15
0 200 400 600 800 1000 1200 1400 1600 1800 2000 2200 2400 2600 2800 3000 3200 3400 3600 3800 µm

6(c)



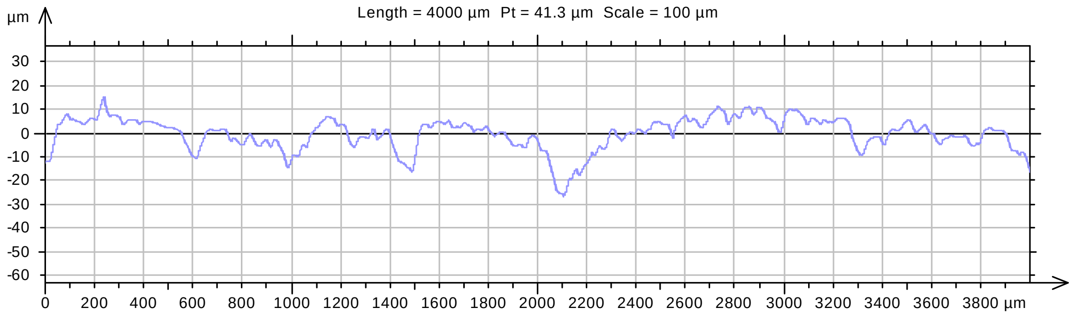
Length = 4000 µm Pt = 27.6 µm Scale = 50 µm
µm
20
15
10
5
0
-5
-10
-15
-20
-25
0 200 400 600 800 1000 1200 1400 1600 1800 2000 2200 2400 2600 2800 3000 3200 3400 3600 3800 µm

7(a)

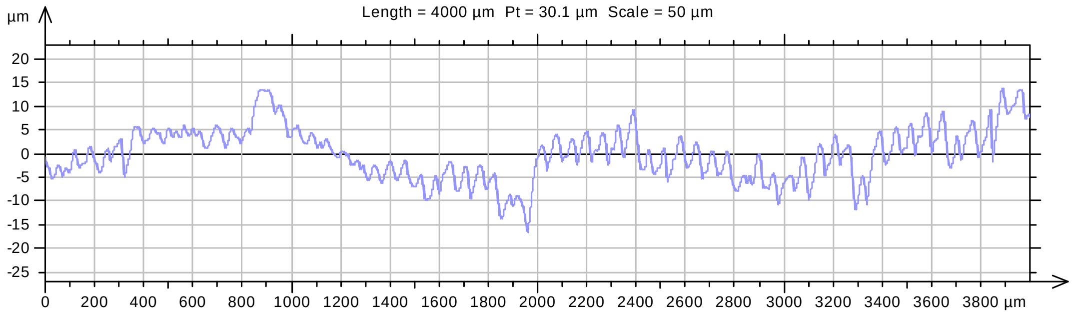


Length = 4000 µm Pt = 30.1 µm Scale = 50 µm
µm
20
15
10
5
0
-5
-10
-15
-20
-25
0 200 400 600 800 1000 1200 1400 1600 1800 2000 2200 2400 2600 2800 3000 3200 3400 3600 3800 µm

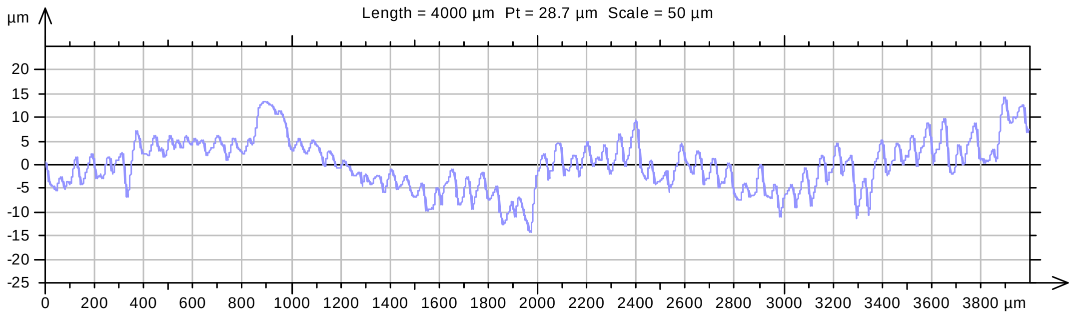
7(b)


Length = 4000 µm Pt = 41.3 µm Scale = 100 µm
µm
30
20
10
0
-10
-20
-30
-40
-50
-60
0 200 400 600 800 1000 1200 1400 1600 1800 2000 2200 2400 2600 2800 3000 3200 3400 3600 3800 µm

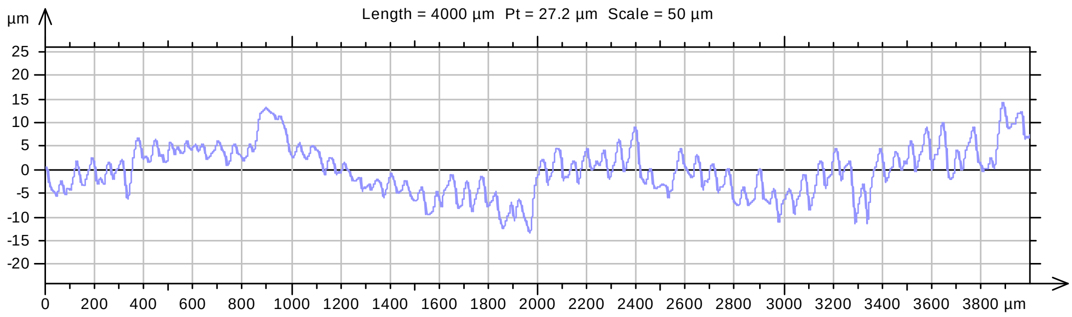
7(c)


Length = 4000 µm Pt = 30.1 µm Scale = 50 µm
µm
20
15
10
5
0
-5
-10
-15
-20
-25
0 200 400 600 800 1000 1200 1400 1600 1800 2000 2200 2400 2600 2800 3000 3200 3400 3600 3800 µm

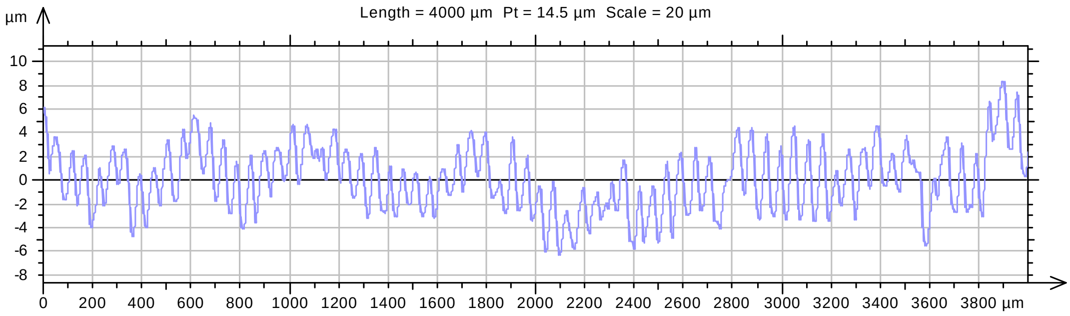
8(a)


Length = 4000 µm Pt = 28.7 µm Scale = 50 µm
µm
20
15
10
5
0
-5
-10
-15
-20
-25
0 200 400 600 800 1000 1200 1400 1600 1800 2000 2200 2400 2600 2800 3000 3200 3400 3600 3800 µm

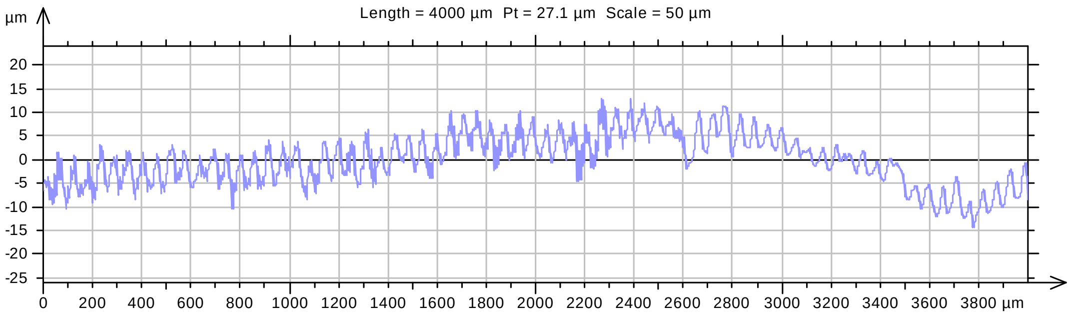
8(b)


Length = 4000 µm Pt = 27.2 µm Scale = 50 µm
µm
25
20
15
10
5
0
-5
-10
-15
-20
0 200 400 600 800 1000 1200 1400 1600 1800 2000 2200 2400 2600 2800 3000 3200 3400 3600 3800 µm

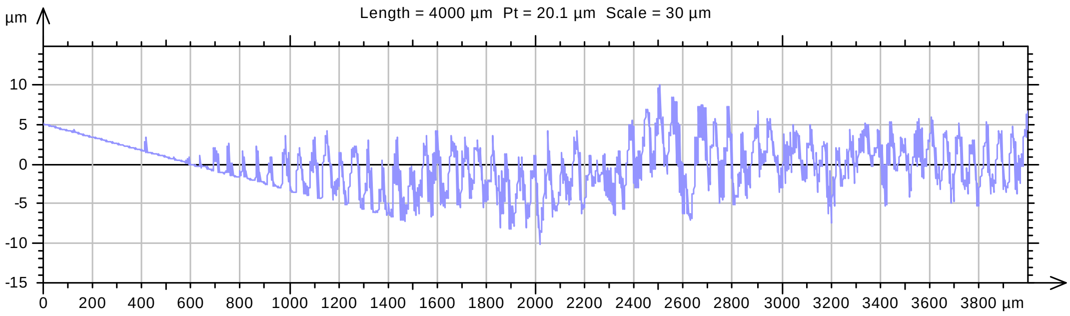
8(c)


Length = 4000 µm Pt = 14.5 µm Scale = 20 µm

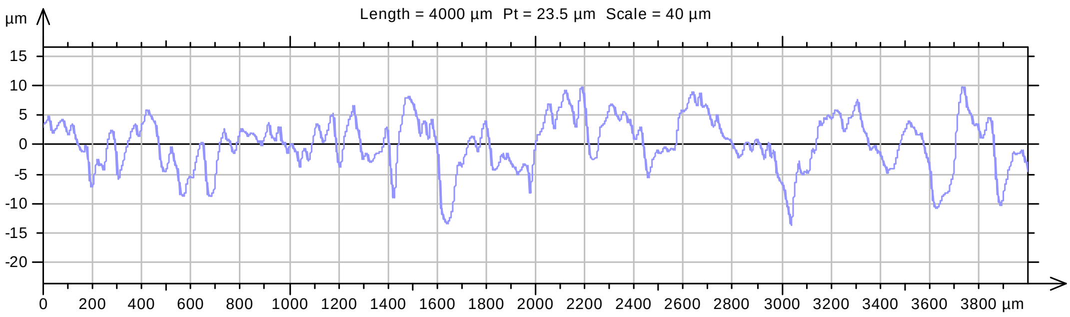
9(a)


Length = 4000 µm Pt = 27.1 µm Scale = 50 µm

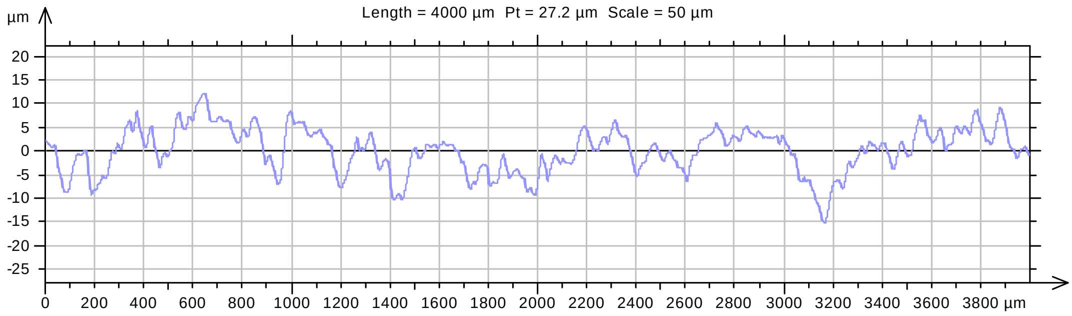
9(b)


Length = 4000 µm Pt = 20.1 µm Scale = 30 µm

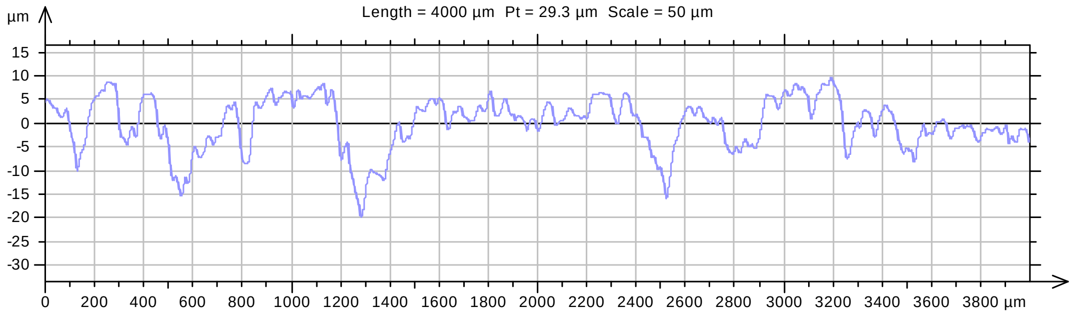
9(c)


Length = 4000 µm Pt = 23.5 µm Scale = 40 µm

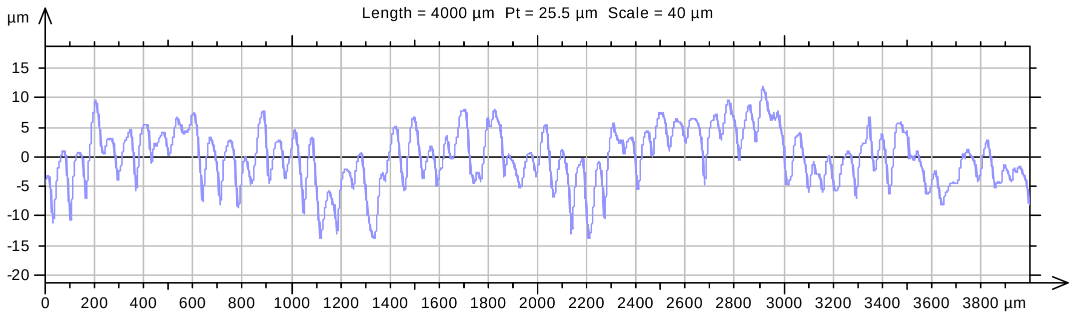
10(a)



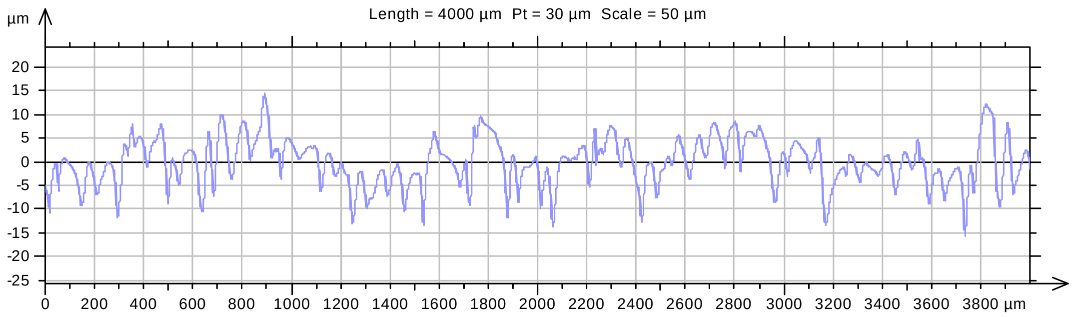
10(b)



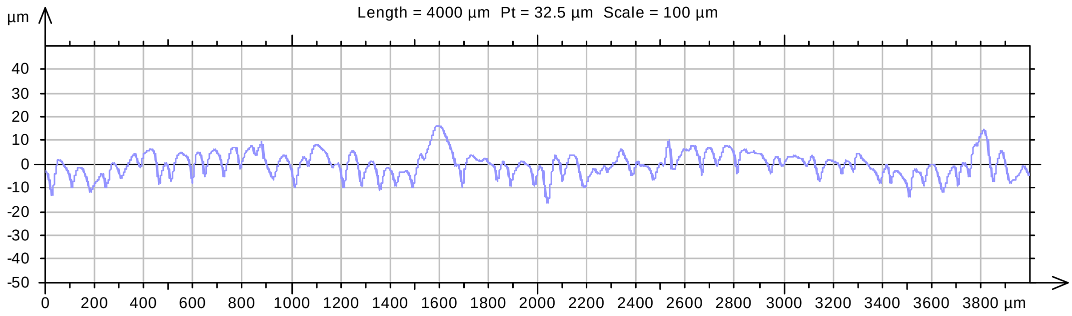
10(c)



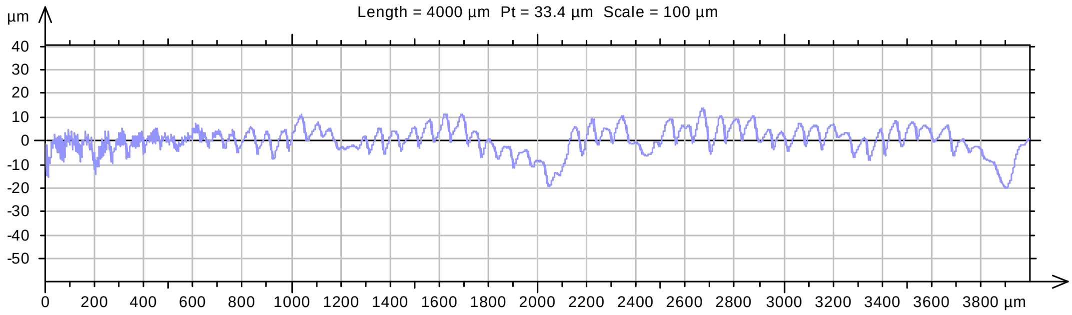
11(a)



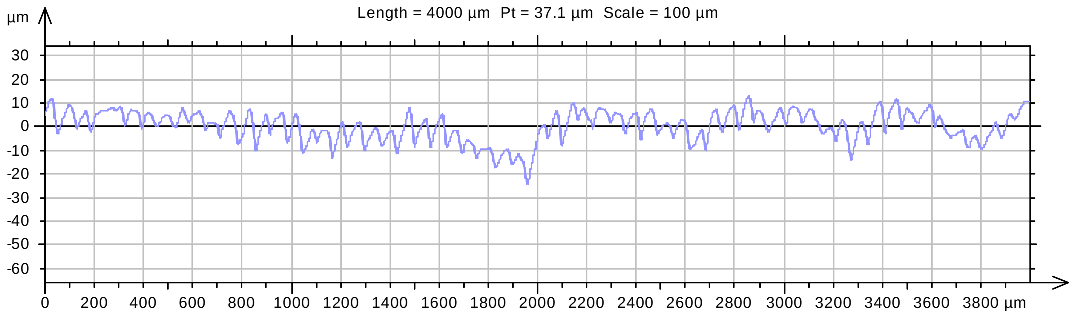
11(b)



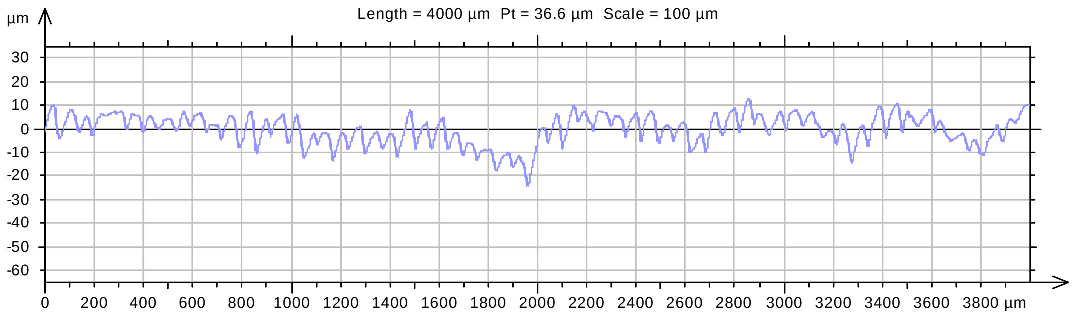
11(c)



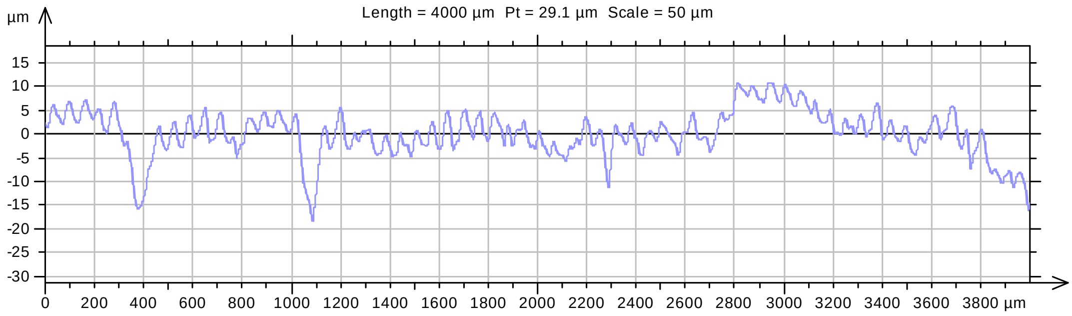
12(a)



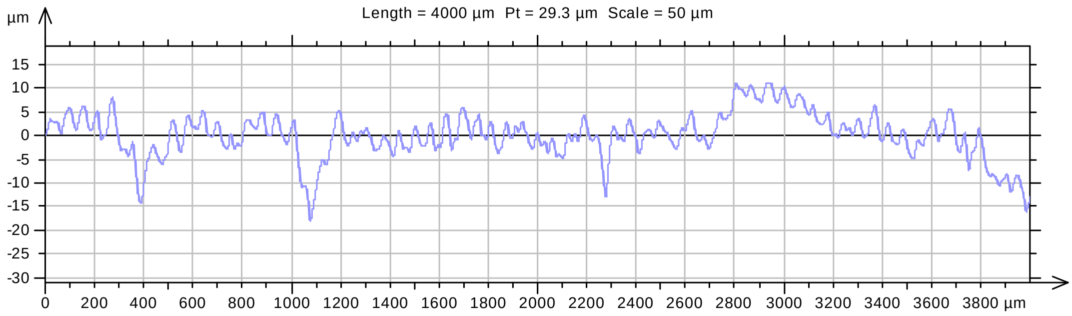
12(b)



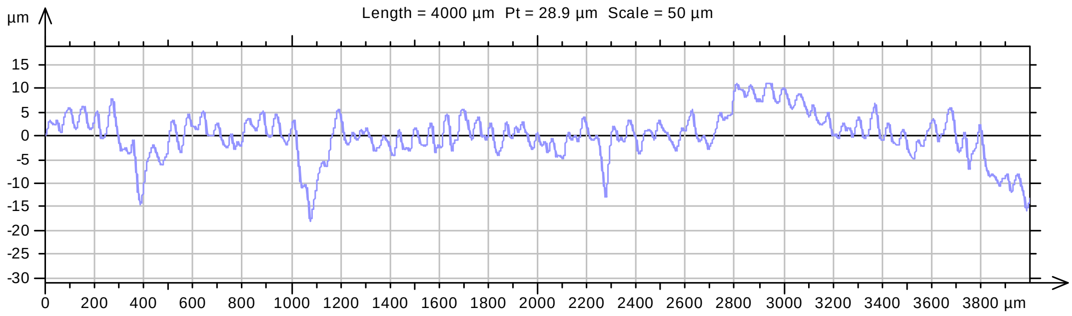
12(c)



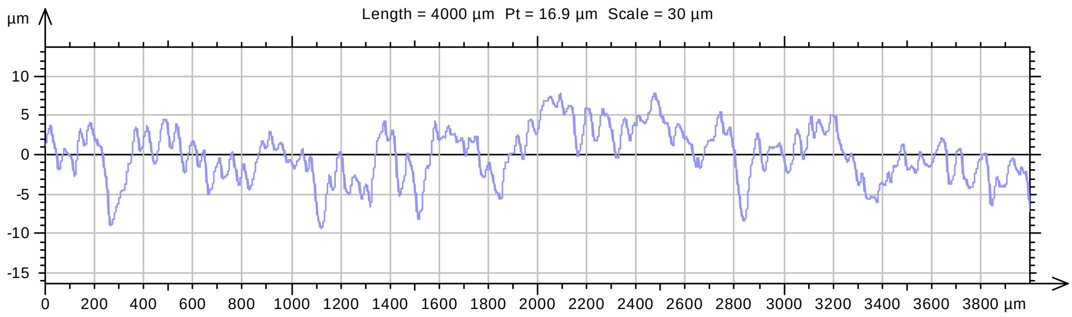
13(a)



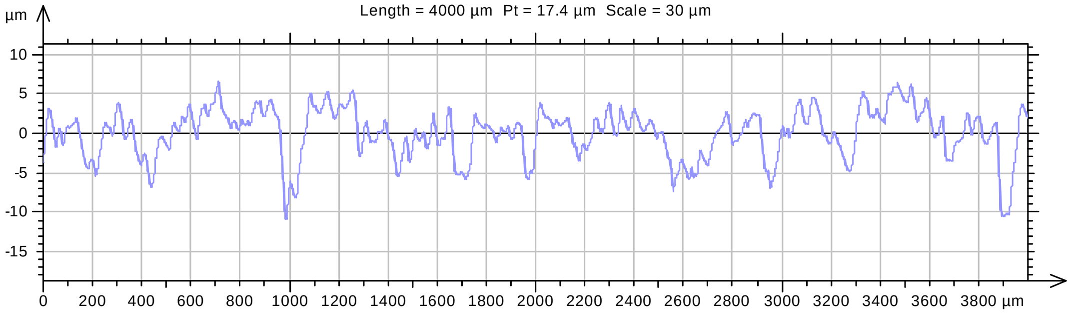
13(b)



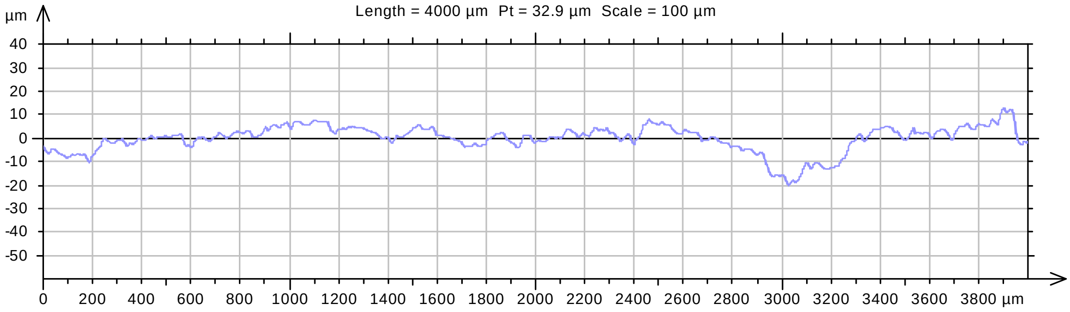
13(c)



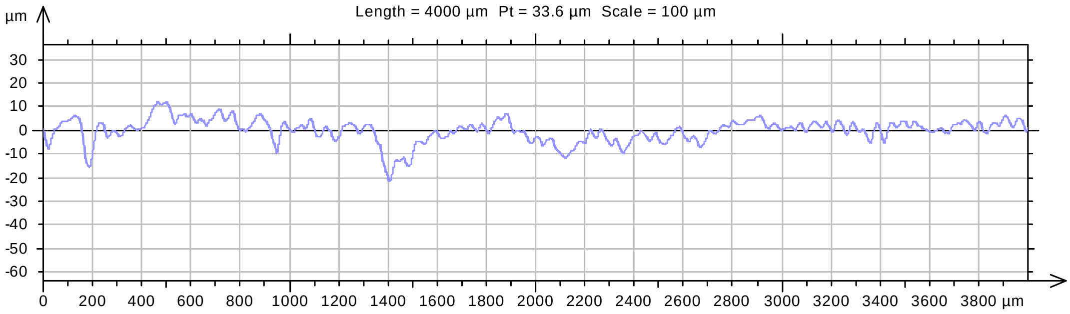
14(a)



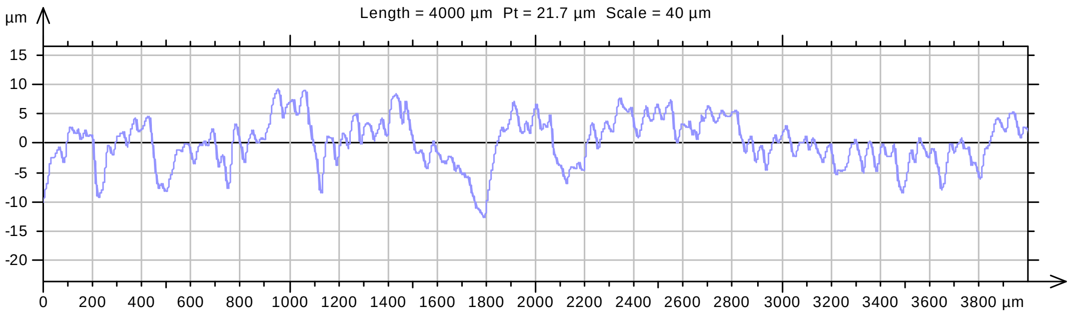
14(b)



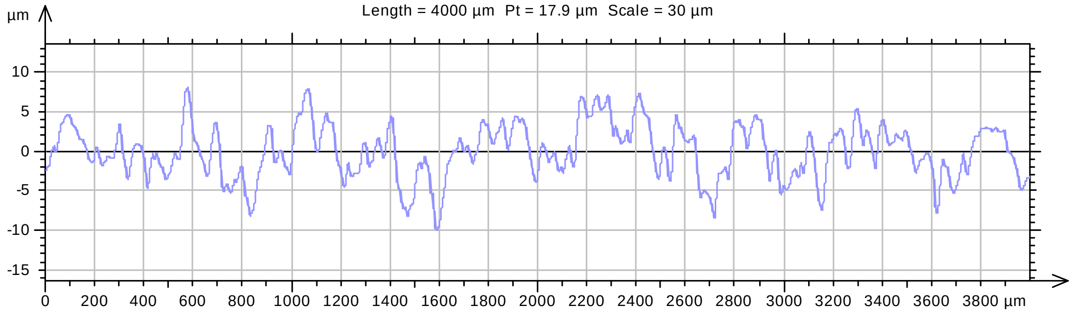
14(c)



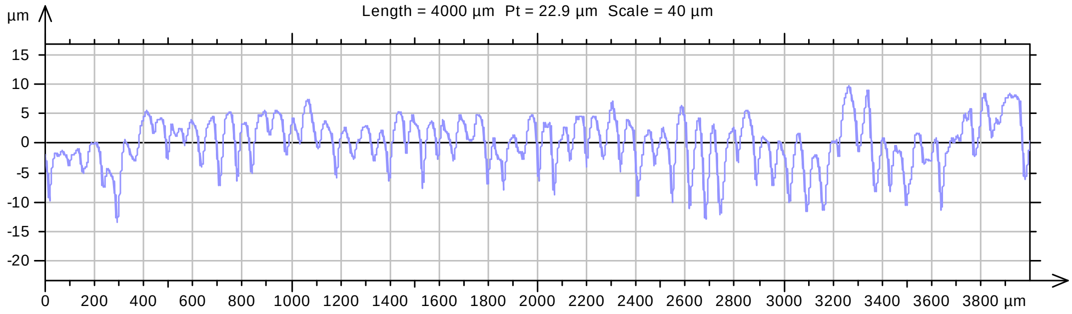
15(a)



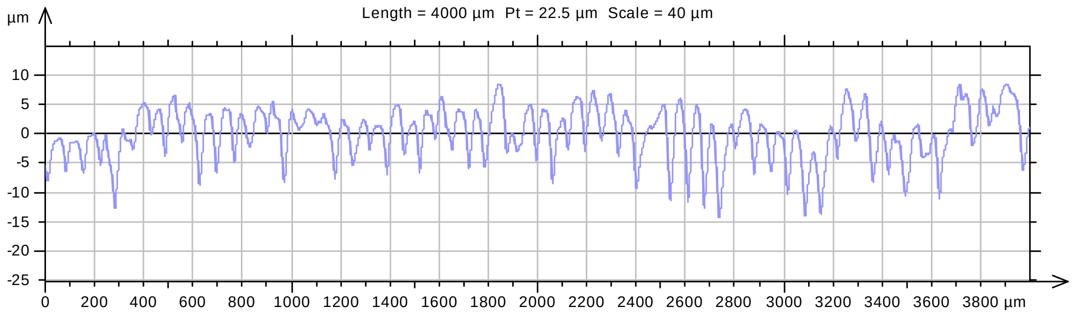
15(b)



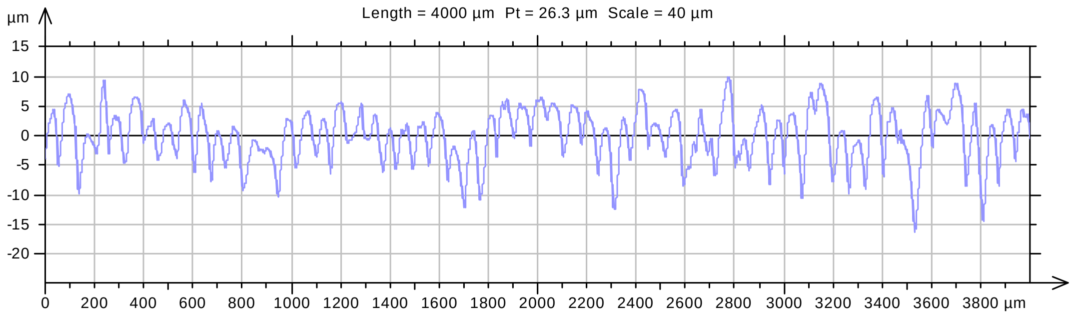
15(c)



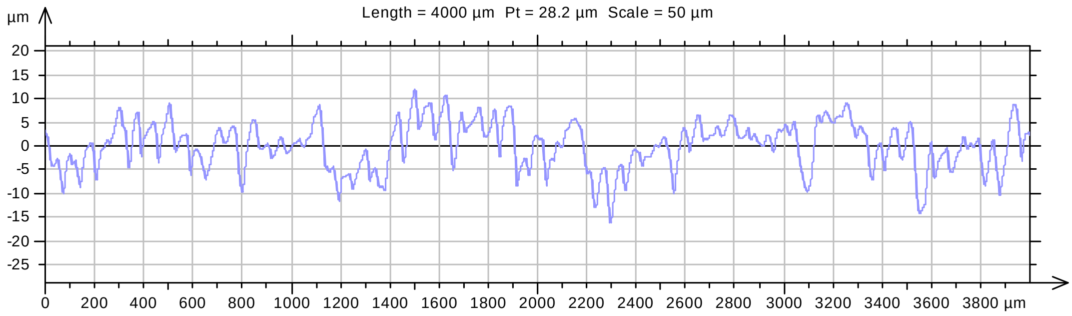
16(a)



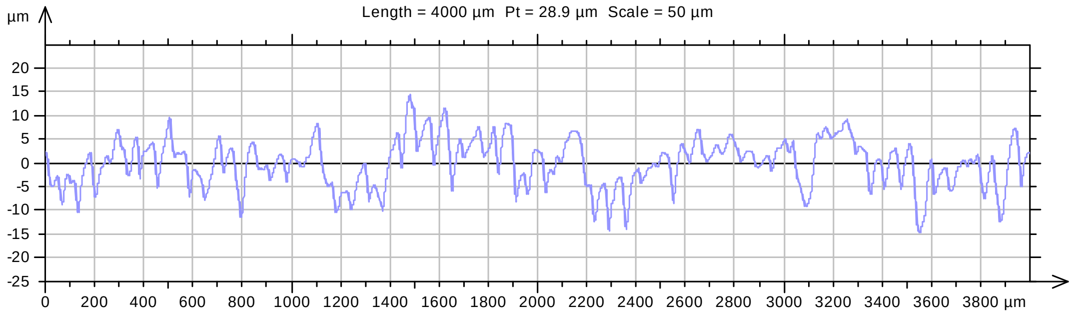
16(b)



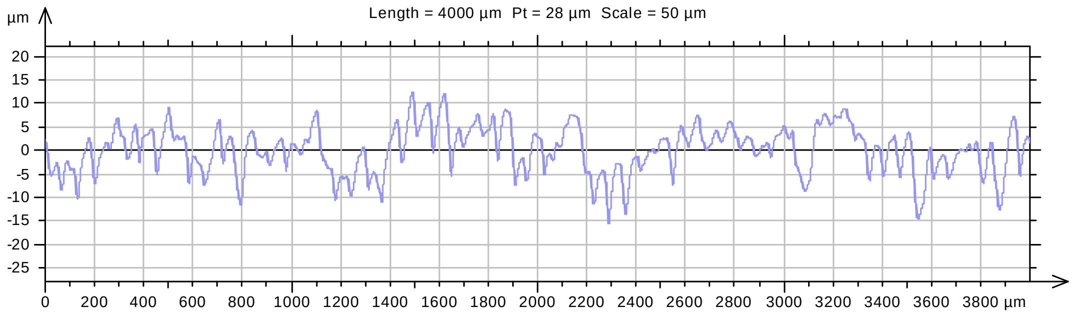
16(c)



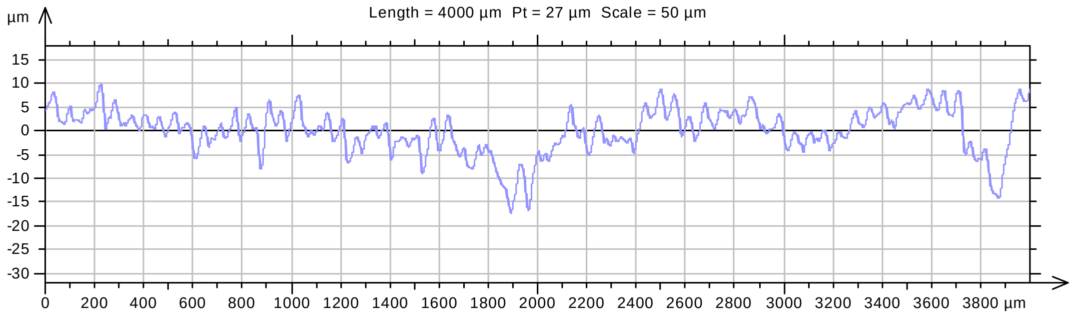
17(a)



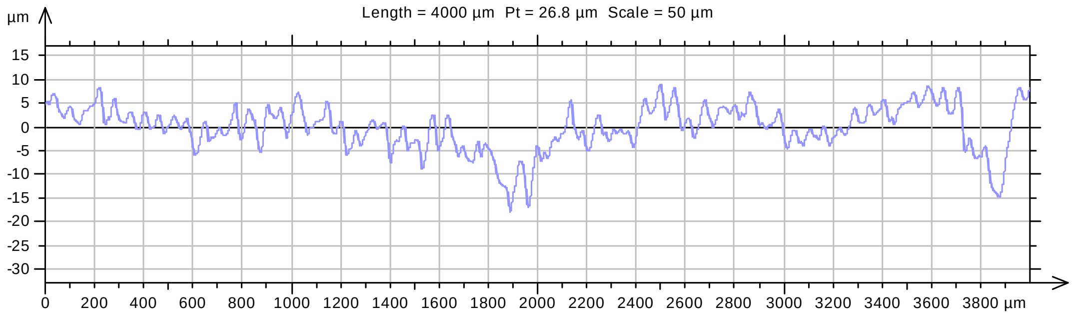
17(b)



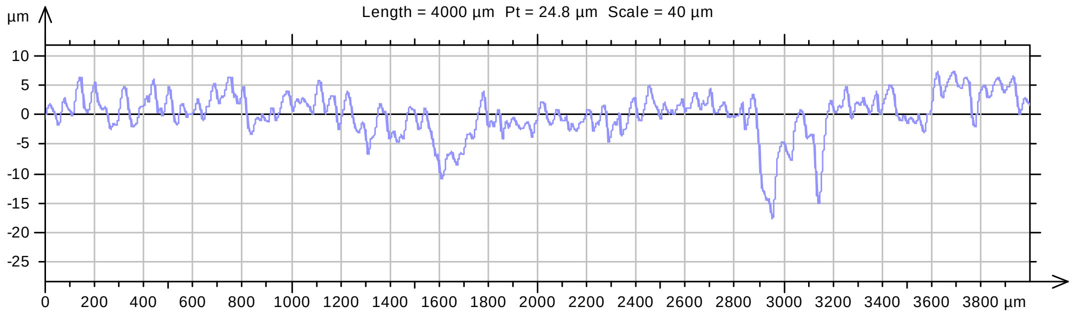
17(c)



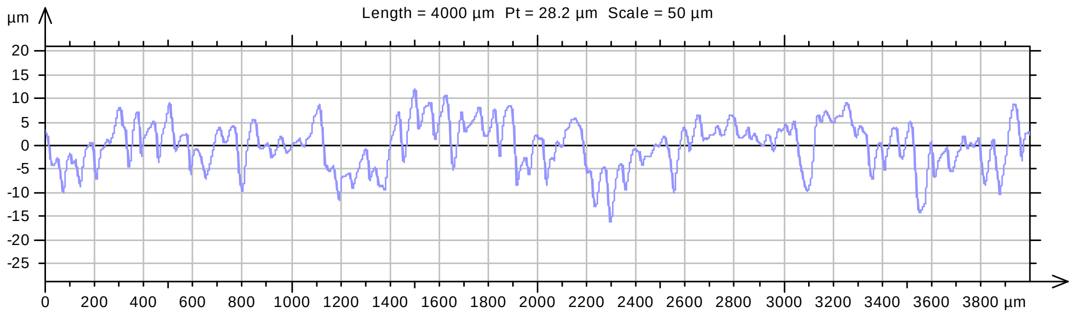
18(a)



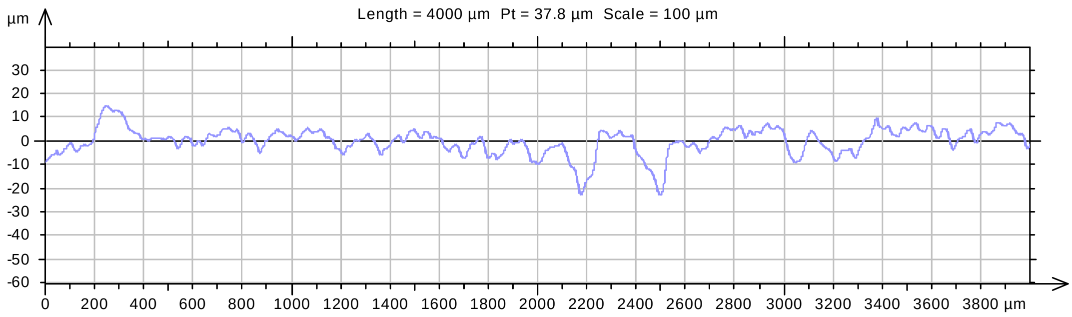
18(b)



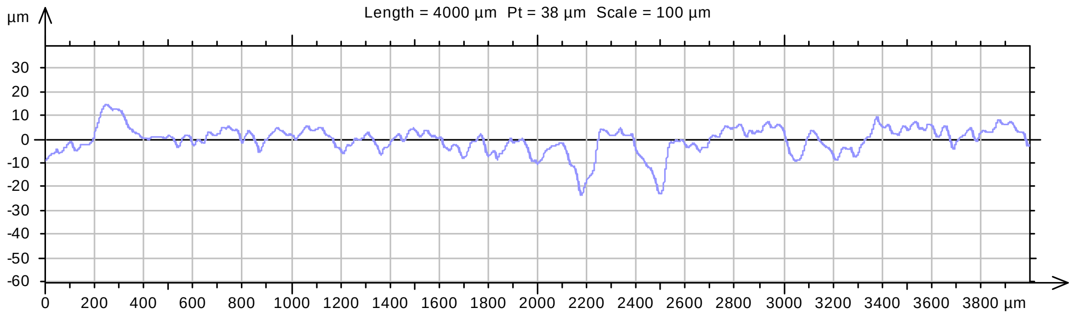
18(c)



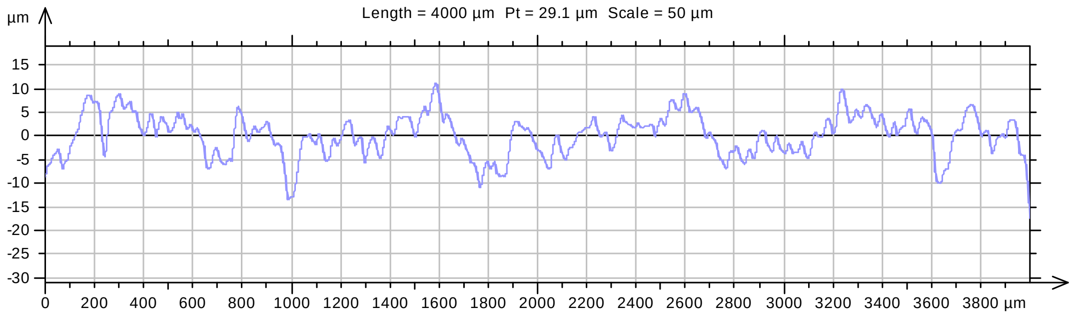
19(a)



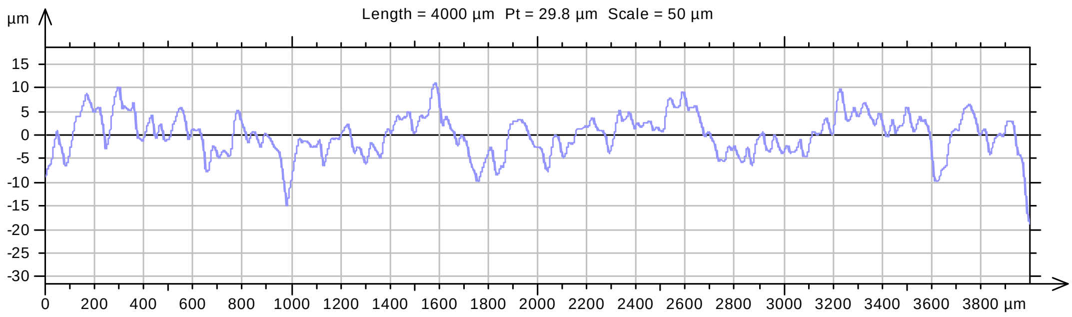
19(b)



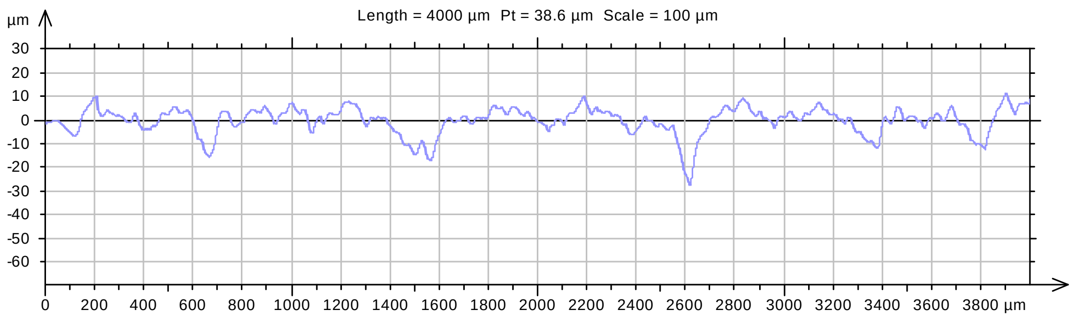
19(c)



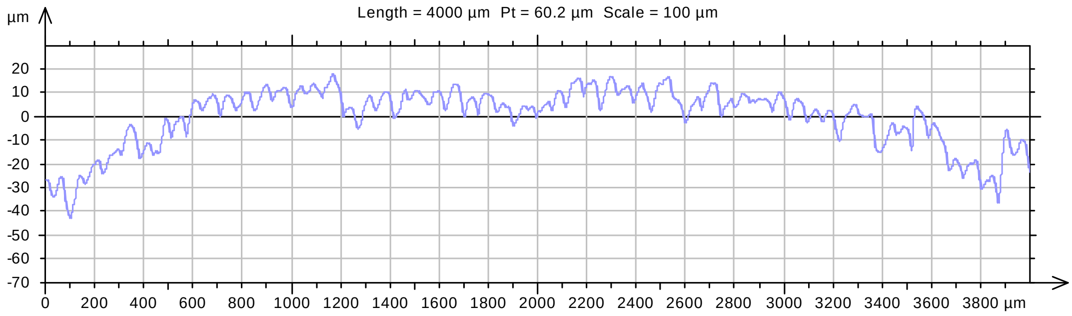
20(a)



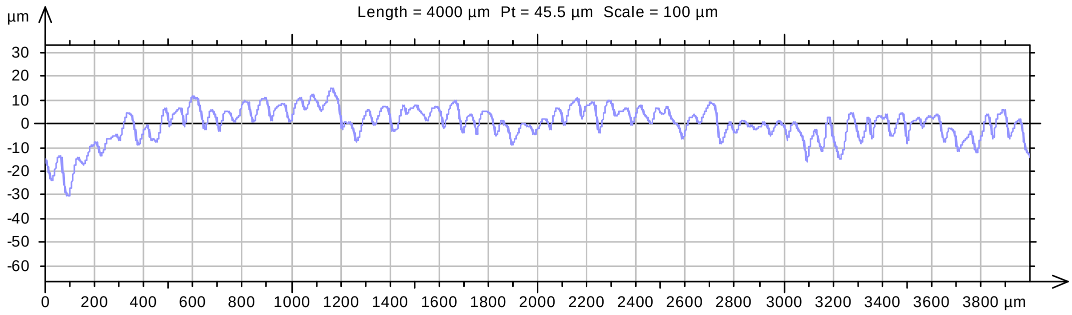
20(b)



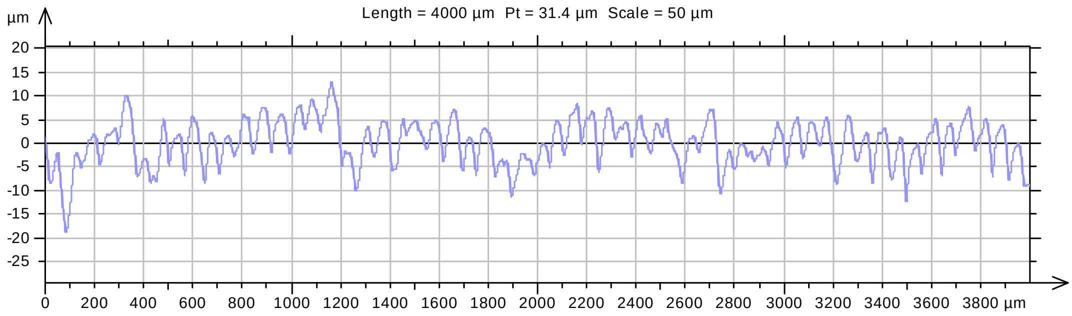
20(c)



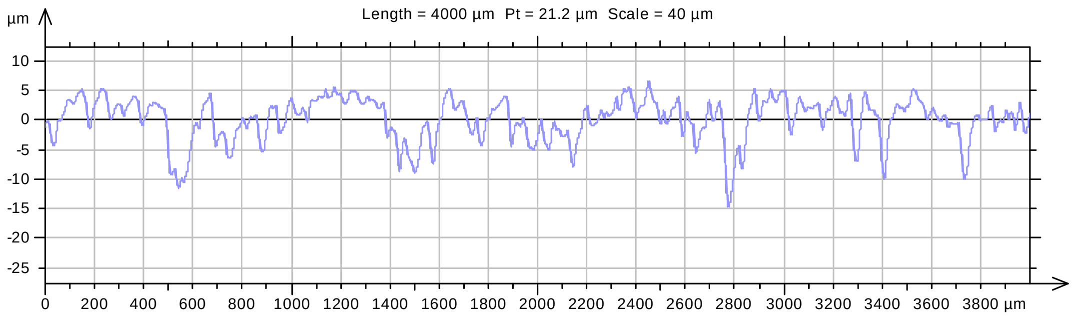
21(a)



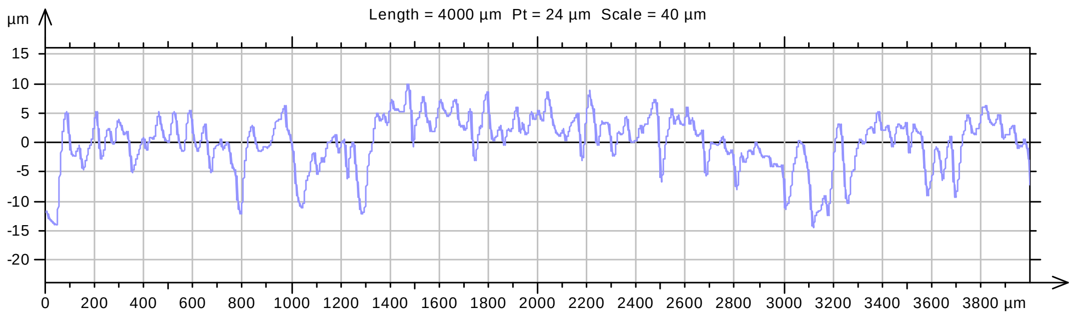
21(b)



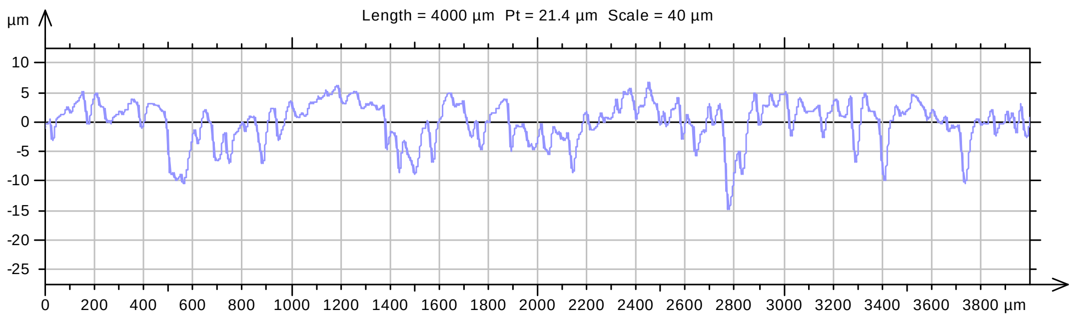
21(c)



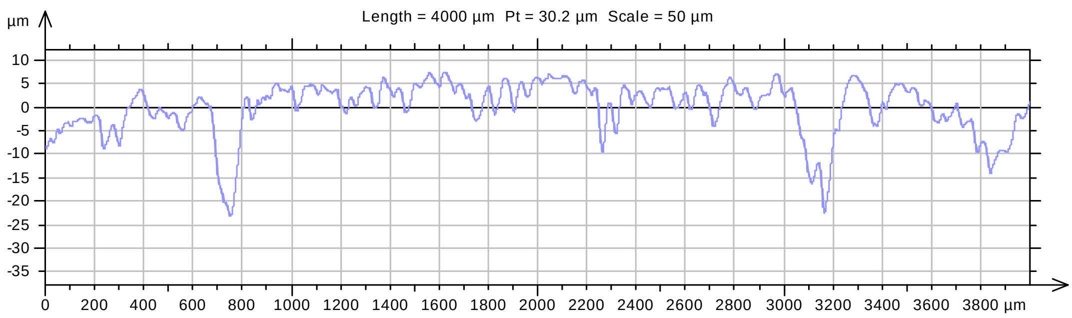
22(a)



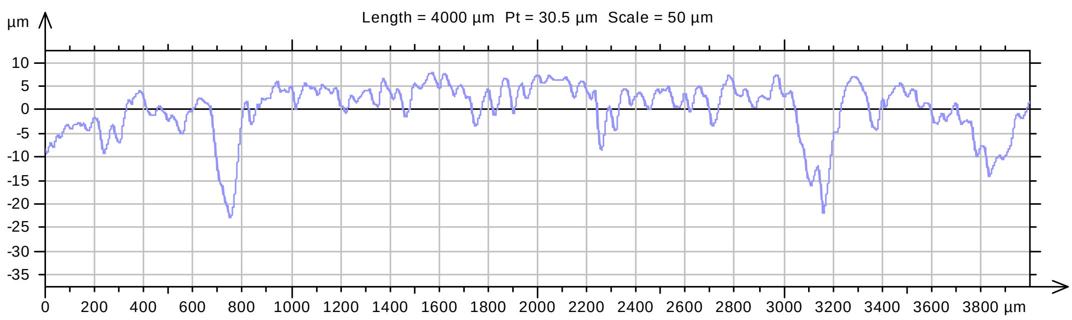
22(b)



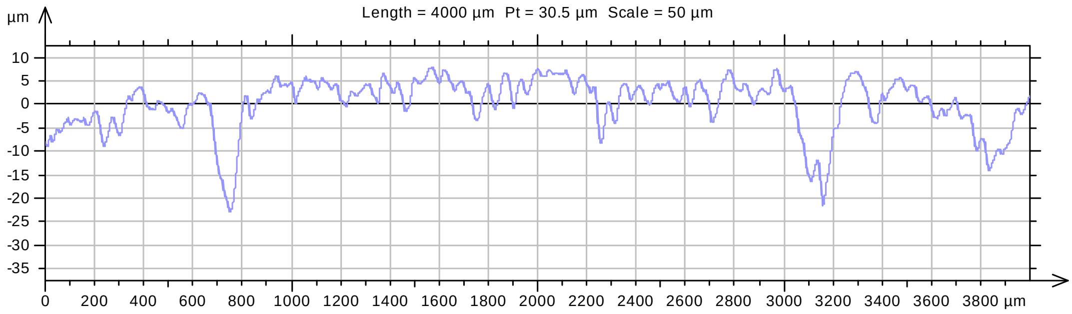
22(c)



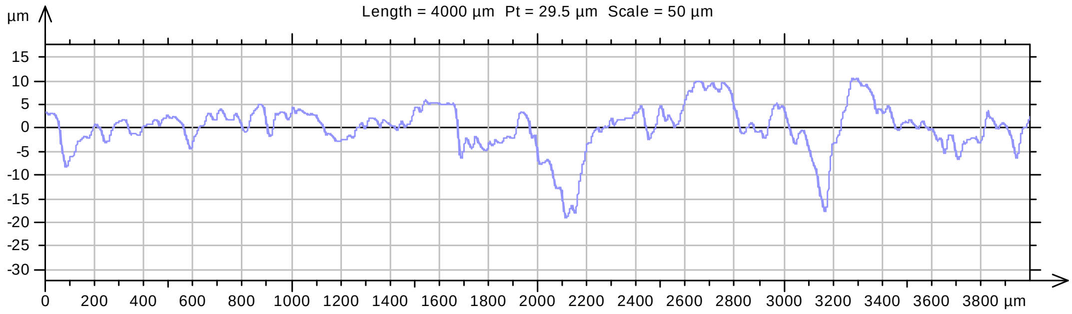
23(a)



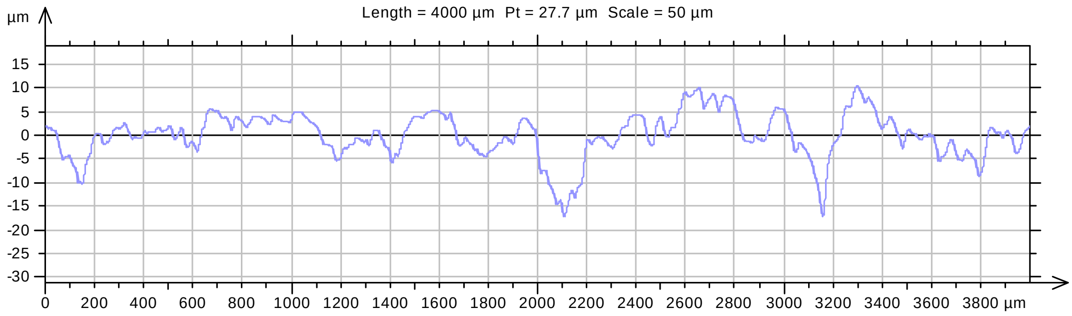
23(b)



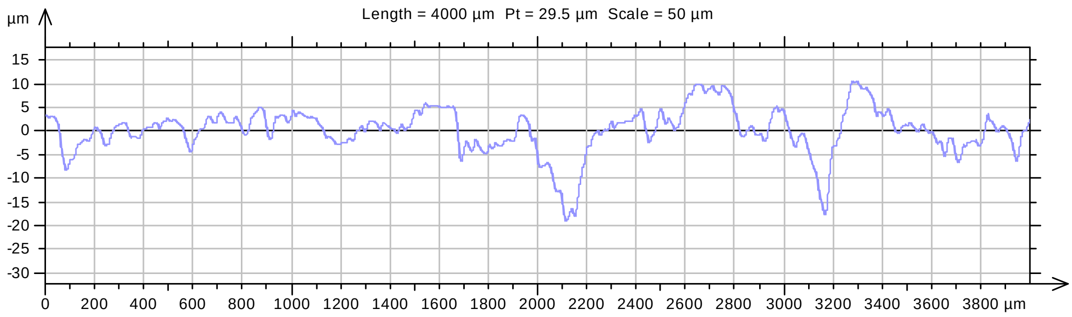
23(c)



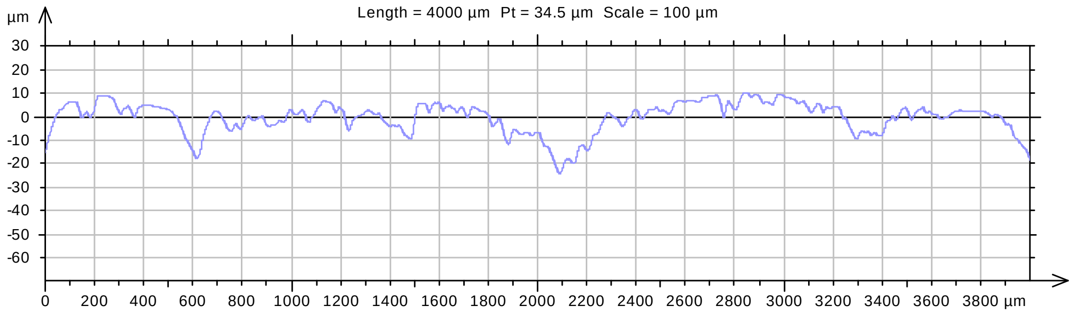
24(a)



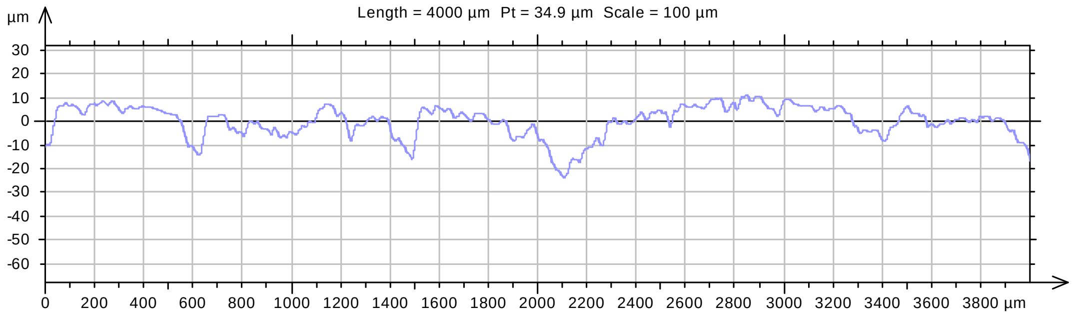
24(b)



24(c)


µm
Length = 4000 µm Pt = 34.5 µm Scale = 100 µm
30
20
10
0
-10
-20
-30
-40
-50
-60
0 200 400 600 800 1000 1200 1400 1600 1800 2000 2200 2400 2600 2800 3000 3200 3400 3600 3800 µm

25(a)


µm
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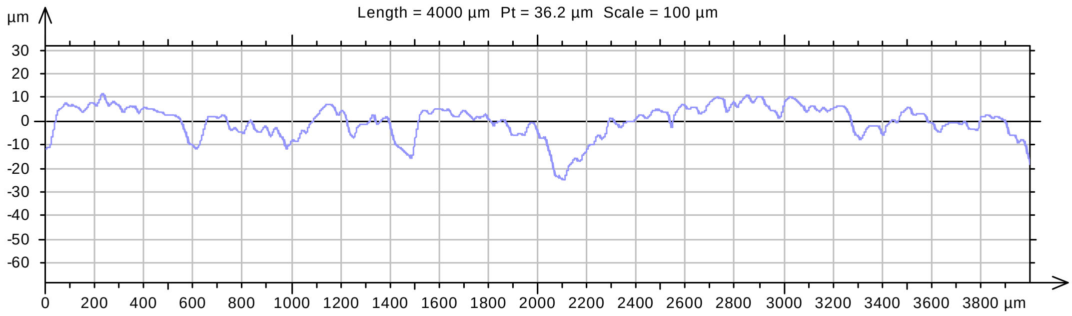
0
-10
-20
-30
-40
-50
-60
0 200 400 600 800 1000 1200 1400 1600 1800 2000 2200 2400 2600 2800 3000 3200 3400 3600 3800 µm

25(b)


µm
Length = 4000 µm Pt = 36.2 µm Scale = 100 µm
30
20
10
0
-10
-20
-30
-40
-50
-60
0 200 400 600 800 1000 1200 1400 1600 1800 2000 2200 2400 2600 2800 3000 3200 3400 3600 3800 µm

25(c)

List of Publications

1. **Kumar Abhishek**, Saurav Datta, Siba Sankar Mahapatra, Asish Bandyopadhyay, "*A Case Study on Surface Quality Improvement in Machining PTFE using PCA based TOPSIS method*', **International Conference on Advances in Modeling, Optimization and Computing (AMOC-2011)**, organized by Department of Mathematics, **Indian Institute of Technology Roorkee**, Roorkee-247667, held during December 5-7, 2011.

2. **Kumar Abhishek**, Saurav Datta, Siba Sankar Mahapatra, "*Utility Based Fuzzy Approach for Multi-Objective Optimization in Nylon Machining*", **International Conference on Advances in Supply Chain and Manufacturing Management, Achieving Growth, Profitability and Sustainability in a Globalized Environment (ASCMM 2011)**, December 16-18, 2011, organized by Department of Industrial Engineering and Management, **Indian Institute of Technology**, **Kharagpur**, West Bengal.

3. **Kumar Abhishek**, Saurav Datta, Siba Sankar Mahapatra, "*PCA-TOPSIS for Multi-Response Optimization: An Off-Line Quality Engineering Problem in Nylon-6 Machining*", ***N*ational Conference on Recent Advances in Chemical and Environmental Engineering**, **(RACEE 2011)**, 20-21 January, 2012**,** Organized by Department of Chemical Engineering, **National Institute of Technology**, **Rourkela**, Orissa.