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CONDITION MONITORING METHODOLOGY FOR MANUFACTURING AND DESIGN

Irem Y. Tumer
The University of Texas at Austin
Mechanical Engineering, ETC 5.160
Austin, Texas, 78712
Phone: 512-471-3087
Email: irem@shimano.me.utexas.edu
http://shimano.me.utexas.edu/˜irem

Kristin L. Wood
The University of Texas at Austin
Mechanical Engineering, ETC 5.160
Austin, Texas, 78712
Phone: 512-471-3087
Email: wood@mail.utexas.edu
http://shimano.me.utexas.edu/kris.html

Ilene J. Busch-Vishniac
The University of Texas at Austin
Mechanical Engineering, ETC 5.160
Austin, Texas, 78712
Phone: 512-471-3087
Email: ilenebv@mail.utexas.edu
http://www.me.utexas.edu/˜microbot/IBVmain.html

ABSTRACT

Part production requires constant monitoring to assure the effective manufacturing of high-quality components. The choice of monitoring methods can become a crucial factor in the decisions made during and prior to manufacturing. In an ideal world, designers and manufacturers will work together to interpret manufacturing and part data to assure the elimination of faults in manufacturing. However, manufacturing still lacks mathematically robust means of interpreting the manufacturing data so that a channel of communication can be established between design and manufacturing. To address part production concerns, we present a systematic methodology to interpret manufacturing data based on signals from manufacturing (e.g., tool vibrations, part surface deviations). These signals are assumed to contain a fingerprint of the manufacturing condition. The method presented in this paper is based on a mathematical transform to decompose the signals into their significant modes and monitor their changes over time. The methodology is meant to help designers and manufacturers make informed decisions about a machine and/or part condition. An example from a milling process is used to illustrate the method's details.

BACKGROUND AND MOTIVATION

In this paper, we present a method to detect faults and monitor changes during manufacturing. The method extends a mathematical transform, namely, the Karhunen-Loève transform, to provide a mathematical decomposition of manufacturing signals into their fundamental components. These components are monitored to detect significant stationary and nonstationary changes in the manufacturing fingerprint. The methodology is presented for use by both designers and manufacturers with the purpose of providing an accurate and clear picture of the manufacturing condition. In the following, we begin with an example in manufacturing, then present the steps of a fault detection and monitoring methodology, including a set of guidelines to interpret the results. We then apply the methodology steps and guidelines to an example in manufacturing, namely, the surface condition of parts from a milling process.

Engineering Surfaces and Their Analysis

The motivation for this work stems from a crucial need in part production to assess the condition of a part and control deviations from the specified design. An important question when manufacturing a component is how to enable the workpiece to work according to the designer's specifications and goals. The designer has a specific function in mind and the manufacturer has to make sure that the part is produced to satisfy this functionality (Whitehouse, 1994). By gaining an understanding of process variation, the design and manufacturing engineers can work as a team to assess the process capability and determine whether a part will function properly (Zemel and Otto, 1996).

To assess the functionality of a workpiece, it is crucial to identify possible deviations and control them. As a first step, it is crucial that we measure and characterize these deviations. Dimensional measurement satisfies part of this need: by measuring the length, area, position, radius, etc., we assure that the workpiece conforms to the designer's specifications. This step, in turn, ensures that the component will assemble into an engine, gearbox, etc. However, the measurement of the dimensional characteristics of the component is not sufficient to ensure that the workpiece will satisfy its function. To complement the dimensional measurement, surface measurement is used to assure that all aspects of the surface geometry are known and controlled. In other words, if the shape and texture of the component are correct, then it will be able to move at the speeds, loads, and temperatures specified by the designer. As a result, the measurement of the surface characteristics of the component hence becomes a crucial factor in assuring its quality (Whitehouse, 1994).

These surface characteristics are typically lumped together in the form of surface texture measurement, which includes the roughness, waviness, and form errors on the component. Roughness refers to irregularities on component surfaces, such as tool marks left on the surface as a result of a milling process, or the marks left on the surface by a grinding process. Waviness refers to irregularities of longer wavelength typically caused by an improper manufacturing condition, such as vibration between the workpiece and the cutting tool. Very long waves are the form errors caused by errors in workpiece table motion, errors in rotating members of the machine, or thermal distortion.

The surface texture of a manufactured component provides a "fingerprint" of the machine, process, and part condition (Whitehouse, 1994). The factors which result in one of these three types of errors are often different. As a result, it becomes crucial to accurately decompose the different components of the surface and attempt to understand their nature and potential for damage to the part's quality (Sottile and Holloway, 1994). In particular, it is important to enable the monitoring of the factors which result in these deviations and determine their severity and originating source so that they can be controlled or eliminated. Traditionally, Statistical Process Control (SPC) is used to measure the process during production, and correlated to a model to understand the sources of variation (Zemel and Otto, 1996). SPC often uses average measures, such as surface roughness and waviness measures, which often fail to provide accurate information about the nature of the surface errors (Whitehouse, 1994; Rohrbaugh, 1993). To overcome this shortcoming, random process analysis tools from the signal processing field are often adapted to the field of surface characterization (Bendat and Piersol, 1986; Whitehouse, 1994; Braun, 1986; Serridge, 1991; Spiewak, 1991). More advanced methods in the research community involve mathematical transforms, such as the wavelet transforms and higher-order spectral transforms (Berry, 1991; Jones, 1994; Rohrbaugh, 1993; Geng and Qu, 1994; Fackrell et al., 1994). The shortcomings of these techniques are provided in (Tumer et al., 1995; Tumer et al., 1997a).

Current Focus

In our work, we have proposed the use of an alternative transform, namely, the Karhunen-Loève transform, for the purpose of condition monitoring in manufacturing (Tumer et al., 1997a; Tumer et al., 1997c; Tumer et al., 1997b). Specifically, we have demonstrated that a fault detection and monitoring method in manufacturing, based on the Karhunen-Loève transform, provides an accurate decomposition of the fault patterns in manufacturing signals, and a means to monitor any significant changes over time.

In this paper, we present the details of this method in the form of steps of a methodology and a set of guidelines for interpretation. The guidelines are based on extensions to the aforementioned method, assuring that the results are clear and easily interpretable for manufacturers and designers. The details of the extensions are not presented in this paper. Instead, the set of guidelines provided contain these extensions in a summarized form. Specifically, the KL-transform-based method is extended for use in manufacturing and design, by assuring that the outputs provide an accurate and physically-meaningful interpretation of manufacturing signals. Our goal is to provide designers and manufacturers with a common means of exchanging accurate information about the manufacturing condition and making informed decisions about the status of the manufacturing process, machine, and part (Eppinger et al., 1995; Zemel and Otto, 1996). A thorough systematic approach in detecting and monitoring faults on manufactured component surfaces, with the purpose of integrating design and manufacturing tasks, does not exist. We believe that the set of specific steps and guidelines based on our method provides an accurate representation of the part surface condition. We also believe that the physical understanding of the fault condition for manufactured parts will help bridge the gap between designers and manufacturers, as well as reduce scrap during manufacturing and reduce the time and money spent to produce a part.

KL-Based Detection and Monitoring

To analyze and monitor manufacturing signals, the Karhunen-Loève (KL) transform decomposes the signals into completely decorrelated components in the form of empirical basis functions that contain the variations in the original data. An estimate of the original signal is computed using a linear combination of these empirical basis functions and their respective coefficients in the new transform domain. To obtain a KL decomposition of a collection of signals, zero-mean input data are assembled in a covariance matrix, from which the eigenvectors and eigenvalues corresponding to the principal axes of highest variability are computed. These axes correspond to the fundamental modes in the input data, and their corresponding coefficient vectors are used to monitor stationary and nonstationary changes in the fundamental modes. The mathematical details of the method are presented in previous publications by the authors (Tumer et al., 1997a; Tumer et al., 1997b; Tumer et al., 1997c), and are hence not repeated here.

The KL transform has been used in many signal processing applications in literature, ranging from the characterization of pictures of human faces (Sirovich and Keefe, 1987), to the analysis of turbulent flow mechanics (Ball et al., 1991). The literature background is described in further detail in (Tumer et al., 1997c; Tumer et al., 1997b; Tumer et al., 1997a). In this work, the transform is applied to signals measured from manufacturing processes, to analyze and quantify the fingerprint indicative of potential errors on part surfaces. The application of the KL transform to manufacturing is rare, limited to multivariate statistical process control (Martin et al., 1996; Zhang et al., 1995), mainly due to the difficulty in obtaining physically-significant outputs. Improvements proposed as a set of guidelines in this paper assure that we will obtain physically-meaningful outputs.

Signals and Modes from Manufacturing

Signals contain many characteristics which can be categorized either as deterministic or stochastic. An example of a deterministic signal is a periodic waveform (Bendat and Piersol, 1986; Braun, 1986). As opposed to deterministic signals, which can be predicted by known models, stochastic signals require probabilistic statements to describe their structure. Most signals contain a combination of stochastic and deterministic signals, and exhibit either stationary or nonstationary characteristics. Nonstationary characteristics are indicative of a time-varying structure in the data, where the statistical properties vary with time. Nonstationary signals, which can be regarded as deterministic factors operating on otherwise stationary random processes (Bendat and Piersol, 1986; Box et al., 1994), are difficult to predict, and often cause difficulties in the detection of otherwise predictable modes.

In this work, we focus on signal types that are encountered typically in manufacturing processes. Most manufacturing processes generate periodic waveforms that are indicative of many potential error sources. Examples are the tool marks from a turning process, feed marks from a milling process, or roller chatter marks from a Selective Laser Sintering process (Tumer et al., 1998; Tumer et al., 1997b). Stationary or nonstationary changes in these periodic waveforms can be indicative of potential or already existing faults in the machine or material. Furthermore, the appearance of additional periodic components (e.g., harmonics) can be indicative of inherent errors in the manufacturing machine. In addition, component surfaces may contain linear trends such as slopes and offset changes due to impulsive forces during machining (e.g., surface hardness variations, chip breakage, and tool wear). As a result, in this work, we focus on periodic and linear trends, and their stationary and nonstationary changes in the presence of high-variability stochastic noise.

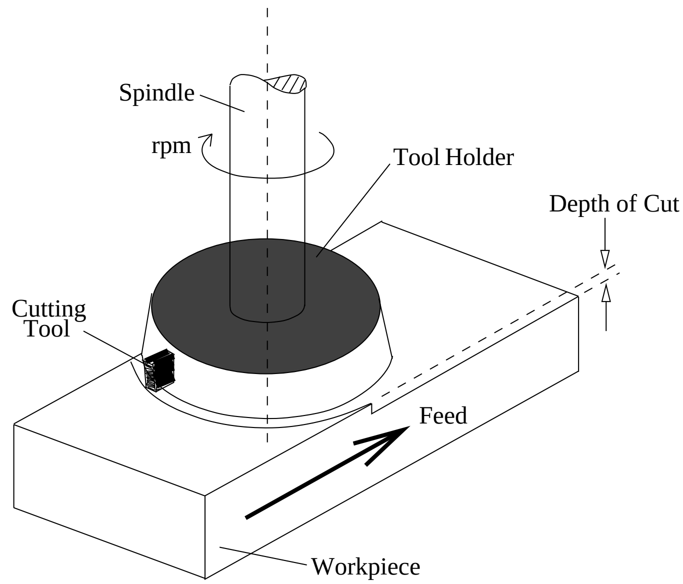


Figure 1. The Face Milling Process.

CASE STUDY: APPLICATION IN MANUFACTURING

Before presenting the steps of our method, let us introduce a case study involving the quality of parts from a milling process. We will use surface profiles measured from such parts to apply the steps of our methodology later on.

The Milling Process

Milling is one of the most versatile cutting processes, used to manufacture parts with nonrotational symmetry (Schey, 1987). To illustrate the use of our method in manufacturing, we use parts manufactured using a vertical milling machine. Vertical mills have an axis of the cutter perpendicular to the workpiece surface. In particular, in face milling, the cutting tooth is attached to the cutter face which is perpendicular to the axis, as shown in Figure 1.

Part Surfaces from a Milling Process

We collect surface profile measurements from a part manufactured using the face milling process shown in Figure 1. A flat feature, made of Aluminum 2024, has been milled using a vertical milling machine. The cutting tool material is high speed steel. No cutting fluid has been used. Surface measurements have been collected for analysis, as shown in Figure 3. The cutting speed is $s = 0.508\ m/sec$ ($100\ fpm$); the feed is $f = 2.54\ 10^{-4}\ m/rev$ ($0.010\ in/rev$); the depth of cut is $d = 2.54\ 10^{-4}\ m$ ($0.01\ in$) (Srinivasan et al., 1996; Srinivasan and Wood, 1997).

There can be multiple sources of variation on surfaces of parts manufactured by milling. Examples are misalignment of the workpiece due to clamping, nonstationary hardness variations, tool wear, machine and tool vibrations, etc. These mechanisms can leave undesirable patterns on part surfaces. In particular, the vertical milling process produces a dominant periodic pattern on part surfaces, due to the feed marks produced during cutting. In addition, nonstationary linear trends appear on the surfaces due to misalignments of the work table, as well as other nonstationarities due to time-varying wear of cutting tool, or sudden chip breakage, etc. Such nonstationarities make it difficult to detect the exact nature of the main periodic component. For example, linear trends often appear as a dominant low-frequency periodic component using Fourier-based methods, which makes the automatic detection of the relevant component difficult. In addition, the nature of the nonstationarities is impossible to determine with Fourier-based methods. As a result, to get more reliable surface information, we analyze such surfaces using our Karhunen-Loève-based condition monitoring method, described next.

KL-BASED CONDITION MONITORING METHOD

The methodology has five main stages, as shown in Figure 2. The first stage is problem identification, second, data preparation, third, data decomposition, fourth, output interpretation, and fifth verification and prediction. The first, fourth, and fifth stages are shared by manufacturers and designers, while the middle stages, two and three, are performed by manufacturers only. The designer's involvement at the first phase is crucial in assessing the potential problems that might affect the part's designed functionality. A discussion of potential problems with the manufacturer is a crucial requirement in concurrent engineering (Zemel and Otto, 1996). The exchange of information about the part and machine condition at phases four and five is also an essential element in analyzing the existing and potential problems with the purpose of understanding the nature and source of process deviations. Note that phase four contains the summarized extensions to the KL-based detection and monitoring technique. The set of guidelines provided as part of this step in the methodology are essential in assuring the correct interpretation of the KL results, and hence the method's acceptance in manufacturing practice.

In the following subsections, these five stages are further decomposed into several steps to present the methodology in a systematic and logical manner. The details of the steps are first presented and then followed by an example application in the manufacturing of milled parts. Note that M input signals of dimension N are collected, where $\mathbf{Z}_j$ is the zero-mean version of the input data, $\mathbf{X}_j$; $\hat{\mathbf{S}}$ is the sample covariance matrix using the zero-mean data; Φ is the KL eigenvector matrix, with eigenvalue matrix Λ; $\mathbf{Y}$ is the matrix containing the coefficient vectors for the eigenvectors. Also note that the steps outlined below are to be implemented using an algorithm in order to automate the KL analysis and decision-making process.

Step One: Problem Identification

The first stage for manufacturers and designers is to identify the problem to be analyzed. This obvious step is crucial in identifying which manufacturing signal will best represent the condition of the manufacturing process. For example, we focus here on surface profile measurements of manufactured parts as containing a fingerprint of the machine condition. Another possibility is the monitoring of vibrational signals from rotating machinery in the manufacturing machine. The choice of the manufacturing signal can be made by the designers and/or the manufacturers, either based on the manufacturer's experience about which output is most likely to show faults, a particular component that the designer is testing, or various different manufacturing signals can be monitored at the same time to eliminate the need for past experience or biased results.

Step Two: Data Preparation

As with every data analysis methodology, an important step is to prepare the data for analysis. Before starting the KL analysis, manufacturers must follow the following steps:

1. Collect M measurements $\mathbf{Z}_j$ of the signal of N points each, using a set time interval Δt:
   (a) Check Nyquist (sampling frequency at least twice the highest frequency of interest (Bendat and Piersol, 1986));
   (b) Decide about decimation (spectral energy concentrated at the lower frequencies);
   (c) Determine required N (one wavelength of the lowest frequency sine (Fukunaga, 1990));
   (d) Determine required M (large M to assure high signal-to-noise ratio, small M to assure computational efficiency) (Bendat and Piersol, 1986; Fukunaga, 1990));
2. Convert output data to reflect time or length as the x-axis scale, instead of sampled points;
3. Compute ensemble mean and remove from each input vector: $\mathbf{X}_j = \mathbf{Z}_j - \frac{1}{M}\sum_{j=1}^{M}\mathbf{Z}_j$.

Step Three: KL Decomposition of Data

Once the data is prepared for analysis, the manufacturer can decompose the data into the KL outputs. To decompose the data, the following steps must be applied:

1. Form covariance matrix using the M zero-mean input vectors: $\hat{\mathbf{S}} = \frac{1}{M}\sum_{j=1}^{M}\mathbf{X}_j\mathbf{X}_j^T = \frac{1}{M}\mathbf{X}^T\mathbf{X}$;
2. Compute eigenvectors and eigenvalues of the covariance matrix: $\hat{\mathbf{S}}\Phi = \Phi\Lambda$;
   (a) If $M < N$, then compute $M \times M$ covariance matrix and retransform the eigenvectors:
      i. covariance matrix: $\mathbf{X}^T_{M\times N}\mathbf{X}_{N\times M}$;

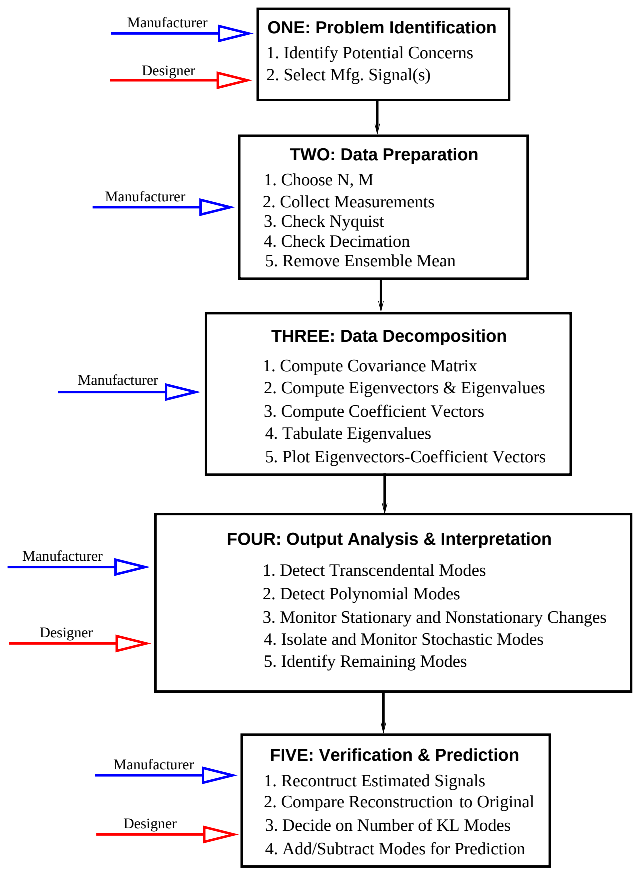


Figure 2. The Steps of the KL-Based Fault Detection and Monitoring Methodology.

   ii. eigenvector equation: $\frac{1}{M}(\mathbf{X^T X})_{M\times M}\Phi_{M\times M} = \Phi_{M\times M}\Lambda_{M\times M}$;
   iii. retransformation: $\Phi_{N\times M} = \mathbf{X}_{N\times M}\Phi_{M\times M}$;

(b) If $N < M$, then compute the $N \times N$ covariance matrix and its eigenvectors:
   i. covariance matrix: $\mathbf{X}_{N\times M}\mathbf{X}^T_{M\times N}$;
   ii. eigenvector equation: $\frac{1}{M}(\mathbf{X}\mathbf{X}^T)_{N\times N}\Phi_{N\times N} = \Phi_{N\times N}\Lambda_{N\times N}$;

3. Compute coefficient vectors ($\mathbf{Y} = \Phi^T\mathbf{X}$);
4. Tabulate eigenvalues in descending order;
5. Plot eigenvector and coefficient vector pairs (comparable scales) for the first dominant m eigenvalues that add up to 99% of the total energy.

Step Four: Interpretation of KL Outputs

The most crucial part of the methodology is the correct interpretation of the analysis results. Designers and manufacturers can consult the following set of guidelines to help with the interpretation of the results. Manufacturers can use these results to make on-line changes to improve the quality of the manufacturing signal. Designers can make off-line changes about the manufacturing process or the design parameters, and make redesign decisions based on the interpretation and prediction of results.

General Results The eigenvectors provide the average fundamental modes in the inputs; the coefficient vectors provide the change in the fundamental modes over time; and the eigenvalues provide the significance of each mode. In the following, the interpretation of essential modes of relevance on manufactured surfaces is presented (e.g., transcendental and polynomial modes). The stationary and nonstationary changes in these modes will be monitored by means of the coefficient vectors. General multicomponent signals are addressed next to complete the methodology.

Interpretation of Sinusoidal Modes Sinusoidal modes of the form $x^k(t) = \sum_{k=1}^{K} A_k sin(\omega_k t + \theta(k))$ are very common in manufacturing. (A_k is the amplitude, ω_k is the frequency, and $\theta(k)$ is the phase angle of the sinusoidal waveform). For example, rotating elements, such as bearings, rollers, and grinding wheels, introduce a fundamental frequency component (Wowk, 1991). In addition, cutting tools introduce periodic components such as feed marks during the turning and milling processes. Vibrations of the rotating machinery may also introduce harmonics (i.e., integer multiples) of the fundamental frequency components. Additional frequency components or changes in the magnitudes of the existing frequency components are introduced in cases of bearing faults, tool wear, etc. The following guidelines must be followed to interpret sinusoidal modes:

1. Each sinusoidal mode in input data results in a pair of eigenvectors:
   (a) Observation of a pair of eigenvectors for a sinusoid is indicative of phase differences in input data.
   (b) The two eigenvectors reflect a similar functional form (amplitude and frequency), but are shifted by 90 degrees, due to the orthogonality requirement of the eigenvectors: it is sufficient to observe only one of the eigenvectors in the pair in order to obtain frequency and amplitude information.
   (c) Similarly, stationary and nonstationary changes in the sinusoidal modes can be monitored using only one of the coefficient vectors in the pair.
   (d) Phase information can be obtained and monitored by reconstructing a linear combination of the pair of eigenvectors and corresponding coefficients.
   (e) Real phase information can be determined by resampling the original data to capture one full period of the sinusoidal waveform and running the decomposition algorithm again: if there still is an additional eigenvector, then there exists real phase information; this information can be captured by following the same reconstruction procedure as above.
2. Decomposition of multicomponent sinusoidal modes results in eigenvectors with each individual frequency components:
   (a) If sinusoids have different magnitudes (e.g., $A_1 >> A_2 >> \cdots >> A_k$), then there will be one dominant sinusoidal mode per eigenvector.
   (b) If sinusoids have similar magnitudes (e.g., $A_1 \approx A_2 \approx \cdots \approx A_k$), then the eigenvectors will have combinations of multiple sinusoids:
      i. If the eigenvectors indicate a combination of several modes, then increase the number of inputs to reduce the variance of the eigenvector estimates. The cutoff for an acceptable decomposition must be determined based on the physical problem. The maximum number of inputs M is determined by increasing the number M and observing the cutoff in the KL eigenvectors. The adequacy of M can be verified by computing the variance of the eigenvalue estimators to make sure an asymptotic value is reached.
3. Stationary and nonstationary changes in the amplitude of the sinusoidal components will be indicated by the corresponding coefficient vectors.

Interpretation of Linear Modes Linear modes $x_k(t) = At + B$ in manufacturing are introduced due to several factors: (1) linear trends with a non-zero slope are often introduced due to misalignments in the workpiece or clamping mechanisms; and, (2) linear offset changes may occur during manufacturing due to tool tip breakage, impulsive blow to the machine, etc. The linear changes constitute nonstationary changes that are difficult to detect with averaging methods. The following guidelines must be followed to interpret linear modes:

1. Plot the eigenvectors: linear modes appear “linear” compared to the rest of the eigenvectors.
2. Nonstationary changes in the linear modes are observed by means of the corresponding coefficient vectors:
   (a) Linear trends manifest as a nonstationary increase in the slope of the coefficient vector over time;
   (b) Linear offsets manifest as a nonstationary jump in the coefficient vector over time;
   (c) Impulsive changes manifest as an impulse in the coefficient vectors corresponding to the linear eigenvector.

Interpretation of Stochastic Modes Stochastic modes are an essential part of signals from manufacturing and can happen for various reasons. For example, an additive noise component may be introduced due to stochastic vibrations, noise from outside disturbances, measurement errors: $x(t) = y(t) + n(t)$, where $E[n(t)] = 0$ and $Var[n(t)] = \sigma_0^2$. In addition, a manufacturing signal may be stochastic by nature: for example, grinding introduces a stochastic profile on manufactured surfaces due to the random cutting tool structure on the grinding wheel, or, the fracture mechanisms during cutting result in a fractal structure in the measured signals (Srinivasan and Wood, 1997).

Additive stochastic modes in the input signals are collected in the low-eigenvalue eigenvectors; as a result, once the coherent modes are removed, only the stochastic modes remain. The stochastic structure can be analyzed using random measures, such as fractal measures, which are shown to describe inherent “structure” in stochastic data, once the deterministic modes have been removed (Srinivasan et al., 1996; Tumer et al., 1997a). In this paper, the fractal dimension is adapted to show feasibility.

To detect changes in the stochastic nature of the data, the following guidelines can be followed:

1. The stochastic mode can be obtained by forming a linear combination of the coherent KL modes and subtracting them from the input vectors.
2. The remaining stochastic-only inputs can be analyzed by means of fractal measures (or other stochastic measures):
   (a) Compute the fractal dimension of each input;
   (b) Observe changes in the fractal dimension to determine changes in the stochastic structure over time.

Other Modes The above modes represent the frequently-encountered modes in manufacturing. To allow the decomposition of general functions, the same procedure is followed. Specifically, a linear combination of various arbitrary functions, $a_1 f_1(x,t) + a_2 f_2(x,t)$ will result in the isolation of each function $f_1(x,t)$ and $f_2(x,t)$ in the form of eigenvectors, which can then be monitored by means of the corresponding coefficient vectors. Any functional form can be extracted in the form of KL eigenvectors. However, the analyst has to refer to some library of possible functions to determine the function of the KL eigenvectors. An example of an arbitrary function, not addressed in this work, is a transient, which is a nonstationary change in the data. In addition, a nonlinear combination $f_1(x,t) f_2(x,t)$ results in eigenvectors that contain this product form, instead of decomposing the functions further. Examples of such nonlinear functions include polynomials and exponentially-decaying sinusoids.

This work only addresses specific types of nonstationary changes. Specifically, nonstationary changes in the amplitude of sinusoidal modes, classified as a change in the mean-square value (variance), are identified, as well as nonstationary changes in linear trends, classified as a change in the mean value (i.e., slopes, offsets, impulses). More complex forms of these nonstationarities are not yet addressed. Specifically, nonstationary changes in the frequency structure, such as a frequency-modulated signal, can be identified by the introduction of various eigenvectors for the changing frequency value. The change in the frequency structure can be detected by plotting the coefficient vectors for each frequency component. This will indicate a “zero” significance of the second frequency component introduced due to frequency modulation, prior to the modulation.

Step Five: Verification and Prediction of Modes

Finally, the analysis results must be validated by comparing the effect of the detected modes (i.e., eigenvectors) on the input signals. To perform this comparison, an estimate of the input signals can be reconstructed using a linear combination of the fundamental eigenvectors and coefficient vectors and adding this to the ensemble averaged vector. Such a reconstruction can be used to determine and study the effect of specific components on surface quality as well. Specifically, designers can make *a priori* design changes, estimate the surface profiles based on the dynamic or static modes introduced due to these changes, and hence determine their potential effect on surface quality. For example, changing a bearing will introduce a fundamental frequency component with known amplitude. Estimates of the expected surface patterns based on this redesign change can be reconstructed and compared to the actual surface profiles with the worn bearing, to determine the improvement on surface quality. Finally, specific surface patterns can be compared to the expected (estimated) surface patterns to provide an additional warning mechanism, to complement the condition monitoring of KL eigenvectors and coefficient vectors.

KL-BASED MONITORING OF MILLED PARTS

In this section, we return to the components produced from the vertical milling process introduced in Figure 1, and apply the steps of our methodology to analyze their surface structure.

Step One: Problem Identification

Recall that the first step of the methodology requires the selection of a manufacturing signal. In this case, we select the surface profile measurements as the output signal of interest. Surface profiles contain a fingerprint of the manufacturing condition and often can pinpoint incipient faults in the manufacturing machine (Whitehouse, 1994). In addition, the quality of the manufactured product surfaces is one of the essential factors when manufacturing functional parts which will get assembled with other parts.

Step Two: Data Preparation

The second stage of the methodology requires the collection and preparation of data for analysis. $M = 60$ input profile measurements are collected, with $N = 1000$ points each, as shown in Figure 3. These input profiles are sampled at a rate of 799 $points/mm$, over a surface traverse length of $TL = 1.25$ mm along the longitudinal. The different measurements are collected in the direction perpendicular to the longitudinal in order to detect possible nonstationary trends in the transverse direction, as shown in Figure 4. Notice that by measuring short sequences along the longitudinal direction, we assure the detection of periodic patterns. The nonstationary trends in the transverse direction are detected as well, if there is a significant change. To detect nonstationary patterns along the longitudinal direction, the direction of the measurements needs to be reversed. A very long measurement of the longitudinal direction can be collected and then divided into smaller sequences to represent snapshots. The changes in the longitudinal direction can then be detected by means of the coefficient vectors along the data sequences. Longer measurements will require the data to be decimated down to a reasonable number of sampled points.

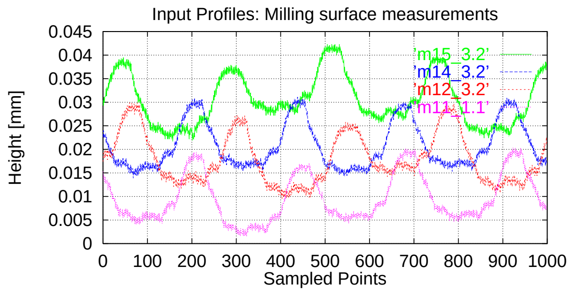


Figure 3. Milled Profiles.

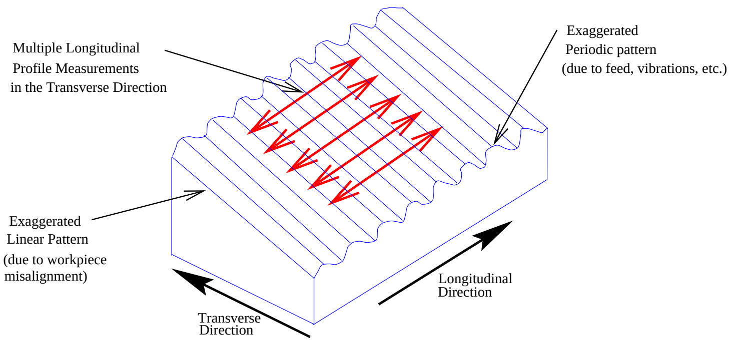


Figure 4. Milled Part and its Measurement.

Following the steps of the methodology, the ensemble mean profile is removed from each input measurement, resulting in $M = 60$ zero-mean input sequences.

Step Three: Decomposition of Milled Surface Data

The zero-mean data are assembled in a data matrix and entered into the KL algorithm. The results of the KL analysis of the milled surface measurements are then prepared for further analysis and interpretation, presented next.

Since we have $M = 60$ inputs (rank $r \leq M = 60$ (Tumer et al., 1997c; Tumer et al., 1997b)), the KL analysis results in 60 eigenvalues and eigenvectors. Among those, only a few are significant, representing the fundamental modes in the data. The eigenvalues resulting from the KL analysis are presented in Table 1 (only $M = 20$ are shown). The first five eigenvalues represent significant modes, as discussed next.

Step Four: Analysis and Interpretation of Results

This crucial analysis stage of the methodology requires a careful interpretation of the KL decomposition outputs by manufacturers and/or designers.

Fundamental Eigenvectors and Coefficient Vectors

The Karhunen-Loève transform of the collected milling profile measurements results in five fundamental eigenvectors, with the main three modes shown in Figure 5, which correspond to a linear trend, a low-frequency sinusoidal pattern, and a high-frequency sinusoidal pattern (twice the frequency of the first one) (note that the "pairs" for the sinusoids are not shown). The corresponding coefficient vectors are shown in Figure 6.

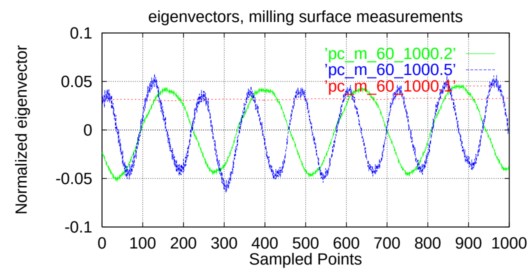
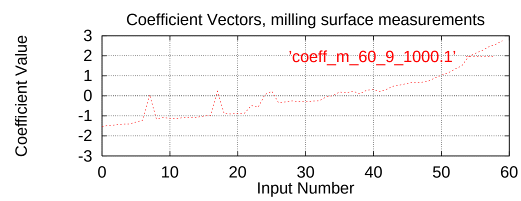
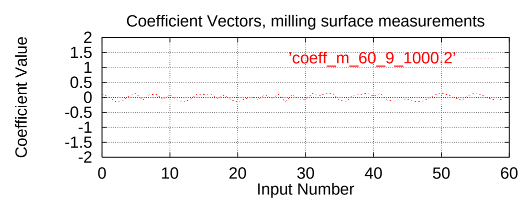


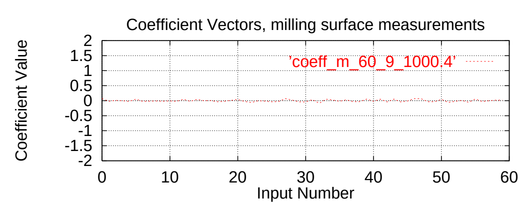
Figure 5. Milling Decomposition: Three Fundamental Modes.



(a) Coefficient Vector 1.



(b) Coefficient Vector 2.



(c) Coefficient Vector 4.

Figure 6. KL Coefficients for Milled Profiles.

The first mode (first eigenvector), shown in Figure 5, corresponds to the linear slope which exists on the milled surface, indicated by a linear eigenvector. The eigenvector, which is compared to the two sinusoidal eigenvectors, has the general form of

Table 1. Eigenvalues for Milling Analysis.

Eigenvalue Number	Eigenvalue	Individual Energy	Cumulative Energy
λ_1	1.243794	0.9811	0.9811
λ_2	0.009579	0.0076	0.9886
λ_3	0.008497	0.0067	0.9953
λ_4	0.001446	0.0011	0.9965
λ_5	0.001280	0.0010	0.9975
λ_6	0.000867	0.0007	0.9982
λ_7	0.000540	0.0004	0.9986
λ_8	0.000399	0.0003	0.9989
λ_9	0.000221	0.0002	0.9991
λ_{10}	0.000184	0.0001	0.9992
λ_{11}	0.000174	0.0001	0.9994
λ_{12}	0.000121	0.0001	0.9995
λ_{13}	0.000090	0.0001	0.9995
λ_{14}	0.000085	0.0001	0.9996
λ_{15}	0.000067	0.0001	0.9996
λ_{16}	0.000056	0.0000	0.9997
λ_{17}	0.000040	0.0000	0.9997
λ_{18}	0.000038	0.0000	0.9997
λ_{19}	0.000033	0.0000	0.9998
λ_{20}	0.000028	0.0000	0.9998

a linear vector. Such a trend is caused by misalignments of the worktable, which is identified as a source of error in this case. The corresponding coefficient vector, shown in Figure 6a, indicates the change in slope and severity of this fundamental pattern along the transverse direction (see Figure 4). The nature of this nonstationary pattern can be characterized by monitoring the eigenvector and coefficient vector pair.

The second mode (second and third eigenvectors), shown in Figure 5, corresponds to the main periodic pattern generated on milled surfaces due to the feed marks during milling. A frequency component at $f_1 = 3.19\ cycles/mm$ is clearly identified with the periodic eigenvector, without the adverse effects of nonstationary trends. Any changes in this component, or the relative severity of its magnitude, can be monitored and detected by means of the corresponding coefficient vector, shown in Figure 6b. The sinusoidal eigenvector, in this case, is accompanied by a second eigenvector to represent the phase information in the data (not shown). The third eigenvector is equivalent to the second eigenvector in frequency and amplitude; this eigenvector is indicative of the phase shift in the collected snapshots. This phase effect is due to the fact that the surface is sampled at random locations, hence introducing a random phase component to the data (Tumer et al., 1997c).

The third mode (fourth and fifth eigenvectors), shown in Figure 5, corresponds to the second frequency component on the surfaces. This additional frequency component at $f_2 = 2f_1 = 6.39\ cycles/mm$, corresponds to the harmonic of the main frequency component due to the feed marks, and is generated due to vibrations of the cutting tool during the spindle rotation. Once again, a second eigenvector accompanies this frequency component, due to the phase component (not shown). Changes in the magnitude of this frequency component can be monitored by means of the corresponding coefficient vector, shown in Figure 6c.

Phase Information To compute the phase information between the inputs due to each sinusoidal component, a linear combination of the pair of eigenvectors and coefficient vectors corresponding to the sinusoidal component of interest. Recall that the eigenvectors (#2 and #3 in this case) are always 90 degrees to each other, therefore not providing any information on the phase difference between the inputs.

Figure 7 shows the linear combination of eigenvectors and coefficient vectors #2 and #3 to reconstruct the first two surface measurements. Note that these linear combinations are different than the original surface measurements since they only contain the information corresponding to the main frequency component of the signal. Also note that the *x*-axis has been converted to the proper scale of “traverse length” instead of using the sampled points. Finally, since the phase shift between two sinusoidal functions is a function of the linear shift (along the x-axis) between the sinusoids and the frequency of the sinusoid: $\omega|\Delta x| = \theta$, where Δx is the linear shift between the two sines in millimeters, θ is the phase angle between the two sines in radians, and, ω is the frequency of the sine in radians per millimeter (Tumer et al., 1997c; Tumer et al., 1997b).

The linear shift between the two linear combinations shown in Figure 7 is equal to $\Delta x = 0.075\ mm$. The discrete frequency of the sinusoid in the second eigenvector is equal to $l = 4$ (computed

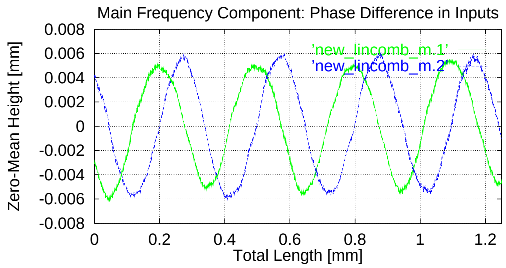


Figure 7. Phase Difference Between Milling Profiles, Linear Combination Using Main Frequency f_1 Component Only.

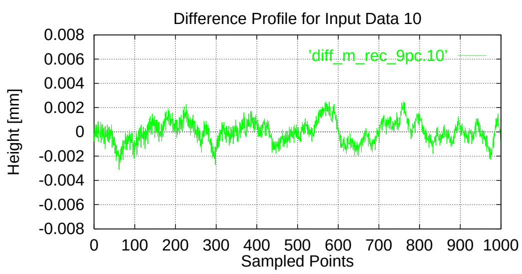
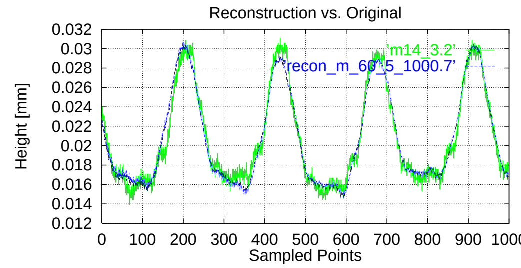
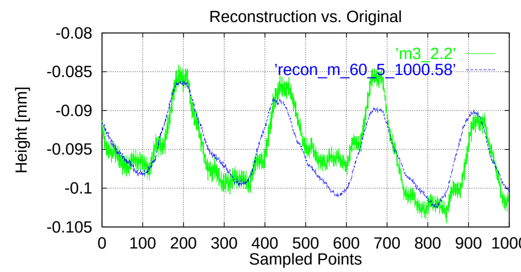


Figure 8. Difference Milling Profile, Input #10.



(a) Reconstructed Profile 7.



(b) Reconstructed Profile 58.

Figure 9. KL Reconstruction of Milled Profiles Using 5 Eigenvectors.

from a simple power spectrum). Discrete frequency is converted to real frequency using $f = l f_s / N_{total}$, where f is the actual frequency in cycles per millimeter, f_s is the sampling frequency in points per millimeter, and N_{total} is the total number of points per input signal. The frequency f is converted to a frequency value in radians per millimeter using $\omega = 2\pi f$. The sampling frequency in this case is $f_s = 799.9\ rad/mm$, and the total number of points is $N_{total} = 1000$ points. The resulting frequency corresponding to a discrete frequency of $l = 4$ is equal to $\omega = 20.1\ rad/mm$. The resulting phase angle between the first two input vectors due to this sinusoidal component is $\theta = 1.5$ radians.

Monitoring The Stochastic Component As discussed previously, the Karhunen-Loève decomposition of a signal acts as a filter. This is because the first few eigenvectors contain the coherent modes, leaving the noise components to the low-frequency eigenvectors.

A difference profile is obtained to remove the coherent KL modes from the profile measurements, as shown in Figure 8, which is then used to compute the fractal dimension. The fractal dimension for this profile can be computed using the method described in (Tumer et al., 1997a). For this difference profile, the regression coefficient is $\beta = 1.269$, which implies a fractal dimension $D_f = 1.86$, computed as $(5-\beta)/2$.

This fractal dimension can be computed for each input measurement to monitor the change in the fractal dimension over the part surface. The plot of the fractal dimensions can be used to detect any changes in the stochastic structure not detected by the KL eigenvectors and coefficient vectors. An example of a stochastic change is the sudden breakage of the teeth of a grinding wheel during a finishing process, or wear in the teeth of a grinding wheel, causing minute nonstationary changes in the resulting part's surface profile. Such sudden changes can be detrimental to the quality of the final product.

Step Five: Analysis Verification and A-Priori Prediction

The fifth step in the methodology provides manufacturers and designers with a tool to verify the analysis results and a potential to make further predictions on the quality of the manufacturing signals based on design changes. To verify the accuracy of the resulting eigenvectors and coefficient vectors, it is important to reconstruct an estimate of the original input profiles and compare them to the original profiles. Figure 9 shows a comparison of the profile estimates using the five fundamental eigenvectors and the original profiles (two profile examples are shown). Notice that the stochastic component is filtered out of the fundamental eigenvectors. As a result, the reconstructed estimates have a much less noisy shape. The general shape of the profiles is captured accurately using the first five eigenvectors. As a result, the KL decomposition is deemed satisfactory. This comparison will provide manufacturers and designers with a means of deciding on the accuracy of the KL analysis results.

The reconstruction of estimates of surface profile measurements can be used to help designers in another way as well. Specifically, the reconstruction profiles can be used as a means to predict what a surface profile will look like, given specified modes to the system. This scenario can happen in the case of a change in one of the machine components by the designer, for example. The designer will have a model of the mode this change will generate. This additional mode can be modeled as a potential eigenvector, and superimposed on the reconstruction estimates to study the effect on the surface profiles. Such a tool can become a valuable aid in making *a-priori* design decisions about the manufacturing machine.

CONCLUSIONS FOR MANUFACTURING AND DESIGN

The systematic steps described above are necessary to provide a thorough analysis of the manufacturing signals and understand their nature. The analysis and interpretation of the data based on the Karhunen-Loève (KL) transform provides crucial insights about the manufacturing condition and is a very useful tool in assuring the production of high-quality parts. In this paper, we use extensions to the KL-based method and present them in the form of a set of guidelines. Using these guidelines, we present a fault detection and monitoring methodology based on an accurate representation of manufacturing data using fundamental KL eigenvectors and coefficient vectors. We then apply the steps of our methodology to an example in milling.

By providing an accurate and mathematical means of interpreting and communicating the manufacturing data, the fault detection and monitoring method opens the door for an effective integration of the manufacturing and design fields. However, in order to completely bridge the fields of manufacturing and design, it is necessary to provide a means of accurately diagnose the origin of the faults. The diagnosis step is not addressed in this work and is being investigated by the authors. A schematic of a possible design and manufacturing methodology bridging the gap between the two fields is illustrated in Figure 10. In this scenario, vibration from the manufacturing machine and surface profiles from manufactured parts are measured in parallel and compared to each other following a KL analysis of the surface measurements. The comparison and classification of the decomposed KL modes and measurements from the manufacturing machine will lead to the diagnosis of fault origins which result in the degradation of part surface quality. Such results will then help designers and manufacturers in making informed changes to improve the quality of the parts, such as redesign of faulty machine components, modification of product specifications, and readjustment of process parameters.

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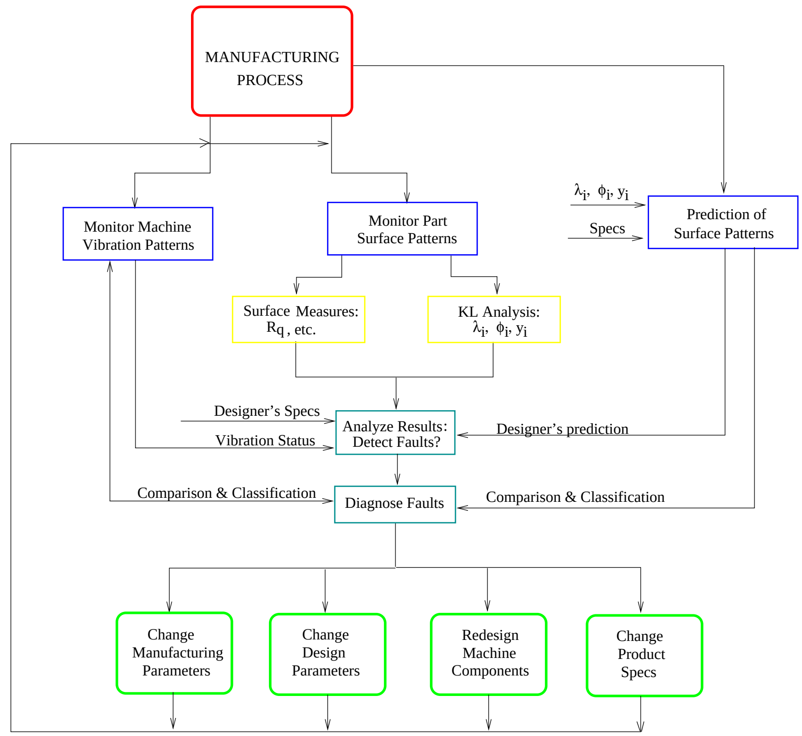

Figure 10. Fingerprinting for Manufacturing and Design.

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