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QUALITY AND INSPECTION OF MACHINING OPERATIONS: REVIEW OF CONDITION MONITORING AND CMM INSPECTION TECHNIQUES 2000 TO PRESENT

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ABSTRACT

In order to consistently produce quality parts, many aspects of the manufacturing process must be carefully monitored, controlled, and measured. The methods and techniques by which to accomplish these tasks has been the focus of numerous studies in recent years. With the rapid advances in computing technology, the complexity and overhead that can be feasibly incorporated in any developed technique has dramatically improved. Thus, techniques that would have been impractical for implementation just a few years ago can now be realistically applied.

This rapid growth has resulted in a wealth of new capabilities for improving part and process quality and reliability. In this paper, overviews of recent advances that apply to machining are presented. Moreover, due to the relative significance of two particular machining aspects, this review focuses specifically on research publications pertaining to using tool condition monitoring and coordinate measurement machines to improve the machining process.

Tool condition has a direct effect on part quality and is discussed first. The application of tool condition monitoring as it applies to turning, drilling, milling, and grinding is presented. The subsequent section provides recommendations for future research opportunities. The ensuing section focuses on the use of coordinate measuring machines in conjunction with machining and is subdivided with respect to integration with machining tools, inspection planning and efficiency, advanced controller feedback, machine error compensation, and on-line tool calibration, in that specific order and concludes with recommendations regarding where future needs remain.

TOOL CONDITION MONITORING

An effective method and implementation of tool condition monitoring for cutting processes could yield significant cost savings for manufacturers. Sensor-based approaches for tool condition monitoring provide a means to assess the underlying tool condition during the cutting process itself; thus, achieving better process control, improved tool usage, less wear intensive usage of the machine tool and, consequently, more cost-efficient machining. The main issues to be addressed regarding utilizing sensory information for tool condition monitoring is the low signal-to-noise ratio that necessitates integration of sensing into the tool or tool holder, and the use of advanced signal processing, feature extraction and multi-sensor pattern recognition methods to extract the relevant information [1].

Sensor-based tool condition monitoring represents a significant area of Condition-Based Monitoring (CBM), where physical phenomena related to system degradation and faults are inferred based on a set of features and indicators extracted from sensor readings. Thorough reviews of research in CBM of mechanical systems are given in [2, 3, 4]. These papers survey several hundred publications addressing achievements related to data acquisition, data processing and maintenance decision-making. A more focused survey can be found in [5], reviewing the area of applications of wavelet-based analysis of non-stationary signals for fault feature extraction, singularity detection, noise reduction and extraction of weak signals, signal compression, system identification and other applications. Even though no machining process monitoring application is reported in [5], potential application of non-stationary signal analysis and advanced pattern recognition methods in cutting tool condition monitoring are tremendous since machining signals are highly non-stationary and are influenced by a number of factors [6].

The state of various aspects of metal cutting technology is reviewed in [7], including a view of the recent achievements in cutting process monitoring in terms of basic research and industrial implementation. The authors identify a gap with respect to monitoring complex cutting processes, such as sculptured surface milling. Since the publication of [7], the aforementioned situation has not changed and the main obstacle is the need for the development of elaborate sensor fusion methods addressing the continuously varying cutting conditions that are typical of such processes.

In addition, a significant gap is apparent between achievements in the academic circles and state-of-the-art in the use of tool condition monitoring. This situation was noted in [8] and the reasons have been attributed to the fact that even though many sensors are available, they can be expensive, interfere with machine use, and adversely affect machine stiffness. In addition, the need for highly flexible tool controllers is essential for proper development and implementation of cutting process monitoring. In a recent publication [9], the authors describe the concept of a smart machine tool system that seamlessly integrates current process information (*e.g.*, tool position, velocity, spindle speed, etc) with inexpensive and non-invasive sensors, and models of the machining process, with applicability to automatic feed rate selection and tool condition monitoring. Nevertheless, such elaborate machine tool control architectures are virtually non-existent in the industry today.

In the remainder of this section, presents the most recent advances in the area of sensor and integrated-sensor based tool condition monitoring for traditional cutting processes *(i.e.*, turning, milling, drilling and grinding).

Turning

Turning is a less complex process than other processes with defined cutting edges (drilling and milling) because only one cutting edge is engaged with the material, and the depth of cut is usually constant (at least in the case of machining of cylindrical features). This makes turning an ideal process for sensor based tool condition monitoring. A comprehensive review of 138 publications addressing the use of Artificial Neural Networks (ANNs) for on-line and indirect tool condition monitoring in turning is given in [10]. These papers focus on the use of ANNs for continuous wear monitoring, as well as detection. The techniques can also differentiate tool breakage and collision from tool wear. They also present a thorough synthesis of a decade of generic research regarding the adequate sensing, signal processing, and extraction of features from sensor signals. It can be concluded from these publications that various sensors can be used for tool condition monitoring in turning, including cutting forces, vibrations of the tool or tool holder, power or energy of electrical current from the spindle motor, cutting temperature, and on-line measurements of surface roughness. At the process model and decision-making levels, the ANN paradigm becomes the focus of these papers. Other recent surveys of the use of other methods for process model creation and decision-making, such as expert systems, fuzzy logic or statistical pattern recognition can be found in [11].

More recent advances have been made in two main research thrusts. The first thrust relates to the improvement in the signal to noise ratio using new sensing hardware employed closer to the tool. The second thrust relates to the elaborate use of advanced signal processing and pattern recognition methods that employ non-stationary signal analysis and multi-sensor fusion to address the inherent poor signal to noise ratio that is a characteristic of remote sensing locations for tool condition monitoring.

In [12], one can see excellent examples of research on new systems to improve the signal to noise ratio for tool condition monitoring. The authors describe a cutting process diagnostic method using a newly designed “smart cutting tool.” Based on the tool tip position sensing and piezoelectric actuation signals integrated into a newly developed boring tool, the well-known disturbance observation method [13] (from traditional control theory) is used to provide an on-line estimate of the cutting forces. This tool design gives greatly increased flexibility during the boring process, without decreasing its accuracy, since increased compliance in the cutting tool is compensated through the piezoelectric tool tip actuator and the tool tip deflection measurement sensor. These signals are used to indirectly observe the cutting force, bypassing the need for direct force measurements, which are both costly and may incur changes in cutting tool dynamics due to the presence of a force/torque sensor. The estimated force patterns were used to successfully detect tool breakage and misalignment of the workpiece. The estimated forces might also be used for tool wear monitoring, even though this application is not considered in [12].

Examples of the use of advanced signal processing and pattern recognition methods with more traditional sensing techniques are more numerous. Some researchers divided tool states into discrete categories: either two-state (sharp/fresh and worn) [14, 15, 16] or multi-state (sharp, usable, and worn) [17]. Some researchers attempted to monitor progressive wear of cutting tools [1, 18, 19]. The capability to classify tool wear into multi-state or to monitor progressive tool wear provides more information than the two-state approaches.

In order to monitor tool wear, a source signal needs to be identified and its change over time as a cutting tool wears needs to be well understood. An ideal source signal should be sensitive to tool wear and insensitive to environment noises. Vibration in the feed direction was the source signal for [14], [19] and [16]. As a result, the signal was direction-dependent. While Wang et al. [14] sought to understand the vibration signals without special external excitation (passive approach); Gong et al. [19] applied impact diagnostic excitation to the cutting tool by a hammer (active approach). Acoustic emission was the major source signal in [15] and [17]. Cutting force was the source signal of [19] and part of the source signal of [17].

A critical element of cutting tool condition monitoring is extracting useful information from the source signal and filtering out the noise. Based on the extracted information, the monitoring system should be able to correctly classify the tool's state for the approaches dividing tool states into discrete categories or accurately predict the tool wear for the approaches monitoring progressive wear of cutting tools. Wang et al. [14] extracted dynamic characteristics of tool wear from Daubechy's wavelet coefficients and normalized the extracted features by analyzing vibration signals. Signal energies at various scales were used as a feature set for a Hidden Markov Model (HMM) that evaluated the likelihood that the observed signals came from either a worn or a sharp tool. The tool was assigned to the worn or sharp tool class based on which situation had a higher likelihood, according to the HMM. It is reported that HMMs make efficient use of the training data as compared with "traditional classifiers" and thus can perform well with limited amount of training data. A similar method was also used in [16], where flank wear in turning was assessed using sound signals.

Sun et al. [17] extract the feature vectors that are sensitive to the tool conditions via signal processing techniques and choose a suitable feature vector set with feature selection technique as the input to the neural networks based classifier. They use a revised support vector machine (SVM) approach together with one-versus-one method to classify a tool into three states. They differentiate the impact of two types of errors that a tool condition monitoring algorithm can make: false alarms and missed failures. This differentiation appears to have practical value; however, it is not seen in other papers. Training of neural networks is a critical and challenging task. Sun et al. [15] propose a method to effectively select training data for a tool condition monitoring system. Their method divides the generalization error surface into three regions and introduces sampling factors to prune redundant samples. They claim that the pruning process does not compromise the generalization accuracy. Gong et al. [18] present an active method of monitoring tool wear states by impact diagnostic excitation. There is no feature extraction or training involved. With a vibration model, they calculate the damping ratios of the tool after impact excitation and claim that there is a unique relationship between the damping ratio in the feed direction and the development of flank wear. They fit this relationship with curves and are able to predict the flank wear as it progresses by giving the tool an impact. The impact may cause the flank worn land to interfere with the finished surface of the workpiece in the feed direction. The resulting effect on surface finish may be a detrimental aspect of this approach, depending on the magnitude of this interference. If there is a major change in tool wear between the diagnostic impact excitations, significant damage may be generated before the system discovers that the cutting tool is worn and needs be replaced. Oraby et al. [19] use time series autoregressive moving average (ARMA) procedures to model and analyze the stochastic component of the cutting force signals. For each wear level, the corresponding model is reduced to the equivalent "Green's Function" (GF). They claim that they can model various level of progressive tool wear; however, models with higher order of autoregressive parameters are found for higher wear levels.

Scheffer and Heyns [1] offer an example where developments in hardware are combined with advanced signal processing and pattern recognition to yield a tool condition monitoring system for facing and boring that is implemented in an industrial environment. The authors use a strain gage rosette on the tool-holder to accurately measure machining forces with high bandwidth. A Fast Fourier Transform (FFT) based method was used to extract signal energies in various frequency domains. Additionally, a set of time-domain features and wavelet-based features was considered in conjunction with the frequency-domain features, as suggested in their earlier publications [20]. Features indicative of wear were selected based on the degree of correlation and statistical overlap factor of each feature with wear. An elaborate ANN architecture is utilized to obtain estimates of tool wear based on the strain readings and process parameters, yielding a remarkable match between the estimated and directly measured flank wear on the tool. Discussion on requirements and obstacles for migrating this application from one tool to another, such as retraining of the network and re-usability of the network architecture, would be very valuable, but is not offered in [1].

Drilling

Monitoring tool wear in a drilling process is the subject of study in the review work [21]. In [22, 23, 24], the tool's state is either classified into one of the three states (sharp, workable, or dull [22, 23]), or one of the two states (usable or worn [24] or usable or broken [25]). Source signals are drilling forces and power [22, 23], spindle current [24], and spindle input impedance [25], the last two of which are approaches that utilize sensors built into the existing machine tool.

HMM is utilized in both [22] and [23]. Two approaches using HMM are investigated: the bargraph method and the multiple modeling method. In the bargraph method, time series data due to drilling are used to develop HMMs and measured data signals are processed continuously using the corresponding HMM. Each model generates a probability quantifying the similarity between the current measurement signal and the signal obtained from a sharp drill. If the normalized probability falls below a threshold, the drill is considered dull. In the multiple modeling method, different HMMs corresponding to sharp, workable, and dull drill states were developed. These HMMs are used to classify drill wear status. The authors do not draw conclusions regarding which method is superior. They claim that thrust signals are better indicators of tool status compared with torque signals. The main difference between [22] and [23] is that three more methods: phase plane method by plotting data signals on the Cartesian plane with a reference rectangle, transient time method by calculating tool entry time, and model-based torque prediction by relating estimated force coefficients to drill wear are developed in [22]. All three methods use a threshold based approach. Results from all models are fused together by the global decision fusion center to monitor the drill conditions based on a preset threshold. The objective of the fusion is to achieve improved consistency. They recognize the need to fine tune the decision fusion center algorithm to improve reliability and robustness.

Franco-Gasca et al. [24] uses the current signal from the servomotor spindle driver that is filtered by a low-pass filter. A subsequent Discrete Wavelet Transform is used to enhance the cutting force signal by its filter bank property. Two continuous pulses are processed and an autocorrelation asymmetry algorithm is used to classify drill state. A threshold was needed and its determination is application dependent. In [25], input impedance of the spindle motor evaluated using the current and voltage readings are utilized to detect drill breakage in micro-drilling. Input current of the driving motor is routinely used for breakage detection and wear monitoring in manufacturing processes. Nevertheless, impedance is independent of voltage or current fluctuations, making impedance methods advantageous to the more traditional voltage or current based methods. An ANN is used to recognize waveform patterns and accurately promptly find tool breakage.

Milling

With changing tool engagement conditions in normal cutting, a milling process presents unique challenges to tool condition monitoring due to its inherent characteristics. The ability to recognize an impending tool failure in milling is of great value for a tool condition monitoring system and this capability is the predominant subject of study for monitoring cutting tool conditions of a milling process among the papers [9, 26-33]. In addition, tool wear is also studied [34], where a tool state is classified into either new or worn.

In order to monitor tool failure/wear, a source signal needs to be identified and its change over time as a cutting tool fails/wears during milling needs to be well understood. An ideal source signal should be sensitive to tool conditions and insensitive to disturbances and noise. Cutting force is a frequently used source signal for milling tool condition monitoring [26, 28, 32]. In addition, signals relating to cutting force are also used [27, 31, 34, 35]. Other information such as acceleration [29, 30], and power [9, 33] have also been employed.

A critical element of cutting tool condition monitoring is the extraction of useful information from the source signal while reducing the impact of noise and disturbances. Based on the extracted information, the monitoring system should be able to detect an impending tool failure or correctly classify tool state. Zhu et al. [26] divide their methodology into two steps. Step 1 is fault detection for flute chipping/breakage and cutter runout and step 2 is fault diagnosis. The monitoring index is based on the spectrum analysis of the cutting forces. In order to address the challenges resulting from continuously changing tool engagement conditions in free-form surface milling, the cutting engagement condition is determined in order to obtain the correct threshold value determined off-line. Fault detection is done by comparing the measured monitoring index against the threshold value. Once a fault is detected, the fault diagnosis step is executed in order to estimate fault magnitude. A vector of wavelet coefficients is extracted from both the measured and simulated force signals. The fault magnitude is estimated by finding the values of fault variables in the process model minimizing the deviation between the simulated feature vector and measured feature vector. A micro-genetic algorithm is used in search of the minimum deviation.

Jesus et al. [27] extract cutting force signals from driver current waveform using an analogue filter. Wavelet transformation is used to compress the data from which an autocorrelation model extracts the cutting force asymmetry to estimate tool breakage. Li [78] employs an indirect method of tool breakage detection via monitoring the motor current. Dransfeld et al. [79] accomplish tool wear and failure using tool or part vibrations. Peng [28] investigates the effectiveness of a time-frequency analysis technique, empirical mode decomposition (EMD) method dealing with the nonlinearity, nonstationarity, and uncertainties in cutting force signals. EMD decomposes cutting force signal into intrinsic mode function (IMF). Peng claims that the variation of energies of characteristic IMFs can be used to detect tool breakage. The time-instantaneous frequency distribution (Hilbert Spectrum) can also detect tool breakage. The main objective of Roth [29] is to identify an effective cutting tool monitoring methodology independent of the direction of cutting and the orientation of the sensor, which is important for monitoring a milling process. With theoretical derivations and experiment results under varied conditions, Roth shows that the eigenvalues of the spectral matrix at the tooth-pass frequency appear to be independent of both sensor orientation and cutting direction. Multiple techniques for achieving directional independence during milling operations, including Fourier, discrete cosine, autoregressive, and correlations techniques, are also examined by Suprock and Roth in [30]. Amer et al. [31] uses a sweeping filter technique for frequency analysis of the acquired monitoring signals. The change of peak-to-peak amplitudes of the frequency components and in the overall frequency spectrum of the signal could indicate a tooth breakage. In addition, they develop tooth rotation energy estimation (TREE) that can also detect tool breakage. Two methods work together to minimize false alarms.

Ritou et al. [32] focus on developing the solution for small-batch or one-off parts. Their approach is through the estimation of cutter eccentricity and chose to characterize tool state using force peaks. In an attempt to develop an indicator independent of cutting conditions, they link the tool eccentricity with the peak force. In order for their approach to work, they must pause the monitoring system during significant changes in cutting conditions, making the approach somewhat awkward to implement. Shao et al. [34] develop cutting power models with tool wear as one of the input variables. They filter the power signal by low pass filter and compare the moving average of the filtered signal against a cutting-condition-dependent threshold to classify tool state. A method of monitoring for tool breakage is also presented by Alaniz-Lumbreras et al. [35]. In this work, servoamplifier currents are analyzed using the wavelet transform and a neural network in order to determine the tool's state. This work focuses on developing an on-line technique of processing that allows the classification of the tool's condition, (good or bad) on a two insert face mill.

A realization of the smart machine tool system concept from [9] is described in [33] for the case of a complex milling process with variable cutting geometry and a large number of short moves during which cutting takes place. A signal from a low-cost power sensor is used in conjunction with a simple analytical model of power dependency on the average material removal rate and the velocity of change of the contact area between the tool and the workpiece. It was observed that the power ratio increases with the tool wear, but that the increase of power with tool wear is not consistent across various cutting conditions. It was judged that on-line tracking of cutting power model parameters is more effective in terms of tracking both the edge chipping/breakage, as well as flank wear. Similarly, Choi and Chung [36] utilize machine vision to determine when the tool needs to be changed when micro-drilling.

Robustness is a major challenge for a cutting tool condition monitoring system. Zhu et al. [26] provides a sensitivity analysis of their fault diagnosis method in terms of cutting conditions (feed rate and tilt angle), cutting coefficients, and stock size. They claim that normalizing feature vectors alleviated the effects of possible process variations. Ritou et al.'s work [32] highlights this challenge: they evaluate three process-based criteria retrieved from literature and draw the conclusion that the criteria are unreliable. Al-Habaibeh et al [81] Develop a self-learning methodology for system state classification (both normal and fault states) and the selection of the most appropriate sensors and signal processing methods for detecting machining faults in end milling. The proposed approach permits the incorporation of previous system faults or incidents into the design of new on-line monitoring systems, reducing development time and cost.

A unique approach was adopted in [37], who used a neural network based sensor fusion to estimate tool wear during CNC milling, based on readings of cutting forces, spindle vibrations, spindle current and sound pressure levels. The method has been validated in both laboratory and industrial conditions. Even though the work reported in [37] represents a significant simplification of usual milling conditions and can deal solely with single insert cutting tools (which greatly simplifies the challenge of discontinuity of cutting conditions and the problems imposed by the engagement of multiple cutting edges with the workpiece), one can conclude that sensor fusion based paradigm drawing information from multiple sources seems to have significant promise in finally moving the milling (and general machining process monitoring) closer to reliable and cost-effective usage in actual production conditions [7]. Matsumra and Useui [80] developed a self adaptive tool wear monitoring system using a laser scanning micrometer to measure the tool while the mill is not engaged in the work piece. It predicts the wear process with monitoring, and determines monitoring intervals sequentially with estimating the prediction performance and time loss for monitoring.

Grinding

Grinding is by far the most important abrasive process which plays a prominent role in generating the final surface quality of machined parts. Monitoring grinding processes is particularly challenging because of the large and unknown number of cutting edges, as well as variable and stochastic cutting geometry. Both the number of cutting edges and cutting edge geometries vary spatially across the grinding wheel, as well as temporally during the grinding process. It is therefore not a surprise that grinding process monitoring has been a research topic for several decades now, as documented in comprehensive review papers [38] and [39].

In the recent years, research seems to have progressed in several directions. Advances in physics based modeling of the cutting process enable the use of relatively cheaper (but slower) force and power sensors, in spite of the poor signal to noise ratio. Such a concept was reported in [40], where detailed model-based simulations of form grinding processes developed in [41, 42] are used to establish bounds on the spindle power signals that are characteristic of normal processes.

Another new trend in grinding process monitoring is increased and improved use of Acoustic Emission (AE) sensors. AE includes a class of phenomena, in which elastic waves are generated by rapid release of energy from local sources in the material [39]. AE waves propagate through structural elements of the machine and workpiece, thus reliably carrying information in the Megahertz frequency domain and giving high dynamic potentials for grinding process monitoring [43]. Hence, for high precision machining process monitoring aimed at uncovering conditions that affect the surface roughness and subsurface damage phenomena on the workpiece, which is crucial for grinding processes, AE shows the highest signal to noise ratio to the most critical process conditions [44]. The information-rich high dynamic content of AE signals was in the same time an impediment for more widespread use of AE for grinding (or any machining process monitoring) because the amount of data generated by an AE sensor during a grinding process imposes even today an enormous computational load on the monitoring system. Hence, almost all the grinding process monitoring work reported so far utilizes root-mean-squared (RMS) values of AE averaged within some moving window, which significantly reduces the amount of data that needs processing (at the expense of reducing the dynamic content in the data). AE has been successfully used in detection of spark and contact in grinding and wheel dimensional characterization [44]. Liao et al. [45, 46] investigated AE-based grinding wheel condition monitoring, using discrete wavelet decomposition procedure to extract discriminate features from raw AE signals and an adaptive genetic clustering algorithm to classify the wheel state into either sharp or dull. Lee et al [82] discuss the use of acoustic emission (AE) as a monitoring technique at the precision scale for a variety of precision manufacturing processes including grinding, chemical–mechanical planarization (CMP) and ultraprecision diamond turning.

An interesting work is reported in [47], where RMS averaged AE readings were coupled with spindle power readings (obtained from spindle motor currents), thus achieving a grinding monitoring method based on sensor fusion. The quantity of Fast Abrasive Process is introduced, combining AE and spindle power readings, with spindle power compensating for sensitivity of AE signals to external factors, such as sensor assembly, position, workpiece geometry etc), while higher dynamic content of AE readings augmented the slow response characteristics of the power signals.

Finally, just like in the case of other machining processes, possibilities of improving signal to noise ratio for grinding process monitoring through embedding of sensors near the location where actual cutting takes place (i.e. into the grinding wheel) are also explored. In [48], a piezoelectric sensor was integrated into the grinding wheel, enabling sensing of forces in grinding as well as in dressing processes. Such relatively direct measurement of the cutting forces performed as closely as possible to the cutting area, facilitates grinding and dressing process monitoring more robust to workpiece (material, shape etc.) or machining conditions (cooling lubricant supply, machine set-up parameters etc.). In [49], the concept from [48] was augmented through integration of a thin film thermocouple along with miniature force sensors into segmented grinding wheels. The concept was implemented in an external cylindrical grinding operation of bearing rings in the finishing line of a bearing manufacturer, thus demonstrating reliability and robustness of the new concept.

Future Tool Condition Monitoring Needs

While all of the tool condition monitoring papers strive to prove that there exist unique relationships between features extracted from the source signals and the tool states, the robustness aspect of the cutting tool condition monitoring with their proposed approach still needs to be further addressed in most cases. This relates to noise and disturbance rejection as is mentioned in each of the previous sections. Understanding the robustness of a source signal and monitoring approach is critical for industrial applications because the source signal can be contaminated in various ways on a shop floor and certain level of process variations is expected. In many industrial applications, numerous tooling types/geometries are used, along with variable depths of cut and feed/radial engagements. There is still a need for techniques to be developed that are proven to be broadly applicable across tooling types. Furthermore, schemes must be developed that are capable of tracking tool health irrespective of depth of cut or engagement. Without these capabilities, the applicability of the monitoring scheme is highly restricted, since 3D/sculpted surfaces will normally require both of these variables to constantly change.

COORDINATE MEASUREMENT ASSESSMENTS FOR THE QUALITY CONTROL OF MACHING SYSTEMS

The Coordinate Measuring Machine (CMM) has been in use for decades as a versatile, high-precision off-line measurement device. The CMM has the capability for multiple types of measures using a single sensor head, and a multitude of measures can be made on a single program without manual intervention, making the CMM highly efficient and allowing evaluation of a greater percentage, or even 100% of manufactured parts.

The CMM’s versatility and efficiency have led to its more recent use as an on-line measurement device, particularly as an advanced feedback sensor for machining processes and their tooling. A number of advances have recently been made in this area, and it is the authors’ intent to present a brief review of some notable accomplishments.

Coordinate Measuring Machines

The Coordinate Measuring Machine (CMM) is used to digitize a measured part for purposes of inspection or model creation as in the reverse engineering process. A CMM has the capability of measurement in three dimensions, but is also widely used for two-dimensional (planar) or one-dimensional (linear) evaluations. The classical configuration of the machine is Cartesian movable bridge design, but some CMMs have been developed that utilize a cylindrical coordinate system for polar-specific artifact evaluation [50]. Additionally, recent developments have been made in design of a multi-jointed passive measurement device requiring manual probe placement, but allowing greater freedom of motion and part accessibility [51].

CMM operation has seen a recent evolution in manufacturing from a quality-based activity (driven by the organizational metrology function) to a manufacturing-based activity (driven by the operations function). This movement is beneficial in that the lag from production to evaluation is reduced and overhead related to logistics and thermal stabilization is eliminated. This capability is enabled by recent advancements in automatic calibration and error compensation, allowing operation in harsh or and more temperature-variant environments.

The next logical step is to integrate the CMM directly to the machine tool. Obvious advantages in addition to a further reduction in processing-measurement lag are: a known fixture state (part does not need to be identified in space if the measurement device-fixture relationship is known) and opportunity for immediate feedback to the machine controller.

However, some issues emerge with the integration of inspection or measurement with value-added processing that should be addressed before such integration can become widespread. The first such issue is the obvious loss of machine availability during inspection, leading to a tradeoff between accuracy and inspection efficiency. If the part remains fixtured, is there opportunity to perform aligned machining activities during inspection, or is this perceived disadvantage outweighed by the previously stated benefits? The second issue is related to the reference plane for on-machine inspection. If the measurement platform is integral to the machine, how is the machine geometric error removed or compensated from the measurement signal? Aside from issues similar to those encountered when the CMM left the controlled metrology lab atmosphere (*e.g.*, temperature compensation), these are the major hurdles to overcome for successful integration of machining and inspection.

CMM Integration with Machine Tool

The CMM can evaluate surfaces in 1, 2 or 3 dimensions in different coordinate systems depending on application and quality requirements. CMMs can generate single point data or scanned point clouds with fitting routines for characterizing part surfaces, and can measure any surface that can be reached by the probe [52].

The off-line CMM as a quality evaluation tool has been a manufacturing mainstay for decades. Originally designed as a modified machine tool, the CMM has been able to improve measurement accuracy and automation to a great degree [53].

However, the time lag between manufacture and off-line evaluation of a part leaves no room for direct process control. In fact, a number of defective parts can potentially be made during the wait for inspection. In-line inspection using a CMM directly integrated with the machine tool allows for immediate inspection, but such designs must be evaluated on the basis of measurement time, quality objectives, design configuration and integration with fixturing [54]. Such integration coupled with currently achievable measurement time and accuracy capability enables 100% inspection and direct feedback to machine control or statistical process control (SPC) process evaluation [55, 56].

Kuang-Cho integrated a laser measurement probe directly with a CNC machine to characterize free-form surfaces after machining [57]. Algorithms are developed for edge detection and determination of shape error for on-machine mold manufacturing.

Hua develops a spindle-referenced measurement device incorporated into a machining center for measuring 3D freeform contours with automatic following. The device is innovative in that it uses a combination of laser detector and linear encoder feedback to rapidly characterize surfaces and identify errors [58]. An additional integration development is a micromachining center adapted to be a measurement device by force feedback to the positioning servomotors [59]. The device is constructed from off-the-shelf parts and the achievable resolution is down to 5 nm.

Machine reconfigurability becomes an important aspect of this process-inspection integration. The machining center must act as a material removal device in one instant, utilizing high force and controlled feed, to acting as a measurement device the next instant, utilizing rapid traverse speeds and positioning accuracy. To address this new reconfigurability need, Wei proposes a new programming framework to replace the traditional M- & G-code programming of CNCs. The software utilizes dynamic link libraries (DLLs) for rapid reconfiguration, and is demonstrated on a 3-axis milling machine [60].

Inspection Planning and Efficiency

An immediate benefit of locating the CMM directly in the machining operation is elimination of part transfer time and tracking logistics, and a subsequent ability to inspect a greater percentage of parts. However, some new issues arise in this situation, primarily calibration of the measurement instrument, thermal influences on the measurement, and the inherent tradeoff between accuracy and measurement efficiency.

A primary disadvantage of machining and inspection integration is the logistic issues it introduces to material flow through the machining process, most notably the loss of machine uptime during inspection. The inspection planning process is critical to successful integration of the CMM and the machine tool. Of most importance is the tradeoff analysis of measurement time vs. accuracy (*i.e.*, inspection efficiency). Vafaeesefat gives a comprehensive inspection planning process for the CMM that produces an efficient inspection result for both simple and complex parts [61]. To improve computational efficiency, Mu-Chen presents approaches based in genetic algorithms (GAs) for ideal surface fitting to the point cloud, and successfully demonstrates it for sphericity evaluation [62]. Jiang presents a method for determining the ideal number of measurement points to evaluate part features for rapidly closing the computer-aided inspection (CAI) control loop [63]. The proposed methodology is automated for on-line applications.

Zhengyi introduces a virtual coordinate measuring machine (VCMM) that utilizes haptic feedback from solid part models [64]. This device is used to provide heuristic input and immediate validation and collision prediction for measurement path planning.

Inspection efficiency is also addressed as it relates to overall shop floor flow planning. Specific issues with integration of a CMM to a flexible machining cell are job sequencing and inspection planning, shown by simulation to have a major effect on overall cell performance [65]. Alternative flow strategies are presented as a result. Additional advancements in inspection planning for direct integration that have been addressed by the automotive manufacturing industry are in throughput and software control [66].

Advanced Controller Feedback

The CMM can be used not only as a device for tracking of part quality, but on a more fundamental level as feedback directly to the process for improved process control. One benefit of direct three-dimensional coordinate feedback is ability to provide control actuation not to individual axis actuators, but directly to the cutting tool position itself.

The movement of the CMM directly to the manufacturing floor has enabled its use for multi-dimensional statistical process control (SPC). SPC software specific to the CMM is surveyed by [67]. This technique is able to provide real-time multivariable monitoring and detection of process trends; application to limited process control is also addressed. Add to these facts that SPC now transitions from a manual measurement and input or fixed-gauge single-variable automated activity to a fully-automated and flexible software-driven evaluation tool for process characterization.

The next logical step is to integrate the feeding of part measurement information to the machine for direct process control. This capability is enabled as the CMM and machine tool are integral and time lag between processing and evaluation is minimized. Yongjin investigates closed-loop error as relates to integrated inspection [68]. He shows a potential for improved efficiency and quality using this technique. However, a factor that needs to be addressed is the relative error between the machine base and the global base.

Machine Error Compensation

Another inherent shortcoming of on-line inspection, besides potentially reduced process efficiency, is reference error of the measurement. The fact that machined parts are used as an input to the calibration procedure introduces an inherent error. This leads to a need to understand the error deviations in the machine as a result of departure from the ideal kinematic model, and the error behavior with absolute or processing time.

Tan addresses geometric error modeling and compensation using a neural network approach [69]. A machine error map is created using interferometric measurements, and the model applied to compensation through a learning algorithm. This error map is also readily applicable to the integrated inspection process [70].

Error components based on the machine rigid body kinematic model are approximated using polynomial functions by [71]. The application is in improving the absolute error of in-machine touch probe measurement, which was reduced to 5 μm for a hemispherical test part. Huang improves machine accuracy for a general 3D shape by 60% using similar techniques (8-point interpolation method) [72].

On-Line Tooling Calibration

A number of theoretical calibration tools and techniques have resulted from application of the CMM directly to the machining process. Moving the measurement process from the controlled metrology lab environment to the shop floor or even more environmentally harsh machining process introduces numerous environmental error sources. Contamination, temperature fluctuations and potential for physical contact drive a need for increased and therefore more efficient calibration methods. The telescoping ball bar used for cylindrical machine tool error mapping is adapted to the inspection process by [73, 63]. This “quick check” technique replaces artifact evaluation and allows for more frequent inspection.

On-line evaluation of CMM performance degradation due to harsh environmental factors is treated by [75]. This work proposes a rapid on-line diagnostic procedure integrated to the normal measurement cycle that identifies measurement error and monitors machine performance.

Sensing Technology

The traditional CMM is fitted with a contacting touch probe that senses deflection magnitude and direction. Integrating such a sensor into a high-speed machining system introduces issues such as probe wear and dynamic limitations. A number of approaches have recently been proposed to improve CMM sensing for efficiency and accuracy, enabling their use in production machining equipment.

Advances in data processing and signal analysis capability have enabled the use of new sensing technologies for measurement. Non-contact laser sensors and analog scanning probes require high positioning performance, now achievable in modern systems. Orban retrofits a standalone CMM with improved motion control hardware, enabling the use of alternative sensors [76]. Such technology could be readily incorporated into the integrated manufacturing-inspection system, improving measurement performance. Kuang-Cho demonstrates this novel sensor incorporation using an on-machine laser measurement probe [57].

Sitnik introduces a hybrid optomechanical measurement machine (OMMM), taking advantage of the accuracy afforded a contact probe with the efficiency of an optical system [77]. The OMMM is developed for manufacture of large parts for the automotive industry, and provides for automatic process control.

Future CMM Development Needs

There are current efforts underway to integrate CMM inspection directly with machining processes. The immediate benefits are reduced lag time between processing and inspection, and application of on-machine inspection to multidimensional SPC and direct process feedback control, which are limited in availability when using traditional off-line CMM inspection.

A number of issues arise when integrating the CMM directly with the machine tool. Of particular importance are efficiency and throughput of the machining process after integration, and issues related to measurement error and calibration due to the inspection reference to the machine itself (machine errors also become integrated to the inspection). Additionally, environmental errors in the machine pose challenges for this development. These challenges are being addressed through simulation, error compensation, rapid calibration techniques and incorporation of new sensing technologies.

CONCLUSIONS

This paper presents a review of recent tool condition monitoring algorithms and the use of coordinate measuring machines in conjunction with machining. With the advent of more powerful processing capabilities, these technologies are becoming not only more efficient and accurate, but more accessible to the machine tool user as well.

Condition monitoring algorithms are reviewed for drilling, milling and grinding. The major points highlighted are:

- Effective tool condition monitoring can translate directly to manufacturing cost savings
- A primary barrier to implementation is low signal-to-noise ratio for sensing. This has been addressed through both location of sensing near the tool tip, and through advanced signal processing techniques
- Sensors only provide data. Models must be developed and implemented to translate to the physical phenomena related to system degradation
- Results of Condition-Based Monitoring (CBM) can be used for maintenance decision-making. Collaboration with Decision Science can improve this area
- The ideal source signal should be sensitive to tool wear and insensitive to environment noises. Machine vibration, cutting forces, active excitation and acoustic emission signals have been explored.
- One obstacle in recently more prevalent sculpturing processes is the need for development of elaborate Cartesian sensor fusion methods that could be used to deal with the continuously varying cutting conditions that are encountered in such processes
- Another gap in advancement of these technologies is simple implementation. Though academic advancements have been made with respect to sensor implementation and wear models, these systems are still not widely seen in industry. Primary reasons noted are cost, complexity and effect on machine performance and stiffness.

The use of coordinate measuring machines in machining processes is reviewed; particularly the issue of integration of this technology as applied directly to the machine tool itself. The major points and recommendations are:

- Coordinate measuring systems are accurate, highly flexible and widely used as off-line post process evaluation tools. Recently, integration of such systems directly to the machine tool has been explored.
- There is a growing evolution of the CMM from a quality-based to a manufacturing-based activity, reducing production-measurement lag. This movement is enabled by new automatic calibration and temperature compensation routines.
- Integration of measurement directly to the machine tool is enabled by known geometric relationships to fixturing, and allows for direct process feedback.
- Barriers to this integration include loss of machine availability during measurement, and inability to separate machine and part geometric errors.
- Measurement device calibration and relation of measurement error to machine tool geometric error are primary concerns. Error compensation schemes and rapid on-line calibration routines are evaluated.
- Machine reconfigurability becomes an important aspect of process-inspection integration. The machining center must operate with high force and controlled feed for material removal, and rapid traverse speeds and accurate positioning for measurement. Control architectures have been proposed for this duality.

Overall, the fundamental issue with these measurement and monitoring technologies is proper integration of the measurement and material removal functions to result in an effective production system. As an example, [8] describes the concept of a *smart machine tool system* that seamlessly integrates current process information with inexpensive and non-invasive sensors, and use of models to automatically and continuously control the process; however, such an integrated system has yet to be realized.

We have highlighted a number of issues which if left unconsidered in the overall design can result in inefficient or inaccurate results. Only through a systems approach to machine tool design can monitoring, measurement and material removal functions be effectively integrated.

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