Chapter 1

Introduction

1.1 Background and motivation

Manufacturing processes (e.g. casting, rolling, and forging) give a basic shape to raw material which in turn control the progress of an industry. Increasing requirement of better product quality, higher production rate with reduced cost demands the advancement of automated manufacturing. Automation in manufacturing needs a continuous monitoring to maintain the precision of products. Thus, an economic benefit is the ultimate output with automated manufacturing.

Conventional machining (viz. turning, milling, and drilling) sets the goal to maintain desired dimensionality and surface finish of basic manufactured products. This goal leads to maintain product precision with less cost using unmanned machining. However, tool wear and breakage are most important obstacles for fulfilling these criteria. Machining conditions, machine tool condition, cutting tool and work piece material, work piece geometry, tool geometry, alignment of work piece and cutting tool and cutting chip condition are the main factors affecting product quality. Cutting tool condition is the most important attribute among them. Machine tool downtime is an obvious consequence due to cutting tool wear and breakage. Machine tools also get affected severely due to the extra load given by worn tools. Thus, tool condition monitoring (TCM) is inevitable for advancement of unmanned machining (Rehorn et al., 2005).

TCM system consists of intelligent sensors for acquisition of signals, signal processing phase for extracting useful features to describe degree of cutting tool wear and a decision making phase for automatic recognition of cutting tool condition based on extracted features. In machining, signals of cutting force, power, current, sound energy, vibration, surface finish, temperature, which are influenced by cutting tool geometry and machining process parameters, are monitored by force sensor (viz. dynamometer), power and current sensor, acoustic emission sensor, accelerometer, surface profiler or vision based system, temperature sensor, respectively, in indirect TCM (Teti et al., 2010). Visual measurement of cutting tool wear by using optical microscope or camera is performed in direct TCM. In signal processing phase, process signals obtained from machining are analyzed by methods viz. analogue to digital conversion, filtering to remove noise, digital signal or image processing in temporal/spatial, frequency or time/space-frequency domain to extract useful features for describing degree of tool wear (Abellan-Nebot and Subirón, 2010). Extracted features are then fed into decision making algorithms to predict the condition of cutting tool (Roth et al., 2010).

Advantages and disadvantages of commonly used sensors in indirect TCM are described briefly. Force sensors (strain gauge or piezoelectric dynamometers) are most commonly used sensors for TCM. Force of machining increases with an increase in tool wear. Based on this reason, force sensors are used to detect degree of tool wear. Tangential, axial and radial force components result from cutting speed, feed force and angle between tool and workpiece, respectively. Feed force is mainly sensitive to flank wear and a substantial drop in tangential force signal can be noticed at the time of tool breakage. The elastic deformation of transducer or sensing material due to the change in cutting force is the main working principle of force sensors. However, the high cost, intrusive nature, poor overload protection capability in collision, sensitivity to small frequency band are the main drawbacks of force sensors used in industrial environment. Accelerometers are low cost sensors used in TCM to monitor chatter or vibration. Vibration or chatter during machining affects the surface quality of the job. However, signals acquired by accelerometers are dependent on the location of the sensors from the cutting area, inaccuracy of signal features, chance of damage of sensors, specific range of cutting speed (Ertekin et al., 2003). Acoustic emissions (AE) sensors are capable to grab signals with a large frequency range (kHz to MHz) in the form of AE signals. When tool breakage, fracture, chip deformation, abrasion occur in machining, stresses are then developed due to the effect of mechanical vibration. As a consequence, a spontaneous energy is released from the tool or workpiece material in the form of AE. However, AE sensors are disadvantageous for progressive monitoring of tool wear due to difficulty in positioning, complex calibration and more sensitiveness to noise of machining. Power sensors are low cost and embedded in CNC machine tools. Spindle power can estimate the condition of cutting tool breakage, roughly and it is more suitable for rough machining. Power sensors are more sensitive to machine tool condition than the condition of cutting tool. With the increase in tool wear, torque of direct current (DC) motor increases resulting in an increase of motor armature current which is measured using current sensors. Though the current sensors are low-cost but non-linearity, complex calibration, limited frequency range and inaccuracies are the main obstacles for their practical use in TCM. Temperature sensors are dealt only with the average temperature around the cutting tool which affects the accuracy of TCM. In any machining process, ultimate goal is to obtain a good surface finish. Thus, measurement of machined surface topography is an important task in TCM. Surface profiler is used to measure machined surface topography by tracing a linear path perpendicular to the lay direction of the machined surface. However, only one-dimensional measurement at a time is possible and there is a chance of surface damage in soft material due the invasive nature of surface profiler. However, over the years, tool wear was directly inspected using machine vision system in direct monitoring. But, this method is very much complex in terms of accessibility for on-machine tool inspection (Dutta et al., 2013b).

Therefore, there is a need to develop a flexible, low-cost, non-invasive, precise for progressive wear monitoring, frequency range independent, location independent and easy to use technique for TCM. Machine vision system can be used in indirect TCM by inspecting machined surface topography for detecting progressive tool wear due to its advantages by fulfilling the above mentioned requirements. Inspection of surface topography using machine vision is also capable to evaluate two-dimensional surface finish at a time by utilization of area-scan camera. Therefore, this current research is accomplished with the motivation to develop a machine vision system for on-machine tool inspection of machined surface to monitor progressive tool wear in turning operations.

1.2 Contribution of the thesis

Summary of the major contributions of this work are as follows.

- This work is based on the feasibility of application of machine vision system in TCM of turning and end milling.
- On-machine tool condition monitoring of average tool flank wear in turning is performed using machine vision system.
- The choice of experimental set up with CMOS camera, macro zoom lens, fibre optic guided front lighting is performed for acquisition of turned surface images. Proper selections of aperture and magnification of lens system are also performed.
- Three techniques, such as gray level co-occurrence matrix (GLCM) based, Voronoi tessellation (VT) based and discrete wavelet transform (DWT) based texture analyses are applied on turned surface images to depict the change in waviness, feed marks distribution and roughness affected by progressive tool flank wear. GLCM, VT and DWT based texture analyses are based on statistical, geometrical and signal processing based approaches, respectively. Theoretical background of those texture analysis techniques are also explained in this thesis.
- A methodology to select proper mother wavelet and decomposition level for accurate analysis by using DWT is presented in this thesis.
- Six texture features are extracted from turned surface images by utilizing these three texture analyses to describe average tool flank wear ($VB_{average}$).
- The repeatability of each of the texture features is studied in this work for all the machining conditions.
- Tool flank wear prediction in turning is performed in this work using support vector machine based regression (SVR) by utilizing the extracted six texture

features in turning. A brief explanation of the theory related to SVR is also discussed in this thesis.

- Offline TCM in end milling by varying the end mill cutter, machine tool and machining conditions is also discussed in this thesis.
- In this work, end milled surface images are captured using an optical microscope to perform the offline TCM.
- Four texture features are extracted from end milled surfaces utilizing GLCM based and DWT based texture analysis techniques as tool flank wear descriptors.
- In this research, tool flank wear prediction is also performed in end milling utilizing SVR technique.

1.3 Organization of the thesis

Excluding this chapter this thesis is organized as follows:

Chapter 2 discusses the literature related to the utilization of machine vision in manufacturing. First section of this chapter deals with the utility of machine vision system in manufacturing for quality evaluation of manufactured components. Second section discloses the research done on the application of machine vision system in manufacturing. This chapter is also subdivided to discuss the tool condition monitoring by analyzing tool flank wear directly and by analyzing the machined surface quality. Previous research based on indirect TCM utilizing machine vision is discussed here under the sub headings of statistical, signal processing based, model based and geometrical texture analysis techniques. Tool wear classification techniques for TCM and surface quality inspection are also discussed here. Finally, the objectives of this research are set to fill the gap present in the ongoing research on this topic and the same is mentioned in this chapter.

Chapter 3 deals with the theoretical background of the image texture analysis and tool flank wear prediction methods applied in this research. First section of this chapter discusses the definition of texture and texture analyses utilized in machine vision. Second section provides the theory of image pre-processing to overcome the inhomogeneity present in the machined surface images. Theory of GLCM based, VT based and DWT based texture analyses applied in this research are explained briefly in the subsequent sections. Proper selection of GLCM parameters and features, features from VT based texture analysis to obtain precise results are presented in this chapter. Also a method to select proper mother wavelet and decomposition level developed and utilized in this research is explained here. Proper selection of features extracted from machined surface images to describe tool flank wear by using DWT based texture analysis is also discussed here. Theoretical background of SVR analysis used to predict tool flank wear, is also explained in this chapter.

Chapter 4 explains the experimental set-up along with the machining conditions. Selection of eleven machining conditions for turning experiments with a particular tool-workpiece combination is explained here. Details of image acquisition system used for on-machine tool capturing of turned surface images are presented in this chapter. The image acquisition system consisting of proper illuminator, camera, lens and filters are explained in subsequent sub-sections. A methodology adopted for selection of proper numerical aperture to capture good quality turned surface images is explained here.

Chapter 5 deals with the results and discussion of TCM in turning. Results of tool flank wear, GLCM based features, VT based features, DWT based features and predictions of tool flank wear in turning are presented in the subsequent sections of this chapter. Repeatability of each texture feature for all the machining conditions is discussed here to establish the precision of these features. Results to select proper mother wavelet are presented here. Results of kernel selection for SVR analysis is also presented here. The kernel parameter and hyper parameters of the SVR models are also selected in this chapter to obtain accurate prediction of tool flank wear. The correlation between the measured and predicted tool flank wear values are discussed also.

Chapter 6 deals with the application of offline TCM system in end milling by varying the end mill, machine tool and machining conditions as a special case study. GLCM based and DWT based texture analysis techniques are applied on captured end milled surface images to extract four texture features for describing tool flank wear. SVR technique is used here also to predict tool flank wear in end milling.

Chapter 7 presents the conclusions and directions of future work.

Finally, a list of references used in this thesis is presented.