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Machine vision based condition monitoring and fault diagnosis of machine tools using information from machined surface texture: A review

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ABSTRACT

Machine vision based condition monitoring and fault diagnosis of machine tools (MVCMFD-MTs) is a vital technique of condition-based maintenance (CBM) in both metal removal manufacturing and metal additive fabrication. In these domains, many methods utilize information from imaging matrices of machined surfaces to extract sensitive features and obtain potential degradation tendencies. Over recent years, no comprehensive review covers the whole monitoring or diagnostic procedures. To fill this gap, this paper systematically summarizes MVCMFD-MTs, which aims to provide researchers and engineers with a theoretical basis and roadmap to further study or build MVCMFD-MTs using information from the machined surface texture. Firstly, two data acquisition systems and several institutional public datasets are revisited. Secondly, the methodologies are illustrated in two aspects, feature descriptors and diagnostic decision-making. Thirdly, an intuitive illustration on applications is provided from the perspective of surface quality monitoring (i.e., roughness evaluation, surface defect inspection) and indirect tool condition monitoring (i.e., tool wear monitoring, chatter identification). Finally, this paper discusses current challenges and potential research directions in nowadays intelligent manufacturing.

1. Introduction

Machine vision based condition monitoring and fault diagnosis of machine tools (MVCMFD-MTs) are widely adopted for unmanned metal-cutting machining and additive manufacturing, which are essential parts of industrial management systems to ensure reliable operation and timely maintenance. As a typical instance of condition-based maintenance (CBM), these vision-based monitoring systems recommend maintenance strategies or actions based on the information extracted from machined surfaces. A CBM program can significantly reduce manufacturing costs by reducing unnecessary maintenance operations with a properly designed manufacturing strategy [1]. Mechanical failures resulting from abrasions and fatigues accounts for nearly 79.6% of the downtime of machine tools

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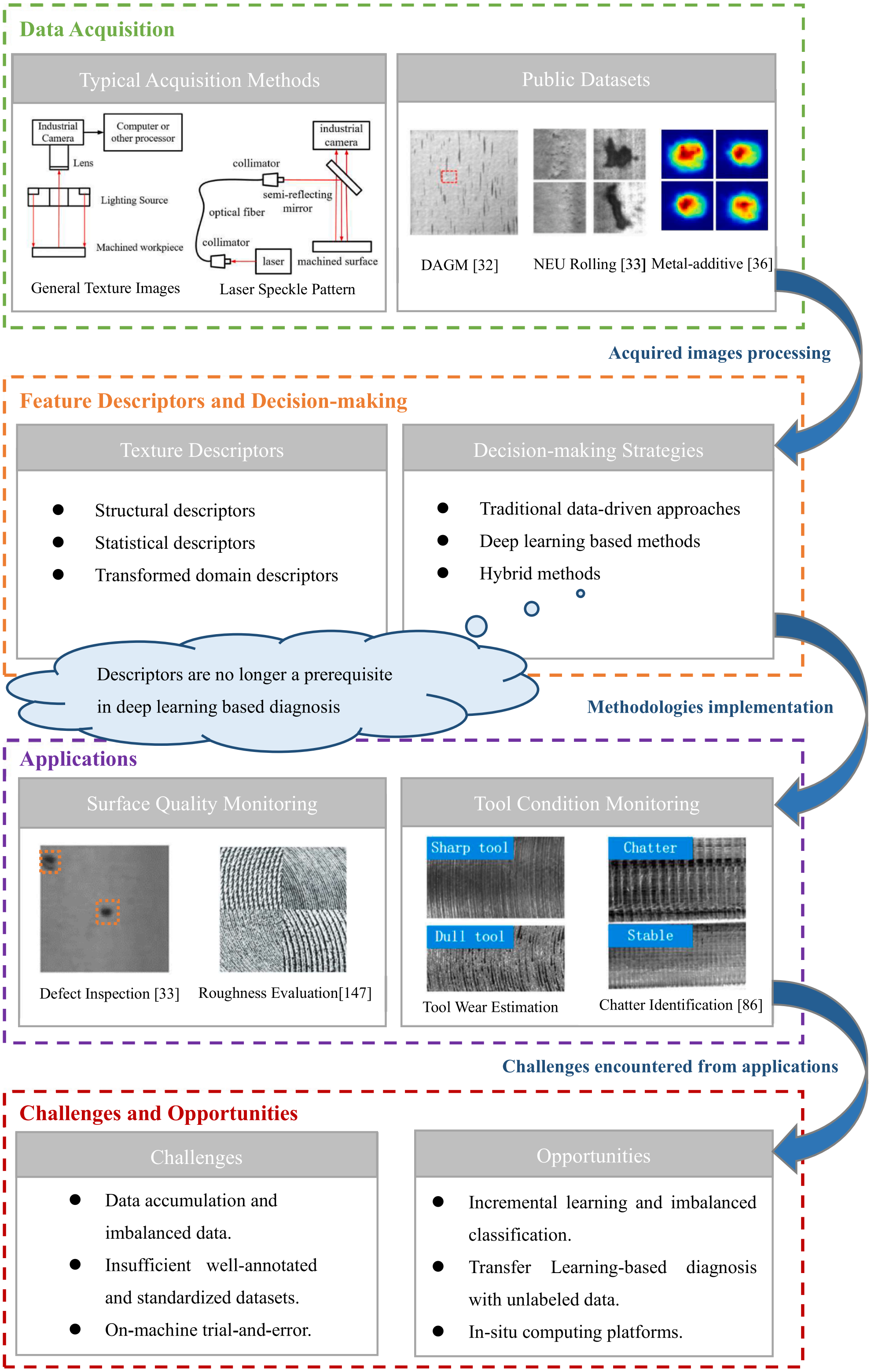
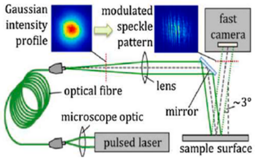
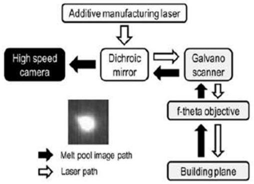
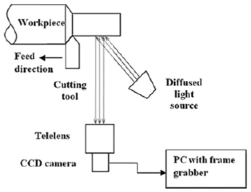
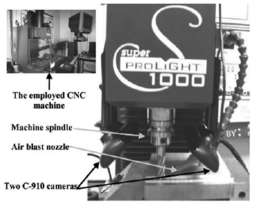
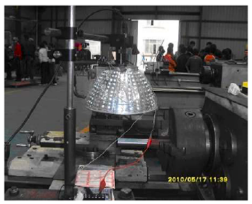


Fig. 1. The procedure of MVCMFD-MTs based on machined surface information.

Table 1
Representative illumination settings.

Illumination Types	Schematic Diagram	Illumination Specification	Authors	Involved Machining	Remarks
Laser		Gaussian intensity profile	Fischer et al. [12]	Rolling	Nanometer-scale, in-process roughness inspection
		Auxiliary equipment: dichroic mirror, galvanometer scanner, F-theta lens	Kwon et al. [13]	AM	Melt pool imaging, Laser power monitoring
Diffused light		Tele-lens with UV filters, CCD camera, surface roughness tester	Datta et al. [14]	Turning	Progressive wear monitoring
Ambient light		Logitech C-910 high-resolution camera, specular light minimization	Al-Kindi et al. [15]	Milling	Both machine surface quality inspection and tool state evaluation
Ring Light		Microscopic ring LED illumination	Aminzadeh et al. [16]	AM	Image collected from every layer of AM parts
Dome illumination		CMOS camera with miniature zoom monocular video microscope	Wang et al. [17]	Turning	Tool condition monitoring using machined surface images

[2]. Critical tool degradation may cause frequent unscheduled maintenance or even accidents (e.g., tool breakage) that dramatically reduce production efficiency. With a robust and efficient tool condition monitoring system, a cost-effective tool life management can be designed to optimize the maximum allowable wear and guarantee the high quality of machined surface [3]. Moreover, the product quality of additive manufacturing also relies heavily on the devices of MVCMFD-MTs. Sensors including infrared cameras, general complementary metal-oxide semiconductor cameras (CMOS cameras) and charge-coupled device cameras (CCD cameras) are usually adopted. As a relatively easy-obtained form of monitoring data, surface texture images provide rich information for diagnosis and monitoring applications. How to mine highly relevant degradation information from massive and unstructured raw image data becomes an urgent issue currently [4,5].

MVCMFD-MTs, as a typical data-driven method, is promising for on-machine monitoring processes because of its cost-effective data acquisition devices [6], along with emerging technologies in image processing [7] and computer vision [8,9]. The texture information of machined surfaces can be directly used for machined surface quality evaluation and, at the same time, indirectly used to reflect the abnormal condition of machine tools (i.e., chatter vibration, tool wear) [10]. In applications of metal-cutting manufacturing and emerging metal-additive fabrication, vision-based techniques are gaining increasing attention from academia and industries.

Specifically, the rest of this review is structured as follows, illustrated by Fig. 1. The paper's remaining sections consist of four parts, data acquisition, texture descriptors and decision-making strategies, applications, and challenges and opportunities. Sect. 2 discusses the general setup for vision-based data acquisition and summarizes some widely used institutional public datasets. Sect. 3 addresses the image descriptors for feature extraction and methodologies for diagnosis processes. Sect. 4 presents applications from two aspects, surface quality evaluation and tool condition monitoring. Based on the discussions and reviews, the current challenges and future opportunities are stated briefly in Sect. 5, followed by a summary remark to conclude the current achievements and foresee future trends in Sect. 6.

2. Data acquisition

For the CBM system, data acquisition is vital in collecting and checking the validity of raw data. So a standardized and validated dataset can be built after experiments. Before the degradation or defect features are processed and learned by the designed classification or regression algorithm, it is vital to develop proper data acquisition systems to ensure the quality of training and test datasets [11].

2.1. Typical acquisition methods

Sect. 2 provides the acquisition setup from most of the current researches of MVCMFD-MTs for the analysis of machined surface information. Particularly, the general image acquisition setting and other representative kinds of light source equipment are illustrated. In brief, infrared cameras can be used for temperature field measurement (i.e., pores and other irregularities detection caused by insufficient heat dissipation). General CMOS or CCD cameras, on the other hand, are more suitable for general detection tasks, such as the discontinuities of powder supply processes. Table 1 summarizes the common settings of light sources used in different applications of MVCMFD-MTs. Specifically, the laser-based measurements showed high accuracy in detecting roughness anomalies in the rolling operations [12]. However, for most metal-cutting operations, problems encountered by on-machine experiments (i.e. limited

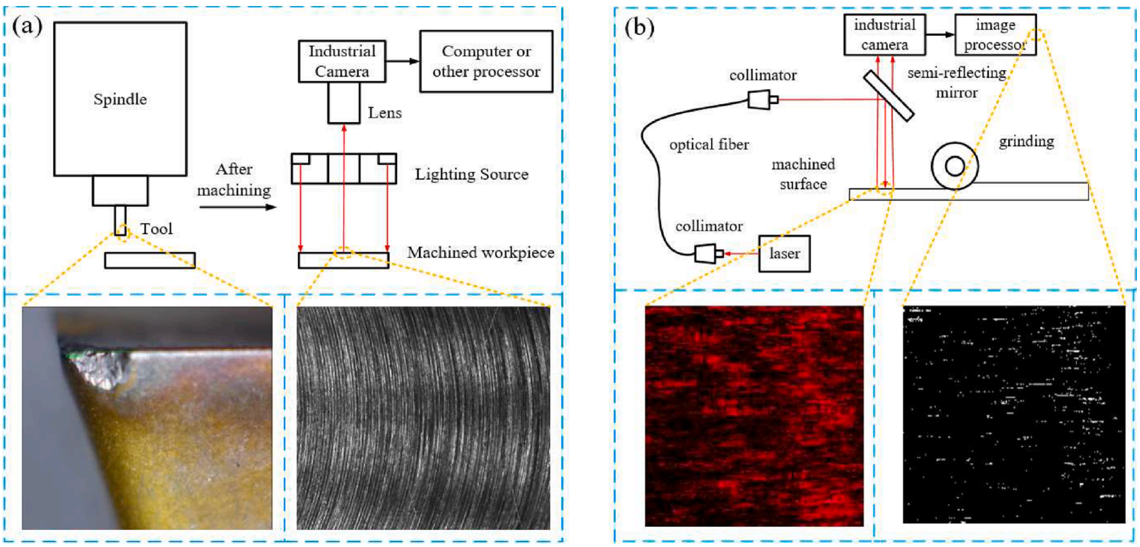


Fig. 2. Experimental setup and procedure. (a) A general surface texture acquisition in milling. (b) A laser speckle pattern acquisition setup in grinding [12].

installation space, vibration during operation) make it difficult to implement in-situ applications with the additional high-power laser auxiliaries. While in metal-additive manufacturing, existing laser equipment and the vibration-free operation make laser imaging an important diagnostic method in metal-additive manufacturing. Some other general visible light schemes are also widely employed in machining monitoring and diagnosing metal-cutting and metal-additive manufacturing, including diffused light, ambient light, ring light and dome light.

2.1.1. General image acquisition

The general texture acquisition is a capturing procedure using a common lighting source (e.g., ring typed, dome typed light). In this way, the reflected ray from the machined surface texture is directly acquired by lens and CMOS or CCD camera.

The captured grayscale image can be expressed as a two-dimensional matrix function. In this matrix, every independent amplitude value $\mathrm{f}(x,y)$ at the location (x,y) represents the intensity or gray level of the image, where the amplitude value is generally normalized and discretized. The raw image matrix will be further compressed according to its specific encoding, i.e., portable network graphics (PNG), joint photographic experts group (JPG). The spatial location relationship is represented by the matrix records the texture information, including machined surface topography, surface defect and tool path texture. Fig. 2(a) sketches a general surface image acquisition procedure after milling. With the progress of metal-cutting machining, the cutters gradually degrade, and the quality of the machined surface will also change. As typical visual evaluation indicators, flank wear and the change of machined surface texture can be measured and analyzed by image processing technology and texture analysis method. Once the direct measurement value of the tool wear and the corresponding machined surface texture data set are obtained and labeled, a correlation model can be established between the degradation of machine tools (i.e., flank wear) and the machined surface texture [3]. Fig. 2(b) illustrates a typical laser-speckle pattern based surface roughness monitoring system. For a detailed description, please refer to subsection 2.1.2.

Fig. 3(a) illustrates a general data acquisition setting in steel surface defect inspection systems, where bright-field imaging and dark-field imaging are deployed. Other auxiliary device includes the light control, fast image processor, server and operator interface. In a bright field illumination setup, the imaging sensors capture the most specular reflection light and diffusely reflected light. In this case, the defect features appear brighter while the defect parts appear darker. In a scheme of the dark-field illumination, the light ray irradiates the specimen with a high incident light anger, resulting in a dark appearance of the surface, whereas some defects appear to be bright in the image. Many studies indicate that the combination of these two settings shows more robust detection performance [18]. Fig. 3(b) illustrates the intensity value distribution regarding the Xeon lights reflection from the steel surface [20]. The light source setting is also one of the influencing factors for data acquisition. The imaging results from in-situ experiments can provide the best suggestions for light source placement. A reasonable optimized light intensity distribution can highlight the target part to be detected, which also results in a simplified algorithm layout and debugging process.

2.1.2. Laser speckle pattern acquisition

Since the invention of laser technology in the early 1960s, the phenomenon of laser speckle or granularity has been discovered and then widely studied [22]. The speckle pattern can reflect the roughness quality of the high-precision machined surface due to the good coherence of the laser rays [23]. The methodology of surface quality evaluation based on laser speckle pattern analysis is briefly illustrated by Fig. 2(b). The capturing process of the laser-speckle pattern can be demonstrated by the following steps. Firstly, the collimated laser ray enters the beam splitter. Refraction occurs on the beam splitter. The reflected laser ray irradiates on the surface of the workpiece. Owing to the coherence of laser rays, a unique speckle pattern is formed due to the scattering diffuse reflection on the target rough surface. Then, the micro-topography measurement is deployed to analyze the captured laser speckle pattern, from which a correlation between the laser scatter pattern and the surface quality index (i.e., surface finish) can be established. The surface quality evaluation based on laser speckle pattern made significant progress in recent years, especially in high-precision manufacturing. Fischer et al. [12] built an in-situ and nano-scale machined surface roughness evaluation system in sheet rolling using a high-speed camera with imaging capability of micro-seconds level exposure. The problem of minimal achievable uncertainty limitation of laser-based

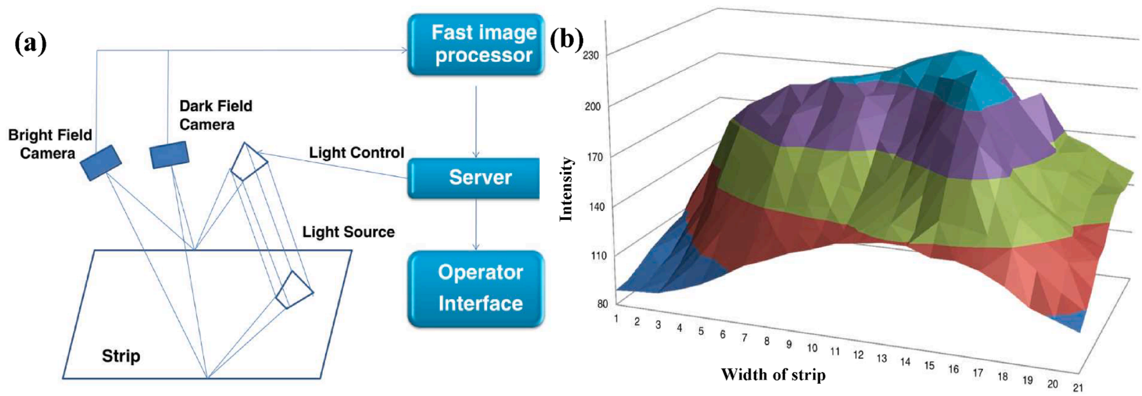


Fig. 3. A general data acquisition setup in steel surface defect inspection system. (a) Bright field imaging and dark field imaging [20]. (b) Illumination pattern [167].

measurement (i.e., short laser noise, detector noise) is addressed by Patzelt et al. [24]. The laser speckle method also shows strength in the estimation of surface finish in other manufacturing processes. Research from Bharathi et al. [25] and Xu et al. [26] also revealed the effectiveness of the laser speckle pattern-based method in surface roughness evaluation regarding milling and grinding, respectively.

2.1.3. Specialized acquisition equipment

Considering the demand in some non-traditional manufacturing machining operations, some specialized sensors and auxiliary devices for intelligent monitoring are desired. For instance, spectrometer and photodiodes were used for welding large structures based on high-power lasers [27], and photodiodes were also deployed for the low-cost monitoring scheme [28]. Fig. 4 depicts a deposition system with closed-loop cooling rate control of micro-structure. Both infrared camera and CCD camera are employed to feedback the temperature of the melt pool and its surroundings. A real-time deposition control system is realized with the feedback from both imaging sensors and other auxiliary sensors [29]. It's also reported that an off-axis vision system using a high-speed camera can be adapted for in-situ monitoring of plume and melt pool in powder bed fusion additive manufacturing [30]. A high-speed infrared camera or the CCD/CMOS camera is usually adopted for defect detection of the melt pool because the most laser energy is rapidly absorbed by powder particles [13]. Zhang et al. [31] studied an in-situ observation system for the surface defect inspection of K9 glass after grinding with an acquisition system utilizing a high-speed camera equipped with telephoto lenses and a high-frequency lighting system.

2.2. Institutional public datasets

The development of standardized public datasets can ensure the verification and validation of the algorithm and reduce the discrepancy between laboratory experiment and factory-ready implementation, further accelerating the promotion and development of algorithms. This paper reviews several MVCMFD-MTs datasets, where detailed descriptions regarding their defect types or degradation patterns, acquisition methods are provided.

2.2.1. DAGM dataset

The DAGM dataset is one of the earliest surface defect benchmark datasets proposed by Matthias Wieler and Tobias Hahn, sponsored by the German association for pattern recognition (DAGM), the German chapter of the European neural network society (GNNS) [32]. As an earlier publicized texture data set, it aims to promote and facilitate optical texture monitoring applications of industrial optical inspection. It is simulated according to real-world application scenarios, which includes 6 classes of similar real-world material texture. In each category, 1000 defect-free samples and 150 defective ones are collected. As illustrated in Fig. 5(a)–(f), the surface defects are annotated in a weak manner, circled by an external ellipse. These defects are synthesized artificially according to real-world applications. The dataset possesses several characteristics, including varied statistical background, weakly-labeled training data, the discrepancy between the training set and test set.

2.2.2. NEU hot-rolled steel surface dataset

The Northeastern University (NEU) hot-rolled dataset is a standardized, high-quality dataset for automatic surface defect detection. Song et al. firstly introduced this dataset in their work on noise-robust local binary patterns (LBP) for steel strip surface defect detection [33]. Further researches based on deep learning methods [34,35] also indicated the superiority of multiple feature fusion for surface defect inspection tasks. Fig. 6(a) illustrates the general acquisition setting in the NEU-DET sub dataset. The automated surface defect inspection system is installed after laminar cooling, composed of the auxiliary light source, industrial cameras. As a typical and

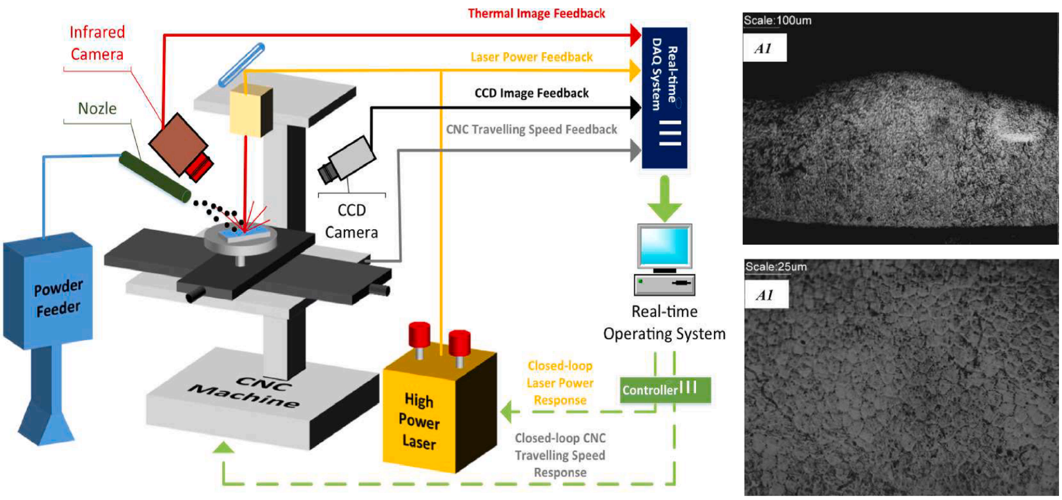


Fig. 4. A diagram for in-situ camera based additive manufacturing monitoring system [29].

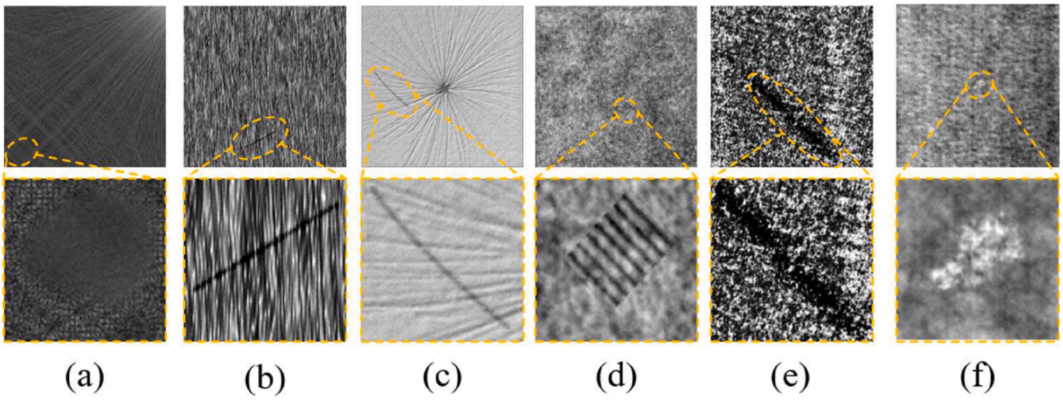


Fig. 5. The original labeled images and its zoom-in illustration of the six defect classes in DAGM with defect region marked with external eclipse [32].

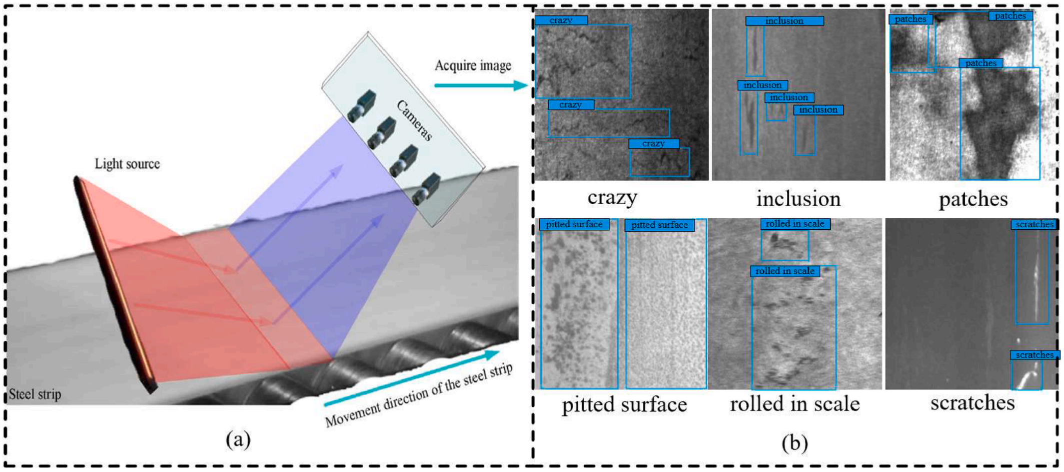


Fig. 6. An illustration for the defects in NEU hot rolled steel dataset with defect region marked with bounding box [33]. a) Application settings. b) Representative defects.

standardized dataset collected from the real industrial pipeline, Fig. 6(b) illustrates the six representative types of defect from the hot rolled steel strip, including rolled-in-scale (RS), patches (Pa), pitted surface (Ps), etc. The resolution of each raw image is 200 × 200. Every defect type class contains 300 annotated images with tight-fitted bounding boxes. The metal-additive manufacturing dataset

The Conv-LBM laser manufacturing dataset was proposed by Gonzalez-Val et al. [36]. It contains two small datasets and one primary dataset, and the datasets are collected from two major kinds of metal-additive manufacturing, laser metal deposition (LMD) and laser welding, respectively.

The primary dataset is a large and standardized set with more than 1600,000 images from 405 tracks of laser cladding over a series of diversified laser power and speed setting, where 316L steel is adopted as powder and base material. The two smaller datasets contain dilution information and labeled laser welding defects, respectively. A Tachyon 1024 FPA camera obtains the images with a fixed coaxial installation to the laser head. The dilution experiment uses M2 tool steel as powder and base material instead of 316L used in the primary dataset. Fig. 7(a) and (b) illustrates the medium-wavelength infrared (MWIR) imaging of monitoring applications in laser manufacturing and the representative defects on laser welding beads [36]. The MWIR images are collected during the laser process by an infrared camera with high-speed capturing and high thermal dynamic range. Fig. 7(c) depicts a welding quality classification problem on a laser weld bead, proposed by Zhang et al. [37]. The blue rectangles highlight the defective sections in the segments due to undercuts, while the ellipses annotate the regions where some points possess excessive porosity problem. Li et al. [88] further conducted a deep learning-based domain-adaptation experiment on welding classification. The dataset was labeled by material experts according to three distinct qualities of each machined parts, including under-melt, beautiful-weld and over-melt.

Compared with traditional metal-subtractive manufacturing, the emerging additive manufacturing (AM) can efficiently fabricate sophisticated and fully functional 3D metallic objects in ways that the conventional manufacturing technologies cannot perform. However, as all emerging manufacturing techniques should undergo, quality control in additive manufacturing remains an obstacle that hinders its promotion and development [89], especially in the field of surface defect inspection.

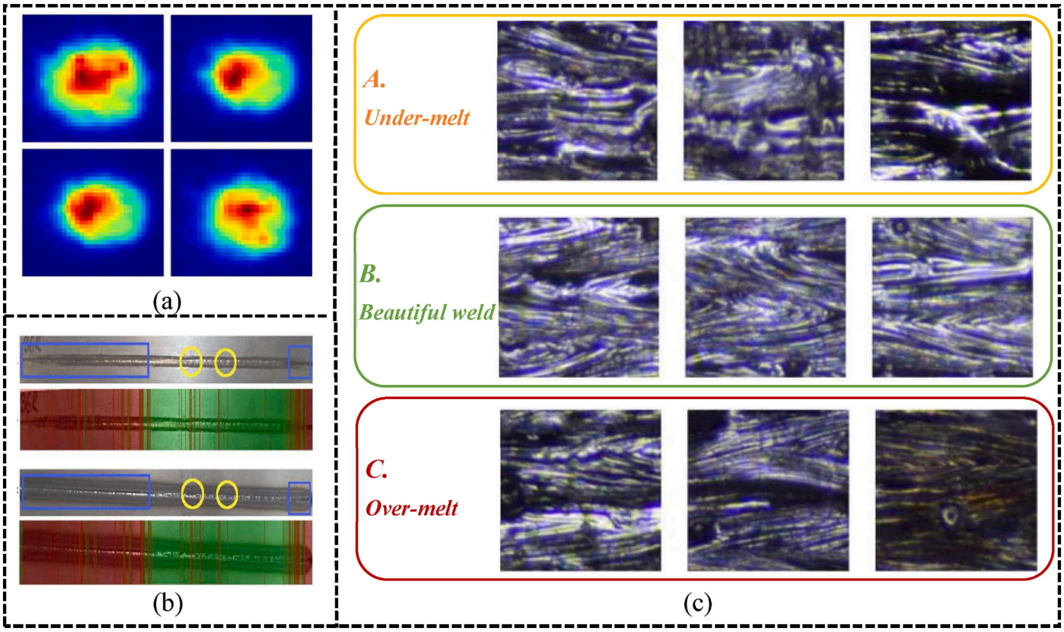


Fig. 7. Representative laser manufacturing dataset. a) Infrared imaging in Conv-LBM [36]. b) Defective welding beads in Conv-LBM [36]. c) Welding quality classification task [37]. (b) Defects of laser welding bead sub dataset in Conv-LBM [36] (c) Microscale welding image classification task [37].

3. Feature descriptors and decision-making

In this section, the feature descriptors and decision-making strategies of MVCMFD-MTs are summarized, which are focused on ones utilize information from machined surface texture. The first subsection reviews the feature descriptors, covering structural descriptors, statistical descriptors, and transformed domain descriptors. The second subsection reviews some representative classification methods for tool wear evaluation, chatter identification, and surface defects inspection, along with the regression methods for roughness evaluation and tool wear estimation.

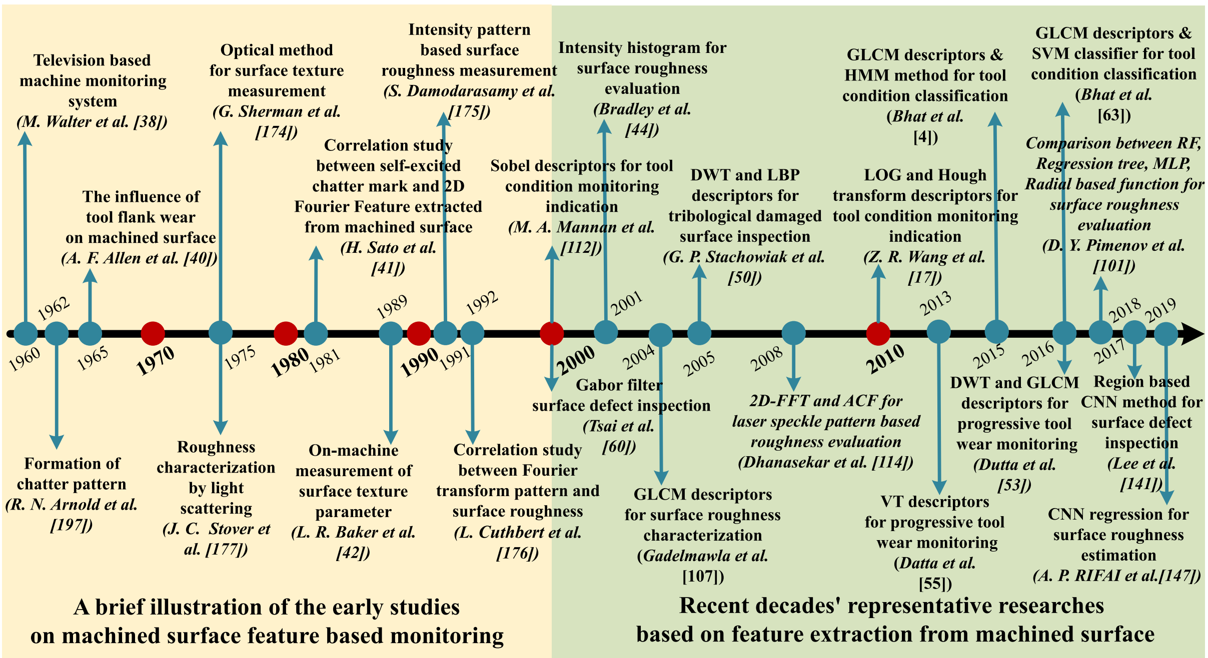


Fig. 8. The evolution of the MVCMFD-MTs using features extracted from the machined surfaces.

Fig. 8 illustrates the development of the MVCMFD-MTs based on the analysis of machined surface texture, which sketches up the milestones of early studies in the 20th century and recent decades. For abbreviations, please refer to Table 2. The study of MVCMFD-MTs can be traced back to the work of Walter et al. [38], in which the feasibility of a telemonitoring system was studied. During the 1970s to 1980s, the feasibility [191], mechanism [183], and hardware layout of MVCMFD-MTs were intensively investigated. In the 1990s, experiments on the degradation behavior became popular, including the correlation between wear of machine tools and the machined surface texture [40], the feature characterization using light scattering patterns [41], the correlation between chatter marks and features of the machined surface texture [42].

Since the new 21st century, many studies focused on improving hand-coded feature extraction, selection and decision-making methods (i.e., classification and regression). With the rise of emerging industrial concepts (e.g., big data, intelligent manufacturing) in recent years, massive sensors mounted to the manufacturing scenarios. These sensors produce numerous data with the sparse and high-dimensional fault or degradation information. Hand-coded features became increasingly difficult to accurately represent those tasks, where the data characteristics are complex, and distribution discrepancy occurs due to varied working conditions. These drawbacks motivated the development of recent studies on intelligent data-driven methods utilizing artificial intelligence [184]. The research focus has also gradually shifted from traditional machine learning to deep learning.

3.1. Texture descriptors for feature extraction

In recent decades, many researchers studied the methods of extracting features from machined surfaces. The descriptors for machined surfaces are a series of hand-coded algorithms for feature extraction, supporting further decision-making strategies. In this paper, the development of three main kinds of descriptors is discussed, including structural descriptors, statistical descriptors and domain transformation descriptors, as shown in Table 3.

3.1.1. Structural descriptors

Structural descriptors are simple texture descriptors that can extract features from global-uniformed texture images, which include projection-based descriptors and descriptors based on encoding patterns. Many approaches based on this methodology can be found in the first decade of the 21st century. In 2000, Kassim et al. [43] presented a study on the classification of a sharp, semi-dull, or dull tool using the Sobel descriptor and thresholding-based classification method. In 2001, Bradley et al. [44] adopted the intensity histogram-based method for the surface roughness evaluation task. In 2007, Castejon et al. [45] performed an on-line tool monitoring using nine geometric descriptors, including the length of major axis, the length of minor axis, eccentricity, orientation, etc., and their result showed that the linear discriminant analysis descriptor outperforms others by providing 98.63% of the support information for classification. In the same year, Kassim et al. [46] presented a TCM based on the analysis of the machined surfaces, where features extracted from column projection analysis, fast Hough transform and run-length encoding. In 2008, Prasad et al. [47] presented a TCM method based on machined surface texture using basic statistics covering RMS, skewness, kurtosis. In the same year, Barreiro et al. [48] also presented a tool wear monitoring method using a series of moment-based descriptors, in which Hu and Legendre’s descriptors provided the best performance. In 2010, Wang et al. [17] presented a tool wear monitoring method using the statistical length and direction extracted from the Hough transform, and then the edge images were processed by the LOG operator. Structural descriptors provide rich information for texture classification. One difficulty of these methods lies in texels extraction [51].

3.1.2. Statistical descriptors

In the past decade, the statistical descriptor is also a typical type of feature extraction method widely studied in MVCMFD-MTs based on machined surface information [49,50]. Early works used the first-order statistical texture analysis method [44,51] to extract features from the pixel-level histogram statistics while the spatial relation of texture primitives is neglected. Ai-kindi et al. [15] proposed a histogram-based first-order statistical texture analysis method for milled specimens surface roughness evaluation. Ashour et al. [52] presented a study on the classification of different types of machining using histogram-based features. A further study from

Table 2
Abbreviations for representative feature descriptors.

Abbreviations			
PCA	principle component analysis	V-M	vertical milling
SVM	support vector machine	H-M	horizontal milling
GLCM	gray level co-occurrence matrix	DWD	discrete wavelet decomposition
DCT	discrete cosine transform	CNN	convolutional neural network
DWT	discrete wavelet transform	MLP	multi-layer perceptron
VT	Voronoi tessellation	EMD	empirical mode decomposition
HMM	hidden Markov model	RF	random forest
PSD	power spectral density	WT	watershed transform
FFT	fast Fourier transform	FNW	frequency normalized wavelet
2D-FFT	2 dimensional fast Fourier transform	MIA	multivariate image analysis
LBP	local binary pattern	WTA	wavelet texture analysis
ANN	artificial neural network	HCA	hill climbing algorithm
FSA	Fourier spectral analysis	ARF	adaptive random field
LOG	Laplacian of Gaussian	ACF	auto-correlation function

Table 3
Representative descriptors for MVCMFD-MTs.

Types of Descriptors	Involved Machining Operations	Year	Authors	Data	Specific Techniques
Structural descriptors	Grinding, Milling, Shaping	1993	Ramamoorthy et al. [130]	Machined surface images	Gray level histogram
	Turning	2000	Mannan et al. [112]	Machined surface images, sound data.	Sobel descriptor, thresholding-based segmentation, PSD
	Turning	2000	Kassim et al. [43]	Machined surface images	Sobel descriptor & thresholding
	Turning	2008	Prasad et al. [47]	Machined surface images	Amplitude parameters
	Turning	2010	Wang et al. [17]	Machined surface images	LOG operator, Hough transform
	Grinding	2017	Zhang et al. [31]	Machined surface images	Intensity histogram-based analysis
	AM (Powder bed fusion)	2019	Zhang et al. [30]	meltpool, plume & spatters	Median filtering, global thresholding, designed comparison function
First-order statistical descriptors	End milling	2001	Bradley [44]	Machined surface images	Intensity histogram, spatial domain texture descriptors
	Turning, face milling, polishing	2004	Gadelmawla et al. [107]	Machined surface images	GLCM descriptors, maximum width of the matrix
	Milling	2008	Elango [11]	Scattered pattern Image of machined surface	Taguchi technique
	Milling	2012	Ai-kindi [15]	Machined surface Image	Histogram-based feature extraction
	Turning, Grinding, H-M, V-M, Lapping, Shaping.	2016	Ashour et al. [52]	Machined surface image	Histogram-based Feature extraction, PCASVM
	Laser welding	2018	Chen et al. [27]	Plume	Geometric features (area, Perimete, etc.)
Second-order statistical vdescriptors	Turning	2012	Dutta et al. [57]	Machined surface images	GLCM descriptors, pixel pair spacing
	Turning	2013	Datta et al. [55]	Machined surface images	VT descriptors
	Turning	2016	Dutta et al. [3]	Machined surface images	VT & DWT descriptors
	Turning	2016	Bhat et al. [4]	Machined surface images	GLCM descriptors
Transformed dvomain descriptors	Textile fabrics, Milling.	2000	Tsai et al. [60]	Machined Surface images	Gabor Filter
	eight engineering processes comparison	2001	Josso et al. [59]	Machined surface images	FNW transform-based descriptors
	Rolling	2004	Bharatiet al. [49]	Steel surface image	PLS-DA, 2D- FFT, MIA, WTA
	Sandblasting, abrading	2005	Stachowiak et al. [50]	Tribological damaged surface image	DWT, Gabor Filter and LBP descriptors
	End milling	2016	Dutta et al. [53]	Machined surface images	DWT, GLCM descriptors
	Milling	2017	Lei et al. [148]	Machined surface images	FSA descriptors

Elango et al. [11] indicated that illumination source variance could interfere with the histogram-based approaches seriously. It is worth mentioning that the first-order statistical method discarded the local correlation information hidden in the pixel array. To overcome this limitation, many researchers then worked on the second-order statistical texture analysis, including gray level co-occurrence matrix (GLCM), Voronoi tessellation (VT), etc. Grayscale images can be read as a $N_x \times N_y$ array, with each pixel having a grayscale value Z, which is normalized as an integer ranging from 0 to 255. The co-occurrence matrix contains $P_d(i,j)$, which maps the distribution of the probability of occurrence of pairs of gray level points, (i,j) separated by a distance D. Each element in the GLCM denotes the total of the co-occurrence of the corresponding pixel pair for a specified direction in the array of raw gray-level image. Bhat et al. [4] presented a hidden Markov model-based (HMM-based) tool wear classification model using GLCM features extracted from the machined surface. Dutta et al. [53] proposed a progressive tool flank wear prediction method of end milling based on SVM regression from machined surface images using feature extracted from GLCM and discrete wavelet transform (DWT). Other typical forms of second-order statistical texture descriptors, including VT, were also well-studied. The VT-based texture analysis is derived from the work of Ahuja et al. [54], the first one that studied the region enclosed by Voronoi polygon for dot pattern processing. The Voronoi diagram provides a correlation between the region vertices along with the description of region topography. Then, the neighborhood information and topography description can be further used as features for monitoring or diagnosis. Datta et al. conducted a quantitative assessment study for cutting tool flank wear by analyzing turned surface images using the VT method [55]. Dutta et al. deployed an on-machine monitoring system using texture features extracted from both GLCM and VT [3]. In addition, the information fusion of first-order statistics and second-order ones also shows significant improvement based on a bilinear CNN architecture [74].

3.1.3. Transformed domain descriptors

The transformed domain descriptors mainly include two categories, namely spatial frequency-based methods and filter-based methods. Since the spatial frequency-based methods decompose the image matrices into a series of spatial frequency channels, they show the information of the original image texture at different spatial frequencies (different scales and orientations). Fine-grained features from both the global-view and the local-view can be extracted. In 2005, Chang et al. addressed a surface roughness prediction method using a DWT-based analysis method, from which spatial-frequency localization features were extracted [56]. Researches

Table 4
Representative decision-making strategies of MVCMFD-MTs.

Types	Involved Machining Operations	Year	Authors	Data	Decision-making Strategies
Traditional Data-Driven methods	Turning	2002	Ho et al. [132]	Machined surface images	Neuro-fuzzy inference system
	High-speed end milling	2005	Kang et al. [118]	Machined surface images & flank wear images	Fractal Analysis
	End milling, turning	2006	Kassim et al. [138]	Machined surface images	Fractal analysis, HMM.
	Grinding, milling	2008	Dhanasekar et al. [117]	Laser speckle patterns of Machined surface images	FFT, ACF analysis
	End milling	2011	Palani et al. [128]	Machined surface images	ANN, 2D-FFT.
	Turning	2015	Bhat et al. [62]	Machined surface images	GLCM feature, SVM classifier.
	Face milling	2017	Pimenov et al. [101]	Machined surface images	Comparison between RF, Regression tree, MLP, Radial-based function.
	Grinding	2017	Zhang et al. [31]	Machined surface images	Intensity histogram-based analysis
	Grinding and VM	2018	Xu et al. [26]	Machined surface images	Fractal analysis, speckle intensity evaluation
	Sheet Rolling	2019	Fischer et al. [12]	Laser speckle patterns of Machined surface images	ACF analysis
Deep learning methods	Drilling	2017	Kurek et al. [146]	Drilled hole images	Shape and shredding estimation, deep learning.
	Rolling	2018	Lee et al. [141]	Metal surface defect images	Region-based DCNN
	Turning, milling	2019	Rifai et al. [147]	Machined surface images	DCNN, regression model.
	Casting	2019	Liu et al. [149]	Surface images	DCNN, saliency-based visualization
	AM (SLM)	2019	Caggiano et al. [8]	Powder layer, part slice	Bi-stream DCNN
Hybrid Methods	Milling	2015	Kumar et al. [145]	Machined surface images & Flank edge images	GLCM, statistical and spectral texture analysis, regression model.
	Turning	2016	Dutta et al. [3]	Machined surface images	GLCM, DWT, VT, Linear SVM.
	Turning	2016	Li et al. [144]	Machined surface images & Wear tool edge images	WT, HCA, sum modified laplacian focusing evaluation function, ARF.
	End milling	2016	Dutta et al. [53]	Machined surface images	GLCM, RMS, DWD descriptors, SVM classifier.
	Milling	2017	Sun et al. [72]	Machined surface images & vibration signals	GLCM, EMD descriptors, hybrid neural network.
	AM (PBF)	2018	Dunbar et al. [150]	multispectral sensor & laser scanner position	Computed tomography using threshold analysis, placement function

on the wavelet-based method demonstrated a good defect inspection capability on a uniform texture [57,58]. Josso et al. reviewed applications of wavelet methods on surface roughness analysis and characterization [59]. Filter-based methods, also known as another form of transformed domain methods, always been used for defect inspection. They possess the ability to find the local anomalies in global-uniformed machined surface images with homogeneous texture. In 2000, Tsai et al. presented an optimized Gabor filter that computes the output energy from the convolution of images from machined surfaces with defect discrimination based on simple thresholding [60]. In 2006, Zhang et al. presented a defect classification method in grinding and polishing, which reaches 82% accuracy with the Gabor filter feature and statistical feature [61]. In 2017, Lei et al. studied chatter identification of high-speed milling using FSA feature extracted from machined surface images [148].

All these traditional hand-crafted feature-based methods follow a procedure, data acquisition, feature extraction, selection and the final degradation behavior learning. Once the feature descriptors are designed and optimized, classification and regression methods can be adopted to realize the final decision-making function based on these feature representations.

3.2. Classification and regression in machine condition monitoring

The classification and regression methods are designed to analyze the features extracted from the machined surface texture described in the previous subsection. This subsection adopts the above-mentioned feature descriptors for decision-making (i.e., classification and regression) to achieve the final function of MVCMFD-MTs. Decision-making strategies can be divided into three categories (i.e., traditional data-driven methods, deep learning methods and hybrid methods), shown in Table 4.

3.2.1. Traditional data-driven methods

After features are extracted, classification methods (e.g., support vector machines, random forest (RF) methods) and regression methods (e.g., autocorrelation functions) can further extract feature information to achieve the final decision-making. Pimenov et al.

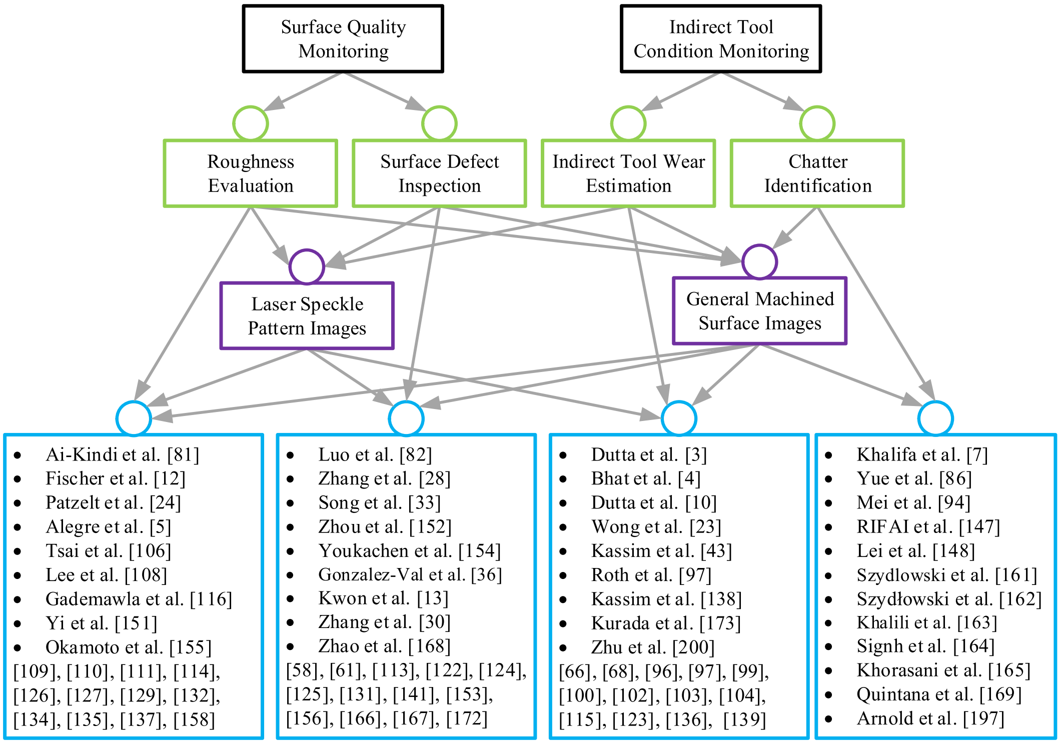


Fig. 9. Development of MVCMFD-MTs grouped by applications in the past a few decades.

[101] tested a series of traditional artificial intelligence methods for mill surface roughness prediction, including multilayer perceptron (MLP), RF, regression tree, etc. The results show that the RF-based method has the highest model accuracy, followed by regression trees, which has higher accuracy than the standard MLP and the radial-basis function. Bhat et al. [63] proposed a TCM method derived from SVM classification using a gray level co-occurrence feature extracted from tuned surface images. However, many of these traditional shallow feature-based classification and regression methods show good results, mainly based on a setting with hundreds of images testing in a laboratory environment. Besides, hand-coded based features need further validation and optimization to figure out the most sensitive one for degradation process monitoring [12]. The trial-and-error tests for hand-coded features designing in nowadays automated manufacturing implementation are time-consuming and labor-intensive. To this end, it is of great significance to develop more efficient and robust monitoring approaches for nowadays gigabyte-level data scenes. The inherent difficulty of hand-coded feature-based methods in obtaining the state of the art texture representation lies in two contradictory evaluation indexes: high efficiency and high accuracy.

3.2.2. Deep learning methods

As one of the emerging techniques, deep learning-based approaches are capable of representing the degradation process without the requirement of much prior expertise [229]. Deep learning-based methods are gaining increasing attention in data-driven machine TCM [117,119]. Specifically, deep convolutional neural network-based (DCNN-based) methods have strong abilities to directly process the raw image matrices [141,146]. In 2012, Alex-Net [178] achieved a record-breaking classification accuracy in an authoritative large-scale dataset, PASCAL VOC [9]. Further research in deep learning validated the powerful representation ability of DCNN, which uses the hierarchical architecture to progressively extract abstracted features. The superior ability of nonlinear representation without introducing hand-crafted rules or much prior expertise before training also makes deep learning-based industrial monitoring and diagnosis an active research field. Mikołajczyk et al. [95] presented a single category-based classifier neural network method for image analysis of cutting edge wear under different working times. Lee et al. [141] presented a region-based DCNN method for defect detection on the metal surface. Luo et al. [140] presented an early fault diagnosis of tools using deep learning and dynamic identification under time-varying conditions. Caggiano et al. [8] studied a Bi-stream DCNN method for selective laser melting (SLM) manufacturing. It should be noted that the success of deep learning methods is based on the high quality and super-huge annotated datasets. These DL-based methods witness a significant development stimulated by the prognostics and health management (PHM) competition [180]. However, the lack of large-scale and standardized public datasets in MVCMFD-MTs always hinders the algorithm validation and application optimization process. Besides, massive data collection in a short time for real applications leads to a huge

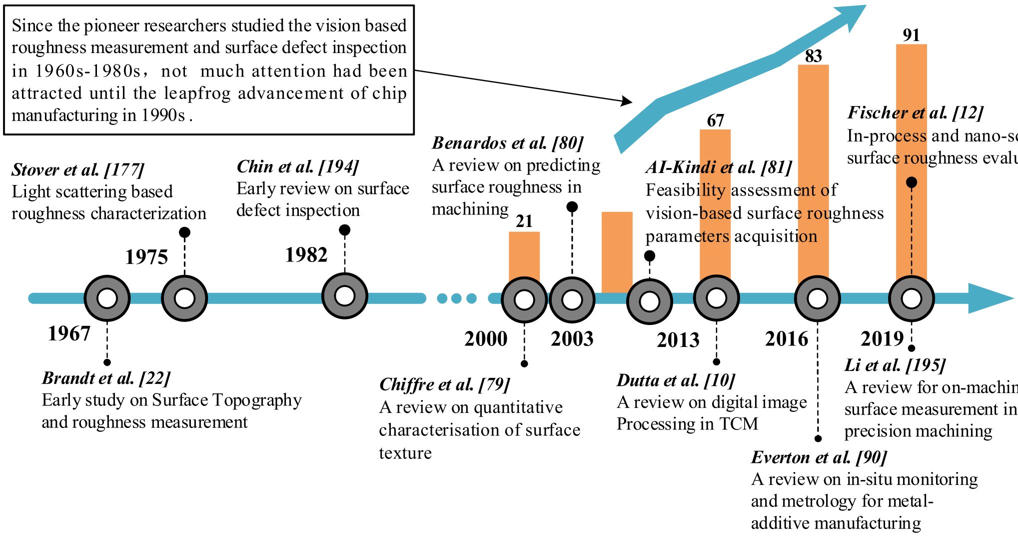


Fig. 10. Development history and statistics of machined surface quality evaluation using machine vision.

financial and human investment. The premise of huge cost and time consumption to the customized data annotation for MVCMFD-MTs suppresses the application of deep learning approaches. Although massive sensors are applied to smart monitoring applications, many industrial data has not been utilized appropriately due to its inherent characteristic (i.e., imbalance categories, background noise and other confidentiality issues). That hinders the construction of a large-scale standardized dataset. Very few standardized image datasets exist for diagnostic tasks (i.e., tool condition monitoring, surface quality evaluation). To improve the monitoring performance in the real automated production environment, many researchers then studied the solution for imbalanced classification in machine tool monitoring. The transfer learning-based method gives a solution to the machine condition diagnostic tasks where the target domain data is unlabeled or limited [179], or the domain shift phenomenon occurred resulting from evolving working conditions [181]. Sun et al. proposed a deep transfer learning network based on sparse auto-encoder for tools remaining useful life prediction [76]. Kassim et al. performed a HMM-based tool wear state classification method using features based on fractal analysis [138]. Kurek et al. [142] presented a transfer learning method using CNN to recognize the drill state from hole images drilled in the laminated chipboard. Ko et al. [64] presented a tool breakage monitoring methodology consisting of an unsupervised adaptive resonance theory-based neural network and an adaptive time-series modeling algorithm. Although deep learning has been widely studied in mechanical CBM systems, how to achieve effective on-line or in-situ diagnosis of machining potential degradation behavior with imbalanced categories and unlabeled data is still a topic worthy of further exploration.

3.2.3. Hybrid methods

Over the preceding decades, various types of methods for MVCMFD-MTs were studied. However, due to system difference, data availability and other application constraints, it is challenging to find an excellent method with universal applicability. Some researchers considered the integration of multiple methods or data fusion strategies [92]. Studies of hybrid methods aim to leverage the advantages of different types of basic methods [71]. In 2015, Kumar et al. [145] addressed a prognostic model for tool life prediction in milling using both the statistical and spectral texture analysis methods. In 2018, Dunbar et al. proposed [150] a hybrid monitoring system for powder bed fusion (PBF) processes using multispectral sensor and laser scanner positions.

Some researches focused on complementary and redundant feature fusion based on the combination of different types of feature descriptors. In 2016, Dutta et al. proposed a progressive tool flank wear value prediction method of end milling based on SVM regression using features extracted from both GLCM and DWT [53]. Li et al. presented research on tool wear monitoring using workpiece texture and tool wear part measured by an adaptive MRF image segmentation method in tuning [144]. In 2017, Lei et al. compared the vision-based chatter identification method with sound emission-based approaches [148]. In 2019, Zhu et al. studied a big data-oriented deep learning method based on a multiple sensors data fusion strategy [199].

Some researchers also studied the correlation between signals from different sensors. In 2017, Sun et al. proposed a hybrid neural network using GLCM for feature extraction of machined surface texture and empirical model decomposition for vibration feature extraction, from which a mapping relationship between image features and vibration signal features was established [72]. As an emerging and active research direction, future researches on hybrid methods involving data fusion strategies [199,221] and multiple data modalities [231].

4. Applications of MVCMFD-MTs

The MVCMFD-MTs is capable of recognizing the fault modes that progress from incipient fault to failure [230] based on the analysis of machined surface texture, which can be applied to a variety of monitoring tasks as shown in Fig. 9, including surface quality monitoring and indirect tool condition monitoring.

The set of literature is grouped and listed according to these four kinds of major applications (i.e., roughness evaluation [109,110,113,114,116,126,127,129,133–135,137,151,158,177,225], surface defect inspection [122,124,125,131,152,154,156,157,168,170,172,194], indirect tool wear estimation [66,68,96,97,99,100,102,103,123,136,139] and chatter identification [163,165,169]) and data acquisition methods (i.e., laser-speckle pattern and general machined surface images).

4.1. Machined surface quality evaluation

Satisfying surface quality is always of great importance for the functionality of machined parts and this leads to the rapid development of surface quality monitoring in the past two decades. Fig. 10 illustrates the development history and statistics of machined surface quality evaluation. In most cases, due to the process-dependent nature of the surface formation mechanism and uncertainty from evolving machining parameters, surface quality evaluation (SQE) systems based on accurate physical modeling of the machining are more costly and less competitive than data-driven methods [69]. In the domain of data-driven SQE methods, early studies studied the basic problems of texture formation [40,198], texture measurement [173,174], texture analysis [175] and feature extraction [176] from the machined surface. Early study also reported the correlation between surface topography and roughness measurement [22]. With the stimulations of chip manufacturing and advances in image processing, machine vision is widely used in various machining process monitoring applications. The recent two decades studies explore the monitoring and metrology tasks of emerging in-situ additive manufacturing [90]. In-process ultra-precision machining surface quality measurement is also studied [195].

4.1.1. Surface finish evaluation

The diversified metallic properties significantly impact the mechanical strength, wear-resistance and machinability of the workpiece. Many of these properties are always directly related to the machined surface finish level, which heavily depends on the setting of manufacturing parameters and the selection of machine tools. Hence, the measurement of the machined surface is an inevitable problem concerned by many researchers.

In traditional CNC machining processes, the machined surface quality is always determined by an off-line operation using mechanical stylus profilers [21]. For the quality characteristics of machined surfaces (e.g., surface roughness), it is difficult to satisfy the technical specifications with a simple one-step operation [79]. Besides, the daily preliminary judgment for machine tool health management is often based on empirical rules and periodic inspection considering the total machining time or the noise of the processing process with manual observation [80]. Compared to the stylus-based measurements, machine vision-based roughness evaluations are capable of accomplishing tasks with higher speed and trace cone-like irregularities without torching or scratching the surface. Moreover, machine vision approaches are more convenient and have better inspection consistency than manual inspection approaches based on experience, expertise and conventions.

According to standard ISO 8688 [186], surface topography can be characterized by geometric parameters, including Ra (i.e., the average of the set of independent measurements of a surfaces' peaks and valleys), Rmax (i.e., the maximum height roughness), etc. However, considering the nonstationary and multi-scaled characteristics [192,193], these parameters are not sufficient descriptors for the tasks of quality inspection of the machined surface finish. In the past decades, many works focusing on vision-based finish control were reported. In 1998, Tsai et al. presented an automated surface roughness classification method based on the machined surface images from the two-dimensional Fourier transform [106]. In 2002, Josso et al. presented a frequency normalized wavelet transform for surface roughness analysis and characterization [120]. In 2004, Gadelmawla et al. presented a surface roughness evaluation method based on a new parameter called the maximum width of the matrix and gray level co-occurrence matrix [107]. In 2005, Niola et al. proposed a roughness feature extraction method based on the discrete wavelet transform for 3D reconstruction and roughness evaluation [105]. In the same year, Kumar et al. presented a surface roughness evaluation method using the regression analysis method and the linear edge crispening algorithm [111]. In 2007, using vision-based measurement and stylus-based measurement, Al-Kindi et al. compared the performance of intensity-topography compatible (ITC) model and light-diffuse (LD) model in terms of surface roughness evaluation. The comparison shows the superiority of the vision-based method both in data processing and accuracy [73]. In 2008, Al-Kindi et al. further presented a surface roughness evaluation method both in micro- and nano-scale using data filtering, cavity graphs, and autocorrelation techniques [70]. Another study in 2008 presented a feasibility assessment, which compared the vision-based surface roughness parameters with stylus-based measured data. Their results show that the vision-based method is a cost-effective technique within a certain limit of accuracy [81]. Lee et al. presented an accurate estimation method of surface roughness based on texture features using an adaptive neuro-fuzzy system [108]. In 2009, Hu et al. presented an evaluation of three–dimensional (3D) surface roughness parameters based on digital image processing using stereo-microscope and digital camera, in which normalized cross-correlation and surface fitting method are adopted for the final roughness evaluation [118]. In ISO 25178–2 (2012), 3D surface characterization parameters are discussed, and new parameters are defined while retaining the old SQE index [185].

Recently, some researchers also studied the roughness evaluation method based on the analysis of laser speckle pattern, which can provide both micrometer and nanometer level surface properties evaluation. In 2016, Townsend et al. [171] systematically reviewed the application of morphology analysis of machined surface texture in the monitoring of metal-additive manufacturing. Fischer et al. [12] presented in-process roughness quality inspection for metal sheet rolling using a speckle-based measurement method with optical scattered light measurement techniques. Patzelt et al. [24] further studied the uncertainty of laser-based measurement. It's reported that through the machine vision based inspection system of cutters' marks detection based on statistical texture analysis, the roughness quality of the polishing process can be recognized with Ra of 0.12 um [155].

However, some researches indicated that it is costly and impractical to create speckle patterns for on-machine inspection, especially for applications with limited equipment installation environments [6,153]. As a quality control step, usually after the machining procedures to assure specific machinery functional performance. The disturbance factors from the machining process are nonnegligible in high-precision roughness evaluation. In the cases of on-site roughness measurement at the micro and nano level, accuracy is often constrained by the limits of the physical principles behind the instrumentation. That includes microsecond-level exposure techniques with high resolution, limited light imaging [12] and motion blur for microscopic imaging [24].

As sketched by Appendix A (Table 5), notable efforts can also be found for in-process quality monitoring based on time-series analysis in metal-cutting operations, where correlations between the surface roughness and the indirect measurements (e.g., sound characteristics [235,236], vibration features [238,239]) are established. Several types of roughness levels of product can be identified in a specific working condition. The measurements based on vibration signal achieved mean relative errors within 15%. It can be seen that recognition rates of many techniques based on time-series analysis are not competitive compared to vision-based methods. The CNN method and the GLCM-based method have been validated that can achieve the best accuracy of around 80%-90% compared with the stylus-based profilometer in milling and turning operations. In brief, compared with the in-process indirect monitoring techniques, the vision-based technique possesses a more intuitive measurement principle, and clearer uncertainty analysis can be established.

4.1.2. Surface defect inspection

Most surface defect inspection technologies are developed to improve product consistency and facilitate detection efficiency, which may progressively substitute or partially replace manual inspection in traditional manufacturing lines. Representative defect detection scenarios include hot-rolling [19] and cold-rolling [82], additive manufacturing (e.g., welding, laser cladding [36]) and some metal-cutting machining operations (e.g., grinding, polishing [245]).

Previous studies on surface defect inspection mainly adopt vision-based techniques. As a typical type of vision-based technique, defect inspection based on the texture analysis has been applied to various metallic machined surface monitoring processes. In 2006, Zhang et al. [61] collected images with surface defects on work-pieces after grinding and polishing through a designed machine vision system and conducted a preliminary defect classification test on the production line. In 2008, Xie et al. [84] reviewed the surface defect inspection on texture analysis focusing on the defecting detection based on local textural irregularities, whereas other defects appearing in the form of deviation of color or texture were not well-addressed. In 2012, Saini et al. [224] reviewed the effects of cutting parameters on surface roughness, tool wear and residual stress distribution during hard turning. In 2014, Tapia et al. [89] reviewed the monitoring of metal-additive manufacturing processes in the aerospace and industrial fields, focusing on analyzing the continuous monitoring process of the molten pool based on industrial cameras and thermal imagers. Neogi et al. [83] surveyed the steel surface defect detection and classification techniques, which covered all aspects of machined steel surface type (e.g., cold steel strip, hot strips, bars, rods). In 2016, Everton et al. [90] reviewed the machine vision methods in laser additive manufacturing processes, where investigation specifically focused on the process of on-line testing and in-situ defect monitoring related to powder bed melting molding and directional energy deposition. In the same year, Luo et al. [153] studied the modularization and equipment cost reduction of automatic steel defect detection equipment for rolling processing using an efficient in-situ computing platform based on the FPGA scheme.

A comparison of vision-based technique and other techniques is provided in Appendix A (Table 5). Different from the in-process

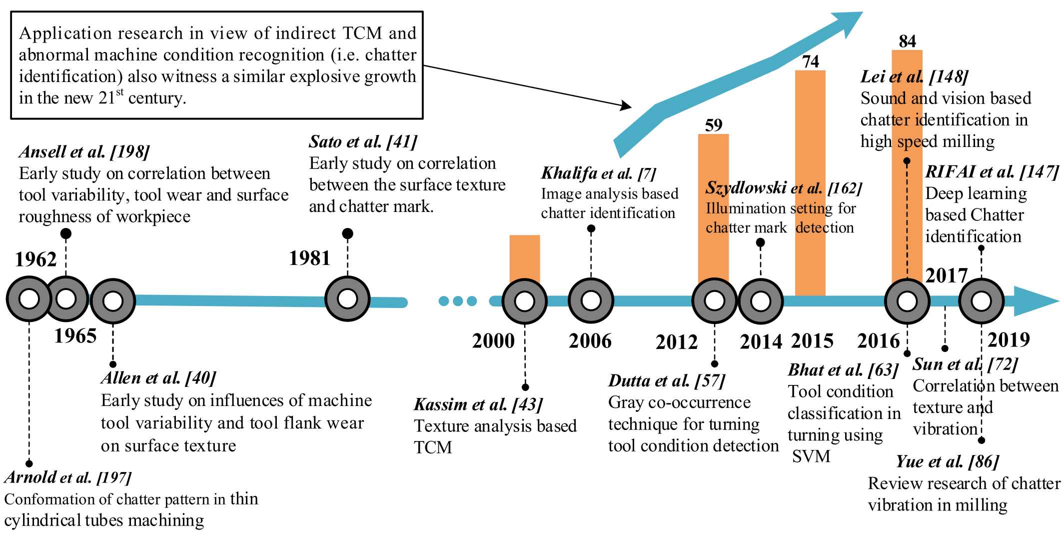


Fig. 11. Development history and statistics of TCM using machined surface texture.

condition monitoring applications (e.g., tool wear estimation and chatter identification), defect inspection tends to be defined as a post-process inspection task. Hence, there are usually no or limited disturbance factors from the machining processes (e.g., vibration from the metal-cutting process, interference from chips, cutting fluid, etc.). Hence, the machined surface usually can be easily accessed and checked by vision-based techniques in these cases. Compared with the indirect monitoring techniques based on time-series analysis, the machine vision method is clearer and more intuitive in characterizing defects. Several pieces of defect inspection literature [242] can be found employing analysis of the acoustic emission signal. Compared with the vision-based method, they provide a timely response but often get relatively vague results. Besides, they are difficult to quantify the defect type and size employing time-series analysis. It should be noted that denoising and dehazing algorithms are necessary for some on-site inspection cases to improve robustness. It is also reported that the influence from high temperature, dense mist and cooling water brings challenges in flat-steel manufacturing [82].

4.2. Indirect tool condition monitoring

On the other hand, many previous studies also indicated the potential mapping correlation between the texture of the machined surface and degradation or abnormal conditions of the parts of machine equipment (i.e., tool wear [55], chatter [147]) as well as machine parameters (e.g., feeding speed, cutting depth and speed [9]). Fig. 11 depicts the development history and statistics of tool condition monitoring (TCM) based on machined surface texture. The basic problem of texture analysis based TCM lies in the correlations of tool variability, tool wear, surface roughness and machined surface texture. Early studies on machine monitoring methods based on machine vision were designed to figure out these indirect mapping relationships and quantify them using the texture descriptors extracted from the machined surfaces. Studying such coupling relationship between tools and machined surfaces can further guide the analysis of the remaining useful life prediction and the maintenance strategy of machine tools [75–77]. Previous studies also suggest the correlation between chatter pattern and machined surface texture [41,197]. The development of image processing techniques and feature descriptors makes it possible to distinguish the occurrence of chatter problem according to machined surface texture [7]. The recent study also verified the coupling relationship between features of sound emissions, vibration and machined surface texture [72,148].

4.2.1. Tool wear monitoring

Tool failures (e.g., excessive wear, breakage of the cutting tool edge) accounts for 7%-20% of total machine downtime directly or indirectly [140]. Dull or damaged cutting tools also put extra scratches and strain on the machined parts, which in turn affect the surface finish. The degradation of machine tools (e.g., crater wear, flank wear, fracture wear) and chatter vibration are among the influencing factors for surface roughness quality [78]. To reduce the downtime rate in machining processes, reliable prediction of tool wear is essential in ensuring a maximized tool life above the safety threshold and guaranteeing the machining surface finish [98]. According to the international standard ISO 8688-2 [187], wear measurements require tools being removed from spindles and using micro-measuring equipment to measure the tool edge wear, which is an off-line manner. However, repeated disassembly and installation processes not only lower the production efficiency but also make it difficult to control installation errors. Hence, indirect tool condition evaluations using features extracted from the machined surface become a potential technique to properly address the problem. It should be noted that, in early studies, many studies of TCM are based on the analysis of cutting force signals, acoustic emission signals, vibration signals and tool temperature [196]. Due to recent progress in image processing and chip technology, CBM methods for cutting tools based on texture analysis are developed as one cost-effective method for indirect TCM. These techniques use machined surface texture as the guidance for maintenance plan adjustment and decision-making. In 2000, Mannan et al. [112] proposed a *meta*-cutting TCM system based on texture analysis of machined surfaces and sound generated by the metal removal processes. In 2004, Kassim et al. [115] presented a connectivity oriented fast Hough transform for tool wear monitoring, which detects all line segments in binary edge images of machined surfaces. In 2005, Kang et al. [119] researched fractal analysis for in-process tool wear monitoring from machined surfaces. In 2008, Elango et al. [11] researched the effect of lighting conditions in surface roughness evaluation by machine vision. The work also discussed the influence caused by the grazing angle, the distance between specimen and light, and the orientation of the image striations. Galdenmawla et al. [121] studied a machine vision-based cutting tool condition prediction model, which is based on the gray level co-occurrence matrix features in milling and achieves the prediction error of 10.6%. In 2012, Dutta et al. [57] presented a TCM system using a gray level co-occurrence matrix to extract features from the turned surface images, where the pixel pair space and offset parameters were optimized using power spectral density. In 2016, Bhat et al. [63] presented a SVM classification of machined surface images in turning using Gaussian and polynomial kernels with feature extracted from GLCM.

As a typical on-line and in-process monitoring scenario, many studies put effort on the time-series analysis method for tool wear monitoring. For instance, the AE signal can provide stress-energy information of the workpiece's plastic deformation, tear and chip-formation by elastic wave measurement [104]. Vibration [189] and cutting-force [159] signals can describe the changing of dynamic characteristics in the workpiece-cutter system. These in-process techniques provide a timely response to abnormal changes in machining processes, which ensures effective and real-time feedback of tool wear status and abnormal machining conditions. But time-series techniques also have some evitable shortcomings, including sensitivity to noise, deviation errors due to different installation. As

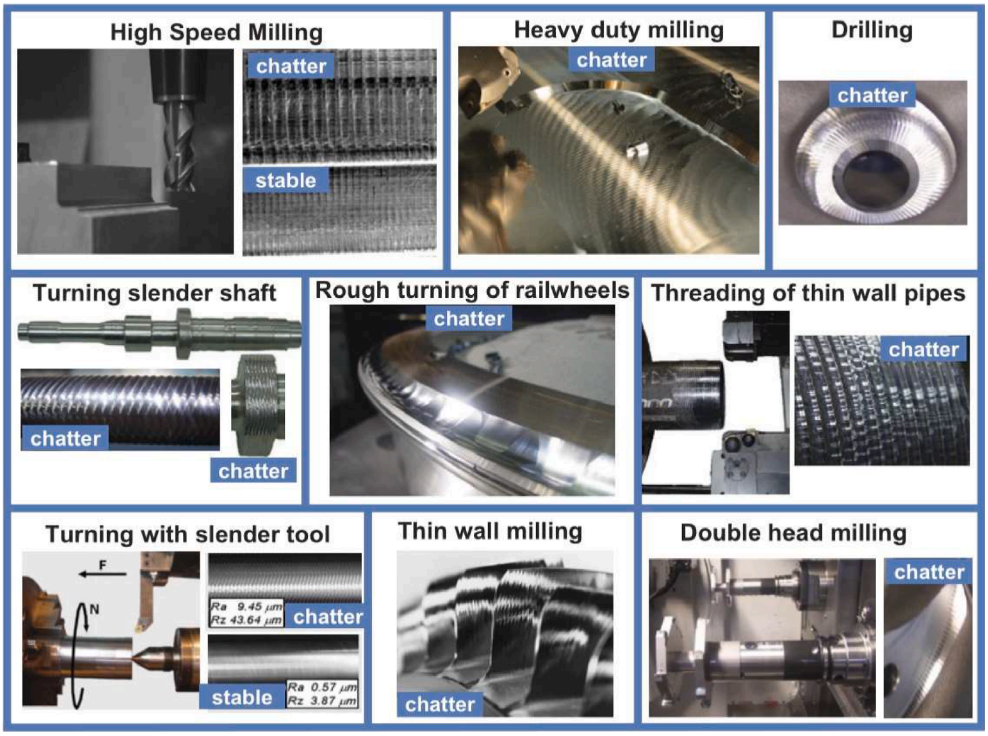


Fig. 12. Chatter problems in various machining applications [85].

a typical in-process monitoring scenario, machine vision methods often can only be adopted in an indirect and sparse sampling manner to control the impact on cutting processes, and therefore often lack descriptive information about the metal-cutting dynamics. However, note that vision-based measurement can not only judge tool wear status by analyzing the machined surface texture [53–55] but also indirectly reflect the machined surface quality [237]. Hence, it is possible to develop texture analysis algorithms with compound function (e.g., tool wear estimation, roughness evaluation). Besides, with the progress and promotion of photo-sensitive technology and market guidance on the mobile phone industry, machine vision systems are becoming popular in recent years because of their cost-effective hardware and technology advances in image processing and computer vision. In general, as an intuitive and cost-effective technique, vision-based measurement possesses strong potential in TCM applications. The techniques based on analysis of time series signals (e.g., acoustic emission, cutting force) also plays an irreplaceable role in revealing the changing of metal-cutting dynamics in nowadays TCM applications.

4.2.2. Chatter identification

Chatter vibration, also referred to as self-excited vibration, is caused by unsteady machining processes with improper cutting parameter settings [7]. Excessive vibration between the cutting tool and the workpiece brings about a poor surface finish and exacerbated tool wear [87], which reduces the reliability and remaining useful life of machine tools [65,91]. Some researches indicated that chatter is the main reason for poor surface finish [188,189] and one of the main limitations of the metal removal machining processes [79]. Fig. 12 shows the representative chatter problems in a series of metal-cutting machining operations, covering milling, turning, drilling, threading, etc. A distinctive cutter mark is formed according to the various operations and different working conditions. As a major limitation of productivity in the metal cutting process, it is of great importance to make early and reliable recognition of the excessive vibration. Then, the suppression technique can be accurately carried out. Munoa et al. [85] remarked that chatter is an inevitable and persistent problem for the metal-cutting industry considering its developing trend for low friction guiding systems, lightweight designs, and unpredictable damping behaviors. The occurrence of chatter on machine tools not only limits manufacturing productivity but also prevents from obtaining a satisfying machined surface finish, especially for manufacturers involved with complex and high-dimensional curved surface parts (i.e., aerospace and automotive sectors). Hence, it is of great importance to make an early and reliable recognition and further suppression for this undesirable vibration state.

According to a review report from Yue et al. [86], previous studies prefer using time series signals for chatter identification problems. As another typical in-process monitoring scenario, generally, there're three representative types of chatter recognition methods employing time series signals, covering force measurement, acceleration or placement measurement and sound

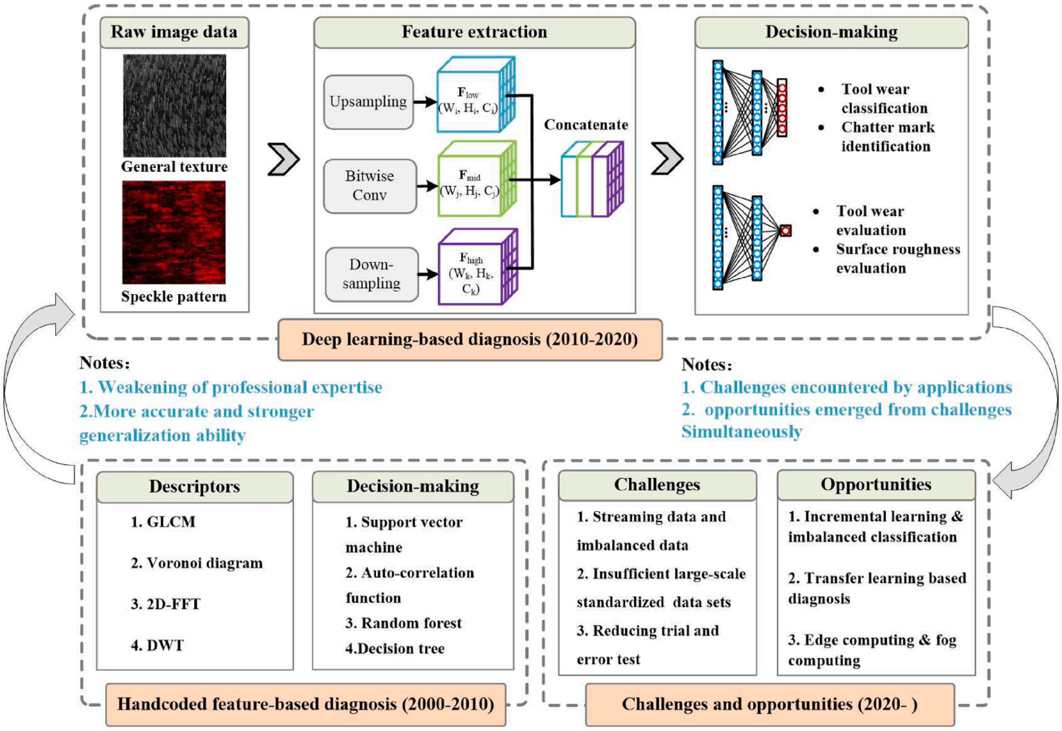


Fig. 13. Development, challenges, and opportunities in recent decades.

measurement. The characteristics and limitations of these measurement techniques are summarized as follows. Force measurement is capable of recognizing chatter problems in the machining process with relatively low or median level frequency sampling, but it faces challenges encountered by the limited bandwidth for high-speed machining scenarios [86]. Acceleration or displacement measurement possesses a high-frequency operation range. However, these vibration measurements may not adequately reflect the chatter problem in scenarios with excessive noise and other disturbance factors [240]. Sound measurement also suffers extraneous noise problems resulted from direction consideration during installation, enclosure of workspace, etc. [241]. It is worth mentioning that some researchers also studied the vision-based methods regarding this issue. In 2011, Bamberger et al. [190] studied the detection of vibration blade pattern of ring parts by using a circle fitting and gray co-incidence matrix method. In this method, it is necessary for the manufacturer to establish a reasonable detection threshold to realize the quality control process. In 2012, Szydlowski et al. [161] proposed an experimental study on SQE based on the error graph method of the machine vision system to recognize whether chatter occurred or not. In 2014, Szydlowski et al. [162] further proposed a light source design method for machine vision systems. An in-situ chatter detection system was designed and tested in the milling operation, where the texture image was analyzed by spatial wavelet transform. However, this research did not mention the specific setup of the image processing computing platform and how the hardware was designed to be suitable for on-machine monitoring tasks for manufacturing equipment such as multi-axis machining centers. In 2015, Stepan et al. [143] presented a numerical simulation of the machined surface corresponding to no vibration, forced and self-excited vibration. Singh et al. [164] analyzed the machine vision-based chatter detection of high-speed micro-milling processes and designed an experiment for chattering identification in high-speed milling of titanium alloys. In 2017, Lei et al. [148] studied the detection of chatter caused tool pattern and proposed a frequency recognition method of chatter vibration based on texture analysis and digital image processing. The relationship of frequency spectrum between frequency of tool passing, sound frequency and spatial frequency of machined surface texture are analyzed.

In brief, the direct analysis and recognition of chatter marks on the machined surface is intuitive and accurate. This advantage prompts studies of chatter recognition employing machine vision methods. However, as an in-process monitoring scenario, metal chips and cutting fluid put an obstacle to the further application of machine vision methods. Compared with cutting force and other time-series signals, it has an evitable time delay for chatter detection. Besides, intermittent and discrete sampling is usually adopted where the information of metal-cutting process is absent. In-process and on-machine machine vision methods with continuous sampling still need further exploration.

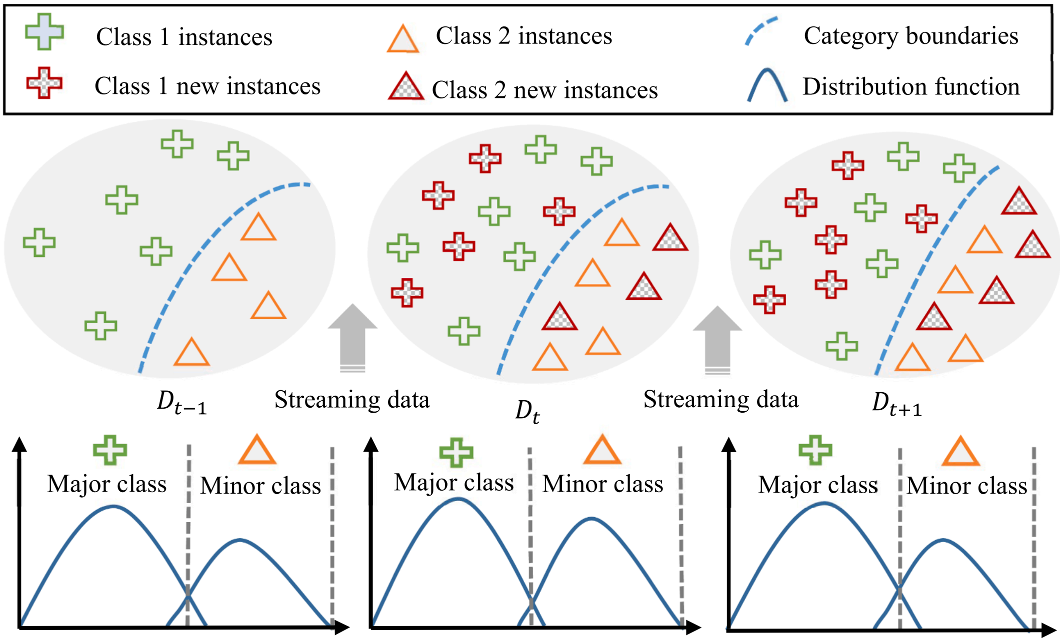


Fig. 14. Deep learning from streaming data and imbalanced data.

5. Challenges and opportunities

Despite tremendous advancements achieved in the field of MVCMFD-MTs, new challenges arise at the same time. Considering the availability of vast amounts of raw data collected from intelligent monitoring systems, data-driven diagnosis becomes a progressive research field for technique refinement. Fig. 13 illustrates the recent development of diagnostic methodology in the past two decades. Recent international PHM competition results [180] and natural scene classification tasks [9,231] indicate that, for today's super vast and standard datasets, most of the well-trained deep learning-based (DL-based) methods can achieve an end to end and automatic monitoring or diagnosis function, which is more accurate and robust than shallow feature-based (SF-based) methods. The designed stacked deep learning layers (e.g., up-sampling, down-sampling) can progressively extract and learn sensitive features from the raw image data (e.g., machined surface texture, laser speckle pattern) and automatically compute the final decision-making results (e.g., tool wear classification, chatter recognition). Hence, the obstacles of prior expertise in designing the SF-based method are surmounted. Besides, it is reported that when the data-scale expands to a certain extent, SF-based methods become too sensitive to disturbance factors, and parameter setting often requires a lot of trial-and-error tests [212]. However, it should not be neglected that traditional SF-based methods (e.g., SVM [52], RF [101]) based on hand-coded feature descriptors (e.g., GLCM [4], VT [55]) still account for a large percentage of manufacturing applications. The data accumulation process in the early stage of the industrial big data era makes many industrial applications still rely heavily on algorithms designed by SF-based methods. These methods are capable of achieving real-time and relatively stable detection performance in scenarios with limited data, where the DL-based methods are often hard to converge to a satisfying result. However, due to their relatively weak nonlinear representation capability compared with the DL-based method, the SF-based methods do not perform well enough in scenarios where a high-quality, large-scale dataset has been established. It should be noticed that few-shot learning [201], incremental zero-shot learning [202], edge computing, and deep transfer learning [226] methods have made some significant progress in image retrieval and classification and some diagnostic domains, but they still have a long way to go in real-world industrial applications due to accuracy, efficiency and robustness issues resulting from imbalanced data, limited annotated data and trial and errors.

The concept of industry 4.0, identified as the fourth revolution in manufacturing industries, introduces a new paradigm of autonomous and decentralized control of manufacturing processes [205]. In retrospect of the recent industrial transition towards automated and intelligent manufacturing, several aspects of challenges and potential research directions in machined surface-based MVCMFD-MTs will be discussed in the following section.

5.1. Deep learning with stream data and imbalanced data

Compared with traditional hand-coded feature extraction methods, deep learning-based (DL-based) methods for general tasks including image retrieval, recognition, and classification achieved great success on gigabyte-level datasets [9,231] in recent years.

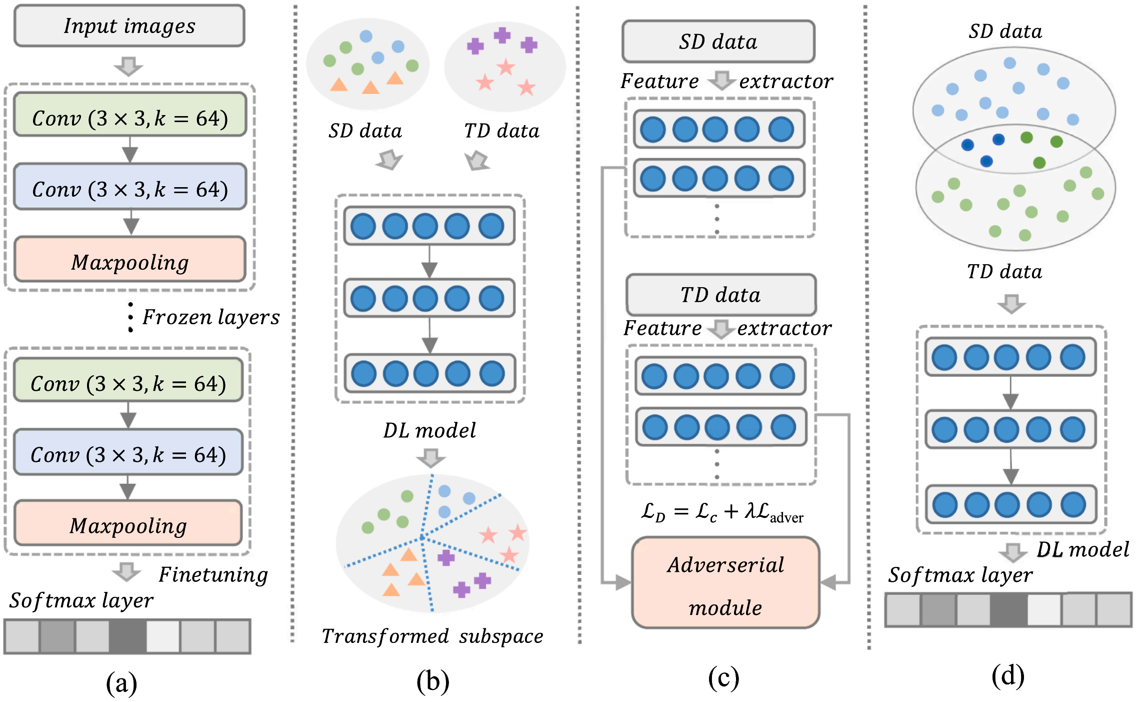


Fig. 15. An illustration of four representative DTL methods. (a) Network-based DTL. (b) Mapping-based DTL. (c) Adversarial-based DTL. (d) Instance-based DTL.

Many researchers carried out researches on DL-based monitoring methods for MVCMFD-MTs tasks. In 2017, Kurek et al. [146] presented work on drill condition assessment using DCNN methods. In 2018, Lee at al. [141] studied the region-based DCNN method for metal surface defect inspection. RIFAI et al. [147] presented a DL-based surface roughness evaluation and chatter identification, where limited contribution was addressed for data acquisition and validation procedures.

With these efforts, robust and accurate monitoring in machining manufacturing should be carried out under the premise of large-scale data collection. However, in real applications, standardized and large-scale datasets are rare [200]. Low-quality data (i.e., imbalanced data [206], distribution fluctuation [212]) is an inevitable problem in the early stage of the industrial big data era and a practical issue that many manufacturing cases face at present. Furthermore, the quantity of abnormal condition or degradation patterns is scant due to the high mechanical equipment reliability. Those minority samples are of much more interest while the majority are with low information about degradation or faults. He et al. [217] firstly addressed this potential problem in a review regarding imbalanced classification. Fig. 14 shows the streaming data with highly-skewed class distribution [208] and distribution characteristic fluctuation caused by flowing of new instances [209], where a two-classes classification problem abstracted from the real manufacturing scenarios is presented, where the cross pattern represents the instances in class 1, and the triangle pattern denotes the instances in class 2. From D_{t-1} to D_{t+1}, the streaming data from on-line monitoring scenarios continuously imported into the database, which results in a fluctuation of data characteristics and skewness of the class distribution. How to perform appropriate offline analysis and on-line monitoring to streaming data from both history database and real-time monitoring devices becomes a pivotal issue, especially for unmanned intelligent manufacturing processes [218].

5.2. Deep transfer learning with limited labeled data

Deep transfer learning (DTL) was first introduced to accelerate the convergence of deep neural networks (DNNs) [222]. To some extent, it also improves model generalization ability. Here, the domain refers to the corresponding data space. Industrial data collection always experiences varying working conditions or environments, which leads to limited availability of well-annotated data from the target domain [227]. So, in most cases, the majority of training data is collected in laboratory platforms with a specific range of working load and parameter setting (the source domain). However, the legacy training of DNNs is based on the assumption that the data from both the target domain and the source domain are independent and identically distributed (IID) [228]. Many practical applications do not strictly obey this assumption [182]. To this end, the DNNs trained by these laboratorial data suffer accuracy decline when they are performed in real industrial applications. DTL relaxes this basic assumptions, by transferring the prior knowledge in the source domain to solve training problem of DL-based diagnostic applications (the target domain), where data is little or unlabeled [93]. Specifically, DTL mainly contributes to two problems.

1) Trial-and-error tests in real applications is costly. DTL utilizes partial information from the source domain (i.e., laboratory data) to train DNNs, which means that the models do not need to be trained from scratch. Because fewer parameters need to be trained, DTL converges faster than DNN models trained by the legacy way.
2) DTL also significantly reduces the data required in real applications. It is challenging to construct well-labeled large-scale dataset in many target domains due to costly manual-annotation and time-consuming on-machine experiments [230]. For this reason, the traditional training way of DNNs is insufficient for the actual applications because it follows the assumption: target domain and source domain are IID. In contrast, DTL relaxes the assumption with some techniques to resist the domain discrepancy [179]. Therefore, the data collected by the laboratory environment can better support practical applications.

According to the deployed specific techniques, DTL can be classified into four categories as shown in Fig. 15, including instance-based DTL, mapping-based DTL, network-based DTL and adversarial-based DTL [226]. Fig. 15(a) depicts an example of network-based DTL. It reuses a partial network that is trained in advance by the data from the source domain (SD data), covering network structure and weights. The non-transferred part and the final output layer (e.g., Softmax layer) of DNNs are similar to the general ones. Then, a further fine-tuning process is conducted using the data from the target domain (TD data) with the frozen layers (i.e., fixed trained weights). As shown in Fig. 15(b), the dot pattern and triangle pattern denote the SD data, while the cross pattern and star pattern signifies the TD data. Mapping-based DTL maps instances from both the source domain and the target domain to a new transformed subspace, where instances from two domains shares a joint probability distribution and independent. As illustrated by Fig. 15(c), adversarial-based DTL introduces joint loss function L_d derived from generative adversarial network (GAN [232]), where the training process optimizes both the domain adversarial loss L_{adver} and the loss for final decision-making L_c [179] to improve the generalization ability of the features extracted from SD and TD data. Instance-based DTL selects partial instances from the source domain to supplement the training set in the target domain [219]. But appropriate weights should be assigned to those instances from the source domain. As illustrated in Fig. 15(d), compared to other shallow color ones in the source domain data, the dark blue instances have a more similar distribution with the target domain data. Therefore, they are selected to train DNNs along with the target domain data in a weighted form.

Although transfer learning has been widely studied in fault diagnosis using time series signals [233,234] (e.g., vibration, cutting force), it is still rarely mentioned in the field of machined surface based MVCMFD-MTs. Most of the existing researches of MVCMFD-MTs focus on network-based DTL. For instance, Lee et al. [141] compared the region-based DCNN for defect detection in the metal surface, where the DNNs for object detection are trained in advance by some super-large datasets [231]. Kurek et al. [142] studied the DCNN-based classification of the drilling tool status using ImageNet data [178] for pretraining DNNs. Future research can also explore other existing DTL methods (i.e., instance-based DTL, mapping-based DTL and adversarial-based DTL).

5.3. On-machine diagnostic methods from laboratories to applications

Since the early 1960 s, the studies of visual test bench design, the feasibility analysis of MVCMFD-MTs [67], the development of descriptors, and the decision-making (e.g., fault classification, roughness and tool wear regression) have made unprecedented progress in terms of accuracy and robustness. However, today's transition in automated production towards smart manufacturing requires monitoring systems to be accurate and efficient [166], along with cost-effective on-machine test [203]. Traditional hand-coded feature-based methods need time-consuming trial-and-error tests in parameter settings to satisfy diagnosis requirements in real applications [212]. Meanwhile, supervised DL-based methods also require a large standardized annotated dataset for training before they can be used for diagnosis tasks. How to apply these algorithms to modern automatic machining manufacturers becomes an urgent problem.

The edge computing (EC) platform can be a potential solution to efficiently support building standardized large-scale dataset considering the possible constraint installation space in real diagnosis scenarios and bandwidth costs for cloud computing. The EC technique, which is capable of processing the data at the edge of the network, is an emerging computing scheme attributes to the proliferation of the industrial Internet of things (IIoT) and the prosperity of cloud service communities [39]. During the transition from labor-intensive manufacturing to unmanned automatic production, many traditional metal-cutting manufacturers deploy massive sensors on production facilities for TCM [140]. With this coming to a vast amount of raw monitoring data to be processed [210]. It poses a huge challenge to the efficiency of data transmission and processing in nowadays automated manufacturing factories [211]. EC-based [39] monitoring systems may solve this problem by the capability of local computing capability. According to the international society of automation standard 95 (ISA-95 [213]), the legacy industrial automation systems can be classified into a five-level reference architecture, where levels 0, 1 and 2 focus on automation control and monitoring. With advances and cost reduction of on-board central process units, storage and communication, self-management capability including self-discovery, self-learning and self-optimization can be achieved at the device level. That means devices including sensor, programmable logic controller (PLC) and

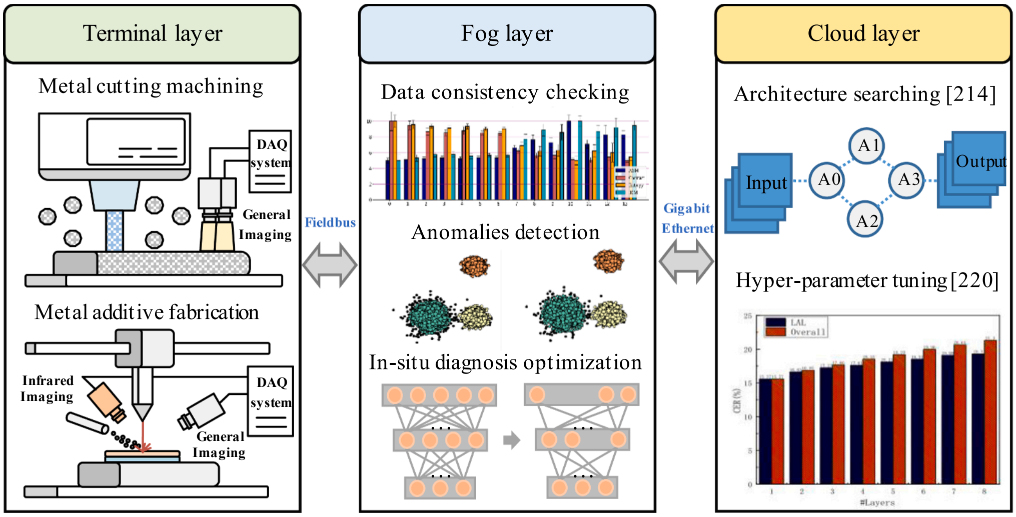


Fig. 16. A schematic framework of fog computing based cyber manufacturing system.

human–machine interface (HMI) in the device layer can be armed with more powerful data processing and analysis capability to serve nowadays intelligent manufacturing processes. In the past five years, edge computing techniques were employed in a variety of industrial applications [213]. The local and in-situ computing capability not only caters to the data privacy requirement, but also solves the communication delay problem in industrial monitoring [39]. Besides, edge computing devices have the potential to address the concerns of response time requirement and bandwidth cost for communication devices in automated factories.

Fog computing (FC) is another platform derived from the scheme of cloud computing and edge computing. FC retains the local computing capability and data privacy protection of edge computing in the industrial field environment equipment layer. Meanwhile, FC emphasizes efficient information interaction between the diagnosis systems from factories and the cloud server layer that possesses powerful computing and storage capacity. The concept of FC was first proposed by Stolfo et al. [215], considering the potential risk and defense strategy optimization in cloud computing systems. It is further applied to smart grids, traffic control [216] and machining process monitoring [204] in recent years. FC is designed considering the following reasons:

1) Sensors produce gigabytes of stream raw data by monitoring machining operation in a real-time manner [218]. Without effective processing and analyzing techniques, many data that may pertain to important feature information are discarded due to insufficient data storage capability [209]. Hence, effective and reasonable utilization of industrial monitoring data requires efficient data acquisition, checking and analysis methods to improve the efficiency of information and feature extraction from raw monitoring data [207].

2) Besides utilizing advances in local computing capability, FC [204] also emphasized the interaction efficiency between the device layer and the cloud layer based on low latency network communication (i.e., the Gigabit Ethernet, the high-speed LAN). The FC layer acts as a middle role for local computing to address communication delay and security requirements [39]. In this case, raw data is processed and converted to structured data before it is uploaded to the cloud server layer, which lowers the high load demands on computing resources and storage. These interconnected things enhance the cooperation among edge nodes, industrial clouds and operators from the perspective of agile connectivity, real-time monitoring, control and smart decision-making [223].

Fig. 16 depicts a schematic framework of an FC-based cyber manufacturing system. In the terminal layer, massive sensors in applications of MVCMFD-MTs (i.e., CMOS / CCD camera, infrared camera) provide continuous and abundant data, which is also referred to as the streaming data. The large volumes of streaming data collected by data acquisition systems (DAQ systems) from the automation production industries (i.e., metal cutting machining, metal additive fabrication) are then uploaded to a local fog layer and then further saved to the remote public cloud after consistency checking, anomalies detection and in-situ diagnosis procedures. The Fog computing layer serves as a preliminary role of data processing, which can minimize the pressure of real-time communication and consumption of computing resource brought by massive data pouring into the cloud layer. The cloud layer plays an important role for tasks with high computational requirements (e.g., neural architecture searching [214] and hyper-parameter tuning of DNNs [220]).

6. Concluding remarks

This paper reviews the development of MVCMFD-MTs focused on methods that learn degradation information or fault patterns from machined surface texture. The paper follows four procedures: data acquisition and standardized datasets, feature descriptors and decision-making, applications, challenges and opportunities. The concluding remarks are listed as follows:

1. Two representative data acquisition setups (i.e., general texture acquisition, laser speckle pattern acquisition) are revisited. Several institutional surface texture datasets are discussed, including DAGM dataset, NEU surface dataset and two metal-additive manufacturing datasets.
2. The development and statistics of descriptors for feature extraction, methods for diagnostic function realization (i.e., regression, and classification) are provided with two major application aspects: surface quality evaluation and indirect tool condition monitoring.
3. The surface quality monitoring is further addressed by two major sub-sections (i.e., surface roughness evaluation and surface defect inspection), while the indirect tool condition monitoring further derives two sub-sections (i.e., indirect tool wear monitoring, chatter identification).
4. Challenges and opportunities are illustrated in the following three aspects.
5. Emerging deep learning methods and current transition processes towards intelligent manufacturing brings new challenges and opportunities, which are mainly discussed from two aspects, streaming data processing and imbalanced classification.
6. Considering the lack of standardized datasets in the early stage of the industrial big data era, transfer learning-based method is a potential solution where labeled data are insufficient. The role and function of transfer learning, along with its representative categories, are discussed.
7. The increasing upgrading speed of products in modern industries results in an emphasis of short cycle-based manufacturing with fast response capability. The trial-and-error tests of on-machine monitoring equipment have a great impact on productivity. How to reduce such responsive time for parameter setting of in-situ MVCMFD-MTs becomes an urgent issue currently. Specifically, edge computing-based and fog computing-based platform of on-machine data acquisition, validation and diagnosis are discussed.
8. As shown in Appendix A (Table 5), the comparison between the vision-based techniques and other representative techniques is summarized employing several metrics (e.g., accuracy, effectiveness and applicability) according to the four scenarios discussed in Sect. 4.1 and Sect. 4.2. The sensors' type and resolution are also provided to improve readability and comparability.

In brief, application scenarios can be divided into two major categories: demand for in-process and on-line applicability. For monitoring scenarios that tend to be defined as in-process applications (e.g., tool wear monitoring, chatter identification), vision-based techniques are often used as a post-process monitoring method for discrete monitoring and diagnosis. Therefore, it often lacks process dynamic characteristics information and cannot give a timely response. Of course, the visual method can still provide intuitive detection results with relatively high accuracy, while for the analysis based on other sensors time-series signal, algorithm design is often more complicated because of the varied working conditions and harmonic noise. For monitoring scenarios that tend to be defined as general on-line applications (e.g., surface finish evaluation, surface defect inspection), vision-based techniques possess stronger and broader application possibilities. These scenarios often provide vibration-free and stain-free installation conditions. Thus, a high-performance monitoring model can be constructed through accurate texture analysis of high-resolution images.

CRediT authorship contribution statement

Yuekai Liu: Methodology, Conceptualization, Investigation, Visualization, Writing - original draft. **Liang Guo:** Conceptualization, Project administration, Funding acquisition. **Hongli Gao:** Resources, Supervision, Funding acquisition. **Zhichao You:** Resources, Investigation. **Yunguang Ye:** Resources, Writing - review & editing. **Bin Zhang:** Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Table 5
The comparison between vision-based techniques and the other techniques in the four scenarios.

Scenarios	Technique type	Sensor (resolution)	Accuracy	Effectiveness	Applicability
Surface finish evaluation	Vision-based techniques	CCD (768 × 576 pixels)	Standard deviation ratio of $R_a(1.14\% - 23.8\%)$	$P_v : R_aR_qR_{tm}R_tR_vR_p$; $P_i : R_{sk}R_{sm}$	5 operations, with 20 specimens [81] (off-line)
		LSPI (2048 × 1088 $pixels, 8bits$)	$u_{stat}(Sa) = 0.22nm$ $u_{slow}(Sa) = 0.41nm$ $u_{fast}(Sa) = 0.45nm$	Static scenario $V_{slow} = 15.5m/min$ $V_{fast} = 87m/min$	Metal sheet rolling [12] (on-line)
		Live MOS (480 × 480pixels)	$A_{Ra} = 90.38\%$ $A_{Rz} = 90.97\%$ $A_{Rzj} = 87.27\%$	Varied cutting parameters and Ra ranges	Turning, slot milling [237] (Quick prediction)
	Other techniques	Microphone (44.1 kHz, 16bits)	Classification accuracy rate = 85.7% – 100%	$V_{cp} : 186 - 240m/min; V_{fr} : 0.10 - 0.23mm/rev$ $C_d : 0.10 - 0.23mm$	Hard turning [236] (on-line)
		Accelerometer (50 kHz)	$\bar{e}_{r1}(\%) = 14.42\%$ $\bar{e}_{r2}(\%) = 14.62\%$	$PRED_1(0.25) = 90\%$ $PRED_2(0.25) = 91.1\%$	Cylinder turning [238,239] (on-line)
Surface defect inspection	Vision-based techniques	CCD $D_r : 1024 \times 1024pixels$	Average recognition accuracy: 98.93%	$V_{rs} : 3 - 18m/s$ $W_{ss} = 1580 - 2160mm$ $T_s : 500 - 700℃$	Rolling defect with noise [33] (on-line)
		CMOS ($640 \times 480pixels24bits$)	Accuracy: regions (84.9%) edges (78.2%) Standard errors: regions (3.1%) edges (2.3%)	Brittle area proportion: 30%-81.1%; Cutting depth: 0.1–5.1 um	Optical glass grinding [31] (on-line)
		CMOS 4096 pixels /70 kHz	CRR = 92.11% FPR = 7.89% FR = 5.54%	$V_{rs} : 0.5 - 20m/sW_{ss} : 450 - 1800mm$ $DS_{min} : 2.0 \times 2.0mm$	Rolling defect [153] (on-line)
		FPA (Focal plane array) ($32 \times 32pixels$)	Recall = 0.972; Fallout = 0.044 F1-Score = 0.974	405 tracks of laser cladding and 20 tracks of LMD	Laser process [36] (real-time)
		CCD ($1024 \times 428pixels$)	Overall accuracy:0.997 ± 0.001	Overheating; normal; irregularity; balling	Selective laser melting [160] (on-line)
	Other techniques	Acoustic emission (800 kHz); force and torque (10 kHz)	\	Independent of the number of teeth; Effective for both 3- and 5- axis machining	Multiple-teeth end milling [246,247] (on-line)
		Acoustic emission	Clustering accuracy: $C_d = 0.1mm : 74\%$ $C_d = 0.2mm : 72\%$	Varied cutting depth	Dry milling [242] (on-line)
Tool wear monitoring	Vision-based technique	CMOS (2048 × 1536 pixels)	Average correlation $94.8\% \pm 3.9\%$	Several combinations of cutting speed, depth and feed rate	End-milling [53] (off-line)
		CMOS (1024 × 768 pixels)	Average of correlation coefficients of features: 0.964,0.953,0937,0.989	Ten combinations of cutting speed, depth and feed rate	Semi-finish turning [3] (on-line)
	Other techniques	Acceleration sensor	Mean relative error = 9.2%	Feed rate = 0.15 mm/rev; Cutting speed = 200 m/min; Cutting depth = 2 mm	Tool RUL prediction [93] (on-line)
		Acoustic emission (1 MHz)	MAE = 0.6581 RMSE = 0.9333	Spindle speed = 200 rpm; feed rate = 15 mm/min	Slotting tool [243] (on-line)
Chatter identification	Vision-based technique	Live MOS (4608×3456 $pixels$)	Average error of turning < 2%; Average error of milling < 7.13%	4 machine tools with varied working condition	Turning and milling[147] (on-line)
		Camera ($96 \times 96pixels$)	Accuracy: 98.3%; MCC: 95.5%; F1-Score: 98.8%	\	Thin-walled milling[244] (on-line)
		Camera, LED ring light with polarizer	\	A 5-axis machining center of varied cutting parameters	High-speed milling[148] (off-line)
	Other techniques	Dynamometer (50000 Hz)	Capturing chatter using first 50 singular values within 11.7 s	Spindle speed:3000–9000 rpm; Cutting depth:1–3 mm; Feed rate:180–600 mm/min	Milling [94] (on-line)
		Current sensor (100 kHz) and acceleration sensor	Self-adaptive for non-stationary chatter signal & multi frequency band	Wheel speed: 2000, 4000 rpm; Feed rate: 0.03, 0.02, 0.12 mm	Grinding [245] (on-line)

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