Tool Wear Estimation using Support Vector Machines in Ball-nose End Milling

S. Huang, X. Li, and O. P. Gan

Singapore Institute of Manufacturing Technology, 71 Nanyang Drive, Singapore 638075
shuang@simtech.a-star.edu.sg
xli@simtech.a-star.edu.sg
opgan@simtech.a-star.edu.sg

ABSTRACT

This paper introduces a method to determine the tool wear by measured cutting force in Ball-nose End Milling. The features will be extracted from the measured cutting force with different flank wear. As the adaptive window width in wavelet transform is an advantage for analyzing and monitoring the rapid transient of small amplitude of cutting force signals when cutting engagement changes along the sculptured surface tool path, wavelet transform (WT) is more effective than FFT monitoring index for ball-nose end milling. In this research, cutting force signals will be analyzed in time-frequency domain to explore sensitive monitoring features in ball-nose end milling slope surfaces. As a supervised method, support vector machines (SVM) was developed for the classification problem to take advantage of prior knowledge of tool wear and construct a hyper-plane as the decision surface. In this paper, SVM will be formulated into regression problem to estimate tool wear rather than decision maker.*

1. INTRODUCTION

In mould and die production, the ball-nose end milling process is a critical machining operation due to the complex geometry of workpiece, high requirements on surface quality and high accuracy. On-line tool condition monitoring systems are required from industry to reduce production cost and improve product quality. According to ISO 8688-2, flank wear is the change in shape at tool flank, which is caused by the progressive loss of tool material during cutting. As there is no direct way to measure tool wear online, Artificial Intelligence (AI) techniques have to be adopted to estimate tool wear from cutting force signals measured during machining process. The method comprises data acquisition, signal processing, feature extraction, feature selection and tool wear estimation by regression method.

In order to estimate tool wear in milling applications, requirements for tool wear model are:

1) The model shows non-linear relations between the input features and tool wear.

2) Input of the model includes the cutting parameters such as spindle speed and feed rate.

In recent researches, neural network applications are proposed for decision making system to map the features (input) to tool wear level (output) by training via examples. Neural network approaches have been widely used in tool wear estimation because of their learning capability. Li et al. (2009) used a fuzzy neural network (FNN) approach to establish tool wear reference models in ball nose end milling process. Ghosh et al. (2007) developed a neural network-based sensor fusion model for tool wear estimation in face milling. Different features were extracted from RMS of cutting forces, spindle current, and spindle voltage. Zhou et al. (Zhou et al. 2009) proposed a recursive least squares (RLS) method to build a tool wear regressive model. They developed a dominant feature selection method to reduce feature space. In the work of Bhattacharyya et al. (2007), multiple linear regression (MLR) models were developed to estimate the tool wear in face milling process. They used different signal processing techniques to extract features from cutting force signals. Isotonic regression and exponential smoothing techniques are used to process the extracted features.

As a supervised method, support vector machines (SVM) was developed for the classification problem to take advantage of prior knowledge of tool wear and construct a hyper-plane as the decision surface (Sun et al., 2006). In recent publication, Cho et al. (2005) applied support vector machines for regression (SVR) to model the power and maximum cutting force in an end milling application. In their investigation, the SVR approach was better than multiple variable regression (MVR) approach. Dong et al. (2006) implemented two neural network methods to estimate tool wear in face milling applications. In their work a nonlinear regressive model is proposed to describe the dependence of flank wear (VB) on cutting force feature vector. They compared the performance of Bayesian multilayer perceptrons (BMLP) and Bayesian support vector machines for regression (BSVR), and found that BSVR method is more accurate than BMLP in estimating flank wear. So far, SVR for on-line tool wear estimation solutions in ball-nose end milling are still lacking. Therefore, in this paper, SVM will be explored to formulate into regression problem to estimate tool wear.

2. FEATURE EXTRACTION

Due to the complexity of the ball-nose end milling process, the cutting force signals may not indicate the cutting conditions directly. We need to process the cutting force signals to identify the tool condition. As tool-workpiece contacts in milling process have periodic nature, cutting forces can be analyzed and processed in frequency domain and time-frequency domain to find some reliable signal patterns indicating the tool states (Prickett and Johns, 1999). Since Fast Fourier Transform (FFT) needs a certain time window on the signal to fulfill the resolution of the frequencies in the power spectrum, it is only suitable for near constant engagement conditions.

To determine the tool wear by measured cutting forces, the feature will be extracted from the measured cutting forces with different flank wear. As the engagement condition of sculptured surface always changes, time-frequency monitoring index, such as wavelet transform (WT), is more effective than FFT monitoring index. Wavelet transformation requires smaller time window than FFT, but it can still analyze frequency pattern of the periodic cutting force signal. The adaptive window width in wavelet transform is an advantage for analyzing and monitoring the rapid transient of small amplitude of cutting force signal when cutting engagement changes along the sculptured surface tool path. In this research, cutting force signals will be analyzed in time-frequency domain to explore sensitive monitoring features in ball-nose end milling sculptured surfaces.

According to Mallat pyramidal algorithm (Hong et al., 1996), original signal f(x) can be decomposed to different frequency bands by discrete approximation component and discrete detail components. Wavelet analysis can be considered as a series of band pass filters. It extracts information from the original signal f(x) by decomposing it into a series of approximations A and details D distributed over different frequency bands. Given the sampling frequency fs, the frequency of the signal f(x) is 0.5 fs. The bandwidths of the approximation A and detail D at the level l are $\left[0, \frac{1}{2} f_s 2^{-l}\right]$ and $\left[\frac{1}{2} f_s 2^{-l}, \frac{1}{2} f_s 2^{-(l-1)}\right]$ respectively.

According to the observation by Choi et al. (2004), the approximations in wavelet coefficients will reflect tool wear in end milling process. After the signal is decomposed through wavelet transform, the signal energy is represented by the approximation coefficients. Therefore, the measured cutting forces can be processed through wavelet transform to obtain sensitive feature vectors using approximation coefficients.

Table 1: Features for tool wear estimation

Index	Definition
X1	Maximum Approximation Coefficients at X direction
X2	Maximum Approximation Coefficients at Y direction
X3	Maximum Approximation Coefficients at Z direction
X4	Average Approximation Coefficients at X direction
X5	Average Approximation Coefficients at Y direction
X6	Average Approximation Coefficients at Z direction
X7	Average Energy at X direction
X8	Average Energy at Y direction
X9	Average Energy at Z direction
X10	Feedrate
X11	Spindle speed

Since Daubechies wavelets perform well in separating the frequency bands during signal decomposition, they are selected for feature extraction in this research. The wavelet transformation on each data block was conducted using a Daubechies wavelet. The wavelet transformation was repeated two times to obtain the coefficients. The vector of wavelet approximations of the measured force signals are used for feature extraction. Three kinds of measurements are used in this work:

1) Maximum Approximation Coefficients.

2) Average Approximation Coefficients.
3) Average Energy of Approximation Coefficients.

For tool wear estimation, the cutting conditions such as the feed rate and spindle speed are also used as features related to tool wear. Table 1 shows the features that are used as inputs of SVR to monitor the tool wear. Among these features, feedrate and spindle speed are cutting conditions. The others are energy related features. These features have been evaluated by correlation coefficients. As cutting forces are measured in X, Y and Z direction, a total of eleven features are used to train and test the SVR model.

3. TOOL WEAR ESTIMATION USING SUPPORT VECTOR REGRESSION (SVR)

Support vector machines for regression (SVR) is based on statistical learning theory (Haykin 1999). As a supervised method, SVR takes advantage of prior knowledge and performs well for generalization. It also guarantees the local and global optimal solutions are exactly the same (Widodo and Yang 2007).

SVR is a good alternative to traditional multiple variable regression (MVR) approach. According to Cho et al. (2005), the SVR performs higher accuracy than MVR with a tight threshold value to tool breakage determination.

Compared with artificial neural networks (ANN), SVR has better generalization and high accuracy for a smaller number of samples. It also overcomes the over-parameterization and non-convergence problems (Bhattacharyya and Sanadhya 2006).

3.1 Theory of Support Vector Machines for Regression (SVR)

In this work a nonlinear regressive model is proposed to describe the dependence of flank wear (*VB*) on cutting force feature vector (**x**):

$$VB = f(\mathbf{x}) + v \qquad (1)$$

where v is noise term which is independent of feature vector **x**.

For a given set of training data $\{(\mathbf{x}_i, d_i)\}_{i=1}^{N}$, where $\mathbf{x}_i \in R^m$ is a sample value of the input feature vector x and di is the corresponding tool wear value in model output VB. Support vector machines for regression (SVR) is to provide an estimate of the dependence of VB on x:

$$VB_e = \sum_{j=0}^{m_1} w_j \varphi_j(\mathbf{x}) = \mathbf{w}^T \varphi(\mathbf{x}) \qquad (2)$$

where w is the weight vector, $\varphi(\mathbf{x})$ denotes a set of non-linear transformation from the input space into the feature space of dimension m_1.
The estimate is constructed to minimize the cost function:

$$\Phi(\mathbf{w}, \xi, \xi') = C(\sum_{i=1}^{N}(\xi_i + \xi_i')) + \frac{1}{2}\mathbf{w}^{\mathrm{T}}\mathbf{w} \quad (3)$$

Subject to the constraints:

$$d_i - \mathbf{w}^T \varphi(\mathbf{x}_i) \le \varepsilon + \xi_i, \qquad i = 1,2,\ldots,N$$

$$\mathbf{w}^T \varphi(\mathbf{x}_i) - d_i \ge \varepsilon + \xi_i', \qquad i = 1,2,\ldots,N$$

$$\xi_i \ge 0, \qquad i = 1,2,\ldots,N$$

$$\xi_i' \ge 0, \qquad i = 1,2,\ldots,N$$

where $\{\xi_i\}_{i=1}^{N}$ and $\{\xi_i'\}_{i=1}^{N}$ are two sets of slack variables. Using the method of Lagrange multipliers, we may now state the dual problem for nonlinear regression using a support vector machine as follows:

Given the training sample $\{(\mathbf{x}_i, d_i)\}_{i=1}^{N}$, find the Lagrange multipliers $\{\alpha_i\}_{i=1}^{N}$ and $\{\alpha_i'\}_{i=1}^{N}$ that maximize the objective function

$$Q(\alpha_i, \alpha_i') = \sum_{i=1}^{N} d_i(\alpha_i - \alpha_i') - \varepsilon \sum_{i=1}^{N}(\alpha_i + \alpha_i') - \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}(\alpha_i - \alpha_i')(\alpha_j - \alpha_j')K(\mathbf{x}_i, \mathbf{x}_j) \qquad (4)$$

subject to the following constraints:

1) $\sum_{i=1}^{N}(\alpha_i - \alpha_i') = 0$

2) $0 \le \alpha_i \le C, \qquad i = 1,2,\ldots,N$

$0 \le \alpha_i' \le C, \qquad i = 1,2,\ldots,N$

where C is a user-specified constant.

3.2 SVR Model Building

As a supervised method, support vector machines (SVM) will be formulated into regression problem to estimate tool wear rather than decision maker. In the training phase, training datasets are used to build SVR model for the estimation of the tool wear. Firstly, the training datasets are used to tune the model parameters by k-fold cross validation method. Secondly, the training datasets are used to obtain the weights of the estimation function by optimization algorithm. After the SVR model has been built, the regression accuracy can be tested by the test datasets.

In the objective function, the kernel function, $K(\mathbf{x}_i, \mathbf{x}_j)$, is to map the feature data from the original space into the high dimensional space. In this work, Gaussian kernel is chosen as the kernel function:

$$K(\mathbf{x}_i, \mathbf{x}_j) = \exp\left(-\frac{\left\| \mathbf{x}_i - \mathbf{x}_j \right\|^2}{2\sigma^2} \right) \tag{5}$$

According to (4) and (5), for different problem, the penalty parameter C, the error tolerance threshold ε and the value of σ from the kernel function have to be tuned to achieve good performance with SVR models. The optimum parameters for a given problem are found by grid search method using cross-validation. The prediction accuracies for cross-validation are compared in terms of the averaged absolute estimation error:

$$AAEE = \frac{\sum_{i=1}^{N} \left| d_i - \mathbf{w}^T \varphi(\mathbf{x}_i) \right|}{N} \tag{6}$$

The generalization error is estimated by using k-fold cross validation:

1) Divide the training data set into k subsets (the folds) randomly. The subsets are mutually exclusive approximately equal size.

2) Train the SVR using k-1 subsets.

3) Test the SVR using the remaining 1 subset and obtain the error.

4) Repeat (step 2 and 3) k times to ensure that each subset has been used to test SVR once.

5) Estimate the generalization error by averaging all the test errors over the k tests.

In this way, each data of the whole data set has been predicted once for calculating the generalization error. In this work, 5-fold cross-validation on the training set is used to find the optimum parameters.

4. RESULTS AND DISCUSSION

4.1 Experimental Set-up

Milling a slope surface is a representative experiment for analyzing the sensor signals in ball-nose end milling applications. The presented experiments (shown in Figure 1) will focus on milling a slope surface with a fixed angle at different spindle speed and feed rate.

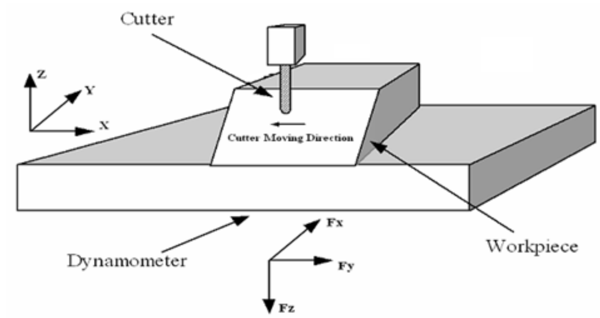

Figure 1: Ball-nose end milling a slope surface

The experiments were conducted on a 3-axis milling machine. The workpiece material was hardened Stavax mould steel and the hardness is 45 HRc. 10mm insert based carbide ball nose end mills with 30° helix angle were used in the experiments. The cutting force was measured by a Kistler quartz 3-component platform dynamometer. The dynamometer was mounted between the workpiece and machining table. The cutting forces in the X, Y and Z directions were sampled by PC208AX Sony data recorder. The tool wear was measured by Olympus microscope.

The milling process in the experiments is to create an oblique plane surface on a workpiece by ball-nose end milling operation. The geometric form is created by means of the tool path, not the cutter shape.

The target of this experiment is to mill a 45° sloping surface. The tool moves forward to create one horizontal cut on the sloping surface. The horizontal cuts were repeated at fixed pitch and depth of cut. The experiments were performed at different feed rate and spindle speed. The tool wear was measured at a fixed interval. Then the cutting was repeated again until the severe tool wear happened. The cutting forces in the X, Y and Z directions were sampled with 3,000Hz sampling rate.

4.2 Energy Distribution

The inputs of SVR model are feature vectors extracted from cutting force signals. Feature extractions are conducted based on the wavelet signal processing techniques. After the cutting force signals are decomposed by Discrete Wavelet Transform, the energy distribution can be described by Parseval's theorem (Gaing, 2004):

$$\frac{1}{N}\sum_t |f(t)|^2 = \frac{1}{N_J}\sum_k \left|cA_{J,k}\right|^2 + \sum_{j=1}^{J}\left(\frac{1}{N_j}\sum_k \left|cD_{j,k}\right|^2 \right) \tag{7}$$

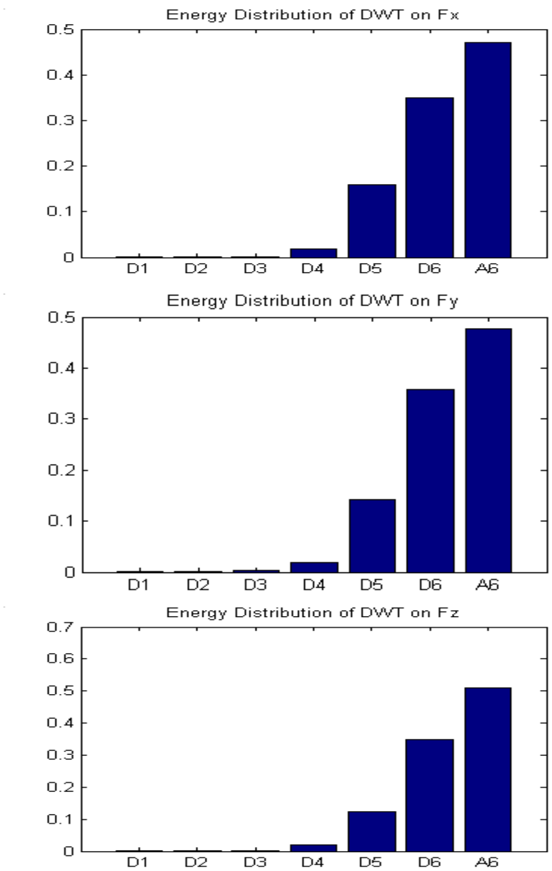

Figure 2: Energy distributions of cutting force in X, Y and Z direction

Figure 2 shows the energy distributions of cutting force in X, Y and Z direction. As the sampling rate is 3000Hz in this experiment, the frequency band in the figures are A6: [1 Hz, 23 Hz], D6: [24 Hz, 46 Hz], D5: [47 Hz, 93 Hz], D4: [94 Hz, 187 Hz], D3: [188 Hz, 375 Hz], D2: [376 Hz, 750 Hz], D1: [751 Hz, 1500 Hz]. It can be seen that the energy level of the low frequency band (1-375Hz) is much higher than middle and high frequency band. The reason is that the energy of the cutting force signal is concentrated at tooth passing frequency and its low frequency harmonics.

Therefore, the wavelet transformation was repeated two times to obtain the coefficients. Through wavelet transformation, the experimental cutting force signal can be decomposed into the constituent parts at frequency band [1 Hz, 375 Hz], [376 Hz, 750 Hz] and [751 Hz, 1500 Hz], respectively. The vector of wavelet approximations of the simulated force signal and measured force signal are used for feature extraction.

4.3 Tool Wear Estimation

In the experiments, a total of 60 measurement samples (22500 data in every sample) corresponding to various tool wear value were collected, when tool wear experiments were conducted to train and test the SVR model.

Table 2: Cutting conditions

Spindle speed (rpm)	Feed rate (mm/min)
800	40
800	80
800	100
800	120
1000	50
1000	75
1000	100
1000	125
1000	150

In addition to cutting force features, cutting conditions are also used as feature inputs for the SVR model. In this way, SVR model is suitable for various cutting conditions. Table 2 shows the cutting conditions being used in training data sets. To perform the generalization tests, the training data sets incorporate different cutting conditions used in this experiment. The remaining data sets are used for testing.

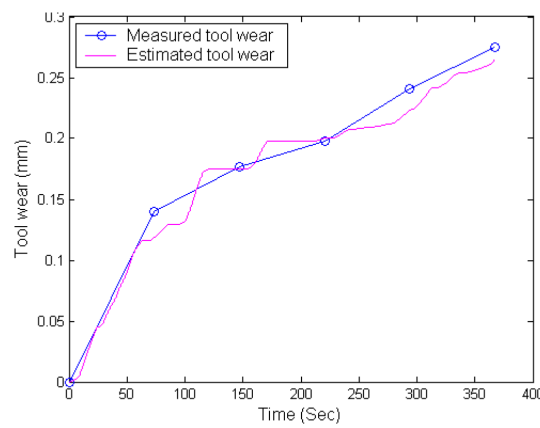

Figure 3: Tool wear estimation results (spindle speed 800 RPM, feed rate 80 mm/min)

Figure 3 shows a result of a tool life test which was conducted using a set of typical cutting condition. As this set of cutting condition is not used in training, the result shows the generalization performs well in this method.

To improve the performance of the SVR model, wavelet selection is an important factor. The family of Daubechies wavelets is chosen as the basis functions in most of the fault diagnostics applications. Daubechies wavelets are classified according to the number of vanishing moments. To investigate the influence of number of vanishing moments, typical wavelets, db4, db8 and db20, are used to process cutting force signals for feature extraction. (In some literatures, db4, db8 and db20 are named as db2, db4 and db10 respectively.) The same testing set was used for comparison on the performance of tool wear estimation by different wavelets. Table 3 shows some typical SVR results for different wavelets. In these results, the performance is indicated by averaged absolute estimation errors (AAEE).

Table 3: Comparison of SVR results using different wavelet and kernel function

Number of vanishing moments	Kernel Function	AAEE
db4	Gaussian kernel	6.6 µm
db8	Gaussian kernel	10.0 µm
db20	Gaussian kernel	13.6 µm
db4	Polynomial kernel	6.9 µm
db4	Sigmoid kernel	14.8 µm
db4	Spline kernel	34.1 µm

Another factor that affects the SVR performance is the kernel function. The kernel function is used for nonlinear mapping the input features into a higher dimensional feature space, and thus linear regression in the feature space is feasible. The optimal kernel (including the type of kernel and kernel parameters) is needed to get the high generalization performance to estimate tool wear. The polynomial kernel, Gaussian kernel, Sigmoid kernel and spline kernel are explored in this study to estimate the tool wear for the same data set and same feature extraction methods.

The polynomial kernel function is

$$K(\mathbf{x},\mathbf{x}_i) = \left(\mathbf{x}^T\mathbf{x}_i + 1\right)^p \qquad (8)$$

The Gaussian kernel function is

$$K(\mathbf{x},\mathbf{x}_i) = \exp\left(-\frac{\|\mathbf{x}-\mathbf{x}_i\|^2}{2\sigma^2}\right) \qquad (9)$$

The Sigmoid kernel function is

$$K(\mathbf{x},\mathbf{x}_i) = \tanh\left(\beta_0\mathbf{x}^T\mathbf{x}_i + \beta_1\right) \qquad (10)$$

The spline kernel is

$$K(\mathbf{x},\mathbf{x}_i) = 1 + \left(\mathbf{x}^T\mathbf{x}_i\right) + \frac{1}{2}\left(\mathbf{x}^T\mathbf{x}_i\right)\min\left(\mathbf{x}^T\mathbf{x}_i\right) - \frac{1}{6}\min\left(\mathbf{x}^T\mathbf{x}_i\right)^3 \qquad (11)$$

Table 3 shows that the performances are quite different when four kinds of kernel are used for tool wear estimation applications. From the results we can observe that kernel selection will affect the tool wear estimation performance.

5. CONCLUSION

A tool wear estimation method is proposed to monitor ball-nose end milling process. Cutting force signals are processed using wavelet techniques. Features are extracted using approximation coefficients and cutting conditions. Support vector machines for regression (SVR) are trained by the feature vectors to build a tool wear estimation model to on-line predict tool wear. The experiment results showed that the model based approach is feasible and effective.

There are some further works to improve this method:

1) To improve the quality of the extracted features, we need extract comprehensive, relevant and non-redundant information.

2) To build an efficient regression model for tool wear estimation, kernel selection methodologies will be explored to find optimal kernel including the type of kernel and kernel parameters.

3) To design a practical sculptured milling experiments to evaluate the model-based tool wear estimation methodologies.

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Sheng Huang (Singapore Institute of Manufacturing Technology) is a research engineer in the Manufacturing Execution and Control Group. He is involved in the research and development of tool condition monitoring, fault characterization, proactive real time diagnosis, fault diagnostics & prognostics for equipment and system.

Xiang Li (Singapore Institute of Manufacturing Technology) is a research scientist at the Singapore Institute of Manufacturing Technology, Singapore. She received her Ph.D from Nanyang Technological University, Singapore, in 2000. She has more than 15 years of experience in research and applications of data mining, artificial intelligence and statistical analysis, such as neural networks, fuzzy logic systems, data clustering and multiple regression modeling. She has led and was involved in many research and industrial projects, including computational intelligence for tool and surface integrity monitoring in precision machining, auto mould designs using intelligent optimization and simulation for semiconductor equipment builder, automation and integration of manufacturing executive system (MES) for semiconductor in Taiwan, data warehousing for semiconductor in Singapore, rule-based AEC object library for building constructor, customer demand knowledge discovery in new product design for electronics in Singapore and web-based intelligent forecasting system. Her current research interest include data mining, machine learning, computational intelligence, decision support systems, intelligent forecasting, knowledge-based systems, real time equipment condition monitoring and performance prediction. She is a member of the Decision Sciences Institute, USA and and member of IEEE.

Oon Peen Gan (Singapore Institute of Manufacturing Technology) is a research scientist at the Singapore Institute of Manufacturing Technology, Singapore. He is Group Manager of Manufacturing Execution and Control Research Group. He is also Technical Lead of National RFID Centre Singapore. He received his Ph.D from National University of Singapore, Singapore, in 1997. His research interests are RFID middleware, track and trace, ad-hoc networking, intelligent control, distributed networks, embedded systems, operation research, and industrial automation.