Dynamic Bayesian Network-based Surface Roughness Accuracy Grade Prediction in Turning

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Abstract. A hybrid DBN model - Discrete and gaussian mixture hidden markov model with the weighted evidence fusion strategy (DGWEFS), based on Discrete hidden Markov model (DHMM), Mixture of Gaussians hidden Markov model (MoGHMM), and DS evidence theory, is developed for surface roughness accuracy grade prediction. By analyzing the influence of tool vibration on the surface topography, the singular spectrum with wavelet analysis is proposed to extract the fusion feature ($Ec$). The $\rho$ comparison is developed to overcome defect of the traditional probability comparison. For the multiple outputs of DHMM and MoGHMM, the weighted evidence fusion strategy based on the DS evidence theory is proposed for final decisions. Experiment of turning the workpiece with multi-material and hardness scale shows that, compared with the DHMM (prediction accuracy 85%) and MoGHMM (prediction accuracy 78%), the DGWEFS proposed estimates the surface roughness with higher accuracy (prediction accuracy 93%). Therefore, the monitoring strategy proposed can be better used for supervising accuracy grade, which can be readily integrated into a computer integrated manufacturing environment.

1. Introduction
Surface roughness is a vital attribute to achieve the desired product quality in evaluating and measuring the machined surface characteristics in manufacturing industry. Surface properties have an enormous influence not only on the tribological properties, fatigue strength, friction coefficient, corrosion resistance, but on the transmission accuracy, reliability and life. Many factors affect surface roughness, such as the machining parameters, tool geometry, cutting phenomena, workpiece material, chatter, and cutting fluids. However, several uncontrollable factors that impact the surface roughness increase the difficulty for monitoring online in a timely manner[1].

He et al. review the state of the art of surface roughness prediction and provide an extensive study of the main research lines and different approaches. It is pointed out that the artificial intelligence model based technique has higher accuracy and practicability than other existing prediction methods. They recommend to consider as many state signals (the state signal of equipment itself and cutting phenomena) as possible to input the model. However, for so many input signals, the literature does not indicate which state signals have a significant effect on the surface roughness prediction [2]. Radha Krishnan et al. develop a methodology to achieve a roughness accuracy value above 95% by using an ANN. The turning workpiece image, feed rate, depth of cut, speed, frequency range, gray scale value, etc., are regard as the input parameters of ANN and experiments validate the effectiveness. However, the authors
point out that the prediction accuracy of ANN is affected by its parameter settings, and there is still no exact solution so far[3].Correa et al. used ANN and BN to predict the surface roughness in high speed milling. The experimental results show that BN has higher prediction accuracy and model explainability than ANN[4].

Of all the signals employed for surface roughness monitoring, cutting vibration signal plays an important role[5, 6]. In single point diamond turning, Wang et al. take into account the impact of workpiece on the tool-tip and the effect of process damping[5]. They propose a impact model of the pendulum system to correlate the relationship between the characteristic peak and the tool-tip vibration. The effect of the tool-tip vibration in the cutting force direction to the surface generation is studied. By power spectrum density (PSD) analyses, an index named Characteristic Peak Ratio (CPR) is defined for the surface roughness monitoring in turning process. Taking into account the cutting vibration in three directions (the axial, radial and tangential direction), Misaka et al. employ the Co-Kriging method to predict the surface roughness[7, 8]. The study indicated that only small amount of data is available, the approach improved the prediction accuracy. Suhail et al.[6] propose a method for surface roughness prediction in turning operation. Based on the root mean square extracted from the tool feed vibration and workpiece surface temperature, grey relational analysis is developed to identify the surface roughness by utilizing the grey relational coefficient and grey relational grades for combined effects of tool vibration and workpiece surface temperature. A series of cutting experiments confirmed the effectiveness of the method proposed.

In addition to cutting vibration signals, the influence of tool characteristics on the accuracy for surface roughness prediction is also analyzed in many literatures [9]. However, the effect of the workpiece material properties, such as the workpiece hardness, on the accuracy of surface roughness prediction is long neglected[10]. Mohamed et al.[11] analyze the effect of cutting parameters and workpiece hardness on surface roughness in hard turning. The variance analysis indicates that the feed rate, workpiece hardness, and cutting speed have a significant effect on the surface roughness. Hamdi Aouici et al. [12] studied the effect of cutting speed, feed rate, depth of cut and workpiece hardness on surface roughness. By using cutting parameters and the workpiece hardness as the influencing factors for variance analysis, the secondary regression model is proposed based on the response surface method for surface roughness prediction. Studies have shown that feed rate and workpiece hardness have a significant effect on the surface roughness. However, in the current literatures[6, 7, 10, 11, 13], the surface roughness prediction strategy in the multi-material and hardness conditions is scarce relatively.

Surface roughness prediction strategy based on the vibration signal in single direction has made significant progress [6, 7]. However, the strategy for surface roughness prediction based on multi-channel fusion feature is rarely discussed. In addition, many literatures for surface roughness prediction is mainly related to the error accuracy analysis for a single sample value [2, 6, 10-12]. However, according to the national standard GB / T1031-2009, surface roughness accuracy grade prediction is also an important way to ensure the machined surface quality. To this end, based on the cutting vibration signal and using the multi-directional fusion feature extracted by the singular spectrum with wavelet analysis as input , A hybrid DBN model - Discrete and gaussian mixture hidden markov model with the weighted evidence fusion strategy (DGMWEFS) is developed to predict surface roughness accuracy grade in turning process.

2. Features and Modeling

2.1. Feature analysis and extraction
Defined in international standards DIN4760-1982, surface roughness refers to deviation from the nominal surface of the first up to sixth order[7]. The first and second-order deviations are mainly refer to form the surface waviness, corresponding to the low frequency components due to cutting vibration, deformation, material inhomogenities and erroneous clamping; The third and fourth order deviations refer to periodic grooves, cracks and dilapidations, which are connected to the shape of cutting edges, chip formation and process kinematics. The fifth and sixth order deviations are connected to the material
structure, such as the grain and lattice scale. All of these different order deviations are superimposed together to form the workpiece surface profile [2]. It can be seen that, in the case of machine tools, tool and clamping system unchanged, cutting vibration and workpiece material characteristics have a significant effect on the surface morphology. Mohamed et al. [11, 12] have made the variance analysis for the process conditions and workpiece materials. The result indicated that the hardness of workpiece has a significant effect on the surface roughness. Many research literatures show that cutting vibration is most closely related to the surface roughness [2, 5-7]. Taking into account the effect of process damping, Wang et al. [5] studied the influence of tool-tip vibration on the surface morphology in single point diamond turning. Assuming that only the geometry and tool-tip vibration contribute to the formation of surface profile, the geometric representation is developed to show the influence of tool-tip vibration on surface roughness. The effect of tool-tip vibration in the three coordinate directions on the surface morphology is shown in Fig.1.

![Tool-tip Elastically recovered surface](image)

**Figure 1. Influence of tool-tip vibration on surface roughness**

Based on the coordinate system in Fig.1, the feed direction is denoted by z and the thrust direction is denoted by y. As shown in the enlarged view in the x-y coordinate plane, the tool-tip contacts with the elastically recovered surface when the tool moves from position $p_2$ to position $p_1$ due to vibration [5]. Therefore, the depth of cut in the y direction is affected by the amplitude of tool-tip vibration in the x direction. The amplitude overlay $A_1$ along the y direction results in a change in the depth of cut in the thrust direction. The circled area of chip root is magnified in the y-z coordinate plane, which shows the effect of the change of tool-tip vibration displacement in the z direction on the surface morphology. In the actual turning process, the tool-tip vibration displacement in the feed direction substantially changes the intersection of the adjacent two tool nose radius trajectory on the workpiece surface. As shown in the y-z coordinate plane, the point $p'$ is the ideal (without tool-tip vibration) profiles intersection, and the corresponding mean line is denoted by $oo'$. However, if the tool-tip vibration is considered, the overlap leads to the interference between two adjacent turning marks in the region denoted by $\varepsilon$, which moves the intersection position $p'$ from position $p$. Such phase shift affects the calculation of the mean line, i.e. the ratio of $h_{o'1}/h_{01}$ is changed into $h_{1'}/h_{1}$, which thus determines the
variation of surface roughness processed. As can be seen from the above discussion, the offset of tool-tip vibration can be regarded as the superposition of vibrational offsets in three directions. Therefore, the multi-directional fusion features extracted from the cutting vibration signals can be more comprehensive and objective represent the changes of surface roughness in turning process. In this paper, the singular spectrum analysis with wavelet multi-resolution analysis is employed to extract the multi-directional fusion features from the acquired monitoring signals.

Singular spectrum analysis (SSA) is a nonparametric time series analysis technique based on the multivariate statistics[14, 15]. Let \( F = (f_0, f_1, \cdots, f_N) \) be a original time series of length \( N \), \( L \) be the length of the sliding window, and set \( K = N - L + 1 \). The trajectory matrix \( X \) can be obtained: \( X = (X_1, X_2, \cdots, X_K) \), where \( X_j \) is the \( L \)-lagged vector, \( X_j = (f_{j}, f_{j+1}, \cdots, f_{j+L-1})^\top \in \mathbb{R}^L, j = 1, 2, \cdots, K \). Let \( S = X \times X^T \). The original time series \( F \) is projected onto the multidimensional vector space \( S \) based on singular value decomposition (SVD). Let \( S = \{ s_i | 1 \leq i, j \leq L \} \) and \( \Delta = \{ j-i \}, \) then \( s_i = \{ \sum_{k=1}^{N-A} f_k f_k^\top \}^\top \). And its main component \( a^i \) is: \( a^i = \sum_{k=i+1}^{L+i-2} f_k u^k_{i+1} \), \( 1 \leq j \leq L \). In which \( u^j_i \in U_i \) with \( S \times U_i = \lambda_i \times U_i, 1 \leq k \leq d, d = \max (\{ i | \lambda_i > 0 \} \). Let \( \hat{F} \) be a collection of the reconstructed time series, \( \hat{F} = \{ \hat{f}_i^j | 0 \leq i \leq N, 1 \leq j \leq L \} \) there is:

\[
\hat{f}_{i-1}^j = \frac{1}{L} \sum_{m=1}^L u^m_i \alpha^{j-m+1}_i, \quad 1 \leq i \leq N, 1 \leq j \leq L \tag{1}
\]

Since the decomposition and reconstruction for the time series by SSA is based on the singular value decomposition of the trajectory matrix rather than the band segmentation [16, 17], the wavelet multi-resolution analysis is employed to further decompose \( \hat{F}^j \). Let \( \{ V_j, j \in \mathbb{Z} \} \) be a list of closed subspace of \( L^2(R) \), \( W_j \) is the fill space of \( V_j \) in \( V_{j+1} \), then \( V_0 = V_M \oplus \bigcup_{j=1}^M W_J \). Therefore, for the reconstructed time series \( f^k (1 \leq k \leq L) \), the orthogonal decomposition can be expressed as:

\[
\hat{f}^k(t) = \sum_{j=-\infty}^{M} \sum_{i=-\infty}^{+\infty} a_{i,j} \phi_{i,j}(t) + \sum_{j=-\infty}^{M} d_{i,j} \psi_{i,j}(t) \tag{2}
\]

where \( M \) is the number of decomposed layers, \( a_{i,j} \) is the wavelet decomposition coefficient, and \( d_{i,j} \) is the \( j \)th layer scale decomposition coefficient. The feature extracted from the cutting vibration signals in a single direction can be be expressed by:

\[
E_i = \frac{\| A_i \|^2}{\sum_j (\| A_j \|^2 + \| D_j \|^2)} \tag{3}
\]

where \( I \) denotes the coordinate direction, \( I \in \{x, y, z\} \); \( A_i = \{ a_{i,j} \} \); \( D_i = \{ d_{i,j} \} \). The weight coefficient of each feature is obtained by the covariance analysis, and the fusion feature extracted can be formulated as follows:

\[
E_e = \frac{1}{V_e} \partial_1 E_i \tag{4}
\]

where \( V_e \) is the cutting speed

2.2. Accuracy grade recognizing strategy

The manufacturing processes is usually subject to the great uncertainty and randomness. Therefore, comparing with the ANN employed by many literatures for surface roughness prediction [4], the stochastic model, such as BN, is more suitable for dealing with such process state monitoring problems [18]. As an extension of the traditional BN, Dynamic Bayesian Network (DBN) is a powerful tool for simulating sequence data. The modeling for HMM based on DBN not only accelerates its reasoning speed but also easily expresses its various variant structures [19]. As a special case of DBN, HMM has been successfully applied in the field of speech recognition, and can simulate dynamic and static signals more accurately and effectively [20]. However, its application in the field of mechanical engineering is
still very limited [18]. Normally, the HMM with a single chain, in the form of DHMM (discrete) and MoGHMM (continuous), is applied in the field of manufacturing engineering. DHMM and MoG-HMM have their own advantages and disadvantages for different research subjects [18, 19]. In order to make full use of their advantages, a hybrid DBN model - Discrete and gaussian mixture hidden markov model with the weighted evidence fusion strategy (DGMWEFS) is developed for surface roughness accuracy grade prediction. Fig. 2 shows the DBN representation for DGMWEFS with $T$ time slice unfold.

![Figure 2. DBN representation for DGMWEFS](image)

Similar to the standard HMM, DGMWEFS is also a double random process. The state transition satisfies the markovian property, and the process of generating observation symbols for each state is a general stochastic process. As shown in Figure 2, the DGMWEFS is divided by the hidden state $q_i$ which upper part is the discrete signal input and the lower part is the continuous signal input. Therefore, a DGMWEFS is characterized by the following parameters: (1) $N$, the number of states in the model. Denoting as $S_1, S_2, \cdots, S_N$, the state at time $t$ is $q_t \in \{ S_1, S_2, \cdots, S_N \}$. (2) $M$, the number of distinct observation symbols per state. Denoting as $v_1, v_2, \cdots, v_m$, the observation symbol at time $t$ is $o_t \in \{ v_1, v_2, \cdots, v_m \}$. (3) $\pi$, the initial state distribution. $\pi = \{ \pi_i \}$, where $\pi_i = P(q_1 = S_i), 1 \leq i \leq N$. (4) $A$, the state transition probability distribution. $A = \{ a_{ij} \}$, where $a_{ij} = P(q_{t+1} = S_j | q_t = S_i), 1 \leq i, j \leq N$. (5) $\Omega$, the observation symbol probability distribution. $\Omega = \{ \Omega^{(1)}, \Omega^{(2)} \}$, where $\Omega^{(1)}(o) = \Omega^{(2)}(o) = P(o = v_i | q_t = S_i)$. These parameters are assumed to be time-invariant and the complete specification of a DGMWEFS can be written as:

$$\lambda = \{ \pi, A, \Omega \}$$

The expectation maximization algorithm is employed to estimate the parameter $\lambda$. That is, the joint log likelihood probability of the observation sequence $O = \{ o_1, o_2, \cdots, o_T \} \in \{ v_1, v_2, \cdots, v_m \}$ and the hidden state sequence $Q = \{ q_1, q_2, \cdots, q_T \} \in \{ S_1, S_2, \cdots, S_N \}$ is maximized. Substituting $\log P(O, Q | \lambda) = \log \pi + \sum_{t=1}^{T} \log a_{i,j} + \sum_{t=1}^{T} \log (\theta_j | k)$ into Baum’s auxiliary function yields

$$E(\lambda, \overline{\lambda}) = \sum_{q \in Q} \log \pi_q \cdot P(O, Q | \lambda) + \sum_{q \in Q} \sum_{j=1}^{J} \log a_{i,j} \cdot P(O, Q | \lambda)$$

$$+ \sum_{q \in Q} \sum_{k=1}^{K} \log (\theta_j | k) \cdot P(O, Q | \lambda)$$

where $\overline{\lambda}$ are the initial estimates of the parameters, $\lambda$ the optimized new parameters with the maximum expectation, and $Q$ the space of all state sequences of length $T$.

Obviously, equation (6) contains three independent terms that can be maximized individually. According to the Gibbs’ inequality [21], the initial state distribution $\pi$ and the state transition probability distribution $A$ of DGMWEFS are derived by maximizing the first two terms as follows:

$$\hat{\pi}_i = \gamma_t(i), \quad \hat{a}_{i,j} = \frac{\sum_{t=1}^{T-1} \xi_t(i,j)}{\sum_{i=1}^{T} \gamma_t(i)}$$

$$\overline{\lambda} = \{ \overline{\pi}, \overline{A} \}$$

where $\gamma_t(i)$ is the state occupation probability and $\xi_t(i,j)$ is the state transition probability.

Figure 2. DBN representation for DGMWEFS.
where \( \xi(i, j) \) denotes the joint probability of being in state \( S_i \) at time \( t \) and state \( S_j \) at time \( t+1 \), given observation sequence \( O \) and the model \( \lambda \), \( \xi(i, j) = P(q_t = i | S_t = S_j, q_{t-1} = S_i, O, \lambda) \). Since \( \Theta^P \) and \( \Theta^G \) denote the parameters estimated by the discrete signal input and the continuous signal input, respectively, they need to be derived separately. For the \( \Theta^P \), the third term on the right-hand side in equation (6) is maximized and can be formulated as:

\[
\sum_{q=0}^{T} \sum_{i=1}^{N} \log \left( \Theta_i^P \right) P(O, Q | \lambda) = \sum_{i=1}^{N} \sum_{t=1}^{T} \left( \sum_{q=0}^{T} P(q_t = i | \lambda) \rho(q_t, v_t) \right) \log \left( \Theta_i^P \right).
\]

Based on the Gibbs inequality [21], it can be expressed by:

\[
\Theta_i^P(o_i) = \frac{\sum_{l=1}^{M} \gamma_i^l(j)}{\sum_{l=1}^{M} \gamma_i^l(j)}
\]

For the \( \Theta^G \), the third term on the right-hand side in equation (6) is also maximized as follows:

\[
\sum_{q=0}^{T} \sum_{i=1}^{N} \sum_{\ell=1}^{M} \log \Theta_i^G(o_i, m_{i, \ell}) P(O, Q, M | \lambda)
\]

\[
= \sum_{i=1}^{N} \sum_{\ell=1}^{M} \sum_{t=1}^{T} \log c_{i, \ell} P(O, q_t = S_i, m_{i, \ell} = \ell | \lambda)
\]

\[
+ \sum_{i=1}^{N} \sum_{\ell=1}^{M} \sum_{t=1}^{T} P(O, q_t = S_i, m_{i, \ell} = \ell | \lambda)
\]

\[
\times \left( \frac{1}{2} \ln \left( \Sigma_{\ell=1}^{M} \right)^{-1} \right) \left( o_i - \mu_{i, \ell} \right)^T \left( o_i - \mu_{i, \ell} \right) \right]
\]

Maximizing the first term on the right-hand side in equation (9) and using the Gibbs inequality [21], the final update parameters is derived as follows:

\[
\hat{c}_{i, \ell} = \frac{\sum_{t=1}^{T} \gamma_t(i, \ell) \gamma_t(i, \ell)}{\sum_{t=1}^{T} \gamma_t(i, \ell) \gamma_t(i, \ell)}
\]

where \( \gamma(i, \ell) \) denotes the joint probability of being in state \( S_i \) at time \( t \) with the \( \ell \)th Gaussian mixture component at time \( t \), given observation sequence \( O \) and the model \( \lambda \), \( \gamma(i, \ell) = P(q_t = i | S_t = S_j, q_{t-1} = i, O, \lambda) \). Similarly, maximizing the second term on the right-hand side in equation (9), taking the derivative of \( \mu_{i, \ell} \) and setting the corresponding equation to be zero, it is given by:

\[
\hat{\mu}_{i, \ell} = \frac{\sum_{t=1}^{T} \gamma_t(i, \ell) o_t}{\sum_{t=1}^{T} \gamma_t(i, \ell) \gamma_t(i, \ell)}
\]

In the same way, maximizing the second term on the right-hand side in equation (9), taking the derivative of \( \Sigma_{i, \ell}^{-1} \) and setting the corresponding equation to be zero, it is also given by:

\[
\hat{\Sigma}_{i, \ell} = \frac{\sum_{t=1}^{T} \gamma_t(i, \ell) (o_t - \mu_{i, \ell})(o_t - \mu_{i, \ell})^T}{\sum_{t=1}^{T} \gamma_t(i, \ell) \gamma_t(i, \ell)}
\]

Now that a complete parameters set of \( \Theta^G \) has been obtained, \( \Theta^G = \{ \hat{c}_{i, \ell}, \hat{\mu}_{i, \ell}, \hat{\Sigma}_{i, \ell} \} \).

Normally, random or uniform initial estimate parameters \( \pi \) and \( A \) are adequate in most cases [22]. However, the initial estimate parameter \( \Theta \) has a large impact on the results of the model convergence. Here, the best state sequence, determined by the Viterbi algorithm based on the random initial model \( \lambda \), is employed to estimate the initial parameters \( \Theta^P \). For the \( \Theta^G \), the Viterbi algorithm with the K-means clustering algorithm is employed for the the initial parameter estimation [23]. According to the accuracy grade of arithmetic mean deviation \( Ra \) divided by the national standard GB / T1031-2009, the surface roughness in turning can be partitioned into different precision intervals, which thus transforms the surface roughness prediction problem into the pattern classification problem.

Similar to HMM, the output of DGMWEFS is also the probability distribution. However, due to the complexity of the cutting process and the non-stationary characteristics of the cutting vibration signals,
not every probability comparison will have a definite result. To this end, a \( \rho \) comparison method is proposed to replace the probability comparison method in tradition.

**Definition:** Given an observation sequence \( O=\{O_1, O_2, \ldots, O_k, \ldots, O_m\} \), where \( O_k = \{o_{k1}, o_{k2}, \ldots, o_{kn}\} \), and \( o_k \) is the \( i \)th variable sub-observation sequence with length \( ki \). Supposing the model being trained is \( \rho \), which denotes the \( S_j \) th state of the \( \rho \)th accuracy grade, the number of times that \( O_k \) is judged as the state \( S_j \) (\( 1 \leq j \leq N \)) is \( N_{j,k} = \sum_{i=1}^{\infty} \max \{\log P(o_{ki}, \mathbf{Q})(\rho, S_j)\}, 1 \leq i \leq m \), and then the \( \rho \) is defined as:

\[
\rho_j = \frac{N_{j,k}}{1 \leq k \leq K, 1 \leq j \leq N}
\]  

(13)

Surface roughness accuracy grade that the observation sequence belongs to can be directly inferred from \( \rho \). For example, the surface roughness accuracy grade corresponding to the \( k \)th observation sequence is: \( \rho_k = \max\{\rho_j\} \).

For the multi-decisions \( \rho \) distribution provided by DGMWEFS, it needs to be effectively integrated. In order to effectively overcome the influence of random information in machining process and avoid the contradiction between the conclusions and the common sense when the high conflict evidence is synthesized, a weighted evidence strategy based on DS evidence theory is proposed for the \( \rho \) distribution decision fusion.

Assuming there is a total of \( U \) evidences supporting the surface roughness accuracy grade, the evidence similarity for any of the two evidence \( u_i \) and \( u_k \) (\( 1 \leq i, k \leq U \)), \( \mathbb{S}_{i,k} \), can be derived as follows:

\[
\mathbb{S}_{i,k} = \frac{1}{\sqrt{\sum_{j=1}^{U} (u_{i,j} - u_{k,j})^2}}
\]  

(14)

The evidence similarity of \( u_i, \mathbb{S}_i \), can be obtained by equation (14):

\[
\mathbb{S}_i = \sum_{j=1}^{U} \mathbb{S}_{i,j}
\]  

(15)

The evidence similarity indicates the similar degree between the evidences. The higher the value is, the smaller the evidence conflict is, and vice versa. In order to effectively weaken the impact of the sporadic conflict evidences on the data fusion results, it needs to make the necessary corrections for the evidence similarity. For each evidence, to find the focal elements with the largest basic probability assignment, if the values of the focal elements are equal, these evidence can be regarded as the same class. The set with the most of evidence in each category is denoted as set \( \mathbf{P}_r \), and the rest is denoted as set \( \mathbf{P}_o \). If the minimum value of evidence similarity \( \text{Min}(\mathbb{S}_c) \) in set \( \mathbf{P}_r \) is less than or equal to the maximum value of evidence similarity \( \text{Max}(\mathbb{S}_o) \) in set \( \mathbf{P}_o \), let the revised factor be \( \tau \) and the revised evidence similarity be \( \mathbb{S}'_c = \text{Min}(\mathbb{S}_c) + \tau, \mathbb{S}'_o = \text{Max}(\mathbb{S}_o) - \tau \), it meets the requirement:

\[
\mathbb{S}'_c > \mathbb{S}'_o, \forall \text{Min}(\mathbb{S}_o) - \tau > 0
\]  

(16)

where the range of the revised factor \( \tau \) is: \( \text{Min}(\mathbb{S}_o) \geq \tau \geq \frac{1}{2}(\text{Max}(\mathbb{S}_o) - \text{Min}(\mathbb{S}_c)) \). Then the weight of each evidence can be expressed as:

\[
\kappa_i = \frac{\mathbb{S}'_{i}}{\sum_{j=1}^{U} \mathbb{S}'_{j}}, 1 \leq i \leq U
\]  

(17)

where \( \mathbb{S}'_{i} \) is the revised evidence similarity of \( u_i \).
3. Experiments and results
A CNC horizontal lathe (Model CK6140) is used to gather the experimental data. The prediction is performed using vibration data collected during the turning process (Figure 3). The work material in the experimental study used are AISI D2 steel (hardness 55HRC and 60HRC), AISI 4340 steel (hardness 50HRC and 55HRC), and S45C (hardness 25HRC and 30HRC). Experiments are carried out with CBN inserts of Japan's Sumitomo Electric (BNC160).

The acceleration amplitude of tool vibration is measured with tri-axial PCB accelerometer. The sampling rate is assigned as $f_s=20$ kHz for 200 ms. The signals from the accelerometers are processed and logged by means of a 24-bit multi-channel A/D analysis test system (model: TST5915) connected directly to a PC (Pentium IV 2.4 MHz) driven from the Matlab 7.8 environment. The surface roughness is measured by the stylus-type surface roughness tester (model: HMCT2205). Using the Taguchi method, a total of 48 trials (including 27 trials with full factorial design and 21 random trials) are conducted within the technical parameters recommended by the cutting tool maker. The results obtained are shown in Table 1.

![CNC horizontal lathe testbed](image)

**Figure 3.** CNC horizontal lathe testbed

Based on the feature extraction method discussed above, the original feature denoted as $E_c$ is extracted and encoded by $4\times 4$ codebook based on self-organizing feature map neural network. The results are shown in Table 1. After being initialized, the DGMWEFS is trained using the data as shown in Table 1 (rows 1-21). According to GB/T1031-2009, three models, denoted as $\lambda_{G9}$, $\lambda_{G8}$, and $\lambda_{G7}$, which indicate the 9 grade precision ($G9, Ra0.2\sim Ra0.4$), the 8 grade precision ($G8, Ra0.4\sim Ra0.8$) and the 7 grade precision ($G7, Ra0.8\sim Ra1.6$), respectively, are trained separately. After training, the DGMWEFS is validated using the data in Table 1 (rows 22 – 48). For the sake of comparison, DHMM and MoGHMM are also tested separately.
| No. | Material | Hardness | Cutting parameters | Response variable |
|-----|----------|----------|-------------------|-------------------|
|     |          |          | \( V_c \) (m/min) | \( f \) (mm/rev) | \( A_p \) (mm) | \( E_c \) | Code | \( R_a \) (\( \mu \)m) |
| 1   | AISI4340 | 50HRC    | 180               | 0.03              | 0.2             | 0.1891 | 6     | 0.675  |
| 2   | AISI4340 | 50HRC    | 180               | 0.12              | 0.3             | 0.1778 | 7     | 0.496  |
| 3   | AISI4340 | 50HRC    | 180               | 0.21              | 0.1             | 0.1015 | 15    | 1.019  |
| 4   | AISI4340 | 55HRC    | 180               | 0.03              | 0.1             | 0.1756 | 7     | 0.611  |
| 5   | AISI4340 | 55HRC    | 180               | 0.2               | 0.2             | 0.2250 | 5     | 0.701  |
| 6   | AISI4340 | 55HRC    | 140               | 0.12              | 0.3             | 0.2314 | 7     | 0.373  |
| 7   | AISI4340 | 55HRC    | 140               | 0.04              | 0.1             | 0.3742 | 1     | 0.283  |
| 8   | AISI4340 | 55HRC    | 140               | 0.03              | 0.1             | 0.1208 | 16    | 0.611  |
| 9   | AISI4340 | 55HRC    | 140               | 0.03              | 0.2             | 0.1077 | 16    | 0.698  |
| 10  | AISI4340 | 55HRC    | 140               | 0.21              | 0.1             | 0.1782 | 12    | 0.526  |
| 11  | AISID2   | 60HRC    | 100               | 0.12              | 0.3             | 0.2024 | 15    | 0.457  |
| 12  | AISID2   | 55HRC    | 100               | 0.18              | 0.1             | 0.2632 | 10    | 0.618  |
| 13  | AISID2   | 55HRC    | 100               | 0.21              | 0.1             | 0.3660 | 1     | 0.873  |
| 14  | AISID2   | 55HRC    | 100               | 0.03              | 0.3             | 0.4661 | 1     | 0.834  |
| 15  | AISID2   | 60HRC    | 100               | 0.04              | 0.1             | 0.4740 | 1     | 0.887  |
| 16  | AISID2   | 55HRC    | 100               | 0.21              | 0.3             | 0.2601 | 10    | 0.537  |
| 17  | S45C     | 30HRC    | 155               | 0.12              | 1               | 0.4494 | 15    | 0.540  |
| 18  | S45C     | 25HRC    | 60                | 0.12              | 1.8             | 0.2211 | 5     | 0.901  |
| 19  | S45C     | 25HRC    | 107               | 0.12              | 1               | 0.5635 | 16    | 0.624  |
| 20  | S45C     | 30HRC    | 60                | 0.06              | 1               | 0.2553 | 2     | 1.211  |
| 21  | S45C     | 30HRC    | 60                | 0.12              | 1.5             | 0.2406 | 2     | 0.846  |
| 22  | AISI4340 | 50HRC    | 180               | 0.03              | 0.3             | 0.1925 | 6     | 0.651  |
| 23  | AISI4340 | 55HRC    | 180               | 0.12              | 0.2             | 0.2227 | 5     | 0.471  |
| 24  | AISI4340 | 50HRC    | 180               | 0.21              | 0.2             | 0.1361 | 12    | 1.081  |
| 25  | AISI4340 | 50HRC    | 180               | 0.21              | 0.3             | 0.1817 | 6     | 0.750  |
| 26  | AISI4340 | 50HRC    | 180               | 0.04              | 0.1             | 0.1435 | 11    | 0.977  |
| 27  | AISI4340 | 50HRC    | 180               | 0.18              | 0.1             | 0.2756 | 5     | 0.586  |
| 28  | AISI4340 | 55HRC    | 140               | 0.1               | 0.2             | 0.2829 | 3     | 0.366  |
| 29  | AISI4340 | 55HRC    | 140               | 0.14              | 0.3             | 0.2919 | 2     | 0.397  |
| 30  | AISI4340 | 50HRC    | 140               | 0.2               | 0.3             | 0.1647 | 12    | 0.689  |
| 31  | AISI4340 | 50HRC    | 140               | 0.21              | 0.3             | 0.1666 | 12    | 0.528  |
| 32  | AISI4340 | 55HRC    | 140               | 0.03              | 0.3             | 0.1006 | 16    | 0.793  |
| 33  | AISI4340 | 55HRC    | 140               | 0.21              | 0.2             | 0.1311 | 16    | 0.551  |
| 34  | AISID2   | 60HRC    | 100               | 0.12              | 0.2             | 0.0913 | 16    | 0.467  |
| 35  | AISID2   | 55HRC    | 100               | 0.14              | 0.2             | 0.1844 | 12    | 0.515  |
| 36  | AISID2   | 60HRC    | 100               | 0.03              | 0.2             | 0.4636 | 1     | 0.908  |
| 37  | AISID2   | 60HRC    | 100               | 0.21              | 0.2             | 0.1907 | 12    | 0.576  |
| 38  | AISID2   | 60HRC    | 100               | 0.2               | 0.3             | 0.4006 | 1     | 0.835  |
| 39  | AISID2   | 55HRC    | 100               | 0.12              | 0.1             | 0.2650 | 10    | 0.705  |
| 40  | AISID2   | 60HRC    | 100               | 0.03              | 0.1             | 0.4033 | 1     | 0.813  |
| 41  | S45C     | 30HRC    | 131               | 0.12              | 1               | 0.5683 | 16    | 0.561  |
| 42  | S45C     | 25HRC    | 60                | 0.12              | 1               | 0.2085 | 1     | 1.119  |
| 43  | S45C     | 30HRC    | 84                | 0.12              | 1               | 0.4107 | 15    | 0.655  |
| 44  | S45C     | 25HRC    | 60                | 0.12              | 0.9             | 0.2512 | 2     | 1.157  |
| 45  | S45C     | 30HRC    | 60                | 0.12              | 0.3             | 0.5722 | 16    | 0.759  |
| 46  | S45C     | 25HRC    | 60                | 0.09              | 1               | 0.1845 | 1     | 0.876  |
| 47  | S45C     | 25HRC    | 60                | 0.12              | 0.6             | 0.1365 | 1     | 1.172  |
| 48  | S45C     | 30HRC    | 60                | 0.12              | 1.2             | 0.2116 | 1     | 0.991  |
Surface roughness accuracy grade recognition results by MoGHMM, DHMM and DGMWEFS are shown in Figure 4 ~ 6, respectively. The range \((G9, G8, G7)\) indicated by the arrows in figures denotes the accuracy interval that the test samples are actually belongs to. \(P(O|\lambda_{G9}), P(O|\lambda_{G8})\) and \(P(O|\lambda_{G7})\) stand for the log likelihood probability calculated by the models \(\lambda_{G9}, \lambda_{G8}\) and \(\lambda_{G7}\), respectively. \(\rho_{G9}, \rho_{G8}\) and \(\rho_{G7}\) stand for the \(\rho\) values calculated by the models \(\lambda_{G9}, \lambda_{G8}\) and \(\lambda_{G7}\) with the weighted evidence fusion strategy, respectively. It can be seen from Figure 4 ~ 6 and Table 2 that although the probability comparison method is adopted at the same time, the accuracy grade recognition rate of DHMM is higher than that of MoGHMM. It may be the reason that, although the SOM coding is usually considered to introduce errors, this clustering method narrows the internal spacing between the similar features, increases the class spacing between the samples, and makes the samples easier to identify. In addition, the recognition accuracy of DGMWEFS with \(\rho\) comparison method is obviously higher than that of the former two models. This is because that one hand, DGMWEFS combines the advantages of MoGHMM and DHMM for condition monitoring under the conditions of continuous and discrete feature input, respectively. On the other hand, DGMWEFS takes full account of the local and global information of features extracted, and achieves the effective integration for the decisions obtained from these different informations by the weighted evidence fusion strategy. Which improves the recognition accuracy of DGMWEFS for surface roughness accuracy grade in turning.
Tabel 2. Accuracy grade recognition rate comparison

| Models    | Methods            | Samples in test set | Recognition rate |
|-----------|--------------------|---------------------|------------------|
| MoGHMM    | Probability comparison | 27                  | 78%              |
| DHMM      | Probability comparison | 27                  | 85%              |
| DGMWEFS   | $\rho$ comparison   | 27                  | 93%              |

4. Conclusion

Surface roughness is a vital attribute to achieve the desired product quality. It is affected by a number of factors (such as machine tools, fixture system, cutting tools, workpiece materials and cutting vibration, etc.). Therefore, it is still a challenge to build an effective monitoring system for surface roughness. In this work an attempt has been made to initially predict surface roughness by DGMWEFS proposed using the cutting vibration in turning process. The following conclusions can be drawn from the present study.

(1) The influence of tool vibration along the axial, radial and tangential direction on the surface morphology of workpiece is analyzed in detail, and thus the singular spectrum analysis with wavelet multi-resolution analysis is proposed to extract the multidirectional fusion features $Ec$ from the acquired monitoring signals. This technique does not require to make any assumption to process the signal and the multi-directional fusion features extracted from the cutting vibration signals can be more comprehensive and objective represent the changes of surface roughness in turning process.

(2) Using the fusion features $Ec$, the DGMWEFS is developed for surface roughness accuracy grade prediction and found to have satisfactory prediction ability. To check the adequacy of models developed, the DHMM, MoGHMM and DGMWEFS are validated with the data not used in development of models. Experimental results in turning the workpiece with multi-material and hardness scale show that the proposed strategy with $\rho$ comparison can predict surface roughness accuracy grade with high accuracy (prediction accuracy 93%), comparing to the DHMM with probability comparison (prediction accuracy 85%) and MoGHMM with probability comparison (prediction accuracy 78%). It can be concluded that the DGMWEFS proposed predicts the surface roughness accuracy grade within reasonable accuracy making them suitable for in process prediction, which provides a vital opportunity to control the surface finish in a timely manner in turning process.

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