

TOOL WEAR MONITORING BASED ON WAVELET TRANSFORM OF RAW ACOUSTIC EMISSION SIGNAL

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Summary

The paper presents a new efficient method of evaluation of relevancy of signal features extracted from the wavelet coefficients of raw AE signal while rough turning of Inconel 625. Several meaningful signal features were automatically extracted from band pass signals using 22 different wavelets and used for tool condition monitoring. Accuracy of tool condition evaluation was employed as main criterion for selection of the most indicative wavelets and decomposition level of Discrete Wavelet Transform (DWT) and Wavelet Packet Transform (WPT).

Keywords: tool condition monitoring, acoustic emission, wavelet transform

Monitorowanie zużycia ostrza z zastosowaniem transformaty falkowej surowego sygnału emisji akustycznej

Streszczenie

W artykule przedstawiono analizę przydatności miar sygnałów pasmowych uzyskanych za pomocą Transformaty Falkowej (WT). Zastosowano Dyskretną Transformatę Falkową (DWT) oraz Pakietową Transformatę Falkową (WPT). Do wykonania WT użyto 22 typy falek. Analizie poddano surowy sygnał emisji akustycznej rejestrowany podczas toczenia zgrubnego Inconelu 625. Automatycznie selekcjonowane miary sygnałów pasmowych użyto do monitorowania stanu narzędzia. Dokładność oszacowania zużycia ostrza na ich podstawie stanowiła kryterium oceny przydatności poszczególnych falek i transformaty falkowej.

Słowa kluczowe: nadzorowanie stanu narzędzia, emisja akustyczna, transformata falkowa

1. Introduction

Tool wear is a severe problem in machining nickel-based heat resistant super alloys such as Inconel 625, employed in aeronautic and aerospace applications due to their high shear strength, work hardening tendency, highly abrasive carbide particles, tendency to weld and form build-up edge and low thermal conductivity [1]. All of these difficulties lead to high tool wear and compromise the attainment of high material removal rates. During machining

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Inconel 625, the cutting tool often bears extreme thermal and mechanical loads close to the cutting edge leading to rapid tool wear. Therefore the tool wear is not repeatable and has tendency to finish catastrophically (chipping or breakage of the cutting edge). Hence, tool wear monitoring plays a critical role in guaranteeing sustainable machining of nickel-based alloys. Development of robust and reliable tool condition monitoring system requires application of the most meaningful signal features which best describe the tool wear. As reliable tool wear evaluation based on one signal feature (SF) is impossible, the key issue in tool condition monitoring (TCM) is finding numerous signal features correlated with tool condition [2-4]. Various methods for tool wear monitoring have been developed, most often based on acoustic emission (AE), cutting forces and vibrations [2, 5]. Among the various approaches that have been taken to analyze these signals, spectral analysis such as fast Fourier transform (FFT), has been found to be one of the most informative for monitoring tool wear [3, 6]. A disadvantage of the FFT method is that the resolution in frequency domain is a compromise with the resolution in time domain – it is impossible to have them both at good resolution. Wavelet transform was invented to overcome this drawback. It allows for the use of long time intervals where more precise low frequency information is required, and shorter regions where high-frequency information is needed. Over the past 15 years, wavelet transform has become one of the emerging and fast-evolving mathematical and signal processing tools. It has been used for surface metrology [7], chip form monitoring [8], grinding wheel condition monitoring [9]. An interesting review of many applications of wavelet transform in fault diagnostic and condition monitoring presented Peng et al. [10]. Recently it is more and more often applied in catastrophic tool failure detection [11-13], and tool wear monitoring. Kwak [14] applied discrete wavelet decomposition to detect tool failure and to conduct the de-noising of the cutting force signal in a turning process. Li et al. [15, 16] applied wavelet packet transform to tool wear monitoring in boring. They used a RMS value of band pass of AE signal to assess the tool state. Scheffer [17] used wavelet packet transform based on strain and vibration signal, to assess tool wear in turning. Several signal features indicative of tool wear were automatically extracted from wavelet packet analysis. A correlation coefficient between the feature and the ideal trend was used for automatic selection of the best features. Li et al. [18] applied fast algorithm of wavelet transform to recognize the tool wear states in automatic machining processing. They have shown that wavelet analysis based on the fast algorithm is more sensitive, more reliable and faster than the Fourier analysis for recognizing the tool wear states for the different cutting conditions. The major advantage of using AE to monitor tool condition is that the frequency range of the raw AE signal is much higher than machine vibrations and environmental noises and does not interfere with the cutting operation [5, 11]. Acquisition and on-line processing of such high frequency signals (0.8-1 MHz)

was not available in industrial practice until recently. Therefore, RMS of raw AE signal was usually used [3, 19, 20], which is kind of envelope of the raw signal. The fast development of computers and DAQ systems now enables exploitation of raw AE signal. The objective of this paper is to extract features from raw acoustic emission signal in rough turning of Inconel 625, using wavelet transform method.

2. Discrete wavelet transform

The wavelet transform can decompose a signal into different components in different time windows and frequency bands through the wavelet scale function, and scaled and shifted versions of the mother wavelet. Practically it can be reduced to filtering the signal by high-pass and low-pass filters derived from the wavelet and the scaling function. The Discrete Wavelet Transform (DWT) decomposes the signal into the scaling coefficients (approximations A) and the wavelet coefficients (details D) by convolution of the signal and impulse response of the low-pass and high-pass filters. The filter's outputs are subsampled by 2. At the first level the original signal is decomposed into A_1 and D_1 , then approximation A_1 can be decomposed again into A_2 and D_2 . A three level DWT decomposition tree is presented in Figure 1a. Generally approximations (A_{j+1}) and details (D_{j+1}) at level $j+1$ can be expressed by convolutions:

$$A_{j+1}[n] = \sum_{k=-\infty}^{\infty} h[2n-k]A_j[k] \quad (1)$$

$$D_{j+1}[n] = \sum_{k=-\infty}^{\infty} g[2n-k]A_j[k] \quad (2)$$

where h and g are impulse responses of low-pass and high-pass filters respectively, which are discrete equivalents to scaling function and wavelet. From a mathematical point of view, the structure of computations in a DWT is exactly an octave-band filter band, thus approximations and details are band pass signals.

Another type of wavelet transform is Wavelet Packet Transform (WPT) where both – approximations and details are decomposed, providing much more frequency bands (see Fig. 1b). This provides more opportunities to find useful signal features. On the other hand, for n levels of decomposition, the DWT produces $2n$ sets of coefficients as opposed to $(2^{n+1}-2)$ sets for the WPT. Thus

the computational cost of the DWT is much less than the WPT. In this research both transforms were used for comparison. Several wavelet basis function types are available in the literature. Despite the results of wavelet transform depends on the type of the wavelet, usually it is selected arbitrary, without any explanation. Occasionally sentence like: ‘The coiflet 3 wavelet was chosen for analysis because it yielded the best results after experimentation with a number of different wavelets’ [17] can be found.

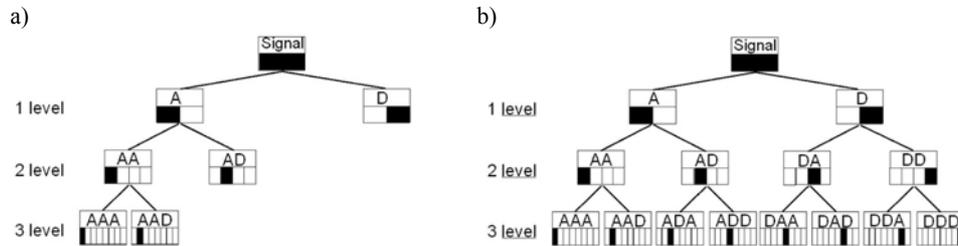


Fig. 1. Three levels wavelet decomposition tree: a) DWT, b) WPT. Blackened fields indicate the frequency band of the original signal

3. Experimental setup and conditions

The experiments have been performed on turning center TKX 50N equipped with industrial AE sensor (Kistler 8152B121) mounted on the turret. The tool was CRSNL 3225P12 MN7 with whisker-reinforced ceramic inserts RNGN 120700T01020 CC 670. The workpieces were impeller case made of Inconel 625 machined in subsequent perpendicular cuts (Fig. 2a) with the depth of cut $a_p = 2.5$ mm, feed $f = 0.2$ mm/rev and cutting speed $v_c = 220$ m/min. Three such workpieces were machined, during which 7 tools were worn out. All the experiments were conducted until the appearance of drastic decrease of the surface finish (Fig. 2b) or burr formation (Fig. 2c) – indirect criteria for tool life estimation applied in factory floor conditions. A tool notch wear (direct, laboratory criteria for tool life estimation) was also measured (Fig. 3). As the notch wear appeared on the other side of the cutting edge, than this which created the machined surface, it was not correlated with the surface finish. I also was not correlated directly with the burr formation. All three phenomena (notch wear, surface finish and burr formation) appeared autonomously, making determination of the tool life end rather difficult, subjective, dependent on machine tool operator experience. Therefore tool condition monitoring in machining of Inconel 625 can be especially vital.

AE raw signal was acquired with sampling frequency 2MHz using DAQ card NI PCI 6111. As this sampling frequency produces enormously large

amount of data, only 0.05 s (100000 samples) every 10 seconds was recorded and analyzed. Each cut lasted 96 seconds. Eight AE_{raw} recordings taken from the middle part of each cut was taken for further analysis using wavelet transforms.

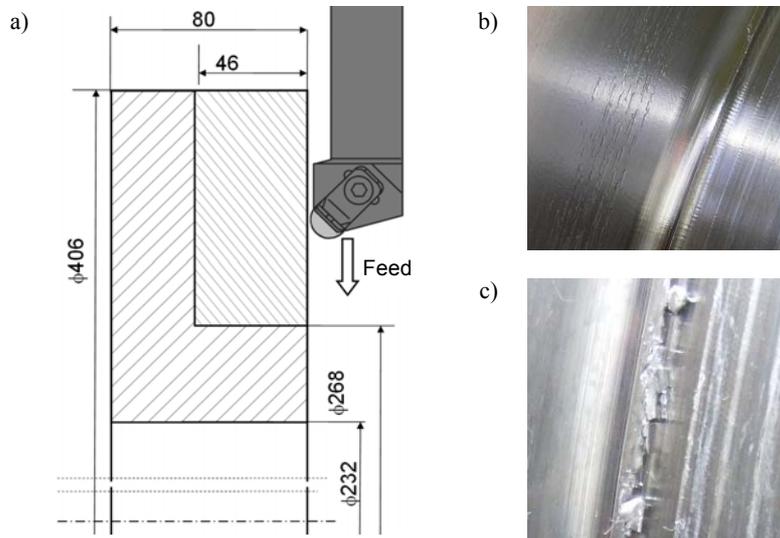


Fig 2. The workpiece and tool (a), and indirect tool life criteria: b) surface roughness, c) burrs

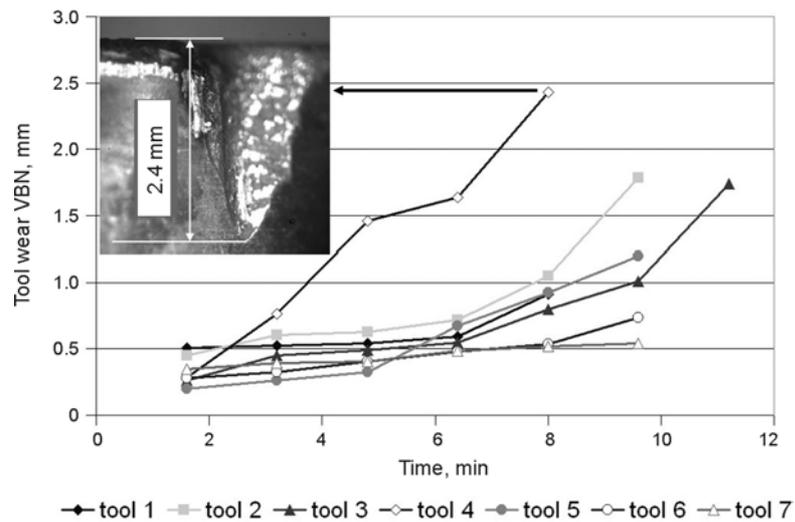


Fig 3. Tool wear measurement example and development in all tests

4. Signal feature extraction and integration

4.1. Extraction of wavelet coefficients features

As mentioned above, there are many wavelet basis function types available. Selection of the most indicative wavelets for tool condition monitoring is one of the major goals of this paper. Wavelet transform was performed using following 22 wavelets: daubechies (db2, db3, db4, db5, db6), symlets (sym2, sym3, sym4, sym5, sym6), coiflets (coif2, coif3, coif4, coif5), biorthogonal (bior2.2, bior2.4, bior2.6, bior2.8, bior3.3, bior3.5, bior3.7, bior3.9). Both DWT and WP coefficients were calculated up to 5 level decomposition. As the output of the wavelet transforms are low-pass and high-pass filtered signals, informative features must be extracted from the A and D coefficients. Wavelet coefficients were treated as separate signals, each characterized by the six signal features: logarithmic energy (E), skew (Sk), kurtosis (Ku) effective value (root mean square – rms), ring down count: number of times AE_{raw} signal crosses the threshold level ($Count$) and pulse width the percentage of time during which the signal remains above this threshold ($Pulse$). The threshold level was calculated as 30% of max-min of the coefficient value during the first measurement (first 100000 samples) for each tool life independently. For 5 level decomposition there are 10 DWT coefficients and 62 WPT coefficients, and 60 and 372 signal features respectively for each wavelet. Number of possible features was very large, while most of them were very distorted or hardly correlated with the tool condition. Figure 4 presents examples of signal features obtained from wavelet decomposition based on biorthogonal wavelet bior3.7 of the AE_{raw} signal.

The first – energy of approximation on the first level is apparently very distorted and not correlated with the tool condition, thus should be eliminated from further decision making algorithm. The second – energy of detail seems to be growing more or less regularly with the tool wear. The third – pulse width of the same detail, changes both with the tool wear and the position of the tool on the workpiece despite distance of the AE sensor from the tool is constant. Also this feature is not useful for tool condition monitoring. Of course, selection of useful signal features must be performed fully automatically, without any intervention of machine tool operator. Here signal feature selection, evaluation and integration into one tool condition model was performed using results of three tool life experiments, while four others were employed for verification of selection of the most indicative wavelets and decomposition level of WPT and DWT.

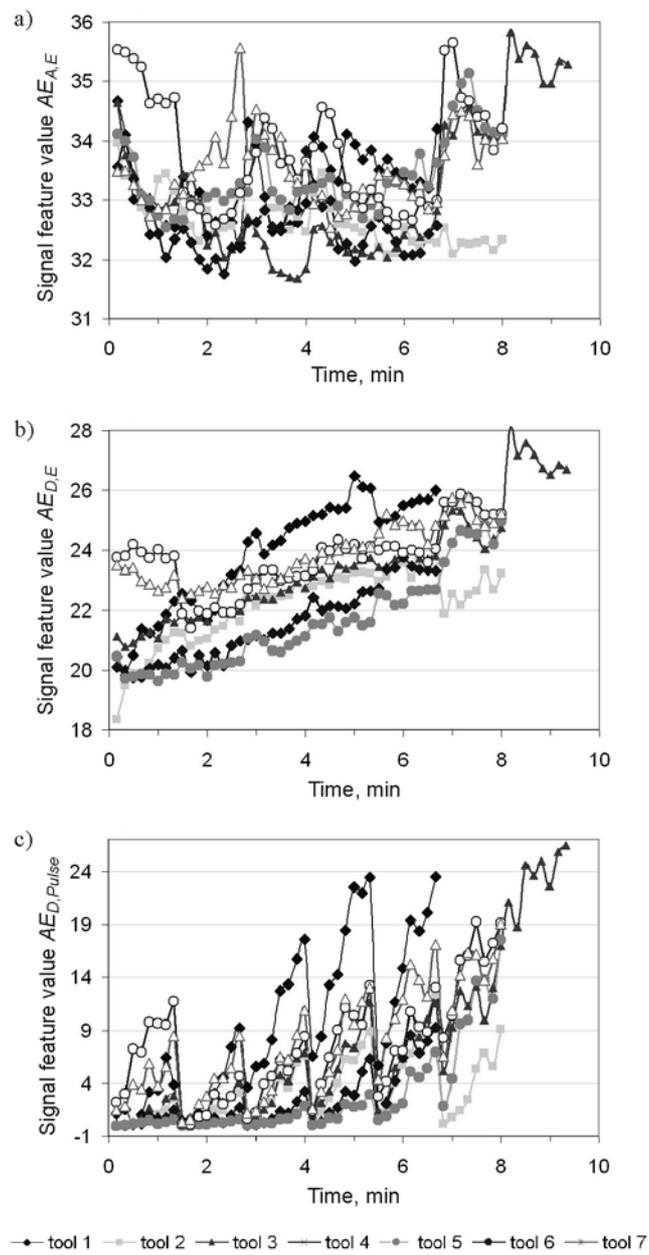


Fig 4. Examples of wavelet bior3.7 coefficients on the first level:
a) energy of approximation, b) energy of detail, c) pulse width of detail

4.2. Selection of useful features

The selected features should be relevant, sensitive to process condition. However every SF, even well correlated e.g. with the tool wear, can be sometimes disturbed randomly. Therefore number of features should be high enough to cover these possible random disturbances of any SF – the robustness of the monitoring system can be improved by a certain amount of redundant input information. On the other hand, if select features are too similar or dependent on one another, the goal of proper sensor fusion can be missed. Before the evaluation of signal feature usability, some preliminary processing was necessary. First, the original SF was normalized in time, which meant interpolation of original SF array into array SF_T containing 101 elements (0-100% of tool life). Thus SF_T is dependence of signal feature on used-up portion of the tool life (ΔT), defined as the ratio of the cutting time as performed so far (t) to the overall tool life span (T) [4, 21, 22]. The ΔT is tool condition measure which is practically used in factory floor condition, where measurements of the tool wear is very rare. Then SF_T was low-pass filtered into SF_{Tf} . Selection of useful signal features was based on two criteria. First, it is assumed, that SF should smoothly change with the ΔT . Coefficient of determination R_s^2 which is a statistical measure of how well any SF_{Tf} approximates the SF_T was used for SF 's smoothness evaluation:

$$R_s^2 = \frac{\sum_i (SF_{Ti} - SF_{av})^2 - \sum_i (SF_{Ti} - SF_{Tfi})^2}{\sum_i (SF_{Ti} - SF_{av})^2} \quad (3)$$

where SF_{Ti} , SF_{Tfi} is a single value of SF_T and SF_{Tf} respectively ($i = 0..100$), SF_{av} is average value of SF. Three tools were used for training, so three determination coefficient values were calculated for each SF. These SFs, for which average $R_s^2 > 0.7$ were considered as smooth and taken into account in further considerations. The second criterion applied here was repeatability of signal feature. Three SF_{Tf} courses obtained during the first three tool lives were averaged into $SF_{Tf_{av}}$ which was then treated as a model of $SF(\Delta T)$ relationship. Another determination coefficient R_r^2 which is a statistical measure of how well any $SF_{Tf_{av}}$ approximates all three SF_{Tf} was used for SF 's repeatability evaluation:

$$R_r^2 = \frac{\sum_j \sum_i (SF_{Tfji} - SF_{av})^2 - \sum_j \sum_i (SF_{Tfji} - SF_{Tf_{avi}})^2}{\sum_j \sum_i (SF_{Tfji} - SF_{av})^2} \quad (4)$$

where SF_{Tfji} is value of SF_{Tf} in i -th point ($i = 0..100$) and j -th tool life ($j = 1..3$), SF_{Tfavi} is average value of SF_{Tfav} i -th point. Signal features for which $R_r^2 > 0.5$ were considered repeatable.

Dealing with a large number (up to 372 here) of signal features, it usually appears that, among those that meet the criteria, there are groups of SFs that are similar (correlated) to each other. To eliminate the features that do not contain additional information, the following procedure was applied. First, the best feature (with the highest R_r^2) was selected. Then the Pearson correlation coefficients r^2 between this feature and all others one by one were calculated, and those with $r^2 > 0.98$ were rejected. From among the remaining signal features, again the best one was selected, and the SFs correlated with it were rejected. The procedure was repeated until no signal feature meeting the $R_r^2 > 0.5$ criterion remained.

4.3 Signal feature integration into tool wear evaluation

As mentioned above, SF_{Tfav} calculated as average from the first three tool lives, was the model of $SF(\Delta T)$ relationship. During the subsequent four tool lives, the used-up portion of the tool life was estimated in two stages [21, 23]. In the first stage, the ΔT_s are evaluated separately using each SF [22]. The SF_{Tf} array is searched for the SF value closest to the measured value, starting with the value obtained in the previous, final ΔT estimation (in the second stage). In the second stage, the ΔT estimations obtained in the first stage were averaged. Examples of such estimation are presented in Fig. 5 as the used-up part a of tool's life evaluated by the system (ΔT_{ev}) vs. actual ΔT . Errorless estimation is shown by the straight, dashed line and deviations from this line are presented as the root mean square error (RMSE). Accuracy of tool condition evaluation measured by RMSE, was employed here as main criterion for selection of the most indicative wavelets and decomposition level of Discreet Wavelet Transform (DWT) and Wavelet Packet Transform (WPT).

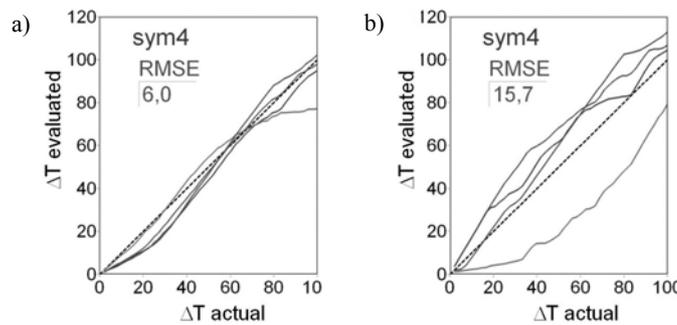


Fig 5. Examples of evaluation of used-up portion of tool life based on wavelet transform of raw AE signal using symlet 4 wavelet and 5 (a) and 2 (b) levels of decomposition

5. Selection of the most indicative wavelets and decomposition level

Results of tool condition estimation depends on which tool lives were selected for the training set. There is 35 combinations of three tools live tests selected from seven. Six combination were selected randomly and applied for final testing. Obtained results (RMSE) were averaged. This creates really strong, representative test of the wavelet transform effectiveness evaluation. All 22 wavelets were applied at four levels of decomposition (2–5) for both DWT and WPT. Average root mean square errors of ΔT estimations are put together in Fig. 6. Of course the lower the error the better. So the best result ($RMSE_{av} = 8.4$) was achieved for bior2.6 wavelet at fifth level of WPT decomposition. However there were several other cases with the result not much worse ($RMSE_{av} < 9.5$). So the second criterion of the wavelet transform selection is computational cost. This cost is much lower for DWT than for WPT. However it appeared, that no matter which decomposition level of DWT was applied, only SFs from the first one were automatically selected, thus results were independent on the level. Not surprisingly these results were relatively poor, usually the worst of all obtained for particular wavelet. This is strong indication of WPT superiority over DWT, despite higher computational cost. This cost is very much dependant on WPT decomposition level because of number of wavelet coefficients and signal features which have to be calculated (84 SFs at 3rd level, 180 SFs at 4th level and

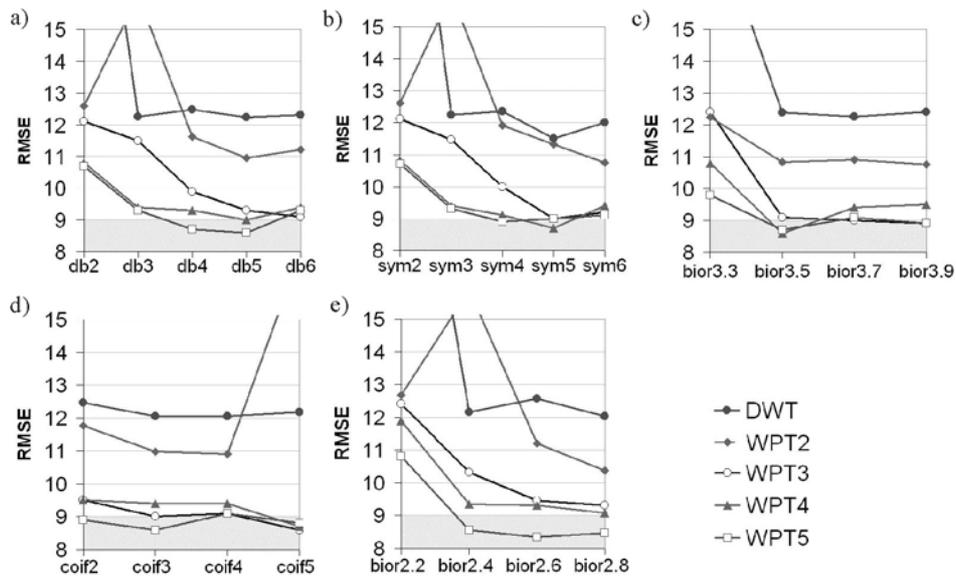


Fig 6. Average root mean square errors (RMSE) of ΔT estimation using different WPT and DWT level based on different wavelet families: a) daubechies, b) symlets, c) coiflets, d), e) biorthogonal

372 SFs at 5th level). Therefore the lower decomposition level is efficient enough, the better. As can be seen in Fig. 6 second level of WPT decomposition appeared to be not good enough for all types of wavelet – $RMSE_{av} > 10$. For higher levels generally the higher the wavelet order, the better the result, and only the simplest wavelets (db2, sym2, bior2.2, bior3.3) produced not satisfactory results. Computational cost is also slightly increasing, but this rise is almost negligible as are the differences between the types of wavelet. Finally – on the third level of decomposition (lowest computational cost) the best result ($RMSE_{av} = 8.6$) was achieved for coif5 wavelet. Not much worse results ($RMSE_{av} < \sim 9$, marked green in Fig. 6) were obtained for db6, sym5, coif3, coif4, bior3.7 and bior3.9. Such results can be easily achieved on 5th level of decomposition, but on much higher computational cost.

6. Conclusions

While machining of Inconel 625 different phenomena notch wear, surface finish and burr formation appear autonomously which makes determination of the tool life end difficult, subjective, dependent on machine tool operator experience. Tool condition monitoring can improve the process reliability and help to avoid or serious tool or workpiece damage. Wavelet transform of raw acoustic emission signal provides useful signal features, which can be exploited in TCM system. Because the features are extracted from numerous wavelet coefficients, number of potentially useful features is very large. Their usability can be evaluated automatically using two criteria – smoothness and repeatability. To avoid repetition of the same information, the features closely correlated one to each other should be eliminated. Selection of the most indicative wavelets and decomposition level, based on accuracy of used up portion of tool life evaluation proven superiority of Wavelet Packet Transform over Discrete Wavelet Transform, thus WPT is recommended for such application, despite higher computation cost. On the other hand, to keep this cost on reasonably low level, the lowest possible decomposition level should be used. Presented experiments shown that the third level should be sufficient enough. Out of 22 tested of types wavelets the best results on this level were obtained for coif4 wavelet, so but not much worse appeared to be db6, sym5, coif3, coif4, bior3.7 and bior3.9, thus these wavelets are recommended for tool condition monitoring based on raw AE signal.

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