

Development of a Condition Monitoring Algorithm for Industrial Robots based on Artificial Intelligence and Signal Processing Techniques

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ABSTRACT

Signal processing plays a significant role in building any condition monitoring system. Many types of signals can be used for condition monitoring of machines, such as vibration signals, as in this research; and processing these signals in an appropriate way is crucial in extracting the most salient features related to different fault types. A number of signal processing techniques can fulfil this purpose, and the nature of the captured signal is a significant factor in the selection of the appropriate technique. This chapter starts with a discussion of the proposed robot condition monitoring algorithm. Then, a consideration of the signal processing techniques which can be applied in condition monitoring is carried out to identify their advantages and disadvantages, from which the time-domain and discrete wavelet transform signal analysis are selected.

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1. INTRODUCTION

Industrial robots are extremely complex mechanism and hence the application of condition monitoring for them differs from that of 'simple' rotating machinery. This is basically due to the instantaneous change of geometrical configuration of the robot arm. However, there are two approaches to condition monitoring, which are model-based and model-free. Either of these approaches or a combination of both has been adapted in industrial robot condition monitoring. Filaretov, et al. [1] used a nonlinear model to address problems of fault detection and isolation in complex systems, such as in robot manipulators. Algebraic functions were implemented to design the nonlinear diagnostic observer, which was able to dispense with the linearization in nonlinear models to avoid model errors. The robot modeling was conducted using Matlab in discrete time. It was shown that, despite the fact that the use of this model dispenses with linearization, it does not allow some faults to be isolated. In another paper, a model-based fault detection and isolation (FDI) scheme for rigid manipulators was designed which depends on a suboptimal second-order sliding-mode (SOSM) algorithm [2]. In order to make the procedure of FDI possible, an input signal estimator and output observers were adopted and SOSM was used to design the input laws for the observers. Experimental work and theoretical simulations were accomplished with a COMAU SMART3-S2 robot manipulator, and the results showed that the scheme has a good ability to detect and identify faults. On the other hand, the proposed scheme was not able to deal with multiple faults in more than one actuator or sensor, and is also neglected elastic effects in the robot. However, because precise mathematical models for complex systems like a robot are difficult to obtain, model-free methods based on AI or statistical approaches

have become prevalent choices for robot health monitoring. The backlash and looseness in the power transmission system of a robot may cause torque variations. The electric motor itself generates what is known as a back electromotive force (EMF) when subjected to mechanical load making them acting as a torque transducer [3]. The torque variations measurements via current fluctuations on robotic actuators have been applied for robot monitoring [3], [4]. The advantage of this technique, as early mentioned, to robot health monitoring is that the motor current can remotely be measured along the power cables utilizing standard current sensors without supplementary instrumentation on the robot.

Robots are required to perform a variety of different repetitive tasks and are as designed programmable and configurable machines; and consequently the joints are subjected to continuously varying loads and speeds. Therefore, designing a CM system for a robot being adaptable for different robot tasks is challenging. In this work, to achieve this, it was decided to conduct the robot CM using two stages, as shown in Figure 1. The first stage is only responsible for detection the fault and is performed during the robot movement for accomplishing whatever the task. The vibration signals are captured and features are extracted using time-domain signal analysis technique (as explained later). Then, the features are analysed in order to select the most fault-sensitive one. From the extracted features that are related to the robot healthy state, threshold values are calculated, in order to be used as a baseline reference, using the statistical control chart (SCC) approach, a technique by which a plant (or process) is monitored to investigate whether or not the plant remains in control. The above mentioned steps have to be done offline, before running the monitoring system and the purpose is to compute the threshold values. If the robot is reprogrammed for a different task than the previous, the same steps are needed to be followed, in order to establish different threshold values for the new task. During the online operation the selected (most) fault-sensitive feature will be calculated and compared to the reference thresholds. The result of the fault detection stage will report either the robot is healthy or a fault is developing. If a fault is detected, the robot should be stopped and the second stage of the CM system conducted. In the first stage, the time-domain signal analysis and SCC have been selected because they are relatively computationally easy to implement and the fault category is not needed to be known at this stage.

The aim of the second stage of the monitoring algorithm is to accurately identify in which joint the fault has occurred and what is its type exactly, for example, backlash, gear tooth wear or bearing fault. To achieve this, the robot will be programmed to move each joint independently in a cyclic movement. The vibration signals are captured and analysed, but this time using multi-resolution signal analysis technique based on the discrete wavelet transform (DWT), since it has been found very appropriate for non-stationary vibration signal analysis, which is the case in industrial robots in which the speed and load on each joint is continuously changing, and can assist in the precise diagnosis of faults. Then, the features related to the healthy state and different fault conditions are determined and used for design and training an artificial fault classification system using the artificial neural network (ANN). The established ANN is then employed for online fault diagnosis.

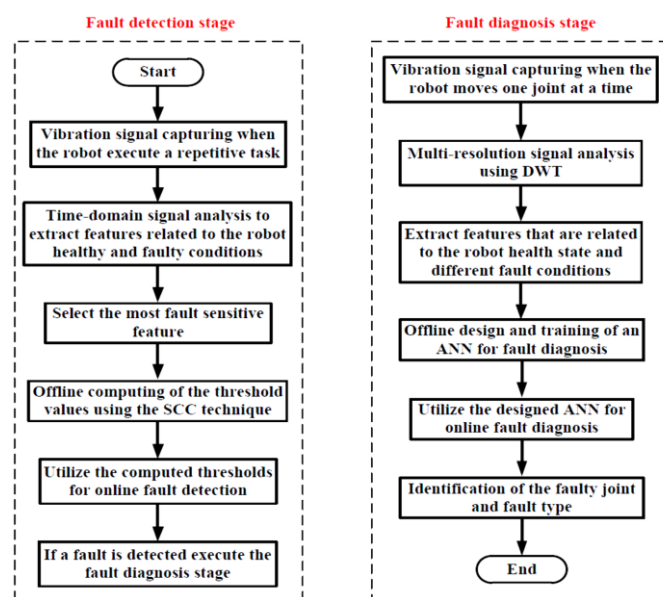


Figure 1. Descriptive flowchart for the proposed intelligent condition monitoring algorithm

2. BASIC CONCEPTS OF SIGNAL

A signal can be defined as a function that describes a physical variable as it evolves over time. Analogue signals, such as sound, noise, light and heat, represent the majority of signals in nature. Variations in these signals are continuous over time and the processing of analogue signals is called analogue signal processing (ASP). By sampling such continuous signals at repeated time intervals using data acquisition equipment, they can be converted into discrete format, and the processing of the digital (discrete) signal is named digital signal processing. A discrete signal, on the other hand, has values only at specific time periods. The benefits of converting signals from analogue to discrete (digital) form are that it can avoid the degradation and corruption of the signals. Knowing the type of signal to be analyzed has a significant influence on the type of analytic technique chosen. Subsequently, it is necessary to carefully inspect the various types of signal that are encountered in practice. Thus, signals can be classified as shown in Figure 2 below.

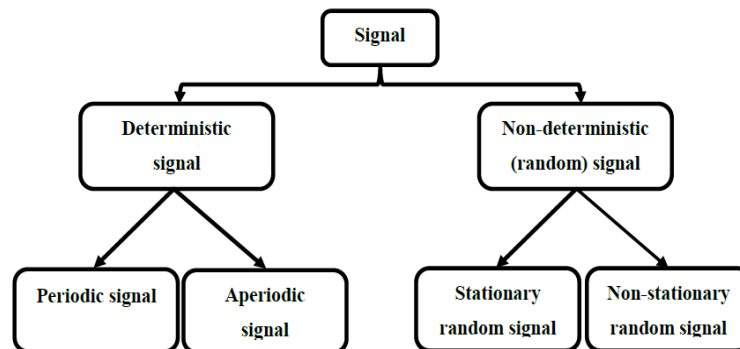


Figure 2. Schematic diagram of signal classification

Deterministic signal: If, after a suitable number of measurements, the signal can be described by an analytical expression and its values can be predicted at any time in the past and future, then it is called a deterministic signal, such as a sinusoid. A deterministic signal may be classified as a periodic signal if the change in the magnitude of the signal repeated at regular time intervals, and if not it is termed an aperiodic signal [Figliola and Beasley, 2011].

Non-deterministic: Conversely, non-deterministic or random signals cannot be described by a deterministic mathematical expression and they are more complex than deterministic signals. By determining their statistical properties, random signals can be broken down into stationary and non-stationary parts. Therefore, if the statistical properties of the random signal do not change with time, then it can be called a stationary signal, otherwise, it is named non-stationary [Wilkinson, 2008]. However, a majority of the signals emitted from industrial machines are non-deterministic. And when a fault starts to appear in a machine the signals monitored tend to non-stationary in nature. Therefore, a suitable signal processing technique has to be applied to analyse this type of signal, as discussed in the coming sections.

3. SIGNAL ANALYSIS TECHNIQUES

After a signal is being captured, a large number of signal processing techniques can be utilized to extract the most sensitive and interesting features concerning defects. As a matter of fact, choosing the most suitable method for each specific task represents a major challenge in condition monitoring. Signal processing techniques are classified as using time domain, frequency domain, and time-frequency domain methods. These methods are not totally independent, and in many situations they complement each other. Some of the widely used signals processing techniques are discussed in the following sub-sections to establish their suitability for robot fault detection and diagnosis.

3.1. Time-Domain Signal Analysis Technique

The technique used in processing the signal can be classified as a time-domain method if it processes a raw signal directly in the time domain without being transformed into another domain, such as the frequency domain [5]. It is considered one of the cheapest and simplest approaches to implement for fault detection. The purpose of time-domain analysis is to determine the statistical features of the original signal

by manipulating the series of discrete numbers. With this technique, however, only the fault can be detected without diagnosing its source. Statistical parameters such as peak value (PK), which represents the maximum amplitude in the signal regardless of sign, can be used to give useful information about the hidden defects represented in the time domain signal. Some of these parameters are illustrated as shown:

Root-mean-square (RMS) is defined as the square root of the average of the sum of the squares of the signal samples, (Equation (1)). RMS can be used for measuring the overall level of average power in the vibration signal [6], [7].

$$RMS = \sqrt{\frac{1}{N} [\sum_{n=1}^N (x[n])^2]} \quad (1)$$

where $x[n]$ is the original sampled signal, N is the total number of samples, and n is the sample index.

Crest factor (CF) is a non-dimensional parameters defined as the ratio of maximum absolute value (or PK value) to the RMS value of the signal, and is given by [6], [7]

$$CF = \frac{PK}{RMS} \quad (2)$$

CF is a normalized measurement of the amplitude of the signal which increases in the presence of a small number of high amplitude peaks, such as in the case for some types of local tooth damage in a gearbox. The sensitivity of CF to the changes in the sharpness of the signal is much higher than the RMS value, and it is much less likely to give false alarms than using the (PK) on its own [8].

Skewness (Sk) and Kurtosis (Ku) are also dimensionless parameters and denote the statistical moments of the signal [9]. The distribution shape of the signal can be described using the 3rd moment or skewness, which is a gauge of symmetry of the probability density function (PDF) around its mean. If the distribution is symmetric, its value is zero. The skewness becomes negative if the distribution develops a longer tail left of the mean, and positive if the other way around, indicating that something is going wrong in the monitored system, as shown in Figure 3 [10]. The 4th moment or kurtosis represents a measure of the relative flatness or spikiness of a signal compared to its normal state. Skewness and Kurtosis can be calculated using the following equations:

$$Sk = \frac{\frac{1}{N} \sum_{n=1}^N (x[n] - \bar{x})^3}{\sigma^3} \quad (3)$$

$$Ku = \frac{\frac{1}{N} \sum_{n=1}^N (x[n] - \bar{x})^4}{\sigma^4} \quad (4)$$

where \bar{x} and σ are the signal mean and standard deviation, which represent the first and second moment of the signal respectively, as given by:

$$\bar{x} = \frac{1}{N} \sum_{n=1}^N x[n] \quad (5)$$

$$\sigma = \sqrt{\frac{1}{N} \sum_{n=1}^N (x[n] - \bar{x})^2} \quad (6)$$

Every signal distribution has different kurtosis values as shown in the Table 1 [11]. The monitored signal usually shows a normal pattern with a kurtosis value of approximately 3 if it is healthy. When a fault is developed in the system, the kurtosis value increases indicating that the signal is no longer normally distributed, and therefore, it is useful in identifying the machine nature [12].



Figure 3. Positive and negative skewness [10]

Table 1. Kurtosis values for different signal distribution

Type of signal distribution	Ku
Normal-peak	3
Flatter than normal	3
Sharper	3

A substantial number of papers have employed time-domain technique to identify defects in many applications. Zhen and Zhang [13] and Li and Frogley [14] utilized time-domain analysis to detect faults in wind turbine bearings and gears respectively. Piezoelectric accelerometers and capacitive sensors were used to acquire vibration signals from healthy and faulty bearings. Statistical parameters include peak value, average, variance, RMS and kurtosis have been calculated for the bearings and by comparing their results, the status of bearing has been found easily. Although time-domain analysis has many advantages, including straightforward signal processing and simple calculations, it is relatively insensitive tool for early stage fault detection and severely distributed defects if used without being combined with other machine health evaluation techniques [15]. This was verified in two other papers on bearing health monitoring [16], [17], who concluded that most of the bearing fatigue time is consumed during the development of material accumulative damage, whereas the period of crack propagation and development is comparatively short. The time available for initiating a maintenance action before a catastrophic failure after confirming a defect will be very short if this traditional technique is used. In contrast, Tseng, et al. [18] and Kamiel, et al. [19] have shown that utilizing the statistical process control (or statistical control chart) techniques combined with the time-domain features have effectively improved the fault detection process, but could not diagnose it. Thus, as it was mentioned previously that the first stage is in charge of only detecting the fault, so the combination of time-domain signal analysis with SCC will be applied at this stage.

3.2. Frequency-Domain Signal Analysis Technique

In most applications, signal representation in the time domain is not the most appropriate, since much of the relevant information is hidden in the frequency content of the signal. Frequency or spectral analysis provides additional information about time series data, and can be used to explain the spectra of frequencies which exist in the signal. The parameters of frequency domain analysis are more reliable in damage diagnosis than time domain parameters. However, time-domain signals can be represented by a family of complex exponents with infinite time duration using Fourier transforms (FTs). Additionally, any given time-domain signal can be written as a function of all of the frequencies present within it using Fourier transforms, which allows analysts to concentrate on all or specific frequencies. This is achieved by representing a time-domain signal $x(t)$ by sinusoidal components with infinite time duration [20], [21], which are given by:

$$X(f) = \int_{-\infty}^{\infty} x(t)e^{-j2\pi ft} dt \quad (7)$$

where $X(f)$ is the transformed signal, f is frequency, and t is time. To regenerate the time domain signal back from the frequency domain signal, an inverse Fourier transform has to be applied:

$$x(t) = \int_{-\infty}^{\infty} X(f)e^{j2\pi ft} df \quad (8)$$

However, the continuous-time Fourier transform can only be applied to signals of continuous time and infinite duration. Additionally, in most applications, signals are commonly acquired and sampled at a specific frequency, which is called the sampling frequency (f_s), and converted into a set of digital data points, and therefore it is necessary to use the discrete version of the Fourier transform (DFT) [20], [21], which is:

$$X[k] = \sum_{n=0}^{N-1} x[n]e^{-j(2\pi nk/N)} \quad (9)$$

$$x[n] = \frac{1}{N} \sum_{k=0}^{N-1} X[k]e^{j(2\pi nk/N)} \quad (10)$$

where $X[k]$ and $x[n]$ denote discrete frequency and time signal respectively, k and n represent the frequency and time indices, and N represents the total number of points that are equally spaced. To perform

the DFT, a large number of complex computations are involved. This is a computationally intensive process and not practical when performing real-time signal analysis. Thus, an algorithm that is able to perform rapid calculation of the DFT by greatly reducing the number of computations was developed in the early 1960s [22]. This algorithm is known as the fast Fourier transform (FFT) and commonly used in industry for analyzing the data. The FFT algorithm requires the time domain sequence $x[n]$ to have a length of data points equal to the power of 2; which means that 2^m samples are required where m is a positive integer [22]. Generally speaking, the FFT is a useful technique for transforming difficult operations into very simple ones, and for analyzing stationary signals, which have spectral content that does not change over time. Also, in many signal processing applications, the Fourier transform represents an adequate analytic method.

However, the Fourier technique can become less effective and inefficient if the analyzed signal is non-stationary and transitory, with characteristics that change over time, due to its constant time and frequency resolutions [23], [24]. Furthermore, it has a major drawback that when it is used in transforming the signal from the time domain to the frequency domain, all of the information belonging to time will be lost [24]. Nevertheless, provided that the signals are stationary, the task of distinguishing faulty from normal conditions based on the FFT can be accurately achieved. This is performed by investigating particular estimated frequencies related to some component in the machine, such as gears or bearings. If a fault has developed in these components, the amplitude of these particular frequencies will change or some sideband frequencies will be distributed around them. Therefore, many fault diagnosis studies using this technique have been published, having been successfully applied for the condition monitoring of electrical motors, cutting tools, bearings and gears [25-27].

Industrial robots, on the other hand, are required to function under a wide range of joint speeds and variable loading within a large working area and varying joint articulation. Also, the typical cycle of robot motion starts with an acceleration from the initial position, then moving at constant speed, and finally deceleration towards the end position, which means movement at a time-varying speed [28], [29]. This motion makes the robot a highly non-linear dynamic system and introduces the non-stationary phenomenon in the captured vibration signal, and this will be more complicated if a fault is progressed in the robot. Using a conventional FFT signal analysis technique to process such signals with transiently nature is not feasible for accurate robot fault diagnosis in second stage. Therefore, several methods of signal processing have been developed to cope with this category of signals, such as joint time-frequency techniques, as discussed in the following section.

3.3. Time–Frequency Signal Analysis Technique

The signals from faulty parts have a non-stationary nature. However, if the frequency component of the non-stationary signals is calculated using the Fourier transform, the results will represent the frequency composition averaged over the duration of the signal [30]. Consequently, the characteristics of the transient signal cannot be described adequately using the Fourier transform, however, time-frequency analysis has been investigated and applied for the fault diagnosis of machinery because of its capability of signal representation in both the frequency and time domains [24], [30]. This unique feature of time-frequency analysis techniques means that it is suitable for non-stationary signals. Moreover, time-frequency methods can give interesting information with regard to energy distribution over frequency bands. A number of techniques of time-frequency analysis, such as the short time Fourier transform and wavelet transforms, have been used for fault detection and diagnosis. These techniques will now be discussed to identify the main differences between them and select the best to be used at the diagnosis stage.

3.3.1. Short time Fourier Transforms

To overcome the limitations of the Fourier transform technique, Gabor introduced a windowing technique in 1946 known as the short time Fourier transform (STFT). The STFT algorithm is based on the division of the signal into small portions which are assumed to be stationary. Then, a window function is located at the start of the signal and multiplied together. After that, the Fourier transform will be taken for the result of this product. Next, this window function is moved to a new segment of the signal and the above-mentioned process is repeated. This sequence is repeated until the end of the signal is reached [31]. As a result, the STFT outlines the time-domain signal into a two-dimensional time-frequency representation. This can be mathematically expressed and graphically revealed as follow.

$$STFT(t, f) = \int_{-\infty}^{\infty} x(t) \cdot g(t - \tau) e^{-j2\pi f t} dt \quad (11)$$

Figure 4 shows the signal analysed by STFT [32].

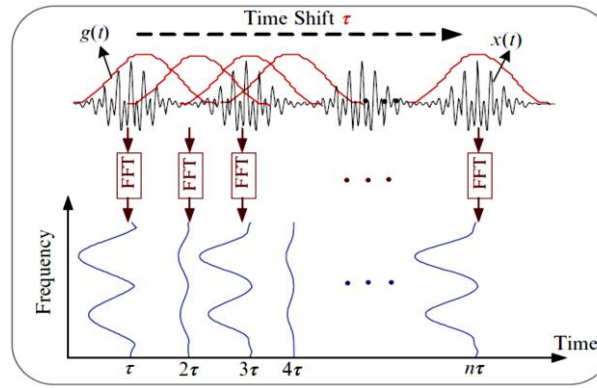


Figure 4. Signal analysed by STFT [32]

$STFT(t, f)$ is the Fourier transform of the signal $x(t)$ which has already been windowed by the window function $g(t)$ with respect to the time shift variable τ . Various window types, with each one employed for a particular application, have been developed over the past decades. For instance, the Hann and Hamming windows are utilized for analyzing random and narrowband signals [32], whereas a Gaussian window is exploited for analyzing transient signals. Selection of the window function has a direct influence on the time and frequency resolutions of the analyzed signal. Generally, superior separation of the essential components within a signal can be achieved if high resolution in the time and frequency domains is used. To illustrate the difference between FFT and STFT a LabVIEW programme, designed by Kehtarnavaz [21] was used, in which three forms of signals were combined to produce a non-stationary signal with 512-input points. The forms of the combined signals are a chirp signal with linearly decreasing frequency from 200 Hz to 120 Hz, a sinusoidal signal of 75 Hz, and an impulse signal located at the 256th sample and having amplitude of 2. The composite signal and its FFT and STFT are shown in the Figure 5.

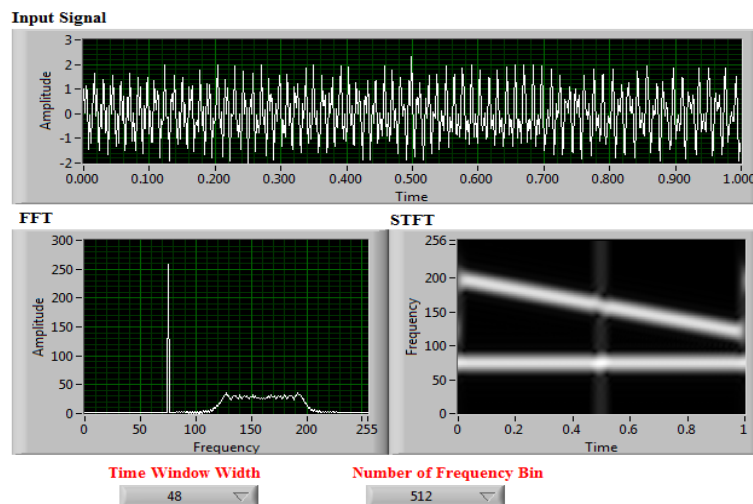


Figure 5. The difference between FFT and STFT for a non-stationary signal

From Figure 5 it can be observed that in the FFT spectrum graph there is one major peak at 75 Hz, and also there is an indication of presence of a signal from 120 Hz to 200 Hz. However, the impulse signal, which has short time duration, cannot be recognized in the spectrum, although it can clearly be observed in the STFT graph at 0.5 second, which shows the spectrogram for a time increment of 1 second and a rectangular window of width 48 points. Although the STFT provides both the frequency spectrum and the time evolution of the signal, it does have a major drawback: it has a fixed resolution with respect to the time window size at all frequencies, and can be explained as follows. When the FFT is used it can be noticed that there is no time resolution, but on the other hand the frequency resolution is very high. The reason for this

high resolution is related to the fact that the window function used in FFT covers the entire time interval from $\pm \infty$. Conversely, the frequency resolution when the STFT is implemented becomes poorer than the resolution given in the FFT, since the window function has a finite length and therefore only a small segment of the signal will be covered. In order to increase the frequency resolution, the window function has to be wide enough, but that will lead to missing time information as well as violating the stationarity assumption which requires the window to be very small. Accordingly, there is a trade-off relationship between time and frequency in the STFT. A wide window gives good frequency resolution but poorer time resolution and vice versa [33]. This is well illustrated in the Figure 6 below depending on the above analyzed signal.

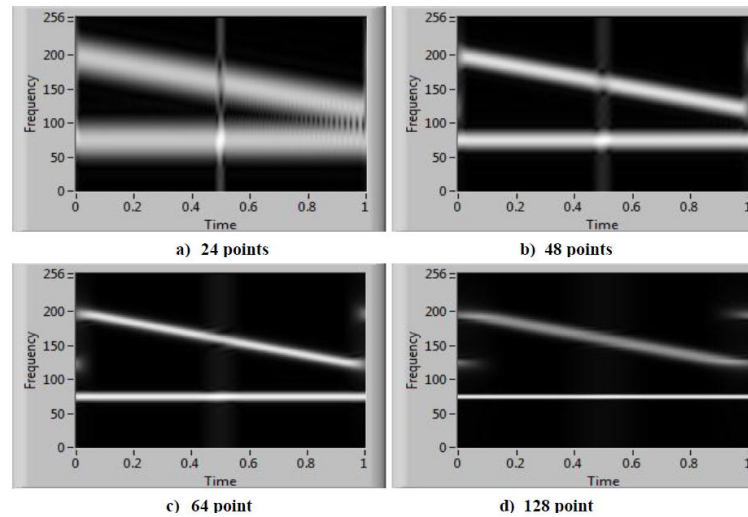


Figure 6. STFT with different window widths

3.3.2. Wavelet Transforms

The wavelet transform (WT) was introduced to overcome the resolution limitation of the STFT. The main difference between the WT and the STFT is that the former has varying window lengths, and represents the signal as a sum of wavelets at different scales [34]. To clearly understand the differences among the time-frequency resolution of the DFT, STFT and WT, their time-frequency mapping is compared in Figure 7, from which it can be seen that, and as stated earlier, the DFT allows extraction only of the frequency content of a signal and any information concerning time-localization of the frequency components is eliminated. The area of each rectangular box in both STFT and WT has a fixed value [35]. However, in the STFT the window has fixed dimensions in both time and frequency axes which offer a constant time-frequency resolution. In WT the window dimensions are not constant, and when the height of the box is greater this corresponds to wide frequency bandwidth, which leads to low frequency resolution, but on the other hand the time resolution is improved. Similarly, if the width is greater, long time duration is covered providing coarser time resolution in contrast to better frequency resolution. So, the WT behaves rather like a mathematical microscope, as condensing the wavelet corresponds to increasing the magnification of the microscope, which increases more of the signal detail [35].

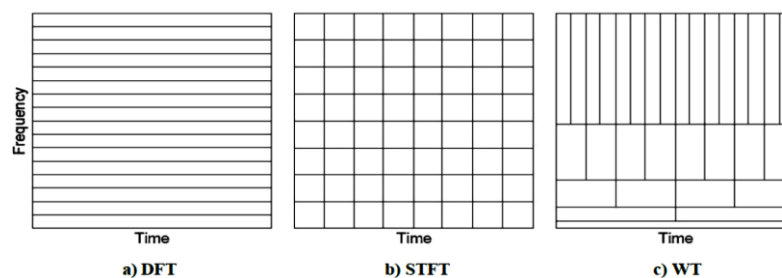


Figure 7. Time-Frequency signal mapping [21]

Complex sinusoids are used in the Fourier transform for signal decomposing, whereas in wavelet analysis a mother wavelet function is utilized. In Fourier analysis sines and cosines are used to fit the signal in order to generate a set of coefficients, however, in wavelet analysis the mother wavelet is fitted on the signal and then the inner product between the analyzed signal and a series of daughter wavelets is performed. The daughter wavelets are generated by scaling and shifting the mother wavelet by controlling the scaling (s) and shifting (τ) parameters. Scaling the mother wavelet is equivalent to stretching or dilating it; although the wavelet is squashed in the vertical axis if it is stretched horizontally, this is to ensure that the energy content in the scaled wavelet is equal to the original mother wavelet [36]. In the shifting step, the wavelet is moved along the X-axis until it covers the analyzed signal entirely, which can be expressed mathematically as follows [35]:

$$WT(\tau, s) = \frac{1}{\sqrt{s}} \int_{-\infty}^{+\infty} x(t) \psi\left(\frac{t-\tau}{s}\right) dt \quad (12)$$

Where $WT(\tau, s)$ is the wavelet transform of the signal $x(t)$ and $\psi(t)$ is the mother wavelet (or the transforming function). The mother wavelet differs from the infinite sine and cosine functions, as it has a finite start and finish. Mathematically, it can be said that the mother wavelet has "compact support" [37], the importance of which appears in that when the mother wavelet fit to the signal, a localized result will be obtained rather than a global result. A series of coefficients that vary with time will be extracted instead of getting a single coefficient for each sine and cosine as in Fourier analysis, and consequently the wavelet decomposition can accommodate the local and sharp changes in the monitored signal; thus it is suitable for those signals whose spectral content changes over time. Accordingly, it represents the most appropriate method that can be applied for analyzing the expected robot vibration signal for precise fault diagnosis and hence it will be adopted in this study.

3.4. Discrete Wavelet Transform (DWT)

The above Equation (12) is called the continuous wavelet transform (CWT) and offers greater accuracy in signal analysis; however, theoretically it is infinitely redundant, which means a significant amount of unnecessary information is produced when it is implemented, and such it is impractical [38]. The redundancy problem is a result of the continuous scaling and shifting of the mother wavelet. This increases the required computational time, power and memory, making the CWT impractical in many situations, particularly when applying real-time wavelet analysis on an embedded system which is the case here. To reduce required power and time it is appropriate to remove any unnecessary information and reduce the number of wavelets without loss of the essential information. The discrete wavelet transform (DWT) was developed to achieve this, in which the mother wavelet is not continuously scaled and shifted, but is instead only at discrete steps along the signals. By using DWT, the original signal is often decomposed into several signals each with a specific frequency band each of which can be handled as an independent signal on which separate analysis can be implemented. The strength of the DWT is that filters with different cut-off frequencies are utilized to analyze the signal at different scales. First, the signal is passed through a high-pass (HP) filter to analyze high frequencies, and then it is passed through a low-pass (LP) filter to analyses low frequencies. Using digital techniques such as this, a time-scale representation of a digital signal can be obtained. Another type of wavelet analysis called complex wavelet transform and is represented by the dual-tree complex wavelet transform. It is an alternate, complex-valued extension and enhancement to the standard DWT, and has important properties that provides multiresolution, sparse representation and the capability to reduce the aliasing effects, which is caused by the overlap of opposing-frequency pass-bands of the wavelet filters [39], [40]. Two parallel DWTs with different low-pass and high-pass filters in each scale are used for decomposition and reconstruction in the dual-tree implementation. The two DWTs use two different sets of filters, with each satisfying the perfect reconstruction condition. However, the drawback of this transform is that it exhibits redundancy compared to the standard DWT at the expense of extra computational power; therefore, it was not considered in this study due to the expected computational limitation of the embedded system.

3.4.1. Multi-Resolution Analysis using DWT

Generally speaking, by using the DWT, a multi-resolution analysis can be performed at different frequency bands with different resolutions by decomposing the time domain signal [30], [34]. Two sets of functions are employed in the DWT, called the wavelet function and the scaling function, which are associated with the HP and LP filters respectively. At the first level, the original signal $x[n]$ is decomposed by passing it through both of these filters and emerges as two signals, each one having the same number of samples as the original signal, and are termed as coefficients. In order to keep the total number of coefficients

in the produced filtered signals equal to the original signal samples they are then down-sampled by a factor of 2, by keeping only one sample out of two successive samples. Thus, the extracted signal coefficients from the HP filter and after down sampling are called the detail coefficients of the first level (cD_1). These coefficients contain the high frequency information of the original signal, whilst, the coefficients that are extracted from the LP filter and after the down sampling process are called the approximation coefficients of the first level (cA_1). The low frequency information of the signal is hidden in these coefficients. This can be expressed mathematically as [41]:

$$cD_1[k] = \sum_n x[n] * h[2k - n] \tag{13}$$

$$cA_1[k] = \sum_n x[n] * g[2k - n] \tag{14}$$

where $h[n]$ and $g[n]$ are the high- and low-pass filters respectively. After obtaining the first level of decomposition, the above procedure can be repeated again to decompose cA_1 into another approximation and detail coefficients, as articulated in Equations (15) and (16) [41]. This procedure can be continued successively until a pre-defined certain level up to which the decomposition is required to be found.

$$cD_l[k] = \sum_n cA_{l-1}[n] * h[2k - n] \tag{15}$$

$$cA_l[k] = \sum_n cA_{l-1}[n] * g[2k - n] \tag{16}$$

where $cD_l[k]$ and $cA_l[k]$ are the DWT coefficients at level l , and $cA_{l-1}[n]$ is the approximate coefficient at level $l - 1$. At each decomposition level, the corresponding detail and approximation coefficients have specific frequency bandwidths given by $[0 - F_s/2^{l+1}]$ for the approximation coefficients (cA_l) and $[F_s/2^{l+1} - F_s/2^l]$ for the detailed one (cD_l) where F_s is the sampling frequency [30], [41]. However, at every level, the filtering and down-sampling will result in half the number of samples (half the time resolution) and half the frequency band (double the frequency resolution). Also, due to the consecutive down sampling by 2, the total number of samples in the analysed signal must be a power of 2 [42]. By concatenating all coefficients starting from the last level of decomposition, the DWT of the original signal is then produced, and it will have the same number of samples as the original signal. A schematic diagram illustrates how the multi-level decomposition is performed shown in Figure 8. The number of decomposition levels is identified by the lowest frequency band needed to be traced, and a higher number of decomposition levels are required if very low frequency band is investigated. However, the highest decomposition level that can be achieved is up to that the individual details consist of a single sample [43].

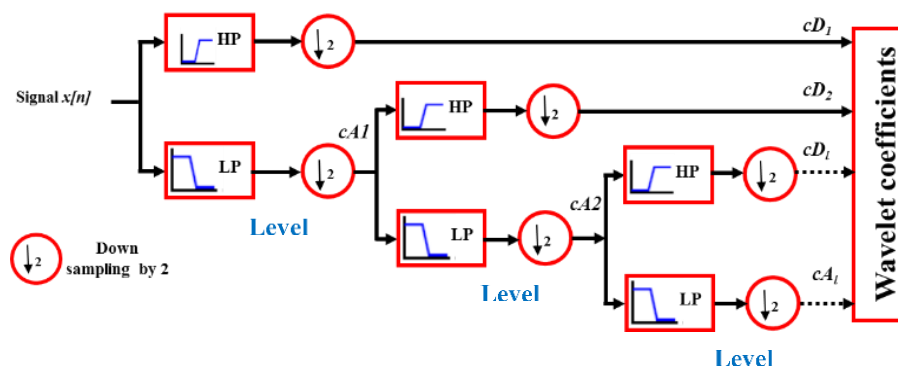


Figure 8. Multi-level signal decomposition using DWT

Once the approximation and detail coefficients are computed to different levels of decomposition, it becomes possible to reconstruct the approximation and detail signals at each level, in order to extract features, such as standard deviation and mean, related to the frequency bands in each level. Each signal, however, will have the same number of samples as the original signal but with a definite frequency band. This can be achieved by up-sampling the approximation (or details) coefficients by two, since they were produced previously by down sampling by 2, and then passing them through high- and low-pass synthesis

filters. For instance, to reconstruct the approximation signal of the first level ($A1$), just the approximation coefficients at this level are required and a vector of zeros is feed in place of the detail coefficients. Similarly, the first-level detail signal ($D1$) can be constructed using the analogous process. The concept of signal synthesizing is illustrated in Figure 9.

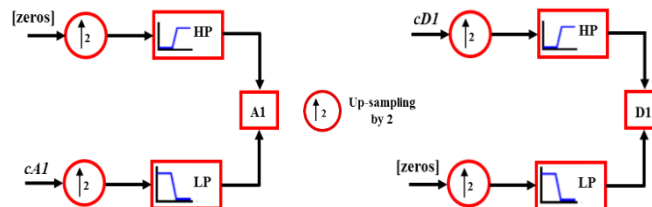


Figure 9. Reconstruction the approximation and detail signals with zero padding

3.4.2. Selection the Optimum Mother Wavelet

There are available a number of commonly used wavelet families for performing the DWT. Any discussion of wavelets starts with *Haar* wavelet, which is the first, simplest, and resembles a step function. However, to find the optimum wavelet function for this research, a survey has been conducted to uncover the different types of mother wavelets researchers have used for the purpose of fault diagnosis. Some examples of common wavelets families previously used are Daubechies (dbN), Coiflet (coifN) and Symlets (symN) (Figure 10), where N is the order number in the wavelet family [30], [44]. The N value also identifies the number of filter coefficients in each wavelet order; for instance, the wavelet dbN and symN have 2N coefficients in each order. Generally, the use of different wavelets to analyze the same signal would lead to different results, and to date no generic theoretical procedure has been published describing on how to select the optimum wavelet family [39], [45],[46].

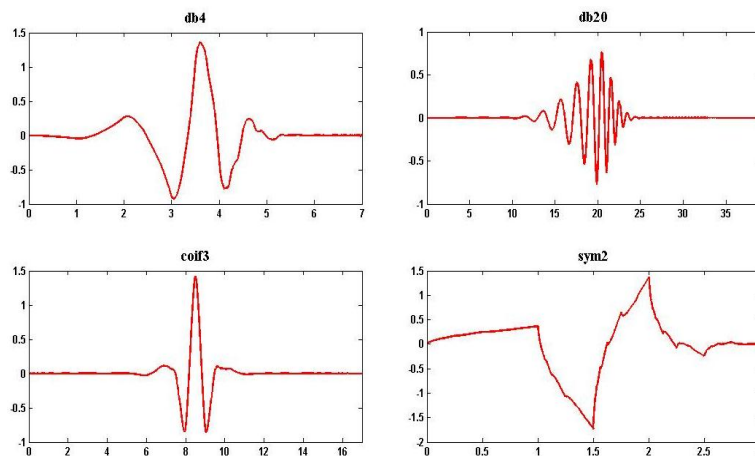


Figure 10. Examples of mother wavelets

The selection in many cases is achieved by trial and error. Indeed, the wavelet function is considered appropriate for analyzing the signal under study if there is a significant similarity between the signal and mother wavelet [47], and based on this several quantitative methods have been proposed to measure the similarity between the signal and the mother wavelet. For example, Bouzid [48] has proposed calculating the cross correlation coefficient between the signal and the mother wavelet. The wavelet that maximises this coefficient considered as the optimum mother wavelet. So, an important question now raised is which wavelet family should be utilized for analyzing the robot vibration signals in the second stage. From the reviewed work it has been observed that the majority of researchers are performing either off- or on-line condition monitoring using PC platforms. In this case there is no need for concern about computers' memory or processing power, since they are designed for conducting daunting tasks such as this. In this

research, however, it is intended to achieve on chip wavelet analysis in conjunction with intelligent fault classification system, and thus the above mentioned factors need to be carefully considered. Therefore, the number of wavelet's filters coefficients in each order of specific wavelet family has to be counted. Some wavelet functions, such as *db10* or *sym7*, have many coefficients in their filters, which will raise the execution time required for real-time wavelet analysis because of the increased computational burden on the embedded system. Also, higher order wavelet function will generate higher number of coefficients from the analysed signals that may case exceed the available system memory [39], [49].

The mother wavelet selection has been limited to the lower order families and hence there is no need to apply further quantitative methods as the remaining options are very few. *Daubechies* and *Symelet* families are recognized as very effective in vibration signal analysis and have various wavelet orders, thus, in this project *Daubechies's* second order (*db2*), which is the same as *Symelet's* second order (*sym2*), has been selected. It has four filter coefficients and Figure 11 shows the low and high pass decomposition and synthesis filters extracted from the Matlab software. Extracted features using this wavelet showed high sensitivity to different robot faults, as will be explained later in Chapter 6.

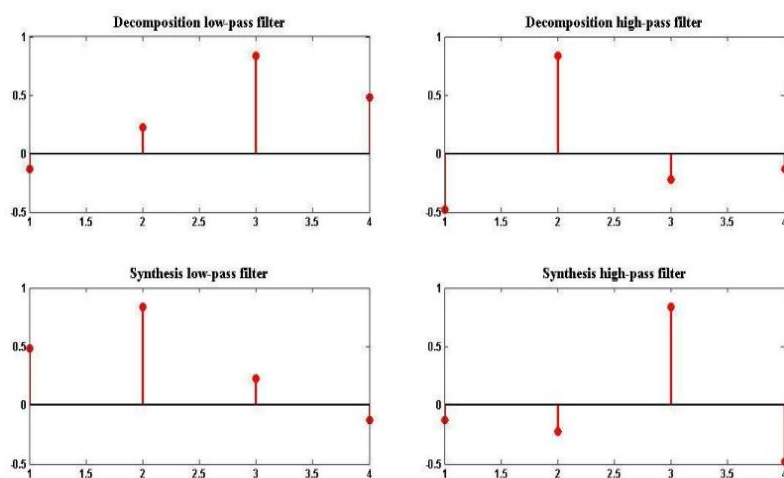


Figure 11. Filter coefficients of Daubechies order 2 (*db2*) mother wavelet

4. SUMMARY

In this paper, an intelligent condition monitoring algorithm composed of two stages that can be used for robot fault detection (first stage) and diagnosis (second stage) has been proposed. An outline of three conventional signal analysis techniques that are commonly utilized in developing condition monitoring systems has been provided, in order to choose the appropriate techniques for the robot fault detection and diagnosis; these techniques are time-domain, frequency-domain and joined time-frequency domain. The advantages and disadvantages along with a brief theoretical background for each method were discussed. Time-domain analysis represents the simplest signal processing technique; it can provide an efficient fault detection performance if it is used with other fault evaluation methods. Subsequently this will be used in combination with statistical control chart (SCC) technique in the first stage for robot fault detection. Frequency-domain signal analysis based on fast Fourier transform (FFT) is a valuable and widely used technique for analysing signals that have spectral content that do not change over time (stationary signals), but its effectiveness is reduced if applied for analysing signals that have characteristics which change over time (non-stationary signals). The limitations in Fourier transform have been overcome by using time-frequency signal analysis techniques such as short time Fourier transform (STFT) and wavelet transform (WT). The main advantage of these techniques over the Fourier transform is their ability in revealing the non-stationary and random components within the signals of interest. However, STFT is based on fixed window size which means it has fixed resolution for all the frequencies in the signal, which is not appropriate when a non-stationary signal is investigated. Wavelet transform represents an efficient method of time-frequency analysis and was introduced to surmount the drawback of the STFT, since it uses variable window size to get high frequency resolution at low frequencies and high time resolution at high frequencies. By applying wavelet analysis, the signal can be analyzed down to its sub-band frequencies and it is increasingly being utilized for fault diagnosis. Hence, it will be adapted in this thesis for analyzing the robot transitory vibration signals in order to diagnose the fault in the second stage. Thus, more focus has

been placed on examining the practical use of the WT as an efficient signal processing technique for health monitoring. The differences between the continuous wavelet transform (CWT) and the discrete wavelet transform (DWT) are discussed and it was concluded that DWT is more appropriate to be implemented, along with an intelligent classification system, using an embedded system. Before it is applied using the embedded system a preliminary robot vibration analysis will be undertaken in Chapter 6, in order to extract the salient signal features and use them for designing the intelligent embedded system.

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