Automated Ultrasonic Classification of Defects in Aluminum Die Castings

Introduction

Casting is the most ancient metal-shaping technique exploited by man, and is the process of forming metal objects by melting metal and pouring into moulds[1]. There has always been the problem of discontinuities in castings such as irregularities, breaks, or gaps in the material structure. If the discontinuities are sub-surface they must be detected and identified before they can be eliminated. Automotive castings often are subject to fluids under pressure which includes transmission fluid, engine oil and coolant. A common problem is fluid leakage through sub-surface discontinuities. Therefore, the detection of porosity and other discontinuities that cause leakage is of paramount importance in maintaining quality.

Nondestructive testing (NDT) techniques (including ultrasonic, x-ray, liquid penetration, eddy current and magnetic particle testing) have previously been used in different areas of the casting industry[2]. Most of these techniques have experimented with machined castings. At present, in the automotive die casting industries, defective castings are detected off-line either through x-ray or leak testing of castings. The focus of this research work was to investigate the possibility of identifying sub-surface defects using ultrasonic inspection prior to machining the die castings. A difficulty with this technique is that a significant amount of ultrasonic energy is scattered by the rough surface of the as-cast components. Furthermore, the castings have variable internal grain size structure which leads to problems with scattering of the ultrasonic signal. Another major focus was to automate the defect classification of ultrasonic signals using various signal processing techniques.

The objectives of this research program emphasized the necessity of obtaining an understanding of the casting process and use of ultrasonic inspection. Once the casting process and ultrasonic NDT methodologies are understood, then it should be possible to duplicate the expertise of a human inspector in the inspection area through an automated identification system. The experimental set-up and results obtained from ultrasonic immersion testing of the sample castings are also described in this paper. Finally, the results of an initial implementation of the inspection system are presented.

Ultrasonic Testing of Castings

Ultrasonic NDT utilizes sound waves at frequencies beyond human hearing (greater than 20 kHz). It is a widely accepted technique for flaw detection3. Ultrasonic waves have the property of being transmitted by solids,
but reflected by internal discontinuities in the material structure, such as the surface of the internal defects. The behavior of the ultrasonic beam thus provides a means to detect, locate and estimate the size of defects[4].

Castings could be ultrasonically inspected to detect manufacturing defects such as shrinkage cavities, blowholes, porosity, inclusions and cracks[5]. Ultrasonic inspection is possible in the inspection of castings of simple design where the echo pattern can be reliably interpreted. Nelligan[6] has demonstrated that ultrasonic flaw detectors could be used to detect internal flaws in castings. However, for shop floor applications, the operator should be experienced and have reference standards to be able to reliably interpret the echoes. Nelligan[6] also stated that defect detection could be automated in situations where relatively simple casting geometries, smooth surface finish and proper flaw detectors are involved. Similarly, Adler et al.[7] investigated the application of an ultrasonic immersion technique for evaluation of porosity in smooth surface aluminum cast materials. They also found that the major limitations on the use of ultrasonics for inspection of castings were size, shape, thickness, surface roughness and orientation of defects.

At rough surface areas of the castings, it is hard to detect any sub-surface defects because the ultrasonic signals are scattered at the rough surfaces, such as fracture surfaces resulting from trim operations. Therefore, it is difficult to inspect a rough surface and it also requires considerable time to carry out the inspection. Ultrasonic inspection also requires vast amount of knowledge and experience to properly establish inspection techniques and interpret results. Hence, it is proposed that, by applying an artificial neural network technique to the interpretation of the ultrasonic signals, the necessity for manual inspection could be eliminated.

Both contact and immersion methods were used to detect defects in castings. Since, the surface roughness is a perpetual problem in ultrasonic inspection and its effects are hard to overcome with contact testing[8], the immersion method was preferred for castings having rough surfaces. Hence ultrasonic immersion testing has been selected to carry out inspection of sample castings.

Automated Interpretation of Ultrasonic Signals

As previously mentioned, ultrasonic inspection is often difficult and time consuming to implement and relies on the skills and experience of the inspector. In the field of ultrasonic NDT, the application of an artificial neural network (ANN) has a relatively long history. Previously, a wide variety of signal processing techniques have been used in classifying defects in different applications. However, there is no evidence of ANN systems being used to classify sub-surface defects in die castings with high surface roughness (Ra > 50 microns). Most of the research work carried out on signal processing associated with ultrasonic signals has been related to the classification of weld defects[9] and plate defects[10].

Ultrasonic defect classification in general has been carried out using different neural network principles in different applications. It has been identified from the literature that a feed forward back propagation based network structure is appropriate for ultrasonic defect classification of plate, weld and shaft inspection[9-11]. However, in this situation, pre-processing steps were required to enhance ultrasonic signals prior to classification. This was possible using neural networks. The Fast Fourier Transformation (FFT) is a standard pre-processing technique used in digital image processing[12]. The idea was to expand the signals of an object in a Fourier series and use a limited number of Fourier coefficients to reduce the signal noise. Similarly, decomposing a signal into coefficient wavelets has been used for signal pre-processing as it permits the determination of a particular time-scale where the signal has significant energy[13]. For example, the energy at small time-scales is mostly due to noise either from grain size variation or surface roughness. Therefore, by removing small-scale wavelet components of the original signal, it is possible to reduce signal noise and compress the signal data noise[14]. Data compression reduces the amount of input data to the neural network without losing the critical elements of the input signal.

The neural network type used in this application is a feed-forward network as shown in Figure 1. The first group of units (neurons) comprise an input layer, which accepts the data values to be interpreted. The next group of units form a hidden layer and the final layer of units is the output layer, which is often related to the number of sets to be classified. The MATLAB neural network and wavelet toolboxes were used for neural network and signal pre-processing analysis respectively.
Sample Casting
A sample casting, structural oil sump pan was selected, as a typical casting for inspection. This casting suffered from leakage problems caused by porosity and other defects in the in-gate region. The shearing of the in-gate section during the trimming operation further aggravates the porosity problem. This exposes any porosity, and causes a rough surface with openings of up to 2-3 mm in depth. If sub-surface defects are present and extend through to the other side, a leak will result and the casting would be considered faulty.

Procedure
In order to compare data from separate measurements and obtain trends in the type of defects it was necessary to ensure the measurements were reproducible. Hence, in an earlier investigation Palanisamy et al.[16] had verified the reliability of the probe handling device and flaw detector for its repeatability and accuracy to generate ultrasonic signals from the similar castings. For this investigation, the sample castings were machined into small

Experimental Methodology

Experimental Set-up
The experimental set-up used in this research work is shown in Figure 2. It consisted of an ultrasonic flaw detector with immersion focus probes, a water tank, calibration blocks and a probe handling device. A sample part was immersed in the water tank and a PUMA type industrial robot (probe handling device) was used to move the transducer. The readings obtained were transferred via the flaw detector, to a personal computer for processing.
sections (100 mm x 15 mm x 8 mm) from the in-gate region. The surface roughness (Ra) varied from approximately 50 µm to 150 µm because trimming operations caused fracture surface along the in-gate section. Moreover, taking into account the impracticability of collecting a sufficiently high number of experimentally representative situations, porosity defects were simulated by 1 mm side drilled holes along the cut section of the sample castings. Only the end section of the side drilled hole was considered for inspection as it replicated the gas porosity in sample castings.

After building up a database of A-scan signals from both simulated and real defects, the training data for the neural network was generated by taking the signal amplitudes of the A-scan. These signals corresponding to known features were converted into the frequency domain using FFT. The frequency components of these A-scan sections together with their known classification (defect and no-defect) were then fed into the neural network for training.

Prior to inspection, the experimental parameters had to be selected for sample castings. The initial experimental parameters like water path distance and ultrasonic velocity in the material had been obtained from previous research on ultrasonic inspection of aluminum die castings [16]. The material properties have an effect on the selection of experimental parameters and they affect the sensitivity of ultrasound frequencies in inspection applications. The frequency of a transducer is a determining factor in its use.

In this work, ultrasonic immersion testing experiments were carried out with different surface roughness values to select a suitable frequency for the particular range of surface roughness. Previous research investigations have been confined to roughness values (Ra) less than 50 µm mainly due to the factor that the casting inspection has been carried out on the machined castings [17,18]. However, in this investigation the sample castings had surface roughnesses between 50 µm and 150 µm (i.e. prior to machining off the as-cast surface). If a suitable probe and pulse were selected for the larger surface roughness then it would improve the identification of sub-surface defects.

Results & Discussion

Influence of Grain Size on Signal Amplitude

The initial experiments were undertaken to verify the hypothesis that background noise of the ultrasonic signal was proportional to the grain size. To do this, experiments were carried out on the castings with a large grain size relative to the ultrasound wavelength. By doing this a large amount of background noise was generated. Grain size measurements were carried out on the sample parts and correlated with the ultrasonic attenuation for different frequencies of the incident signals. A typical microstructure of a CA313 (A380) die casting aluminum alloy is shown in Figure 3. The grain size from the metallographically prepared specimens was determined by the linear intercept method19 [19]. Most of the sample castings consisted of fine to medium grain sizes (0.2 mm to 0.5 mm in diameter).

Figure 4. is plotted for Back-Wall Echo amplitude (BWE) versus frequency for various grain sizes. BWE is the signal echo reflected from the back surface of the casting. When testing sample parts at the in-gate section of the casting, the attenuation of the test signal increased as

![Figure 3: Microstructure of CA313 Aluminium alloy at the in-gate section of the casting.](image-url)
the grain size increased as shown in Figure 4. To reduce the dampening of ultrasound within the test material with large grain size, lower frequency probes were used. As the frequency increased, the BWE for a given grain structure decreased. Similarly, an increase in grain size resulted in a decrease in BWE. It was assumed that the loss in BWE amplitude was due to the scattering occurring at the internal grain boundaries. By exhaustive experimentation it was found that the frequency range of 5 to 10 MHz was suitable for inspecting the selected sample castings.

Influence of Surface Roughness on Defect Signal

Experiments were carried out on castings with a thickness of 8 mm and fine grain size (0.2 mm). For this the surface of castings was machined such that roughness values (Ra) varied from 150 µm (rough) to less than 10 µm (smooth). The defect signal amplitude (signal height on ultrasonic A-scan display) was evaluated as a function of surface roughness and incident frequency from the simulated defects (flat bottom side drilled holes) with 1 mm hole size. The roughness of the rear side of the casting was ignored because in most of the castings it was less than 10 µm (i.e., similar to smooth surface). The results of this analysis are presented in Figure 5. It can be seen that it was difficult to detect the defect signal for surface roughness (Ra) in the region of 150 µm with any of the selected frequencies. This effect was due to scattering of the ultrasonic signal at the rough front surface. The lower frequencies of up to 10 MHz showed a higher defect signal amplitude compared to the higher frequencies (15 MHz and 20 MHz) for surface roughnesses up to 100 µm. There was no defect signal obtained for surface roughness values beyond 125 µm with 15 MHz and 20 MHz frequency probes. This was due to scattering of the ultrasonic waves from the rough surface, which was nearly equal to the half wavelength distance of ultrasonic signal. From the experimental results the percentage loss of ultrasonic signal for different roughness values could be determined for similar die cast parts.

Once ultrasonic signals were obtained for the selected frequency on sample castings with varying surface roughness and grain structure, the next step was to analyse them in order to identify the defect signal within the background noise. Even though a suitable frequency had been selected it was difficult to classify defects from the rough surface as shown in Figure 6a. At the front surface of rough surfaces the defect signal mostly merged with the clustered front wall echo due to signal scattering. However, in the case of machined surfaces, the defect signal and BWE were clearly identified as seen in Figure 6b. Hence to classify the defect signals from the rough surface, there was a requirement for

![Figure 4: Variation of BWE amplitude (%) and probe frequencies for three different grain size.](image1)

![Figure 5: Variation of defect signal amplitude with surface roughness for different frequencies.](image2)
signal processing. It also needed to classify the smooth surface signals through appropriate signal processing and compare it with rough surface signal classification.

**Signal Processing of Ultrasonic Signals**

The neural network topology had 220 inputs to accept the frequency signal and one output to determine whether the signal represented a defect or not. The optimized neural network had 20, 10 and 1 neuron in the first, hidden and output layers respectively. Nearly 100 data samples were gathered from tests containing real, simulated and also non-defect signals. Using random initialization weights for the neural networks the average performance of the different designs have been calculated. The results obtained from the feed-forward neural network classification on rough and smooth surfaces are shown in Figure 7. They were compared with the results obtained from pre-processing of ultrasonic signals using FFT and WT. From Figure 7, it had been observed that the application of the raw signal to the neural network had the least successful classification percentage compared to signals classified after passing through preprocessors.

In comparing FFT and WT pre-processing, the percentage classification of signals is higher in FFT. There was not as great a variation in wavelet classification percentage compared to FFT classification with nearly 80 percent and 75 percent classification for the machined smooth surface and rough surface castings respectively. One of the reasons for achieving a better classification in FFT was due to the utilization of ultrasonic signals with higher amplitude. The data compression performance was in the same order as that of WT. In the case of FFT, it was more reliable in eliminating many of the larger errors (high noise signals) at the same time. But the wavelet method needed the largest number of coefficients to achieve the desired performance. Hence, the pre-processing of ultrasonic signal using FFT provided a better classification percentage when passed through

![Figure 6: Ultrasonic A-scan signal display from a defective casting having (a) Rough surface (b) Machined smooth surface using 10 MHz frequency probe.](image)

![Figure 7: Percentage of successful classifications using different signal processing techniques with both rough and smooth surface castings.](image)
the feed forward neural network.

Conclusions

In this research project considerable useful information in relation to ultrasonic immersion testing has been obtained from the literature review and the experiments carried out on the sample castings provided by the industry partners. Castings with medium to coarse grain structure can be inspected using probes of a suitable frequency. The proposed method of detecting and classifying gas porosity and simulated defects using ultrasonic inspection presented in this article performed well with the given data. The neural network approach has successfully eliminated the disturbing noise in the casting with surface roughness ranging from 50 µm to 125 µm, but defects cannot be classified for surface roughness beyond 125 µm. The defects from raw signals were difficult to classify using the neural network approach but the pre-processing of signals using FFT and wavelet increased the percentage of classification. In comparing the two pre-processing techniques used here, FFT had a better classification percentage compared to the wavelet transform. Even though FFT provided better classification compared to WT, it could not achieve more than 80 percent level classification. This was mainly due to concealment of the defect signal within the noise signal generated by grain size and surface roughness variations. In future this work can be extended to classify different sub-surface defects in aluminium die castings.

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