Sound Detection in Noisy Environment – Locating Drilling Sound by using an Artificial Ear

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***Abstract*- In rock drilling, as in many industries today, the drive towards unmanned equipment and full automation is a big issue. A challenge in the automation process for rock drilling is the retraction of the drill steels when the drilling is completed. Today the drilling can be performed automatically to some extend, but a human ear is required for the final part: when the splices between the drill steels are opened up enough to allow retraction.**

This paper discusses a Fast Fourier Transform (FFT) method to search through audio data in order to detect and locate specific sounds appearing when retraction of the drill steels is possible, and to investigate if achieving full automation of the drilling process is possible. The use of Wavelets has also been evaluated. As far as the authors know, there is no system today for automatic retraction of the drill steels.

By recording and analysing sounds from rock drill rigs, a comparison between a system implemented with an electronic ear and a human ear has been evaluated. The FFT has been applied as a pre-processing method and examines features of power spectrum for the detection of the sound, when the splices are opened up. This sound contains higher power spectrum than sounds from the rest of the drilling procedure. Using these features, a classification program has been designed. The experimental results shows that there is a good possibility to make a commercialized product that automatically detect when the drill steels are ready to be retracted.

I. INTRODUCTION

The use of the human sense hearing as a part of examination and diagnosing is used in many fields. The piano teacher listens to the students chords to evaluate the correctness of them, the same way the car engineer listens to the sounds of the car engine to analyse possible damaged parts. A doctor listens to a patients heartbeat to detect abnormalities. In the aim of letting technology perform human tasks, we have to let a system imitate the human conception of "normal behavior" and teach the system to react when there is an unexpected deviation, the same way the senses informs humans. By using different analysing methods this imitation is implemented in many applications. James Walker [1] describes a method to detect abnormal heart rhythm by using Wavelets Transforms (WT). Kotani *et al* [2] describes the use of frequency and amplitude to extract a gas leakage sound from a noisy environment. Another system based on Artificial Neural Networks (ANN) and sound recordings for aircraft identification is evaluated by Claesson, unpublished, [3].

Also in the mining industry the use of the human perception is essential, and some research has been done in this area. Fu *et al.* [4] have developed a matching pursuit approach to predict small drill bit breakage in the drilling process. By applying ANN, Abu-Mahfouz [5] uses vibration features for detecting drilling wear. The approach described in this paper, however, is focused on automatic sound measurements, not vibration measurements.

In the aim of producing drill rigs with a high level of automation, Atlas Copco Rock Drill Equipment AB is developing a rig control system, RCS, for a new generation of more automated drill rigs. Using the control system to its full extend, by gathering information from sensors located on the rig, it can perform a complete drilling without the interference of a machine operator. The part still missing for full automation, is the retraction of the drill steels when the drilling is completed, see Fig. 1. Today, a machine operator must determine if the splices between the drill steels are opened up enough to be retracted. This is achieved by listening for a specific sound appearing when the splices open up. If a system could be able to detect this specific sound, it would be one step closer to an unmanned rig.

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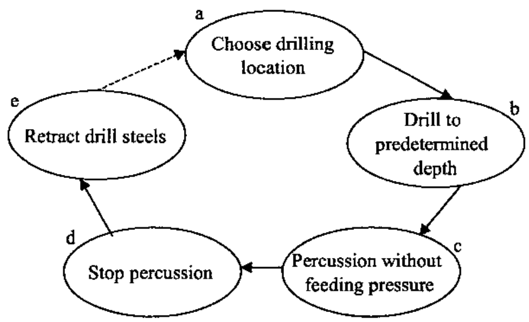

Fig. 1. First the location of the drill hole is decided (a), then the drilling is performed until preset depth is reached, by joining drill steels together (b). The percussion runs for a short while without pressure until the machine operator hears the specific sound, carrying the informing that the splices are opened up (c). The percussion is terminated (d) and the drill steels can be retracted (e).

II. PROBLEM DEFINITION

The rig control system, designed by Atlas Copco, is implemented on their tophammer surface drill rig ROC D7 C. The drill rigs used for measurements are ROC F9 (next drill rig to be implemented with RCS) and ROC D7 C. The drill rigs will be referred to as F9 and D7 C.

The RCS is based on CAN-bus technology and consists of I/O units, calculation units and operator units. The operator sets the parameters, such as depth and leaning of the hole, and activates the automatic rod handling. The control system then drills the hole to the preset depth by joining the drill steels together, and constantly gathering information from the sensors located on the rig for controlling the progress of the drilling. In Fig. 2 the principle of tophammer drilling is presented, and Fig. 3 show how a drill rig is designed.

The percussive drilling breaks the rock by hammering impacts transferred from the rock drill to the *drill bit* (Fig. 2) at the hole bottom. A hydraulic or pneumatic rock drill generates the energy required to break the rock. When the energy is released, the built up pressure drives the piston (*impact piston*) forwards. The piston strikes on the *shank adapter*, which converts the kinetic energy of the piston into a stress wave. This wave is transferred to the bottom hole through the drill steel (*drill rod*). When the shock wave reaches the drill bit, it is forced against the rock, thereby crushing it.

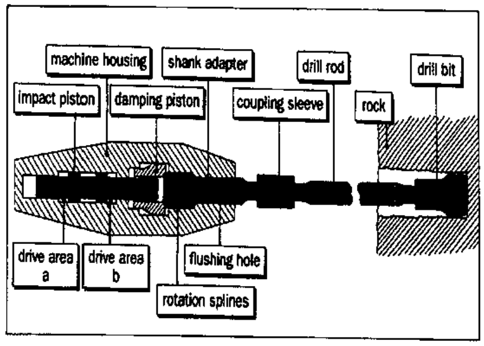

Fig. 2 Principle of tophammer drilling.

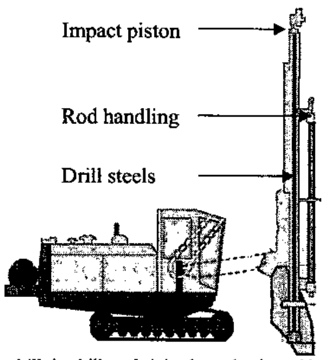

Fig. 3. Tophammer drill rig, drill steels joined together by rod handling.

The splices between the drill steels are hard drawn together during the drilling. When the drill hole is completed, the machine operator has to "open up" the splices in order to separate the drill steels and retract them. This is achieved by letting the percussion run for a short while without pressure, to "shake" the splices open. The part of the drilling sequence when the percussion runs without pressure in order to open up the splices, will be referred to as *shaking*. When the splices have been opened up, normally after 0.5 - 2 seconds, there is a characteristic sound appearing from the drill steels. The machine operator describes this sound to be more intense than the rest of the drilling sound. When this distinct sound appears, the machine operator stops the shaking and retracts the drill steels one at a time from the completed drill hole.

The part missing in the RCS, for achieving a completely automatically drilling, is the retraction of the drill steels.

RCS knows today what the current state is in the drilling process:

- *Drilling*
- *Shaking*
- *Machinery*

What must be complemented for achieving full automation is to let the system know when the splices are opened up and the drill steels are ready to be retracted. For this purpose, a fourth state is introduced:

- *Drill Steels Apart*

Fig. 4 shows the different states in a drilling process as a time - amplitude plot.

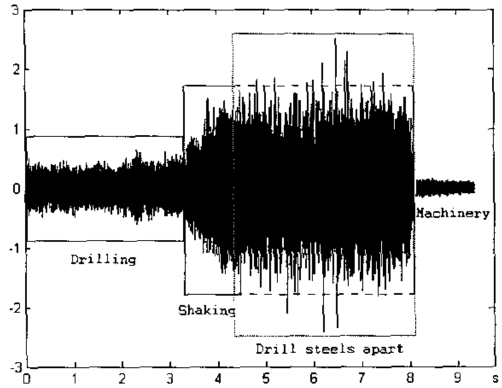

Fig. 4. Plot of a drilling sequence. Notice that Drill Steels Apart is a part of Shaking.

The sound change characteristically when the splices open up, and if the human ear is capable to recognize the sound, it should also be possible for an artificial system to detect it. The main goal of the project in the future is to further develop the full automation of the drill rig. The control system can then perform a complete drilling process, including the retraction of the drill steels. The first part of the project was to investigate the possibility of a system that is able to detect the distinct sound that appears when the splices open up and the drill steels go apart.

III. EXPERIMENTALS

Sound and vibration are possible features for trigging the control system to retract the drill steels from the completed drill hole. Sound signals have been chosen in these experimentals, due to the consideration that the vibrations are too substantial on the rigs in interest.

The sound recordings from the drill rig contain the four basic states of a drilling sequence: Drilling, Shaking, Machinery and Drill Steels Apart. Fig. 4. presents all four states in a time-amplitude plot. The amplitude easily separates the states Drilling, Shaking and Machinery, but since the splices are opened up *within* the Shaking state, it is therefore a condition that the states have to be separated.

During the measurements, the microphone was placed outside the cabin at a distance of 3 meters respectively 4.5 meters from the drill steels, see Fig. 5. The distances where chosen based on a suitable future distance in a drill rig and to make the recordings resemble real environmental circumstances.

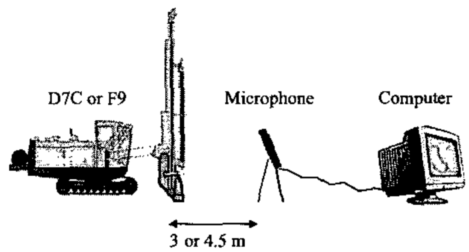

Fig. 5. Measurement setup. Microphone placed at a distance of 3 or 4.5 meters from the drill steels and connected to a computer.

One limitation in the measurements was the large amount of data the sound recordings produce. To be able to analyse the whole frequency spectrum that can be heard by a human ear, i.e. 20 Hz – 20 kHz, the sample frequency was set to 48 kHz, with a resolution of 16 bits. Each measurement is a 20-second sequence, which means that one single measurement produces 960000 values, i.e. a file at about 1.8MB.

IV. SIGNAL PROCESSING

To be able to separate the different drilling states from each other, analyses of the frequency content were performed. Both the use of fast Fourier Transform (FFT) and Wavelet Transforms (WT) has been evaluated.

The basic idea of using FFT is to investigate presence of typical changes in the frequency content between the states Shaking and Drill Steels Apart (Fig. 4). By using a bandpass filter to focus on a few frequency spectrums, the amount of data is reduced. The optimal result of applying the WT, is to detect a waveform that is typical for the exact time when the splices open up and create a new wavelet. This new wavelet can then be used to compare incoming data with. The example shown in Walker [1] is based on the idea that a wavelet is created after a specific abnormality in an ElectroCardioGram, ECG, and the new wavelet is then compared in real time with a patients ECG to detect the presence of these specific abnormality.

A. FFT

The FFT (1) decomposes a signal (or a function) into sinusoids of various frequencies, which when added together again recreates the original signal (or function). What this transform does, in short words, is that it separates the different frequencies along with their respective amplitude. This makes it possible to detect and analyse the frequency content of any signal or function.

$$F(\omega) = \int_{-\infty}^{\infty} f(t)e^{-j\omega t}\,dt \tag{1}$$

One method for the detection of the sound when the splices are opened up, is to apply the FFT as a pre-processing method and then examine features of power spectrum. In Fig. 6. and Fig. 7 Power Spectral Density, *PSD*, plots can be seen. The plots show how the energy changes over the frequency domain. In Fig. 6 the drill rig is F9 and the distance from the drill steels is 3 meters. In Fig. 7 the distance is 4.5 meters from the drill steels, and the drill rig is D7 C. The figures show the frequency content of the four different states.

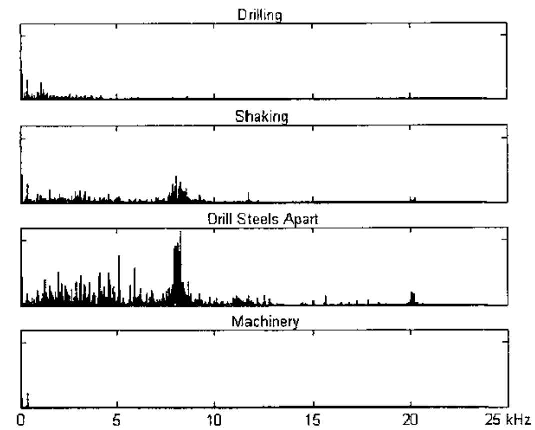

Fig. 6. All four states represented in the frequency domain, in a PSD plot. The signal is from the drill rig F9.

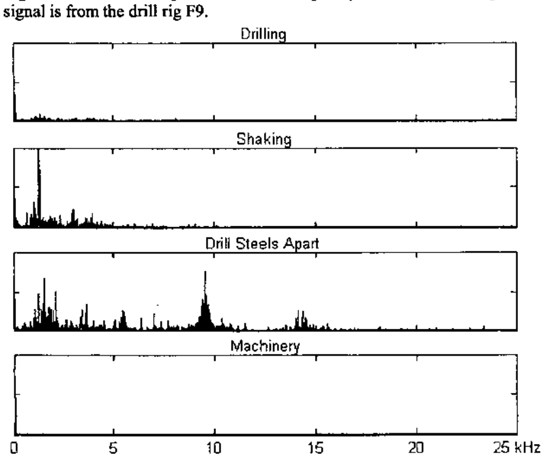

Fig. 7. All four states represented in the frequency domain, in a PSD plot. The signal is from the drill rig D7 C.

In Fig. 6 and Fig. 7 the drilling is divided into four subplots, each representing on of the four states: Drilling, Shaking, Drill Steels Apart and Machinery. Each subplot is a FFT analysis on respective state, visualized as PSD plots. The energy content is continuously increasing from the state Drilling to state Drill Steels Apart, to be very low in the state Machinery. The states Shaking and Drill Steels Apart, consists of higher frequencies (> 7 kHz) and the energy content is higher than in the states Drilling and Machinery. Comparing the states Shaking and Drill Steels Apart, the state Drill Steels Apart has the highest energy content. In Fig. 8. and Fig. 9. the difference in frequency between Shaking and Drill Steels Apart is visualized. Drill Steels Apart (black) contains more energy than Shaking (grey). Fig. 8 – 9 are both FFT plots with one FFT analysis on a file containing only Shaking data (grey) and another file containing only Drill Steels Apart data (black).

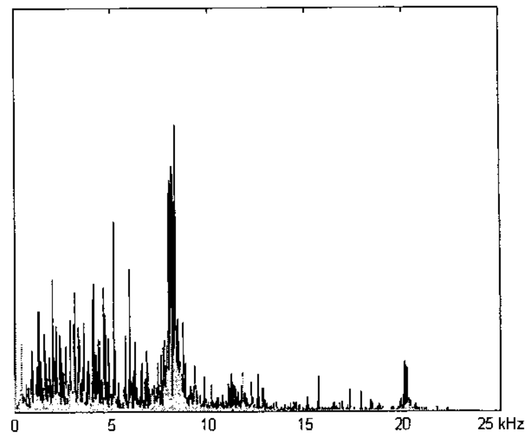

Fig. 8. Differences between Shaking (grey) and Drill Steels Apart (black) on the F9.

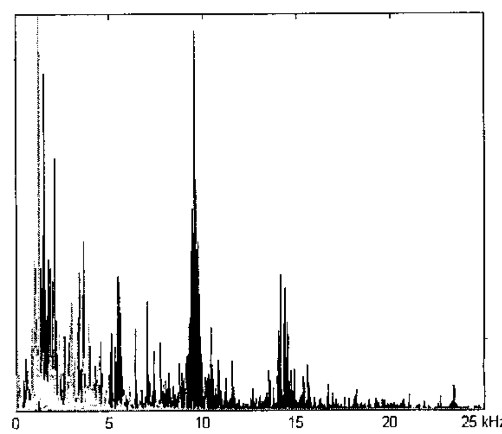

Fig. 9. Differences between Shaking (grey) and Drill Steels Apart (black) on the D7 C.

For classifying the state Drill Steels Apart, two frequency intervals for the two different drill rigs have been tested. The first interval used to test the idea of classification with FFT for the first rig type, F9, was [7,5 – 8,5 kHz] (Fig. 8). The interval [9 – 10 kHz] was used at the second rig type, D7 C, (Fig. 9). The intervals was chosen based on where the state Drill Steels Apart shows distinguished differences in the frequency content, compared to the state Shaking. By using these intervals, it is possible to separate the state Drill Steels Apart from Shaking, by using algorithm (2).

The energy content of the intervals shown in Fig. 8 - 9 has been used for classification:

$$E_T = \sum_{i=f_l}^{f_h} E_i \qquad (2)$$

where E_t = total energy, E_i = energy at respective frequency, f_l = lower frequency limit, f_h = higher frequency limit

Using this energy function E_T with data from the F9, the lower frequency limit is set to 7.5 kHz, and the upper frequency limit to 8.5 kHz. In a similar way, the lower limit for the D7 C is 9 kHz and the upper limit is 10 kHz.

When classifying a measured signal containing all four states, a windowing method was used. The window function splits the signal into short segments, of 1024 samples (0.02 seconds), performs a FFT analysis on each segment and classifies the segment as one of the four states. This depends on which preset threshold value the segment folds into. The position where the state Drill Steels Apart is separated from the state Shaking is hereby found.

The systems performance can be evaluated by comparing result from the FFT classification and a decision based on a human ear. The tests show that FFT analyses recognize the sound when the splices are opened up at the same time, or in some cases a little while before, than the human ear does. In the test shown in Fig. 6 and Fig. 8, the Drill Steels Apart state is located 0.17 seconds earlier with the artificial system, compared with an experienced operator's human ear.

B. Wavelet Transforms

In many applications the FFT is not enough efficient to perform adequate analyses because, of the time information loss. In this cases, the WT (3) can be very useful, mainly because it is not only based on sine waves like the FFT, but it is also able to use almost any waveform in analysing signals. The advantage of this analysing technique is that it has the possibility to detect all kinds of changes in a signal and also the possibility to present the signal in a time-frequency plot [6].

$$W_t(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} s(t)\psi\left(\frac{t-b}{a}\right)dt \qquad (3)$$

Wavelet analysis has, as a complement to FFT analysis, been used in order to detect the exact time when the splices open up. When this event occurs, the sound from the Shaking changes and becomes more "varied and intense". The signal changes at this time and this can be considered as a significant change, that a wavelet analyse can be able to detect.

In MatLab:s toolbox "Wavelet" [6], there are a large number of wavelets. In this project the Daubechies wavelets have been tested. By using these wavelets, rapid changes of the signal are expected to be detected. In order to detect discontinuities, db1 to db10 has been tested.

In Fig. 10, the original signal can be seen. In this original signal there is no information visible regarding any abrupt behavior in the signal. In order to extract the relevant features for Drill Steels Apart, a special technique has been applied while using the wavelet transform. The Drilling, Shaking and Machinery states have been considered as the main trend (or behavior) of the whole signal in order to classify the opening of the splices as an abnormal behavior to be detected. Then the first level approximation obtained by daub10 wavelet was subtracted from the original signal (s) in the aim of getting a resulting signal from which the opening of the splices could be seen. Fig. 11 shows the resulting signal, in a time plot, where the square indicates a different behavior of the signal, at the time around 8 seconds. The position of this change of behavior matches the human ear recognition very well, i.e. the human operator also detect the change of the sound characteristic in the same interval.

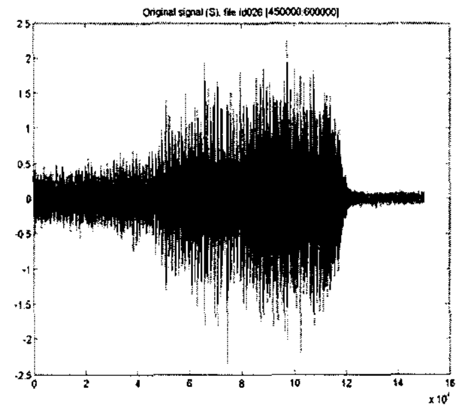

Fig. 10. Original time – amplitude plot of signal from the drill rig F9.

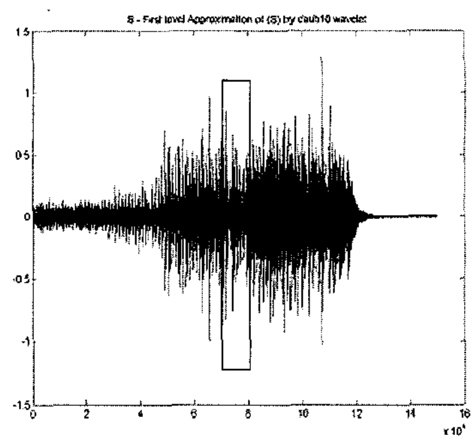

Fig. 11. The first level approximation of Daub10 has been subtracted from the reconstructed signal S, shown in a time – amplitude plot.

V. CONCLUSION

The best result for identifying and classifying a drilling sound comes from the FFT analyses, however, both tested analysing methods exhibit the same performance as the experienced operator. The analyses in this paper show that there are measurable frequency differences between all four states in a drilling process, and it has been shown that it is possible to separate the state Drill Steels Apart from the state Shaking. It has also been shown that the frequency range for a human ear (20 Hz – 20 kHz) can be applied to an electronic ear system. It has, furthermore, been shown that the frequency spectrum can be filtered to reduce the amount of incoming data, and the remaining data can still be classified by identifying the energy content. This indicates that a future sound recognition system will have small needs from the processor power on the drill rig.

Human ear classification has been compared with classification of a sound detection system, in order to verify the performance of the classification algorithms tested in this approach. The electronic ear is able to detect the specific drilling sound characteristic at the same time, or even before, the human ear. This implies the advantages of further testing on the systems performance on surface drilling rigs.

VI. ACKNOWLEDGMENT

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