Acoustic identification of rocks during drilling process

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Akustická identifikácia hornín počas vrtného procesu

This article deals with an intention to identify the specific acoustic signature of each drilled rock type or at least rock class. It describes experimental software for acoustic rock identification based on Hidden Markov Models. The real experiment results are included.

Key words: *acoustic, identification, drilling, minerals, HMM, kepstrum, GMM.*

Introduction

Drilling into a rock massif is energetically extremely consumptive process. Hence the optimization of drilling regime with objective of energy consumption minimization, is very important. Proposed article discusses partial problem of this problem. During the drilling process it is useful to know the drilled rock type, whereas to particular drilled rock needs convenient drilling regime, which is considered as optimal according to energy consumption towards one drilled meter. One of possible ways to determine the actually drilled rock type (class) is to analyze the noise produced by drilling process. The intention is to identify the specific acoustic signature of each drilled rock type or at least rock class.

Acoustic signal processing algorithm

During the process of rotary drilling, the noise raise from three frameworks. The first is the drilling tool engine, the second noise is produced as a result of contact between drill and rock. Cooling water represents the third part of the resulting stationary ergodic, quasiperiodic signal with wide spread spectrum. Previous analyses (Zborovjan, 2001), (Zborovjan, 2002) showed, that relevant signal, porting the rock acoustic signature can be found between 5000 – 8000 Hz. The lower half of signal spectrum represents mostly the drilling engine noise and cooling water.

The first phase of signal processing is the same for training and identification testing algorithm. It uses a Discrete Fast Fourier Transform algorithm windowed with Hanning weight function. The window size is 200ms with 50% frame overlapping, because of signal correlation and elimination of the DFFT algorithm wrong time accession concerning to signal periodicity produced by rotary drill.

Power spectrum is calculated from the DFFT coefficients, which is consecutively transformed to Mel frequency scale. The next step is application of logarithm and discrete cosine transform calculation. The Mel-cepstral coefficients vector as a results of previous calculations is hence distributed to the next three branches of signal processing to acoustic model training algorithm.

Acoustic model training

The first branch takes few whole acoustic vectors and calculates entropy across those frames. The result is compared to a constant, which affects the selectivity of learning algorithm. If calculated entropy is greater than selected constant (sensibility), the acoustic parameters vector, which is result of the rest two processing branches, is accepted for Hidden Markov Model (HMM) parameters re-estimation. Second algorithm branch takes the upper half of acoustic vector and retains it until the third branch finishes its job. The third computation branch is responsible for noise filtering, produced by drilling stand engine. The aim is to isolate and emphasize signal component containing the rock specific acoustic signatures. If the condition from branch one give true the vector from first and second part concatenates and advance to the HMM parameter re-estimation.

The goal of re-estimation is to find accurate parameters of model λ, which might enable to find a global maximum (but usually local) of function $F(\lambda)$. This is known as Maximum Likelihood Estimation (MLE) algorithm. There is used a Baum-Welch (BW) Forward – Backward algorithm, which goal is to find maximal probability $p\{O|\lambda\}$, where O is observed signal coefficients. As there is no vector quantization before the HMM parameters re-estimation, the observed sequence O can theoretically consists of infinite state combinations.

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Therefore in case of here proposed program, there is used a continuous HMM, using Gaussian Probability Density functions (GMM).

Noise to model likelihood estimation

The algorithm for signal identification, returns likelihood ratio of tested noise to acoustic model. The returned result is so-called score non dimensional value, which is positive when observed noise belong to acoustic model. If score is negative or near to zero, tested noise does not appertain to model. As higher is the score as identified noise mach better to selected acoustic model. Score is a fraction of observed noise likelihood to trained model to non-trained elementary acoustic model.

Program realization and experimental results

The experimental software is build over GNU/Linux operating system and Open Source data oriented development environment named Overflow. Here are proposed some results of signal identification on their acoustic models. There are four a bit different signals, from which was build four appertaining acoustic models. The aim of this experiment is to test identification of every sound on its and foreign model appertaining to other signal. On Table 1. you can see results of this test. Lines represents acoustic model and columns are tested sound signals. Each number is score as result of test sound to model.

Tab.1. Sound signals to models likelihood score.

ac.model / signal	Sig1	Sig2	Sig3	Sig4
Sig1-model	*10,627*	0,003	5,884	-0,107
Sig2-model	0,332	*12,834*	1,098	0,400
Sig3-model	10,154	-0,638	*12,389*	0,247
Sig4-model	-7,015	0,281	-5,293	*24,399*

The Sig1 and Sig3 have very similar positive score although they are cross tested Sig1 on model Sig3 and Sig3 on model Sig1. In reality those sounds are very similar by hearing and represents the same drilled rock class. The Sig4 represents the drilling noise of hard rock e.g. granite. Testing on Sig1-model or Sig3-model gives strongly negative score, which means clear rejection, contrariwise Sig4 to Sig4-model gives clear acceptation of sound.

The next results propose influence of identified signal length to score by testing Sig4 and Sig1 sounds on Sig4 acoustic model.

Tab.2. Influence of identified signal length to score.

	right sound - Sig4		false sound - Sig1	
Sig. duration[sec]	**test. Signal**	**score**	**test. Signal**	**score**
0,318	Sig4-1	11,4975	Sig1-1	-7,9703
2,622	Sig4-2	19,8711	Sig1-2	-7,4924
12,862	Sig4-3	25,2809	Sig1-3	-7,5192
25,662	Sig4-4	25,7262	Sig1-4	-7,5645
38,462	Sig4-5	24,8665	Sig1-5	-7,6275
51,262	Sig4-6	24,0925	Sig1-6	-6,0971
64,062	Sig4-7	24,3047	Sig1-7	-6,7098
76,862	Sig4-8	24,6181	Sig1-8	-7,0221

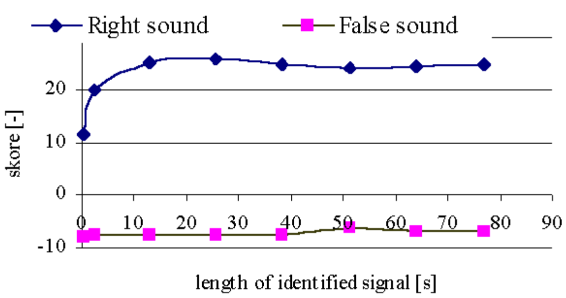

Fig.1. Influence of identified signal length to score.

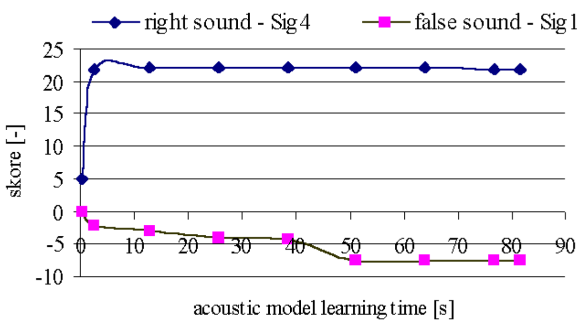

Fig.2. Model learning time influence to score.

From Figure 1. it is clear, that identified signal longer than 25 seconds, does not gives better results, on the contrary too long signal achieve worse results. The same trend can be observed at the process of acoustic model training. As it can be seen in Figure 2. over trained acoustic model does not achieve better score in accepting or rejecting the right or false signal.

Conclusion

The proposed experimental software based on continuous Hidden Markov Model gives the satisfying results in rock class acoustic identification. As the software is built over reusable binary blocks connected to a signal processing network via standard UNIX pipes, it gives vacant variability and rapid prototyping possibility by modification of open source code. The result of its functionality is score, the non dimensional value representing the likelihood of tested signal to the acoustic model. This value can be easily passed to the rest of optimization – control system of the drilling stand via standard output.

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