IDENTIFYING ACOUSTIC SIGNATURE OF INFLOW CONTROL VALVE'S CONDITION USING DISTRIBUTED ACOUSTIC SENSORS

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ABSTRACT

In this paper, we present a novel method to identify the acoustic signature of Inflow Control Valve's conditions and classify them. The proposed method consists of three stages: preprocessing sounds data, acoustic feature extraction and multi-class classification. In the preprocessing stage, we applied power normalisation to smooth the acoustic signals and then fed the normalized acoustic data into feature extraction algorithms. We analysed the series of acoustic features in time domain, frequency domain and also in an unsupervised feature extraction algorithm. In time domain, we performed an extensive feature statistic analysis by comparing six audio features and selected the best one. In frequency domain, the features from wavelet transform was extracted. In addition, acoustic data is converted to frequency domain by applying short time Fourier transform and its output fed into Principal Component Analysis algorithm. Our proposed method combined all extracted features from different methods and composed the novel feature set. In the last, two classification algorithms, Artificial Neural Network and support Vector Machine, are implemented to test and validate the novel feature set. We evaluated our method by performing an experiment on seven real word datasets and experimental results demonstrated its superior performance compared to other method.

Index Terms— Acoustic feature extraction, inflow control valves classification, wavelet feature extraction, principal component analysis.

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1. INTRODUCTION

Unlike a conventional well, an intelligent well is equipped with monitoring and completion components such as packers (sealing parts), sensors, and inflow control valves. Intelligent well systems are becoming a necessity in the oil and gas industry because they allow an efficient and more controlled production. In addition to the cost effectiveness of long term operations, the operator can manage where water is injected or oil is extracted to mobilize unswept reserves [1].

An Inflow Control Valve (ICV) is a component which is installed in a well completion to control the flow into the well. In a multilateral well, ICVs are used to control the flow from each branch or lateral, which allows the production from the well to be optimised. An Autonomous Inflow Control Device (AICD) was developed and patented [2] to improve extraction of extra heavy oil production from mature and marginal fields.

ICVs can be controlled remotely from the surface, in which a permanent downhole cable is used to provide electric and hydraulic conduits [3]. Cable electric intelligent well completion system (EIWS) was recently tried in Tuha oilfield at a 3000 m deep well long in conjunction with a rod pump to remotely control and monitor the valve opening degree. The system consists of control circuit, downhole valve, temperature and pressure sensor. It is connected to a ground control device by a tubing-encased conductor cable that is used for power supply and signal transmission. They reported EIWS is reliable and convenient to observe the changes in pressure and temperature trends [3].

The real time wellbore monitoring can assess well integrity for possible leaks, monitor the opening and closing of Inflow Control Valve (ICV) actuators to make sure they are operating as expected, to assess the amount of sand and hydrates in the flow and ratios of oil, gas or water in wells. However, most recently Distributed Acoustic Sensor (DAS) instrumentation has been developed which records the acoustic sounds and vibrations along the whole length of well pipeline. The DAS are optical fibres which lie beside the main fluid filled pipeline. Their operation is described in [4–6]. The DAS are effectively an array of microphones spaced about half a metre apart along the whole length of the pipeline so acoustic sounds and vibrations can be monitored along the whole pipeline length. At each effective microphone the acoustic sound as a function of time is recorded.

Determining whether an ICV is fully open, partially open, or fully shut is crucial for the downhole oil management. It is possible that the ICV controlling signal breaks down, which makes it difficult to determine its status directly. Hence, determining the condition of an ICV using alternative methods, such as using data obtained from intelligence Acoustic Sensors (iDAS) [7], could be a potential monitoring tool for the oil industry.

In this paper, We proposed the new method to identify the condition of ICVs by extracting its acoustic signature. Firstly we normalized the acoustic signals that were recorded from Distributed Acoustic Sensors (DAS). The analysis followed by extracting the acoustic features in time domain and frequency domain. The extracted features from all the methods were combined and formed a new feature set as it shown in Diagram 1. We employed two popular classification methods, Support vector Machine and Artificial Neural Network, to evaluate our new feature set and compared the performance of the classifiers with the time and frequency domain feature set. The proposed method is tested and validated on real word dataset that contains the acoustic signals from seven different ICVs, exhibiting favorable performance compared to the other methods.

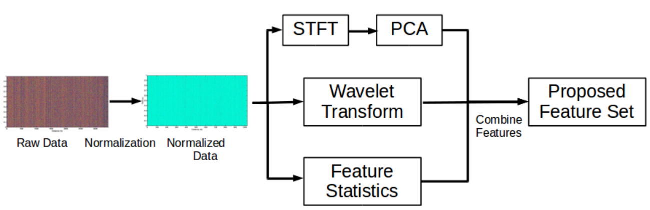

Fig. 1. The proposed method to form a new feature set by combining features that are extracted from time domain, frequency domain.

2. THE PROPOSED METHOD

2.1. Preprocessing Acoustic Data

The raw acoustic data is pre-processed by applying normalization methods. As some parts of the optical fibre DAS are tightly bound to the fluid filled pipe they will record a higher amplitude acoustic signal so it is essential to normalize the acoustic datasets. Statistical normalisation, power normalization and scaling normalization are three normalization techniques that have been implemented as suggested by the literature [8]. However, we selected power normalisation 1 as it outperforms the other two methods for our datasets where X is an input acoustic data, $\bar{X}$ is mean of data and X' is a normalized data.

$$X' = \frac{X - \bar{X}}{\sqrt{X \cdot X}} \tag{1}$$

2.2. Acoustic Feature Extraction

Extraction of characteristic features (acoustic signature) is the most significant and crucial task in ICV's condition detection. A sound generated by flowing the fluid through pips and at the ICV location. The characteristic features from sound generated by travelling the fluid in the pipe could be different when ICV is open, fully shut or partially open. Acoustic signals have very few representations and we must find the most important coefficients or characteristic, which contain information that will be used to discriminate among input classes. This set of characteristic features is known as a feature vector [9] and has a significant role on the performance of the classification algorithm. Therefore, in this study we concentrate on forming a novel feature vector to achieve the best performance of ICV's condition classification. In the following sections we extracted acoustic features in time domain, frequency domain and also applying dimensionally reduction technique.

2.2.1. Time Domain Features

Audio feature extraction in time domain is the simplest method because no transformation is required so computationally it is less complex [9]. In particular, six audio features and respective statistics are extracted for each audio file. The feature statistics are; Energy Entropy Standard Deviation (std), Energy Entropy Standard Deviation (std), Signal Energy Std by Mean (average) Ratio, Zero Crossing Rate Std, Zero Crossing Rate Std, Spectral Rolloff Std and Spectral Flux Std by Mean Ratio. A simple algorithm [9] is used for estimating the separability of the audio classes. Two of the six features that demonstrated a higher probability of being classified easily are Zero Crossing Rate Standard Deviation and Spectral Centroid Standard Deviation.

2.2.2. Frequency Domain Features

The techniques used to extract features in time-frequency domain are Wavelet Transform (WT) and Short Time Fourier Transform (STFT) [10]. In particular wavelet scattering is implemented to produce low-variance representations of the data by propagating datasets through a series of wavelet transforms, non-linearities, and averaging. These low-variance representations are then used as inputs to a classifier [11]. In order to create the wavelet time scattering decomposition we used the framework suggested by [12] as it works for many applications. The suggested framework [12] has two wavelet filter banks such that the first one has eight wavelets per octave and the second one has one wavelet per octave.

Short time Fourier Transform (STFT) is also applied on acoustic data in which STFT divides a acoustic signal into small parts so they can be overlapped and windowed. Then, DFT is computed for each part separately and calculated by;

$$x(k,n) = \sum_{m=0}^{N-1} x(m+n)w(m)e^{-j2\pi km/N} \qquad (2)$$

where $w(m)$ is a finite window to select a segment from the sliding signal $x(m+n)$, which can be of different types. A Hamming window can be used to reduce spectral leakage, as opposed to a rectangular window. Frequency and time indices are denoted by k and n respectively [13]. Fig. 2 shows the spectrograms of acoustic data from an ICV during 15 seconds, with a sliding Hamming window of length 512 samples. The windows are overlapped by 511 samples in time.

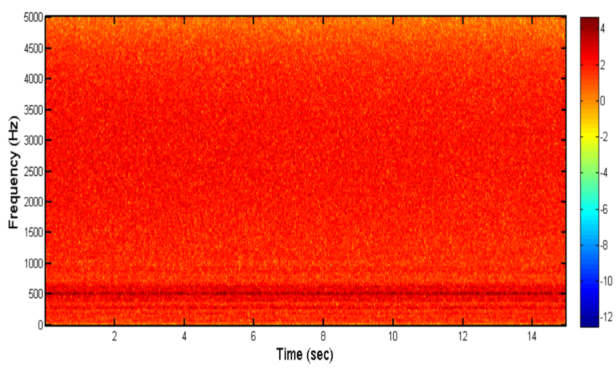

Fig. 2. A sample of acoustic data after applying Short Time Fourieh Transform (STFT)

Principal Component Analysis (PCA) is a popular statistical technique for dimensionality reduction technique. PCA computes principal eigenvectors of the covariance matrix of the set of signals. These eigenvectors can be considered as characteristic feature vector which is used to characterize the variation between ICV signals [14]. The spectra of acoustic signals are obtained by applying a Short Time Fourieh Transform (STFT) on a moving Hamming window in the time domain with one second length. The resultant spectra are truncated at 1 kHz to remove redundant data. Fig. 3 shows a 2D plot of the first 100 eigenvalues corresponding to the first 100 Principal Components, and their perceptual weights. The first, second and thirds Principal Components account for up to 67.9% of the data variance.

2.3. Acoustic Classifcation Method

This is the final stage of a Inflow Control Valves condition detection process in which the condition of the ICV (open,

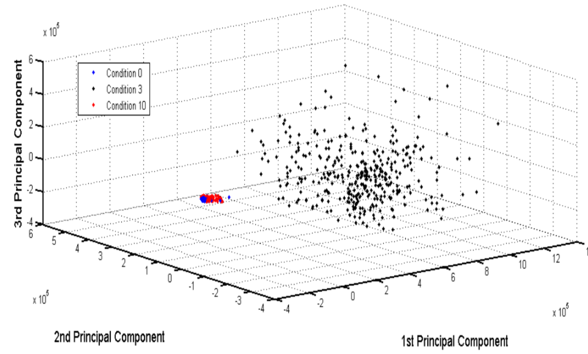

Fig. 3. Reduced spectra using the first three Principal Components.

closed, partially open) is determined by the help of classifier. A classifier provides the functions that is used to divide the feature space into various regions, where each region belongs to a particular class [15]. Classifiers can be mainly categorized as parametric and non-parametric, depending on the knowledge of signal distribution parameters [9]. We implemented one parametric and one non-parametric classifier called Support Vector Machine (SVM) and Artificial Neural Network (ANN) respectively for acoustic data classification stage as recommended by the literature [15]. In a parametric classifier, some assumptions are made about the probability density function for each class whereas in non-parametric classifiers no assumptions are made about density function [9].

A ANN can have a variety of forms depending on the number of hidden layers, number of inputs and outputs, and the underlying structure. A 3-layer NN is implemented since studies on this type account for around 80% of the current studies on multilayer NNs [16]. The reduced data is fed to the NN input layer linearly. A hyperbolic tangent is used as the activation function in the hidden layer, since it is one of the most used non-linear functions in NNs. A softmax function is used in the output layer, so that the outputs are between 0, and 1. Cross validation is implemented to avoid overfitting. Data is divided into 15%, 35%, and 50% for training, validation and testing, as suggested by my supervisor. Early stopping is used to stop the learning once the validation error is not decreasing anymore. Weights are initialised randomly to improve speed of convergence. The used cost function is the cross entropy.

We fed all different the set of extracted features from the acoustic data into our classifiers, SVM and ANN and compared the performance of with our proposed features set. The result is presented in section 3.2.

3. EXPERIMENTS

The data was recorded from real subsea wells and so has a lot of apparent noise. The Distributed Acoustic Sensor is an optical fibre which is usually placed along the outside of the pipeline and is strapped to the pipeline in intimate contact at binding points. The acoustic signal strength is stronger at these binding points as the sound does not exit the pipe, travel through the air and then enter the optical fibre as it can go directly from the pipeline into the fibre. These binding points are approximate and not exactly evenly spaced along the pipeline. The optical fiber cables were permanently clamped and installed along the production and injection tubing pipe. In some cases the central pipeline is surrounded by a larger radius exterior pipeline with the annulus between being filled with seawater or gas which may also be flowing down the annulus. The central fluid filled pipe radius changes at points where a pipe of one radius is bolted to a pipe of another radius. The Inflow Control Valve (ICV) actuators also throttle the flow at various points along the pipeline. The pipeline is vertical as between the well head on the production platform passing down through the sea and into the sea bed where it usually turns through an angle so the remainder of the well is at an angle to the horizontal. Several side pipes receiving oil from several reservoirs through ICVs are attached to the main flow pipe.

3.1. Dataset

Data is taken from an oil producer, having three different ICVs. Each ICV is used to control the flow from a specific lateral. The mother bore (MB) ICV, installed at 14 distance 2867.6 m, is used to control the flow in the mother-bore. Similarly, a lower lateral (L1) ICV, and an upper lateral (L2) ICV (located at 2519.2 m, and 1874.5 m respectively) are used to control the flow from their corresponding laterals. To indicate the condition of an ICV, three numbers are used. Conditions 0, 3, and 10, indicate whether an ICV is fully shut, partially open or fully open accordingly. A sensitivity refers to a set of settings of three ICVs. Table 1 shows the available different sensitivities taken by the iDAS from the well.

Table 1. ICV Setting

Sensitivities	MB ICV	L1 ICV	L2 ICV
Sensitivitiy B	10	0	0
Sensitivitiy 1	10	0	3
Sensitivitiy 2	10	3	3
Sensitivitiy 3	10	10	10
Sensitivitiy 4	0	10	10
Sensitivitiy 6	3	10	0
Sensitivitiy 7	10	3	0

Table 2. Result of Classification Algorithms

Feature extraction method	SVM classifier	ANN classifier
PCA	80.5%	89.8 %
Statistic features	68.5%	70.9 %
Wavelet transform	81%	88%
Propsed feature set	93.3%	99.1%

3.2. Results

We validated our method by applying our feature extracted techniques on the validation dataset (MB ICV). Both classifiers, ANN and SVM, produced a higher classification rate for condition 3 of ICV which is partialy open status. In partially open ICV, more noise is produced when fluid flowing through the pipe in comparison with fully open or fully shut condition. Therfore more acoustic characterstics is presented in a partially open ICV data and this explain the classification result. The result of classification on validation dataset shown in Table 2 where the proposed method is demonstrated the best clssification rate.

4. CONCLUSION

To our knowledge, this is the first time a study has been performed to classify the condition of Inflow Control Valve (ICV) by analyzing acoustic datasets that collected form Distributed Acoustic Sensors. We validated and evaluated our proposed method on the new dataset and compared the performance of the classifiers with the existing feature extraction techniques. We proved our proposed method to form the feature set can achieve the higher performance and identified an acoustic signature for each condition of ICV. We performed our testing and validation on real word datasets and the result of this analysis will lead to industrial applications.

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