Investigating pump cavitation based on audio sound signature recognition using artificial neural network

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Abstract. How to investigate the occurrence of cavitation in the pump? Several studies have shown the sound characteristic that occurs during cavitation. This research attempts to build a pump cavitation detection system based on the audio signal of the operating pump. Audio signal is recorded using a microphone through a computer sound card. Then perform the frequency domain feature extraction and the correlation analysis for feature selection. From this process, 9 frequency domain features are selected as the artificial neural network classifier input. This artificial neural network classifier is trained with the Resilient backpropagation algorithm. The performance of this detection system is able to determine the existence of cavitation with an accuracy rate of 82.5%.

1. The prior arts
Cavitation is the phenomenon of the fluid vaporization bubbles formation due to locally decreasing fluid pressure[1][2]. This event should be avoided as much as possible[1] because it causes pressure losses and reduces fluid flow[2][3][4], excessive sound and vibration [2][5][6], reducing impeller and bearing life [3][7][8], increase energy consumption[2][9]. Some researchers have developed various methods and systems to detect cavitation in several types of pumps. Casoli, et.al.[10], Buono, et.al.[1], Chini, et.al.[6], Dong, et.al.[7], they have attempted to detect the presence of cavitation based on mechanical vibrations[10][1] or audio sound[6][7]. Sensors commonly used in cavitation detection systems are accelerometer[10][11][1], microphone[6], hydrophone[7][9], pressure sensors[12][3], sound pressure transducers[9][7], encoder[3] and flow rate sensor[12][3].

Among the signal feature extraction methods used for cavitation detection are cyclostationarity theory[11], cycloergodic theory[10], signal decomposition into periodic components[10] and noise components[6][10], Time-Frequency analysis[5], Hilbert transform[13][14], Fourier spectrum analysis[6][10], discrete eigenvalues[7][9], statistical analysis[9], wavelet packet decomposition[9][13], discrete wavelet transform[5][14], Autoregressive and Moving Average mathematical technique[1][15], cyclic spectral coherence[11], cyclic modulation spectrum[10], spectral correlation density[10] and spectrum of liquid-borne noise[7]. While the classifier method uses Support Vector Machine
[10][16][17], Artificial Neural Network[9][18], Ensemble Classifier[10], Discriminant Analysis[10], K Nearest Neighbor Classifier[10] and Decision Trees[10].

2. The research objectives and experiment methods
The aim of this study is to develop a pump cavitation detection system based on audio noise of pump under normal operating conditions and when cavitation occurs. Audio signal recording is performed
using a condenser microphone through a computer sound card line-in as a data acquisition system. Signal recording is performed at 44.1 kHz sampling rate and 2048 sampling size of data points. The data acquisition system records 8000 audio noise samples of pump operating normally and pump under cavitation. Signal feature extraction is performed on the frequency domain by performing the fast Fourier transform (FFT) of 8000 audio noise samples. Before performing the FFT, it is essential to normalize the sound signal, to equalize the sound amplitude volume.

The fast Fourier transform turns out frequency spectrum from sound samples, formed a row matrix of 512 length. The next step is normalize the features to construct features data-sets with zero mean and unity variance. Feature normalization is performed before the regression analysis in order to get the coefficient of correlation unbiased from the attenuation of the audio signal. Regression analysis is performed to find the frequency spectrum that correlates with pump cavitation conditions. Frequency spectrums with coefficients of correlation higher than 0.6 are selected as classifier input features. The classification used in this pump cavitation detection system is an Artificial Neural Network (ANN).

3. The setup of experiment
The pumps used in this research setup are GL75JXK water pumps with a capacity of 16L/min, 20m total head, ⅝ inch suction line, ⅝ inch discharge line and input power of 120 Watts. The sound cards used as DAQ is Taffware USB TC-03 Sound Card Adapter. The microphone used in this study is the Samsung Condenser microphone. The pump is installed to drain water from the bottom reservoir to the upper reservoir at a height of 2m. Artificial cavitation in this study was induced by inserting air into the suction lines through a 0.5mm diameter hole. Air entering through the suction lines creates air bubbles in the pump similar to the cavitation. The microphone is placed at a distance of 10cm from the pump housing. The computer used in this cavitation detection system is a Lenovo core i5 laptop with matlab script.

| ANN Iteration | Training MSE | Accuracy  |
|---------------|--------------|-----------|
| 1st           | 0.19633      | 94.52%    |
| 2nd           | 0.19673      | 94.98%    |
| 3rd           | 0.19901      | 94.67%    |
| 4th           | 0.21707      | 93.94%    |
| 5th           | 0.22555      | 93.78%    |
| 6th           | 0.19275      | 94.31%    |
| 7th           | 0.18952      | 94.97%    |
| 8th           | 0.18973      | 94.64%    |
| 9th           | 0.21038      | 94.05%    |
| 10th          | 0.19189      | 94.97%    |
| Best          | 0.18952      | 94.98%    |
| Mean          | 0.20089      | 94.48%    |
| Worst         | 0.22555      | 93.78%    |

| Validation MSE | Accuracy  | Validation MSE | Accuracy  |
|----------------|-----------|----------------|-----------|
|                |           | 94.88%         | 82.50%    |
|                |           | 94.88%         | 80.00%    |
|                |           | 94.38%         | 81.25%    |
|                |           | 94.25%         | 80.00%    |
|                |           | 93.75%         | 82.50%    |
|                |           | 94.88%         | 77.50%    |
|                |           | 95.00%         | 82.50%    |
|                |           | 95.38%         | 81.25%    |
|                |           | 93.63%         | 80.00%    |
|                |           | 94.88%         | 82.50%    |
| Best           |           | 95.38%         | 82.50%    |
| Mean           |           | 94.59%         | 81.00%    |
| Worst          |           | 93.63%         | 77.50%    |

4. Results and discussion
4.1. Audio signal recording
Examples of waveforms and frequency spectrum of sound sampling recorded from pump cavitation are shown in figure 1. There are visible peaks of the spectrum at 199th, 748th, 1087th and 1196th frequencies. Whereas the waveforms and frequency spectrum of sound sampling recorded from the pump under normal operation shown in figure 2. The sound frequency spectrum of normal operating pump shows clearly visible two peaks at 41st and 680th frequencies. There are a visible shift in the peak of the spectrum to the higher frequency during cavitation.
4.2. Feature extraction and feature selection

Further analysis seeking frequency spectrums that are firmly correlated with pump cavitation based on correlations analysis of 8000 sound sample. The coefficient of correlation of the 1st frequency spectrum to the 512th frequency spectrum is displayed in the graph of figure 3. From the correlation analysis, 9 sound signal features were selected, they were: f41th, f40th, f43th, f83th, f44th, f42th, f39th, f38th, f85th.

![Figure 3. The correlation coefficient of full spectrum of frequency.features](image)

![Figure 4. Detail of the top nine of correlation coefficient of frequency spectrum.](image)

4.3. Artificial Neural Network classifier

The classifier used in this study is the Artificial Neural Network (ANN) with three layers, the first layer is the 9 nodes input layer, the second layer is the 8 nodes hidden layer with hyperbolic tangent sigmoid transfer function, the third layer is a single node output layer with a symmetric saturating linear transfer function. This ANN is trained with the Resilient backpropagation algorithm. The ANN iteration summary is shown in the table 1. The average of mean square error (MSE) during the ANN training process was 0.20089 and the lowest MSE of 0.18952 was achieved at the 7th iteration. The accuracy of ANN classifiers in the training phase and test phase did not differ significantly in the range of 93.8% to 95.3%,
but the accuracy during the validation phase drops to as low as 77.5%. This phenomenon shows the symptom of overtrained ANN, the ANN classifier too far recognizes the specific pattern of the training data and test data so that it exceeds the generality of the sound feature pattern as a whole.

5. Conclusion and further research

This research has succeeded in investigating pump cavitation based on pump sound signals. Signal feature extraction in the frequency domain can still provide features that characterize the existence of cavitation. Feature selection with a simple correlation analysis technique is also able to select the best features. The accuracy of classification reached 82.5%. This achievement can still be improved again. The next research that can be pursued is the extraction of signal features using the wavelet transforms, selection of the features using genetic algorithms, or optimization of the classifier training.

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