An Approach to Hydraulic Machine Evaluation Using Classification of Symmetrised Dot Patterns

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Topics

- Overview
- Background
- The Story
- Analysis
- Lessons learned
- Summary
- Conclusion
- References
- Glossary of acronyms and corporate terms
- Questions and comments
Overview

- An approach for condition monitoring of a hydraulic control device is presented.
- The approach uses multiple sensor signals from the machines to generate symmetrised dot pattern (SDP) images which are classified by an automated process.
- The SDP classifier is based on a support vector machine (SVM) acting on feature vectors consisting of image moments in windows.
Various approaches have been used for analysing signals from hydraulic machines.

These include harmonic analysis, data-driven state-space reconstruction, neural networks and support vector machines.
Background

- SDPs have been used for diagnosing faults in rotating machinery by viewing the SDP (manual classification)
- Some work on automatic classification of SDPs has been carried out using template matching
- We have tried a two step approach to diagnosis of hydraulic machines. That is SDP generation followed by automatic SDP classification
Symmetrised Dot Patterns

An SDP is a two dimensional pattern \( \Pi \) derived from a signal waveform window \( \{ F_j : j = 1, \ldots, N \} \) where \( \Pi \) is of the form

\[
\Pi = \bigcup \{(r_i, \Theta_{ij}) : j = 1, \ldots, N-1 \} \cup \{(r_i, \Phi_{ij}) : j = 1, \ldots, N-1 \} : i = 1, \ldots, m, \]

in polar coordinates space in which

\[
r_j = \left( \frac{F_j - L}{H - L} \right) \xi, \]

\[
\Theta_{ij} = \Theta' + \left( \frac{F_{j+1} - L}{H - L} \right) \xi, \]

\[
\Phi_{ij} = \Theta' - \left( \frac{F_{j+1} - L}{H - L} \right) \xi, \]
Where

- \( j = 1, 2, 3, \ldots, N - 1 \),
- \( \Theta' = (360°/m)i, \ i = 1, 2, 3, \ldots, m \),
- \( m \) is the number of mirror planes,
- \( \xi \) is the upper boundary used to normalise the gain of the input waveform,
- \( H \) and \( L \) are the highest and lowest values in the original waveform window
Sound Flake
SDPs have been used to analyse financial data
SDP

- SDPs are commonly predominantly curve or cloud or a mixture of both.
- SDPs provide a useful way for a human observer to view data.
- It has been suggested that the symmetry present in an SDP enhances the capability of a human analyst.
- A typical operation that an analyst might perform on an SDP is classification of the SDP. For example in the diagnosis of a system on the basis of a signal coming from it an analyst might look at an SDP and classify it as being OK or not OK or else OK or in fault state 1 or in fault state 2 and so on.
- Classification by human is time consuming and expensive.
- Therefore it would be desirable to have an automated system for classifying SDPs
A Class of SDP Classifiers

- A general procedure for carrying out classification of SDPs is to extract features from an SDP image and then to feed these features into a classifier.

- Generally the dimensionality of the feature set is considerably less than the dimensionality of the image data.
Some Possible Features

- Fourier wedge-ring sampling
- moments
- window counts
- centroid, bounding box, area of convex hull
- differential geometric features
- image histograms
- area of cloud, length of curve
- Fourier descriptors of curve
- fractal features
- colour features
- profile features
- random windows
- texture features, e.g. using the Gabor filter, grey-level co-occurrence matrices
- compute principal axes
- in general one might look at the number of connected components of the image and the number of connected components of successive dilations of the image
- compute the skeletonisation of the image and then compute the Fourier descriptors of the skeleton
- threshold the Sobel edge image and measure the edgeness of the image as the area of the thresholded Sobel image
- compute the boundary of a cloud region and then its Fourier descriptors. An approach to computing the boundary is to dilate the image a number of times and then use the Sobel edge detector.
- there are methods for reducing a feature set given that the feature set has been defined. The most common is the method of principal components analysis (PCA), also known as the Hotelling transform.
Feature Vector

- It was decided to try using moments in windows.
- Moments were used because of their simplicity and low dimensionality.
- Using windows results in local features rather than global features.
- In the SDP classifier method that we tried the image domain of SDP images is divided up into an array of windows and then a feature vector is computed consisting of moments of order up to 2 of the image in each window and then the feature vector is fed into a classifier.
- The windows are obtained by dividing the horizontal and vertical axes into N and M sub-intervals respectively where currently N = 3 and M = 3. If N and M are too small the analysis may be too coarse while if N and M are too large then the feature vector may be too large for the classifier.
For a window \([t,b] \times [l,r]\) the moments calculated are discretizations of

\[
\mu_{p,q} = \int_t^b \int_l^r (x-t)^p(y-l)^q I(x,y) \, dx \, dy,
\]

for \(p \geq 0, q \geq 0, p+q \leq 2\) and \(I\) is the fundamental image of the SDP.

Thus the moments are calculated in the local coordinate system of each window. It was not thought to be appropriate to use central moments where the moments would be calculated relative to the centroid of the image in the window because their use would impede uniformity and comparability across different images.
Classifier

Possible classifiers include

- ANN (Artificial Neural Networks)
- NN (Nearest Neighbour Classifier)
- Bayesian approach
- SVM (Support Vector Machines)
- We chose SVM because they are state of the art and have a number of desirable properties
SVM

- SVM are statistical learning models. The main objective of statistical learning is to find a description of an unknown dependency between measurements of objects and certain properties of these objects.
- The measurements are also called input variables and are assumed to be observable for all objects.
- By contrast the object properties which are also called output variables are in general available only for a small subset of the objects called examples.
- The purpose of estimating the dependency between the input and the output variables is to be able to determine the value of the output variables for any object of interest.
- Let $\mathbf{X}$ denote the space of input variables and $\mathbf{Y}$ denote the space of output variables. The structure of $\mathbf{Y}$ defines the learning task.
- If $\mathbf{Y} = \mathbb{R}$, the real numbers, then the learning task is known as regression.
- If $\mathbf{Y} = \{1,2,3\}$ then the learning task is a classification problem with three classes.
SVM

- Non-separable data and classification errors can be allowed for by introducing slack variables to relax the hard margin constraints.
- SVM optimisation is too complex for standard quadratic programming tools such as CPLEX.
- Decomposition algorithms can be used.
- The Sequential Minimal Optimisation (SMO) algorithm is a popular and efficient algorithm for SVM training.
Hydraulic Machine Test

- The SDP classifier was tested on a problem involving signals from hydraulic machines.
- The machines were either OK or fell into one of five fault classes.
- The classes for the machines were:
  - 0 OK
  - 1 High asymmetric gain (unknown failure)
  - 2 Reduced gain in one side only
  - 3 Clogged filter
  - 4 Clogged filter + high asymmetric gain at one side only
  - 5 Broken FB wire
Hydraulic Machine Test

- The SVM is acting as a multiclass classifier
- This can be implemented in a number of ways given a two class classifier
- The data describing the hydraulic machine problem is given in 25 data files
- Each of these data files contains the signals from a machine over an extended period of time
- Each of the signals is divided into 16 time windows and the SDP is computed for each time window
- This results in 400 SDP cases
Typical SDP from the Hydraulic Machine Data
Procedure for Training and Testing the SVM

- At this point each set of data for 16 time windows for a run with one machine is present in one file.
- Now the classification associated with each run is manually inserted into the files.
- Next the moment features are extracted for each case.
- Then all the different files of features and classifications are amalgamated into one file and its rows are randomly permuted.
- This file is broken up into a training set file of 300 cases and a testing set file of 100 cases.
- Next the features in the training set data and the testing set data are rescaled to lie between 0 and 1.
- Now the SVM training algorithm is run on the training data.
- The training algorithm can be run with different parameter values to optimise the training.
- Then the resulting model can be tested on the test data.
Test results

<table>
<thead>
<tr>
<th>class</th>
<th>count</th>
<th>no_right</th>
<th>no_class_0</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>53</td>
<td>47</td>
<td>47</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>3</td>
<td>30</td>
<td>6</td>
<td>24</td>
</tr>
<tr>
<td>4</td>
<td>4</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>5</td>
<td>8</td>
<td>0</td>
<td>4</td>
</tr>
</tbody>
</table>

- **count** is the number of cases of the given class
- **no_right** is the number of cases of that class which were correctly classified
Prediction Accuracy

- The prediction accuracy is 53%
- A random classifier would classify correctly 1 time in 6 and therefore have an accuracy of $1/6 = 17\%$
Analysis

- It appears that the only previous work on automatic classification of SDPs was the work of Wu and Chuang on fault diagnosis of internal combustion engines based on vibration signals.
- They use template matching to classify the SDPs.
- They do not report on the numerical accuracy of their technique.
Lessons Learned

- Further work that could be carried out includes
  - Further adjust parameters for SVM training and for SDP computation
  - Try different data
  - Try different features other than moments in windows
Summary

- An approach to SDP image classification has been described.
- It involves classification by SVM of a feature vector consisting of moments in windows.
- It was tested on data from a hydraulic machine control and resulted in prediction accuracy better than expected from a random classifier.
Conclusion

- Further work needs to be done to determine whether the method can be improved to make a commercially useful system
References

Glossary/Acronyms

- SDP Symmetrised Dot Pattern
- SVM Support Vector Machine
Questions and discussion

Thank You