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Dimensionality Reduction in a Hydraulic Valve Positioning Application

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Abstract. This paper presents an application of neural network signal processing to estimate the position of a hydraulic valve spool, based on acoustic excitement of the spool's end chamber. The spool's end chamber acts somewhat like a Helmholtz resonator whose frequency response changes based on its volume (and therefore spool position). However, non-ideal characteristics of the system including wave propagation effects and distributed parameters mean that estimating the volume is more complicated than simply evaluating the resonant frequency. In this case the frequency response has high dimensionality with high redundancy and noise. We present the use of linear and nonlinear principal component analysis to preprocess the frequency response data prior to neural network regression.

1 Introduction

Hydraulic valves are used to control the flow of pressurized fluid in the hydraulic systems of construction, automotive, mining and industrial machinery. By shifting a valve's cylindrical spool axially in a bore, orifices can be opened and closed to redirect or throttle the flow. It is often desirable to measure the position of the spool while in service, for closed loop control, power management or diagnostic reasons. This is often achieved in the laboratory using linear variable displacement transformers (LVDTs), laser or eddy current sensors but these have proved impractical for field installation.

We propose using pressure measurements in a novel way to estimate the valve position: Helmhotz-style resonance. A classical Helmholz resonator is a rigid sphere with a neck [1]. The interaction of the compressibility of the fluid in the sphere with the mass of the fluid in the neck results in a resonant frequency

$$\omega_H = \frac{c}{2\pi}\sqrt{\frac{A}{VL}} \tag{1}$$

where c is the wave speed, A is the cross-sectional area of the neck, L is the neck length, and V is the cavity volume. The resonant frequency is strongly affected by the volume of the cavity, an effect that has been exploited for a number of volume measurement schemes [2], including food volume measurement [3] and the volume of fluid in spacecraft fuel tanks [4].

In our application we wish the measure the volume of the spool end chamber (as shown in Figure 1), which can be related to the spool position. In this case the frequency response of the chamber and attached passageways is affected by the volume, but the response is non-ideal and the Helmholtz equations no

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longer apply. This is primarily due to the non-ideal shape of the inlet (changing cross section and branching) and wave propagation within the system, creating internal reflections that can cause resonances at multiple frequencies other than the Helmholtz frequency. Although complex, there *is* a relationship between the volume and the frequency response that this can be exploited for position measurement.

2 Experimental Method

An experimental appartus was built to generate training data to test this method. The pressure compensator valve from a 28 cc/rev axial piston pump was removed from the pump and mounted on a test block. This valve spool has a diameter of 7.0 mm and moves 3.6 mm axially, as shown in Figure 1. A piezo disc actuator was connected to the compensator inlet port via a length of flexible hose to reduce the transmission of structural vibrations. The dynamic pressures at the inlet, p_1, and within the end chamber, p_2, were recorded using high frequency piezo pressure sensors. For each test a repeating Maximal Length Sequence (MLS) was generated from the piezo actuator [5]. We used a sequence of length 8191, broadcast at a rate of 33.3 kHz, synchronized with the pressure measurements. The position of the spool was set by rotating the threaded end cap.

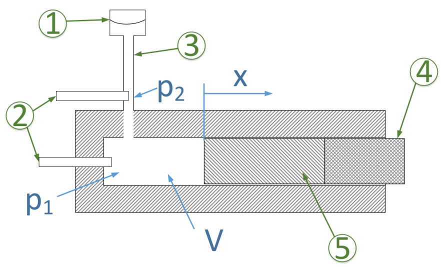

Fig. 1: Experimental schematic, showing (1) piezo actuator, (2) pressure transducers, (3) flexible hose, (4) threaded end cap, (5) spool. Note that this is not to scale, and the inlet between p_2 and p_1 is a convoluted passageway.

The complex frequency response for each time response was calculated using the Empirical Transfer Function Estimate (ETFE) $G(\omega) = \frac{P_2(\omega)}{P_1(\omega)}$ where $P_2(\omega)$ and $P_1(\omega)$ are the discrete Fourier transforms of $p_2(t)$ and $p_1(t)$.

3 Results

The resulting frequency response data is quite noisy, as shown in Figure 3 for 1038 repetitions at a single fixed spool position. Averaging can be used to reduce the influence of noise, but this takes an impractical amount of time for dynamic measurements. For example, Figure 2 shows the average frequency response for

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each spool position, using about 5 minutes of data for each. Clearly the spool position has an influence on the expectation of the frequency response, but it would be difficult to manually pick out features in an individual measurement that would rise above the noise.

We therefore attempted to apply an artificial neural network regression to estimate the spool position from the frequency data. The experimental data collected above resulted in a dataset with 9089 examples, each with 8191 input variables (magnitude and phase for each frequency). Our data matrix has only slightly more observations than input variables, so overfitting is a concern.

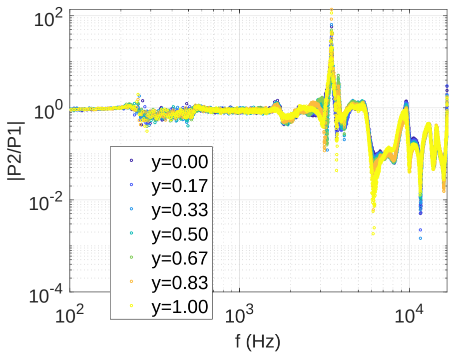

Fig. 2: Magnitude frequency response for six spool positions. These plots are derived from approximately 5 minutes of data for each position. The phase is also used as an input, but not shown here.

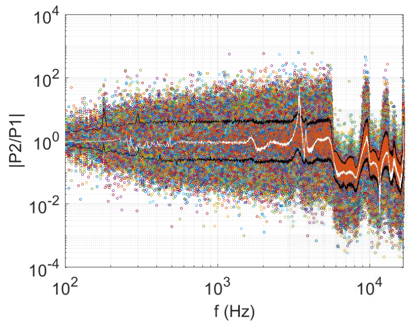

Fig. 3: A total of 1038 measurements of the frequency response at normalized position y=0. The white line shows the response derived from mean measurements and 90% of data falls between the black lines.

3.1 Linear Principal Component Analysis

As the noisy data has high dimensionality with high redundancy, it was expected that the useful information can be compressed into a more compact form using principal component analysis (PCA). This involves finding an orthogonal transformation resulting in the data not being linearly correlated, and ordered by variance [6]. Specifically, the eigenvectors and eigenvalues of the covariance of the data are calculated. The eigenvectors can be used to transform the data into principal components, and the eigenvalues give the "strength" of a the corresponding principal component. The eigenvalues can be plotted to estimate the number of components that must be included to accurately represent the data. As shown in Fig 4, the frequency data recorded has one strong component, with the remainder of lower strength. The first three eigenvectors are also plotted, showing the relative weighting applied to each parameter (related to each frequency's importance in the solution). As shown in Figure 5, when the transformation is applied to the data there is still considerable variation between

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measurements, but the mean of the first principal component is well correlated with the normalized position data.

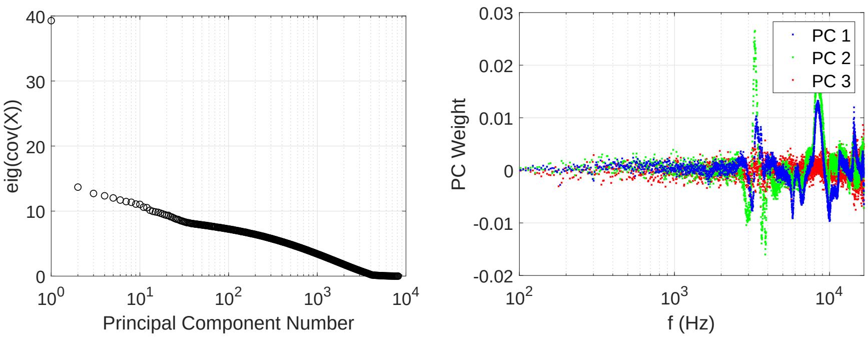

Fig. 4: Principal component analysis eigenvalues (left), and eigenvectors for the three strongest components (right). This shows one strong principal component followed by a gradual reduction of the following weaker components.

3.2 Nonlinear Principal Component Analysis

The linear PCA above requires linearly separable principal components. However, we know that the system under study is nonlinear so the analysis may be incomplete or misleading. In order to evaluate the number of nonlinear principal components in the data, we performed a nonlinear PCA by training an autoassociative autoencoder network with a bottleneck layer [7]. In our case, we used 30 perceptron neurons in the hidden layers before and after the bottleneck layer. The resulting error curve is shown in Figure 6. By looking at the point where the error is reduced we can estimate the number of principal components: approximately 10 if one looks at the median error or 5 for the minimum error.

3.3 Artificial Neural Network Training

A multilayer perceptron network was used to perform a nonlinear regression on the data: estimating the spool position from the frequency response. All training was performed using scaled conjugate gradient backpropagation with Tikhonov regularization [8]. This was performed using Matlab 2018 on a desktop PC with an Intel i7-8700 processor, 32 GB RAM and GeForce GTX 1080 Ti GPU.

First we performed a naive training on the raw data. The high dimensionality of this data caused a relatively long training time as well as considerable variability in performance. Figure 7 shows the validation error for multiple repetitions while varying the network size (a randomly selected 20% of the data was used for validation). It also shows the resulting position estimation. This naive regression has an adequate performance with a RMS validation error of 0.0820 and training time of 76.7 s, but the high variability of the result means the training should be repeated multiple times to obtain good results.

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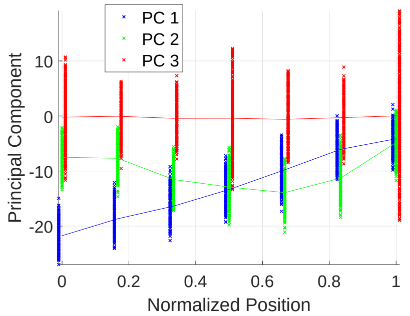


Fig. 5: Principal components, calculated for the three strongest eigenvectors. This shows both the transformed individual observations, as well as the mean (solid line).

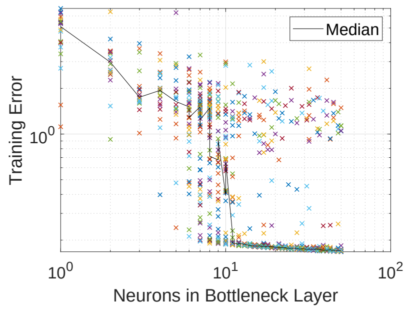


Fig. 6: Nonlinear principal component analysis, showing autoencoder error as the size of the bottleneck layer is varied.

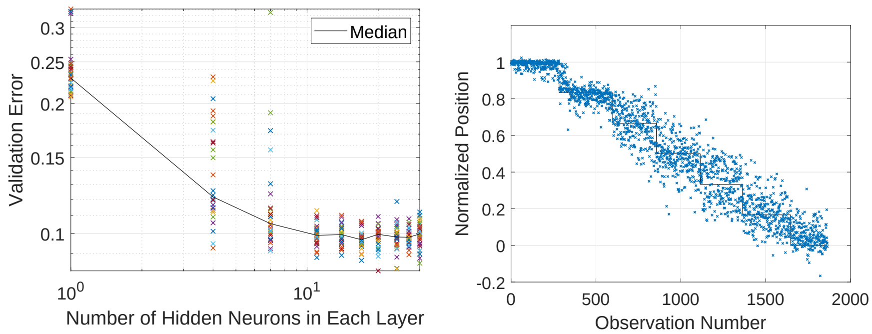
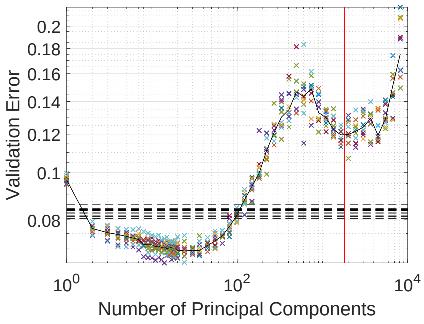


Fig. 7: (Left) Root mean squared validation error for a conventional neural network, as the number of neurons in each of the two hidden layers is increased. At right, validation outputs for the best network, with a RMS error of 0.0820.

We then trained the network using the linear principal components as inputs. Figure 8 shows the validation error as principal components are added. The best validation performance occurs for 14 principal components, with an RMS error of 0.0652 and a training time of 14.2 s. The individual position estimations for the validation data are also shown. Clearly, reducing the dimensionality of the data allows for better performance, faster training and calculation time, as well as less risk of overfitting. There was less variation in the validation results, so an acceptable set of training weights can be expected requiring fewer repetitions. We found good results for a network with 10 neurons in each of two layers (although performance was not particularly sensitive to the network size).



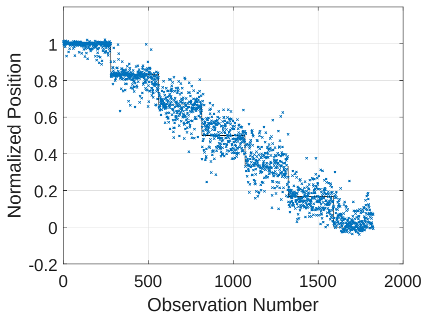


Fig. 8: (Left) Root mean squared validation error while varying the number of principal components used for the network inputs. The black horizontal lines indicate the accuracy of a naive network for a number of runs and the red vertical lines indicates the point where the input matrix is square. At right, validation results for the best network, with a RMS error of 0.0652.

4 Conclusion

This paper presents the application of principal component analysis and dimensionality reduction to highly correlated and noisy data: the case of using the pressure frequency response of the hydraulic spool end chamber to estimate the spool's position. We found that the best conventional neural network had a validation error of 8.20% and took 76.7 s to train, with large variability in validation performance. By contrast, by using the linear principal components as inputs to a neural network, the validation error was reduced to 6.52% (a 20% improvement), training time was reduced to 14.2 s, and the variability in was reduced.

References

[1] H. Helmholtz. *On the sensations of tone as a physiological basis for the theory of music*, Longmans, Green, London, 1875.

[2] E. Webster and C. Davies, The use of Helmholtz resonance for measuring the volume of liquids and solids, *Sensors* 10:12, 10663-10672, 2010.

[3] T. Nishizu, et al., Automatic, continuous food volume measurement with a Helmholtz resonato, *Agricultural Engineering International: CIGR Journal*, 2001.

[4] A. Nakano et al., Liquid volume measurement with a closed Helmholtz resonator under micro-gravity conditions, *Cryogenics* 46:2-3, 126-131, 2006.

[5] S. Golomb. *Shift register sequences.* Aegean Park Press, Walnut Creek, 1967.

[6] H. Hotelling. Analysis of a complex of statistical variables into principal components. *Journal of Educational Psychology* 24.6, 417, 1933.

[7] U. Kruger, J. Zhang, and L. Xie. Developments and applications of nonlinear principal component analysis-a review. *Principal manifolds for data visualization and dimension reduction*, Springer, Berlin, Heidelberg, 2008.

[8] A. Tikhonov, et al. *Numerical methods for the solution of ill-posed problems.* Springer Netherlands, 1995.