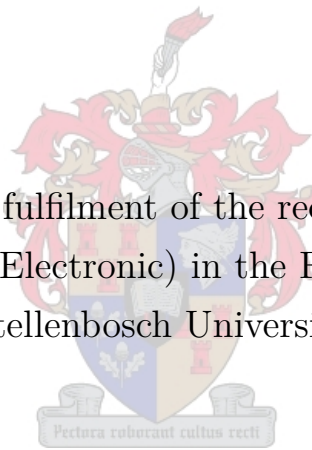


Data-Driven System Identification etc

Luke Skywalker

99652154

Thesis presented in partial fulfilment of the requirements for the degree of
Master of Engineering (Electronic) in the Faculty of Engineering at
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Department of Electrical and Electronic Engineering

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I would like to thank my dog, Muffin. I also would like to thank the inventor of the incubator; without him/her, I would not be here. Finally, I would like to thank Dr Herman Kamper for this amazing report template.



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Abstract

English

The English abstract.

Afrikaans

Die Afrikaanse uittreksel.

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Nomenclature

Variables and functions

$p(x)$	Probability density function with respect to variable x .
$P(A)$	Probability of event A occurring.
ε	The Bayes error.
ε_u	The Bhattacharyya bound.
B	The Bhattacharyya distance.
s	An HMM state. A subscript is used to refer to a particular state, e.g. s_i refers to the i^{th} state of an HMM.
\mathbf{S}	A set of HMM states.
\mathbf{F}	A set of frames.
\mathbf{o}_f	Observation (feature) vector associated with frame f .
$\gamma_s(\mathbf{o}_f)$	A posteriori probability of the observation vector \mathbf{o}_f being generated by HMM state s .
μ	Statistical mean vector.
Σ	Statistical covariance matrix.
$L(\mathbf{S})$	Log likelihood of the set of HMM states \mathbf{S} generating the training set observation vectors assigned to the states in that set.
$\mathcal{N}(\mathbf{x} \mu, \Sigma)$	Multivariate Gaussian PDF with mean μ and covariance matrix Σ .
a_{ij}	The probability of a transition from HMM state s_i to state s_j .
N	Total number of frames or number of tokens, depending on the context.
D	Number of deletion errors.
I	Number of insertion errors.
S	Number of substitution errors.

Acronyms and abbreviations

AE	Afrikaans English
AID	accent identification
ASR	automatic speech recognition
AST	African Speech Technology
CE	Cape Flats English
DCD	dialect-context-dependent
DNN	deep neural network
G2P	grapheme-to-phoneme
GMM	Gaussian mixture model
HMM	hidden Markov model
HTK	Hidden Markov Model Toolkit
IE	Indian South African English
IPA	International Phonetic Alphabet
LM	language model
LMS	language model scaling factor
MFCC	Mel-frequency cepstral coefficient
MLLR	maximum likelihood linear regression
OOV	out-of-vocabulary
PD	pronunciation dictionary
PDF	probability density function
SAE	South African English
SAMPA	Speech Assessment Methods Phonetic Alphabet

Chapter 1

Introduction

The last few years have seen great advances in speech recognition. Much of this progress is due to the resurgence of neural networks; most speech systems now rely on deep neural networks (DNNs) with millions of parameters [?,?]. However, as the complexity of these models has grown, so has their reliance on labelled training data. Currently, system development requires large corpora of transcribed speech audio data, texts for language modelling, and pronunciation dictionaries. Despite speech applications becoming available in more languages, it is hard to imagine that resource collection at the required scale would be possible for all 7000 languages spoken in the world today.

I really like apples.

1.1. Section heading

Chapter 2

Modelling

This chapter discusses the mathematical modelling of a quadrotor with a suspended payload which is based on a practical quadrotor UAV named Honeybee. The model is first derived as a 2D model. The system identification and control system techniques in later chapters will then be explained based on the 2D model to avoid unnecessary complexity. Finally, it will be described how this model and the techniques in later chapters are extended to the 3D case. This 3D mathematical model will be used in a nonlinear simulation of a quadrotor and suspended payload.

2.1. Coordinate frames

2.2. States

2.3. Forces and moments

2.4. Lagrangian mechanics

2.5. Linearised model

2.6. Discretised model

2.7. Model verification

2.8. Dynamic payloads

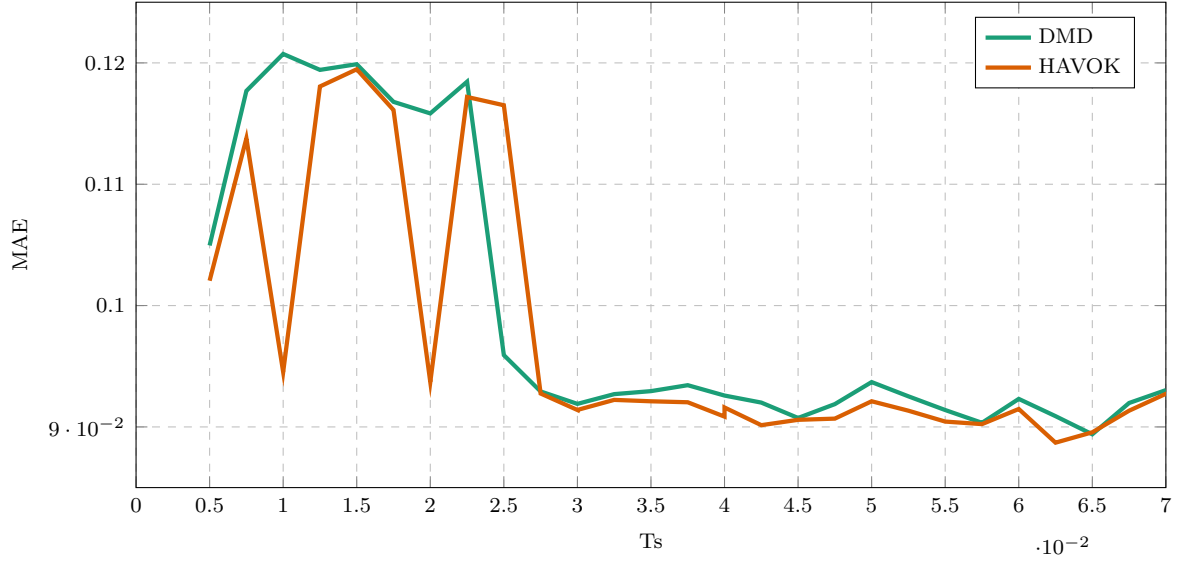


Figure 2.1: DMD and HAVOK predictions error for different lengths of noisy training data ($m = 0.2 \text{ kg}$, $l = 0.5 \text{ m}$, $T_s = 0.03 \text{ s}$, $T_{train} = 60 \text{ s}$.)

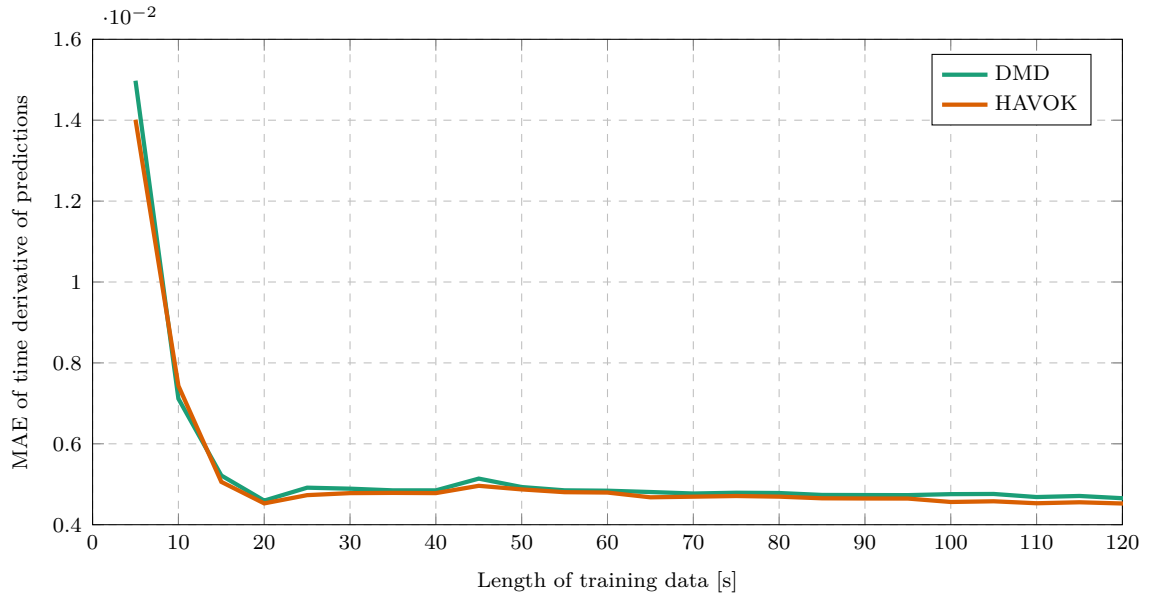


Figure 2.2: DMD and HAVOK error of time derivative of predictions for different lengths of noisy training data ($m = 0.2 \text{ kg}$, $l = 0.5 \text{ m}$, $T_s = 0.03 \text{ s}$).

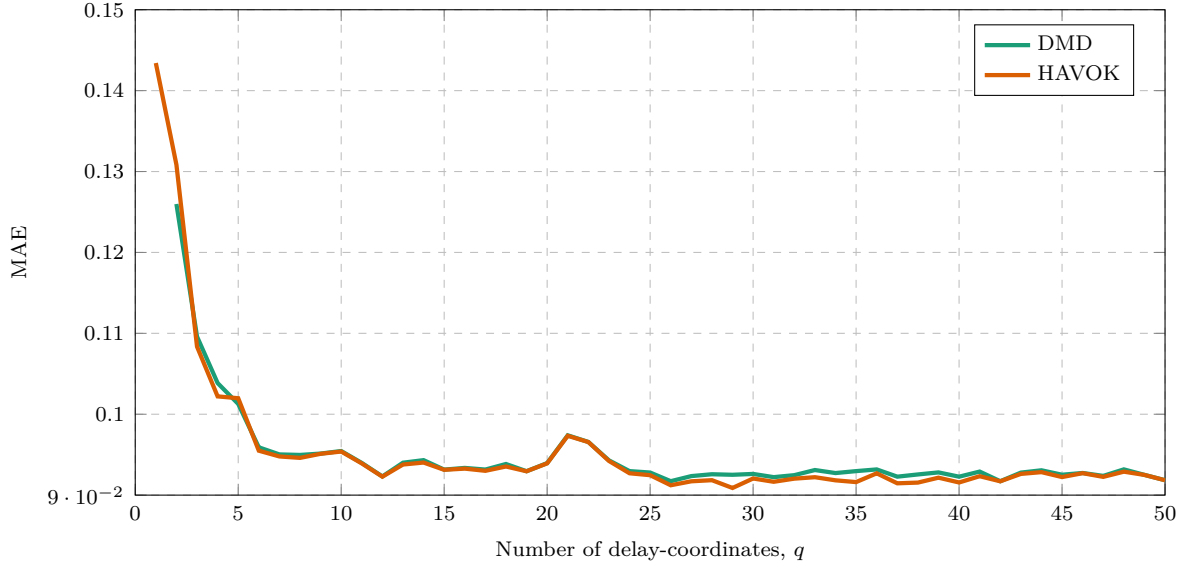


Figure 2.3: DMD and HAVOK predictions error for different lengths of noisy training data ($m = 0.2 \text{ kg}$, $l = 0.5 \text{ m}$, $T_s = 0.03 \text{ s}$, $T_{train} = 60 \text{ s}$.)

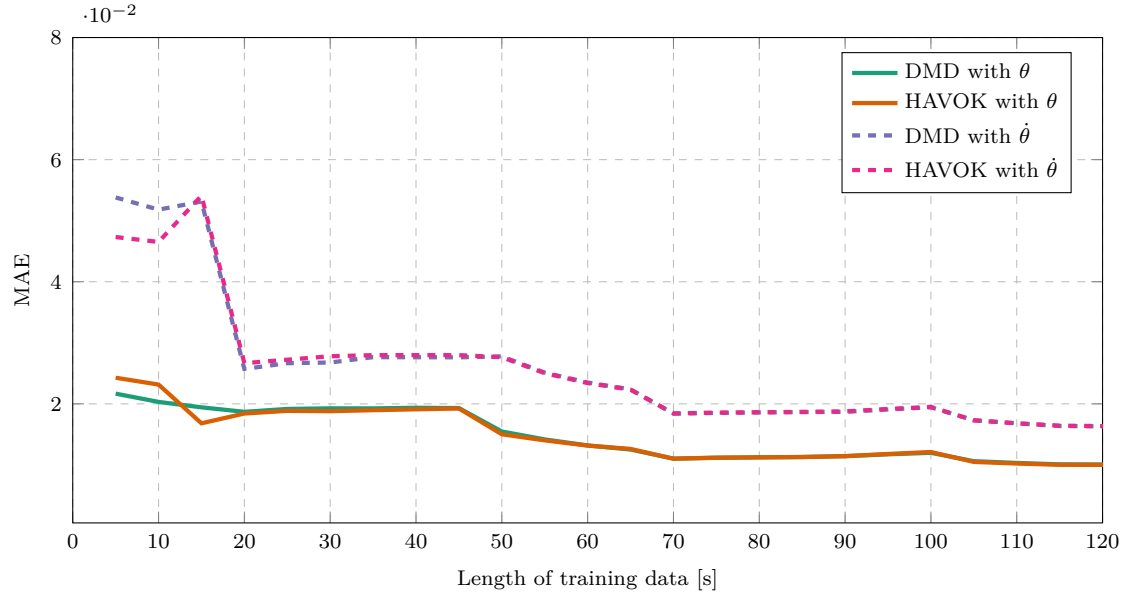


Figure 2.4: Prediction MAE for models using angle or angular rate measurements ($m = 0.2 \text{ kg}$, $l = 0.5 \text{ m}$, $T_s = 0.03 \text{ s}$).

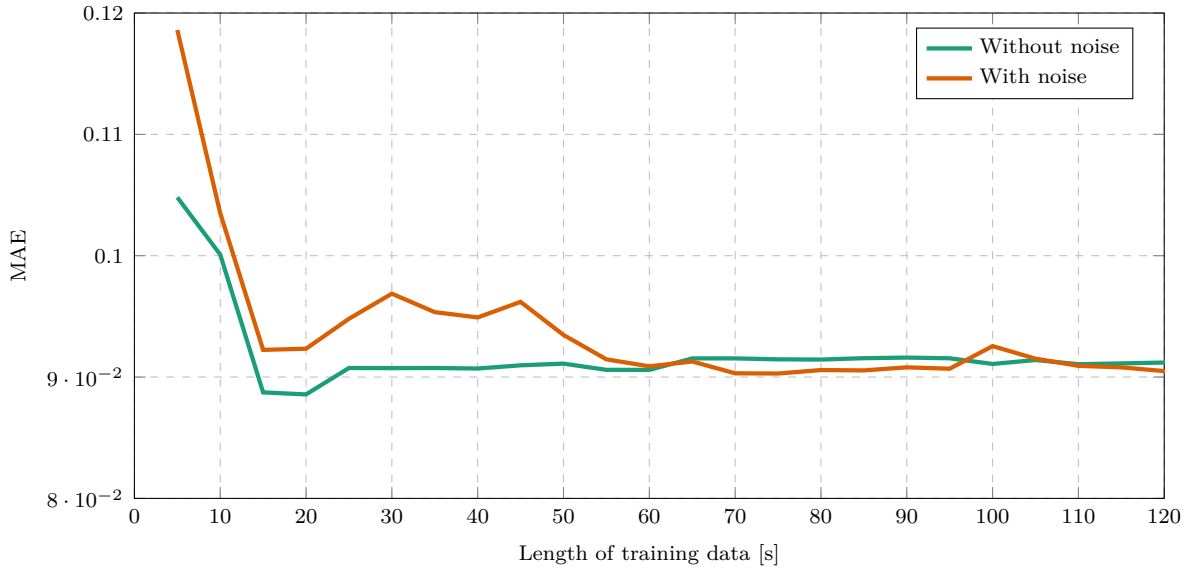


Figure 2.5: HAVOK prediction error for different lengths of training data with and without noise ($m = 0.2 \text{ kg}$, $l = 0.5 \text{ m}$, $T_s = 0.03 \text{ s}$).

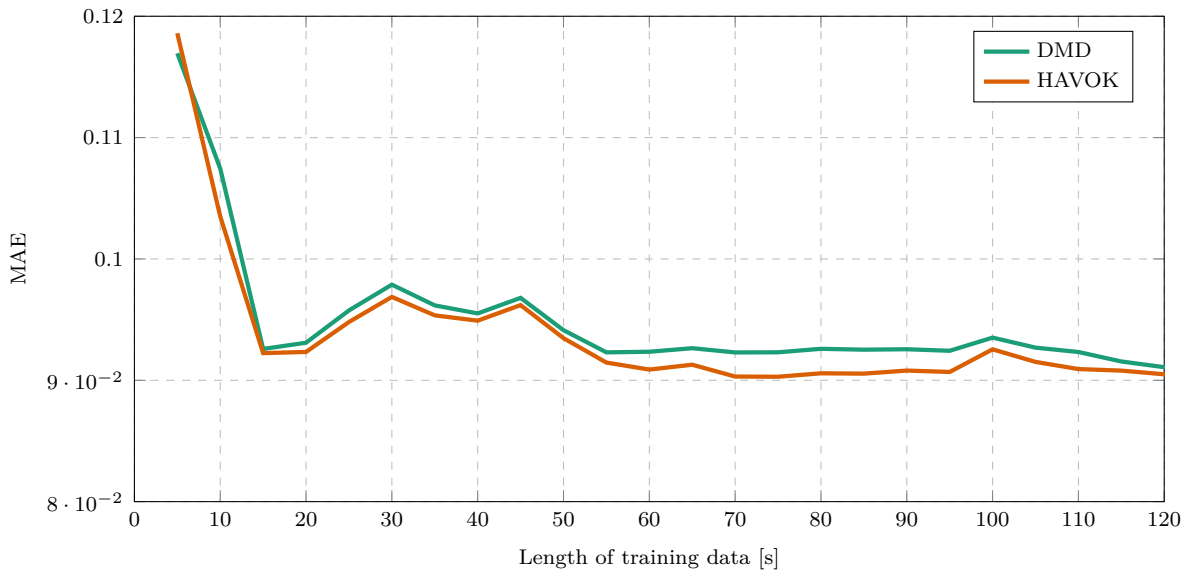


Figure 2.6: DMD and HAVOK prediction error for different lengths of noisy training data ($m = 0.2 \text{ kg}$, $l = 0.5 \text{ m}$, $T_s = 0.03 \text{ s}$).

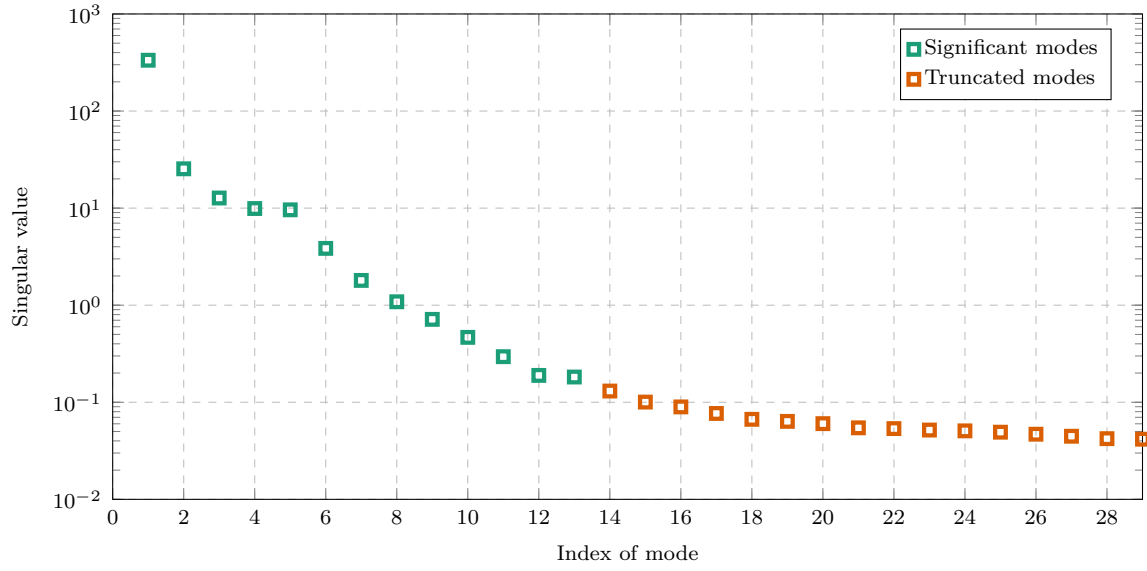


Figure 2.7: Significant and truncated singular values of a HAVOK model produced from noisy data ($m = 0.2$ kg, $l = 0.5$ m, $T_s = 0.03$ s, $T_{train} = 60$ s.)

Chapter 3

Summary and Conclusion

Bibliography

Appendix A

Project Planning Schedule

This is an appendix.

Appendix B

Outcomes Compliance

This is another appendix.