

Contents

| | |
|--|-----------|
| Preface | ix |
| 1 Introduction | 1 |
| 1.1 Latency and misfit | 1 |
| 1.2 Data fitting examples | 2 |
| 1.3 Classical vs. behavioral and stochastic vs. deterministic modeling | 9 |
| 1.4 Chapter-by-chapter overview* | 10 |
| 2 Approximate Modeling via Misfit Minimization | 15 |
| 2.1 Data, model, model class, and exact modeling | 15 |
| 2.2 Misfit and approximate modeling | 17 |
| 2.3 Model representation and parameterization | 18 |
| 2.4 Linear static models and total least squares | 19 |
| 2.5 Nonlinear static models and ellipsoid fitting | 21 |
| 2.6 Dynamic models and global total least squares | 23 |
| 2.7 Structured total least squares | 24 |
| 2.8 Algorithms | 25 |
| I Static Problems | 27 |
| 3 Weighted Total Least Squares | 29 |
| 3.1 Introduction | 29 |
| 3.2 Kernel, image, and input/output representations | 33 |
| 3.3 Special cases with closed form solutions | 35 |
| 3.4 Misfit computation | 38 |
| 3.5 Misfit minimization* | 40 |
| 3.6 Simulation examples | 46 |
| 3.7 Conclusions | 47 |
| 4 Structured Total Least Squares | 49 |
| 4.1 Overview of the literature | 49 |
| 4.2 The structured total least squares problem | 51 |
| 4.3 Properties of the weight matrix* | 54 |
| 4.4 Stochastic interpretation* | 58 |
| 4.5 Efficient cost function and first derivative evaluation* | 60 |

| | | |
|-----------|--|------------|
| 4.6 | Simulation examples | 64 |
| 4.7 | Conclusions | 68 |
| 5 | Bilinear Errors-in-Variables Model | 69 |
| 5.1 | Introduction | 69 |
| 5.2 | Adjusted least squares estimation of a bilinear model | 70 |
| 5.3 | Properties of the adjusted least squares estimator* | 72 |
| 5.4 | Simulation examples | 74 |
| 5.5 | Fundamental matrix estimation | 75 |
| 5.6 | Adjusted least squares estimation of the fundamental matrix | 77 |
| 5.7 | Properties of the fundamental matrix estimator* | 79 |
| 5.8 | Simulation examples | 80 |
| 5.9 | Conclusions | 80 |
| 6 | Ellipsoid Fitting | 83 |
| 6.1 | Introduction | 83 |
| 6.2 | Quadratic errors-in-variables model | 85 |
| 6.3 | Ordinary least squares estimation | 86 |
| 6.4 | Adjusted least squares estimation | 88 |
| 6.5 | Ellipsoid estimation | 91 |
| 6.6 | Algorithm for adjusted least squares estimation* | 92 |
| 6.7 | Simulation examples | 94 |
| 6.8 | Conclusions | 96 |
| II | Dynamic Problems | 97 |
| 7 | Introduction to Dynamical Models | 99 |
| 7.1 | Linear time-invariant systems | 99 |
| 7.2 | Kernel representation | 101 |
| 7.3 | Inputs, outputs, and input/output representation | 103 |
| 7.4 | Latent variables, state variables, and state space representations | 104 |
| 7.5 | Autonomous and controllable systems | 105 |
| 7.6 | Representations for controllable systems | 106 |
| 7.7 | Representation theorem | 107 |
| 7.8 | Parameterization of a trajectory | 109 |
| 7.9 | Complexity of a linear time-invariant system | 110 |
| 7.10 | The module of annihilators of the behavior* | 111 |
| 8 | Exact Identification | 113 |
| 8.1 | Introduction | 113 |
| 8.2 | The most powerful unfalsified model | 115 |
| 8.3 | Identifiability | 117 |
| 8.4 | Conditions for identifiability | 118 |
| 8.5 | Algorithms for exact identification | 120 |
| 8.6 | Computation of the impulse response from data | 124 |
| 8.7 | Realization theory and algorithms | 128 |
| 8.8 | Computation of free responses | 130 |

| | | |
|-----------|--|------------|
| 8.9 | Relation to subspace identification methods* | 131 |
| 8.10 | Simulation examples | 134 |
| 8.11 | Conclusions | 137 |
| 9 | Balanced Model Identification | 139 |
| 9.1 | Introduction | 139 |
| 9.2 | Algorithm for balanced identification | 142 |
| 9.3 | Alternative algorithms | 143 |
| 9.4 | Splitting of the data into "past" and "future"* | 144 |
| 9.5 | Simulation examples | 145 |
| 9.6 | Conclusions | 147 |
| 10 | Errors-in-Variables Smoothing and Filtering | 149 |
| 10.1 | Introduction | 149 |
| 10.2 | Problem formulation | 150 |
| 10.3 | Solution of the smoothing problem | 151 |
| 10.4 | Solution of the filtering problem | 153 |
| 10.5 | Simulation examples | 155 |
| 10.6 | Conclusions | 156 |
| 11 | Approximate System Identification | 157 |
| 11.1 | Approximate modeling problems | 157 |
| 11.2 | Approximate identification by structured total least squares | 160 |
| 11.3 | Modifications of the basic problem | 163 |
| 11.4 | Special problems | 165 |
| 11.5 | Performance on real-life data sets | 169 |
| 11.6 | Conclusions | 172 |
| 12 | Conclusions | 175 |
| A | Proofs | 177 |
| A.1 | Weighted total least squares cost function gradient | 177 |
| A.2 | Structured total least squares cost function gradient | 178 |
| A.3 | Fundamental lemma | 179 |
| A.4 | Recursive errors-in-variables smoothing | 180 |
| B | Software | 183 |
| B.1 | Weighted total least squares | 183 |
| B.2 | Structured total least squares | 187 |
| B.3 | Balanced model identification | 190 |
| B.4 | Approximate identification | 190 |
| | Notation | 195 |
| | Bibliography | 197 |
| | Index | 203 |