Skolkovo Institute of Science and Technology, Skoltech
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Course “Experimental data processing”

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The goal of this course: to introduce students to practically useful approaches of data processing for control and forecasting. The focus will be on identifying the hidden and implicit features and regularities of dynamical processes using experimental data.
The course exposes data processing methods from multiple vantage points:
- Standard data processing methods and their hidden capacity to solve difficult problems
- Statistical methods based on state-space models
- Methods of extracting the regularities of a process on the basis of identifying key parameters

The course addresses the problems in navigation, solar physics, geomagnetism, space weather and biomedical research and will be useful for broad range of interdisciplinary applications.

Student Participation
To facilitate development of practical skills, foster active interest, and deep understanding, the course includes practical problems in the form of homework/small research projects to be accomplished with Matlab or Python. At the end of term the final project and the oral exam is planned.

Course content and main topics
1. **Introduction to statistical analysis**
   Regression analysis and least squares methods (LSM). Limitations of LSM application in regression problems.

   Laboratory works:
   1. Relationship between solar radio flux F10.7 and sunspot number
   2. Converting a physical distance to a grid distance using least-square method

2. **Quasi-optimal approximation under uncertainty**
   2.1. Running mean. Classification of estimation errors and accuracy analysis
   2.2. Exponential mean. Comparison with running mean
   2.3. Applications in solar physics and biomedicine

   Short description:
   The model-independent methods are widely applied to reconstruct dynamical processes subject to uncertainties. However the simplicity of use without proper analysis of estimation error may be a trap leading to false conclusions. First part of the course covers feature analysis of processes for which simple methods provide effective solution and discuss conditions under which they break down.

   Laboratory works:
   1. Comparison of exponential and running mean for random walk model
      Part 1. Determination of optimal smoothing constant in exponential mean
      Part 2. Comparison of methodical errors of exponential and running mean
   2. Determining and removing drawbacks of exponential and running mean
      Part1. Backward exponential smoothing
      Part 2. Drawbacks of running mean
      Part 3. Comparison of the traditional 13-month running mean with the forward-backward exponential smoothing for approximation of 11-year sunspot cycle.

3. **Optimal approximation at state space**
   3.1. Introduction to Kalman filter
   3.2. Construction of navigation filter for tracking objects
   3.3. Ill-conditioned tracking problem
   3.4. Observability and controllability
   3.5. Optimal smoothing. Forward - Backward Kalman filter

3.6. Equivalence of exponential mean and stationary Kalman filter for the random walk model
3.7. Optimal choice of smoothing gain
3.8. Backward exponential smoothing and estimation accuracy increase
3.9. Applications in navigation and solar physics

Short description:
The methods of filtration and smoothing based on state-space model provide optimal state estimation and estimation error. This section analyzes conditions for quasi-optimal methods to match the optimal ones. This allows increasing the utility of quasi-optimal methods under uncertainty.

Laboratory works:
1. Tracking of a moving object which trajectory is disturbed by random acceleration
2. Analysis of accuracy decrease of filtration in conditions of correlated biased state and measurement noise
   Part 1. Divergence of Kalman filter when bias of state noise is neglected in assimilation algorithm. Development of optimal Kalman filter that takes into account bias of state noise.
   Part 2. Sensitivity of estimation results obtained by a Kalman filter that doesn't take into account correlation of state noise (acceleration) and measurement noise.
3. Development of forward-backward Kalman filter in conditions of correlated state noise.
   Part 1. Development of optimal Kalman filter in conditions of correlated state noise.
   Part 2. Development of optimal smoothing to increase the estimation accuracy.
4. Tracking and forecasting in conditions of measurement gaps.
5. Development of tracking filter of a moving object when measurements and motion model are in different coordinate systems.
   Part 1. Instability zone of a tracking filter due to ill-conditioned coordinate transformations of measurements
   Part 2. How to increase tracking accuracy of a moving object by taking into account available prior information?

4. Process reconstruction free from any constraints and assumptions

4.1. Constraints and assumptions to reconstruct the process
4.2. Broken-line and smooth curve. Optimality criterion
4.3. Well-conditioned optimization problem
4.4. Comparison with other approaches
4.5. Applications in solar physics

Short description:
False assumptions about the process in question may significantly distort estimation output and lead to false conclusions. This topic covers the methods of processing the experimental data that do not need any prior assumptions about the process.

Laboratory works:
1. Sunspot cycle reconstruction free from any constraints and assumptions

5. Model construction at state space under uncertainty Prior mathematical model justification

5.1. Stochastic adaptive models. Uncertainty modeling
5.2. Nonlinear models. Extended Kalman filter
5.3. Noise statistics identification (state and measurement errors)
5.4. Applications in navigation, solar physics and biomedicine

Short description:
One of the core problems of state estimation is the mismatch between the model and true process dynamics. Furthermore there is an uncertainty of measurement noise. One way to reduce the resulting mismatch is to use the stochastic adaptive filters on the basis of noise statistics identification. In addition we discuss how to find new and unexpected ways to extract hidden process regularities, key parameters determining the process dynamics to improve estimation and forecasting.

Laboratory works:
1. Noise statistics identification to construct tracking filter of a moving object
2. Extended Kalman filter for navigation and tracking
3. Joint assimilation of navigation data coming from different sources
4. Vehicle tracking based on GPS and odometry data fusion

Examples of final projects

1. Bicycle tracking based on GPS, speedometer and gyroscope data fusion.
2. Estimation of Lava Volcano flow speed.
3. Forecasting the meeting of two moving vehicles using GPS data.
4. Forecasting the meeting of two moving vehicles using radar data and nonlinear models.
5. Forecasting the meeting of two moving vehicles using radar data. Coordinate transformation of measurements.
6. Catching a target with the extended Kalman filter.
7. Catching a target with the linear Kalman filter using coordinate transformation of measurements.
8. Estimation of a site where motion of a moving vehicle started using GPS data.
9. Estimation of a site where motion of a moving vehicle started using radar data and nonlinear models.
10. Estimation of a site where motion of a moving vehicle started radar data. Coordinate transformation of measurements.
11. Tracking of a maneuvering vehicle using GPS and radar data. Linear and Extended Kalman filter.
12. Prediction of the electron flux at the geostationary orbit.
13. Calibration of wheel odometry data using GPS for accurate localization of a vehicle.
14. Detection of early evolution of coronal mass ejections to estimate the speed of their propagation
15. Solar activity prediction using sunspot and radio flux data

Learning Outcomes:

Knowledge

1. Knowledge of state of the art data processing methods, their distinctive peculiarities and possibilities.
2. Knowledge of actual data processing problems for space applications.
3. Knowledge of approaches to estimate the accuracy and reliability of obtained results.

Skills

1. Transform theoretical knowledge into useful skills of data processing
2. Identify specific features of experimental data and choose an appropriate way of data processing
3. Detect and analyze shortcomings of data processing methods for a particular dynamical process

Experience

1. Experience in the development of estimation and forecasting algorithms of a system state in conditions of uncertainty
2. Experience in methods of process reconstruction, extraction of its tendencies and regularities
3. Experience in accuracy and reliability estimation of obtained results, prevention of false conclusions

References

The classical fundamentals in estimation theory and the state-of-art achievements in the related areas of science.

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