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OPTIMAL & MULTI-MODEL ESTIMATION TECHNIQUES IN CIVIL INFRASTRUCTURE & ENVIRONMENTAL PROBLEMS

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Abstract: *Optimal estimation, adaptive filtering and multi-model techniques are initially presented and widely applied in specific engineering fields such as the aerospace or signal processing. Nowadays, these methods are increasingly applied in many other scientific fields, ranging from construction engineering to medicine. In this work, we present and analyze the application of optimal estimation and adaptive or multi-model techniques in the various fields of the civil, infrastructure & environmental engineering. The range of applications vary from structural health monitoring, to river flow forecasting, from vehicle traffic to tides and offshore problems and from pollution detection to environmental processes. The applied optimal, nonlinear or adaptive methods are modelling the uncertainty and heterogeneity of these processes in order to produce more accurate estimations or predictions. The analysis of the presented applications indicates clearly that the use of multi-model partitioning techniques may improve significantly the accuracy of the results*.

1. INTRODUCTION

Optimal estimation techniques received great attention after 1960, when Kalman presented his algorithm [1] the widely known today Kalman Filter (KF). Initially most KF applications came from signal processing and aeronautical problems, as these fields necessitated on-line extraction of a signal or real-time estimation of a system state using noisy and indirect observations.

Until the late 80's the Kalman Filter and its extensions were applied successfully in aerospace, naval, financial, and other problems with complex, unknown or stochastic nature. The advances in personal computers during the last two decades gave the possibility to bring the power of optimal estimation techniques to every desktop or laptop computer and to apply these techniques in a other scientific domains.

Today, we have a lot of KF extensions or successors at hand. The most promising are the Adaptive Filters or Multi-Model Partitioning Algorithms (MMPA) [2],[3]. These advanced filters have a naturally parallel structure that is ideal for distributed implementation, and, when combined with the latest advances in distributed and parallel processing they permit us to tackle in real-time any large scale problem with increased state and/or data dimensionality.

The availability of estimation techniques and processing power at our desktop, boosted further their application to other technical and scientific areas with satisfactory results. Nowadays, these techniques are increasingly applied in many other scientific fields, ranging from construction engineering to medicine. In practice, these optimal and adaptive estimation techniques may be applied whenever an on-line, real-time monitoring or estimation/identification of a system state is required, in order to obtain early and more accurate predictions about its future condition.

In this work, we present and analyze applications of optimal estimation and adaptive or multi-model identification techniques in the various fields of the civil, infrastructure & environmental engineering. The range of applications vary from structural health monitoring, to river flow forecasting, from vehicle traffic to tides and offshore problems and from pollution detection to environmental processes. The applied optimal, nonlinear or adaptive methods attempt to model the uncertainty and heterogeneity of these processes in order to produce more accurate estimations or predictions. In the following sections we present a survey of related applications and how the use of these techniques may improve significantly the accuracy of their results. Research directions in the following fields are presented: Surface Traffic and Transportation (traffic signal control, pedestrian detection, urban traffic flow, locomotive navigation, land use), Structural Integrity (SHM, Bridges, Multi-storey buildings, concrete inspection, port inspection), Environmental Processes (Soil properties, River flow, rainfall, flood forecasting), etc.

2. SURFACE TRAFFIC AND TRANSPORTATION

Transport infrastructure plays an integral part in our daily lives. It is gradually becoming more sophisticated, due to the expansion and diversity of technologies applied in environment, and related safety and security measures.

Traffic-adaptive signal control

Vehicle arrival at a traffic signal is stochastic; vehicles arrive sometimes singly and sometimes in batches. Inter-arrival times vary non-deterministically, being affected by time-of-day traffic conditions, the vehicle mix, upstream incidents and bottlenecks, the mix of driver types (defined by purpose, socioeconomic and demographic variables, and driver personality), and the physical layout of the road and lanes. To be effective, real-time traffic-adaptive signal control must proactively respond to the arrival streams to minimize vehicle stops and delays as much as possible. The feedback control diagram in Figure 1 illustrates an effective traffic-adaptive signal control system. The sensors monitor the traffic on the network. Using a traffic model, the system estimates the current traffic flow and predicts future traffic flow. Using an optimization algorithm or an optimum-seeking heuristic, it then determines the best plan or phase timing to apply for the next control period. Using the above concept, RHODES (Real-Time Hierarchical Optimized Distributed Effective System) proposed by [4] produces real-time predictions of traffic flow and "optimally" controls the flow through the transportation network, using phase timing.

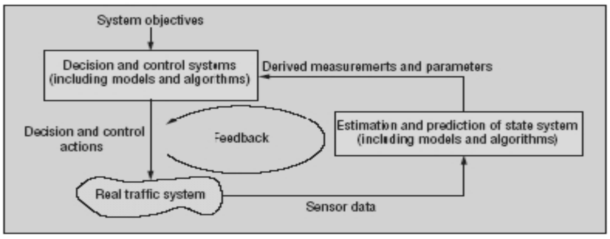


Figure 1: A feedback control diagram for traffic-adaptive systems [4].

Pedestrian Detection

Although crossing car detection is a rather trivial procedure today, traffic-adaptive signal control requires the detection of crossing pedestrians. Real-time track & detection of pedestrians by still traffic video-cameras is proposed by [5] using image processing techniques and maximum likelihood-matching algorithms.

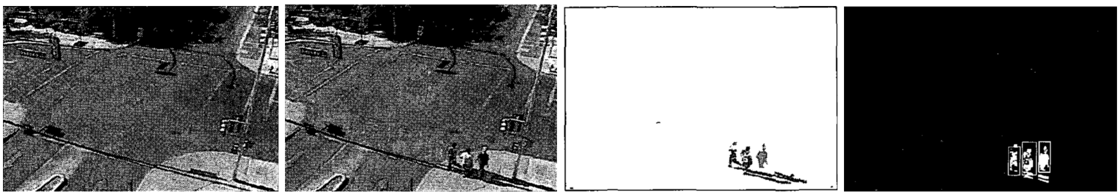


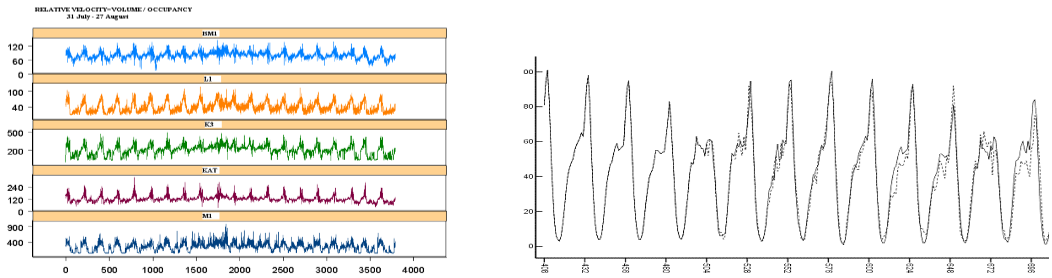
Figure 2: Background frame, current frame, denoised image, and final pedestrian detection, by [5].

Pedestrian detection and tracking from a vehicle, is also considered, using night vision video cameras. The two-step detection/tracking method proposed by [6] uses successfully, for the tracking phase, a combination of Kalman Filter prediction and Mean Shift Tracking.

Urban Traffic Flow Modelling and Detection

Short term forecasting of traffic flow conditions in urban networks is performed by time series or state space models. These models may be either univariate, local and more flexible, or, multivariate, spatiotemporal and more accurate by incorporating closely located sites [7].

Individual space-time properties or periodic behaviours may be used to create a specific models for normal or expected traffic conditions. Multi-model techniques may identify on-line the current traffic flow model and detect normal conditions or traffic network anomalies from unexpected events [8].



(a) (b)

Figure 3: Traffic flow periodicities a) in [7] and b) in [8].

Railroad

The new high speed rail systems require precise and real-time train location in order to maximize the use of railroad track and equipment and improve safety and service reliability. GPS train location data alone do not provide the accuracy required, especially identification of which track the train is on when moving in a multiple track territory with track centres as close as 13 feet.

Kalman filtering techniques may optimally integrate GPS or DGPS data with measurements from accelerometer sensor arrays, odometers, gyros or conventional accelerometers, for locomotive navigation. These techniques provide a low-cost alternative to conventional rate gyros or laser fibre optic gyros used for precise navigation [9].

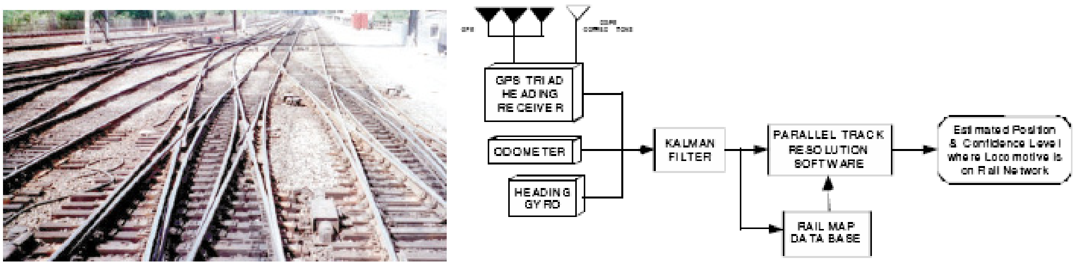


Figure 4: Locomotive navigation systems must also detect movement into a parallel track [9].

Land Use – Transportation Cycle Modelling

In recent years, the "generated traffic" or "induced travel" phenomenon attracts much attention among transportation planners. Induced travel is the additional travel resulting from improvements to transportation facilities intended to provide greater capacity. The initial reduction of congestion tends to gradually increase until congestion again reaches high levels. Transportation demand leads to road improvements, road improvements attract mode citizens and or buildings, resulting to more transportation needs.

Univariate and multivariate time series may be used to create spatiotemporal models of this typical Land Use- Transportation cycle, as suggested by [10],[11]. Application of estimation techniques may eventually forecast new infrastructure demands caused by changes in land use and vice-versa.

3. STRUCTURAL INTEGRITY

Many aspects of our technical infrastructure are approaching or exceeding the initial design life. These civil, mechanical, and aerospace structures are being used in spite of aging and damage accumulation. Therefore, the ability to monitor the health of these structures is becoming increasingly important. Due to the economic and safety implications of the potential for performing global damage identification, many new technical advances have been applied for Structural Health Monitoring (SHM) in recent years.

Structural Health Monitoring (SHM)

Civil engineering structures are unique in that each structure is custom designed for a specific location and environmental conditions. Developing a custom SHM technique for each structure is unfeasible. It is clearly preferable to develop a more economical and generic technique capable of adapting itself to the properties of each structure. Ideally these techniques will be easy to deploy, reliable, and computationally efficient.

In addition, SHM sensor installations raise several problems on effective data analysis. The continuous nature of structural monitoring and the relatively large number of sensors, generate vast quantities of data, ranging from MB to GB per day. Due to these large quantities several problems of data storage, on-line processing, and, information management must be resolved.

Several research projects have been funded to improve the damage detection methods including the use of innovative signal processing, control theory and non-destructive evaluation methods [12].

Bridges

Bridge infrastructures have been under pressure from aging and increased traffic flow. Today's bridges are becoming increasingly susceptible to structural degradation. At present, visual inspections are carried out periodically where damage could go undetected or cracks could grow to critical levels between inspection intervals. Extreme events such as storms or traffic collisions can also increase damages. The employment of a system that monitors the structural health of bridges can help to prevent accidents such as structural collapse and to plan any structural maintenance required while safety is ensured and interruptions to the public minimised. Bridge health monitoring system are using large numbers of various sensor types i.e.: accelerometers, thermocouples, displacement transducers and metal-foil or fibre-optic strain gauges. Data collected by the sensors are subsequently treated by an estimation and/or identification algorithm, in order to extract information regarding the structural heath of the bridge.

State-space identification methods are used, in [13],[14], for modal identification from earthquake records. The bridges are equipped with an adequate array of accelerometers and the identification of modal frequencies and damping rations is performed using parametric and non-parametric methods, time series and Kalman Filter.

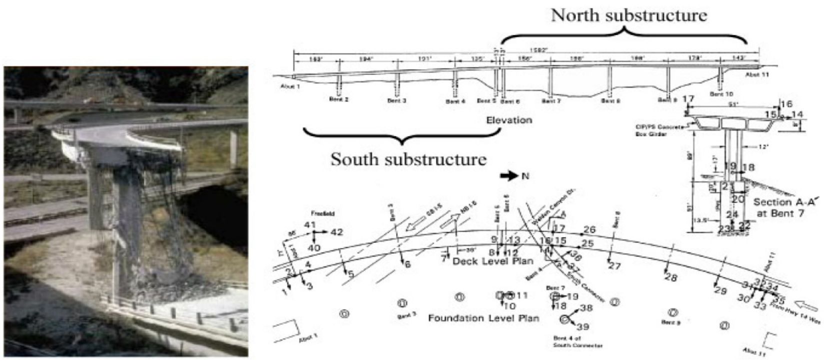


Figure 5: Sylmar I5/14 interchange bridge from [14]

An Extended Kalman Filter (EKF) is applied in [15] to detect changes in the time series model coefficients that relate to unusual events. The bridge is monitored continuously and the Vector Seasonal ARIMA model is formulated from the recorded strain signals.

Smart Bridges and smart structures have integral sensors to interpret their state and adjust the structure intelligently with respect to environmental conditions. For example, actuators can dump unwanted vibrations. In [16], a fibre-optic system is developed in order to monitor new materials such as fiber-reinforced-prolymer used for repairing a damaged bridge.

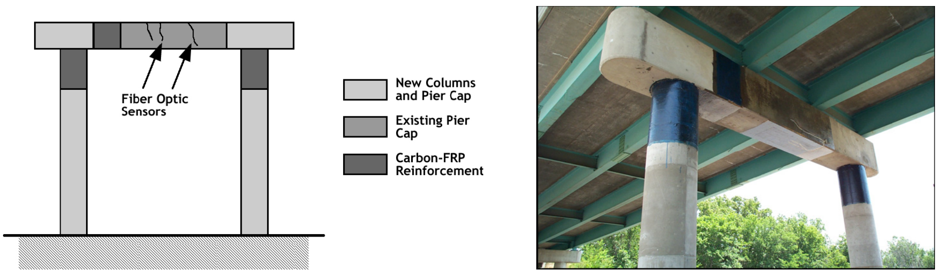


Figure 6: Fiber-optic sensors installed on the reconstructed pier cap of an I-44 overpass. [16]

Treatment of the sensor data is performed by ANN or other model identification methods. ANN and multi-model techniques can learn bridge's normal responses and they are capable of identifying and locating events from vehicular traffic, seismic activity, wind loading or other environmental conditions [17].

Substructures and Multi-storey Buildings

The same techniques apply for SHM of multi-storey buildings, or substructures. The construction response to vibrations is modelled using time series or state space models that are subsequently used to detect or diagnose structural damage using Kalman Filter, Extended Kalman Filter and Adaptive techniques [18-21].

Concrete Structure Inspection

Failures of concrete structures are often attributed to chemical attack, either from outside (sulphate, steel corrosion, etc.) or from the inside of the structure (alkali silica, etc.). For example, the effect of chloride containing environment on the integrity on reinforced concrete structures is studied by [23], using multiple Monte-Carlo simulations. Furthermore, [24] applies a model of the degradation mechanism with the aid of Kalman and Extended Kalman Filters, in order to estimate the advancement of the concrete degradation.

Port Infrastructure Inspection

A set of tools, incorporating estimation techniques and Kalman Filter, is being developed for the automated inspection of rubble-mount breakwaters. The proposed tool and the KF combine GPS and Sonar data from periodic inspections, to obtain accurate estimates and finally assess the condition of the submerged part of the breakwater [22].

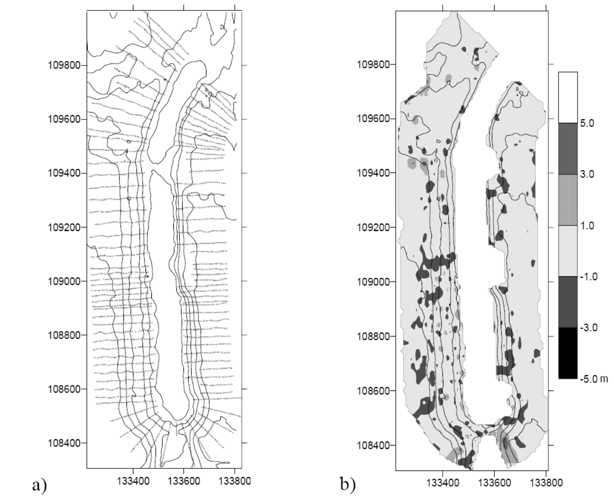


Figure 7: Plot of breakwater's surveyed lines and the differences between 2003 and 2000, from [22].

4. ENVIRONMENTAL PROCESSES

Soil Properties

In order to estimate soil properties, a procedure is developed in [25] for nonlinear system identification of soils using strong-motion records. Data are obtained by a down hole seismograph array and the identification is conducted by the Extended Kalman Filter. An optimal multi scale Kalman filter is applied by [26] to predict the assimilation of near surface soil moisture. The performance of the ensemble Kalman filter for soil moisture estimation is studied in [27] and the results indicate that the ensemble KF is a flexible and robust data assimilation option that gives satisfactory estimates.

River Flow, Flood and Rainfall Modelling

River flow, Flood and Rainfall modelling and forecasting is a very active research field offering numerous applications for the optimal estimation techniques. Multi-model, time series and neural nets are applied to model the evolution of the water flow due to the environmental conditions. Flow and flood predictions are crucial for the design and control of urban drainage systems.

A study of six alternative methods on multi-model data fusion by [28] indicates that multi-model techniques perform similarly if not better than single modelling solutions. Time series, neural network, fuzzy, multi-scale stochastic and modular learning models are also applied to forecast river flow by [29-31] with satisfactory results. River flow and flood forecasting models may be further enhanced by associated rainfall input models. In [32] an adaptive forecasting scheme is used in order to incorporate rainfall as an additional input component to the river floe forecast model.

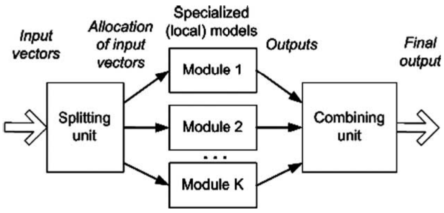


Figure 8: Modular multi-model structure in [31].

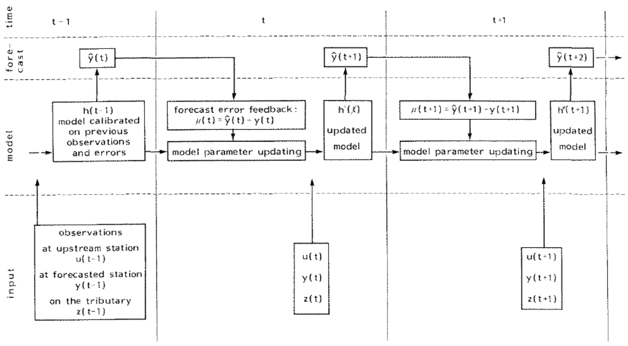


Figure 9: Adaptive forecasting in [32]

In 2004, Chou et al. [33] presented an application of a multi-model method using a wavelet-daseb Kalman filter bank to simultaneously estimate decomposed state variables and unknown parameters for real-time flood forecasting. Validation results demonstrated that the method is effective because of the decomposition of wavelet transform, the adaptation of the time-varying Kalman filter and the characteristics of the multi-model method. They also reveal that the resulting method enhances the accuracy of the runoff prediction of the rainfall–runoff process.

5. CONCLUSIONS

A short survey of current research trends is presented regarding the application of optimal estimation techniques, either Kalman filtering of more advanced adaptive and multi-model techniques, in several fields of civil, infrastructure & environmental engineering. More precisely, research topics in the following fields are presented: Surface Traffic and Transportation (traffic signal control, pedestrian detection, urban traffic flow, locomotive navigation, land use), Structural Integrity (SHM, Bridges, Multi-storey buildings, concrete inspection, port inspection), Environmental Processes (Soil properties, River flow, rainfall, flood forecasting). The results indicate that the application of optimal, nonlinear or adaptive methods and the modelling of the uncertainty and heterogeneity of these processes, produce more accurate estimations and predictions. The presented efforts indicate clearly that the use of multi-model partitioning techniques may improve significantly the accuracy of the results in monitoring, detection or forecasting of current and future material and environmental conditions.

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