Considerations on modeling for early detection of abnormalities in locally autonomous distributed systems
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Chapter 9

Concluding Remarks

The thesis concentrates on the detection of abnormal behavior, in locally autonomous distributed systems with a global function. It argues the case for a new methodology through a radically new perspective on systems and modeling for detection. Surprising and new are the need for a monolithic data-driven process model and the design trade-off between redundancy and statistical optimality. The added contribution is the analysis revealing the causes of the limitations of classical detection techniques, which serves to motivate the new perspective. We can now relate detection design to properties of a detection problem. Thus we clarify why computational intelligence complements the classical arsenal. We recommend a combination of the emerging methodology and classical process modeling to address the complexity issue in detection.

9.1 Contribution of this research

We have investigated the problem of detecting systematic disturbances to facilitate preventive action prior to undesirable performance degradation of distributed systems. The essential contribution of this research is an alternative perspective on systems and abnormalities, leading towards a different detection strategy. The next contribution is the analysis to establish the limitations of the existing arsenal of the detection techniques and strategies, and the causes of these limitations. This links to the original research questions posed in chapter 1:

1. Is it possible to identify the presence of a priori unknown potentially harmful structure from time-variant behavior?
2. Can we point out and explain possible limitations of the existing well-founded arsenal of strategies and techniques?
3. Can we relate these limitations to properties of the detection problem, i.e. the properties of system and its abnormalities?
4. Can the limitations be overcome in a methodological way? How is it different from the existing arsenal?

First we pay attention to the analysis results in 8.1.1; then, in 8.1.2, we summarize our assessment of the specific techniques in neural modeling to the purpose of detection.

Our understanding of the limitations of the existing arsenal of methods can only start from an extensive overview of detection strategies and techniques based on signal detection and dynamical systems theory.

Claim 1. We offer a novel classification of the detection methods based on the complexity of the systems and disturbances presumed in the modeling. This reveals the independent modeling of systems and abnormalities in the conventional approaches. There exist four common strategies, (figure 4.4: dedicated filters, projection methods, adaptive filtering and blind identification) from the two disciplines that are the pillars of detection. We have revealed
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Contribution of this research

that the key differences between process-oriented modeling and data-driven blind methods lay particularly in the area of modeling and fitting. The differences arise from different views on systems and abnormalities. The varying use of a priori and assumed knowledge about the system physics, and the logic behind the system and possible abnormalities particularly affects the modeling and signature computation. From here we classify detection mechanisms, figure 4.5, according to the general properties of the detection problem, i.e. the assumed properties of the system and abnormalities. We offer an alternative classification of techniques based on the complexity of the systems and disturbances presumed in the modeling. Conventional methods implicitly pursue a projection to orthogonalize the signatures in detection space of ideal system behavior from abnormal behavior. More specifically, both process-oriented and data-driven strategies are predominantly finite and fixed in dimensionality.

Computational Intelligence is the discipline for problem solving and modeling by mimicking human and biological behavior, such as in artificial neural networks, self-organizing feature maps, evolutionary algorithms and fuzzy logic. In subsection 4.4.1 we touch the surface of the problems with a motivation for resorting to computational intelligence. Apart from the desire to incorporate qualitative human expert knowledge, this motivation comes from complexity, unpredictability, non-smooth parameter spaces and the existence of non-cardinal values. A specific potential capability of computational intelligent adaptive techniques is the ability to learn patterns which have not been a priori configured in the architecture of the model.

Claim 2. We have revealed the causes of the limitations of existing approaches for detection in locally autonomous distributed systems. This was achieved through an analysis of three typical cases and a general comparison of the properties of the detection problem in this setting compared to the detection problem the conventional detection approach have been designed for. In chapter 5, we find what causes the limitations in the existing well-founded arsenal of strategies and techniques. Hence we can relate these limitations to properties of the detection problem (the system and it's abnormalities). First, we have established that blind detection is inaccurate in any real-world situation, as detection thresholds are defined on model-free projections of the measurements resulting in a very coarse separation between "signal" and "null" space. These blind detection strategies completely ignore the relation between behavior and internal states, or internal state transitions. Acceptable variations, resulting from inherent time-variance, prevent a threshold optimization for sensitive detection of potentially harmful abnormalities. Second, we have considered the properties of LADS compared to classical applications of FDI and signal detection (see table in section 5.4.2) and related them to issues in modeling for detection.

Claim 2a. One cause of the limitations is the invalidation of the assumption of compositionality. The methods in chapter 4 are adequate for LADS as long as the nominal system model is valid. However, relative to the reductionistically modeled dynamics from the system design, there are global disturbances and abnormal behavior. These indicate the presence of a non-modeled, unknown dimension: the global disturbance must come from an a priori unknown dependence between variables in an ignored obscure dimension. One is often aware that the system's blueprint cannot cover all accepted dependencies and influences, nor can the environment be adequately modeled, and one accepts it as a time-variant behavior to be dealt with during detection. In practice one lacks a coherent unified model synthesized bottom-up from the underlying principles, although local processes are fully comprehended. Every model consists of some equations describing the desired or acceptable traversing through the systems.
state space. Differential equations and finite state machines are suitable paradigms to model these dynamics. The composition of models describing the desired traversing is the composed nominal system model. The state changes can be related to changes in input-output behavior with such a model (and partly vice versa).

Claim 2b. A second cause of the limitations is the invalidation of the superposition assumption. The heart of the detection problem is to find the dimensions in which the behavior can be projected, such that acceptable, desired and potentially harmful behavior are maximally separated. In the classical process-oriented approach the nominal process model is invariant and the abnormalities are assumed to be superpositional to this process model. The essential complications are that abnormal is not defined a priori, and corresponds to change in the system itself; moreover, the system is time-variant itself. The optimal basis to span the detection space is chosen in a classical detection approach on the basis of a number of conditions from conventional modeling that are not applicable to distributed systems with an intentional global function. Consequently the chosen spanning base is not optimal. This problem worsens with increasing complexity of the system, since the nominal process model is by necessity increasingly simplified. Compartmentation of the state-space and isolation of the model for local dynamics is the root cause of the detection limitations.

Claim 2c. A third limitation of conventional approaches is the issue that abnormalities cannot be sufficiently known a priori at all. In practice they are not known in advance, not even sufficiently known to provide a parameterized model. Most abnormalities are unforeseen and rare. They are the consequence of intrinsic system changes under the influence of the environment and a different utilization than intended or specified.

The properties of LADS to be covered by a detection model are in conflict with the conditions for proper process-oriented modeling: compositionality of a system model, superposition of an underlying model and occurring abnormalities, and a finite and bounded abnormality space.

A new perspective: towards a motivated method capable to overcome the limitations

In chapter 5 our analysis has also brought us closer to understanding the detection problem, particularly it clarifies the question whether it is possible to identify the presence of a priori unknown, potentially harmful structure from time-variant behavior. The cases and the analysis have resulted in a more profound understanding of the nature of time-related disturbances in systems, at least pertaining to the challenging class of global disturbances. We have learned that the actual challenge is that systems and abnormalities are intertwined and that the prevention of harmful failures is distributed. Consequently, detection of global disturbance in locally autonomous systems depends on dynamic models for global system behavior.

Claim 3. The manifesting system behavior is the proper basis for modeling, rather than the underlying principles that are assumed. The reason is that system behavior is not compositional as a sum of parts, particularly because the abnormalities are intricately intertwined with the system itself. Abnormalities, that truly matter and require monitoring beyond capabilities of the existing arsenal of methods, are a priori unknown and are inherently unforeseen in the system design. A fortunate advantage of dense system monitoring is that a seemingly ad-hoc and irregular variable can be interpreted and modeled on a fine-grain. A fairly regularly over-sampled signal can be analysed with signal processing techniques on coarse and macroscopic scale (as illustrated in section 5.2). Severity denotes a quantitative attribute for the extent of "failing" in a system. It is a matter of fact, and often an ‘after the fact’
attribute of a system. It is our quest to prevent a severe degradation by the preceding change. Sustaining evolution of the system towards harmful degradation causes profound abnormalities. We have defined three levels of profoundness, related to the degrees of freedom, as illustrated in figure 4.5: 1) additive errors, 2) state space aberrations; and 3) change in dynamics of the system. The amount of information in a disturbance is a better indicator of abnormality than the integrated error.

Claim 4. We have identified the two key drivers for early detection: observability and earliness, and we have derived the essential modeling requirements based on these drivers and prevention of the false assumption causing other methods to fail. These drivers are distinctive, especially when combined. Throughout this thesis observability and solvability for the model parameters are a key topic, yet it is surprising that it is not frequently mentioned in detection literature. The new perspective is found in the key propositions of chapter 6:

- When modeling for detection, make no assumptions on the system’s internal structure. The model parameters must be fully controlled through some data fitting procedure. Further: make no assumptions on the way systems and abnormalities are intertwined.
- Redundancy should consequently be inside the model to reflect abnormality.
- The model should be monolithic to identify the common features from multiple instances of the same system and to prevent a priori structuring causing bias.
- The model should have a soft-scaling complexity, since it requires an effective redundancy without unnecessary statistical risk or bias that harms observability. The model, in a sense, should have potential degrees of freedom, regulated by the model parameters on a soft scale.

Claim 5. We have provided a different perspective that offers a trade-off for some conflicts in the essential modeling requirements that cannot be resolved by modeling approaches in conventional detection approaches. The essential conflicts that we have found in the modeling for early detection are: observability vs. reductionism; blind-estimation vs. earliness; and redundancy vs. minimal risk. Our analysis provides a different perspective on the design objectives, as the key conflicts are different. Classically conflicts are between the detection criteria sensitivity, promptness and robustness. We have shown in chapter 6 that the classical modeling approaches (linear, polynomial, orthogonal components) in classic detection strategies are fundamentally incapable of offering a trade-off for the new conflicts in early abnormality detection. This is a serious limitation caused by the reigning paradigm in modeling: reductionism.

9.2 Recommendations

9.2.1 Applications

In the past few years the relevance of monitoring strategies for complex distributed applications has only increased. We have witnessed natural disasters and human errors that call for improved security and environmental monitoring [NRC, 2003]. The sixth framework proposal for Early Detection of Earthquakes through a Network of Satellites (EDENS) was one promising initiative for purposeful exploration of technological possibilities [Bleier and Freund, 2005] based on signatures that still lack a physical model. The Dutch LOFAR project displays a vision for high-resolution on-line models of the environment to the benefit for agriculture,
energy production and ecological monitoring. Such projects bring focus and purpose to technological advancements. The complexity of wide area and even global systems is unprecedented.

**We firstly recommend to embrace the emerging approaches that help to manage complexity, such as methodological model-driven and aspect oriented design strategies.** Key capabilities in the development are the agility to adapt to technological advancements and to anticipate evolution rather than one-off designed systems and applications. Design space exploration is gaining importance with increasing system complexity to focus on critical design issues.

**Second we recommend to utilize both data-driven behavioral modeling as well as process-oriented modeling.** The key capabilities of a complex system are self-diagnosis and self-healing. The required monitoring of locally autonomous distributed systems should stand on two legs. One leg is the process-oriented modeling such as pursued with Lydia models supporting Bayesian diagnostic systems. The other leg is the blind data-driven dynamic behavioral modeling approach for early detection proposed in this thesis. This second leg may be perceived as a competing perspective, but it is not: the two legs are essential to bring balance in a complex monitoring responsibility. Both legs depend on observability of all system modules e.g. through the implementation of local self-tests on all hierarchical levels in the system.

When the complexity of systems you are architecting or operating expands beyond understanding, and you are sure that the behavior of the system is not sufficiently predictable to meet expectations such that it causes unacceptable risks, you have two choices. Either you continue solely with physically plausible and mathematically founded modeling, using the blueprint at the heart of detection while accepting it’s limitations due to necessary simplifications and assumptions; or you apply the less conventional computationally intelligent methods, accepting that you cannot interpret their intrinsic workings, which is reasonable since you could not arrive at a complete consistent and coherent system model anyway. We recommend you pursue along the lines of both strategies. We have provided the arguments and explanations for the limitations of the classical approaches to detection, and we have pointed out a road towards an alternative.

**9.2.2 Future research**

Engineering and operational environments are now reluctantly adopting blind dynamic modeling approaches, such as neural networks. Future research should target the improvements to increase acceptance of computational intelligence. We ponder enrichment of the techniques in the proposed detection strategy that will smooth the introduction of such approaches.

Give a non-semantically understandable model, such as a neural network, it is very helpful when patterns in the parameter space can be transformed and linked to corresponding input-output patterns. Specifically it helps to generate some typical examples of abnormalities associated with any chosen signature boundaries in the parameter space. Generally it is a major challenge to extract distinct clarifying scenarios from the parameter space of complex system models to help understanding key system design issues. A related key research challenge is to arrive at system concepts combining domain models on various levels of detail with adequate intermediate abstractions and views.

We know symmetries in the neural weight-space cause different weight solutions that are just permutations between connections in the hidden layer. In a set of models some parts of any two
models of the set will be identical. Consequently the computation of weight-space metrics for either of the models considering this part is obsolete. We can save on computations if these parts are identified. A permutation insensitive similarity-test between neural networks is required. Such a test must be based on SVD or EVD on the weight-space.

Given a black-box dynamic model, such as a dynamical neural network, it will greatly improve acceptance if through some kind of rule-extraction the typical dynamics can be read back from the model, ideally by simple differential equations or state machines and possibly by a description of conditions for their validity. This brings scientifically interpretable dimensions to the black-box model. Moreover this allows for a merge between classical diagnostic methods and data-driven black-box approaches. Mixing computational intelligent techniques with modeling expertise and human diagnostic capabilities remains an essential direction for future research.

9.3 Conclusions

Locally autonomous distributed systems with global objectives are rapidly emerging in various branches of industry and society. These systems will never operate all the time within desirable specifications. Due to our dependence on such systems for energy, transport and environmental monitoring, the costs of malfunctioning become very high. The complexity of man-made systems has grown beyond a desirable level of manageability. This calls, apart from new approaches to design such systems, for process monitoring based on early detection of emerging change that has a propensity to evolve towards undesirable behavior.

We have arrived at an approach differing from the prior art. The early detection for distributed systems with intentional global functions and qualities, such as sensor networks and automatic plants and Grids, have particular requirements on the detection modeling:

- A monolithic data-driven process model is required as a consequence of the non-composable functions and qualities (section 6.4.2), despite the modularity of the system.
- A detection process model, for sensitivity to blind spots of reductionistically obtained nominal process models, requires potential degrees of freedom that are gradually utilized when the model adapts to behavior of a profoundly changing system (section 6.5)
- The essential trade-off in modeling for early detection is between superfluous degrees of freedom vs. accurate and statically sound modeling (section 6.5).
- Key design drivers are earliness (section 6.3.1) and observability (section 6.2.1). Short-term analysis has to be separated from impact analysis and diagnosis (section 6.3) and susceptibility must be optimized in terms of the amount of information rather than the amplitude of the disturbance (section 6.4).

The undetermined dimensions of the parameter-space and the gradual scale of complexity of the neural model comply with the requirements for modeling for early detection (section 8.1). We have illustrated the possibility to extract stable signatures from the neural weight space (section 8.2) and demonstrated a quantitative correspondence between signature response and profoundness of system changes (section 8.3).

There are some key observations in practical real-world cases which directly indicate the need for a monolithic data-driven modeling corresponding to a stochastical and holistic view on the system without relying explicitly on underlying physical and logical principles.
Conclusions

Chapter 9

Concluding Remarks

- Adaptive data-driven models of a batch-oriented production process are better capable of dealing with gradual, a priori unknown changes in a time-variant system than finite sets of model extension with condition-based model patching (section 5.2.1, figure 8.1).

- Software engineering research is persistent in attempts to provide quasi-formal methods for complete and consist modeling to facilitate software design. Nonetheless, despite the intended deterministic design on the highest level of detail (microscopic), novelty detection in network monitoring profits from a stochastical and macroscopic view on network traffic and machine logging data. (section 5.2.2)

- Views, models and measures from different disciplines are often incommensurable. Therefore it is impossible to arrive at a consistent and coherent system model from the applied physical and logical principles (section 5.2.3) in large multidisciplinary systems.

A categorical analysis had led from the observations in real-world cases to the synthesis of key requirements and trade-offs for early detection. This analysis significantly increases understanding of the limitations of the existing arsenal of detection approaches. Key insights are:

- The exactness and physical plausibility of the model are imperative in the design and control of the system, while detection of abnormalities has to be optimized for sensitivity to disturbances that are not explained by the design models, and that cannot be mitigated by control (section 5.3.4)

- The time-varying system is not invariant w.r.t. abnormality (section 6.1.1)

- The essential complication for a quantitative separation of abnormal from acceptable behavior is the unfamiliarity with abnormal behavior. Consequently the dimensions of the (parameter) space that efficiently describe behavior cannot be chosen optimally for the separation (section 6.2).

- In a classical approach the dimensions for modeling behavior are determined by assumptions on the system and abnormalities (figure 4.5). However abnormalities are an indication of the invalidity of the nominal model, and therefore the chosen dimensions spanning the parameter space are not optimal to distinguish acceptable variations from abnormal behavior. The parsimonious state-space as well as the dynamics expressible in such models limits the capacity for early detection of abnormalities (section 5.4).

- The granularity of classical modeling is preset, and the complexity of the system yields unavoidable simplifications of the process model. Therefore classical modeling cannot meet the requirements for early abnormality detection (section 6.5).

The treatment of exploding system complexity requires an approach, complementary to the existing detection arsenal, which reduced the complexity problem differently from the classical reductionistic simplifications. The key objectives and trade-offs for such a complementary approach for early abnormality detection demand a radically different course to deal with systems complexity: it must include a blind abstraction. Improved theory for design and system health management is essential to improve the managebility of the complex distributed systems that we have come to depend on. The results of this research offer a new perspective to start the development of such theories.