A Survey on Prediction Methodologies

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Abstract

This paper covers increasing need for next state prediction in the field of the avionics system that will predict and overcome the faults caused by the avionics systems. "Next State Prediction" is used for the predication of the possible states that the system can exist. This paper explains about how Markov models and hidden markov models can be used for the prediction of the state in which the system exist based on which it could be stated if it is in a safe state. In the current scenario it is not possible to have 100% test coverage for all the test cases. There will be instances where some of the portions that will not be covered by the test coverage and may lead to catastrophic faults. A very good process of verification and validation is carried out before the software is operational. However, all these are carried out before the software is commissioned on the target for its stipulated use. Further, the V&V is carried out in a simulated environment. It is very difficult to simulate the environment in to. There could be some environmental conditions which have not been simulated and which could trigger the software state to an unsafe condition. Hence we use this methodology so as to predict if the current state or any further states in which an aircraft could exist would be safer one , if not, necessary steps could be carried out so as to make it safer.

Keywords*:* Next state prediction, Markov Models, Hidden Markov models, Avionics systems

I. INTRODUCTION

We address in this paper the problem of predicting the state (fail or normal) for the landing gear system for an aircraft by using Hidden Markov Models. There is a vast literature on this topic, and many different systems have been suggested to solve this problem. The basic idea of this approach is to develop a model of the transition process with the different states as a hidden variable of this process, to apply statistical estimation theory to compute the future states, and to necessary operations to prevent the failure.

Objects have both behavior and state or, in other words, they do things and they know things. Some objects do and know more things, or at least more complicated things, than other objects. Some objects are incredibly complicated, so complex that developers can have difficulty understanding them. A state is an observable mode of behavior of the system. States are represented by the values of the attributes of an object. The state prediction is a process of understanding the transition of the possible states of a finite-state automaton and the allowable transitions between such states. There are several different dialects of State Transitions. Each one depicts the states, transitions, and event(s) that can cause each transition .State Transitions may also indicate conditions that control whether a legal transition is allowable, or actions that are undertaken either during a transition or on entry to a new state. Because a State Transition defines a finite-state automaton, the object being modelled may be only in one state at a time. State Transitions can be used to define the control structure of a software module, or to define the modes of operation of large systems. A Markov Chain is a statistical model of a system that moves sequentially from one state to another. The probabilities of transition from one state to another are dependent only on the current state (not on previous states).It is generally modelled as a stochastic process and can be described by a transition matrix. On the similar hands, a hidden Markov model (HMM) models a Markov process, but assumes that there is uncertainty in what state the system is in at any given time. A common metaphor is to think of the HMM as if the Markov Model were a mechanism hidden behind a curtain. The observer doesn't have any knowledge of how the mechanism is operating, and only knows what is going on behind the curtain from periodic reports that are emitted by the mechanism.

In the current scenario, where we are planning to use the next state prediction algorithm for the avionic system, it is not possible to have 100% test coverage for all the test cases. There will be instances where some of the portions that will not be covered by the test coverage and may lead to catastrophic faults. These faults could be identified using the proposed algorithm so as to understand the cause of the fault, henceforth predict the path in which the fault would have occurred and necessary steps could be taken in advance to predict the failure and prevent it. The main objective is to study the effect of the environmental conditions towards safety and suitable mitigation methods are planned Identify the functional modules Prediction of the next state so as to overcome the faults caused by the aircraft.

The first part gives an introduction to the basics of the process. The second section gives the existing prediction methodologies and their introduction. The third section gives the application of hidden markov models in different fields. The last section we will able to conclude the paper

II. EXISTING PREDICTION METHODOLOGIES

A *Markov chain* is a discrete-valued Markov process. *Discrete-valued* means that the state space of possible values of the Markov chain is finite or countable. A *Markov process* is basically a stochastic process in which the past history of the process is irrelevant if you know the current system state. In other words, all information about the past and present that would be useful in saying something about the future is contained in the present state.

There are three kinds of processes, namely discrete-time, continuous-time, decision Markov processes.

A *discrete-time Markov chain* is one in which the system evolves through discrete time steps. So changes to the system can only happen at one of those discrete time values. A *continuous-time Markov chain* is one in which changes to the system can happen at any time along a continuous interval.

A *Markov decision process* is just a Markov chain that includes an agent that makes decisions that affect the evolution of the system over time.

A significant amount of work has been published in the area of state prediction research. This section provides a basic prediction approaches in order to structure the manifold of approaches. In order to predict upcoming failures from measurements, the causing factors, which are faults, have to be made visible.

The prediction mechanism can be divided into four different categories:

- Failure Tracking
- Symptom Monitoring
- Detected Error Reporting
- Undetected Error Auditing

Failure Tracking, the basic idea of failure estimate based on failure tracing is to draw inferences about upcoming failures from an event of preceding failures.

System Monitoring, the motivation for evaluating sporadically measured system variables such as the amount of available memory in order to recognise an impending failure is the fact that some types of errors affect the system even before they are detected

Detected Error Reporting, when an error is detected, the detection event is usually recounted using some logging facility. Hence, failure prediction approaches that use error reports as input data have to deal with event-driven input data. This is one of the major differences to symptom monitoring-based approaches, which in most cases operate on periodic system observations [13].

Bayesian Predictor. The key idea of Bayesian prediction is to estimate the probability distribution of the next time to failure from the knowledge obtained from previous failure occurrences in a Bayesian framework. One such application used is the Jelinsky-Moranda model, where Bayesian predictive approach is used and applied in order to produce enhanced estimation of the next time to failure distribution.

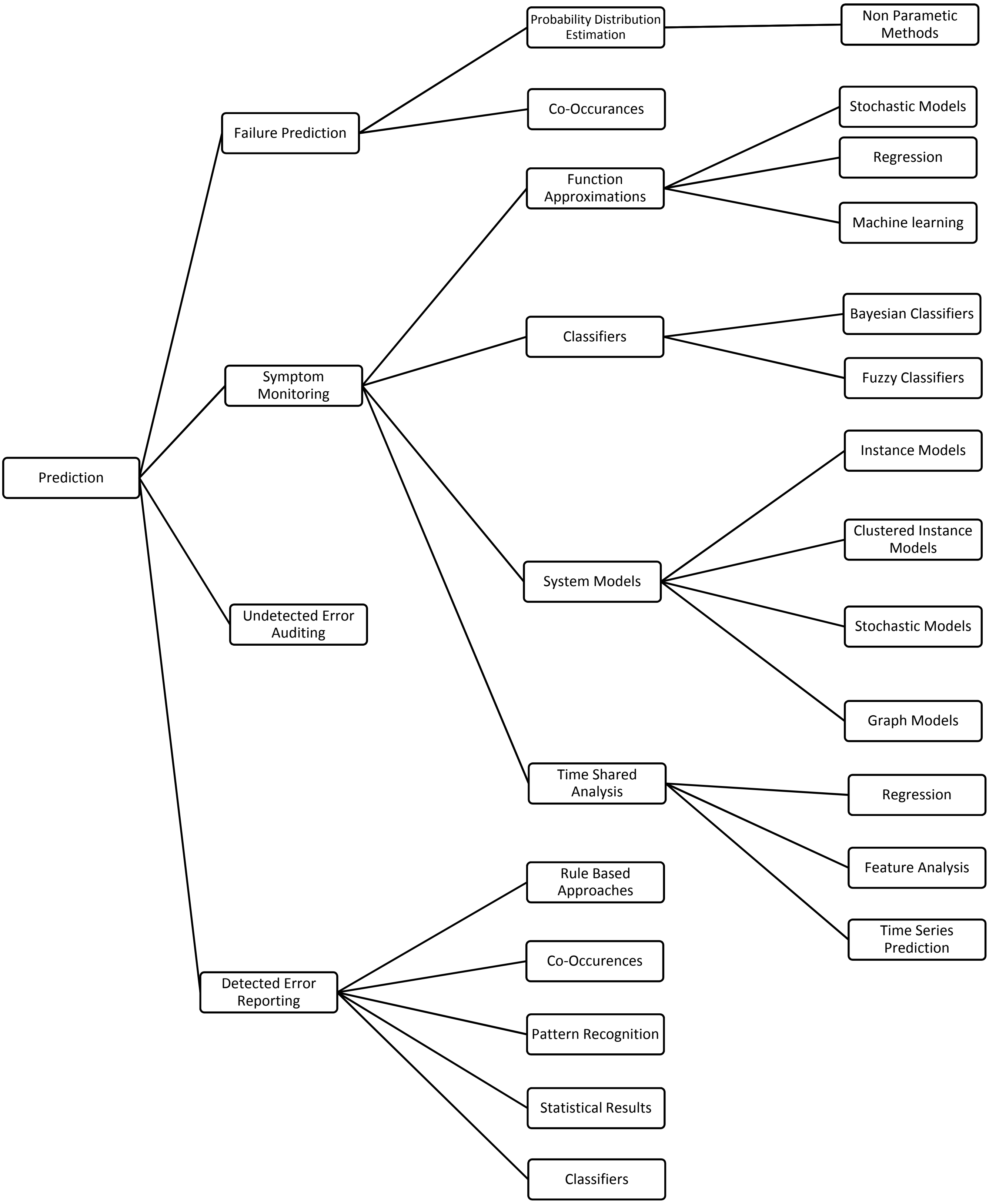

Figure 1 shows a broad classification of all the above mentioned categories

Non-parametric Methods. It has been experimentally proven that the failure is non-stationary and hence the probability distribution of mean time-between failures (TBF) fluctuates. Reasons for this are diverse, since the fixing of errors, changes in conformation or even varying utilization patterns can affect the failure process. In such cases, methods such as histograms will result in poor estimations. In such cases, the Pfefferman and Cernuschi-Frias [2002] non parametric method assumes the failure process to be a Bernoulli-experiment where a failure of type *k* occurs at time *n* with probability *pk* (*n*) [13].

Using this assumption the probability distribution of TBF for failure type *k* is predicted geometric since only the*n*-th outcome is a failure of type *k* and hence the probability is:

$P\ r\ \{T\ BFk\ (n) = m \mid \text{failure of type } k \text{ at } n\} = pk\ (n)\ 1 - pk\ (n)^{m-1}$[16]

III. APPLICATIONS IN DIFFERENT FIELDS USING THE MARKOV MODELS AND HIDDEN MARKOV MODELS

"Increasing effectiveness of model-based fault diagnosis:A dynamic Bayesian network design for decision making" [1] by Philippe weber, Didier Theilliol, Christophe Aubrun and Alexandre Evsuk off ,this paper targets to design a new approach in order to increase the performance of the decision making in model-based fault diagnosis when signature vectors of various faults are identical or closed. The proposed approach in the paper consists on taking into account the knowledge issued from the performed reliability analysis and the model-based fault diagnosis. The decision making which is formalised as a Bayesian network is established with a priori understanding on the dynamic component degradation (DCD) through Markov chains. The effectiveness and performances of the technique are illustrated on a heating water process corrupted by faults.

A large diversity of advanced methods for the automated fault detection and isolation (FDI) exists on the basis of fault diagnostic principle. Faults in systems are diagnosed using the *analytical redundancy* while taking into account the measured and estimated outputs of the system. The diagnosis procedure consists of three stages: residuals generation, residuals evaluation and finally decision making.

To illustrate the approach, they propose to consider a simulation example: a heating water process. This proposed approach was designed with the help of the software Bayesia Lab. The process comprises of a tank equipped with two heating resistors R1 and R2. The inputs are the water flow rate, Qi, the water temperature Ti and the heater electric power P. The outputs are the water flow rate Qo and the temperature T which was regulated around an operating point. The temperature of the water Ti was assumed to be constant. The objective of the thermal process was to assure that there was a constant water flow rate with a given temperature. In this analysis only sensor and components failures were considered: level sensor H, output temperature sensor T and output flow rate sensor Qo. In order to illustrate the performance and the limitation of the proposed method, various faults scenario has been considered.

The paper also points out the limitations of this approach, stating that the design of the Dynamic Bayesian Network (DBN) requires the miss-detection probabilities of the residual evaluation methods which are not always possible to measure. However, the results, obtained in this paper, allows to advocate the method in order to optimize the maintenance actions. Hence, for a system which is liable to various faults simultaneously or which is defined through an incidence matrix with similar fault signatures, the fault probabilities, provided by this method, will enable to plan the maintenance actions.

"Classification Method for Faults Diagnosis in Reluctance Motors Using Hidden Markov Models" [2]by Bouchareb Ilhem, Bentounsi Amar, this paper presents Switched Reluctance Machine (SRM) as an ideal machine for safety critical applications due to its fault-tolerance characteristics. It is stated that the fault diagnostic in the SRM in the critical applications is a very difficult and overwhelming task. This paper focuses on the development, and application of Hidden Markov Model (HMM), which is amodern statistical classifier method, associated with a smoothed uncertainty plane Time-Frequency Representation (RTF) for the diagnosis based classification of electrical faults in the particular machine.

The RTF-HMM Technique consists of two steps: the Feature Extraction step and the classification step. The feature Extraction step is based on the smoothed ambiguity plane designed for maximizing the separation between the classes using the Fisher's discriminant ratio and Hidden Markov Model algorithm is applied for the classification step. Classifier development and training data is carried out by the HMM using a set of fault scenarios, which are healthy, single and combined faults, in terms of torque at different load level in order to realise the fault severity

The paper is concluded by showing how the evolution of process towards any type of fault can be predicted. The paper is concluded by showing how the evolution of process towards any type of fault can be predicted. He states that the HMM based classifier for a more complicated problem would allow to obtain better classification results without taking into consideration the type of machine or type of fault. Finally this technique will allow understanding of a preventive maintenance ensuring the safety of the material and the personnel.

"Prediction Of Financial Time Series With Hidden Markov Models" [9]by Yingjian Zhang,In this thesis, the author has develop an extension of the Hidden Markov Model (HMM) that has addressed two of the most important challenges of financial time series modelling: *non-stationary* and *non-linearity*. He extends the HMM to include a novel exponentially weighted Expectation-Maximization (EM) algorithm to handle the two above mentioned challenges. He shows that this extension will allow the HMM algorithm to not only model the sequence data but also dynamic financial time series. He also shows that the updated rules for the HMM parameters can be written in a form of exponential moving averages of the model variables so that the advantage of existing technical analysis techniques can be used. He further proposes a double weighted EM algorithm that is able to adjust training sensitivity automatically.

In the thesis he introduces the basics of Financial Time Series and also points out the traditional techniques and their limitations. He then gives a briefs introduction about the Markov models and Hidden Markov Models. He puts forward the Baum-Welch Re-estimation for Gaussian mixtures in the Hidden Markov Models. He gives the Weighted EM Algorithm for Gaussian Mixtures using the Hidden Markov Models.

He concludes by stating that his experiments can be sorted into three categories: testing of HMGM with the different training window sizes; testing of the weighted EM algorithm in comparison with the existing classic EM algorithm; and the use of supporting time series to help predict the targeting series. He introduce an important concept in the model design which is the, training window.

The future work as mentioned by the author is that rather than the predefined 20-day training window, the size of the training pool and training window can be decided by a hill climbing or dynamic programming approach. Identifying useful side information for prediction, such as the evolving of new indicators will help in the making of better predictions. Then the prediction can be extended to a form of density function rather than simply values. This way can the output will have richer information about the market movements.

IV. CHALLENGES

There are three basic challenges associated with the Hidden Markov Model.

- These are the evaluation Problem, the decoding problem and the learning problem.
- The calculation involved in the evaluation problem involves a number of operations which are in the order of n^T. In case of the decoding problem his method does not give a physically meaningful state sequence.
- Generally, the learning problem is how to adjust the HMM parameters, so that the given set of observations (called the *training set*) is represented by the model in the best way for the intended application.

V. CONCLUSION

This paper gives the detail study of different survey methodologies existing system. It mentions the work done in the different methodologies and gives the advantages and disadvantages for each of these methodologies. We are rapidly moving to a situation in which computers are being embedded. The result is that serious consequences of failure arise not only for all the traditional safety-critical application but also for entirely new application domains. Avionics is also a part of the safety critical system and failures in these systems can cause catastrophes. This survey paper gives a study of models and techniques that have used for the prediction faults using the Markov and Hidden Markov Models. This paper also mentions advantages and disadvantages of each paper.

It also gives a comparison study of the various other methodologies and their drawbacks

In the future work, these models can be used for the prediction of the failure in the aircrafts and be able to predict the failure of the aircrafts well in advance and necessary precautions can be taken to prevent it from happening taking case study as Avionics.

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