AN AUTOMATED GOAL SEEKING APPROACH TO MACHINERY PROGNOSTICS AND LIFE EXTENSION

Kenneth Blemel and Carl Stern
Management Sciences, Inc.
Albuquerque, New Mexico, USA
ken_blemel@mgtsciences.com
carl_stern@mgtsciences.com
Eric C. Hansen
Autonomous Maritime Navigation
Combatant Craft Department
Naval Surface Warfare Center Carderock Division
hansenec@nswccd.navy.mil

Abstract:
In this paper we discuss ongoing work in development of an intelligent platform for automated health management and machinery life extension. This work exploits the rich opportunities that are arising from the integration of a new generation of onboard intelligent technologies. These technologies include smart monitoring, prognostic modeling, and intelligent control. We describe two new technologies that our research group is bringing to onboard health management: *teleo-adaptive control* provides adaptive goal-seeking behavior that optimizes mission performance while minimizing stress and mitigating risk. *Dynamic Bayesian models* provide continuous online estimates for equipment condition, performance and stress levels, and evolving fault trajectories. We show how these two technologies can be fruitfully integrated into a single proactive framework called *Teleo Health Management* (THM). THM is a total systems approach to machinery health management and life extension, providing a range of functionality beginning at the level of conventional CBM and extending to machinery life extension through *in situ* stress reduction and risk mitigation.

Keywords: Goal-seeking; health management; intelligent; prognostics; stress reduction

Introduction:
We discuss ongoing work in development of an intelligent platform for automated health management and machinery life extension. This work exploits the rich opportunities arising from the integration of a new generation of onboard intelligent technologies. These technologies include smart monitoring, prognostic modeling, and intelligent control. We describe two new technologies that our research group is bringing to onboard health management: *Teleo-adaptive control* provides adaptive goal-seeking behavior that optimizes mission performance while minimizing stress to equipment and mitigating risk to successful mission execution. *Dynamic Bayesian models* provide continuous online estimates for equipment condition, performance and stress levels, and evolving fault

trajectories. We show how these two technologies can be fruitfully integrated into a single proactive framework called *Teleo Health Management* (THM). The integration of these two technologies into a single platform for automated health management and machinery life extension has resulted in some very important synergies that will be described here.

We believe that systems for automated self-maintenance and life extension represent the future state of the art in health management, a proper successor to CBM and PHM approaches. We describe our own first cut at such a system, the *Teleo Health Management* (THM) framework. THM is based on a total systems approach to machinery health management and life extension including ground-based maintenance operations, onboard self-maintenance operations, and *in situ* stress and risk reduction. We have identified four levels of potential THM functionality:

Level 1. Condition-based management of the schedule and scope of human maintenance operations;
Level 2. Onboard condition-based management of autonomous self-maintenance operations;
Level 3. Onboard real time control for machinery stress reduction and life extension;
Level 4. Onboard prognostic operations management for machinery life extension.

Current and emerging CBM/PHM technologies for health monitoring and prognostic health management provide support for **Level 1** functionality. Current CBM approaches can be further enhanced by exploiting intelligent technologies for onboard monitoring and situation awareness. Monitoring of indicator parameters (e.g., vibration) and performance parameters (e.g., engine efficiency) can be correlated with situation components such as operational state, stress level, and environmental conditions (temperature, air currents, turbulence), leading to more accurate systems for state-aware health monitoring.

Our research interest in capabilities at **Levels 2 – 4** is partly motivated by the requirements of health management for the current and emerging generations of unmanned vehicles, particularly vehicles that are required to operate without human maintenance for extended periods of time. In the case of unmanned boats, for example, these requirements might include the need for self-maintenance functions such as autonomous oil filter replacement, cleaning of water filters, oil processing, etc. This form of self-maintenance clearly benefits both in efficiency and effectiveness from an autonomous CBM-style condition-based approach.

A natural next step for a system capable of state-aware monitoring, a system capable of detecting, for example, that oil temperature or engine rotation speed is rising rapidly and will soon exceed the limits of normal non-destructive operation, is to anticipate and prevent damage or accelerated wearout before it occurs. This has motivated our interest in **Level 3** technology, technology for intelligent reactive control that is capable of reducing the destructive effects of equipment stress while robustly pursuing mission goals, strategies, and requirements. We describe in the next section a technology that is capable of performing this simultaneous management of performance goals and stress reduction goals, a technology for adaptive task-execution called *teleo-adaptive control*.

Teleo-adaptive control provides rapid reactive stress management based on short time horizons. If prognostic models are also available that allow estimation of remaining useful life relative to projected equipment utilization and stress levels, a **Level 4** approach becomes feasible. A **Level 4** approach involves performance and stress management over longer time horizons. It uses a planning and scheduling algorithm to find a performance schedule that optimizes expected utility with respect to mission goals while managing the risk of potential equipment failure. A schedule that optimizes expected utility in this case is one that handles the equipment's expected remaining useful life as a resource to be allocated amongst mission goals so as to minimize the risk of premature equipment failure. Implementing a **Level 4** long term stress management approach that is effective and that is capable of rapidly adapting to changes in equipment state, environment, or mission goals, presents a set of interesting and formidable challenges falling outside the scope of the current paper.

We turn now to a description of the key enabling technologies of the *Teleo Health Management* framework.

Teleo-adaptive Control:

Teleo-adaptive control is based on the *Teleo-Reactive Control framework* originally developed by Nils Nilsson and his students in the Stanford robotics lab [1]. The term *teleo-reactive* comes from the Greek work *telos* meaning goal. Teleo-Reactive programs are reactive goal-seeking programs that implement linear plans or plans with conditional branching by iteratively sequencing the actions in those plans on a moment to moment basis in accordance with current state of environment and the current state of success in achieving the plan's subgoals. The Teleo-Reactive Control framework is designed to provide robust goal-pursuit in a dynamic partially unpredictable environment where the ability of actions to achieve their goals within a specified window of time is itself uncertain. Teleo-Reactive Control is intended to be used as a middle level of executive control between an agent's top level planning and scheduling layer and its bottom level of primitive behaviors implemented in hardware or with conventional fast closed loop control.

More formally, a teleo-reactive control program consists of a sequence of condition-action pairs:

$$
\begin{aligned}
&C_o \rightarrow \alpha_0 \\
&C_1 \rightarrow \alpha_1 \\
&\ldots \\
&C_n \rightarrow \alpha_n
\end{aligned}
$$

At each cycle, the action associated with the highest true condition executes. C_o corresponds to top level goal and α_0 is typically the null action (i.e., do nothing when the highest level goal is achieved). Actions are expected to (eventually) make some condition higher in the tree true. Under this assumption, it is mathematically provable that a TR program will achieve its top level goal.

Insofar as a teleo-reactive program typically contains alternative paths to the same goal, it is also called a *Teleo-Reactive Tree*. In the TR tree in **Figure 1**, the circles, labeled C_i, represent conditions or states and the arrow labels α_i represent actions. When the program starts, execution typically begins near the bottom of the tree, selecting branches based on whether a condition on the left or right is true. As progress is made, execution tends to move up the tree, although some unexpected event may undo this progress and push execution back down the tree. In the case of such an unexpected event, the program will relentlessly re-execute the lower level actions that push performance back up the tree. At the same time, if the environment is already in a favorable state, the program will start opportunistically from a higher level of the tree and skip all the unnecessary actions at the lower levels.

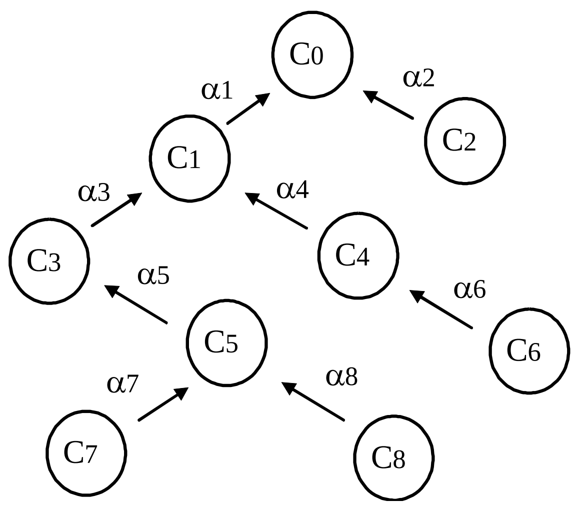

Figure 1. A typical Teleo-Reactive Tree with conditional branching.

Stern, Klein, and others [2, 3] have extended and enhanced Nilsson's original *Teleo-Reactive Control* framework in a number of ways. While Nilsson's original formalism clearly supports symbolic condition variables (as opposed to numeric values from sensor data) in a TR program, our implementation includes a managed framework for *condition monitors*, small real-time classification programs that implement decision rules for determining whether a symbolic condition is true.

While Nilsson's original formalism also supports hierarchically structured TR Programs, programs in which an entire TR program is treated as a primitive action of a higher level TR program, we have developed a formal approach for aggregating simple behaviors into larger more complex or sophisticated behaviors. This approach is based on the idea that a teleo-reactive program is intended to organize and sequence behaviors rather than simple actions. The intelligent organization of behaviors means that behaviors become active or dormant based on the prioritized challenges or opportunities presented by a situation. For example, the set of behaviors for collision avoidance becomes the dominant behavior in a situation where a collision is imminent whereas vigorous waypoint navigation or other behaviors dominate when no collision threats are imminent.

The most important and critical extensions to the TR framework that we have developed address the need to anticipate emerging situations and to react in a timely fashion, taking into account the intrinsic time delays in many types of control actions. For example, in navigation control, it is often the case that collision avoidance behavior must be initiated well ahead of time based on the anticipation of a collision. This presents a significant challenge for developers of teleo-reactive programs in that a critical element for the success of these programs will be the ability to define effective trigger conditions for transitioning between behaviors, i.e., for transitioning into collision avoidance behavior far enough in advance. Our solution has been to develop an algorithm for deriving effective behavior transition triggers using prognostic Bayesian models that model condition and state trajectories. Using these models, together with Monte Carlo and other simulation frameworks, we have implemented a method for automatically generating effective behavior transition triggers in the form of the condition monitoring programs and decision rules described above.

We now turn to a brief description of our work in prognostic Bayesian modeling.

Prognostics with Dynamic Bayesian Models:
A key enabling technology for our work in prognostic modeling is a new probabilistic modeling framework called *Loopy Logic* originally invented at the University of New Mexico (UNM) [4] and later refined and extended in joint work with Management Sciences (MSI). *Loopy Logic* extends the first order probabilistic logic, characterized by Kersting and de Raedt, [5] with recursion, allowing it to represent recursive time series models such as Hidden Markov Models (HMMs) and Dynamic Bayesian Networks (DBNs). The *Loopy Logic* framework combines this recursive probabilistic logic with an approximate inference algorithm called *Loopy Belief Propagation* (LBP) [6].

The Loopy Belief Propagation algorithm (also called Iterative Belief Propagation) for inference and learning constitute a significant step towards real-time performance of probabilistic models in computationally resource-limited environments. The UNM/MSI implementation of probabilistic learning, based on Loopy Expectation Maximization, has provided the ability to train probabilistic models to recognize dynamic behavioral signatures rapidly enough so that the trained model can be immediately used in the same situation for object re-identification and/or object classification. It has allowed MSI to build applications that interleave inference and learning, so that a rough initial model can be quickly induced and then continuously refined for ongoing improvement in pattern recognition and classification accuracy.

We have used the framework of Loopy Logic to experiment with a large range of probabilistic models. Hidden Markov Models are already widely used in domains such as speech recognition, protein sequence analysis, etc., providing linear time pattern recogni-

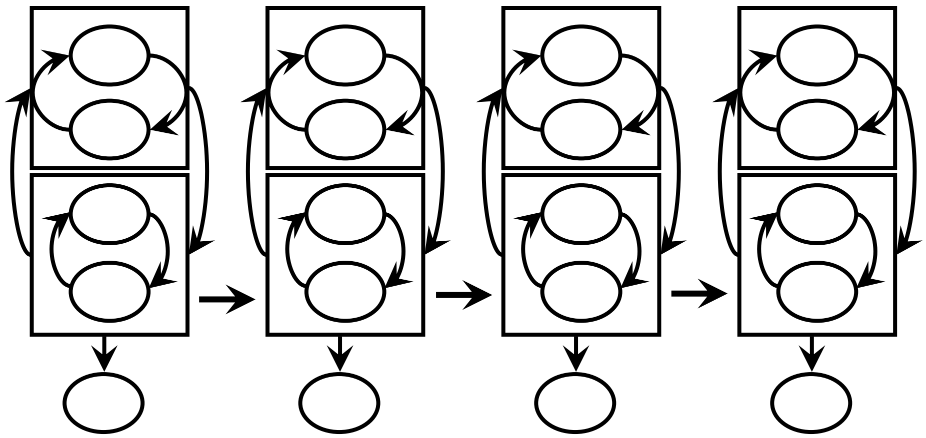

Figure 2. A Loopy Dynamic Bayesian Model

tion. However the simple state representation of HMMs sometimes precludes their application to complex pattern recognition and prediction problems, particularly problems requiring multi-scale pattern recognition and prediction. For this reason we have exploited the recursive representation of Loopy Logic to implement a number of other model types, including Hierarchical Hidden Markov Models, Segmented Semi-Markov Models, and Loopy Dynamic Bayesian Networks. These models give us the capability of analyzing complex patterns with multiple levels of granularity and multiple time-scales (Figure 2). We are able to employ these more powerful and sophisticated probabilistic models without losing near real-time performance because of the linear time scaling of the LBP algorithm for many problems of interest. We have found that Hierarchical Hidden Markov Models, in particular, have worked particularly well in pattern recognition and analysis of vibration data coming from misaligned or cracked rotors, because of the presence of elements in these vibration patterns occurring at two different time scales.

Example Applications:

In a Department of Defense project we are developing use of THM for monitoring and diagnostics during mission execution with rules for goal based self-maintenance. Dynamic Bayesian models are used to anticipate emerging fault conditions and extend survival of propulsion systems and fighting capability. In flight THM will perform stress limiting and self-maintenance control functions. Stress limiting functions include anticipatory vibration damping and pre-emptive thermal control to avoid thermal stress. Self-maintenance functions include engine lubrication analysis, thermal control, and multi-engine vibration management. Self preservation functions include control of thrust and RPM limits to avoid consequential damage. We are preparing for engine test cell demonstrations that will demonstrate THM that anticipates, prepares, reacts, and adapts to accomplish mission objectives while maintaining the sustained health of the engine propulsion system.

In another example, we are developing an extended form of THM that deals with machinery failure prevention for the propulsion systems of unmanned military boats.

Teleo-reactive programs produce significant behavior transitions depending on the context of surveillance, training and warfighting. Learning how to cope with debris is common to all and knowing health status to work the edges of the envelope of performance is important to survival. Requirements for completing the mission and preventing failures often conflict, and priorities change as the battle progresses. Much knowledge engineering work remains to be done to address the complexity of these battlefield situations.

Summary:

We have discussed ongoing work in development of an intelligent platform for automated health management and machinery life extension. This work exploits the rich opportunities that are arising from the integration of a new generation of onboard intelligent technologies. We describe two new technologies that our research group is bringing to onboard health management: *teleo-adaptive control* provides adaptive goal-seeking behavior that optimizes mission performance while minimizing stress and mitigating risk. *Dynamic Bayesian models* provide continuous online estimates for equipment condition, performance and stress levels, and evolving fault trajectories. We show how these two technologies can be fruitfully integrated into a single proactive framework called *Teleo Health Management* (THM). THM is a total systems approach to machinery health management and life extension, providing a range of functionality beginning at the level of conventional CBM and extending to machinery life extension through *in situ* stress reduction and risk mitigation.

References:

[1] Nilsson, N.J., Teleo-Reactive Programs for Agent Control. Journal of Artificial Intelligence Research, 1, 1994, 139-158.

[2] Stern, C., Olsson, E., Kroupa, M., Westervelt, R., Luger, G., Klein, W. A Control System for Accelerator Tuning Combining Adaptive Plan Execution with Online Learning, Proceedings of ICALEPCS'97, 1997.

[3] Klein, W., Stern, C., Luger, G., Olsson, E.. An Intelligent Control Architecture for Accelerator Beamline Tuning, Proceedings of IAAI 97, 1997.

[4] Pless, Dan and Luger, George F. "Toward General Analysis of Recursive Probability Models", Published in the *Proceedings of the Uncertainty in Artificial Intelligence Conference-2001*, San Francisco: Morgan Kaufmann, 2001.

[5] Kersting, K., De Raedt, Luc, “Bayesian Logic Programs”, Proceedings of the Work-in-Progress Track at the 10th *International Conference on Inductive Logic Programming*, 2000.

[6] Murphy, K., Weiss, Y., and Jordan, M., Loopy Belief Propagation for Approximate Inference: An Empirical Study, *Proceedings of Uncertainty in AI*, 1999.