Control Design for Diagnostic and Prognostic of Hardware Systems[1]

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***Abstract*—In this paper we present the modeling and control system's design of a laser pointing system. The aim of the paper is to provide means of detecting the relative errors of the system to correct them using actuating signals both directly and indirectly. The proposed control system will be used as part of a diagnostic and prognostic analysis for both systems. The paper includes the mathematical model of the two systems and Matlab simulations of the designed controller as well as its response to different stimulus. Diagnostic and prognostic approaches for actuator faults will be presented.**

I. Introduction

Hardware systems have been addressed for as long as classical and modern control theories have been around. However some systems involving electronic positioning of laser system would require unusually high precision and care needs to be taken when designing them. The problem is not as critical for electro-mechanical systems, one of which is the chiller subsystem of an air conditioning system. The required precision that a laser can provide has its advantage from the utility point of view but it also has its disadvantage from the control, diagnostic and prognostic points of view: the control system will need to be as accurate as the laser beam is and, since the object of the pointing system is light, which means no delay in getting to the objective; our control system must also be fast. This reduces our chances of finding a simple tradeoff choice among speed, precision and simplicity, which makes this work a real challenge.

For the laser pointing system, two potential setups and control system designs are presented and its speed and precision characteristics analyzed by means of computer simulations. A mathematical model of the physical setup is also developed and presented as fundamentals for the computer simulations. The system considered in this paper is the design of a fuzzy controller and a prognostic and diagnostic system for a laser pointing system [1], which is an ongoing experimental effort at the ACE Center.

II. Laser Pointing System

The two different physical setups of the laser pointing system are presented and developed as shown in Fig. 1 and 2. Although the first setup is direct and the second one is indirect (by means of a reflective surface), both are strongly related. It is important to note that one of the advantages of the proposed system is the independence of the control problem with respect to the X and Y coordinates. These two control systems constitute 2 decoupled subsystems. Since each motor is independent, and the position errors in the X and Y directions are also independent, the system can be modeled by a simple one-dimensional position-tracking problem as is explained below.

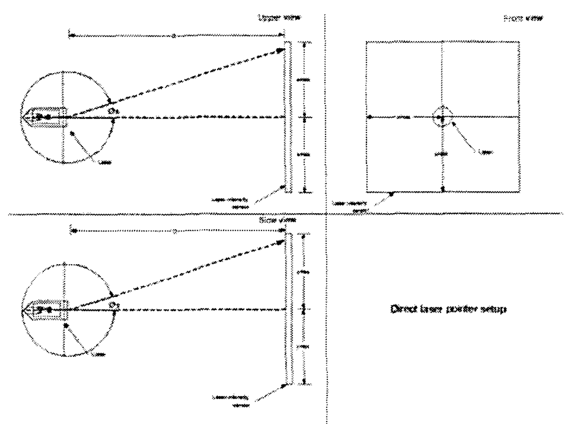

Fig. 1. Direct laser positioning system

Direct Laser Pointing System The first setup proposed is a direct laser pointing system where the mobile part is the laser beam. The angular positions of the laser beam in the X and Y planes are governed by two DC motors as actuators. Based on the separability of the problem in the X and Y directions, it is clear that the angular position of each motor has a simple relationship with the linear position of the beam

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in the X and Y directions. This relationship is described by (1) and (2). We are assuming that the distance from the origin of the laser beam to the object is known as D.

$$x = D\tan(\phi_x). \quad (1)$$

$$y = D\tan(\phi_y). \quad (2)$$

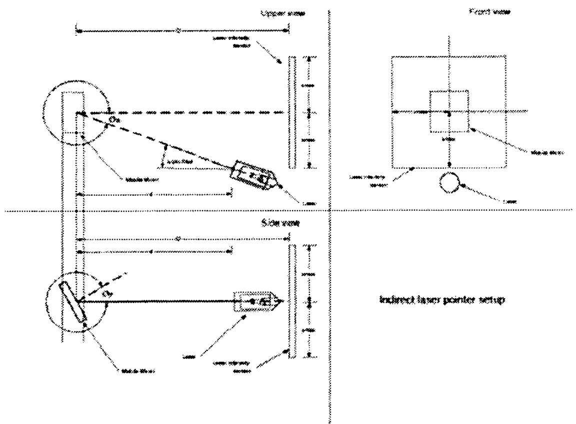


Fig. 2. Indirect laser positioning system

Indirect Laser Pointing System The second physical setup proposed is an indirect laser pointing system where the mobile part is a reflective surface, which will be used to reflect the laser beam into a detector. The reflective surface or mirror will have 2 degrees of freedom, allowing it to rotate in its X and Y directions. Again, the relationship between the angular position of the mirror (which is governed by two DC motors, as actuators, in the case of the laser in the direct laser pointing system) and the linear position of the beam in the X and Y directions on the sensor is trivial and is described by (3) and (4). We are assuming the relative distances among the laser, reflective mirror and sensor are known.

$$x = D\tan(\frac{\pi}{2} + \phi_x + \alpha). \quad (3)$$

$$y = D\tan(\phi_y). \quad (4)$$

III. DC Motor Position Model

This system uses a DC motor as an actuator. As it was already stated, the control system is separable in the sense that independent motors will have control over the X and Y coordinates, respectively. Thus, the model of a DC motor [3] can be used to model both X and Y linear movements based on the angular position of the motor, whose relationship is expressed by (1) through (4). The electric circuit of the armature and the free body diagram of the rotor are shown in Fig. 3.

The constant parameters required for this model are (assuming the motor and shaft to be rigid):

1) Moment of inertia of the rotor (J)
2) Damping ratio of the mechanical system (b)
3) Electromotive force constant ($K = K_e = K_t$)
4) Electric resistance (R)
5) Electric inductance (L)
6) Input voltage (V)
7) Angular position (ϕ)

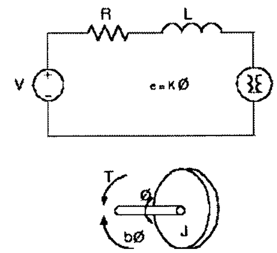


Fig. 3. Schematics of the armature circuit and free body of the shaft and load of the DC motor

The motor torque, T, is related to the armature current, i, by a constant factor K_t in (5). The back electromotive force (emf), e, is related to the angular velocity $\omega = d\phi/dt$ by (6):

$$T = K_t i. \quad (5)$$

$$e = K_e\ddot{\phi}. \quad (6)$$

Solving for the circuit of the armature, Kirchhoff's law and the free body diagram, Newton's law we obtain (7), (8):

$$J\ddot{\phi} + b\phi = Ki. \quad (7)$$

$$L\frac{\partial i}{\partial t} + RI = V - K\dot{\phi}. \quad (8)$$

Taking as state variables the angular velocity $\omega = d\phi/dt$ and the current i the following state representation of the system is derived in (9):

$$\begin{bmatrix} \ddot{\phi} \\ \partial i \end{bmatrix} = \begin{bmatrix} -\frac{b}{J} & \frac{K}{J} \\ -\frac{K}{L} & -\frac{R}{L} \end{bmatrix} \begin{bmatrix} \phi \\ i \end{bmatrix} + \begin{bmatrix} 0 & \frac{1}{L} \end{bmatrix}^T V. \quad (9)$$

The output of interest is the linear position y and x on the sensor ((1) through (4)). The relationship between the output and the angular position is not linear, therefore we need to linearize it around the equilibrium point $\phi = 0$ before incorporating it into our state space representation.

For the direct laser pointing system the linearized relationship will be:

$$\dot{y} = D\sec^2(\phi_y)\partial\phi_y\Big|_{\phi_y=0^\circ} = D\dot{\phi}_y \quad (10)$$

$$\dot{x} = D\sec^2(\phi_x)\partial\phi_x\Big|_{\phi_x=0^\circ} = D\dot{\phi}_x \quad (11)$$

For the indirect laser pointing system case:

$$\dot{y} = D\sec^2(\phi_y)\partial\phi_y\Big|_{\phi_x=0^\circ} = D\dot{\phi}_y \quad (12)$$

$$\dot{x} = D\sec^2(\frac{\pi}{2} + \phi_x + \alpha)\partial\phi_x\Big|_{\phi_x=0^\circ} = D\psi\dot{\phi}_x \quad (13)$$

where $\psi = sec^2\ \alpha$, which is a constant. The final state space representation for the direct case will be:

$$\begin{bmatrix} \dot{y} \\ \ddot{\phi}_y \\ \delta i \end{bmatrix} = \begin{bmatrix} 0 & D & 0 \\ 0 & -\frac{b}{J} & \frac{K}{J} \\ 0 & -\frac{K}{L} & -\frac{R}{L} \end{bmatrix} \begin{bmatrix} y \\ \dot{\phi}_y \\ i \end{bmatrix} + \begin{bmatrix} 0 & 0 & \frac{1}{L} \end{bmatrix}^T V. \quad (14)$$

$$y = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} y \\ \dot{\phi}_y \\ i \end{bmatrix}. \quad (15)$$

Consider that in the case of the direct setup, where the variables x, y and Φ_x, Φ_y are interchangeable. The final state space representation for the indirect case will be exactly the same in the case of the Φ_y coordinate, but in the case of the Φ_x coordinate the resulting system has the form:

$$\begin{bmatrix} \dot{x} \\ \ddot{\phi}_x \\ \delta i \end{bmatrix} = \begin{bmatrix} 0 & D\psi & 0 \\ 0 & -\frac{b}{J} & \frac{K}{J} \\ 0 & -\frac{K}{L} & -\frac{R}{L} \end{bmatrix} \begin{bmatrix} x \\ \dot{\phi}_x \\ i \end{bmatrix} + \begin{bmatrix} 0 & 0 & \frac{1}{L} \end{bmatrix}^T V. \quad (16)$$

$$x = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} x \\ \dot{\phi}_x \\ i \end{bmatrix}. \quad (17)$$

From (14) through (17) it is clear that the precision of the control system will be directly affected by the distance D. Since as D increases, the precision to control the angular position of the motor must also increase. In the case of the indirect system, this also depends on ψ.

IV. Software Verification

Two approaches have been simulated for the control of the system described in previous sections, a PID controller and a fuzzy logic controller (FLC). Note that the simulations we present now are based on theoretical DC motor parameters and that a final evaluation must be done after the real motor parameters are estimated. Although the parameters used are not final, the conclusions and comparisons between both approaches are valid.

A. PID control simulation

A PID control for the system described was simulated using Matlab. K_i (=4), K_d (=1) and K_p (=2.5) were found by educated guesses and a trial and error process. The system's impulse response is shown Fig. 4.

Settle time can be improved at cost of a bigger overshoot. Depending on the application of the system a trade off decision will be a must.

B. Fuzzy logic approach

A fuzzy controller was simulated using membership functions, two inputs: position error and position error variation; and one output: voltage variation. The composed rules implemented for the fuzzy control were [4]:

- IF Speed Error is zero AND Speed Error Variation is negative THEN Voltage Variation is positive.
- IF Speed Error is zero AND Speed Error Variation is null THEN Voltage Variation is zero.
- IF Speed Error is zero AND Speed Error Variation is positive THEN Voltage Variation is negative.
- IF Speed Error is negative AND Speed Error Variation is negative THEN Voltage Variation is positive.
- IF Speed Error is negative AND Speed Error Variation is null THEN Voltage Variation is zero.
- IF Speed Error is negative AND Speed Error Variation is positive THEN Voltage Variation is negative.
- IF Speed Error is positive AND Speed Error Variation is negative THEN Voltage Variation is positive.
- IF Speed Error is positive AND Speed Error Variation is null THEN Voltage Variation is negative.
- IF Speed Error is positive AND Speed Error Variation is positive THEN Voltage Variation is positive.

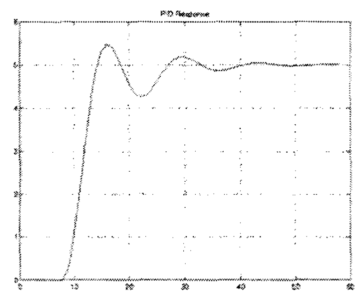


Fig. 4. PID control

A faster settling time and smaller overshoot was obtained as shown below. Although the controller was not tested or simulated on a different system, expected to be robust to handle variations of the laser pointing systems (i.e. the different setups presented in this paper). Fig. 5 shows the laser spot pointer y using a FLC.

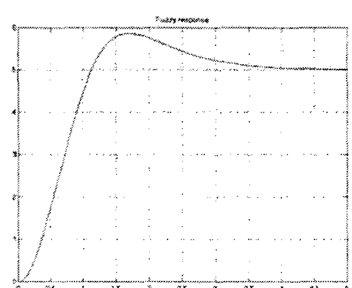


Fig. 5. Fuzzy control

V. PROGNOSTIC AND DIAGNOSTIC SYSTEMS

Traditional Fault detection systems have a reactive characteristic, which almost surely implies high cost in terms of time and money when a fault occurs. On the other hand, prognostic and diagnostic systems provide a way to detect in advance a future fault which allows taking preventive actions to avoid the fault. In other words, diagnosis implies to find an explanation for a set of observations and prognosis implies to forecast the course of events. The challenges that diagnostic and prognostic systems face are the ability to a changing environment which must allow the distinction between normal wear or desired system changes and the reportable system deviation [5].

A. *Intelligent Model-Based Diagnostic and Prognostic*

A system oriented approach for prognostic requires the failure detection and inspection based methods to be augmented with forecasting of parts degradation, mission critically and decision support. Such prognostics must deal not only with the condition of individual components, but also the impact of this condition on the mission-readiness and the ability to take appropriate actions.

A proposed intelligent diagnostic and prognostic process is proposed with six major blocks: model, sense, develop and update test procedure, infer, adaptive learning and predict. A graphical view is shown in Fig. 6 [6].

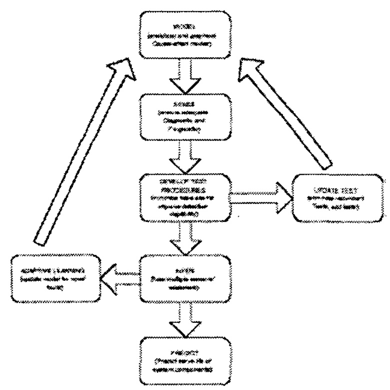


Fig. 6. An intelligent Prognostic System Architecture

- Model: In this step, models to understand fault to error characteristics of system components are developed. This is achieved by a hybrid modeling technique, which combines quantitative models (simulation models) and graphical cause-effect models in the failure space, through an understanding of failure modes and their effects.
- Sense: The sensor suite is typically designed for a specified problem. On this case we are using a quadrant sensor, sensor on the intensity motor.
- Develop and update procedures: Smart test procedures that detect failures, or onset thereof, have to be developed. These procedures have to be carefully tuned to minimize false alarms, while improving their detection capability. The procedures should have the capability to detect trends and degradation and assess the severity of a failure for early warning.
- Infer: An integrated on board and off board reasoning system capable of fusing results from multiple sensors/reasoners and driver to evaluate the health system.
- Adaptive learning: If the observed fault signature does not correspond to faults modeled in the graphical dependency model, system identification techniques are invoked to identify new causes effect relationships.
- Predict: Lifting algorithm, which interface with on board usage monitoring systems and parts management databases are used to predict the useful life remaining of system components.

B. *Prognostic Techniques*

Prognostic can be classified as being associated with one or more of the following two approaches: data driven and model based [7, 8].

i. Data Driven Prognostic: Data driven approaches are derived directly from routinely monitored system operating data (e.g. calibration, voltage, torque, vibration). In many applications, measured input/output data is the major source for gaining a deeper understanding of system degradation behavior. This approach is based on statistical and learning techniques from the theory of pattern recognition.
ii. Model-based prognostic: In this case it is assumed that an accurate mathematical model is available. The model-based methods use residuals as features where the residuals are the outcomes of consistency checks between the sensed measurements of a real system and the outputs of a mathematical model. The premise is that the residuals are large in the presence of malfunctions, and small in the presence of normal disturbances, noise and modeling errors. Statistical techniques are used to define thresholds to detect the presence of faults. The three main ways of generating the residuals are based on parameter estimation, observers (e.g. Kalman filters, reduced order unknown input observers) and parity relation. Fig. 7 shows a functional block diagram for a data-mining-based prognostic system [9].

VI. DIAGNOSTIC AND PROGNOSTIC STUDY RESULTS

In this section, our objective is to develop and demonstrate the application of a predictive algorithm based on advanced pattern recognition techniques. Due to shortage of space here, we only consider neuro-computing among other options such as multivariate statistics, genetic algorithms, neural networks, signal analysis and mathematical logic - which identify the partitions that separate the early signatures of functioning systems from those later signatures of malfunctioning systems, thereby allowing the prediction of specific machine or system malfunctioning events prior to their occurrence [9]. The ultimate objective is to develop a data driven prognostic system that provides advanced warning of failure, fault, and other error events.

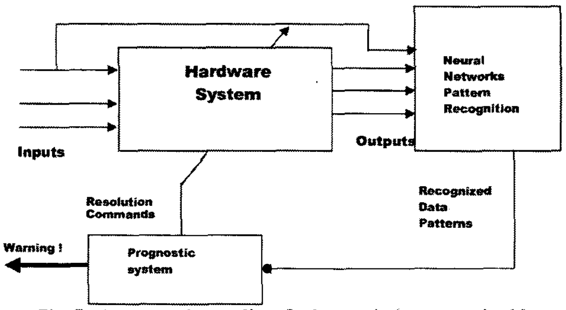


Fig. 7. A prognostic paradigm for laser pointing system health management

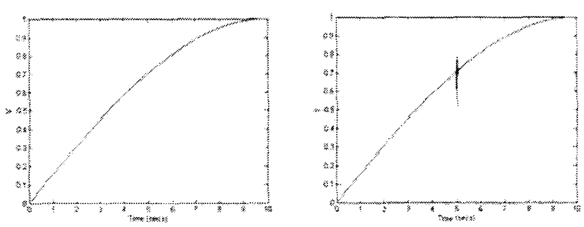
The development of the predictive algorithm is to be general, that is, it should be able to be ported to different systems and environments. However, to test and prove the efficiency of various approaches, the algorithm should be developed for the entire system under study, which consists of the mechanical subsystem, an electronic subsystem or an optical subsystem, etc. Many hardware systems in industry and other sectors are interested in developing technologies that will enable better health monitoring, management and life prediction for critical components.

A viable prognostic system should be able to provide an accurate picture of faults, component degradation, and predictive indicators of failures will be extremely useful, allowing our operators to take preventive maintenance actions to avoid costly or catastrophic damage on critical parts and to maintain availability/readiness rates for the system. The initial stage of the work will involve defining target events for prediction.

Although the current system is a simple one, but the approaches discussed here for diagnostic and prognostic work will be expandable for a large complex system involving adaptive optics, multiple sensors, mechanical and electro-mechanical subsystems, etc. In practical situations, one can often expect to see many sensor values from different sections of a hardware system. The large amount of data has to be reduced intelligently for any careful fault diagnosis. In other words, we need to reduce the superficial dimensionality of data to intrinsic dimensionality (i.e., number of independent variables with significant contributions to nonrandom variations in the observations). This problem is a classic case of feature extraction for which many techniques are available, e.g., Partial Least Square (PLS) [10], Fisher Discriminant Analysis [11], Canonical Variant Analysis [12], and Principal Component Analysis (PCA) [13]. Due to its wide applications and simplicity of the approach, PCA and its non-linear relative (NLPCA) are mostly used in this area. The paper in [14] can be consulted for more extensive discussions on the above techniques.

A. Prognostic Study of the Laser Pointing System

We did the prognostic study on the laser pointing system. We applied the direct laser pointing in the system and the state space equations of the DC motor represented in (14) and (15). The DC motor is connected with a position sensor, which is a linear model. X, Y directions are independent each other and they have similar models so only one of them is studied. We applied PID (K_i =100, K_d = 0.1 and K_p =20) controller in the system. The position response to a sine input is shown in Fig. 8. A fault was induced at t = 5secs due to a changed K. Three algorithms are applied, including Extended Auto-Associative Neural Network (E-AANN), Kohonen Self-Organizing Map (SOM), and Radial Basis Function Based Clustering (RFBN) [15]. In all these three algorithms the laser inputs (the input voltage V) and outputs (the output position y) together are fed into the inputs of each algorithm.



(a) Input volatge V (b) Output position y

Fig. 8. Response of the laser pointing system

The difference between the inputs and outputs of the E-AANN is shown in Fig. 9. There is a jump at t = 5secs in the difference of y, which shows there was some fault happened in the system.

Similarly, we applied SOM [16] and RBFC to detect the fault. The outputs from the diagnostic algorithms are shown in Fig. 10 and Fig. 11. They can also show that there was some fault in y when t = 5secs. In Fig. 11, RBFC not only correctly detects the fault in y but also wrongly gives the fault in V. So not only every algorithm is applicable in any case for any system to improve the diagnostic and prognostic ability we need to combine them together. One of the integrating examples is shown in our companion paper submitted to this conference by Dr. Berenji et al.

VII. Conclusions

On the laser pointing system, a standard PID and a fuzzy controller were designed. It is well know that PID controllers rely on K_p, K_i and K_d, which are obtained after the parameters of the system are obtained. Therefore, K_p, K_i and K_d are parameter dependent and will need to be estimated again if the system suffers a change in its original configuration. Also, these constants rely on the system's mathematical model, which is not always available.

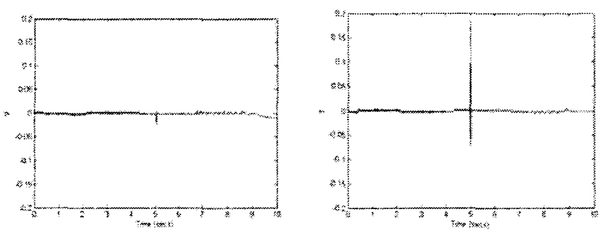


Fig. 9. E-AANN diagnostic outputs

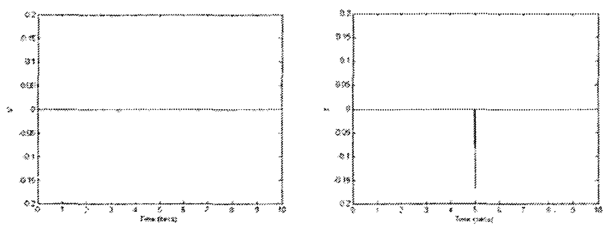


Fig. 10. SOM diagnostic outputs

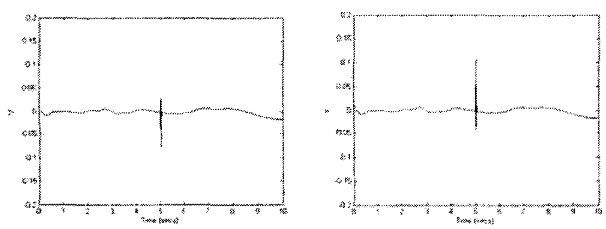


Fig. 11. RBFC diagnostic outputs

The fuzzy logic controller is designed, by means of a set of expert rules, from an array of parameters calculated from characteristics of the process as it reacts to various operating conditions. This characteristic makes it robust and flexible to changes on the system's configurations. In the case of the laser pointing system, fuzzy represents advantage in terms of control, simplicity and physical setup migration.

In this paper, a number of control diagnostic and prognostic issues have been raised for hardware systems. The laser pointing system has been tested on the prognostic and diagnostic study. Three different algorithms were used to diagnose the laser system. They work differently but can effectively detect the fault existence.

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