Toward Intelligent System Health Monitoring for NASA Robonaut

JUYI PARK
Center for Intelligent Systems
Vanderbilt University
Nashville, TN 37235-0131 USA

STEVEN C. FERGUSON
NILANJAN SARKAR
KAZUHIKO KAWAMURA
Center for Intelligent Systems, Vanderbilt University
Nashville, TN 37235 USA

BILL BLUETHMANN
ROB AMBROSE
KEN ALDER
Automation, Robotics and Simulation Division, NASA Johnson Space Center
Houston, TX 77058 USA

Abstract*—This paper presents an intelligent system health monitoring technique for a humanoid robot, Robonaut, which was developed at JSC to be used in space. Robonaut's lower level controller publishes sensor information through NDDS, network middleware, and Self Agent analyzes the data to monitor the status of the robot. A hierarchical system health monitoring (SHM) technique is developed. As a base level of the SHM, a nonlinear model-based observer and a fuzzy logic framework are developed to detect faults and identify the fault source in the robot.*

Keywords *– Robonaut, Self agent, System health monitoring, Fault detection and identification, Model based fault detector, Fuzzy logic*

1. Introduction

Like most humanoid robots, Robonaut is a complex electromechanical system comprised of many sensors and actuators. Overall task performance of such a system depends greatly on the proper functioning of its components. Despite the best design and maintenance practices, it is unlikely that such a complex system will be immune to random system faults. Any fault that may occur in the system may adversely affect the humanoid. Therefore it is necessary to detect, isolate, and if possible accommodate these faults as soon as they arise. In order to perform the above-mentioned task, we plan to design an automated monitoring system for Robonaut that is expected to provide a real-time status of each sensor and actuator, and to analyze of the possible task failures given a knowledge base of system faults.

A robotic assistant that is expected to work autonomously alongside humans is a highly complex system. It includes many actuators to provide multiple degrees-of-freedom needed for dexterous operation, and a host of sophisticated sensors for intelligent interaction with a human as well as the environment. We have developed self-monitoring capabilities for the robot that can be seamlessly integrated with the rest of the system to endow it with this unique fault tolerant feature.

There are several studies on sensor fault detection in control systems. Hanlon and Maybeck used a residual correlation Kalman filter bank to detect sensor fault in multiple mode of an aircraft [1]. Roumeliotis et al. employed a multiple model adaptive estimation (MMAE) to detect sensor faults in a mobile robot [2]. Both research groups detected sensor failure by comparing the sensed value with the estimated value from the bank of the Kalman filter. Scattolini and Cattane used Beard-Jones' fault detection filter to detect sensor faults in a large space structure [3]. Tinos et al. [4] used artificial neural networks for fault detection and isolation in cooperative manipulators, by utilizing a multilayer perception to reproduce the dynamics of the cooperative system.

A radial basis function network to produce fault information classifies the residual in the system's actual and modeled velocity. The paper written by Goel et al. [5], as well as the paper written by Romueloitis et al. [6] detect and identify faults in mobile robots using a Multiple Model Adaptive Estimate (MMAE), in particular a bank of Kalman Filters with a specific embedded failure model, and neural networks. Mohamed and Ibrahim [7] used a model based fault diagnosis using a knowledge base and fuzzy logic techniques. Authors such as Schneider and Frank [8][9], or Benitez-Perez et al. [10] used a non-linear model based observer to produce an error residual, coupled with a Fuzzy Logic residual evaluation to detect an identify faults. This is the method used in this paper since a sufficiently accurate dynamic model has been derived (eliminating a need for adaptive estimators), and sufficient data to formulate a fuzzy rule base for fault identification is available in Robonaut's architecture.

The proposed SHM is designed in a hierarchical manner consisting of levels. The lowest level is component fault detection. Robonaut's lower level controller publishes sensor information through NDDS, which is a network middleware, and Self Agent analyzes the data to monitor the status of the robot. The higher level is for cognitive control.

This paper is organized as follows: Section II describes Robonaut's hardware and software architecture. System health monitoring is presented in Section III. Section IV presents fault detection technique using model-based observer and fuzzy logic for fault identification with simple experimental results using experimental data gathered from Robonaut. Conclusions are presented in the final section.

2. Robonaut

2.1 Hardware

With 43 degrees of freedom, Robonaut (Figure 1) is the first humanoid built for space. It incorporates technology advances in dexterous hands, modular manipulators, lightweight materials, and telepresence control systems. Robonaut is human size with a 3-DOF articulated waist, and 2 seven-DOF arms, giving it an impressive workspace for interacting with its environment. It has a pan/tilt stereo vision camera unit that provides ranging information for both teleoperators and machine vision algorithms.

In addition to having the correct anatomy to work with EVA equipment, the Robonaut system is designed with space operations in mind. Robonaut's single leg design includes a stinger to directly mate with the same ISS worksite interface (WIFF) used by crew for stabilization. During the design phase, the ability to work in space was considered for nearly every aspect, including materials selection, thermal endurance, lubricants, avionics, and computer selection.

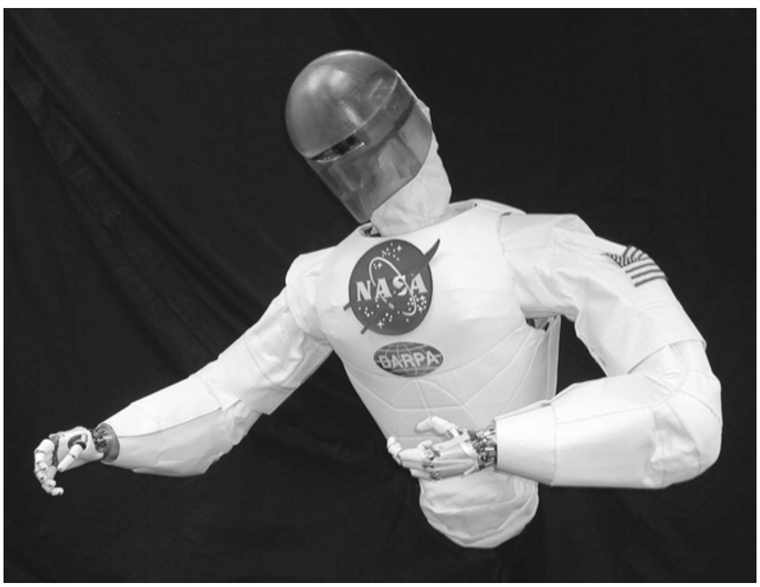

Fig. 1. Robonaut.

Robonaut's arms, neck and waist are human scale manipulators designed to fit within EVA corridors. Beyond its volume design, these appendages have human equivalent strength, human scale reach, thermal endurance to match an 8-hour EVA, fine motion, high bandwidth dynamic response, redundancy, safety, and a range of motion that exceeds that of a human limb. Both the arms and waist have a dense packaging of joints and avionics developed with a mechatronic philosophy. The arm and waist house thermal-vacuum-rated motors, harmonic drives, fail-safe brakes and 16 sensors in each joint. The arm's small size, strength-to-weight ratio, density, and thermal vacuum capabilities make it the state-of-the-art in space manipulators today.

Robonaut's hands set it apart from any previous space manipulator system. These hands can fit into all the same places currently designed for an astronaut's gloved hand. A key feature of the hand is its palm degree of freedom that allows Robonaut to cup a tool and line up its long axis with the roll degree of freedom of the forearm, thereby, permitting tool use in tight spaces with minimum arm motion. Each hand assembly has a total of 14 DOFs, and consists of a forearm, a two DOF wrist, and a twelve DOF hand complete with position, velocity, and force sensors.

The forearm is 4 inches in diameter at its base and approximately 8 inches long. It houses 14 motors, the motor control, power electronics, and all wiring for the hand. Joint travel for the wrist pitch and yaw is designed to meet or exceed that of a human hand in a pressurized glove.

2.2 Architecture for control

To control Robonaut with various intelligent algorithms, NASA developed an integrated control architecture that is depicted in Figure 2. In developing control architecture, our approach was to provide a sliding scale of intervention options for a remote human, ranging from low levels of teleoperation through supervision during routine work, to high levels of instruction for new tasks.

Likewise, an adjacent human teammate will be able to guide the machine through new task primitives, while the lower level motor learning system is active and transparent to other agents during autonomous work using mastered tasks and sensorimotor competencies.

Joints are controlled through standard PD loops: an inner velocity loop, and an outer position loop. Joint position comes from filtered encoder or resolver measurements. Joint velocity is derived from back-differenced position. The tele-operator generated joint position commands are position and velocity limited and shaped through a 2 Hz second-order filter. The shaped command is back-differenced to provide a commanded velocity signal that drives the motors through a feed-forward path, thus minimizing the required closed-loop effort. Through the command shaper, joint servo bandwidth is typically 1 to 2 Hz. Joint rates are typically limited at 15 dps. The loops execute at 400 Hz. At the Cartesian level, a standard impedance force control mode can be turned on in parallel with the position controller. To protect the hardware, max servo error aborts and soft and hard max position limit aborts are provided.

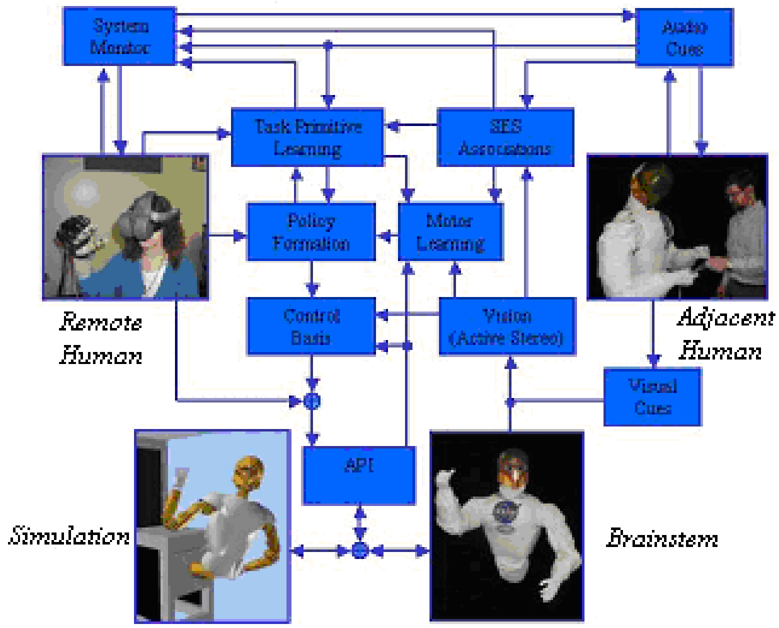

Fig. 2. Architecture for control.

3. System Health Monitoring

The Robonaut control system design philosophy is inspired by the human brain anatomy. The human brain embeds some functions, such as gaits, reactive reflexes and sensing, at a very low level, in the spinal cord or nerves [11]. Higher brain functions, such as cognition and planning take place in other parts of the brain, including the cerebral cortex and cerebellum. Within the Robonaut control system, the very low-level functions are referred to as the brainstem. The brainstem contains the motion controllers for the 49 DOFs, sensing, and low-level sequences. The lowest-level System Health Monitoring (SHM) is designed to handle any abnormality in this level. The brainstem approach permits higher-level cognitive functions to operate independently of the low-level functions. This allows the Robonaut system to implement a variety of control methods ranging from teleoperation to full autonomy with the brainstem unaware of which higher-level control system is being used. In the human brain, this is called cognitive control [12].

3.1 Low level sensor monitoring

The fundamental component on which the SHM relies is its ability to monitor signals to detect faults. There are several possible component faults that can occur within Robonaut which are summarized in Table 1.

Table 1. Possible components failure in Robonaut

Components	Faults
Power	Power supply failure
Actuator	Lost connection, Transmission failure
Sensor	Encoder fault, Camera fault, Proximity sensor fault

Figure 3 illustrates a system block diagram and typical plots of sensor signal and residual using a nonlinear model based error residual generator. The SHM concept with a modification is being applied to the Robonaut at NASA-JSC under a joint project with the Center for Intelligent Systems at Vanderbilt University.

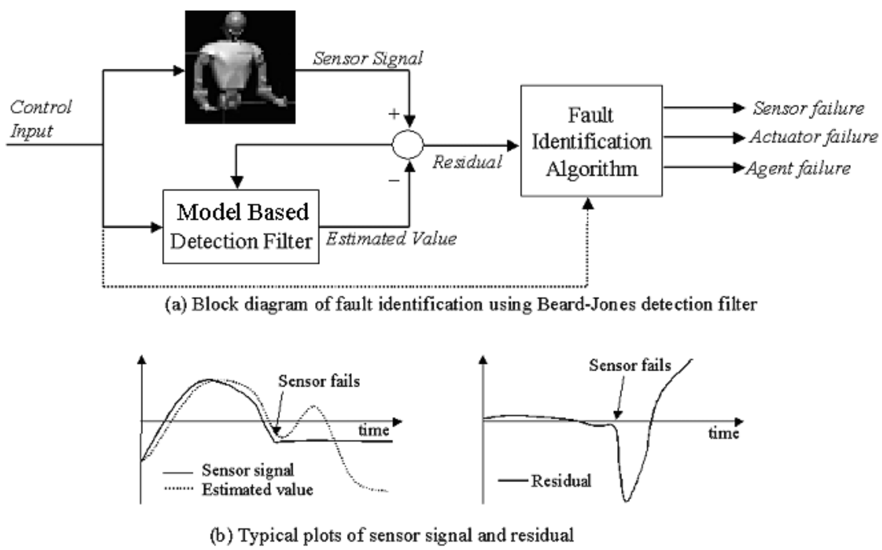

Fig. 3. System block diagram and plots of sensor signals.

3.2 High-level task control monitoring

NASA's vision for the future of space exploration is to bring humans and robots together to achieve mission goals. In order to form an effective human-robot teaming, however, existing human-robot interaction methods must be greatly improved. Before intelligent robots like the Robonaut are fully developed and integrated as team members, robot's cognitive capabilities must be improved so that a robot can serve as an effective assistant for humans while performing collaborative task in space. At vanderbilt, we are implementing a high-level *cognitive control* for our humanoid robot called ISAC (Intelligent SoftArm Control) [13] using modular controllers, working memory and a central executive [14]. This concept could be transferred to the Robonaut to control Robonaut behaviors in new or difficult situations. Figure 4 depicts how cognitive control interacts with low-level sensorimotor-based actions.

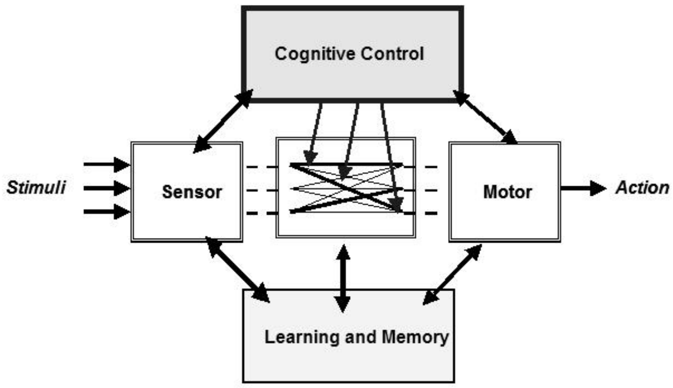

Fig. 4. Concept of Cognitive Control.

4. Fault Detection and Identification

4.1 Model for the right arm of Robonaut

The right arm of Robonaut consists of seven joints as shown in Figure 5.

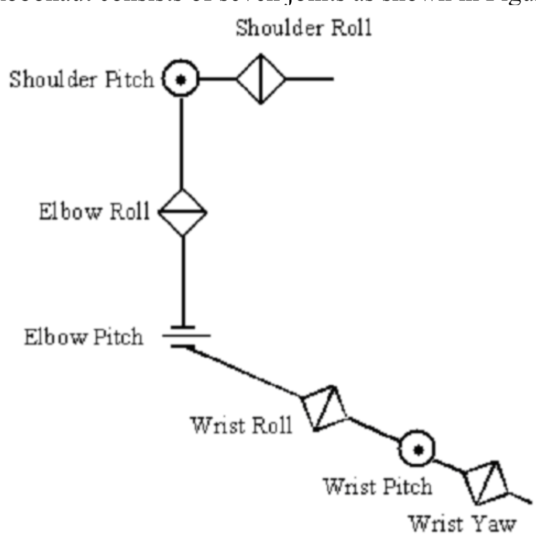

Fig. 5. Joints in Robonaut's right arm.

Each joint has a servo control loop that is implemented on the real-time OS, VxWorks. In order to derive the transfer function between the motor command and the joint velocity, we made the following assumptions based on observations and heuristic knowledge:

- Transfer function between the motor command and the joint velocity is assumed to have a constant gain.
- Gravity and Coulomb friction are the dominant external forces.
- Stick-slip friction force is considered.
- Gravity is regarded as a constant because the range of joint motion was relatively small, though it is a function of joint position.
- Assume no external control forces.

Based on the above assumptions, the following structure of the model was chosen:

$$\omega = K(u - F_g - F_c sign(\omega) - F_{ss}(\omega)) , \tag{1}$$

where ω, u, F_g and F_c are joint velocity, motor command, gravity and Coulomb friction respectively. $F_{ss}(\omega)$ is the stick-slip friction.

Using the experimental data, we estimated the parameters of the model given by Equation (1) using a least square error method. Figure 6 shows the block diagram of the whole control system with the estimated parameters. As shown in the figure, the controller consists of an outer position control loop with a position gain k_P and an inner velocity control loop with a velocity gain k_V , a feed-forward gain k_F and a gravity compensation term F_{g_comp} . The motor command, *u*, is expressed in the following form.

$$u = k_V k_P \left(\theta_d - \theta\right) + k_V \left(\dot{\theta}_d - \omega\right) + k_F \dot{\theta}_d - F_{g\_comp} . \tag{2}$$

Note that equation (2) has the same form as a PD controller except the addition of the feed-forward and gravity compensation terms.

The developed model was used to find a position error residual. To emulate encoder fault in experiments, the encoder value was set to a constant value on the control level in Robonaut's real-time control architecture. When the encoder value was set constant, the motor command increased due to the control action in Equation (2) causing the error residual to increase and hence we had to quickly stop Robonaut. One advantage to our fault detection system is that the stopping action would be automated as well as respond faster than a human who was observing and anticipating the fault, much less a human who was not paying close attention to the humanoid.

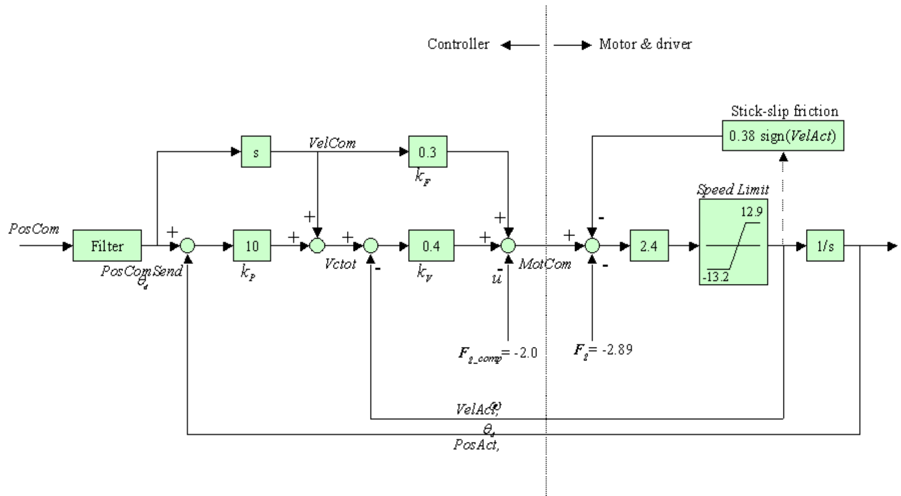

Fig. 6. Block diagram for controller and motor in the Elbow Pitch joint.

4.2 Fuzzy logic for fault identification

We examined the possible sources for faults and decided to begin our focus on the following:

- Sensor failure
    - There are many kinds of sensors including encoders in joints, force/torque sensors in wrist and shoulder, touch sensors in hands, and cameras. As a basic step, we concentrated on detection of encoder fault because of its importance.
    - In simulation, the motor current should increase and the error residual should increase.
    - The derivative of the sensor output should be zero.

- Actuator failure
    - This occurs when the actuator breaks and the joint goes limp. Because the motor driver supports motor health monitoring signal for malfunction of the motor, we can use this signal for fault isolation.
    - In simulation, the motor current should be near zero (implies low torque.)
    - The derivative of the sensor output should be non-zero.

We observed the experimental data to build a fuzzy logic analyzer for fault identification. Triangular membership functions were defined for all inputs to the fuzzy logic rules:

- The **Error Residual** (Encoder Reading –Estimated Model Value) could be Large Positive (LP), Positive (P), Near zero (P), Negative (N), or Large Negative (LN)
- The **Encoder Value** could be Positive (P), Negative (N) or Near Zero (NZ).
- The **Estimated Model** Value could be Positive (P), Negative (N), or Near Zero (NZ).
- The **Motor Current** could be Positive (P), Negative (N), or Near Zero (NZ).
- The **Derivative of the Encoder Value** could be Positive (P), Negative (N) or Near Zero (NZ).
- The **Derivative of the Estimated Model Value** could be Positive (P), Negative (N) or Near Zero (NZ).

The Fuzzy Logic Output Membership functions are

- **Healthy Output** (0)
- **Sensor Failure** (2)
- **Actuator Failure** (4)

Figure 7 illustrates a sample simulation screenshot for one joint.

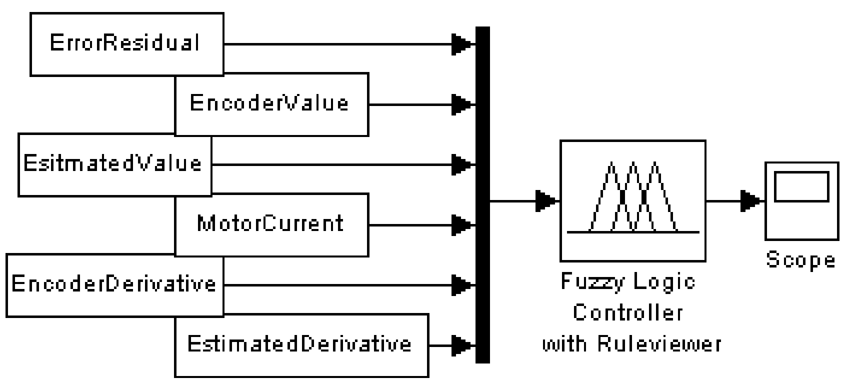

Fig. 7. Sample simulation screenshot for one joint.

To identify a difference between an actuator fault and a sensor fault, the most important factors are if the residual is either no longer zero (either LP, LN, P or N), if the Motor Current acts almost normal or if it decreases dramatically (as one may expect if the actuator breaks and the motor spins), and also if the velocity of the sensor output immediately goes to zero, or if there is some oscillation.

Here are a few sample rules:

- If Residual is NZ, AND Desired Velocity is N, AND Actual Velocity is N, THEN output is Healthy Signal (0)
- If Residual is LP, AND Desired Velocity is N, AND Actual Velocity is NZ, AND Motor Current is P, THEN output is Sensor Failure (2)
- If Residual is LN, AND Desired Velocity is P, AND Actual Velocity is NZ, AND Motor Current is NZ, THEN output is Actuator failure (4)

5. Simulation and Experiment

Using data gathered from the Robonaut API, we calculated the desired encoder value using the derived dynamic model. Figure 8 shows at 6.5 seconds, the encoder signal was kept at a constant value of -90°, which emulates an encoder fault.

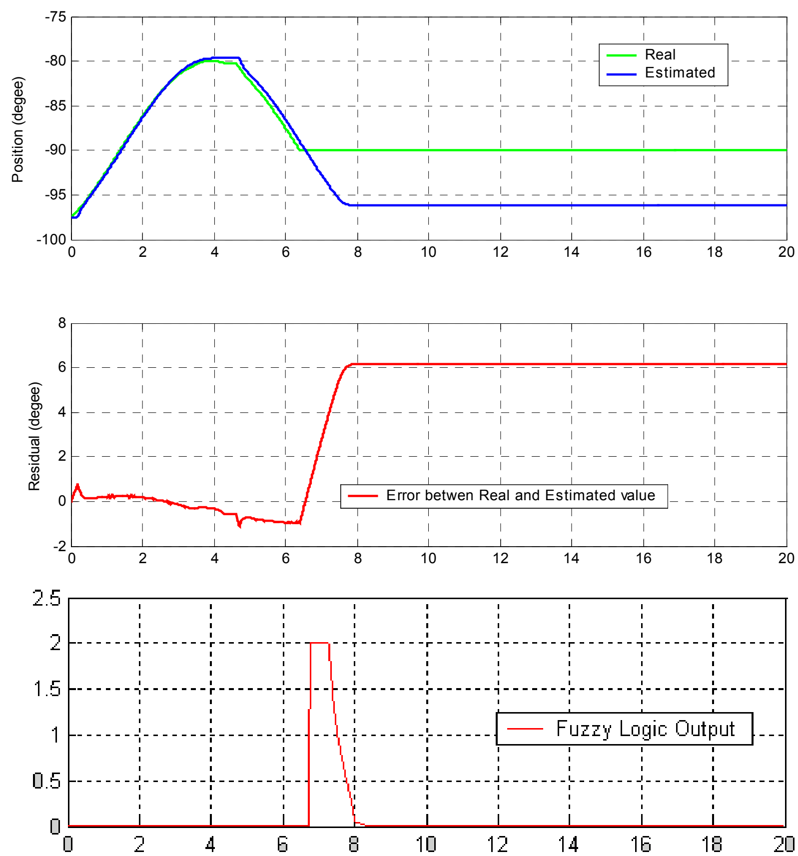

Fig. 8. Encoder fault detection: (a) Actual and estimated encoder value;
(b) Difference between actual and estimated encoder value;
(c) Output from fuzzy logic based fault identification block.

Figure 8 also shows that the error between the estimated value and the real encoder value increased after the occurrence of the encoder fault. Therefore, we could easily detect the encoder failure by observing the residual. The third diagram shows the output of the fuzzy logic rules. While the encoder reading matches well with the model based estimator, the output of the Fuzzy Logic is 0 (for a healthy signal). Once the fault is introduced, the Fuzzy Logic outputs a value of 2, which corresponds to an Encoder Fault. At 8 seconds, the emergency stop button was pressed causing many sensor values to stop. As shown in the error residual plot, when everything is functioning correctly, the residual is not exactly zero. However, using Fuzzy Logic to set tolerances and to examine other important information, we can know that everything is functioning properly.

6. Conclusions and Further Work

In order to monitor system health in the humanoid robot Robonaut, we proposed a model based fault detection scheme and fuzzy logic for fault identification. Simulation using experimental data was performed to verify the proposed fault detection and identification scheme. We were able to detect and identify when the arm is functioning properly, when a sensor fault is present, and when an actuator has failed.

Further work is required to detect collision and other types of faults such as power and transmission failure.

Acknowledgement

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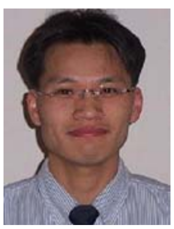

Juyi Park received his M.S. in precision engineering and Ph.D. in ME from Korea Advanced Institute of Science and Technology, Daejon, Korea. He has been a research associate at the Department of Electrical Engineering and Computer Science in Vanderbilt University since 1982. His research interests are suppression of residual vibration in flexible structure, robots for disabled people and real time robot control.

Steven C. Ferguson received his B.E in ME from Vanderbilt University. Currently he is pursuing his M.S. in Mechanical Engineering at Vanderbilt. Steven has been a student member of ASME and TSPE since 2001. His current research interests are control based fault detection methods in robotic manipulators and nonlinear control methods.

Nilanjan Sarkar received his M.E. in ME from the Indian Institute of Science and Ph.D. in ME and Applied Mechanics from the University of Pennsylvania. He was a postdoctoral fellow in the CS, ME and Psychology departments at Queen's University, Kingston, ONT. He is currently an Associate Professor in the Department of Mechanical Engineering, Vanderbilt University. Dr. Sarkar has been active in dynamics, control and robotics research. He has more than 50 publications in archival journals and conference proceedings. He is an Associate Editor for the *IEEE Transactions on Robotics and Automation* and the Vice Chair of the Robotics Panel of the ASME Dynamic Systems and Control Division. He is a member of the ASME and the IEEE.

Kazuhiko Kawamura received his M.S. from the University of California, Berkeley and Ph.D. in EE from the University of Michigan, Ann Arbor. He is a Professor of Electrical and Computer Engineering and of Management of Technology and Director of the Center for Intelligent Systems (CIS), Vanderbilt University, Nashville, TN. He has published over 150 research papers, a book, and book chapters in the fields of intelligent systems, intelligent robotics, human-robot interfaces, behavior learning, computational intelligence and cognitive robotics. He directs research projects at the CIS in humanoid robots, computational intelligence, multiagent-based robot control, automatic behavior generation, and brain-machine interfaces. Dr. Kawamura is a Fellow of IEEE. He is a member of the editorial board of *Applied Intelligence*, *International Journal of Humanoid Robotics*, and *International Journal of Human-Friendly Welfare Robotic Systems*.

Rob Ambrose, Ph.D., is the Project Manager for Robonaut. His publications topics include robot design, control, space environmental modeling, actuator development, kinematics, kinetics, interactive design software and non-linear optimism. He has built intelligent robotic systems for space, microelectronics, nuclear and agricultural applications.

Bill Bluethmann, Ph.D. is currently employed by Hernandez Engineering, Inc. at the NASA Johnson Space Center and serves as Chief Software Engineer on the Robonaut project. His research interest includes manipulation, robotic control and task-level autonomy.

Ken Alder currently works on Robonaut's controllers for Hernandez Engineering, Inc. at NASA Johnson Space Center. He has a BSME degree from Texas A&M.