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Diagnostics and Data Fusion of Robotic Sensors

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Diagnostics and Data Fusion of Robotic Sensors

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ABSTRACT

Robotic systems for remediation of hazardous waste sites must be highly reliable to avoid equipment failures and the subsequent possible exposure of personnel to hazardous environments. Safe and efficient clean-up operations also require accurate and complete knowledge of the task space. This paper presents the progress made on a 18 month program, sponsored by the Department of Energy (DOE) Morgantown Energy Technology Center (METC), under Contract DE-AR21-95MC2093 with Mechanical Technology Inc., to meet these needs. To enhance robot reliability, a conceptual design of a monitoring and diagnostic system is being developed to predict the onset of mechanical failure modes, provide maximum lead time to make operational changes or repairs, and minimize the occurrence of on-site breakdowns. To ensure safe operation, a comprehensive software package is being developed that will fuse data from multiple surface mapping sensors and poses so as to reduce the error effects in individual data points and provide accurate three-dimensional (3-D) maps of a work space.

INTRODUCTION

The safe and cost effective cleanup of hazardous waste sites within the U. S. nuclear weapons production complex requires the use of remotely controlled robotic systems. These robotic systems have to be robust to stand the demands of the hostile envoirnment. Due to the physical dangers associated with the waste site surroundings, failed robots are not easily accessed by humans to perform repairs and in extreme cases may have to be hauled out by other robots or abandoned altogether. Monitoring and diagnostic systems are the only means of providing early stage detection, isolation, and tracking of developing faults before they result in catastrophic failure.

A typical decontamination and decommissioning (D&D) task involves facilities that contain a complax maze of pipes, valves, gages and tanks supported on large steel structures. Because of the uncertain knowledge of these facilities, due to incomplete and/or missing records, sufficient information about the task space has to be generated in situ to allow collision free movement and sensor based grasping to support dismantlement activities. Task and tooling needs can only

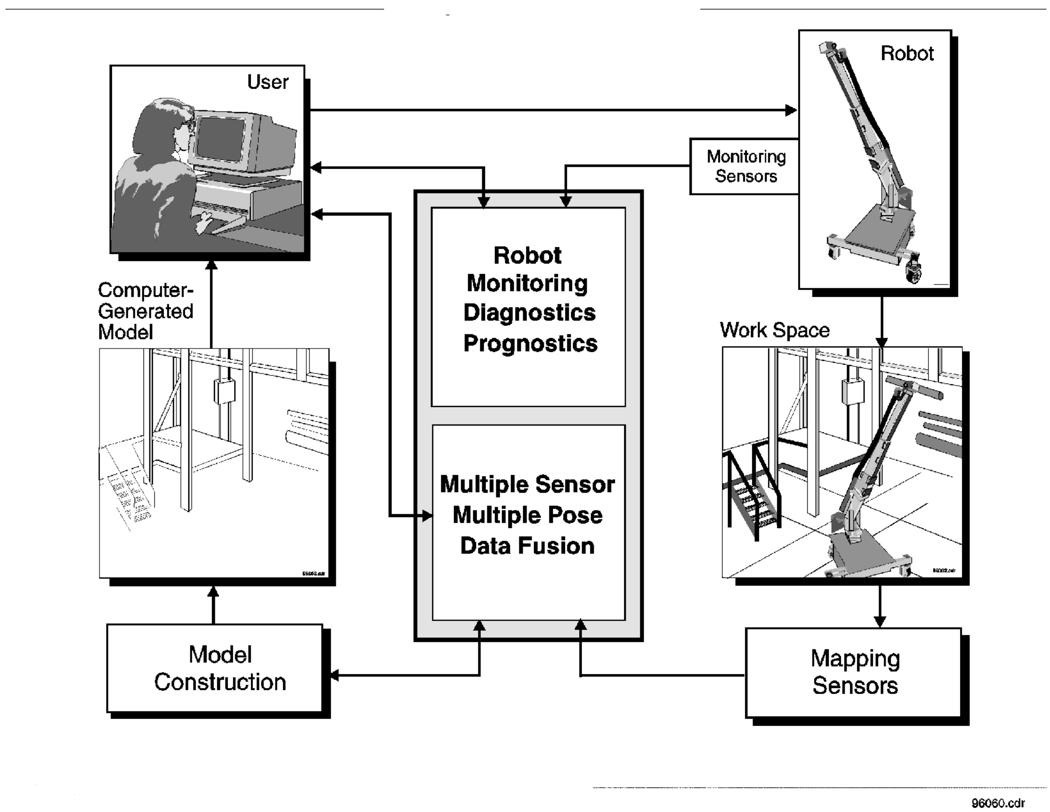

Figure 1. Model-Based Supervisory Control Archtecture

be determined as more information is revealed about the site. The robotic actions, in addition, must be performed with high confidence due to the extreme safety hazard. To address the above demanding requirements, DOE has undertaken the development of a model-based supervisory control architecture (Figure 1). The key elements of this architecture are the inclusion of an operator in the control loop, a three-dimensional (3-D) "world model" of the task space, surface mapping sensors to generate topological information, a data fusion and a visualization software module to integrate sensor data and confirm and update the world model, and monitoring and diagnostic technologies to provide information about robot health. The overall development approach and progress made to date on the data fusion software module and the monitoring and diagnostic technologies are described below.

DATA FUSION SOFTWARE MODULE

A typical decontamination and decommissioning (D&D) facility contains a complex maze of pipes, valves, gages, and tanks supported on large steel structures. Many sensors in several different locations will be used to create a complete 3-D model of this task space. When a surface mapping sensor scans a scene, the resulting data is expressed in the coordinate frame associated with the sensor's physical location and orientation. If the sensor moves, then any subsequent data will be expressed in a different coordinate frame related to the new location and orientation. Therefore, an essential requirement for combining data sets from different poses is to first convert all data into a common coordinate frame. This process, called data (scene) registration, requires the computation of the transformation that exists between two sets of data acquired from different poses of the sensor. Although registered data from multiple sensors/poses can be combined directly without any further processing, a fusion algorithm that weights sensor error will achieve significantly better results by reducing the effects of error in individual data points. Such an algorithm will thus provide a more accurate map of the work space.

The development objective for the data fusion module is to produce software that performs data registration and data fusion functions for robotic remediation systems. To provide the most flexibility for different applications, the data fusion module will contain three components: a registration software component, a fusion software component, and a graphic user interface (GUI) software with file management capability. Each of these software components is described below.

Registration Software Component

The registration software component serves two operational needs: 1) to transform the data into a common representation to permit the creation of a composite map of a task space, and 2) to locate a robot in that task space. The first need arises from the requirement of accurately combining data from multiple sensor scans, acquired from different poses within a task space, in order to build a 3-D representation of the task space that is adequate for subsequent planning and execution activities. In this case the registration process determines the relative transformation that exists between two or more data sets acquired from different sensor poses. The second need arises from the requirement of accurately locating a robot by means of measurements from a sensor mounted on its end effector. In this case, the registration process will estimate the pose of the robot end effector by determining the transformation between the data generated by its sensor and a set of corresponding spatial coordinates stored in the GUI control files.

An evaluation of the available registration algorithms and software were carried out in order to identify the best technical solution that is compatible with the schedule and cost constraints of the project. Because the preffered solution is a package of appropriate algorithms and codes that have already been developed and tested, inquiries were made with key members in the DOE robotics community. This interaction identified the following six registration algorithms:

> ***Feature Based Algorithm.*** Developed by MTI for Topographical Mapping Systems, this technique uses three or more naturally occurring noncolinear objects in the task space of simple geometric shapes, common in the two data sets, to derive the transformation that

will bring the coordinate frames of the two data sets into coincidence.

Iterative Closet Point (ICP) Algorithm. Improved by Carnegie Mellon University (CMU), this technique was devised to avoid the problem of feature extraction for high-speed applications. Scanned data is matched to a model of a free-form surface, using an iterative, least-squares ICP algorithm.

ICP plus Spherical Attribute Image (SAI). Developed by CMU, SAI is a technique for registering scenes which have no features or fiducials, but only free-form objects.

Geometric Hashing. Developed by CMU, this algorithm provides a means to automate the registration process by fitting data to a member of a library of objects. The technique provides a good initial estimate of the pose which is refined by the ICP algorithm.

Coleman Research Corporation (CRC) Approach. In this approach, registration is done with the help of artificial targets placed in the work space. These targets are typically spheres whose centers are the fiducial points. With corresponding data points, the pose is estimated via an iterative, least-mean-square technique.

Fourier Transform. Developed by the University of Florida, this technique was devised for efficient updating of robotic world models. The Fourier transform technique is used to register the two images (in scale, rotation, and translation), so that a subtraction will reveal the changes present in the current configuration.

Based on the comparative evaluation of the above techniques, the state of development, and the programmatic risk considerations, the feature-based registration technique was selected. This technique is a four-step process that requires algorithms for feature data segmentation, feature surface characterization, computation of fiducial points, and computation of the transformation (pose estimation) required to converge the two data sets. The following operational scenario illustrates this approach.

C Using existing facility drawings, video images, and 3-D visualization software, a set of reference targets are identified. These targets are naturally occuring objects of simple geometric shapes having features that allow computation of fiducial points. (A target has features which define a fiducial. For example, the intersection of two pipes contains two cylinders, whose closest approach defines a line segment whose mid-point is a fiducial) The reference targets should be distributed so that any data set gathered by a mapping sensor will contain data from at least three of these targets. The present design supports the following set of reference features.

Corner formed by three walls. The components are three plane surfaces. The fiducial is the point where the line formed by the intersection of two of the planes intersects the third plane.

Pipe intersecting a wall. The components are a cylinder and a planar surface. The fiducial is the intersection of the axis of the cylinder with the plane.

Intersection of two non-parallel pipes. The components are two cylinders while the fiducial is the midpoint of the line connecting the closest approach of the two non-parallel cylinder axes.

Cylinder tank with an end-cap or dome. The components are a cylinder and a quartic surface. The fiducial is the intersection of the cylinder axis with the quartic surface.

- For each target feature component in each data set, the system operator encloses the relevant data in a region-of-interest box. The enclosed spatial data is segmented and ouput to the registratin software.

- Geometric forms are fit to the segmented data (plane, a quadric surface, or a cylinder) and the fiducial points computed. The output of this algorithm is the estimated position of the fiducial point and a goodness of fit metric.

- The corresponding fiducials in the two data sets of interest are identified and forwarded to the pose estimation algorithm that computes the transformation between the two sensor poses.

The individual elements in the fiducial algorithms and the pose estimation algorithm have been checked using MATLAB. Coding has begun but has not advanced where module testing is possible. When the module coding is complete, a simple test data set will be used to validate the code at its unit level. To test at the system level a more complex task space will be modeled.

Fusion Software

The purpose of the fusion software component is to convert sensor measurements of the geometry of the task space into a 3-D spatial data representation, called occupancy maps (see Figure 2). These occupancy maps store a scalar parameter, the probability of occupancy, the value of which indicates, to various degrees of certainty, the areas that are free regions and the areas where encounters with solid surface is likely. Along with the occupancy map, the software will compute a 3-D confidence map. The scaler value stored in each cell of the confidence map represents the degree to which the corresponding probability of occupancy value is supported by the source data. The 3-D occupancy map and 3-D confidence map are basic outputs of the fusion software that will be interpreted through visualization using the Interactive Computer-Enhanced Remote Viewing System (ICERVS), being developed by MTI under separate DOE funding. In summary, as the above discussion indicates, the fusion software requires three key elements, the sensor error model, the occupancy map algorithm, and the confidence map algorithm.

<u>Sensor Error Model</u> The sensor error model is a user supplied external function which is dynamically linked to the Fusion Software Module at the run time. The sensor error model is specific to each sensor and contains the effects of many factors including basic sensor physics, its mechanical repeatability, the target surface roughness, color, and reflectance, and the envoirnmental effects such as task space temperature and humidity

Surface mapping sensors selected by DOE for facility mapping system will include a laser radar and a structured light sensor. For the laser radar, the typical error sources after calibration include noise in the light detection hardware, mechanical scanner jitter, signal attenuation from surface tilt and curvature, and variation in speed of light due to changes in temperature and humidity. For structured light sensor the errors include quantization error associated with the basic optical resolution, mehanical positioning errors, and the surface induced distortion of the laser illumination. In general these errors have Gaussian distribution in the three orthogonal directions and can therefore be spatially described by three variance values. Given the coordinates of a measured point, the sensor error model will compute the set of variances associated with the range, azmuth, and elevationof the particular point. These variances are used to generate probability density function using Gaussian uncertainty distribution.

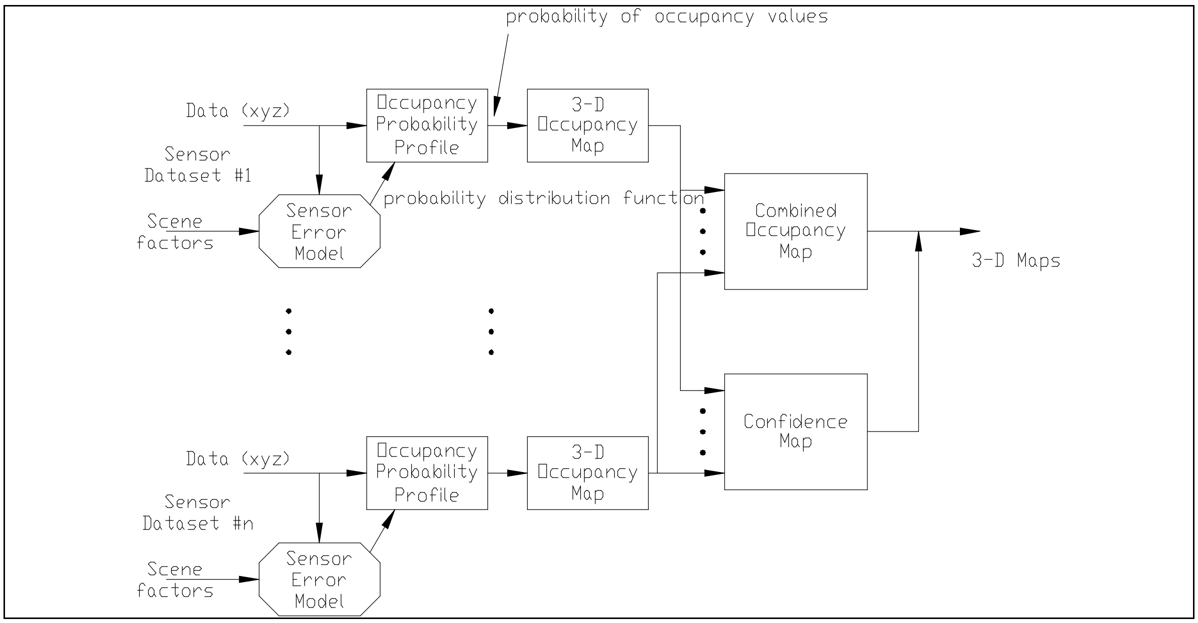

Figure 2. Topographical Data Fusion Software

Published, theory based, sensor error models show extremely small errors. Since the surface and envoirnmental effects generate significant errors, the error model, for it to be useful, needs to be based on experimental characterization. For the present project, the sensor error model for the structured light sensor is based on experimental work performed at MTI for the development of a Topographical Mapping System (TMS). The laser radar sensor error model will be based on the results obtained from the ORNL testing of a Colemon FM laser sensor.

Occupancy Map Software Given a set of sensor measurements and the associated sensor error model, the occupancy map algorithm constructs a three dimensional occupancy grid where each cell in the grid is characterized by the probability that it is occupied. A value of "0" indicates that the cell is known to be unoccupied or empty, while a value of "1" indicates that the cell is known to be occupied or full. Initially, the probability of occupancy for all cells is set equal to 1/2 and flagged as unmapped.

To create the occupancy map for a data set, the fusion software retrieves the sensor error model for that sensor and determines the error variences for each point. This permits the computation of a spatial occupancy profile for a data point that also reflects the fact that the sensor must have a clear line of sight to that data point. This computation is repeated for each data point to create the occupancy map for that data set. Data fusion is performed when the individual occupancy maps such as those described above, are combined using Bayesian integration, to form a fused occupancy map.

All algorithms required for implementation of the Fusion software have been defined. 1D and 2D versions of these algorithms have been evaluated and checked. Prototyping of the 3D algorithm is in process. The preliminary design of the occupancy map software is complete and the detail design is in progress.

Confidence Map Software

Development of Confidence Map software is subcontract to Dr. Mongi Abidi of University of Tennessee-Knoxville. For each cell in the confidence map, a confidence metric will be computed to estimate the extent to which the corresponding probability of occupancy value can be presumed valid. For the initial occupancy map, the confidence metric will reflect the relative insensitivity of the probability of occupancy to the assumptions made in computing it. These assumptions include, for example, the parameter values choosen in the sensor error model. When fusing different occupancy maps, the confidence metric will include the number of different sensor poses involved, the extent to which the line of sights are different for each sensor pose, the number of different sensors used, and the relative corroboration among the individual probability estimates.

Graphic User Interface

The ICEERVS graphic user interface (GUI) will be expanded to provide a user friendly interface to Data Fusion module. A system archetecture has been provided that integrates the Data Fusion Module with ICERVS and provides a seamless interface between the two systems with the user (Figure 3) . The GUI will interface with both the Registration and the Fusion software. The prelimnary design of the GUI is complete and the detail design is in progress.

MONITORING AND DIAGNOSTICS TECHNOLOGIES

To address the need to maintain the health of robot systems used in D&D operations, the subject DOE program also involves the development of a monitoring and diagnostic system for DOE robots. The Rosie mobile worksystem developed by Redzone Robotics and CMU is the reference system. A second-generation prototype, this robot is a telerobotically operated, hydraulically driven mobile worksystem consisting of a locomotive platform and a four degree-of-freedom heavy manipulator arm that can be equipped with various tools and robot manipulators. Specially designed for D&D work in nuclear environments, the Rosie mobile worksystem is largely representative of the type of robots DOE hopes to deploy in the future.

The simplest form of condition monitoring of robots is implemented by periodic inspections. Periodic inspections comprise an important part of maintenance programs because they effectively detect problems that provide visible evidence before affecting operation (cracked hoses, leaky seals, dust-clogged radiators). Problems not manifested in this manner will be missed. Periodic inspections obviously offer no value if a sudden failure occurs during operation.

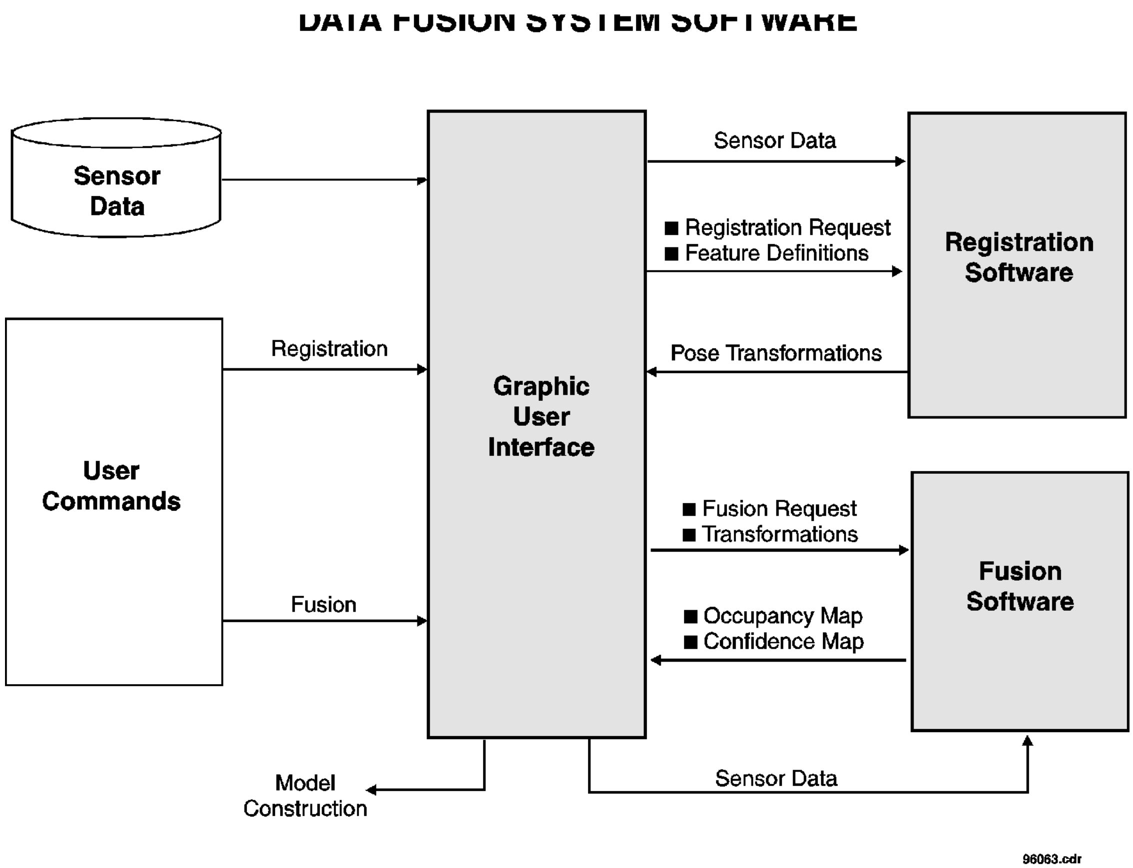

Figure 3. System Architecture Integrating Data Fusion Module with GUI

The maintenance program planned for the Rosie mobile worksystem calls for inspections to be made between tasks or every 100 to 200 hours of operation. After a high-pressure water or steam wash down to remove surface contamination, suited maintenance workers check the system for damage or wear such as hydraulic leaks, frayed wiring, structural tightness, etc. The only components designed to require periodic replacement in Rosie are the high- and low-pressure hydraulic fluid filter elements.

Limit-checking of onboard sensors is the next step and another important part of condition monitoring of robots. With this approach, a fault is assumed to have occurred if a sensor measurement exceeds a prespecified threshold value. Used where there is a direct relationship between signal level and a developing fault, limit-checking is typically employed to protect against sudden overload, control breakdowns, and serious operator errors by annunciating or shutting down the system in trouble when thresholds are exceeded. The main advantages of using limit-checking is that it is computationally simple to implement and provides protection when major faults occur; however, this is often too late to avoid serious operational problems and work interruptions. Also, limit-checking provides very little diagnostic information regarding the exact failure mode and root cause. Lacking this data, a full shutdown may occur resulting in a premature or unnecessary interruption. Rosie currently has several onboard sensors; however, these are only used for motion feedback. Other sensors installed for monitoring purposes (e.g., hydraulic flow, temperature, reservoir level, etc.) were found to be noisy and unreliable, and are being redesigned.Developing a practical monitoring and diagnostic system for the Rosie mobile worksystem and other similar robots is no small task. It is likely that a successful system will use several approaches ranging from simple limit checking for certain failure modes to some of the more exotic techniques that will be discussed below. It is also likely the best robot reliabilities will be achieved when deployment of such a system is done in combination with a maintenance program which includes at least some periodic inspections. It is also clear that the development of a successful system design must be preceded by several steps including: 1) analysis of D&D robots, represented in this case by the Rosie mobile worksystem, to determine failure modes, relative criticalities, and fault-symptoms; 2) review and evaluation of the current literature to search out applicable diagnostic and prognostic methodologies; 3) specification of the system requirements; and 4) development of a design strategy. Once these steps are completed, the conceptual design will be developed and evaluated. Analysis of the Rosie and the literature review have been completed, and development of system requirements and a design strategy is underway. The following subsections note the results and the progress achieved in these areas.

Identification of Component Failure Modes

One of the most important aspects in the analysis of robot failure modes is the criticality of different components and different failure modes to robot operation. Establishing a criticality ranking is necessary to ensure that the monitoring and diagnostic system gives highest priority to those failure modes with the greatest effect on robot operation. Without such prioritization, the resulting monitoring system winds up trying to cover too many components and failure modes (monitoring parameters that are not critical and spending too little time on more important elements) or monitoring those components where it is easy to obtain signals, whether their performance is critical to robot health or not.

Another key aspect is the so-called fault-symptom relationship which connects degradation in a component (wear, corrosion, fracture, etc.) to an observable effect on the system (increased bearing torque, decreased flow, higher vibration, etc.). Many such relationships evolve, producing different symptoms as the failure mode progresses from early to late stages. Fault-symptoms form the basis for selecting the most appropriate sensor and detection techniques, and, in accordance with their typically progressive nature, the logical basis for the diagnostic system to determine the stage of the degradation and hence the urgency for notifying the operator.

To develop failure mode criticality, fault-symptoms and other important related data, information was gathered from several sources and put into a relational database. Engineering data describing the design of the Rosie platform was supplied by Redzone Robotics. Information regarding the work application including environmental and operational factors was sought from ORNL where the Rosie platform is being evaluated.

The material obtained from Redzone consisted primarily of assembly drawings, parts lists and various written descriptions. A functional schematic was generated describing each major subsystem and function path. Figure 4 shows the left front wheel drive, steer and extension assembly, and the hydraulic power supply and part of the valve manifold that supports its operation. From this schematic, it is easy to see the individual function paths and hence the individual mechanical elements required to execute the three functions. It also shows the components common to all of the function paths, i.e., the hydraulic power supply and supply manifold.

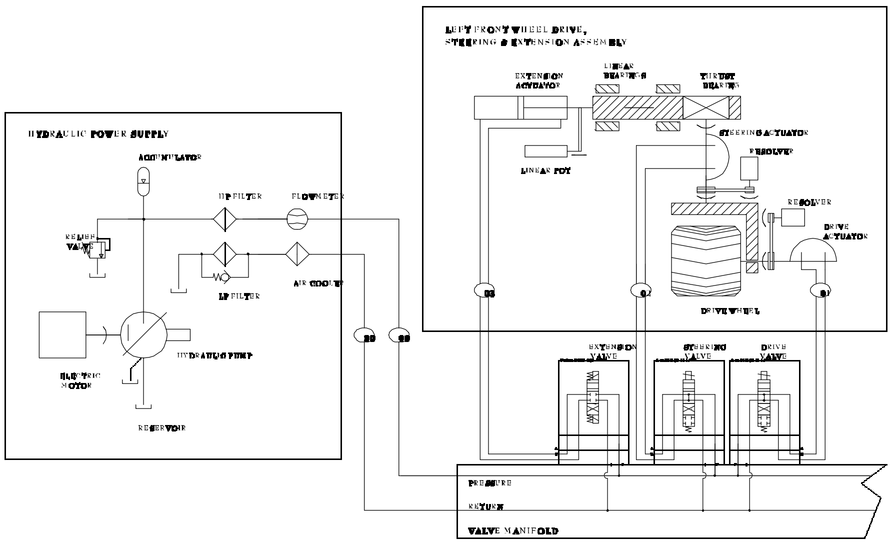

Figure 4. Functional Schematic of Rosie Mobile Worksystem

As a next step a Component Application Table was generated listing each mechanical element. Generally, the breakdown stopped at the individual components as assembled onto the platform such as the wheel drive motor rather than smaller pieces such as rotors, housings, seals, bearings, etc. This generally worked well as failure mode data areavailable describing such mechanisms as complete components. All hydraulic tubing, hoses, and fittings and all threaded fasteners generally within each function path were lumped together as two groups. A part of the Component Application Table, noting the parts in the left front wheel assembly, is given in Table 1. Type ID and model ID define the component type and link it to the associated Component Type Table, which provides further information such as manufacturer, design, specification, etc. The criticality level (column 4) places each component in one of three categories based on failure effects:

- Category I: Possible damage to robot or work area; self removal may not be possible.
- Category II: Work assignment cannot be completed; self removal may be possible.
- Category III: Work assignment can be completed; maintenance is necessary.

Table 1. Portion of Component Application Table

Component Application Table

Appl. ID	Subsys. ID	Function Path ID	Crit. ID	Type ID	Model ID	Function
1	1	0	III	f	RF 660	High pressure filter
2	1	0	III	f	2	Low pressure filter
4	1	0	II	he-fa	OKO 50-4 230/460/3/60	Cooler
6	1	0	I	m-e	1	Main hydraulic pump drive
7	1	0	I	p-d	1	Main hydraulic pump
8	1	0	III	rs	2	High pressure accumulator
11	1	0	I	v-p	2	Main hydraulic supply relief valve
13	3	1	II	m-h	PGRF 280 GWS 100	LF drive motor
14	3	1	II	bd	16 AT5/690-V	LF drive motor pot. belt drive
15	3	1	II	fc	1	LF drive fluid components
16	2	1	II	v-s	DLHZO-TE-L7	LF drive motor flow control valve
17	3	1	II	x-r	Series 2510	LF drive motor feedback resolver

Table 2. Portion of Failure Modes Tables

Possible Failure Modes Table

Mode Type ID	Comp Type ID	Failure Mode	Speed of Failure	Probability of Failure	Primary Cause	Primary Symptom
1	a-l	end seal - leakage	G	L	abrasive wear of end seal and/or piston rod due to ingestion of contamination	external leakage
2	a-l	piston - jamming	G	L	excessive side loads due to misalignment.	increasing loss of stroke/erratic motion
3	a-l	piston - jamming	G	L	stiction due to excessive contamination.	increasing loss of stroke/erratic motion
4	a-l	piston seal - leakage	G	M	abrasive wear of piston seal and /or cylinder wall.	increasing loss of piston force/internal leakage
5	a-r	bearing - failure	G	L	(see bearing failure)	erratic motion/loss of positioning precision
6	a-r	shaft seal - leakage	G	L	abrasive wear of end seal and/or piston rod due to ingestion of contamination	external leakage

A Possible Failure Modes Table was also put together. For each (component) Type ID, this table lists each failure mode that is thought to be reasonably possible within the existing application. The table currently contains 177 failure modes. Various sources in the open literature and MTI internal reports were used as sources for this data. The primary information for each failure mode is as shown in Table 2 which lists the failure data for several representative component types. Primary cause and symptoms are given. The former generally serves to complete the definitions of a given failure mode. For example, there are about a dozen modes associated with "running surface damage" to rolling element bearings, while the causes, e.g. "abrasive wear", brinelling", "corrosion," etc., complete the picture. Primary symptoms note the overall effects on the system, including the progression from early stage to more severe problems. Although, in some cases, the corresponding failure mode can be pinpointed by detection of those symptoms, in others, additional, more specific or more subtle data is required. Again, using rolling element bearings as an example, it is observed that most failure modes result in increasing noise, vibration, torque, form, etc. However, certain types of vibration analyses such as signature analyses, envelope detection, or Kurtosis analysis may help to distinguish between the different modes. In some cases, a visual inspection of the bearing may be required to make the determination. Thus, in addition to primary symptoms, MTI is also working to define a set of "secondary symptoms" where they needed. These have not yet been added to the database. Speed of failure and probability of failure are also included in the table. The former is given as either sudden (S) or gradual (G) and provides the logical basis to prompt the diagnostic system to act quickly for sudden faults while allowing additional diagnostic time for gradual failure modes. Probability of failure is assigned as low (L), medium (M), or high (H) and is based on a qualitative assessment of the failure mode for the application.

The Component Application Table and the Possible Failure Modes Table are in the process of being combined to form a Master Component Failure Mode Table. This will combine some 600 system failure modes. As the design process gets underway, a down selection of the most important failure modes will be made to keep the system a manageable size.

Identification of Applicable Technologies

A survey was conducted to identify monitoring and diagnostics systems available in the literature for robot manipulators. The literature survey revealed diagnostics methods for robots in four broad areas: dynamic model-based diagnostics, expert systems, pattern classifiers, and hybrid diagnostic systems. In model-based diagnosis, the main motivation is to represent the robot dynamics in the diagnostic system for early detection of faults. Merits and problems of four model-based methods, namely parameter estimation [5], analytical redundancy [6], stochastic filtering [7], and dynamic thresholds [8] were evaluated.

In the expert systems area, two types of methods based on shallow and deep knowledge are available. Shallow expert systems which derive their knowledge from a human expert represent it in form of Fault Trees, Failure Mode and Effects diagrams, Event Trees or if … then rules. Deep expert systems, on the other hand, derive their diagnostic knowledge from the structure and function of the robot components and store it in form of rules for diagnosis. Only one such system was developed by Krishnamurthi and Phillips [9] to address fault diagnosis of robot electronics.

In pattern classification based diagnosis, two methods using fuzzy set theory and neural networks have been applied to robot diagnosis. A fuzzy pattern classifier has been developed by Tzou et al. [10] for detection of abrupt speed changes in the robot using vibration sensors. In the neural network application, a Cerebellar Model Articulation Controller (CMAC) algorithm has been developed for manipulator fault detection [11].

Hybrid diagnostic methods have been proposed in the literature to overcome the problems associated with individual methods by using combinations of dynamic models, expert systems, and pattern classifiers. Two well-developed hybrid methods are available. Isermann and Freyermuth [12,13] developed a hybrid method using a combination of parameter estimation method and fault-symptom trees to identify abnormality in the robot and relate the abnormality to component faults, respectively. Schneider and Frank [14] proposed a fuzzy logic-based threshold adapting expert system for observer-based dynamic fault detection system. Most of the advanced methods for robot diagnosis are included in a survey by Dhillon and Anude [15].

The literature survey revealed very few papers in the area of prognostics of robots indicating that this area is not as mature as the diagnostic area. There are two prognostic methods for predicting the reliability of general mechanical components. The first method predicts the failure of a component due to fatigue resulting from cyclic loading using fatigue strength models, whereas the second method uses probability-based models (Gaussian and Weibull distributions) to predict the number of cycles a component will survive.

Although fault tolerance methods are not directly related to fault diagnosis, because of their importance with regard to robot reliability and their abundance in literature, these methods have also been reviewed. This review provided information that will be considered in development of a diagnostic system for the Rosie mobile worksystem which has an interface/capability to incorporate fault tolerance algorithms. This interface will allow the diagnostic system to use fault tolerance algorithms for on-line identification of components critical to the mission in the presence of impending component failures.

Based on information obtained from the literature review, a list of diagnostic methods applicable to the Rosie mobile worksystems have been compiled along with a list of possible sensors for monitoring the worksystem. This list currently includes position sensors (encoders, resolvers), tachometers, flow sensors, pressure sensors, liquid level indicators, vibration sensors, acoustic sensors, etc.

A trade-off study has been conducted to understand the relevance and applicability of the various diagnostic methods to the Rosie mobile worksystem. The study included the types of sensory signals these methods operate on, the signal preprocessing required, the computational requirements of these methods, and their sensitivity to faults.

Design Strategy and Conceptual Design

In order to develop a design strategy for a diagnostic system, a set of design requirements are needed. For the Rosie mobile worksystem, these design requirements were developed based on the operational requirements of a robot to be used for D&D, the literature survey, discussions with the customer and the end user, and prior MTI experience in the area of diagnostics. The following design requirements have been identified for developing a diagnostic system for the Rosie mobile worksystem:

- The diagnostic system must operate on-line.
- It must give indication of critical failures at the earliest possible time.
- It must have the ability to cope with the dynamic nature of robot operation.
- It must be able to represent complex relations between faults and sensors signals.

- It must be able to use approximate diagnostic information in the form of approximate probability of failure values and failure propagation rates.
- It must have the ability to integrate sensory information (from diverse set of sensors, human input, etc.) into a cohesive diagnostic strategy.
- It must consider the influence of the robot's environment on component failures.
- It must require the least number of sensors.
- It must have an interactive interface for user to enter information he/she perceives through others sensors (e.g., video images).
- It must be computationally inexpensive.
- It must be conducive to integration of prognostic and fault tolerance algorithms.

It is clear from the above list that many of these requirements are in conflict. For example, the ability to integrate various sensors would require large processing time which directly conflicts with the on-line operation requirement. The design of a diagnostic system for the robot will aim at achieving a balance between these conflicting design requirements.

Based on the above requirements, a preliminary conceptual design of a diagnostic system has been developed for the Rosie (see Figure 5). This diagnostic system will be a hybrid between dynamic-model-based methods and shallow expert systems. The dynamic model will be used to generate deviations in position/velocity during the robot’s operations. Along with other sensor signals (e.g., pressure, temperature, flow, etc.), these deviations will then be used for hierarchical fault detection and diagnosis. In the first hierarchy, fault detection will be performed using signals from various robot sensors, while in the second, third, and fourth hierarchies, faulty robot subsystems, components and component failure modes will be identified. A hierarchical diagnostic system was deemed necessary to achieve a good balance between providing fast on-line fault detection and diagnosis and a time-consuming search process required to identify individual faults. A hierarchical design will allow for fast fault detection to be performed on-line. On detecting a fault, the diagnostic system will immediately inform the operator and then perform the more time-consuming fault diagnosis.

After completely developing the conceptual design of the diagnostic system, a cost-benefit analysis will be conducted to evaluate the cost of implementing the diagnostic system and the expected benefits. Based on estimates of the number of robot units to be put operation in the near future, the types of operation they would be performing, the expected benefits from the diagnostic system in terms of down time and money saved will be evaluated. Also, the hardware/software required to implement the diagnostic system and integrate it with the robot's subsystems will be assessed.

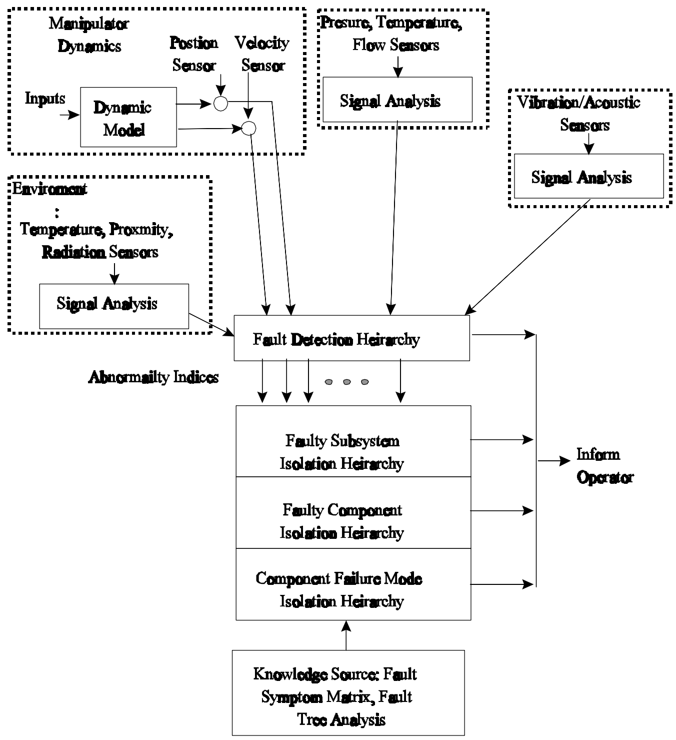

Figure 5. Preliminary Conceptual Design of Diagnostic System for Rosie MobileWorksystem

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