ON A SMART STRUCTURE VARIABLE SUPERVISORY CONTROL CONCEPT FOR HUMANOID ROBOTS

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Abstract: Flexible and safe control of smart human interactive multi-sensory robots which have to interact with a complex environment (humanoid robots) is a tough problem due to the extremely nonlinear and variable system behavior or the conflicting goals within the different process phases. Since conventional robot control concepts can not comply with it the introduction of a hierarchical Neuro-Fuzzy (NF) based fault tolerant control concept is proposed in this paper.

Keywords: fault tolerant systems, diagnosis, fuzzy control, neural networks, multisensor, robot control, mode selector

1 INTRODUCTION

The increasing complexity of robot tasks both in the industrial manufacturing area and more and more in the private human environment requires a new generation of safe and flexible robots. More intelligence can be achieved by

- multi-sensorics for the communication and interaction with its environment
- a close man-robot partnership for joint solving of complex tasks as well as
- learnability of the robot control system.

Enhanced safety and flexibility of the robot requires the introduction of advanced structure variable super-visory control concepts which permit a dynamical situation responsive reconfiguration of case specific hardware and software components (e.g. sensors, sub-controllers) situations which require a dynamic reconfiguration of the control algorithm may be e.g. special process phases or fault events. Robot control systems available on the market cannot comply with such advanced requirements.

As regards position and velocity control of robots in the free unforced motion mode many efficient control concepts have been developed and put into practice within the last 20 years [1-4]. Both model based approaches (e.g. inverse system technique, adaptive algorithm, predictive control) as well as heuristic Fuzzy or Neuro-Fuzzy (NF) approaches applied to rigid and elastic robot structures have been proposed. The state of the art for robot control concepts with external sensorics is quite different. While for some special industrial applications with force/torque and visual sensors [5], [6] considerable results have been achieved there remains a lack of generic multi-sensor based surveillance and control concepts. The special application specific control software is not flexible enough to be adopted for adjacent problems.

Normally complex robot tasks consist of a sequence of completely different motion phases which require phase and sensor specific control algorithms each. Obviously a point-to-point motion (PTP) has to be controlled by a different algorithm than a force controlled deburring or hole fitting operation. Moreover, in cases of hardware or software faults as well as disturbed robot motion by external forces (e.g. obstacles, load impacts) case specific recovering control algorithms have to be activated.

2 SUPERVISORY CONTROL CONCEPT

In order to cope with such manifold scenarios a hierarchically structured Neuro-Fuzzy (NF) based supervisory control concept is proposed (cf. Fig. 1) which has been successfully applied by IITB for the flexible automation of a complex industrial batch process [7]. It relies on the decomposition of the complex control problem into a sequence of smaller, more transparent phase specific sub-control problems. In the upper control level the actual process phase is identified by NF based multi-sensor diagnosis followed by a heuristic Fuzzy based decision and activation of the corresponding phase specific sub-controller. The lower level of the control structure consists of different low level sub-controllers which are optimized with respect to specific process phases. Principally the various low level sub-controllers may have any structure (Fuzzy control, model-based or hybrid). Depending on the process phase identified by NF diagnosis a heuristic Fuzzy based mode selector activates the most appropriate control mode, which can comprise both - the *adaptation* of control parameter sets without structural changes, or the *switching* of different situation-specific low level controller structures.

Switching between the low level controllers is more useful if the performance requirements have to be changed. For a fast and precise change between very different set-points e.g. it may be useful to apply a time-optimal bang-bang control strategy for large state differences whereas a well damped PID controller in the vicinity of the target state. Of course, structural switching requires necessarily the compatibility of the alternative controller structures. Moreover, shock disturbances have to be avoided by introducing a Fuzzy-based soft switching strategy (cf. [4,7] for details). Aim of this paper is to discuss the application of the NF supervisory control concept t smart multi-sensory robots which is the objective of an ongoing project at the robot laboratory of the IITB.

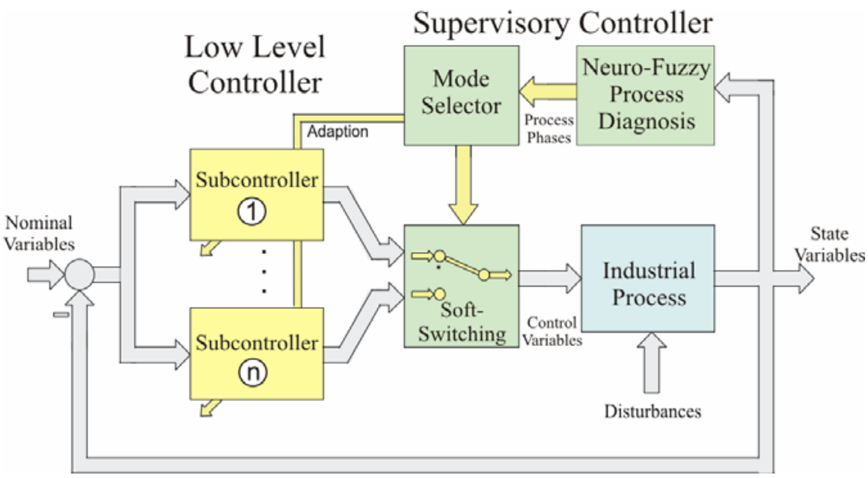

Fig. 1. Basic Scheme of the Neuro-Fuzzy (NF) based structure variable supervisory control concept

3 PROCESS AND FAULT DIAGNOSIS

In order to diagnose automatically malfunctions and special phases or states of a technical process the successive steps of residual extraction and evaluation have to be performed [8]. This general abstract model, shown in Fig. 2, allows a broad variety of different realizations and implementations.

Within the residual extraction step the available sensor signals of the process are preprocessed for the purpose of extracting relevant signal characteristics. The generated residuals can be regarded as a condensed signal representation, ideally containing all important signal information. Basically residual extraction in technical processes is performed by following methods [8]:

- signal based methods, e.g. threshold comparison, frequency analysis, pattern recognition, or
- model based methods, e.g. parameter estimation techniques.

In the next stage, the residual evaluation, a small number of meaningful residuals that optimally represent the given process phase without redundancy are identified. Finally the classification of the actual situation is carried out, i.e. the selected residuals for a given situation are assigned to a specific class by suitable methods like e.g. [8]:

- statistical evaluation, e.g. Bayes linear classifier, k-nearest neighbor or polynomial classifier,
- artificial intelligence methods, e.g. neural networks, Fuzzy Logic and NF classification.

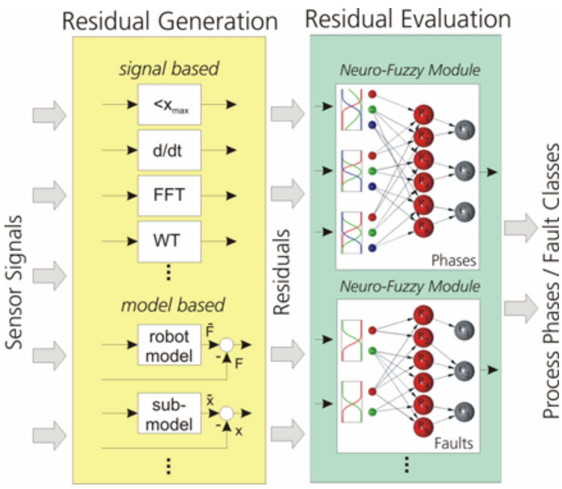

Fig. 2. Neuro-Fuzzy process phase and fault diagnosis

3.1 *Model Based Residual Generation*

The model based residual generation relies on the knowledge of an analytical model which describes the nominal process behavior. Using a Lagrangian approach, the dynamic model of the robot is given by

$$\tau - \tau_f = M(q)\ddot{q} + C(q,\dot{q}) + g(q) + f(\dot{q}) \qquad (1)$$

where q denotes the robot joint positions, M the inertia matrix, C the Coriolis forces, g the gravity vector, f the various friction terms (viscous and dry friction), τ and τ_f, respectively, the commanded (nominal) and the (unknown) fault torques.

By the term τ_f every kind of fault can be captured; for example, the following ones can be considered:

- *total actuator fault* $\rightarrow \tau_{fi} = \tau_i$;
- *partial actuator fault* $\rightarrow \tau_{fi} = k \cdot \tau_i$, $0 < k < 1$;
- *collision fault* $\rightarrow \tau_{fi} = J_i^T(q) \cdot F$, where F is the force due to the collision and J_i the i-th column of the jacobian associated with the collision point;
- *actuator saturation* $\rightarrow \tau_{fi} = \tau_i - sign(\tau_i) \cdot \tau_{i,max}$ where $\tau_{i,max} > 0$ is the maximum absolute torque allowed;
- *actuator bias* $\rightarrow \tau_{fi} = b_i$, with b_i constant of polarization;
- *locked actuator fault* $\rightarrow \tau_{fi} = \tau_i - z_i$, with z_i equal to the right side of equation (1).

Using a scheme based on the generalized momenta $p = M(q)\dot{q}$, the residual vector can be defined as

$$r = K\left[\int(\tau - \alpha - r)dt - p\right] \qquad (2)$$

with $K > 0$ diagonal and

$$\alpha_i = -\frac{1}{2}\dot{q}^T \frac{\partial M}{\partial q_i}\dot{q} + g(q) + f(\dot{q}) \qquad (3)$$

The residual dynamics is therefore given by

$$\dot{r} = -Kr + K\tau_f \qquad (4)$$

Thus, in accordance to equation (4), the evolution of each component of the residual vector r_i reproduces the evolution of each fault torque τ_{fi}: in such a way the fault can be detected and isolated by the so defined diagnostic signals (cf. [10] for details).

In the case, that an accurate model of the system is not available, an adaptive scheme for the residual generation can be applied.

3.2 *Neuro-Fuzzy Residual Evaluation*

The purpose of the residual evaluation step is reliable assignment of the available signal residuals to the possible diagnosis statements (cf. Fig. 3). With respect to the problem considered in Chapter 4 the process of residual evaluation can be understood as a classification problem, i.e. the generated residuals within a typical process phase are classified and assigned to the corresponding process phase.

Several methods for residual evaluation have been proposed in the past [8], which can roughly be divided into statistical and artificial intelligence based methods. All methods differ considerably with respect to their practical realizations and the in developer interaction during the design phase. E.g. developing an evaluation system based on the Bayes linear classifier, as one of the most commonly used statistical method, the user has to select the relevant residuals manually and adjust the parameters of the probability distributions carefully by hand to obtain an optimal classification system. On the other hand artificial neural networks (ANN) are capable of managing this user-controlled tuning automatically by applying their learning strategy in a self organizing optimal manner.

Beside these aspects concerning the implementation and design of the evaluation module, in practical applications the interpretability of the system and the possibility to include available expert knowledge is of outmost importance. Standard neural networks, e.g. the MLP, can not provide these essential residuals. In a MLP the inherent decision knowledge is implied in specific weight coefficients of the underlying network structure and cannot accessed or supplemented easily. The so-called black-box-behavior represents a substantial restriction of standard neural networks.

Desirable is a residual evaluation module which stores the decision knowledge in an interpretable and modifiable form. In this respect Fuzzy Logic provides an ideal tool for realizing residual evaluation modules. Fuzzy Logic gives the possibility to describe knowledge by linguistic rules like e.g.:

if *Residual 1 is ... and*
Residual 2 is ... and
Residual n is ...
then *Process Phase...* (5)

The implementation of a Fuzzy module for residual evaluation can be very difficult with an increasing number of residuals taken into account. The problem of finding appropriate membership functions and rules is often a tiring process of trail and error. Just like linear classifiers Fuzzy systems require in contrast to ANNs manual tuning to obtain good classification results. In order to automate the design phase of the Fuzzy system in the proposed diagnosis scheme NF approaches are used for designing Fuzzy residual evaluation modules.

Basically NF approaches can be understood as the employment of learning strategies derived from the domain of neural network theory to support and accelerate the development of a Fuzzy system. Several NF concepts have been described in the literature, in the proposed diagnosis scheme we follow the NEFCLASS (Neuro Fuzzy CLASSification) approach proposed by Nauck [9]. The NEFCLASS model provides a NF classification approach derived from the generic fuzzy perceptron. The structure of the model is illustrated in Fig. 3. The NF model is characterized by a three layer topology. The input nodes I in the input layer are connected by Fuzzy sets μ with the rule nodes R in the hidden layer. For semantical reasons each rule unit is assigned to a single output node C in the output layer, in order to avoid weighted rules, this weights are fixed to 1.

To obtain an optimal classification result the learning algorithm creates the rules and adjusts the Fuzzy sets from training examples. For initialization the user has to define the initial Fuzzy sets for partitioning the domains of the several inputs and the maximum number of rules that may be created in the hidden layer. After training the system corresponds to a simple Fuzzy system, the classification knowledge can be easily accessed and extended by the user [9].

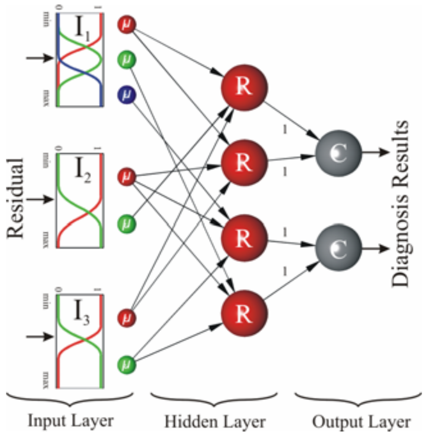

Fig. 3. NEFCLASS Neuro-Fuzzy system for residual evaluation

4 APPLICATION TO HUMANOID ROBOTS

Advanced robot-sensor systems within the next decade are characterized both by a close man-robot partnership for the cooperative management of sophisticated task as well as by open reconfigurable interfaces between robot, sensors and actuators ("plug and play" features).

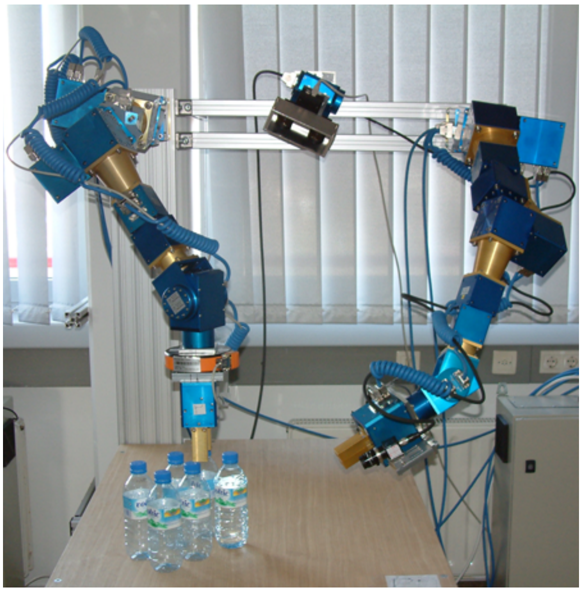

Fig. 4. Humanoid robot platform at IITB

The corresponding extreme safety and availability requirements can only be guaranteed by the introduction of a structure variable supervisory control concept providing a high structural and parametric flexibility of the multi-sensory controller

with respect to malfunctions of system components (sensors, actuators) and stochastic human actions as well. Existing marketable robot control systems can not comply with such enhanced safety and availability features.
In order to cope with the above objectives within the framework of the on-going German Humanoid Robot Project supported by the German Research Foundation (DFG) at the IITB the above described NF supervisory control concept is going to be adapted to human interactive multi-sensory robots. For its investigation an experimental multi-sensory robot-sensor platform with different external and internal sensors is going to be implemented (Fig 4).
Two of the external sensors are integrated in the 2 robot arms and two are mounted on a pan-tilt unit attached at the ceiling (denoted as sensor head). The sensor head is equipped with a 3D stereo camera and a stereo acoustic sensor (microphone array). The sensors integrated into the robot arms are an optical 3D sensor integrated in the gripper as well as a force–torque sensor mounted between wrist and gripper.
The basic scheme of the adapted NF based fault tolerant supervisory control concept for humanoid robots is shown in Fig. 5. It enables the robot both to detect and isolate fault and non-fault process phases (modes) as well as the dynamic activations of corresponding supervisory control measures. The lower stage of the control structure consists of different sub-controllers which are optimized with respect to specific modes. Characteristic non-fault process phases may be the position and velocity controlled free motion mode, the constrained force control mode or the hybrid force-position control mode. Typical fault modes are malfunctions of any joint servo-control system, internal or external sensor faults, collision modes or loosing parts carried by the robot gripper.

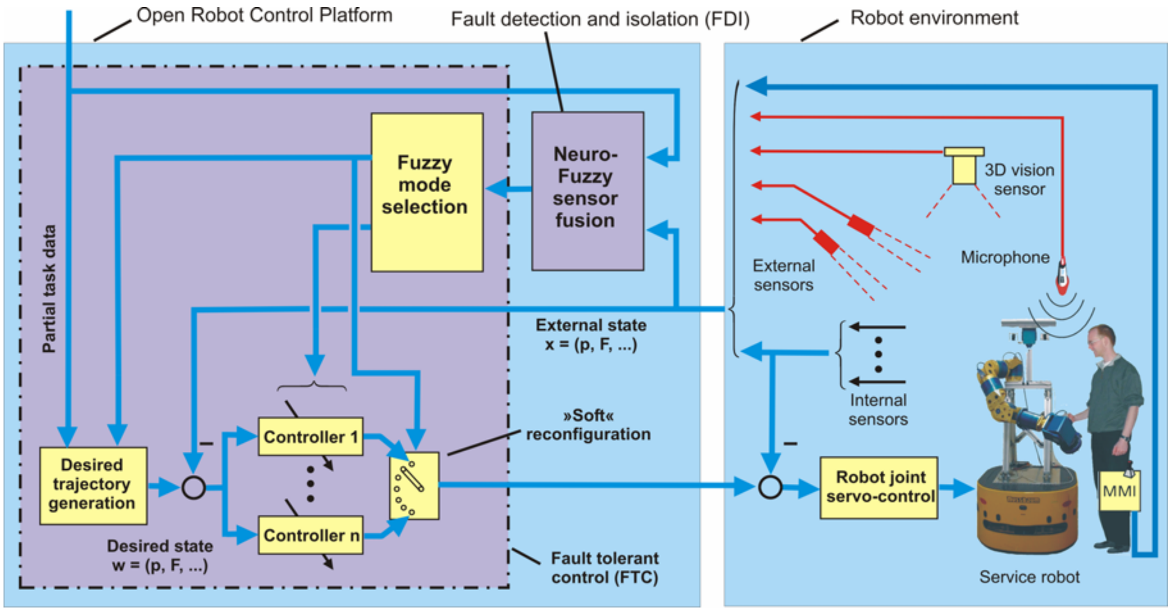

Fig. 5. Scheme of NF based structure variable supervisory control of humanoid robots

The various controllers which may have any structure (PID, Fuzzy control, model based control etc.) are activated by the NF based supervisory controller in the upper level of the hierarchy. Depending on the identified process phase a smart mode selector (e.g. Fuzzy or model based) activates the most appropriate control mode which can comprise both the adaptation of control parameter and/or "soft" switching of different mode specific controller structures (dynamic reconfiguration).
The online diagnosis concept for the identification of process phases or fault classes applied to humanoid robots implies both signal and model based residual generation in combination with a NF based residual evaluation (cf. chapter 3). Characteristic residuals may comprise amplitudes, trends, Fast Fourier Transformations and Wavelet Functions as well as model based residuals. Since the robot mechatronics can be well described by Lagrange equations of motion [10] it is useful to assume the difference between model outputs and measured values as additional process residuals. For a qualified fine classification of a process phases and fault events model and/or heuristic signal based

residual extraction will be succeeded by a NF based heuristic residual evaluation.

In order to demonstrate the functionality of the NF supervisory control concept a benchmark experiment shown in Fig. 6 has been selected. A planar circular motion of the robot tool center point (TCP) will be considered. The robot motion will be disturbed by two succeeding fault events. At the time t = 1.5 sec in the servo-controlled joint 4 an actuator bias will occur (cf. chapter 3.1). Moreover, at t = 5..6 sec a collision will occur when the TCP trajectory will intersect a brick like obstacle. The corresponding signal responses of the joint positions 1, 4, 7 and the corresponding joint torques are shown in Fig. 7.

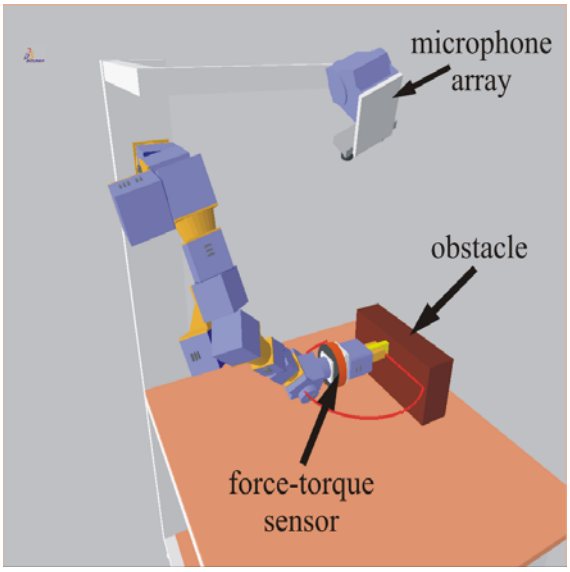

Fig. 6. NF based supervisory control of the robot-sensor system

Obviously by naked eye it is very difficult clearly to detect (not to mention to classify) the malfunction in joint 4. The signal disturbances due to collision can be clearly detected but without additional information it is difficult to distinguish it from other fault classes. A clear detection and isolation of both faults will be achieved if the NF online diagnosis concept is applied. Additional to the joint position and torque signals an acoustic sensor signal measured in the robot sensor head will be introduced (cf. Fig. 8).

In a first step residual generation according to the model and signal based methods described in chapter 3.1 will be applied. The residuals for three of the seven joints are generated; these signals, together with the response of the microphone, are analyzed by the NF based diagnosis module. Based on these extracted residuals a NF residual evaluation is applied. The obtained output responses show 3 different cases: the nominal case FF (fault free), the fourth actuator fault FJ4 and the collision situation FC.

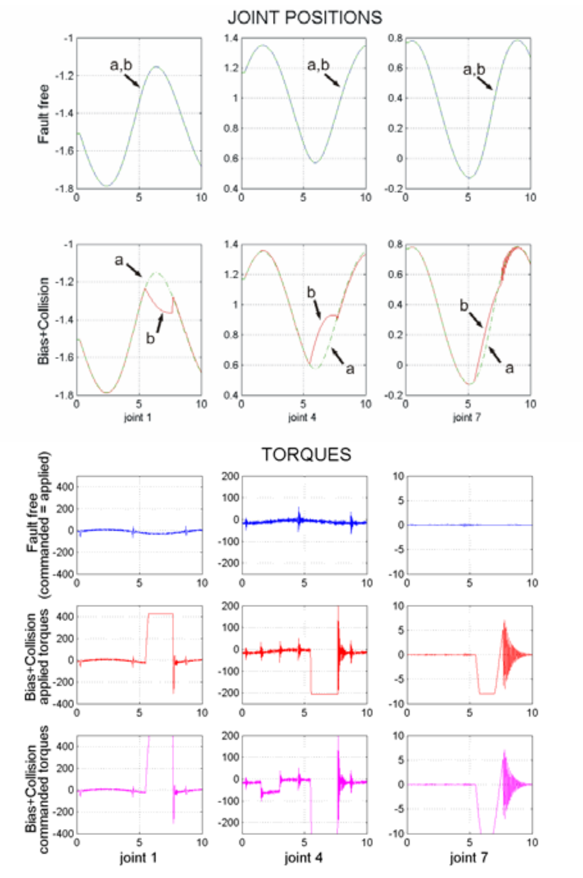

Fig. 7. Simulated time responses of torques and joint positions (a-desired position, b-actual position)

While the increase of the residuals to values different from zero only indicates some malfunction in the various robot joints, a succeeding heuristic and NF based residual evaluation can finally distinguish between the different fault classes like an actuator fault (FJ1-4) or a collision event (FC).

5 Conclusions

In this paper, a new structure variable NF based supervisory control concept for advanced multi-sensory robots (humanoid robots) is presented. It relies on a reliable identification of the actual process phases or fault cases. For each identified process phase and fault scenario by means of a heuristic Fuzzy Logic mode selector a dynamic reconfiguration of optimal situation-specific sub-controllers will be activated. About first results with its implementation within the framework of the on-going German Humanoid Robot Project will be reported.

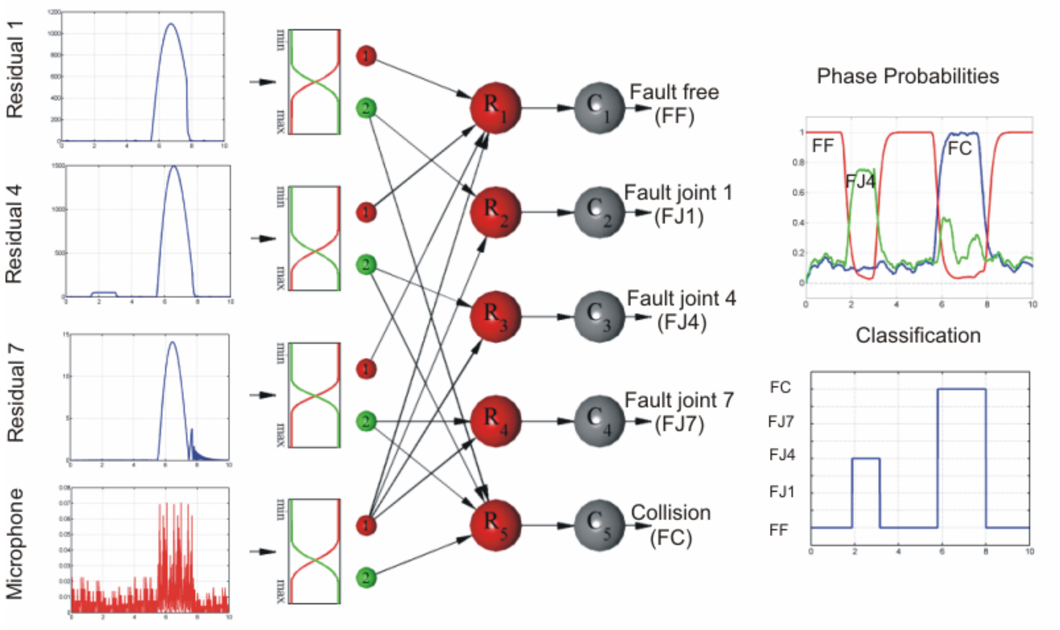

Fig. 8. Robot failure detection based on a NF residual evaluation module

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