

# INTERACTIVE AND COOPERATIVE SENSING AND CONTROL FOR ADVANCED TELEOPERATION

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## ABSTRACT

This paper presents the paradigm of interactive and cooperative sensing and control as a fundamental mechanism of integrating and fusing the strengths of man and machine for advanced teleoperation. The interactive and cooperative sensing and control is considered as an extended and generalized form of traded and shared control. The emphasis of interactive and cooperative sensing and control is given to the distribution of mutually non-exclusive subtasks to man and machine, the interactive invocation of subtasks under the man/machine symbiotic relationship, and the fusion of information and decision-making between man and machine according to their confidence measures. The proposed interactive and cooperative sensing and control system is composed of such major functional blocks as the logical sensor system, the sensor-based local autonomy, the virtual environment formation, and the cooperative decision-making between man and machine. The Sensing-Knowledge-Command (SKC) fusion network is proposed as a fundamental architecture for implementing cooperative and interactive sensing and control. Simulation results are shown.

## INTRODUCTION

Early attempts on teleoperation were based on tight coupling between the manipulator and the operator through mechanical linkages or steel tapes, as is the case of the AEC Argonne Laboratory series<sup>1</sup>, or electrical or hydraulic connections, as is the case of the GE telemanipulators built by Mosher<sup>2</sup>.

The telemanipulation based on the direct coupling between man and machine severely limits its performance: it neither accommodates the desirable mechanical dexterity due to the difficulty of manually coordinating multiple joints, nor allows high task complexity due to the difficulty of achieving required compliance. It gives an

excessive burden on the operator, which may cause long task completion time with a high failure rate.

The need to improve mechanical dexterity in teleoperation and achieve desirable compliance during teleoperation, so as to deal with more complex tasks under a partially constraint environment but with the comfort of human operator, has prompted the development of the following teleoperation paradigms:

- 1) The generalized bilateral telemanipulation<sup>3, 4, 5, 6</sup> in which the tight and one-directional coupling between the master and the slave is replaced by loose and two-directional coupling characterized by computer-based bilateral information transformation and exchange. This allows that the slave arm may not need to be the exact kinematic replica of the master arm, and that the operator can feel the contact force felt by the slave arm through force feedbacks, which allows human to execute compliance control.
- 2) The supervisory control with shared and traded control<sup>7, 8</sup>, in which a task is decomposed into temporarily (traded control) or spatially (shared control) disjoint subtasks that are to be distributed to man and machine. For instance, the operator can be supported by software jigs or spatial support means<sup>9, 10</sup> which take advantages of spatial constraints in the task to allow the slave manipulator to control those degrees of freedom specified by the motion constraint, while the operator controls the rest of degrees of freedom. Or, the slave arm with force/torque sensors is responsible for automatic compliance control, while the operator is responsible for the motion control. The supervision of telemanipulation<sup>11</sup> is done by the supervisory loop closed through the human operator, for which visual and graphic displays and force reflections from the remote site play an important role.

The recent advancement in the theory and practice of robotics and intelligent systems makes it necessary to exploit new generation of teleoperation which fully utilizes the high degree of mechanical dexterity provided by redundant and multiple arms and the capability of a robot performing sensor-based local autonomy. Especially, the role of man and machine should be redefined for advanced teleoperation in such a way that the slave arm becomes an active partner of the human operator, supporting perception, decision-making, and cooperative task execution. To achieve this requires to explore a fundamental mechanism of integrating and fusing the strengths of man and machine for advanced teleoperation.

This paper presents a paradigm of interactive and cooperative sensing and control as the fundamental mechanism of integrating and fusing the strengths of man and machine for advanced teleoperation. The interactive and cooperative sensing and control is considered as an extended and generalized form of traded and shared control. The emphasis of interactive and cooperative sensing and control is given to the distribution of mutually nonexclusive subtasks to man and machine, the interactive invocation of subtasks to achieve the man/machine symbiotic relationship, and the fusion of information and decision-making between man and machine according to their confidence measures.

## **THEORY OF INTERACTIVE AND CO-OPERATIVE SENSING AND CONTROL**

The quality of teleoperation depends on the performance of the operator in perceiving and understanding task mechanisms correctly and in generating control commands precisely in consistency with his/her perception and intention. The quality of teleoperation also depends on the performance of the machine (as a master-slave system) in providing accurate and sensitive control which is stable and robust under disturbances, system nonlinearities, and time delays.

As a means of enhancing the performance of the operator, there have been developed methods for accomplishing powerful telepresence based on sensory feedbacks using visual displays and force reflections, as well as methods for effectively training the operator to achieve the high level of expertise. On the other hand, the development of advanced teleoperator controllers based on the concept of impedance, passivity, dynamic coordination, and predictive modeling has been pursued as a means of improving the performance of the machine.

However, there exist fundamental limitations for the op-

erator to achieve accurate perception of task geometries and control behaviors and, even more so, to accomplish precise coordination between perception and action. This is mainly due to the impreciseness and low bandwidth in human sensory-motor coordination: human depends heavily on sensor-based adaptive motion corrections to compensate for imprecise positioning and is unable to respond to high bandwidth tasks. And, partly due to the difficulty of implementing powerful telepresence as well as high performance of control.

The best way of relaxing the above limitations is to fully utilize the strengths of man and machine in such a way as to achieve the mutual compensation of individual weaknesses. The strength of human lies in understanding task mechanisms, recognizing objects, generating task and motion plans under global constraints, whereas the strength of machine lies in precision positioning, quantization of primitive features, repetition of memorized tasks, and sensor-based local reflex. Attempts have been made to incorporate the strengths of man and machine in teleoperation: traded control temporally decompose a task and assigned to human and machine according to whether human or machine fits for a give subtask, while shared control spatially decompose a task into subtasks to be carried out by man and machine simultaneously. An instance of shared control is that compliance control is automatically accomplished by machine based on sensed forces, while position control is done through operator's manual control.

Although traded control and shared control provide a means of combining the strengths of man and machine, they do not present a general and powerful methodology of integrating man and machine. This is because traded and shared control is based on clear-cut decomposition of tasks into subtasks to be distributed individually to man and machine, where such decomposition is often difficult to achieve, resulting in overly simplified distribution of a task. More importantly, such a clear-cut decomposition eliminates the possibility of fusing multiple sources of information and decision-making from man and machine.

We propose interactive and cooperative sensing and control as a fundamental paradigm of integrating and fusing the strengths of man and machine for teleoperation. The interactive and cooperative sensing and control is an extended and generalized form of traded and shared control. The emphasis of interactive and cooperative sensing and control is given to the distribution of mutually non-exclusive subtasks to man and machine, the interactive invocation of subtasks with symbiotic relationship, and the fusion of information and decision-making from man

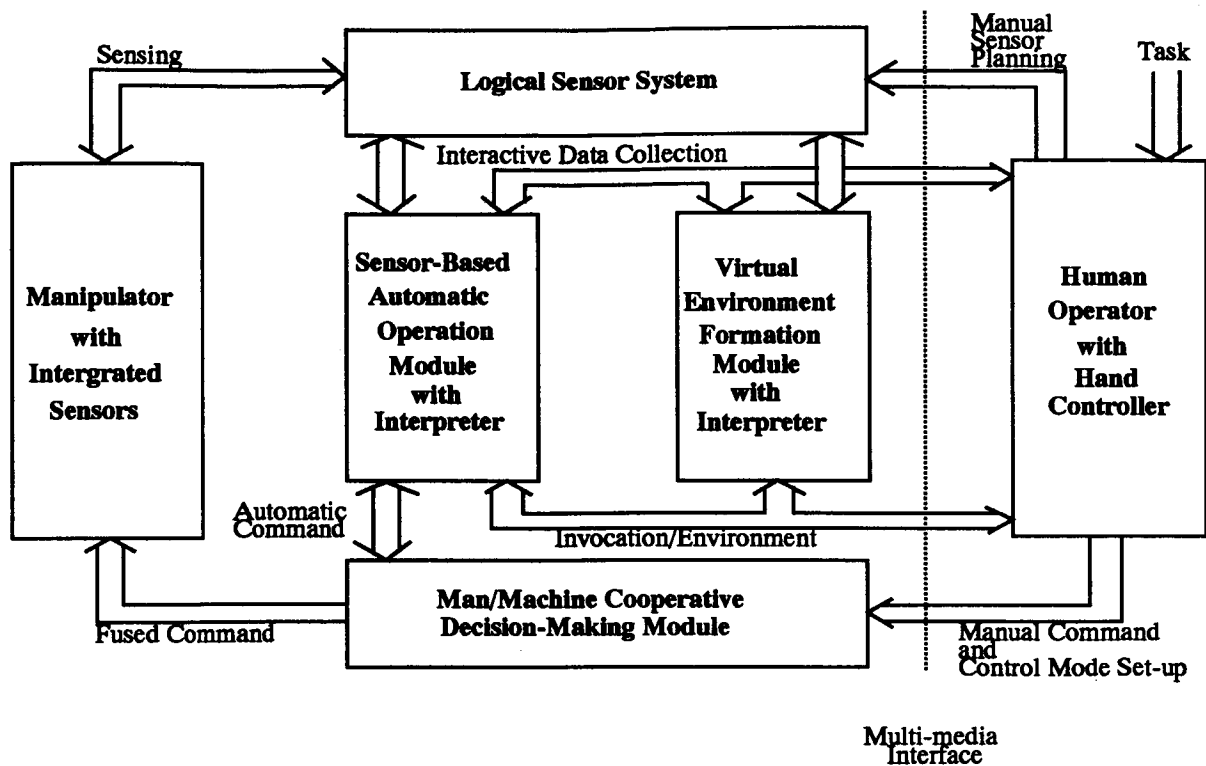


Fig.1 Interactive and Cooperative Sensing and Control for Advanced Teleoperation.

and machine according to the degree of their confidence.

The interactive and cooperative sensing and control consists of the following major functional blocks : 1) logical sensor system. 2) sensor-based local autonomy, 3) virtual environment formation. 4) cooperative decision-making between man and machine.

### Logical Sensor System

A logical sensor represents, in an abstract form, one of the many functional capabilities that the integrated sensor system can provide. The distance sensor, the surface orientation sensor, the force/torque sensor, the feature finding sensor, etc. are a few examples of logical sensors. There may or may not exist a direct association between a logical sensor and a physical sensor, such that a logical sensor can achieve its goal (to generate its output) based on the outputs of other logical sensors and/or physical sensors. Logical sensors can be hierarchically organized into a logical sensor system based on their functional interdependency. A logical sensor system not only provides a symbolic list of the various perceptual capabilities of a robot, but also represents a number of different ways of accomplishing the goal of a logical sensor. The latter is especially useful for sensor fusion. The symbolic representation of a logical sensor system pro-

vides an effective tool for the intelligent interface with the operator performing interactive and cooperative sensing. For instance, a logical sensor can be invoked by the operator in response to the system's request for providing sufficient information for a sensor-based automatic operation or a virtual environment formation initiated by the operator.

### Sensor-Based Automatic Operations

Sensor-based automatic operations are for providing the manipulator with the capability of local autonomy, such that man/machine cooperative control can be accomplished. A list of sensor-based automatic operations are predefined, out of which the operator can select and invoke a desired sensor-based automatic operation. Examples of sensor-based automatic operations include automatic tracking, automatic centering, automatic aligning, automatic compliance, etc. Once invoked, it is sent to the interpreter to transform it into a sequence of actions executable by the manipulator; during the process of interpretation, the interpreter automatically inquires the logical sensor system and/or the operator for the information necessary for the complete specification of the corresponding sensor-based operation. The operator performs, if necessary, sensor planning and interactive sensing, and invokes logical sensors.

## Virtual Environment Formation

Virtual environment formations are for providing the operator with an artificially created environment (called virtual environment) which enhance the operator's understanding of control environment and task mechanism, and, consequently, improve the fidelity of operator's manual control. The generated virtual environment provides a guidance and assistance for operator's manual control. A list of virtual environment operations are pre-defined, out of which the operator can select and invoke a desired virtual environment operation. Virtual environment operations generates displays or reflects forces which partially or fully inform the operator of the task specifications obtained by logical sensors for sensor-based automatic operations, or provide sensory feedback indicating the discrepancy from the sensor-based automatic operation. Examples include the surface normal display, the virtual force field in free space, the display of desired end effector orientations, etc. As is done for sensor-based operations, once invoked, it is sent to the interpreter to transform it into a detailed sequence of operations with interactive information collection. A virtual environment formation may or may not accompany with the corresponding sensor-based automatic operation.

## Man/Machine Cooperative Decision-making

Since it is allowed that sensor-based automatic operations and operator's manual operations carry out mutually non-exclusive tasks, we need to provide a mechanism for fusing two different source of decisions, or, simply decision fusion. The degree that individual decisions contribute to the final (optimal) decision should depend on their credibility. The credibility of decision by the machine can be estimated in terms of the certainties involved in the sensor measurements, the decision-making rules, and the constraints used in the decision making. Whereas, the credibility of decision by the operator depends on the level of expertise obtained by the experience. However, it should be noted that such credibilities are subject to variation not only with respect to time but also with respect to control situations: For instance, in case a jamming situation occurred in the peg-hole insertion process, the operator's capability of making an error correction operation based on a global planning may be more dependable than the solution based on the sensor-based automatic insertion process. To handle this variations, the operator is allowed to set the degree of contribution of individual decisions heuristically.

## Information Flow

Fig1. illustrates the information flow between the major functional blocks of the interactive and cooperative sensing and control system. The information flow can be summarized as follows:

1) Given a task, the operator may invoke the sensor-based automatic operation and/or virtual environment formation, by selecting a menu from the prespecified lists.

2) The operator can also select the system control mode as manual control, shared control, cooperative control, or automatic control, by simply adjusting the relative weight between the sensor-based automatic operation and the manual operation in cooperative decision-making. It should be noted that the sensor-based automatic operations can be used solely for the purpose of virtual environment formation, without participating in cooperative control, in case the operator invokes both the sensor-based automatic operation and the virtual environment formation, but assigns zero weight to the sensor-based automatic operation in cooperative decision-making.

3) Prior to the invocation of the sensor-based automatic operation module or the virtual environment formation module, the operator may need to perform sensor planning to ensure that the invoked operation can retrieve correct information from the logical sensor system. The interpreter of the sensor-based automatic operation or the virtual environment formation generates executable commands by filling out the existing templates through the interaction with the logical sensor system and/or the operator.

4) The virtual environment formation module provides the operator with the information representing the current control situation, especially in terms of the deviation of manual control from the sensor-based automatic operation, based on the multi-media interface using graphic displays, Cartesian space force fields at the operator's hand, and sound. The virtual environment formation offers, among other things, the visual servoing guidance and the virtual compliance which keep the manipulator from moving away from the desirable pose.

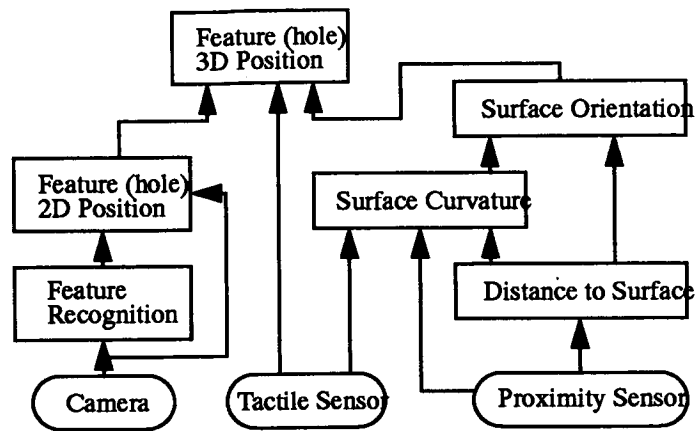


Fig.2 A part of the logical sensor system chosen for illustration

## Scenario

To explain the above concept in more detail, a typical scenario of interactive and cooperative sensing and control for advanced teleoperation is described in the following based on the peg-hole insertion task:

- Let us assume that the manipulator in a remote site has various sensors such as proximity sensors, force/torque sensors, tactile sensors, and a mini-camera mounted on the end effector, as well as stereo cameras fixed in space for the purpose of globally monitoring the task space. The capabilities of the above sensors can be summarized and organized in a logical sensor system, e.g., as shown in Fig2. Each logical sensor has its own sensing goal to be achieved through the logical sensor hierarchy. The data that a logical sensor represents is associated with a confidence measure to be used in sensor fusion, which may occur when multiple paths of achieving the sensing goal exists in the logical sensor hierarchy, and in cooperative decision-making.

- With the aid of the various sensors mounted on the end effector, the manipulator is able to perform various simple sensor-based automatic operations: maintaining orientations, tracking predefined features, reaching identified positions, reacting to contact forces for compliance, centering on a geometric feature, aligning to a surface normal, etc. These sensor-based automatic operation primitives require a minimal operator intervention for interpretation. For instance, the "Align Surface Normal" primitive requires the operator to position the end-effector near the corresponding surface prior to the invo-

cation of the primitive. The executable command will then be automatically generated by the interpreter filling out the corresponding template through the interaction with the logical sensor system, and/or the human operator.

- Let us also assume that the system is capable of providing the operator with virtual environments based on visual displays using video images and graphics, 3D force field at the operator's hand, and sound. The virtual environment can be formed by representing the discrepancy between the sensor-based automatic operation and the operator's manual operation. In fact, a sensor-based automatic operation can be invoked solely for the purpose of virtual environment formation, should the operator desired to do so. Other list of virtual environment include a force field about surface normals, a graphic overlay of commanded manipulator configuration on the video image, a graphic display of contact force and moment, etc.

- Now, let us consider that the operator is given a peg and hole insertion task, where the hole is assumed to have very small tolerance. The major difficulty of the above peg-hole teleoperation lies in the operator's generation of accurate peg motion with correct peg orientation and position. Especially, maintaining correct peg orientations throughout the insertion process is considered vital for avoiding jamming, but often not so easy to be achieved by the human operator.

- Thus, the operator can invoke "Align Surface Normal" for a sensor-based automatic operation as well as a virtual environment formation, so that not only the force field about the surface nor-

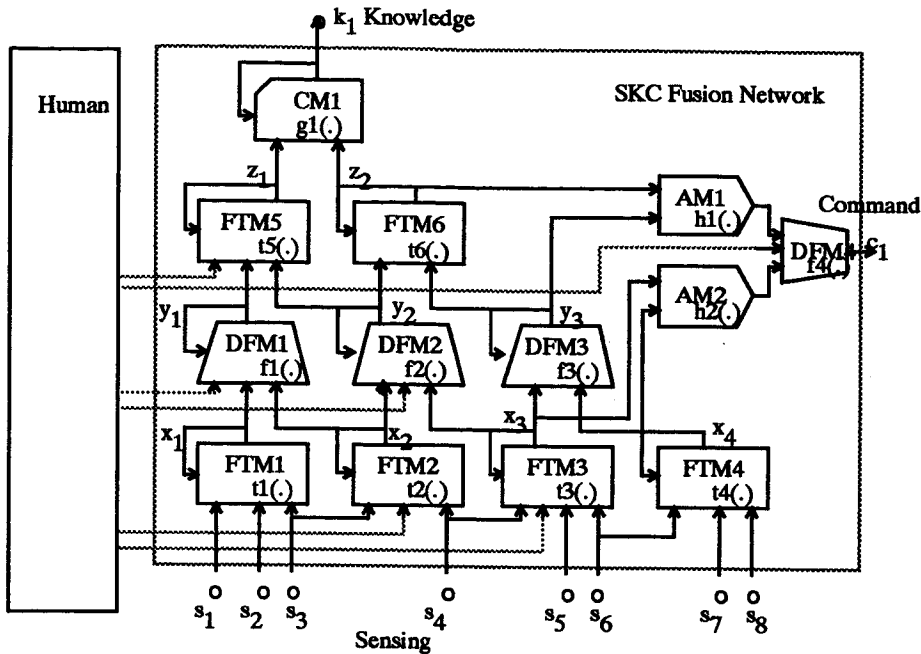


Fig. 3 The SKC fusion network architecture composed of 4 different modules: FTM, DFM, CM and AM

mal, generated by the virtual environment formation module, guides the orientation of the operator's motion, but also control decision is shared by the operator and the sensor-based automatic operation module according to their strengths.

## SENSING-KNOWLEDGE-COMMAND FUSION

The mechanism of sensor data fusion<sup>12,13,14,15,16,17</sup> can provide a fundamental means for achieving system integration since it combines multiple uncertain sensor data into more accurate and reliable estimates, identifies faulty sensors through consensus verification, and maintains consistency with existing constraints. We extend the notion of "sensor data fusion" toward a more general concept of "Sensing-Knowledge-Command(SKC) fusion" to include the integration of feature transformation and abstraction, data and concept fusion, knowledge propagation for consistency satisfaction and cooperative planning and decision-making.

The "SKC fusion network" provides a fundamental architecture for implementing cooperative and interactive sensing and control for advanced teleoperation system<sup>18</sup>. The SKC fusion network establishes the mechanism of achieving network consistency in real-time through dynamic evolution of network states: once invoked by inputs or stimuli, the SKC fusion process enforces the

network to converge to new equilibrium states through the network dynamics of data fusion, feature transformation, and constraint propagation. The cooperative control of man/machine systems is then accomplished through the SKC fusion process invoked by stimuli from both human and machine, where sensing, knowledge, and command of a human and a machine are tapped into the network to provide inputs or stimuli for the network.

## SKC Fusion Network

"SKC fusion network" represents a fundamental robotic architecture based on which the real-time connection between perception and action is accomplished. The SKC fusion network is formed by the interconnection of four basic modules: the data fusion module, the feature transformation module, the constraint module, and the action module, as shown in Fig. 3. A data fusion module(DFM) takes one or more data representing an object feature and produces the optimal estimate for the feature in cooperation with the initial state of the module. A feature transformation module(FTM) extracts a primitive features from the raw sensory data or transforms a set of primitive features into the more abstract, higher level features. An action module(AM), as a special case of a feature transformation module, issues the command to the environment based on the predefined laws triggered by a set of features. A constraint module(CM) represents system knowledge which put a constraint upon a set of feature values associated with the knowledge: the feature values

should be adjusted in such a way as to achieve a maximum consistency with the associated knowledge. The output of each module indicates the current estimates of the corresponding feature or knowledge, and is kept as the current state of the module. The state transition of a module propagates in both directions (forward and backward), and invokes the state transition of other modules having functional relationship with it. In this sense, the interconnection among modules is considered bidirectional, as represented in Fig. 3 by a feedback loop associated with each module. The domain knowledge is embedded in the network in two ways: explicitly by the constraint module, and implicitly by the functions of feature transformation modules as well as the network structure.

### Network Dynamics

The mechanism of SKC fusion network can be interpreted in terms of two operational modes: the forward mode and the backward mode. The forward mode first extracts primitive features from sensor data through low level feature transformation modules, and subsequently produces more abstract form of features through higher-level feature transformation modules. The forward mode also allows the data and concept fusion to occur through data fusion modules, whenever multiple and redundant data are available for a single feature or concept. The backward mode starts to operate upon the activation of a constraint module: based on the error detected at the constraint module, all the feature values connected to that constraint module are adjusted to satisfy consistency. The new updated feature values (as the output of feature transformation modules) in turn invokes the adjustment of lower level features connected to the module. Through a cycle of forward and backward information propagations, the network reaches an equilibrium state, i.e., all the features and concepts have consistent estimates which are optimal in the sense that redundant sources of information are fused under the constraints provided by system knowledge.

The entities of the SKC fusion network, such as data, features, concepts, and knowledge, are represented by their nominal values or equations and the degree of uncertainties associated with the normal values or equations. Thus, during a cycle of forward and backward information propagations, not only the nominal values or equations but also the degree of their uncertainties need to be adjusted. Probabilistic modeling and inference can provide a means of achieving the adjustment of the nominal values or equations, and the degree of their uncertainties. For instance, in the forward process, the output of a FTM can be characterized by a random variable,  $x$ ,

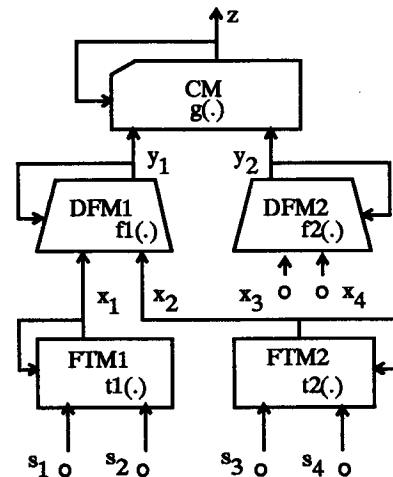


Fig. 4 A simple SKC Fusion Network used for the Description of Network Dynamics

where the probability density function,  $p(x)$ , of  $x$  is determined based on the input random variable,  $s$ , of a known probability density function and the corresponding feature transformation function,  $x = t(s)$ . The output,  $y$ , of a DFM can be determined based on the maximum likelihood estimate, the successive Bayes estimate, and the minimum variance estimate. The backward process for a CM or a FTM can be accomplished by the nonlinear optimization or the inverse mapping paradigm based on input update rule. The backward process for a DFM can be accomplished simply by the direct propagation of the output to individual inputs. The problem associated with the above approach based on successive computation of forward and backward propagation is that it is not suitable for real-time implementation due to the computational complexity involved in the processes, as well as the difficulty of processing non-Gaussian signals generated by non-linear transformations. Therefore, in this paper, we present a new approach for accomplishing forward and backward processes of individual modules simultaneously and concurrently, based on the dynamic evolution of the states of modules. The approach is based on representing the SKC network as a dynamic system in which the network dynamic state is evolving toward the equilibrium state, once invoked by input stimuli, as described in more detail in the following.

#### Dynamics of SKC Fusion Network

For the clear description of the concept of dynamic evolution of the SKC fusion network, let us consider a simple SKC fusion network illustrated in Fig. 4. Let us assume that, upon the stimuli given to the network, FTM1 and FTM2 have new inputs  $s_1$  and  $s_2$ , and  $s_3$  and  $s_4$ , respectively. This involves the states of individual modules simultaneously evolve toward the new equilib-

rium states that maintains network consistency. We propose that the evolution of system states is governed by the following dynamics:

1) The DFM-CM dynamics:

$$y_1 = -\lambda_{y_1} \{y_1 - f_1(x_1^t, x_2^t)\} - \gamma_{y_1} \nabla \phi \{z^0 - g(y_1, y_2)\} \quad (1)$$

2) the FTM-DFM dynamics:

$$x_1 = -\lambda_{x_1} \{x_1 - t_1(s_1, s_2)\} - \gamma_{x_1} \nabla \phi \{y_1 - f_1(x_1, x_2)\} \quad (2)$$

$$x_2 = -\lambda_{x_2} \{x_2 - t_2(s_3, s_4)\} - \gamma_{x_2} \nabla \phi \{y_1 - f_1(x_1, x_2)\}$$

where the initial conditions are given by the equilibrium states.

(1) and (2) represent a set of fundamental dynamic equations governing the behavior of the SKC fusion network in reaching a new network equilibrium state. The first term of a dynamic equation represents the forward process, whereas the second term represents the backward process. To deal with more complex networks, we need to simply repeat the same form of dynamic equation used for (1) and (2) for individual module of network with the proper assignment of module functions and coefficients.

The variation of  $y_1$  due to the forward process and the

variation of  $y_1$  due to the backward process should be determined in terms of the uncertainty associated with the forward process and the backward process. These variations can be controlled by the ratio between the coefficients,  $\lambda_{y_1}$ ,  $\gamma_{y_1}$ ,  $\gamma_{x_1}$  and  $\gamma_{x_2}$ . It is possible that the above dynamic coefficients can be assigned in such a way that the result of dynamic evaluation approximately matches the result from a probabilistic model. In fact, the above dynamic equations can be considered as a general form of the minimum variance estimate described previously. This observation allows not only to obtain the optimal dynamic coefficients but also to update the uncertainties (represented by covariance matrices) involved in individual states.

## SIMULATION

To demonstrate the operation of the SKC fusion network based on network dynamics given by (1) and (2), we chose the following simple example. A robot is given a task to pick up a right triangle among many different shapes of triangles. The robot is assumed to have two logical sensors:<sup>4</sup> one for the measurement of edge normals (called the "edge-normal sensor") and the other for the measurement of internal angles (called the "angle sensor"). The angle sensor is easier to handle, but has more uncertainty than the edge-normal sensor. For a given triangle, the robot measures each angle twice with the angle sensor and takes the average of two measurements. On the other hand, the robot measures the edge normals with the edge-normal sensor, and computes the internal angles from the measured edge normals. Then, a decision

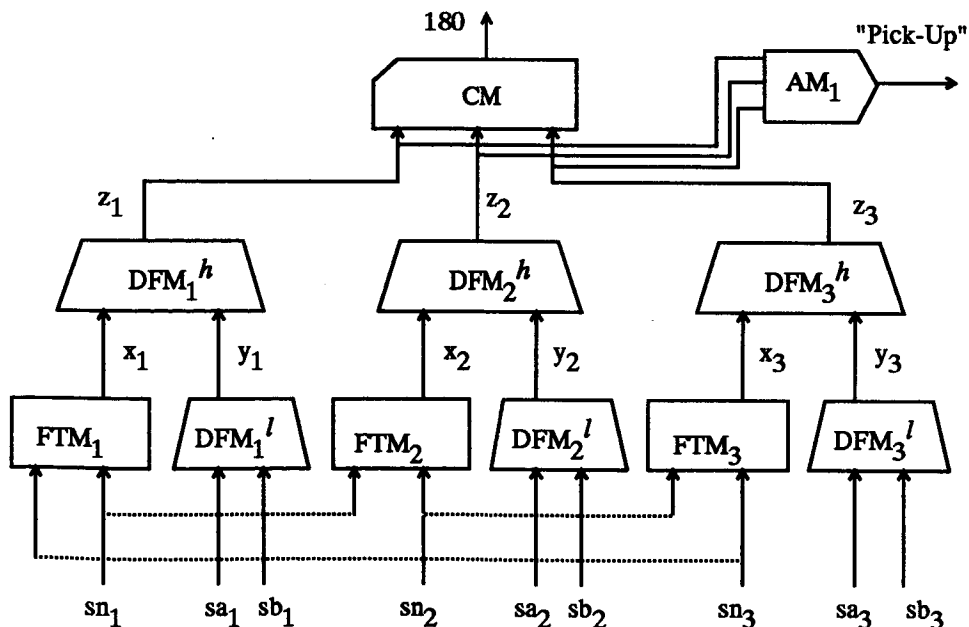


Fig.4 The SKC Fusion Network for the Task to Pick-Up the Right Triangle



is made on the size of each angle based on data from both sensors. If any of three angles is a right angle, the "pick-up" command is issued. The sum of three internal angles is subject to be 180 degrees. It is assumed that the sensor data have the known, independent Gaussian distributions.

For the task described above, we can organize the SKC fusion network as shown in Fig. 4. The two sensed data from the angle sensor,  $sa_1$  and  $sb_1$ , are fused into  $y_1$ ,

through  $DFM_1^l$ .  $FTM_1$  takes the edge normals  $sn_1$  as its input, and computes the internal angle,  $x_1$ , between those two edges. Through the feature transformation equation, these  $x_1$  and  $y_1$  are in turn fused into the angle estimates,  $z_1$ , through the higher level  $DFM_1^h$ . CM checks if  $z_1$  satisfy the constraint, i.e., the sum of internal angles is 180 degrees. As mentioned in section 3, if an error is detected in CM, it is used to adjust  $z_1$ , and propagated backward to adjust  $x_1$  and  $y_1$ . The variances of  $x_1$ ,  $y_1$ , and  $z_1$  can be computed from those of sensor data, based on the assumption of the independent, Gaussian distribution. The feature transformation function in  $FTM_1$ ,  $t_1(\cdot)$  is defined as:

$$t_1(sn) = (180 - (sn_1 - sn_2)) \text{ MOD } 360$$

where  $sn_1$  and  $sn_2$  are two edge normals, and we simply use the averaging function as the data fusion function,  $f_1(\cdot)$ , i.e.,

$$f_1(s) = (\sum_{j=1, M} s_j) / M$$

where  $s$  is the input vector with dimension  $M$ .

Based on (1) and (2), the dynamic equation for  $z_i$  is formulated as:

$$z_i = -\tau_{zi} z_i + (x_i + y_i) / 2 + \sigma_{zi} * (180 - \sum_{j=1,3} z_j), \text{ for } i=1,2,3.$$

The second term of the right hand side comes from the forward process through  $DFM_1^l$ , whereas the third term from the error in CM. Since the standard deviation  $\sigma_{zi}$  is used for the coefficient of the CM output error, with a smaller variance of  $z_i$  is less affected by the output error of CM. Similarly, the dynamic equations for  $x_i$  and  $y_i$  are formulated as:

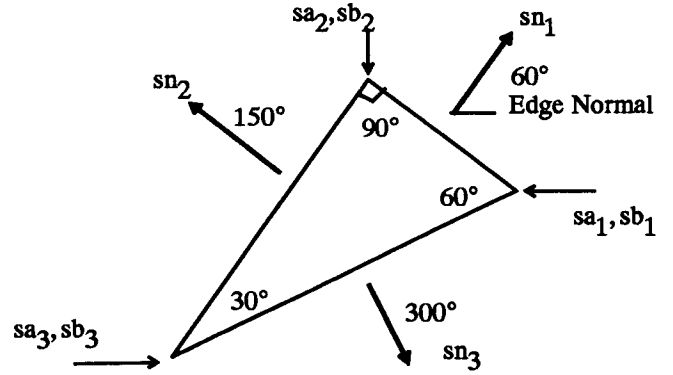


Fig. 5 The Sample Triangle and the sensing location

$$x_i = -\tau_{xi} x_i + ((180 - (sn_i - sn_j)) \text{ MOD } 360) + \sigma_{xi} * (z_i - x_i), \text{ for } i=1,2,3$$

$$y_i = -\tau_{yi} y_i + (sa_i + sb_j) / 2 + \sigma_{yi} * (z_i - y_i), \text{ for } i=1,2,3$$

Note that the error is defined here as the difference of  $z_i$  from  $y_i$  and  $x_i$ , since the input and output of DFM should be equal when an equilibrium state is reached.

Although the SKC fusion network shows the different result according to the input, a typical result for a triangle in Fig. 5 is shown in Fig. 6 with the sensor statistics and data in Tab. 1. The initial equilibrium state is chosen as the ideal data for the equilateral triangle in which all the  $x$ ,  $y$ , and  $z$  are  $[60.0 \ 60.0 \ 60.0]$  without any errors in CM and DFMs1. The sensed edge-normal data vector,  $sn$ , is quite accurate due to its small variance while the sensed angle data vector deviates a lot from the actual data. Starting from the initial equilibrium state, the top level estimate vector of angles,  $x$ , converges to the equilibrium states,  $x_e = [59.6 \ 89.4 \ 31.5]$ , which is very close to the real accurate value,  $[60.0 \ 90.0 \ 30.0]$  as shown in a). The error between  $x$  and the real value decreases gradually and finally converges to a small value as shown in b)

The error in CM remains as almost zero all the time as shown in c), and the errors in DFMs grow during the transient state, and then converge to near zero as shown in c) and d). Note that  $x$  and  $z$  are almost same in the new equilibrium state while the deviation of  $y$  from  $z$  is big. This is because there exist considerable errors in the data from the angle sensor, but  $y$  has been adjusted toward the real value in the new equilibrium state.

To explore the effect of the backward process, the above simulation is repeated with change that the backward process is invoked at time  $t=2$ , and its results are shown

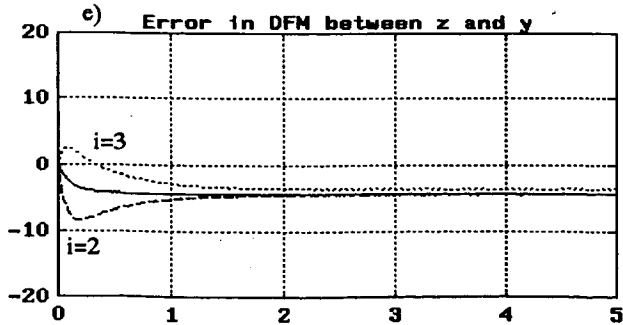
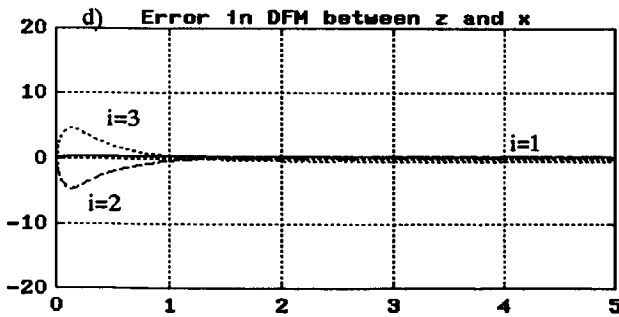
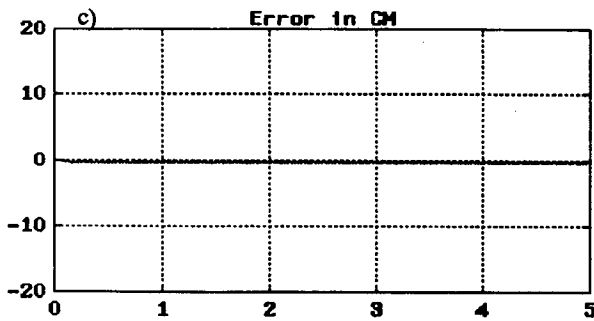
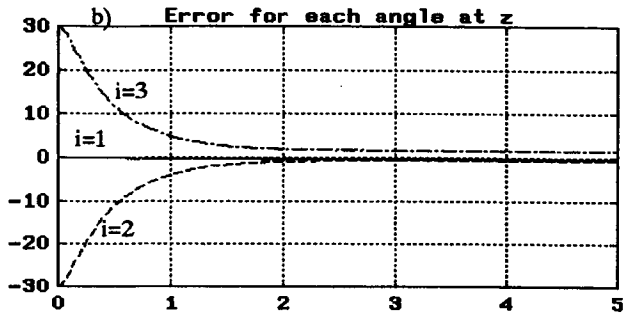
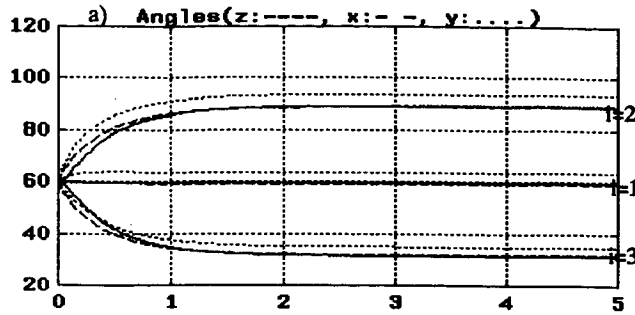


Fig. 6 Simulation results for the triangle in Fig. 5 with the parameter in Tab.1.

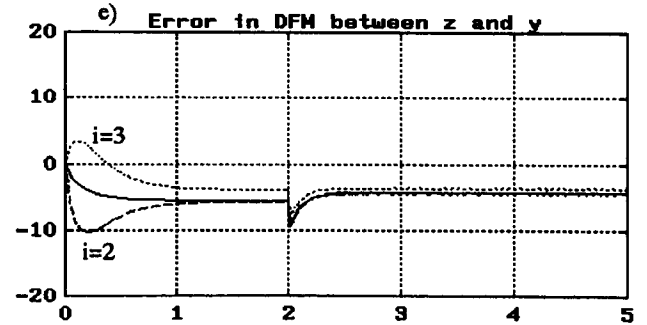
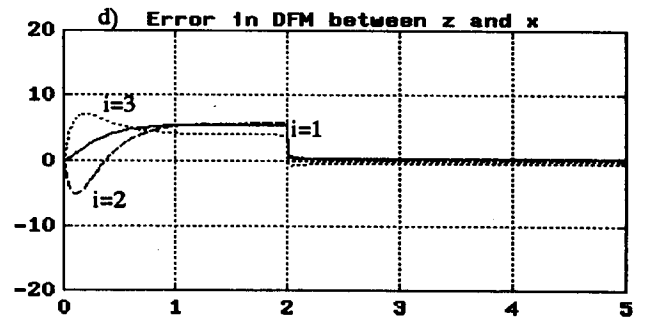
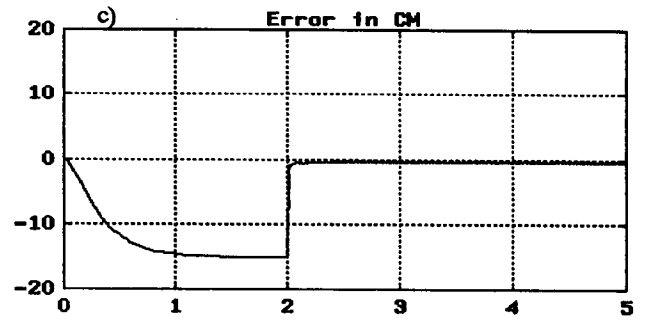
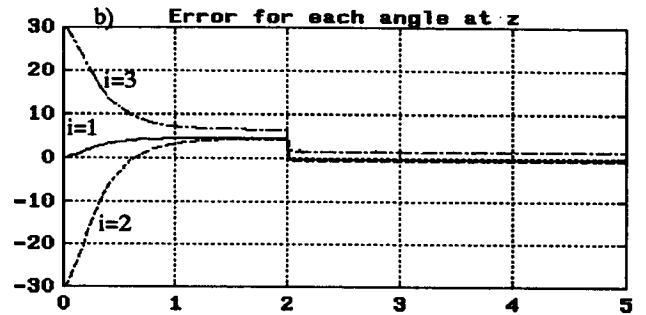
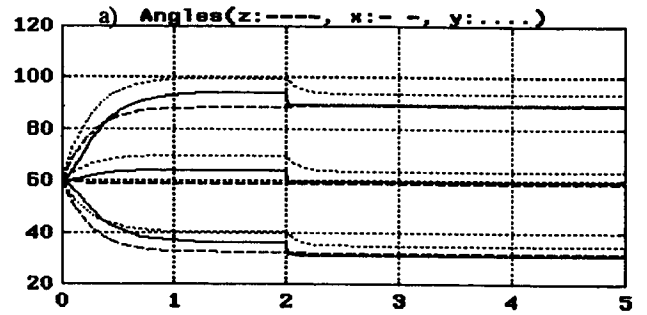


Fig. 7 Simulation results for the triangle in Fig. 5 with Backward Process started at  $t=2$ .

<b>Actual Values</b>	<b>i=1</b>	<b>2</b>	<b>3</b>
. Edge Normal, $n_i$ :	60	150	300
. Angle, $\alpha_i$ :	60	90	30
<b>Sensed Data</b>			
. Edge Normal, $sn_i$ :	59.5	151.0	298.5
. Angle, $sa_i$ :	71.5	101.5	39.5
$sb_i$ :	68.5	98.4	41.5
<b>Variance of Sensor</b>	angle:100,	edge-normal:25	
<b>Time Constant:</b>	$\tau_{xi} = \tau_{yi} = 4,$	$\tau_{zi} = 10$	

Tab.1 Actual and Sensed Data, and Sensor Parameters

in Fig. 7. Only with the forward process,  $x$  converges to equilibrium value which deviates from the real value considerably. However, it moves to another equilibrium value which is very close to the real value, just after the beginning of the backward process, as shown in a). The error between  $x$  and the real value is drawn in b) which shows clearly the error correcting effect of the backward process. The graphs in c), d) and e) also show the adjusting effects of the backward process on the errors in CM and DFMs.

## CONCLUSION

This paper presents a theory of interactive and cooperative sensing and control as a fundamental paradigm of implementing advanced teleoperation. The proposed paradigm was intended to take full advantage of the current and future capabilities of a robot performing dextrous manipulation and sensor-based local autonomy.

A new method of achieving sensing-knowledge-command (SKC) fusion was presented as a basic computational mechanism for the proposed interactive and cooperative sensing and control.

A system architecture and man/machine interface protocol was described to show the preliminary implementation of the proposed system.

There still remains much work to do to refine and consolidate theory and implementation of the proposed interactive and cooperative sensing and control for advanced teleoperation.

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