A paradigm of interactive and cooperative sensing and control is presented as a fundamental mechanism of integrating and fusing the strengths of man and machine for advanced teleoperation. Interactive and cooperative sensing and control is considered as an extended and generalized form of traded and shared control, with emphasis on the distribution of mutually nonexclusive 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 system is composed of such major functional components 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.

Early Attempts

Early attempts at teleoperation were based on tight coupling between the manipulator and the operator through mechanical linkages or steel tapes, in the case of the AEC Argonne Laboratory series [1], or electrical or hydraulic connections, in the case of the GE telemanipulators built by Mosher [2].

Telemanipulation based on the direct coupling between man and machine severely limits performance: the system 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 the required compliance. Excessive burden is typically placed 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 constrained environment, but with the comfort of the human operator, has prompted the development of the following teleoperation paradigms:

1) Generalized bilateral telemanipulation [3]-[6] 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. In this case the slave arm may not need to be the exact kinematic replica of the master arm, and the operator can feel the contact force felt by the slave arm through force feedback, which allows the human to execute compliance control.

2) Supervisory control with shared and traded control [7], [8], in which a task is decomposed into temporally (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 [9], [10] which take advantage 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 remaining degrees of freedom. Or, the slave arm with force/torque sensors is responsible for automatic compliance control, while the operator is responsible for motion control. The supervision of telemanipulation [11] 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.

Recent advances in the theory and practice of robotics and intelligent systems [12]-[15] make it necessary to exploit a 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. 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 exploration of a fundamental mechanism of integrating and fusing the strengths of man and machine for advanced teleoperation.

This article 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 focus here is on 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 Cooperative 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, methods have been developed 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 telemotor 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 operator 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 imprecision and low bandwidth in human sensory-motor coordination; the human depends heavily on sensor-based adaptive motion corrections to compensate for imprecise positioning and is unable to respond to high bandwidth tasks. Also, the difficulty of implementing powerful telepresence as well as high performance of control adds to these fundamental limitations.
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 the human lies in understanding task mechanisms, recognizing objects, and generating task and motion plans under global constraints. The strength of the 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 decomposes a task and assigns it to human and machine according to whether human or machine fits for a given subtask, while shared control spatially decomposes a task into subtasks to be carried out by man and machine simultaneously. An instance of shared control is compliance control that is automatically accomplished by machine based on sensed forces, while position control is done through an 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 relies on clear-cut decomposition of tasks into subtasks to be distributed individually to man and machine. 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.

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. There 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 provides 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 queries the logical sensor system and/or the operator for the information necessary for the complete specification of the corresponding sensor-based operation. If necessary, the operator performs sensor planning and interactive sensing, and invokes logical sensors.

Virtual Environment Formation
The virtual environment formation module provides the operator with an artificially created environment (called virtual
environment) which enhances the operator's understanding of control environment and task mechanism, and consequently improves the fidelity of operator manual control. The generated virtual environment provides guidance and assistance for the operator's manual control. A list of virtual environment operations are predefined, out of which the operator can select and invoke any desired operation. Virtual environment operations generate displays or reflect 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.

Virtual environment formation may or may not accompany 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 nonexclusive 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 the 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 his/her level of expertise obtained by 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 these variations, the operator is allowed to set the degree of contribution of individual decisions heuristically.

Information Flow

Fig. 1 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.

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 existing templates through 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 multimedia 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 desired pose.

Scenario

To explain the above concept in more detail, a typical scenario based on the peg-hole insertion task is described:

- Let us assume that the manipulator in a remote site has various sensors such as proximity sensors, force/torque sen-

Fig. 2. Part of the logical sensor system for illustration.
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 Fig. 2. 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 exist 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 orientation, 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 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 invocation 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 a virtual environment based on visual displays using video images and graphics, a 3D force field at the operator’s hand, and sound. The virtual environment may be formed by representing the discrepancy between the sensor-based automatic operation and the operator’s manual operation. In fact, sensor-based automatic operation can be invoked solely for the purpose of virtual environment formation, should the operator desire to do so. Other features of a virtual environment might 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. Maintaining correct peg orientations throughout the insertion process is considered vital for avoiding jamming, but is often not so easy to achieve by the human operator.

- Thus, the operator can invoke “Align Surface Normal” for a sensor-based automatic operation as well as for virtual environment formation, so that not only the force field about the surface normal, generated by the virtual environment formation module, guides the orientation of the operator’s motion, but also control decision is shared by both the operator and the sensor-based
automatic operation module according to their respective strengths.

Sensing-Knowledge-Command Fusion

The mechanism of sensor data fusion [19]-[26] 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 in advanced teleoperation systems [27]. 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 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 pieces of 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 primitive features from the raw sensory data or transforms a set of primitive features into 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 predefined laws triggered by a set of features. A constraint module (CM) represents system knowledge which puts 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 estimate 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 a 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 by 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 forms of features through higher-level feature transformation modules. The forward mode also allows 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 invoke 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 nominal 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
needs 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 in-
stance, in the forward process, the out-
put of a FTM can be characterized by
a random variable \( x \), where the pro-
bability density function of \( x \), \( p(x) \), is
determined based on the input random
variable \( s \) of a known probability den-
sity function and the corresponding
feature transformation function \( s = \pi(x) \).
The output \( y \) of a DFM can be deter-
dined based on the maximum likeli-
hood 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 in-
verse mapping paradigm based on the
input update rule. The backward pro-
cess for a DFM can be accomplished
simply by the direct propagation of
the output to individual inputs. The prob-
lem associated with the above ap-
proach based on successive computa-
tion 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-Gauss-
ian signals generated by nonlinear 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 module
states. The approach is based on representing the SKC network
as a dynamic system in which the network dynamic state evolves
toward the equilibrium state, once invoked by input stimuli, as
described in more detail in the following.

Dynamics of SKC Fusion Network. For a 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 \( s_1 \) and \( s_2 \), 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 trian-
gle, 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 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

\[
\begin{align*}
\dot{x}_1 &= -\lambda_{x1} x_1 - \ell_1 (x_1, x_2) - \gamma_{x1} \nabla \phi \cdot x_1 - \gamma_{y1} \nabla \phi \cdot y_1 - f_1 (x_1, x_2), \\
\dot{x}_2 &= -\lambda_{x2} x_2 - \ell_2 (x_3, x_4) - \gamma_{x2} \nabla \phi \cdot x_1 - \gamma_{y2} \nabla \phi \cdot y_1 (x_1, x_2) \\
\end{align*}
\]  

where the initial conditions are
given as an equilibrium state.

Equations (1) and (2) represent
a set of fundamental dynamic equa-
tions 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 modules of the
network with the proper assign-
ment of module functions and co-
efficients.

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, \( \lambda_{x1}, \gamma_{x1}, \gamma_{y1} \) and \( \gamma_{y2} \). It
is possible that the above dynamic
efficients 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
us to not only obtain the optimal dynamic coefficients but also
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: one for the meas-
urement 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 trian-
gle, 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 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

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angles is constrained to be 180°. It is assumed that the sensor data have a known, independent Gaussian distributions.

For the task described above, we can organize the SKC fusion network as shown in Fig. 5. The two sensed angles from the angle sensor sa1 and sb1, are fused into yik, through DFMik. FTMi takes the edge normals sn as its input, and computes the internal angle xik between those two edges. Through the feature transformation equation, xik and yik are in turn fused into the angle estimates zik through the higher level DFMik

CM checks if the zik satisfy the constraint, i.e., the sum of internal angles is 180°. As mentioned in the Network Dynamics section, if an error is detected in CM, it is used to adjust zik, and propagated backward to adjust xik and yik. The variances of xik, yik, and zik can be computed from those of sensor data, based on the assumption of the independent, Gaussian distribution. The feature transformation function in FTMik, ti(.), is defined as:

\[ ti(sn) = (180 - (sn_i - sn_j)) \mod 360 \]

where sni and snj are two edge normals, and we simply use the averaging function as the data fusion function fi(.), i.e.,

\[ fi(s) = \left( \frac{\sum_{j=1}^{M} s_j}{M} \right) \]

where s is the input vector with dimension M.

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

\[ z_i = -\tau_z z_i + (x_i+y_i)/2 + \sigma_e z_i \left( 180 - \sum_{j=1,3} z_j \right). \]

for i = 1, 2, 3. The second term of the right hand side comes from the forward process through DFMik, whereas the third term comes from the error in CM. Since the standard deviation \( \sigma_e \) is used for the coefficient of the CM output error, with a smaller variance, zik is less affected by the output error of CM. Similarly, the dynamic equations for xik and yik are formulated as:
Figure 8. Simulation results for the triangle in Fig. 6 with backward process started at t=2.

\[ \hat{x}_i = -\tau_i x_i + ((180 - (s_{n_i} - s_{n_j})) \text{MOD} 360) + \sigma_{x_i} (z_i - x_i) \]

for \( i = 1, 2, 3 \),

\[ \hat{y}_i = -\tau_i y_i + (s_{a_i} + s_{b_i}) / 2 + \sigma_{y_i} (z_i - y_i) \]

for \( i = 1, 2, 3 \).

Note that the error is defined here as the difference of \( z \) from \( y \) and \( x \), since the input and output of DFM should be equal when an equilibrium state is reached.

Although the SKC fusion network shows a different result according to the input, a typical result for a triangle in Fig. 6 is shown in Fig. 7 with the sensor statistics and data in Table I. 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 DFM.

The sensed edge-normal data vector \( s_n \) 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 angular estimate vector \( x \) converges to the equilibrium state \( x_{eq} = [59.6, 89.4, 31.5] \), which is very close to the real 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 always remains near zero as shown in c), and the errors in DFMs grow during the transient state, then converge to near zero as shown in c) and d). Note that \( x \) and \( z \) are almost the same in the new equilibrium state while the deviation between \( y \) and \( z \) is large. 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 the change that the backward process is invoked at time \( t=2 \); results are shown in Fig. 8. With only the forward process, \( x \) converges to the 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 effect of the backward process on the errors in CM and DFMs.

Taking Full Advantage of Robot Capabilities

The theory proposed here, of interactive and cooperative sensing and control as a fundamental paradigm of implementing advanced teleoperation, 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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References


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