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Information Technology for Interactive Robot Task Training Through Demonstration of Movement[1]

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Abstract

Remote robot control (telecontrol) includes the solution of the following routine problems: surveillance of the remote working area, remote operation of the robot situated in the remote working area, as well as pre-training of the robot. The current paper describes a new technique for robot control using intelligent multimodal human-machine interfaces (HMI). The first part of the paper explains the robot control algorithms, including testing of the results of learning and of movement reproduction by the robot. The application of the new training technology is very promising for space robots as well as for modern assembly plants, including the use of micro-and nano-robots.

Keywords: Robot, telecontrol, task training by demonstration, human-machine interfaces.

5.1 Introduction

The concept of telesensor programming (TSP) and relevant task-oriented robot control techniques for use in space robotics was first proposed by G. Herzinger [1].

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Within the framework of the ROTEX program, implemented in April 1993 for the SPACE-LAB space station, a simulation environment for multisensory semiautonomous robot systems, with powerful man-machine interfaces (laser range finders, 3D-stereo graphics and force/torque effort reflection), was developed. This allowed the space robot manipulator to be remotely programmed (teleprogrammed) from Earth.

The solution for the problem of remote control under non-deterministic delays in the communications channel is based on the use of TSP with training by demonstration for the sensitized robot.

Tasks such as assembly, joining of connectors and catching flying objects were practiced. Actually, it was the first time that a human remotely trained a robot through direct movement demonstration using a graphic model with robot sensor simulation.

The effectiveness of interactive control (demonstration training) is highlighted in all cases of the application of pre-training technology to space and medical robots, as the most natural way to transfer the operator's experience (SKILL TRANSFER) in order to ensure autonomous robot manipulator operation in a complex non-deterministic environment [2–5].

However, in these studies it was only possible to conduct training with the immediate recording of the movement trajectory positioning data and the possibility of motion correction as per the signals from the robot's sensors.

These studies did not solve the problem of complex robot motion representation as a certain data structure that is easily adjustable by humans, or "independently" modified by the autonomous robot, depending on changes in the remote environment.

The current paper describes a new information technology-based approach for interactive training by demonstration of the human operator's natural hand movements based on motion representation in the form of a frame-structured model (FSM).

Here, a frame means a description of the shape of motion with indications of its metric characteristics, methods and sequence of execution of the separate parts of the movement. Training by demonstration means intelligent robot manipulator programming aimed at training the robot for autonomous work with the objects (among the objects) without point-to-point trajectory recording. That is, by providing only separate fragments of movement in the training stage, and sequentially executing them, depending on the task.

In order to train a robot manipulator to move among objects it was suggested to use a remotely operated camera, fixed to the so-called "sensitized glove". This allows not only the registration of position and orientation of the hand in space, but also the position of the object (experimental models) models' characteristic points relative to the camera on the hand.

5.2 Conception and Principles of Motion Modeling

5.2.1 Generalized Model of Motion

A variety of robot motion types in the external environment (EE), including manipulation of items (objects and tools) as well as the complexity and variability of EE configurations, are typical for aerospace, medical, industrial, technological and assembly operations.

Let us consider the problem of training the robot manipulator to perform motion relative to EE objects in two cases: examination motion and manipulative motion. The main issue in forming the motion patterns, set, in this case, by the motions of the operator's head and arm, is to have a method for recording and reproducing the three-dimensional trajectories of the robot manipulator grip relative to EE objects.

The problem of the alignment of the topology and the semantics of objects, well known in geographic information systems (GIS), is basically close to the problem of motion modeling and route planning in robotics.

In the case of navigational routing tasks using intelligent GIS, the authors basically consider motion along a plane (on the surface of the sphere) or several planes (echelon gratings). Moreover, in most cases, the moving object is taken as a mathematical point, not having its own orientation in space.

The motion path configuration in space often does not matter, so routing is carried out over the shortest distance. Thus, while following the curvature of the relief, the motion tracks its shape.

For object shape modeling and motion formation, we propose using a common structured description language, which considers that the object shape model is defined and described by a frame of its elements, and the motion trajectory model is described by a frame of descriptions of the elementary motions. It is important to note that the elementary motions (fragments) can be given appropriate names and be considered to be the language operators, providing the possibility of describing robot actions in a rather compact manner.

For interactive motion demonstration robot training, we propose using a combination of the EE (MEE) objects' shape models and the motion shape models (MFM). In this case, the generalized frame-structured model (FSM) is defined as a method for storing information not only about the shape of the EE objects, but also about the shape of the motion trajectory.

The description language used in FSM is a multilevel hierarchical system of frames, similar to M. Minski frames [6], containing a description of the shape elements, metric characteristics and methods and procedures for working with these objects. MFM, as one of the FSM components, stores the structure of the shape of motion trajectories demonstrated by the human operator during the process of training the robot to perform specified movements [7, 8].

The generalized FSM of the remotely operated robot IE includes:

- Object models, models of the objects' topology (location) in a particular IE (MIE);
- Models of different typical motions and topology models (interrelations, locations) of these movements in a particular IE (MIE).

It is also proposed to store, in the MIE, the coordinates and images of objects from positions convenient both for remote-camera observation (which enables the most accurate measurement of the coordinates of the characteristic features of object images) and for grabbing objects with the robot gripper (Figure 5.1) [9].

Training of motion can be regarded as a transfer of knowledge of motor, sensory, and behavioral skills from a human operator to the robot control system (RCS), which in this case should be a multimodal man-machine interface (MMI), developed to the greatest possible extent (intelligent) to provide adequate and effective perception of human actions. Consequently,

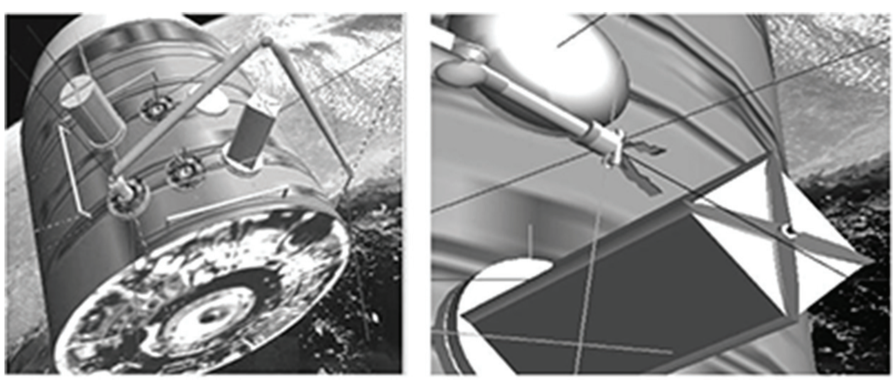

Figure 5.1 Images of the Space Station for two positions: "Convenient for observation" and "Convenient for grabbing" objects with the virtual manipulator.

it is assumed that a generalized model of description of the robot knowledge on the EE based on the FSM will be created, including the robot itself and its possible (necessary) actions within it.

The preliminary results of the research on algorithms and technologies for the robot manipulator task training by demonstration, using the motion description in the form of MFM, are presented below.

5.2.2 Algorithm for Robot Task Training by Demonstration

In order to task-train the robot by demonstration, a special device, the so-called "sensitized glove," is put on the hand of the trainer. It is equipped with a television camera and check points (markers) [10].

This allows the execution of two functions simultaneously (Figure 5.2):

- Using the television camera on the glove, record the image and determine the coordinates of the objects' characteristic points, over which the hand of the human operator moves;
- Using the sensors of the intelligent MMI system, determine the spatial position and orientation of the hand in the work location by means of 3–4 check points (markers) on the glove.

Considering the processes for task-training a robot to perform elementary operations and reproducing these operations, an important feature is revealed. This feature consists in the fact that algorithms for training and reproduction present fragments, which are used in different operations without

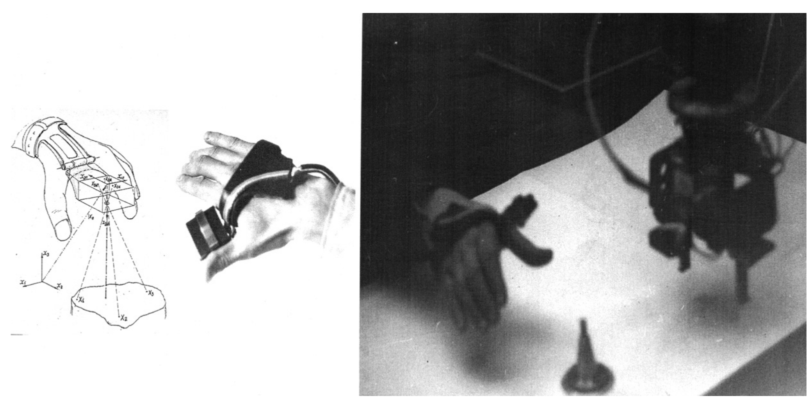

Figure 5.2 "Sensitized Glove" with a camera and the process of training the robot by means of demonstration.

modifications or with very minor changes, and may also be repeated several times in a single operation.

From among the various movements of the robot manipulator, most of them can be represented as a sequence of a limited number of elementary motions (motion fragments), for example:

- Transfer motion of the gripper along an arbitrary complex trajectory $g = g(l)$ from the current position to a certain final position;
- Correction motion, using the sequence of characteristic points (CP) of the EE objects' images, as input information;
- Surveillance movement in the process by which the following are sequentially created: matrices of the gripper position T_b, T_{b1}, T_{b2}, joint coordinate vectors g_b, g_{b1}, g_{b2}, and geometric trajectory $g = g(l)$;
- Movement to a convenient position for surveillance;
- Movement to a convenient position for grabbing;
- Movement for "tracking" the object (approaching the object);
- Movement to grab the object.

In traditional training systems using one or the other method, a sequence of points of the motion trajectory of the robot gripper is obtained. It can be represented as a function of some parameter l, which can be considered as the preliminary result of training the robot to perform the fragment of the gripper movement from one position to the other:

$$g = g\left(l\right), l_b \ \le \ l \ \le \ l_e$$

$$g_b \ = g\left(l_b\right), g_e \ = g\left(l_e\right),$$

where: l_b – parameter of the trajectory in the initial position, l – parameter of the trajectory in the current position, l_e– parameter of the trajectory in the final position.

In this case, the training algorithm for performing motions ensures the formation of geometric trajectory $g(l)$ and includes the following:

- Formation of a sequence of triplets of the two-dimensional vectors ${x_{imb}}^{(1)}$, ${x_{imb}}^{(2)}$, ${x_{imb}}^{(3)}$; ${x_{imI}}^{(1)}$, ${x_{imI}}^{(2)}$, ${x_{imI}}^{(3)}$; $\ldots$; ${x_{ime}}^{(1)}$, ${x_{ime}}^{(2)}$, ${x_{ime}}^{(3)}$, conforming to the image positions of the 3 CP on the object during training;
- Formation of the sequence T_b, T_I, $T_{II}, \ldots, T_e$ of the matrices of the glove position;
- Solution of systems of equations (5.1):

$$x_{im}^{(i)} = \ (x_{im1}^{(i)}, x_{im2}^{(i)}) \ = \ k^{(i)}\widehat{T}X^{(i)}, \tag{5.1}$$

where: $k^{(i)}$is a variable scale, defined as: $k^{(i)} = f / d^{(i)}\text{-}f$, where $d^{(i)}$ is the distance from the point to the TV camera showing the plane; f is the focal distance of the lens, $\widehat{T}$is a (2x4) matrix made up of the first two rows of matrix: $T = \left|\begin{array}{c|c} \alpha & Xn \\ \hline 0 & 1 \end{array}\right|$, characterizing the rotation and displacement of the system of coordinates (CS), in conjunction with the camera on the glove, relative to the object CS, where a is the direction cosine matrix of the reference CS rotation angle, X_n the displacement vector of the beginning of the CS and $X^{(i)}$ – the two-dimensional vectors of the position of the image of the characteristic points of the object in the image plane.

This data is sufficient to construct a sequence of matrices of the gripper positions T_b, T_1, T_{II}, ..., $T_e$during movement. The orientation blocks in these matrices are matrices α_b, α_1, α_{II}, ..., α_e. The block of the gripper pole position corresponds to the initial position of the gripper. According to this sequence, the geometric, and, in line with it, the temporal motion trajectory of the gripper can be built.

When teaching this action, the operator must move his hand with the glove on it in the manner in which the gripper should move during the process of the surveillance motion, whereas the position of the operator's wrist can be arbitrary and convenient for the operator.

Furthermore, for each case of teaching a new motion, it is necessary to memorize a new volume of motion information in the form of several sets of coordinates mentioned above.

When teaching the motions, e.g. IE surveillance, it is necessary to store a considerable amount of information in the memory of the robot control system (RCS), including:

- Values of matrix *T,* which characterize the position and orientation of the glove in the coordinate system of the operator's workstation, corresponding to initial T_b, final T_e and several intermediate T_1, T_{II}, ... gripper positions, which it must take when performing movements;
- Several images of the object from the glove-mounted TV camera, corresponding to the various gripper positions, to control the accuracy of training;
- Characteristic identification signs, characteristic points (CP) of the different images of the object, at different glove positions during the training process;
- Coordinates of the CP of the images of the object in the base coordinate system;

- Parameters of gripper opening and the permissible compressive force applied to the subject.

To reduce the amount of information and to present the motion trajectory in a language is close to the natural one, it is suggested to use a frame-structured description in the motion shape model (MFM), the basic principles of which are described in the previous papers by the authors [11, 12].

5.2.3 Algorithm for Motion Reproduction after Task Training by Demonstration

The specific feature of the robot's motion reproduction in a real IE is that fragments of elementary movements, stored during task training can follow a different sequence depending on the external conditions when reproduced. Due to the aforementioned features, it appears to be reasonable to teach the robot to do different fragments of motion in various combinations of the given fragments.

The number of applied elementary motions (fragments) increases along with the number of reproduced operations. However, this increase will be much smaller than the increase in the number of operations for which the robot is used. It is important to note that proper names can be assigned to the given elementary motions and they can be considered to be operators of the language with the help of which the robot's actions can be described in a sufficiently compact manner.

On the basis of the frame-structured description of the MFM, obtained during task training, the so-called "tuning of the MFM" for a specific task is performed before starting the reproduction of motion by the robot in a particular IE situation.

Practically, this is done by masking or selection of only those descriptions of motion in the MFD that satisfy the conditions of the task and the external conditions of the situation in the IE according to their purpose and shapes (semantic and topological features). The selected movements are automatically converted into a sequence of elementary movements $g = g(l)$.

In the case of the reproduction of the elementary motion along the trained trajectory $g = g(l)$ in systems without sensor offsetting it is necessary to construct a parameter change function $l(t)$ in the area $l_b \leq l \leq l_e$. Typically, the initial and final velocities $l(t)$are known, and they are most commonly equal to zero:

$$l'_b = l'_e = 0.$$

In the simplest case of the formation of *l(t),* three intervals can be singled out in it: the "acceleration" interval from the initial velocity (l'_b) to some permissible speed (l'_d), the interval of motion at a predetermined speed and the deceleration interval from the predetermined velocity to zero (l'_e).

During acceleration and deceleration a constant acceleration (l''_d) must take place. Its value should be such that the value of the velocity g' and acceleration g'' vectors can be physically implementable under the existing restrictions of the control vector *(U)* of the robot manipulator's motors.

The values of these limitations can be determined based on the consideration of the dynamic model *(R)* of the robot manipulator, which connects the control vector *(U)* to the motion dynamics vectors (g, g', g''):

$$U \; = \; R \; \left(g, \; g', \; g''\right).$$

In the case of the motion reproduction transfer of function *l = l(t)*, it is defined by the following ratio:

- During the acceleration interval ($0 < t = t_1$), where $t_1 = sign \; (l'_d) \, \frac{|l'_d|}{|l''_d|}$;
- During the interval of motion at a constant velocity - ($t_1 \leq t \leq t_2$), where $t_2 = \; t_1 + \frac{|l_e - l_b|}{|l'_d|} - \frac{|l''_d| t_1^2}{|l'_d|}$: $\; l\,(t) \; = l'_d\,(t - t_1) + l_b \frac{sign(l'_d) \cdot t_1^2}{2|l''_d|}$;
- During the deceleration interval ($t_2 \leq t \leq t_3$), where $t_3 = 2t_1 + \frac{|l_e - l_b|}{|l'_d|} - \frac{|l''_d| t_1^2}{|l'_d|}$:

$$l\,(t - t_1) \; = \; l'_d\,(t - t_1) + l_b + \frac{sign(l'_d) t_1^2}{2} - \frac{sign(l'_d) l''_d (t - t_2)}{2}.$$

The reproduction of movement over time by the robot is carried out as per the implementation of the obtained function *l(t)* in the motion trajectory *g(l)*:

$$g \; = \; g\,(l\,(t))\,.$$

To determine the drives' control vector $U = R\ (g,\ g',\ g'')$ the substitution of values g, g', g'' by the values of function *g = g (l (t))* is carried out. This results in the formation of the control function of the motors of the robot manipulator over time.

It should be noted that a man performs natural motions with constant acceleration, in contrast to the robot manipulator, whose motions are characterized by a constant rate (speed). Therefore, the robot has to perform its motions as per its own dynamics, which differ from the dynamic properties of the human operator.

5.2.4 Verification of Results for the Task of Training the Telecontrolled (Remote Controlled) Robot

Remotely operated robots must be sufficiently autonomous and trainable to be able to efficiently perform operations in remote environments distant from the human operator. Naturally, task training for space robots must be performed in advance right here on Earth, and medical robots shall be trained out of the operation theaters.

At the same time, a possibility for the remote correction of training outcomes must be provided, for possible additional training by the human operator, located at a considerable distance from the robot in space or from a remotely controlled medical robot.

For greater reproduction reliability, it is necessary to implement an automated process control over motion reproduction by the remotely controlled robot using copies of the MFM and MEE from the RCS. Remote control over the robot movements by a human operator must be carried out using prediction, taking into consideration the potential interference and time delays in the communications channel.

Actual remote control of the space robot or the remotely operated medical robot must be carried out as follows:

- With some time advance (prediction), simultaneously with working motion execution by the robot, control over the current robot motion is performed on the simulator, which includes the MEE, MFM and the intelligent MMI system;
- Data from the RCS, arriving with delay, is reflected on the MEE and MFM and is compared to the predicted movement in order to provide the possibility of emergency correction;
- The trajectory of motion relative to the real location of the MEEs is automatically adjusted by the RCS as per sensor signals;
- By human command (or automatically by the RCS) correction of parameters and operational replacement of the motion fragments are carried out in accordance to the pre-trained alternative variants of the working motion.

After the execution by the robot of the regular working movement, actual motion trajectories in the form of a description in the language of MFM, compiled after an automatic motion analysis in the RCS, are transferred from the RCS to the human operator in the modeling environment. This information, together with the results of the real EE scanning by the robot during the robot's execution of the working movement, is to be used for correction of the MFM and MEE.

In the absence of significant corrections in the process of executing the working movement, the training is considered to be correct, understanding between the human operator and the RCS is considered to be adequate, and the results of the robot task training can be used in the future.

5.2.5 Major Advantages of Task Training by Demonstration

The proposed algorithm for task training by demonstration of the motion has a number of advantages over conventional methods of programming trajectories or motion copying, when the operator, for example, moves in space the manipulator's gripper along the desired trajectory with continuous recording of the current coordinates in the memory of the robot. Let us list the main ones.

Using the professional skills and intuitive experience of the human being. The human being, using his professional skills and intuitive experiences, demonstrates motions by hand, which are automatically analyzed by the MMI (for configuration acceptance and safety) and are conveyed to the robot in the form of a generalized MFM description. Conventional means of supervisory control, in which remote control or a joystick, are used to set the generalized command, are further developed in this case.

Simplicity and operational efficiency of training. Training is performed by simple movements of the human hand without any programming of the complex spatial displacements. It is more natural and easier for the human being to control the position of his hand during the execution of movement, than doing the same using the buttons, mouse or joystick. Experiments have shown that practically everyone can learn to control a robot through hand motion and it can be done in just a few hours. Time and cost of personnel training, for the control and training of robots are significantly reduced.

Relaxation in the requirements for motion accuracy. Instead of the exact copying and recording of arrays of coordinates of the motion trajectory during robot manipulator training, the operator gives only assignment (name) and shape of the spatial motion trajectory, including the manipulation of items, tools and EE objects. The free movement is set by the human being and is reproduced by the robot at a certainly safe distance from the objects; therefore, minute accuracy of such movements is not required. In the case where the robot gripper approaches the object, the motion is automatically adjusted according to information from the sensors, including the force-torque sensing. There is no need to copy the exact motions by the remotely operated robots, which are commonly used in partially nondeterministic EE, when there is no precise information about the location of the robot and obstacles.

Reliability of control over the autonomous robot. One of the advantages lies in the fact that there is no need for the operator to be close to the working area or to be present in the working area of the remotely operated robot, for example, inside the space station, or on the outer surface of the orbital station for operational intervention in the robot's actions, avoiding therefore delays and interferences in the communications channels. Based on the descriptions of the MFM and MEE, the intelligent RCS can automatically adjust the shape, and even the sequence of the trained motions of the robot.

Ease of control, correction and transfer of motion experience. The visual appearance of motion presentation in a MFM, its proximity to natural language of the frame structured movement description, allow reliable checking, in-flow change of composition, sequence and shape of the complex working movements directly according to the motion description text using the graphical model of robot manipulator, as well as a human model ("avatar") [13].

5.3 Algorithms and Models for Teaching Movements

5.3.1 Task Training by Demonstration of Movement among the Objects of the Environment

Robot task training and remote control is performed using the modeling environment, which contains an EE model (MEE), a model of the shape of motion (MFM) and an intelligent system for the multimodal interface (IMI), creating the so-called human "presence effect" in a remote EE using the three-dimensional virtual models and images of real items. Using the IMI, the operator can observe 3-D images on either side, like in holographs, can touch or move the virtual objects, feeling with his hand the tactile and force impact through simulations of object weight or its weight in zero-gravity environment [14, 16].

Instead of real EE models the virtual MEE image can be used, as well as a computer hand model, controlled by the hand position tracking system (HPTS), included in the IMI [17].

The process of training the robot to move among OE objects implies that the operator's hand, dressed in a sensitized glove, executes the motion in OE space that must be subsequently performed by the manipulator gripper. In order to do this, it is necessary to perform the following operations (in on-line mode) in the training stage:

- Demonstrate a fragment of the operator's hand motion among objects of the OE model or of the virtual hand model in the graphical model of the OE (MOE);
- Register through the IMM system and store in memory the fragment of motion containing the timestamps and a corresponding vector *(X)* of 6 dimensions ($x = x\ (l)$, $y = y\ (l)$, $z = z\ (l)$) and orientation ($\varphi_x = \varphi_x(l)$, $\varphi_y = \varphi_y(l)$, $\varphi_z = \varphi_z(l)$) of the operator's hand;
- Recognize the motion shape through the IMI system and record the results in the form of a frame-based description in MFM;
- Record the images of objects, obtained through the TV camera on the glove in the process of moving the hand and carry out recognition, identification and measurement of the coordinates of the characteristic points of the objects' images and enter this data into the MOE;
- Add to the MFM the information about the location of MOE objects relative to the glove at the moment of execution of the fragment of movement.

The position of the sensitized glove relative to objects of the EO model is determined during the process of training by demonstration by solving the so-called "navigation task". This research offers a unique solution of the navigation task for the given case [18].

While training the robot by means of demonstration, the objects (models) of the OE come in view of the TV camera fixed on the sensitized glove. There can be objects of manipulation or foreign objects (obstacles).

For the industrial and aerospace application of robots, the objects generally have regular geometric shapes, angles and edges, which may be used as characteristic features and characteristic points.

Characteristic points (CP) can be small-sized (point) details of objects, which can be easily distinguished on the image, as well as special marks or pointed sources of light. These points are the easiest way to determine the position and orientation of the camera on the sensitized glove relative to the OE objects, that is, to solve the so-called "navigation problem" during the process of robot task training.

Let us consider a case, where the position vectors of the object's CP $X^{(i)}$, (i = 1, 2, 3 – No. of CP) in a coordinate system associated to the object (CS) are known beforehand. Images of 3 CPs of the object (${X_{im}}^{(1)}$, ${X_{im}}^{(2)}$, ${X_{im}}^{(3)}$) on the TV camera's image surface are projections of the real points

(CP1 ... CP3) on this plane in a variable scale $k^{(i)}$=f /$d^{(i)}$-f, inversely proportional to the distance $d^{(I)}$ from the point to the imaging plane of the lens, where f is the focal length of the lens.

Let us assume that the CS, associated with the camera lens, and, therefore, with the glove, is located as shown in Figure 5.3, i.e. axes x_1 and x_2 of the CS are located in the image plane, x_3 is perpendicular to them and is directed away from the lens towards the object. In Figure 5.3: x_1, x_2, x_3 are the axes of the coordinate system associated with the object; $x^{(1)}$, $x^{(2)}$, $x^{(3)}$ are the vectors defining the position of characteristic points in the coordinate system of the camera lens; ${x_{im}}^{(2)}{}_1$, ${x_{im}}^{(2)}{}_2$ are 2 projections of the vector from the center of the CCD matrix to the image of point 2 (this can also be shown for points 1 and 3).

Then, distance $d^{(i)}$ is equal to the projection of the i-th CP on the third axis of the CS associated with the camera: $d^{(i)}$ = ${x_{im3}}^{(i)}$, and the location of the object $X^{(i)}$ in the image plane will be represented by two-dimensional vectors:

$$x_{im}^{(i)} = (x_{im1}^{(i)},\ x_{im2}^{(i)}) = k^{(i)}\widehat{T}X^{(i)}, \tag{5.2}$$

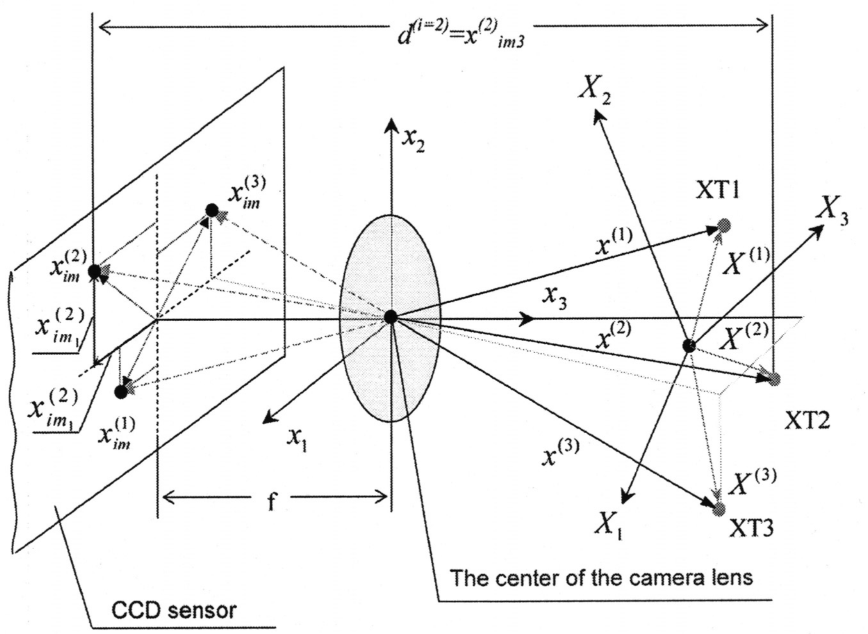

Figure 5.3 Formation of images of 3 characteristic points of the object.

where: $\widehat{T}$ is a (2×4) matrix made up of the first two rows of matrix $T = \begin{vmatrix} \alpha & Xn \\ \hline 0 & 1 \end{vmatrix}$ characterizing the rotation and displacement of the CS associated to a camera on the glove, relative to the CS of the object, where a is a direction cosine matrix relative to the turning angle of the SC and $X_n = (X_{n1}, X_{n2}, X_{n3})$ is the displacement vector of the SC's origin,

$$X^{(i)} = (x_1^{(i)}, x_2^{(i)}, x_3^{(i)}, 1).$$

Then: $d^{(i)} = x_{im3}{}^{(i)} = T_3 . x^{(i)}$, where T_3 is the third row of matrix T.

It is obvious that matrix *T* completely determines the spatial position of the glove in the CS associated to the object, and its elements can be found as the result of solving the abovementioned navigation problem of determining the spatial position of the glove during training.

During the CP image processing, vectors $x_{im}{}^{(i)}$, $i = 1, 2, 3$ are determined, so the left side of Equations (5.2) is known, and these equations represent a system of six equations concerning 12 unknown elements of matrix *T*, which are the three components of vector X_n and nine elements of matrix a.

Since the elements of matrix a are linked by six more equations of orthogonality and orthonormality, there are a total of 12 equations, that is, as many as the unknowns. These are obviously sufficient to determine the desired matrix *T*.

During the "training" motion of the operator's hand at a given frequency, a procedure involving an operation for the selection of the object's CP image and an operation for calculating the values of two-dimensional vectors $x_{im}{}^{(i)}$, $i = 1, 2, 3$ and their position in the image plane must be performed.

As a result of these actions, a sequence of values of the vector triplets from the starting one $X_{imb}{}^{(i\,=\,1,2,3)}$ to the finishing one $x_{ime}{}^{(i\,=\,1,2,3)}$: $(x_{imb}{}^{(1)}, X_{imb}{}^{(2)}, X_{imb}{}^{(3)})$; $(x_{imI}{}^{(1)}, X_{imI}{}^{(2)}, X_{imI}{}^{(3)})$; $(x_{imII}{}^{(1)}, X_{imII}{}^{(2)}, X_{imII}{}^{(3)})$; … $(x_{ime}{}^{(1)}, X_{ime}{}^{(2)}, X_{ime}{}^{(3)})$ is accumulated in the IMI database, corresponding to the sequence of the glove's positions during the movement of the operator's hand, which will be later reproduced by the robot. Each element of this sequence carries enough information to solve the navigation task, that is, to obtain the sequence $T_b, T_I, T_{II}, \ldots, T_e$ of the matrix values, which is the result of training.

After training, the robot reproduces a gripper motion based on sequence $T_b, T_I, T_{II}, \ldots, T_e$ using a motion correction algorithm based on the signals from the camera, located in the gripper, by solving the so-called "correction task" of the gripper relative to real OE objects.

5.3.2 Basic Algorithms for Robot Task Training by Demonstration

The most typical example of the robot's interaction with OE objects is the manipulation of arbitrarily oriented objects. In practice, the task of grabbing objects has several cases. The simplest case is when there is one known object. The robot must be trained to perform an operation of grabbing this object irrespective of any minor changes in its position and orientation.

A more complicated case is when the position and orientation of a known object are not known beforehand. The most typical case is when there are several known objects with a priori unknown positions and orientations. And an even more complex task is when among the known objects there are unknown objects and obstacles that may hinder the grabbing procedure.

5.3.3 Training Algorithm for the Environmental Survey Motion

During the training to perform the environmental survey motion, the operator's hand executes one or more types of search movements: rotation of the hand at two angles, zigzag motion, etc. Information about the typical search motions is recorded in the MFM. Survey motion may consist of several fragments of different movements. The sequence and shape of these motions, dependent on the task, are determined during the training phase and stored in the MFM. After the execution of separate motion fragments, a break can be taken for further analysis of the OE objects' images.

Any OE object recognition algorithm suitable for a particular purpose can be used, including a structural recognition algorithm [19].

It is necessary to note that object image analysis must include the following:

- Recognition of the target subject through a set of characteristic features (XT*1*, XT2, ... XT*k*) that are sufficient to identify it using the description stored in the MOE;
- Selection of a set of reference points (XT*1*, XT2, ... XT*n*) that are sufficient for navigating the robot gripper in the space of the real OE, from among a set of points (XT*1*, XT2, ... XT*k*), usually no more than $n = 4–6$, depending on their location.

If the number of CPs observed on the object is insufficient $(k < n)$, it is necessary to perform the following search motions:

- Change the position or orientation of the camera on the glove so that $k = n$ or change the CP filter parameters in the recognition algorithm;

- Change the observation conditions or camera parameters for reliable detection of CP, such as lighting of the operator workstation or focus of the camera lens:
  - Add artificial (contrasting, color) marks on the graphical model or on the object model to recommend the use of these marks on real objects;
  - If $k \geq n$, it is possible to skip to the calculation of the spatial position and orientation of the glove relative to the object in accordance to the algorithm of the "navigation task" (see above).

Once the specified object is detected and identified and the position and orientation of the hand (glove) relative to this object is determined, the training to execute the first survey motion is deemed finished.

The purpose of the next motion the robot is trained to execute involves a gripper motion to the so-called "convenient for observation" position. In this position, the maximum identification reliability and measurement accuracy of the gripper position relative to the object are achieved.

The variants of the shift from the starting point of object detection to the position which is "convenient for observation" must be shown by the movement of the operator's wrist using his intuitive experience.

There is also an option of task training by demonstration, for survey movement, performed through natural head movements. In this case, the camera with a reference device is fixed on the operator's head.

The training process ends automatically, for example, upon a signal from the IMI system after reaching the specified recognition reliability and measurement accuracy parameters for the position of a hand or a head relative to the OE object. A training halt signal can be given by voice (using the speech recognition system of the IMI) or by pressing the button on the glove. In this case, the object coordinates defined by its image are recorded in the MFM as a vector of coordinates (X_0).

5.3.4 Training Algorithm for Grabbing a Single Object

In this case, the grabbing process consists of three movements:

- Gripper motion from the initial position to the "convenient for grabbing" the object position;
- Object gripping motion, for example, a simple translational motion along the gripper axis;
- Object grabbing motion, such as a simple closing of the gripper, exerting a given compression force.

Let's consider the task training to perform only the first action, where the operator freely moves his hand, with sensitized glove on it, to the object (model) from the initial position at the most convenient for grabbing side and sets it at a short distance from the object with the desired orientation. Information about the motion path and the hand position relative to the object, at least at the end point of the motion, is memorized in the MFM through the IMI system, which is necessary for adjusting the robot's gripper position relative to the object during the motion reproduction. It's also desirable that at least 1 or 2 CPs of the object's image get into the camera's view in the "convenient for grabbing" gripper position, so that the grabbing process can be supervised.

The training of the grabbing motion is performed along the easiest path, in order to reduce the guidance inaccuracy. If the gripper is equipped with object detection sensors, then the movement ends upon receiving signals from these sensors.

During the training to grab objects, it is necessary to memorize the transverse dimensions of the object at the spot of grabbing and the gripper compression force, sufficient for holding the object without damaging it. This operation can be implemented using additional circuit-torque and tactile sensors in the robot gripper.

In case of the presence of multiple OE objects, the training implies a more complex process of identification of the objects' images and the necessity to train additional motions, such as obstacle avoidance, changing of altitude convenient for survey in case of any shading, flashing and interference to image recognition by the camera on the glove, as well as for the camera in the robot manipulator's gripper, during the reproduction of movements.

5.3.5 Special Features of the Algorithm for Reproduction of Movements

As a result of performing the required number of training movements by the human hand, "motion experience" is formed, which is accumulated in the form of a frame-structured description in the MFM, stored in the memory of the intelligent IMI system.

The transfer of the "motion experience" from the human to the robot occurs, for example, by simply copying the MFM and MEE from the IMI memory to the RCS memory or even by transferring this data to the remotely controlled robot over communications channels. Of course, preliminary checking of training outcomes is performed, for example, on a graphical model of the robot.

Prior to the robot performing the trained movements, in accordance to the assigned task and the EE conditions, the MFM is tuned, as already mentioned (in Part I of the current paper), for example, by masking (searching) among the total volume of the MFM data for the required types of motions. Descriptions of motions, selected according to the intended purpose and shape of the trajectory, are converted by the RCS into typical motion trajectories for their reproduction by the robot in real EE.

When the robot-manipulator reproduces motions in a real EE, after training by demonstration, it is possible to execute, for example, the following typical motion trajectories:

- Survey movement in combination with EE image analysis in order to identify the object to be taken;
- Shifting of the gripper into the "convenient for observation" position;
- Corrective gripper movement relative to the object based on the signals from the robot's sensors;
- Shifting of the gripper to the "convenient for taking" position;
- Motion for grabbing the real object;
- Motion for taking the object.

Before the work starts, a complete check of the TSHP operation and telecontrol system is carried out. Then, operation of the TSHP is checked using a graphical model (GM) at the control station without using a robot and exchanging information over the communications lines. Checks of the training outcomes are performed using the surveillance MFM or manipulation MFM, located in the RCS, without switching on the robot at this moment. If necessary, additional adjustment of the MFM is performed through task training by demonstration of the natural human-hand movements and their storage in the MFM of the RCS.

The robot is switched on and it executes motions in terms of the original EE inspection, selection of objects, position selection, convenient for grabbing or convenient for visual control over object grabbing and manipulations, as well as safe obstacle avoidance, before a transition to remote control mode is performed.

The human operator sits in front of the monitor screen, which displays a graphical model or a real object image, and controls the robot through natural movements of the head and hand with the glove.

5.3.6 Some Results of Experimental Studies

The effectiveness of the proposed training technology using demonstrations of the movements, the algorithms and theoretical calculations was tested on the basis of the "virtual reality" environment at the laboratory of Information Technology in Robotics, SPIIRAS (St. Petersburg) [20].

The hardware-software environment includes:

- Two six-stage robotic manipulators of the «Puma» class, equipped with remotely operated stereo cameras and force-torque sensing;
- Models of the fragment of the space station surface, two graphic stations to work with three-dimensional models of the external environment (MEE);
- Intelligent multimodal interface (IMI) with a system for tracking hand movements (TSHP) and a system for tracking the head motions (THM) of the human operator.

The "Virtual reality" environment enables the performance of experimental studies of various information technology approaches for remote control and task training of robots:

- "Immersion technologies" of the human operator in the remote environment using the robot-like device that moves surveillance stereo cameras in the room with models of the fragment of the space station surface and containers for scientific equipment;
- "Virtual observer" technologies using the model of the freely flying machine (equipped with the surveillance camera, which allows the examination of the three-dimensional graphical model of the space station), as well as the simulation of an astronaut's work in outer space;
- Technologies for training and remotely controlling a space (medical) robot manipulator with a force-torque sensing system, which provides operational safety during manipulative operations, reflection of forces and torques on the control handle, including when working with virtual objects.

Experimental studies were performed on some algorithms for training by demonstration and remote control of a robot manipulator, including:

- Training of the robot manipulator to execute survey motions through motions of the human head;
- Scanning the surroundings by the robot and remotely operated camera on the glove;
- Using the IMI for training by demonstration of hand movements and human voice commands;
- Training the robot manipulator to grab items by demonstration of the operator's hand movements.

The motion reproduction of the robot manipulator among the real EE objects based on the use of the virtual graphical models of the EE and the robot manipulator with force-torque sensing system was also practiced in the experimental environment.

5.3.7 Overview of the Environment for Task Training by Demonstration of the Movements of the Human Head

A functional diagram of the equipment for remotely monitoring the EE is shown on Figure 5.4.

The operator, located in the control room, sets coordinates and orientations of the manipulator gripper and remotely operated camera on it using the tracking system for head position (THM). He observes the obtained EE image on the monitor screen.

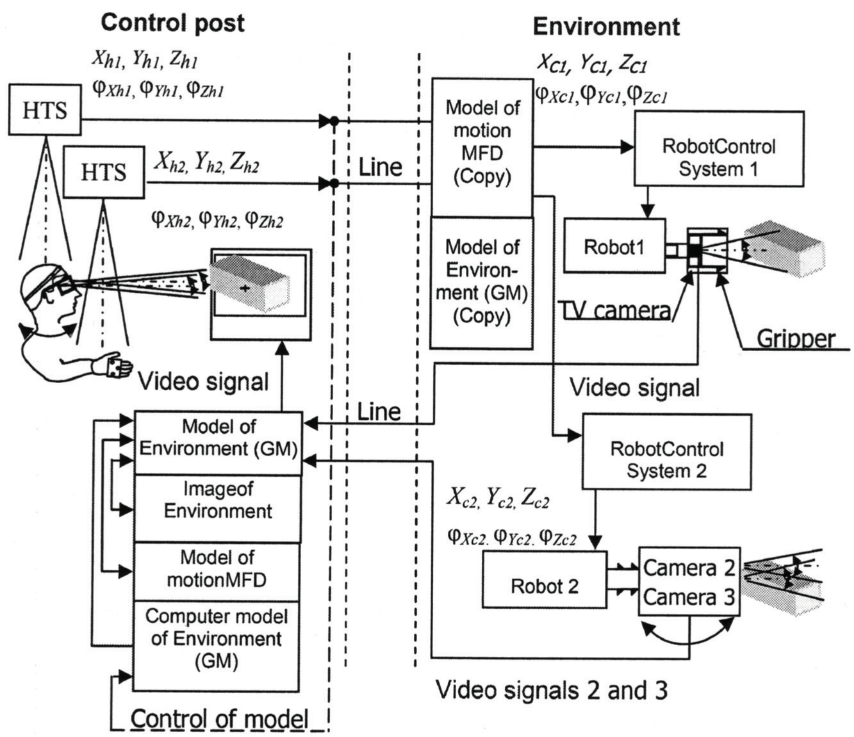

Figure 5.4 Functional diagram of robot task training regarding survey motions and object grabbing motions using THM and RCS.

Before starting, the human operator must be able to verify the THM in an off-line mode. For this purpose, a graphical model (GM) and a special communications module for controlling 6 coordinates were developed. Training the robot manipulator to execute EE surveillance motions by demonstration is carried out in the following way (Figure 5.5).

The human operator performs the EE inspection based on his personal experience in object surveillance. The robot repeats the action, using the surveillance procedure and shape of the trajectory of the human head movement. In this case, the cursor can first be moved around the obtained panoramic image, increasing (decreasing) the scale of separate fragments, and then, after accuracy validation, the actual motion of the robot manipulator can be executed.

5.3.8 Training the Robot to Grab Objects by Demonstration of Operator Hand Movements

There are several variations of the implementation of the "sensitized glove" (Figure 5.6): a remote-operated camera in the bracelet with control points and laser pointers, bracelet with active control points (infrared diodes), manipulation object - stick with the active control points [21].

When training by demonstration of human hand movements, through a sensitized glove with camera and control points, a greater range and closeness to natural movements is achieved, as compared to the use of joysticks or handle like "Master-Arm» (Figure 5.7).

This provides for the natural coordination of movements of the hand and head of the human operator. Using the head, the human controls the movement of the remotely operated surveillance camera, fixed, for example,

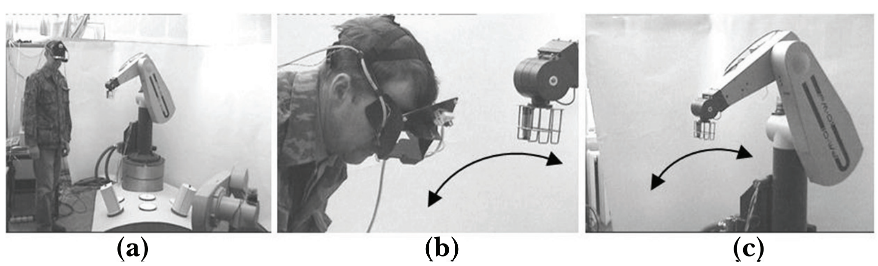

Figure 5.5 Robot task training to execute survey movements, based on the movements of the operator's head: Training the robot to execute survey motions to insect surroundings (a); Training process (b); Reproduction of earlier trained movements (c).

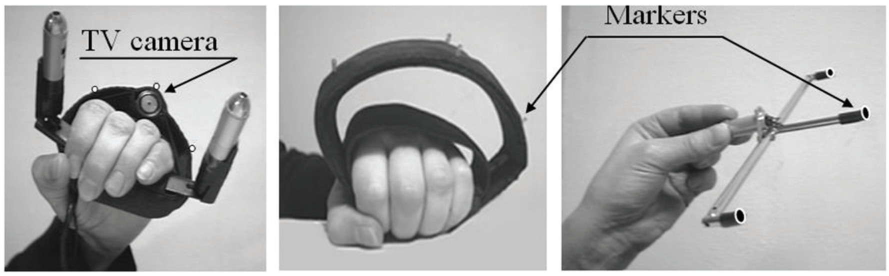

Figure 5.6 Variations of the "Sensitized Glove" construction.

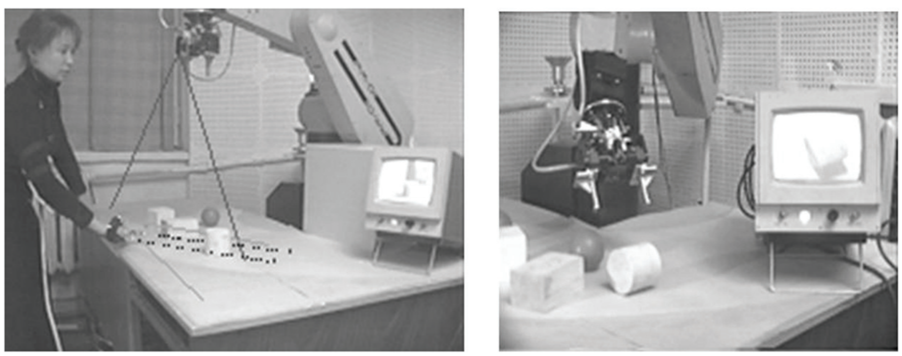

Figure 5.7 Using the special glove for training the robot manipulator.

on an additional manipulator, and with the hand he controls the position and orientation of the main robot gripper (Figure 5.8).

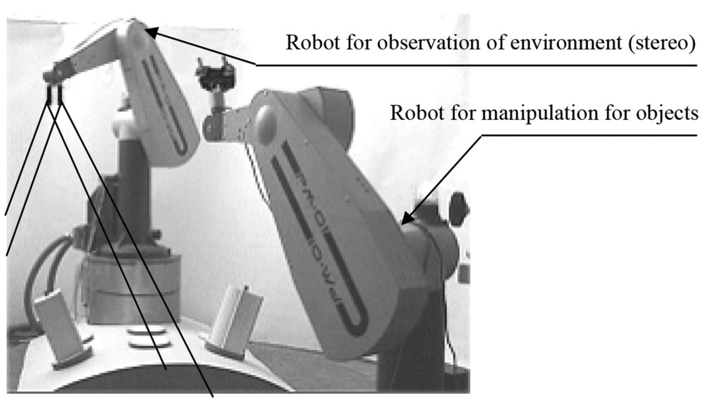

Figure 5.8 Stand for teaching robots to execute motions of surveillance and grabbing objects.

The coordination of simultaneous control using the operator's hand and head during training and remote control through natural human operator movements was put into practice in order to control the complex objects (Figure 5.9).

A new prototype of the intelligent IMI equipment with recognition of the operator's hand without markers, while performing manual control and training by demonstration of natural hand movements, was experimentally studied (Figure 5.10). In the future it is planned to continue research on new algorithms for training and remote robot control of intelligent mechatronic systems based on the use of advanced intelligent multimodal human-machine interface systems and new motion modeling principles using frame-structured

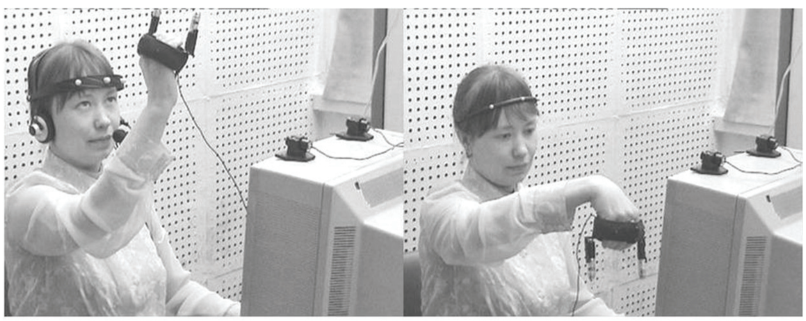

Figure 5.9 Training of motion coordination of two robot manipulators by natural movements of human head and hand.

Figure 5.10 Training with the use of a system for the recognition of hand movements and gestures without "Sensitized Gloves" against the real background of the operator's work station.

MFM descriptions, including for medical robots, mechatronic systems and telemedicine [22].

5.4 Conclusions

A new information technology approach for training robots (mechatronic systems) by demonstration of movement is based on the use of a frame-structured data representation in the models of the shape of the movements that makes it easy to adjust the movement's semantics and topology both for the human operator and for the autonomous sensitized robot.

Algorithms for training by demonstration of natural movements of the human operator's hand using a television camera, fixed on the so-called "sensitized glove", allow not only the application during the training process of graphical models of objects in surroundings but also of full-scale models, which enables the operator the possibility to practice optimal motions of the remote-controlled robots under real conditions.

It is sufficient to demonstrate the shape of a human hand movement to the intelligent system of the IMI and to enter it into the MFM, and then this movement can be executed automatically, for example, by a robot manipulator with adjustment and navigation among the surrounding objects based on the signals from the sensors.

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