Robot Kinematics and Motion Planning

Wayne Adams
Editor

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ROBOT KINEMATICS AND MOTION PLANNING

PREFACE

The authors of this book focus on the latest developments in robot kinematics and motion planning. The first chapter seeks to identify the governing rules implemented in the central nervous system (CNS) to solve redundant mapping problems from an experimental observation approach. The novelty of this chapter is in the obtained motion planning results for a constraint elbow joint during reaching movements. The second chapter focuses on the problems that exist in the two-norm and infinity-norm and solutions to these problems involving bi-criteria (BC) motion planning schemes of different joint-level vectors. In the third chapter, trajectory generation methods for the application of thermal spraying processes are introduced. In the fourth chapter, an investigation on the robot kinematics is proposed to find the rules of motion in an application case. The results demonstrate the motion behavior of each axis in the robot that consequently permits the identification of the motion problems in the trajectory. In the fifth chapter, kinematic properties of a new planar parallel manipulator is investigated by means of the theory of screws.

The human arm can perform versatile reaching actions to achieve various goals in activities of daily living. For the motion planning of a point–to–point reaching task, the CNS (central nervous system) resolves two redundant mapping problems: 1) hand trajectory formulation and 2) arm posture selection. Chapter 1 seeks to identify the governing rules implemented in the CNS to solve such redundancies from experimental observation approach. The novelty of this work is in the obtained motion planning results for a constraint elbow joint during reaching movements. The authors believe that the CNS generates the motion by following the governing rules despite reduced arm mobility and this enables us to tap into fundamental principles of the human motor coordination with the redundancy resolution. Specifically, the paper discusses point-to-point reaching motions performed by multiple subjects with an elbow locking brace. The recorded motion kinematics of the experimental data is compared to multiple computational models for analyzing the behavior from hand path geometry and temporal control aspects. For the arm posture selection, the kinematic and dynamic contributions of each joint DOF (degrees of freedom) are computed to identify the governing strategy. Our results suggest that the hand path geometry is close to the least kinematic effort (LKE) model. With regard to the temporal control of motions, it was found that the hand speed profile is generated in the same context as healthy arm motions, maximum smoothness, regardless of the reduced mobility. For the arm posture selection, our observations show that the humeral rotation DOF is actively incorporated for both the hand path formulation and the arm posture selection. The analysis on the kinematic and dynamic contributions of each joint DOF show that the CNS tends to adopt minimum kinetic energy (MKE) cost principle to resolve the inverse kinematics problem.

To remedy the problems that exist in the two-norm and infinity-norm solutions, more balancing solutions called bi-criteria (BC) motion planning schemes of different joint-level vectors (e.g., joint velocity, acceleration and torque vectors) are summarized and presented in Chapter 2. Such kinematic and/or dynamic schemes of redundant manipulators can incorporate joint physical limits, such as joint limits, joint velocity limits and joint acceleration limits simultaneously. Furthermore, the presented schemes could finally be unified into quadratic programming (QP) formulations which could be solved simply by using recurrent neuronet solvers [e.g., dual neuronet, DN, and linear variational inequality (LVI)-based primal-dual neuronet, LVI-PDN] due to the adaptive processing nature. Computer simulations based on different kinds of robot manipulators (e.g., PUMA560 and PA10) are summarized and presented to illustrate the validity and advantages of such neural bi-criteria motion planning schemes for redundant robot manipulators.

With the increasing demands for accuracy, repeatability and working intensity in industry, more and more industrial robots are introduced to replace manual operations. In order to ensure and improve the robot performance in industrial applications, the studies concerning the trajectory generation and the kinematic analysis of robots are becoming more and more important. For robot programming, most operations are still done online: online programming, online measurement, online testing, etc. The most common method is called programming by teaching, which is appropriate for simple trajectories. However this method will be tedious and time-consuming when the robot movement is complex, and the trajectory quality is dependent on the operator's skill. Another programming technology called offline programming is a good solution that can overcome the online programming tolerances by using the CAD/CAM software.

In Chapter 3, the two programming methods mentioned above are introduced and the application of robot offline programming in thermal spray is described. An add-in program called Thermal Spray Toolkit (TST) is developed to provide a complete solution for trajectory generation in the thermal spraying process. With this program, operator can automatically generate trajectory based on the workpiece geometry and operating parameters, which includes the trajectories for plane surface, circular surface, curved surface and rotation workpiece as well. In order to obtain a desired coating profile, a coating thickness simulation method is also introduced in this chapter, which enables the operating parameter optimization after trajectory generation. Besides, the application of external axis in thermal spray is also presented, which provides a solution to extend robot reaching space and the possibility to improve robot productivity for complex workpieces.

In Chapter 3, the trajectory generation methods for the application of thermal spraying process are introduced. An add-in program to provide automatic generation of trajectory for different kinds of workpieces geometry is presented. Although the robots are designed as highly accurate manipulators and the trajectory generation methods are also largely improved, the payloads and their performance limit can cause dynamic divergences between the expected and the actual robot trajectories during the manufacturing process. In the cases where complex workpieces are put forward, the robot performance is found to be limited. Thus, in order to ensure and improve the robot performance in industrial applications, the studies concerning the kinematic analysis and optimization methods of robots are becoming more and more important and drawing more attention.

In Chapter 4, an investigation on the robot kinematics is proposed to find the rules of motion in an application case. The results demonstrate the motion behavior of each axis in the robot that permits to identify the motion problems in the trajectory. This approach allows to optimize the robot trajectory in a limited working envelope. With the kinematic analysis approach, the optimization method for torch setup and workpiece placement are proposed. And as the trajectory is generated, optimization methods focusing on the target point and its orientation are presented. With the optimization methods proposed in this chapter, it is able to improve robot performance and achieve a more accurate trajectory.

In Chapter 5 some kinematic properties of a new planar parallel manipulator equipped with four actuable kinematic pairs to realize three degrees of freedom is investigated by means of the theory of screws. The forward displacement analysis, a challenger task for most parallel manipulators, of the robot is carried-out by handling closure equations formulated upon the coordinates of a point embedded to the moving platform yielding a univariate solution, a nearly closed-form solution. After, simple and compact input-output equations of velocity and acceleration are obtained by resorting to reciprocal-screw theory. The escapement from singular configurations of the robot, an open problem of parallel manipulators, is investigated based on the properties of the Lie product of the Lie algebra *se(3)* of the Euclidean group *SE(3)*. A case study covering most of the topics treated in the contribution is included with the purpose to show the application of the method. Furthermore, the result of the velocity and acceleration analyses obtained by means of the theory of screws are verified with the aid of commercially available software. As far as the authors are aware, the topology of the robot under study was not considered in previous works. Finally, although the issue of escapement from singular configurations has been deeply investigated for serial manipulators some years ago, its inclusion for the parallel manipulator at hand can be considered as an outcome of the contribution.

CONTENTS

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Chapter 1

EXPERIMENTAL OBSERVATIONS ON HUMAN REACHING MOTION PLANNING WITH AND WITHOUT A REDUCED MOBILITY

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Abstract

The human arm can perform versatile reaching actions to achieve various goals in activities of daily living. For the motion planning of a point–to–point reaching task, the CNS (central nervous system) resolves two redundant mapping problems: 1) hand trajectory formulation and 2) arm posture selection. This paper seeks to identify the governing rules implemented in the CNS to solve such redundancies from experimental observation approach. The novelty of this work is in the obtained motion planning results for a constraint elbow joint during reaching movements. The authors believe that the CNS generates the motion by following the governing rules despite reduced arm mobility and this enables us to tap into fundamental principles of the human motor coordination with the redundancy resolution. Specifically, the paper discusses point-to-point reaching motions performed by multiple subjects with an elbow locking brace. The recorded motion kinematics of the experimental data is compared to multiple computational models for analyzing the behavior from hand path geometry and temporal control aspects. For the arm posture selection, the kinematic and dynamic contributions of each joint DOF (degrees of freedom) are computed to identify the governing strategy. Our results suggest that the hand path geometry is close to the least kinematic effort (LKE) model. With regard to the temporal control of motions, it was found that the hand speed profile is generated in the same context as healthy arm motions, maximum smoothness, regardless of the reduced mobility. For the arm posture selection, our observations show that the humeral rotation DOF is actively incorporated for both the hand path formulation and the arm posture selection. The analysis on the kinematic and dynamic contributions of each joint

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DOF show that the CNS tends to adopt minimum kinetic energy (MKE) cost principle to resolve the inverse kinematics problem.

Keywords: Human motion planning, motor coordination principles, reduced mobility

Introduction

Human arms perform versatile reaching motions in daily activities to achieve complex desired position and orientation of the end-effector (i.e., hand). Although it seems effortless, producing such limb motions involves a branch of redundant mapping problems, so-called degrees of freedom problem, described by Bernstein [1]: how does the CNS (central nervous system) solve the complex problem of motor control without conscious effort to complete skillful actions? This question can be interpreted within the human point-to-point reaching process as presented in Figure 1.

There are two redundancy problems in the overall process of the point-to-point reaching. The human subject sets the target point as the final hand location in the workspace (usually with respect to the visual coordinates) while the current configurations (e.g., hand location and arm posture) are perceived by the sensory inputs (i.e., visual and proprioceptive information). Assume that there is no external contact during the reaching motion so that the subject's CNS does not need to incorporate obstacle avoidance or direct force control (i.e., controlling the contact force and moment to desired value with explicit closure of a force feedback loop [2]). Then the overall control procedure can be modeled as a position mode control of the human arm as a serial linkage manipulator. Since the main objective of the point-to-point reaching is maneuvering the end-effector to a certain position in the workspace, the subject's hand naturally gets the greatest attention of the CNS [3]. Therefore, in order to fill out the gap between the initial and the final task points in the workspace, the point-to-point reaching needs to be planned in a hand trajectory format. In this process, the first redundancy problem occurs when the geometry and the speed of hand trajectory should be selected among infinite numbers of possible ways and their combinations (see Figure 1(a)). As an example shown in Figure 1, grey hand paths indicate possible candidates while the red path describes a patterned path generated by the CNS. Once the hand trajectory is determined, the CNS needs to configure the arm posture by resolving another redundant mapping problem (see Figure 1(b)) to generate control commands for each controlling DOF (degrees of freedom). As an example, the arm posture can be fully specified in the joint space by solving the corresponding inverse kinematics problem. Note that the number of independent joint DOF is greater than the sufficient six DOF needed to specify the hand kinematics in a spatial workspace (three positions and three orientation angles). Furthermore, on the actuation level, the redundancy of the problem is magnified due to multiple connections of skeletal muscles spanned over each joint DOF motion.

What is the best explanation for the efficient and optimal problem solving ability of the CNS? From many experimental observations, it is generally accepted that governing rules (either innate or learned) in the CNS impose some additional constraints and induce a finite set of preferred patterns (e.g., the tendency of synchronizing inter limb coordination [4]). Such governing rules can be observed from the experimental results and approximated as computational models. Multitude models have been studied to approximate behaviors of such governing rules in the point-to-point reaching actions. Most of them fall into either minimum principles or data fitting formats as presented later in this chapter.

This study seeks to identify the governing rules of the point-to-point reaching within the CNS from an experimental observation approach. Unlike most of experimental studies on the human arm reaching, a kinematic constraint on the elbow joint DOF (i.e., elbow locked in place) is imposed to collect the experimental data and its result is compared to the data without the elbow constraint. The reason of the imposed elbow joint constraint is on the base assumption of this study that even though the imposed physical constraint can yield adaptations in resulting motions, the governing rules are preserved in the CNS. Therefore, by observing the invariant features of the motion kinematics and dynamics, we can induce key characteristics of such governing rules implemented in the CNS. This idea is supported by the observations on the motor recovery for reaching in stroke patients. Roby-Brami et al. [5] found that the stroke patients seek a way to recover the original control strategies through therapeutic arm reaching tasks against their physical impairments.

As the elbow locking condition constraints the arm workspace on a curved surface, the condition affects the hand trajectory planning process shown in Figure 1(a). Some experimental studies have been conducted on the arm reaching on a geometrically constrained surface. In their reaching experiments on a hemispheric constraint surface, Sha et al. [6] showed that a healthy subject preserved a bell–shaped velocity profile while the hand paths approached to the geodesic curves (i.e., shortest path on the constraint surface) by training. Liebermann et al. [7] characterized the hand trajectories on a similar workspace constrained on a hemisphere by a mechanical linkage system. From the similar experimental results, they came up with a different conclusion on the hand path geometry that it may follow the smoothest paths (i.e., rhumb lines on the hemispheric surface) rather than the shortest paths (i.e., geodesic curves). The temporal characteristic (i.e., smooth bell-shaped velocity profiles), however, was preserved regardless of the hand path geometry. Similar results of above studies support the underlying idea of this study: the CNS keeps the governing rules while it generates adapted hand paths against the constrained hand kinematics due to extrinsic factors (e.g., contact specified tasks such as surface welding). However, the hand kinematics constrained on the curved surface only affects the first redundancy problem (i.e., the hand path formulation, see Figure 1(a)) due to fully applicable arm mobility in the joint DOF space.

We believe that the loss of arm mobility can extend its effects up to the other redundancy resolution process: arm posture configuration along the hand path (see Figure 1(b)). Therefore, it is expected that the adopted elbow constraint condition in this study will enable us to tap into fundamental principles of the human arm reaching coordination by disturbing both of redundancy problem solving processes within the CNS. Some previous studies applied computational models to understand reaching behaviors with a joint constraint condition.Bullock et al. [8] introduced a self-organizing neural model to justify the automatic corrections in the reaching with clamped joints. Rosenbaum et al. [9] explained the compensatory reaching motion against the elbow restriction with weighted sum of stored postures in the CNS. Furthermore, to explain the motor equivalence phenomenon (i.e., the ability to complete the desired task with different combinations of controllable DOF [9]), Saltzman and Kelso [10] focused on a task dynamic approach which regards the compensatory strategy as an implicit consequences of the task dynamics. Mussa Ivaldi et al. [11] approached the issue from the equilibrium point control viewpoint. It is expected that the resulting observations from this study can contribute to shed a light on researches on the human motor coordinations by providing a novel technique to describe the underlying principles of such complex behaviors, and to reproduce the human-like natural motions with relatively simple synthesis for various robotic and mechatronic applications.

Background Knowledge on Motor Neuroscience

In which Representation the Motion Is Characterized?

In his work, Brooks [3] classified the CNS into two interactive functional subsystems: limbic and sensorimotor systems. For the motion generation, the limbic system deals with emotional needs (i.e., feeling and desire) by recognizing the significance of a need-initiated stimulus while the sensorimotor system governs the perception and motor functions. In his work, the link between two subsystems is explained as follow: the "*need-directed motor activity*" initially formulated in the limbic system is converted into overall plans for the "*goal-directed motor actions*" in the highest level hierarchy of sensorimotor system [3]. Then in which representation the reaching motion is characterized in the sensorimotor system, kinematics or dynamics? It seems that the kinematics and dynamics of reaching motion can be independently controlled. In their study on the limb position drift during repetitive reaching, Brown, et al. [12] showed that the dynamics (joint torque pattern) can be independently adapted to maintain the kinematics of motion.

Without any specially imposed instructions regarding the dynamics of motion (e.g., hit the object with a certain amount of force or maintain the end–effector force vector during reaching), it can be argue that the point-to-point arm reaching is first planned with respect to the kinematic representation due to its primary function, locating the hand as desired. The hierarchical control structure proposed by Brooks [3]supports the idea in a way that the motion kinematics is planned in the highest level hierarchy in the sensorimotor system while the motion dynamics is separately controlled by the middle and the lowest level hierarcies. However, it seems that the motion kinematics is not the only factor that the CNS takes into account. The dynamic representation is considered equally important in the motion planning process. In his feedback error learning model, Kawato [13] explains that accurate feed forward control commands in skillful motions are due to a well-trained internal model (i.e., inverse dynamics model) of the neuromuscular system.

In which Coordinate System the Motion Kinematics is Defined in the CNS?

In which coordinate system this motion kinematics is defined in our CNS, extrinsic (e.g., Cartesian coordinates) or intrinsic (e.g., joint or muscle coordinates)? As stated by Hogan [14], *"One way to address this question is to look for patterns or regularities in motor behavior"*. According to the Bernstein's hypothesis, the motion information formulated in higher levels of the CNS has projections of extrinsic space rather than intrinsic joints and muscles over lower levels of CNS activities [1].Morasso [15] supports the idea from his observations on horizontal reaching experiments that the reaching pattern is relatively well organized with respect to the hand motion in the task space due to the invariant movement features, straight hand path with a single peaked velocity, while no patterns or regularities were observed in the joint space. Also, in his explanations on the consistent one peaked hand velocity profile of the reaching, Brooks [3] mentioned that *"This property is applied to the path of the object of greatest attention of the central nervous system for intended multi-joint movements"*. Since arm reaching motions are brought mainly for a final hand manipulation or a grasping task, the greatest attention of the CNS naturally occurs on the hand (i.e., end-effector) paths. In addition, regarding the joint paths, Brooks [3] described that *"They are not necessarily continuous since they are fitted to support the intended hand path"*.

On the other hands, Soechting and Lacquaniti [16, 17] report that invariant features of movements can be observed in joint coordinates that the ratio of joint angular velocities (elbow to shoulder) tends to be constant in the deceleration phase. After this finding, Soechting and his colleagues [18-20] insist the shoulder-centered coordinate system based on their observations on pointing experiments. In their earlier studies, they showed that systematic errors of pointing arise from the transformation of perceived target position in extrinsic coordinates into intrinsic coordinates, and these errors are centered at the shoulder joint[18, 19]. In a later study, they argue that there exist both head-centered and shoulder-centered coordinates to represent the target position in the CNS from experimental error analysis results[20].

Multiple experimental studies found that the hand path curvature is depending on movement directions (e.g., forward/backward, left/right or vertical) [21-23], and it seems that joint coordinates can better explain such characteristics than task coordinates. In order to explain such phenomenon, Klein Breteler et al. [24] proposed that the variance of hand path curvatures can be explained more consistently with the motion planning in joint coordinates than in task coordinates. In order to explain straight hand paths in joint coordinates, Hollerbach et al. [25] proposed the strategy of "*staggered joint interpolation*", which approximates the straight hand path by scaling the amplitude and the duration of individual joint angular velocity profile.

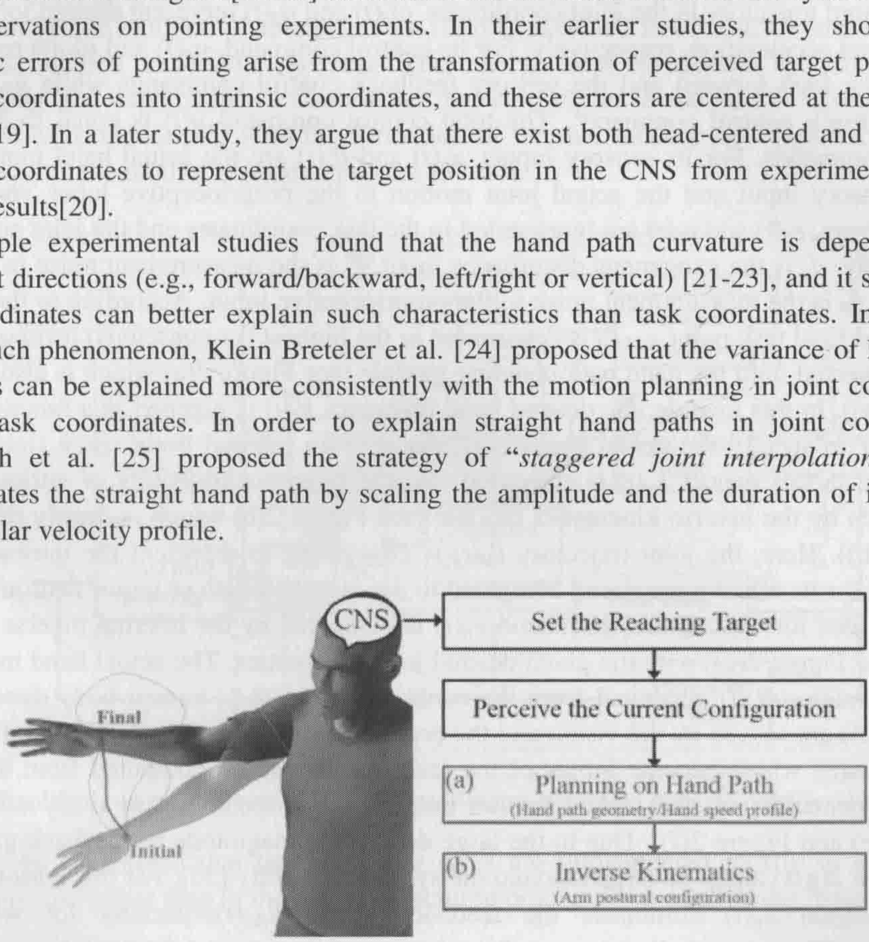

Figure 1. Schematic plot on overall procedures of the point-to-point reaching [26].

Against the hypothesis that the motion is planned in joint coordinates, Hogan [14] argues that two observations are not explained with the joint coordinates hypothesis: 1) lack of patterns or regularities of motion in the joint space, and 2) common experimental observations that are against the joint coordinates hypothesis (especially the *staggered joint interpolation* [25]). Even though there are up to date opinions that support the motion planning in joint coordinates (e.g., [4, 24, 27]), the hypothesis of the motion planning in hand coordinates (or extrinsic task coordinates) is accepted in this study for neuronal evidences observed from primate cortex activities along the hand motion [28-32]. Also, note that this hypothesis is in accordance with the general path planning algorithm in the conventional robotics control [33].

Human Sensorimotor System from the Control Engineering Viewpoint

Figure 2 represents a simplified control structure of the human sensorimotor system for a point-to-point reaching from the control engineering viewpoint. In the figure, $x_{d,final}$ indicates the final task point, $x_d(t)$ is the desired hand trajectory in the task coordinates and $\theta_d(t)$ refers to the desired trajectory in the joint coordinates. $\omega_d(t)$ and $\alpha_d(t)$ represent desired joint angular velocity and acceleration, respectively. For its control command, $u_{ff}(t)$ and $u_{fb1}(t)$ respectively indicate the feed forward and the sensory feedback control commands while $u_{fb2}(t)$ is the rapid feedback control command[1]. The total control command $u(t)$ is equal to sum of all control commands. For its sensory inputs, $x_a(t)$ and $\theta_a(t)$ are the actual hand motion in the visual sensory input and the actual joint motion in the proprioceptive input, respectively. Motion errors, e_x(t) and $e_\theta(t)$ are represented in the task coordinates and the joint coordinates, respectively. d_u is the exogenous disturbance input, ξ_x is the measurement noise in the visual input and ξ_θ is the measurement noise in the proprioceptive input. According to the diagram, the desired final task point $x_{d,final}$ is determined in the highest (or conscious) level of the CNS and is projected onto the hand path planning module (see Figure 2(a) which is also related to Figure 1(a)). In this module, the desired hand trajectory $x_d(t)$ is planned as a function of time t. In order to specify the actual control command in an internal body space (joint DOF is considered in this paper), $x_d(t)$ is converted into the reference trajectory of intrinsic control coordinates by the inverse kinematics module (see Figure 2(b) which is deeply related with Figure 1(b)). Here, the joint trajectory $\theta_d(t)$ is considered to represent the intrinsic motion command for its relative simplicity compared to the muscle length or motor neuron activities. Then the feed forward control command $u_{ff}(t)$ is computed by the internal inverse dynamics model (see Figure 2(c)) with the given desired joint kinematics. The actual hand motion $x_a(t)$ and joint motion $\theta_a(t)$ generated from the controlled plant (i.e., human body dynamics, see Figure 2(d)) are sensed by the vision and the proprioception, respectively. The motion errors, $e_x(t)$ and $e_\theta(t)$, which become inputs of the feedback loops, are computed from the desired motion kinematics and the sensed motion output after respective time delay effects[2] (see Figure 2(e) and Figure 2(f)). Due to the large delays, the magnitude of feedback gain matrix (see Figure 2(g)) cannot be large to avoid the system instability [35]. For this reason, the feed forward signal $u_{ff}(t)$ dominates the feedback signal $u_{fb1}(t)$especially for well-trained movements. There are studies support the existence of the internal forward dynamics model (see Figure 2(k)) that estimates the resulting sensory inputs from the efference copy of the motor command $u(t)$. In their review paper, Desmurget and Grafton [34] shows the possibility and the evidence of a rapid feedback control enabled by the forward dynamics model. In this

[1] Desmurget and Grafton [34] proposed that the forward dynamics model with an efferent copy of motor command signal can enable the CNS to control fast reaching movements by a feedback control.

[2] Approximate range of time delay for the visual feedback on xa(t) is 150~250 ms where the spinal feedback of the proprioception on θa(t) has shorter delay about 30~50 ms [35].

study, however, we assume that such rapid feedback $u_{fb2}(t)$ cannot be physically faster than the $u_{ff}(t)$, which is reasonable in the sense of control engineering.

The overall control structure shown in Figure 2 can be classified into two main processes, motion planning process (see Figure 2(i)) and motion execution process (see Figure 2(j)), by which motion characteristics is dominant, kinematics or dynamics. Note that it is assumed that those two motion characteristics can be independently controlled in the CNS (e.g., the study of Brown et al. [36]). Based on this independency, it is considered that motion planning and actual execution processes are independently developed in the CNS, and the Figure 2 proposes that the point-to-point reaching is planned mostly in terms of motion kinematics while the motion execution process handles plant dynamics to realize the planned motion. Brooks [3] supports the idea with his hierarchical structure of the entire motion processes based on physiological findings. According to his concept, reaching is planned in the highest level hierarchy (i.e., motion planning process) and is executed in the middle and the lowest levels (i.e., motion execution process). The idea is also supported by physiological, neuroimaging and experimental evidence that the cerebellum in the middle level hierarchy has a significant relationship with the formation of internal models (see Figure 2(c) for an example) within the motion execution process [37-40].

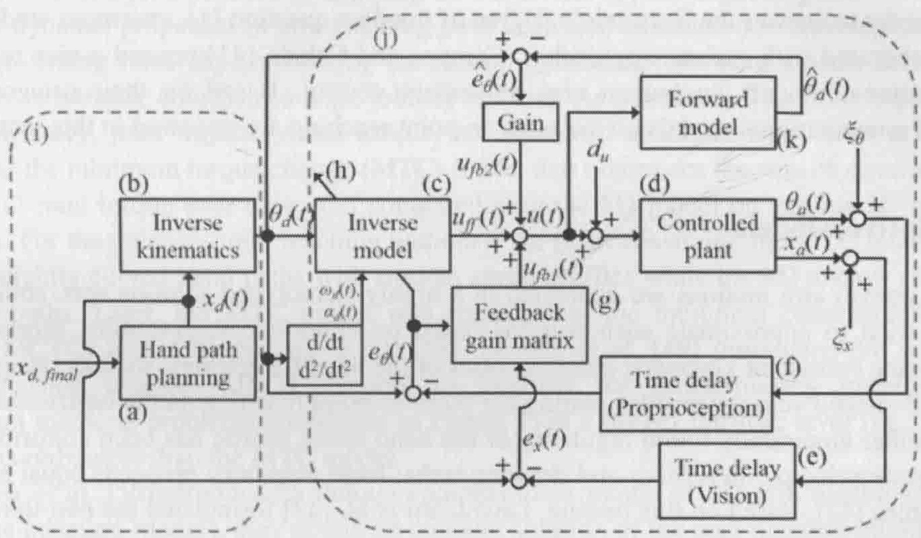

Figure 2. Simplified control structure of human sensorimotor system on point-to-point reaching.

It can be considered that the governing rules are implemented mostly in the motion planning process rather than in the motion execution process for the following reasons:

1) Each module in the motion planning process (see Figure 2(a, b)) is directly linked to the corresponding redundancy problem of motion generation (see Figure 1(a, b)), and
2) From the control engineering perspective shown in Figure 2, the governing rules can keep their simplicity by being separated from the disturbances and uncertainties of the controlled plant (e.g., time varying body dynamics, noise in neural signals and changing actuator dynamics due to muscle fatigue).

In reaching motions, the elbow joint governs the distance control of the hand, which can be explained by the fact that the hand keeps a constant distance from the shoulder when the elbow joint is locked. Therefore, the point-to-point reaching with the elbow joint constraint may require a similar control process in the CNS as for the reaching on a frontal plane without the joint restriction. The experimental setup in this study is also designed to let the subjects focus on the hand directional control without effort on the hand distal control. In other words, the imposed elbow constraint condition does not induce much of learning or adaptation in the CNS. Recall that the feed forward control command dominates the feedback signal for well-trained motions (i.e., the internal inverse dynamics model depicted in Figure 2(c) is already established and tuned enough accurate). Therefore, in order to observe the governing rules implemented in the motion planning process, features induced by the desired motion kinematics (i.e., desired joint angle $\theta_d(t)$, joint angular velocity $\omega_d(t)$ and angular acceleration $\alpha_d(t)$) and the feed forward control signal $u_{ff}(t)$ should be extracted from the captured motion kinematics $x_a(t)$ and $\theta_a(t)$.

Literature Survey

In order to answer the Bernstein's degree of freedom question [1], enormous studies have been elaborated with various approaches. Campos and Calado [41] present a nice review on computational models on human arm movement control. Based on their categorization, selected computational models on the point-to-point reaching are reviewed in this section.

Descriptive Models

As human arm motions are generated in a highly stereotyped solution sets, some initial studies tried to approximate such patterns based on empirical observations. Morasso [15] found some consistent kinematic characteristics of the hand trajectories, such as straight paths with bell-shaped velocity profiles, during the point-to-point reaching on the horizontal plane.

Another empirically found regularity of the hand speed profile has been confirmed from the isogony principle in writing and drawing tasks: hand trajectory proceeds equal angles in equal times [42]. Based on this finding, Lacquaniti et al. [43] formulated the two-third power law that represents the instantaneous hand velocity as a power function of path curvature in 2D motions.

Fitt's law is the well-known empirical relation between the movement time and the relative difficulty of the reaching (or pointing), which can be quantified by the distance and the dimension of the target [44]. In this law, the movement time for a reaching can be estimated as a log-scale fitting model that is proportional to the index of difficulty based on the information processing theory.

Minimum Principles

Beyond descriptions of empirical relations, later studies tried to extend the computational model work to understand the underlying principles of the CNS. From consistent experimental findings on the highly patterned kinematics of arm movements, it was considered that certain movements are preferably chosen by the CNS for satisfying some efficiency criterion. Such selections are similar to a process of cost function minimization. In this context, Engelbrecht [45] categorizes those efforts as minimum principles named after the minimum theories in a variety of science and mathematics fields.

There are a number of researchers who focused on the kinematic aspect of the reaching. From their experimental observations, Flash and Hogan [46]confirmed the Morasso's finding (i.e., a straight hand path and a bell-shaped hand speed profile) and approximated such hand kinematics in 2D reaching with a mathematical model, the minimum jerk (MJ) model. This MJ model stresses on the smoothness of natural human motions by minimizing the hand jerk along the motion profile. The authors found that the hand kinematics follows similar rules for the via-point reaching case (i.e., intermediate point passing or obstacle avoidance) as well by observing low curvature hand paths joined with a high curvature path around the via-point. Datas et al. [47] supported the same idea by comparing the minimum jerk hand paths with the human experimental data of reaching on the horizontal and the vertical planes. From their model on the 3D reaching motion, Klein Breteler and Meulenbroek [4] assumed that there is a movement optimization scheme in the joint level which makes arm joint rotations in a synchronized manner instead of independently controlling each joint DOF rotation. This model derives full joint profiles by applying the MJ model in joint angular space.

The dynamic properties of arm reaching have been also considered to represent an aspect of the governing rules. By considering the motion dynamics, following models derive their solutions in intrinsic coordinates (e.g., joint or muscle). As a result, full motion outputs (e.g., hand trajectory, joint trajectory and torque) are produced simultaneously. Uno et al. [21] proposed the minimum torque change (MTC) model that minimizes the sum of squaredrate of change of joint torque over time, and compared with the MJ model on various 2D reaching motions. For the point-to-point reaching without a via-point constraint, the MTC model could mimic slightly curved hand paths with smooth speed profiles while the MJ always generated straight paths. Later, the MTC model was corrected as the minimum commanded torque change(MCTC) model by Nakano et al. [48]. Dornay et al. [49] introduced the minimum muscle-tension change (MMTC) model to interpret the indeterminacy problem (i.e., redundant mapping problems introduced in Figure 1) in a deeper intrinsic level (i.e., skeletal muscle coordinates) than the MTC model.

Biess et al. [50]introduced a unique computational model of 3D arm reaching. Unlike other optimization models, they obtain an analytic solution of the cost function minimization based on the assumption that optimization principles are separately applied at the geometric and temporal levels of control. In their model, geometric properties (i.e., hand path and posture) are specified by the joint trajectories derived from geodesic curves in the Riemannian configuration space with respect to the kinetic energy metric. Once geometric properties are derived, the temporal property (i.e., speed of the movement) is determined by another independent optimization process that minimizes the squared third time derivative of the selected hand path's arc length.

Some research groups have focused on the resolution of the arm posture configuration problem (see Figure 1(b)). Kang et al. [51] considered mechanical work minimization. Kim et al. [52] introduced an interesting concept of effective feeding potential by maximizing a projection of the largest major axis of manipulability ellipsoid on a vector connecting hand and mouth positions. Kashi et al. [53] adopted a multi criteria cost function to minimize angular joint displacement and shoulder joint range availability. In order to determine the upper body