Assembly Robot Motion Reconstruction from Multiple Task Models

著者	OKODI SAMUEL MCMONDO
号	54
学位授与機関	Tohoku University
学位授与番号	工博第4232号
URL	http://hdl.handle.net/10097/62079

氏　　　　　名	おこでぃ さみゅえる まくもんど Okodi Samuel McMondo
授　与　学　位	博士（工学）
学位授与年月日	平成２１年１２月９日
学位授与の根拠法規	学位規則第４条第１項
研究科，専攻の名称	東北大学大学院工学研究科（博士課程）航空宇宙工学専攻
学位論文題目	Assembly Robot Motion Reconstruction from Multiple Task Models (複数タスクモデルからのロボット組み立て動作再構築)
指　導　教　員	東北大学教授　内山　勝
論文審査委員	主査　東北大学教授　内山　勝　東北大学教授　小菅　一弘 東北大学教授　田所　諭　東北大学准教授　近野　敦

論文内容要旨

A robot performs complex human skills for manipulation of objects during assembly, the robot tasks are reproduced by synthesising a sequence of motion segments with specific mechanical characteristics of the end effector including: when the end effector exerts a force against an object; inducing end effector compliance upon an exerted external force, from an object; exerting stiff motion to maintain a set trajectory, among others.

This research explores a multiple task model strategy to reconstruct assembly robot motion tasks from: a GUI task synthesis by kinematics simulation model *(Figure 1. Left)*; a human force and position task demonstrations model *(Figure 2.)*; a stiffness estimation model *(Figure 4. Right)*; a task geometry estimation, reconstruction and geometric optimisation model *(Figure 4. Left);* and a direct kinematics model. Generation of robot motion reconstructed from multiple task models solves the time inefficiency problem of the GUI task synthesis by kinematics simulation, by fast extraction of spatial and force properties of a task from the task demonstration. The segmentation of the teaching data into primitive task motions with the optimum motion control mode properties is systematically solved by using an intuitive task fragmentation and reconstruction model. The reconstruction depends on the force, spatial and geometric features inherent in the demonstration data. Stiffness task properties cannot be extracted directly from the structured human task demonstrations. It is estimated using empirical data. Task teaching of one kind has been performed by Asada and Asari to estimate the hand impedance, but only in the direction of the constraint using the direct teaching method, but this does not apply to tasks using 6-DOF position and force for primary motion control. Teaching by observing humans perform a task has also been done by Kuniyoshi *et al.*, and Suehiro and Ikeuchi, producing symbolic motion macros from the visual task observations, there work does not capture the force and thus the dexterity from expert human skill demonstrations. The inductive teaching used by Dufay and Latombe makes simple task teaching less taxing to the user, but it is inefficient to script with complex motion skills. Other methods of estimating hand stiffness by Mussa-Ivaldi *et al.*, Tsuji *et al.*,

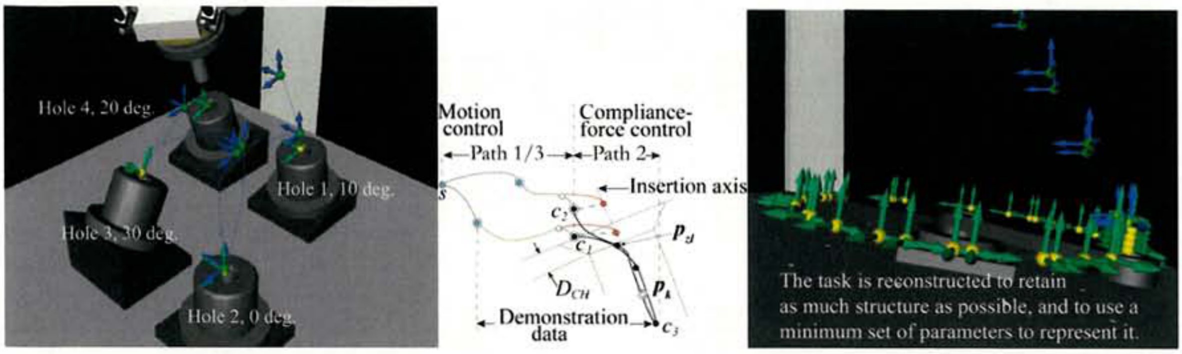

Figure 1. (left to right), The GUI simulation model, the task structure and the cranking robot task.

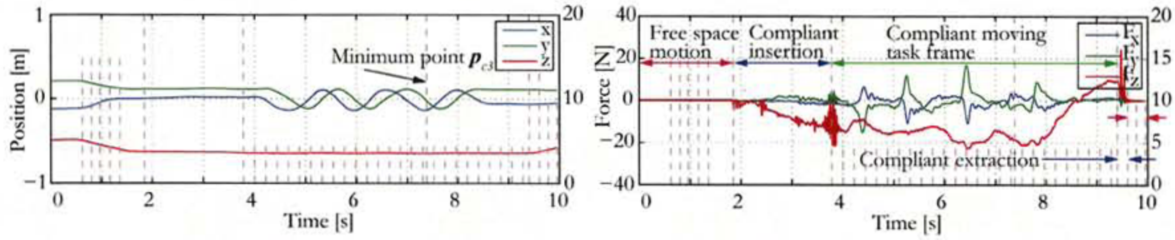

Figure 2. Graph of the human position and force data used for task reconstruction.

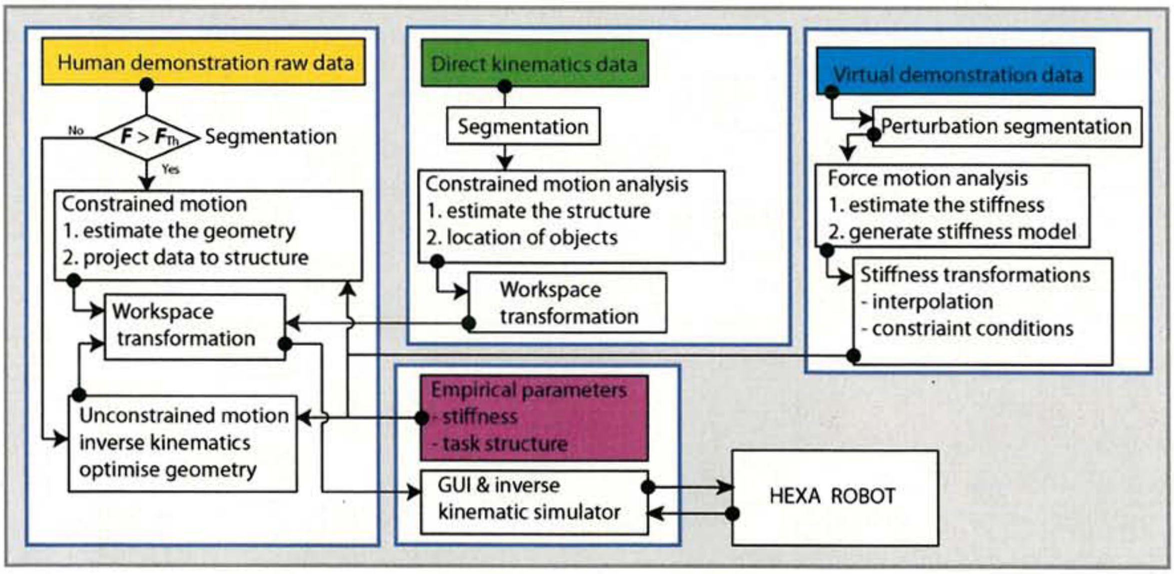

Figure 3. The algorithm integrating the multiple (coloured) models.

and Moraso *et al*. among many others have focused on static and freely moving hand. This stiffness cannot directly be applied as the constrained task teaching stiffness, their models are dimensionally simple, but do not capture the ergonomics of natural task execution.

In a new stiffness estimation model, the stiffness is measured from unstructured human demonstrations, by analysing the effects of force perturbations against the human hand, eliciting a response to stabilise manipulation against such uncertain contact motion.

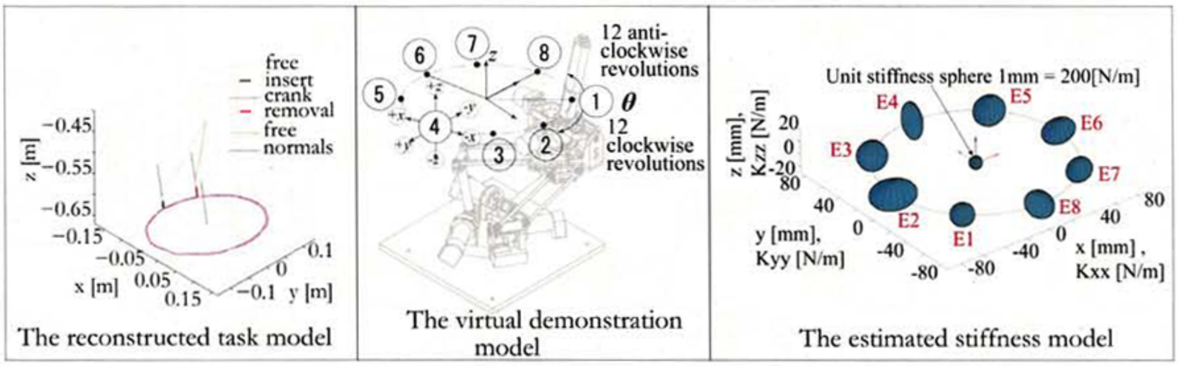

Figure 4. Position, force and stiffness estimation models for the constrained cranking task.

The directly estimated stiffness is validated by the GUI task simulation empirical models of the actual tasks.

This work includes a direct kinematics model for task calibration experiments that directly addresses any erroneous workspace transformation assumptions. The work is motivated to model the tasks by analytically and systematically simplifying task representation *(Figure 1. Centre),* into regular geometric functions, this is achieved by estimating, optimising and incorporating their parametric and geometric definitions as the basis of the task definitions. And thus, explicit task definitions simplify the complexities in generating robot motion. A simple geometric task segment can be subjected to algebraic operations, this flexibility is important for abstractions and modifications. Motion data is broken down into its constituent primitive motion representations, then using systematic analysis and intuitive techniques for generating and reconstructing the inherent task motion. The task is reproduced from the multiple, independent task models. The overall task is, in essence, a combination of the independent models. Complimentary mathematical estimation and optimisation methods and models are used to optimise certain features in heuristic models.

A virtual task demonstration provides a flexible and active method to model and simultaneously obtain all the three independent variables: the position, force and stiffness, as one novel contribution of this research. With the specification of position, force and stiffness as the three cardinal inputs into assembly motion generation, in addition to the modelled inputs that include friction and gravity compensation, a new level of autonomy for task teaching is practically achieved.

The problem with the available models is that they cannot be readily used. This thesis formulates models to evaluate and represent robot tasks as finite parameters that achieve comparable and consistent results as human empirical tasks and data, using intuition, estimation, and optimisation of parameters that cannot be efficiently intuited by human observation. Generation of robot motion from human demonstration presents problems of representation of the task, other than the spatial and force information in the demonstration task; there are ambiguities in representation and what features to be used for characterising the task. In addition, only position and force, of the three independent variables needed for task specification is readily extractable from the teaching demonstrations, the third variable, stiffness or compliance is not. The human task demonstration model is applied for the efficient acquisition of position and force data during a task demonstration session, in its raw state, the data cannot be used for robot motion.

A direct kinematics model can solve the accuracy problems encountered from erroneous assumptions that do not analytically establish the positional transformation relationships between the robot workspace and the external task demonstration workspaces. The task geometry reconstruction model estimates and recovers the task inherent in the demonstration to reproduce the expert functional skill of the human. The direct stiffness estimation model analyses the force and position during the time range of the involuntary human muscle response to stimuli, after a perturbation applied to the hand. A GUI task synthesis by kinematics simulation model is used for explicit task trajectory parameter specification to empirically and heuristically contextualise the task, provide background knowledge on the important aspects, and to provide robot motion performance criteria for the task. The model provides complimentary model parameters that cannot be determined from direct parameter models.

The problems solved in this thesis are, one, to address the accuracy and robustness deficiencies observed in representation of human demonstration skill by a robust solution built synergistic on human skill, empirical observation and mathematical optimisation. A solution that directly applies to ameliorate the arduous, explicit trajectory node data by operator-inputs teaching used before. Two, stiffness estimation during task teaching is underscored by realising that human arm stiffness is variable, it depends on the mental process models of the anticipated task, on the stiffness of the environment registered, on the strength of each individual, and on the desired magnitude and direction of the environment interacting force. This work addresses the problem of representation of human demonstration skill by robust methods, a solution that is consequently applied to solve the arduous nodal explicit teaching approach.

Stiffness abstracted empirically does not portray the flexibility apparent in human skill; this limitation is solved by virtual task simulations to evaluate stiffness at multiple stages of the task. This presents a challenge with how to estimate stiffness, and the challenge is met with an elaborate stiffness estimation methodology.

The approach taken realises that a singular task model is not sufficient to solve for all the three requirements of the end-effector force, position and stiffness. Therefore multiple models are formulated to deal with particular interest parameters and a holistic synthesis integrating the multiple model outputs is applied in the task reconstruction. The approach taken on task reconstruction from a human skill demonstration imitates both the objective quality of human motion; this is done by reproducing a minimum parameter set that completely defines the simplest constituent sub motions of a task. Such a task is not robust to robot workspace non- modelled dynamics such as friction. Task robustness is achieved by intuiting the human skill intention inherent in the data by analysing local data trends that satisfy the objective qualities.

The objective intuitive task skills are superimposed upon the simple constituent sub-motions to achieve robustness. The task is closely reconstructed to retain as much of the structure of the demonstrations spatial skill trajectory as possible. The task shape defines the expert skilful human motion that is not well captured by using symbolic motion macros used in many of the robot motion task synthesis literature. The skills are also regular geometric functions; these are superimposed, subtracted and abstracted, to provide flexibility and robustness of the reconstructed task.

To tackle the complexity and deficiencies of dealing exclusively with one particular model, an intuitive algorithm was formulated, it analyses force and position and rates of change in spatial structure of the raw teaching trajectory. The task is broken down according to the motion modes characterised by force thresholds from the analysis. Task features are extracted based on an intuitive and *a priori* task estimation functions. The task representation is optimised to reflect robot-motion-quality data. There are purges of segments of the tasks that do not satisfy kinematic or objective constraints and motion segment patches to satisfy such constraints. The task features are amalgamated into a robot task. Thus, the algorithm adaptively reconstructs the robot assembly motion, from the interest features or strengths of separate models applied on the raw human position and force demonstration data.

Feature extraction and optimisation is based on intuition of intention, and uses robust analysis of the expected task parameters to maximise the likelihood of isolating the inherent spatial geometry of the task. The direct kinematics model is applied to object location and workspace calibration for disambiguating the task features from the disparate configuration spaces. This resolves any erroneous workspace transformation assumptions.

The approach taken on stiffness estimation is twofold. The first uses an empirical heuristic model of analysing offline, the force-stiffness relationship during task teaching trials, using GUI simulation *(Figure 1. Left)*. However, because of the strenuous nature of the heuristics, a faster model is sought that can be applied directly. The task stiffness is determined as a task dependent parameter *(Figure 4.)*, where the constrained task stiffness is estimated in one model. Another model explores unconstrained stochastic estimation of the stiffness during a position and force capturing demonstration task.

The robust heuristic models formed the basis for analysing and evaluating assembly contact and stiffness, which after validation provide the context, background knowledge and performance criteria for the new model of stiffness estimation. The stiffness is abstracted and applied to the more time efficient motion generation model based on an intuitive task reconstruction algorithm *(Figure 3.)*.

The requirement to simultaneously estimate stiffness together with the position and force begs for unstructured task demonstration model, an active 6-DOF position and force measuring robotic haptic interface system simulates a virtual task demonstration that robustly models an approach to estimate 3D human hand stiffness *(Figure 4. Centre)*. Ideally, it is difficult to measure the actual maximum force and stiffness during a structured trajectory teaching demonstration. The human skill position and force from a structured demonstration only portrays the force that would be required to overcome constraint friction or maintain contact, but stiffness is a measure of resistance to deviation from a set trajectory. Human hand stiffness is thus modelled in a novel setup that harnesses realistic perturbations on a set trajectory during a simulated assembly motion task. The perturbation elicits the force and deviation interactions that are linear to compute and characterise hand stiffness.

Results are presented from the empirical task model used which validates the applicability of compliance and explicit force control on estimated task features. Human offline analysis techniques and intuition are revamped with closed form analytical methodologies to avert the onerous manual trajectory optimisation approach, from one based solely on human observation, intuition and heuristic disambiguation to a faster and robust analytical approach. The formulation to extract human skill objectives from task teaching demonstrations is presented as a fast algorithm of formulations to apply similar strategies, as logic and human skill intuition. Intuitive skill execution strategies and techniques formulated are reported, showing the process of skill reconstruction. Features extracted, purges from the skill demonstration and patches added to the body of features comprise the reconstructed task, showing the human skill objective that was inherent in the task teaching demonstrations *(Figure 4. Left)*. These results overcome the necessity of intensive human involvement during the task reconstruction. This attribute makes this implementation much faster than the nodal path specification. It requires less dependence on human skill, a factor that makes the teaching system easily and fully applicable in generating accurate and efficient robot motion data. In the background, the algorithm provides a platform for more technically complex requirements to be addressed, ranging from safety, a priori assumptions on known task features, representations and solutions to disambiguation of the task spaces; kinematics, logical decisions and intuitive trajectory considerations; estimation, formulations and optimisations, among others. In a way the complexities are removed from the foreground process, to make the task teaching easily manageable, involving specifying of fewer parameters, and conducting skill demonstration in an inconspicuous environment. At the same time, much of the intricate model issues are formulated to be handled autonomously by the algorithm.

Results of the human hand-held distal-end assembly-part stiffness, estimated by analysing simulations of assembly manipulation against periodic stochastic disturbances, and against motion uncertainties are shown *(Figure 4. Right)*. The stiffness is evaluated for practical applicability against an empirical stiffness model. Two stiffness estimation methods are presented, the generalised impedance and the linear stiffness, with two stiffness measurement models evaluated, namely, perturbations during a non constrained, and during a constrained task.

Results on stiffness indicate that constrained trajectory perturbations satisfactorily estimate comparable stiffness to the heuristic stiffness. Another finding shows task performance occurs over a wide range of stiffness values. In addition, a combination of skilful motion and proper stiffness substantially reduce the interaction forces during compliance control.

A 6-DOF high speed parallel robot was used to validate the task reconstructions. Without loss of generality, specific considerations for the platform were used in teaching the robot assembly tasks, and assumptions tailored to develop motion control algorithms suitable for such tasks. A claim on generality of the task reconstruction stems from the fact, that the stiffness in analysed at the point of interaction with the environment. Results of the algorithm, using heuristic task parameters from offline teaching, analysis of the demonstration data, the stiffness estimation models, and the autonomous reconstruction of the task trajectory are shown depicting the decomposition of raw data into primitive modular segments, of motion under stiff position, force and compliance control. These three modes adequately define the control modes necessary to reconstruct the demonstrated human skill from the raw data.

In conclusion, for trajectory reconstruction, the algorithm integrates data synchronisation, demonstration space disambiguation and task space transformations, inverse kinematics verifications, trajectory scaling, error minimisation and data filtering to produce an optimised trajectory for simulation verification and playback. The time is considerably reduced and the teaching procedure is substantially eased. The implementation is fast and offers a succinct interface that supports less savvy user requirements to produce typical high precision assembly tasks. For stiffness estimation, two formulations are reported, the linear stiffness estimation model and the impedance-stiffness estimation model. The linear stiffness model shows similar stiffness to the heuristic model. The impedance-stiffness estimation model shows lower and fluctuating stiffness values compared to the heuristic model. Task performance stiffness applies over a wider range of stiffness than previously known, as shown in the evaluation and validation of the stiffness estimation methods. Linear stiffness shows closer agreement to the heuristics model than impedance model stiffness.

Stiffness estimation in the constrained task is higher in the direction against the constraint, but for constrained motion stiffness is required to be higher orthogonal to the constraint direction. A generalised stiffness model for the constrained task requires more experiments to investigate effects stiffness on the perturbation frequency, and a representative sample of subjects must also be large enough, and address the diverse physiological disparities in the subjects.

論文審査結果の要旨

これまでのロボットへの作業教示は，作業者がティーチングペンダントなどでロボットを直接操作し，ロボットが通過すべき点を指定していく方法が一般的であった。しかし，このような方法では，動作教示に膨大な労力と時間を要してしまうため，近年になって作業者が作業を実演し，それを計算機で解析し，ロボットの動作を自動的に生成する「実演による教示」と呼ばれる手法が盛んに研究されるようになった。この手法は作業教示に要する労力を大幅に軽減し，時間を短縮するのに貢献するが，実演中の作業者の力情報を無視しているため，熟練者が実演しても初心者が実演しても，生成されるロボットの動作に大きな違いは生まない。

本論文は，以上の問題を解決するために，力情報や人間の腕の剛性を含む複数の作業モデルから熟練者のスキルをロボットで再現する手法について論じたもので，全編6章からなる。

第1章は序論であり，本研究の背景および目的を述べている。

第2章では，本研究で用いる実験システムおよび作業教示システムの概要と，ロボットの運動学について述べている。

第3章では，作業実演中の作業者の腕の動きと力の履歴を計測し，その作業をロボットで再現する手法について述べている。提案する手法では作業環境の幾何モデル，及び腕の動きと同期して得られる力情報から，作業内容を同定し，作業動作軌跡を再構成している。また，位置制御モード，剛性制御モードなどの制御モード切り替えを自動化している。提案する手法を用いて，ペグ挿入作業，クランク回し作業を6自由度パラレルロボットで再現する実験を行い，その有効性を検証している。

第4章では，作業実演中の作業者の腕の剛性を測定する手法について論じている。熟練者のスキルにおいては，第3章で考慮した力の加え具合のみならず，作業中の腕の剛性が重要な役割を果たしていると考え，その剛性を測定し，ロボットで再現することを提案している。提案する手法では，ハプティックデバイスを用い，作業者に仮想空間内で作業を行わせ，その作業中に，手先の位置，力，剛性の履歴を測定する。自由空間での人間の腕の剛性を測定した研究は過去に多数あるが，環境から拘束を受ける作業中の作業者の剛性を測定した研究例は少なく，この提案は非常に重要である。

第5章では，第4章の手法で測定した作業者の腕の剛性を6自由度パラレルロボットに実装し，熟練作業者のスキルを再現する実験について述べている。クランク回し作業を対象として，実演中の手先の位置，力，剛性の履歴を測定し，それらをロボットで再現する実験を行い，提案する手法の有効性を検証している。この手法により，ロボットの教示動作の高機能化，及び教示時間の短縮が可能となる。これは重要な成果である。

第6章は結論である。

以上要するに本論文は，熟練作業者の実演から，そのスキルをロボットで再現するための手法を提案し，実験によりその有効性を確認したもので，提案された作業測定法及び教示法の応用性，汎用性を考慮すると，航空宇宙工学およびロボット工学の発展に寄与するところが少なくない。

よって，本論文は博士（工学）の学位論文として合格と認める。