The Fifteenth International Symposium on Artificial Life and Robotics 2010 (AROB 15th '10),
B-Con Plaza, Beppu,Oita, Japan, February 4-6, 2010

ANN Dexterous Robotics Hand Optimal Control Methodology Grasping and Manipulation Forces Optimization

Ebrahim Matter Al-Gallaf[1], Khaled Al Mutib[2] and Hani Hamdan[3]

[1]*College of Engineering, Box 13184, University of Bahrain, Kingdom of Bahrain*
[2]*College of Computer & Information Sciences, Box 51178, King Saud University, Kingdom of Saudi Arabia*
[3]*Dept. of Signal Processing and Electronic Systems, SUPELEC, 3 rue Joliot-Curie, 91192 Gif-sur-Yvette cedex, France*
ebrgallaf@eng.uob.bh, mutib@ccis.ksu.edu.sa, Hani.Hamdan@supelec.fr

Abstract: This article presents an efficient scheme for computing optimal grasping and manipulation forces for dexterous robotics hands. This is formulated as Quadratic Optimization problem formulation. Computation has been based on non-linear model of fingertips contacts and slips. In achieving grasping while in motion, hand inverse Jacobian is considered an important matrix to be computed, however, it is considered as highly intensive to be computed. Consequently, we investigate an efficient approach by using Artificial Neural Networks (ANN) for learning grasped optimal forces. ANN is used to learn the optimal contact forces relating hand joints torques to object result force. Results have indicated that ANN have reduced the computational time reasonable values, this is due to the ability to map nonlinear relations. Furthermore, results have revealed that ANN are capable of learning highly nonlinear relations relating distributed fingertips forces and the joints toques.

Keywords: Dexterous Manipulation, ANN Approximation, Optimal Forces.

I. INTRODUCTION

Kinematics and optimal distributed force control issues for Multi-fingered hands have been a theme for considerable research [1,2]. AI techniques have also been introduced by many researchers in areas of robotics control. ANN, for example, have been heavily employed in robotics technology such as robot arm visual control [3,4], kinematics of high degrees of freedom robot arm [5], furthermore, the study introduced by [6] in which they employ a real-time learning neural system in solving inverse kinematics, the research introduced by [6], in which they employ an artificial neural network for tracking and grasping a moving object observed by a six degrees of freedom robotics arm system. Maciejewski et. al. [7] introduced a methodology to reduce computational burdens based on Givens rotations. Research contributions in task space measure can also be found in [8], as static and dynamic manipulability ellipsoids have been used. An alternative employment of artificial neural networks has been the one presented by Wohlke, [9], here conception of control system was based on combination of a ANN for an adaptation of grasp parameters and a fuzzy logic for the correction of parameters values given to a conventional controller. [10] has proposed a Fuzzy-Neural system control system that learns specific hand-object mapping, without considering the issue of interaction forces among the fingers.

In this contexts, this manuscript rather glances at exerting optimal grasping forces while a grasped object is in motion. Jacobian hand inverse has been avoided to compute, as compared to other techniques which used other numerical algorithms to compute the inverse via the Singularity Robust Inverse. Mapping hand Jacobian inverse, i.e. joints space to fingertips optimal force distribution, to a set of ANN neurons interconnection weights facilitates a reduction of computational execution time. In addition, this gives an ability to add more training patterns that are valuable, particularly once a hand passes singularity.

II. DYNAMICS FORMULATION

Grasped object undergoes a motion, once fingertip forces are exerted, Fig. (1). Dynamic behavior of a grasp object is defined as time response of an object to change motion or force trajectories. It is quantitatively represented by natural frequencies and damping ratios of a grasp on each object frame degree of freedom. Defining a Cartesian based posture error of an object as $e \in \Re^{6\times1}$ as $e \cong u_d^c - u_a^c$. Entire object-hand contact system is described in terms of joint-space torques τ_h joint torques and Euler dynamics by :

$$\tau_h = \left(M_h J_h^{-1} X_h + T_{ex}\right) \quad (1)$$

$$T_{ex} = N_k + C_k + J_h^T\left(\phi_{cd} - Z_i\int_0^x\left(\phi_{cd} - \eta\lambda\right)\right)$$

$$X_h = \left(\Gamma^{+1}\Theta_a - J_h\Theta_k\right) \in \Re^{12\times1} \quad (2)$$

Control law stated in Equ. (1) depends on dexterous Hand inverse grip transform, Γ^{-1}. Computation of hand kinematics is not an easy task, specifically in real-time. Also inverting hand Jacobian matrix J_h^T, is complicated, due to fingers collectively to do movement. Fingertip force distribution depend on Γ^{-1} and J_h^T.

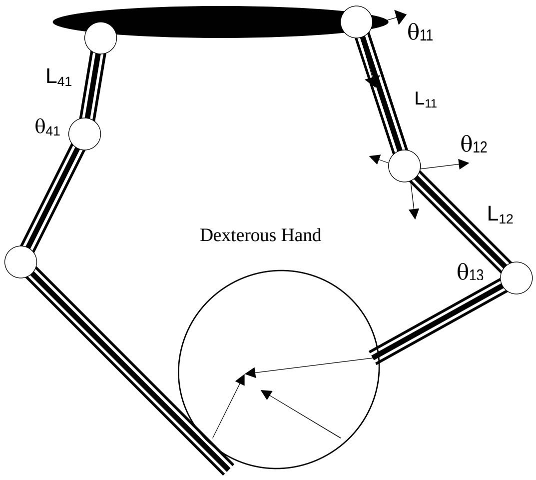

Fig. 1. Dexterous Manipulation.

III. OPTIMAL FINGERTIPS DISTRIBUTION

Fingertips forces and moments do yield a resultant force and moment acting on a grasped object. This is computed from eight vectors according to the following geometric vector-space relation :

$$f_{bi} = f_{oi} \tag{3}$$

$$m_{bi} = m_{oi} + f_{oi} \times r_{oi} \tag{4}$$

where r_{oi} defines a vector from an i^{th} contact location to object centre of gravity frame. For the case of no change from centre of each fingertip to the centre of the object (i.e. no fingertips slip), external forces f_e and moments m_e on a grasped object can be calculated (in terms of object results force F_b) from κ_{bi} and m_{bi} as :

$$F_b^T = \Gamma \kappa_{tip}^T \qquad \Gamma \in \Re^{6\times24} \tag{5}$$

For frictional point contacts, general contact forces f_{tipi}, transmitted from fingertips to an object surface are filtered and reduced to three forces rather than a six-dimensional vector of forces f_{oi} and moments m_{oi}. Hence, contact force vector for the entire hand is expressed as :

$$\kappa_{tip}^T = \begin{bmatrix}\kappa_{tip1} & \kappa_{tip2} & \kappa_{tip3} & \kappa_{tip4}\end{bmatrix} \in \quad \Re^{12\times1} \tag{6}$$

According to Lee,, [8], fingertip force vector associated with an object dynamic F_b is defined by :

$$\kappa_{tip} = \left[\Gamma\Gamma^T\right]^{-1}\Gamma^T F_b + \eta\lambda \tag{7}$$

Equ. (7), represents a solution of a force distribution redundancy with possible adjustable force vector f_{hom} in such a way, a solution of f_{tip} must satisfy a contact cone and hand actuator's torque constraints. Once fingertips do not slip, (*i.e. firm grip at contact point*), few inequalities conditions must be satisfied. If the unknown contact force vectors onto the object are expressed at contact frame, hence with a contact normal (f_z^c) along the (z) direction and directed outward with a coefficient of friction (μ), the friction force cone constraints may be then expressed by $\sqrt{\left(\kappa^2{}_x + \kappa^2{}_y\right)} \le \mu\,\kappa_z$.

To contrast a newly adopted force optimisation algorithm with already used and previously presented methods, (i.e. algorithms for linearizing the nonlinear contact constraints and the simplex optimization), an optimal internal forces optimisation method is also investigated for a four-finger case. In finding a solution to force inequality formulation, an optimisation approach is used, as due to Nahon and Angeles whom they formulated quadratic objective function. Optimisation variables are the internal forces' magnitudes, which are used to determine the amount of stress on an object to be manipulated according to the following well know robotics hand linear equality and linear inequality constraints are thus defined by :

$$\begin{aligned} &\text{optimize} && \chi(\kappa_{tip}) \\ &\text{Subject to} && \Gamma\,\kappa_{tip} = F_b \\ & && \Psi\,\kappa_{tip} \le B \end{aligned} \tag{8}$$

Once a multi-fingered hand comes in a content with a grasped object The need for minimization of a grasp stress (or amount of squeeze) requires the minimization of the actuator torques τ_a. If the vector of all the actuator torques in the system is given by τ_a, then ½ $(\tau_a^T \tau_a)$ defines the actuator torque norm. Furthermore, the τ_a vector consists of two torques: the unconstrained torque τ_u and the torques needed to grasp the object given by $J_h^T \kappa_{tip}$:

$$\varphi(\kappa_{tip}) = ½\,\tau_a^T\,\tau_a \tag{9}$$

In this respect, we are computing f_{tipi} for a four multi-fingered robotics and fingertips, as this will be based on optimizations method, with a given constrains. After then, we shall generate large amount of training patterns to teach a four layers ANN structure. By this, we are designing a learned ANN for dexterous hand force optimization. In this respect, the main duty of a learned ANN system is to let teach a ANN the optimal distribution of fingertip forces to manipulate a grasped object. Optimal distribution are to be obtained using the classical optimization routines, as the system is formulated in terms of nonlinear optimization problem.

IV. ANN NONLINEAR APPROXIMATION

Four layers of fully connected neurons are thus used for approximating the nonlinear mapping function. That was done from a set of available examples called learning samples or training patterns. For the Hand-Object control system, the relation which we shall let the employed neural network to learn, Fig. (2), is defined in terms of some training patterns of object Cartesian posture u_a^c, rate of change of object posture Δu_a^c, and entire hand joints rate of change, $\Delta\Theta_{k-1}$ as expressed by :

$$\Delta\Theta_k = \beta\left(\kappa, \Delta u_a^c, u_a^c, \Delta\Theta_{k-1}\right) \qquad (10)$$

In (10), κ is the ANN function, changes in hand joints space ($\Delta\Theta_k$) is made a function of the neural network structural parameters in addition to grasped object motion parameters (Δu_a^c, u_a^c, $\Delta\Theta_{k-1}$). The focal purpose of neural network structure is to approximate the nonlinear mapping involving changes in hand joints to changes in the object position and optimal force distribution. Neural approximation of Equ (10) is used by hand Cartesian PID based controller, which indeed depends on nonlinear mapping between changes in hand joints to changes in the object position.

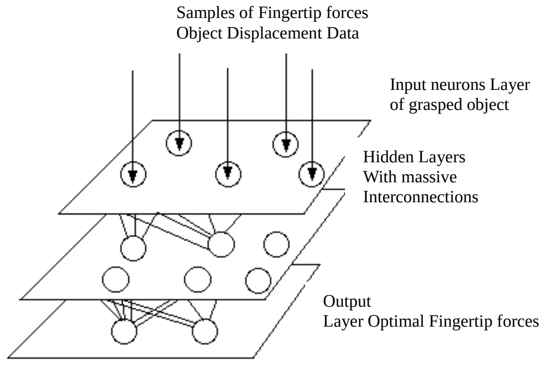

Fig. 2 . A four layers mapping ANN.

Inputs to the neural system are: desired Cartesian object forces u_a^c, changes in such Cartesian forces Δu_a^c, one step change in position of the entire joints in radians $\Delta\Theta_{k-1}$. Neural outputs are the required changes in joint forces for the entire hand $\Delta\Theta_k$. The desired object forces values are obtained in advanced by moving the object to the required position. Hence after, the neural network learns such a nonlinear relation between input and output patterns sufficiently, it shows a nonlinear map between the forces and orientation of the fingers and those of the object, which usually computed using hand Jacobian inverse.

V. TASK-SPACE SIMULATION

Dynamic simulation was done using kinematics and dynamics models for a four fingers hand. Object path of motion was defined. Learning patterns were generated via once the hand was to follow a pre-defined trajectory, while grasping. To illustrate aspects of computation, object Cartesian motion that passes the object through a (non-singular configuration) is employed. The task is to create 3-D sinusoidal object motion with no change in orientation. Articulated hand has been simulated, and hand dynamic motion simulation is presented in Fig. (3). The multi-layer neural network (for mapping object motion to hand joints toques) used in the simulation. The neural network does consist of 18 inputs, 12 outputs and 50 hidden units. These nets map the 18 inputs characterizing the object.

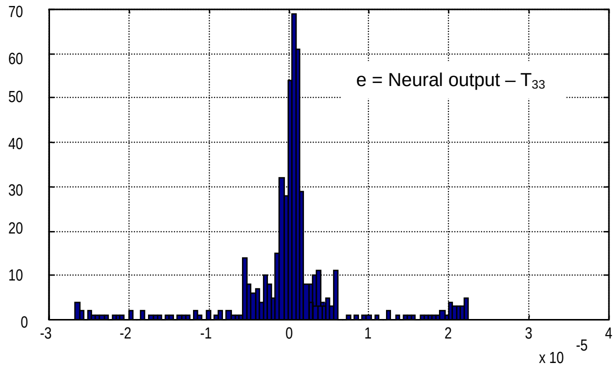

Fig. 3. Validating the neural hand controller : Training patterns and errors

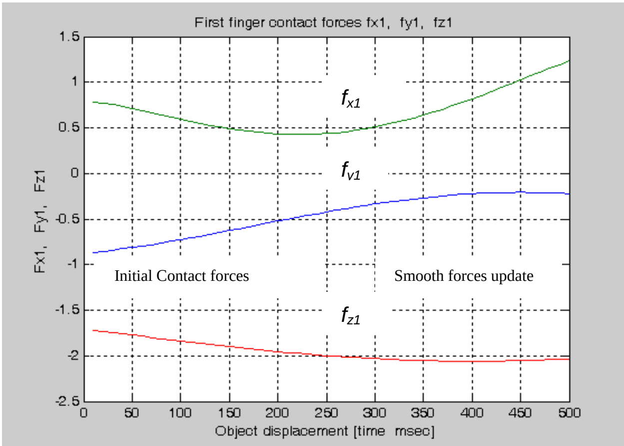

Fig. 4. Optimized fingertip contact forces.

To assess used control methodology, simulation of a constrained dynamics system has been initially achieved using both kinematics and dynamic models of an articulated robotics hand. The hand has been simulated with conventional inverse kinematics algorithms and optimal force distribution, where training patterns have been generated. Training patterns have been based on object Cartesian motion and associated joints displacement. The hand has been run for large number of trials to produce as large as possible of training patterns. The hand has been allowed to follow a pre-defined path over 5 sec. of manipulation time. In this sense, the associated patterns Δu_a^c, u_a^c, $\Delta\Theta_{k-1}$ are tabulated in the proper format to be suitable for the neural network training. The quantity of the training pattern was reaching a size of (500) for a single variable (e.g. Δu_a^c). Hence to validate the neural network ability to model the hand inverse kinematics, the error between a typical neural output node (e.g. θ_{33}) with the actual one has been computed and analyzed.

Execution process starts first with employing the trained ANN controller. Once grasped object position and orientation have been defined, the ANN, hence computes the associated hand joint torques by presenting the network with some patterns which were not included during the training process. Once the neural network presented with such pattern, it associates input patterns with trained joint displacement patterns. The ANN is employed in the hand controller for the calculation of joint displacement as required by the full controller already presented by (1). The employed ANN has proven it was able to reproduce a good mapping mechanism as compared to other full kinematics-based relations.

For instant, Fig. (3) shows training error associated with the object displacement by fingertips movements. Contrary to the method of internal forces optimisation, Fig. (4) shows distributed contact forces based on the use of nonlinear constraint optimisation of Equ (8) for training ANN. Contact forces do satisfy geometric, kinematics, and frictional constraints. It can be observed, distributed contact forces are symmetrical around the middle of the path. Normal forces along (z) axis direction are much greater than the two associated frictional forces by a factor determined by the type of material used at the fingertip-surface interaction. It is noticeable, how the employed optimisation technique has indeed computed the most suitable forces while satisfying all stated constraints.

It has been shown a computational methodology to compute an optimal set of fingertip forces, while updating the kinematics relation via an artificially learned neural network for multi-finger robot hands. Larger training patterns could result in longer hand training time and the possibility of not getting a convergence neural network.

VI. Conclusion

This article has presented a novel approach for computing both optimal set of fingertip forces distribution and an updating mechanism of the interrelated kinematics relations for dextrous robot hand. The problem has been quadraticlly formulated and structured, that was based on ANN, as to compute fingertip forces at object-fingertips contact. Computed forces are hence used in hand closed loop force control. Secondly, for achieving a manipulation task, the issue of the inverse kinematics for multi-fingered robot hand has been also considered. In this context, object motion is defined in a Cartesian based system, therefore differential Jacobian plays an important role in Cartesian object motion. Nonlinear relation between Cartesian object posture and hand joint-space settings, and control signals mapping were learned via four layers artificial neural networks trained for almost possible object displacement.

REFERENCES

[1] I. Yamano, and Takashi M., " Five-fingered Robot Hand using Ultrasonic Motors and Elastic Elements," Proceedings - IEEE International Conference on Robotics and Automation, vol. 2005, pp. 2673-2678, Barcelona, Spain 2005.

[2] Zhao, Jie, Li, Mu, Yan, Ji-Hong, Li, Ge, and Cao, Yu. , "Study on Algorithm of Dynamic Uncalibrated Eye-in-hand Visual Servoing system," Journal of Harbin Institute of Technology, vol. 14, no. 4, pp. 445-449, 2007.

[3] N. Xi, J. Tran, & K. Bejczy, " Intelligent Planning and Control for Multi-robot Coordination : An Event-Based Approach", IEEE Transactions on Robotics and Automation, 12(3), pp. 439-445, 1996.

[4] H. Hashimoto, T. Kubota, M. Kuduo & F. Harashima, "Self-organizing Visual Servo System Based on Neural Networks," IEEE Control Systems Magazine, pp. 31-36, 1992.

[5] Köker Rasit, Oz Cemil, Çakar Tank, and Ekiz Hüseyin" A Study of Neural Network Based Inverse Kinematics Solution for a Three-joint Robot, " Robotics and Autonomous Systems, vol. 49, no. 3-4, pp. 227-234, December 31, 2004.

[6] G. Schram, F. Linden, B. Krose & F. Groen, Visual Tracking of Moving Objects Using a Neural Network Controller, International Journal of Robotics and Autonomous Systems, (18), pp. 293-299, 1996.

[7] A. Maciejewski & C. Klein, "The Singular Value Decomposition: Computation and Applications to Robotics," International Journal of Robotics Research, vol. 8, no. 6, pp. 63-79, 1989.

[8] S. Lee, "Dual Redundant Arm Configuration Optimization with Task-Oriented Dual Manipulability," IEEE Transactions in Robotics and Automation, vol. 5, (1), 1989, pp. 78-97.

[9] G. Wohlke, "Neuro-Fuzzy Based System Architecture for the Intelligent Control of Multi-Finger Robot hands", Proceedings of the IEEE International Conference on Fuzzy Systems, ORLANDO, pp. 26-29, 1994.

[10] E. Al-Gallaf, "Neuro-Fuzzy Inverse Jacobian Mapping For Multi-Finger Robot Hand Control, International Journal of Intelligent & Robotic Systems, vol. 18, no.1, 2003.