Abstract— For advanced and skillful manipulation behaviors and dexterities, an innovative phase of robotics hands has been developed recently with Biomimetically oriented functionalities. Within this manuscript, we shall survey in details biomimetic based dexterous robotics hands designs and implementations. In particular, the study focuses on a number of developments that have been evolving and taking place over the last decade in recent development and technologies related to this vital filed of research. In terms of bio-oriented fingers, the article, furthermore, looks in details at the complicated issue of fingertips forces computation and distribution, and how they are balanced using a knowledge based approach for BIOMIMETIC Dexterous Robotics Hands.

Keywords- Biomimetic, Robot Hands, Manipulation Skills.

I. INTRODUCTION

Over the earlier two decades, large number of dexterous robotics hands have been developed that explicitly emulate human like hand shape and skills. However, it was vibrant that biological functionalities could not be emulated due to lucks of the precise technologies. Over the past few years, engineering such biomimetic intelligent creatures, such as robots, was hindered by physical and technological constraints and limitations. Making robotics systems that can reason and grasp objects safely without risking damage to the mechanism, even making body and facial expression of bliss and excitement are very easy tasks for human and animals to do. Use of AI related tools, effective artificial muscles, and other biomimetic technologies are expected to make the possibility of realistically looking and behaving robotics hands into more practical. Dexterous multi-fingered robot hands have became of great attention in robotics due to their advantages over conventional grippers.

Literatures in such a vital field have been focused since the early 1990, when MIT academicians published their research work in 1984, the UTAH Hand, refer to Jacobsen et. al. [1]. Since that time, optimization of fingertips movements to achieve a force closure has been an important issue ever since. Biomimetic based robot hands, Cohen [2], have been introduced lately over the few years. This is due to a number of potential advantages over purely mechanical based designs robot hands, as known here as “Conventional Hands” designs.

Therefore, within this manuscript, we shall survey a number of potential research frameworks that have been focused lately towards BIOMIMETIC robot hands implementations. In reality, it is not an easy task to review all such kinds of technologies related to the Biomimetic based robot hands designs, however, we shall be dividing this manuscript to include a number of interrelated issues. This would include, (i) Hand Design, (ii) Hand Sensing, (iii) Hand Actuation system, (iv) Hand Force Closure. Within this present manuscript, we also provide a framework for describing dexterous manipulation phenomena which build on recent discussions in the biological literature. Out of large number of biomimetic approaches, we have chosen a subgroup for this review, namely those that (i) were implemented on a real applications, and (ii) mimic actually observed manipulation behavior of animals or humans.

II. BIOMIMETIC DEXTROUS HANDS DESIGNS

A. Hand Biomimetic Compliance Control

Structures of Human Finger

Byoung-Ho et. al. [3] have stated that, for an object grasped by a robotics hand to work in compliance control domain, they analyzed necessary circumstance for successful stiffness modulation in an operational work-space. Next, they proposed a new compliance control method for robot hands which consist of two steps.

RIFDS (Resolved Inter-Finger Decoupling Solver) is to decompose the desired compliance characteristic specified in the operational space into the compliance characteristic in the fingertip space without inter-finger coupling, and RIJDS (Resolved Inter-Joint Decoupling Solver) is to decompose the compliance characteristic in the fingertip space into the compliance characteristic in the joint space without inter-joint coupling.

According to specific analysis results, the finger structure should be biomimetic in the sense that either kinematic redundandy or force redundandy are required to implement the proposed compliance control scheme. Five-bar fingered robot hands are treated as illustrative specimen to implement the proposed compliance control technique. Refer to [3].
B. Control of A Multi-finger Prosthetic Hand

Abboudi et. al. [4], have developed a controller of multi-finger prosthetic hand. The prosthetic hand is controlled by extrinsic flexor muscles and tendons of the metacarpalphalangeal joints.

The hand is equipped with a Tendon-Activated Pneumatic (TAP) control and has provided most subjects, including amputees and those with congenital limb absence, control of hand multiple fingers. TAP hand restores a degree of natural control over force, duration, and coordination of multiple finger movements. This is shown in Fig. 1.

C. Biomimetic Tactile Sensor For Grip Control

Wettels et. al., in [5], have presented a research to show their efforts in developing a biomimeticly novel, robust tactile sensor array that mimics the human fingertip and its distributed set of touch receptors. Mechanical components are similar to a fingertip, with a rigid foundation surrounded by a weakly conductive fluid contained within an elastomeric skin, refer to Fig. 2. It uses a deformable properties of the finger mat as part of the transduction process.

Multiple electrodes are mounted on a surface of the rigid core and connected to impedance measuring circuitry within the core. External forces deform the fluid path around electrodes, resulting in a distributed prototype of impedance changes containing information about those forces and the objects that applied them. They have published initial results with prototypes of the sensor, and proposed strategies for extracting features related to mechanical inputs and using information for reflexive grip control.

D. Tendon Arrangement And Muscle Force Requirements for Humanlike Robotic Finger

In [6], Pollard and Gilbert, proposed that an adapting human examples to a robot manipulator is a challenging problem, though, in part due to differences between human and robot hands. Even hands that are anthropomorph in external design may differ dramatically from the human hand in aptitude to grasp and manipulate objects due to internal design differences. For instance, force transmission mechanisms in robot fingers are generally symmetric about flexion / extension axes, but in human fingers they are focused toward flexion. Their paper describes how a tendon driven robot finger can be optimized for force transmission capability equivalent to the human index finger. As presented in Fig. 3, Pollard and Gilbert, demonstrated that two distinct tendon arrangements that are analogous to those that have been used in robot hands can achieve the same range of forces as the human finger with minimal additional cost in total muscle force requirements.
E. Principal Components Analysis Based Control of a Multi-DOF Underactuated Prosthetic Hand

In [7], Matrone et al. have stated that, at present, prosthetic hands are controlled by means of non-invasive interfaces based on electromyography “EMG”. Driving a multi degrees of freedom (DoF) hand for achieving hand dexterity implies to selectively modulate many different EMG signals in order to make each joint move autonomously, and this could require substantial cognitive effort to a user, [7]. Therefore, a Principal Components Analysis (PCA) based algorithm is used to drive a 16 DoFs underactuated prosthetic hand prototype (known as the Cyber-Hand) with a two dimensional control input, in order to perform the three prehensile forms mostly used in Activities of Daily Living (ADLs). Such PCA set has been derived directly from the artificial hand itself, through collecting the sensory data while performing 50 samples of different grasps, and consequently used for control.

Trials have shown that two independent input signals can be successfully used to control the posture of a real robotic hand and that correct grasps (in terms of involved fingers, stability and posture) may be achieved. The work demonstrates the effectiveness of a bio-inspired system successfully conjugating the advantages of an under-actuated, anthropomorphic hand with a PCA-based control strategy, and opens up promising possibilities for the improvement of an intuitively controllable hand prosthesis.

F. A Shape Memory Alloy-Based Tendon-Driven Actuation

Bundhoo et al. [8] have presented a novel biomimetic tendon-driven actuation structure for prosthetic and wearable robotic hand applications. It is based on the mixture of compliant tendon cables and one-way shape memory alloy wires that form a set of agonist–antagonist artificial muscle pairs for the required flexion/extension or abduction/adduction of the finger joints. The performance of the suggested actuation system is demonstrated using a 4 DOF (three active and one passive) artificial finger test-bed, also developed based on a biomimetic design methodology. A microcontroller-based pulse-width-modulated proportional derivation feedback controller and a minimum jerk trajectory feed-forward controller are implemented and tested in an ad hoc fashion to evaluate the performance of the finger system in emulating natural joint motions. Further research work within same field (Part II), describes the dynamic modeling of the above nonlinear system, and the model-based controller design. Such a design is shown in Fig. 5.

G. Biomimetic Grasp Planning for Cortical Control

Ciocarlie et al., [9], outlined a grasp arrangement system designed to augment the cortical control of a prosthetic arm and hand. An important feature of this task is the presence of on-line user input, which will ultimately be obtained by identifying and extracting some relevant signals from brain activity. The grasping system can combine partial or noisy user input and autonomous planning to enable the robot to perform steady grasping tasks. Ciocarlie et al. use principal component analysis applied to the observed kinematics of physiologic grasping to condense the dimensionality of hand posture space and simplify the planning task for on-line use. The planner then accepts control input in this reduced-dimensionality space, and uses it as a seed for a hand posture optimization algorithm based on “Simulated Annealing”. They presented two applications of this algorithm, using data collected from both primate and human subjects during grasping, to demonstrate its ability to synthesize stable grasps using partial control input in real or near-real time.
H. Grip Control: Biomimetic Tactile Sensing Systems

In [10], Wettels et. al., have presented a proof-of-concept for controlling a grasp of an anthropomorphic mechatronic prosthetic hand using a biomimetic tactile sensor, Bayesian inference and simple algorithms for estimation and control, refer to Fig. 7. The sensor takes advantage of its compliant mechanics to provide a tri-axial force sensing end-effector for grasp control. By calculating normal and shear forces at the fingertips, the prosthetic hand is able to maintain perturbed objects within the force cone to prevent slip. A “Kalman Filter” is then used as a noise-robust method to calculate tangential forces. Biologically-inspired algorithms and heuristics are presented that can be implemented on-line to support rapid, reflexive adjustments of grip.

I. Development of Bio-Mimetic Hand Parallel Mechanisms

Seokwon et. al. [11], have described a development of bio-mimetic robot hands and a control scheme. Each robot hand has four under-actuated fingers, which are driven by two linear actuators coupled. According to a study of the human hand, it is noted that, the coupled muscles, like the flexor and extensor muscle, generate the finger motion. Each fingertip can influence toward objects by curved surface workspace in 3D-space. The robot hand was designed considering the dexterity and the size suited for human tools and has tactile sensors equipped on the fingertips of each finger. The robot hand has four fingers with totally nine DOFs, including two linear actuators and linkage knuckles. Similar research papers, and as a focus part of this paper, computational simulations are described. Simulations results show the performance of the robot hand to manipulate tools of various shapes.

J. Biomimetic Sensing For Robotic Manipulation

A set of four robot end-effectors was equipped with force sensors to provide haptic feedback to aid in accomplishment a manipulation tasks of rotating a sphere and a cube was presented by Petroff, [12]. The motion planning algorithm used to compute the robots’ joint angles is called steering-using-piecewise-constant-inputs, and is applicable to under actuated, nonlinear, nonholonomic, drift-less systems. Nonholonomic constraints arise throughout contact, requiring fingers to only roll relative to the object. However, the algorithm gives rise to new vector fields, known as “Lie Brackets” that allow the fingers to be reconfigured without releasing the object. Thus, effectively increasing the workspace of the manipulation system. Experiments were conducted with fixed-point manipulation to create a baseline for comparing reconfigurable manipulation experiments. Both open loop and closed loop, reconfigurable manipulation experiments were conducted on a spherical object.

K. Design And Control of a Shape Memory Alloy Based Dexterous Robot Hand

Darwin et. al. [13], have presented a modern externally powered upper-body prostheses are conventionally actuated by electric servomotors. Although these motors do accomplish reasonable kinematic performance, they are huge and heavy. Deterring factors such as these lead to a substantial proportion of upper extremity amputees avoiding the use of their prostheses. Consequently, it is apparent that there exists an essential for functional prosthetic devices that are compact and lightweight.

Realization of such a scheme requires an alternative actuation technology. In this respect, biological inspiration suggests that tendon based systems are beneficial. Shape memory alloys are a type of smart material that exhibit an actuation mechanism resembling the biological equivalent. As such, shape memory alloy enabled devices promise to be of major importance in the future of dexterous robotics, and of prosthetics in particular.

Hence, Darwin et. al. investigated the design, instrumentation, and control issues surrounding the practical application of shape memory alloys as artificial muscles in a three-fingered robot hand.
L. Adaptive Grasping with Tactile Sensor Based on Robust Force and Position Control

Takahashi et al. [14], proposed a different robust force and position control method for property-unknown objects grasping. The proposed control method is capable of selecting the force control or position control, and smooth and quick switching according to the amount of the external force.

The proposed method was applied to adaptive grasping by three-fingered hand which has 12-DOF. Experimental results revealed that, the smooth collision process and the stable grasping is realized even if the precise surface position, the mass and the stiffness are unknown.

In addition, a novel algorithm determines the grasp force according to a “slip” measured with a tactile sensor, and the viscoelastic media on the fingertip.

The algorithm works at starting and stationary state, so the friction and mass unknown object grasping is realized by the effectual force.

![Figure 10](image)

**Figure 10** Two soft fingers in contact model.

III. CLOSED CHAIN SYSTEM

Consider a grasp of a rigid object with a multi-fingered robotics hand as illustrated, as in Fig. 10. There exist a Coulomb friction with friction coefficient, and there exits a Coulomb friction with friction coefficient \( \mu \), at contact points, such that: \( \sqrt{f_u^2 + f_n^2} \leq \mu f_u \), and together each of the side components are orthogonal components and \( f_u \) is a normal component of the contact force, as with respect to the object coordinate frame.

Describing a cartesian based posture error \( (e) \) of an object as \( e \in \mathbb{R}^{16} \), as an error between a defined posture \( u^* \), and the real object posture \( u_i \) as \( (e \equiv u^* - u_i) \). Object-hand closed system is described in terms of hand joint-space torques \( (\tau_h) \) joint torques and Euler dynamics by:

\[
\tau_h = M_h J_h^T x_h + T_n \tag{1}
\]

\[
T_n = N + C + J_k (F_c - Z_0 (\Theta + \eta \lambda)) \tag{2}
\]

\[
X_h = (G^T \Theta - J_h \Theta) & \quad F_i = G f_i \tag{3}
\]

Each of the hand fingers maps joints torque to an object via an whole hand grasp \( G \) which is formulated as functions of: \( G = (G_1 \ G_2 \ G_3 \ G_4) \), as grab sub-matrices \( G_i \in \mathbb{R}^{6 \times 3} \) for \( i = (1, \ldots, 4) \) are defined in terms of contact location by:

\[
G_i = \left[ \frac{1}{\gamma_i} \right] \tag{4}
\]

In reference to Fig. 10, and as in Equ 3, hand fingertip forces depend individually on two heavily computed matrices, \( G_i \) with an irregularity matrix, and a time dependent hand Jacobian inverse matrix as the \( J_i^* \).

IV. FORMULATION OF FINGERTIPS FORCE DISTRIBUTION

When a fingertip makes a contact, fingertips forces and moments do yield a resultant force \( F_i \) and moment \( m_i \) acting on a grasped object. For a four fingered hand, these are computed from twelve matrices according to the following geometric vector-space relation:

\[
F_i = \left( f_i \ m_i \right) \quad \tau_i = f_i \tag{5}
\]

\[
m_i = \left( m_i + f_i \times \gamma_i \right) \quad \text{for } i = 1 \ldots 4 \tag{6}
\]

\( \gamma_i \) defines a vector from a contact location to object centre of gravity. For the case of no change from centre of each fingertip to the centre of the object, external forces \( (f_i) \) and moments \( (m_i) \) on a grasped object can be calculated in terms of object results force \( F_i \) in terms of \( f_i \) and \( m_i \) as:

\[
F_i = G f_i^m \quad G \in \mathbb{R}^{6 \times 24} \tag{7}
\]

Since we are working at a situation of frictional point of contact, only three forces are transmitted from a fingertip to the object surface.

Contact force vector for the entire hand with four fingertips gripping an object is hence expressed as:

\[
f_i^{m_{all}} = \left( f_{i_{sp1}} \ f_{i_{sp2}} \ f_{i_{sp3}} \ f_{i_{sp4}} \right) \tag{8}
\]

Fingertip force vector associated with an object dynamic is defined by the following distribution:

\[
f_{i_{sp}} = (G^T G)^{-1} G^T F_i + \eta \lambda \quad \text{and should satisfy } \sqrt{f_{i_{sp}}^2 + \lambda^2} \leq \eta \lambda \tag{9}
\]

\( \lambda \eta \) is a set of internal forces. Equ. (9), represents a solution of a force distribution redundancy with possible adjustable force vector in such a way, a solution of \( f_{i_{sp}} \in \left( f_i \ f_{i_{sp}} \ f_{i_{sp}} \ f_{i_{sp}} \right)^2 \) must satisfy the contact cone and hand actuator's torque constraints.
V. Hand Force Closure

Quadratic Formulation: Nonlinear Constraints

For finding a solution to maximum force inequality formulation of (9) and achieving a force closure, an optimization approach is therefore defined, this is based on formulated quadratic objective function. Optimization variables do indicate a strength of a grasp. This can be formulated by:

\[ \text{Optimize } \phi(f_w) = \left( \frac{1}{2} f_w^T f_w \right), \text{ Subject to } G(f_w) = f_c, \quad \Psi(f_w) \leq B \]

\[ B = \begin{bmatrix} P & P & P & \tau_1 & \tau_2 & \tau_3 \end{bmatrix}, \quad P \in \mathbb{R}^{3 \times 3}, \quad \tau_1, \tau_2, \tau_3 \in \mathbb{R}^{3 \times 1} \]

If a vector of all the actuator torques in the system is expressed by \( \tau_a \), and \( \tau_a^T = \begin{bmatrix} \tau_1 & \tau_2 & \tau_3 \end{bmatrix} \in \mathbb{R}^{3 \times 1} \) then \( \phi(f_w) \) defines the actuator torque norm to be minimized. The \( \tau_a = \begin{bmatrix} \tau_a & \tau_a & \tau_a \end{bmatrix} \) vector consists of forces in terms of dual torques: Unconstrained torque \( \tau_u \), \( \tau_c \) constrained torque, and torques needed to grasp the object given by \( J_k f_w \):

\[ \phi(f_w) = \left( \frac{1}{2} \tau_a^T \tau_a \right) \quad \tau_a = \tau_u + \tau_c \]

\( \phi(f_w) \) is the optimization function to be minimized. \( \tau_o = \tau_u + \tau_c \) is the hand joint-space torques. This is defined in terms of minimizing the amount of object squeeze while grasping.

VI. A Learning Rule-Based Force Closure Hand

Fuzzy model can be represented by a special type of neural network topology which is termed here a Neuro-fuzzy topology. For this case, fuzzy reasoning is capable of handling uncertain and imprecise robotics hand force distribution information while a neural network is capable of learning from examples. This is illustrated in Fig. 11.

To show how to construct a rule-based fuzzy system, let us to visualize a fuzzy inference system with two inputs \( x(k-l) \) and \( y(k-R) \) and one output \( y(t) \). For a case, if the rule base contains two fuzzy "if-then" rules of TAKAGI AND SUGENO’S type, formerly a rule is defined as:

If \( f_u(k-l) \) is \( A_1 \) and \( f_u(k-2) \) is \( B_1 \), then

\[ \tau = p_x (k-l) + q_x f_u(k-2) + r_x \]

If \( f_u(k-l) \) is \( A_2 \) and \( f_u(k-2) \) is \( B_2 \), then

\[ \tau = p_x (k-l) + q_x f_u(k-2) + r_y \]

here \( (p_x, q_x, r_x) \) are constants. They are known as the fuzzy parameter set. The "if" parts of the rules are same as in the ordinary fuzzy if-then rules, "then" parts are linear combinations of the all input variables. Within LAYER-1, each of the \( i^{th} \) node in such a layer is a square node with a node function, refer to Eq. (19):

\[ O_i = \mu A_i f_u(k-1) \]

\( f_u(k-l) \) is an input to \( (i^{th}) \) node at \( (k) \) time sample. \( (A_i) \) is a fingertip force linguistic label (tiny small, small force, large force, etc.) associated with this node function. We selected the relation for \( \mu A_i f_u(k-1) \) to be a bell-shaped with maximum equal to unity and minimum equal to zero. This is expressed by:

\[ \mu A_i f_u(k-1) = \frac{1}{1 + \left( \frac{f_u(k-1) - c_i}{a_i} \right)^2} b \]

\[ \mu A_i (f_u(k-1)) = \exp \left( -\left( \frac{f_u(k-1) - c_i}{a_i} \right)^2 \right) \]

\( \{a_i, b, c_i\} \) is set of parameters to be identified. In LAYER-2, every node is a circle node, it multiplies incoming signals and sends their product out. For this case:

\[ y_i = \mu A_i f_u(k-1) \times \mu B_i f_u(k-2) \quad i = 1,2 \]

Individual output nodes, do represent the connection strength of a fuzzy rule. In LAYER-3, every node in this layer is a circle node. The \( i^{th} \) node calculates the ratio of the \( i^{th} \) rule’s firing strength to the sum of all rules’ firing strengths:

\[ y_i = \frac{y_i}{y_i + y_j + \cdots + y_n}, \quad i = 1,2 \]

For the case of LAYER-4, each individual node is defined as:

\[ O_i^4 = \overline{y}_i f_i = \overline{y}_i (p_i f_u(k-l) + q_i f_u(k-2) + r_i) \]

\( \overline{y}_i \) is the output of layer-3. \( \{p_i, q_i, r_i\} \) is the parameter set. Finally, for LAYER-5, nodes in this layer are circle node. They compute the overall output as an aggregate of all incoming signals, i.e.:

\[ O_i^5 = \text{overall output} = \sum_{i} \overline{y}_i f_i = \sum_{i} \overline{y}_i f_i \]

Fuzzy Training Phase: From the designed Neuro-fuzzy architecture shown in Fig. 11, it is observed that, given

Figure 11. Employed learning system architecture.
values of precondition parameters, the entire output is expressed as a linear combination of the consequent parameters. More precisely, output $\hat{y}$ can be expressed as:

$$
\hat{y}_n = \frac{y_1}{y_1^2} \hat{y}_1 + \frac{y_2}{y_1^2} \hat{y}_2 + \cdots + \frac{y_m}{y_1^m} \hat{y}_m 
$$

(19)

this is a linear in the consequent parameters ($p_1, q_1, r_1, p_2, q_2, r_2$). The identified consequent parameters, are optimal (in the consequent parameter space) under the condition that the premise parameters are fixed. A model’s weights are commonly identified by performing maximum likelihood estimation.

Given a training data set $Z^n = \{y(k), x(k)\}_{k=1}^n$, the task is to find a weight vector which minimizes the following cost function:

$$
J_w(w) = \frac{1}{N} \sum_{k=1}^N (y(k) - \hat{y}(k))^2
$$

(20)

As the model shows, $\hat{y}(k)$, is nonlinear with respect to the weights, hence, linear optimization techniques cannot be applied.

For achieving a hand-object force closure, the relation which we shall let the employed Neuro-Fuzzy to learn, is defined in terms of some training patterns hand joints torques and fingertip forces, as $\Delta T^{i_1}_{w_1}$, $\Delta T^{i_2}_{w_2}$ and $\Delta T^{i_3}_{w_3}$, expressed by:

$$
\Delta f^{i_1}_{w_1} = \mu (\Delta f^{i_1}_{w_1} + \Delta f^{i_2}_{w_2} + \Delta f^{i_3}_{w_3})
$$

(21)

In reference to the relation defined by Eq. (21), the parameter $\mu$ is the Neuro-Fuzzy mapping function. It relates that changes in hand fingertips forces space $\Delta f^{i_1}_{w_1}$ is made a function of the Neuro-Fuzzy structural parameters, in addition to grasped object motion parameters $\Delta f^{i_2}_{w_2}$.

Inputs to the employed Neuro-fuzzy system are listed as follows:

(i) The desired cartesian object forces $F_o$.

(ii) Changes in fingertips forces $\Delta f^{i_1}_{w_1}$, step.

(iii) A number of steps change in forfeit forces of the entire joints in radians $\Delta \Theta^{i_3}_{w_3}$.

The used Neuro-fuzzy outputs, are designated as the required changes that is happening in hand joint torques.

VII. BIOMIMETIC BUILT FINGERTIP HAND SIMULATION:
A CASE STUDY ANALYSIS

A numerical quadratic optimization approach was used to compute fingertip forces, for a biomimetic built fingertip type, using the definitions in (10). This allows to generate large number of learning patterns. Learning patterns were generated once the hand was to follow a pre-defined trajectory, while grasping. To illustrate aspects of computation, an object cartesian motion is employed. The assignment is to move within the 3-D, sinusoidal object motion with no change in orientation.

Hand fingers movements have been simulated as a realtime simulation. In this sense, the associated pattern, are tabulated in a appropriate format to be suitable for the Neuro-fuzzy training.

Execution process starts first with employing the trained Neuro-fuzzy structure in hand closed loop control. The Neuro-fuzzy system computes the associated fingertips forces. That was done by presenting the trained Neuro-fuzzy with specific patterns which were not included during the training process.

Once the Neuro-fuzzy have been presented with unknown patterns, it associates input patterns with trained joint torques patterns. The employed Neuro-fuzzy system has shown excellent capabilities to reproduce a good mapping mechanism as compared to other evaluation approaches.

To validate the network ability to learn and model hand optimal forces distribution, error between a typical Neuro-fuzzy output nodes, e.g. $(f_3)$, with the actual third finger joint torque used for training been computed and analyzed. Resulting numerical data are hence used to train the employed Neuro-fuzzy system.

After learning, maximum force distribution was found. It is a good measure of best force closure. Error between the reference object resultant force and object real force can be easily seen close to zero, as shown in Fig. 12.

Figure 12. Hand-Object moving dynamics $\equiv$ zero in 6-D space.

Making hand-object dynamics approaching very small numeric ($\equiv$ zero), this indicates object-fingers are moving together with no slipping.

The figure also indicates a good degree of accuracy in moving the grasped object while generating a body results force $F_o \equiv$ zero.
This signifies how the adopted Neuro-fuzzy system, was efficient in mapping the highly nonlinear distribution of forces. Finally, to demonstrate how the adopted algorithm has learned the best grasping forces (from a number of examples), Fig. 13 shows the updated learned fuzzy membership functions after the Neuro-fuzzy has learned the mapped relations. Changes in shape of memberships is indicating an update on neural net weights, thus signifying the learning conception. By this, a learning fuzzy system has shown a considerable extent of accurate results for building a force-closure, even for a for a biomimetically built fingertip robotics hand.

VIII. CONCLUSION

In this manuscript, we have looked in details into the innovative trends related to the usage of Bio-mimetic built Robotics Hands. Such a new research venue has revealed new research directions to a use of bio-oriented materials in building robotics hands. This has a number of advantages over the utilization of motor driven hands. In this sense, this paper is also a part of work, which is in progress, that is prepared to be looking into and surveying a number of research efforts towards building biomimetic based dexterous robotics hands. This investigation has clearly indicated that, there are tremendous number of efforts towards building dexterous robotics multi-fingered hand with BIOMIMETIC based ideas and initiatives. In addition, it was shown that research is even moving towards muscle type hand fingers, which means moving totally from the concept of motor driven fingers movements and grasping. In terms of bio-inspired robotics hand design and force controller synthesizing, technology is promising us with vital solutions in this directions, however, the concept of force closure is still remaining an issue. In this sense, the research has also looked into the concern of computing a right set of tips forces for grasping and moving object for Bio-mimetic designed Robotics Hands. This has been based on building a trainable BIOMIMETIC contact-type grip by each of fingertip. The employed algorithm has indicated very accurate results in achieving an accurate force closures.

REFERENCES


Figure 13. Initial and final adjusted fuzzy memberships. (This shows a high degree of accuracy in while in motion).