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Imitation of basic hand preshapes by fluid based method: fluidics formation control

Umut TİLKİ, İsmet ERKMEN, Aydan Müşerref ERKMEN
Department of Electrical and Electronics Engineering, Faculty of Engineering, Middle East Technical University, 06531 Çankaya, Ankara-TURKEY
e-mails: utilki@metu.edu.tr, erkmen@metu.edu.tr, aydan@metu.edu.tr

Abstract

In this paper, a new approach is developed, avoiding the correspondence problem caused by the difference in embodiment between imitator and demonstrator in imitation learning. In our work, the imitator is a fluidic system of dynamics totally different than the imitatee, which is a human performing hand gestures. The fluidic system is composed of fluid particles, which are used for the discretization of the problem domain. In this work, we demonstrate the fluidics formation control so as to imitate by observation basic hand preshaping features. Our fluidic formation control is based on setting suitable parameters of Smoothed Particle Hydrodynamics (SPH), which is a particle based Lagrangian method, according to imitation learning. The fluid parameters adjusted by the fluidics imitation controller are body force (f), density and velocity of particles (V) so as to lead formations of fluidic swarms to human hand preshapes.

Key Words: *Multi-dynamics imitation, robot grasping, swarm formation, robotics imitation, imitation by swarm.*

1. Introduction

Learning by observation is an essential and noninvasive part of imitation without interfering with the imitatee's task. Many problems have to be handled for learning to imitate without affecting the imitatee. The primary difficulty is the correspondence problem, which is the mapping of actions or action sequences between a demonstrator (imitatee) and an imitator. This difficulty can be overcome if imitatee and imitator have similar kinematic structures. However learning to imitate by observing others that are different kinematically, is the recent focus of machines imitating human or animals, or machines imitating other machines [1]. For systems having kinematically different structures, the correspondence problem becomes an initial important issue that prevents imitation by observation, if not solved within the imitation methodology. Even when two human beings of the same dynamical structure imitate each other, it has been found in the medical literature that there exists a chronic disease called ideomotor apraxia that hampers the correspondence problem, leading to faulty organ matching, e.g., the demonstrator lifting a hand, the imitator may lift a leg [2]. During the imitation between two kinematically different systems, this disease is inherent. For example, imitation of human hand motions by a 3-fingered robot hand has an inherent correspondence problem where no one to one organ matching exists, the imitator being under actuated with less limbs than that of the demonstrator. The correspondence problem aside, many researchers speculated that imitative learning has valuable characteristics such as being noninvasive in the learning process which may in many cases speed up learning by not requiring communication between teacher and student thus, not interrupting the imitatee's task through interference [3].

In this work, we tackle the problem of imitating human hand postures by a system that possesses a completely different dynamics, thus unable to initiate an imitational organ matching. Such an imitation is performed in nature by animals such as dolphins imitating their trainer's postures and gestures. We focus on developing an approach for imitation through observation of an imitatee's pose or gestures without the need of any organ matching. Towards this end, we focus on imitation of a human hand gestures by a swarm having totally different dynamics than a human. More specifically this imitation is handled as the colony formation control of the swarm so as to resemble basic human hand preshapes. We consider in this work, a swarm that has a strikingly different dynamics than a human, as a colony of fluid particles.

The contribution of this paper is the fluidics formation control imitating human hand gestures. This formation control is achieved using parameters of fluid dynamics approximated by Smoothed Particle Hydrodynamics (SPH) which is a mesh free computational particle based Lagrangian method, which resolution can easily be adjusted by fluid variables such as density. The most important advantage is the adaptive mesh free nature of the SPH method: Since it is not a grid based formulation, SPH is not affected by the arbitrariness of the particle distribution, and grid size. Therefore, it can handle the problem of large deformations which resides at the very foundational nature of a colony of particles imitating large deformations (curving, branching etc.) in hand gestures. We have found that SPH allows the fluidic formation control of a swarm imitator, imitating human hand posture with variable degree of resolution in the interpretation of observed movements based on features extracted from human poses. This novel approach is introduced in Section 3 of this paper and its performance demonstrated by simulation results of Section 4. Section 4 also provides discussions based on sensitivity of our approach to some SPH parameters. This novel imitation framework is motivated in Section 2, supported by works in the literature most relevant to imitation learning and fluidics. Section 5 concludes the paper.

2. Related work and motivation

Learning to imitate by observing another system of totally different dynamics has the inherent problems of understanding what to imitate, when and how to imitate. Imitation by observation provides the advantage of speeding up the learning process, since the focus is on "learning on the flight of observation" process which is learning online where the demonstrator (imitatee) is not required to spend time with the imitator, to specifically train the imitator by leaving his/her own tasks. The demonstrator can continue doing his/her job and the imitator usually observes and learns in parallel to imitate without interrupting the demonstrator tasks.

Such imitation learning requires a complex set of mechanisms that detect what to learn from an imitatee by observing his/her movements and map them onto its own movements by transforming the imitates behavior features into its own dynamical features. Such a process includes movement recognition, pose estimation and tracking, body correspondence, coordinate transformation, matching of observed movements, etc. [4]. Alissandrakis et al. [5] introduced ALICE, the "Action Learning for Imitation via Correspondence between Embodiments," a generic imitation framework that can be used by an imitator agent to find corresponding actions that produce similar states and effects as a model agent. In another work, laser scanner data are used to determine rough human body positions, body orientation and pose information [6]. For tracking and velocity control, particle filter approach is used in this research. Minato et al. [7] use a grid-based approach in their

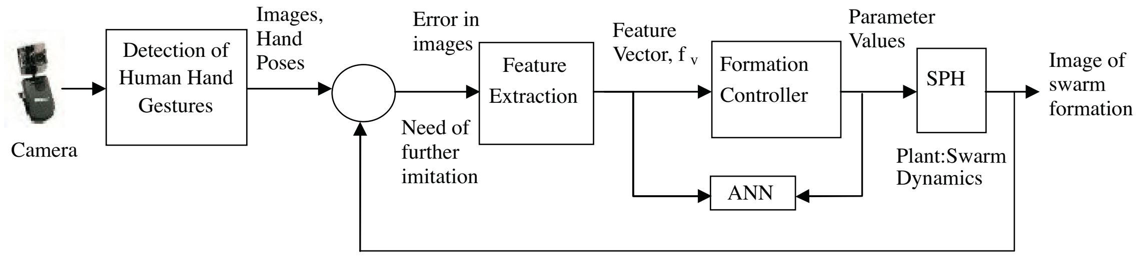


Figure 1. Fluidic formation controller for swarms.

approach on an android by mapping human posture in three-dimensional position space. They attempt to naturally animate a robot to maintain social interaction. For posture transformation from human subject to android they use a motion capture system which can measure the posture of human subject and the android by attaching markers on the android so that all joint motions can be discriminated. Then the same markers are attached to the subject's body. In this kind of experimental setups, the major constraint is that there must be a large set of sensory data, collected from data gloves, magnetic trackers, stereo vision systems etc. to track and understand the movements of the demonstrator.

Our main objective in the present work is to deal with imitation by observation between two dynamically different systems that carries a total mismatch of organ correspondence (inherent ideomotor apraxia disease in the imitator system [2]) so that imitation requires the understanding of what to imitate, when and how to imitate without the case of pattern matching for organ correspondence. Our imitator is a fluid body imitating through sensing, the human hand pre-shapes. We provide in this paper, the "proof of concept" demonstration that our proposed fluidic formation control can make the fluid body assume postures that mimic basic human hand preshapes. Our approach is based on generating the control of flow field variables in order to get desired behaviors and shapes of the fluid body, by observing human hand behaviors.

Fluid based modeling has been used in robotics, generally for swarms and recently in the formation of geometric patterns with multiple robots [8, 9]. In these works, mobile robots are modeled as fluid particles and are controlled by the help of fluid dynamics parameters. There are various characteristics of fluid flows which are desirable in swarm robotics, such as obstacle avoidance and source to sink optimal path finding behaviors of the fluid. In this work, we combine these behaviors to get the desired shape of the colony of particles for mimicking human hand postures based on fluidic formation control. Such a formation control is nonexistent in the literature where the work that resembles by far is [8] where the swarm group was controlled by the help of the SPH parameters were used only for obstacle avoidance, without generating any effects on the swarm formation. In another work [9], again mobile robots were modeled as fluid particles and their motions were generated using given geometric patterns. There, besides the SPH theorem, Finite Element Method (FEM) and electrostatic fields were also used to drive the fluid particles towards the given geometric pattern which were also treated as environmental obstacles.

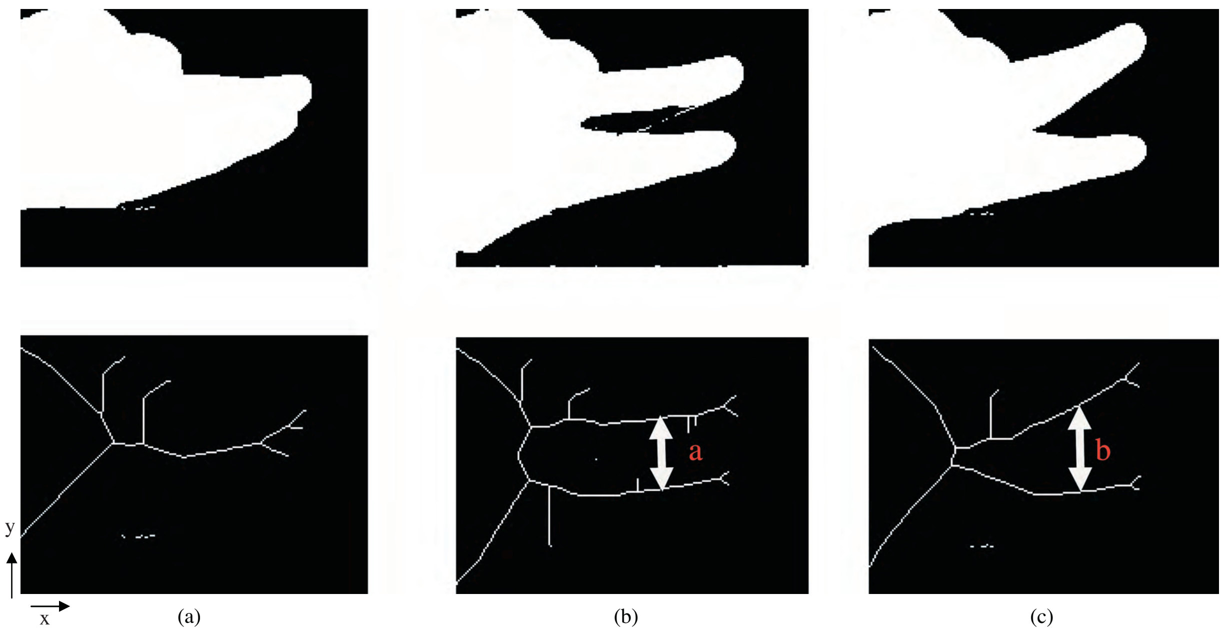
3. Fluidic formation control

3.1. Control architecture

The control architecture for formation control of the swarm having an SPH modeled dynamics, to mimic human hand gestures which are captured from a camera is shown in Figure 1.

2D images of human hand gestures are captured by a camera. The need for imitation by swarm is generated upon control of swarm formation shape with the hand image. The residual image gives the differences that need to be eliminated by imitation. After that, the need of imitation is triggered, feature extraction (section 3.2) is performed on the hand posture image that needs to be imitated. Feature extraction generates the feature vector which forms the input to the formation controller. The fluidic formation controller adjusts the parameters of the SPH swarm dynamic model (the plant, section 3.3) according to the input and the supervisor. The supervisor of the controller is based on an Artificial Neural Network (ANN) based learning module that is a feed forward neural network with single hidden layer composed of 5 tan-sigmoid layers. Its input layer has as many neurons as the feature vector components. The number of neurons in its output layer represents the number of parameter to be controlled in the plant. In this paper we only control the body force parameter, thus the ANN has only a single output. Examples of training sets and controller behavior are introduced in section 3.4.

$$f_v = \begin{bmatrix} \text{V shape fitting} \\ \text{U shape fitting} \\ \text{line edge} \\ \text{distance between branches} \\ \text{orientation of reference edge} \end{bmatrix}$$



$$f_v = \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \\ x \end{bmatrix} \qquad f_v = \begin{bmatrix} 0 \\ 1 \\ 0 \\ a \\ x \end{bmatrix} \qquad f_v = \begin{bmatrix} 1 \\ 0 \\ 0 \\ b \\ x \end{bmatrix}$$

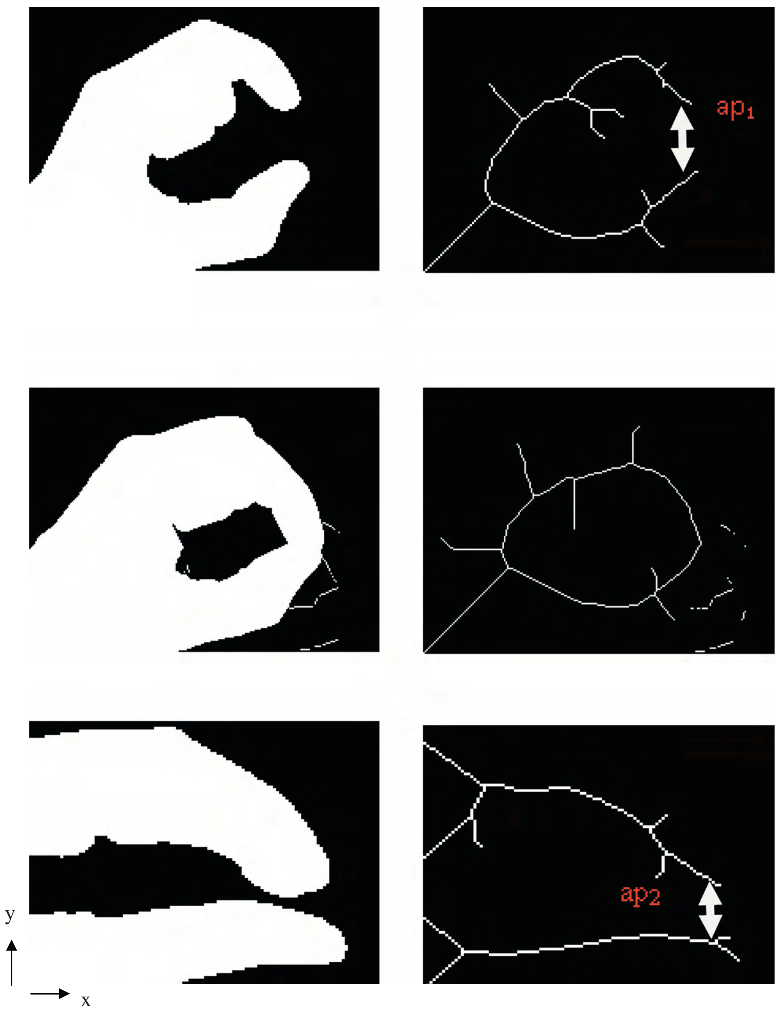
Figure 2. Feature extraction and feature vectors of scissor movement-like hand behavior.

3.2. Feature vector extraction of human hand postures

In this section we introduce examples of feature extractions based on captured images of hand preshapes. Consider the case where the colony has to imitate different branching of the fingers, corresponding to different hand postures, as shown in Figures 2(a–c). Images of the hand are skeletonized by first-filtered, to avoid noisy artifacts coming from skin texture, then passing the hand images through a sobel operator for a binary output on which edge detection can easily be conducted. The obtained binary image is then dilated in order to obtain continuous distinct edges. Then skeleton of the hand preshapes is determined by finding the equidistant pixels from the boundaries. After skeletonizing, the characteristic features differentiating each hand postures are extracted in this case for scissor like finger behaviors where feature vector we extract is given in Figure 2.

The feature vectors of the pinching fingers and C-shaped finger postures are given in Figure 3, after

$$f_v = \begin{bmatrix} \text{2 curves fitted} \\ ap \\ \text{1 curve fitted} \\ \text{1 line} \\ \text{orientation of line} \end{bmatrix}$$



$$f_v = \begin{bmatrix} 1 \\ ap_1 \\ 1 \\ 0 \\ x \end{bmatrix}$$

$$f_v = \begin{bmatrix} 1 \\ 0 \\ 1 \\ 0 \\ x \end{bmatrix}$$

$$f_v = \begin{bmatrix} 0 \\ ap_2 \\ 1 \\ 1 \\ x \end{bmatrix}$$

Figure 3. Feature vectors for pinching and C-shaped hand gestures.

skeletonizing the preshapes. The feature vector in this case is developed as parameters of curve fitting and aperture of finger loops; as such, the feature vector becomes like in Figure 3.

Figure 3 also gives the respective feature vectors of the individual pinching behaviors. These feature vectors f_v form the input of the ANN either in training mode or testing mode (which is the actual imitation run).

3.3. Modeling the swarm imitator as a colony of fluid particles

While compressible fluids (like gases) are spread around the environment homogeneously, incompressible fluid motions (like liquids) have directional characteristics. Since in human hand gestures, preshape features are generated from directional movements, we model our fluid particles as element of an incompressible fluid flow. We control these incompressible fluid particles by changing parameters of the fluid flow dynamics to get the desired hand preshapes. The fluid flow dynamical formalism based on SPH is introduced in detail in this section, in which parameters are controlled by the fluidics controller architecture introduced in Section 3.1. In Section 3.4 the training sets of the controller will demonstrate which parameter change of SPH will lead the colony of particles to mimic features of human finger behaviors such as scissor-like or pinching behaviors.

Our SPH formulation of the dynamics of our fluid based imitator is adapted from [10], solving the momentum equation to determine the particle accelerations based on parameters, such as density, pressure viscosity, obtained from neighbor particles in the support domain.

In the SPH method, the problem domain is represented by a set of arbitrary distributed particles and no specific discretization connectivity for these particles is needed (mesh-free). In our work, these particles are controlled by the help of fluid parameters to get the desired shapes looking like human hand pre-shapes. In our colony each particle is affected by a finite set of neighboring particles forming the "support domain" of that particle (Figure 4). All calculation of the field variables depend on these neighboring particles. Since SPH is an approximation method, integrals are approximated based on field functions representation method is used for field function approximation. This is also known as kernel approximation in the SPH method. The kernel approximation is then discretized based on particle units (particle approximation). It is done by replacing the integration in the integral representation of the field function with summations over all the corresponding values at the neighboring particles the support domain.

More specifically, consider the integral representation of a function $f(x)$ in the SPH method:

$$f(x) = \int_{\Omega} f(x')\delta(x - x')dx', \tag{1}$$

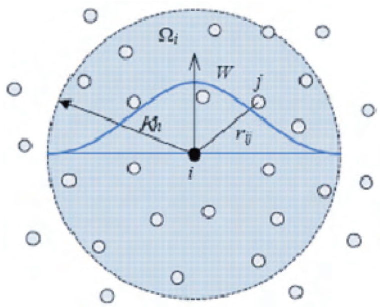


Figure 4. The support domain for particle i and 1D projection of a smoothing function over it.

where Ω is the volume of integral that contains three-dimensional position vector, f is a field function like viscosity or pressure, and $\delta(x - x')$ is the Dirac delta function. For the approximation of the integral representation in equation (1), Dirac delta function is replaced by a smoothing (kernel) function W:

$$< f(x_i) >= \int_{\Omega} f(x')W(x - x', h)dx', \tag{2}$$

where the angle brackets indicate the approximation and W is the smoothing function which not only determines the pattern for the function approximation but also defines the dimensions of the support domain of particles. Parameter h is the smoothing length defining the influence area of the smoothing function. This smoothing function is used in the calculation of fluid variables approximation. The smoothing function plays a very important role in the SPH approximations, as it determines the accuracy of the function and efficiency of the computation. For the smoothing function, there are various choices such as Gaussian kernel, the cubic spline kernel, the quadratic smoothing function etc. Due to its smoothness, stability, and accuracy we chose the Gaussian kernel (3) in our simulations:

$$W(R_{ij})=\begin{cases} \alpha_d e^{-R_{ij}^2} & R_{ij} \leq Kh \\ 0 & \text{otherwise} \end{cases}. \tag{3}$$

where $\alpha_d = \frac{1}{\pi h^2}$ for two-dimensional space, $K = 2$, $R_{ij} = |x_i - x_j| / h$.

For the particle approximation, the continuous integral representation of the kernel approximation is converted to a discretized form of summation over all the particles in the support domain shown in Figure 4.

The particle approximation of the function is obtained as

$$< f(x_i) >= \sum_{j \in \Omega_i} \frac{m_j}{\rho_j} f(x_j)W(x_i - x_j, h) \tag{4}$$

where m_j and ρ_j are the mass and density of particle j. Equation (4) states that the value of a function at particle i is approximated using the average of those values of the function at all particles in the support domain of the particle i weighted by the smoothing function.

Density approximation is computed via the relation

$$\rho_i = \sum_{j=1}^{N} m_j W_{ij} \tag{5}$$

where ρ is density, N is the number of particles which are in the support domain of particle i, m is the mass of particle j and W_{ij} is the smoothing function of particle i evaluated at particle j computed as

$$W_{ij} = W(x_i - x_j, h) = W(|x_i - x_j, h|) = W(R_{ij}, h) \tag{6}$$

where R_{ij} is the relative distance between particle i and j. Since density approximation (5) determines the particle distribution and the smoothing length evolution, it is really important in the SPH method and simply states that the density of a particle can be approximated by the weighted average of the densities of the particles in the support domain of that particle.

As the density equation is one of the important equations for fluid flow, so is acceleration and momentum. The momentum equations calculate the time rate of change of velocity using substantial derivative $\mathrm{D}/\mathrm{D}t$. Momentum and acceleration couple to density via the relations

$$\frac{Du_i}{Dt} = -\sum_{j=1}^{N} m_j\left(\frac{p_i + p_j}{\rho_i \rho_j} + \Pi_{ij}\right)\frac{\partial W_{ij}}{\partial x_i} + \sum_{j=1}^{N} m_j\left(\frac{\mu_i \varepsilon_i^{xx} + \mu_j \varepsilon_j^{xx}}{\rho_i \rho_j}\frac{\partial W_{ij}}{\partial x_i} + \frac{\mu_i \varepsilon_i^{xy} + \mu_j \varepsilon_j^{xy}}{\rho_i \rho_j}\frac{\partial W_{ij}}{\partial y_i}\right) + f_i^x \tag{7}$$

$$\frac{Dv_i}{Dt} = -\sum_{j=1}^{N} m_j\left(\frac{p_i + p_j}{\rho_i \rho_j} + \Pi_{ij}\right)\frac{\partial W_{ij}}{\partial y_i} + \sum_{j=1}^{N} m_j\left(\frac{\mu_i \varepsilon_i^{xy} + \mu_j \varepsilon_j^{xx}}{\rho_i \rho_j}\frac{\partial W_{ij}}{\partial x_i} + \frac{\mu_i \varepsilon_i^{yy} + \mu_j \varepsilon_j^{yy}}{\rho_i \rho_j}\frac{\partial W_{ij}}{\partial y_i}\right) + f_i^y, \tag{8}$$

where u_i and v_i denote velocities for particle i along the x- and y-directions, respectively. p is the pressure, $\rho$is the density of the specified particle, Π_{ij} is the artificial viscosity (9), W_{ij} is the smoothing kernel, and ε denotes the stress factor.

In momentum equations (7) and (8) are three terms on the right hand side. The first term is the major portion of the equations due to the pressure gradient with the dissipative artificial viscosity which is mainly used in order model the shock waves in the tube in fluid flow simulations. The second term shows the viscosity and stress parameters. One of the particles starts to move, the other particles are affected because of this motion. ε^{xx} and ε^{yy} denote normal stress, and ε^{xy} denotes shearing deformation, for generating dragging effect (11). The last term, f, is the body force. Since it directly enters the momentum equation, it has a direct effect on the flow. In fluid physics the typical body force is the gravitational force. It is suitable for the guidance of the particles. In this paper we demonstrate the control of the body force to get the desired trajectories of the particles in the imitation learning of a human hand preshape.

The artificial viscosity term in equations (7) and (8) can be written as

$$\Pi_{ij} = \begin{cases} \frac{\beta_\pi \varphi_{ij}^2}{\bar{\rho}_{ij}} & v_{ij} x_{ij} < 0 \\ 0 & v_{ij} x_{ij} \geq 0 \end{cases}, \tag{9}$$

where

$$\varphi_{ij} = \frac{h_{ij} v_{ij} x_{ij}}{|x_{ij}|^2 + \phi^2}, \quad \phi = 0.1 h_{ij}, \quad \bar{\rho}_{ij} = \frac{1}{2}(\rho_i + \rho_j), \quad h_{ij} = \frac{1}{2}(h_i + h_j). \tag{10}$$

The shear stress rates in equations (7) and (8) have a form similar to

$$\begin{aligned} \varepsilon_i^{xx} &= \frac{2}{3} \sum_{j \in \Omega_i} \frac{m_j}{\rho_j} \left(2u_{ji}\frac{\partial W_{ij}}{\partial x_i} - v_{ji}\frac{\partial W_{ij}}{\partial y_i}\right) \\ \varepsilon_i^{xy} &= \sum_{j \in \Omega_i} \frac{m_j}{\rho_j} \left(v_{ji}\frac{\partial W_{ij}}{\partial x_i} + u_{ji}\frac{\partial W_{ij}}{\partial y_i}\right) \\ \varepsilon_i^{yy} &= \frac{2}{3} \sum_{j \in \Omega_i} \frac{m_j}{\rho_j} \left(2v_{ji}\frac{\partial W_{ij}}{\partial y_i} - u_{ji}\frac{\partial W_{ij}}{\partial x_i}\right). \end{aligned} \tag{11}$$

Besides these differential equations, there is a suitable state equation between pressure p and density ρ for modeling compressible and incompressible fluid flow in the form of the equations

$$p_i = \rho_i R_i T_i \qquad \text{for compressible (gas like behavior) flow} \tag{12}$$

$$p_i = B_i((\frac{\rho_i}{\rho_0})^\gamma - 1)\text{for incompressible (liquid like behavior) flow} \quad (13)$$

where R is the specific gas constant, T is the temperature, B is a constant, ρ_0 is the reference density and γ is a constant around 7.

As a state equation, we used equation (13), since incompressible flow is much more suitable for our purpose. We are mainly interested in the directions and trajectories of the particles, to get the desired shape. The particle acceleration is calculated from the momentum equation (7) and (8) by using equations (9–11). For calculation of the particle velocity time marching method is used, since the Navier-Stokes Equations have no analytical solution.

Up to this point we gave the mathematical background about our swarm modified SPH methodology. These equations are based on the Navier-Stokes equations and since the Navier-Stokes equations cannot be solved analytically, the SPH kernel and particle approximations are used for discretization of partial differential equations. The aforementioned SPH formulation is derived by discretizing the Navier-Stokes equations spatially, leading to a set of ordinary differential equations with respect to time that can be solved via time integration.

Our ultimate goal is to learn to control the SPH-based flow model parameters for the colony to resemble the hand gesture features of a human. An example of formation control action performed by the controller is given here for demonstration is the flow chart of Figure 5. Here, the controller uses the body force term in the momentum equations. After updating the particle positions, an appropriate force set is then calculated and applied them to the particles for that iteration.

The flow chart of this instance of control action algorithm is given as an example in Figure 5. First, for particle i, the controller initializes its fluid dynamic parameters for the set control command value. Then particle i needs to know the fluid variables of its neighbor particles which are inside the support domain.

To solve the governing equations, it collects the information of position, velocity, and density of these neighbor particles. To solve the momentum equations in (7), and (8), particle i needs the values of pressure (13), density (5), and viscous stress (11) and collects these information from its neighbor particles which are in the smoothing length. After calculation of these fluid variables, the acceleration of the particle is calculated from the momentum equation. After updating the position of the particle with time integration, the flow chart goes back and gets the new commands from the controller to form the desired formation.

3.4. Generating the training sets of our controller

The ANN shown in Figure 1 has been trained by I/O pairs which are preshape features and fluid parameters. The principal fluid parameter demonstrated in this work is the body force.

The results given in Figures 6, 7 and 8 demonstrate the importance of controlling body force in fluid flow and the influence this parameter has, in the orientation and fingering effects of formation control. Each figure shows the captured hand posture image (in the left) for which feature vector is extracted. The fluidic controller output in terms of body force value (with middle) and the fluidic swarm formation outcome of the system (in the right). The I / O training pairs of the ANN is f_v feature and body force vector.

Another imitation is that of pinching, where the desired fluid trajectory is first to separate the fluid particles and then aggregate them in a point, as shown in Figure 9. To generate this finger tip grasping-like motion, we again use body forces.

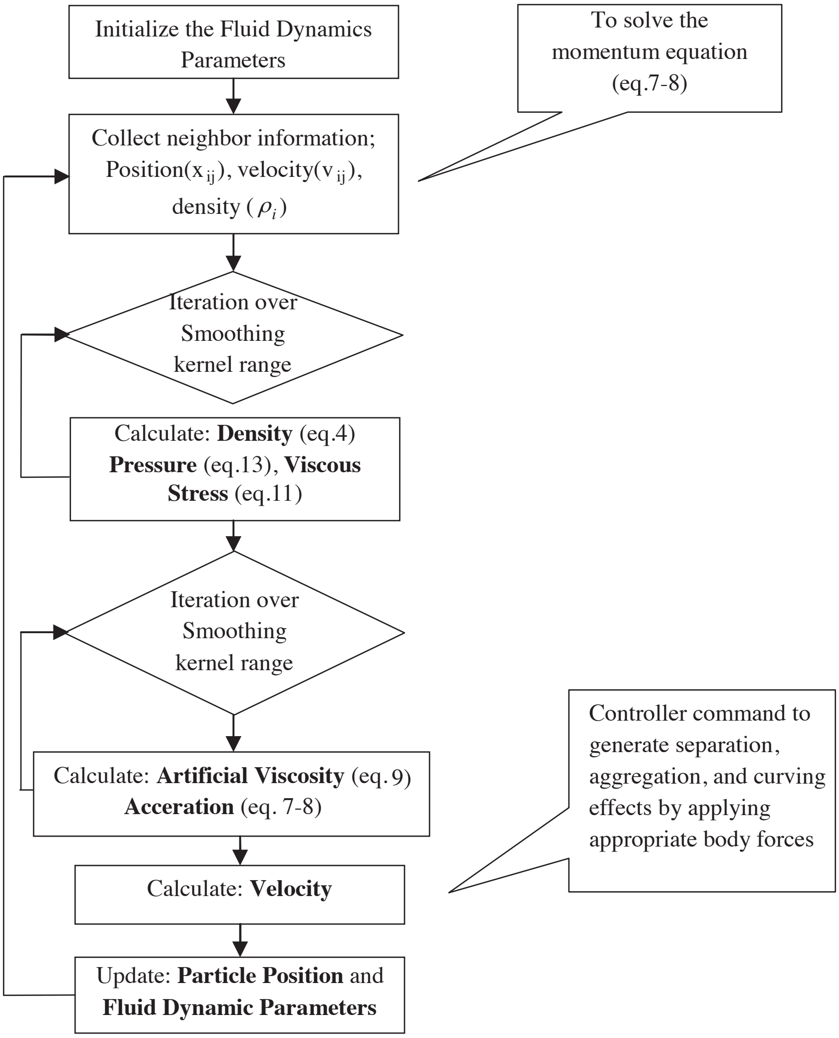


Figure 5. Flow chart diagramming the instance of control algorithm, performed for each particle i.

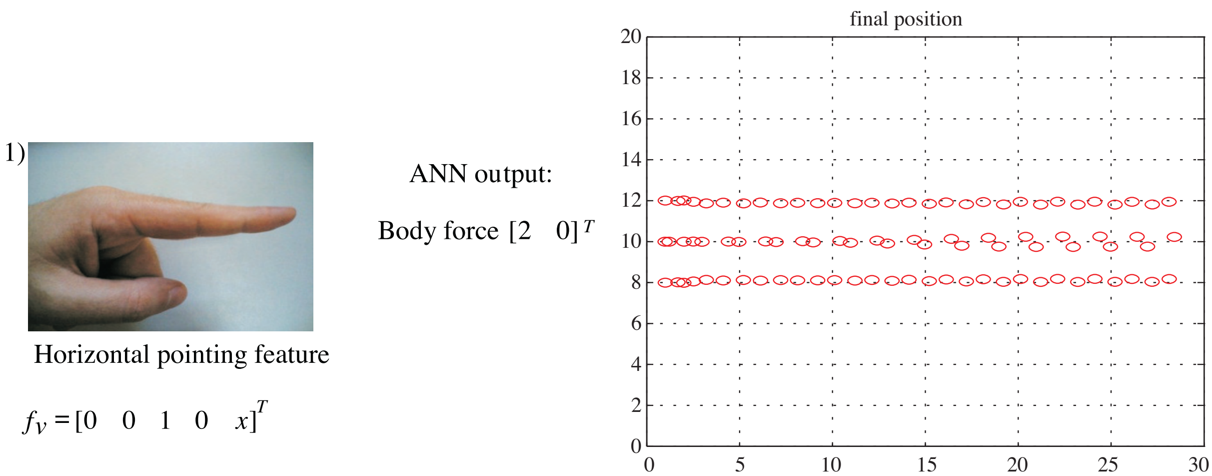
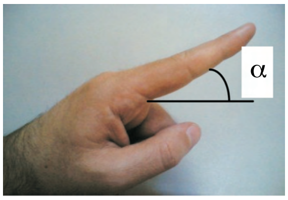


Figure 6. Horizontal pointing training set.

2)



Pointing at angle feature

$f_V = [0 \quad 0 \quad 1 \quad 0 \quad \alpha\,]^T$

ANN output:

Body force $[1 \quad 0.3]^T$

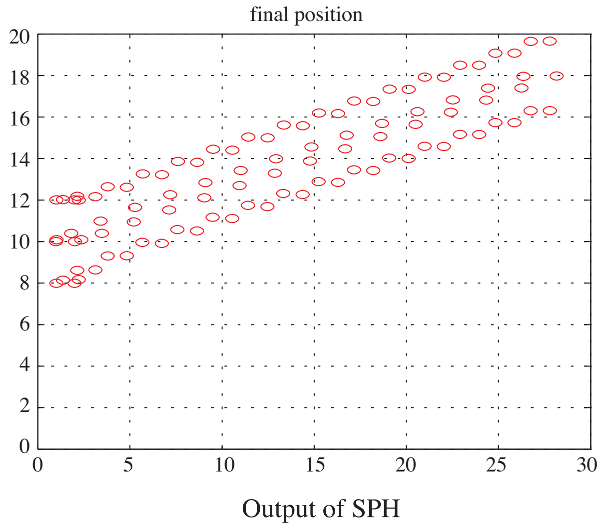
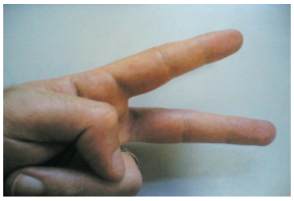


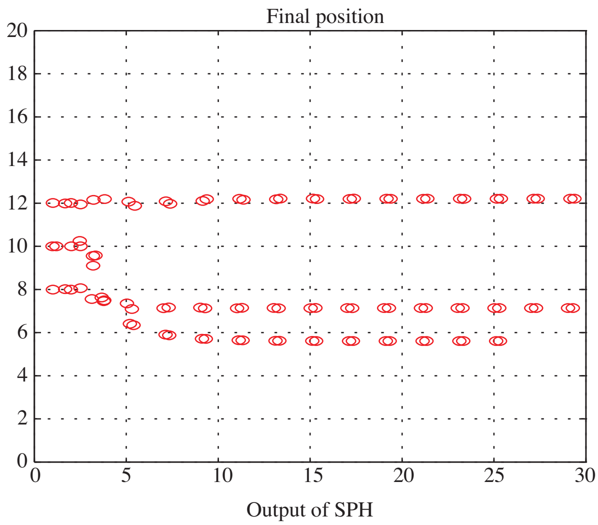
Figure 7. Pointing at angle behavior.

3)

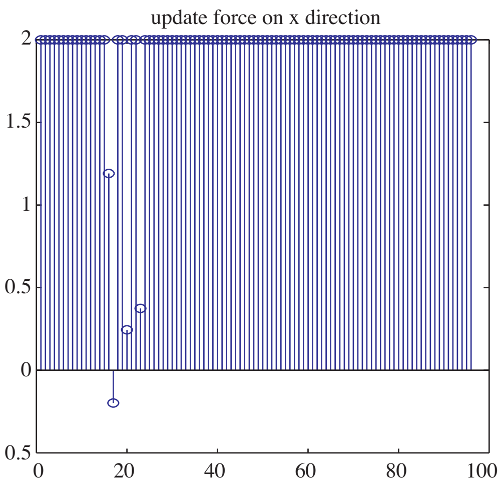


V seperation of fingers

$f_V = [1 \quad 0 \quad 0 \quad b \quad \alpha\,]^T$



Ann outputs sequence of body seen on graphs at the right



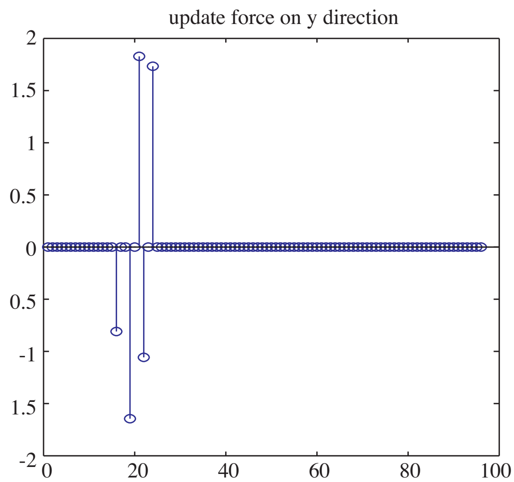


Figure 8. Separation of fingers training set.

Figure 9 not only gives the feature vector (fv) / body force training sets of the fluidic formation controller, but also shows the fluidic swarm imitating the pinching behavior.

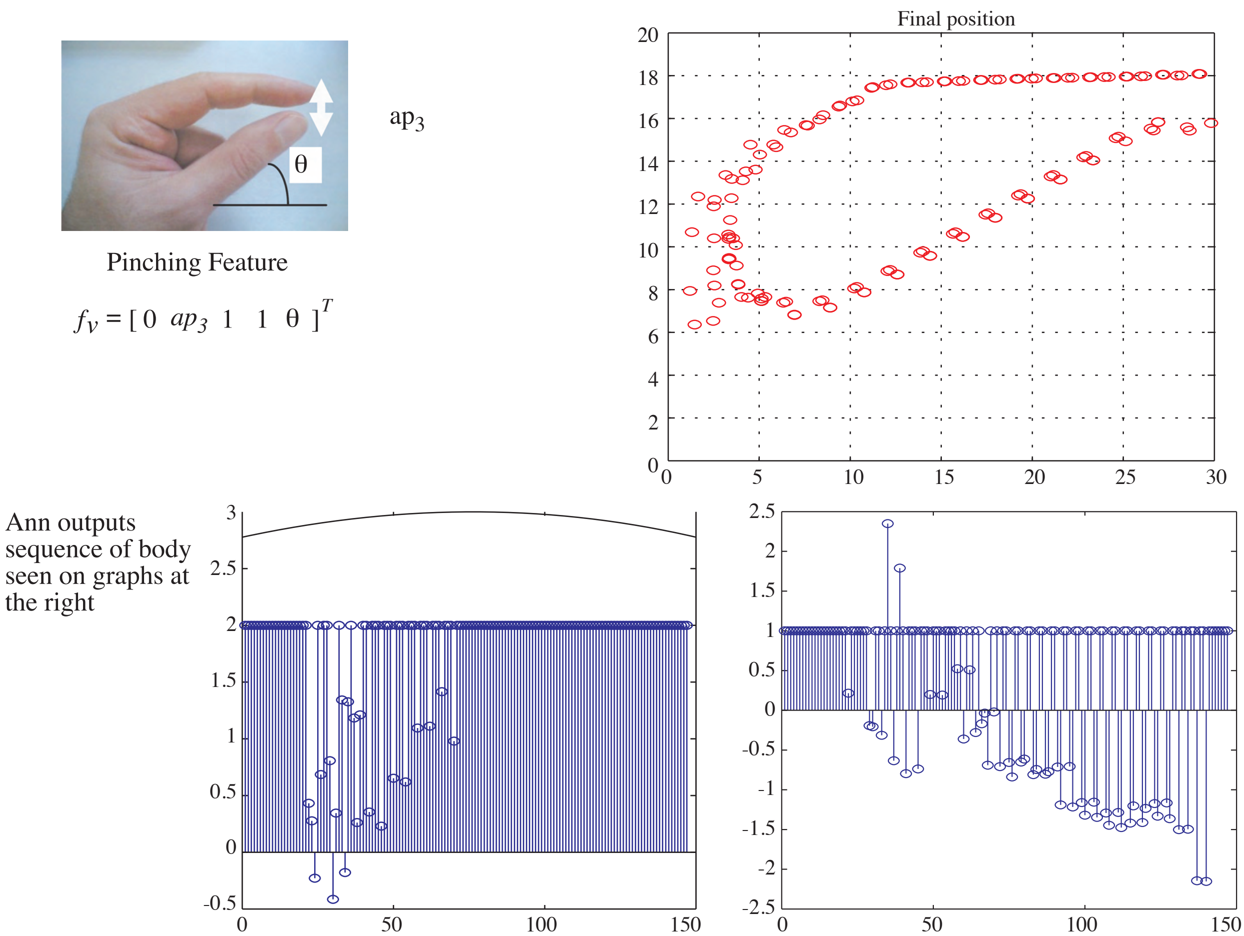


Figure 9. Pinching training set.

4. Imitation results

By using our fluidics imitation learning control we generated the results on simulated SPH fluid swarm formation that mimics some basic hand preshapes based on body force control commands.

We give here full sequence from preshape feature vectors to swarm imitation for two examples, namely that of scissor like hand behavior and that of pinching preshape.

Figure 10 gives the captured hand preshape image together with its skeletonized rendering, and the swarm particle distribution together with the particle force distributions for each imitation run. The force distribution that corresponds to the scissor like behavior clearly shows a close imitation of the skeleton of the captured image, imitating the basic feature of the hand posture. For the pinching example, the desired imitation should lead to separation of particles in two opposing curve like feature converting to a point at each tip of the curves. The force distribution of the particles found in the second part of figure 10 shows a close resemblance to feature of the hand posture where an aperture error only occurs. This error is easily minimized if more particles are injected in the swarm colony.

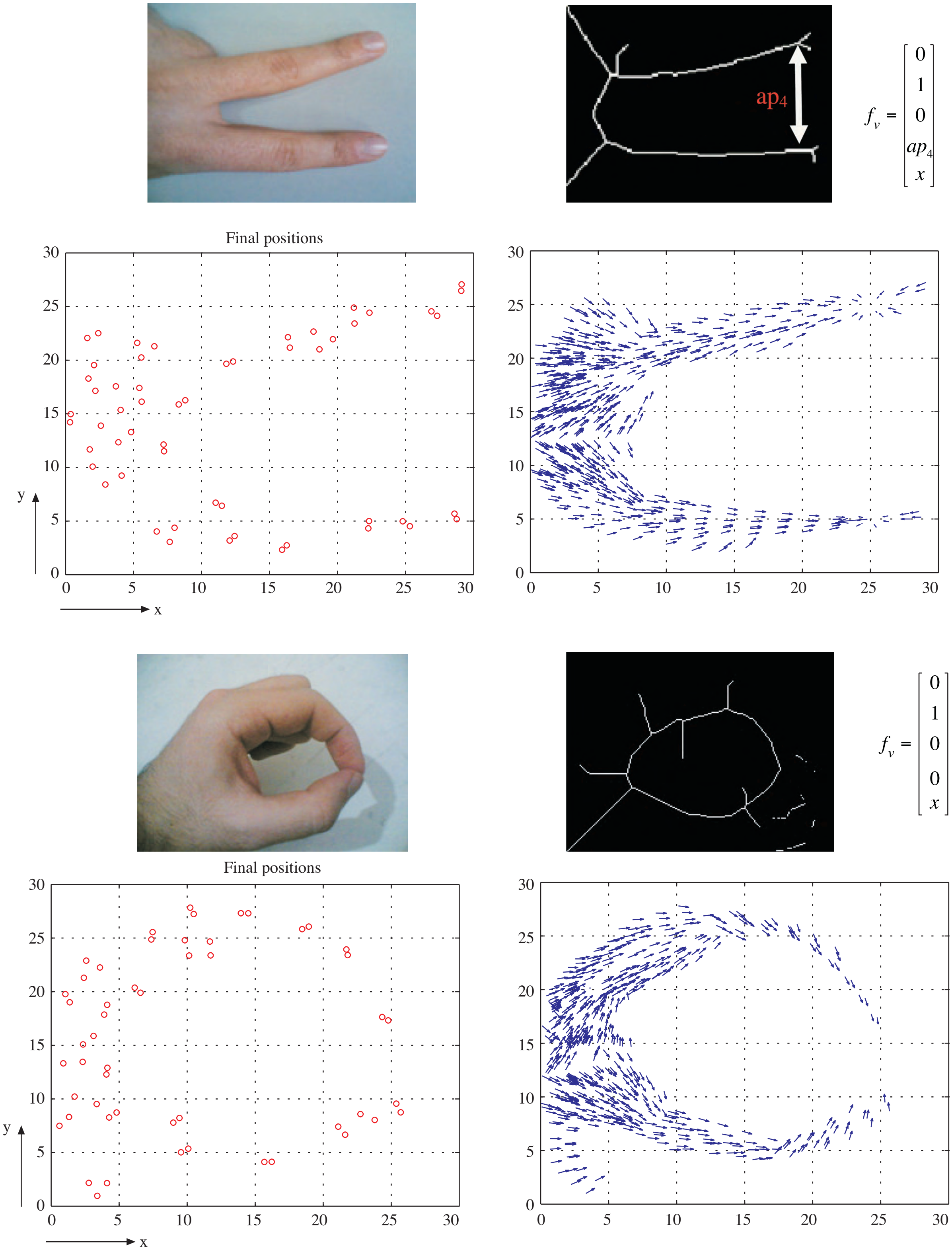


Figure 10. Imitation of scissor-like and pinching hand postures and the imitation force distributions.

5. Conclusion

In this work, we tackled the problem of imitating human hand postures by a system that possesses a completely different dynamics, thus unable to initiate an imitational organ matching. We focused on imitation of a human hand gestures by a swarm having totally different dynamics than a human. We consider in this work a swarm that has a strikingly different dynamics than a human, as a colony of fluid particles. In the balance of this paper work, we introduced the novel architecture of a fluidics formation controller to tune fluid flow parameters to get the desired colony formations which resemble human hand preshapes.

The fluidics formation controller commands on SPH approximated dynamics of a fluidic swarm, and has the ability to learn imitation based on hand feature/fluid parameters I/O pairs which form its training sets.

This paper provides the proof of concept lay out of this controller commanding only the body force vector of swarm particles. Our present research work resides on incorporating more fluid parameters with the control action of the fluidics formation controller so as to imitate complex human hand postures.

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