Imitation of Hand Postures with Particle Based Fluidics Method

Umut Tilki, Ismet Erkmen, and Aydan M. Erkmen

***Abstract*— The correspondence problem is an important problem when the subjects have two different kinematical structures imitating each other. In this new approach, the imitator and the imitate have totally different dynamics systems, the first one is the fluidic system, the second one is the human hand gestures. The motion of the fluidic system is composed of the combination of fluid particles which are used for the discretization of the problem domain. Observed human hand gestures are imitated by these fluid particles by appropriately adjusting the parameters of the Smoothed Particle Hydrodynamics (SPH), which is a particle based Lagrangian method. In this paper we analyzed the dynamics of the SPH, and used an artificial neural networks (ANN) based controller which automatically adjust the SPH parameters, specifically the body force, to create the desired hand preshapes.**

***Index Terms*— Swarm Formation Control; Smoothed Particle Hydrodynamics (SPH); Robot Grasping; Robotics Imitation; Imitation by Swarm**

I. INTRODUCTION

Learning by observation is an essential and noninvasive part of imitation without interfering with the imitatee's tasks. Many problems have to be handled without disturbing the imitatee during the imitation. The important problem is the correspondence problem, which is the mapping action or action sequences between the demonstrator (imitatee) and the imitator. This difficulty may occur even if the imitator and demonstrator have similar kinematic structure. Learning to imitate by observing others that are different in kinematically is the recent focus of the machine learning [1]. For the two systems having different structures, the correspondence problem is the important issue that makes difficult the imitation by observation. Even if the two human beings have same dynamical structures, the imitation problems called ideomotor apraxia in medical literature may occur [2]. During the imitation between two kinematically different systems, this disease is inherent since there is no one to one organ matching. Besides the correspondence problem, imitation learning has some valuable characteristics such as it speeds up the learning process by not requiring direct communication between demonstrator and the imitator thus, not interrupting the imitatee's task through interference [3].

In this work, we tackle the problem of imitating human hand postures by fluid particles, thus unable to initiate an imitational organ matching. In this manner, we focus on imitation of a human hand gestures by a swarm having totally different dynamics than human hand movements. In other words, this imitation is the colony formation control of the swarm as to resemble basic human hand preshapes. In this work our contribution 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. The advantage of the SPH is the adaptive mesh free nature, so SPH is not affected by the arbitrariness of the particle distribution, and the grid size. Therefore, it can handle the large deformations on the particle distribution in hand gestures.

This paper organized as follows. In the second section our motivation and some related works about imitation learning and fluid dynamics are summarized. Third section explains our control structure of the fluid flow and also fluid dynamics approach based on SPH. Section four presents our simulation results based on the proposed approach. Section five concludes the paper.

II. RELATED WORKS AND MOTIVATION

Imitation learning which is useful for the agent based systems instead of ad hoc approach is a powerful learning mechanism so far. The traditional imitation learning questions are about who to imitate, when to imitate, what to imitate, how to imitate etc [4-5]. Although imitation learning consists of this kind of complex problems, it has valuable characteristics such as speeding up the learning process since the demonstrator can continue doing his/her tasks and the imitator usually observes and learns in parallel to goes on doing his/her tasks while the imitator observes and learn how to imitate.

This kind of learning requires some complex mechanisms, such as movement recognition, pose estimation and tracking, action mapping, matching of observed movements etc. that detect what to learn from the imitatee by observing its movements and map them onto its own movements [6].

The ALICE imitation framework "Action Learning for Imitation via Correspondence between Embodiments" was introduced by Alissandrakis et al [7] which can be used by an imitator agent to find the corresponding actions that produce similar states and effects as a model agent so that the error

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First Author Umut Tilki is with Department of Electrical and Electronics Engineering Department, Middle East Technical University, 06531, Ankara, Turkey (phone: 90-312-210 45 90; fax: 90-312-210 23 04; e-mail: utilki@metu.edu.tr).

Ismet Erkmen is with the Department of Electrical and Electronics Engineering, Middle East Technical University, Ankara, Turkey (e-mail: erkmen@metu.edu.tr).

Aydan M. Erkmen is with the Electrical and Electronics Engineering Department, Middle East Technical University, Ankara, Turkey (e-mail: aydan@metu.edu.tr).

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distance between the imitator actions and the imitatee actions is minimum.

In another work, the laser scanner data are used to determine the rough human body positions, body orientation and pose information [8]. For tracking and velocity control, particle filter approach is used in this work. Minato et al. [9] use a grid based approach in their work on an android by mapping human posture in three dimensional position spaces. They attempt to naturally animate the android to maintain social interaction with human. For posture transformation from human subject to android they use motion capture system which can measure the posture of the 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 both [8] and [9], the major constraint is that there must be a large sensory date, collected from magnetic trackers, stereo vision systems, data gloves etc. to track and understand the movements of the demonstrator.

The main objective of this work is to deal with imitation of the observed hand preshapes with a dynamically different system. In this imitation applications there is an inherent organ matching problem in other words correspondence problems between the imitator and the imitate. In our work, the imitator is a fluid body imitating through sensing the human hand preshapes. Our approach is based on generating the control flow field variables in order to get the desired behavior and shapes of the fluid body, by observing human hand preshapes.

In robotics, fluid particle based modeling has been used for swarms and recently in the formation of the geometric pattern generation with multiple robots [10-11]. In these works, mobile robots are modeled as fluid particles and are controlled by the help of fluid dynamic parameters for obstacle avoidance or source to sink optimal path finding. 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.

III. FLUIDIC FORMATION CONTROL LAYER

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

A. Control Architecture

As one can understand from the Figure 1, 2D human hand gesture images are captured by a camera. The input of the control layer is a feature extraction process from captured these images. Preshape features are generated such as attributes of branching of fingers, those of curving of index fingers etc. such preshapes intended for human grasping. Examples of feature extraction for a sample of preshapes are given in section B. The formation control unit adjusts the parameters of the SPH swarm dynamic model according to the desired hand prespahes which are given as inputs of the system (section C). In this paper we only use the body force to demonstrate imitation of simple hand postures by fluid particles.

The Artificial Neural Network (ANN) provides the imitation learning capability of our controller which has input nodes, in number equal to the number of features in each preshepes, such as V shape fitting, U shape fitting, line edge, separation distance etc. for branching of finger preshapes. The number of output nodes of the ANN is equal to the number of fluid dynamics parameters which are body forces acting on particles, particle densities, shearing and viscous stresses of the particles. These parameters are used within the SPH model given in section C. In this paper, the ANN is feed forward neural network with single hidden layer composed of 5 tan-sigmoid layers, and having 1 output node namely corresponding to the body forces acting on each particles.

B. Feature Vector Extraction of Human Hand Preshapes

This section introduces extracting the relevant features of the observed human hand preshapes based on the captured images. When the colony has to imitate the hand preshapes shown in figure 2-a, b, c, d, e, and f, the corresponding distinct feature vectors have to be extracted. Before extraction of the feature vectors, first the images are filtered against the noisy artifacts coming from the skin, and then hand preshapes edges are determined by the sobel operator. After that, the skeleton of the hand preshapes is obtained by finding the equidistant pixels from the boundaries. After skeletonizing, the distinct feature vectors differentiating each hand postures are extracted when the hand preshapes such as scissor like finger behaviors, pinching fingers, and C-shaped finger postures where extracted feature vector is:

$$f_v = \begin{bmatrix} \mathrm{a} & b & c & d & e & \mathrm{f} \end{bmatrix}^T$$

where a to f entries correspond line edges, U-shape fitting, V-shape fitting, 2-curves fitting, 1-curve fitting and the aperture between branches respectively. The distinct feature vectors for different hand preshapes will be the input of the ANN either in training mode or testing mode which is the actual imitation run.

C. Modeling the Fluid Particles as Swarm Imitator

In nature, the compressible fluids are spread around the environment homogenously after a time while incompressible fluids have directional motions. Since human hand preshapes and gestures are composed of directional movements, we have to model our fluid particles as an incompressible fluid flow. Fluid particles are controlled by changing parameters of the fluid flow dynamics to get the desired hand preshapes. The fluid flow dynamical formalism based on Smoothed Particle Hydrodynamics (SPH) adapted from [12] is introduced in this part in details, which parameters are controlled by the control architecture introduced in section A. The formulation of the SPH is based on the solving the momentum equation to determine the particle accelerations from the collected information of the neighbor particles in the support domain such as density, pressure, viscosity etc.

SPH is a computational method developed to simulate fluid flows. Differently from other mathematical models of fluid dynamics, SPH describes the mean from the lagrangian point of view. This means that the fluid body is divided into a set of discrete fluid elements, like little balls (mesh-free).

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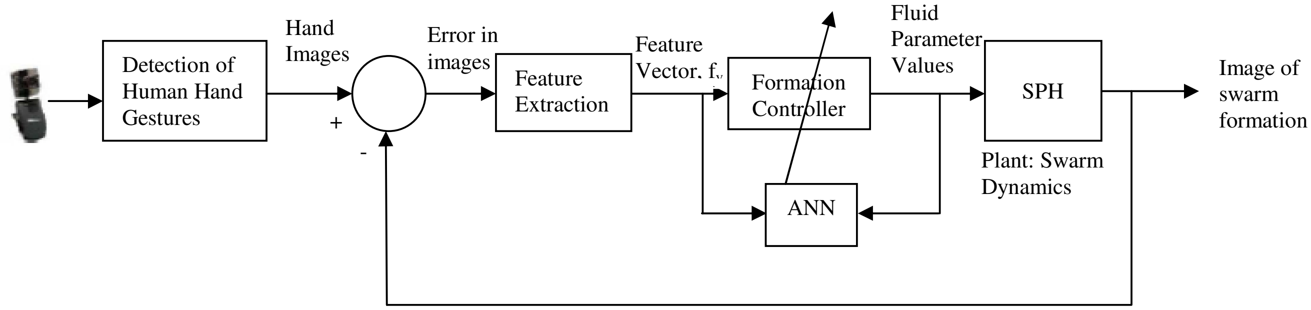
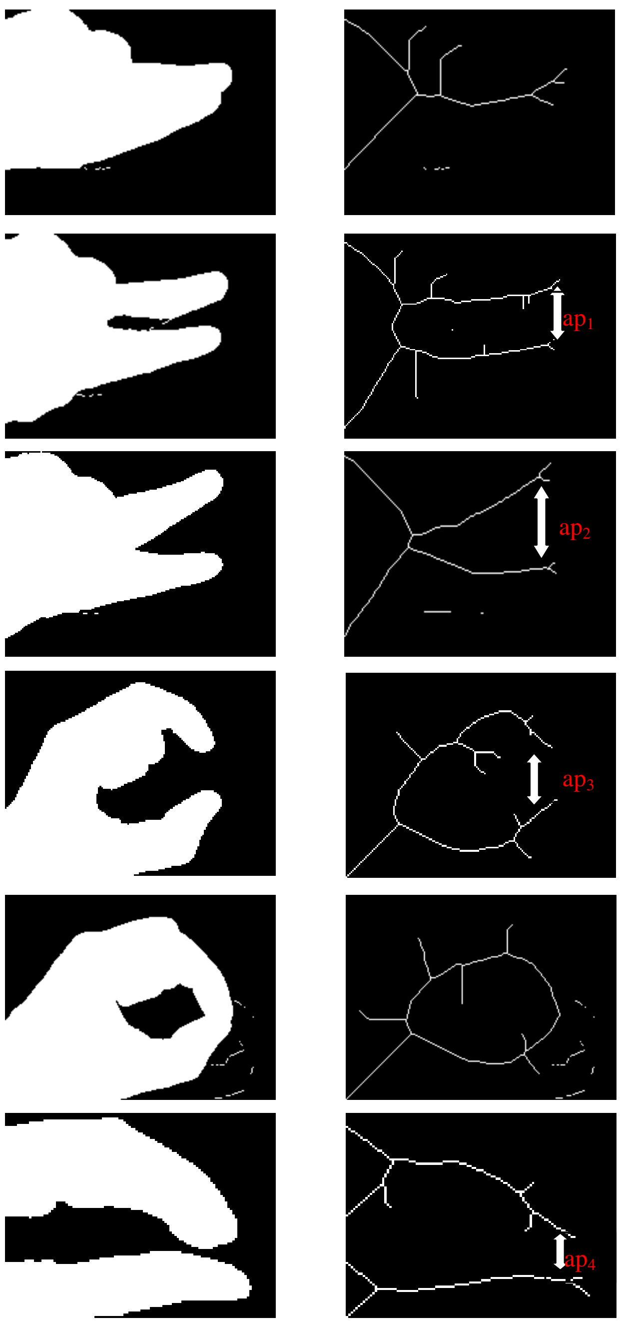


Fig.1 Fluidic Formation Control for Swarms



(a) $f_{v1} = [1 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0]^T$

(b) $f_{v2} = [0 \quad 1 \quad 0 \quad 0 \quad 0 \quad ap_1]^T$

(c) $f_{v3} = [0 \quad 0 \quad 1 \quad 0 \quad 0 \quad ap_2]^T$

(d) $f_{v4} = [0 \quad 0 \quad 0 \quad 1 \quad 1 \quad ap_3]^T$

(e) $f_{v5} = [0 \quad 0 \quad 0 \quad 1 \quad 1 \quad 0]^T$

(f) $f_{v6} = [1 \quad 0 \quad 0 \quad 0 \quad 1 \quad ap_4]^T$

Fig.2 Feature vectors of scissor like, pinching and C-shaped hand gestures

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Each particle has its own properties (such as pressure, mass) and it moves according to the interactions with other particles. The result is composed of the particle positions, which will be the similar hand preshapes in our problem.

Fundamentals and the formulations of SPH are approximated governing equations, representing physical principles such as conservation of mass and momentum. The SPH equations are obtained from a set of differential Navier-Stokes equations (1,2) in lagrangian form which represents the continuum equations of fluid dynamics by interpolating from a set of points which may be disordered.

$$\frac{1}{\rho}\frac{dp}{dt} + \nabla.u = 0 \qquad (1)$$

$$\frac{du}{dt} = -\frac{1}{\rho}\nabla P + g \qquad (2)$$

where ρ is the density, P is the pressure, u is the velocity, g is the gravitational acceleration and ∇ is the gradient operator. The first equation (1) which is the conservation of mass in lagrangian form is represented by density of fluid continuum in control volume. The momentum equation (2) is composed of two force terms, pressure gradient and body forces. The changes of acceleration for each particle occur due to action external forces on the entire of fluid particles.

The interpolation is based on theory of integral interpolants using interpolation kernels which approximate a delta function. In this paper, due to its smoothness, stability, and accuracy we chose the Gaussian kernel (3) in our simulation.

$$W(R_{ij}) = \begin{cases} \alpha_d e^{-R_{ij}^2} & R_{ij} \le Kh \\ 0 & otherwise \end{cases} \qquad (3)$$

where $\alpha_d = 1/\pi h^2$ for 2 –dimensional space, h is the smoothing length, K = 2, R is the scaled distance between the particle for which the kernel is being calculated and its neighbors in the support domain, $R_{ij} = \left| x_i - x_j \right| / h$.

The interpolants are analytic functions which can be differentiated without using of grids. The SPH equations describe the motion of the interpolating points which can be taught as particles. Each particle carries a mass m, a velocity v, and other properties depending on the problem [13].

The momentum equation for a particle becomes,

$$\frac{dv_a}{dt} = -\sum_b m_b \left(\frac{P_a}{\rho_a^2} + \frac{P_b}{\rho_b^2} + \prod_{ab}\right)\nabla_a W_{ab} + F_a \qquad (4)$$

where the summation is over all particles other than particle a (neighbor particles contribute), P is the pressure, ρ is the density, $\prod_{ab}$ produces a shear and bulk viscosity, F_a is a body force, W_{ab} is the smoothing kernel, and Δ_a denotes the gradient of the kernel with respect to the coordinates of particle a.

Besides these differential equations, there is a suitable state equation between pressure (p) and density (ρ) for modeling incompressible fluid flow (5).

$$p_i = \beta_i\left(\left(\frac{\rho_i}{\rho_0}\right)^{\gamma} - 1\right) \qquad (5)$$

where β is a problem defined constant, ρ_0 is the reference density and γ is a constant around 7.

IV. Simulation Results

In this study our ultimate goal is to control the SPH based flow model parameters for the colony to resemble the hand gesture features of a human. In the following flow chart (Fig. 3), an example of formation control performed by the controller is given. In this example, the controller uses the body forces acting on particles during each iteration in the momentum equation (4). For particle i, the algorithm initializes its fluid dynamic parameters. 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. While solving the momentum equation (4), particle i needs the value of pressure, density, and viscous stress and collects these values from its neighbor particles which are in the smoothing length. The solution of the momentum equation gives us the acceleration of particle i, and the position of particle i is updated simply integration of the step time into the acceleration of the particle. After updating the particle position, the flow chart goes back and gets new commands from the controller to form the desired hand preshapes.

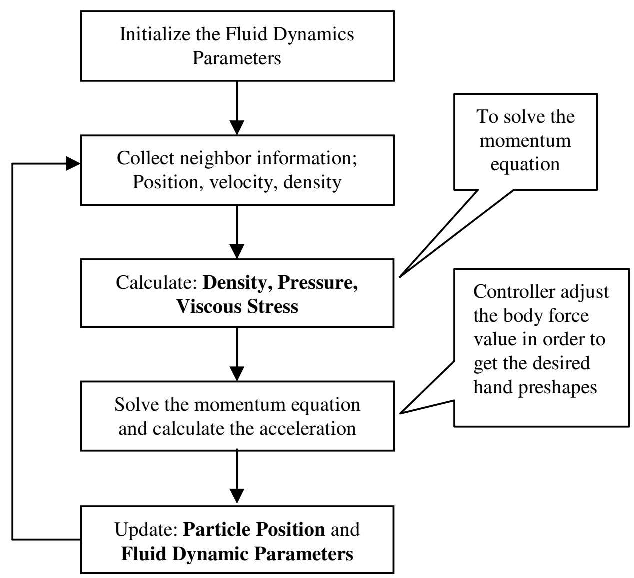

Fig.3 Flow Chart of the SPH based algorithm

The controller shown in Fig.1 has been trained by input/output pairs which are hand preshape features and fluid parameters, specifically body forces in this work. For training of the ANN, we used 13 different hand preshapes and extracted corresponding feature vectors. These feature vectors are the input of the ANN and for the output of the ANN; we classified the body forces acting on each particle as shown in Fig.4.

For testing the controller, different hand preshapes are used with different apertures of the finger tips. The output vector will be the corresponding body force term classes, which are applied to the particles during the imitation and the combination of the updated particle positions will be similar to the input hand preshapes.

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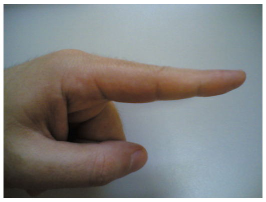
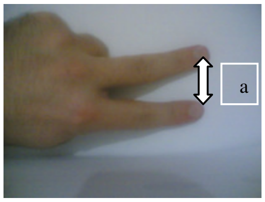


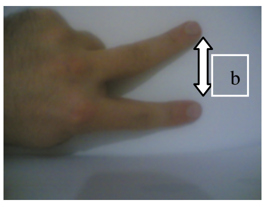
Corresponding ANN output vector class: [1]

$$f_v = [1 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0]^T$$



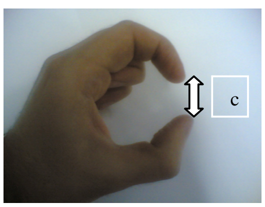
Corresponding ANN output vector class: [5]

$$f_v = [0 \quad 1 \quad 0 \quad 0 \quad 0 \quad a]^T$$



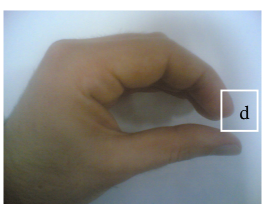
Corresponding ANN output vector class: [10]

$$f_v = [0 \quad 0 \quad 1 \quad 0 \quad 0 \quad b]^T$$



Corresponding ANN output vector class: [15]

$$f_v = [0 \quad 0 \quad 0 \quad 1 \quad 1 \quad c]^T$$



Corresponding ANN output vector class: [20]

$$f_v = [1 \quad 0 \quad 0 \quad 0 \quad 1 \quad d]^T$$

Fig.4 Input / Output Pairs of the ANN

The feature vectors and the corresponding output vector of the body force classes for taken 13 hand preshapes are given in below respectively P and T matrixes.

$$P = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & a & b & c & d & e & f & g & h & 0 & j & k & l \end{bmatrix}$$

$$T = [1 \quad 5 \quad 5 \quad 5 \quad 10 \quad 10 \quad 10 \quad 15 \quad 15 \quad 15 \quad 20 \quad 20 \quad 20]$$

where in P matrix, the last row shows the aperture of the two fingers and a to l letters mean that the aperture distance of the fingers are different. In P matrix, first column corresponds a line edge, and the corresponding body force class in T matrix is 1, the following 3 columns show the hand preshapes have U-shaped curvature and the corresponding body force class is 5, the next 3 columns are used for the V-shaped curvature, and the output class is 10, the next triple columns are used for 2-curves fitting hand preshapes and the output body force class is 15, and the last triple columns show the hand preshapes have 1 line edge and 1-curve fitted, and the corresponding body force class is 20.

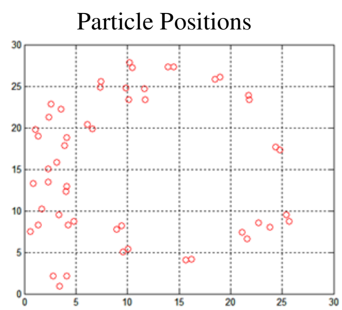
For testing our controller we used 5 different hand preshapes with different apertures of the finger tips, and the corresponding output vector, Y, is given below.

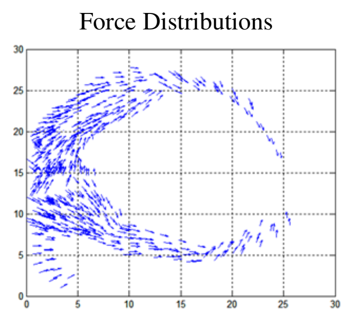
$$Y = [1.0958 \quad 4.8286 \quad 9.9974 \quad 15.0178 \quad 20.2348]$$

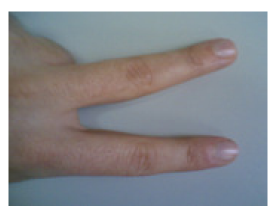
Even though there are some mistakes when we look the output vector since the input data set may not be sufficient, the corresponding colony formations (given in fig.6) are sufficient.

$$f_{v1} = [0 \quad 0 \quad 0 \quad 1 \quad 1 \quad 0]^T$$

ANN output: [15.0178]

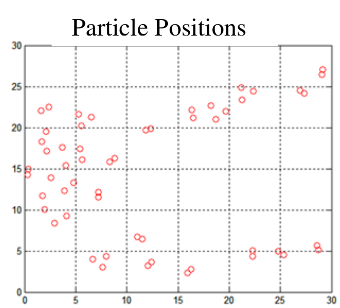






$$f_{v2} = [0 \quad 1 \quad 0 \quad 0 \quad 0 \quad ap_1]$$

ANN output: [4.8286]



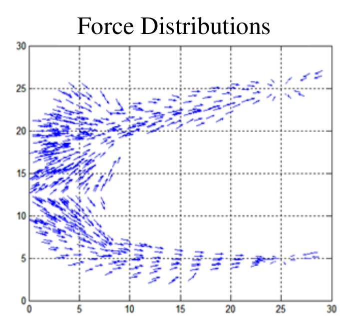


Fig.5 Imitation of scissor like and pinching hand postures

At the top of Figure 5 the captured hand preshapes, the corresponding feature vectors and the ANN outputs as the corresponding body force classes and at the bottom the swarm

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particle distributions with the particle force distributions are given. The imitation results of the particle positions both scissor like and pinching like hand behavior show close imitation of the hand posture. Also force distributions of the particles show similar characteristics with desired hand preshapes.

V. Conclusion

In this work, our main contribution is the imitation of the human hand postures by a system that possesses a completely different dynamics, thus there is no one to one organ matching or in other words there is a corresponding problem.

As we stated previously, we focused on imitation of the human hand gestures by a swarm having totally different dynamics than a human.

In this paper, we proposed a novel ANN based controller to adjust the fluid dynamics parameters, which is the input of the particle based system namely SPH, to get the desired hand preshapes. This controller commands only the body force vectors of the swarm particles. At the output of the proposed system, the fluid particles have a similar path flow with the images of the human hand postures given as the input to the system.

References

[1] A. Billard, “Learning motor skills by imitation: a biologically inspired robotic model”, in Cybernetics & Systems, special issue on “Imitation in animals and artifacts”, C. Nehaniv & K. Dautenhann editors.Summer 2000

[2] Raffaelle I. Rumiati, Joana C. Carmo, Corrado Corradi-Dell’Acqua, “Neuropsychological perspectives on the mechanism of imitation”, Phil. Trans. Soc. B 2009, 2337-2347

[3] J.Demiris and G. Hayes, “Imitative Learning Mechanism in Robots and Humans”, in Proceedings of the 5th European Workshop on Learning Robots, pp. 9-16, Bari, İtaly, July 1996

[4] S.Calinon, F. Guenter, A. Billard, “On Learning, Representing and Generalizing a Task in a Humanoid Robot” IEEE Transactions on Systems, Man and Cybernetics, Part B, Special Issue on robot learning by observation, demonstration and imitation, 37 (2007) 286-298

[5] A. Billard and R. Siegwart, “Robot learning from demonstartion”, Robotics and Autonomous Systems, vol.47, no. 2-3 pp. 65.67, 2004

[6] Schaal, S.; Ijspeert, A.; Billard, A. “Computational approaches to motor learning by imitation” in Frith, C.D.;Wolpert, D. (eds), The Neuroscience of Social Interaction, 1431, pp. 199-218, Oxford University Press, 2004

[7] Alissandrakis, A., Nehanic, C. and Dautenhahn, K. “Imitation with ALICE: Learning to Imitate Corresponding Actions across Dissimilar Embodiments”, IEEE Transactions on Systems, Man, and Cybernetics – Part A: Systems and Humans, Vol.32, No.4, July 2002

[8] Glas, D.F., Miyashita, T., Ishiguro, H., Hagita, N. “Laser Tracking of Human Body Motion Using Adaptive Shape Modeling”.. IEEE/RSJ International Conference on, IROS 2007, San Diego, California, USA

[9] Minato, T., Ishiguro, H. “Generating Natural Posture in an Android by Mapping Human Posture in Three-Dimensional Position Space”. IEEE/RSJ International Conference on, IROS 2007, San Diego, California, USA

[10] Pac, M.R., Erkmen, A.M., Erkmen, I. “Control of Robotics Swarm Behaviors Based on Smoothed Particle Hydrodynamics”, IEEE/RSJ International Conference on, IROS 2007, San Diego, California, USA

[11] Pimenta, L.C.A., Mendes, M.L., Mesquita, R.C., Pereira, G.A.S. “Fluids in Electrostatic Fields: An Analoghy for Multirobot Control”, IEEE Transactions on Magnetics, April 2007

[12] G.R. Liu and M. B. Liu, “Smoothed Particle Hydrodynamics: A meshfree Particle Method”, World Scientific, 2003

[13] J.J. Monaghan “Simulating Free Surface Flows with SPH”, Jurnal of Computational Physics 116, 399-406 (1994)

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