❑   163

Automated Sequential Pushing of Micro Objects by Using Adaptive Controller

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Article Info	ABSTRACT
	This paper focuses on precision automated pushing of multiple micro objects. An adaptive control system is proposed to accurately push and position the micro objects on a substrate. Each micro object exhibits different characteristics in terms of the surface micro forces governing the manipulation process. The controller is designed to compensate for the effect of the micro forces whose aggregated magnitude varies during the process. An experimental setup is designed to validate the performance of the proposed controller. The results of the experiments confirm that the proposed adaptive controller is capable of learning to adjust its parameters effectively, when the surface micro forces change under varying surface and ambient conditions.

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1.   INTRODUCTION

In recent years, research efforts in the development of Micro Electro Mechanical Systems, (MEMS) including microactuators and micromanipulators, have attracted a great deal of attention. The development of microfabrication techniques has resulted in the advancement of surface machined-based microfabrication, which has made it possible to develop not only smaller microchips, but also various types of microsensors [1], microactuators [2], and lab-on-a-chip devices [3]. The microfabrication techniques are based on deposition and etching processes both of which are limited to fabrication of 2-dimentional structures. In order to fabricate 3-dimentional MEMS devices, it is inevitable to develop reliable tools for post-fabrication processes by which the precise and dexterous manipulation of individual 2-dimentional micro size objects is possible. Most of the micromanipulation methods reported in literature are tele-operated and labour intensive, requiring the intervention of a human user [4]-[7]. Current automated microassembly systems are comprised of a microgripper mounted on a multi DOF macro robotic station [8]-[10]. The long links in such microassembly manipulators significantly limit the dexterity of the manipulation within a very small space, where the micro structure lies. Therefore, multi DOF microactuators and microrobots are the ideal hardware for dexterous micromanipulation.

Over the last decade, a number of micorobotics research labs have been established, and various microactuators and micro robots have been developed. These micro robots are either manually controlled, or their proper automation is limited to a specific system configuration [11]. The biggest challenge, regarding automated micromanipulation, has been the existence of micro forces that are dominant in micromanipulation, and barely known to researchers. Often, the arms and linkage in microactuators are compliant, and undergo a considerable amount of deflection during micromanipulation. Also, the power requirement of these microactuators is highly dependent on the micro forces exerted at the end effector [11],

[12]. Therefore, the precise positioning of the end effectors during micromanipulation is possible, only if a controller is implemented to effectively compensate for the micro forces in the process.

In our previous paper, weintroduceda non-linear adaptive controller for automated pushing of a single micro-sized object using compliant microactuatorsalong a desired path [15]. In this work, we increase the complexity of the problem by letting the size and surface characteristics of the micro object change during the process of automated pushing.In other words, the goal of this paper is to design a non-linear adaptive controller to sequentially push multiple mizro-sized objects using compliant microactuators.

This paper is organized as follow. The specification of the problem is defined in Section 2. In Section 3, dynamics of micromanipulation and design of a nonlinear control system is presented and its stability is discussed. Section 4 describes the hardware setup. Details of the controller parameters and specification of the software is explored in Section 5. Results of the experiments are provided in Section 6, and finally, Section 7 and 8 comprises discussion, conclusions, and application of this research.

2. PROBLEM STATEMENT

The specifications of the experiments in this paper follow. Three flat micro components are placed along a line with a separation distance of a few hundred micrometres. The components are fabricated from a silicon wafer but have different dimensions and will be microassembled. A microassembly process is designed to operate according to the following procedures:
a) The micro components are continuously fed to the microassembly line and placed at their initial station.
b) Each of these components are then accurately pushed and positioned in a target station.
c) In the target station, another micromanipulator is available to perform the post-pushing manipulation.

In this paper, the automated sequential pushing of these three micro components from their initial stations to their specific target stations is discussed. The automated operation is performed with precision even under varying ambient conditions.

3. CONTROL STRATEGY

Consider the block diagram in Figure 1 where the micro objects are sitting on a glass which is, in turn, placed on a micro-stepper-motor-driven stage. A silicon cantilever tip is fixed from one end and is tangent to the side of one of the micro cube from its other end without any deflection. The x axis of the stage is resting in its origin. To push the micro object, we send the new position command X to the micro stage position controller. The micro stage motion moves the micro object against the micro tip, thus "pushing" the micro object along the x axis. The dynamic equation of motion of the micro object is described as:

$$m\ddot{q} + f_{mf} + F_d = K_s X \tag{1}$$

Where f_{mf}, F_d, , m and $\ddot{q}$ are the micro forces in the contact area, disturbance, mass and acceleration of the micro object, respectively, and K_s is the spring constant of the cantilever. The term, f_{mf}, which is also referred to as the surface micro forces, is affected by parameters such as surface roughness, temperature, humidity, velocity, applied force, geometry of the surface, materials, and electrostatic charge. This makes it extremely challenging to derive a model for this surface force. Unlike the case of conventional macro manipulation systems, this force is considerably large in comparison to the well-known gravitational force resulting from the mass, and cannot be treated as a negligible term. Also, the micro forces are dominant in micromanipulation, and therefore, cannot be incorporated into the disturbance, F_d, in (1). Therefore, it is advantageous to define a learning mechanism which can be trained to estimate this force under varying operating conditions. Therefore, the control strategy proposed consists of a linear PD controller and a nonlinear adaptive neural networks (NN) described in the following.

In our previous work [13], we described a comprehensive methodology to aggregate all the influential parameters necessary to determine the overall micro surface force. This force can be represented as a function of the following variables:

$$f_{mf} = f(q, \dot{q}, F_a, A, \phi) \tag{2}$$

Where q is the position of the micro object on the substrate, $\dot{q}$ is the velocity of the two surfaces in contact, $F_a$is the applied force, and ϕ is a vector of the environmental parameters, defined as follows:

$$\phi = \phi(RH, T) \tag{3}$$

Where RH is the relative humidity, and T is the temperature.

Given the desired position trajectory, the tracking error and its derivative are $e = q_d - q$ and $\dot{e} = \dot{q}_d - \dot{q}$. The filtered tracking error is expressed as:

$$r = \dot{e} + ke \tag{4}$$

With $k > 0$. By differentiating (4) and invoking (1), the pushing dynamics can be described in terms of the filtered tracking error as:

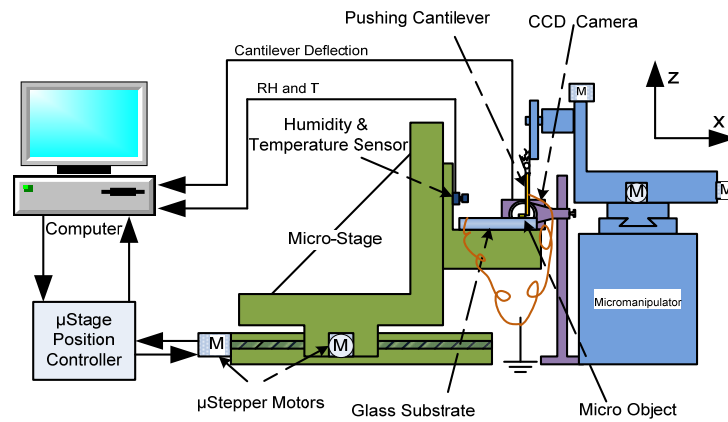$$m\dot{r} = kmr + f_{mf}(q,\dot{q},F_a,A,\phi) + F_d - K_s X + m\ddot{q}_d - k^2 me. \tag{5}$$

Figure 1. Block diagram of the experimental setup

The control law is defined as the following:

$$X = \frac{1}{K_s}[\hat{f}_{mf}(q,\dot{q},F_a,A,\phi) + k_v r + m\ddot{q}_d - k^2 me] \tag{6}$$

Where $\hat{f}_{mf}$ is an estimate of f_{mf}, and $k_v r = k_v \dot{e} + k_v ke$ is an outer PD tracking loop.

According to the universal approximation property of NN [14], there exist a two-layer NN such that:

$$f_{mf}(x) = W^T \sigma(V^T x) + \varepsilon \tag{7}$$

Where $x = (q, \dot{q}, F_a, A, RH, T)$ in the vector on input parameters affecting the micro forces, and the weight matrices, W and V, are unknown parameters that can be tuned online during pushing processes. These ideal target weight matrices are not necessarily unique. The approximation error is bounded on a compact set by $\varepsilon \le \varepsilon_N$, with ε_N a known bound. The activation function σ at the hidden layer is a nonlinear function (typically a sigmoid function) given by:

$$\sigma(x) = \frac{1}{1 + \exp(-x)} \tag{8}$$

It is very challenging to find the size of the matrices, W and V, which gives the arbitrary approximation error of ε. ε Therefore, the weight estimates of $\hat{W}$ and $\hat{V}$ are adopted to approximate the function, such that:

$$\hat{f}_{mf}(x) = \hat{W}^T \sigma(\hat{V}^T x) \qquad . \tag{9}$$

Consider the dynamic system of the micromanipulator, described by (5), for a bounded, continuous desired trajectory with bounded velocity and acceleration. In our previous work [15], we proved that the NN controller, (6), guarantees the Uniform Ultimate Boundedness (UUB) of the close-loop system with the gains satisfying k_v-$km>0$, and the NN weight tuning functions given by:

$$\begin{cases} \dot{W} = M\hat{\sigma}r \\ \dot{V} = Nx(\hat{\sigma}'^T \hat{W}r)^T \end{cases} \qquad , \tag{10}$$

Where, M and N are the constant positive definite matrices. In the controller, used for sequential pushing in this paper, the parameter of the surface area is added to the input of the NN according to (9). The value of the surface area is bounded. Therefore, the NN input vector is bounded, and consequently, the UUB of the nonlinear controller for sequential pushing of micro objects with different sizes is guaranteed. Moreover, the filtered tracking error, $r(t)$, vanishes over time, similar to the controller discussed in [16].

4.   HARDWARE SETUP

The experimental setup is depicted in Figure 1. To track the micro cube and micro tip and to capture the camera frames of the pushing process, a high-definition CCD camera mounted on a high magnifying zoom lens is installed next to the stage, aligned along y axis. Attached to the microstage is a humidity-temperature sensor which monitors the ambient conditions in real time.

Figure 2 is a schematic of how the objects are initially positioned, as well as the target position after pushing operation.

The square objects used for this experiment are diced out from a 50µm thick silicon wafer. The sizes of the objects are 125x125µm, 150x150µm, and 200x200µm. Also, the substrate on which the objects are and the cantilever to push the objects consists of silicon. The cantilever is 14mm long, 200µm wide, and 50µm thick. The cantilever and micro objects are rinsed with acetone and IPA. Then, they are rinsed once more with acetone. The cantilever is placed in its containing clip and grounded to prevent any static charges on the surface.
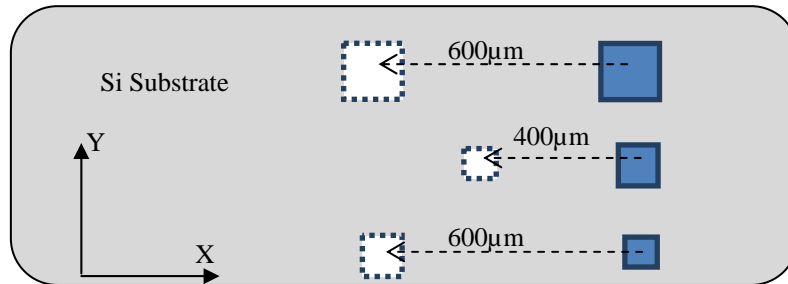

Figure 2. Initial and target position of the micro objects during the automated sequential micromanipulation

5.   CONTROLLER AND SOFTWARE DESIGN

Three sinusoidal trajectories are chosen as the desired trajectories of the pushing. The sinusoidal trajectory is smooth and contains different pushing velocities over time and is therefore a suitable choice for gathering the data to train the NN and optimize the network weights to a better approximate f_{mf} in (9).

The weight matricesof the NN are tuned in two manners: i) off-line back-propagation training [14] and ii) dynamic learning during pushing by using (10). The former is known as supervised learning (requires training data) or static NN, whereas the latter is called unsupervised learning or dynamic NN. The dynamic NN-based controller is the application of the control law in (6), which is designed to ensure tracking and UUB stability in the Lyapunov sense.

Three different control systems are used for automated sequential pushing: a linear conventional PD controller, a static NN-based non-adaptive controller, and, the proposed dynamic NN-based adaptive

controller. The block diagrams describing the structure of each of these three controllers are provided in Figure 3.

5.1. Artificial Neural Network Structure

Equation (2) identifies six distinct variables that determine the magnitude of the micro forces at any given instance. These parameters, forming the input vector to the NN, are listed here.

- A: Surface area of the object at the interface with the substrate
- q: Current Position of the micro Object
- F_a: Amount of force being applied on the object
- $\dot{q}$: Velocity that the object is travelling at
- RH: Relative humidity
- T: Temperature of the enclosure

Table 1. NN size and structure

Number of inputs	6
Neurons in hidden layer	10
Number of outputs	1
Number of training data sets	2550
Number of testing data sets	500

The proposed two layerfeed forward NN model in (9) outputs the approximate values of the nonlinear micro forces described in (2). Table 1 lists the parameters that define the structure and size of the NN used in the sequential micro object pushing experiments. These parameters are obtained through a trial-and-error process [15].

5.2. Tuning NN Weights

A series of open-loop pushing operation are conducted at the relative humidity (RH) of %45 and temperature of 40° Celsius to identify the key characteristics of the micro forces. 3050 data sets are extracted from these experiments. 2550 of these data sets are used to train the NN and the remaining 500 are utilized to test the NN, prior to integrating it into the closed-loop control system shown in Figure 3(c).

a) Linear PD controller

b) Non-linear Static NN-based controller

c) Proposed non-linear adaptive NN-based controller

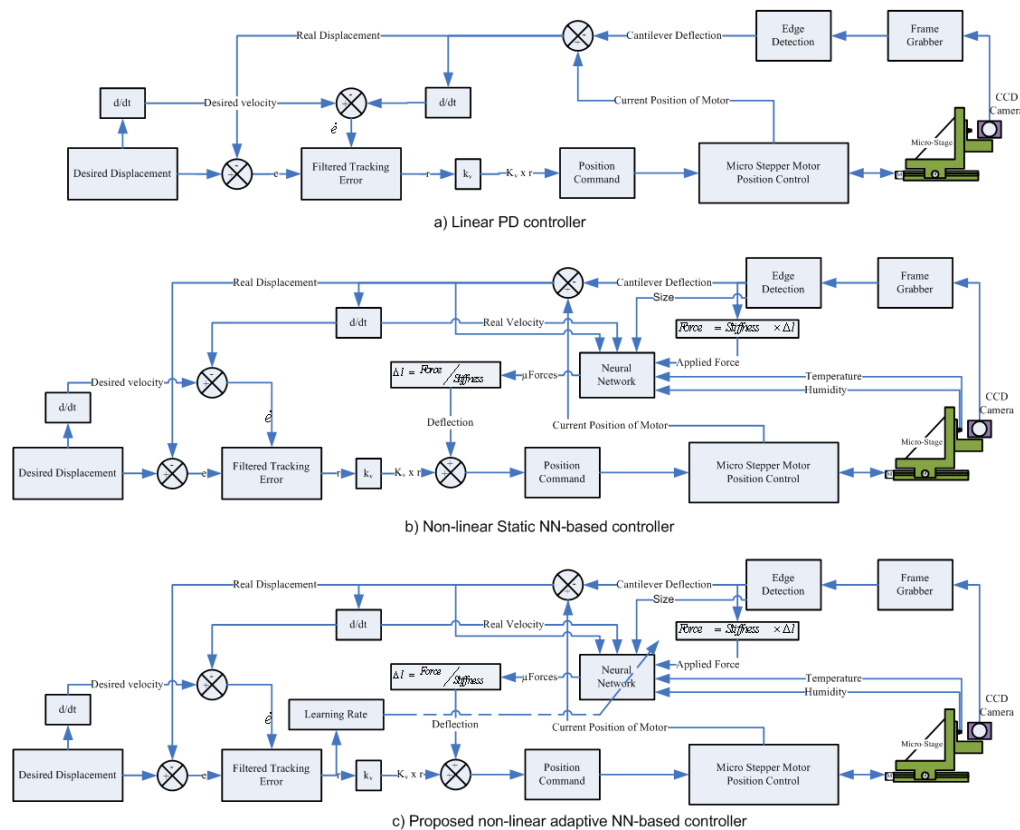*Automated Sequential Pushing of Micro Objects by Using Adaptive Controller (Mohsen Shahini)*

Figure 3. Sequential micro object positioning controllers with different strategies

The micro objects and the ambient conditions selected in automated sequential pushing differ from those employed in characterization experiments to prepare training data sets. Consequently, the resulting micro forces have considerably different magnitudes. Nevertheless, the proposed adaptive NN, as demonstrated in the following sections, is capable of adjusting its weights in real time under varying operating conditions by applying the proposed weight tuning algorithm in (10).

Several micromanipulation cycles must be run, until the adaptive controller has effectively adjusted its weight to the new operating conditions. After each of these automated sequential micromanipulation cycles are complete, the program outputs an updated W matrix which is a modified version of the original matrix obtained during the static NN training. For the next run of the automated micromanipulation, this new matrix is fed into the program, replacing the previous one as its initial W matrix. This ensures that the program always uses the most accurate data during the micromanipulation process, and, therefore, guarantees continuous learning.

6.   RESULTS

In this section, the results of sequentially pushing three objects are provided. The objects are initially positioned according to

Figure 2, and are pushed along the desired sinusoidal trajectory. The sequential micro object pushing is repeated with three different controllers.
a) Conventional PD controller in Figure 3(a)
b) PD controller, augmented with static NN in Figure 3(b), and trained as described in Section 0
c) The proposed adaptive NN-based controller in Figure 3(c) with weight updates according to (10).

In total, seven runs of automated sequential pushing of three micro objects are carried out. The first experiment is conducted by using PD controller for positioning. The second run is performed by adding the static NN to the PD controller.

The experiment is continued by conducting 5 additional cycles of sequential pushing in which the W matrix of the NN is dynamically updated through the experiment according to (10). The performance of the control system in each case is reported in the following sections.

The automated pushing experiments are carried out when the chamber is at the relative humidity (RH) of %52 and temperature is measured 32^oCelsius.

a.   Sequential Micromanipulation Using the PD Controller

Figure 4 illustrates the results of the automated sequential pushing of the three micro objects on a silicon substrate by using conventional PD controller.

A stick-slip characteristic is almost always present at the start of the pushing as is clearly seen in the plots. After the pushing has commenced, the micro objects frequently slow down and might completely cease depending on the characteristics of the surfaces. For example, the displacement curve for the third object hits a horizontal line for a period of time on several occasions during the manipulation, demonstrating astick-slip behaviour of the object. In the case of the second object, the displacement curve suggests that the object slows down at two separate time instances throughout the pushing process. In contrast, the first object almost smoothly follows the desired trajectory beyond the initial stick-slip phenomenon. For this object, the static error at the end position can be brought to zero if the PD controller is augmented by an integral component.
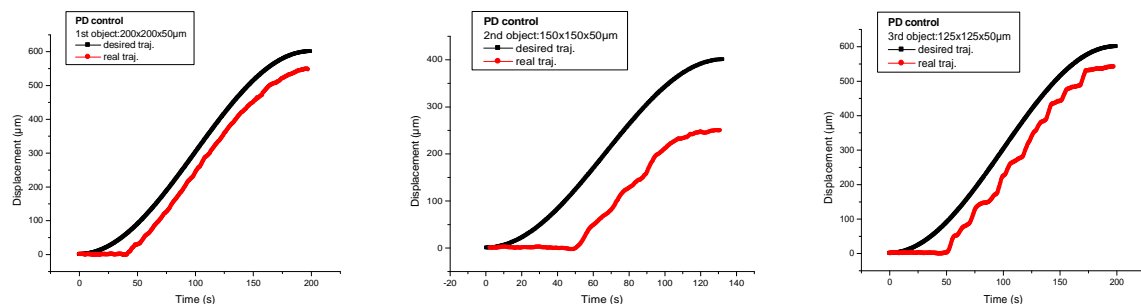

Figure 4. Actual trajectories of the micro objects in sequential micromanipulation by PD controller (Run#1)

The plots in Figure 4 verify that the PD controller is incapable of compensating for the non-linear micro forces during the pushing. It can also be inferred that, when the object being pushed exhibits a varying stick-slip behavior throughout the pushing process, using a PID controller will not cancel the trajectory error effectively.

b. Sequential Micromanipulation Using PD Controller Augmented with Static NN

The sequential micromanipulation of the same three objects, along the same path is repeated by augmenting a NN to compensate for the nonlinear micro forces during the pushing process. The NN is trained according to the procedure described in Section 0. In Figure 5 the performance of this control system is demonstrated.

Adding the static NN does not produce any noticeable improvement of the overall performance of the automated sequential micromanipulation in Figure 5. This stems from the fact that the data used to train the NN does not truly represent the conditions under which the manipulation process takes place. The ambient condition in this run of the experiment differs from that of the training data sets. No micro forces characterization is performed on these specific micro objects used in the experiment in order to train the NN. This strategy is chosen to demonstrate the limitation of a non-adaptive control system for such micromanipulation where the governing forces are highly sensitive to any changes in the surface and ambient conditions.
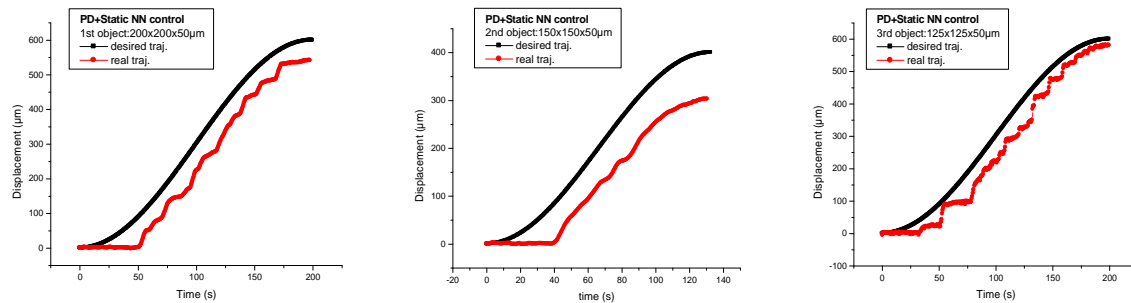

Figure 5. Actual trajectories of the micro objects in sequential micromanipulation by static NN-based controller (Run#2)

c. Sequential Micromanipulation Using Proposed Adaptive NN-based Controller

The next five cycles of the automated sequential pushing are carried out by using the adaptive control system in which the W matrix is updated during the process according to (10) in the manner discussed in Section 0. Figure 6 represents the trajectories obtained in the second cycle of the experiment with the proposed adaptive NN-based controller. From these plots, it is evident that the controller is effectively adapting its parameter, progressively leading to an accurate positioning of the micro objects, based on the desired predefined trajectory.
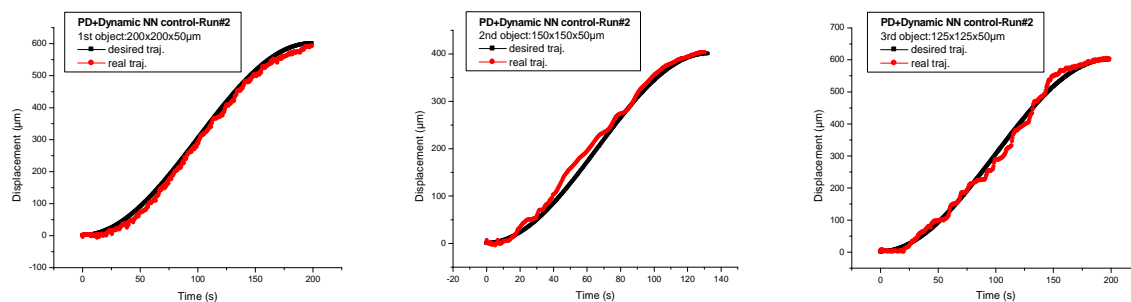

Figure 6. Actual trajectories of the micro objects in sequential micromanipulation by adaptive NN-based controller (Run#4)

To fine tune the controller parameters, the learning rate is decreased by half after the third cycle of the sequential micromanipulation is complete. Lowering the learning rate parameter implies taking smaller steps toward the "near" optimal values of the *W* matrix weights, thus, avoiding the problem of over tuning commonly encountered if the learning rate is larger than what is required after several epochs of training.

Fine tuning the adaptive controller results in an even more superior positioning of the micro objects. This can be seen from the plots in Figure 7. The three objects very closely follow the desired path.
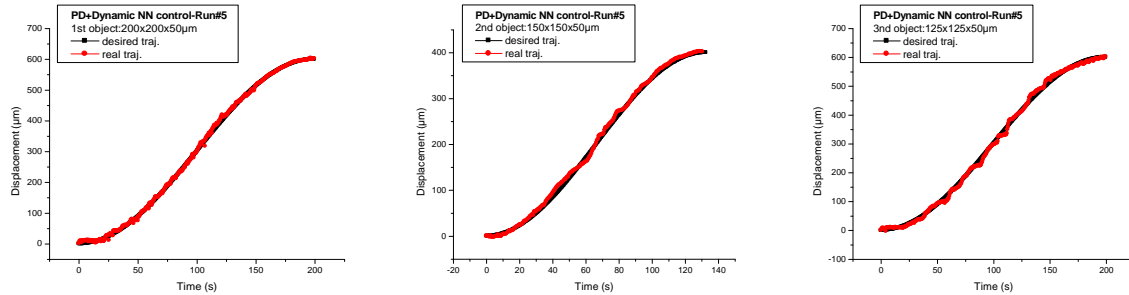

Figure 7. Actual trajectories of the micro objects in the sequential micromanipulation by adaptive NN-based controller (Run#7)

An example of the configuration of the micro objects before and after the automated sequential pushing is illustrated in Figure 8. As seen in this figure, the surface of the silicon substrate is not perfectly polished and contains a number of scratches. Despite this, the proposed adaptive controller learns how to correctly compensate for the micro forces at the different places on this substrate. The learning for adapting to various characteristics of the surface asperities is facilitated by choosing the "position" of the object as a varying parameter in the input vector of the adaptive NN.
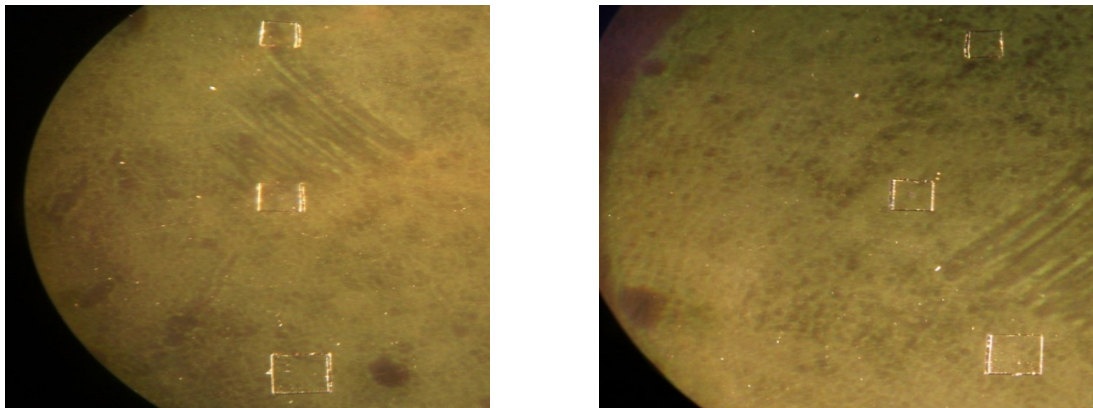

Figure 8. Position of micro objects before (left) and after (right) automated sequential pushing experiment (Note: the two pictures are taken from different experiments)

7. NUMERICAL ANALYSIS OF THE RESULTS

The performance of the control system is evaluated by using the Root Mean Square (RMS) of the errors over the course of the automated sequential micromanipulation. In sequential micro pushing, the average RMS error is calculated as follows:

$$E_{RMS} = \frac{1}{3}(E_{RMS_1} + E_{RMS_2} + E_{RMS_3}) \tag{11}$$

Where $E_{RMS_i} = \sqrt{\frac{1}{n}\sum_{k=1}^{n} e_k^2}$ E_{RMS_i} is the RMS for each individual pushing operation in the experiment of sequential pushing of the three objects. The results of these calculations are summarized in Table 2. Figure 9 compares the overall performance of the controller by plotting the average RMS error calculated in Table 2 for different control approaches implemented in this paper.

Table 2. Average RMS trajectory errors in automated sequential pushing experiment by different controller systems

Run index	Controller	RMS$_1$	RMS$_2$	RMS$_3$	Average RMS
Run #1	PD only	54.35	121.84	79.01	85
Run #2	PD + static NN	66	75.93	53.50	65.14
Run #3		27.24	22.11	25.23	24.86
Run #4		15.67	14.32	16.30	15.43
Run #5	PD + dynamic NN	14.24	14.56	18.21	15.67
Run #6		5.23	7.22	7.24	6.56
Run #7		4.89	5.65	7.91	6.15

After several tests are completed and no significant change of the parameters affecting the micro forces are observed, the RMS curve typically hit a plateau at which the controller is no longer capable of learning more. At this point, the *W* matrix values undergo little or no updates, and the proposed adaptive NN is deemed to be trained satisfactorily. Any further decrease in the value of the learning rate has no significant effect in the average RMS. In this experiment, the adaptive controller performance does not improve beyond the fourth training cycle of the completed automated sequential pushing with the dynamic NN (Experiment Run#6).

8. DISCUSSION AND CONCLUSION

In this paper, the automated sequential precise positioning of multiple micro objects is successfully realized by means of a novel control strategy utilizing an adaptive neural network-based controller. For the first time, the entire micromanipulation path is controlled by accurately compensating for the dominant micro forces involved.

Promising results, reported in the automated sequential manipulation, can promote the applicability of an adaptive NN in a precise manipulation in the micro scale under varying environmental conditions. In serial automated microassembly lines, the dominant resisting micro forces distort the compliant micromanipulator tips, impairing the accuracy of the automated positioning. Micromanipulator systems with stiff arms do not have this issue; however, they have a very large physical footprint compared to that of the micro objects. This imposes a restriction on installing multiple manipulators to perform multi-degree-of-freedom (DOF) assembly tasks. The proposed compensation mechanism for micro forces enables the use of multiple miniaturized micromanipulators for the automated serial assembly of 3-D micro systems.
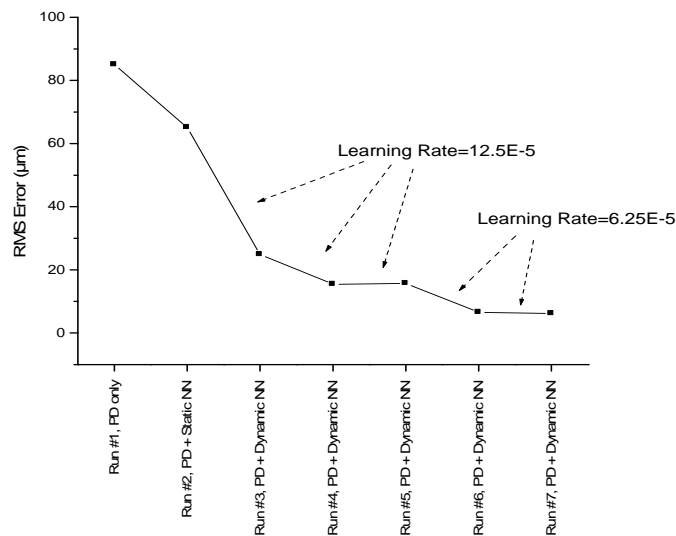
Figure 9. RMS trajectory errors at different runs of the automated sequential pushing experiments

In this work, a slim micro cantilever with a high aspect ratio was employed. The deflection of the cantilever under a lateral load in the experiments closely simulated the effect of dominant micro forces on compliant microactuators. For future work, the proposed adaptive controller will be implemented to command multi DOF microactuatorswith compliant arms for accurately positioning micro objects.

The results reveal that pushing micro objects with a flat surface area on a flat substrate is a very slow process, when compared to manipulation of objects in macro scale. Future works also includeexploring innovative solutions to overcome the limitation, such as the selection of appropriate materials, roughening the surfaces, and conducting the operation at a specific ambient temperature, relative humidity, and air pressure.

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Mohsen Shahini received his B.A.Sc and M.A.Sc. degrees in manufacturing engineering, from Amirkabir University of Technology, Tehran, Iran, and PhD degree in mechanical and mechatronics engineering from the University of Waterloo, Waterloo, ON, Canada in 2001, 2004, and 2011, respectively. He is currently the Chief Academic Officer at Top Hat Monocle Corp which he co-founded in 2009 to promote interactive teaching in the classroom. In addition to pedagogy and interactive teaching, his current research interests include MEMS and its application in health science and biotechnology.

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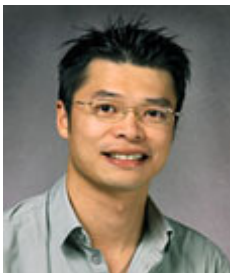
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