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Suction Control of a Robotic Gripper: A Neuro-Fuzzy Approach ⋆

NIKOS C. TSOURVELOUDIS⋆⋆, RAMESH KOLLURU,
KIMON P. VALAVANIS and DENIS GRACANIN
Robotics and Automation Laboratory, The Center for Advanced Computer Studies and A-CIM Center, University of Louisiana at Lafayette, Lafayette, LA, USA;
e-mail: {*nikost, rxk*}*@acim.usl.edu, kimon@cacs.usl.edu, dg@acim.usl.edu*

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Abstract. This paper discusses a fuzzy logic control system designed to determine, regulate and maintain the amount of suction needed by a robotic gripper system to perform reliable limp material manipulation. A neuro-fuzzy approach is followed to determine the amount of desired suction (depending on experimentally derived data and plant characteristics). A knowledge-based valve controller is then designed to generate, regulate and maintain the amount of suction calculated by the neuro-fuzzy suction module. The performance of the overall suction control system is compared with actual experimental results obtained when using a prototype gripper system to handle limp material. Further, performance of the fuzzy logic based valve controller is compared to conventional PD and PID controllers. The proposed control scheme is found to enhance the overall functionality of the prototype robotic gripper system.

Key words: robotic gripper, knowledge-based systems, neuro-fuzzy control, suction control, limp material.

1. Introduction

This research is the natural outgrowth of the authors' previous work, in the area of robotic grippers for limp material manipulation. The system design, prototyping, stability analysis, performance evaluation and control architecture have been presented in [1, 2]. A review of existing commercial and research limp material handling systems, and gripping mechanisms such as electrostatic, suction, thermal and chemical adhesion, has been presented and discussed in [3].

The developed gripper prototype, shown in Figure 1, has been integrated with AdeptOne and AdeptThree robot arms. Suction was found to be the most appropriate mechanism to handle delicate deformable material such as fabric, due

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⋆⋆ Dr. Tsourveloudis is currently with the Technical University of Crete, Department of Production Engineering and Management, 73100 Chania, Greece.

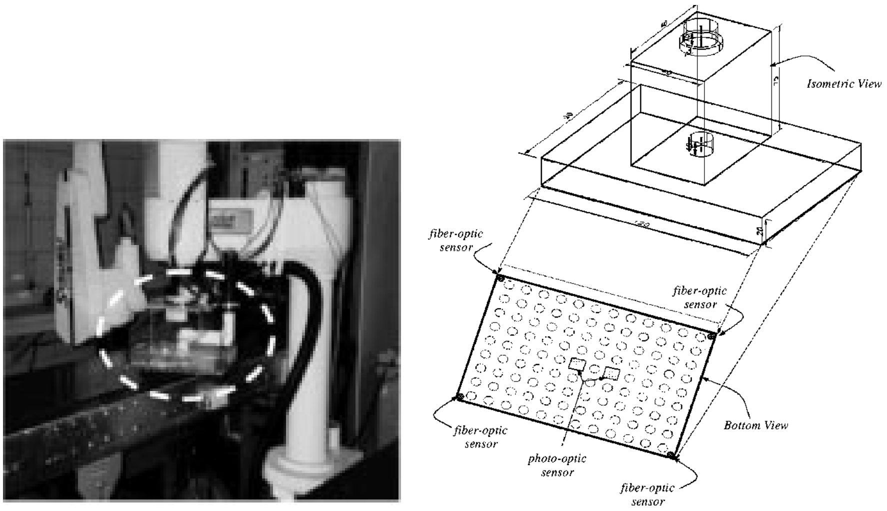

Figure 1. The developed gripper system.

to its non-intrusive and non-incisive characteristics. Suction offers high gripping strength, low cost and ease of implementation.

The integrated robotic gripper system in its current configuration has been proven to:

- manipulate single or multiple limp material panels without causing distortion, deformation or folding of the material,
- pick and place more than 12 panels per minute, as required by the industry*, while the maximum rate reaches about 22 panels per minute, and,
- operate with reliability of at least 99%.

However, in previously reported work [1, 2], a constant amount of suction was generated and applied to pick and place limp material panels. But in reality, the amount of suction required for reliable and distortion free limp material manipulation varies; it depends on parameters such as material porosity, weight, speed of robot, distance of travel, number of panels to be lifted, etc. Since a precise mathematical relation among these parameters is lacking, fuzzy logic methodologies may be implemented to model the suction control system.

The overall control system consists of two coupled inference modules. The first module, which is responsible for determination of the required suction, uses a *neuro-fuzzy* ([10, 11]) technique, adapting itself to experimentally derived input-output data pairs. The second module that is responsible for the generation and maintenance of suction uses heuristically tuned fuzzy control laws.

* Industrial requirements specified by the American Apparel Manufacturers Association (AAMA) and Textiles and Clothing Technology Corporation [TC]^2.

The paper is organized as follows: In Section 2, the operation of the robotic gripper system is presented, followed by a brief discussion on grasp stability and air flow dynamics issues. Section 3 presents a discussion on the two suction modules, namely, *suction determination module* and *suction generation module*. Experimental and simulation results are presented in Section 4, while conclusions and future research topics are included in Section 5.

2. Operation of the Gripper System

The experimental set-up of the overall robotic gripper system is shown in Figure 2. The operation of the gripper system is coordinated by hierarchical control architecture shown in Figure 3. The gripper prototype is integrated with AdeptOne and AdeptThree industrial robot arms. The AdeptVision AGS system has been used for visual processing. The sensor coordinator uses vision sensors (cameras) to detect the presence of the material on one of the two conveyors and to communicate the object pose information to the robot. The position coordinator then transforms the object pose from the world coordinate system to the gripper coordinate system. The robot arm positions the gripper over the piece of material. Gripper-mounted fiber-optic proximity sensors and capacitive sensors are used to facilitate accurate positioning of the gripper, for exact alignment with the material. Suction is then activated to enable material manipulation. This operation is governed by the overall suction control system that consists of two modules: (i) *Suction Determination (SD) module* – an off-line process used to determine the amount of suction based on material and plant characteristics, and (ii) *Suction Generation (SG) module* – an on-line component that achieves the value of the desired suction determined by the SD module.

In order for the overall system to perform reliably, the grasp needs be stable. The suction generated needs be greater than the weight of the material and also overcome the shear forces (due to robot accelerations) and suction losses (due to air leaks, etc.). Issues relevant to grasp stability and suction dynamics are discussed next.

GRASP STABILITY AND SUCTION DYNAMICS

Consider that the robot arm is accelerating at a rate of a_x and a_y in the horizontal and the vertical directions, respectively. The equilibrium of forces in the horizontal and vertical directions is resolved as follows (Figure 4):

$$\sum F_x = -F_f = ma_x \tag{1}$$

$$\sum F_y = P_g - W - N = ma_y \tag{2}$$

where, m is the mass of the material. The frictional force F_f holds the material on the gripper during the translation in the horizontal plane. The value of the normal

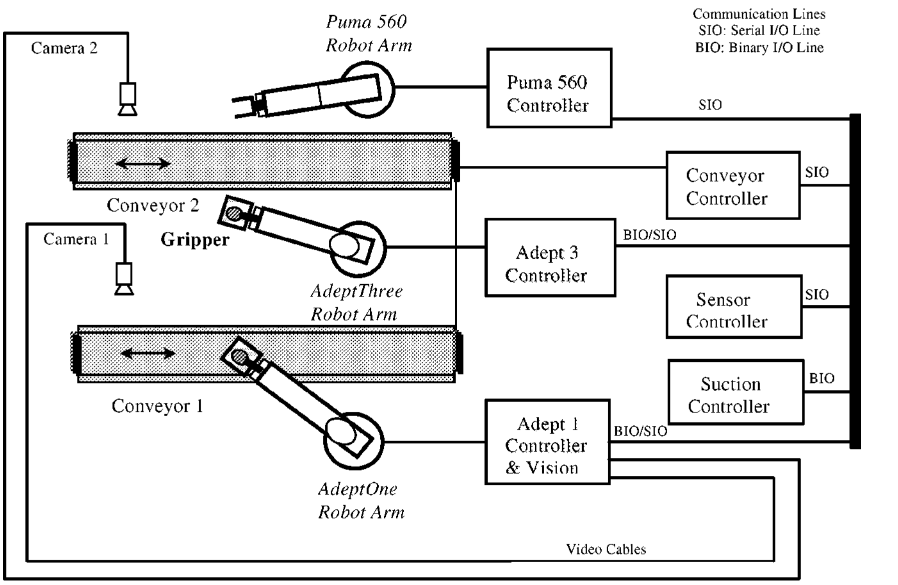

Figure 2. Configuration of the gripper's testbed.

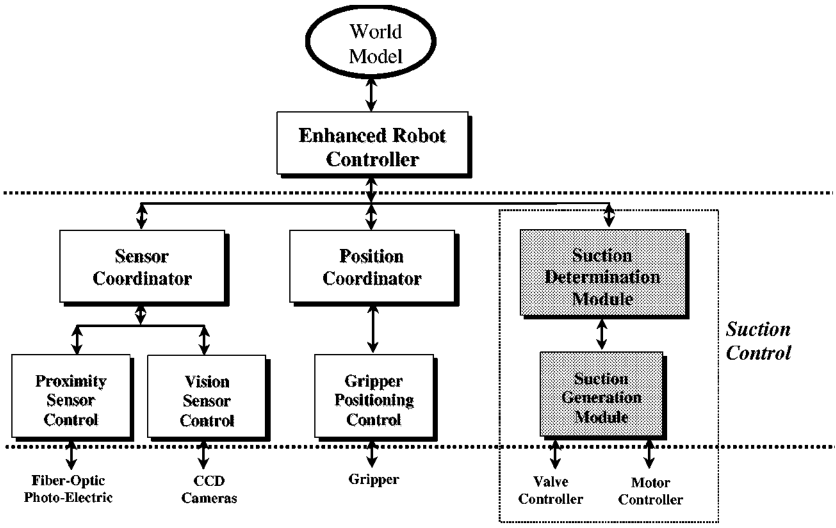

Figure 3. The hierarchical control architecture.

force N is determined by the equilibrium of forces in the vertical plane. Consequently, the magnitude of F_f, is determined by the equation $F_f = \mu N$, where μ is the coefficient of friction. For grasp stability it is necessary that $F_x \leqslant \mu N$. The suction, P_g generated at the gripper must be sufficient to overcome the slippage effect due to the acceleration of the robot arm, and also the weight and slippage of the material, as computed from Equations (1) and (2). The above mathematical formulation implicitly assumes no suction losses due to air leaks, material porosity, etc., making the physical model of the system overly simplistic and unrealistic. These parameters, though experimentally measurable, are difficult to be incorporated into the mathematical model of the system. An analytic approach, based on fluid dynamics theory is now presented to derive the value of P_g.

The suction generator is connected to the gripper via a series of pipes with bends, sudden enlargements and contractions in the conduits and control valves as shown in Figure 5.

The flow of air through the pipes of the suction system, assuming incompressible and isentropic flow conditions, may be approximated by the Bernoulli equation

$$\frac{P_{\text{in}}}{w_{\text{in}}} + \frac{v_{\text{in}}^2}{2g} + z_{\text{in}} = \frac{P_{\text{out}}}{w_{\text{out}}} + \frac{v_{\text{out}}^2}{2g} + z_{\text{out}} + H_{\text{m}} \tag{3}$$

where P_{in} is the pressure at the inlet port of the impeller, w_{in} is the specific weight of air at the inlet, v_{in} is the velocity of air at the atmospheric inlet point, z_{in} is the height of the inlet port above the ground level (datum), P_{out} is the pressure of the fluid at the outlet port, w_{out} is the specific weight of air at the outlet, v_{out} is the velocity of air at the outlet port, z_{out} is the height of the outlet port from the ground level (datum), H_{m} is the overall manometric head, and g is the acceleration due to gravity.

The flow of air at pipe inlets, valves, bends, and pipe outlets is generally not fully developed. This results in a loss of pressure that takes energy away from the flow. In piping systems, the losses due to fluid flow through valves or fittings are known as minor losses. In the design of pipelines, energy loss due to friction is dominant for pipe lengths of 100 feet or greater. For shorter lengths (as is the case in the present system configuration), losses at elbows and tee joints due to a change in direction of flow, losses at valves due to sudden *vena contracta* are substantial, in addition to the frictional losses.

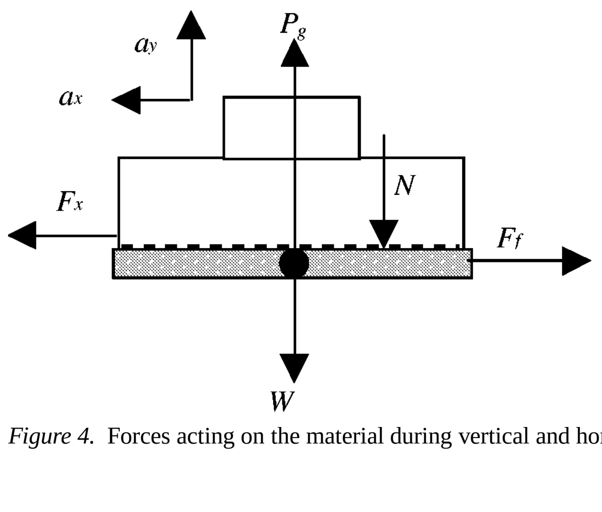

Figure 4. Forces acting on the material during vertical and horizontal motion.

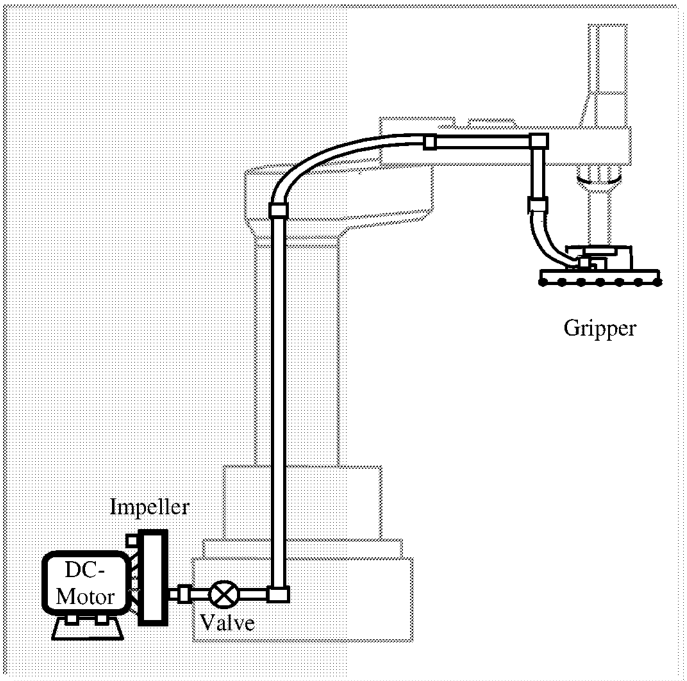

Figure 5. The suction system integrated with a robotic arm.

These minor losses, incorporated into Equation (3), result in the following equation:

$$\frac{P_{\text{in}}}{w} + \frac{v_{\text{in}}^2}{2g} + z_{\text{in}} = \frac{P_{\text{out}}}{w} + \frac{v_{\text{out}}^2}{2g} + z_{\text{out}} + H_{\text{m}} + \sum \frac{fL}{D}\frac{v_{\text{in}}^2}{2g} + \sum k\,\frac{v_{\text{in}}^2}{2g} \tag{4}$$

which is called the *modified* Bernoulli equation. The suction generated at the outlet port of the suction generator needs to exceed the suction needed at the gripper by at least the amount of the overall losses in suction, in order for the gripper to perform reliably. Losses due to friction and minor losses due to fittings are added, in order to determine the overall losses:

$$P_{\text{(losses)}} = P_{\text{(fall due to friction)}} + P_{\text{(fall due to bends)}} + P_{\text{(fall due to fittings)}}.$$

Thus,

$$P_{\text{(losses)}} = \frac{v_{\text{m}}^2}{2g}\left(\frac{fL}{D} + k_{\text{b}} + k_f\right) \tag{5}$$

where f is the friction factor, v_{m} is the mean velocity of air, L is the length of the pipe, D is the diameter of the pipe, k_{b} is a coefficient which depends on the total angle of the bend, and k_f is a coefficient dependent on type of pipe fitting.

For many fittings, k_f must be experimentally measured, however, in a few simple cases, it is possible to determine k_f analytically. It was experimentally found that the friction factor f varies *approximately* with the square of velocity [12]. Further, the friction factor depends on roughness conditions and the *Reynolds number*, which in turn depends on the density, velocity, and viscosity of the fluid and the pipe's diameter [13]. The value of k_{b} depends upon the type of the joint, the angle of the bend, the curvature of the bend, etc. The effective suction generated at the gripper surface is dependent on all of the above factors, which are difficult to quantify and evaluate.

The overall complexity of the system model renders justification and motivation for use of a fuzzy logic formulation, presented in the next section. Traditional controllers require an accurate mathematical model of the system that is to be controlled. On the other hand, fuzzy logic controllers have been proven to work effectively in real-world systems, which are difficult to be analytically modeled, but can be adequately described and controlled by humans [8, 9].

The role of the suction control is to compute the amount of suction needed for handling certain materials and to produce and regulate the predetermined amount of suction, by adjusting the air flow in the system. In the next section a discussion on the suction control system is presented.

3. Suction Control

It has been experimentally found that the suction required for material manipulation depends on the following parameters:

1. *Porosity* (Π) of material: It is experimentally found that the amount of suction needed to manipulate the material reliably changes significantly with the porosity of material. Porosity of a panel of material (fabric) may be mathematically computed as follows [11]:

$$\Pi = 1 - \frac{m}{dAL} \tag{6}$$

   where m is total mass of the panel, d is density of the material's fiber, A is the cross-sectional area of the panel and, L is length of the panel. The value of porosity computed using Equation (6) may vary across different samples of the same material, because parameters such as fiber density and cross-sectional diameter may vary over the length of the material. This results in uncertainty in the computed value of porosity. It is thus proposed to classify fabrics based on the computed values of porosity into certain classes of linguistic values.
2. *Weight* (W) of material: Material weight determines the amount of suction needed to overcome the effect of gravity on the object. Since the effect of suction permeates through a stack of porous panels, it is possible to increase the number of panels picked, by increasing the amount of suction. However, there does not exist a linear relationship between the amount of suction to be generated and the number of panels picked, due to material-specific properties, such as, inter-ply electrostatic adhesion, mechanical fusion of the edges of the panels, etc.

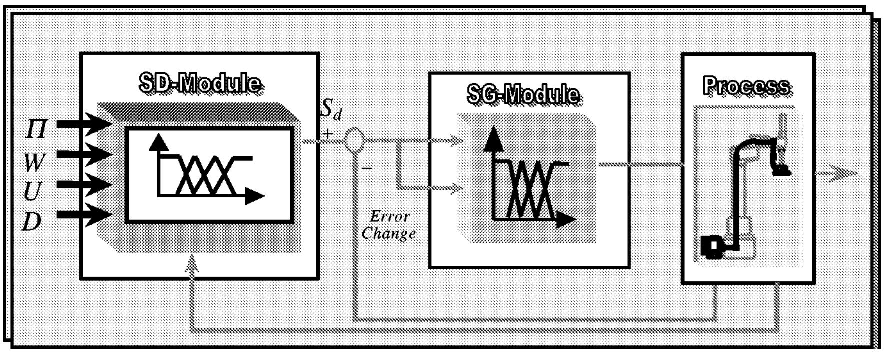

Figure 6. Suction Control Block Diagram.

3. *Robot Speed* (U): The amount of suction to be generated should be large enough to overcome of the downward force due to the material weight, and the shear force, due to the robot speed. As the speed of the robot arm increases, the value of shear forces acting to strip the object/material from the gripper's surface increases. Thus, speed of the robot is an important parameter to be considered while generating the desired amount of suction.
4. *Distance of Travel* (D): Once the amount of suction is generated and the object is picked up, it is transported to a "drop-off" area. During the transportation, there is a steady decrease in the static suction head within the gripper chamber, due to fluid losses and air leaks within the system. The longer the travel distance, the greater are these losses. It is necessary to overcome these losses by continuously generating an incremental amount of suction, once the initially desired suction has been generated.

These parameters serve as fuzzy inputs to the suction determination (SD) module.The output of the SD-module is a single-value, specifying the amount of desired suction S_{d}, for the given input variables. It is the responsibility of the suction generation (SG) module to attain and maintain this value. The overall control scheme is presented in Figure 6.

3.1. SUCTION DETERMINATION (SD) MODULE

Since the output variable from the SD-module is the desired *Suction* (S), the generic fuzzy rule used for suction determination is

$$\begin{aligned} R^{(i)}\!:\ & \text{IF } \Pi \text{ is } L\Pi^{(i)} \text{ AND } W \text{ is } LW^{(i)} \text{ AND } U \text{ is } LU^{(i)} \text{ AND } D \text{ is } LD^{(i)} \\ & \text{THEN } S \text{ is } LS^{(i)} \end{aligned} \tag{7}$$

where $L\Pi^{(i)}$, $LW^{(i)}$, $LU^{(i)}$, $LD^{(i)}$ and $LS^{(i)}$, are linguistic term sets for *Porosity*, *Weight*, *Robot Speed*, *Distance of Travel* and *Suction*, respectively. All input and output variables take values, which instead of being "crisp" numbers, are natural language words (*linguistic values*) such as, *Low*, *Average*, *High*, etc. The mathematical meaning of these values is represented by the membership functions of

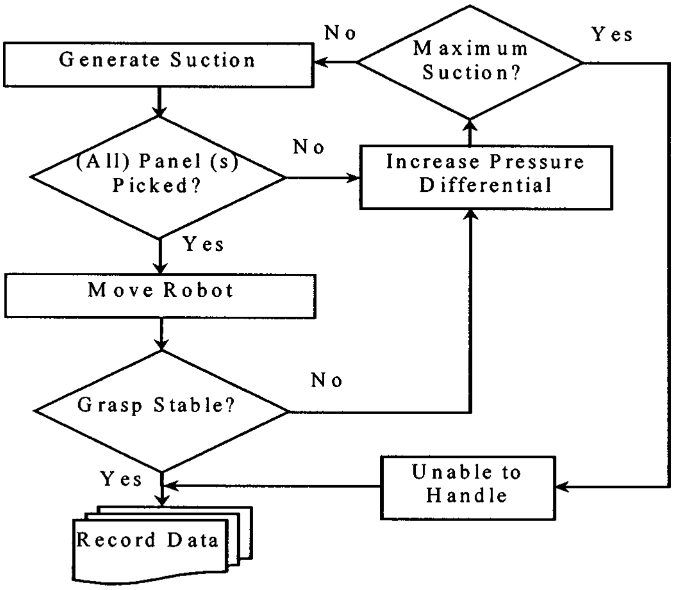

Figure 7. Knowledge and data acquisition.

the corresponding fuzzy sets. It should be noted that the fuzzy set theory does not provide an analytical method for determining problem-specific membership functions. The generic rule in (7) represents the knowledge acquired from experiments that determined the amount of suction needed when handling various types of material panels. The knowledge and data acquisition procedure is schematically presented in Figure 7. Repeating this procedure for different values of Π, W, U and D, several values of S were derived.

Both membership functions and rules were initially created by using the acquired knowledge. However, since there is no analytic methodology to convert human expertise into `if-then` rules and membership functions, extensive trial and error type of testing is required, which again does not guarantee output optimality. Recently, various *neuro-fuzzy* systems [10, 11] have been developed to provide a systematic approach in selecting appropriate fuzzy systems. Neuro-fuzzy systems combine both fuzzy systems and neural networks in the sense that the parameters (membership functions and rules) of the fuzzy systems are trained by a learning algorithm derived from the neural network theory. Some guidelines for selecting neuro-fuzzy models may be found in [12]. One advantage of neuro-fuzzy systems is that they keep the semantic properties of the underlying fuzzy system and cause only local modifications, mainly on the shape of membership functions.

The *Adaptive Neuro-Fuzzy Inference System* (ANFIS) presented in [13] is used in this paper. The ANFIS system approximates the function that is partially defined by the acquired data, and which may be mathematically presented as

$$S = f(\Pi, W, U, D) \tag{8}$$

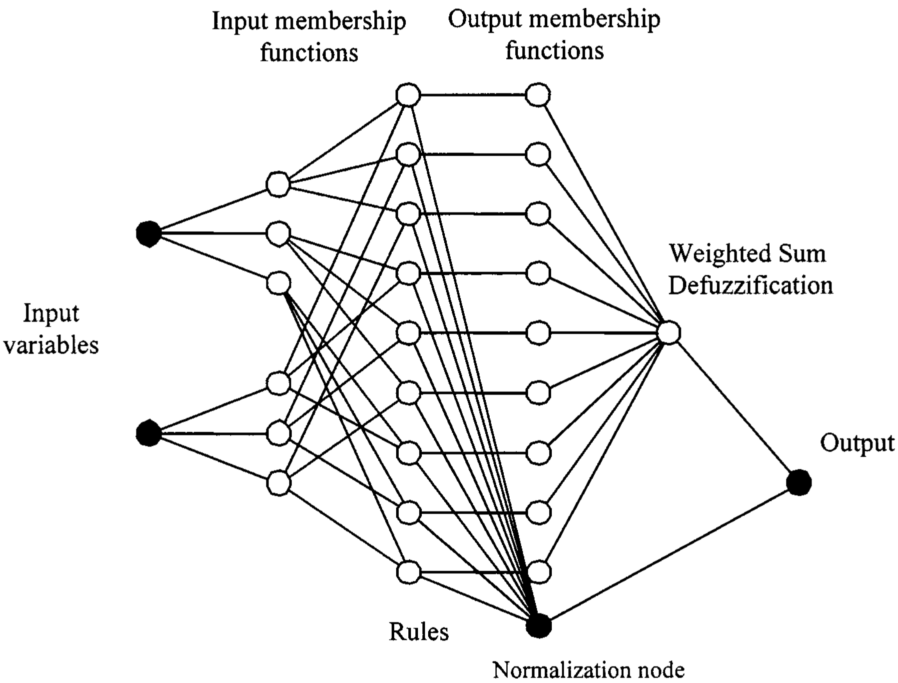

Figure 8. ANFIS architecture of the two-input/nine-rule SD-module.

Equation (8) represents the behavior of the system to be modeled. ANFIS minimizes the difference between fuzzy system's actual and desired performance and identifies the parameters of the fuzzy inference system through a hybrid learning rule, which combines the back-propagation gradient-descent and a least-squares method. From a structural point of view, ANFIS can be viewed as a 5-layer feed-forward neural network. The first layer generates the membership grades of the input linguistic values. The second layer calculates the membership function of the connective operator (AND) of the antecedents part of a rule, i.e. the firing strength of each rule. In the third layer the ratio of each rule's firing strength to the sum of firing strength of all the rules, is calculated. In layer 4, the parameters of the consequent part of a rule are determined and the overall output is aggregated at the node of layer 5. The network of the SD-module for 2 inputs (material's porosity and weight) and one output (suction value) is shown in Figure 8.

Since ANFIS accepts only the so-called Takagi–Sugeno (T–S) type of fuzzy rules [15], expression (7) is converted as follows:

$$\begin{aligned} R^{(i)}\colon\ &\text{IF } \Pi \text{ is } L\Pi^{(i)} \text{ AND } W \text{ is } LW^{(i)} \text{ AND } U \text{ is } LU^{(i)} \text{ AND } D \text{ is } LD^{(i)} \\ &\text{THEN } S = \operatorname{def}(LS^{(i)}) \end{aligned} \tag{9}$$

where $\operatorname{def}(LS^{(i)})$ is the number obtained by applying the center-of-area defuzzification formula on $LS^{(i)}$. From now on we will refer to T–S fuzzy system or rule representation or controller, as just Sugeno system, representation, etc. Regardless of rule representation, the value of desired suction is computed as follows.

Every time a new material or a material of known porosity but different in quantity needs to be manipulated, the SD-module has to output the suction force need for this operation. The crisp values of Π, W, U and D are fuzzified and converted to membership functions denoted by $\mu^*_{L\Pi}$, μ^*_{LW}, μ^*_{LU} and μ^*_{LD}, respectively. These functions are inputs to the knowledge-based inference block and can be defined on $T = \Pi \times W \times U \times D$, where Π, W, U, and D represent the physical domain over which the variables are defined. The combined membership function of the antecedent part is $\mu^*_{\mathrm{AND}}(\Pi, W, U, D)$.

The membership function $\mu_{\mathrm{S}}(s)$ of suction level is then computed as follows

$$\mu_{\mathrm{S}}(s) = \max\, \min\bigl[\mu^*_{\mathrm{AND}}(\Pi, W, U, D),\ \mu_{\mathrm{R}}(\Pi, W, U, D, S)\bigr] \tag{10}$$

where $\mu_{\mathrm{R}}(\Pi, W, U, D, S)$ is defined over $T \times S$ and represents the union of all individual rule meanings, i.e.,

$$\mu_{\mathrm{R}}(\Pi, W, U, D, S) = \bigcup_{i=1}^{n} \mu^{(i)}_{\mathrm{R}}(\Pi, W, U, D, S) \tag{11}$$

and

$$\mu^*_{\mathrm{AND}}(\Pi, W, U, D) = \min\bigl[\mu^*_{L\Pi}(\pi),\ \mu^*_{LW}(w), \mu^*_{LU}(u), \mu^*_{LD}(d)\bigr]. \tag{12}$$

The crisp value of suction S_{d} to be generated is computed at the defuzzification block and it serves as the reference value for the *suction generation module* described in the next section.

3.2. SUCTION GENERATION (SG) MODULE

The objective of the suction generation (SG) module is to achieve and maintain the desired amount of suction S_{d} computed by the SD-module. In order to effectively maintain the amount of suction at the desired level, it is important to accurately derive the dynamics of fluid flow within the conduits of the system and the gripper. However, as shown in Section 2, the mathematical description is approximate and exhibits non-linear characteristics, making the use of conventional controllers difficult in practice.

There are two ways to regulate suction developed within the gripper system. One way is to adjust the continuous-position valve connecting the gripper to the suction generator (from now on, the valve control method); an alternative approach is to directly adjust the rotational speed of the impeller of the motor (i.e., the motor control method). Both methods have been tested and evaluated. The valve control fuzzy controller has been implemented first due to its apparent simplicity. Results of the valve control method, presented here, have been compared with the results obtained using the motor control method, presented in detail in [13].

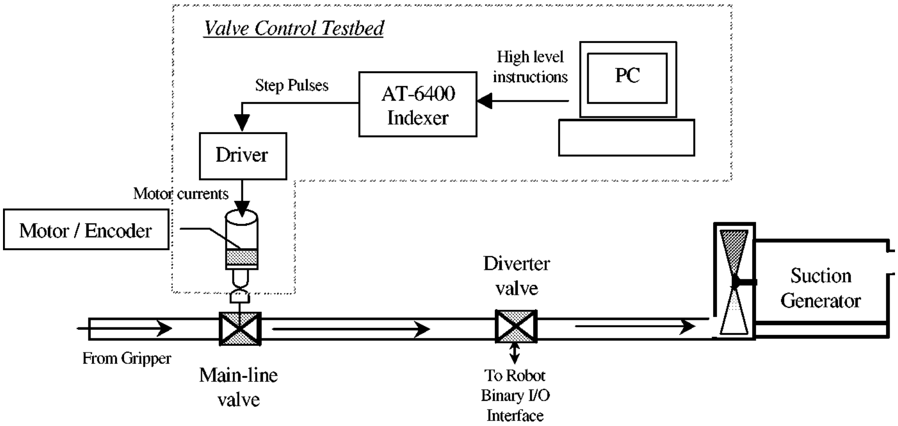

Figure 9. The physical components of the suction system.

The overall suction system is shown in Figure 9. A three-way diverter valve, connected to the robot controller, is used to activate or deactivate airflow through the pipes. By adjusting the main valve, one can regulate the amount of suction applied to the material. The testbed for the valve controller it is schematically presented in Figure 9. It consists of a Compumotor AT-6400 microprocessor based four-axes indexer. The indexer is integrated with an IBM PC-AT machine using an interface card. The Matlab's *Fuzzy Logic Toolbox* [14] running on the PC is used to generate high level instructions to control the speed and the amount by which the valve needs to be opened or closed. The indexer, which has a 2 millisecond update frequency and capabilities for encoder feedback and accurate motor position capture, sends the "move" signals to the driver, in order to control the motion of the motor. The driver receives step input signals from the indexer and converts them to motor currents to drive the motor. The stepper motor converts the digital input signals into fixed mechanical increments. The encoder serves as a position verification device that indicates the extent and the direction of motion.

Immediately after the SD-module calculates the desired suction S_d, the SG-module takes over and generates/regulates the airflow. The generic fuzzy rule for the suction control is of the following form:

$$\text{IF } e(k) \text{ is } T_e \text{ AND } \Delta e(k) \text{ is } T\Delta_e \text{ THEN } u(k) \text{ is } T_u \tag{13}$$

where

- $e(k) = S_\mathrm{d} - S(k)$, is the *suction error* and S_d, $S(k)$, are the desired and the current suction level, respectively; k is the sampling time,
- $\Delta e(k) = e(k) - e(k-1)$, is the *change-of-error,*
- $u(k)$ is the *control action*, i.e. valve adjustments
- T_e, $T_{\Delta e}$ and T_u are the linguistic term sets of $e(k)$, $\Delta e(k)$ and $u(k)$, respectively.

The simple rules used for the control of the valve are presented in Figure 10. $T_e = T\Delta_e = \{$Negative (N), Zero (Ze), Positive $(P)\}$ and $T_u = \{$Open_Fast (O_F), Open_Slow (O_S), No_Change (N_C), Close_Fast (C_F), Close_Slow (C_S)$\}$.

Δe / e	*N*	*Ze*	*P*
N	C_F	C_F	C_F
Ze	O_S	N_C	C_S
P	O_F	O_F	O_F

Figure 10. The fuzzy rules of the valve controller.

The motor controller consists of rules identical to (13). The only difference with the valve controller is that the control variable is the *voltage change*. It has been found that the suction generated by the blower varies at the square of the speed of the impeller. By applying varying voltages to control the motor speed, it is possible to change the amount of suction generated [13].

4. Experimental Results and Simulation

A series of experiments have been performed to validate the performance of the overall suction control system. Matlab's Fuzzy Logic Toolbox within SIMULINK environment has been used for modeling and simulation and testing of both SD and SG modules. Experimental data was collected to determine the amount of suction needed when handling materials of different porosity and weight. This information was needed to train the membership functions of the SD-module, leading to a neuro-fuzzy approach for the SD-module. A pure fuzzy approach was found to be adequate for the SG-module. This is primarily due to the fact that the inference rules and membership functions of the SD-module are complex, non-intuitive and possibly erroneous, due to complicated nature of the inputs and their interdependencies. On the other hand, knowledge relevant to the SG-module is simpler and more accurately encoded within the linguistic rules of the system.

4.1. SD-MODULE: LEARNING FROM DATA

By setting the robot speed to be always the maximum and the distance of travel as constant (which is the case for the testbed of Figure 2) we gathered porosity and weight data for 21 types of fabrics. These data were derived in order to train the SD-module. The data consist of porosity and weight (inputs) readings for each material and the suction value (output) needed for reliable manipulation (pick-up, transportation, place-down) of the fabric. Data extraction and knowledge acquisition procedure was shown in Figure 7. By representing the core of the acquired knowledge via fuzzy rules, we take the following Mamdani-type rules [14]:

M1: *If* Π *is low and* W *is low then* S *is low*

Table I. Experimentally derived data for the training of the SD-module

No	Porosity	Weight (gr)	Suction (in of HG)	No	Porosity	Weight (gr)	Suction (in of HG)
1	0.157	17.5	1	**12**	0.125	8	0.57
2	0.156	11	0.75	**13**	0.625	38	2.6
3	0.313	9.5	0.6	**14**	0.032	35	1.2
4	0.282	10	0.65	**15**	0.14	22	1.6
5	0.063	37	0.9	**16**	0.125	19	1.3
6	0.11	8	0.45	**17**	0.157	20	1.3
7	0.625	9	2.3	**18**	0.079	18	1.05
8	0.079	8.8	0.4	**19**	0.14	24	2.2
9	0.219	12	1.2	**20**	0.11	22	2.7
10	0.188	11	0.9	**21**	0.188	28	2.2
11	0.391	14	1				

M2: *If* Π *is high or* W *is high then* S *is high*

M3: *If* Π *is low and* W *is high then* S *is about high*

M4: *If* Π *is average then* S *is about high*

M5: *If* Π *is low and* W *is medium then* S *is average.*

Although, a Mamdani-type fuzzy system reflects the heuristic knowledge in a better manner, it is not widely used in neuro-fuzzy models (some recent exceptions include NEFCON and NEFPROX [16]). In order to use some of the knowledge contained in the above rules within ANFIS, we have to convert the Mamdani-type rules into Sugeno-type rules [15]. The rules of the zero-order Sugeno system are:

S1: *If* Π *is low and* W *is low then* $S = 0.3321$

S2: *If* Π *is high or* W *is high then* $S = 2.768$

S3: *If* Π *is low and* W *is high then* $S = 2.275$

S4: *If* Π *is average then* $S = 2.275$

S5: *If* Π *is low and* W *is medium then* $S = 1.55$

The returned Sugeno rules have constant output membership functions determined by applying the center-of-area defuzzification on the consequent part of each of the original Mamdani rules [9]. While the antecedents remain unaltered in the Sugeno system, the consequent is a crisp number. The Mamdani to Sugeno transformation should be viewed as a trade-off between the readability and intuitiveness of the former to the precision of the latter.

Data of Table I is used within ANFIS for two purposes: (i) to train the existing (Mamdani converted to) Sugeno system, and, (ii) to generate a new Sugeno system

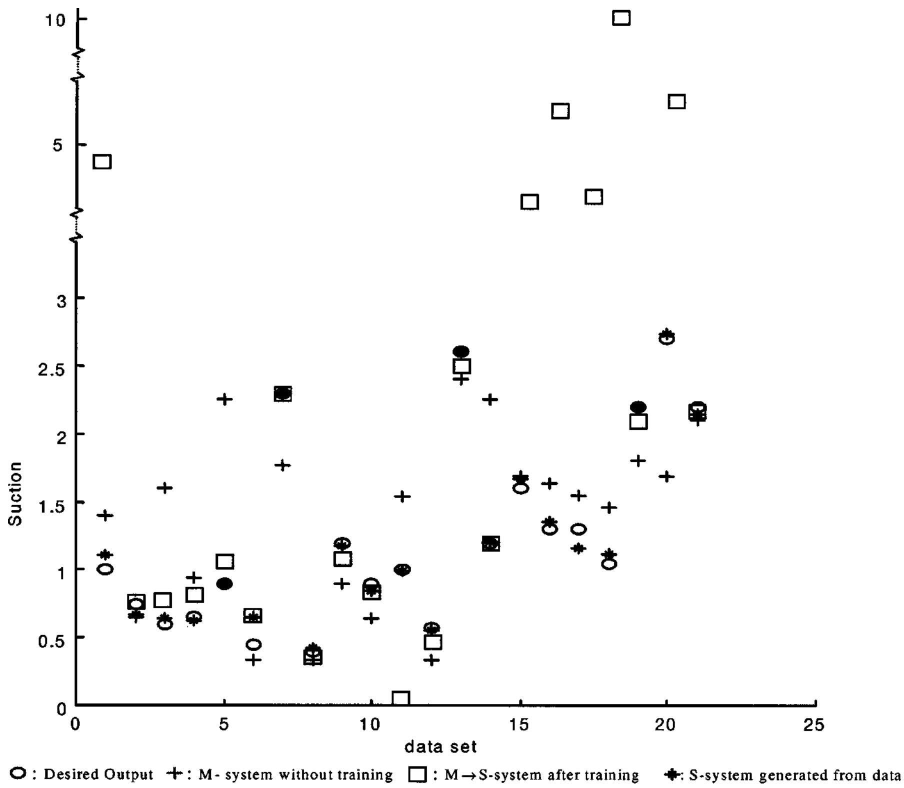

Figure 11. Fuzzy inference systems performance in suction determination.

Table II. Error Comparisons of the three inference systems

	M-system (+)	M→S-system (□)	S-system (∗)
L_2	2.5555	11.2081	0.3889
L_∞	1.35	8.8	0.27

in which the parameters are solely based on the information described by this data. The *Fuzzy C-means* algorithm is used in the latter case for data clustering. Cluster centers are selected randomly in the beginning and a membership grade is assigned to each data point. Each iteration of the algorithm updates the cluster center until the weighted sum of distances from all data points is minimized.

The performance of the inference systems under examination, namely, Mamdani (M), Mamdani-to-Sugeno (M→S) and Sugeno (S), is shown in Figure 11. The Mamdani system is based on acquired knowledge and contains 9 linguistic rules. The training of the M→S-system is based on both heuristic knowledge and data. Prior to training it contained the 5 zero-order (constant output) Sugeno rules presented earlier in this section. After training, the structure of the consequent part

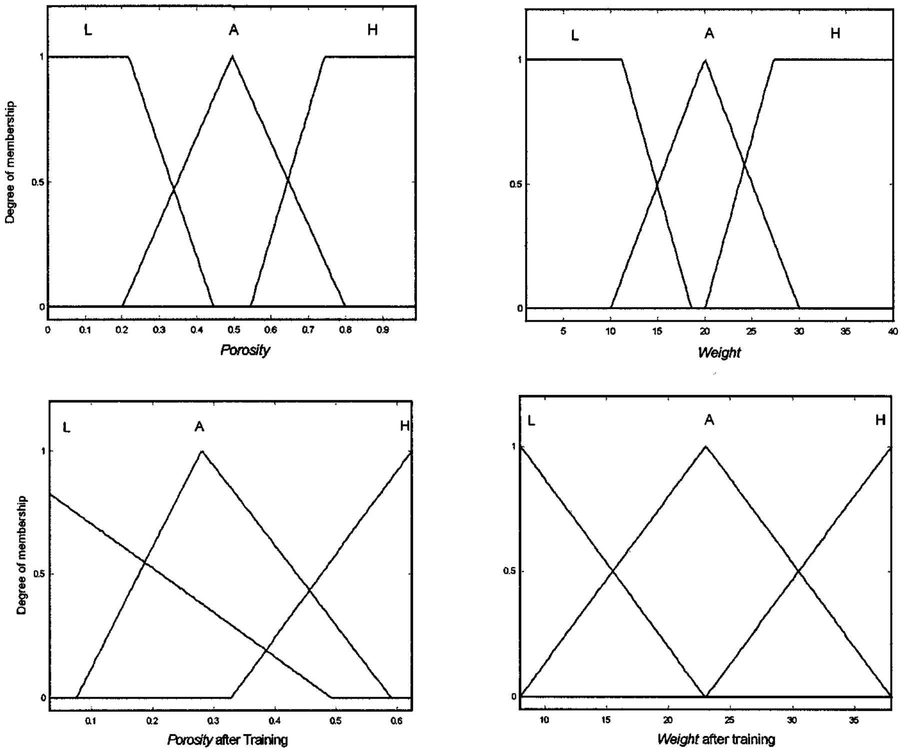

Figure 12. The membership functions of input variables *Porosity* and *Weight* before and after training. L: low, A: average, H: high.

of rules changed to first-order (output is linear combination of inputs) Sugeno. For example, two such rules are presented:

S1: *If* Π *is low and* W *is low then* $S = 39.31\Pi - 0.5022W + 6.052$,
S5: *If* Π *is low and* W *is medium then* $S = -53.07\Pi - 1.181W + 38.68$.

The average error of the M$\rightarrow$S-system after 120 periods of training is 1.2616, which is big considering that the maximum suction in the training data is 2.7 inches of Hg. Indeed, this system failed to give values close to the desired output at the points 1, 11, 15, 16, 17, 18 and 20. This may be attributed to the inaccuracies contained within the theoretical knowledge encoded within the inference rules, and membership functions. The S-system is generated directly from the data set presented in Table I. The training period was 120 time epochs and the average testing error over the entire data set has been found to be 0.048261. This inference system performs better than the others in almost all test cases. It contains nine first-order Sugeno-type rules. In Figure 12 the membership functions of Π and W, before training (i.e., the M-system) and after training (i.e., the S-system) are shown. It can be clearly seen that the membership functions after training have been tailored to the measured data. It has been found that the triangular shape of membership results in the best output performance of the S-system, although other membership shapes such as gaussian, result in slightly smaller data fitting error.

Table II presents a performance comparison of the three inference systems based on two well known error norms, the L_2 and L_∞. A reliable general picture of the overall convergence of the systems is given by $L_2 = [(d_{ij} - D_{ij})^2]^{1/2}$, where d_{ij} stands for the actual output value of the system at some point ij, while D_{ij} is the desired value. The errant behavior of isolated points far away from the desired values is better identified by $L_\infty = \max|d_{ij} - D_{ij}|$.

4.2. SG MODULE: VALVE CONTROL

As justified earlier, the valve controller has been implemented first, due to its apparent simplicity. The testbed for the valve controller has previously been shown in Figure 9. The performance of the valve controller is illustrated in Figure 13.

It may be seen that the controller reaches the set point with no substantial delays, and is reactive to the changes in the desired set point (shown as dotted line). The changes in the set point are indicative of the changes in the desired suction due to varying material porosity, number of panels, robot speeds. Prior to it's implementation, the behavior of fuzzy valve controller was simulated against traditional controllers. The fuzzy controller appeared to be faster than conventional PD and PID controllers in achieving the amount of suction, dictated by the SD-module, as illustrated in Figure 14. It should be noted that the gains of the PD/PID are experimentally tuned by trial and error, since no analytical methods are available to determine the parameters of PID controllers. The numerical integration method used for the simulation runs is the fifth-order Runge–Kutta method. The initial step size is 0.0001 and the simulation period is 10^4 time epochs. The fuzzy controller is found to attain the desired suction level the fastest and is observed to be most stable during the course of several simulation runs. Further simulations with more complicated set-points show that the fuzzy controller attains the desired level without additional tuning.

The motor control method to regulate the suction has been simulated. In Figure 15, a comparison of the two approaches is presented. It is found that the simulated motor control method is faster, more accurate and stable than the implemented valve control method in reaching and maintaining suction at the desired set point. The motor controller seems to accomplish the set point with no delay, higher stability, albeit with a minor overshoot. On the other hand, the valve controller seems to get the job done, even though it demonstrates minor oscillations mainly at low suction levels. This is because of the dynamics of the valve, and the inherent overshoot in the controlling the mechanical position of the valve. It is to be noted that valve control method is an indirect way of regulating suction: it is a by-product of increasing or decreasing the effective diameter of the conduit from the suction generator to the gripper. On the other hand, the motor controller directly regulates the speed of the motor that is responsible for suction generation, making it more

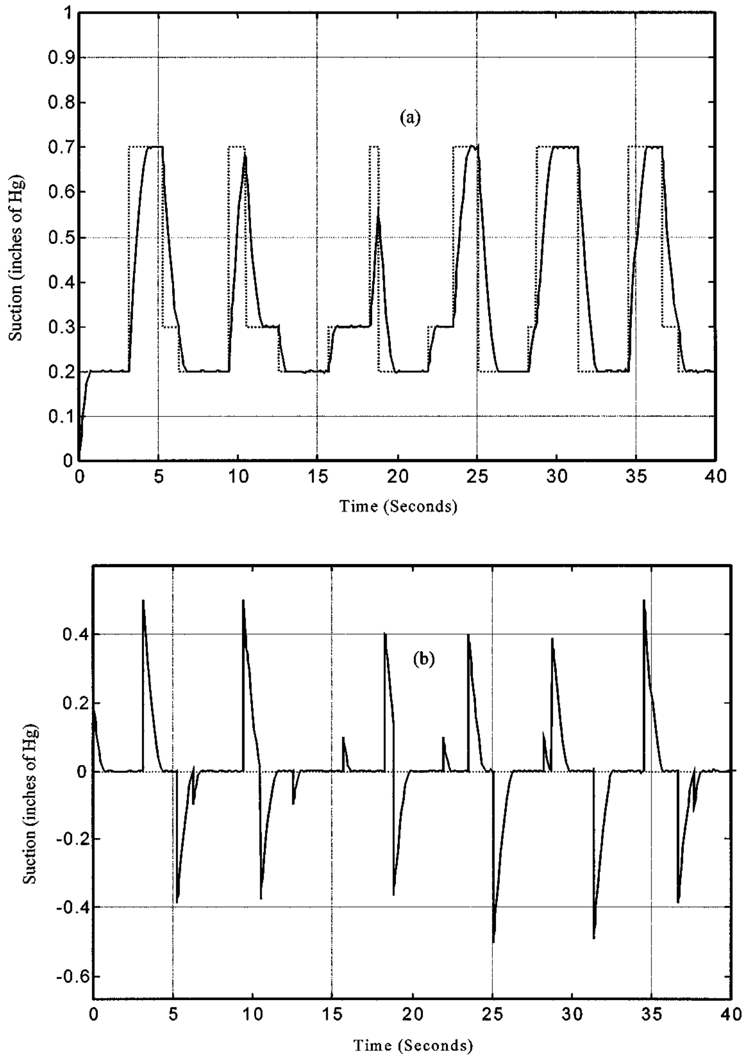

Figure 13. (a) Performance of the valve controller, (b) The corresponding error.

reactive, faster and more stable. Implementation of the motor control method is thus one of our immediate goals.

5. Conclusions

The design and development of a knowledge-based control system (i) to derive a desired amount of suction, and, (ii) to regulate, control and maintain the suction needed to perform reliable manipulation of limp materials has been discussed. The developed control system consists of a neuro-fuzzy suction determination (SD) module, which determines the amount of suction based on a set of material spe-

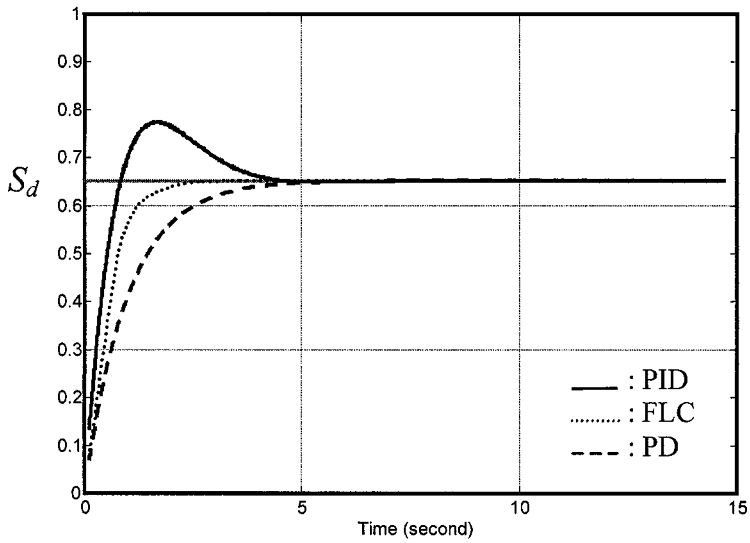

Figure 14. Simulated performance comparisons of the proportional-derivative (PD), proportional-integral-derivative (PID) and fuzzy logic (FLC) controller for the suction control problem.

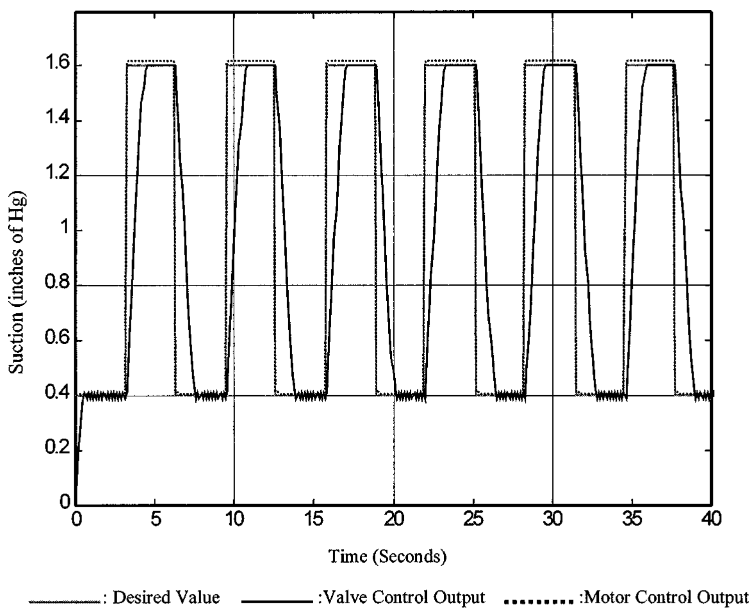

Figure 15. Performance of the valve controller versus the simulated motor controller.

cific and plant specific parameters. Experimentally obtained values of suction for handling a variety of fabric materials ranging in porosity and weight (21 samples: from 100% cotton to 100% silk, rayon, polyester, denim, matted materials, hand-woven and machine-woven fabrics) have been used to train the neural network. Comparison of the trained and untrained system has been presented.

Two possible approaches for controlling and regulating the amount of suction determined by the SD-module have been presented. The suction generation (SG) module regulates the air flow, by either adjusting a valve or controlling the motor voltages, to maintain the desired level of suction throughout the "pick and place" process. Implementation of the valve controller and the testbed has been discussed. Simulation results of the motor control approach are promising, and its implementation is identified as one of the immediate goals of the project. Further directions for future research include:

- enhancement of the sensor-based position controller with a fuzzy knowledge-based controller to enhance the performance of the robotic gripper system, and,
- design and development of a knowledge-based controller to control and coordinate the operation of a multi-degree-of-freedom reconfigurable robotic gripper system.

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