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Model Reference Fuzzy Learning Force Control for Robotized Sewing

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Abstract: A fuzzy model reference adaptive controller for regulating the fabric's tensional forces applied by a robot during the sewing task is developed. The adaptive fuzzy logic controller closes the loop outside the internal scara robot controller. The robot guides a piece of fabric in a conventional industrial sewing machine while its controller maintains a desired constant tensional force applied to the fabric during the sewing process. In each loop, the proposed controller calculates the appropriate robot end-effector displacement. A force sensor mounted on the wrist of the robot manipulator measures the actual force applied to the fabric, and the formulated force error is used in order to adapt the controllers' parameters. The performance of the controller is investigated experimentally and the results show the effectiveness of the FMRL approach and its wide range of applications.

Keywords: Force control, Fuzzy adaptive control, Fabrics, Robot handling

1. INTRODUCTION

The robotic handling of non-rigid objects, such as fabrics, is a very complicated problem since it is very difficult to model and predict the behavior of the fabric. The non-linearity, the large deformations and the very low bending resistance of the fabrics increase the complexity and difficulty of the robotic handling. In this paper, the robotized sewing is examined, where the fabric must be held taut and unwrinkled. Actually, a constant tensional force, which must be applied to the fabric throughout the feeding to the sewing machine, affects the seam's quality to a great extent [1]. Gershon [2] clearly justified the need for force feedback control, in order to obtain a fabric's constant tensional force in the sewing task.

While there is a big variety of force control methods on handling of rigid objects, the robotic research literature is not so rich concerning the handling of limp materials.

In the FIGARO system [3], a PI controller is used, where the gains were chosen by trial and error. These gains should be modified when a new type of fabric should be handled. Gershon [2] strongly suggested that the conventional control methods are inadequate to handle the fabric tensional force. An adaptive control approach was adopted by R. Patton et.al [4] for controlling the tensional forces applied to a fabric, where the fabric's stiffness was the unknown variable. They mentioned that non-adaptive control schemes are unsuitable for fabric handling due to high variations of fabrics' stiffness. Koustoumpardis et al [5] introduced an intelligent force control scheme based on a feedforward neural network (FNN) controller, using a force sensor mounted on the robots wrist.

In some control applications, where it is very difficult to obtain the plant model or the required computation time is too high, fuzzy adaptive control was introduced. The direct fuzzy adaptive control is the most common approach, particularly the fuzzy model reference learning control (FMRLC). The main advantage of this approach is the simplicity together with the high performance [9], a fact that makes it appealing for implementation in a wide range of industrial processes.

H. F. Ho et.al. [6], used direct fuzzy adaptive control for a nonlinear helicopter system. The control objective was to maintain the elevation and azimuth angles to maintain the desired trajectories. Rehman [10] used a fuzzy model reference learning controller in order to regulate the speed of an induction motor. Tarokh [7], proposed an adaptive fuzzy control scheme for explicit force control of a robot manipulator in contact with an environment whose parameters are unknown and vary considerably but slowly. The adaptation mechanism modifies the fuzzy force controller according to the difference between the actual and the desired force responses.

The robotics group of the department of the Mechanical Engineering and Aeronautics has been working the last years on the robotic handling of fabrics. The robotic sewing is one of the tasks that consist the group's research. In this framework, a feedforward neural network (FNN) controller [5], able to guide a wide range of fabric types, was implemented. The target of the controller was to apply a desired constant tensional force to the fabric during the whole sewing process. In order to investigate further this area, the implementation of a FMRL controller was decided. Also, the fact that no work using fuzzy adaptive control has been found in the robotics handling of fabrics area consisted an additional motive to use this method.

In the present paper, the FMRL force control scheme is designed, tested and evaluated. The goal is the

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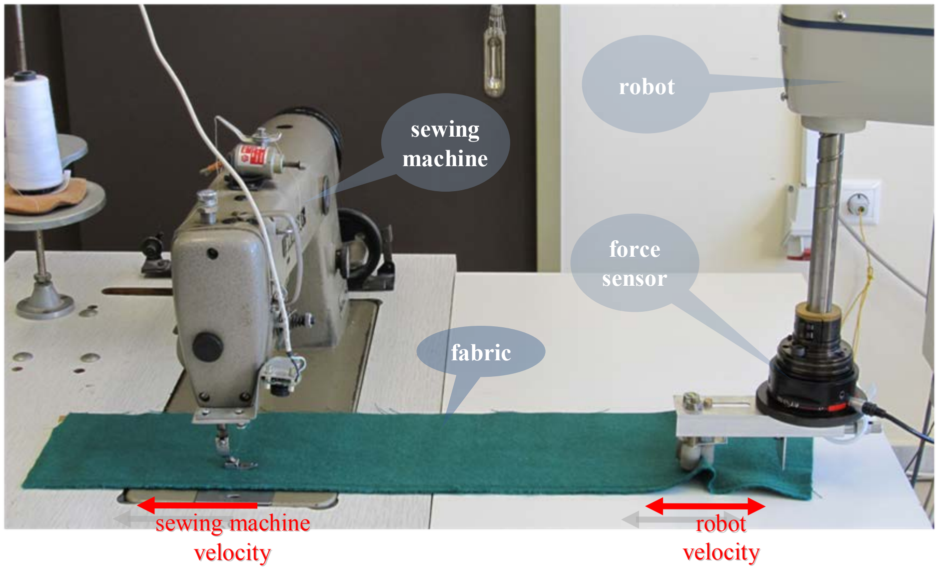

Fig. 1 The robotic sewing system.

successful guidance of fabrics towards sewing by a robot. The robotic handling of fabrics, particularly sewing, is an area with model uncertainty, non-linearity, with very noisy force signals and fast varying characteristics. Since no similar work has been found in this area, this paper shows the wide application range of the FMRL approach.

2. PROBLEM DEFINITION/MOTIVATION

The robotic sewing system is shown in Fig.1 . A piece of fabric is gripped by a robot manipulator holding the right edge while the opposite left edge of the fabric is moving with unknown velocity by the feed dog mechanism of the sewing machine. During the sewing process the fabric should be kept taut so as to prevent the buckling and ensure qualitative stitches. The desired tensional forces for each fabric are depended on the fabric type and properties [1].

The aim of the presented approach is to develop a flexible controller that could be able to guide a wide range of fabric types without knowing the properties or the model of each fabric. The target of the proposed controller is to apply a desired constant tensional force to the fabric in the begging and during the sewing process, independently of the sewing machine velocity. The force sensor mounted on the wrist of the robot manipulator is used to measure the force applied to the fabric which is the only feedback signal in the outer control loop relative to the internal controller of the robot. The tensile stiffness coefficient of the fabric is non-linear and changes by decreasing the nominal length as the sewing proceeds.

3. FUZZY MODEL REFERENCE FORCE CONTROLLER

In this paper, a FMRL control scheme is adopted. The adaptation mechanism observes the signals from the control system and adapts the parameters of the fuzzy controller to maintain the performance even if there are changes in the plant. The desired performance is characterized with a reference model and the controller seeks to make the closed-loop system behave as the reference model would. The FMRLC, besides of tuning, remembers to some extend the values tuned in the past, in contrast to the conventional approaches which simply continue to tune the controller parameters.

The proposed FMRL control scheme is shown in Fig. 2. The fabric and the sewing machine’s velocity are unknown. The goal of this system is considered to be achieved when its controller maintains a desired constant force applied to the fabric.

The presented FMRLC includes: the fuzzy controller, the robot-fabric system to be controlled, the learning mechanism, the reference model and a filter [8].

3.1 The fuzzy controller

The fuzzy controller has two inputs: the force error $e(kT) = f_d - f(kT)$ between the desired force f_d and the actual force $f(kT)$ applied on the fabric, and the change in error $c(kT) = \dfrac{e(kT) - e(kT - T)}{T}$, where T is the sampling period. The controller has one output, the

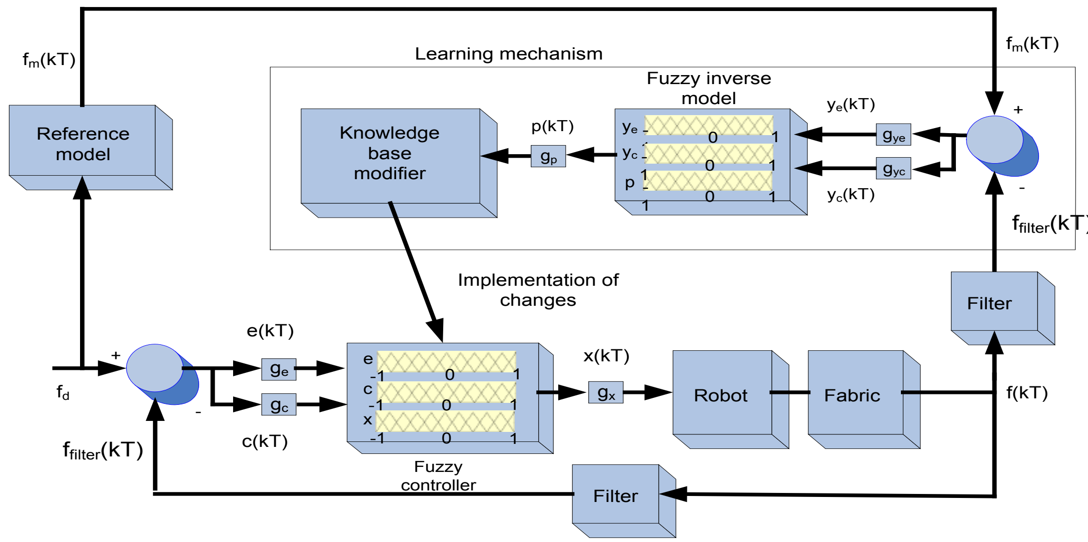

Fig. 2 The FMRL control scheme

displacement $x(kT)$ of the robot's end-effector. All the membership functions, 17 for each input and output, are triangular and uniformly distributed. The triangular function is chosen since its universe of discourse is limited and specific, hence only certain rules are activated at each loop, and also because only three parameters are needed to define it. A choice of another function with more parameters, such as trapezoidal, or without limited universe of discourse, such as the Gaussian function, would increase the computational cost which is critical for online applications. The input universes of discourse are normalized and tuned by the gains g_e and g_c respectively, where $g_e = 1/5$ and $g_c = 1/20$. The gains are determined through experimentation. The original centers of the membership functions in the output universe of discourse, which consist the subject for adaptation and learning, are picked based on a reasonable guess that concerns the desired operation of the controller. So, in the particular case, this operation is depicted by an initial rule base which expresses the following:

1. The bigger (positive/negative) the error is, the bigger (positive/ negative) the robot's displacement should be.
2. The bigger (positive/ negative) the change in error is, the bigger (positive/negative) the robot's displacement should be.

So, the initial rule base is a 17×17 uniformly distributed rule base, similar to the one presented for the fuzzy inverse model (Table 1). The rule base's table is not presented in the paper due to its size.

The initial rule base is normalized and tuned by the gain $g_x = 5$. The premise and the implication are represented by minimum and the type of defuzzification is Center of Gravity (COG). The crisp output is given by the equation:

$$x_{crisp} = \frac{\sum_{i=1}^{R} b_i \int x\mu_i(x)dx}{\sum_{i=1}^{R} \int x\mu_i(x)dx} \qquad (1)$$

where R is the number of rules, b_i is the center of the output membership function of the i^{th} rule and $\mu_i(x)$ is the membership function of the i^{th} rule after the implementation of the premise's and the implication's operators.

3.2 The reference model

According to the mechanical model that describes the tensional part of the behavior of a fabric [2], the transfer function of the system results in a second order function. Nevertheless, the performance requirements for the plant to be covered are sufficiently completed by a first order reference model. So, after experimentation, the transfer function of the chosen reference model in the continuous time is:

$$G(s) = \frac{f_m(s)}{f_d} = \frac{k_r}{s + a_r} \qquad (2)$$

where $k_r = a_r = 1$, f_d is the desired force and f_m the output of the reference model.

x		e								
		-1	-0.75	-0.5	-0.25	0	0.25	0.5	0.75	1
c	-1	-1	-1	-1	-1	-1	-0.75	-0.5	-0.25	0
	-0.75	-1	-1	-1	-1	-0.75	-0.5	-0.25	0	0.25
	-0.5	-1	-1	-1	-0.75	-0.5	-0.25	0	0.25	0.5
	-0.25	-1	-1	-0.75	-0.5	-0.25	0	0.25	0.5	0.75
	0	-1	-0.75	-0.5	-0.25	0	0.25	0.5	0.75	1
	0.25	-0.75	-0.5	-0.25	0	0.25	0.5	0.75	1	1
	0.5	-0.5	-0.25	0	0.25	0.5	0.75	1	1	1
	0.70	-0.25	0	0.25	0.5	0.75	1	1	1	1
	1	0	0.25	0.5	0.75	1	1	1	1	1

Table 1 The inverse fuzzy model's rule base

Using a bilinear transformation to find the discrete equivalent, s is replaced with $\frac{2}{T}\frac{z-1}{z+1}$. After some mathematical operations (2) results in:

$$f_m(kT) = \frac{(2-a_rT)f_m(kT-T)+2k_rf_dT}{a_rT+2} \qquad (3)$$

where T is the sampling period.

3.3 The learning mechanism

In this section, the learning mechanism of the FMRL controller is presented. The signals from the control system are observed and, subsequently, the parameters of the fuzzy controller are changed so that the controller achieves the desirable performance. The learning mechanism consists of two parts: the fuzzy inverse model and the knowledge base modifier.

3.3.1 The fuzzy inverse model

In the inverse fuzzy controller, the first input is the performance $y_e(kT) = f_m(kT) - f(kT)$, which is the deviation of the actual force f from the output f_m of the reference model. The second input is the change of the performance $y_c(kT) = \frac{y_e(kT)-y_e(kT-T)}{T}$. The output $p(kT)$ represents the change of the output centers of the fuzzy controller which is used for adaptation and learning. The input and output membership functions are triangular, their universes of discourse are normalized and tuned by the gains g_{ye}, g_{yc} and g_p respectively, where $g_{ye} = 10/49$, $g_{yc} = 1/19$ and $g_p = 1.5$. The gains are determined through experimentation. The minimum operator is used for the premise and implication (Mandani) and the COG method for defuzzification. The rules of the inverse model are based on the same principals as the rule base of the fuzzy model and its rule base is presented in Table 1.

3.3.2 The knowledge base modifier

Given the information about the changes p that will force y_e to zero, the knowledge base modifier changes the rule base of the fuzzy controller so that the previously applied control action will be modified. In other words, for all the rules in the active set the modifier applies the following change:

$$b_i = b_i + \mu^i_{impl}(e,c)p \qquad (4)$$

where b_i is the center of the i^{th} output membership function of the fuzzy controller and $\mu^i_{impl}(e,c)$ is the maximum value of the implication membership function of the i^{th} rule. In this way, rules that are more active and, thus, have bigger maximum value of the implication's membership function, will be affected more than others. In order to retain the values of the velocity in the area $[-g_x, g_x]$ during the adaptation, the modifier applies the following rules:

If $b_i < -g_x$ then $b_i = -g_x$.
If $b_i > g_x$ then $b_i = g_x$.

3.4 The filter

A first-order low-pass filter (Eq. 5) is used in order to avoid the influence of the force sensor's noise to the inputs of the fuzzy and the inverse fuzzy model:

$$f_{filter}(kT) = \frac{T}{2\tau+T}\left(f_{filter}(kT-T)\frac{2\tau}{T-1} + f(kT) + f(kT-T) \right) \qquad (5)$$

where f_{filter} is the filtered force, which was applied on the fabric and τ is the filter time constant.

4. EXPERIMENTAL RESULTS

The FMRL force controller closes the loop outside the internal of the controller (SmartController CX) of the Adept Cobra s800 robot. The force is measured using the F/T system (Gamma 65/5) from ATI Industrial Automation, which is mounted on the wrist of the robot. It should be mentioned that the resolution of the sensor is 0.05 Nt.

In the conducted experiments, the cooperation of the robot with a conventional sewing machine is examined. The characteristics of the fabric related to its size are changed as the distance between the robot end-effector and the sewing point is decreased throughout the sewing process. The controller should be robust enough to reject, as much is possible, the disturbances caused by the stepwise movements of the sewing machine's feed dog mechanism.

Before the actual sewing task, the robot should apply an initial constant tensional force to the fabric. The force of this preliminary state but also the desired force during the whole sewing task is assumed to be 2 Nt.

Lots of experiments were carried out in order to decide whether the fuzzy and the inverse fuzzy controller would be of P, PI or PD type. The PI controller exhibited the best performance at the preliminary state as it managed to keep up very closely with the reference model, without overshooting. However, during the sewing task the PI controllers presented unacceptable oscillations. A similar oscillatory behavior was observed when P controllers were used. Finally, the PD fuzzy controller is chosen since it is the one with the best performance in the actual sewing task and also presented a very good result in the case of the preliminary state.

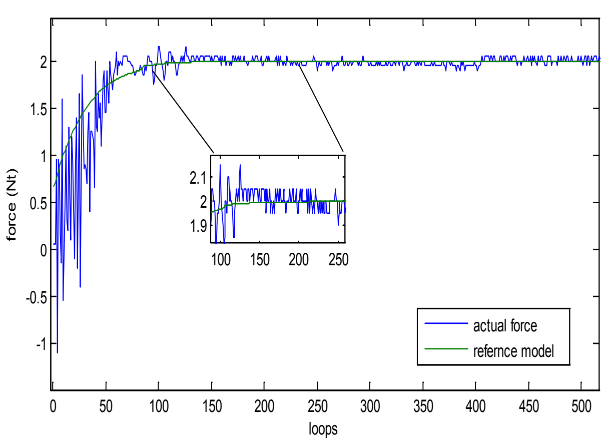

Fig.3 Performance of the FMRL controller when applying a constant force – preliminary state

Fig. 3 depicts the performance of the FMRL controller in the preliminary state where an initial constant force is applied to the fabric. The force, which is applied to the fabric, follows very closely the reference model and after 100 loops, which correspond to less than 3 seconds, it approaches the 2 Nt. Taking into account the resolution of the force sensor (0.05 Nt), the force's deviation from the 2 Nt, which results in 0.05 Nt, is considered reasonable and expected.

After the application of the initial tensional force, the sewing machine is turned on and the sewing task in started. The tensional force applied to the fabric rises and the controller should react in order to maintain the desired force of 2 Nt.

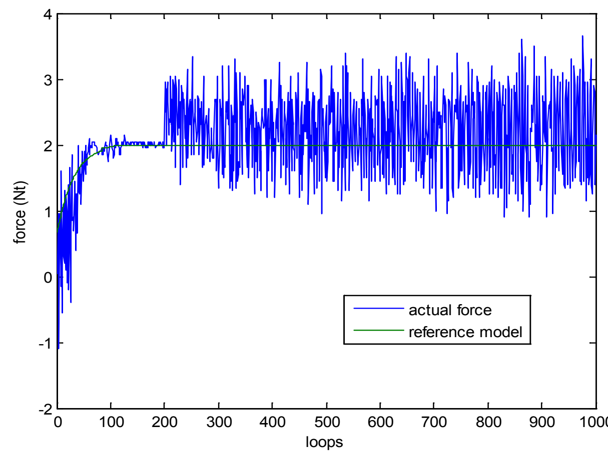

Fig.4 Robotic sewing with a FMRL controller

Fig. 4 shows the robotic sewing with the FMRL controller. At the beginning, a constant force is applied to the fabric, as described in the previous experiment. When the sewing machine is turned on the controller presents a more oscillating response due to stepwise attraction of the fabric by the sewing machine. Although, as the time passes, the controller gets more trained, its performance does not improve. This fact is partly caused because the more the robot's end-effector approaches the sewing machine, the more the oscillations of the machine's motors affect the fabric and thus the force sensor reading. In addition, as the robot comes closer to the sewing needle the extensibility of the fabric decreases, approaching gradually the stiffness of a rigid body. The displacement of the robot end effector is 32 cm.

5. CONCLUSION

In this paper, an effort to control the tensional force applied to the fabric during the robotized sewing process is presented. An FMRL controller is designed, implemented and evaluated. The application of such a controller in an area with model uncertainties and very noisy signals shows the wide range of this approach.

Despite the satisfactory results of the controller, further investigation is needed in order to limit the oscillations of the controller's responses. For future elaboration, a force controller that can determine the position and the velocity of the robot is planned.

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