

An Intelligent Assembly Algorithm for Chamferless Parts Mating In An In-Line Continuous Transfer System

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ABSTRACT

This paper describes an intelligent assembly algorithm for part mating in an in-line continuous transfer system by integrating neural net work and fuzzy set theory. The fuzzy set theory copes with the imprecision and vagueness associated with actual assembly task, while the neural net theory copes with limitation of fixed fuzzy rule by learning. The assembly performance of the intelligent algorithm is evaluated through a series of experiments. Experimental results show that the method can be an effective method for assembly in an in-line continuous transfer system.

1. INTRODUCTION

Various automated assembly systems have been developed to perform various tasks of mating parts, but most of the assembly processes have been accomplished at fixed part location[1-3]. Since such an assembly process is executed under three separate phases -positioning, composing, and transporting- the assembly task requires normally rather long process time. In order to reduce the task time, Park et al.[4] proposed a new concept of robotic assembly system in which the three phases of the assembly task is performed simultaneously. The main difference between the previous system and the proposed works on robotic assembly is that the latter system requires a continuous synchronization of the mating parts because a position error causes a stiffness force due to the geometric interference, while velocity error can develop an impact force between parts to be mated. Such forces may damage the mating parts and even the system itself as well as slow down the process. In order to overcome the problems, some works[4,5] have been proposed, in which the misalignments between mating parts were compensated by tracking algorithm and a passive compliant device.

However, when it comes to mate unchamfered parts, a passive compliant device is of no use in searching phase. To cope with above problem, we present an intelligent algorithm and its performance is evaluated through experimnts.

2. ASSEMBLY SYSTEM DESCRIPTION

In order to achieve the intelligent algorithm which will be described in next section, a following prototype assembly system is constructed. The system is composed of four subsystems, which are a computer system, a 4 degree of freedom SCARA type robot, a DC motor driven linear motion guide, a 2-dimensional position sensitive detector(PSD), and a 2-dimensional x-y table which is controlled by position controller.

The robot subsystem is composed of a 4 degree of freedom SCARA type robot and a robot controller. The USER DI/DO parallel port of the controller is used to communicate with the computer. The computer is used to supervise the assembly system and as a main controller which has the following functions: It communicates with the force sensor via RS-232C serial port with the speed of 19200bps and infers a positioning error between the mating parts from force/moment signals using intelligent algorithm. Also, it generate a control action to achieve velocity synchronization between mating parts. The conveyor system consists of a DC servo motor, power amplifier, ball screw, tachogenerator, and carriage. In order to measure the positional deviation between the mating parts in moving state, an accurate but simple structural sensor using the two dimensional PSD is utilized. The x-y fine motion table is composed of two DC servo motors driven in x and y axes and generates

a planar movement. The main function of this table is to compensate the misalignments received from main computer.

3. INTELLIGENT ALGORITHM

The intelligent algorithm consists of two hierarchical levels as shown in Fig.1. The lower one is a rule-based fuzzy controller. The higher one is the rule learning mechanism which is based upon two neuron-like elements, and learns control rules iteratively until the assembly task can be successfully performed so that no further changes in rule base are necessary.

3.1. Fuzzy Controller

This controller consists of four modules: fuzzy decoder, rule base, fuzzy reasoning, and defuzzification[6,7].

The fuzzy decoder inspects the incoming system state and activates the corresponding rules in parallel. In this system, the fuzzy input/output variables are defined by two force components(f_x and f_y), two moment components(m_x and m_y), and corrective motion components(u_x and u_y), respectively. Using these fuzzy variables, the rule base takes the form:

$$R^k: \text{IF } f_x \text{ is } F_x^k, f_y \text{ is } F_y^k, m_x \text{ is } M_x^k, \text{ and } m_y \text{ is } M_y^k \text{ THEN } u_x \text{ is } U_x^k \text{ and } u_y \text{ is } U_y^k \quad (1)$$

where F_i^k , M_i^k , and U_i^k are the fuzzy subsets corresponding to fuzzy variables.

The fuzzy reasoning consists of four steps: scaling the basic variables, calculation of the membership function, updating the membership function for the output variable, and aggregation of rules. Finally, to determine the crisp control action of the corrective motion, the defuzzification is processed using the center of area method[8].

3.2. Learning Mechanism[9]

Up to now, although four modules of the fuzzy controller are briefly described, they can not present the fuzzy subsets of fuzzy set of control action part in Eqn.(1). The remaining problem is to learn the linguistic fuzzy subsets, U_i^k . Such learning capability is performed by the learning mechanism, which consists of two neuron-like elements: the associative critic neuron(ACN) and the associative learning neuron(ALN). The learning procedure is done as follows: first, if force signals are measured, the fuzzy decoder investigates the current contact state of the mating parts, and next generates the outputs which are output activities of the fuzzy rules corresponding to input signals. The overall signal flow of the intelligent algorithm is shown in Fig.1. More specific description is referred to the previous work[8].

4. EXPERIMENTS

4.1. Experimental Procedure

In order to evaluate the assembly performance of the intelligent algorithm experimental procedure is made as follows: Initially, the robot and the conveyor system are at rest. To initiate the tracking, the host computer sends a starting signal to USER DI/DO port of the robot controller via a I/O port of the Lab-master (TM-40PGH). According to the signal the robot and the conveyor move along the axis of the conveyor with different initial velocities. Then, the PSD sensor installed in the carriage starts detecting the position error between the robot end-effector and the carriage of the conveyor. The PSD output signal is sent to the computer via A/D converter. Using this signal, a feedforward control action is generated by the controller[4] and sent to the DC servo driver of the conveyor via D/A converter. Then, the tracking motion starts. It is noted that although the velocity synchronization between robot end-effector and conveyor carriage is perfectly accomplished some positioning errors still exist because of initial tracking error and some other position errors caused by robot gripping mechanism and part dimensional accuracy. Therefore, we must compensate the positioning error, which is compensated by the previously mentioned intelligent algorithm.

4.2. Experimental Results and Discussions

Fig.2 shows the cause of the 1st assembly trial, while Fig.3 shows that of the 10th trial. In the figures, searching trajectories and the corresponding reaction forces and moments are displayed for the case of robot's velocity of 30 mm/sec. In all cases, the learning parameters shown in Fig.1 are

fixed as follows: $\alpha = 50$, $\beta = 0.8$, $\zeta = 0.9$, $\lambda = 0.7$, and $\kappa = 2500$. It is also noted that the figures display only the signals for searching and inserting stages because approaching stage has no reaction force/moment signals. As it can be seen from these figures, the 1st trial needs the searching step number (38 steps), while the 10th trial needs only 8 steps. This results from the fact that the control system learns the characteristics of the assembly process as trial number increases. In other words, the first trial is started by initially set rules that have no information on assembly task, whereas the 10th trial is executed according to skilfully trained rules which have been learned during previous nine trials[10].

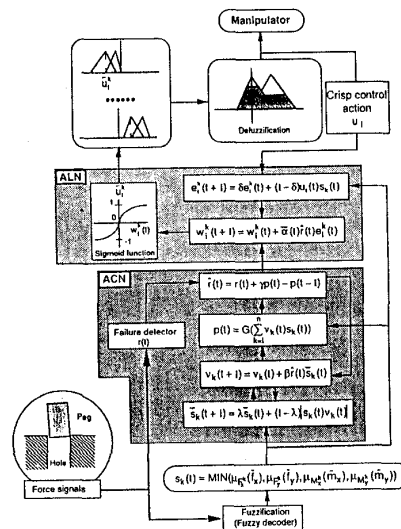
5. CONCLUDING REMARKS

An intelligent assembly algorithm has been presented for robotic assembly in an in-line continuous transfer system. Its assembly performance is evaluated through a series of experimnts. Experimental results show that the intelligent assembly method can be an effective method for mating parts in an in-line continuous transfer system.

6. REFERENCES

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Fig. 1. Signal flow of the intelligent assembly method.



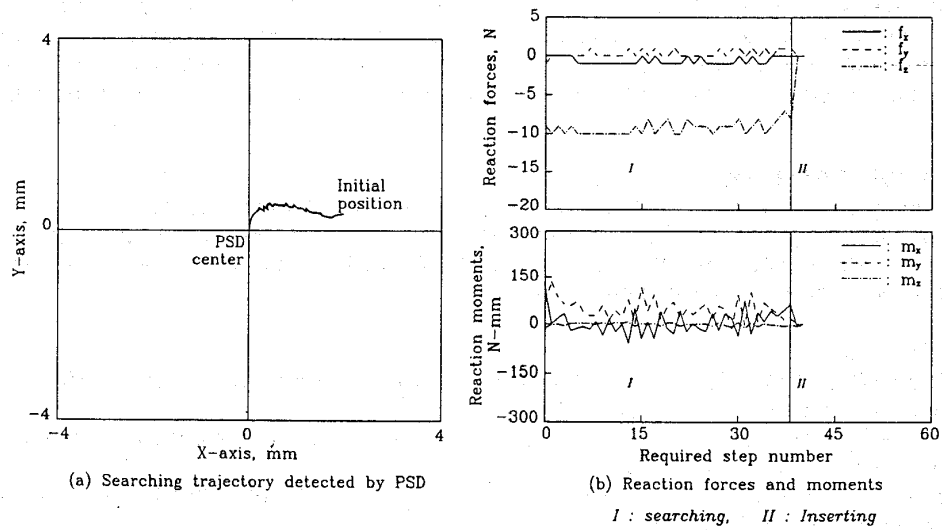


Fig.2. Experimental results for intelligent assembly method with the 1st trial rule base at moving velocity = 30 mm/sec.

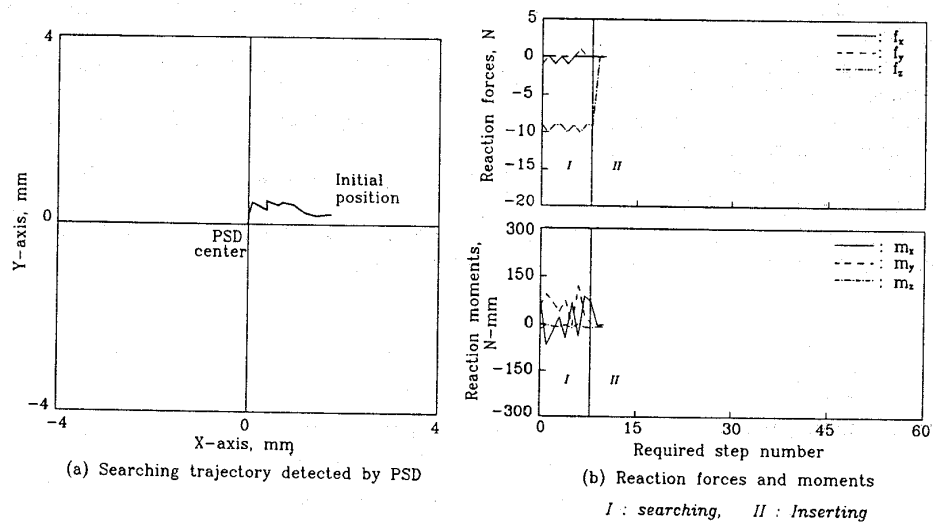


Fig.3. Experimental results for intelligent assembly method with the 10th trial rule base at moving velocity = 30 mm/sec.