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Contact-State Modeling of Robotic Assembly Tasks Using Gaussian Mixture Models

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Abstract

This article addresses the Contact-State (CS) modeling problem for the force-controlled robotic peg-in-hole assembly tasks. The wrench (Cartesian forces and torques) and pose (Cartesian position and orientation) signals, of the manipulated object, are captured for different phases of the robotic assembly task. Those signals are utilized in building a CS model for each phase. Gaussian Mixture Models (GMM) is employed in building the likelihood of each signal and Expectation Maximization (EM) is used in finding the GMM parameters. Experiments are performed on a KUKA Lightweight Robot (LWR) doing camshaft caps assembly of an automotive powertrain. Comparisons are also performed with the available assembly modeling schemes, and the superiority of the EM-GMM scheme is shown with a reduced computational time.

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1. Introduction

Assembly is considered one of the vital topics for both industry and research institutions and automating the assembly for different products drew the attention of many practitioners from both academia and production sectors. Robots are considered the most important tools in automating productions and hence researches in this field are considered hot research topics. One of the most important topic in automating the assembly tasks is the modeling of robotic assembly itself; that is adding the necessary skills to the robot that makes it aware of its surrounding environment using the wrench (Cartesian forces and torques) and pose (Cartesian position and orientation) signals of the manipulated object.

Contact States (CS) modeling of the force-controlled robotic tasks was solved by different approaches. Petri net was successfully employed in modeling and planning robotic assembly tasks and promising results were obtained [1]. In [2], fuzzy classifiers and neural networks were successfully employed in the recognition of different CS's using only the wrench signals. Modeling of peg-in-hole assembly process was successfully performed in the framework of finding analytical solutions of the contact forces for different situations between the manipulated object and the environment [3]. Hidden Markov models was successfully used in developing models for compliant motion robots and hence opening the door to the probabilistic modeling approaches [4,5]. In [6,8], the authors were successful in linking the CS modeling to the geometrical parameters estimation and efficient models were obtained for each CS. Stochastic Gradient Boosting (SGB) classifier was efficiently used in recognising different CS's without the need for knowing the task sequence or task graph [9]. In [11], the authors were successful in using fuzzy clustering technique in building efficient fuzzy models. The fuzzy clusters are tuned by Gravitational Search Algorithm (GSA) and excellent mapping capability was obtained for each model. A common feature to all of the approaches above is that the signals are considered stationary, i.e. their distribution is normal.

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However, for the cases of robotic assembly in which the signals are non-stationary, then performance degradation would be resulted.

In this article, the Expectation Maximization-based Gaussian Mixtures Models (EM-GMM) [7] is used in modeling the force-controlled peg-in-hole assembly tasks. Through employing the EM-GMM, the non-normal distribution of the captured signals is accommodated through assigning multiple Gauss distributions for each signal. Furthermore, finding the parameters for each distribution is done through the EM algorithm that would increase the log-likelihood and improved performance would be obtained.

The rest of the paper is organized as follows; section 2 contains the description of the robotic peg-in-hole assembly process. Section 3 details the EM-GMM modeling process. Experimental validation on the assembly of camshaft caps is presented in section 4 and section 5 summarizes the concluding remarks and recommendation for future works.

2. Robotic Peg-in-Hole Assembly

Consider the robotic peg-in-hole assembly task shown in Fig. 1 that is composed of inserting a certain object (peg) into a certain hole and such a task is considered the backbone in many assembly tasks. In order to model the peg-in-hole task, the overall motion is segmented into different phases according to the location of the manipulated object with respect to the environment. For each segment different signals are collected and models are developed accordingly. Vision-based systems can be used in building the models for a robotic peg-in-hole assembly process. However, vision-based systems would fail for occluded parts and time varying illuminations that urged the researchers to consider developing the CS models using the wrench and pose signals that are measured by suitable sensors. Suppose that the wrench signals of the manipulated object, of the peg-in-hole assembly process shown in Fig. 1, are described as:

$$w=[f_x, f_y, f_z, \tau_x, \tau_y, \tau_z] \tag{1}$$

Where f_x, f_y, and f_z are the Cartesian forces and τ_x, τ_y, and τ_z are the torques around the Cartesian axes both measured for the manipulated object. Likewise to the pose of the manipulated object, it can be written as:

$$p=[x, y, z, \Psi_x, \Psi_y, \Psi_z] \tag{2}$$

with x, y, and z are the Cartesian position and Ψ_x, Ψ_y, and Ψ_z are the orientation around the Cartesian axes of the manipulated object. Hence, each classifier has 12 input signals, say $x_k=[x_{1,k},x_{2,k},\dots,x_{12,k}]^T$. The CS classification problem can be formulated as:

$$y_k=\begin{cases}1 & if \quad x_k \in CS_k \\ 0 & Otherwise\end{cases} \tag{3}$$

y_k is the output of the k^{th} CS classifier. (3) is a nonlinear mapping between x_k and y_k and the goal of almost all modeling and classification researches is to approximate or realize this mapping as accurate as possible. In the next section, the proposed modeling approach, that approximates (3), will be explained.

3. Expectation Maximization-based Gaussian Mixture Models (EM-GMM)

Before detailing the EM-GMM process, the principles of the Bayesian modeling (or classification) is explained.

3.1. Bayesian Classification

Consider a vector set $x_k=[x_{1,k},x_{2,k},\dots,x_{D,k}]^T$ with D to be the width of the vector. Suppose that the vector x_k belongs to one of the classes set $y_k=\{c_1,c_k,\dots,c_C\}$. Then the vector x_k belongs to a class c_i implies that:

$$p(c_i \mid x_k) \geq p(c_j \mid x_k) \tag{4}$$

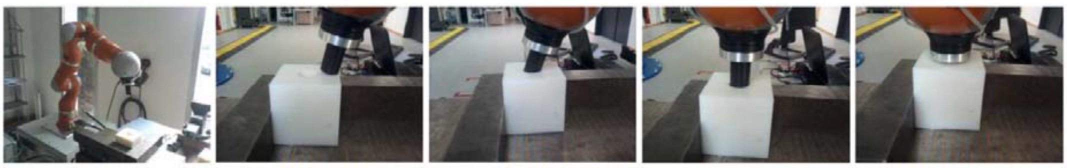
for $i \neq j$. $p(c_k|x_k)$ is called the a posterior probability of class c_k given the vector x_k and can be computed as:

$$p(c_i \mid x_k)=\frac{p(x_k \mid c_i)p(c_i)}{p(x_k)} \tag{5}$$

$p(x_k|c_i)$ is the probability density function (pdf) of class c_i in the vector space of x_k, $p(c_i)$ is the a priori probability that represents the probability of class c_i, and $p(x_k)$ is the probability of the vector space x_k which can be computed as:

$$p(x_k)=\sum_{i=1}^{C} p(x_k \mid c_i)p(c_i) \tag{6}$$

From (6), it can be seen that for equal class a priori $p(c_i)$, the term $p(x_k)$ of (5) would be merely a scaling factor. Therefore, one can say that the vector x_k belongs to a class c_i implies that



(a) (b) (c) (d) (e)

Fig. 1. Robotic peg-in-hole assembly phases: (a) phase 1(free space); (b) phase 2; (c) phase 3; (d) phase 4; (e) phase 5.