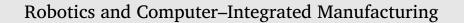
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# Development of an intelligent transformer insertion system using a robot arm

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#### ABSTRACT

Technologies for inserting electronic components are necessary within the electronics industry. Previously this was done by manual assembly, but todays customized machines have been specially designed for automatic assembly. A number of these machines even employ robot arms to insert nonconventional components. However, because special-purpose machines are unable to insert transformers with six manually soldered pins onto printed circuit boards, this study proposed a learning system for such machines that incorporates image characteristics into the insertion motions performed by a robot arm to solve problems related to transformer insertion. The proposed system operates in three layers; vision, motion, and decision. The vision layer involves preprocessing image data, extracting pin image features by locally linear embedding (LLE), and setting parameters for teaching insertion motions to the robot arm. In the motion layer, motions qualified for inserting the transformers were collected and the weighted Fuzzy C-means was used to converge the insertion motions and create target markers for the decision layer. The decision layer uses one-against-rest support vector machines (SVMs) to establish classifiers for applying the collected image characteristics to the calculation of insertion motions. Experiments were performed to verify the various research methods by using 300 transformers as training samples and 200 transformers as test samples. By imposing a number of rules to limit image characteristics, this study applied three classifiers (SVMs, Bayes, and a neural network) to the test samples and compared their accuracy. The experimental results indicated an accuracy rate of 88%, an average area under the receiver operating characteristic curves of 0.88, and that the employed SVM classifiers were more accurate than the other two classifiers.

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#### 1. Introduction

In the 1960s, electronic components were mostly assembled using a pin-assembly method, which requires substantial manual labor. In the 1980s, surface mount technologies gradually matured, resulting in the creation of various single-motion part-insertion machines that were later developed into machines with precise positioning and automatic partinsertion abilities. These special-purpose insertion machines generally employ robot arms with four degrees of freedom (DOF; hereafter 4-DOF robot arms), which exhibit adequate point-to-point control. However, they are limited to inserting parts on the xy plane. Therefore, inserting unconventional components, such as the transformer examined in this study, still requires substantial manual labor because 4-DOF robot arms are unable to insert these components in a fixed position.

In the process of part insertion, the most crucial element is inserting components onto the target locations, which requires sensors to enhance the robustness of the insertion system. Various studies have identified force control for robot arms (manipulators) as a key topic [1]. Raibert and Craig [2] employed the proportional-integral-derivative control law to design a method for accurate force and position control of manipulators and conduct experiments on peg-in-hole insertion operation. However, this control method cannot be properly defined when used in solving complex assembly problems. Polverini et al. [3] applied a dualarm robot to solve insertion problems without using any force sensors, only force feedback to generate real-time trajectories through an optimization approach. A robot arm requires force control for trajectory generation because precision is critical for inserting small-size components into small holes.

Peg-in-hole insertion is a typical example of force control. The insertion process is divided into two stages. The first stage is the search stage, which is completed by defining the gap between the centers of the peg and hole. The second stage is the insertion stage, which is conducted using the direction adjustment and calibration of the peg and the hole to achieve a smooth insertion. Gullapalli et al. [4] solved search problems by using an associated learning network, which learns to perform adequate insertion motions under various conditions and identify

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the characteristics of these motions. When incomplete input (force feedback) was provided, the learning system would generate an action most pertinent to the input. This peg-in-hole action was performed under conditions of uncertainty and noise. Majors and Richards [5] devised a neural network-based learning method for peg-in-hole insertion. Force sensors on robot arm terminals were utilized to collect force and torque data, which were used to create a mathematical model for peg-in-hole insertion. Sharma et al. [6] used mathematical concepts to determine whether a hole location was accurately searched and peg correctly inserted, and applied real-time and dynamic approaches for calculating gradient descent values to reach the accurate hole location. Hovland and McCarragher [7] used force sensor signals collected from a manipulator and employed hidden Markov models to recognize discrete events representing contact state transitions in a peg-in-hole assembly. The experiment results indicated that the average recognition performance achieved an accuracy rate of 98% for 12 events.

Problems pertaining to the use of robots in peg-in-hole operations cannot be solved only by force control. A number of studies have developed hybrid control methods that combine machine vision and force feedback. Adopting visual servoing in robots was used to enhance force sensing and search results. Abatzoglou and O'Donnell [8] resorted to visual complementary approaches to approximate hole locations and performed peg-in-hole tasks by using the gradient relationship between workpieces and holes. A coordinate gradient descent method was employed to calculate this gradient relationship. Later, Morel et al. [9] used a visual system to generate reference trajectories and adopted a force feedback-based impedance control approach to modify these trajectories. Lopez-Juarez et al. [10] applied machine vision and force sensing to completing peg-in-hole insertion tasks. A two-dimensional method was employed to approximate hole locations and force feedback was utilized to accurately insert components into targeted holes. Su et al. [11] solved off-center peg-in-hole insertion problems by recognizing the visual motions of the employed components and reducing the multidimensional configuration space into two-dimensional space. Huang et al. [12] proposed a component alignment method on the basis of visual compliance by installing two high-speed cameras to provide feedback for adjusting robot motions for further peg-in-hole insertion operations. Xing et al. [13] proposed a hybrid control strategy from the perspective of component angles. A vision and motion recognition system was developed to adjust component motions and angles according to the obtained force feedback.

In automatic insertion systems, machine vision inspection is generally used to identify the status of workpieces and work environments and provide necessary data to robot arms during peg-in-hole insertion procedures. Presently, industrial machine vision inspection technologies are mostly applied to circuit board inspection. To address visual feature variance problems, these technologies incorporate various visual features into a fuzzy neural network as a learning solution. Acciani et al. [14] separated circuit board images according to grayscale levels (i.e., separating board, IC, and PIN regions) and various features were extracted from each region of interest. In a visual inspection, image features can be extracted extensively and locally. Extensive feature extraction leads to a clear data distribution of the raw image but cannot be used to capture changes in local regions. By contrast, local feature extraction can be used to distinctively display features of all local regions. In addition, an image is characterized by various features, including space, shape, color, texture, and gray level. For instance, image features of printed circuit boards (PCBs) and surface mounted devices include: color sensitivity and solder-joint area and shape. Kon and Cho [15] adopted sensitivity to the three primary colors in circuit board soldering as a characteristic parameter and employed a neurofuzzy network to detect solder-joint defects. Giaquinto et al. [16] employed solder-joint area and shape as characteristic parameters and applied neurofuzzy networks and fuzzy rule-based modules to examine soldering defects. Moreover, Belbachir et al. [17] incorporated wavelet transformation, which was used as the characteristic parameter, into neural networks to detect circuit board defects. Fanni et al. [18] adopted fast Fourier transformation as a characteristic of image processing to conduct neural network training procedures.

Although a large number of studies have focused on developing pegin-hole insertion methods using visual guidance and force control, these methods resulted in long insertion times and therefore are unable to satisfy the needs of the transformer insertion system proposed by the present study because of considerable pin-angle differences (i.e., some pins were too tilted to be used for component insertion). Thus, adopting conventional force control approaches may lead to long operation cycles and cause disruptions to the overall production line. However, studies have revealed that image features and fuzzy neural network learning generated more optimal results for detecting electronic component defects than conventional methods.

In a nutshell, the difficulties of the transformer insertion problem are as follows: (1) Methods of vision inspection to detect the pin centers are insufficient to achieve a fair accuracy due to image noises; (2) although the pin centers of a transformer are identified as bending by vision inspection, the transformer still can be inserted with a certain pose but finding the pose from the pin centers is an intractable; (3) the insertion task is not applicable using a Cartesian coordinate robot; (4) methods of visual guidance and force control are too slow to fulfill the speed requirement of the industrial insertion task. Therefore, to overcome transformer insertion problems, the present study adopted a 6-DOF robot arm rather than a 4-DOF robot arm to increase operational flexibility. Moreover, visual inspection technologies were employed to obtain transformer pin features, and the concept of machine learning was also used to determine the relationship between pin features and robot arm motions. Thus, the present study proposed a model that can be generalized into solving nonconventional component insertion problems.

The present study assumes that a certain level of similarity exists between pin images of transformers assembled by the same insertion motion. When certain electronic components do not feature standardized pin locations, these components cannot be assembled by merely one insertion motion. This problem can also be observed in the transformers employed in the present study, because their pins were all manually soldered and therefore these transformers could not be assembled by merely one insertion motion. However, designing an exclusive insertion motion for each transformer is not practical because teaching insertion motions to all transformers on the production line is impossible. Therefore, a number of the employed transformers were used as a training set for insertion motion teaching. Representative insertion motions were identified by clustering, and these representative motions were performed by the proposed system. Thus, transformer training was conducted to obtain image and motion data. Machine learning strategies were adopted to determine the relationship between image features and insertion motions and thereby estimate the ideal insertion motions for the other transformers. In addition, a flexible 6-DOF robot arm was used to perform peg-in-hole insertion tasks to generate an intelligent insertion system for multiple-pin transformers.

Using the concept of machine learning, this study proposed an intelligent transformer insertion system to estimate robot arm insertion motions by utilizing the features of transformer pin images. In other words, visual feature recognition, robot arm insertion motion clustering, and machine learning were employed to develop a system for inserting nonconventional components. The operation of the proposed system was divided into three layers: (1) Vision layer: image noise was effectively filtered and the pin image features of each transformer were preserved; (2) Motion layer: insertion motions for a number of the employed transformers were manually taught to the system and a clustering algorithm was employed to search for representative motions among these manually taught motions; (3) Decision layer: multilayer SVM modeling was employed to estimate robot arm motions according to input-image features to generate ideal insertion motions. These three operating procedures led to the following contributions: Download English Version:

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