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AI-Assisted Automation and Future Development of Automatic Soldering Machines

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Abstract. Automatic soldering machines have become increasingly important in electronics manufacturing as production requires higher efficiency, precision, and consistency. Traditional soldering automation has developed from early mass soldering methods, such as wave and reflow soldering, to more programmable CNC-based systems and vision-guided robotic platforms capable of handling complex and flexible electronics. The integration of machine vision and positional feedback has extended the adaptability of these systems in responding to workpiece variation. Existing studies show that artificial intelligence can be applied across multiple aspects of soldering, including quality prediction, process parameter optimization, defect inspection, and long-term reliability estimation. Neural network models, deep learning-based inspection, and AI-driven simulation frameworks have demonstrated performance improvements over traditional approaches that rely on fixed parameters and manual evaluation. These applications have the potential to reduce defect rates, lower repair costs, and improve overall process consistency. However, challenges such as data quality requirements, model generalization across different production conditions, system integration complexity, and implementation cost remain. Many current AI applications are still evaluated in research or laboratory settings rather than full industrial deployment. Future development will likely focus on transitioning into more adaptive and integrated soldering systems that combine AI-based decision-making with real-time control.

Keywords: Automatic Soldering Machines, Artificial Intelligence, Machine Vision, Robotic Automation, Intelligent Manufacturing

1. Introduction

Soldering is a critical process in electronics manufacturing as it directly affects the functionality and reliability of electronic products. Automatic soldering has been used for decades to improve production efficiency and reduce the dependence on manual operation [1]. However, new challenges arise as electronic products are continuously advancing in terms of complexity. Many conventional systems still rely on predefined parameters and programmed operations, which limit their ability to respond to the change in technology.

In recent years, artificial intelligence has been highly incorporated in the electronic industry. Similar approaches are also being introduced into soldering processes, where AI can be used to

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process and inspect data to support quality prediction, parameter optimization, defect detection, and reliability analysis.

This review examines the development of automatic soldering machines from traditional mass soldering to programmable and robotic systems, continuing with the application of AI technologies in soldering. Current limitations and future development toward more adaptive and intelligent soldering systems are also discussed.

2. Development of automatic soldering machines

2.1. Traditional and semi-automatic soldering systems

Automatic soldering has developed from manual operations to a more programmable and flexible system. In the traditional electronic industry, hand soldering is used in special cases such as soldering individual components that are difficult or problematic to solder in mass, or reworking and repairing [1]. As soldering developed, mass soldering, also called automatic soldering or machine soldering, comes to place, in which several components are soldered onto a printed board (PCB) simultaneously without manual application of solder [1]. Typical methods include dip soldering, drag soldering, wave soldering, and reflow soldering. The dip and drag methods are rarely used nowadays, while wave soldering is mainly used in through-hole components, and reflow has become the main technology for surface-mount components due to flexibility and high throughput [1]. As electronic production gets more complex, a higher adaptability provides more value than dependence on fixed process settings and predefined operations.

2.2. Development of fully automatic and robotic soldering

To keep up with the complexity of current electronic production, automatic soldering machines began to include more programmable control over the soldering process. Wahid et al. [2] proposed an integration of a CNC system with a temperature-controlled soldering station to create a lower-cost automated soldering machine. This represents a step toward programmable automation compared with traditional mass soldering methods. Two key components of this process are the Mach3 software and the Arduino Nano. Mach3 software mainly controls the CNC motion, while Arduino Nano bridges the CNC system and the soldering and controls the wire-feeding rate. This approach of utilizing CNC provides a lower cost and less comprehensive operation, which is best suited for smaller-scale production.

2.3. Transition toward intelligent soldering

As the current 3C (computer, communication, and consumer electronics) manufacturing requires higher demand on the soldering of flexible PCBs, the limitation of fixed robotic positioning soldering methods is exposed. Since uncertain PCB deformation changes solder-pad position, a predetermined setting for rigid objects will not be enough to compromise this challenge. Li et al. [3] proposed a dual-arm robotic system to solve this issue. It consists of two robotic arms, one assistive arm for stabilizing the flexible PCBs and one soldering arm for soldering, and a high-resolution camera for visual-based tracking assistance of soldering position. The experiment performed in the paper also demonstrated successful soldering on 3 flexible PCBs at the desired position, showing the feasibility of a more adaptive robotic soldering system.

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3. Core technologies of automatic soldering machines

3.1. Motion and positioning control

Automatic soldering machines rely on several different techniques. One of the most important ones is motion and positioning control. Wahid et al. [2] demonstrated that the CNC-based system utilizes the XYZ movement to control the soldering tool. The main hardware includes stepper motors, lead screws, motor drivers, and limit switches. With Mach3 software incorporated, G-code/M-code is used to control the position, movement direction, and movement speed of the CNC system [2]. This type of programmable motion provides advantages in precision and repeatability. However, the fixed or programmed positioning better suits a rigid PCB, which has consistent positions. If PCB deformation occurs or a target position changes, the original fixed coordinates might not be accurate enough [3]. This leads to the need for robotic and vision-guided positioning.

3.2. Temperature and solder feeding control

Apart from accurate positioning, temperature and solder feeding also play a significant role. Wahid et al. [2] introduced a temperature-controlled soldering station to continuously adjust heating based on the temperature of the soldering iron tip. If the temperature drops below the set temperature, heating power is increased, while power is decreased when the temperature rises over the set value. The goal is to maintain a stable soldering temperature. As for solder wire feeding, Arduino Nano was used by Wahid et al. [2] to connect CNC and soldering systems and control the wire-feeding rate. Therefore, the machine not only has to control the placement, but also the temperature, solder amount, and timing conditions. Additionally, Liukkonen et al. [1] show that wave soldering can be affected by multiple process parameters such as preheating, solder temperature, conveyor (track speed), and solder-wave pump setting. This indicates that multiple elements should be taken into consideration to maintain consistency in soldering quality.

3.3. Machine vision and feedback control

As soldering tasks become more complex, machine vision provides an additional way for automatic systems to respond to changes in the workpiece. The most challenging problem is the deformation of flexible PCB as it changes the desired soldering position. If a robot only uses predetermined coordinates, accuracy could be highly affected. Li et al. [3] introduced a high-resolution camera to provide visual feedback. The soldering arm utilizes vision-based tracking to find the desired soldering position, while the assistive arm stabilizes the flexible PCB. The soldering arm will then execute soldering motion after PCB deformation is stabilized. With vision, the machine observes where the target currently is and allows the robot to adjust its motion. Together, these technologies highly improved the accuracy, consistency, and flexibility of automatic soldering machines compared to the traditional methods. However, conventional control systems still largely rely on predetermined parameters and programmed rules. This creates an opportunity for AI to further improve the entire system.

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4. AI technologies for automatic soldering machines

4.1. AI-based solder joint inspection and defect detection

Artificial intelligence provides a path beyond predefined control by learning from process and inspection data. One important application of AI in soldering is the prediction of soldering quality based on process data. Liukkonen et al. [4] used multilayer perceptron (MLP) neural networks to predict wave soldering defect formation. The dataset includes 1073 samples with 30 variables, including 23 process variables and 7 defect types. The input is soldering process parameters, and the output is the different defect types. The paper also compares nonlinear MLP and multiple linear regression. The results show that the neural network approach has better modeling potential for multiple defect types. Another study by Seidel et al. [5] applied K-nearest neighbors (KNN) to selective-wave soldering to predict whether the solder can fill the hole properly. With inputs including solder-joint characteristics, component characteristics, and soldering process parameters, the overall accuracy of the prediction is approximately 75%. Together, Liukkonen et al. [4] and Seidel et al. [5] demonstrate that process data and component information can be used to predict expected soldering quality and improve beyond merely trial-and-error.

4.2. Intelligent process monitoring and parameter optimization

Other than predicting soldering quality, AI can also be applied to optimize process settings for improving production quality. Liukkonen et al. introduced a self-organizing map (SOM) to analyze wave-soldering process data. The main idea of SOM is to organize or map multiple process variables that affect each other together, which allows researchers to identify which operating conditions are associated with better or worse soldering quality. Building on their previous work [4], Liukkonen et al. further developed a repair-cost function. For instance, the paper considers factors such as the number of defects, the probability that each defect requires repair, the repair time, and labor cost [4]. These factors are then combined to calculate the total defect repair cost for each PCB. This cost function is used together with the SOM to evaluate which process conditions are associated with lower repair costs. The researchers then identify low-cost regions on the map and use them to estimate more suitable process parameters. This demonstrates that AI-based methods can support the selection of process conditions that may reduce repair costs and improve soldering quality. However, the process data plays a significant role in the effectiveness of this optimization. The paper also emphasizes that the dataset should cover the probable operating range of the machine in order to produce reliable parameter recommendations [6].

4.3. Predictive maintenance

AI can also improve solder joint inspection by using image data to identify defects. Zhang et al. [7] introduced deep learning models to improve automated X-ray inspection (AXI). The study found that only approximately 15% of the solder joints marked as defective by AXI are actually defective. To reduce false positives, the authors applied CNN, 3D CNN, and LSTM-based AI inspection, with the best method filtering about 73.29% of normal joints [7]. A similar approach was applied in Shimomura et al. [8], where image processing and CNN are used to differentiate real cracks from other external characteristics. The crack or non-crack classification accuracy reached around 93.7%. Together, these studies show that AI inspection can support different imaging methods while reducing manual workload.

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4.4. Toward adaptive soldering systems

More recent research has extended AI from immediate defect detection toward predicting the long-term reliability of solder joints. Akhtar et al. [9] utilized 3D FEA data combined with 3D CNN and PointNet to predict solder-joint lifetime and reliability. Unlike traditional approaches that rely on manually averaged strain values, PointNet can process the full 3D spatial information and link FEA-derived features with experimentally measured lifetime. As discussed in Gao et al. [10], broader manufacturing AI has been incorporated in process modeling, optimization, quality assurance, maintenance, and automation, giving an opportunity for the combination of prediction, inspection, optimization, and control in the future.

5. Current challenges and limitations

Despite the benefits of AI-assisted soldering, the current technology still poses challenges that limit its wider implementation in industrial production. Current studies mainly focus on separate tasks such as quality prediction, process optimization, defect inspection, or reliability assessment rather than integrating all these functions into one closed-loop system. Practical implementation also requires additional sensing, computing, and control systems, which create another issue of complexity and cost that would be critical for small- and medium-scale businesses [2]. Therefore, the wider adoption of AI in the industry would require further development of generalizable, integrated, and economically practical soldering systems.

6. Future development trends

Future development of automatic soldering machines will likely focus on more adaptive manufacturing systems. There are three major directions for consideration. First, AI-based prediction and optimization could be integrated directly with machine control. Current studies have shown the ability of AI to predict soldering quality and identify better process settings, but these functions are still mostly theoretical or in the laboratory stage. Second, machine vision can be further combined with robotic control. Li et al. [3] demonstrated that visual feedback has already been incorporated to assist robotic systems in responding. Future systems may use AI to make this process more adaptive. Third, AI can also be used for long-term reliability prediction. As shown in Akhtar et al. [9], solder-joint lifetime can already be predicted based on AI and 3D FEA data. This may allow future systems to predict possible failures and support maintenance decisions. In all, these developments may gradually turn automatic soldering machines from pre-programmed systems into more intelligent and adaptive systems.

7. Conclusion

Automatic soldering machines have come a long way from traditional mass soldering systems into more intelligent manufacturing systems. Traditional mass automation improved production efficiency by reducing manual soldering, while the incorporation of CNC and robotic systems further improved control over positioning, temperature, solder feeding, and visual feedback [1-3]. The development of vision-guided robotic platforms further extended the capability of these systems to handle more demanding tasks such as flexible PCB soldering, where fixed programming alone is insufficient to address workpiece deformation.

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The incorporation of AI laid a new blueprint in this development. Studies have shown that AI can be used to predict soldering quality, optimize process settings, inspect solder joints, and estimate long-term reliability [4-9]. These studies demonstrate the potential improvement AI can bring, especially in using process data and image information to support decision-making that goes beyond what traditional rule-based systems can achieve. Methods such as MLP, KNN, SOM, CNN and PointNet-based approaches have each shown measurable improvements in different aspects of the soldering process, suggesting that data-driven methods are broadly applicable across different challenges in soldering automation.

However, there are still limitations to the wider implementation of AI-assisted soldering. Current studies mainly focus on individual functions rather than combining them into a unified system. The effectiveness of current models also highly depends on the quality and coverage of available training data, and integrating additional sensing and computing equipment may increase system complexity and implementation cost, which is a practical concern especially for small- and medium-scale manufacturers.

In the future, the main focus would be to combine machine vision, robotic control, quality prediction, process optimization, and reliability analysis to develop a more comprehensive and adaptive soldering system [10]. Overall, the future of automatic soldering machines lies in the integration of AI, which has the potential to transform current systems from pre-programmed operations into more intelligent and responsive manufacturing platforms capable of adjusting to varying production conditions.

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