Glue Level Estimation through Automatic Visual Inspection in PCB Manufacturing

Bruno P. Iglesias[1], Mario Otani[2] and Felipe G. Oliveira[1]

[1]*Institute of Exact Sciences and Technology (ICET), Federal University of Amazonas (UFAM), Itacoatiara, Amazonas, Brazil*

[2]*Cal-Comp, Institute of Research and Technological Innovation (ICCT), Manaus, Amazonas, Brazil*

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Abstract: Nowadays, the increasing use of automatic visual inspection approaches in the manufacturing process is remarkable. The automation of production lines implies profitability and product quality. Moreover, optimized human resources result in process optimization and production increase. This work addresses the problem of optimizing the glue tube replacement in Printed Circuit Boards (PCB) manufacturing, warning a human operator only just in time to replace the glue tube. We propose an approach to estimate the glue level, in the glue injection process, during PCB manufacturing. The proposed methodology is composed of three main steps: *i*) Pre-Processing; *ii*) Feature extraction; and *iii*) Glue level estimation through machine learning. The proposed predictive model learns the relation between visual features and the glue level in the tube. Real and simulated experiments were carried out to validate the proposed approach. Results show the obtained Root Mean Square Error (RMSE) measure of 0.88, using Random Forest regression model. Furthermore, the proposed approach presents high accuracy even regarding noisy images, resulting in RMSE measures of 3.64 and 4.15 for a Salt and Pepper and Gaussian noise, respectively. Experiments demonstrate reliability and robustness, optimizing the manufacturing.

1 INTRODUCTION

In the current economy, manufacturing companies must be competitive. The mentioned competitiveness depends on increasing production, providing quality to the manufacturing processes. In this context, the inspection process plays a fundamental role in the quality of industrial tasks (Rahman et al., 2019).

The automation of visual inspection approaches has grown consistently in recent decades, with particularly relevant challenges being posed in different industrial scenarios and manufacturing processes (Abdul Rahman et al., 2018).

In some well-stated production lines, it is not always possible to include internal sensors in enclosed devices, like injection glue tubes. Thereby, automatic visual inspection approaches are efficient and reasonable to address the refered problems. Automatic visual inspection can be applied to: *i*) waste reduction; *ii*) quality of final products improvement; or *iii*) process optimization (Thielen et al., 2020).

In this paper, we present an approach to optimize the glue tube replacement, during the glue injection process, in manufacturing of Printed Circuit Board (PCB). The glue level is estimated from visual features, warning the human operator within the appropriate time to replace empty glue tubes. We also introduce a liquid level estimation strategy based on Random Forest (RF), to obtain a more efficient estimation of glue levels. Experiments in real-world scenarios and simulations show that the obtained results are accurate and applicable in industrial scenarios.

Our main contribution is to provide an approach to estimate the glue level in an autonomous glue injection process. Furthermore, the proposed predictive model learns the relation between visual features and the semantic level. Thereby, the human operator is allocated to glue tube replacement only at the appropriate time, optimizing the human resource during manufacturing of PCB. Figure 1 presents a 3D model of an experimental setup used for automatic visual inspection, regarding a glue injection process in PCB production line.

The remainder of this paper is structured as follows. In Section II we present a brief discussion on related works regarding automatic visual inspection.

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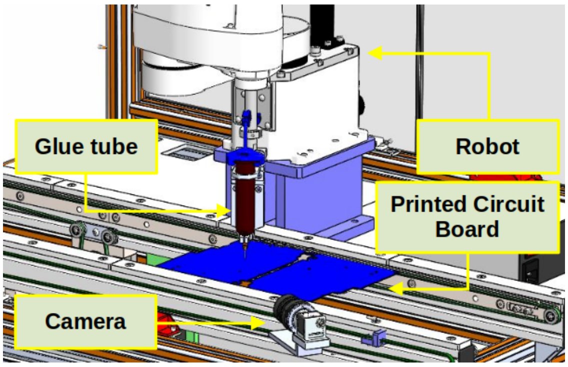


Figure 1: Three-dimensional model of an experimental setup used for automatic visual inspection for glue level control in PCB manufacturing.

The proposed methodology is presented in Section III and validated by real and simulated experiments discussed in Section IV. Finally, in Section V we draw the conclusions and discuss paths for future investigation.

2 RELATED WORKS

Problems related to automatic visual inspection are of significant importance and have been the subject of intensive investigation (Zhang et al., 2018) (Rahman et al., 2019). For fault detection, the majority of works perform classification of presence or absence of faults, in manufacturing processes (Abdul Rahman et al., 2018) (Vafeiadis et al., 2018).

Many industrial applications are addressed as a fault detection approach. In (Rocha et al., 2016), a visual inspection approach is presented to detect absence/presence of surface mount components (SMC) on printed circuit boards (PCB). The authors propose a methodology based on the combination of Machine Vision and Machine Learning (using Support Vector Machine (SVM)) to detect component absence, with more quality and precision, using noisy digital images acquired directly from PCB industrial production line. The obtained results demonstrated the robustness of the methodology, obtaining 97.25% of accuracy.

(Zhou et al., 2017) has proposed a detection approach for oil-air and oil-water interfaces, from images of transparent tubes containing water and oil. A statistical based approach to detect the mentioned interfaces is used. Through real experiments, results show that the multi-interface detection method has high precision and reaches the requirements of industrial applications.

In some industrial applications, liquid control is a paramount task. (Zhang et al., 2018) presents a machine vision approach for liquid particle inspection in pharmaceutical injection. The authors proposed an approach based on particles segmentation, tracking and classification, to reduce potential defects in injection process. From the experiments, the proposed inspection approach demonstrates effectiveness in real application, achieving accuracy above 97%.

The authors of (Abdul Rahman et al., 2018) proposed a strategy to classify bottles regarding shape and level. In shape analysis the bottles are classified in ”good” or ”defect” classes. Meanwhile, in level analysis the liquid is classified in ”overfilled”, ”underfilled” and ”good” classes. For this, a local standard deviation and Hough transform technique are used, using a decision tree as a learning model. The experimental results obtained from the developed technique show an accuracy of 97% for shape and 93% for level analysis.

In (Saad et al., 2017) is presented a real-time inspection approach for beverages product. The proposed system regards color concentration and bottle’s water level. Quadratic distance technique is applied for color concentration analysis based on a combination of Red, Green and Blue (RGB) histogram. The vertical and horizontal coordinates are used to inspect three conditions of the level, which are ”overfill”, ”underfill” and ”passed”. The proposed system has achieved 100% accuracy using 246 samples.

In mounting processes, glue injection and level control are important steps for efficient manufacturing. In (Vafeiadis et al., 2018) the authors proposed the inspection of dies attachment on PCB, using machine learning techniques. For this, an analysis is performed regarding the excess or insufficient glue injection. For the inspection of PCB, a pixel-based vector of the regions of interest is used, altogether with a SVM classifier. The experiments achieved an accuracy of 81.39%.

The existing solutions for liquid level control are based on the classification of the liquid level into ”overfill”, ”underfill” and ”good” classes (Saad et al., 2017) (Abdul Rahman et al., 2018). The closest approach, regarding glue control, only inspect the excess or insufficient level of injected glue on PCB (Vafeiadis et al., 2018). Thereby, although previous works on automatic liquid level control approaches exist, to the best of our knowledge, there is no prior work tackling specifically the automatic glue level control in PCB manufacturing problem.

The presented approach is particularly interesting because it proposes an automatic glue level control for PCB production. Additionally, it predicts the continuous level representation during the glue injection process. In this sense, it is possible to verify the

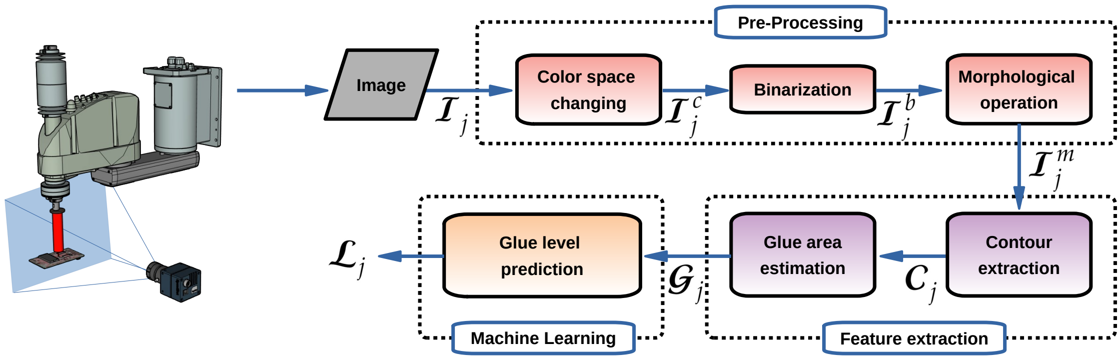


Figure 2: Overview of the proposed approach for automatic visual inspection for glue level control, through the stages: *i*) Pre-Processing; *ii*) Feature extraction; and *iii*) Glue level prediction through machine learning.

percentage of glue into the tube during the injection process, warning the human operator, to replace the empty tube, only in proper time. Moreover, it provides important information for manufacturing management.

3 METHODOLOGY

In this paper, we propose an automatic visual inspection for glue level control process, based on visual features and machine learning combining. An overview of the proposed methodology is shown in Figure 2, whose details will be presented in the next subsections.

In Figure 2 we present an overview of the proposed approach, highlighting the main steps to achieve the glue level estimation, indicating the correct time to replace the empty glue tube. To reach this goal, images are acquired continuously and a pre-processing stage is performed. Shape based features are extracted to quantify the glue level into the tube. Finally, a machine learning technique is applied to predict the glue level.

Our problem can be summarized as follows:

Problem 1 (automatic visual inspection)**.** *Let $\vec{I}_j = \{i_1, i_2, \ldots, i_n\}$ be a series of glue tube images provided by a camera. Also let $\vec{L}_j = \{l_1, l_2, \ldots, l_n\}$ be a series of previously known reference glue levels. Our main goal is to correctly associate an unknown image ($\vec{I}_k$) to the correspondent glue level ($\vec{L}_k$), representing the glue level in the tube.*

3.1 Pre-processing

3.1.1 Color Space Changing

In applications involving structured environment and predefined objects and lighting conditions, color information is used as a feature to represent patterns. In multi-band images, each layer represents a spectrum, corresponding to a complementary information to multi-band image combining. In this sense, individual layers are frequently used to filter patterns in learning processes.

In this work the images ($\vec{I}$) are initially acquired in Red, Green and Blue (RGB) color space and after the images are converted to L*U*V* color space. In L*U*V* color space images, the colors are based on Tristimulus value (L) and Chromaticity (U and V) coordinates, where L component has the range [0,100], U component has the range [-134,220], and V component has the range [-140,122] (Remmach et al., 2020). For glue level estimation, the V component is used, as monochromatic image ($\vec{I}^c$), due to sensitivity to patterns in glue tube images. In Figure 3 are presented examples of raw RGB and V component images.

(a) (b)

Figure 3: Color space changing process. Figures 3a and 3b correspond to RGB and V component images, respectively.

3.1.2 Binarization

Binarization is a technique used to transform a gray level image ($\vec{I}^c$) into a binary image ($\vec{I}^b$). Binarization consists of using a threshold value to separate pixels into two classes, the background (black pixels) and foreground (white pixels). The quality of a binarization method relies on finding an efficient threshold value.

Otsu binarization function is a global method used to find a threshold value based on maximizing the interclass variance of background and foreground (Otsu, 1979) (Gonzalez and Woods, 2017). The Otsu threshold value (T) is computed as folows:

$$\omega_0 = \frac{N_0}{M \times N}. \tag{1}$$

$$\omega_1 = \frac{N_1}{M \times N}. \tag{2}$$

$$N_0 + N_1 = M \times N. \tag{3}$$

$$\omega_0 + \omega_1 = 1. \tag{4}$$

$$\mu = \mu_0 \times \omega_0 + \mu_1 \times \omega_1. \tag{5}$$

Where, M and N are the amount of image rows and columns, respectively. N_0 and N_1 are the amount of pixels that are greater than and less than the threshold (T), respectively. ω_0 and ω_1 are the proportion of pixels. μ_0 and μ_1 are the average gray values of pixels in background and foreground. μ is the average gray value of all pixels. A simplified equation for the interclass variance (g) is given by:

$$g = \omega_0 \times \omega_0 \times (\mu_1 - \mu_0)^2. \tag{6}$$

Thereby, to find the threshold value which maximizes the interclass variance between background and foreground, all gray values must be evaluated. The interclass variance assessment is performed as follows:

$$T_{max} = arg(max(g(T))). \tag{7}$$

Otsu binarization method is used in this work because it can efficiently separate background and foreground in structured environments with predefined objects. Moreover, Otsu method can reduce noise very well.

3.1.3 Morphological Operation

Morphological operations are nonlinear functions that process images based on shape and are especially suited to the processing of binary images. Morphological image processing removes imperfections taking into account the form and structure of the image.

Morphological operations probe an image with a matrix called structuring element. For this, the structuring element is positioned in all locations in the image, being compared with the current position altogether within its neighborhood. Many image processing functions are based on the mentioned strategy, such as: *i*) erosion; *ii*) dilation; *iii*) opening; and *iv*) closing.

Erosion ($\ominus$) shrinks an image by stripping away a layer of pixels from both the inner and outer boundaries of regions. Dilation ($\oplus$) adds a layer of pixels to both the inner and outer boundaries of regions. Opening ($\bigcirc$) opens up a gap between objects connected by a thin bridge of pixels. Moreover, any regions that have survived the erosion are restored to their original size by the dilation. Closing ($\bullet$) fills holes in the regions while keeping the initial region sizes (Gonzalez and Woods, 2017).

In this work, we use the opening morphological operation due to removing small regions and small connections, as can be observed in Figure 4. Furthermore, the glue tube size is preserved during image processing. Additionally, a rectangular structuring element is used, with a size of 5×5. The opening function is represented as follows:

$$A \bigcirc B = (A \ominus B) \oplus B. \tag{8}$$

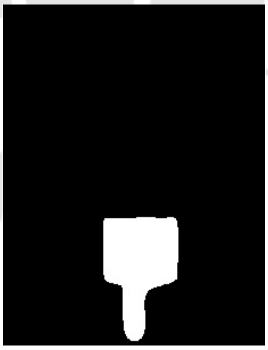


Figure 4: Glue tube image after Otsu binarization and opening morphological operation stages.

3.2 Feature Extraction

3.2.1 Contour Extraction

Contour corresponds to a line connecting all the points along a boundary, representing an object's shape. The technique used in this work to extract the contour from binary images performs the border following for topological analysis. The referred technique is used due to its efficiency in shape representation.

In the mentioned technique, first, a pixel that satisfies the border conditions is defined as a starting point. After, into an auxiliary structure, *i*) a uniquely identifiable number is assigned to the starting point, *ii*) a sequential number of the border is also assigned to the newly found border, and *iii*) the parent border is assigned to the newly found border. A new pixel is assessed, and if the border conditions are satisfied, the new pixel is added to the auxiliary structure as a new border component. In the end, only the binary image contour remains in the output image ($\vec{\mathcal{C}}$), representing the shape of objects (Suzuki and be, 1985). Figure 5 presents the glue contour, extracted from raw glue tube image, representing a shape feature.

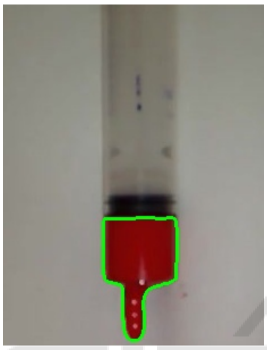


Figure 5: Glue contour extracted from glue tube image.

3.2.2 Glue Area Estimation

After the image pre-processing stage, filtering the most relevant features and reducing noise, and after contour extraction stage, filtering only the remaining glue within the tube, in the current stage the glue area on image is quantified.

Regarding the rectangular glue shape, verified in frontal image of the glue tube, we compute the rectangle which completely covers the glue with minimum area, representing the glue area on image. In this way, it is possible to compute the rectangle area ($\vec{\mathcal{G}}$), from obtained *width* and *height*, as follows:

$$\vec{\mathcal{G}} = width \times height. \tag{9}$$

Thereby, from an image acquired from a glue tube in injection process it is possible to estimate the visual glue area to predict the glue level in unknown scenarios. The estimated glue area corresponds to the shape feature representation used in learning process.

3.3 Glue Level Prediction

The glue level prediction in this work is performed using the Random Forest supervised learning algorithm. Random forest is a bagging technique, where the trees in random forest are run in parallel. It operates by constructing a set of decision trees at training time and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees (Breiman, 2001).

In the Random Forest algorithm, features are randomly selected to build several uncorrelated decision trees. The referred randomness implies in data representation diversity and overfitting reduction, in the training process. Additionally, the Random Forest technique selects the features that contribute the most to the learning process and discards those that do not. Thus, it is possible to create more discriminative models for the regression process (Forsyth, 2019).

The prediction of random forest regression is an average of the predictions produced by the trees in the forest. Each tree prediction corresponds to a weighted average of the response values ($Y_1, \ldots, Y_n$), observed in the original training data. The final random forest prediction at some observed predictor vector (X_0) is a combination of the training response values given by:

$$\hat{Y}(X_0) = \sum_{i=1}^{n} w_i(X_0) Y_i, \tag{10}$$

where $w_i(X_0), \ldots, w_n(X_0)$ are the non-negative weights regarding the constraint $\sum_{i=1}^{n} w_i(X_0) = 1$, as follows:

$$\min_{1 \le i \le n} Y_i \le \hat{Y}(X_0) \le \max_{1 \le i \le n} Y_i. \tag{11}$$

Random Forest regression was used in this work due to robust and efficient results in automatic visual inspection (Thielen et al., 2020)(Dong et al., 2020). Additionally, the predictions given by random forests regression are always within the range of response values in the training dataset.

4 EXPERIMENTS

In this section we present experimental results and compare the performance against existing approaches.

4.1 Experimental Setup

The glue tube is mounted on an Epson SCARA G3-351S robot, in a PCB production line. Images from the glue tube were collected using a Basler AcA5472-17uc camera, mounted with a Lens TS1614 F1.4 f16mm. A Dell laptop with an Intel® Core^{TM} i7-8550U CPU and 16 GiB DDR3-2133 main memory is used to execute the proposed approach (Figure 6).

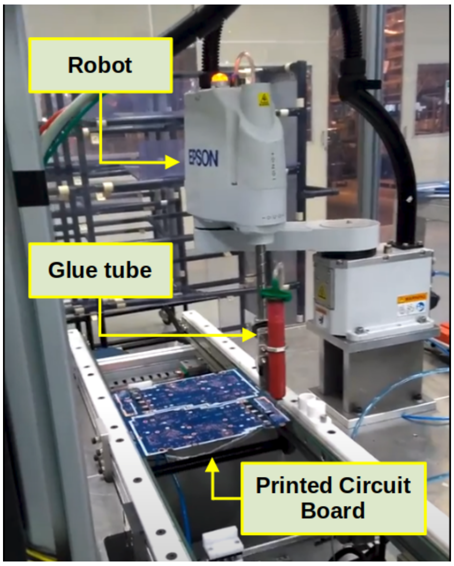


Figure 6: Experimental setup used for automatic visual inspection for glue level control in PCB manufacturing.

4.2 Glue Level Prediction Assessment

This experiment evaluates the accuracy of the proposed approach for glue level control. Glue tubes similar to industrial glue tubes were used in these experiments. Additionally, three different regression models are evaluated: *i*) Random Forest (proposed); *ii*) Polynomial; and *iii*) Neural Network. The comparison regression models were used due to good results obtained in automatic liquid analysis (Saad et al., 2017)(Abdul Rahman et al., 2018) and overall automatic visual inspection context (Rahman et al., 2019)(Thielen et al., 2020).

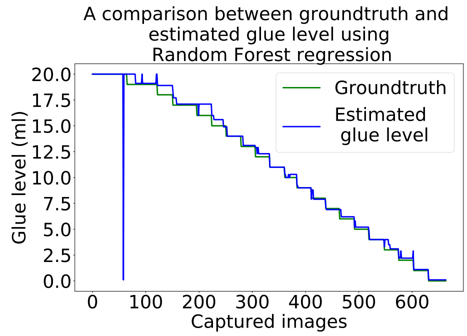
The regression model training is performed from a set of input images and the testing stage regards another set of input images, different from training image dataset. For the training process, are used 205 images, meanwhile for the testing process, are used 3320 images.

The proposed Random Forest regression model uses 100 trees in the forest and the minimum number of samples required to split an internal node equals 2. The used Polynomial regression model is based on 3rd degree polynomial, represented through a cubic spline. Meanwhile, the Multilayer Perceptron (MLP) Neural Network regression model uses a hidden layer of size 15, Adam optimizer and Relu activation function, for 500 epochs.

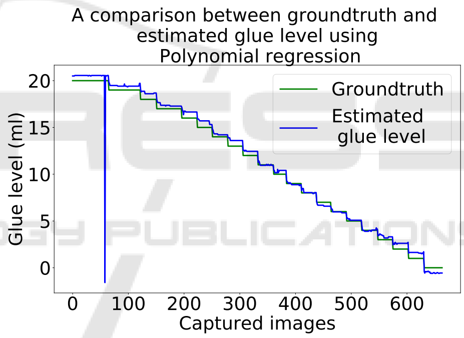
To evaluate the prediction's quality, the RMSE method is used to quantify how similar the known glue levels (groundtruth) and the predicted glue levels are. For RMSE analysis, the closer to zero the result, the more accurate the predictions are. Table 1, shows the glue level control results. Results show that the proposed Random Forest regression model outperforms the other regression models.

Table 1: Results for glue level prediction. This experiment presents the RMSE for Random Forest (proposed), Polynomial, and Neural Network regression models.

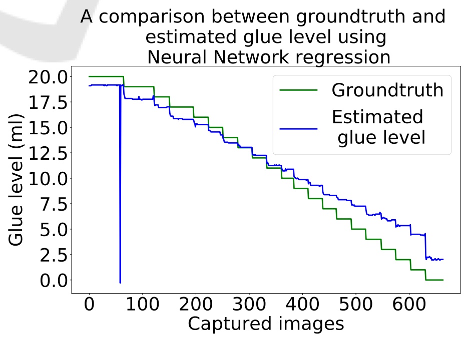
	Random Forest	**Polynomial**	**Neural Network**
RMSE	0.88	0.95	1.83



(a)



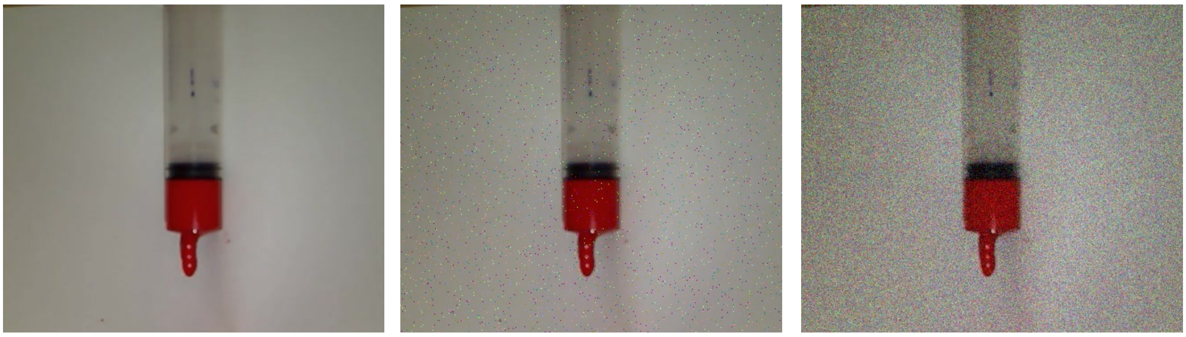
(b)



(c)

Figure 7: Comparison between groundtruth and estimated glue levels. Figure 7a represents the groundtruth and estimated glue level through Random Forest regression. Figure 7b represents the groundtruth and estimated glue level through Polynomial regression. Figure 7c represents the groundtruth and estimated glue level through Neural Network regression.

Additionally, as complementary analysis, Figure 7



(a) (b) (c)

Figure 8: Glue tube images in injection process. Figure 8a corresponds to raw glue tube image. Figures 8b and 8c correspond to raw image with Salt and Pepper noise and Gaussian noise, respectively.

represents the comparison between groundtruth glue levels and the estimated glue levels, regarding the used regression models. From Figure 7 it is possible to verify the proximity between estimated and true glue levels. In Figure 7a we can observe the most accurate predictions, using the proposed regression model.

4.3 Robustness Evaluation of Glue Level Prediction in Presence of Noise

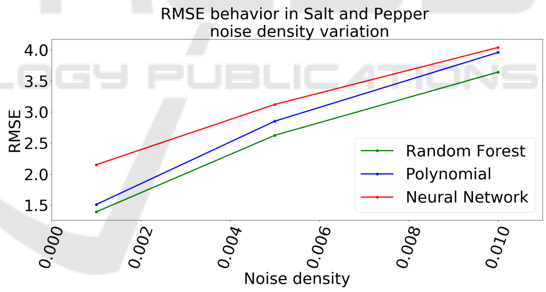
This experiment evaluates the robustness of the proposed approach for glue level control in presence of noise. Two different types of noise are added in glue tube images, Salt and Pepper and Gaussian. The three different regression models, Random Forest (proposed), Polynomial and Neural Network, are evaluated. In this experiment the added noise simulates the image acquisition process regarding the presence of noise.

For this assessment, the regression model training is performed from a set of images without noise and the testing stage regards another set of images with added noise. Figure 8 represents glue tube image examples. Figure 8a represents a glue tube without noise. Figure 8b represents a glue tube with Salt and Pepper noise, with 0.01 noise density. Figure 8c represents a glue tube with Gaussian noise, with 0.01 noise density.

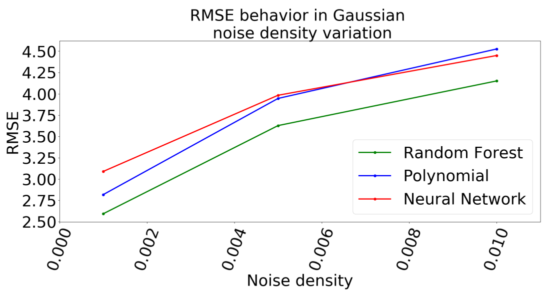
To evaluate the prediction's quality, the RMSE method is used to quantify how similar the known glue levels and the predicted glue levels are. For RMSE analysis, the closer to zero the result, the more accurate the predictions are. Table 2, shows the glue level control results for different types of noise and different regression models. Results show that the proposed Random Forest regression model outperforms the other regression models even in presence of noise, demonstrating the robustness of the proposed approach.

Table 2: Results for robustness evaluation of glue level prediction in presence of noise. In this experiment are presented the RMSE for Salt and Pepper and Gaussian noise.

	RMSE	
Noise	**Salt and Pepper**	**Gaussian**
Noise density	0.01	0.01
Random Forest	3.64	4.15
Polynomial	3.95	4.52
Neural Network	4.03	4.44



(a)



(b)

Figure 9: RMSE behavior in noise density variation. Figure 9a corresponds to RMSE behavior in Salt and Pepper noise variation. Figure 9b corresponds to RMSE behavior in Gaussian noise variation.

Additionally, the proposed glue level estimation is assessed through the noise density variation analysis. Thereby, the glue level estimation accuracy is evaluated regarding different noise densities. In Figure 9 the regression models are applied in two different noises, Salt and Pepper and Gaussian noises, regarding three noise densities, 0.001, 0.005 and 0.01. In Figures 9a and 9b the RMSE behaviors are presented regarding the Salt and Pepper and Gaussian noises, respectively. From Figures 9a and 9b it is possible to verify the proposed approach effectiveness, even in different noise densities.

5 CONCLUSION

In this paper, we addressed the problem of automatic visual inspection for glue level control. Unlike other state-of-the-art approaches, our method continuously monitors the glue level during the glue injection process in PCB manufacturing, aggregating more information to production process.

Real-world and simulated experiments involving different regression models and simulated noise types have shown that the obtained glue level predictions are reliable and accurate considering the obtained results. Additionally, the proposed approach demonstrates robustness, even in presence of noise during image acquisition, and feasibility to real time industrial application, once the experiments were carried out in real time scenario.

As future work, we intend to combine different predictive methods to improve the glue level estimation accuracy. We also intend to concentrate efforts to extend the automatic visual inspection approach to tackle other types of problems related to PCB manufacturing. The volume and position control of injected glue is also a relevant problem we intend to investigate and incorporate in production lines.

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