Flexible Aerodynamic Part Feeding Using High-Speed Image Processing

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Abstract. In modern assembly systems, manufacturers expect a high level of flexibility and efficiency. As an interface between internal logistics and the actual assembly, part feeding technology plays a decisive role in the manufacturing process. Therefore, in this work, we propose a new way of flexible part feeding based on image processing and the proven principle of aerodynamic feeding technology. With a high-speed camera, we analyze the workpiece's movement during the orientation process and automatically adjust the system parameters to ensure reliable and efficient feeding. Based on three parameters of the workpiece's trajectory, we develop an algorithm that can systematically find suitable parameter combinations for efficient and reliable feeding. With the proposed concept, retooling for new workpieces can be achieved quickly, using only few components for the parameter setting. At the same time, no hardware changes are required for retooling when handling new components.

Keywords: Flexible Feeding Systems, Aerodynamic Feeding, High-Speed Image Processing

1 Introduction

In modern production, shortening product life cycles and an increasing number of product variants increase the requirements on automated assembly systems regarding flexibility and reusability [1] [2]. Feeding technology constitutes one of the most complex and expensive sub-systems of automated assembly systems [3]. The most commonly used feeding systems are vibratory bowl feeders [4] [5]. These systems are simple and reliable but lack flexibility since they are usually designed to feed one particular workpiece [6]. Therefore, many approaches have been taken to design flexible feeding systems. LOY AND REINHARDT developed a vibratory bowl feeder with interchangeable orientation modules, consisting of multiple mechanical chicanes [5]. The possibility of quickly changing the chicanes increases flexibility, but every module must still be designed for a specific component. Using air instead of mechanical chicanes, FRÄDRICH ET AL. developed an aerodynamic feeding system, which can feed different workpieces without hardware changes [7]. BUSCH ET AL. and KOLDITZ ET AL. further increased the feeding system's flexibility and robustness (see section 2.1) [8] [9].

In this work, we propose a new approach to adjust the aerodynamic feeding system to new workpieces with the use of digital image processing. Using a high-speed camera, we track the workpiece's movement during the orientation process and extract parameters relevant to the retooling process. By analyzing the orientation process we assume to be able to increase the quality and efficiency of the feeding process and eventually also reduce the setting time of the feeding system.

2 Related Work

As a proof of concept, we implement a high-speed camera and the corresponding image processing into the existing aerodynamic feeding system. Therefore, we first briefly introduce the aerodynamic feeding system used in this work and then present related work regarding digital image processing.

2.1 Aerodynamic Feeding Technology

An aerodynamic feeding system uses air instead of mechanical chicanes to manipulate and reorient workpieces. Fig. 1 shows the principle of the aerodynamic orientation for an exemplary workpiece. Due to specific workpiece properties like the center of gravity and the projected inflow area, the workpiece behaves differently depending on the orientation, in which it enters the orientation process. Since there are no mechanical chicanes, retooling is achieved by adjusting the five system parameters α, β, p, v and z shown in Fig. 1.

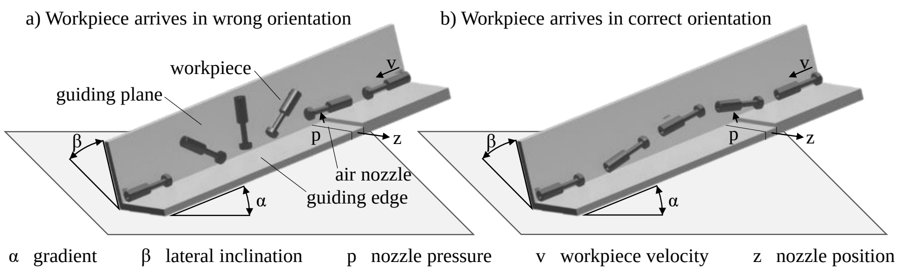

Fig. 1. Principle of aerodynamic orientation

Adjusting these parameters manually can be very time consuming and requires expert knowledge of the feeding system. Therefore, BUSCH ET AL. implemented a genetic algorithm that enables the system to adjust itself to new workpieces (at this time, the system had only four parameters) [8]. Fig. 2 shows the iterative structure of the algorithm. The genetic algorithm starts by generating a random start population, where every individual carries the system parameters (α, β, p, v and later z) as chromosomes. Using recombination and mutation, the algorithm generates new individuals and assesses their fitness by determining the proportion of correctly oriented workpieces in the total quantity of workpieces after the orientation process (orientation rate) using a line scan camera. If the stop criterion (orientation rate ≥ 95 %) is fulfilled, the algorithm stops, otherwise the best individuals are selected and another iteration starts. In order to increase the workpiece spectrum, we implemented the fifth parameter z (nozzle position), as can be seen in Fig. 2 [9]. Experiments showed that this extension also reduced the setting time of the genetic algorithm and increased the robustness of the orientation process.

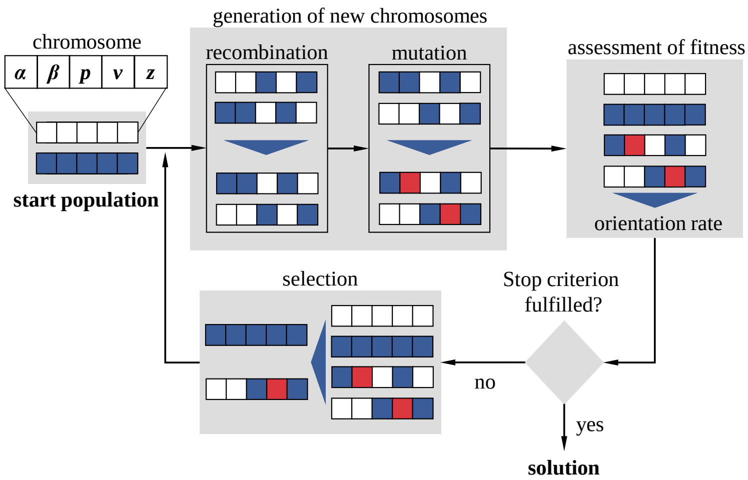

Fig. 2. Structure of the genetic algorithm (cf. [8])

Nevertheless, the genetic algorithm still needs a considerable amount of workpieces for the setting process. For each parameter combination, 100 workpieces are reoriented and evaluated using the line scan camera. According to the data from [9] an average of 2940 fed workpieces is needed to set the feeding system. Furthermore, the setting time of the genetic algorithm varies strongly [9]. Therefore, we want to introduce a new, deterministic approach for a more efficient and reproducible retooling. By directly observing the orientation process with a high-speed camera, we assume to gain more insight into the workpieces' behavior and thus be able to find more efficient parameter combinations (e.g. low nozzle pressure, high reproducibility) and reduce the number of workpieces needed to set the feeding system.

2.2 Digital Image Processing

For the first implementation of digital image processing described in this work, we record the video stream in monochrome frames, which we further process into binary images to track the workpieces. In their survey, YILMAZ ET AL. describe multiple processes for tracking objects in videos [10]. Among newer, more sophisticated methods, YILMAZ ET AL. present an algorithm for tracking an object over time by finding its position in every single frame of a video [10]. BURGER AND BURGE describe an algorithm for finding regions in single binary images [11]. Finding binary regions enables the calculation of further region properties such as the orientation and centroid, which can be used as the basis for tracking an object in a video. Using the introduced method of finding regions in binary images and calculating their properties in every video frame, we can deduce the workpiece trajectory during the orientation process from the camera's video stream.

3 Implementation of a high speed camera

For the high-speed camera, we selected the industrial camera Baumer VCXU-02C with a resolution of 640 x 480 pixels and a maximum frame rate of 891 frames per second (fps). We mounted the camera on the feeding system using an adjustable joint arm, enabling customizable but rigid camera positioning. For proper lighting, we used diffused, non-flickering LED-Panels mounted horizontally besides the camera's axis of vision to provide a shadow and glare-free image. The camera is connected to the image-processing computer via USB 3.0. Due to the limited processing power of the image processing computer, we set the acquisition framerate to 200 fps. We set the exposure time to 1000 µs, resulting in a purposefully overexposed image, separating the dark workpiece from the bright background.

For image processing, we use MATLAB by Mathworks. The camera feeds a continuous video stream into MATLAB via the GenICam Interface. In order to trigger the image acquisition for further analysis, we monitor the video stream for the appearance of a workpiece in a specified image region (cf. Fig. 3). We add up the values of all pixels in the trigger area and when a workpiece enters the area, the sum abruptly changes, triggering the acquisition of a video of predefined length via MATLAB.

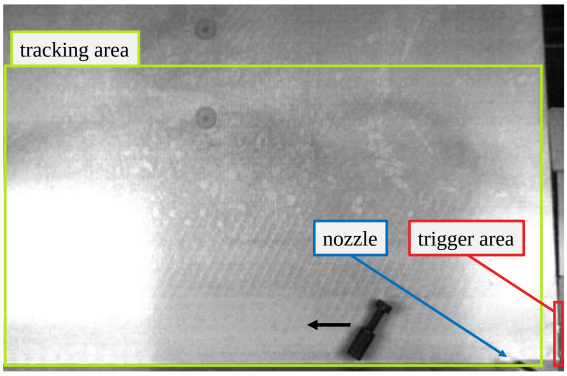

Fig. 3. Trigger and tracking areas in the recorded camera frame

To track the trajectory of a workpiece in the designated tracking area, we first convert the monochrome images to binary images, using thresholding. We then use region labelling [11] to identify the workpiece and determine the position of the centroid and the orientation of the workpiece in each frame of the video. Combining the calculated positions for each frame, we obtain the trajectory illustrated in Fig. 4. Each dot in the red line represents one frame of the recorded video stream.

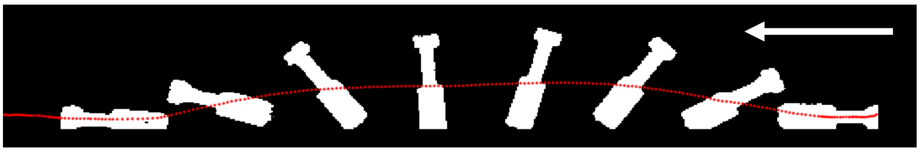

Fig. 4. Calculated Trajectory of an exemplary workpiece

4 Parameter Extraction

As aforementioned, we want to use the high-speed camera data to find a suitable parameter combination for a specific workpiece. Therefore, we need to extract relevant parameters from the gathered trajectories (trajectory parameters) and gain knowledge on how these parameters interrelate with the success of the orientation process. Consequently, in this section, we will define three relevant trajectory parameters, we can extract from the acquired images.

Preliminary testing showed that the workpiece trajectories differ slightly even with the same machine parameter set (cf. Fig. 5). If these deviations are relatively high, this indicates an unstable orientation process, since not every workpiece moves along the same trajectory. If the deviations are relatively low, we can assume reproducible and reliable orientation of the workpieces. Therefore, we introduce the deviation between the trajectories with the same machine parameter settings as the first trajectory parameter. To extract the parameter, we calculate the standard deviation between the trajectories at each workpiece position and then integrate along the x-axis, as shown in Fig. 5.

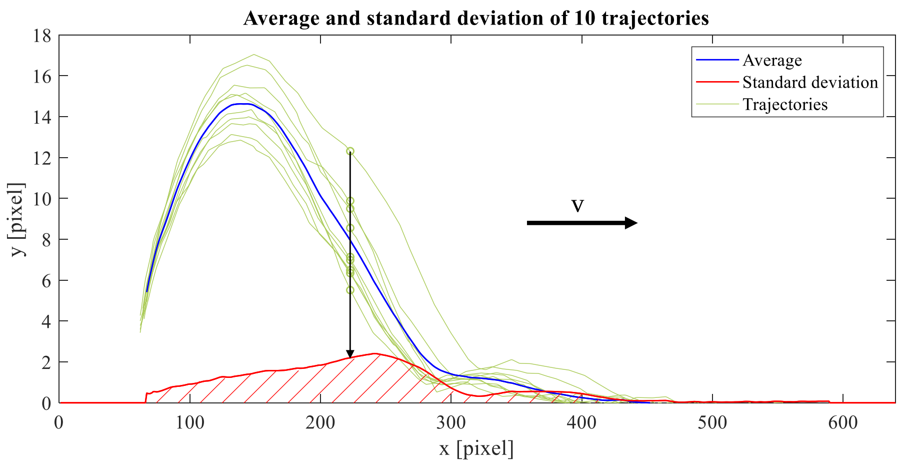

Fig. 5. Average and standard deviation of 10 trajectories recorded with one parameter setting. The hatched area (red) represents the trajectory parameter “deviation”.

The second trajectory parameter is the average maximum height of one set of recorded trajectories. This parameter can be an important indicator for the suitability of the nozzle pressure p. If the maximum height is too low, the workpiece has no room to reorient, indicating too little nozzle pressure; if the maximum height is too high, the workpiece might rotate multiple times, indicating too much pressure.

As the third trajectory parameter, we choose the average total angle of rotation of one set of trajectories. The total angle of rotation is defined as the sum of the workpiece orientation differences between each frame of the video. Looking at Fig. 4, the total angle of rotation would be approximately 180°. This parameter gives insight into whether or not a workpiece was reoriented.

Since the workpieces behave differently, depending on their orientation when entering the orientation process (correct or wrong, cf. Fig. 1), the trajectory parameters are calculated separately for workpieces arriving in wrong orientation and correct orientation respectively. In the following section, we will use the defined trajectory parameters to derive a first concept for the autonomous parameter setting on the aerodynamic feeding system.

5 Concept for system setting

This work aims to demonstrate a vision based setting algorithm for an aerodynamic feeding system. For our concept presented in this work, we specified the following boundary conditions:

- Preliminary testing showed that the machine parameters α and β have little influence on the workpiece behavior. Therefore, we will only use the system parameters p, v and z for the setting of the feeding system. We set the parameters α and β to 25° and 45° degrees respectively.
- We evaluate each system parameter combination using 20 workpieces: Ten arriving in the wrong orientation and ten arriving in the correct orientation (cf. Fig. 1).

From these boundary conditions, we derive the main steps in our algorithm. Following the first boundary condition, we set α and β as constants. In the first iteration, v and z are also set as constants. A sensitivity analysis showed that the nozzle pressure p has the biggest impact on the orientation process, followed by the nozzle position z and the velocity v. Therefore, we start the algorithm with varying p. In this work, we set v_0 = 75 m/min and z_0 = 3 mm. For the pressure p, we manually define a range from the minimum pressure, where the workpiece is barely lifted, to the maximum pressure, where the workpiece rotates multiple times. Accordingly, we then set p_0 = 0.25 bar and start the first iteration. In each iteration, we first evaluate ten workpieces arriving in the wrong orientation. If no reorientation occurs, the algorithm increases the pressure by a defined increment. If a reorientation occurs, ten workpieces arriving in the correct orientation are evaluated. If they do not reorient, a suitable solution is found. The operator can then decide if the algorithm should continue to search for potentially better solutions or if it should stop. If at least one of the ten workpieces arriving in the correct orientation does reorient, the solution is not suitable. The pressure is increased by 0.01 to 0.04 bar, depending on the average total angle of rotation reached by the workpiece and another iteration is started.

When the maximum pressure of 0.65 bar is reached without a suitable solution found, the parameter with the second most influence, z, is varied in defined increments in the range between 2 and 10 mm. Then, another iteration as described above follows. If no suitable parameter combination can be found for different combinations of p and z, the workpiece velocity v is decreased in increments of 5 m/min whereby 50 m/min is the minimum velocity. The process is repeated, until at least one suitable parameter combination is found.

6 Evaluation

In order to evaluate if our newly developed algorithm for the system setting works, we run it on the aerodynamic feeding system and compare the produced suitable parameter combinations (solutions) with the solutions produced by the genetic algorithm. In this work, we will compare the algorithms using only one type of exemplary workpiece (shown in Fig. 3 and 4).

When looking at flexible feeding systems, a key parameter for the versatility of those systems is the time they need to find a suitable parameter setting (setting time) for successful feeding of a new workpiece. A lower setting time reduces overall retooling time and therefore increases machine usage in production. We compare the theoretical setting time by determining the number of workpieces each algorithm needs to find a suitable solution. This way, we exclude effects like the image processing time, which is relatively high due to our provisional test set-up, but can be drastically reduced by the use of specialized hard- and software. Also, we compare the quality of the solutions using the trajectory parameters defined in section 4.

Due to its stochastic nature, the genetic algorithm produces a different solution in every run. Therefore, we run it ten times. Also, analogous to the vision-based algorithm, we run the genetic algorithm with only the three system parameters p, v and z. We set α and β as constants at 25° and 45° for better comparability. The pressure range for the genetic algorithm is 0.25 to 0.65 bar, analogous to the range of our new setting algorithm.

The results show that the aerodynamic feeding system can find suitable parameter combinations using our newly developed algorithm. We find the first solution using only 180 workpieces. When we let the algorithm search for more solutions, we find five solutions using a total of only 620 workpieces. For comparison, the genetic algorithm needs an average of 500 workpieces to find one solution. Of the ten test runs, the minimum number of workpieces used by the genetic algorithm was 200 and the maximum was 900.

Furthermore, we compared the quality of the solutions found by our new algorithm and the genetic algorithm. For this purpose, we analyzed the trajectories of the ten suitable solutions found by the genetic algorithm and extracted the deviation, the average maximum height, the nozzle pressure and the number of workpieces needed to find a solution (Fig. 6). The investigation showed that using image processing, we can find better solutions faster than with the genetic algorithm. For example, the solutions found using image processing, on average, have a lower deviation. This indicates a more stable orientation process. In addition, the maximum height of the trajectories is lower on average, meaning that the solutions are more efficient, since the workpieces are not lifted unnecessarily high. This is supported by the fact that the nozzle pressure p is also generally lower with the solutions found by our new algorithm, which reduces the consumption of pressurized air.

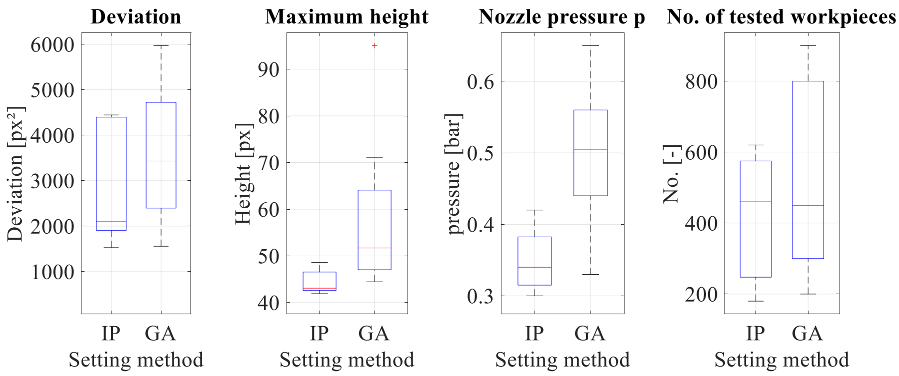

Fig. 6. Deviation, average maximum height, nozzle pressure p and number of tested workpieces using image processing (IP) vs. using the genetic algorithm (GA)

7 Conclusion and Outlook

This work shows that the setting of an aerodynamic part feeding system is possible using digital image processing. Our aim is to increase the quality and efficiency of the feeding process by extracting more information about the workpiece behavior in dependence of the system parameters. Therefore, we implemented a high-speed industrial camera into the feeding system to track the workpieces' trajectories during the orientation process. Based on three trajectory parameters we defined, we developed and evaluated a simple algorithm that can find a suitable solution for the orientation of an exemplary workpiece. A comparison with the genetic algorithm indicates that using our algorithm, we can increase the quality (cf. deviation) and efficiency (cf. maximum height and nozzle pressure) of the orientation process. Also, our algorithm finds more suitable parameter combinations using less workpieces. This indicates that the usage of digital image processing can reduce the setting time and therefore the retooling time of the aerodynamic feeding system, increasing flexibility and machine utilization in an industrial environment.

Nevertheless, we only tested the algorithm with one workpiece and the start values and increments for p, v and z are based on experience. In order to make our new algorithm as robust and universally applicable as the genetic algorithm, in future work, we will carry out further, statistical analyses and use different workpieces as exemplary components. In addition, we will improve the performance and applicability of the image processing algorithm to reduce computation times and extend the flexibility with regard to the workpiece spectrum.

8 Acknowledgements

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