Smart Autonomous Part Displacement System Based on Point Cloud Segmentation

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Abstract: Robotic arms are widely used in manufacturing lines to automate the manipulation of products, providing many advantages, such as increasing production and minimizing labour costs. However, most robotic arms operate in a controlled environment, executing predefined movements. Such a feature prevents the robot arm from working in an environment where multiple product types are in different placements. In this way, this concept paper describes the development of a smart robotic system capable of performing an autonomous pick-and-place task of injected moulded parts from the first conveyor belt to the next, based on its spatial data obtained from a 3D scanner. After obtaining the digital point cloud from the moulded part, the PointNet deep learning model was used to segment and then extract the spatial position of its sprue, which is one of the common structures of any moulded part. Finally, the robotic arm combined with its end-effector can pick up these parts regardless of their shape, orientation, and size. The system proposed is composed of three components, i.e., the IRB 1200 robotic arm from ABB, the PhoXi 3D Scanner from Photoneo, and the two-finger gripper PB-0013 from Gimatic. Moreover, all system components were interconnected using Robot Operating System as middleware. This concept paper discusses the setup and plan for the same.

1. INTRODUCTION

In recent years Industry 4.0 concept has become popular, and many industries are changing their factory process to adapt to this new concept. A few years ago, terms such as Artificial Intelligence (AI), robotics, cloud, Internet of Things (IoT), smart factory were unknown to a large part of society. However, due to the advances in technology, these terms have become part of our activities of daily living (Lasi et al., 2014; Oztemel & Gursev, 2020). Such a term is also known as the fourth industrial revolution, considering that it was a breakthrough in industrial manufacturing (Lasi et al., 2014).

Industry 4.0 raises new meaningful concepts to the industry process, making it more automatized, intelligent, and interconnected. Such features are possible due to terms mentioned before, such as IoT, smart factory, and cloud manufacturing. These concepts enable various parts of a production line to be interconnected controlled virtually (Ghobakhloo, 2020; Roblek et al., 2016). Moreover, industry 4.0 seeks to achieve new advantages compared to the previous concepts, e.g., creation of new business models, integrated and real-time operations, cost reduction, energy savings, optimization of natural resources, and reduction of errors (Bai et al., 2020; Maskuriy et al., 2019; Oláh et al., 2020). In this way, industry 4.0 brings opportunities to the current business model for large and small companies.

Industrial robots are other elements that play a fundamental role in Industry 4.0. More specifically, when it comes to pick-and-place tasks in

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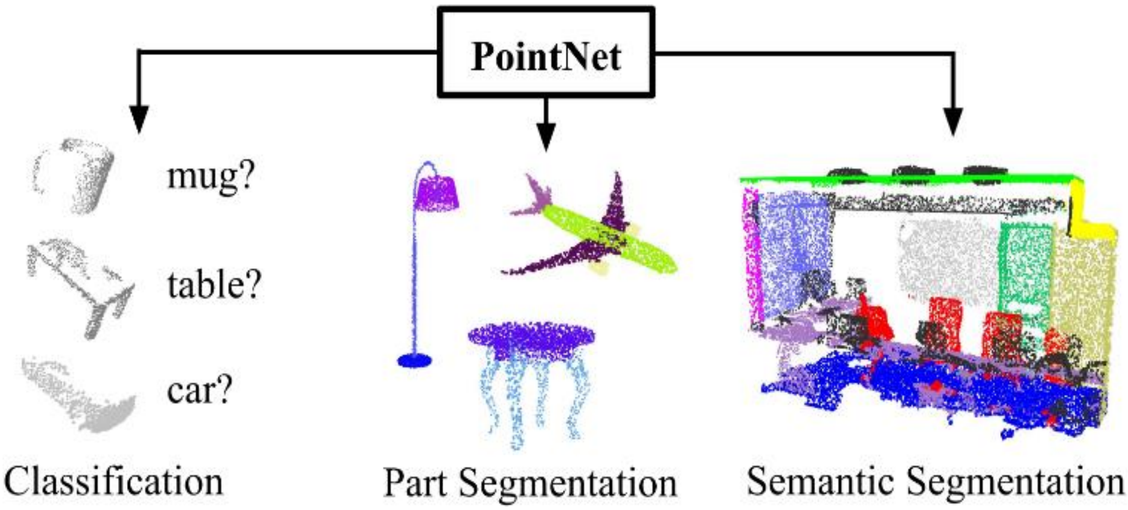

Figure 1: Applications of PointNet. Source: (Qi et al., 2016)

manufacturing lines, our focus is on robotic arms. Robotic arms are widely used in factories to automate the manipulation of products, providing many advantages, such as increasing production and minimizing labour costs (Borkar, 2017; Li et al., 2018; Prabhakar et al., 2021; Ramanathan S et al., 2020). Although they have been present in manufacturing lines since the third industrial revolution, robotic arms are even more robust in Industry 4.0, becoming more intelligent, productive, flexible, versatile, safer, and collaborative (Bahrin et al., 2016). Therefore, robotic arms are becoming a key component in the operation of smart factories as they can complete cooperative tasks intelligently (Ruchiand Goel & Pooja Gupta, 2020).

Pick and place robots have been present in factories for decades due to their precision, high speed, and cost-effectiveness in repetitive tasks compared to manual workers (Chettibi et al., 2004; Perumaal & Jawahar, 2013). When incorporated with Industry 4.0 features, these robots bring many advantages for managing product manufacturing lines, e.g., creating autonomous production lines. However, most robotic arms present in the current factories operate in a controlled environment, executing predefined, repetitive movements and are frequently referred to as ‘pick and place’ robots due to their limited functionality. Such a feature prevents the robot arm from working in conditions where exists multiple product types in different placements. Hence, this presented factory limitation provides the opportunity for developing more intelligent manufacturing line control systems.

In this article, we present the concept of a novel smart robotic system capable of performing an autonomous identification and displacement of injected moulded parts based on their point cloud obtained from a 3D scanner. After getting the point cloud from the moulded part, the PointNet deep learning model is used to extract the coordinates of the part sprue, which is the general structure of any moulded part. Finally, the robotic arm combined with its end-effector must pick up this part regardless of its shape, orientation, and size. The proposed system is part of a manufacturing line, and it is composed of three main components, i.e., the IRB 1200 robotic arm from ABB (ABB, n.d.), the PhoXi 3D Scanner from Photoneo (Photoneo, n.d.), and the PB-0013 pneumatic two-finger gripper from Gimatic (REF). Moreover, all system components were interconnected using Robot Operating System (ROS) as middleware (Willow Garage et al., n.d.).

2. POINTNET NEURAL NETWORK

PointNet is a neural network approach that deals with point clouds. Unlike other methods that require image grids or 3D voxels, the PointNet neural network directly consumes point clouds, i.e., turning the process highly efficient and effective (Qi et al., 2016). Figure 1 shows the three possible applications of the PointNet: classification, part segmentation and semantic segmentation.

Point clouds have many applications, such as the representation of the physical environment inside a virtual one through the data obtained from sensors. Such application is widely seen in autonomous systems that constantly need information about the physical environment.

With the substantial increase in autonomous systems, it becomes crucial to understand how to work with point clouds. Therefore, PointNet neural network has been a breakthrough in computer vision due to its broad number of applications in many areas, such as robotics and autonomous systems.

3. AUTONOMOUS PART IDENTIFICATION AND DISPLACEMENT SYSTEM SETUP

As conveyed before, the autonomous part displacement step of the manufacturing line is composed of three components which are the robotic arm, the pneumatic gripper, and the 3D scanner. These components and their key features are described in the sections below. Furthermore, the IRC5 controller is another fundamental part of this system once it controls external sensors and devices through its I/O ports. Thus, it is also described with more details in the next section.

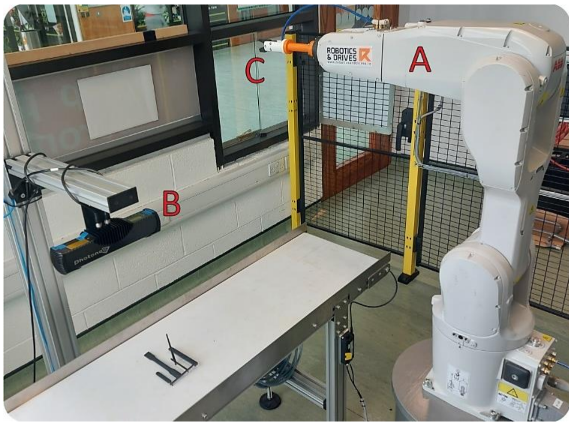

Figure 2: Pick-and-place step components assembled in the manufacturing line. (A) ABB 1200 robotic arm, (B) PhoXi 3D scanner, and (C) PB-0013 pneumatic two-finger gripper.

3.1 IRB1200 Robotic Arm (A)

The IRB 1200 - 5/90 is the robotic arm used in the presented manufacturing line. This robot has a reach of 700 mm and can carry up to 5 kg of payload. Such resources make this robotic arm ideal for a wide range of industrial applications, including the proposed pick and place task of moulded parts described in this article.

3.2 PhoXi 3D Scanner (B)

The PhoXi S 3D Scanner from Photoneo is the component designated for adding computer vision to the manufacturing line, i.e., getting the point cloud of the moulded parts. Such a scanner is ideal for high-resolution, high-precision scanning of static scenes. Its structured light projection technique provides output in the form of point clouds for quick location of any aimed object part.

3.3 PB-0013 Pneumatic Gripper (C)

The Gimatic PB-0013 is the End-Effector which is attached to the robotic arm. Since it is a pneumatic gripper, a compressor combined with a 3/2-way valve is responsible for its actuation. Moreover, this gripper is based on spring return, being normally open with a closing grip torque of 80 N.cm at 6 bar pressure for each jaw.

3.4 IRC5 Compact Controller

The IRC5 compact controller is the core component of the presented system since it controls the I/O ports and connects the robotic arm to ROS scripts. The IRC5 compact controller uses the ABB's RAPID robot programming language. Despite being a high-level programming language, RAPID has some notable features, such as the possibility of connecting it to other languages via socket.

4. METHODOLOGY

4.1 Hardware overview

Figure 3 shows the hardware diagram representing how the system components are interconnected. The core component is the IRC5 compact controller, which its function is to interconnect the system components via I/O ports. Moreover, the controller is connected to the laptop using a Local Area Network (LAN) port, allowing its connection to ROS scripts via socket.

The compressor, the 3/2-way valve, the robotic arm and the end-effector compose the pneumatic side of the system. First, a pneumatic hose connects the compressor to the valve. Next, a second hose connects the valve to a pneumatic input port of the robotic arm. This port allows the airflow inside the robot, which has its pneumatic output port near the robot tip. Finally, the last hose connects this output port to the End-effector, closing the pneumatic circuit. Moreover, a twenty-four volts output port connects the pneumatic valve to the IRC5 compact

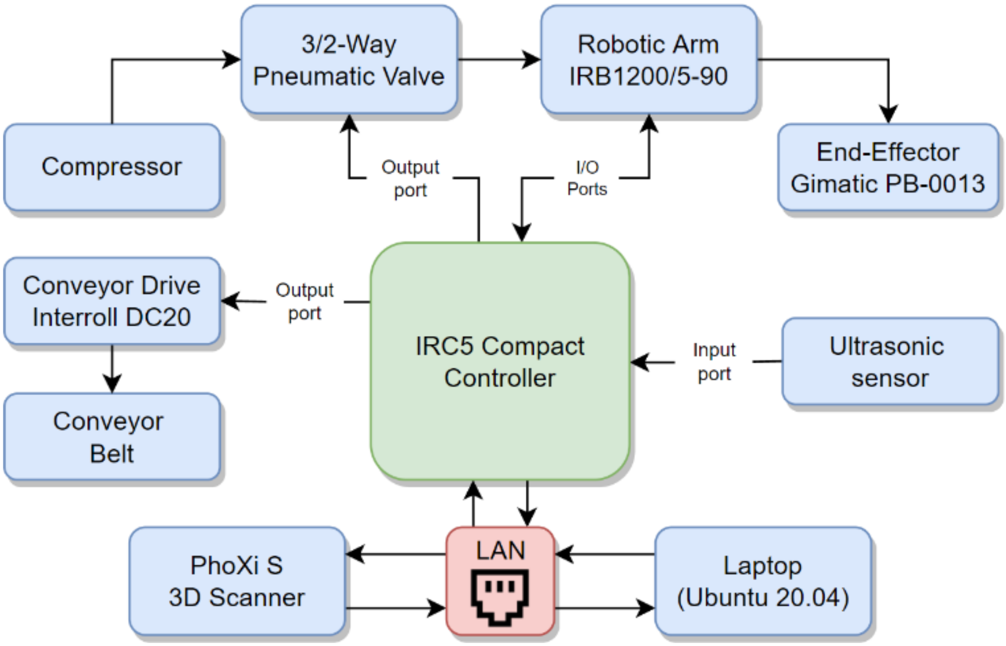

Figure 3: System hardware overview.

controller for switching whether the pressure is released or suppressed.

The conveyor belt has a constant velocity and uses another twenty-four volts output port of the IRC5 compact controller to control whether this conveyor belt is turned on or off. Moreover, an ultrasonic sensor detects moulded parts going through the conveyor belt, i.e., this sensor sends a high-level signal to the controller via its input port every time a moulded part goes through the conveyor belt. On the other hand, the 3d scanner is the last part of the hardware structure and is one of the most fundamental components. The LAN port connects this scanner to the laptop, allowing the execution of its commands via ROS scripts, such as starting a new scan or managing previous scans.

4.2 System control description

This system is being developed for performing on manufacturing lines of moulded parts comes out from injection machines. In this way, it is considered that all objects placed in the conveyor belt have the structure of a moulded part, i.e., sprue, runners, gates, and products. Figure 4 shows two examples of moulded parts and their structure parts.

Figure 5 shows the system flowchart, representing the main steps of the autonomous part displacement task. At the initial stage, the conveyor belt starts and remains on until the ultrasonic sensor detects a moulded part on this conveyor. Next, the conveyor belt stops placing the moulded part below the 3D scanner, getting the object point cloud through its scan. Then, the scanner sends this point cloud to the ROS scripts, starting the displacement stage of the process.

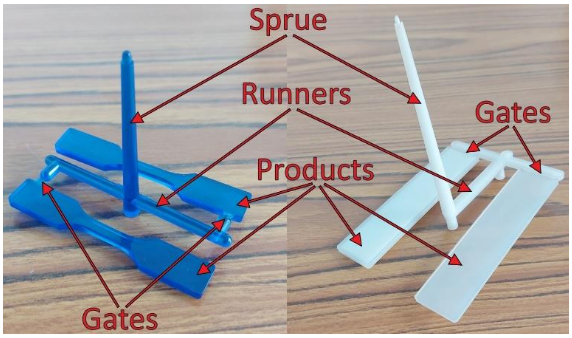

Figure 4: Examples of injected moulded parts, showing their standard components, i.e., sprue, runner, gate and products.

The processing stage consists of the extraction of information from the scanned object. More specifically, the extraction of the sprue coordinates of this moulded part. The first step of this processing consists of segmenting the point cloud into the sprue, runners, gates, and products. In this way, the system uses the PointNet algorithm for realizing this segmentation since it is state-of-the-art in object segmentation, fitting the aims of this work.

The PointNet model training is one of the biggest challenges when dealing with this approach. However, it is intended to create a dataset using the ATOS Core 200 3D scanner, getting a precise and reliable scan of a set of moulded parts. Finally, the PointNet model will be trained and evaluated with point clouds of moulded parts in real-time.

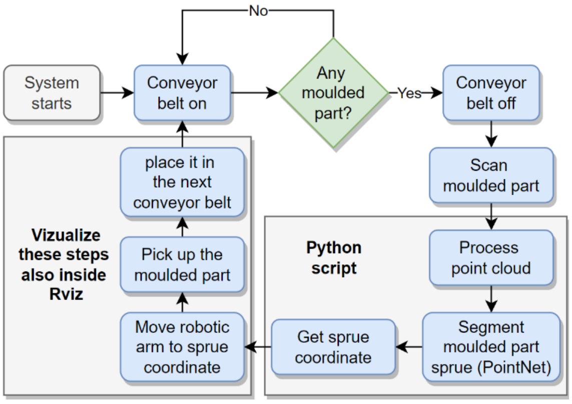

Figure 5: Autonomous pick-and-place process flowchart.

After the system starts to segment and then gets the sprue coordinates, the End-effector attached to the robotic arm must pick the moulded part by its sprue, transferring it to the next conveyor belt or other auxiliary process steps. This stage uses ROS-Industrial and MoveIt [20] packages from ROS to perform the robotic arm navigation. Using ROS-Industrial is possible to control the robotic arm sending the target coordinates. Moreover, MoveIt can manage the navigation process, finding the best route and avoiding collision points with the environment. Finally, all the core steps occurring in the physical layer are also represented digitally inside the Rviz platform, allowing the visualization of these steps in real-time using a computer.

5. DISCUSSION

The development of the proposed system is still ongoing, and preliminary results will be presented soon. Meanwhile, advances have been made in the hardware assembly, interconnecting different system parts, such as controlling the pneumatic valve and the conveyor belt via the I/O ports of the IRC5 compact controller. Furthermore, a digital representation of the robotic arm, the 3D scanner and the conveyor belt were created and then organized inside Rviz, mimicking the physical manufacturing line.

Although the proposed system is being developed for working in a manufacturing line of moulded parts, it is vital to highlight that such an approach might be spread for other scenarios using different objects instead injected moulded parts. Owing to the combination of the PointNet algorithm with 3D vision, it is possible to highly increase the autonomy of industrial processes, such as the gripping of objects placed in a conveyor belt.

6. CONCLUSIONS

The current manuscript presents a conceptual framework for an intelligent system for autonomous part identification and displacement capable of self-adjusting itself according to the injected moulded part displacement on the conveyor belt. This feature ensures the development of a more robust system that is highly sensitive to the object's variations in its shape and dimensions while working autonomously with no or minimum human involvement. Moreover, PointNet networks are state-of-the-art when dealing with point cloud classification and segmentation, making this network a suitable tool for pick-and-place tasks in manufacturing lines.

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REFERENCES

ABB. (n.d.). *IRB-1200-5-90*. Retrieved January 2, 2022, from https://new.abb.com/products/robotics/industrial-robots/irb-1200

Bahrin, M. A. K., Othman, M. F., Azli, N. H. N., & Talib, M. F. (2016). Industry 4.0: A review on industrial automation and robotic. In *Jurnal Teknologi* (Vol. 78, Issues 6–13). https://doi.org/10.11113/jt.v78.9285

Bai, C., Dallasega, P., Orzes, G., & Sarkis, J. (2020). Industry 4.0 technologies assessment: A sustainability perspective. *International Journal of Production Economics*, *229*. https://doi.org/10.1016/j.ijpe.2020.107776

Borkar, V. (2017). Develpoment of Pick and Place Robot for Industrial. *International Research Journal of Engineering and Technology (IRJET)*, *4*(9).

Chettibi, T., Lehtihet, H. E., Haddad, M., & Hanchi, S. (2004). Minimum cost trajectory planning for industrial robots. *European Journal of*

Mechanics, A/Solids, *23*(4). https://doi.org/10.1016/j.euromechsol.2004.02.006

Ghobakhloo, M. (2020). Industry 4.0, digitization, and opportunities for sustainability. In *Journal of Cleaner Production* (Vol. 252). https://doi.org/10.1016/j.jclepro.2019.119869

Lasi, H., Fettke, P., Kemper, H. G., Feld, T., & Hoffmann, M. (2014). Industry 4.0. *Business and Information Systems Engineering*, *6*(4). https://doi.org/10.1007/s12599-014-0334-4

Li, Y., Huang, T., & Chetwynd, D. G. (2018). An approach for smooth trajectory planning of high-speed pick-and-place parallel robots using quintic B-splines. *Mechanism and Machine Theory*, *126*. https://doi.org/10.1016/j.mechmachtheory.2018.04.026

Maskuriy, R., Selamat, A., Ali, K. N., Maresova, P., & Krejcar, O. (2019). Industry 4.0 for the construction industry-How ready is the industry? *Applied Sciences (Switzerland)*, *9*(14). https://doi.org/10.3390/app9142819

Oláh, J., Aburumman, N., Popp, J., Khan, M. A., Haddad, H., & Kitukutha, N. (2020). Impact of industry 4.0 on environmental sustainability. *Sustainability (Switzerland)*, *12*(11). https://doi.org/10.3390/su12114674

Oztemel, E., & Gursev, S. (2020). Literature review of Industry 4.0 and related technologies. In *Journal of Intelligent Manufacturing* (Vol. 31, Issue 1). https://doi.org/10.1007/s10845-018-1433-8

Perumaal, S. S., & Jawahar, N. (2013). Automated trajectory planner of industrial robot for pick-and-place task. *International Journal of Advanced Robotic Systems*, *10*. https://doi.org/10.5772/53940

Photoneo. (n.d.). *PhoXi 3D Scanner S*. Retrieved January 2, 2022, from https://www.photoneo.com/products/phoxi-scan-s/

Prabhakar, M., Paulraj, V., Karthi Kannappan, D. A., Dhanraj, J. A., & Ganapathy, D. (2021). Remote Controlled Pick and Place Robot. *IOP Conference Series: Materials Science and Engineering*, *1012*(1). https://doi.org/10.1088/1757-899x/1012/1/012003

Qi, C. R., Su, H., Mo, K., & Guibas, L. J. (2016). PointNet: Deep Learning on Point Sets for 3D Classification and Segmentation. *CoRR*, *abs/1612.00593*. http://arxiv.org/abs/1612.00593

Ramanathan S, Akash V, Arun Prasad V, & Venkat Rahul M. (2020). Pick and Place Robot for Surface Mounting Devices. *International Research Journal on Advanced Science Hub*, *2*(8). https://doi.org/10.47392/irjash.2020.97

Roblek, V., Meško, M., & Krapež, A. (2016). A Complex View of Industry 4.0. *SAGE Open*, *6*(2). https://doi.org/10.1177/2158244016653987

Ruchiand Goel, & Pooja Gupta. (2020). Robotics and Industry 4.0. In A. Nayyar Anand and Kumar (Ed.), *A Roadmap to Industry 4.0: Smart Production, Sharp Business and Sustainable Development* (pp. 157–169). Springer International Publishing. https://doi.org/10.1007/978-3-030-14544-6_9

Willow Garage, Stanford Artificial Intelligence Laboratory, & Open Robotics. (n.d.). *ROS - Robot Operating System*. Retrieved January 2, 2022, from https://www.ros.org/