Design of VR application in detection line based on industrial robot for optical routers

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Abstract: In this study, an automated detection line for optical routers is designed. The output of the production line is evaluated and optimized on the basis of the product lifecycle management (PLM) data. The VR technology is used to build a 3D virtual reality scene to realize the layout design and planning of industry, while providing functions such as employee training, technological process roaming and interactive experience. Thus, a set of representative transformation schemes for flexible manufacturing cells can be obtained.

1. Introduction
Many parts in the production process of optical routers such as manual insertion, assembly, test, and packing are still subject to manual operation nowadays. A few enterprises that have carried out automation only realize semi-automation on some nodes of the production line. So the situation of relying on manpower has not been significantly improved.

The terminal products in the optoelectronic industry have a short life cycle, and their automated production lines are difficult to be transformed. However, digital production and flexible manufacturing are penetrating the optoelectronic industry, which brings new hope for the transformation and upgrading of the industry[1]. Optical router is the representative of smart home terminal products. Its product models are updated quickly, and its manufacturing life cycle is between half a year and one year, resulting in a greater difficulty in the automation of production lines. For the automation, better flexible production characteristics are required, and the production line needs to meet the production requirements for at least 3-5 models of products.

The manufacturing industry is transforming and upgrading to Industry 4.0. Digital production and flexible manufacturing are gradually replacing traditional manufacturing[2]. The optoelectronic industry cannot make its advantages in this round of transformation and upgrading. The primary causes are that the product life cycle of intelligent terminal products such as domestic optical routers, mobile phones, and tablets are constantly shortened, and that the complex structure and high cost of production line make it difficult to transform to automation improvement [3].

Taking the optical router as an example, this study proposes a demonstrative solution for the upgrading of its production line. The production line nodes are placed in the product lifecycle management (PLM) for output planning and prediction, so as to maximize the output. In addition, VR is used to present the transformation scheme to assist in completing production layout and logistics planning. The information related to the production line operation is dynamically obtained to know the changes in product models and batches in time. On this basis, the optimal output within the unit time is measured, and the design of production processes is scientifically evaluated. As a result, the processes
can be optimized in a timely manner and unnecessary losses caused by design errors in the actual building of production line can be avoided. This study will serve as a reference for the production line transformation, including the building of new digital processes and the simulation of the entire manufacturing process in the optoelectronics industry.

2. Research method and technical characteristics

This study explores the ways of implementing target by integrating the technologies of digital factory and VR, shows up as an interdisciplinary research characteristics.

2.1 Production line design based on PLM

The traditional scheme of production line transformation combines text and drawings, which cannot present the dynamic changes of the production line, especially when the output is complex and there are multiple logistics. It relies on the estimation of production personnel based on their experience, and cannot acquire scientific and accurate data. Using dynamic technologies and system approaches based on digital factory modeling and simulation analysis, this study reproduces the equipment layout in workshops and the simulating optimization of production lines in VR scene, thus dynamically managing the entire operating process throughout the product life cycle. The node on the production line is no longer an independent unit. A variety of factors such as production takt, logistics transport, equipment in idle, and failures affect each other. If the product models and output requirements change, the system then simulates new production planning schemes and supports the comparison of different schemes, thereby helping decision-makers make scientific judgments and choices.

2.2 Flexible manufacturing cell

The optoelectronic terminal products are featured with short product life cycle and mass production. The automation of the optoelectronic product line requires the typical characteristics of flexible manufacturing, which specialize in the response speed of production lines and supply chains. The production line should be highly inclusive for different models of products and output requirements[4]. At present, the automated production lines are less popularized among manufacturers of optical routers. Although some production lines have realized the node automation, they are difficult to undertake the production of multiple models of products. In this study, the automation is made for the complete machine detection of optical routers. Industrial robots are introduced to replace labor, detection procedures are optimized, and detection bases and clamps are modified and redesigned, making the production line a flexible detection unit that is able to detect at least 3 to 5 kinds of routers.

2.3 Algorithmic program for output prediction

Applying the VR technology to the building of digital factories not only show the unique advantages in visual display and evaluation[5], but also has a broad space for development in terms of the integration and interaction of information[6-7]. Being strong capabilities in data processing and program development, the Unity3D-based VR providing reliable technical support for the real-time data acquisition and processing, with the optimized output predication of digital factories[8-9]. According to the task decomposition in the complete machine detection process of optical routers, this study links the data involved in the logistic unit, detection unit, and equipment unit to form an algorithmic program for output prediction. This program can calculate the output reflection through the change of any data variable, and display such changes intuitively in the VR scene by model running. By carrying out pilot runs with different variable parameters, this program can predict the status such as material starving and stacking on the production line, and formulate emergency plans such as equipment failure.

2.4 Bio-IK (Bionics-based inverse kinematics solution)

The ABB120 industrial robot used in this study is a kinematic mechanism with 6 degrees of freedom. In order to obtain the optimal solution for robot track planning and motion planning, the Bio-IK is an algorithmic tool especially suitable for kinematics solution of industrial robot. It avoids the mathematical problems of traditional IK solvers, and it expands well even for higher degrees of freedom.
This algorithm plans the optimal motion track of the end effector by avoiding obstacles, and introduces the concept of virtual shortest path. Thus, the manipulator’s joints are provided with the optimal configuration, minimizing the energy consumption of robots.

3. PLM-based design of automated production line

After several times of field visit in factories, this study obtained the technological processes of optical router’s production lines and key data of each station node. The design philosophy based on PLM is followed throughout the building of digital factory[10-11].

3.1 Process planning

The production processes of optical routers are shown in Figure 1, including circuit board manufacturing, program burning, wifi shielding detection, final assembly, pre-delivery detection, etc. In this study, only the optical power detection process and the CHECK detection process in the complete machine detection are involved. Industrial robots are introduced to the production line to replace manpower, and all processes are finished through programmed operation, thereby improving the output of production lines.

3.2 Workshop layout planning

To reduce unnecessary indirect costs in the production process, the workshop layout planning (Figure 2) takes into full account problems in the actual production such as material transportation costs and idle equipment resource. The size of the detection base and the conveyor is adjusted according to the arm span of the selected industrial robots.

![Figure 1. Schematic of optical router’s production processes.](image1)

![Figure 2. Layout of optical router’s Automated production line.](image2)
3.3 Flexible manufacturing cell design
To ensure the detection line is available to 3-5 models of products, the structure of detection base is redesigned. Within the arm span of ABB120 industrial robots, each detection base is designed with 1*8 stations. At present, routers of different models and brands are mainly distinguished from each other in shape and size as well as power-on self-test time. Therefore, the designed pneumatic clamp can make the manufacturing cell flexible. The pneumatic clamp models as shown in Figure 3 is installed on parallel-aligned tubular detection bases, the span in both x and y directions can be adjusted, so that the clamp can grip routers of different batches and models.

3.4 Optimization of production processes and output of the production line
The positions of the detection base and the conveyor are arranged in the principle of a single-line flow, so as to shorten the conveying distance as much as possible and avoid collision of robot arms due to torsion within the arm span. The work takt of the robot arm is optimized to shorten the material waiting time possible and avoid blocking, so that the robot can keep working efficiently.

4. Application of VR technology
The use of VR technology to present the digital factory design has been increasingly favored in the industry. This multi-disciplinary application can not only demonstrate the preliminary planning of the digital factory, but extend to the online operation and maintenance of the factory and production lines.

4.1 Modeling, rendering and scene building
Equipment on the actual production line is simulated in the VR scene(Figure 4). UG NX and Solidworks are used for modelling, 3Dmax is used for model simplification and grid layout, and 3D max is used for rendering. During the building of Unity scene, elements such as mapping and lighting effect are used to get better visual effect.

4.2 Realization of key mechanism kinematics
The router detection line is renovated as a fully automated and unmanned production line. The assembled routers are conveyed to the detection base 1(Figure 2). After receiving the signal, the industrial robot grabs a router and places it on the locking position for detection. After the detection, the qualified products and defective products are separated via signal instructions. Detection base 2 has similar work flows with detection base 1. The kinematic mechanisms on the production line is orderly arranged in the VR scene to ensure a closely linked and smooth production.

4.3 UI design
The UI interface of the VR scene is simple, conveying information clearly, logically and completely. The UI interfaces presented in the scene include item channel selection interface (Figure 5), map guide interface, video display interface, detection base board interface, fault alarm interface, etc.

4.4 Realization of interactive design
The interactive module provides an interactive experience between the user and the device. The Bio-IK
(bionics-based inverse kinetics, figure 6) algorithm is used to realize the interaction between the industrial robot and the user. HTC-VIVE[12] controller is used to control the ABB robot to drag through the end effector, and the robot can do actions of 6 degrees of freedom.

**Figure 5.** Item channel selection interface

**Figure 6.** Bio-IK(bionics-based inverse kinetics)

The user uses the controller to trigger the crystal block in the front of the demonstrator to view the information related to I/O configuration and I/O channel.

4.5 Realization of output prediction algorithm

According to the process arrangement of the router detection line in the research objectives, a prediction algorithm for the daily output of a single production line is formed in the operation simulation. Nine variables are involved, including the conveying rate of three conveyors, the operating speed of two industrial robots, the probability of defective products, etc. The specific algorithm is described as follows:

The time used for “robot QR code scanning + router incoming (placing router on the detection base) + router outgoing (taking router out of the detection base)” is assumed as $t_0$ seconds, the time for the conveyor to convey a router as $t_1$ seconds, and the time for detection and reset of the detection base as $t_2$ seconds. On the single production line, a single station only uses a single robot and a single conveyor. If multiple detection bases are used, they can detect simultaneously, so the average detention time is $t_2/n$. If there is a low value among $t_0$, $t_1$ and $t_2/n$, i.e. a short detection time, the station will not have the waiting routers, like the “Cask effect”[13]. The larger one among the three values can be adjusted to accelerate the production.

$$\text{Production} = F(M) \cdot (M= \text{Min}(t_0, t_1, t_2/n)) \quad (1)$$

One day has $60 \times 60 \times 24 = 86,400$ seconds, so the Production = 86,400/M (units/day)

Assuming $t_3$ is the time delay caused by failure, maintenance and other factors, we can obtain that:

$$\text{Production} = (86400-t_3)/M \cdot (M=\text{Min}(t_0, t_1, t_2/n)) \quad (2)$$

We adjust the working unit parameters of the automated production line by the simulation software, and make statistics every time based on the one-hour data. The obtained data is shown as follows.

| Average working time of robot T0(s) | Average working time of conveyor T1(s) | Average working time of detection base T2(s) | Other factors Delay time T3(s) | Acceptability Q(%) | Production (unit/day) |
|-----------------------------------|--------------------------------------|-------------------------------------------|-------------------------------|-------------------|----------------------|
| 1                                 | 8.3                                  | 16.8                                      | 35                            | 1,996             | 99.3                 | 5,024                |
| 2                                 | 12.3                                 | 10.2                                      | 40                            | 2,243             | 99.4                 | 6,841                |
| 3                                 | 6.2                                  | 5.6                                       | 50                            | 2,108             | 99.1                 | 13,504               |
| 4                                 | 8.9                                  | 7.2                                       | 45                            | 1,895             | 99.3                 | 9,483                |
| 5                                 | 11.5                                 | 11.5                                      | 60                            | 1,466             | 99.5                 | 7,339                |
| 6                                 | 22                                   | 19.8                                      | 52                            | 922               | 99.8                 | 3,836                |
Table 2 Daily output of the production line with a fixed conveyor speed.

| Average working time of robot T0(s) | Average working time of conveyor T1(s) | Average working time of detection base T2(s) | Other factors Delay time T3(s) | Acceptability Q(%) | Production (unit/day) |
|------------------------------------|---------------------------------------|---------------------------------------------|-------------------------------|-------------------|----------------------|
| 1                                  | 8.3                                   | 35                                          | 2,022                         | 99.2              | 7,028                |
| 2                                  | 12.3                                  | 40                                          | 1,834                         | 99.7              | 6,853                |
| 3                                  | 6.2                                   | 50                                          | 1,566                         | 98.9              | 7,103                |
| 4                                  | 8.9                                   | 45                                          | 1,744                         | 99.1              | 7,056                |
| 5                                  | 11.5                                  | 60                                          | 2,566                         | 99.1              | 6,986                |
| 6                                  | 22                                    | 52                                          | 859                           | 99.8              | 3,824                |

Table 3 Daily output of the production line with a fixed robot working speed.

| Average working time of robot T0(s) | Average working time of conveyor T1(s) | Average working time of detection base T2(s) | Other factors Delay time T3(s) | Acceptability Q(%) | Production (unit/day) |
|------------------------------------|---------------------------------------|---------------------------------------------|-------------------------------|-------------------|----------------------|
| 1                                  | 15                                    | 16.8                                        | 35                            | 2,453             | 99.6                | 7,014                |
| 2                                  | 15                                    | 10.2                                        | 40                            | 2,412             | 99.8                | 5,627                |
| 3                                  | 15                                    | 5.8                                         | 50                            | 1,867             | 98.7                | 5,589                |
| 4                                  | 15                                    | 7.1                                         | 45                            | 2,121             | 99.4                | 5,564                |
| 5                                  | 15                                    | 11.2                                        | 60                            | 1,422             | 99.5                | 5,667                |
| 6                                  | 15                                    | 20.5                                        | 52                            | 1,754             | 98.8                | 3,614                |

We can calculate it backwards and verify it with the virtual software simulation statistics. When the production output is 8000 units/day, and the time delay is 1 hour, i.e., $t_3 = 3600$ seconds, we can obtain that $M = 10.35$ seconds. The ideal robot working speed is about 0.29m/s, the ideal conveyor speed is about 0.2m/s, the ideal production incoming interval is 6s, and the ideal detection time of the detection base is 82.8s. We input these parameters into the virtual software and carry out a 1-hour detection statistic. We get a daily output of $330 \times 24 = 7920$ units / day, which is approximate to the results calculated by the theoretical formula.

5. Conclusions

PLM’s data based on product life cycle is the core of a digital factory. VR technology is used to complete the digital factory planning, and the model-based building of digital factory is successfully implemented. The scheme feasibility is verified through virtual simulation, and the production processes are determined and optimized based on data and models.

The production process is simulated to simulate the output by Unity. A program is written to set the adjustment values of different variables, and the optimal solution for the output is obtained in a statistical manner. When the output target is determined, we can calculate backward the values of variables to adjust equipment parameters of the production line in reality.

The flexible manufacturing cell is realized by the design of the pneumatic clamp. Multiple brands and models can be compatible with each other on the same production line. This has certain referential significance for the production line transformation of other types of products in the optoelectronic industry.

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