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Using IoT and Mobile Robots to Model and Analyze Work Processes with Process Mining Techniques

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Abstract

This research explores the practical application of Internet of Things (IoT) technology using mobile robots to collect and store data from their surroundings, including personal information from wearables on cloud systems. It then employs process mining techniques to analyze these raw data. There are three main processes. These processes are 1) Understanding the fundamental concepts of IoT, developing mobile robots, and learning about process mining principles. 2) Creating a system for storing data or event logs generated by IoT devices and mobile robots. 3) Analyzing the collected data using process mining techniques. Through this method, we can learn in-depth about the activities of an individual user. Therefore, the proposed method is an extension of the IoT system for increasing the performance of decision support systems and automated decision systems in real-world applications. Furthermore, the research showcases how services, particularly robots, can be accessed through the Fuzzy Miner model. These methods have practical applications in real-world scenarios, such as human-robot collaboration, inventory management, service tracking, supply chain management, retail, logistics, healthcare, transportation, agriculture, and manufacturing.

Keywords: Process Mining, Internet of Things, Robotics, Microcontrollers, RFID

1. Introduction

There are 19.8 million Internet of Things (IoT) devices in operation, surpassing the count of traditional non-IoT devices like smartphones, tablets, PCs, and landline phones. This figure is projected to skyrocket to 30 billion by 2025 (1). These IoT devices are adapted to gathering data from their surroundings, including personal information from wearables. The intersection of wearable technology with IoT has resulted in a deluge of data, highlighting the immense potential of these devices. This data, comprising environmental and personal information, can be harnessed for various benefits, particularly by applying process mining techniques to analyze real-world processes using event logs. In this study, we've conducted simulations with an IoT dataset, employing a mobile robot controlled by an STM32 microcontroller. This robot serves as a representative service user (like a patient) accessing services at different points within a healthcare facility or hospital, called "stations." ESP32 microcontrollers control these stations. As service usage data is generated, it's promptly stored and transmitted to an IoT station in real-time. The data is securely stored on the cloud system NETPIE.io, an IoT cloud-based platform-as-a-service, illustrated in Figure 1.

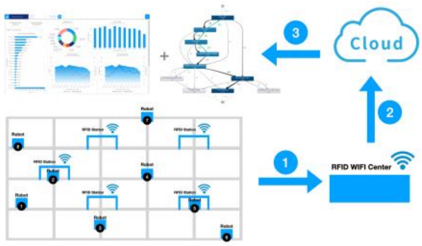


Figure 1 Working model of IoT mobile robot and process mining

The event logs play a crucial role in analyzing the system's operations. We employ process mining techniques to uncover process patterns within the system, specifically utilizing the Fuzzy Miner algorithm (2). This approach helps us visualize and understand the intricacies of the processes, as illustrated in Figure 2.

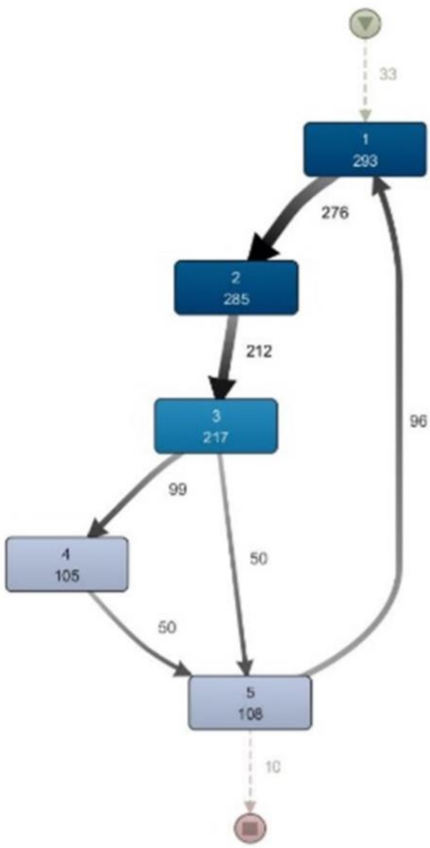


Figure 2 Fuzzy Miner model

By integrating process mining with IoT technology, they are generating simulation data that simulates service usage scenarios. This data is a powerful tool to uncover hidden inefficiencies within processes, enabling organizations to make more informed decisions and enhance operational efficiency. The granular, real-time data from IoT devices is pivotal in this transformation. It empowers organizations to gain a deeper and more accurate understanding of their processes, leading to data-driven improvements and higher operational excellence. The potential impact of the Internet of Things extends far beyond this research. It can revolutionize numerous facets of our lives, from our homes and workplaces to entire cities and industries. IoT's ability to connect devices and facilitate data-driven decision-making allows automation, optimization, and improved experiences for individuals and businesses.

The research is structured around three primary objectives: 1) Understanding the Fundamentals: This involves delving into the core principles of the Internet of Things (IoT), the design and evolution of mobile robots, and the underlying concepts of process mining 2) Data Storage Design: The second objective is focused on designing an effective system for storing data or event logs generated by both mobile robots and IoT devices. 3) Data Analysis: The final objective revolves around utilizing process mining techniques to analyze the accumulated data, drawing valuable insights and patterns from it.

2. Theory and Related Research

Mobile robots play a significant role in education, particularly in the interdisciplinary approach known as STEM (Science, Technology, Engineering, and Mathematics) (3). These educational robots can be broadly categorized into two types: those designed for educational purposes and those intended for research applications. Within these categories, a wide range of commercial and non-commercial models are available. Commercial educational robot models, such as Lego Mindstorms EV3, Ozobot, phero, Edison Robot, mBot (Makeblock), Thymio II, E-puck, Khepera IV, microMVP, and others, are readily accessible for teaching and learning (4). On the other hand, non-commercial models like Aeris, Colias, Arduino-based Robots, MarXbot, Rice r-one, and more cater to educational and research needs

(4). In our study, we concentrate on the development of small line-following robots.

These robots consist of two primary components: a mechanism for movement using wheels and a sensor for detecting lines on the surface (5). To control and manage these robots, we employ an STM32 microcontroller, serving as the central processing unit for creating and developing mobile robots (6).

An RFID (Radio Frequency Identification) data reading station is a technology that utilizes radio waves for the wireless exchange of data between an RFID reader (referred to as the RFID Station) and an RFID card tag. The RFID card tag is a compact device equipped with microchips and antennas, which can be affixed to or embedded within objects or products (7). This technology is seamlessly integrated with the Internet of Things (IoT) (8), operating within the NETPIE.io system to read data from the RFID station. In our research, we have developed and implemented an RFID signal reading station, known as the RFID station, controlled by an ESP32 microcontroller system (9). The ESP32 is a widely adopted wireless system-on-chip (SoC) created by Espressif Systems, tailored for many applications. It boasts built-in Wi-Fi and Bluetooth connectivity and a robust processor core, making it a popular choice due to its adaptability, wireless capabilities, and extensive development support. The ESP32 remains a prevalent choice within the IoT community for projects necessitating wireless connectivity and embedded computing capabilities.

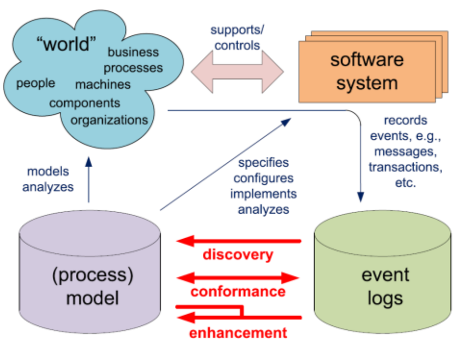


Figure 3 The Overview of Process Mining (13)

Process mining is a vital tool of data science to uncover, validate, and enhance operational processes in Figure 3. Its primary objective is to unearth, monitor, and refine real-world processes, rather than relying on assumed ones, by gleaning insights from event logs readily available within contemporary systems. This methodology establishes vital connections between actual processes and the associated data, bridging the gap between reality and process models, as depicted in Figure 4 (13). In practical terms, organizations can harness process mining to extract valuable insights from their information systems' log data. This, in turn, facilitates a comprehensive understanding of operational performance, uncovering bottlenecks and areas ripe for improvement. Process mining adopts a data-driven approach to process optimization, enabling decision-makers to remain objective when allocating resources to enhance existing processes (13)(14)(15). In essence, process mining is a technique that involves extracting event log data from various enterprise systems and subjecting it to analysis to gain a deeper understanding of how to enhance diverse processes.

Event logs (13) serve as the foundational data input for the process mining technique. Think of these event logs as the digital footprints left behind during business operations. They comprise raw transaction data collected and harmonized from various systems, forming the basis for in-depth process analysis. Each event record in these logs provides valuable insights into the tasks, processes, and work carried out within the team or business unit under examination. These logs are like a trail of digital breadcrumbs that illuminate the journey of business operations.

For an event log to be effective in process mining, it should contain a minimum of three essential properties:

1. CaseID: This property is a unique identifier for tracking any business object or transaction within the event logs. Each CaseID corresponds to a distinct instance or case being analyzed.

2. Activity: Activity records within the event log describe the specific tasks or actions performed as part of a business process. Examples of activities include "approve," "request," "process," or any other relevant action.

3. Timestamps: Timestamps are critical as they provide precise information about when each recorded activity occurred. This

chronological data helps establish the process's sequence and timing of events.

These three properties, CaseID, Activity, and Timestamps are fundamental in allowing process mining techniques to uncover patterns, relationships, and insights within the event log data.

Case id	Event id	Properties				
		Timestamp	Activity	Resource	Cost	...
1	35654423	30-12-2010:11.02	register request	Pete	50	...
	35654424	31-12-2010:10.06	examine thoroughly	Sue	400	...
	35654425	05-01-2011:15.12	check ticket	Mike	100	...
	35654426	06-01-2011:11.18	decide	Sara	200	...
	35654427	07-01-2011:14.24	reject request	Pete	200	...
2	35654483	30-12-2010:11.32	register request	Mike	50	...
	35654485	30-12-2010:12.12	check ticket	Mike	100	...
	35654487	30-12-2010:14.16	examine casually	Pete	400	...
	35654488	05-01-2011:11.22	decide	Sara	200	...
	35654489	08-01-2011:12.05	pay compensation	Ellen	200	...
3	35654521	30-12-2010:14.32	register request	Pete	50	...
	35654522	30-12-2010:15.06	examine casually	Mike	400	...
	35654524	30-12-2010:16.34	check ticket	Ellen	100	...
	35654525	06-01-2011:09.18	decide	Sara	200	...
	35654526	06-01-2011:12.18	reinitiate request	Sara	200	...
	35654527	06-01-2011:13.06	examine thoroughly	Sean	400	...
	35654530	08-01-2011:11.43	check ticket	Pete	100	...
	35654531	09-01-2011:09.55	decide	Sara	200	...
	35654533	15-01-2011:10.45	pay compensation	Ellen	200	...
4	35654641	06-01-2011:15.02	register request	Pete	50	...
	35654643	07-01-2011:12.06	check ticket	Mike	100	...
	35654644	08-01-2011:14.43	examine thoroughly	Sean	400	...
	35654645	09-01-2011:12.02	decide	Sara	200	...
	35654647	12-01-2011:15.44	reject request	Ellen	200	...
...	...	...	...	...	...	...

Figure 4 Example of event logs (13)

3. Research Process

The research process involves five detailed steps: 1. Creation and development of mobile robots. In this initial step, the focus is on designing and building mobile robots. 2. Create and develop RFID stations and IoT stations. Next, RFID stations and IoT stations are created and developed to facilitate data collection and communication. 3. Design the walking path of a mobile robot. This step involves planning and configuring mobile robots' routes as they navigate their environment. 4. Collect data from mobile robots. Once the mobile robots are operational and the stations are set up, data is collected from them as they move along their designated paths. 5. Analyze data by process mining techniques to create a Fuzzy miner model. The final step involves applying process mining techniques to the collected data. The goal is to create a Fuzzy Miner model to reveal process patterns and insights.

These steps collectively form the research process, enabling the study to achieve its objectives related to mobile robots, RFID stations, IoT stations, and process mining.

3.1 Create and Develop a Mobile Robot

Following a thorough investigation of small mobile robots suitable for educational purposes, this research employs a set of five units that have been purposefully designed. These units are engineered to navigate using two wheels, one independently moving wheel, and a central plastic core that maintains stability. Notably, the wheels responsible for controlling movement are strategically positioned at the robot's midpoint, granting it a pivotal turning point at its center. For the control system, each of these mobile robots is equipped with an STM32 microcontroller board (referred to as POP-32). To power these robots, 2-cell lithium polymer batteries are utilized, providing a voltage output of 7.4V. Central to the functionality of these small mobile robots is the incorporation of RFID technology, resulting in RFID Mobile Robots; as depicted in Figure 5, RFID technology integration enhances the robots' capabilities and opens up various possibilities for their applications within the research context.

Figure 5 Components of the RFID Mobile Robot

Upon completing the creation and development process, the result is the result is the RFID Mobile Robot, which is depicted in Figure 6. The subsequent phase involves the development of a program to control the robot's movement along the predefined path. To accomplish this, the Arduino IDE Software (10) is employed as the programming environment, allowing for creating program code using the C/C++ programming language. This programming step is pivotal in enabling precise control and navigation of the RFID Mobile Robot along its designated route. The example of the code is shown in Figure 7.

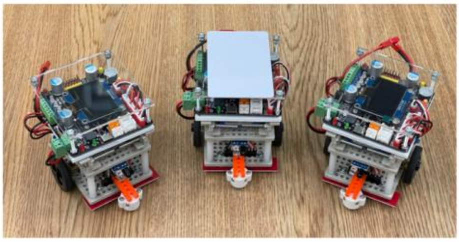
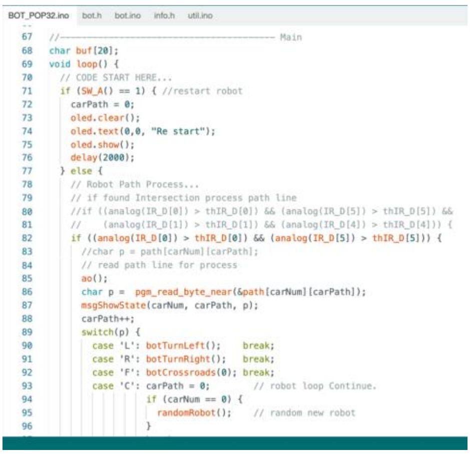


Figure 6 RFID Mobile Robot



BOT_POP32.ino bot.h bot.ino info.h util.ino

```
//--------------------------------------- Main
char buf[20];
void loop() {
  // CODE START HERE...
  if (SW_A() == 1) { //restart robot
    carPath = 0;
    oled.clear();
    oled.text(0,0, "Re start");
    oled.show();
    delay(2000);
  } else {
    // Robot Path Process...
    // if found Intersection process path line
    //if ((analog(IR_D[0]) > thIR_D[0]) && (analog(IR_D[5]) > thIR_D[5]) &&
    //    (analog(IR_D[1]) > thIR_D[1]) && (analog(IR_D[4]) > thIR_D[4])) {
    if ((analog(IR_D[0]) > thIR_D[0]) && (analog(IR_D[5]) > thIR_D[5])) {
      //char p = path[carNum][carPath];
      // read path line for process
      ao();
      char p =  pgm_read_byte_near(&path[carNum][carPath]);
      msgShowState(carNum, carPath, p);
      carPath++;
      switch(p) {
        case 'L': botTurnLeft();    break;
        case 'R': botTurnRight();   break;
        case 'F': botCrossroads(0); break;
        case 'C': carPath = 0;         // robot loop Continue.
                  if (carNum == 0) {
                    randomRobot();    // random new robot
                  }
```

Figure 7 Code example

3.2 Create and Develop RFID Stations and IoT Stations

In the creation and development of both the RFID card reading station and the IoT data transmission component, an ESP32 microcontroller processor is utilized in both systems. The initial system involves connecting this processor to the RFID card reading module, referred to as the RFID Card Reading Station, commonly known as the RFID Station. The critical components and the station's physical configuration are illustrated in Figure 9

To highlight the scope of this research, a total of five RFID card reading stations were constructed. A dedicated program was also developed to facilitate precise control of the robot's movement along a predefined path. These combined efforts aim to enhance the capabilities and functionality of the RFID Mobile Robots within the research framework.

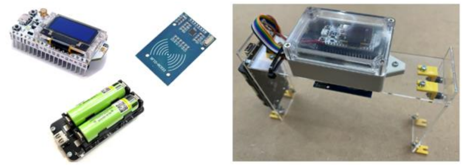


Figure 8 RFID Station equipment and station

The IoT data transmission station, known as the IoT station, plays a pivotal role in the research. It serves as the receiver of data originating from the RFID stations in Figure 8, employing a Wi-Fi connection facilitated by the ESP-NOW protocol for seamless data transmission between stations. To facilitate this data exchange, the IoT station uses two interconnected processors via UART (RS-232) communication. One of these processors receives data from the RFID Station and then forwards it to the second processor, responsible for transmitting the data to its destination. The IoT station is also responsible for storing the received data at NETPIE.io, ensuring that the data is securely archived and accessible for further analysis and utilization within the research framework.

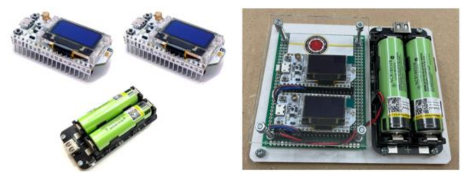


Figure 9 RFID IoT devices and stations

3.3 Design the Walking Path of a Mobile Robot

In this research, the mobile robots are programmed to navigate by tracking a line that leads them to RFID stations, each representing a medical access point. Specifically, five designated medical service stations serve a distinct purpose in healthcare. These stations are as follows:

1. Service Entry Point: This is the initial entry point into the medical service system.

2. History Reviews: The station reviews the patient's medical history.

3. Doctor Examinations: The station is allocated for doctor examinations.

4. Payments: This station handles the financial aspect of the medical service.

5. Medical Receptions: Here, patients can collect prescribed medications.

The locations of these medical service stations have been thoughtfully determined, and their positions are defined within the walking field for the robots. The layout of these stations and the robot's path are visually represented in Figure 10 The walking field spans approximately 120x120 centimeters in width and length, with a surrounding edge measuring about 5 centimeters. This setup provides the spatial context within which the mobile robots operate as they navigate the healthcare service process so that data can be imported.

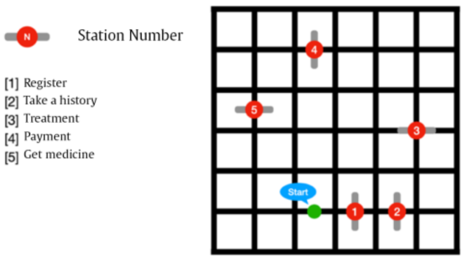


Figure 10 Schematic installation of service stations 1 to 5.

There are a total of 5 robot walking plans. The experiment encompasses five distinct robot walking plans, each characterized by its unique sequence of stations. These walking plans are outlined as follows:

1) Type 1: [1]-[2]-[3]-[4]-[5]
2) Type 2: [1]-[2]-[3]-[5]
3) Type 3: [1]-[2]-[3]-[4]
4) Type 4: [1]-[2]-[3]
5) Type 5: [1]-[2]

These five predefined walking plans serve as the foundation for the experiment, guiding the robots through various sequences of stations to evaluate and collect data on their interactions with the RFID and IoT stations.

3.4 Collecting Data from Mobile Robots

The experiment involves the utilization of five robots and 33 RFID cards, symbolizing the service recipients. These RFID cards have been randomly affixed to the robots. The experiment is structured so that each robot is set to navigate the predefined path individually. As they traverse the path, they complete five distinct path patterns.

A random service time is introduced at each station along the path before the robot proceeds. This simulated service time falls within 2 to 5 seconds, mirroring the real-world service durations at each station. During this time, the RFID station reads the RFID card affixed to the robot, extracting the RFID card number. This information is then transmitted to the IoT station and stored within the system.

Figure 11 provides a visual representation of the format of data acquired from each station. This data format is a crucial component of the experiment, capturing vital information about the interaction between the robots and the stations, including RFID card numbers and service times.

1. time (timestamp): date and time the data was recorded

2. a_Station: RFID station number where the robot enters or exits the station.

3. b_FRID: RFID number read at a_Station.

4. c_InOut: number 1 (in) or 0 (out) from station a_Station

time	a_Station	b_RFIDID	c_InOut
2023/03/17 09:56:40	1	F220C82E	1
2023/03/17 09:56:46	1	F220C82E	0
2023/03/17 09:56:47	2	F220C82E	1
2023/03/17 09:57:05	2	F220C82E	0
2023/03/17 09:57:06	3	F220C82E	1
2023/03/17 09:57:06	3	F220C82E	0
2023/03/17 09:57:12	4	F220C82E	1
2023/03/17 09:57:18	4	F220C82E	0

Figure 11 Cloud data storage format

The experiment was rigorously conducted by repeating it ten times, involving all 33 RFID cards. To collect data on the movement of the robots, a dedicated experimental environment was set up, as illustrated in Figure 12 Within this controlled environment, the experiment was systematically carried out multiple times.

After each experiment iteration, the data obtained was extracted from the NETPIE.io system (11), which serves as the data repository. Subsequently, this data was securely stored on a computer, as visualized in Figure 13 This data collection and storage process was pivotal in ensuring that the experiment's results were well-documented and could be effectively analyzed and evaluated.

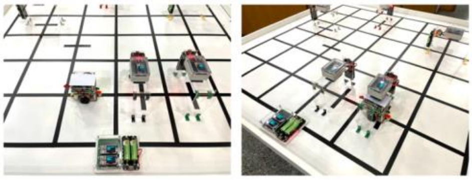


Figure 12 Environment of the experiment

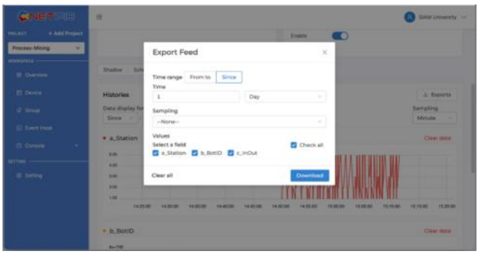


Figure 13 Backing up data from the Internet (11)

3.5 Analysis of Data with Process Mining Techniques

Before the data obtained from the experiment were analyzed using process mining techniques with the Disco software, data must first be prepared in a format that can be used with the Disco software. The data must include at least three attributes: 1. Timestamp 2. Activity and 3. Case ID so that data can be imported for further analysis using process mining techniques.

3.5.1 Preparing the Input Data

Before importing data into Disco software (12) for analysis, it is essential to perform data cleansing. This process involves several key steps:

1. Error Checking: First, thoroughly review the data to identify and rectify any errors or inconsistencies. This includes addressing missing or erroneous values, duplicates, and outliers.

2. Data Organization: Organize the data into structured files with suitable extensions like Excel or CSV. This organized format ensures that the data is readily compatible with Disco software.

3. Defining Attributes: Upon importing the data into Disco, the three required attributes—Timestamp, Activity, and Case ID—must be explicitly defined. This step is crucial for Disco to recognize and interpret the data correctly.

Figure 14 illustrates the outcome of importing the prepared and cleansed data into Disco software. The software's interface displays the data, making it accessible for further analysis using process mining techniques.

	time	a_Station	b_RFIDID	c_InOut
1	2023/03/17 09:56:40	1	F220C82E	1
2	2023/03/17 09:56:46	1	F220C82E	0
3	2023/03/17 09:56:47	2	F220C82E	1
4	2023/03/17 09:57:05	2	F220C82E	0
5	2023/03/17 09:57:06	3	F220C82E	1
6	2023/03/17 09:57:06	3	F220C82E	0
7	2023/03/17 09:57:12	4	F220C82E	1
8	2023/03/17 09:57:18	4	F220C82E	0
9	2023/03/17 09:57:25	5	F220C82E	1
10	2023/03/17 09:57:29	5	F220C82E	0
11	2023/03/17 09:57:48	1	72E3391A	1
12	2023/03/17 09:58:25	1	72E3391A	0
13	2023/03/17 09:58:25	2	72E3391A	1
14	2023/03/17 09:58:25	2	72E3391A	0
15	2023/03/17 09:58:25	3	72E3391A	1
16	2023/03/17 09:58:25	3	72E3391A	0

Figure 14 Labeling data with Disco software (12)

3.5.2 Process Analysis Using Process Mining Techniques

The Disco software simplifies the process of process mining and model creation. It automates the steps involved and generates process discovery results using the fuzzy miner algorithm, ultimately producing a fuzzy miner model. The software showcases two crucial aspects: frequency and performance (time).

Frequency (Figure 15): The software visualizes the frequency of activities or events within the process. This information allows users to understand the sequence and occurrence of actions, for example, from point 1 to point 2 with thickness of the line depends on the amount of path. (Figure 15A), providing insights into the process's most Process 2 was the most used at 586 times. (Figure 15B), and the least common step, Process 4, was used the least 208 times. (Figure 15C) and the intensity of the color in the box is Number of activities taking place. Therefore, a comprehensive and in-depth examination of process data is possible with fuzzy mining in frequency view, which offers insightful information about process for improvement. By taking into account the frequency-based correlations between tasks, as shown in Figure 15.

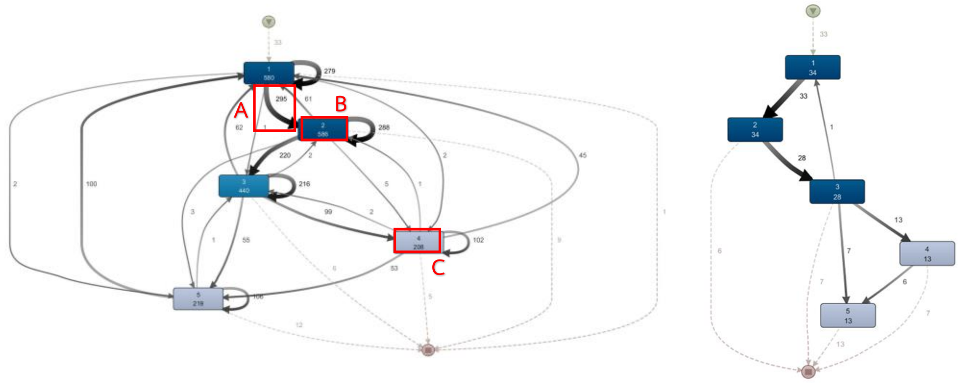


Figure 15 Fuzzy Miner Model (Frequency)

Performance (Time) (Figure 16): Disco software offers insights into the performance aspect of the process, including time-related data. This could include the duration of each activity, and bottlenecks are because there is a time-consuming process coming in from every part. (Figure 16A), and delays are because the longest time is 26 hours with thickness of the line depends on the amount of length of time. (Figure 16B). Understanding the time dimension of the process is crucial for optimizing efficiency and resource allocation.

In summary, fuzzy mining from the time-performance perspective expands its advantages and provides insightful information about the parts of business processes that are related to time, as shown in Figure 16. This data is critical for streamlining processes, maximizing the use of available resources.

With data imported into Disco software, users can comprehensively view the entire process and its continuity. The generated models and visualizations aid in identifying patterns, improving processes, and making data-driven decisions based on the analysis.

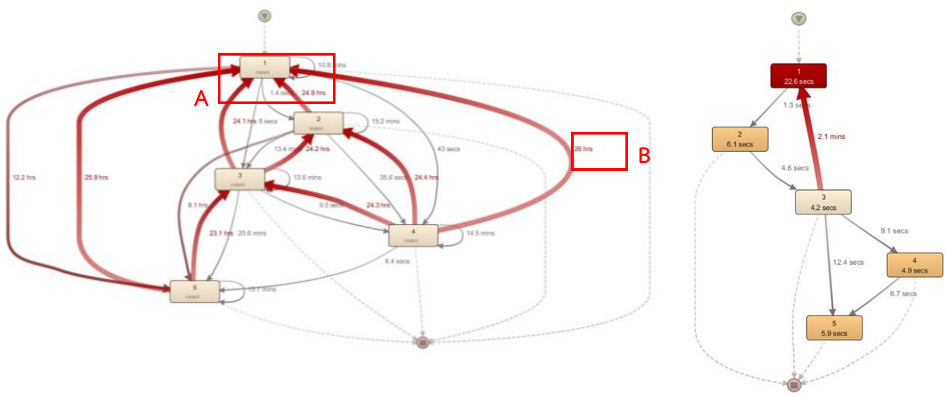


Figure 16 Fuzzy Miner Model (Performance)

4. Summary of Research

This research shows a practical application of the Internet of Things (IoT) integrated with mobile robots, enabling data collection, storage in a cloud system, and subsequent analysis using process mining techniques. The study is divided into three key components:

1. Creation of Educational Mobile Robots: The research explores the development of mobile robots tailored for educational purposes. These robots are then combined with RFID tags to function as agents for accessing medical services.

2. Development of RFID Data Collection Devices: Data collection devices

equipped with RFID or RFID Reader systems are created to represent various medical service points, such as entry points, history reviews, doctor examinations, etc.

3. Data Analysis Using Process Mining: The collected data is analyzed using process mining techniques, enabling insights into process patterns.

The mobile robot experiment demonstrates the robots' capability to navigate predefined routes. In each iteration of the investigation, each robot follows a different path, ultimately completing all five routes and repeating five new paths until all RFID cards are utilized. The data collected from the sending and receiving station systems is stored as event logs in the cloud. Post-experiment, this data is successfully retrieved, saved in the cloud, and stored on a computer for analysis.

The research illustrates how IoT devices and mobile robots can be effectively applied and emphasizes the importance of collecting data from these devices in the required format. Subsequently, event logs are analyzed using process mining techniques, specifically the Fuzzy miner model. The methods showcased in this study have practical applications across various domains, including human-robot collaboration, inventory management, service tracking, supply chain management, retail, logistics, healthcare, transportation, agriculture, and manufacturing. It can be concluded that the research performance of exploring, creating data, and analysis is according to our purpose and can be applied to other applications.

5. Suggestions for Future Work

However, the research also identifies several challenges that require attention in future work:

1. Robot Path Deviations: There is an issue with robots deviating from their designated paths, leading to incomplete data transmission to the cloud system.

2. Internet Connection Stability: The IoT data transmission system faces challenges with internet connectivity, potentially leading to data loss.

3. Power Supply Reliability: The power supply's instability impacts the system's overall stability and performance.

Addressing these challenges in future research will be crucial to enhancing the robustness and reliability of the IoT and mobile robot system.

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Declaration of conflicting interests

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