

Cloud and Edge Computing Based Movable 3D Dynamic Image Recognition and Analysis Layer System for Remote Biological Laboratory

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Abstract—Animal experiments are very important for the validation of pharmaceutical and biotech-related products. To reduce the risk of the affection corresponding to the accuracy and safety of the experiment, this research provide the remote image recognition and analysis based on cloud computing for system management and local edge computing with artificial intelligence integrated with the movable platform. According to the dynamic image recognition, the 3D position of the unmanned movable platform could be located calibrated. Based on the proposed layer structure, the cages or boxes of the animals could be monitored and surround viewed. The local edge computing device on the movable platform could complete the 3D dynamic image recognition of the animals corresponding to the position recognition based on the artificial intelligence service. In addition, the artificial intelligence service could be managed and updated automatically through the network based on the remote cloud with less manual operation cost.

Keywords—Artificial Intelligence, Image Recognition, Edge Computing, Cloud Computing, Unmanned System

I. INTRODUCTION

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Recently, considering the safety and side effect control to human, medicines or cosmetic such as drug or vaccination still require the animal experiment in the biological laboratory. However, to reduce the risk of environmental and manual operation harm, such as the possibility of COVID-19 virus leaked from laboratory [16,17], strictly standardized operation processes for operators and laboratory researchers are defined [1].

In addition, the factors from external environment should not affect the experimental content and results including the air pollution and condition in the laboratory, cleanliness of animal bait and cage, temperature and humidity, etc. For the purpose, the operators should reduce the frequency of in and out the laboratory. The changing of the temperature and humidity, air, etc., should be under control [2]. However, the situation and state of each experimental animal should also be watched and monitored. To measure the long term physiological state of individual animal is required. Therefore,

based on some remote sensors and robots, continuous measurement and management of the biological laboratory could be the available solution.

The Internet of Things (IoT) including the sensors and network communication are generally used in the supply chain. By using the various sensors, the air pollution related to some specific components or PM 2.5 materials could be detected [3]. The state of aerosols in the air can be measured. Some applications or systems also develop the remote wireless livestock identification based on the radio frequency identification (RFID). The related information can be exchanged with the remote server automatically [4]. Through the intelligent system with the IoT sensors such as temperature and humidity sensors, the ventilation fan or air conditioner can turn on corresponding to the measure results [5]. These recent generally used systems and services prove the feasibility of IoT applications in environmental measurement.

However, in addition to the environmental measurement, the monitoring of the experimental animals is also needed. Considering the mobility and available activity space of the individual experimental animal, the sensors for dynamically measuring and monitoring the animal cannot be placed in a fixed position. In addition, due to some side effects, the activity states of experimental animals are not the same. If the animal wears multiple sensors for position emulation or physiological signal measurement, the additional sensors would make the experimental animals more uncomfortable. Furthermore, the changes in appearance of laboratory animals may not be measured by the IoT sensors. Hence, to provide the surround view monitoring with less interaction between animals and operators or sensors are needed.

In this research, we propose the Cloud and Edge Computing Based Movable 3D Dynamic Image Recognition and Analysis Layer System for Remote Biological Laboratory. Based on the proposed system, 1) within the limited space or room of biological laboratory, the layer system can move by following the on demand defined program and route. Each animal observation box can be monitored by the proposed layer system with the camera and IoT sensors. Without on site manual operation, the remote monitoring and management is

available with less environmental impact. 2) The endpoint camera and IoT sensors could capture the images and detect the environment data with surround view or 360 degree detection. The experimental animals can be observed in detail. 3) Based on the various IoT sensors, researchers could obtain more information related to the tested animal and the environment information of the laboratory. According to the sensors, the 3D scan is possible for animal monitoring. It also means that the 3D data can be further managed and analyzed by the artificial intelligence algorithm such as positioning, identification, or 3D modularizing. Researchers could have more various viewpoints about the tests and animals.

The rest of this research is organized as follows. Section 2 provides the related works. The proposed system is given in section 3. The implementation and verifications are shown in section 4. Section 5 gives the conclusion.

II. RELATED WORKS

Recently, many researches about artificial intelligence for object identification and segmentation in the image were proposed [6]. Through the network and artificial intelligence algorithms, the object included in the captured image is segmented. Then, the object can be recognized or identified individually [7]. Some researches use the artificial intelligence algorithm to differentiate and identify the faces. Based on the identification results, the management of operators and security could be enhanced [8]. According to the features, each object or face can be recognized. Since there are various databases with huge amount of object images and digital files, the artificial intelligence algorithm can quickly recognize each object offline or online. The name and position of the object or face included in the original image can be located and segmented. However, through the single camera, the image could only present the single view of the object. The opposite side of the object is not available. In addition, the distance between the object and camera, called depth, is also missed. When the experience or test should be measured by multi-view directions, single fixed position camera cannot provide the useful information.

However, due to the space limitation of the biological laboratory and experimental animal box, or the placement of microbial Petri Dish, cameras with the fixed positions cannot capture the surround image of the experiences. In addition, with multiple cameras, the power consumption and cost also increase. Furthermore, too many IoT sensors and cameras would also affect the laboratory environment stabilities such as temperature, noise, air, etc. Therefore, to appropriately design the platform with the IoT sensors and cameras as less as possible for the experimental animal observation and monitoring is an important issue.

In addition to the biological experience observation, to identify the experimental animals is also important. Since there are many experimental animals for various biological tests, to identify and differentiate each animal in the laboratory is needed. Some applications for identification were proposed based on the radio frequency identification system (RFID). Recently, the RFID system is also generally

used in the supply chain or personal services [9-10]. Users can use an RFID reader to induct and read the information recorded in the RFID tags. Each RFID tag is assigned a unique ID numbers. Therefore, when the RFID tag is used or tagged to an animal, this unique ID numbers can be used instead of the animal. However, the RFID tag would be affected by the moisture or liquid. To tag the RFID tag to the animal would also cause the damage. Inflammation or discomfort of experimental animals would also affect the accuracy of biological experience results. Therefore, if the non-contact devices or sensors could be used for the experimental animal observation, the affection of the laboratory environment due to the manual operation and IoT devices can be reduced. In addition to the observation of the experiences, the position of each experimental animal box should be recorded and located correctly. Today, iBeacon is the popular position service used indoor according to the signal from the embedded device [11].

Artificial intelligence algorithms are generally used for object segmentation and recognition in the images. Based on the training data, the artificial intelligence algorithm could find the object features of the data. Different objects can be represented or described as the different feature sequences. By using the heterogeneous data, the accuracy of data identification and classification can be enhanced. In other words, observing the experience results via using artificial intelligence service could be the possible solution for reducing the manual operation. To enhance the performance of the A.I. service, graphic processing unit (GPU) is required. However, to provide high speed computing for intelligence service would cost a lot for hardware implementation. In addition to the A.I. services for experience observation and recognition, to observe the various experiences within limited time, the observation order or sequence should be also defined.

Since there are multiple positions for experience observation, similar to the travel salesman problem (TSP) [12], to on demand arrange the route for visiting each position is possible. Recently, the TSP is proved as the NP-hard problem. Many algorithms try to solve the problem by providing the optimal solution. Genetic algorithm which follows the concept of "survival of the fittest" is also the popular algorithm for the optimal solution searching [13,14]. By representing, the possible solution is presented as an individual chromosome. The visiting order for each position is shown as a single gene of the chromosome. Through suitable crossover and mutation methods, the order of the genes would be changed. After generation by generation, the chromosome with better fitness value would survive.

To provide A.I. services, algorithm computing, and data management, computing resource is required. Considering the dynamic computing workload from the algorithms and A.I. services, cloud computing is also generally used [14,15]. The cloud computing platform could dynamic arrange the virtual computing resource for computing and storage. In addition, the virtual machines based on the cloud could be rapidly and repeatedly established. Hence, most data management and artificial intelligence computing can provide good

performance based on cloud computing platform. However, all the data transferred through the network would cause the transmission delay and network congested. Therefore, edge computing device at local side for reducing the data is required. Considering the limited cost and space, to develop the edge computing device meeting the demand of data reducing, even tiny intelligence service and observation with less cost is an important issue.

III. PROPOSED SYSTEM

Considering the management and environment of the biology laboratory, the animal boxes or multiple microbial Petri Dish are on demand placed. Therefore, the regular observation of each experimental animal or Petri Dish can be arranged in advance corresponding to the routes and positions. Suppose that the corresponding positions in the laboratory are all on demand defined. Therefore, to observe and monitor the experiences, unmanned vehicle or platform could be the acceptable solution for reducing the manual operation in the laboratory. In this section, the movable unmanned layer system for 3D dynamic image recognition and analysis is introduced. In addition, the algorithm for the shortest path of the observation route for unmanned layer system is given.

A. The movable unmanned layer system with Edge Computing Device

In this research, to observe the animals and experiences, we propose the movable unmanned layer system for 3D dynamic image recognition and analysis which including the unmanned vehicle platform and the image recognition artificial intelligence system. First, considering the three-dimensional space, the observation sensors or devices should be able to relocate to various positions. Second, the platform should be movable. Hence, the layer system including multiple cantilevers and movable platform could be the solution. In this research, there are at least two cantilevers are used. There is a height level or cantilever is used for adjusting height of the depth level or cantilever. The depth cantilever connects horizontally to the vertical height cantilever through the motor joint for changing the height on the height cantilever. In addition, the horizontal depth cantilever can also change the front extending length by the motor joint. At the end of the horizontal depth cantilever, a portable and rotatable stage is attached. The structure of movable unmanned layer system can be shown as follows.

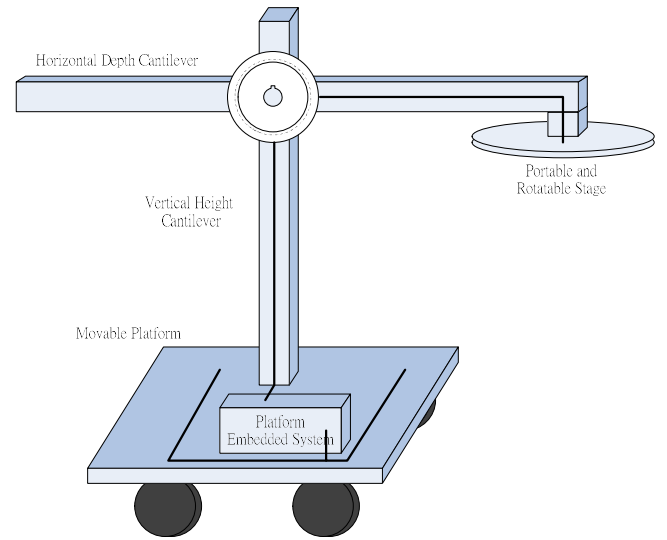


Figure 1. The structure of the proposed movable unmanned layer system

According to Figure 1, since the height of the horizontal depth cantilever can be changed corresponding to the position of animal boxes or the Petri Dish, the observation or monitoring of experiences can be layering or scanned layer by layer.

Based on the portable stage, various IoT devices could be embedded or placed for experience observation and monitoring. The IoT devices could connect to the network through the wireless access point (AP) for data transmission, such as ESP32 with WiFi or Bluetooth connection. Instead of the ESP32, the IoT sensors could also connect to embedded system of the movable platform through the wire signal line. In other words, by on demand installation about the drivers or programs, various IoT sensors can be ported to stage and provide the corresponding services or data to the proposed system. In addition, the stage is round and can be rotated around the center of circle. In this research the camera is placed or ported on the rotatable stage. Therefore, when the camera is used to observe the animal or microbial Petri Dish, the camera can record the almost 360-degree surround view data or image. Of course, any other IoT sensors could also detect the experimental objects by rotate the stage. Hence, by porting different IoT sensors or devices, the experimental animal or microbial Petri Dish could be observed with various perspectives.

In addition to the movement control, the local image processing for experience observation is also considered. Consider the power supply only depends on the movable unmanned layer system, the embedded system can only provide the limited computing resource for the image and object recognition. In this research, the image recognition artificial intelligence system based on the edge computing device, the embedded system, is also proposed. According to the artificial intelligence with graphic processing unit (GPU), the images from the camera on the stage can be processed locally. Since the animals in the laboratory are known in advance, the image training for artificial intelligence can be on demand completed.

B. Algorithm of the observation route based on Cloud Computing

Since the positions of the animal boxes or multiple microbial Petri Dish are defined in advance, each position of box or Petri Dish for observation can be represented as (x_i, y_i, z_i) where i indicates the i^{th} observation position. In addition to individual observation position, the unmanned layer system also can be represented as (x_u, y_u, z_u) where (x_u, y_u) is used to indicate the position of the plane coordinates in the laboratory. Then, the value, z_u , indicates the height of the horizontal depth cantilever. Considering the placement of animal boxes or multiple microbial Petri Dish, there would be a depth distance between the end of depth cantilever or the rotatable stage. Furthermore, the distance between the stage and different boxes or Petri Dish would be various. Therefore, in addition to (x_u, y_u, z_u) , the depth value, d_u , for extending the depth cantilever should be considered. Therefore, the position of the observed experience can be presented as (x_i, y_i, z_i) for animal box or Petri Dish and (x_u, y_u, z_u, d_u) for unmanned layer system.

When the unmanned layer system locates itself at the specific position (x_u, y_u, z_u) , the relative position between the observed object, such as box or Petri Dish, and the portable stage of the unmanned layer system could be presented as follows:

$$\begin{aligned} x_r &= \begin{cases} 0 & x_u = x_i \\ d_u & x_u \neq x_i \end{cases} \\ y_r &= \begin{cases} 0 & y_u = y_i \\ d_u & y_u \neq y_i \end{cases} \\ z_u &= z_i \end{aligned} \quad \text{eq.(1)}$$

where $((x_r = 0) \cap (y_r = 0)) = \emptyset$. It means that when the unmanned layer system would extend the depth cantilever, at least two coordinates would be the same: the same height in z -axis with the same in x -axis or y -axis. Following figure could present the relative position. Z -axis indicates the height of the observed object and the depth cantilever. Therefore, suppose that the height of the observed object and the depth cantilever is already the same, $z_u = z_A$, for further movement. If the observed object is box A, it means that the position on y -axis would be the same: $y_u = y_A$. Therefore, the relative position difference between x_u and x_A can be shown as:

$$x_r = d_u = |x_u - x_A| \quad \text{eq.(2-1)}$$

Therefore, the depth cantilever should be extended according to the value, d_u to locate the portable stage at the correct position. Similar to the box A, the position of box B on x -axis would be the same: $x_u = x_B$. Therefore, the relative position difference between y_u and y_B can be shown as:

$$y_r = d_u = |y_u - y_B| \quad \text{eq.(2-2)}$$

Hence, by on demand defining the position according to three-dimensional space coordinates, the proposed unmanned layer system could find and observe the experience box or Petri Dish individually.

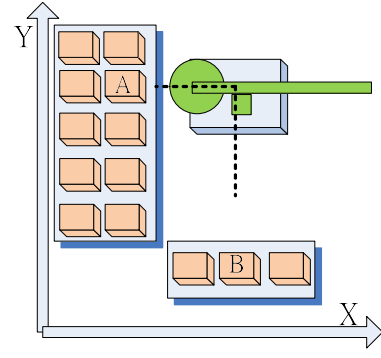


Figure 2. The top-view of the laboratory with unmanned layer system and observed objects.

Suppose that there are multiple boxes or Petri Dish for experience observation. Corresponding to each experience, the time period for observation could be different. Therefore, considering the movement and position of the proposed unmanned layer system, to observe different experiences with various positions should be managed and arranged. In this research, the genetic algorithm is used for the optimal route of the experience observation.

Due to the limitation of the hardware, the delay time for extending the depth cantilever is required. Suppose that the extending speed is v_d . According to the equation 2-1 or 2-2, the delay time, t_d , for extending could be represented as follow:

$$t_d = \frac{d_u}{v_d}$$

Assume that the time spending for observation at the specific box or Petri Dish is defined as t_{ob} . Hence, a single i^{th} observation mission would cause total time spending as follows:

$$t_{0(i)} = 2 \times t_{d(i)} + t_{ob(i)} \quad \text{eq.(3)}$$

There are total M observation missions which can be shown as $\{m_1, m_2, \dots, m_i \mid 1 \leq i \leq M\}$. The movement of the unmanned layer system indicates that the system would move from previous mission to the current mission. In other words, there exists addition delay time for system moving from one position to another. In addition, the movement corresponding to the height, z_i , the raising time is required. Considering the movement of the unmanned layer system, the time spending for reposition on the plane can be shown as follows:

$$t_{m(i,i-1)} = \frac{\sqrt{(x_i - x_{i-1})^2 + (y_i - y_{i-1})^2}}{v_s} + \frac{z_i - z_{i-1}}{v_h} \quad \text{eq.(4)}$$

where t_m indicates the time spending for reposition, v_s indicates the moving speed on plane(ground) of unmanned layer system and v_h indicates the raising speed of the vertical cantilever.

Finally, the object function of the route for multiple observation missions including the moving time spending and observation time spending can be presented as follows:

$$\min T = \sum_{i=1}^M (t_{m(i,i-1)} + t_{0(i)}) \quad \text{eq.(5)}$$

where $t_{m(1,0)}$ indicates the moving time spending from the unmanned layer system initial position to the first observation position.

However, due to the limitations or processing of the various experiences, some specific observations should be completed

or done at the specific time. In other words, if the observation cannot be completed in time, the observation mission is useless or failed. Suppose that the required observation time corresponding to the i^{th} observation mission of experience is defined as $t_{rq(i)}$. Then, the time limitation or subsection can be defined as

$$t_{rq(i)} = \begin{cases} 0 & \text{no limitation} \\ \text{dd: hh: mm} & \text{on demand given time} \end{cases}$$

If the initial time for the unmanned layer system moving is defined as t_{ini} . Then, the object function should be subject to:

$$t_{rq(i)} \text{ is later than } (t_{ini} + \sum_{n=1}^i (t_{m(i,n-1)} + t_{o(i)})) \quad \text{eq.(6)}$$

In this research, to schedule the route of the unmanned layer system for visiting and observing the experiences, the genetic algorithm is used.

Suppose that there are total M observation missions. Therefore, the chromosome can be randomly created with various orders when initialization. Each observation mission could be represented as the single number. One example of the created chromosome with 7 numbers of missions can be presented as follows:

2	6	4	1	7	5	3
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which indicates the order of observation route is: $2 \rightarrow 6 \rightarrow 4 \rightarrow 1 \rightarrow 7 \rightarrow 5 \rightarrow 3$. According to the genetic algorithm, there will be total p chromosomes created initially as the population for evolution. After initial representation, the crossover for data exchanging between chromosomes is used. In this research, we use partially mapped crossover (PMX) for crossover. Two different chromosomes are selected as the parent chromosomes. Based on the PMX, the genes from each parent chromosome can be exchanged with another parent chromosome. Following figure shows the exchanging of the genes. Due to the PMX method, the genes of the chromosome, $4 \rightarrow 1 \rightarrow 7$, are selected and exchanged with the genes of chromosome 2, $1 \rightarrow 2 \rightarrow 5$. Therefore, two new offspring chromosomes are created after crossover. However, there would be some genes repeatedly appearing in one chromosome. Hence, to fix the repeat genes is required. In this research, when the repeat genes appear, it also means that some genes are disappeared due to the crossover. The new appeared genes from the crossover will be reserved. In opposition, the repeat genes located in the original position will be fixed. These genes will be replaced by the missed genes. For example, the gene number 2 appears repeatedly after crossover. Then, the first gene with the same number will be replaced by the missing number 4. In addition, the gene with the repeat number 5 will be replaced as number 7. Finally, all the genes with individual number will be completed and included.

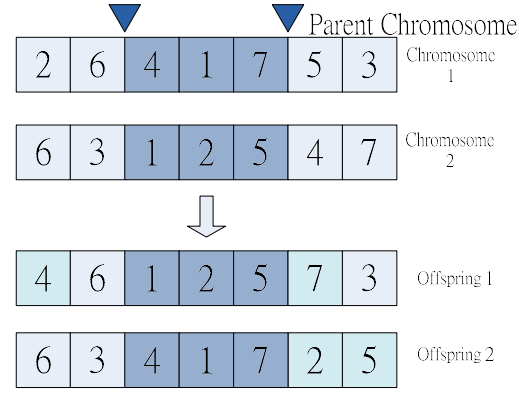


Figure 3. The PMX crossover results of the genetic algorithm

Therefore, the order of the chromosome changes with various numbers. In other words, various possible solutions for searching the optimal solution are created. Finally, according to the objective function, the fitness value corresponding to individual chromosome can be evaluated. The chromosomes of the current generation and new offspring chromosomes are sorted together according to the fitness value. Only the chromosome with the rank below the population value can survive. Therefore, the found the possible solution will convergence to the optimal solution.

IV. SYSTEM IMPLEMENTATION AND VERIFICATION

When the unmanned layer system relocates itself to another, the position calibration is required at each location. Instead of the wireless signal for location estimation, in this research, the QR code is used for calibration. There are multiple QR codes pasted on the specific position corresponding to the plane coordinates. Therefore, every time when the unmanned layer system relocate at a new position, the camera embedded into the platform embedded system will capture the QR code within the on demand limited vision. In other words, when the QR code is located within the vision, it means that the position error is lower than the given threshold. In addition, according to the information of QR code, the unmanned layer system could also complete the calibration corresponding to the current position. Hence, the unmanned layer system can continuously calibrate itself when relocate itself from one position to another. In addition to the plane coordinates, the height displacement is also calibrated by the QR code. In other words, after movement from one position to another, the unmanned layer system could always calibrate itself. Therefore, no matter moving for a new mission of experience observation or power charging at the initial position, position calibration corresponding to the different QR code is always used for checking the current position of the unmanned layer system. Following flowchart presents the position calibration of unmanned layer system.

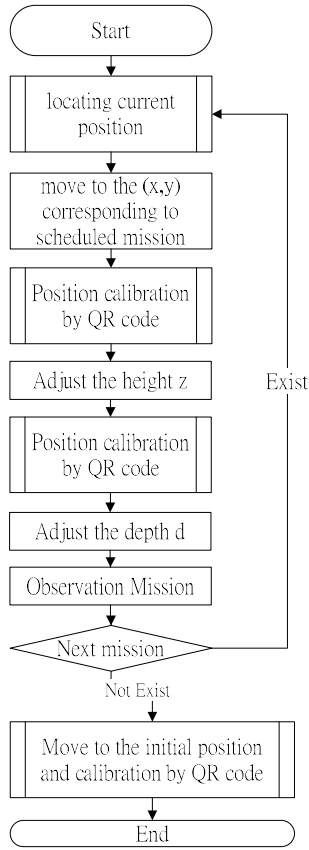


Figure 4. The flowchart related to the position calibration of unmanned layer system.

Since there are multiple observation missions, to provide the observation results corresponding to the assigned time is important. Suppose the observation mission is the i^{th} mission included in the chromosome as the individual gene. It means that the i^{th} mission would be located as the position (x_i, y_i, z_i) corresponding to the specific experience box or Petri Dish. In other words, the complete image or video record during the time period t can be presented as follows:

$$\begin{aligned} \text{ImageReport}_i &= \bigcup_t \text{Image}_i(t) \\ &= \bigcup_t \text{Image}_{\text{record}}((x_i, y_i, z_i, d_i), t) \end{aligned}$$

In this research, different IoT sensing devices and modules are available for portable and rotatable stage of unmanned layer system. By the on demand defined connection of unmanned layer system, the data from the IoT sensors can be transmitted to the unmanned layer system platform embedded system which is used as the edge computing device. Considering the computing requirements for image processing and recognition, the edge computing device as the platform embedded system in this research is nVIDIA Jetson Nano with artificial intelligence applications. Based on the Jetson Nano with 128-core Graphic Processing Unit (GPU), image recognition and segment can be done locally. Furthermore, with the input/output interfaces such as GPIO and I2C, etc., the IoT sensors could connect to

the Jetson Nano directly for data transmission. Hence, the data transmitted from unmanned layer system to the remote server can be reduced. In addition, the image recognition and computer program based on Jetson Nano could provide the local artificial intelligence services for experience observation. For example, by combining with temperature sensor AMG 8831 8×8 and Camera Module V2.1, the object can be recognition with its temperature. All information could be merged as the single image or digital data for further management locally. Therefore, the more detail information of the observation could be obtained with less data transmission through the network.

In this research, to verify the genetic algorithm for searching the optimal route corresponding to the dynamic and various observations, the genetic algorithm is used. Suppose that there are 10 different observation positions with random observation time around 2 minutes in each computing mission. All the observed positions are randomly located within 10 meters width and length space with 2.5 meters in height. Assume that the unmanned layer system could move 10 cm per second ($v_s=10\text{cm/sec}$) on the ground. The raising speed, v_h , of the vertical height cantilever is set as 4cm/sec. In addition, the extending speed, v_d , is also set as 4cm/sec for the vertical height cantilever extension.

Following figures present the fund optimal solutions for various corresponding scenarios. In scenario, the standard optimal solution searching for visiting 10 observation positions are given. The i^{th} position (x_i, y_i, z_i) is set as the $(i \times 100 + 50, i \times 100 + 50, 100)$ where the value i is given from 0 to 9. In this scenario, all the values of the depth are set the same as 4. In addition, every observation mission at the corresponding position is defined as 60 seconds. In other words, total observation time for 10 missions cost about 600 seconds at least. The initial position of the movable unmanned layer system is set as the location $(0,0,0)$. Therefore, according to the proposed genetic algorithm, the optimal solution corresponding to the sequence of the observation missions should be as $\{0,1,2,3,4,5,6,7,8,9\}$. The verification result of Figure 5 presents that the proposed genetic algorithm could converge and find the optimal solution within less than 50 evolution generation. The found optimal solution provides the optimal route for the unmanned layer platform and shortest time for completing all observation missions.

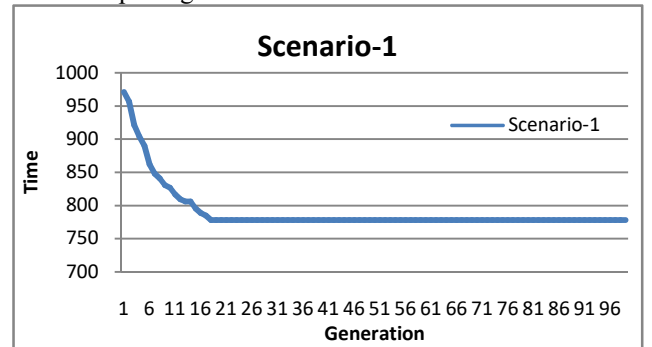


Figure 5. The convergence trend of the genetic algorithm for the unmanned layer platform movement.

In addition to the Genetic Algorithm of the optimal observation route searching based on Cloud Computing, the local image recognition based on edge computing embedded system is also verified. In this research, the Jetson Nano 4G is used as the edge computing device for the object recognition and local computing. By connecting to two independent cameras, the edge computing device could provide the object recognition application locally. Considering that the face recognition is more complex than normal objects in biochemical laboratory, to verify the ability of the object recognition, the human face is used instead of the microbial Petri Dish. Figure 6 presents the available function and service based on two independent cameras which connected to the Jetson Nano. According to the on demand defined evaluation function and artificial intelligence algorithm, the face image can be identified and recognized. In addition, according to the segment size of the face, comparing to the on demand defined size of the face corresponding to the pre-given distance from the camera, the distance from the camera and 3D location can be evaluated and calculated. In other words, when the observer uses two cameras to observe the biological experiments, the biological objects can be monitored and observed by various viewpoints with more three-dimensional observation and position locating.

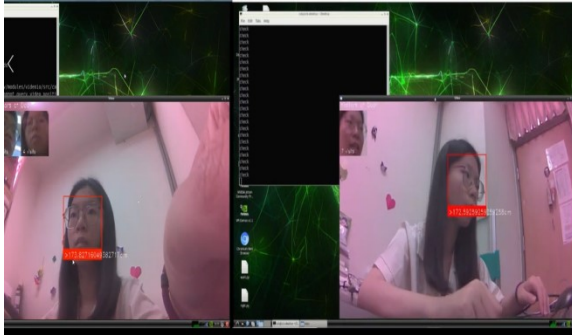


Figure 6. Verification for 3D location evaluation and object recognition synchronizedly based on 2 cameras of edge computing device.

V. CONCLUSION

Based on the proposed Cloud and Edge Computing Based Movable 3D Dynamic Image Recognition and Analysis Layer System for Remote Biological Laboratory, the observation missions of the remote biological laboratory could be completed without or with less manual operation. The quality of the biological experiments could be maintained. In addition, algorithm based on cloud computing could provide the optimal route for multiple observation missions. The edge computing device can support the artificial intelligence algorithm for object segment and recognition with 3D position evaluation. Hence, the observation mission of biological experiments can be long-term continuous observation which automatically completed by the proposed unmanned layer system.

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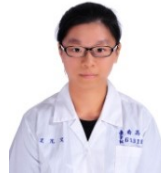


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