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Estimation of the operator comfort level and the layout information based on sensor fusion techniques

Készítette: Halász Gergely Lajos

Témavezető: Dr. Medvegy Tibor, Dr. Ruppert Tamás

Mérnöki Kar, Mechatronikai és Méréstechnikai Kutatócsoport, Folyamatmérnöki Intézeti Tanszék

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Abstract

The most significant problem for manufacturing companies today is human resource shortages. The problem with industrial workplaces is that the operators work long hours on uncomfortable shop floors (noisy, bad condition of air quality) that are not designed individually for the operators. We can get information about these parameters by measuring the environmental data on the shop floor. These aspects have an impact on production performance. The so-called comfort level of the operator can be determined by fusing different sensors. After all, the more comfortable the environment is, the more human worker can be productive, and the company can have a more comfortable workspace.

Our research aims to develop a framework that uses sensor fusion techniques to create a detailed layout. A mobile robot is designed to evaluate the comfort level of the shop floor zones. The mobile robot has different sensors. Thus we developed a so-called mobile measuring unit. We use temperature, noise, and humidity sensors to measure the environmental parameters to derive the comfort level. Besides, the indoor positioning system tracks all resources (including humans) during production. We will use 3D LiDAR in addition to the indoor positioning system to achieve more accurate positioning. Also, the robot provides a visual image (camera) of the inspected area, which will fuse with the LiDAR point cloud to provide a more accurate visual monitoring of the production. The developed mobile measure unit with the sensor-fusion algorithm is tested in the Operator 4.0 laboratory at the University of Pannonia.

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Keywords: Indoor Positioning System, Operator 4.0, comfort level, LiDAR, AGV, sensor fusion

Chapter 1

Introduction

Many countries are concerned about the increased energy usage over the past decade, and this growth will not stop in the coming decades [1]. The ability to control this energy consumption requires a great deal of attention from energy production to energy consumption. The world is tending towards implementing energy-saving infrastructures to counter energy waste [2]. This energy-saving mindset needs to be transferred to industrial life while maintaining productivity. Also important because the comfort of the workers greatly influences productivity, and we need to find solutions to support this comfort that is compatible with an energy-saving approach. Increasing the comfort factor in a plant can maintain or even improve the work morale, performance, and health of all employees, from office workers to operators. However, as comfort decreases, so does the number of workers lost within a company, which is particularly significant among maintenance and operators. To prevent negative consequences, a comprehensive survey of the shop floor can identify areas where a loss of comfort may occur.

Our goal is to explore the zones of a production area where prolonged work can lead to performance degradation and loss of concentration. Indoor environmental sensing consists of static stations, wearable, and mobile sensing. Of these three groups, we examined the possibilities of mobile sensing in this work. By placing the values obtained from the environmental sensors next to each other and then connecting them to the position data of the mobile robot, it became possible for us to discover the areas of the shop floor where the possibility of distraction arises. Prolonged noise exposure to an employee can cause serious problems. Even a noise load of 70 dB can lead to long-term hearing damage, and 120 dB can lead to immediate hearing damage. Different protective equipment is used to avoid injury, but it can also help prevent a lot if we know where the noise load is.

The aim of Operator 4.0 is to give operators all the information they need to discover, use, and benefit from support systems that can help them increase their critical skills for their work, thus increasing their productivity [3]. With these in mind, Operator 4.0

is intrinsically linked to the comfort of operators, minimizing negative influences and negative stimuli in their working environment, and this area is covered by Industry 5.0. The task of Industry 5.0 is to personalize the working environment with the help of support systems. The mission is to create intelligent workstations that adapt to the individual's tasks in real-time, making work easier and improving performance [4].

The main research area of our team is Brownfield Systems. This area aims to upgrade obsolete technologies to meet the requirements of Industry 4.0: high efficiency, flexibility, seamless communication, and interoperability among machines. The main feature of this system is that it modernizes the shop floor cost-effectively and has a low environmental impact. The latter is to be understood in the sense that it is optional to manufacture massive machining equipment for this system and retrofit quite a variety of smaller systems that improve the shop floor's productivity and accuracy of production. The material quality of the product is primarily determined. From an environmental point of view, humidity is one of the most important quantities. It corrodes faster in case of high humidity. The machining equipment we tested is almost 20 to 30 years old, and the corrosion protection layer on these machines is worn and exposed to a greater degree of corrosion. However, this amount can cause irreversible damage to the product and the machining machines.

1.1 Comfort levels of the human workers

In the case of thermal comfort, there is a high risk of accidents in extreme conditions, such as cold stores with temperatures well below minus degrees Celsius and foundries where temperatures above 30 degrees Celsius are typical, in addition to a reduction in comfort levels in such extreme cases. The ideal working environment is between 20 and 24 degrees Celsius. This value is subjective from person to person, so it is easier to define a range than an exact value in the workplace. However, if we look at specific individuals rather than general operators at a typical workplace, we need to look at the individual's working environment and well-being. However, the thermal sensation is not significantly altered by humidity. Too low a humidity level will result in dry air, which will cause various respiratory problems on a closed and hot shop floor. Too high, on the other hand, increases perspiration, can cause breathing difficulties, and promotes mold growth on the shop floor, thus increasing the risk of allergies and reducing comfort levels. The ideal humidity level is between $30 - 60$ % [5].

Workplace lighting conditions play an essential role as they significantly impact our vision. Research has shown that higher illuminance levels improve the comfort and well-being of operators and provide better visual conditions. Furthermore, some research has

shown that combining blue and white light increases productivity [6]. However, ideal lighting conditions and optimal noise reduction are needed to work correctly on the shop floor. Noise is a vital influencing factor on the ability of people to work well. It is almost impossible to work correctly and maintain concentration at high noise levels. It is, therefore, essential to measure the noise to determine its ideal value, which various methods can control.

The variables mentioned above strongly influence universal comfort, the proper maintenance of which has a substantial impact on the effectiveness of the factory and, consequently, on its profit and energy consumption.

1.2 Indoor environmental sensing with mobile robot

The American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) has developed the ASHRAE thermal sensation scale, designed to define thermal comfort. This scale is between -3 and 3; the value of 0 is a neutral feeling, and a cold feeling is a negative and positive area for the scale. The residents or household measurement devices determine the thermal comfort scaling by default. However, it is often helpful to classify the average sensation of heat by measuring physical quantities.

Two models were used to develop this scaling. Fanger developed these in 1970: Predicted Mean Vote (PMV) and the Predicted Percent Dissatisfied (PPD). The two models use four environmental variables: ambient air temperature, relative humidity, wind speed, and mean radiant temperature. And two physiological variables: metabolic rate and clothing insulation.

They used a so-called Autonomous Robotic Environmental Sensor (ARES) to measure physical quantities. The robot's base consists of a triangle and is equipped with Omni wheels for proper maneuvering. ARES is fitted with several sensors that measure environmental impact and position, reducing the number of sensors they want to use in the lab, thus reducing costs. Their work demonstrates how effectively the control of a self-propelled robot can be solved with position sensors and a combination of environmental sensors [7].

1.3 Indoor Positioning System and LiDAR sensors

One of the Real-Time Locating Systems (RTLS) categories is the Indoor Positioning System (IPS). The IPS is an indoor system that can detect people and objects. These are detected by using a tag and the receiving units. It is not suitable for recognizing an object, only to measure the tag position in the area it covers.

RTLS consists of three main groups: Radio-based, No Radio-based, and Hybrid. The No Radio-based leading group also includes, for example, LiDAR. This chapter will talk about UWB (Ultra-Wideband) technology, which belongs to the Ranged base group within Radio-based (Figure 1.1). UWB technology transmits a radio frequency signal over a high bandwidth [8]. It is based on the IEEE 802.15.4a standard, which states that the frequency of the channel used by the UWB can range from 2 to 10 GHz [9]. The pulse it provides requires less energy than technologies that use narrowband signals, allowing UWB to be used at low power. This means it is compatible with active and semi-active tags [10].

We used Sunstone RTLS, which communicates with a tag (radio transmitters). So-called Sunstone RTLS Wall Units perform the measurement. A minimum of four such units must be located in the area for proper measurement. The Sunstone RTLS Wall Units are connected to the Sunstone RTLS Central Unit with an ethernet cable. The Central Unit is responsible for powering and communicating with Wall Unit. Measurement data is processed and stored by an IoT backend, and the calculated data is displayed on an HTTP interface. For the system we use, the manufacturer has guaranteed accuracy of up to 10 cm and maximum area coverage of 3000 m^2, and it can communicate wirelessly with the backend using RS-232 / RS-422 / RS-485 standards.

LiDAR (Light Detection and Ranging), as its name suggests, it is based on the detection of light. It consists of a source and a receiver. The Source emits laser pulses while the Receiver receives the reflected laser pulses. Distance is calculated from the time elapsed between emission and detection, the light's speed, the incident's angle, and reflected light. Based on the sensor's imaging, we can talk about 1D, 2D, and 3D LiDAR.

In our research, we used a 3D LiDAR. This type of sensor is used in many fields for its reliability and accuracy, such as geophysical mapping, meteorology, and autonomous

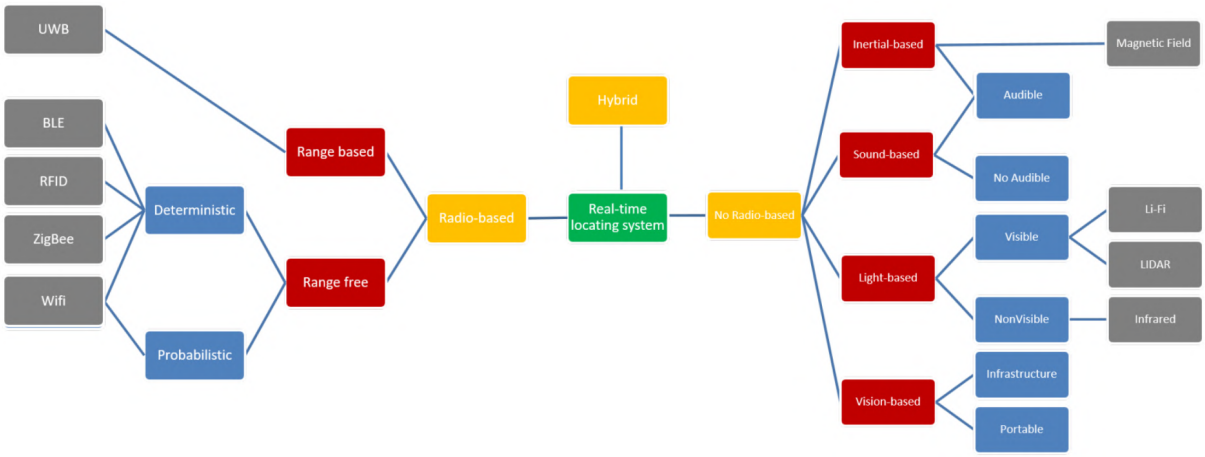

Figure 1.1: Categories of RTLS

vehicles. The autonomous vehicles application is also partially addressed by our research. LiDARs are commonly used for the so-called Simultaneous Localization and Mapping algorithm (SLAM).

SLAM (Simultaneous Localization and Mapping) is one of the most important algorithms used by self-driving vehicles/robots. It creates a real-time map from the data set received by LIDAR and places the given vehicle/robot on this map, thus giving them information about where they are on the map received by SLAM. It can be divided into two large groups, VisualSLAM and LIDAR SLAM. While VisualSLAM uses a camera to collect the data set, LIDAR SLAM, as its name implies, covers the point cloud from the data set sent by LIDAR. The LIDAR SLAM can obtain a two-dimensional or three-dimensional image of an area, depending on the sensor used in the measurement. Due to the flexibility of these methods, they are widely used in industry. The most accurate SLAM algorithms include Cartographer and HectorSLAM, for example.

1.4 Operator 5.0

The idea behind Resilient Operator 5.0 is to combine human creativity, ingenuity, and manufacturing-informed innovation with new, sustainable, energy-saving ways to keep operators thriving in the face of exhausting and unpredictable conditions.

Resilient Operator 5.0 can be broken down into two main groups, Self-resilience and System-resilience. Self-resilience broadly addresses the health, safety, and productivity of operators on the shop floor. Self-resilience is a powerful toolkit for protecting the health of operators. These include a variety of intelligent health wearables, personal protective equipment, exoskeletons technology, augmented reality technology, and virtual reality technology [11].

System-resilience is concerned with the collaboration between human-machine systems, operators, and machines, in such a way that the whole system works as optimally as possible. Performance, comfort, and convenience can be maintained even when the control of the system is shared or changed [12] [13].

Autonomous Mobile Robots (AMR) and Automated Guided Vehicles (AGV) are often used to work collaboratively with operators in semi-automated manufacturing. These robots can transport materials and parts around the shop floor. By monitoring the paths of the operators, an efficient trajectory can be mapped, allowing the robot to work more efficiently and optimize the various processes [14].

Chapter 2

Sensor-fusion based comfort level in a detailed layout

We performed our measurements in the Operator 4.0 laboratory, as we could simulate an event on an actual shop floor, like simulate the operation of the machine tools, the movements of the operators, and the environmental effects of the different machine tools on the operator. In our work, additional information is critical because, with the help of this data, we aim to support the production processes. This information determines the parameters of the production environment that can affect productivity and production quality. This additional data will be associated with the different position data. Thus, we produce proper parameters for the entire shop floor with some average error, but we also have much more accurate information by dividing the shop floor.

The proportion of manufacturing processes and equipment in the industry requires a significant human presence and control. However, the disadvantage of human presence is that the effects of production can cause temporary or even permanent damage to health. Thus, the employer must comply with strict rules regarding the operation of the given factory and the equipment that protects the physical integrity of the employee.

Noise from manufacturing processes can be reduced by developing existing technologies. In this way, emissions can be reduced directly at the noise source. However, it is essential to measure the noise to determine which workflow or equipment has a noise load that exceeds the allowable limit. If a noise meter were installed for each workstation, the process that generated the outbound noise load could be determined. However, the previous suggestion would involve huge costs, both in terms of sensor installation and maintenance. A more cost-effective solution is to look at noise exposure from the employee's perspective, creating a more flexible and efficient system thus, examining the employee, what route, and what load gets inside the shop floor.

In addition to noise exposure, another important environmental factor is temperature exposure. Setting the optimum temperature is vital for the quality of the product and the well-being of the operator supervising the machine. The temperature must not justify wearing unsuitable clothing for the work process. Improper temperature can affect the mental freshness of the operator, thereby losing his ability to concentrate, which can lead to an accident. For this reason, it is crucial to measure the heat load the worker is exposed to in the production environment.

Temperature is closely related to the humidity of the air. It is advisable to be aware of the moisture content of the air when designing the proper corrosion protection. On the human side, inadequate moisture levels can cause asthma, worsen hay fever symptoms, and exacerbate the symptoms of dry eczema skin. With proper ventilation and air filter filters, these problems can be eliminated. However, it is essential to monitor the condition of these devices. Continuous humidity monitoring is best. Closely related to airflows is the change in humidity and the locations on the shop floor where there are outstanding values in terms of temperature. Thus, measuring the moisture on the shop floor in several places is vital.

From the point of view of testing parameters, placing the sensors on a mobile device is advisable, for which purpose an AGV is most suitable. Applying this is practical because you can track the operator's route on the shop floor. Sensors located on it detect the above-mentioned environmental parameters the way. This solution is cost-effective, as installing environmental sensors at all points on the shop floor and the parameters recorded at those points are optional.

The best way to determine the position of the AGV is RTLS technology, so the position of the environmental sensors becomes known. So each point of the shop floor can be characterized according to the environment. For this characterization, we determined a so-called comfort level. The value means how much environmental load the operator can receive in each zone of the shop floor and how comfortable the operator feels in these areas.

The AGV 3D is also equipped with LiDAR and a camera. Based on the information from the sensors, a so-called activity recognition algorithm can detect operator activity. These sensors can also be used to determine the position of the AGV more accurately.

Chapter 3

Developed framework and problem formulation

In this chapter, we present the methodology for fusing the sensors we use. Sensor fusion is the combination of data from different sensors. These sensors are the environmental sensors and the RTLS (Figure 3.1). In the future, we want to include the encoder and LiDAR in this fusion, thus refining the position data.

R is the matrix of position data obtained by RTLS. Each element of **R** can be written as $\mathbf{r}_i = [x_i, y_i]$ where, $i = 1 \dots N_r$, N_r is the number of position data from the RTLS. The values of the environmental sensors (noise, temperature, humidity) can be arranged into three vectors. The noise vector is $\mathbf{o} = [o_1, \dots, o_n]$, the temperature vector is $\mathbf{p} = [p_1, \dots, p_n]$, and the humidity vector is $\mathbf{h} = [h_1, \dots, h_n]$. Since the sampling frequency of these sensors is the same, n is the number of data from the environmental sensor.

Since the measurements frequency of the environmental sensors and the RTLS are not the same, it is necessary to interpolate the values. After interpolation, we can define a

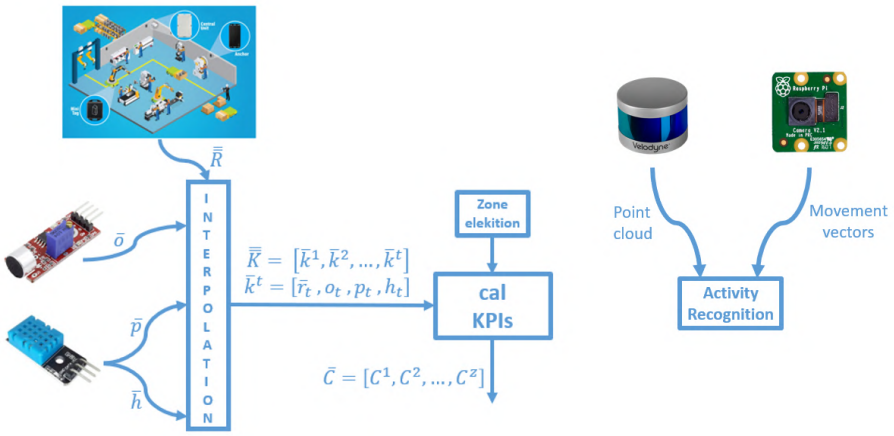

Figure 3.1: The sensor fusion methodology

$\mathbf{K}$ matrix as $\mathbf{K} = [\mathbf{k}^1, \mathbf{k}^2, ..., \mathbf{k}^t]$. Every measured points $\mathbf{k}^t$ in the tth time contains the measurements as the $\mathbf{k}^t = [\mathbf{r}_t, o_t, e_t, h_t]$, where t is the time variable, $t = 0$ at the beginning of the measurement.

We defined zones to characterize the shop floor. The measured environmental values determine the $\mathbf{C}^z$ comfort level for the $\mathbf{r}_t^z$ vectors in each zone, $\mathbf{C} = [C^1, C^2, ..., C^z]$ is the comfort level vector, $z = 1 \dots Z$ where, Z is the number of zones. We obtained the comfort level for KPIs (Key Performance Indicators) from the measured environmental values during the definition. Then we got the comfort level of our zones by averaging them.

Let o^z be the noise level, p^z be the temperature level, and h^z be the humidity level for the given zone.

$$o^z = \sum_{i=1}^{N_o^z} O_i^z = \sum_{i=1}^{N_o^z} \left(1 - \frac{o_i - min(o)}{max(o) - min(o)}\right) \tag{3.1}$$

where, N_o^z number of noise points in the zone, o_i the i-th element of the vector $\mathbf{o}$.

$$p^z = \sum_{i=1}^{N_p^z} P_i^z = \sum_{i=1}^{N_p^z} \left(1 - \frac{|p_i - p_{opt}|}{p_{opt}}\right) \tag{3.2}$$

where, N_p^z number of temperature points in the zone, p_i the i-th element of the vector $\mathbf{p}$, p_{opt} the optimal temperature in the production environment, which in our case $p_{opt} = 24C^\circ$.

$$h^z = \sum_{i=1}^{N_h^z} H_i^z = \sum_{i=1}^{N_h^z} \left(1 - \frac{|h_i - h_{opt}|}{h_{opt}}\right) \tag{3.3}$$

where, N_h^z number of temperature points in the zone, h_i the i-th element of the vector $\mathbf{h}$, h_{opt} the optimal humidity in the production environment, which in our case $p_{opt} = 35\%$.

So the element C^z of the vector $\mathbf{C}$ is equal to:

$$C^z = o^z \cdot p^z \cdot h^z \tag{3.4}$$

Using the Lidar point cloud and the camera image, we can observe different movements, known as activity recognition. In the current phase of our research, we collect these activities as information. The next step of the research will use this information to recognize the different activities on the shop floor.

After the methodology of sensor fusion presentation, we demonstrate the methodology's effectiveness through a case study in the Operator 4.0 laboratory in the next chapter.

Chapter 4

Demonstration in the Operator 4.0 laboratory

In this chapter, we would like to present the method of creating the framework, starting with the location of our measurements and why we used the technologies below. It will also be about how we have transformed some technologies to achieve our goal. The following section describes the operation of the sensors we use.

In the last section, weshow how we managed to model the shop floor of a factory in the Operator 4.0 laboratory [15] at the University of Pannonia. Machining operations were carried out on the machines in this environment while we tested them with our mobile robot to measure the aforementioned environmental parameters in a coordinated manner.

4.1 Automated Guided Vehicle and the Environmental Sensors

AGV (Automated Guided Vehicle) is a mobile robot made by us with a built-in line tracking system (Figure 4.1). A line array board with 16 infrared sensors was used for line tracking. The line tracking system is essential because we can compare the position data set given by the sensors to the pre-surveyed path as a reference.

The I2C communication protocol was used between different microcontrollers of the robot. The four wheels have four separate microcontrollers of type MSP430G2553 that control the speed of the motors. The central unit responsible for communication and control was also implemented with a microcontroller type MSP430G2553. This central unit acts as the Master for I2C communication, and the other microcontrollers for the motors as the Slave.

The so-called omnidirectional wheels, also known as mecanum wheels, are used to refine the line tracking of the AGV. They each have eight freewheels with 45 degrees to

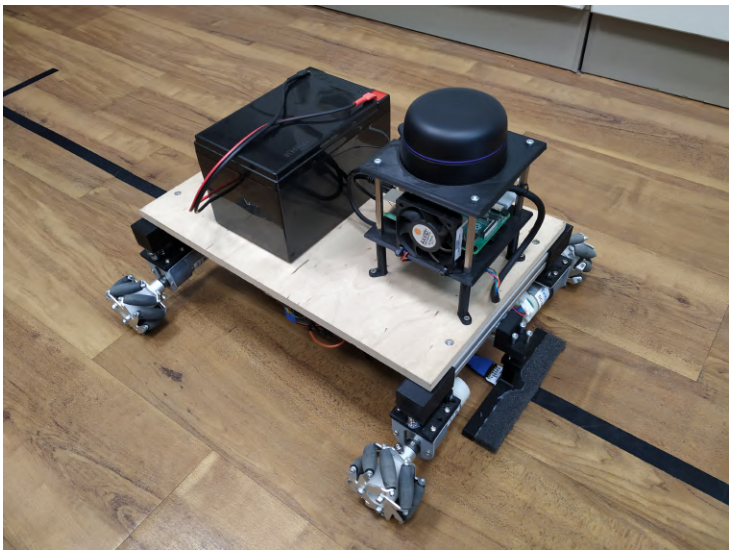

Figure 4.1: AGV used in the measurements.

the wheel axle, which, with proper control, allow the vehicle to move straight, sideways, or diagonally. In addition, it can rotate about an axis through the suspension of any of its wheels, standing around its center or just around the center of its front or rear axle. The outer surface is provided with free-rotating rollers.

20 : 1 gear motors were used on the AGV, and there is an encoder built into the motors. From the measurement of the encoder, the angular rotation of the wheel can be counted back, from which it can be further calculated which wheel has traveled. Suppose the initial position of the robot is known. In that case, the distance values obtained from the encoder can be used to obtain the position values derived from these values for the robot during the measurement.

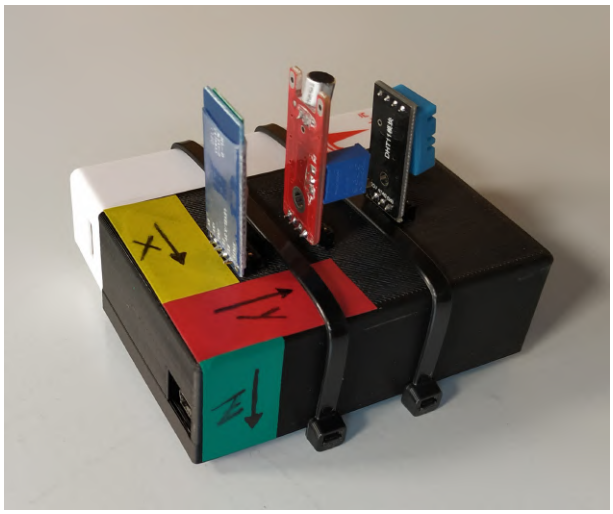

Figure 4.2: Environmental data collection unit.

Noise, humidity, and temperature are measured within one unit (Figure 4.2). Temperature and moisture are carried out by a module called DHT11. The main component of the data acquisition unit is an MSP430FR5739 microcontroller that transmits the data to the processing server. The sensor modules for monitoring the environmental conditions send the requested data to the microcontroller via the UART protocol. With the help of a Bluetooth module, the microcontroller communicates with the server. The microcontroller compresses the data before transmitting the data and stamps them all. On the server side, the compressed information is extracted and stamped.

4.2 LiDAR and camera fusion

The shop floor can be assessed not only in terms of environmental parameters but also by visual methods. Important information can be extracted from the LiDAR point cloud and a video recording. By examining the LiDAR point cloud, we can accurately determine the position of the AGV in space and the place and dimensions of the machines and objects on the shop floor. The camera will also determine the visual characteristics of individual objects and people. The AGV's path and surroundings can be better explored and recognized by fusing the two sensors.

Our current measurements have been carried out in a dedicated area, whereby by simplifying the LiDAR image, we have been able to determine the distance of an object from the sensors accurately. From these measurements, we could determine the exact sensing distance of the sensors, and in these conditions, we could reconcile the data from the two sensors (Figure 4.3).

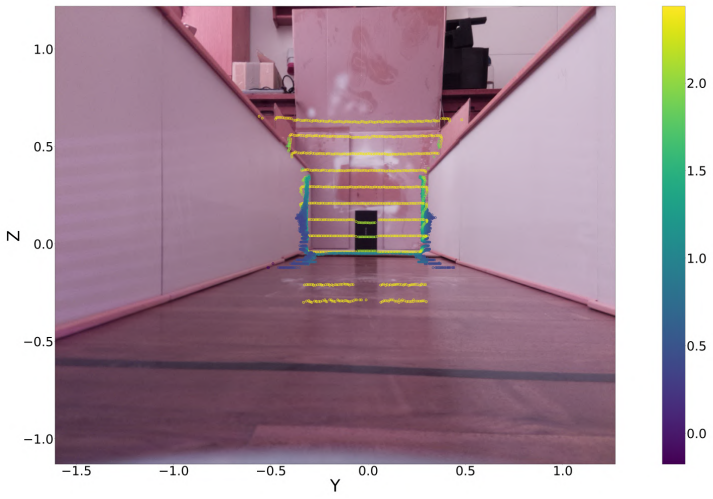

Figure 4.3: A point cloud of the LiDAR fusion with the cameras frame.

The Lidar and camera fusion were not present during the current measurement, but we would like to integrate them for the following measures.

4.3 Indoor positioning system for location-based sensor map

IPS (Indoor Positioning System) tags have many uses as they can also function as a transmitter and receiver [16]. IPS tags are continuously active while their battery is in a charged state. During this time, the signals are constantly broadcast to the beacons [17].

One method is much more efficient than previous indoor positioning methods, and this is ultra-wideband (UWB) technology [18]. UWB uses wireless communication technology [19]. We can group the positioning method according to the information used for positionings, such as Angle of Arrival (AoA), Signal Strength (SS), and time delay information. UWB can be divided into groups based on Received Signal Strength: the Time of Arrival (ToA), AoA, and RSS [20].

We are testing the indoor positioning technology in the Operator 4.0 laboratory of the University of Pannonia. During the project, we installed a platform capable of collecting sensor data on radio frequency (ultra-wideband: UWB), with the help of which, in addition to the exact position (x, y) data, we can also collect and store the signals of sensors built into devices (up to 2000 sensors signal at a time). Thanks to the built-in accelerometers, they can measure the vibrations of the machines with a frequency of up to 100 Hz, all in real time. The system can determine the location of devices indoors with an accuracy of 50 cm.

An RTLS tag was placed on the AGV, thus tracking the route taken by the robot. The tag was set at 1 m, thus simulating a size approaching the height of the human waist. The position data measured by RTLS were stored in a database with a timestamp.

For the system, we built our internal LAN in the lab and installed eight wall units (Anchor), which are the data collection units of the system. The data for these wall units are collected by the central unit (CU) and transmitted to the cloud service where the position calculation occurs. Figure 4.4 shows a schematic diagram of the system's structure.

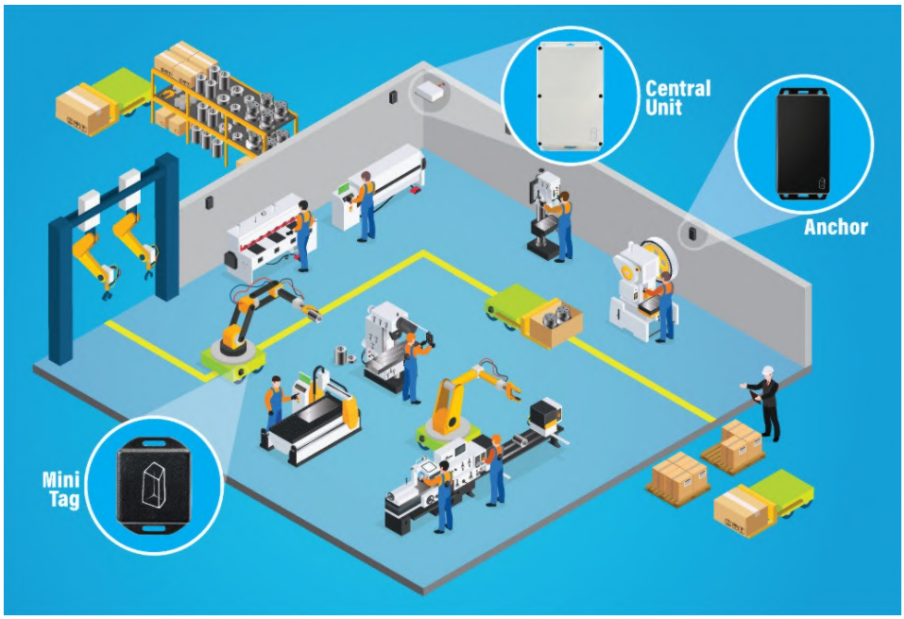

Figure 4.4: Semantic figure of RTLS

4.4 Use case

The laboratory where the measurements were performed is a mechanical engineering laboratory. The lab has a variety of milling machines from 60s to 80s. For this measurement, we tracked the production of a predefined product, shown in Figure 4.5. The product is composed of two parts. The upper part is based on an M22 nut, and the lower part is a cylindrical shaft.

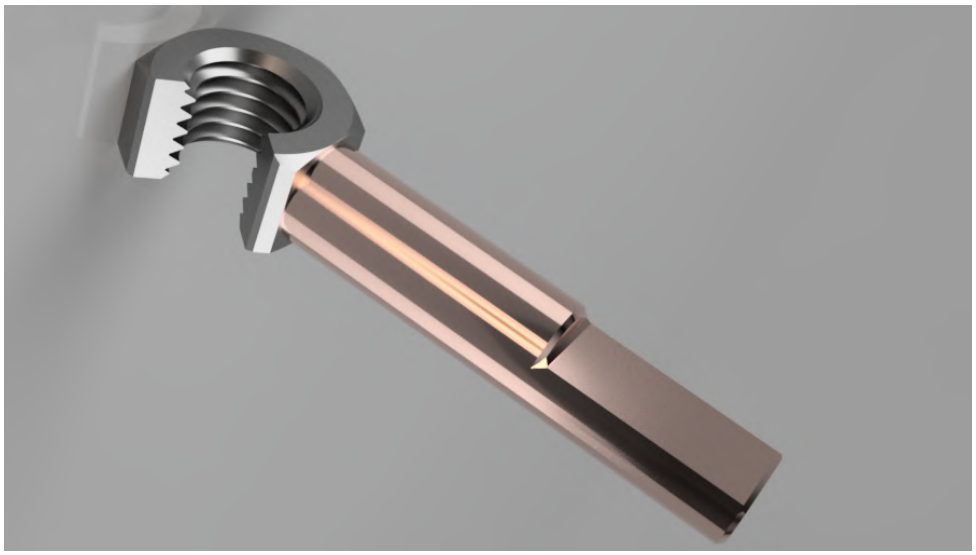

Figure 4.5: Visual plan of the finished product

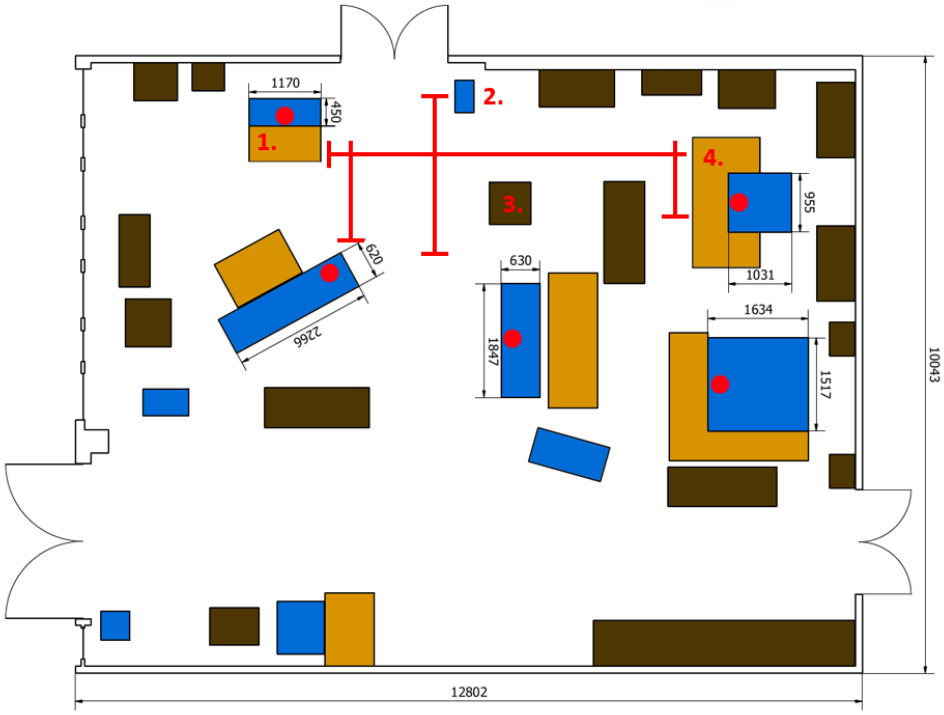

Figure 4.6: Operator 4.0 laboratoray layout

Figure 4.6 shows the laboratory layout, the AGV path (the red lines), and the four workstations where machining operations took place.

1. Lathe machine
2. Drilling machine
3. Workstation
4. Milling machine

The operator designed the copper shaft and the staircase on it on the lathe. During the operation, the operator had to clamp the part twice, as a smoothing faceplate was turned to form a smooth top surface, after which the step was formed. The turned workpiece was then transferred to the milling machine, where the flattening was created. Finally, at the workstation, the part was finished by cutting the thread.

The screw nut was first taken to the drilling machine, where the hole was formed, into which the thread will be inserted later. The cutting operation was then carried out, and the thread was formed. After machining, both parts were deburred.

Chapter 5

Results and further steps

While the AGV followed the designated route, the tag's position placed on it was continuously measured by the RTLS system. Since we put the tag on a 1 m high stump, the tag had large oscillations during the movement of the AGV. This reduces the accuracy of the position data and the fact that the RTLS was able to measure the position of the tag to an accuracy of 50 cm.

At the same time as measuring the position data, the environmental values were measured. However, the two systems are so different that the data was transmitted using various communication and a different sampling frequency. Our solution to the sampling problem mentioned above is interpolation.

Before developing the framework, the results obtained by each environmental sensor were evaluated. We can infer the quality of the information in the finished framework from these data sets. The quality and accuracy of the data sets depend significantly on the sensors' sensitivity we use.

Before evaluating the data set obtained by the noise sensor, the values were averaged at predetermined points to reduce the calculation error from the oscillation. This gives a much better interpretable figure. The sound effects came from a lathe, a drill, a milling machine, and manual machining in the lab. The AGV approached the sources of the sound effects several times during the measurement, which, together with the echo from the laboratory, could have caused the large oscillation. From the fitted line on the measured data, it can be observed that the average magnitude of the noise exposure was nearly constant during the measurement, being 63.65 dB. This value is only minimally below the threshold for the onset of hearing loss. However, the values observed in the Figure 5.1 were quite different, with a maximum noise level of 68.6 dB and a minimum of 59.4 dB.

As mentioned above, temperature and humidity are closely related, an illustration of which is shown in Figure 5.2. Where both measurement data sets are plotted as a function of time. In Figure 5.2, it was observed that the continuous operation of the

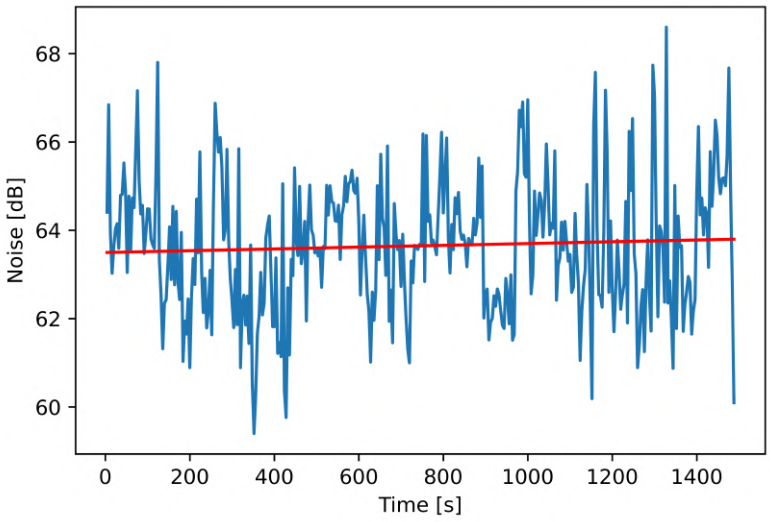

Figure 5.1: The average noise load as a function of the measurement time.

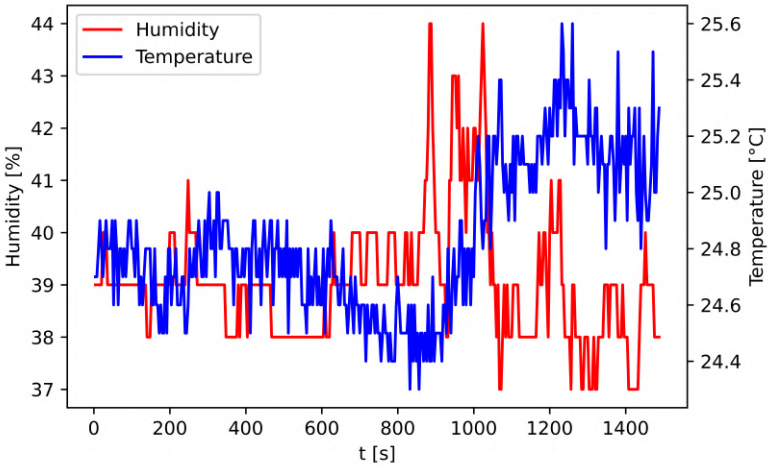

Figure 5.2: Temperature and humidity change over time.

machines increased the laboratory temperature. In the first stage of the measurement, the temperature oscillated around 24.7 degrees Celsius. In contrast, in the second stage, the temperature rose by one degree Celsius after a drop of half a degree Celsius, so the highest temperature was 25.6 degrees Celsius, and the lowest was 24.3 degrees Celsius. Clothing for safe working conditions is ideally suited to such temperatures. The average humidity was around 39 %, which is ideal for working.

Before assigning the comfort level of the associated environmental values to the position, we defined the 4 zones mentioned above beforehand. During the definition, the position values for the zones were selected. The number of points in the different zones is different. This may be because the AGV spent more time at specific points on the route. There were more stopping points in that section. Figure 5.3 also shows the standard deviation of the position values.

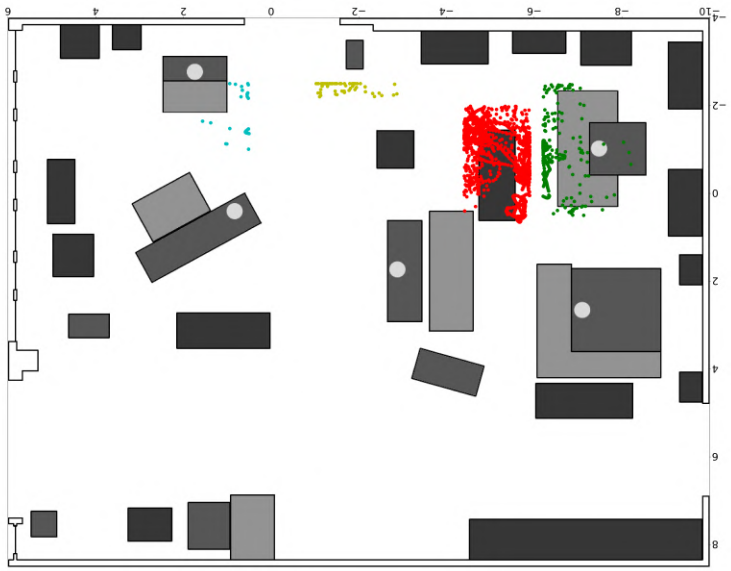

Figure 5.3: Position points on each zone of the shop floor.

The prepared framework can observe the magnitude of the comfort level obtained for each zone (Figure 5.4). The explanation of the symbol shows that light shades are associated with a high comfort level, while darker shades draw attention to higher environmental exposure. Generally speaking, the operator worked in what could be considered ideal conditions in the work areas studied. However, the degree of stress associated with the different work processes can still be observed.

The framework shows that the operator at the milling machine was exposed to the highest environmental load. This could also be caused by incorrect machine settings and the wrong tool. At the same time, it can also be observed that the manual machining station located directly next to it proved to be the most comfortable. The difference in the environmental parameters of the two zones could be caused by the fact that the AGV could also walk between the two areas when the milling machine was temporarily stopped. Alternatively, the deflection of the tag by the movement of the AGV could also have caused the positional inaccuracy associated with the measured parameters.

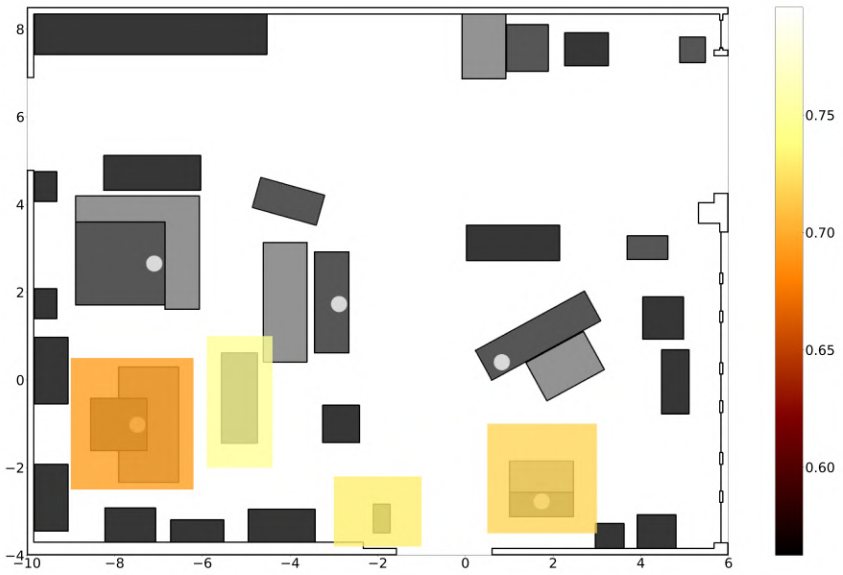

Figure 5.4: Zones of the framework. The color scale in the figure indicates the comfort level of the operator. The lighter the color assigned to the zone, the higher the comfort level. At a higher comfort level, the operator's productivity is easier to maintain, and his concentration is better preserved, which allows him to work efficiently and avoid accidents.

In the project's next step, we want to add the camera's data and LiDAR's point cloud to our existing system. We want to use them to refine the positions obtained by the RTLS, thus eliminating their accuracy errors. As well as using these two sensors to detect the different movements that can be observed in production, we also want to reveal the operator's comfort level from this perspective.

Also, the following steps are to increase the sensitivity of the temperature and humidity sensors to get more accurate environmental results, and look for additional algorithms to eliminate the oscillation of noise data.

Chapter 6

Conclusions

During our measurements at the Operator 4.0 laboratory at the University of Pannonia, we used AGV to create our mobile sensing system. This part of our work was important because it allowed us to follow an operator's route cost-effectively. A temperature sensor, a humidity sensor, and a noise sensor were used to detect environmental changes. These three values are considered to be the factors most influencing concentration.

The robot's position during its movement was measured by UWB technology. The accuracy of this technology became visible to us during the evaluation. We want to improve this accuracy with other position sensors in the future.

Before processing the data, we defined a so-called comfort level. This means how much the operator can concentrate under the given environmental parameters.

We defined zones for the workstations on the layout, thus filtering the shop floor for areas where the operator works more often. Zones assigned the position and environmental data associated with the position value to these zones. This has made it possible for us to determine the comfort level of each zone, making it clear in which areas of the shop floor the operator can work over a more extended period.

Our work will continue to produce a much more accurate framework by refining the position data. We also aimed to provide a more complex characterization of the shop floor than the framework presented here with the help of all three groups of indoor environmental sensing.

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