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Geospatial intelligence system for evaluating the work environment and physical load of factory workers*

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***Abstract*— This study aimed to assess the effectiveness of methods for evaluating the environmental and physical loads on workers in manufacturing plants, considering their locations. Participants were employees of DENSO CORPORATION's manufacturing facilities, and environmental sensors (for temperature and humidity) and BLE beacons were installed to cover the work area. Questionnaires were completed by the participants twice to assess their thermal comfort and fatigue in the work environment. The results showed that a regression prediction model with an adjusted R-squared of 0.418 for fixed-point temperature and 0.495 for perceived temperature was developed for thermal comfort. No linear relationship was found between environmental factors and fatigue, and a decision tree analysis was conducted. Relative humidity and activity level, along with temperature, were selected as predictor variables. The findings suggest that it is possible to estimate the work environment and workload without adding additional measurement-related burdens or challenges. This highlights the usefulness of the proposed method, which takes into account the environmental distribution throughout the work area rather than relying solely on conventional fixed-point observation data, for assessing workers' exposure to the environment and preventing occupational accidents.**

***Clinical Relevance*— The proposed approach, combining indoor localization with environmental status, can estimate the condition of workers and is expected to be a good solution for preventing occupational accidents and enhancing workers' health.**

I. Introduction

Preventing occupational accidents is crucial for both employees and employers. The 13th Occupational Safety & Health Program of the Ministry of Health, Labour and Welfare in Japan highlights the need for measures to prevent industrial accidents in the manufacturing, construction, and forestry industries, which are particularly vulnerable to such incidents. With a declining working-age population and an aging workforce, the safety and health management of workers in these industries is of utmost importance. The causes of occupational accidents are diverse and complex, but most of them are attributed to unsafe conditions or actions [1]. While it is unclear how many accidents are due to unsafe behaviors such as falls, slips, entrapment, and collisions, there are likely many cases where such incidents are a result of impaired judgment and attention due to unsafe behaviors [2].

According to Leso et al. [3], shift workers and night shift workers with irregular work hours and time window reported lower cognitive function at the end of the workday compared to the start of the workday. It has also been reported that those who work in industries with irregular working hours for longer periods of time have poorer cognitive function [4]-[5]. Furthermore, it is widely known that working in hot environments can decrease physical and cognitive functions due to increased core body temperature and dehydration [6]-[7]. The excessive environmental and occupational burden on workers is believed to lead to impaired judgment and attention, potentially resulting in unsafe behaviors and occupational accidents. Hence, it is crucial to evaluate environmental factors such as temperature, humidity, and noise at the work site where workers are exposed, as well as monitor the transitions of their physical workload, to prevent occupational accidents.

We have developed and reported a technology that utilizes geospatial intelligence based on geospatial and location information to track the transition of workers' work area and classify their work patterns [8]-[10]. This technique enables continuous estimation of each worker's work position over time and can be combined with information on their movement speed and distance, i.e. physical activity, and the environmental conditions at each location to accurately evaluate each worker's exposure to the environment.

In this study, we propose a new approach for assessing the exposure environment for workers in manufacturing plants. Unlike the conventional fixed-point evaluation method, which assumes that environmental measurements at a specific location are representative of the exposure environment for all workers in the workplace, our method considers the workers' positional changes within the workplace. The validity of our proposed method was confirmed by comparing the relationship between workers' subjective sensations of thermal comfort, fatigue, and the exposure environment evaluation that takes into account workers' positional transitions.

II. Methods and Procedures

A. Subjects

The study was conducted in automobile parts manufacturing plant of DENSO CORPORATION located in Aichi Prefecture in Japan. The measurement areas were an approximately 3000 m^2 and twelve employees participated.

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The measurement periods were from 1st to 13th August 2022. This plant operates day and night, with two shifts of day and night work, and groups of four to eight workers per shift. This plant was susceptible to the outdoor environment because of the open space inside the factory during operation, and except for some rooms equipped with air-conditioning in a part of the work line, the air-conditioning system was spot cooling system in the space where workers stayed at a certain point and worked. The daily maximum temperatures (mean ± standard deviation) in the area during the measurement period were 33.1 ± 2.3 degrees Celsius at the closest meteorological station.

This study was conducted with the approval of the Ergonomics Experiment Committee, an ethics review organization of the National Institute of Advanced Industrial Science and Technology. Prior to the start of measurement, the purpose and content of the study were explained, and then consent for participation in the study was obtained after sufficient understanding.

B. Measurements and Procedures

- We used the method of Ogiso et al. [10] to estimate the location of factory workers in a real working environment. Participants were asked to carry smartphone from the beginning of the workday to the end of the workday. First, pedestrian dead reckoning (PDR) was estimated from the acceleration and angular velocity sensors in the smartphone [11]. However, the PDR-based position estimation method is known to accumulate estimation errors and should be combined with other absolute positioning methods to improve estimation accuracy. Therefore, BLE beacons were installed to cover the entire manufacturing line and rest areas where the participants were engaged in their work during the measurement period (Fig. 1). The correlation between the received signal strength indicator of the BLE signal and the distance between the positioning terminals was used to calculate the likelihood of the location. At each time point, the prior distribution of positions obtained from the prediction by PDR and the posterior distribution of positions were calculated from the position likelihood obtained by the BLE beacons, and the mean value was considered as the position coordinates to estimate the position of the participants. The smartphones were also used as BLE signal receivers. Although the accuracy of the positioning method used in this study depends on the devices installed in the measurement area, attenuation of signal strength due to human traffic, and beacon installation conditions, the average estimation error was generally 2.8 to 6.9 meters. In order to use the walking speed and distance as an index of intensity of physical activity during work, we converted them into METs (Metabolic Equivalent of Tasks) values [12].

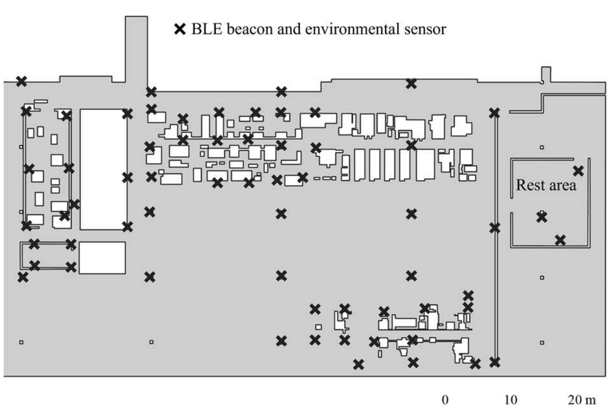

Fig. 1 Overview of the plant with the beacon and environmental sensor placements

- As with the BLE beacons, environmental sensors (temperature and humidity) were installed to cover the entire production line and rest areas where the participants were engaged in their work. The measured values of the two environmental sensors closest to the worker's location estimated in the previous section were used to obtain a weighted average by the distance between the worker's location and the environmental sensors, which was calculated as the measured environmental values at the location where the worker was present, that is, the measured environmental values to which the worker was actually exposed, and were defined as exposed data (exposed temperature, exposed humidity).
- Data from environmental sensors installed in a relatively open space in the work line, where there is no obstruction to air flow and no heat source equipment, were used as representative environmental measurements to which the workers would have been uniformly exposed (fixed-point temperature and humidity).
- Experimental participants completed questionnaires on the thermal environment of the work space and fatigue twice a day, during meal breaks and at the end of the workday. The thermal environment was evaluated by using the Architectural Institute of Japan Environmental Standards [13]; the sense of warmth and coolness in the work environment (9-point scale: 1 very cold to 5 neither to 9 very hot). The Brief Fatigue Inventory was used to evaluate fatigue; 11-point scale (0: no feeling tired at all to 10: too tired to think any more)[14].

C. Statistical analyses

Workload (physical activity estimated from PDR) and environmental information (both fixed-point and exposed data) of 60-minute period prior to the time of questionnaire response was used for analysis. All analyses were conducted using R (ver. 4.1.3). Spearman's rank correlation test was used for univariate regression analysis, multiple regression analysis for multivariate linear regression analysis, and decision tree analysis for hierarchical cluster analysis when linearity was not observed between dependent and independent variables. Wilcoxon rank sum test was used to compare the difference in means between day shift and night shift. The statistical significance level was set at 5%.

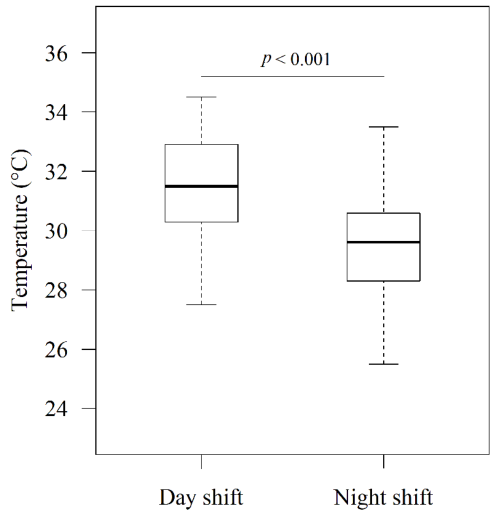

Fig. 2 Boxplot of temperature in plant during measuring period

III. RESULTS

During the measurement period, a total of 104 persons-day data were collected, with a questionnaire response rate of approximately 58%. The temperature during daytime was significantly higher than those in night (Fig. 2). On the other hands, relative humidity in daytime was lower than those in night (data not shown). As with temperature, the day shift workers reported feeling hotter compared to night shift workers (Fig. 3).

The relationship between thermal sensation and fixed-point temperature, exposed temperature is shown in Fig. 4. The adjusted coefficient of determination of the regression model for predicting thermal sensitivity was 0.418 when only fixed-point temperature was used as an explanatory variable, and 0.495 when only experienced temperature was used as an explanatory variable, indicating an approximately 8% improvement in prediction accuracy. Because humidity showed a strong negative correlation with temperature, it was not used in the linear regression analysis due to multicollinearity issues. In addition, the mean and standard deviation of exposed temperature, the mean of METs, the standard deviation of METs were used, and whether the worker worked the day shift or the night shift was used as dummy variables in the multiple regression analysis.

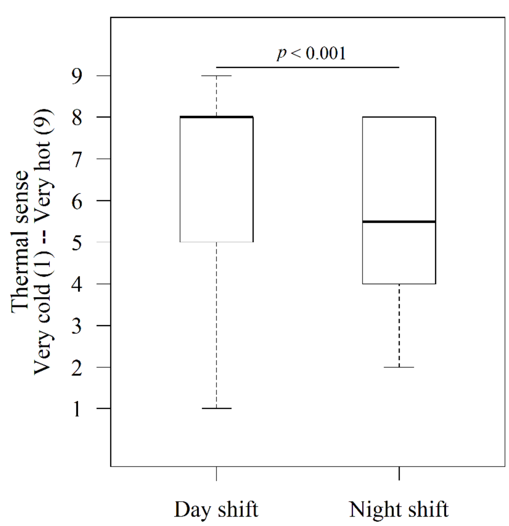

Fig. 3 Boxplot of thermal sense

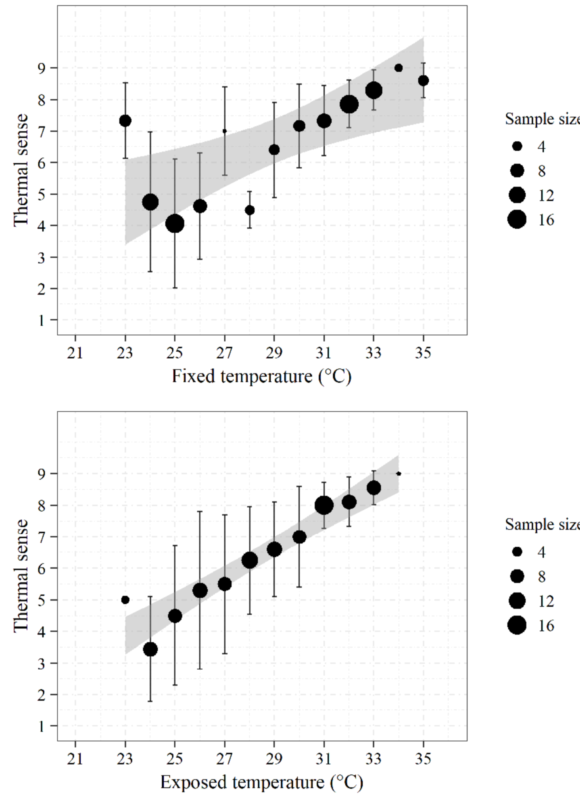

Fig. 4 The relations between fixed- (upper) and exposed- (lower) temperature and thermal sense (Grey bands indicates 95% confidence intervals of regression line)

TABLE I. THE CORRELATION COEFFICIENTS BETWEEN OBJECTIVE AND SUBJECTIVE DATA

Objective data	Subjective data (Questionnaire)	
	Thermal sense	***Fatigue***
Fixed temperature	0.653**	0.391**
Exposed temperature	0.724**	0.409**
METs	0.237**	0.320**

*; $p < 0.05$, **; $p < 0.01$

TABLE II. THE MULTIPLE REGRESSION ANALYSIS MODELS FOR THERMAL SENSE SELECTED BY AKAIKE INFORMATION CRITERION

Independent variables	*B*	*Beta*	*t-value*	*p-value*
Constant	-10.90			
Exposed temperature	0.50	0.67	19.0	< 0.001
METs (mean)	2.48	0.57	5.27	< 0.001
METs (standard deviation)	-1.68	-0.49	-4.58	< 0.001

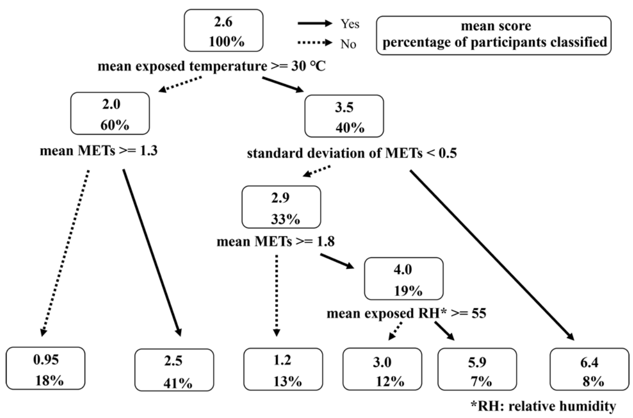

Fig. 5 Diagram of decision tree for predicting fatigue

The model with the smallest Akaike information criterion among the combinations of explanatory variables with VIF (Variance Inflation Factor) less than 10 to avoid multicollinearity was adopted (Table 2).

Since there was significant but weak correlation between fatigue and any of the objective indices, a decision tree analysis was conducted as a hierarchical cluster analysis (Fig. 5). The explanatory variables were mean and standard deviation of exposed temperature, physical activity, relative humidity, and whether the workers were working day or night shifts. The first branch was selected based on whether the exposed temperature was above 30 degrees Celsius. The groups with the smallest standard deviation of physical activity and those with the highest activity level and working in a high humidity environment complained of fatigue.

IV. DISCUSSION

In this study, it was found that the day shift workers reported feeling significantly hotter compared to the night shift workers, due to the strong influence of the external temperature on the plant. A moderate correlation ($\rho = 0.653$) was observed between the workers' thermal sensation and the fixed-point evaluation method, which only took into account the environmental sensors installed in the work area. A stronger correlation ($\rho = 0.724$) was found between the workers' thermal sensation and the exposed evaluation method, which considered both the workers' locations and the environmental information at each location. The regression line's 95% confidence interval was narrower for the exposed evaluation method than for the fixed-point evaluation method, suggesting that the exposed evaluation method more accurately reflects the workers' thermal perception.

The multiple regression model revealed that higher activity levels, meaning more heat produced by the skeletal muscles, or less variation in physical activity led to a feeling of heat. This suggests that while workers who engage in more intense activities may feel hotter, allowing variation in the intensity of activity, rather than keeping them at a constant intensity, could help reduce heat stress.

A weak to moderate relationship was found between environmental measurements, activity level, and fatigue. In the decision tree analysis, the first discriminator for the degree of fatigue was whether the average exposed temperature was above 30 degrees Celsius, implying that working in an environment above this temperature is initially associated with fatigue. The group with the strongest complaints of fatigue was found to be those working in an environment above 30 degrees Celsius and with a small standard deviation of activity level, meaning that the intensity of physical activity or keeping it at a constant intensity without repeated movements, such as moving or stopping, leads to workers' fatigue.

The exposed evaluation method, which this study proposes, is a more precise way to evaluate the environment each worker is exposed to by combining the workers' location information and environmental information at each location. The use of geospatial intelligence in the proposed method allows for automatic and unconscious estimation of the workers' conditions. However, the study has limitations, such as the inability to evaluate activities that don't involve horizontal movement or static muscle contractions, like lifting heavy objects, and not considering factors such as thermal acclimation of workers, thermal resistance of clothing, and the workers' sleep, drinking status, and work status. Future work could aim to improve the positioning technology to increase the accuracy of location estimation and develop a new model to accurately predict the workers' biological status to prevent industrial accidents. Furthermore, in recent years, BLE beacons have been installed in public spaces such as large commercial facilities where people gather. Therefore, we aim to expand the applicability of our proposed method not only for industrial health but also for public health.

V. CONCLUSION

This study demonstrated the usefulness of a method that considers the environmental distribution within the work area rather than conventional fixed-point observation data as a method for evaluating the environmental exposure burden of workers. On the other hand, the relative humidity and physical activity were selected as predictor variables in addition to temperature in the decision tree analysis. These results suggest that it is possible to evaluate the work (thermal) environmental burden and workload without imposing special burdens or tasks on workers, and to predict the thermal sensation and fatigue felt by workers. Briefly, the proposed system can detect the location, the amount and intensity of physical activity, and the exposed environment of workers. Therefore, an employer or on-site manager would be able to take measures to occupational accidents by evaluating real-time worker's workload and those accumulation (overwork). The results also contribute to the visualization of hazards and the prevention of occupational accidents using the IoT, which is being promoted in the 13th Occupational Safety & Health Program of the Ministry of Health, Labour and Welfare in Japan.

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