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# WORK ANALYSIS OF PLASTERBOARD-PASTING WORKERS FOCUSED ON THE SMOOTHNESS OF ACTIVITIES USING ACCELEROMETERS

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**Abstract:** In this study, we conducted a work analysis at an active building construction site, utilizing three-axis acceleration sensors affixed to four plaster-board-pasting workers for five days. Although acceleration data is less accurate than visual or image recognition in identifying specific tasks, it can be easily captured using smartphones, even in challenging conditions such as poorly lit or obstructed construction sites. This accessibility facilitates continuous data collection over extended periods, enabling automated analysis without significant cost or time investment. In addition, this method can identify trends in worker behavior that elude conventional visual inspection. Our approach encompasses various evaluation indices, beginning with an analysis of average work time per plasterboard sheet and the differentiation of walking motions using acceleration data. Furthermore, we introduced a new evaluation index that quantifies the distribution of high- and low-intensity work based on acceleration readings. Through comparative analysis with evaluation indices from previous studies, we confirmed common trends and discussed the strengths and limitations of our proposed index. Our findings suggest a correlation between work experience and performance, as evidenced by smoother operational patterns among seasoned workers. In particular, proficient workers exhibited fewer instances of extremely intense or sporadic movements. This observation underscores the influence of experience on work dynamics.

**Keywords:** accelerometer, operational analysis, plaster board pasting, worker motion

## 1. INTRODUCTION

Various efforts are being made within the construction industry to enhance productivity and efficiency at construction sites. Construction companies actively embrace remote management and efficiency enhancement strategies supported by technological advancements. These include developing and implementing systems capable of recording workers' positions, vital signs, and work-related videos, along with tracking the operating rates of equipment. Numerous studies have also analyzed worker motions at building construction sites. For instance, Luo et al. [1] categorized work statuses of construction workers based on image data obtained from surveillance cameras, while Kim & Cho [2] used motion capture techniques to measure motions of workers by tracking individual joint positions. However, these approaches face certain challenges. First, acquiring data at actual construction sites is difficult; therefore, most of the aforementioned studies have been primarily conducted in laboratories to simulate building construction sites. The availability of electrical infrastructure can be limited at construction sites, posing obstacles to data collection. Furthermore, the size of equipment must be carefully factored to avoid any impact on workers' performance at construction sites. Second, there is a psychological burden on workers associated with data acquisition, which varies depending on the nature of the data being collected. Ensuring that workers can perform their work unhindered requires careful consideration.

Considering the aforementioned challenges, this study proposes a new index for analyzing work activities at building construction sites using accelerometers. Moreover, accelerometers capture only acceleration data; therefore, they impose minimal psychological strain on workers. Additionally, as Yano [3] reported, acceleration data can reveal human behavioral characteristics that cannot be comprehended from qualitative assessments such as visual observation. In light of these considerations, the primary objectives of this study are to discern potential behavioral patterns by measuring worker accelerations at actual construction sites, evaluate the utility of accelerometers in such environments, and identify the limitations of work analysis. To this end, the evaluation methods proposed in previous studies are first reviewed in Chapter 4 [4]. Subsequently, a new work evaluation index based on the consistent trend (U-distribution) identified in Yano's human behavior research is introduced in Chapter 5 [3]. This index is applied to the same dataset examined in Chapter 4 to elucidate the potential behavioral characteristics of workers. Finally, through a comparative analysis of the proposed indices with findings from previous studies, the study discusses the appropriateness of each index and highlight pertinent issues.

## 2. REVIEW

In addition to the research outlined in Chapter 1, Cheng et al. [5] employed ultra-wideband wireless (UWB) and biometric sensors to achieve real-time location recognition of workers at construction sites and perform work analysis. Their study evaluated the practicality of the proposed method via real-time recognition of workers, materials, and machinery at construction sites, aiming to validate the effectiveness of the UWB system. Furthermore, Tsai and Kano [6] outfitted workers with multiple six-axis sensors, enabling the classification and estimation of tasks based on collected data. By constructing a neural network trained on experimental data, they achieved an 87.31% accuracy rate in estimating task configuration. These studies highlight the utilization of diverse sensing technologies in building construction sites, showcasing their capability in classifying, recognizing, and evaluating tasks with high accuracy. However, as discussed in Chapter 1, challenges remain regarding data acquisition and the psychological burden on workers, posing obstacles to the application of these technologies at actual construction sites.

Similar to the current study, some previous studies used accelerometers for work analysis at construction sites. For instance, Gondo & Miura [7] examined various occupational tasks using triaxial accelerometers, finding that the percentage distribution of activity and inactivity throughout the day tended to stabilize over time, with increasing skilled workers converging toward a consistent pattern. Similarly, Gondo & Akaki [4] used triaxial accelerometers to analyze motions at a construction site, introducing a two-axis scatter diagram method for classifying rebar distribution tasks into walking, standing, and sitting categories. Notably, they highly accurately classified walking activities and identified recurring work cycles, such as carrying and tying rebar every 25 min. These studies evaluated the challenges associated with sensing and analysis in real-world settings, offering insights into motion analysis using accelerometers and laying the groundwork for this study. In Chapter 3, this study builds upon the data processing approach proposed by Gondo & Akaki [4], partially improving its efficacy for handling measured acceleration data. In Chapter 4, the authors use Gondo & Akaki's [4] biaxial scatterplot-based walking motion classification method to assess the proportion of walking motions over a specific time interval; moreover, they compare this method with the new method proposed in the current study. However, previous studies lacked sufficient standardization of target workers and tasks, particularly in delineating work units for complex tasks such as rebar handling. By contrast, our study maintains consistency by assigning the same workers to continuous plasterboard stretching tasks over five days, enabling analysis under more uniform conditions. This approach allows us to reevaluate methodologies employed in previous studies and identify any issues.

## 3. Methodology

### 3.1. Accelerometer

A triaxial acceleration sensor (MVP-SD-AC) manufactured by Micro Stone Corp. (Japan) was used in this study. This sensor can capture XYZ three-axis acceleration within a 5–200 Hz. The sensor weighs only approximately 120 g and has a width, length, and thickness of 50, 75, and 20 mm, respectively; therefore it is unlikely to interfere with workers' tasks at construction sites when worn. Moreover, the captured acceleration data are stored in the sensor's built-in microSD (2 GB) storage, eliminating the need for a Wi-Fi environment for data transmission and reception. Equipped with a built-in battery capable of continuous operation for up to 50 h, the sensor facilitates uninterrupted data collection throughout the field survey period. In this study, the battery was recharged daily during the field survey to ensure seamless data acquisition.

### 3.2. Construction Site

The survey was conducted at a high-rise office building construction site in Tokyo over five days from June 7 to June 11, 2021. The survey was conducted on workers engaged in plasterboard application, chosen owing to the task's repetitive nature and the potential for extracting a large dataset. In particular, four workers, labeled as A, B, C, and D, participated in the survey; their work experiences were 18, 2, 9, and 5 years, respectively.

As depicted in Figure 1, the surveyed workers typically operated in pairs (one skilled and one unskilled) for plaster board application. However, workers A and B worked independently for this study, while workers C and D maintained their usual pairing. Work sessions were divided into four terms each day, lasting approximately 6.5 h, excluding scheduled breaks (working from 9:00 to 17:00, with breaks from 10:00 to 10:30, 12:00 to 13:00, and 15:00 to 15:30). Accelerometers were securely fastened to belts with buckles, positioned behind the workers' waists. During the survey, the sensors were worn so that the Y-axis on the surface of the accelerometer was in the vertical direction. Acceleration data were continuously recorded from the commencement to the conclusion of work activities. Simultaneously, the work of individuals A and B was recorded using a video camera. The sensors operated in a measurement cycle of 100 Hz. The construction site had sufficient illumination and visibility, facilitating visual monitoring of workers given their prolonged presence in specific areas owing to the nature of the work.

**Figure 1. Outline of the work process (measuring, processing, carrying, and pasting)**

## 4. Analysis via conventional methods

### 4.1 Visual Analysis

This section compares work activities using commonly employed work analysis techniques and evaluation methods from previous studies. The analysis focuses on the time taken per plasterboard sheet for two workers, labeled as A and B, who were videotaped. To ensure a standardized evaluation, the initial layer of plaster board, directly affixed to the light-iron substrate with an impact driver, was considered part of the board-attaching task for both workers, utilizing only the standard-size, unprocessed boards. Work time was defined as the duration from the commencement of screwing the first screw to the completion of the last screw for each board.

Table 1 shows the number of boards attached by each worker and the average time taken per board on each survey day. Figure 2 depicts the variation in work time for each board on the first day. Average work times were computed over five days, excluding the day without the target task and the fifth day for worker A. Comparing work times revealed that worker A, with longer experience, completed each board in less time. Worker B required considerably more time for the first and second boards owing to the need to remove screws before attaching the boards. In general, worker B took longer to complete his tasks than worker A, possibly owing to differences in screwing speed and the frequency of hand stoppages during work.

Upon video observation and time-based analysis of the workers' tasks, a discernible disparity emerged in the interval between striking of one screw and loading and striking of the subsequent screw: 0.8 s for worker A and approximately 2.5 s for worker B. Furthermore, a higher frequency of hand stoppages was noted for worker B during board application. These differences in motion during detailed work likely contributed to variations in work time per board. Additionally, this visual and video observation method accurately identifies inefficiencies in detailed work and differences in motion among workers.

**Table 1. Number of Boards Pasted by Workers A and B**

| | A | | B | |
|---|---|---|---|---|
| | Boards | Time (s) | Boards | Time (s) |
| Day 1 | 19 | 53.6 | 18 | 98.6 |
| Day 2 | 19 | 57.2 | 0 | - |
| Day 3 | 0 | - | 9 | 95.0 |
| Day 4 | 11 | 71.6 | 0 | - |
| Day 5 | 1 | - | 10 | 128.6 |

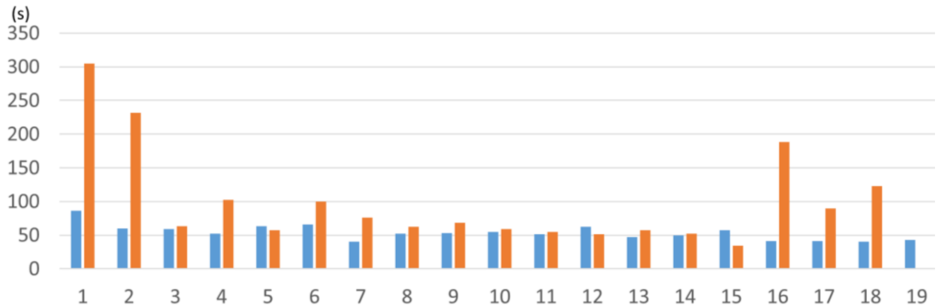


**Figure 2. Time Required for Pasting Each Board (Left: A, Right: B, Day 1)**

### 4.2 Analysis Based on the Classification of Walk Motions

In this section, the authors employ methodologies proposed in previous studies to analyze tasks. In particular, the authors describe the approach introduced by Gondo & Akaki [4], which uses a biaxial scatter plot to discriminate actions, focusing on variations in the proportion of walking motions. Equations (1)–(3), partially adapted from those proposed by Gondo & Akaki [4], are employed to classify walking motions using two-axis scatter plots (Figure 3). The *F* value, representing the harmonic mean of goodness of fit and repeatability, is used as an index of classification accuracy. In this study, the *F* value for walking motion is calculated to be 0.772. Notably, this value compares favorably with the *F* value of 0.751 reported in a previous study [4], indicating satisfactory classification accuracy.

$$a'_y = a_y + 9.80 \quad (1)$$

$$X_i = max\sqrt{a_x^2 + a_y'^2 + a_z^2} - min\sqrt{a_x^2 + a_y'^2 + a_z^2} \quad (2)$$

$$Y_i = \frac{\sum\sqrt{a_x^2 + a_y'^2 + a_z^2}}{frequency} \quad (3)$$

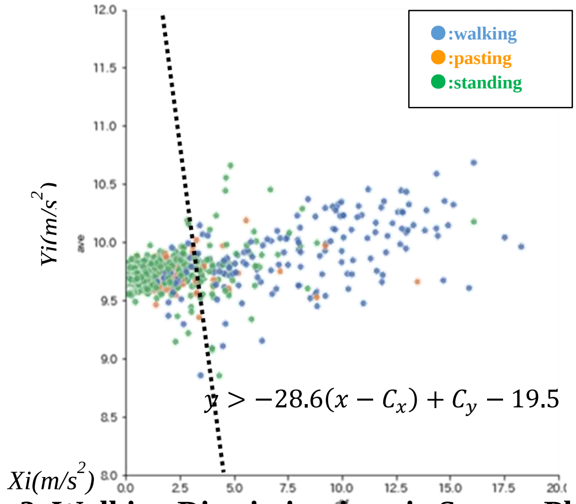


**Figure 3. Walking Discrimination via Scatter Plot Analysis**

Using the classification method outlined in the previous section, the authors classified walking motions across all workers and work hours, subsequently calculating the proportion of walking motions and their variations. Additionally, the authors generated a heatmap illustrating the walking rate every 5 min throughout work hours for each worker and survey day (Figure 4). However, only workers A and B, whose work activities were captured on video, were included in the Figure. Upon analysis of the fluctuations of the walk rate in workers A and B, a consistent trend emerged: the percentage of walking declined during the afternoon hours across all survey days. This finding differs from those of a previous study [4], where the calculated changes in the percentage of walking between morning and afternoon exhibited a mix of increments and decrements. However, in this study, workers A and B consistently demonstrated a decrease in the percentage of walking throughout all survey days.

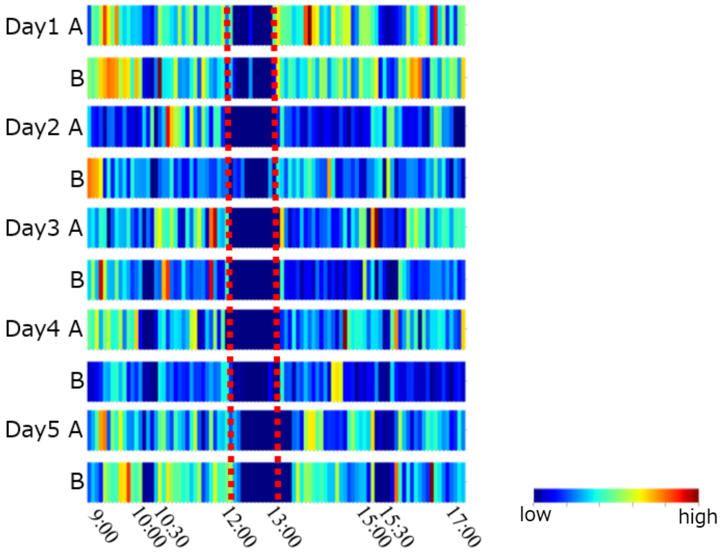


**Figure 4. Distribution of Each Worker by Acceleration Stage**

Figure 4 shows three designated rest periods per day at the sites surveyed in this study. During breaks, the handling of sensors was at the discretion of each worker, resulting in a mix of cases where the sensor was left on or removed. Generally, the percentage of walking during breaks remained low. However, notably, there were instances where the walking ratio remained relatively high even after the scheduled start time of the lunch break, as observed on the fifth day for worker B. On this particular day, work extended beyond 12:00 owing to insufficient breaks, highlighting challenging work conditions. Moreover, on the fifth day, a period with reduced activity was observed from 12:00 to 13:30. This indicates that the site was cleaned every Friday from 13:00 to 13:30 and that the sensors were temporarily removed during breaks for 30 min for cleaning. By interpreting the heatmap in this manner, it is possible to gain insights into the overall schedule of the construction site. Moreover, such analysis is promising for application in real-time working hour management systems, offering potential insights into whether workers are receiving the requisite break periods.

## 5. Proposal and analysis of the evaluation index based on acceleration distribution

### 5.1 U-distribution of Human Activity

Introducing a new evaluation index in this study, the authors calculate the distribution of daily measured acceleration data and propose an index that assesses work conditions based on the degree of variation. This index allows us to identify subconscious behavioral tendencies among workers. Based on a case study conducted by Yano [3], which introduced the number of arm motions per minute as an activity evaluation index, it was observed that the number of arm motions per minute (referred to as a "band") forms a declining U-distribution, a pattern common across various human behaviors and social phenomena. Notably, this U-distribution manifests as a right-skewed curve on a linear scale and as a right-skewed straight line on a logarithmic scale. Leveraging Yano's methodology [3], the authors calculate the proportion of acceleration based on stage and employ the distribution of energy to evaluate work dynamics.

### 5.2 Selection of Target Data

The criteria for data to be used as evaluation indices in this study are defined. The maximum and minimum differences in absolute acceleration values within a one-second interval defined using Equations 1 and 2, are employed as evaluation indices. This metric is unaffected by sensor inclination, enabling us to evaluate changes occurring within a one-second timeframe. Thus, a higher acceleration change within this interval signifies an increased activity level, serving as the basis for the evaluation index.

### 5.3 Percentage Distribution by Acceleration Stage

The data acquired in this survey fell within the 0–40 $m/s^2$ range for all recorded time intervals, as indicated by Equation 2. These obtained values were classified into 10 steps of 4 $m/s^2$ each, and the percentage contribution of each interval throughout the day was computed (Figure 5). For all workers, the proportion of the lowest acceleration stage was consistently the highest, exhibiting a linear decline as the stage increased. In this study, the acceleration distribution among plaster board laminating workers is in line with the trend of human behavioral characteristics described by Yano [3].

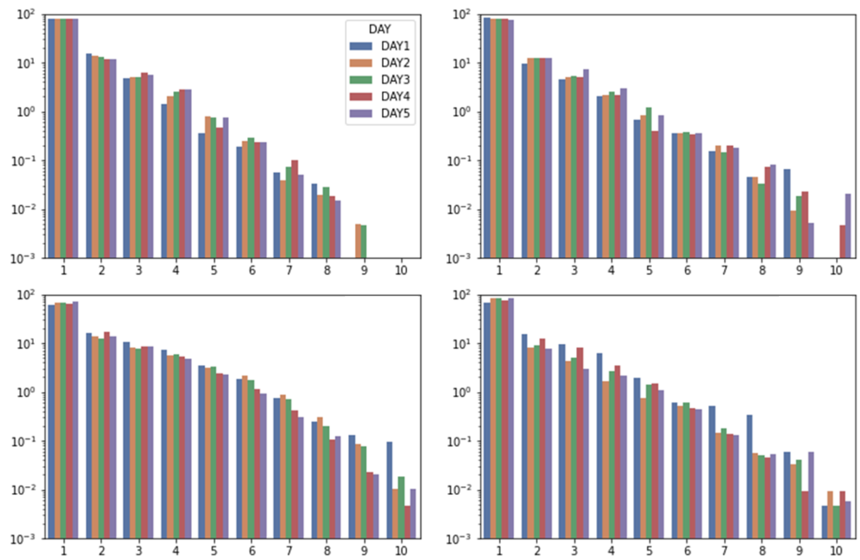


**Figure 5. Heatmap of W**

### 5.4 Limit Quantities Per Stage and Work efficiency

Yano [3] states that when classifying human activity levels based on each stage, as described in the previous section, each stage possesses a specific activity threshold. An optimal scenario involves utilizing the entire activity limit of all stages without excess or deficiency. In other words, the greater the regression of each stage's distribution toward the rightward straight line outlined in Chapter 5, Section 1, the more efficient the activity distribution; conversely, deviation from this straight line signifies decreased efficiency. Therefore, this study introduces an index to evaluate each worker's performance based on previous findings. To establish the evaluation index, the authors initially computed the average percentage of each step over five days and derived a regression function. The resulting value from this regression function served as the ideal activity level for each stage, and conformity with this function was assessed by computing residual variance with the daily data. Notably, the regression function derived in this section adopts an exponential approximation formula. In this formula, the coefficient of determination ($R^2$ value) is unsuitable for assessing goodness of fit; instead, residual variance is utilized for this purpose.

Using the indices defined earlier, residual variance was calculated for each worker for each workday (Table 2). Lower values in the table indicate a higher degree of conformity with the regression function, indicating smoother work performance. The values reveal that worker A consistently demonstrates the smoothest performance across all five days, closely followed by worker C, exhibiting the best fit. Conversely, workers B and D display relatively lower conformity on certain days. For instance, worker D shows better conformity on the first day than worker C on the second, third, and fifth days. However, worker B consistently registers values exceeding 100, indicating lower conformity levels. Comparing the five-day averages, the level of conformity follows the order A > C > D > B, consistent with the workers' respective work histories outlined in Table 1. While a more comprehensive analysis with a larger sample size is warranted, it can be inferred that workers tend to distribute activities more efficiently across stages with increasing work experience.

**Table 2. Residual Variance of Each Worker (by Work Experience)**

| | A(18 years) | | | B(2 years) | | |
|---|---|---|---|---|---|---|
| | AM | PM | Total | AM | PM | Total |
| Day1 | 9.5 | 6.9 | 7.7 | 129.2 | 189.5 | 162.8 |
| Day2 | 6.6 | 20.0 | 10.6 | 103.2 | 141.7 | 124.7 |
| Day3 | 7.8 | 17.3 | 12.0 | 62.0 | 171.5 | 118.2 |
| Day4 | 12.3 | 17.0 | 14.7 | 93.4 | 156.5 | 127.8 |
| Day5 | 13.4 | 17.7 | 15.2 | 75.5 | 127.4 | 101.7 |
| Ave. | 9.9 | 15.8 | 12.0 | 92.7 | 157.3 | 127.0 |
| | | | | | | |
| | C(9 years) | | | D(5years) | | |
| | AM | PM | Total | AM | PM | Total |
| Day1 | 17.6 | 11.6 | 12.6 | 25.6 | 51.2 | 23.6 |
| Day2 | 20.3 | 43.6 | 30.4 | 170.2 | 172.1 | 137.7 |
| Day3 | 43.4 | 34.5 | 37.8 | 159.0 | 134.8 | 114.4 |
| Day4 | 29.0 | 13.2 | 18.8 | 116.0 | 60.7 | 57.2 |
| Day5 | 49.7 | 28.8 | 37.4 | 158.6 | 212.5 | 149.3 |
| Ave. | 32.0 | 26.3 | 27.4 | 125.9 | 126.2 | 96.5 |

Next, the residual variance was calculated separately for each worker during morning and afternoon sessions on each workday (Table 5). The values in the table indicate that even when morning and afternoon averages were analyzed separately, the degree of conformity followed the order A > C > D > B, aligning with job history and the aforementioned assessment of fit throughout the workday.

Furthermore, the goodness of fit tended to increase in the afternoon compared to the morning for the second through fifth days for worker A and across all days for worker B. This suggests a tendency for tasks to become progressively more challenging to execute smoothly in the afternoon. Conversely, the results for workers C and D displayed a mix of increments and decrements, mirroring the fluctuations observed in the percentage of walking during morning and afternoon sessions, as described in Chapter 4.

## 6. Conclusion

Herein, work analysis was conducted at an actual construction site using three-axis accelerometers attached to four plaster-board-pasting workers. Initially, we performed work analysis using various evaluation indices, including an analysis based on the average time per plasterboard sheet and the classification of walking motion based on acceleration data, as proposed in a previous study. Subsequently, we introduced an evaluation index based on a study conducted by a previous study and conducted further work analysis. Through comparative analysis of the results obtained using the proposed evaluation index and those obtained using evaluation indices reported in previous studies, we confirmed common trends and discussed the strengths and limitations of each index.

Experienced workers demonstrated short working times per board, with potential causes of such efficiency observable in accompanying videos. Conversely, the evaluation index introduced in this study is anticipated to quantitatively assess differences in skills between skilled and unskilled workers, potentially uncovering latent behavioral characteristics unattainable through qualitative assessments such as video observation. However, while work duration and conformity levels may not perfectly align, the proposed evaluation index represents a more comprehensive measure for assessing workers' skills.

Future work entails a more detailed investigation of the proposed evaluation index. Notably, given the observed trends in walking rate variation and conformity across different periods in this study, further investigation is warranted to elucidate which behavioral characteristics of workers are assessed by each evaluation index. A detailed examination of the proposed indicators across diverse job types with a sufficient sample size in future studies is expected to facilitate the quantitative evaluation of complex factors such as differences in workers' latent expertise.

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