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Rapid and Contextual Activity Analysis: A Semi-automated Activity Category, Time, Location, and Video Data Collection and Analysis Methodology

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Rapid and Contextual Activity Analysis: A Semi-automated Activity Category, Time, Location, and Video Data Collection and Analysis Methodology

by

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Dedication

To Soo-Jin, my wonderful wife.

To Won-Jun (Brian), my beloved son.

To Sung-Soo Kim and Bong-Hyun Park, my great parents.

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Rapid and Contextual Activity Analysis: A Semi-automated Activity Category, Time, Location, and Video Data Collection and Analysis Methodology

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The performance of construction projects is significantly impacted by on-site labor and the productivity thereof. Despite the benefits from technological advancements in recent decades, construction projects are still labor intensive, and labor is one of the most flexible and largest cost factors in a construction project. Thus, a major concern of construction project management has been labor productivity and its improvement.

To improve it, labor productivity must be measured and analyzed. One way of doing so is through activity analysis - known as an extension of traditional work sampling. Activity analysis measures the efficiency of the workers' time usage at a construction site. Increasing labor efficiency usually has a positive relationship with higher construction labor productivity. Therefore, activity analysis is considered a major labor performance assessment technique in this research.

The objective of this research is to develop a semi-automated data collection and analysis methodology to enable fast and contextual activity analysis. More specifically, this research focuses on the man-machine balanced on-site data collection and the automated data analysis with abundant contextual information to support the interpretation of analysis results for labor productivity improvement study.

The prototype of the proposed methodology is implemented and validated with actual datasets from different construction sites. The prototype system proves capable of collecting data efficiently at construction sites and to analyze it in an automatic fashion. This system is shown to provide abundant contextual information related to the activity analysis results. A project manager can quickly and easily find issues related to their high or low labor performance with various scenarios. The indexed videos also successfully provide information about what/how construction workers were performing work at that point. This information can support productivity improvement planning and expedite the continuous evaluation and improvement process of activity analysis to improve labor productivity.

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Chapter 1: Introduction

The performance of construction projects is significantly impacted by on-site labor and the productivity thereof (Jenkins and Orth 2004; Gouett et al. 2011; Rivas et al. 2011). Despite the benefits from technological advancements in recent decades (Allmon et al. 2000; Goodrum 2001; Grau et al. 2009; Goodrum et al. 2011), construction projects are still labor intensive (Rojas and Aramvareekul 2003; Jarkas 2010; Yi and Chan 2014),[1] and labor is one of the most flexible and largest cost factors in a construction project (Gouett et al. 2011; Hanna et al. 2008; CII 2001). Thus, a major concern of construction project management has been the labor productivity and its improvement.

In order to improve labor productivity, management must, as a starting point, understand the current status by comparing it with standard productivity (Liou and Borcherding 1986; Gong and Caldas 2010; Gouett et al. 2011). However, measuring labor productivity has several issues. Usually, there are several weeks of time-lags between the actual works performed at the site and the labor productivity measurement of the works (Gong and Caldas 2010). This means that management or superintendents could obtain their labor productivity reports a good deal after the occurrence of significant issues. Management may lose opportunities to resolve in a timely fashion the issues (Oglesby 1989; Gouett et al. 2011). Furthermore, measuring the output (quantity)[2] of labor productivity makes its measurement more challenging. The units of output vary by different construction activities such as ton for reinforcing steel and linear feet (LF) or

[1] Although residential and commercial (R&C) construction are more labor intensive, and industrial and heavy (I&H) construction are more capital intensive, most of the work on I&H construction sites is still performed by labor or equipment operated by labor. This means that a certain portion of labor on the I&H construction projects is substituted by capital which produces higher labor productivity (Rojas and Aramvareekul 2003).

[2] Labor productivity (unit rate) is defined as the ratio between work hours (input) and quantity (output).

square foot contact area (SFCA) for forms in place (wall) (Goodrum and Haas 2004; Song and AbouRizk 2008). This variation in output units requires more time and effort to measure labor productivity.

In response to these issues, work sampling, a timely and quantitative workface assessment method, has emerged in the construction industry (Thomas and Holland 1980; Thomas 1981; Thomas et al. 1982; Liou and Borcherding 1986; Jenkins and Orth 2004; Gouett et al. 2011). Work sampling has been extended to activity analysis by the Construction Industry Institute in 2010 (CII 2010).

Activity analysis includes a continuous measurement and improvement process. It also has a more detailed measurement and analysis method. In its data collection process, activity analysis categorizes worker's activities into several groups (CII 2010; Gouett et al. 2011). A major focus of the analysis is direct work, "the act of either exerting physical effort to perform a (construction) activity or physically assisting in these activities" (CII 2010). It usually has a positive correlation with higher construction labor productivity (Liou and Borcherding 1986; Allmon et al. 2000), though there is an exceptional contradictory study (Thomas 1991). Recently, activity analysis/work sampling has been adopted by major construction companies and consulting companies to achieve improvement by benchmarking direct work rates with various construction projects (Gouett et al. 2011). Therefore, activity analysis is considered a useful workface assessment technique for labor productivity improvement study. The main focus of this research is its data collection and process of analysis.

This introductory chapter offers an overview of the overall research. It provides the problem statement, research objective and scope, research questions, research methodology, and the contributions of this research.

1.1 PROBLEM STATEMENT

CII defines activity analysis as a "continuous process of measuring and improving the amount of time that craft workers spend on actual construction" (CII 2010). During its measurement process, activity analysis generally uses the following activity categories: 1) direct work, 2) preparatory work, 3) material handling, 4) tools and equipment, 5) waiting, 6) travel, and 7) personal. Among the categories, direct work is the only productive work; the preparatory work, material handling, tools and equipment, and travel are supportive work; the waiting and personal are periods of idleness or delay. The major goal of activity analysis is to achieve improvement by maximizing direct work rates and optimizing other work rates.

As a useful technique to assess the performance of workface, activity analysis provides the following benefits (Oglesby 1989; Hanna 2010; CII 2010): 1) a quantitative method to identify inefficiency, 2) a statistical technique and provides trends over time, 3) easy results to understand, 4) a relatively inexpensive method with reasonable accuracy, 5) not interrupting worker's regular working process, and 6) a continuous improvement process.

However, activity analysis also has several limitations regarding its data collection and data analysis. The current data collection method of activity analysis requires tedious and time-consuming manual observations (Gong et al. 2011c; Joshua and Varghese 2011; Memarzadeh et al. 2013). The observer carries data collection forms, makes observations, stops walking, and manually records the observation results in the corresponding cell in the forms (Gouett et al. 2011). This manual process is time-consuming and can lead to errors. Furthermore, to obtain the statistical significance of analysis results, a minimum number of observations per hour has to be made based on the number of total workers in the target construction site. This can be hundreds per hour or

more and requires additional observers because it can sometimes be impossible to make the minimum number of observations in an hour. This manual data collection process can offset the benefits of activity analysis (CII 2010; Joshua and Varghese 2011; Memarzadeh et al. 2013; Yang et al. 2015). Therefore, there is a need for an improved method to support the data collection effort.

In terms of data analysis, activity analysis also has several limitations. After completing observations at the site, the records have to be manually entered to the analysis software or spreadsheets to calculate work rates and to create graphic representations of the overall and hourly charts and graphs. This is also a time-consuming process and prone to error. Another important point with data analysis is that the most challenging part is the interpretation of the analysis results. Indeed every project has its own conditions and work environment and different issues with their labor performance. This interpretation is critical because management has to take immediate actions to eliminate any obstacles or constraints if the interpretation indicates any issues affecting labor performance (CII 2010; Gouett et al. 2011). However, activity analysis results do not contain enough contextual information, which supports the understanding of what occurred when observations were made, to support the interpretation of the analysis results. This means that additional surveys such as foremen delay survey or craftsman questionnaire can be required to support the interpretation and to identify the issues with their labor performance. This requires additional time and efforts from project engineers. Therefore, improvement on the data analysis is also required for faster analysis with abundant contextual information.

1.2 Research Objective and Scope

The objective of this research is to develop a semi-automated on-site data collection and analysis methodology to enable fast and contextual activity analysis (Figure 1). More specifically, this research focuses on the semi-automation of on-site data collection and the automation of data analysis for faster analysis with abundant contextual information to support the interpretation of analysis results for labor productivity improvement study.

The semi-automation of on-site data collection means a man-machine balanced approach to collect activity category data. With the current state of the art of technologies, the full automation of identifying and categorizing workers' activities has limitations for general use. The full automation works with specified activities in controlled environments but is limited in applying it to the many different types of construction activities. Regarding the data analysis, this research pursues the automation of data integration and processing to achieve faster analysis with enough context information for easy and intuitive interpretation of the analysis results.

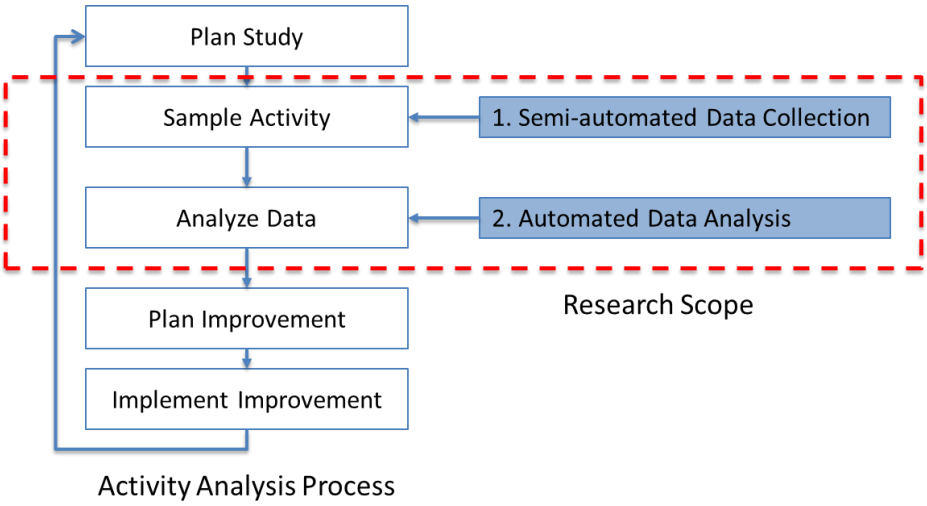


Figure 1: Activity Analysis Process and Research Scope

As shown in Figure 1, activity analysis consists of following continuous processes (CII 2010): 1) plan study, **2) sample activity, 3) analyze data,** 4) plan improvement, 5) implement improvement, and, returning to the first step (plan study) to re-assess the implementation results of improvement plans. Of these steps, the scope of this research covers the semi-automation of the "sample activity" and the automation of the "analyze data." Those two processes are closely related to the issues mentioned in the previous section and have the potential to be beneficial if they are semi- or fully-automated.

1.3 RESEARCH QUESTIONS

Based on the objective and research scope, this study aims, to develop an improved on-site data collection and analysis methodology to answer, the following two research questions.

- **Research Question I:** How can the activity category and its related time, location, and video data be effectively collected under realistic site conditions for activity analysis?
- **Research Question II:** How can the collected data be automatically integrated and analyzed to provide activity analysis results with context information for the study of productivity improvement?

Research Question I: How can the activity category, time, location, and video data be effectively collected under realistic site conditions for activity analysis?

The current practice of activity analysis relies on manual data collection. As mentioned above, it requires a large amount of manual observations to obtain statistical significance in the analysis results (Barnes 1980; CII 2010; Hanna 2010). This has been

one of the obstacles that has hindered the wide use of activity analysis. Therefore, recent studies have discussed in the needs for automated/semi-automated data collection method for activity analysis (Cheng et al. 2013; Gong and Caldas 2010; Joshua and Varghese 2011; Memarzadeh et al. 2013; Park and Brilakis 2012; Peddi et al. 2009; Weerasinghe and Ruwanpura 2009; Weerasinghe et al. 2012; Yang et al. 2015). The automated/semi-automated data collection under realistic site conditions is made challenging by the extreme noise, vibrations, dust, moving obstacles, and occlusions at the site. Furthermore, the continually changing site environment, because of construction progress, exacerbates these challenges. Therefore, the activity category data and its related time, location, and video data collection method should be simple but reliable and flexible at the construction site. The method should also be applicable to various construction tasks because any type of task can be a target of activity analysis.

Research Question II: How can the collected data be automatically integrated and analyzed to provide the activity analysis results with context information for the study of productivity improvement?

Conventional activity analysis requires manual data processing to create analysis results such as work rates, graphs, and charts. This is also time-consuming and prone to error. Furthermore, the activity category and its related time, location, and video data for context information make the manual data processing worse. Regarding the context information, it is critical that the four different datasets are integrated. The activity category data and its related data can have meanings when they are integrated with each other. Nearly impossible is the manual integration of such data. Therefore, automated data integration and analysis method is required to achieve fast and contextual activity

analysis. The analysis method and its results should be comprehensive, intuitive, informative, and dynamically re-analyzed with various analysis scenarios.

1.4 RESEARCH METHODOLOGY

Illustrated in the Figure 2 is an overview of the research methodology that this study employed. This research begins with a background review on productivity definitions, conventional on-site data collection methods for productivity studies, trends in automated on-site data collection, and analysis for productivity studies. It casts a light on construction productivity and its related data collection and analysis methods. It supports the definition of research objectives, questions, and scope. The next step is the development of semi-automated/automated activity analysis data collection and analysis methodology. Major elements of the data collection and analysis methodology are identified, and their detailed process and algorithms are developed in this step. The methodology is implemented in the hardware and software implementation phase. Then, the methodology is validated in the data collection and validation step. It consists of two parts. The first part is data collection using the developed methodology under realistic site conditions. Five construction sites were selected for this purpose. The second part is a validation of the methodology with the collected data. Feedback during the data collection and validation steps is reflected to the methodology. Based on previous research steps, the last step offers conclusions, identifies limitations, and suggests future research.

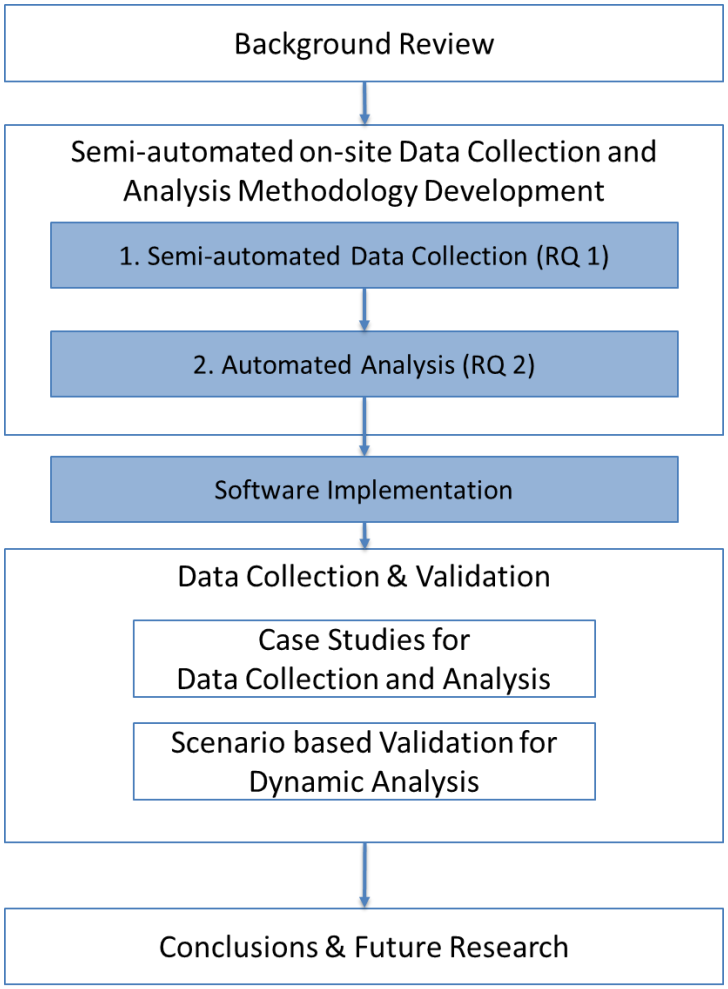


Figure 2: Research Methodology

1.5 Reader's Guide to the Dissertation

This dissertation consists of five main chapters: 1) Introduction, 2) Background Review, 3) Semi-automated Activity Analysis Data Collection and Analysis Methodology, 4) Data Collection and Validations of Proposed Methodology, and 5) Conclusions and Future Research. Below is a brief description of each chapter.

Chapter 1 provides an overview of this research. It contains problem statements, objectives, and research methodology.

Chapter 2 offers background on productivity and its related manual and automated data collection methods.

Chapter 3 explains the semi-automated activity analysis data collection and analysis methodology. This chapter consists of two parts: semi-automated data collection and automated data analysis methods. These parts correspond to the first and second research questions, respectively.

Chapter 4 shows the data collection and validation results of the proposed methodology. It describes the actual process and results of data integration and dynamic analysis.

Chapter 5 lays out the conclusions of this research. It summarizes the contributions of this research to data collection and analysis for Fast and contextual activity analysis. It also points to the limitations, implementation recommendations, and future research areas.

Chapter 2 Background Review

This chapter provides a review of construction productivity, its conventional data collection method, and related research studies. It offers background knowledge of different types of productivity definitions and their characteristics. The chapter goes on to introduce conventional on-site data collection for productivity study. A review of the manual methods provides background information to highlight the research gaps that this research aims to fill. This review sheds light on the methods frequently referred to in this dissertation. The third part goes over recent research trends in the construction industry's methodologies for automated data collection. It focuses on semi-/fully automated construction workers' activity data collection. It also supports the identification of research gaps.

2.1 DEFINITIONS OF PRODUCTIVITY

Productivity is commonly defined as the ratio between output and input. It can be represented as "output/input" or "input/output" (Park 2002). To meet various purposes, productivity is defined in many ways and these definitions generally fall into three categories: 1) Major Industry Sector Level Productivity, 2) Project Level Productivity, and 3) Activity Level Productivity. These categories were originated and modified from a previous study (Thomas et al. 1990). This section introduces the presentive productivity definitions of each category and provide benefits and limitations of the productivities.

2.1.1 Major Industry Sector Level Productivity

Total factor productivity (TFP) for major industry sectors is an economic model that "measures the value-added output per combined unit of labor and capital input in

private business and private nonfarm business" (Thomas et al. 1990; BLS 1997). TFP, also referred to as multifactor productivity (Cheng et al. 2013), is defined by the equation below (Thomas et al. 1990):

$$TFP = \frac{Dollars\ of\ Total\ Output}{Dollars\ of\ (Labor + Materials + \text{Equipment} + \text{Energy} + Capital)}$$

Basically, the TFP input and output are monetary values because money is a common measure (Thomas et al. 1990) and can combine into one value TFP's multiple input factors (i.e. labor, materials, equipment, energy, and capital).

The U.S. Bureau of Labor and Statistics (BLS) defines TFP using the equation below:

$$TFP = \frac{Dollars\ of\ Total\ Output}{Dollars\ of\ (Capital + Labor + Energy + Material + Service)}$$

The input and output are also monetary values, and the input is composed of capital, labor, energy, material, and service. The last factor, service, includes equipment, structures, inventories, and land (BLS 1997).

TFP is useful for major sector-level applications such as policy-making and economic studies because it can provide higher level information such as long-term economic growth (Thomas et al. 1990; Goodrum 2001; Zhi et al. 2003). What TFP is not suitable for, however, is construction projects. This is because estimating inputs at the individual construction project level presents such difficulties. In fact, TFP can in such cases produce highly inaccurate results (Thomas et al. 1990; Park 2002).

2.1.2 Project Level Productivity

Factor Productivity (FP), a simpler version of TFP, is defined as physical output (units) per combined inputs of labor, material, and equipment as shown in the equation below. Because predicting FP's output and input at the project level is easier and more accurate, FP is a more suitable measure for a construction project (Thomas et al. 1990; CII et al. 2013). The output is estimated with a common and representative unit of a certain construction project (e.g., square feet for a building project and miles for a road project). The input is a combined with the monetary value of labor, material, and equipment. In most construction projects, the three factors are common and representative factors. This factor productivity is used for conceptual estimating (CII et al. 2013).

$$FP = \frac{Physical\ Output\ (Units)}{\$\ of\ (Labor\ +\ Material\ +\ Equipment)}$$

A example of FP is as follows:

$$FP\ (Example) = \frac{Square\ Feet}{Dollars}\ \ or\ \ \frac{Miles}{Dollars}$$

Partial factor productivity (partial FP) is another type of simpler TFP. As shown in the equation below, the material cost is removed from the input of FP. This partial FP is used for specific types of project control but can also be used for conceptual estimating (CII et al. 2013).

$$Patial\ FP = \frac{Physical\ Output\ (Units)}{\$\ of\ (Labor\ +\ Equipment)}$$

2.1.3 Activity Level Productivity

Measuring productivity at the activity level requires productivity be more narrowly defined. Labor productivity, a suitable measure for this purpose, is defined as the ratio between workhours (output) and quantity (input) of individual activities shown in the following equation (Thomas et al. 1990; CII et al. 2013). This productivity focuses on individual activities such as masonry, concrete work, steel work, conduit, and pavement. It is a type of single factor productivity and is also called unit rates. Labor productivity, one of the most objective and direct methods of measuring construction productivity (Liou and Borcherding 1986), is the most widely used in the construction industry. Construction companies maintain this productivity internally to maintain their competitiveness in bidding or performing projects.

$$Labor\ Productivity\ (Unit\ Rates) = \frac{Workhours}{Quantity} \quad \left(or\ \frac{Quantity}{workhours}\right)$$

2.2 Manual On-site Data Collection and Analysis Methods for Labor Productivity Improvement

Project managers wanting to improve productivity must measure and analyze it so as to identify problems and their causes. Jobsite management often introduces policies or procedures that, though well intentioned, can introduce additional barriers to productivity. Barriers to productivity can be identified and overcome. This chapter identifies three approaches and seven analytic techniques that are able to do just this (Oglesby 1989; Hanna 2010). These methods are shown in Table 1.

Approaches	Methods	Benefits
Asking	• Craftsmen questionnaires • Foreman delay surveys • Voice of craft workers	• Answer for "Why" • Detection of weaknesses • Suggestions for improvements
Analyzing Work Process	• Crew balance chart • Flow diagram and Process Chart	• Answer for "who/what/when/where/how" • Gathering information on a work method or performance
Observing	• Five-minute ratings • Work Sampling/Activity Analysis	

Table 1: Onsite Data Gathering Method: Modified from CII et al. (2013)

2.2.1 "Asking" Approaches

Craftsmen Questionnaire

Craftsmen questionnaires mainly serve the purpose of investigating the problems that adversely affect labor productivity and motivation (Kaming et al. 1998; Olomolaiye 1998). Craft professionals are knowledgeable, understand well the factors that affect productivity, possess superb notions on how to resolve problems, and are generally willing to share them with management. With such input, managers can identify areas of

inefficiency in onsite construction organizations and daily operations (Oglesby 1989; Rivas et al. 2011).

Foreman delay surveys

Foremen delay surveys are more formal/periodical method to identify adverse factors that affect crews' productivity. Foremen report and underscore problems on the project that are beyond the perspective of an individual foreman (Oglesby 1989). It requires active participation of foremen (Skitmore and Marston 1999). At a slight additional cost, foreman delay surveys supply reasonably accurate information using existing resources and channels of communications (Olomolaiye 1998). Foreman delay surveys can be carried out via several methods: daily, with weekly reporting; daily for several weeks; or as needed. Surveys can cast a critical and unwelcome light on management, so foremen must be assured impunity for honest reporting. They are thus free to point out specific causes of lost productivity and to estimate the costs (Oglesby 1989).

Voice of craft workers

Voice of the Worker (VOW) is a type of survey tools and allows craft workers to help identify factors that influence productivity. It is designed for deployment during front end planning and in the construction phase of a project (CII 2007). It can successfully engage "craft workers in productivity improvement and assist a site management team in controlling factors that impact productivity."(CII 2006)

VOW is composed of ten categories and 56 factors. For each factor on the project productivity survey, craft professionals are asked to assess its potential and actual effects.

The survey is scored on a scale of 1 to 7—the higher the score the higher the impact (CII 2007).

VOW can be used in the planning stage support a craft professional to assess potential critical factors that might affect an upcoming project. During the construction phase, VOW can help identify the most significant factors of the project.

2.2.2 "Analyzing Work Process" Approaches

Crew Balance Charts

To show the interrelated activities of individual members of crews and their effects on the availability of the equipment they employ management can use crew balance charts (Oglesby 1989). It can improve construction productivity (Kuprenas and Fakhouri 2001) by providing balanced resource usage (i.g. balance between crew members and equipment). It is applied to cyclic and high-cost operations (Hanna 2010; Olomolaiye 1998).

An observer completes a crew balance chart while observing a crew for a set amount of time. The observer records the time and equipment each worker devotes to each element of an activity. The observer can use for these observations a stopwatch or time-lapse film. Preferably the observer should allot several cycles to validate the accuracy and variations among cycles (Hanna 2010; Oglesby 1989; Olomolaiye 1998).

Flow Diagrams and Process Charts

Flow diagram is defined as a "two-dimensional scale model indicating the locations of work activities, materials, and worker and equipment movements."(Olomolaiye 1998). Flow diagrams illustrate the work processes on

construction sites (Hanna 2010). Flow diagrams are supplemented in this approach by process charts that categorize work activities into five categories: storage, transportation, operation inspection, and delay. The activities, once categorized, are arranged chronologically (Hanna 2010). Based on the visualization of actual work process in the construction site, project management can analyze the process to identify ineffective processes (Olomolaiye 1998). The work process can be optimized and reviewed by removing or modifying inefficiencies such as inappropriate/redundant processes, storages, or transportation routes.

2.2.3 "Observing" Approaches

Five-minute Ratings

Five-minute rating technique is a quick appraisal of construction activities and effective tool to evaluate the activities. It evaluates the effectiveness of craft's time utilization. Management can use this technique to monitor job delays and to measure the amount of them. This method can also show or estimate the effectiveness of a crew and where savings might be gained by more detailed observations or planning (Oglesby 1989).

Activity Analysis

Activity analysis is another evaluation technique of workface assessment. Not only does this method provide information on the amount of time workers spend performing productive/nonproductive work, it helps identify the site-specific factors that have either a positive or adverse effect on productivity. Additionally, results from the initial work sampling study will serve as a baseline, or benchmark, for future studies. By

comparing the productivity levels of sequential work sampling studies, managers are able to evaluate the effectiveness of their productivity improvement measures and identify the presence of any work trends (Jenkins and Orth 2004).

Activity analysis is an extended version of work sampling. It is defined as "the continuous process of measuring and increasing the amount of time that craft professionals spend on actual construction." (CII 2010). It lets project managers first recognize productivity barriers and then make alterations to reduce or even eliminate those barriers. Figure 3 shows activity analysis's continuous improvement process.

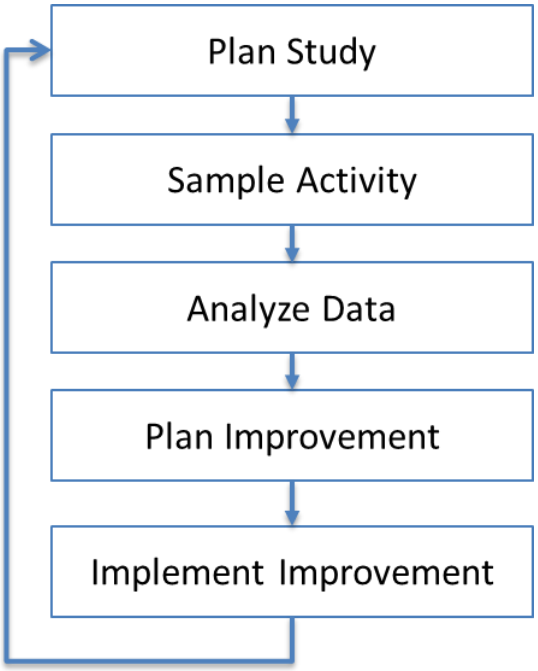


Figure 3: Activity Analysis Process (CII 2010)

The first step is to define the study's objectives and scope and to sort out other details. The second step is to gather a representative sample of activity and categorize the observations. One set of categories could include, for example, direct work, preparatory

work, tools and equipment, material handling, waiting, travel, or personal. Other sets of categories and guidelines for minimum sample sizes can be found in CII Implementation Resource 252-2a, Guide to Activity Analysis (CII 2010b). However, project managers can define more detailed or their own categories based on their measurement purpose as shown in the Table 2.

<table>
<tr><th>Category Type I</th><th>Category Type II</th><th>Category Type III</th><th>Category Type III</th></tr>
<tr><td>Productive</td><td>Effective</td><td>Direct Work</td><td>Direct Work</td></tr>
<tr><td rowspan="4">Supportive</td><td rowspan="4">Essential</td><td rowspan="2">Transport</td><td>Tools and Equipment</td></tr>
<tr><td>Material Handling</td></tr>
<tr><td>Travel</td><td>Travel</td></tr>
<tr><td>Instruction</td><td>Preparatory Work</td></tr>
<tr><td rowspan="2">Idle/Delay</td><td rowspan="2">Ineffective</td><td>Idle</td><td>Waiting</td></tr>
<tr><td>Personal</td><td>Personal</td></tr>
</table>

Table 2: Examples of Observation Categories

Next, the implementation team charts the data to come up with activity percentages and identify the types of activities that are outside the acceptable range. Once potential causes for an unacceptable range have been identified, ways to improve productivity can be assessed. Improvements are based on such factors as feasibility, logistics, and costs. The improvements chosen are then implemented to augment the direct work rate.

The benefits of Activity analysis (Work Sampling) are as follows:

- is a quantitative method to identify inefficiency
- is a statistical technique and provides trends over time
- is easy to understand its results
- is relatively inexpensive, but provides reasonable accuracy
- does not interrupt worker's regular working process

2.3 AUTOMATED ON-SITE LABOR PRODUCTIVITY DATA COLLECTION AND ANALYSIS METHODS

Studies on automated workers' activity data collection for labor productivity fall into the following four categories: 1) contact sensor, 2) 2D vision recognition, 3) 3D vision recognition, and 4) voice recognition. This section will review the current state of the art of the methodologies of research categories.

2.3.1 Contact Sensor-based Data Collection and Analysis

Contact sensors are the measurement devices that detect changes in target objects through direct and physical contact. Due to recent advancements in sensor technologies in terms of size, price, performance, and portability (Culhane et al. 2005; Kwapisz et al. 2011), contact sensors have been applied to the construction industry to recognize workers' and equipment activities for productivity studies. Joshua and Varghese (2011) proposed accelerometer-based construction worker's activity classification method to automatize the work sampling process. Target activities included fetching and spreading mortar, fetching and laying brick, and filling joints of bricklaying work. The authors set up an accelerometer on a worker's waist and collected the movement data of the worker's body. From the data they then extracted time-domain features (i.e., mean, variance, peak, and correlation) and frequency-domain features (i.e., energy and entropy) and identified the three activities of bricklaying. Their experiments include performance tests of various classifiers. The results showed that what gave the best results was the multilayer perceptron, a type of neural network. The authors expanded their study with more sensors and number of activities: eight effective works, five contributory works, and four ineffective works (Varghese and Joshua 2012). They attached three accelerometers on

workers' right and left wrists and their waist. They performed work sampling with this automated measurement method.

Cheng et al. (2013a) introduced a task-level activity analysis method using data fusion of location and worker's thoracic posture-sensing devices. The authors adopted ultra wideband (UWB) and physiological status monitoring (PSM) devices to collect workers' location and posture data, respectively. They fused those data to classify workers activities into four activity analysis work categories: working, traveling, material handling, and idling.

Contact sensors can be utilized to recognize activities of construction equipment for productivity improvement. Akhavian and Behzadan (2015) developed a construction equipment activity recognition method using mobile sensors to provide process knowledge at different process levels. The method is also able to provide input data for data-driven simulation models such as CYCLONE (Halpin 1977), STROBOSCOPE (Martinez 1996), and Simphony (Hajjar and AbouRizk 1999). In order to recognize equipment activities, the authors adopted accelerometer, gyroscope, and GPS sensors embedded in a smartphone. Accelerometers and gyroscopes were used to recognize equipment activities and GPS was used to provide additional contextual information (e.g., the proximity of front-end loader and hauler). They attached a smartphone inside of a front-end loader cabin (i.e., the front window) and collected those three types of data. The authors then extracted equipment activity features from the accelerometer and gyroscope data and trained machine learning classifiers to recognize activities. The authors concluded that the process-level knowledge acquired from the activity recognitions at the different process levels can be used for productivity improvement, safety management, and fuel use and emission monitoring and control.

Contact sensor-based methods have shown reasonable accuracy at activity recognition. Studies have confirmed that these methods can be used for automated work sampling/activity analysis. They can cause, however, several issues when they are applied to a large or entire portion of a construction project. The large-scale application requires as many sensors as the number of target workers or equipment. That is because the data collection of the large scale application has to meet a minimum number of observations to attain statistical significance of work sampling/activity analysis (CII 2010). Depending on the size of the project, the sensors can number in the dozens, hundreds, or thousands. This also incurs increased expenses for the sensors. Another issue can be data logging from multiple and remote sensors to the server at the construction site. Such data logging, considering the dynamic environments of the construction site, calls for wireless communication rather than wired. Workers and equipment, for instance, are continually moving from one location to another, and there are enormous occlusions and closed spaces that interrupt wireless communication. Furthermore, the amount of sensor data sometimes can be critical because accelerometers and gyroscopes require a relatively high sampling rate (e.g. 20 to 100 Hz for accelerometer; Joshua and Varghese 2011; Akhavian and Behzadan 2015), generating a large amount of data. The last issue is that the contact sensor-based methods require an additional daily process in which workers wear or attach sensors to their body. The process can be cumbersome to workers and requires additional preparatory time that can potentially reduce direct work rate.

2.3.2 2D Vision Recognition based Data Collection and Analysis

A type of non-contact sensor that has long been used for productivity study (Oglesby 1989; Eldin and Egger 1990) is 2D vision (e.g., picture and video). 2D video is not expensive to collect at the job-site and contains a great deal of information. Therefore, 2D video-based productivity data collection methods such as videotaping and time lapse video have already been used for productivity analysis of construction job sites (Gong and Caldas 2010).

Historically, the initial attempt to exploit 2D vision technology was time-lapse photography or video (Abeid and Arditi 2002a; Everett et al. 1998; Senior and Swanberg-Mee 1997). Such attempts were mainly used for motion studies to improve productivity. However, to analyze such a study manually requires much time and effort. Thanks to advancements in computer vision technology, however, many researchers in the field of construction use time-lapse photography or video to collect on-site labor productivity data.

2D vision-based activity data recognition basically relies on features from 2D vision data. The features are sets of vectors or other types of mathematical expressions characterizing objects or activities in 2D vision data. Classifiers are then trained with the features (i.e., training dataset) to recognize features from new vision data (i.e., test dataset). Based on this basic methodology, there are, in the field of construction, two types of action recognition studies: human workers' activity recognition, equipment activity recognition, or both. Table 3 shows a brief summary of recent research trends on 2D vision-based human or equipment activity recognition. This is a promising technology, but has limitations in its utilization at an actual construction site (Yang et al. 2015). One challenge is being able to monitor multiple targets or multiple activities in real-time at a construction jobsite (Cheng et al. 2013).

Researcher	Scope	Technologies
Peddi et al. (2009)	Worker's pose recognition	- Silhouette - Human Skeleton - Neural Network
Yang et al. (2009)	Crane tracking	- 2D-3D rigid pose estimation - Density-based tracking algorithms
Gong et al. (2011)	Worker and equipment action recognition	- SIFT descriptor - Bag-of-Video-Feature-Words - Bayesian Network
Heydarian et al. (2012)	Equipment movement tracking	- Space-Time Interest Points (STIP) - Visual Codebook - Multiple Binary Support Vector Machine (SVM)
Rezazadeh Azar and McCabe (2012)	Truck recognition	- Haar-HOG Cascade - Blob-HOG Cascade
Memarzadeh et al. (2013)	Worker and equipment recognition	- HOG + Color descriptor - SVM
Ranaweera et al. (2013)	Tunnel construction process	- Motion Region Segmentation - Parametric Model Fitting

Table 3: 2D Vision-Based Productivity Data Collection: modified from Kim (2014)

2.3.3 3D Vision Recognition based Data Collection and Analysis

3D vision is another type of non-contact sensors. 3D vision sensors collect point clouds or depth image using laser scanning, stereo vision/photogrammetry, and infrared sensors. 3D vision is actively utilized in the area of progress measurement. It is very actively being studied for automated construction progress monitoring. Similar to the 2D

vision-based activity recognition, 3D vision also uses 3D visual features to characterize objects or activities contained in the 3D vision data. It also trains classifiers and recognizes activities from a new set of 3D vision data. Table 4 shows some of 3D vision based studies to collect productivity data.

Researcher	Scope	Technologies
Bosche and Haas (2008)	3D object recognition/search	- As-Planned Point Clouds from 3D CAD model - As-Built Point Clouds - Comparison of the Two Point Clouds
Weerasinghe et al. (2012)	Worker's action recognition	- Microsoft KINECT sensor - Human Skeleton - Pattern Recognition - Object Localization
Escorcia et al. (2012)	Worker's action recognition	- Microsoft KINECT sensor - Human Skeleton - Pose Codebook - K-Means - SVM
Kim and Caldas (2013)	Combination of action and object recognition	- Microsoft KINECT sensor - Human Skeleton - Dense SIFT - Bag of Visual Words - Gaussian Mixture Model (GMM) - Naïve-Bayes
Khosrowpour et al. (2014) & Niebles et al. (2014)	Worker's interior work activity recognition	- Microsoft KINECT sensor - Human Skeleton - Pose Codebook - K-Means - SVM

Table 4: 3D Vision Based Productivity Data Collection: Modified from Kim (2014)

2.3.4 Voice Recognition based Data Collection and Analysis

Voice recognition technology has rarely been used in productivity studies. However, there are many studies that apply it to other areas of the construction industry. Some examples include mobile data entry (Bernold 1993; Kondratova and Durling 2007; Kondratova 2005, 2006), bridge inspection (Sunkpho et al. 2000), traffic data collection (Washburn 2002), a distributed voice-commanded sensory and robotic system (Tyree et al. 2004), on-site information collection–materials management (Tsai 2009), construction worker performance assessment (Weerasinghe and Ruwanpura 2009), vehicle class recognition (Gao et al. 2013), as-built documentation (Abdel-Monem and Hegazy 2013), and many other areas (Table 5).

Research Area	Researchers
Mobile data entry	Bernold (1993); Kondratova and Durling (2007); Kondratova (2005, 2006)
Bridge inspection	Sunkpho et al. (2000)
Traffic data collection	Washburn (2002)
A distributed voice-commanded sensory and robotic system	Tyree et al. (2004)
On-site information collection–materials management	Tsai (2009)
Construction worker performance assessment	Weerasinghe and Ruwanpura (2009)
Vehicle class recognition	Gao et al. (2013)
As-built documentation	Abdel-Monem and Hegazy (2013)

Table 5: Voice Recognition based Data Collection and Analysis

Voice/speech/sound recognition has a long history and is a somewhat stable technology. There are enormous numbers and types of commercial off-the-shelf voice recognition engines and areas in which they can be applied. Based on these trends, many mobile devices or internet search engines have adopted voice recognition technologies as their data or command input tool.

2.3.5 Automation of Activity Analysis in Other Domains

The automation of activity analysis/work sampling has been studied by many researchers. In industrial engineering, Pape (1982) developed Fortran based work sampling data analysis program. It provides daily data input and three different calculation methods. It also provides cumulated analysis results. It uses card based input system and can process only five activity categories, ten workers, and 50 observations per day. In 2001, Salvendy (2001) introduced one of the work sampling software, the mechanized activity sampling technique (MAST) and mentioned the benefits of the software by citing the Niebel and Freivalds (1999)'s book. The benefits are as follows:

- Reduction of routine works
- Rapid analysis results with professional format
- Cost reduction of work sampling study
- Improved accuracy of results
- Fewer errors
- Motivation to use work sampling more actively

Robinson (2010) developed PDA based work sampling system. PDA was used to collect activity data. The collected data is analyzed in the software embedded in the PDA.

The system can collect very detailed data and provide highly accurate multi-level analysis results.

Elnekave and Gilad (2006) developed video-based work sampling system. It used digital video clips and enabled remote work sampling. User of the system can capture videos from a remote location and transfer the videos using File Transfer Protocol (FTP). This system did not use intelligent activity recognition techniques. User reviews the videos and performs work sampling and measurement to provide standard time of work.

2.4 CONCLUSION

There are many different methods to directly/indirectly measure construction labor productivity. Work sampling is one of the timely and quantitative workface assessment methods. It has been extended to activity analysis in 2010. In construction domain and other domains, there are enormous efforts to improve activity analysis using information and sensor technologies. However, they are limited to specific and trained work under controlled conditions. Furthermore, they do not provide enough contextual information to interpret activity analysis results. Therefore, this study aims to develop and validate a novel methodology to computerize and automatize activity analysis and provide enough contextual information as well as conventional activity analysis results.

Chapter 3 Semi-automated Activity Analysis Methodology

This chapter describes the semi-automated activity analysis methodology and its software implementation. It starts with the framework of this methodology. The frame work contains an overview, basic structure, and scope of this methodology. Then, this chapter provides details of semi-automated data collection and fully-automated data analysis methods. Finally, this chapter presents actual software implementation results of this methodology and their detailed functions and structures in the last section.

3.1 Semi-automated Activity Analysis Framework

The framework for semi-automated activity analysis methodology consists of the semi-automated data collection and automated data analysis phases shown in Figure 4. Each phase corresponds to the two research questions of this research, respectively. The data collection phase is composed of standard time acquisition, voice data collection for activity categories, location data collection, and video data collection processes. It collects the observer's voice as workers' activity category data and its related context information: time, location, and workers' video. The data analysis is a post-processing phase to integrate and analyze collected data. The integration is accomplished when its sub-processes are performed: voice and video data time synchronization, voice recognition to obtain activity categories, and zone detection for each activity category datum.

Regarding the data collection phase, this research pursues a semi-automated approach to collect activity category data. A human observer determines activity categories of workers, speaks the categories, and records the observer's voice during the observation tours at the construction site. This is a faster and more reliable approach to

collect the activity category data at the unique, flexible, crowded, and noisy construction site. Time, location, and video data are collected automatically when the observations are made. Once the four types of data are collected, voices and locations are recognized automatically as the activity category and zone data in the data analysis phase. The activity category, time, zone, and video data are then integrated with each other based on their time information (i.e. time-stamp). In this integration process, time plays a major role in tying together all the data because workers' operation occurs continuously over time. Humans can only understand the context related to the operation when it has time sequence data. The project manager can perform a productivity improvement study with the dynamic analysis using the integrated data and their context information. The dynamic analysis includes on-demand generation of work rates, graphs, and charts from the various analysis perspectives such as project, time, location, activity category, observers, and all the possible combinations of the perspectives. The project manager also can review the indexed video of each activity category data to understand actual working situations when the data is collected. The project manager can review not only the simple working condition of individual workers but also their interactions and other factors affecting labor productivity for its improvement study.

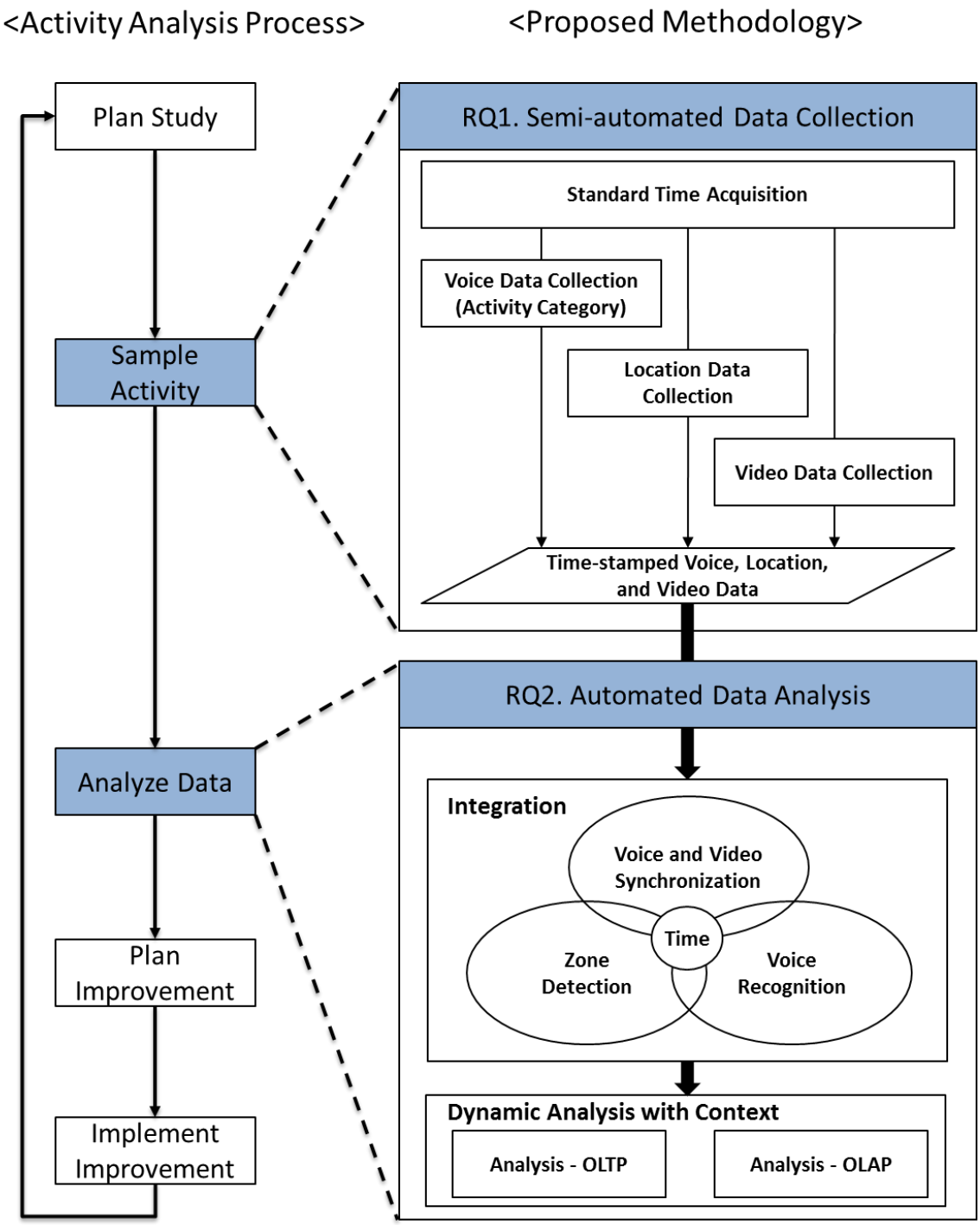


Figure 4: Semi-automated Activity Analysis Framework

3.2 SEMI-AUTOMATED DATA COLLECTION

This sub-chapter describes the details of each process in the semi-automated data collection phase (Figure 5): 1) standard time acquisition, 2) voice data collection, 3) location data collection, and 4) video data collection. The data should be collected by using mobile devices, and the final results are the set of time-stamped voice, location, and video data. Before starting the details of each process, the reasons why the four data (i.e. time, voice, location, and video) are important for activity analysis to provide context information are explained in the first sub-chapter.

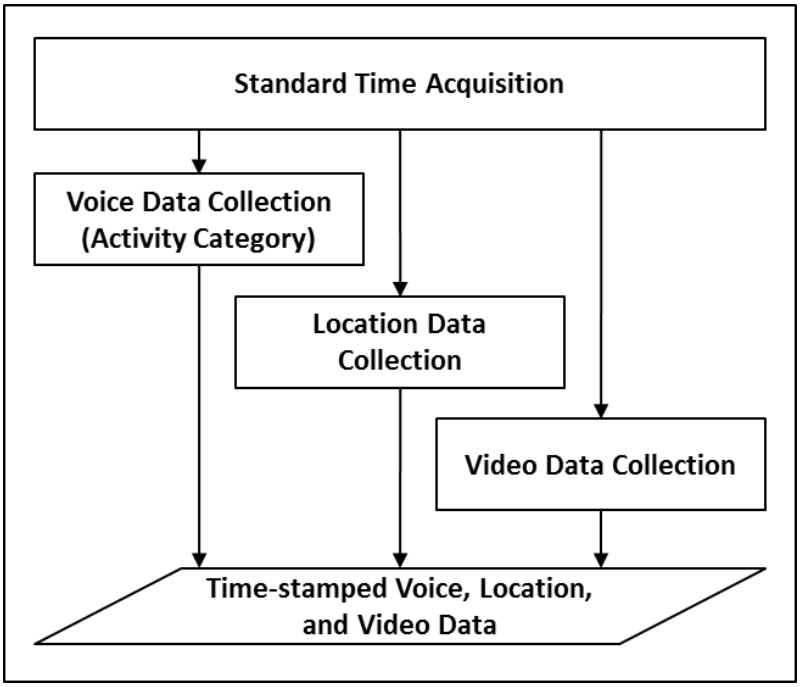


Figure 5: Data Collection Process

3.2.1 Why Time, Location, and Video data are important?

The purpose of this research is not only to provide activity analysis results quickly but also to provide their related context information to support a labor productivity improvement study. When project management performs the productivity improvement study with a conventional activity analysis results, they have limited analysis results, such as overall/hourly work rates tables, charts from the tables, and observation worksheets as raw data. In this case, it may be difficult to understand the reasons why their labor performance was high or low. The several methods to identify the reasons are "asking" methods using foreman delay surveys or craftsmen questionnaires. However, these methods require additional time and effort. Although those "asking" methods are still valid for the productivity improvement study, it might be better if the project management understood quickly the actual situations of the time when the activity category data was collected. The understandings about worker's situation can be called "Context" (Dey and Abowd 2000). Gong and Caldas (2011) identified three types of productivity-related contexts to interpret construction videos: semantic context (task elements), spatial context (work zone layout), and temporal context (task sequences). These contexts are critical to understand actual working situations from the productivity perspective. Video (semantic), location (spatial), and time (temporal) information related to activity category data can provide suitable information to understand those contexts.

In the computer science area, especially for distributed/mobile/ubiquitous computing (Strang and Linnhoff-Popien 2004), many researchers have identified that time, location, identity, and environment[3], and are meaningful contexts for software applications to provide real-time interactive service to users based on the understandings

[3] From the construction labor productivity study perspective, the identity and environment contexts can be obtained from video data. Video contains workers and their working environment information.

about the users' situation or demand. This is called "context-aware computing." Context is defined as "any information that can be used to characterize the situation of an entity" (Dey and Abowd 2000). The entity can be a person, place, or any type of object, and the definitions emphasize that context is related to the information about the "situation" of the entity. This means that software applications can understand the situation of the entity if proper contexts are provided and processed. This also holds true for humans. Researchers have identified various types of context. Schilit et al. (1994) suggested three aspects of context: where you are, who you are with, and what resources are close to you. Ryan et al. (1998) identified types of context as location, environment, identity, and time. Kaltz et al. (2005) also proposed five categories of context parameters: user & role, process & task, location, time, and device. All of these types of context include the following four categories: activity, time, location, and identity (Dey and Abowd 2000). With these types of context, software applications can understand the situation of the "entity" through the proper data processing using context-aware middleware. Similar to this, these four types of context also can support project management to understand what happened at the construction site and the reasons for a good or bad performance.

In the construction industry, there have been examples presenting benefits from the context information derived from time-lapse photography or videos (Senior and Swanberg-Mee 1997; Everett et al. 1998; Abeid and Arditi 2002a; Abeid and Arditi 2002b). By simply reviewing the time-lapse photography or videos, the authors of the studies insisted that project managers could perform various types of analyses such as "observing equipment performance; seeing the impact of adverse weather; monitoring material delivery; investigating accidents; comparing expected durations with actual durations; reviewing crew performance; and assessing site productivity (Gong 2009)."

3.2.2 Standard Time Acquisition

Time information is a key to integrating all of the activity analysis data collected in this research because workers' operations and the observations occur continuously over time. Thus, time is one of the critical contexts for understanding actual working situations. As mentioned earlier, humans understand situations when data includes temporal information. If all of the collected data used different time spans, then the time context would be distorted, rendering it incomprehensible to project management. Therefore, voice, location, and video data can refer to the standard timeline maintained by this process to create a time stamp whenever data is collected.

The steps are delineated in Figure 6. The first step of implementing time standardization is to search for an available standard time network. For the automated data integration and automated data analysis in the next phase – it is important to synchronize device clocks with standard time. The second step is to synchronize device clocks with the standard time then periodically check the availability of the connection to ensure that the device clock is accurate. The output – a standard time-stamp – is provided to the other data collection processes when the processes request it in order to record their data.

There are many methods of acquiring standard time for mobile data collection devices such as Internet via wireless local area network (WLAN), wireless sensor network (WSN), cellular network, and global positioning system (GPS). Whereas WLAN and WSN are not always available at construction sites, a cellular network is stable and accessible from anywhere. Mobile cellular devices can update their internal clocks through standard mechanisms such as Network Identity and Time Zone (NITZ); however, the accuracy of this standard ranges within minutes (3GPP 2014). A GPS provides standard time from anywhere in the world, but one of its limitations is that its signal can

be easily lost in a closed area. However, once a GPS signal is received, the device can easily maintain standard time for several hours using an internal clock. Therefore, a GPS is recommended as the source for standard time.

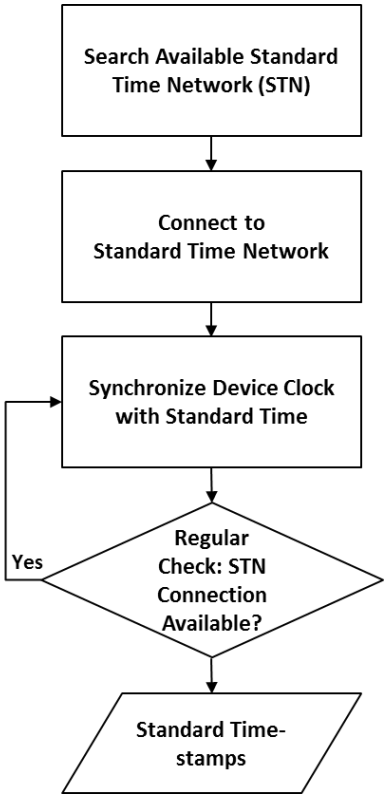


Figure 6: Standard Time Acquisition Steps

3.2.3 Voice Data Collection

Voice data contains activity category data spoken by a human observer. Voice recording replaces the manual process of writing down the activity categories during observations. The observer can walk and pass the work zone while speaking activity categories in a low voice. The voice data is converted into activity category text data

through the voice recognition process in the next phase – namely, automated data analysis. The voice recognition is more convenient method. It does not require stopping or slowing down observer's observation tour pace to write down the observation results on paper forms or click hand-held devices to record them. Codes for activity categories (i.g. "alpha" for direct work and "beta" for preparatory work) can be used when recording voice data. However, natural words (i.g. "D-work" for direct work) are more intuitive to observer. It can be also extended to capture observer's voice comments regarding the productivity related issues found during observation tour. The steps of this voice data collection process are delineated in Figure 7.

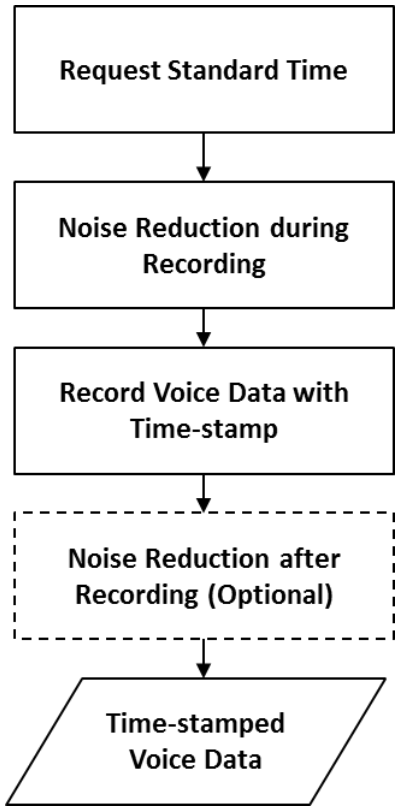


Figure 7: Voice Data Collection Steps

The first step is to acquire standard time from the standard time acquisition component. The second step is to reduce noise while recording voice. This is important because the quality of voice data has a significant impact on the recognition accuracy. There are, however, many sources of sound noise at a construction site, such as tools and equipment operation sounds, wind, and workers' voices. In order to achieve higher recognition accuracy, noises have to be minimized through noise reduction methods. The details of such noise reduction methods are explained in the following part of this section. The third step is to record voice data with a standard time-stamp. The time-stamp will be used to integrate activity categories in the voice data with location and video data. The fourth step is optional; that is, it may be unnecessary if the noise reduction is successful in the second step. The result of this voice data collection process is a time-stamped voice files. Figure 8 shows an example of time-stamped voice data. The standard time-stamp is recorded as a file name. Activity categories recorded in the voice file have internal (i.e., relative) time-stamps. Therefore, standard time-stamps of each activity category can be calculated with the standard time-stamp of the voice file and the internal time-stamp.

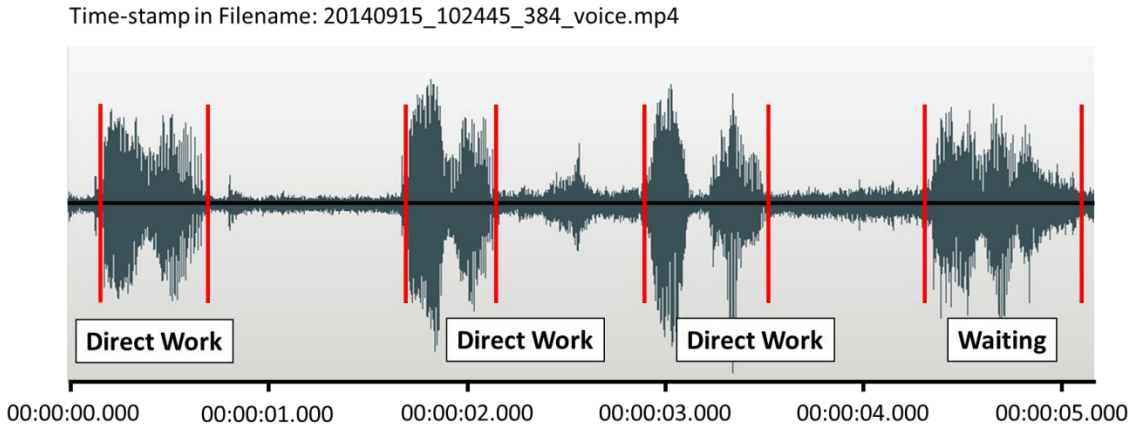


Figure 8: Example of Time-stamped Voice Data

Regarding the noise reduction methods, there are many types that have long been in use. Generally, they fall into two main categories:

- Noise reduction during recording
- Noise reduction after recording

These methods can be combined to increase the quality of voice data and to maximize recognition accuracy.

Noise reduction during recording

Efforts to reduce noise during recording are related to improving the performance of the microphone. The easiest way is to cover a microphone is with a windscreen. This works reasonably well for reducing hissing and wind sounds, but its performance is limited. A more effective way to reduce noise is through the adoption of advanced technologies. There are several types of noise reduction microphones: noise-cancelling microphones, bone conduction microphones, and throat microphones.

The noise cancelling microphone includes passive and active types of reduction mechanisms. The passive mechanism has long been in use, but it is still effective and used for commercial products. Passive noise-cancelling microphones receive sound from a desired direction and an undesired direction at the same time (Figure 9). Sound from the desired direction contains the target sound and noise. The sound is guided to the front of the diaphragm. Sound from the undesired direction mainly contains unwanted sound that is guided to the rear side of the diaphragm. When both sounds arrive at the diaphragm, the noise in the sound from the desired direction is cancelled by the noise in the sound from the undesired direction (Kock 1950; theBoom 2015).

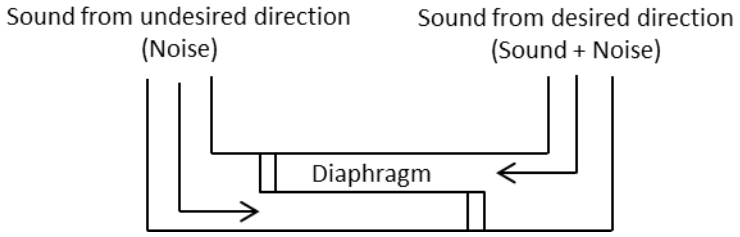


Figure 9: Passive Noise-cancelling Mechanism (Kock 1950; theBoom 2015)

A commonly used active noise-cancelling mechanism is adaptive noise cancelling (ANC). ANC receives the signal source (s) and the noise source (n) as primary inputs. It also receives an auxiliary noise source (n_l) and filters it into an estimation of the noise source ($\hat{n}$) with adaptive filters (e.g., Kalman filter). The output signal $\hat{\boldsymbol{s}}$ is then estimated by the following equation (Widrow et al. 1975; Liang et al. 2015):

$$\hat{\boldsymbol{s}} = (\boldsymbol{s} + \boldsymbol{n}) - \hat{n}$$

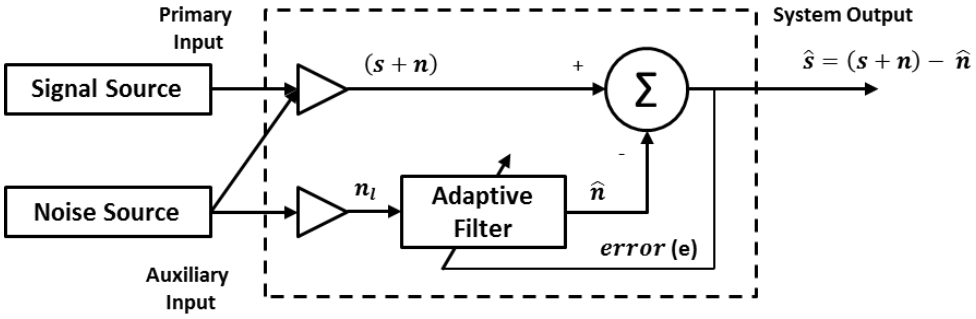


Figure 10: Adaptive Noise-cancelling Mechanism (Widrow et al. 1975; Liang et al. 2015)

There are several more methods for reducing noise during recording. Beamforming uses an array of microphones to create dynamic directionality. Since it is mainly used for a fixed microphone, it is unsuitable for mobile data collection. Bone conduction microphones detect vibrations of facial bones to capture voice (Santori 1974; Tonndorf 1976; Tran et al. 2008). Since the microphone picks up no interference from

outside sources of noise, bone conduction microphones can be effective in very noisy environments. Throat microphones are similar to bone conduction microphones but capture the vibration from the neck. It also largely prevents external noises, but its recording quality is usually lower than that of a bone conduction microphone as pronunciation is completed in the mouth, not in the throat.

Noise reduction after recording

Reduction of noise after recording requires the use of filters, such as high-/low-pass filters, to remove extra sound from voice data. Another way to remove noise is to use recordings of ambient noises and subtract them from the original voice recordings, but this only works well when the noise is simple and static; it is not useful for voice recordings at a construction site because there are many different sources of noise that are usually very dynamic. Therefore, once noise has been included in the voice recordings, it is difficult to remove and requires manual effort. As a result, "noise reduction during recording" is usually preferred.

Again, however, all of these methods can be combined to increase voice recognition accuracy.

Effect of noise reduction

At the beginning of this research, a common omnidirectional microphone was used to record the observer's voice; however, it failed to provide sufficient performance for voice recognition. Voice recognition accuracy with the microphone was in the approximate range of 50-80%, which gave rise to the adoption of noise-cancelling technologies.

In order to confirm the effect of the noise-cancelling technology, voice recognition results were examined from an actual construction site – a hospital project (Figure 11). The site was crowded, and the main tasks being performed at the site were MEP, HVAC, drywall installation, and plumbing. There were high levels of noise from grinding, drilling, beeps from the personal lift, and heavy wind.

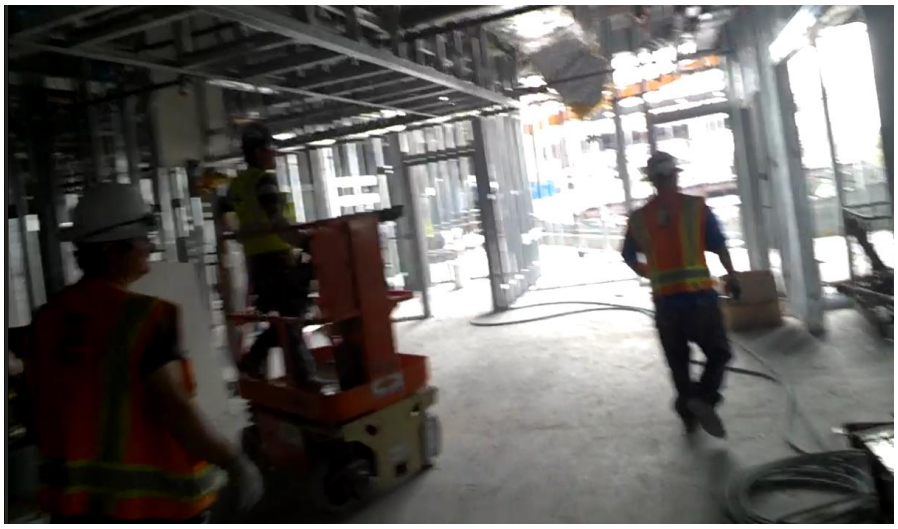


Figure 11: Noise Reduction Performance Test Site

The observer's voice was recorded simultaneously with a common omnidirectional microphone and a passive noise-cancelling microphone. Then, voice recognition confidence levels of the two datasets were compared to see how the voice recognition engine clearly recognized activity categories from each dataset. All the parameters of the voice recognition engine were the same. Table 6 shows that the recognition accuracy of the recordings taken with the omnidirectional microphone was 51.1 percent, while the accuracy with passive noise cancelling was 96.6 percent. This wide variance is due to the omnidirectional microphone capturing all the noises with the voices at the construction site. The voice recognition engine could not successfully

separate the voice from the noises because the signal-to-noise ratio was relatively low. The engine missed 32 activity categories out of a total of 88. Furthermore, 11 activity categories out of a total of 56 recognized categories were wrong. With the recordings from the passive noise-cancelling microphone, however, the engine missed only one activity category, and of the total 87 recognized categories only two were wrong.

Item	Recordings with Omnidirectional Mic.	Passive Noise Cancelling Mic.
Recognition Accuracy	51.1%	96.6%
Average Recognition Confidence Level	0.583	0.751

Table 6: The Effect of Noise-Cancelling Technology

These results can be explained by the difference in signal-to-noise ratio (S/N ratio) between the two voice files. Figure 12 (a) shows the S/N ratio of a regular voice file containing noises. Figure 12 (b) shows the higher S/N ratio of the corresponding noise-cancelled voice file. The voice recognition engine could more successfully identify and recognize activity categories in the noise-cancelled voice file.

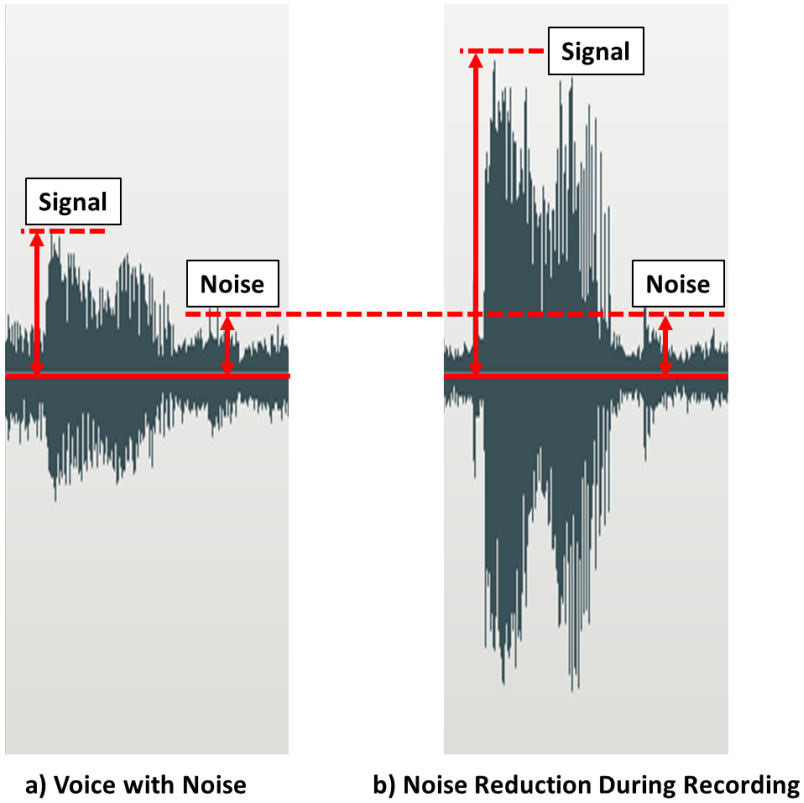


Figure 12: Signal-to-noise Ratio Comparison of Raw and Noise Cancelled Recordings

Regarding recognition confidence levels (Table 6), the average confidence level of the recordings with the omnidirectional microphone was 0.583 out of 1.0; the average confidence level of recordings with the passive noise-cancelling microphone was 0.751. This means that the voice recognition engine more clearly recognized the recordings from the passive noise-cancelling microphone. Therefore, it can be concluded that noise cancelling/reduction during voice recording is critical at the construction site..

3.2.4 Location Data Collection: GPS

Whenever the location of observer changes, that data should be recorded to track the location of the observations. The steps involved in location data collection are delineated in Figure 13. The first step is to make a connection to a location data provider such as a GPS or cellular network. Next, the observer's location is continuously monitored in the second step. If the location change exceeds a predefined threshold, which means that the observer's location has changed, then the time-stamp is requested in the third step and the new location data is recorded in the fourth step. The threshold of the location change can be set by the user as 1, 3, or 5 m of location change. The final result is the set of location data with standard time-stamps (Table 7). The data is plotted on a satellite map, as shown in Figure 14.

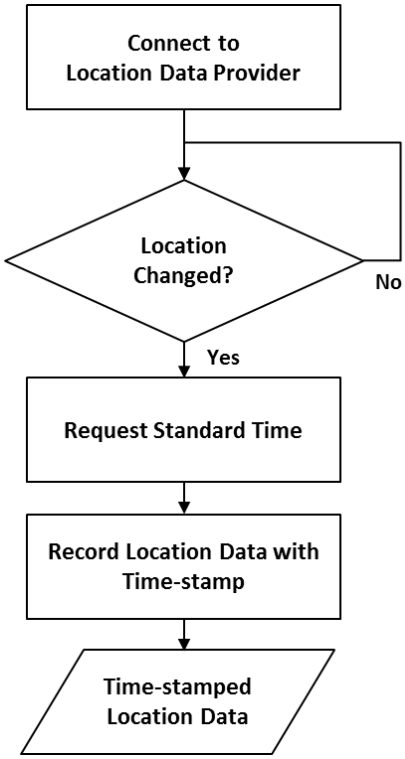


Figure 13: Location Data Collection Steps

Date (YYYYMMDD)	Time (HHMMSS.SSS)	Latitude (Decimal)	Longitude (Decimal)	Altitude (Decimal)	Location Data Source
20140516	095428.000	XX.XX551	-XX.XX494	134	gps
20140516	095440.000	XX.XX55	-XX.XX493	133	gps
20140516	095444.000	XX.XX547	-XX.XX49	132	gps
20140516	095446.000	XX.XX546	-XX.XX489	131	gps
20140516	095448.000	XX.XX544	-XX.XX49	132	gps
20140516	095450.000	XX.XX543	-XX.XX49	132	gps
20140516	095454.000	XX.XX539	-XX.XX489	131	gps
20140516	095456.000	XX.XX537	-XX.XX488	131	gps
20140516	095458.000	XX.XX535	-XX.XX488	130	gps
20140516	095502.000	XX.XX534	-XX.XX487	129	gps
20140516	095504.000	XX.XX532	-XX.XX487	130	gps

Table 7: Example of Location Data (Raw Data)

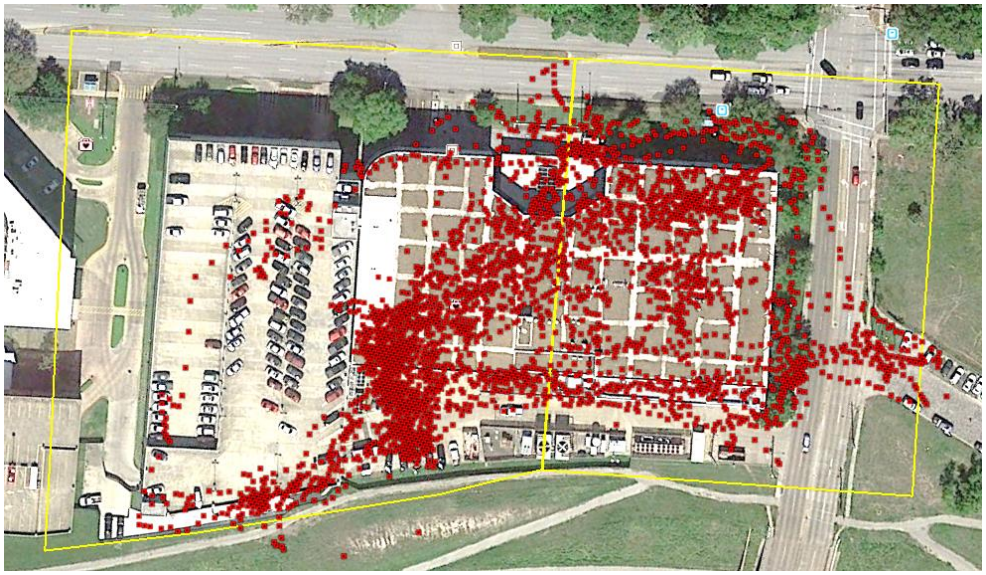


Figure 14: Example of Location Data on Map

Regarding location data sources, there are many different types of technologies. Location data can be collected by radio frequency identification (RFID), ultra-wideband (UWB), WLAN, Bluetooth, cellular network, and GPS, among others (Akinci et al. 2002;

Liu et al. 2007; Razavi and Haas 2012, 2010; Song et al. 2006, 2007; Teizer et al. 2008; Torrent and Caldas 2009).

RFID and UWB provide high accuracy but require additional equipment at the construction site. WLAN and Bluetooth show reasonable accuracy and are more suitable for indoor environments. A cellular network is accessible from almost anywhere, both indoor and outdoor; however, for engineering purposes, its accuracy is low (Liu et al. 2007). GPS has medium accuracy and is accessible from any outdoor location, but GPS is unreliable in indoor environments. In order to compensate for this drawback, wireless-assisted GPS (A-GPS) is available with many commercial mobile devices. It uses a cellular network and GPS to improve accessibility, and can provide reasonable accuracy with an average of 5-50 m (Liu et al. 2007). Regarding location data collection for labor performance assessment, any of these location providers can be used depending on users' requirements and if their time can be synchronized with standard time. As the location provider this research used A-GPS.

The location data sources can be determined based on the required accuracy level and availability at the construction site. Usually, several sources are combined for better reliability and accuracy.

3.2.5 Video Data Collection

Video has been used for many years to collect on-site data for construction productivity studies (Abeid and Arditi 2002a; Everett et al. 1998; Fondahl 1960; Gong et al. 2011c; Gong and Caldas 2010, 2011; Heydarian et al. 2012; Oglesby 1989; Peddi et al. 2009; Ranaweera et al. 2013; Rezazadeh Azar and McCabe 2012). Video data synchronized with activity category data can provide project management with various types of contexts (Gong and Caldas 2011). For this research, any type of video data collection device, such as a handheld video camera, cell phone, or smart glasses, could be used for labor performance data collection if they had access to standard time-stamps.

The steps for collecting video data are delineated in Figure 15. The first step is to acquire a standard time-stamp from the standard time acquisition component. Then, the second step is to record video with the time stamp. The result is a set of time-stamped video files.

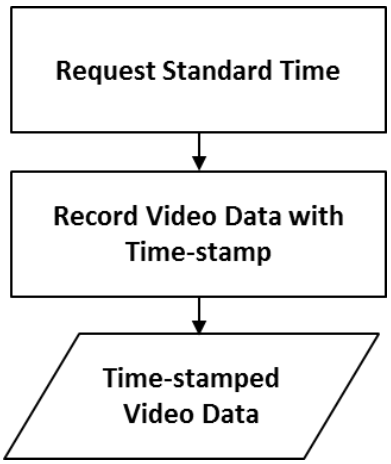


Figure 15: Video Data Collection Steps

Regarding the video recording devices, some handheld video cameras have GPS functions and use standard time when recording videos; however, a handier device is a pair of smart glasses such as Motorola HC1, Vuzix M100, and Google Glass. The point of this research is to validate the applicability of visual data collection techniques at the construction site in order to provide contextual information on the activity analysis results; the point is not to identify the best equipment for data collection. Any device could have been used if its video data could be synchronized with standard time. Figure 16 shows some screenshots of video data collected at a typical construction site.

Figure 16: Screenshots of Video Data Collected

3.3 AUTOMATED DATA ANALYSIS

This subchapter describes the details of each process in the automated data analysis phase (Figure 17): 1) voice and video synchronization, 2) voice recognition (activity category), 3) zone detection, and 4) dynamic analysis. In this data analysis phase, the first three processes are for data processing, whereas the last one involved dynamic data analysis by the project manager. Integration of data is performed during the data processing processes. A time-stamp is the key piece of data for integrating all other data: activity categories, zone, and video data. The integration is performed in all three data processing processes. The dynamic data analysis consists of two parts: 1) operational/online transaction process (OLTP) and 2) online analytical processing (OLAP). The details of each process are described in the following sections.

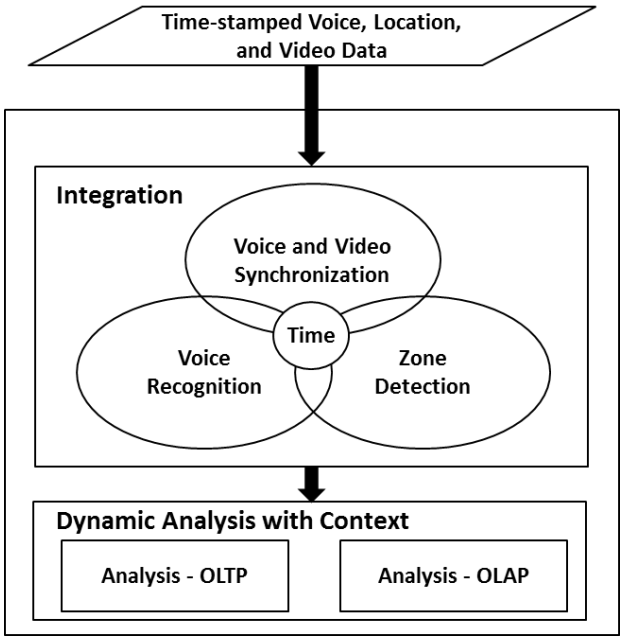


Figure 17: Automated Data Analysis Process

3.3.1 Voice and Video Synchronization

There are two possible options for voice and video recording. The first option is to use the same device to record voice and video. In this case, post-processing synchronization is not required because they can share the same internal time stamp. The second option is to use different devices to record voice and video in order to improve the voice recording quality through the use of a noise-cancelling microphone or noise-reduction technology. Some smart glasses or video cameras contain internal noise-cancelling functions, but they do not perform well enough at noisy construction sites. In such cases, synchronization of voice and video files from different devices is required.

One fundamental method for synchronizing different data is to use a standard time-stamp attached to the voice and video data. Network time protocol (NTP) or GPS can be a source of standard time (Kroll et al. 2014). The voice and video data collection devices can record the standard time-stamp whenever they collect data. Then, their synchronization is just a matter of matching data that contains the same or the closest time-stamp. Two time synchronization methods for voice and video data are explained in the following sections.

Automatic Voice and Video Synchronization

Automatic Voice and Video Synchronization is based on sharing standard time between voice and video files (Kroll et al. 2014). The devices share the standard time and record a time stamp whenever they generate a certain event. This research shares standard time in a similar way (Figure 18). Whenever voice or video is recorded, its time-stamp from the standard time network can also be recorded. In this case, the video and voices are synchronized when they are created.

For this synchronization, there is no need to continuously receive standard time data during recording. Once a standard time network is connected, the time difference between the standard time and device time can be calculated. Then, the standard time can be continuously and accurately estimated by simple calculation with the device. If the standard time network is continuously available, then the time difference is also continuously updated and more accurate time-stamps will be available.

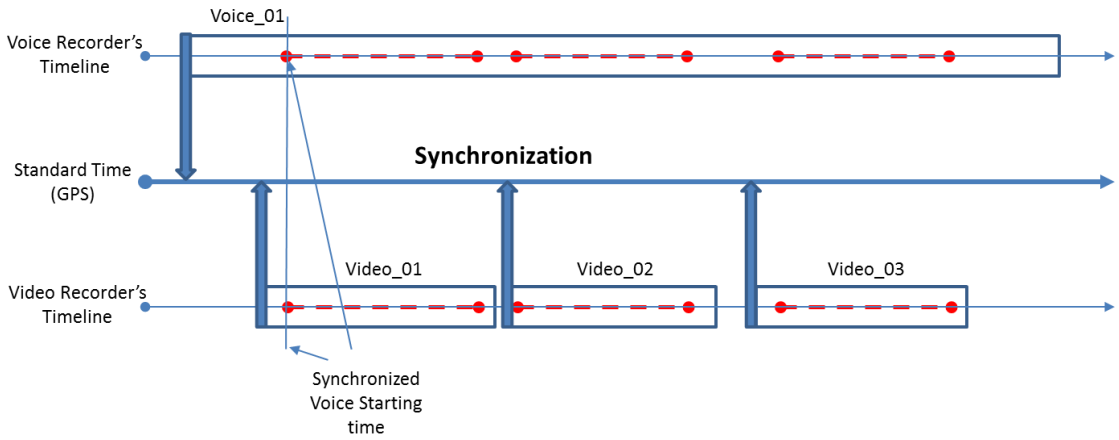
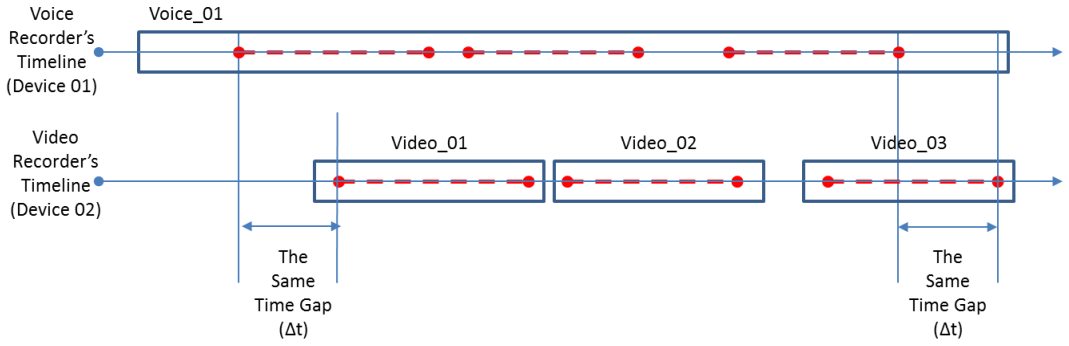


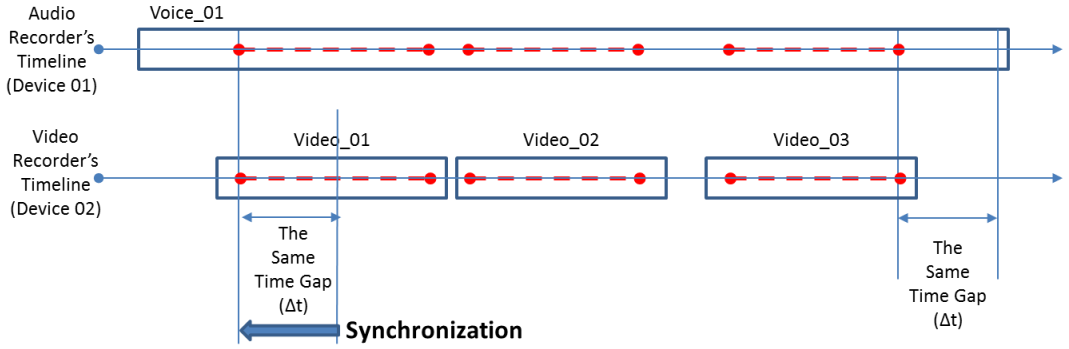
Figure 18: Automatic Voice and Video Synchronization

Human-assisted Voice and Video Synchronization

If the voice and video recording should start without a standard time network, then their time stamps are different from each other as shown in Figure 19 (a); however, if the internal clocks of the two devices are stable, and the initial time gap (Δt) between the two devices is known, then the time-stamps of all video recordings can be shifted by the amount of the time gap because all the video recordings have the same time gap, as shown in Figure 19 (b).



(a) Before Synchronization



(b) After Synchronization

Figure 19: Human-assisted Voice and Video Synchronization

The only manual work required here is to find the activity category voice starting time in the voice file and then the same category voice starting time in the first video file.

Then, the remaining video files can be automatically synchronized with the voice file based on the same time gap. The next step is to extract the voice clips corresponding to each video recording for input into the voice recognition engine. After this, activity categories in original voice file, voice clips and videos are synchronized with each other as shown in Figure 20.

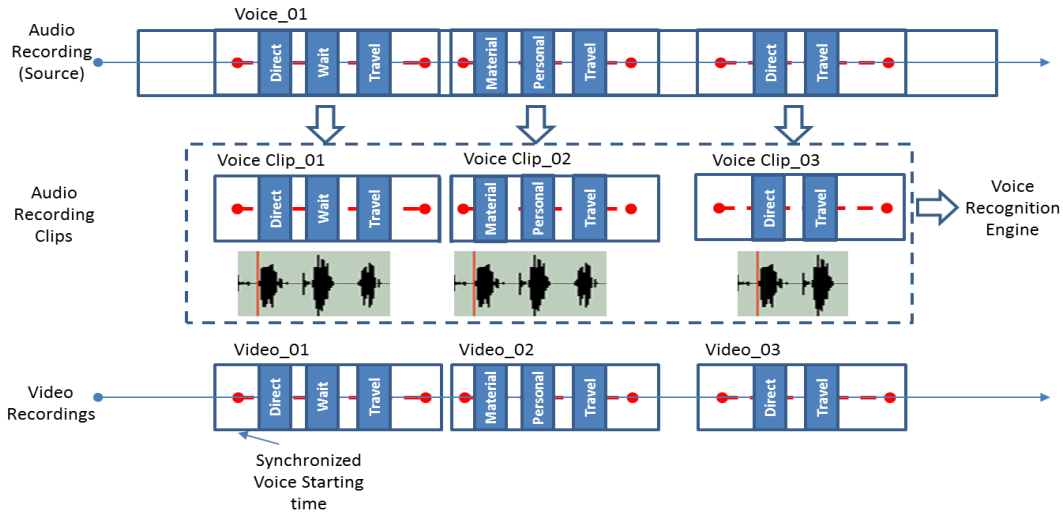


Figure 20: Voice and Video Synchronization Results

3.3.2 Zone Detection of GPS Location Data

A construction site is divided into several zones for more effective project management as shown in Figure 21(a). Zone detection determines which zone each location data point belongs to. In Figure 21 (b), circular location points, triangular points, and quadrangular point were collected in Zones 01, 02, and 03, respectfully. After detecting zones of each location data point, it is possible to determine the zones of each activity category data by comparing the data collection times of location data and activity category data.

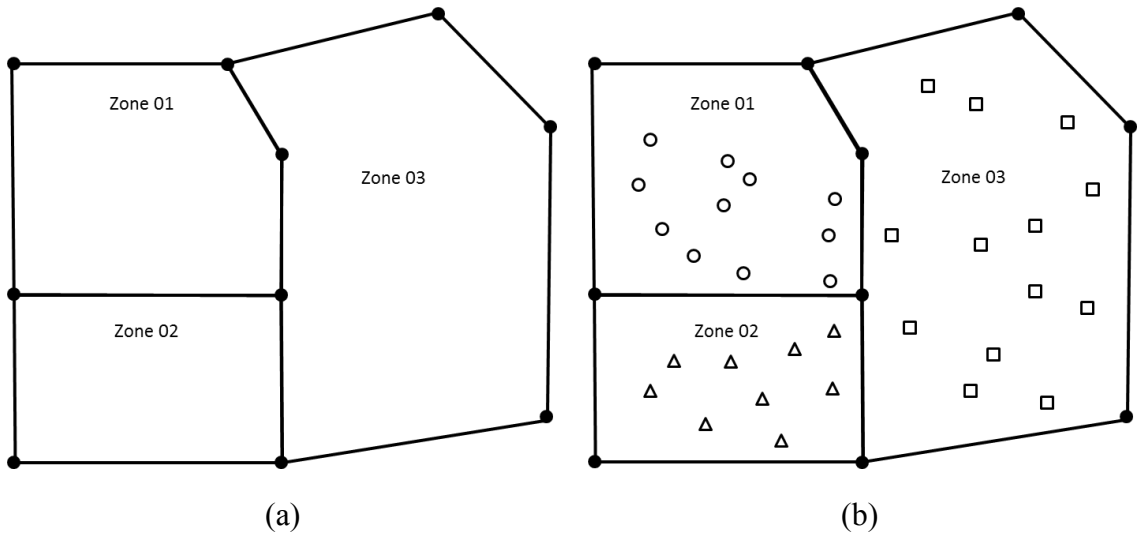


Figure 21: Construction Site Zoning

When preparing labor performance data collection, a zone definition has to be prepared based on the zoning information included in the project documents. Figure 22 show the example of zone definition. A zone is a set of GPS coordinates, and its format was defined for this research. The first column is the name of zone, and the second and the third columns are longitude and latitude. Each zone is separated by “NaN”. The first and last rows (points) of each zone are the same because a zone is a closed polygon.

```
Zone01, 22.8253, 19.8222
Zone01, 17.9344, 19.8222
Zone01, 17.9344, 14.5641
Zone01, 24.0500, 14.5641
Zone01, 24.0500, 17.7545
Zone01, 22.8253, 19.8222
NaN,NaN,NaN
Zone02, 17.9344, 14.5641
Zone02, 17.9878, 10.7567
Zone02, 24.0737, 10.7657
Zone02, 24.0500, 14.5641
Zone02, 17.9344, 14.5641
NaN,NaN,NaN
Zone03, 22.8253, 19.8222
Zone03, 24.0500, 17.7545
Zone03, 24.0500, 14.5641
Zone03, 24.0737, 10.7657
Zone03, 30.1011, 11.7245
Zone03, 30.1804, 18.3824
Zone03, 27.6059, 21.0013
Zone03, 22.8253, 19.8222
```

Figure 22: Example of Zone Definition

Zone detection is performed with this zone definition and the location data collected during observations. To determine the zones of each location data point ('point in polygon'), two representative algorithms are used – ray casting and winding number.

Ray Casting Algorithm

The principle of the Ray Casting algorithm is that if a point is inside a certain polygon or any type of closed shapes, then rays extending from the point to the right or left intersects an odd number of edges (Figure 23). The leftward ray from point A has one crossing, while rightward ray has three crossings. This means that point A is inside

polygon P. Regarding point B, the leftward and rightward rays each cross two edges. This means that point B is located outside of polygon P (Haines 1994).

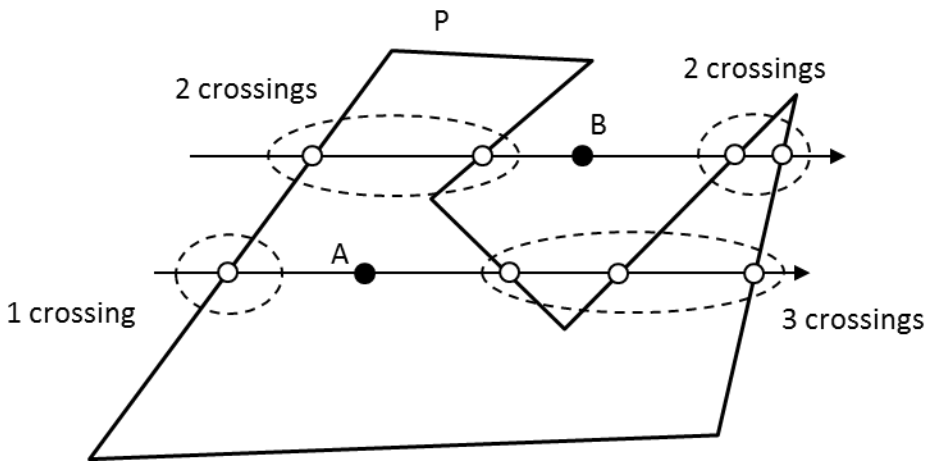


Figure 23: Point in Polygon – Ray Casting Algorithm

Winding Number Algorithm

The principle of the Winding Number algorithm is that the winding number of a certain point along the perimeter of a polygon is not zero if the point is inside the polygon. In Figure 24(a), the winding number of point A along the perimeter of the circle around the point is 1. The default winding direction is counterclockwise. The winding number of point A in Figure 24 (b) is zero because the ray from the point cannot wind around the point when the ray is moving along the circle. In Figure 24 (c), the winding number of point A is -1 because its winding direction is clockwise. In Figure 24 (d), the winding number of point A is 1 while the winding number of point B is 0. This means that point A is inside the polygon P while point B is outside (Hughes 2014). Both algorithms are simple, but the winding number algorithm was used for this research

because the ray casting algorithm sometimes yields incorrect results when a polygon is self-overlapped.

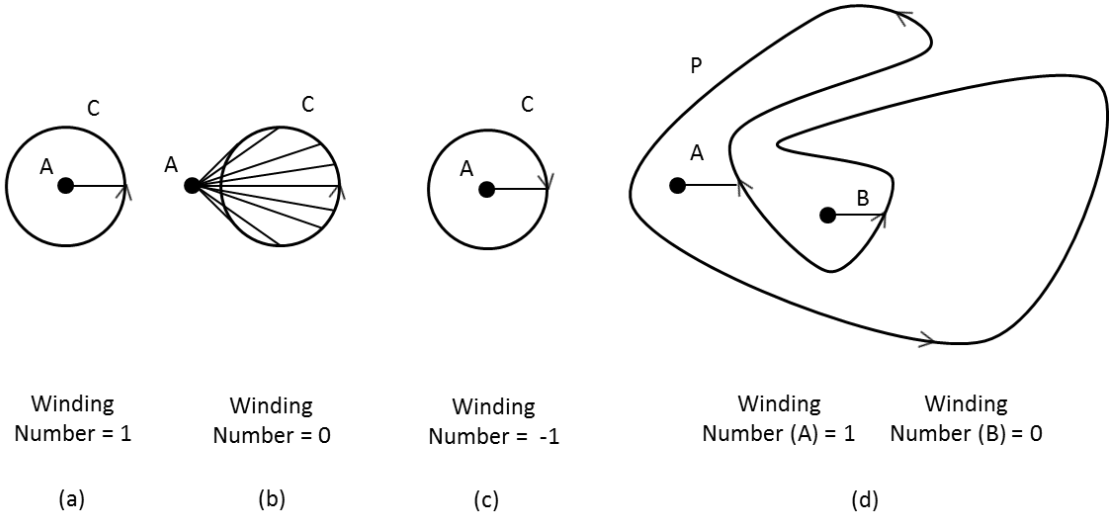


Figure 24: Point in Polygon – Winding Number Algorithm

Figure 25 shows zone detection with the winding number algorithm. Regarding point A, the winding number with respect to Zone 01 is 1 or -1 depending on the winding direction. The winding number for Zones 02 and 03 are zero. Therefore, it can be concluded that point A belongs to Zone 01.

Based on this zone detection method, the example zone detection results of the same location data (i.e., GPS) shown in Table 7 are presented in Table 8.

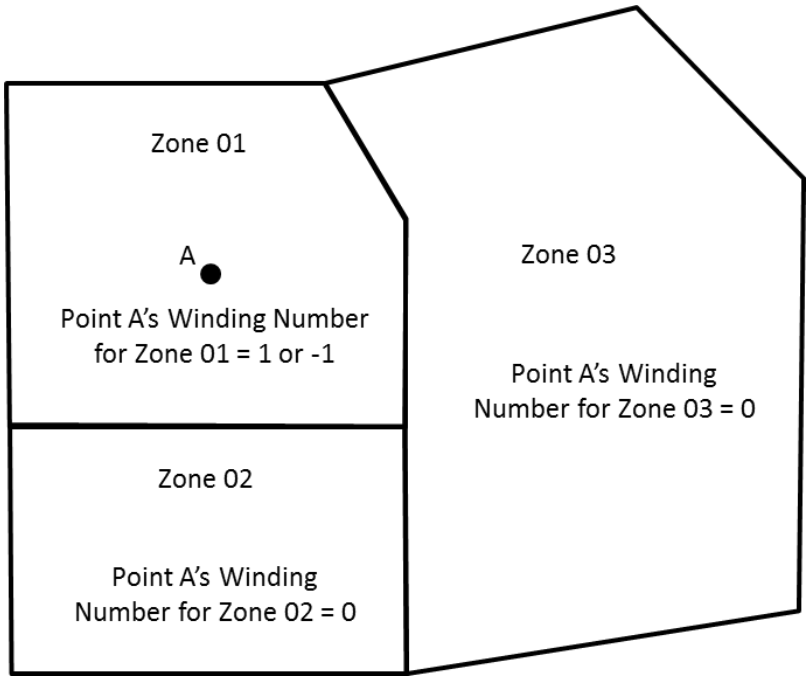


Figure 25: Zone Detection with Winding Number Algorithm

Date (YYYYMMDD)	Time (HHMMSS.SSS)	Latitude (Decimal)	Longitude (Decimal)	Altitude (Decimal)	Location Data Source	**Zone**
20140516	095428.000	XX.XX551	-XX.XX494	134	gps	Zone01
20140516	095440.000	XX.XX55	-XX.XX493	133	gps	Zone01
20140516	095444.000	XX.XX547	-XX.XX49	132	gps	Zone01
20140516	095446.000	XX.XX546	-XX.XX489	131	gps	Zone02
20140516	095448.000	XX.XX544	-XX.XX49	132	gps	Zone02
20140516	095450.000	XX.XX543	-XX.XX49	132	gps	Zone02
20140516	095454.000	XX.XX539	-XX.XX489	131	gps	Zone02
20140516	095456.000	XX.XX537	-XX.XX488	131	gps	Zone02
20140516	095458.000	XX.XX535	-XX.XX488	130	gps	Zone02
20140516	095502.000	XX.XX534	-XX.XX487	129	gps	Zone02
20140516	095504.000	XX.XX532	-XX.XX487	130	gps	Zone02

Table 8: Example of Zone Detection

3.3.3 Voice Recognition – Activity Category Data

Activity category data is collected by voice recorder. The voice files containing activity categories are synchronized and divided into voice clips corresponding to the video files as described in the previous sections. The voice clips are then entered into voice recognition engine and converted into activity category text data with standard time-stamps. Figure 26 delineates the steps of this process. It starts with the time-stamped voice clips as input. The next step is to initialize the voice recognition engine with the proper parameters. The second step is to read the voice clips and recognize the activity categories that they contain. The last step is to calculate standard time-stamps for each activity category. When each activity category is recognized, its internal time-stamp can be acquired. A standard time-stamp is then calculated by the simple summation of the voice clips' standard time-stamp and internal time-stamps of the activity categories.

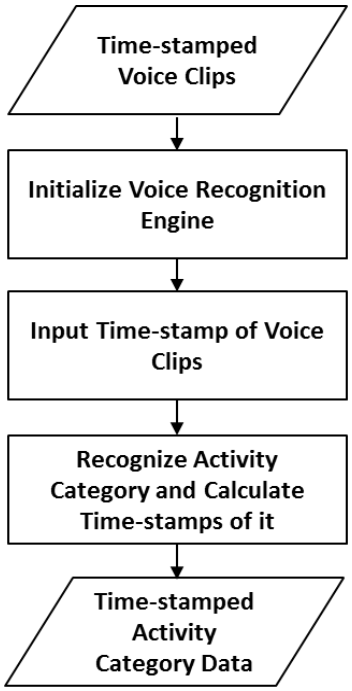


Figure 26: Voice Recognition Steps

Figure 27 shows the process of converting voice clips into activity categories with standard time-stamps.

P20141017CAPTX_JK123_20141017_101041_924.wav
P20141017CAPTX_JK123_20141017_100841_652.wav
P20141017CAPTX_JK123_20141017_100439_436.wav
P20141017CAPTX_JK123_20141017_100108_349.wav
P20141017CAPTX_JK123_20141017_095828_477.wav

Voice Clips

Voice Recognition – Activity Category Data
(Voice Clip Time-stamp: 20141017:09:18:13.493)

Internal Time-stamp	Activity Category	Confidence Level
00:00:03.500	PREPA	0.7938702
00:00:04.610	DWORK	0.8900361
00:00:06.080	DWORK	0.8343076
00:00:07.540	DWORK	0.9146704
00:00:09.480	PERSN	0.3663743
00:00:11.720	WAITN	0.6029176
00:00:12.870	DWORK	0.8391256
00:00:14.140	DWORK	0.9262236
00:00:16.060	WAITN	0.1171849
00:00:18.110	MATER	0.7593986
00:00:21.700	MATER	0.1802334
00:00:27.930	MATER	0.5733628

Standard Time-stamp	Activity Category	Confidence Level
20141017:09:18:16.993	PREPA	0.79387
20141017:09:18:18.103	DWORK	0.890036
20141017:09:18:19.573	DWORK	0.834308
20141017:09:18:21.033	DWORK	0.91467
20141017:09:18:22.973	PERSN	0.366374
20141017:09:18:25.213	WAITN	0.602918
20141017:09:18:26.363	DWORK	0.839126
20141017:09:18:27.633	DWORK	0.926224
20141017:09:18:29.553	WAITN	0.117185
20141017:09:18:31.603	MATER	0.759399
20141017:09:18:35.193	MATER	0.180233
20141017:09:18:41.423	MATER	0.573363

Figure 27: Activity Category Recognition with Standard Time-stamps

The voice recognition technology used in this process is stable and proven, and is used in industrial, military, educational, and gaming applications among others. There are numerous available voice recognition engines/software development kits (SDK) and speech recognition software programs, such as speech-to-text (STT) and text-to-speech (TTS). The following sections introduce and compare some useful voice/speech

recognition engines. Any engine that performs properly can be used for this voice recognition process.

Voice/Speech Recognition Engines

A comparison of some voice/speech recognition engines is shown in Table 9. Nuance Dragon SDK Client Edition is a commercial product that provides a speech recognition engine and voice recognition software development environment. One of its important features is that it does not require a training process for the recognition engine but can adapt to different users. Another important feature is that users can define their own grammar (e.g., list of words and custom commands). For this research, this is especially important because speech recognition engines usually show better performance when they recognize a limited number of words rather than several thousand words. Nuance Dragon SDK Client Edition supports Android, iOS, and Windows operating systems and the mobile software development environment. It can be redistributed based on the type of license purchased.

Sensory System Truly Natural SDK is another commercial product that provides its own speech recognition engine and development environment. Similarly, it does not require a training process for the recognition engine and can adapt to different users. It also provides user-defined grammar. It supports Android, iOS, Windows, Linux, and QNX and can be redistributed with the proper license.

CMU Sphinx is a free and open source speech recognition engine provided by Carnegie Mellon University that contains state-of-the-art algorithms and is often used in practical applications. It requires a training process and supports user-defined grammar. It supports Android, iOS, Linux, Raspberry Pi, and Windows operating systems and can be redistributed for commercial purposes (CMU Sphinx 2015).

Items	Nuance Dragon SDK Client (DSC) Edition	Sensory System Truly Natural SDK	CMU Sphinx	VOICE BOX	Microsoft Speech API (SAPI)	Microsoft Speech Platform SDK
Cost	Yes	Yes	Free	Free	Free	Free
Recognition Engine Training	No/Adaptable to user	No/Adaptable to user	Required	Required	No - It can be optimized to a specific user	No - Speaker-independent
License	Restricted	Restricted	Open	Open	Partially Open (Refer to MS EULA)	Partially Open (Refer to MS EULA)
OS	Android, iOS and Windows	Android, iOS, Linux, QNX and Windows	Android, iOS, Linux, Raspberry Pi and Windows	Any OS (if MATLAB is available)	Windows	Windows
Mobile	Yes	Yes	Yes	NO	Yes	No
Grammar	OK	OK	OK	-	-	OK - User-defined grammar
Redistribution	OK with License	OK with License	OK	OK	OK	OK

Table 9: Comparisons of Speech Recognition Engines

VOICEBOX is a free and open source voice recognition MATLAB toolbox and follows the GNU Public License.[4] It consists of sets of MATLAB functions mainly developed by Mike Brookes at the Imperial College. It requires a training process and can be used in the MATLAB environment. It can be redistributed if the developer opens the source codes.

Microsoft Speech API (SAPI) is a free speech recognition application program interface (API) provided by Microsoft and follows its own license terms. It basically does not require a training process and can be optimized to a specific user. It supports Windows, but there are several open projects underway to migrate SAPI to the other open operating systems. It can be redistributed with SAPI.

Microsoft Speech Platform SDK is another free speech recognition engine by Microsoft, and it also follows its own license terms. It does not require a training process and is speaker-independent. It supports user-defined grammar and Windows, and is redistributable.

The purpose of this research, however, is not to identify the best voice/speech recognition engine but to prove the usefulness of speech recognition for Fast activity analysis.

Detecting the Zone of Activity Category after Voice Recognition

Recognized activity category data do not contain their zone information. They only have standard time stamps; however, their zone can be detected based on the time stamps because the location data points include their standard time stamps and zone information as a result of the zone detection process. The zone detection of activity category data is simple, and Figure 28 illustrates two exemplary cases. The first case

[4] https://www.gnu.org/copyleft/gpl.html

(Figure 28 (a)) occurs when the time stamp of the activity category data is close to the GPS location data A (Zone 01). In this case, it can be reasonably estimated that the activity category data belongs to Zone 01. The other case (Figure 28 (b)) occurs when the time stamp of the activity category data is close to the GPS location data B (Zone 02). In this case, it can also be reasonably estimated that the activity category data belongs to Zone 02.

The reason for these two cases is that each location data point does not completely match with each activity category data because the location data is collected only when the observer's location has changed. Several activity category data can be collected at the same location. In this case, there are several category data, but only one location data. Otherwise, the activity category data can be collected while the observer is continuously moving. In this case, each activity category data collection location is somewhere between two sequential location points in chronological order.

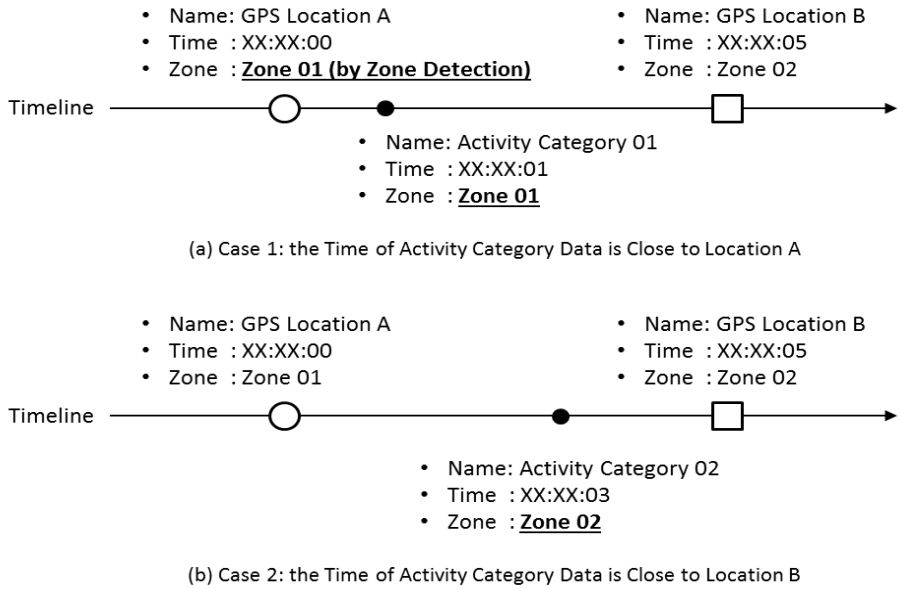


Figure 28: Zone Detection for Activity Category Data

An example of activity category zone detection is shown in Figure 29.

Standard Time-stamp	Activity Category	Confidence Level	***Zone***
20141017:09:18:16.993	PREPA	0.79387	Zone01
20141017:09:18:18.103	DWORK	0.890036	Zone01
20141017:09:18:19.573	DWORK	0.834308	Zone01
20141017:09:18:21.033	DWORK	0.91467	Zone01
20141017:09:18:22.973	PERSN	0.366374	Zone01
20141017:09:18:25.213	WAITN	0.602918	Zone01
20141017:09:18:26.363	DWORK	0.839126	Zone01
20141017:09:18:27.633	DWORK	0.926224	Zone02
20141017:09:18:29.553	WAITN	0.117185	Zone02
20141017:09:18:31.603	MATER	0.759399	Zone02
20141017:09:18:35.193	MATER	0.180233	Zone02
20141017:09:18:41.423	MATER	0.573363	Zone02

Figure 29: Example of Zone Detection of Each Activity Category

3.3.4 Data Integration

In order to systemically analyze the collected data and acquire values from them, the data need to be integrated with each other. As mentioned in Chapter 3.1, the integration of the activity category, time, zone, and video data is performed using their time-stamps. In this integration process, the time-stamps play a major role because workers' operations occur continuously over time. Humans can understand their working situation (i.e., context) when it includes time sequence data. A project manager can perform a productivity improvement study using the dynamic analysis function that contains activity analysis results and their time, location, and video context information. All of the data analysis processes are integrated: Voice and Video Synchronization,

Zone Detection, and Voice Recognition. After the completion of data processing and integration, each data has the following structure as shown in Figure 30.

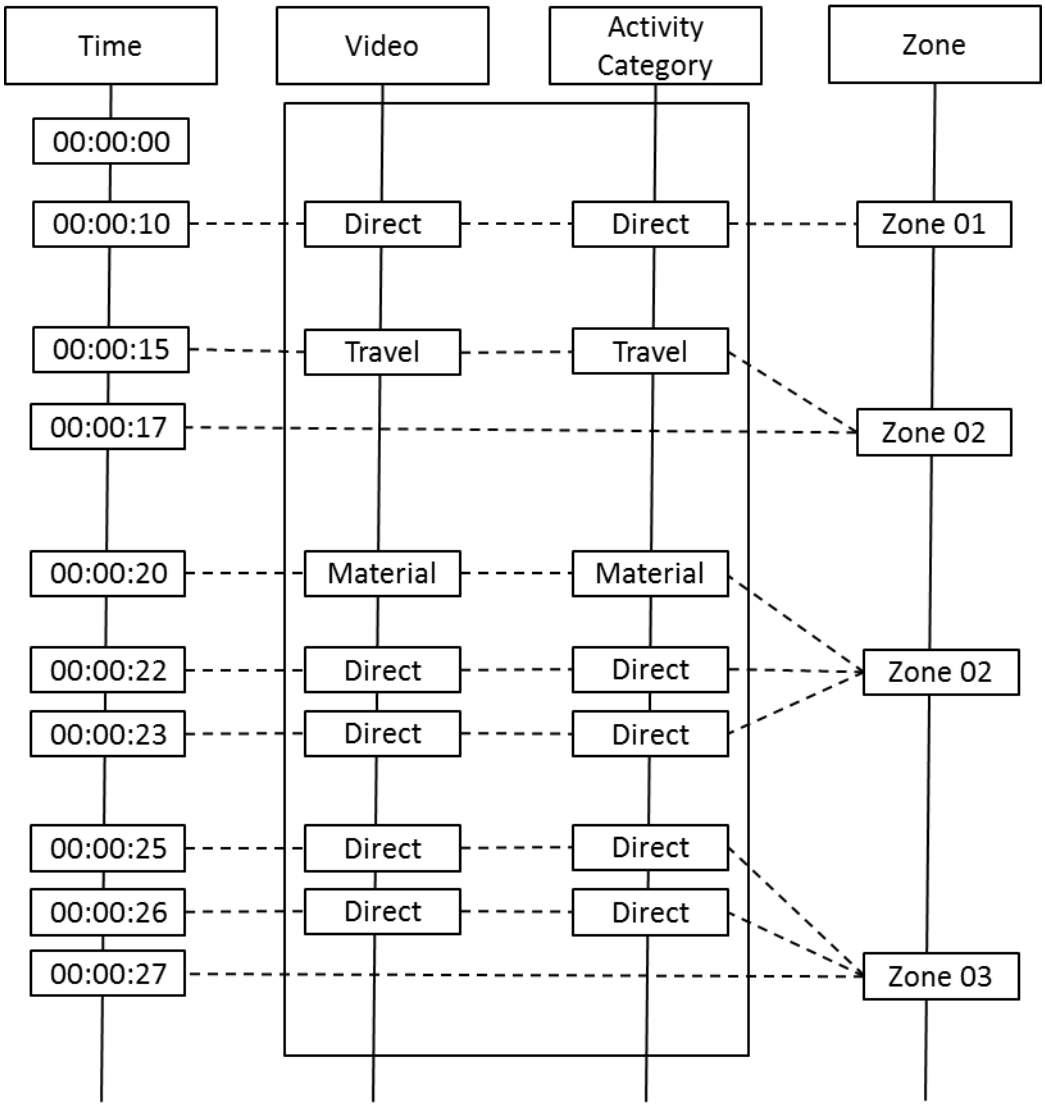


Figure 30: Data Integration Results (Example)

Basically, all activity category, video, and zone data share standard time stamps. Activity category and video data are matched with each other exactly in a 1:1 relationship as they share the same time-stamps. This enables indexed video to provide visual context

information (i.e., contexts regarding who, what, how, and partially where). A project manager can review each activity category data with the matching video. Zone data also has its own time stamps and is integrated with activity category and video data by means of the time stamps. Zone and activity category/video are not exactly matched with each other, but are integrated with reasonable accuracy.

With this integrated data, two types of utilization are available – operational/online transaction process (OLTP) and online analytical processing (OLAP). Data analysis methods with these utilizations are explained in the following sections.

3.3.5 Dynamic Analysis

For a productivity improvement study, dynamic analysis using activity analysis results and their context information can be a useful way to understand actual working conditions and identify issues related to labor productivity. The dynamic analysis includes on-demand/real-time generation of work rates, graphs, and charts from various analysis perspectives, such as project, time, location, activity category, observers, and all possible combinations thereof. With the dynamic analysis method, a project manager reviews activity analysis results under several scenarios. One possible scenario is as follows:

> The scenario can start with a brief review of the overall work rates of Project A over the previous month. During the review, if the overall direct work rate is lower than standard, the project manager can decide to review the work rates of each zone of Project A. If a certain zone shows a lower direct work rate, the project manager can review that zone on a daily or weekly basis. Then, if the zone seems to have labor productivity-related issues, the project manager can choose to review the indexed videos integrated with each activity category data with following questions in mind: 1) Which trades or crews are working in the zone?; 2) What about crew or equipment's working environment?; 3) Is there any interference among trades or crews?; 4) How about material location and their transportation status?; 5) Is there any impact from adverse weather?; and 6) Are there any safety issues?

During the review process, the project manager can also review schedules/plans with this dynamic analysis method to figure out any potential problems related to plan quality. Plan quality is one of the frequent and critical issues affecting labor productivity. This dynamic analysis can also support the project manager to identify plan quality-related issues.

Such dynamic analysis with a computerized system has been dreamed of for a long time. Around 25 years ago, Oglesby (1989) emphasized the importance of well-stored historical productivity data and its utilization. He mentioned that historical data could help project managers to understand actual situations that occurred at the construction site (i.e., context) and provide valuable information to improve productivity and other on-site management practices. Additionally, he mentioned the difficulties involved in the elaborate tasks of gathering, processing, abstracting/rearranging and interpreting data. He envisioned that a computer could support those elaborate tasks, and their results could provide an abundance of valuable information to project management. Today's technologies are now ready to realize this vision.

Two types of dynamic analysis methods – OLTP and OLAP – are explained in the following sections.

Operational/Online Transaction Processing (OLTP)

OLTP is "the original description for all the activities and systems associated with entering data reliably into a database" (Kimball and Ross 2002). More frequently, this term has been used in reference to a traditional database system focusing on transactions for day-by-day operations (Coronel et al., 2013). OLTP usually uses a relational database management system to store, manage, and utilize data. It mainly uses common

"SELECT, INSERT, UPDATE, and DELETE" queries. In this research, OLTP is used to integrate, store, manage, and dynamically analyze activity analysis data (i.e., activity categories, time, location, and video). Figure 31 shows the typical OLTP system structure. The OLTP application directly accesses the OLTP database and performs operational transactions.

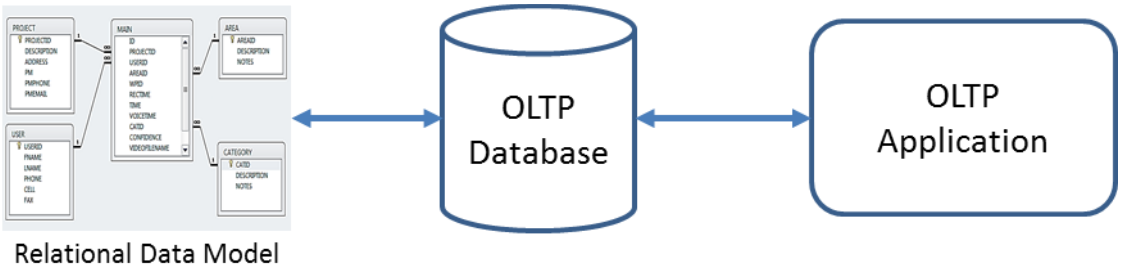


Figure 31: OLTP System Structure

The development of the OLTP data analysis system follows the conventional database development methodology (Figure 32). The first step is to analyze the system requirements. For the dynamic analysis system for a productivity improvement study, various scenarios similar to the scenario mentioned in the previous section can be used as sources of requirements. Interviewing project managers or productivity-related personnel can be helpful for this requirement analysis. Major functions of the system are defined in this step. Examples of such functions include:

- Automatic and real-time calculation of work rates
- Creating a summary table and displaying work rates
- Searching by various combinations of fields and calculating work rates
- Displaying indexed video related to activity category data

The second and third steps are used for the design of a database as well as its application and system development. The last step is to test and debug the system, and make any changes if required.

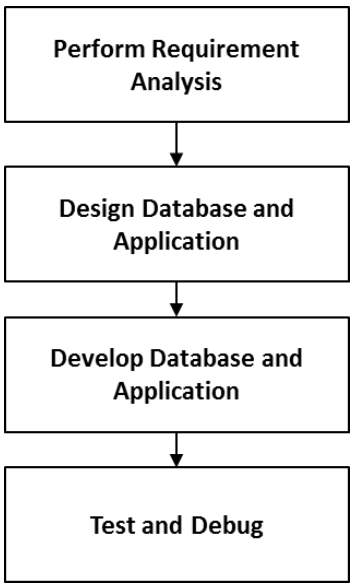


Figure 32: OLTP System Development Steps

An example of the relational data model for this system is shown in Figure 33. The "Main" is the main table containing all the raw data collected and processed by the preceding processes. It has relationships with Project, Observer, Area (Zone), and activity Category table. This star schema is also useful when the project manager performs an OLAP, to be explained in the following section (Coronel et al. 2013). An OLTP-based dynamic data analysis application was developed and explained in Chapter 3.3.5.

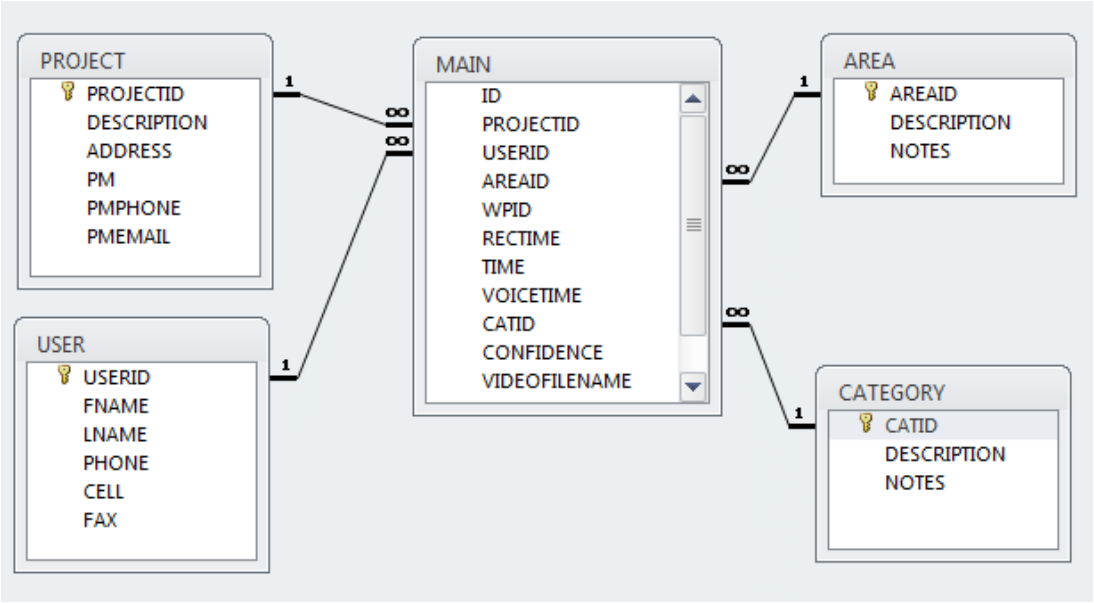


Figure 33: Entity Relationship Diagram – Example

Online Analytical Processing (OLAP)

An OLTP-based system can be useful but has some limitations. One of these limitations is that its functions are fixed when it is designed and developed. It only can provide dynamic analysis results with pre-defined database fields and functions. For example, if an OLTP system contains a dynamic search function that allows a search by project but not by time, then the system has to be modified to provide the 'search by time' function.

OLAP is a more flexible method whereby users can define any dimensions (i.e., fields in OLTP) and their methods of calculation/aggregation. It is more useful for scenario-based analysis, trend searching, and knowledge extraction.

OLAP is defined as "a loosely defined set of principles that provide a dimensional framework for decision support" (Kimball and Ross 2002). It focuses more on historical

data and business measures used for strategic decision making (Coronel et al. 2013). Studies have utilized OLAP for cost data management (Moon et al. 2007), cost control and manpower analysis (Nie et al. 2007), and decision support systems (Ahmad and Nunoo 1999; Cao et al. 2002; Chau et al. 2003) in the construction industry.

OLAP uses a data warehouse. It contains multidimensional data analysis and aggregation methods as shown in Figure 34. This is called a "cube" and is a default element of OLAP analysis. Each cube has as many dimensions as needed. The dimensions represent the perspectives of data analysis, such as project, time, and zone in the figure. These cubes can be divided and aggregated into lower- and higher-level cubes.

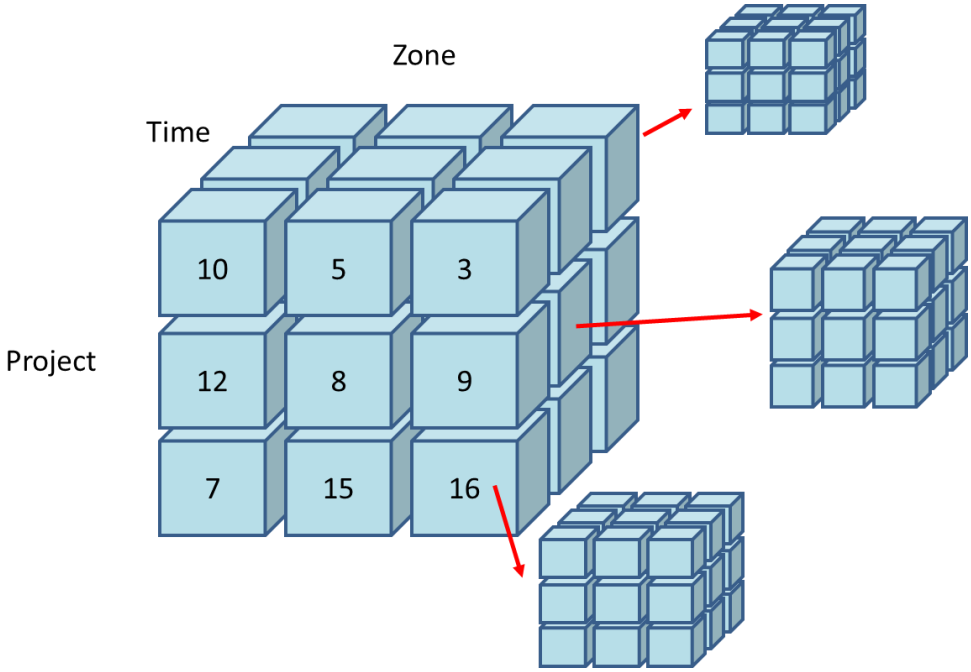


Figure 34: OLAP Cube (Example)

Figure 35 shows a typical OLAP system structure. The data warehouse brings data from existing OLTP databases. OLAP converts data from the data warehouse into strategic information. Users can understand their situation (i.e., context) based on the

information provided by OLAP, such as data from simple calculation/aggregation and time series analysis. For labor performance data analysis, an OLAP data warehouse was developed for this research and is presented in the following section.

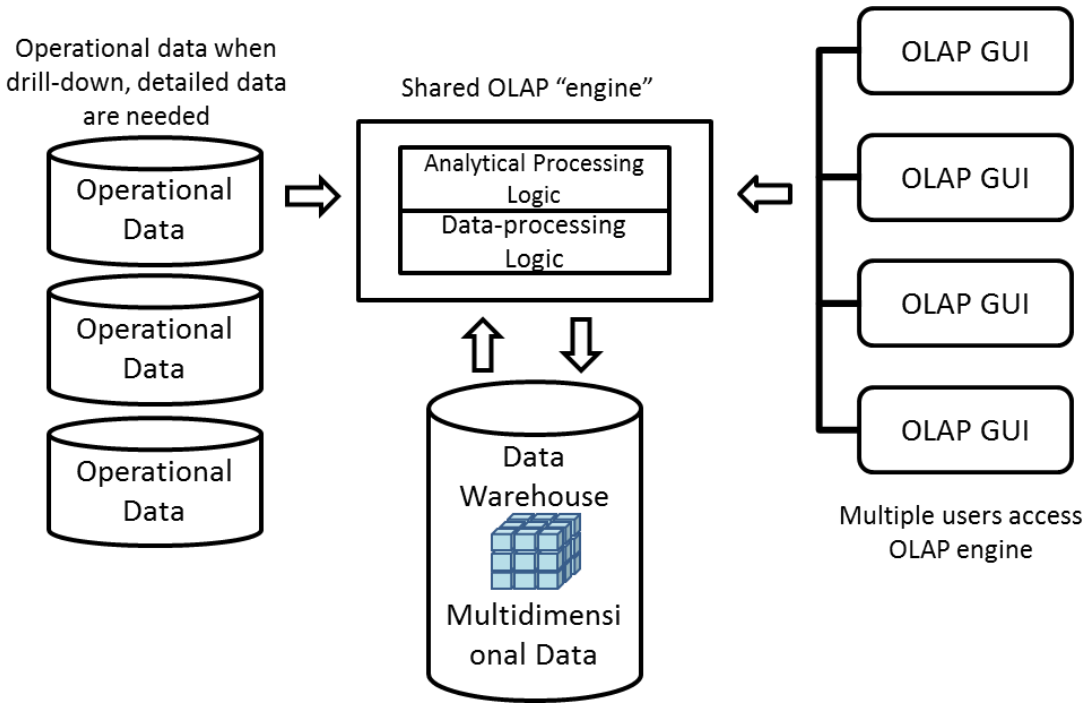


Figure 35: OLAP System Structure (Rob and Coronel 2009)

3.4 SYSTEM IMPLEMENTATION

The semi-automated data collection and analysis method (Figure 36) was implemented, as explained in this section. The data collection module is a mobile-based system, and the data analysis component is a server-based post-processing system. The details of their implementation are delineated in the following sections.

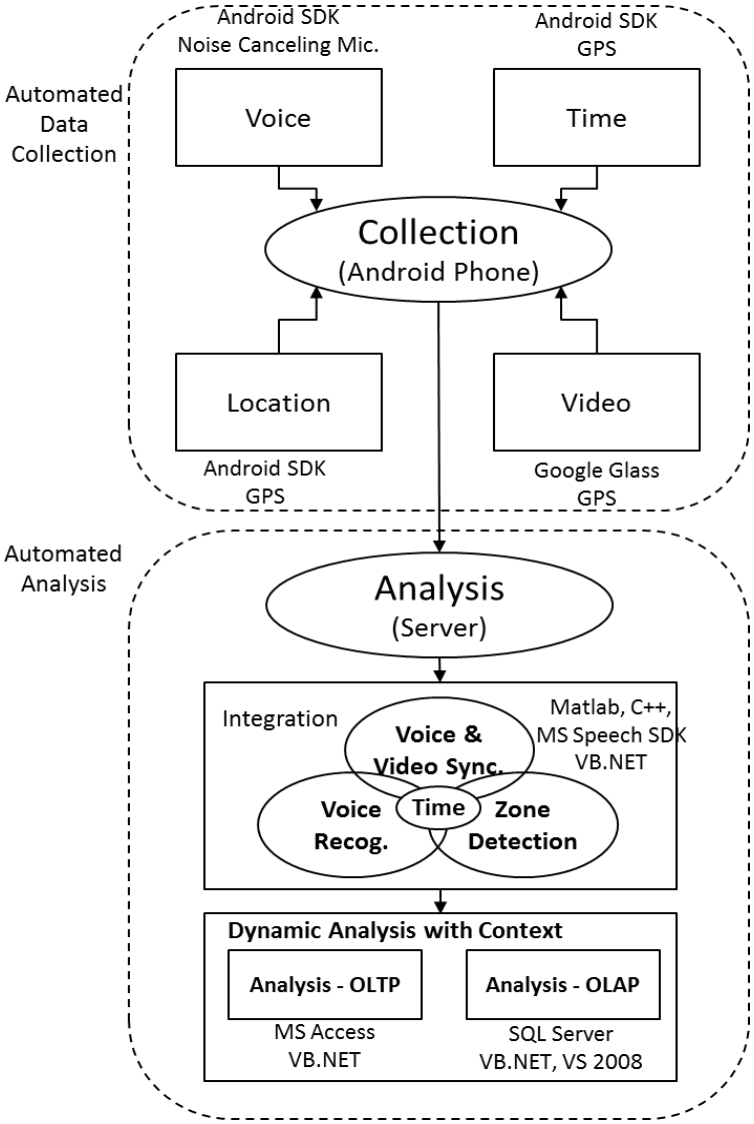


Figure 36: System Implementation

3.4.1 Data Collection

The automated data collection system is composed of five major elements to implement proposed methodology (Figure 37): 1) GPS receiver as the standard time connection module, 2) device clock synchronization module, 3) voice recorder, 4) location recorder, and 5) video recorder. The first and second modules serve the purpose of "Standard Time Acquisition." In this data collection, each sub-module shares the standard time from the GPS for future data integration. First, the GPS sub-module searches for the GPS signal to receive the standard time and location data. A cell phone network and WiFi were used as backup networks. Second, once the GPS signal is received, the device's clock synchronization sub-module maintains standard time information for the other modules. Third, a voice recorder starts to record the observer's voice for the activity category data collection and continuously records until the observation is finished. To improve the voice quality, a noise-cancelling technology is used. When the voice recording is started, its standard time-stamp is also recorded in order to synchronize with the recording of other data. Fourth, the location recorder starts recording the location of the observer it changes. When it records the locations, it also records the standard time-stamp of each location point. Lastly, the observer records videos whenever an observation is made.

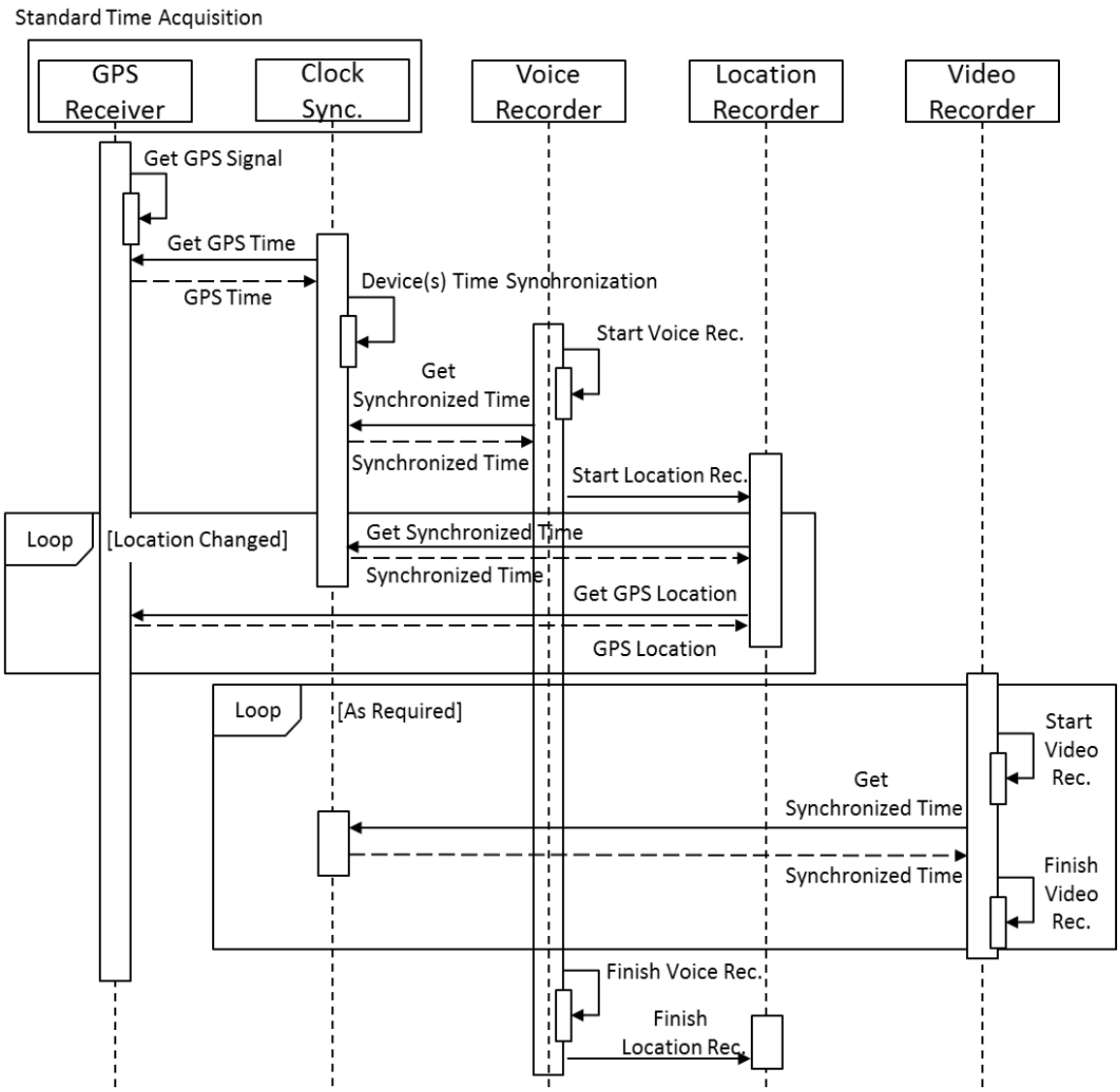
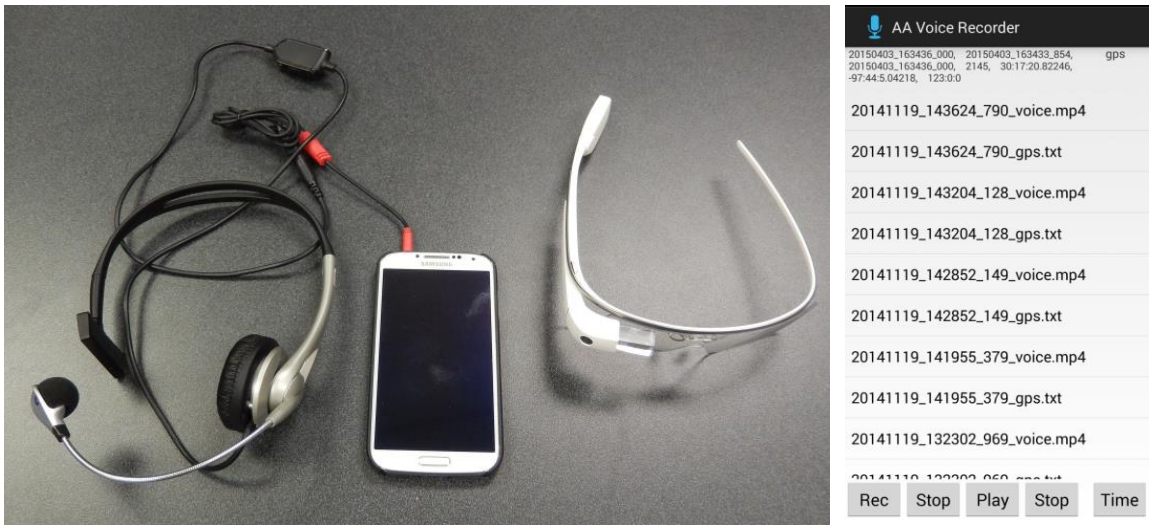


Figure 37: Sequence Diagram of Data Collection

Devices and development tools for data collection module are shown in the previous figure, Figure 36, and Figure 38 (a). Android cell phone was used for GPS time/location data collection, and voice recording. Passive noise-cancelling microphone was used as a voice input device. Google Glass was used as a video recording device. In order to access GPS and acquire voice, time, and location data, a simple Android

application called “AA (Activity Analysis) Voice Recorder” was developed with Android SDK and embedded into the cell phone Figure 38 (b). It serves the functions of connecting to GPS satellite, maintaining standard time, recording voice from the microphone, and recording the observer’s location. All data collection includes standard time-stamps. Google Glass updates its internal clock whenever it receives a GPS signal. Therefore, all video data also contain standard time-stamps. When starting observation, the user has to receive a GPS signal at least once for greater accuracy. Then, the user starts the voice and video recordings whenever activity category data is collected. When voice recording is started, location and all required time-stamp recordings are started. Voice, location, and time-stamp recording lasts until all the activity category data collection is completed. After completing one cycle of data collection, the user has one long voice file, one location file, and several video files.



(a) Data Collection Devices (b) AA Voice Recorder

Figure 38: Data Collection Devices and Application

3.4.2 Data Analysis

The automated data analysis module is composed of four major elements (Figure 39): 1) voice and video synchronization, 2) zone detection, 3) voice recognition, and 4) data analysis sub-phases. In this data analysis module, the first three sub-phases are for data processing and the last is for dynamic data analysis by user. Among the data processing sub-phases, time is essential to the integration of all other data. The integration is performed in all of the data processing sub-phases: voice and video with time, zone detection with time, and voice recognition with time.

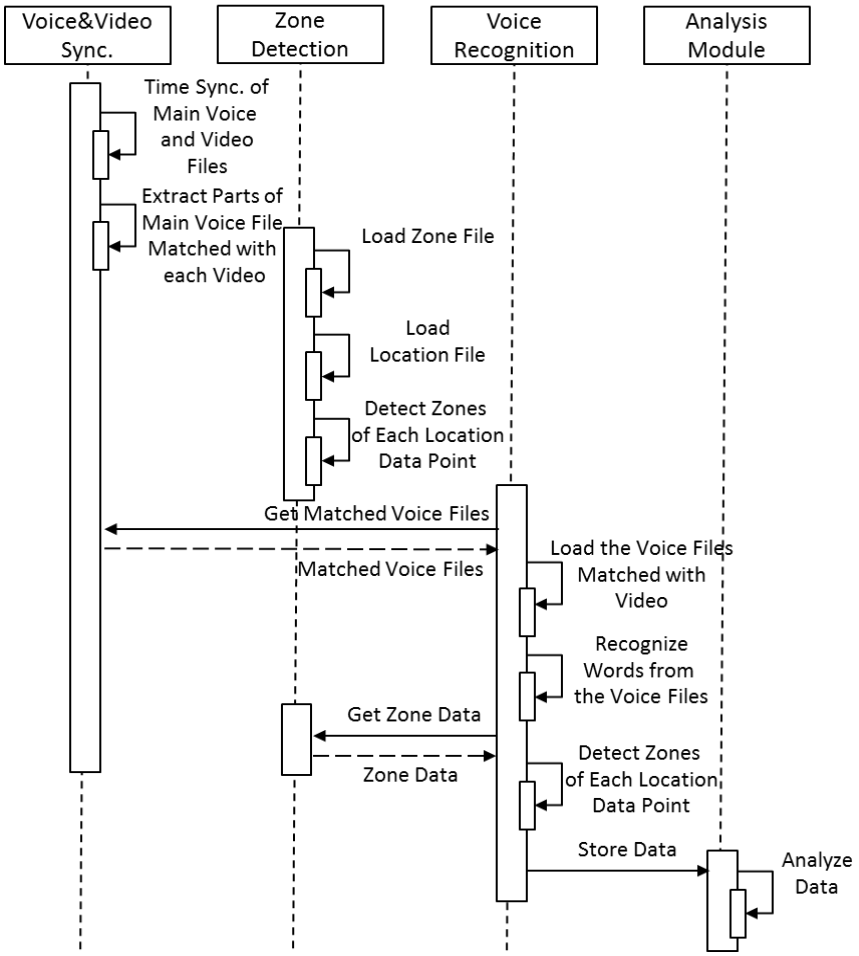


Figure 39: Sequence Diagram of Data Analysis

Voice and Video Synchronization

The Voice and Video Synchronization module was developed with MATLAB. Inputs of the module are the long voice file and its related videos. The module firstly finds the time stamps of the voice file and video files, and then matches them based on the time stamps. Then, the module extracts small voice clips corresponding to each video file for input into the voice recognition engine.

In this module, the GPS time stamp is mainly used to automatically synchronize voice and video recordings, but the human-assisted method is also used as a backup algorithm in the case of losing the GPS signal at the construction site.

Data Analysis – Zone Detection and Voice Recognition

The zone detection and voice recognition functions were developed in one application (Figure 40). Number one (①) area provides the zone detection function of GPS location data. It also functions to convert GPS coordinates into a AutoCAD DXF file to visualize the observation path. Number two (②) area contains voice recognition functions. Microsoft Speech Platform SDK was used as a speech recognition engine, and VB.NET, C++, and MATLAB were used for the user interface and internal processing. In order to use this software, the user selects the data folder, selects the zone definition file and location file (i.e., GPS coordinates), and detects the zones. Then, the user recognizes the voice with the "Recognition from File" function. Recognition results are displayed and stored in the database automatically.

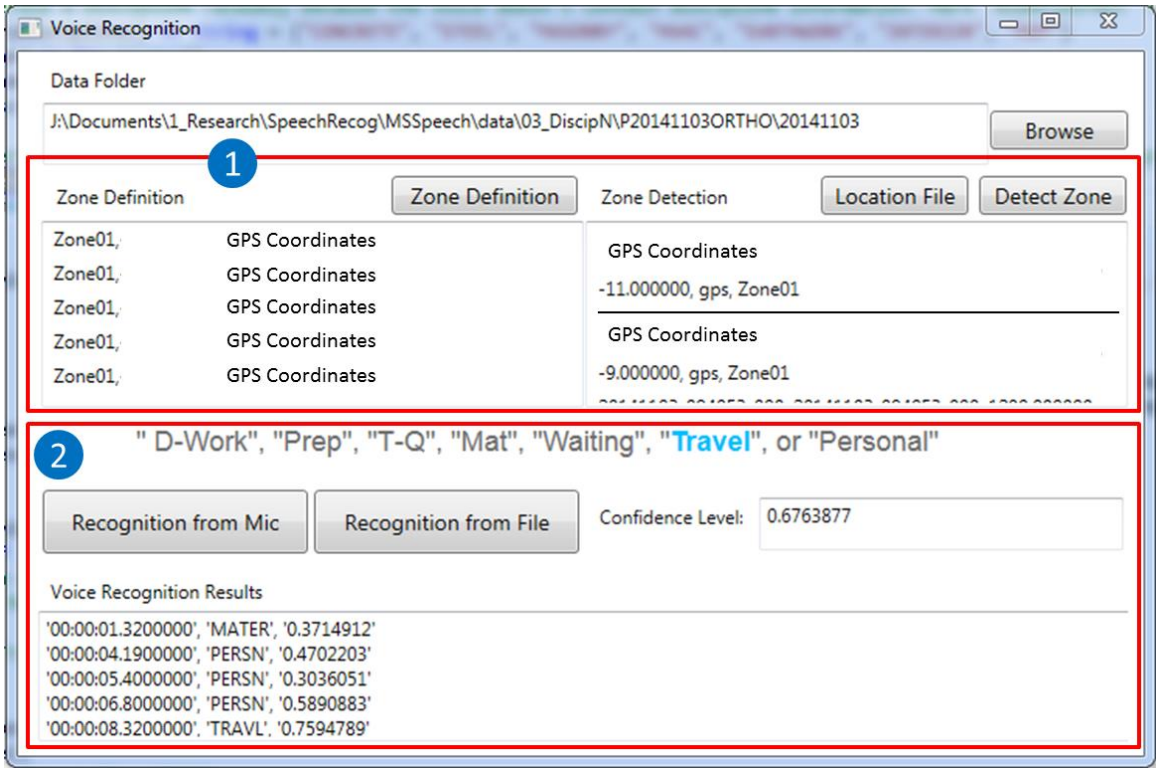


Figure 40: Zone Detection and Voice Recognition Software

Data Analysis – OLTP – Dynamic analysis

This OLTP analysis module (Figure 41) provides a dynamic analysis function from various perspectives: work rates by project; observer (user); project zone; and specific time period. Also possible are all combinations of these perspectives: work rates by project and user; work rate by project during a certain period of time, work rates by project and its zones; raw data count by zones during certain period of time; and so forth (Area ①) . The project manager can review the overall work rate analysis and also closely examine situations at the individual activity category raw data level (Area ②). When the user selects one of the records displayed on the left side, the video indexed at the time when the activity category data was collected is played as well (Area ③).

Therefore, the user can understand actual situations using the knowledge of overall/detail work rates, observation locations, and related visual data. This can provide project management with abundant context about the site and support their productivity study and improvement planning. This integrated data can be archived as historical for future reference. It can be also used as multimedia productivity information to prevent or resolve any disputes or claims. The work rates chart and table are automatically updated whenever the dynamic search results are changed (Area ④).

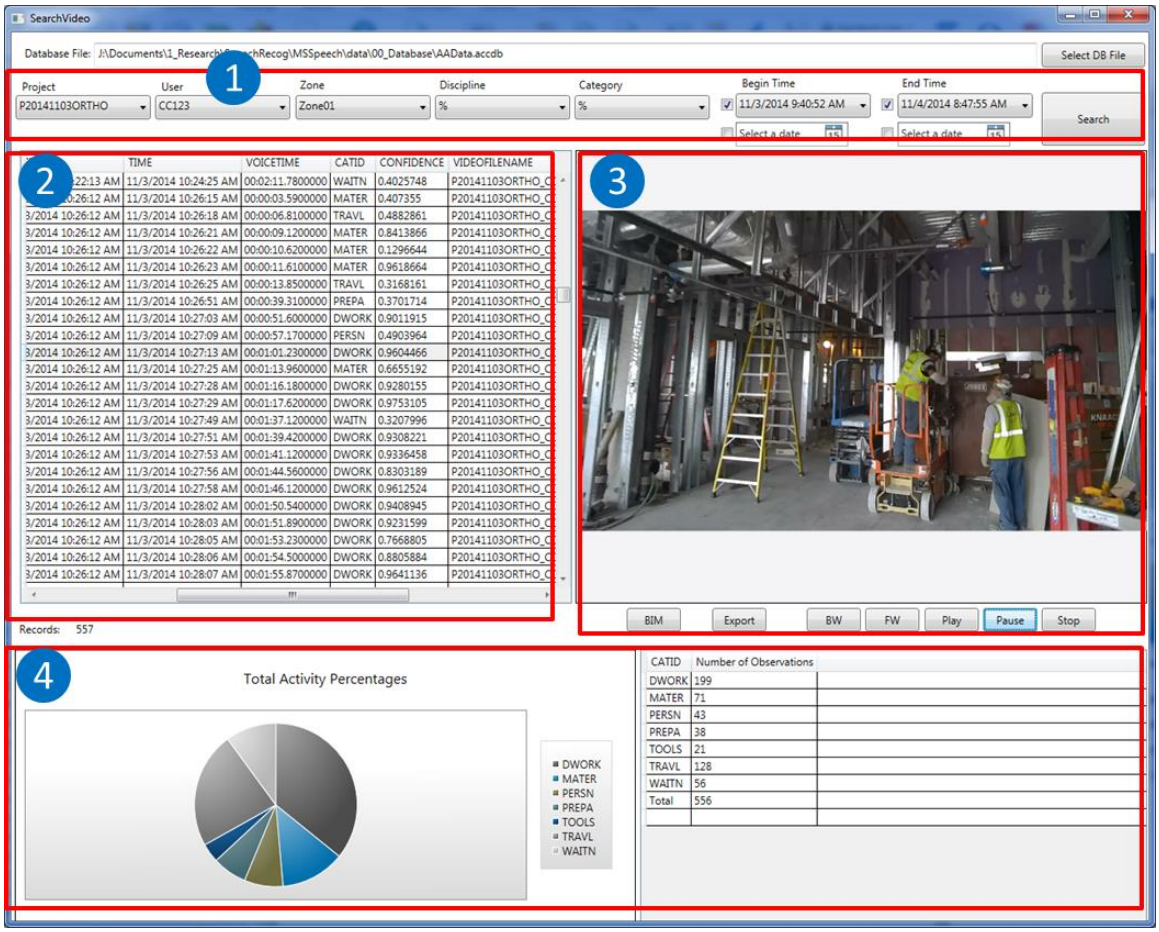


Figure 41: Dynamic Analysis Software – OLTP

Dynamic Analysis – OLAP

With the OLTP database developed in the previous step, a prototype of the data warehouse was implemented in this research. The cube consists of one measure and five dimensions. The one measure is a count of rows in the Main table. The five dimensions are Project, Area (Zone), User (Observer), (Observation) Time, and (Activity) Category in the Figure 42. It was assumed that there is a virtual company that has multiple projects although the projects' data were collected from different companies in reality.

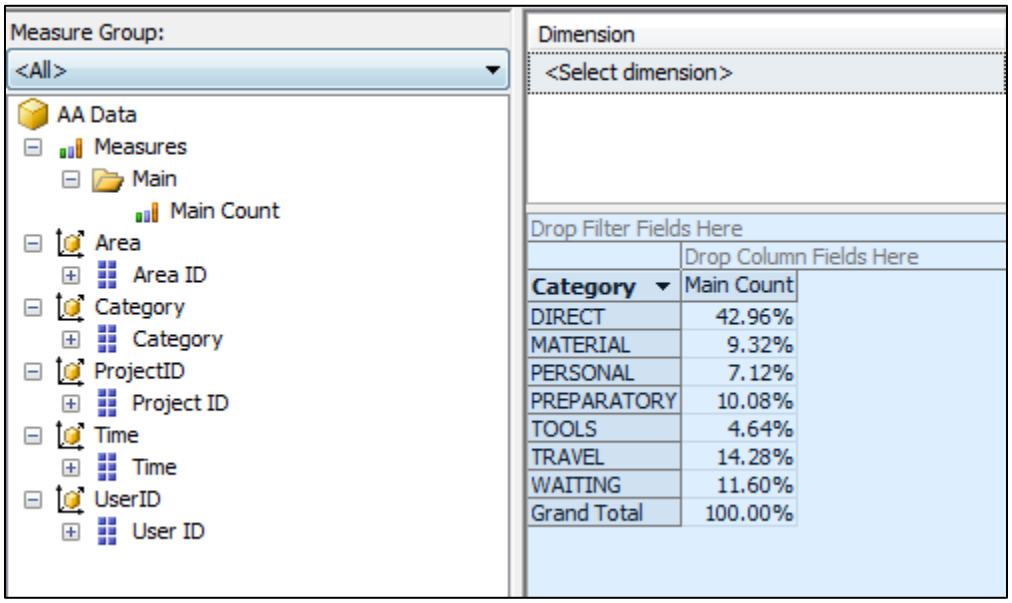


Figure 42: Company-level Work Rates

Activity Diagram of Proposed Methodology

The proposed methodology covers the highlighted activities in the Figure 43. Regarding the "Make Observations" activity, observers do not need to stop their site tour or slow down their tour pace. Observers just need to observe and speak activity categories at the same time during their site tour. Remaining data such as time, location, and video are automatically captured during the observation activity. Regarding "Analyze Data" activity, observers do not need to manually enter data into computer to manually calculate/analyze collected data. Data can automatically be integrated and analyzed with by proposed methodology. The entire project participants can "Review Analysis Results" to interpret the results and identify causes of inefficiencies. The proposed analysis methodology can be a good tool to dynamically review the results and a good communication tool among the participants.

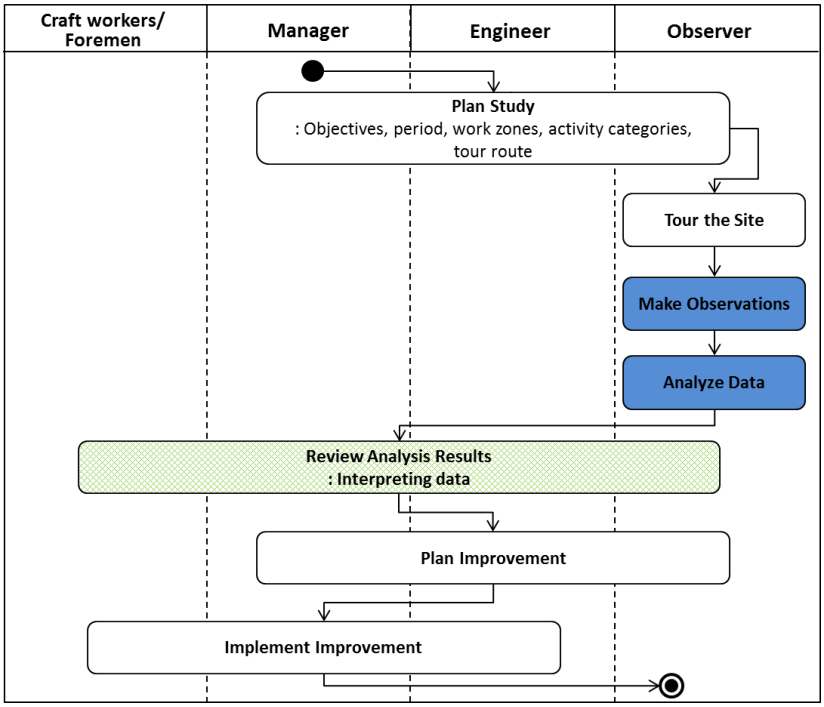


Figure 43: Activity Diagram of Proposed Methodology

Chapter 4 Validation of Proposed Methodology

This chapter describes the validation of the proposed methodology, the semi-automated on-site data collection, and automated analysis. Case studies have been used to validate the methodology. The first part validates the data collection and basic analysis methods. It is composed of an overview of each test project, a brief summary of the collected data (i.e., activity category, location, and video data with standard time-stamps), voice and video time synchronization, zone detection of location data, accuracy comparisons of voice recognition to obtain activity categories, and work rate calculation result comparisons. The second and third parts of this chapter concern the dynamic analysis with the OLTP module and OLAP module. The chapter also details the validation and its results.

4.1 VALIDATION OF PROPOSED METHODOLOGY

4.1.1 Commercial Building

This construction project, shown in Figure 44, was the erection of a new commercial building. Most of the activities observed pertained to concrete formwork. The formwork was performed on the top floor. The weather, work types, and other details of the project and observations are shown in Table 10.

Figure 44: Commercial Building Construction Project

Items	Descriptions
Project Type	• New commercial building construction
Weather	• Sunny; 74ºF
Observation period	• 1 hour
Work types	• Mostly formwork
Work zones	• Two (Zone01 and Zone02)
Number of observations	• 255 observations • Number of workers: 120 ~ 140 • Minimum Observation Required: 116 per hour
Sound Noise Environment	• Crane, compactor, grinder, electronic drill, electric screw driver, and hammer sounds • Workers' and escort engineer's voices • Wind hissing
Activity Categories and their Grammar Words	• 7 activity categories and grammar words o Direct work (D-Work) o Preparatory work (Ready) o Tools and equipment (T-Q) o Material handling (Handling) o Travel (Traveling) o Waiting (Waiting) o Personal (Personal)

Table 10: Project and Observation Description – Commercial Building

Data Collection Results

Two sets of voice, location, and video data were successfully collected with standard time-stamps. The first set includes one voice file containing 93 activity category data, one location file containing 301 location points, and nine video files recorded when activity category data was collected. The second set consists of one voice file containing

162 activity category data, one location file containing 156 location points, and nine video files recorded when the activity category data was collected.

Figure 45 shows the results of location data collection. In this experiment, a GPS signal was successfully received at the beginning of the observations. It was open-space, and the GPS signal stayed strong.

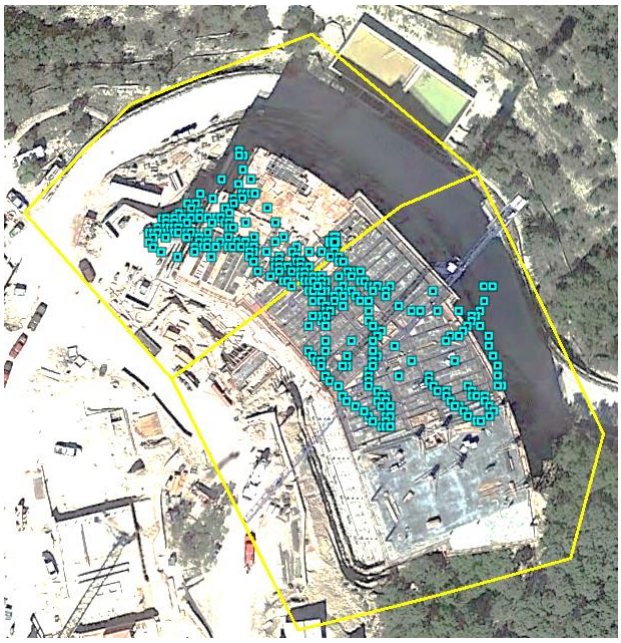


Figure 45: Location Data Collection (GPS) – Commercial Building

Synchronization of Voice and Videos

An automatic method was applied to synchronize voices and videos because both of them contained standard time-stamps from GPS. From the two long source voice files, a total of 18 short voice clips were extracted. These clips were exactly matched with the 18 video files regarding the recording time, duration, and activity category data which they contained.

Zone Detection of Location Data

Zone detection results are shown in Figure 46. Observations were made in both Zone01 and Zone02, and no location points exist outside these zones. Zone detection was performed with a winding number counting algorithm and showed good results. Table 11 shows the accuracy of the zone detection results.

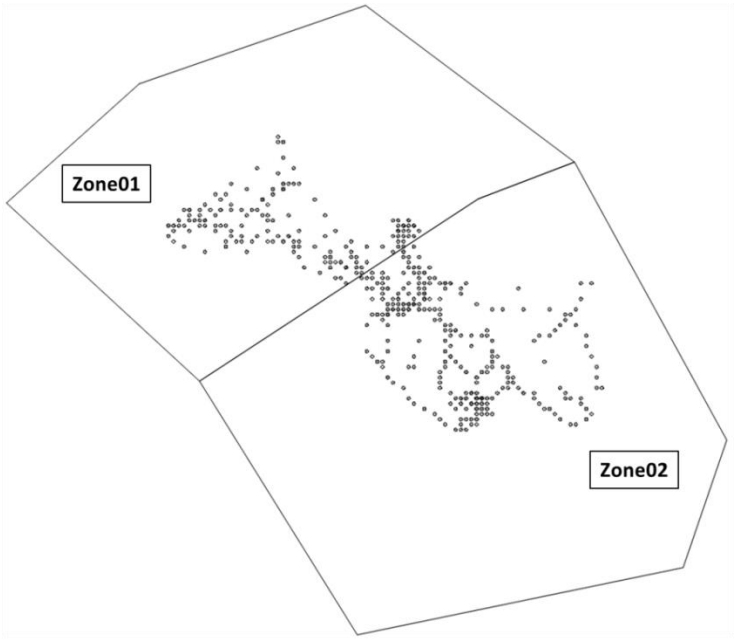


Figure 46: Zone Detection – Commercial Building

	Number of Actual Location Points in Each Zone (a)	Number of Detected Location Points in Each Zone (b)	Detection Accuracy (b / a * 100)
Zone01	162	162	100%
Zone02	295	295	100%
Out of Zones	0	0	-

Table 11: Zone Detection Accuracy – Commercial Building

Voice Recognition Results

The overall voice recognition accuracy was 95.3 %. This means that 243 activity categories out of 255 were correctly recognized. Table 12 shows the confusion matrix of the results. In the confusion matrix, "Travel (grammar: Traveling)" was sometimes confused with "Material Handling (grammar: Handling)" due to the similarity in the vocal features of each grammar.

Items		Prediction								Total
		Direct	Preparatory	Tools	Material	Waiting	Travel	Personal	Noise	
Ground Truth	Direct	91	0	0	0	0	0	0	2	93
	Preparatory	0	25	1	0	0	0	0	0	26
	Tools	0	0	20	0	0	0	0	0	20
	Material	0	0	0	31	0	0	0	0	31
	Waiting	0	1	1	0	32	0	0	0	34
	Travel	0	0	0	7	0	34	0	0	41
	Personal	0	0	0	0	0	0	10	0	10
	Noise	0	0	0	0	0	0	0	0	0
Total		91	26	22	38	32	34	10	2	255

Table 12: Confusion Matrix – Commercial Building

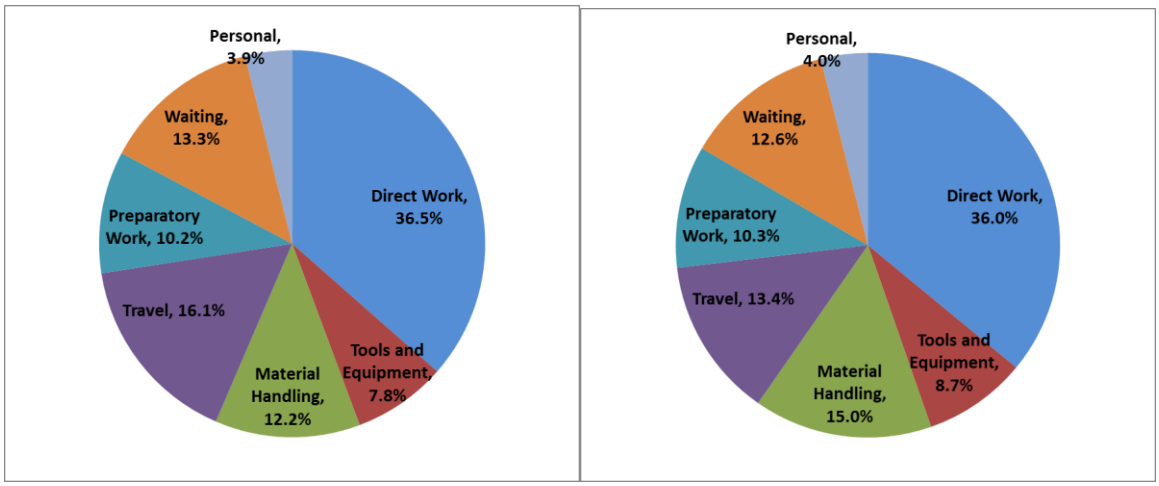
Table 13 shows the confusion matrix for each category and their performance. "Personal" shows the best results. The most important category—"Direct Work"—also shows good performance while "Material Handling" shows the worst accuracy and precision and recall.

DIRECT ('D-WORK')		P	N	Total		PERFORMANCE	
	T	91	2	93		Accuracy	99.22%
	F	0	162	162		Precision	100.00%
	Total	91	164	255		Recall	97.85%
PREPARATORY ('READY')		P	N			PERFORMANCE	
	T	25	1	26		Accuracy	99.22%
	F	1	228	229		Precision	96.15%
		26	229	255		Recall	96.15%
TOOLS ('T-Q')		P	N			PERFORMANCE	
	T	20	0	20		Accuracy	99.22%
	F	2	233	235		Precision	90.91%
		22	233	255		Recall	100.00%
MATERIAL ('HANDLING')		P	N			PERFORMANCE	
	T	31	0	31		Accuracy	**97.25%**
	F	7	217	224		Precision	**81.58%**
		38	217	255		Recall	**100.00%**
WAITING ('WAITING')		P	N			PERFORMANCE	
	T	32	2	34		Accuracy	99.22%
	F	0	221	221		Precision	100.00%
		32	223	255		Recall	94.12%
TRAVEL ('TRAVELING')		P	N			PERFORMANCE	
	T	34	7	41		Accuracy	97.25%
	F	0	214	214		Precision	100.00%
		34	221	255		Recall	82.93%
PERSONAL ('PERSONAL')		P	N			PERFORMANCE	
	T	10	0	10		Accuracy	**100.00%**
	F	0	245	245		Precision	**100.00%**
		10	245	255		Recall	**100.00%**
NOISE		P	N			PERFORMANCE	
	T	0	0	0		Accuracy	-
	F	2	253	255		Precision	-
		2	253	255		Recall	-

Table 13: Confusion Matrix per Category – Commercial Building

Work Rate Calculation Comparisons

Comparisons of work rate calculations by a manual method and the proposed method are shown in Figure 47 and Table 14. The "direct work" shows small amount of difference (0.5%). "Material Handling" and "Travel" were confused for each other. "Material Handling" has the largest difference, 2.9 %. Between the manual and proposed methods, "Personal" shows no differences.



(a) Manual Work Rates (b) Proposed Method's Work Rates

Figure 47: Work Rate Calculation Comparison – Pie Chart – Commercial Building

Category Type I	Category II	True Value (a)	Proposed Method (b)	Difference (a-b)
Productive	Direct Work	36.5%	36.0%	0.5%
Supportive	Tools and Equipment	7.8%	8.7%	-0.9%
	Material Handling	12.2%	15.0%	-2.9%
	Travel	16.1%	13.4%	2.6%
	Preparatory Work	10.2%	10.3%	-0.1%
Idle	Waiting	13.3%	12.6%	0.7%
	Personal	3.9%	4.0%	0.0%
Total	Total	100.0%	100.0%	

Table 14: Work Rate Calculation Comparison – Table– Commercial Building

4.1.2 Hospital - 1

The project shown in the Figure 48 was an expansion project of an existing hospital. Major activities included drywall installation, flooring, plumbing, exterior wall finishing, and formwork for the new canopy. Because the hospital was in operation and many patients were inside and outside it, some restrictions were necessary, such as access to the hospital and vertical transportation. Weather, work type, and other details of the project and observations are shown in Table 15.

Figure 48: Hospital Expansion Project (Hospital – 1)

Items	Descriptions
Project Type	• Hospital; Expansion
Weather	• Sunny; 75ºF
Observation period	• 1 hour
Work types	• Interior, exterior, formwork (canopy)
Work zones	• Two (ZoneA and ZoneB)
Number of observations	• 89 observations • Number of workers: 90 ~ 100 • Minimum Observation Required: 84 per hour
Sound Noise Environment	• Grinder, electronic drill, electric screw driver, and hammer sounds • Workers' and escort engineer's voices
Activity Categories and their Grammar Words	• 7 activity categories and grammar words o Direct work (D-Work) o Preparatory work (Ready) o Tools and equipment (T-Q) o Material handling (Handling) o Travel (Traveling) o Waiting (Waiting) o Personal (Personal)

Table 15: Project and Observation Description – Hospital - 1

Data Collection Results

One set of voice, location, and video data were successfully collected with standard time-stamps (time data). The dataset was made up of one long voice file containing 89 activity category data, one location file containing 118 location points, and six video files recorded when activity category data. The passive noise-cancelling microphone worked well within the noisy environment. Google glass also successfully

synchronized its internal clock with the GPS time and maintained the synchronization during the observation.

Figure 49 shows the results of location data collection. In this experiment, the GPS signal was successfully received at the beginning of the observations. However, it was lost when observations were made inside of the hospital. The site was a closed space owing to the existing walls of the hospital. This explains the near absence of location points inside the hospital, as shown in Figure 49.

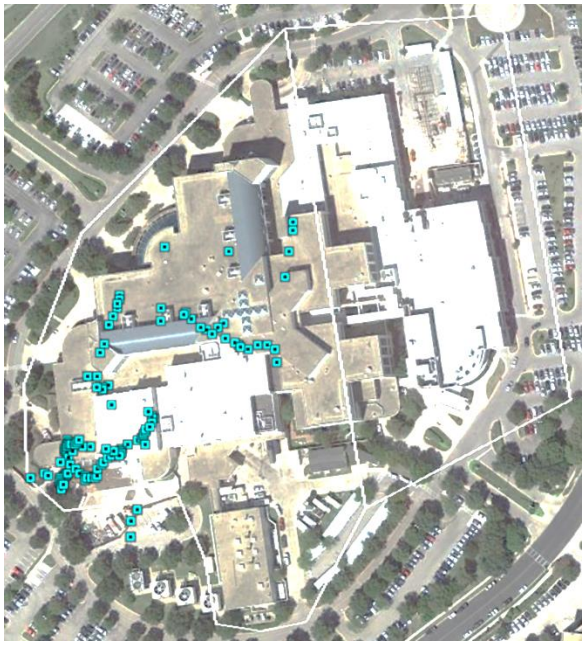


Figure 49: Location Data Collection (GPS) – Hospital - 1

Synchronization of Voice and Videos

The automatic method was applied to synchronize voices and videos because they contained standard time-stamps from GPS. From the one source of a voice file, six voice clips were extracted. These clips were exactly matched with the six video files in terms of their recording time, duration, and activity category data that they contained.

Zone Detection of Location Data

Zone detection results are shown in Figure 50. Most observations were made in Zone A; three location points were outside the zones. Zone detection was performed with a winding number counting algorithm and showed good results. Table 16 shows the accuracy of the zone detection results.

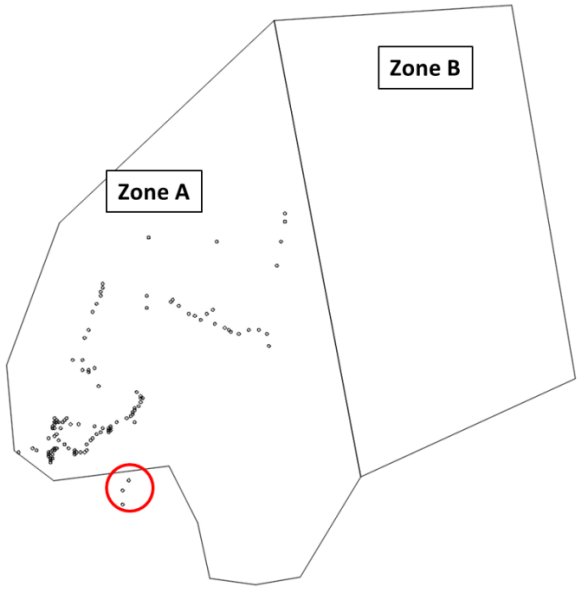


Figure 50: Zone Detection – Hospital - 1

	Number of Actual Location Points in Each Zone (a)	Number of Detected Location Points in Each Zone (b)	Detection Accuracy (b / a * 100)
Zone A	115	115	100%
Zone B	0	0	-
Out of Zones	3	3	100%

Table 16: Zone Detection Accuracy – Hospital - 1

Voice Recognition Results

The overall voice recognition accuracy was 95.6 %. This means that 86 out of 90 activity categories were correctly recognized. The total number of voice recognition accuracy analysis data (90) shown in the Table 17 is different from the total number of real observations (89) mentioned in the previous 'Data Collection Results' sub-section. This is because the voice recognition results contain one false-positive errors on top of the total number of real observations (89). This means that the real number of observations in the voice recording file is 89, but voice recognition engine detected one noise sound as activity category 'Tools'. This type of difference can be occurred in the following cases. Table 17 shows the confusion matrix of the results. In the confusion matrix, Waiting (grammar: Waiting) was sometimes confused for Preparatory (grammar: Ready) and Tools and Equipment (grammar: T-Q). However, there was no significant bias for certain categories. A limitation of this experiment is its small number (90) of observations.

Items		Prediction								Total
		Direct	Preparatory	Tools	Material	Waiting	Travel	Personal	Noise	
Ground Truth	Direct	54	0	0	0	0	0	0	0	54
	Preparatory	0	9	0	0	0	0	0	0	9
	Tools	0	0	1	0	0	0	0	0	1
	Material	0	0	0	9	0	0	0	0	9
	Waiting	0	1	1	0	5	0	0	0	7
	Travel	0	0	0	1	0	7	0	0	8
	Personal	0	0	0	0	0	0	1	0	1
	Noise	0	0	1	0	0	0	0	0	1
Total		54	10	3	10	5	7	1	0	90

Table 17: Confusion Matrix – Hospital - 1

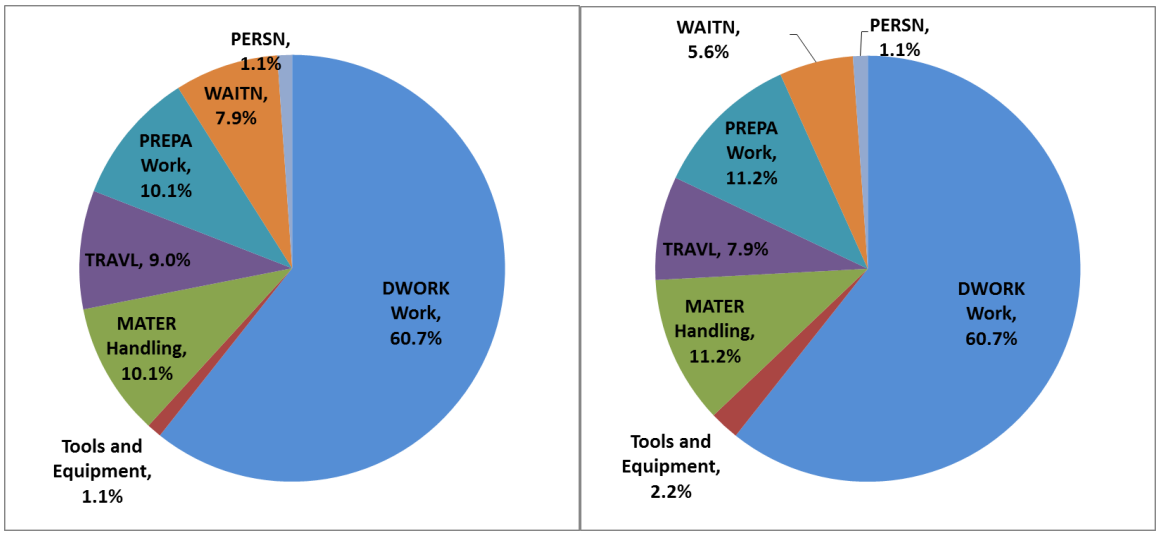
Table 18 shows the confusion matrix for each category and the category's performance. The most important category—Direct Work—showed the best performance while the worst accuracy and precision level belonged to Tools and Equipment.

DIRECT ('D-WORK')		P	N	Total		PERFORMANCE	
	T	54	0	54		Accuracy	**100.00%**
	F	0	36	36		Precision	**100.00%**
	Total	54	36	90		Recall	**100.00%**
PREPARATORY ('READY')		P	N			PERFORMANCE	
	T	9	0	9		Accuracy	98.89%
	F	1	80	81		Precision	90.00%
		10	80	90		Recall	100.00%
TOOLS ('T-Q')		P	N			PERFORMANCE	
	T	1	0	1		Accuracy	**97.78%**
	F	2	87	89		Precision	**33.33%**
		3	87	90		Recall	**100.00%**
MATERIAL ('HANDLING')		P	N			PERFORMANCE	
	T	9	0	9		Accuracy	98.89%
	F	1	80	81		Precision	90.00%
		10	80	90		Recall	100.00%
WAITING ('WAITING')		P	N			PERFORMANCE	
	T	5	2	7		Accuracy	97.78%
	F	0	83	83		Precision	100.00%
		5	85	90		Recall	71.43%
TRAVEL ('TRAVELING')		P	N			PERFORMANCE	
	T	7	1	8		Accuracy	98.89%
	F	0	82	82		Precision	100.00%
		7	83	90		Recall	87.50%
PERSONAL ('PERSONAL')		P	N			PERFORMANCE	
	T	1	0	1		Accuracy	100.00%
	F	0	89	89		Precision	100.00%
		1	89	90		Recall	100.00%
NOISE		P	N			PERFORMANCE	
	T	0	1	1		Accuracy	-
	F	0	89	89		Precision	-
		0	90	90		Recall	-

Table 18: Confusion Matrix per Category – Hospital – 1

Work Rate Calculation Comparisons

The comparison of work rate calculations by the manual and proposed methods is shown in Figure 51 and Table 19. The "direct work" and "personal" rates are the same. The largest difference is "Waiting," 2.2 %. This may be because the voice recognition of the proposed method recognized "Waiting" as other activity categories.



(a) Manual Work Rates (b) Proposed Method's Work Rates

Figure 51: Work Rate Calculation Comparison – Pie Chart – Hospital - 1

Category Type I	Category II	True Value (a)	Proposed Method (b)	Difference (a-b)
Productive	Direct Work	60.7%	60.7%	0.0%
Supportive	Tools and Equipment	1.1%	2.2%	-1.1%
	Material Handling	10.1%	11.2%	-1.1%
	Travel	9.0%	7.9%	1.1%
	Preparatory Work	10.1%	11.2%	-1.1%
Idle	Waiting	7.9%	5.6%	2.2%
	Personal	1.1%	1.1%	0.0%
Total	Total	100.0%	100.0%	

Table 19: Work Rate Calculation Comparison – Table – Hospital - 1

4.1.3 Public Building Project

The project shown in the Figure 52 is the new construction of a public building. Major activities included rebar work and formwork. There were loud sounds from material delivery trucks, cranes, grinders, hand hammers, breaker hammers, and traffic on the main road. Weather, work type, and details of the project and observations are shown in Table 20.

Figure 52: New Public Building Project

Items	Description
Project Type	• Library; New Construction
Weather	• Cloudy; 79ºF
Observation period	• 1 hour
Work types	• Rebar; formwork
Work zones	• 2 (Zone01 and Zone02)
Number of observations	• 360 observations • Number of workers: 120 • Minimum Observation Required: 116 per hour
Sound Noise Environment	• Engine sound of material delivery truck • Traffic noises from the main road • beeping sound of crane • Grinder, hammer, breaker hammer sounds
Activity Categories and their Grammar Words	• 7 activity categories o Direct work (D-Work) o Preparatory work (Ready) o Tools and equipment (T-Q) o Material handling (Handling) o Travel (Traveling) o Waiting (Waiting) o Personal (Personal)

Table 20: Project and Observation Description – Public Building

Data Collection Results

Two sets of voice, location, and video data were successfully collected with standard time-stamps. The first set contained one long voice file containing 116 activity category data, one location file containing 60 location points, and four video files, recorded when the activity category data was collected. The second set consists of one

voice file containing 244 activity category data, one location file containing 142 location points, and seven video files recorded when the activity category data was collected. Due to safety concerns, observations were made from approximately the same place (Figure 53).

Figure 53: Location Data - Library

Synchronization of Voice and Videos

The automatic method was applied to synchronize voices and videos, as they used standard time-stamps. From the two sources of voice files, ten voice clips were extracted. These clips are exactly matched with the ten video files in terms of their recording time, duration, and activity category data which they contain.

Zone Detection of Location Data

Zone detection results are shown in Figure 54. Observations were made in both Zone01 and Zone02, with no location points existing outside the zones. Zone detection was performed with a winding number counting algorithm and shows good results. Table 21 shows the accuracy of the zone detection results.

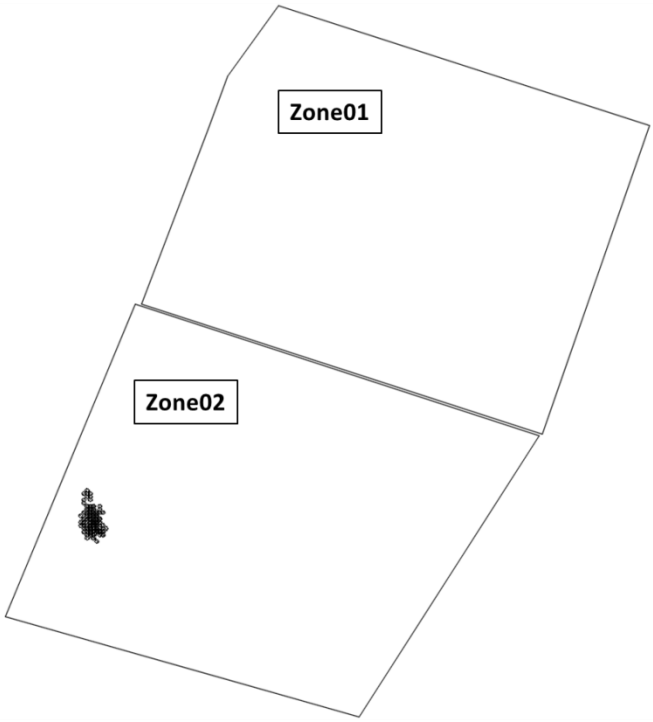


Figure 54: Zone Detection – Public Building

	Number of Actual Location Points in Each Zone (a)	Number of Detected Location Points in Each Zone (b)	Detection Accuracy (b / a * 100)
Zone01	0	0	-
Zone02	202	202	100%
Out of Zones	0	0	-

Table 21: Zone Detection Accuracy – Public Building

Voice Recognition Results

The overall voice recognition accuracy was 92.2 %. This means that 332 activity categories out of 360 were correctly recognized. Table 22 shows the confusion matrix of the results. In the confusion matrix, Travel (grammar: Traveling) was also frequently confused with Material handling (grammar: Handling).

Items		Prediction								Total
		Direct	Preparatory	Tools	Material	Waiting	Travel	Personal	Noise	
Ground Truth	Direct	176	1	0	0	0	0	0	1	178
	Preparatory	0	53	0	1	0	0	0	0	54
	Tools	0	0	2	0	0	0	0	0	2
	Material	0	4	0	21	0	0	0	1	26
	Waiting	0	1	1	1	49	0	0	2	54
	Travel	1	0	0	7	0	27	0	3	38
	Personal	0	0	0	0	0	4	4	0	8
	Noise	0	0	0	0	0	0	0	0	0
Total		177	59	3	30	49	31	4	7	360

Table 22: Confusion Matrix – Public Building

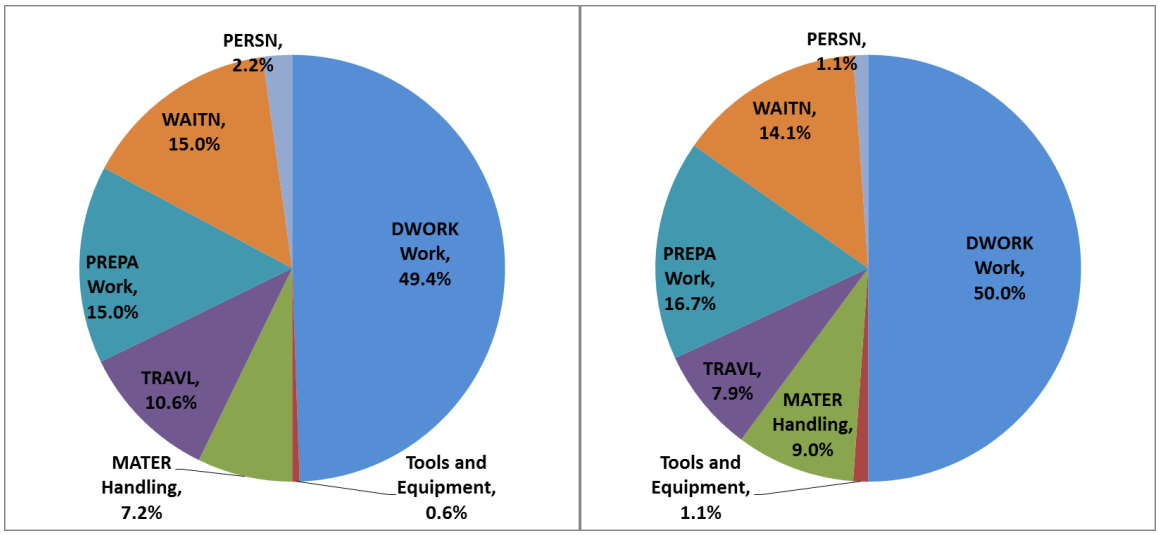
Table 23 shows the confusion matrix for each category and their performance. “Personal” shows the best results. The most important category—“Direct Work”—also shows good performance while “Material Handling” shows the worst accuracy and precision & recall.

		P	N	Total		PERFORMANCE	
DIRECT ('D-WORK')	T	176	2	178		Accuracy	99.17%
	F	1	181	182		Precision	99.44%
	Total	177	183	360		Recall	98.88%
PREPARATORY ('READY')		P	N			PERFORMANCE	
	T	53	1	54		Accuracy	98.06%
	F	6	300	306		Precision	89.83%
		59	301	360		Recall	98.15%
TOOLS ('T-Q')		P	N			PERFORMANCE	
	T	***2***	0	2		Accuracy	***99.72%***
	F	***1***	357	358		Precision	66.67%
		3	357	360		Recall	100.00%
MATERIAL ('HANDLING')		P	N			PERFORMANCE	
	T	21	5	26		Accuracy	96.11%
	F	9	325	334		Precision	70.00%
		30	330	360		Recall	80.77%
WAITING ('WAITING')		P	N			PERFORMANCE	
	T	49	5	54		Accuracy	98.61%
	F	0	306	306		Precision	100.00%
		49	311	360		Recall	90.74%
TRAVEL ('TRAVELING')		P	N			PERFORMANCE	
	T	27	11	38		Accuracy	***95.83%***
	F	4	318	322		Precision	87.10%
		31	329	360		Recall	71.05%
PERSONAL ('PERSONAL')		P	N			PERFORMANCE	
	T	4	4	8		Accuracy	98.89%
	F	0	352	352		Precision	100.00%
		4	356	360		Recall	50.00%
NOISE		P	N			PERFORMANCE	
	T	0	0	0		Accuracy	-
	F	7	353	360		Precision	-
		7	353	360		Recall	-

Table 23: Confusion Matrix per Category – Public Building

Work Rate Calculation Comparisons

The comparisons of work rate calculations by the manual and proposed methods are shown in Figure 55 and Table 24. The "direct work" shows a small amount of difference (-0.6%). "Material Handling" and "Travel" were confused for each other. The "Travel" has the largest difference, 2.6 %.



(a) Manual Work Rates (b) Proposed Method's Work Rates

Figure 55: Work Rate Calculation Comparison – Pie Chart – Public Building

Category Type I	Category II	True Value (a)	Proposed Method (b)	Difference (a-b)
Productive	Direct Work	49.4%	50.0%	-0.6%
Supportive	Tools and Equipment	0.6%	1.1%	-0.6%
	Material Handling	7.2%	9.0%	-1.8%
	Travel	10.6%	7.9%	2.6%
	Preparatory Work	15.0%	16.7%	-1.7%
Idle	Waiting	15.0%	14.1%	0.9%
	Personal	2.2%	1.1%	1.1%
Total	Total	100.0%	100.0%	

Table 24: Work Rate Calculation Comparison – Table – Public Building

4.1.4 Parking Complex

This project is a new parking complex construction as shown in the Figure 56. Weather, work types, and other details of the project and observations are shown in the Table 25.

Figure 56: New Parking Complex

Items	Descriptions
Project Type	• Parking Complex; New Construction
Weather	• Sunny; 71ºF
Observation period	• 1 hour
Work types	• Rebar; formwork; formwork removal
Work zones	• 2 (ZoneA and ZoneB)
Number of observations	• 121 observations • Number of workers: 150 • Minimum Observation Required: 116 per hour
Sound Noise Environment	• Boom forklift sound • Crane engine and beeping sound • Grinder, electronic drill, and hammer sounds • Workers' and escort engineer's voices

Activity Categories and their Grammar Words	• 7 activity categories
	  o Direct work (D-Work)
	  o Preparatory work (Ready)
	  o Tools and equipment (T-Q)
	  o Material handling (Handling)
	  o Travel (Traveling)
	  o Waiting (Waiting)
	  o Personal (Personal)

Table 25: Project and Observation Description – Parking Complex

Data Collection Results

Two sets of voice, location, and video data were successfully collected with standard time stamps (time data). The first set contains one voice file containing 96

activity category data, one location file containing 270 location points, and four video files recorded when activity category data is collected. The second set consists of one voice file containing 25 activity category data, one location file containing 29 location points, and two video files recorded when activity category data was collected.

Figure 57 shows the results of location data collection. In this experiment, GPS signal was successfully received at the beginning of the observations. It was open-space, and the GPS signal was keeping strong.

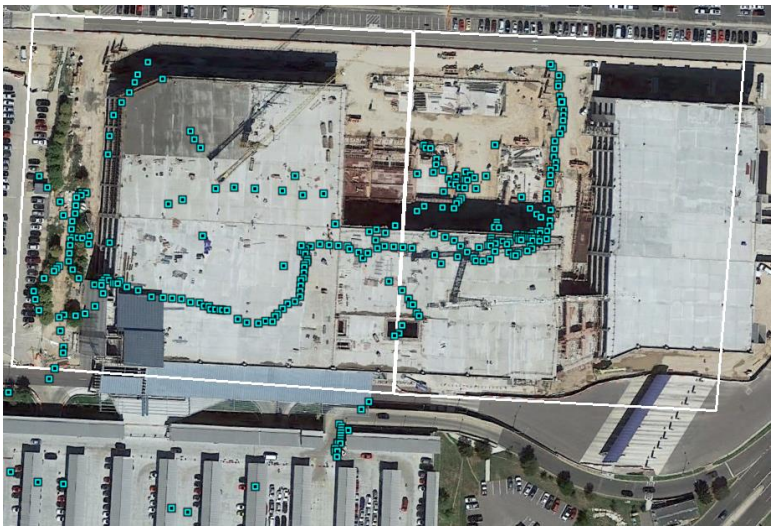


Figure 57: Location Data Collection (GPS) – Parking Complex

Synchronization of Voice and Videos

The automatic method was applied to synchronize voices and videos because they used standard time stamps.

Zone Detection of Location Data

Zone detection results are shown in the Figure 58. Observations were made in the both ZoneA and ZoneB, and there are no location points which are out of any zones. Zone detection was performed by winding number counting algorithm and shows good results. Table 26 shows the accuracy of zone detection results.

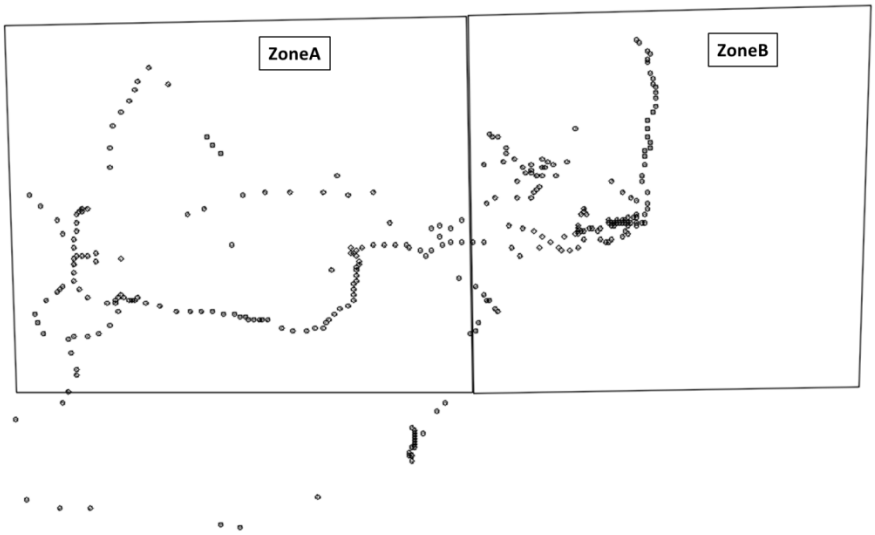


Figure 58: Zone Detection – Parking Complex

	Number of Actual Location Points in Each Zone (a)	Number of Detected Location Points in Each Zone (b)	Detection Accuracy (b / a * 100)
ZoneA	138	138	100%
ZoneB	135	135	100%
Out of Zones	26	26	-

Table 26: Zone Detection Accuracy – Parking Complex

Voice Recognition Results

The overall voice recognition accuracy was 88.6 %. This means that 109 activity categories out of 123 were correctly recognized. There were two false-positives that the voice recognition engine recognized noises as a “Material Handling” and “Travel”. This is the reason why the total number of voice recognition accuracy analysis data (123) is bigger than the number of real observations (121). Table 27 shows the confusion matrix of the results. In the confusion matrix, “Travel (grammar: Traveling)” was frequently confused with “Material Handling (grammar: Handling)” because the grammars, “Traveling” and “Handling”, share similar voice feature.

Items		Prediction								Total
		Direct	Preparatory	Tools	Material	Waiting	Travel	Personal	Noise	
Ground Truth	Direct	36	0	0	0	0	0	0	0	36
	Preparatory	0	18	0	0	0	0	0	0	18
	Tools	0	0	8	1	0	0	0	0	9
	Material	0	0	0	13	0	0	0	0	13
	Waiting	0	0	0	0	16	0	0	0	16
	Travel	0	0	0	9	0	15	0	0	24
	Personal	0	0	0	0	0	1	4	0	5
	Noise	0	0	0	1	0	1	0	0	2
Total		36	18	8	24	16	17	4	0	123

Table 27: Confusion Matrix – Parking Complex

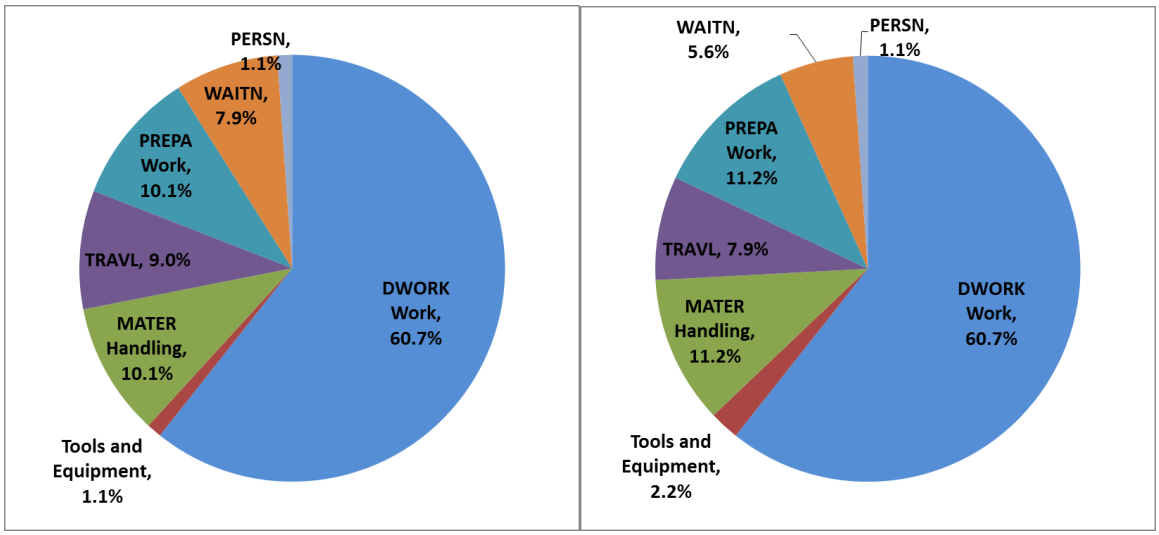
Table 28 shows confusion matrix per each category and their performance. “Direct, Preparatory, and Waiting” shows the best results. “Material Handling” shows the worst accuracy and precision & recall.

DIRECT ('D-WORK')		P	N	Total		PERFORMANCE	
	T	36	0	36		Accuracy	**100.00%**
	F	0	87	87		Precision	**100.00%**
	Total	36	87	123		Recall	**100.00%**
PREPARATORY ('READY')		P	N			PERFORMANCE	
	T	18	0	18		Accuracy	**100.00%**
	F	0	105	105		Precision	**100.00%**
		18	105	123		Recall	**100.00%**
TOOLS ('T-Q')		P	N			PERFORMANCE	
	T	8	1	9		Accuracy	99.19%
	F	0	114	114		Precision	100.00%
		8	115	123		Recall	88.89%
MATERIAL ('HANDLING')		P	N			PERFORMANCE	
	T	13	0	13		Accuracy	**91.06%**
	F	11	99	110		Precision	**54.17%**
		24	99	123		Recall	**100.00%**
WAITING ('WAITING')		P	N			PERFORMANCE	
	T	16	0	16		Accuracy	**100.00%**
	F	0	107	107		Precision	**100.00%**
		16	107	123		Recall	**100.00%**
TRAVEL ('TRAVELING')		P	N			PERFORMANCE	
	T	15	9	24		Accuracy	91.06%
	F	2	97	99		Precision	88.24%
		17	106	123		Recall	62.50%
PERSONAL ('PERSONAL')		P	N			PERFORMANCE	
	T	4	1	5		Accuracy	99.19%
	F	0	118	118		Precision	100.00%
		4	119	123		Recall	80.00%
NOISE		P	N			PERFORMANCE	
	T	0	2	2		Accuracy	-
	F	0	121	121		Precision	-
		0	123	123		Recall	-

Table 28: Confusion Matrix per Category – Parking Complex

Work Rate Calculation Comparisons

The comparisons of work rates calculations by manual method and proposed method were shown in the Figure 59 and Table 29. The "direct work" and "personal" rates are the same. "Waiting" has the largest difference, 2.2 %. This can be because the voice recognition of proposed method recognized "waiting" as other activity categories.



(a) Manual Work Rates (b) Proposed Method's Work Rates

Figure 59: Work Rate Calculation Comparison – Pie Chart – Parking Complex

Category Type I	Category II	True Value (a)	Proposed Method (b)	Difference (a-b)
Productive	Direct Work	60.7%	60.7%	0.0%
Supportive	Tools and Equipment	1.1%	2.2%	-1.1%
	Material Handling	10.1%	11.2%	-1.1%
	Travel	9.0%	7.9%	1.1%
	Preparatory Work	10.1%	11.2%	-1.1%
Idle	Waiting	7.9%	5.6%	2.2%
	Personal	1.1%	1.1%	0.0%
Total	Total	100.0%	100.0%	

Table 29: Work Rate Calculation Comparison – Table – Parking Complex

4.1.5 Road

This project, shown in Figure 60, was a new road construction in a large city. Most of the activities observed pertained to earthwork, structural concrete, and pavement. Observations were made using a car (inside) because the project ranges around 4.5 miles. The weather, work types, and other details of the project and observations are shown in Table 30.

Figure 60: Road Construction Project

Items	Descriptions
Project Type	• New road construction
Weather	• Sunny; 49 ºF
Observation period	• 1 hour and 20 minutes
Work types	• Earthwork, concrete, and pavement
Work zones	• Four (Zone01 to Zone04)
Number of observations	• 295 observations • Number of workers: 100 ~ 120 • Minimum Observation Required: 116 per hour
Sound Noise Environment	• Dozer, scraper, pavement machine • Wind hissing
Activity Categories and their Grammar Words	• 7 activity categories and grammar words o Direct work (D-Work) o Preparatory work (Ready) o Tools and equipment (T-Q) o Material handling (Handling) o Travel (Traveling) o Waiting (Waiting) o Personal (Personal)

Table 30: Project and Observation Description – Road

Data Collection Results

Two sets of voice, location, and video data were successfully collected with standard time-stamps. The first set includes one voice file containing 44 activity category data, one location file containing 365 location points, and four video files recorded when

activity category data was collected. The second set consists of one voice file containing 251 activity category data, one location file containing 1329 location points, and 12 video files recorded when the activity category data was collected.

Figure 61 shows the results of location data collection. In this experiment, a GPS signal was successfully received at the beginning of the observations. It was open-space, and the GPS signal stayed strong.

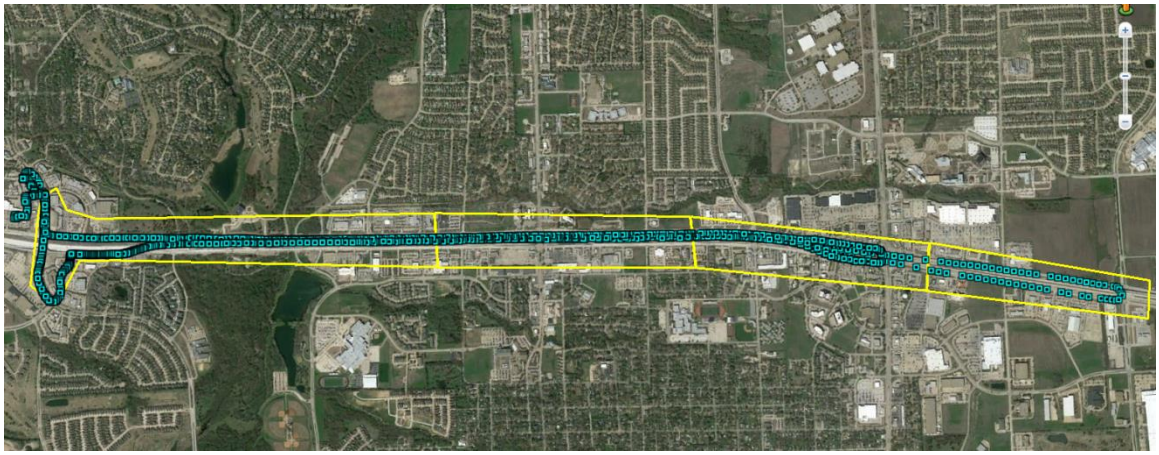


Figure 61: Location Data Collection (GPS) – Road

Synchronization of Voice and Videos

The automatic method was applied to synchronize voices and videos because both of them contained standard time-stamps from GPS. From the two long source voice files, a total of 16 short voice clips were extracted. These clips were exactly matched with the 16 video files regarding the recording time, duration, and activity category data which they contained.

Zone Detection of Location Data

Zone detection results are shown in Figure 62. Observations were made in both Zone01 and Zone02, and no location points exist outside these zones. Zone detection was performed with a winding number counting algorithm and showed good results. Table 31 shows the accuracy of the zone detection results.

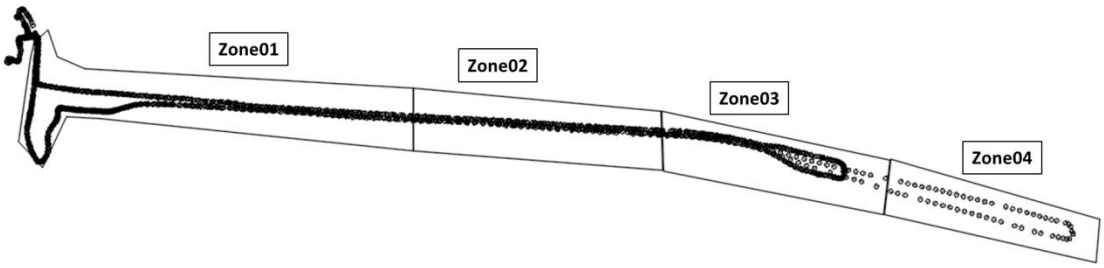


Figure 62: Zone Detection – Road

	Number of Actual Location Points in Each Zone (a)	Number of Detected Location Points in Each Zone (b)	Detection Accuracy (b / a * 100)
Zone01	886	886	100%
Zone02	281	281	100%
Zone03	297	297	100%
Zone04	52	52	100%
Out of Zones	0	0	-

Table 31: Zone Detection Accuracy – Road

Voice Recognition Results

The overall voice recognition accuracy was 95.3 %. This means that 243 activity categories out of 255 were correctly recognized. Table 32 shows the confusion matrix of the results. In the confusion matrix, "Travel (grammar: Traveling)" was sometimes confused with "Material Handling (grammar: Handling)" due to the similarity in the vocal features of each grammar.

Items		Prediction								Total
		Direct	Preparatory	Tools	Material	Waiting	Travel	Personal	Noise	
Ground Truth	Direct	119	0	0	0	0	0	0	0	119
	Preparatory	0	25	1	0	0	0	0	0	26
	Tools	0	0	12	0	0	0	0	0	12
	Material	0	0	0	0	0	0	0	0	0
	Waiting	0	0	2	0	51	0	0	0	53
	Travel	0	0	0	0	0	30	1	0	31
	Personal	0	0	0	0	0	0	53	1	54
	Noise	0	0	0	0	0	0	0	0	0
Total		119	25	15	0	51	30	54	1	295

Table 32: Confusion Matrix – Road

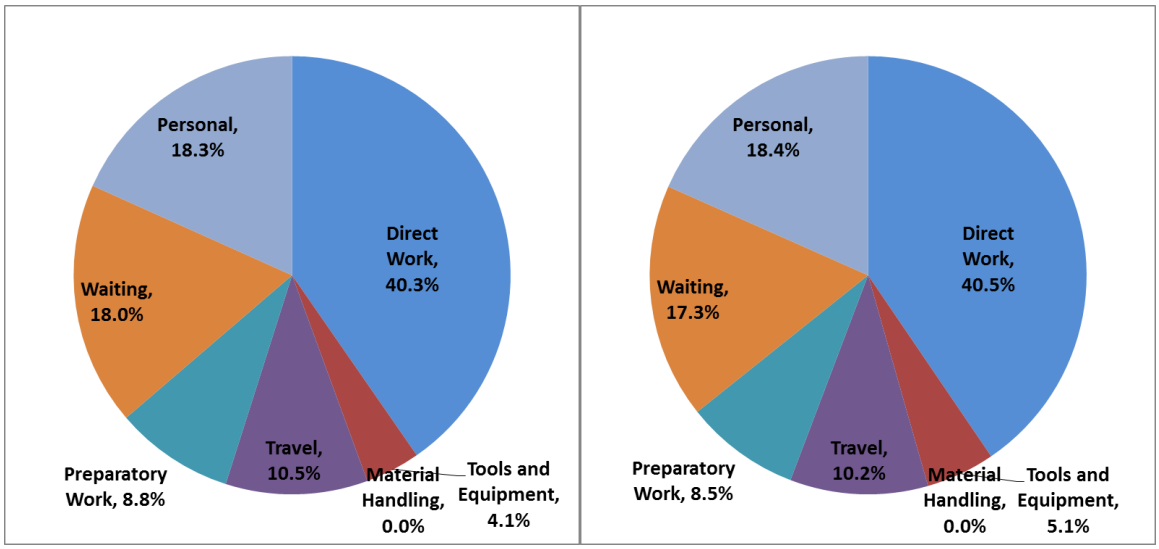
Table 33 shows the confusion matrix for each category and their performance. "Personal" shows the best results. The most important category—"Direct Work"—also shows good performance while "Material Handling" shows the worst accuracy and precision and recall.

		P	N	Total		PERFORMANCE	
DIRECT ('D-WORK')	T	119	0	119		Accuracy	**100.00%**
	F	0	176	176		Precision	**100.00%**
	Total	119	176	295		Recall	**100.00%**
PREPARATORY ('READY')		P	N			PERFORMANCE	
	T	25	1	26		Accuracy	99.66%
	F	0	269	269		Precision	100.00%
		25	270	295		Recall	96.15%
TOOLS ('T-Q')		P	N			PERFORMANCE	
	T	12	0	12		Accuracy	**98.98%**
	F	3	280	283		Precision	**80.00%**
		15	280	295		Recall	**100.00%**
MATERIAL ('HANDLING')		P	N			PERFORMANCE	
	T	0	0	0		Accuracy	100.00%
	F	0	295	295		Precision	N/A
		0	295	295		Recall	N/A
WAITING ('WAITING')		P	N			PERFORMANCE	
	T	51	2	53		Accuracy	99.32%
	F	0	242	242		Precision	100.00%
		51	244	295		Recall	96.23%
TRAVEL ('TRAVELING')		P	N			PERFORMANCE	
	T	30	1	31		Accuracy	99.66%
	F	0	264	264		Precision	100.00%
		30	265	295		Recall	96.77%
PERSONAL ('PERSONAL')		P	N			PERFORMANCE	
	T	53	1	54		Accuracy	99.32%
	F	1	240	241		Precision	98.15%
		54	241	295		Recall	98.15%
NOISE		P	N			PERFORMANCE	
	T	0	0	0		Accuracy	-
	F	1	294	295		Precision	-
		1	294	295		Recall	-

Table 33: Confusion Matrix per Category – Road

Work Rate Calculation Comparisons

Comparisons of work rate calculations by a manual method and the proposed method are shown in Figure 63 and Table 34. The "direct work" shows small amount of difference (0.2%). "Tools and Equipment" has the largest difference, -1.0 %, and "Personal" shows the smallest difference, -0.1%. This is because observations were made in the driving car which is less noisy and more controlled environment.



(a) Manual Work Rates (b) Proposed Method's Work Rates

Figure 63: Work Rate Calculation Comparison – Road

Category Type I	Category II	True Value (a)	Proposed Method (b)	Difference (a-b)
Productive	Direct Work	40.5%	40.3%	0.2%
Supportive	Tools and Equipment	5.1%	4.1%	1.0%
	Material Handling	0.0%	0.0%	0.0%
	Travel	10.2%	10.5%	-0.3%
	Preparatory Work	8.5%	8.8%	-0.3%
Idle	Waiting	17.3%	18.0%	-0.6%
	Personal	18.4%	18.3%	0.1%
Total	Total	100.0%	100.0%	(Rounded)

Table 34: Work Rate Calculation Comparison – Road

4.1.6 Hospital - 2

This is another expansion project of an existing hospital as shown in the Figure 64. The owner of this project requested this activity analysis for the purpose of actual improvement study. Major activities were drywall, windows, exterior insulation, steel, formwork, MEP, HVAC, and Plumbing. It was two days of full observations of the project. Weather, work types, and other details of the project and observations are presented in the Table 35. The focus of this validation is to confirm the performance of the proposed methodology for the real project management purpose.

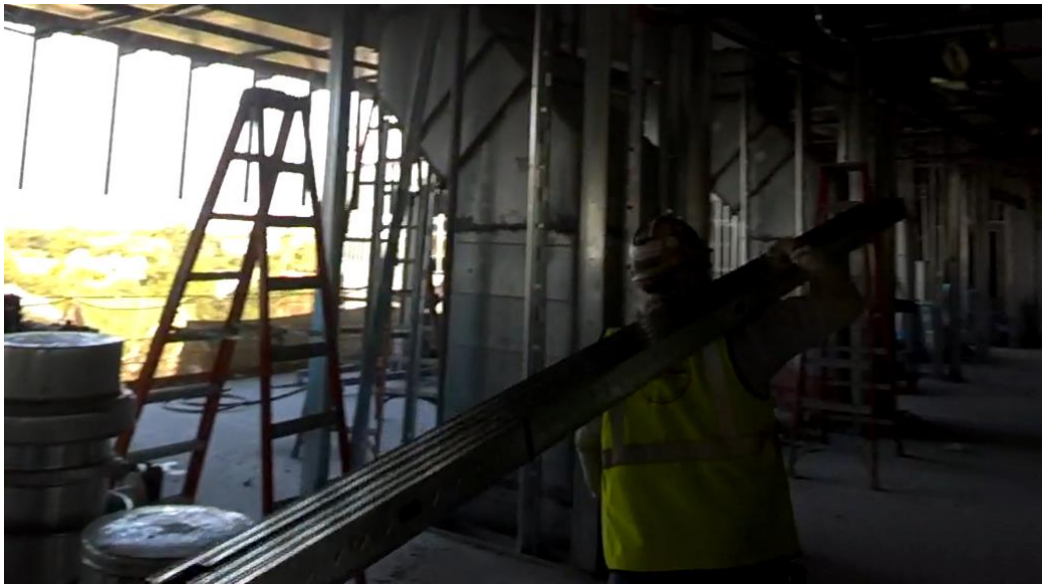


Figure 64: Hospital Expansion Project - 2

Items	Descriptions
Project Type	• Hospital; Expansion
Weather	• Sunny; 66ºF
Observation period	• Day 1 (5 hours), Day 2 (8 hours)
Work types	• Drywall, windows, exterior insulation, steel, formwork, MEP, HVAC, and Plumbing
Work zones	• 2 (Zone01 and Zone02)
Number of observations	• Day 1: 827 observations; Day 2: 1,423 observations • Number of workers: 120~140 • Minimum Observation Required: 116per hour
Sound Noise Environment	• Grinder, electronic drill, electronic screw driver, and hammer sounds • Workers' and escort engineer's voices

Activity Categories and their Grammar Words	• 7 activity categories
	  o Direct work (D-Work)
	  o Preparatory work (Ready)
	  o Tools and equipment (T-Q)
	  o Material handling (Handling)
	  o Travel (Traveling)
	  o Waiting (Waiting)
	  o Personal (Personal)

Table 35: Project and Observation Description – Hospital 2

Data Collection Results

<Day 1>

Two sets of voice, location, and video data were collected with standard time-stamps. The first set contains one voice file containing 491 activity category data, one location file containing 1,212 location points, and 16 video files recorded when activity category data was collected. The second set also contains one voice file containing 336 activity category data, one location file containing 1,043 location points, and nine video files. Figure 65 show the results of the first day location data collection.

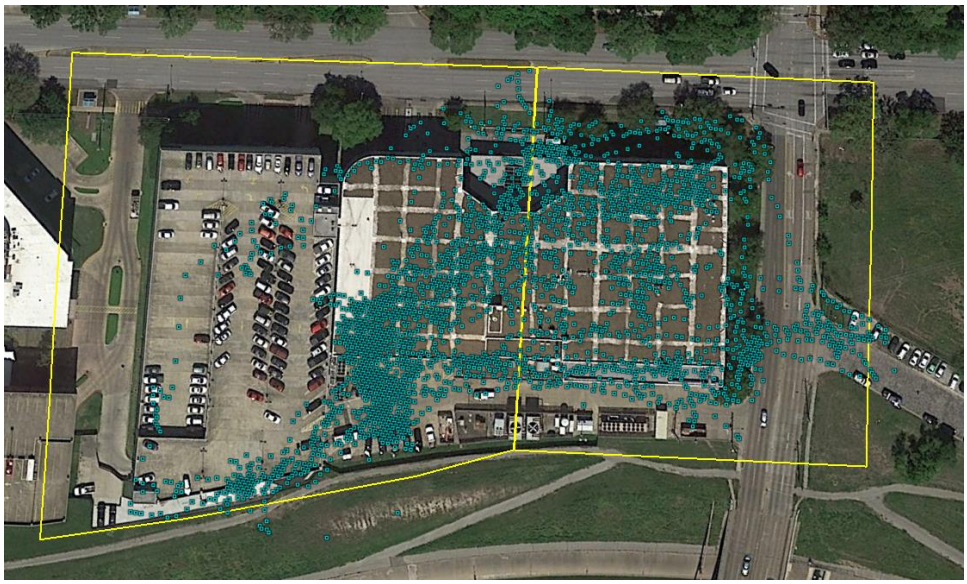


Figure 65: Location Data Collection (GPS) – Hospital – 2 (Day 1)

<Day 2>

During eight hours of observations, the observer collected 1,423 activity category data, five voice files, 42 videos. Figure 66 show the results of the sedon day location data collection.

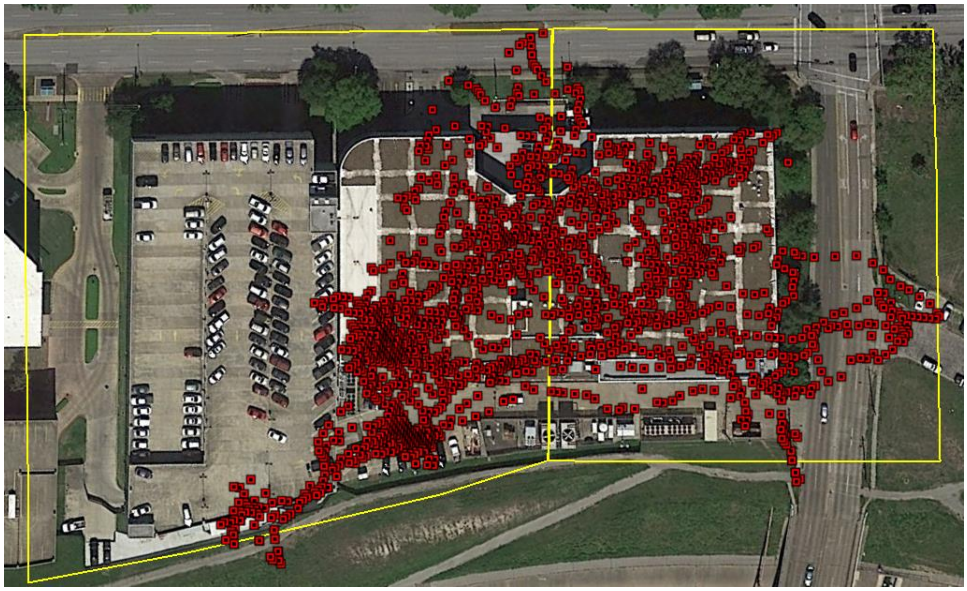


Figure 66: Location Data Collection (GPS) – Hospital - 2 (Day 2)

Synchronization of Voice and Videos

<Day 1 and Day 2>

The automatic method was applied to synchronize voices and videos because they used standard time-stamps. From the source voice file, all video clips are exactly matched with the video files collected in terms of their recording time, duration, and activity category data which they contain.

Zone Detection of Location Data

<Day 1 and Day 2>

Zone detection results are shown in the Figure 67 and Figure 68. Observations were made in the both Zone01 and Zone 02, and there are no location points which are out of any zones. Zone detection was performed by winding number counting algorithm and shows good results. Table 36 and Table 37 show the accuracy of zone detection results.

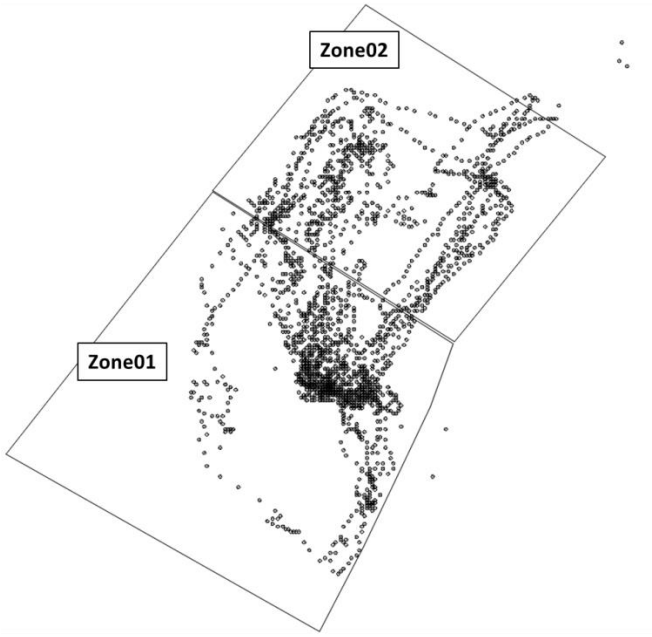


Figure 67: Zone Detection – Hospital – 2 (Day 1)

	Number of Actual Location Points in Each Zone (a)	Number of Detected Location Points in Each Zone (b)	Detection Accuracy (b / a * 100)
Zone01	1357	1357	100%
Zone02	873	873	100%
Out of Zones	25	25	100%

Table 36: Zone Detection Accuracy – Hospital – 2 (Day 1)

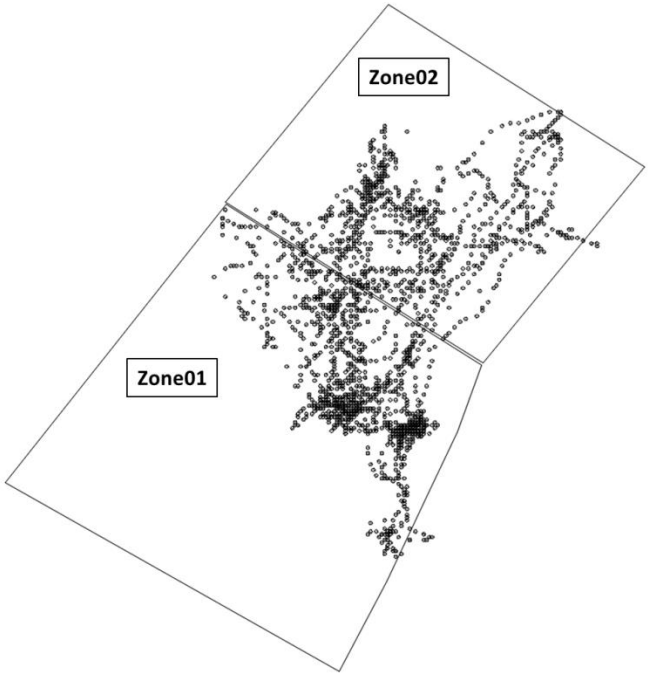


Figure 68: Zone Detection – Hospital – 2 (Day 2)

	Number of Actual Location Points in Each Zone (a)	Number of Detected Location Points in Each Zone (b)	Detection Accuracy (b / a * 100)
Zone01	1128	1128	100%
Zone02	847	847	100%
Out of Zones	26	26	100%

Table 37: Zone Detection Accuracy – Hospital – 2 (Day 1)

Voice Recognition Results

<Day 1 >

The overall voice recognition accuracy was 93.5 %. This means that 778 activity categories out of 832 were correctly recognized. There were five false-positives that the voice recognition engine recognized noises as activity categories. This is the reason why the total number of voice recognition accuracy analysis data (832) is larger than the number of real observations (827). Table 38 shows the confusion matrix of the results. In

the confusion matrix, “Travel (grammar: Traveling)” was frequently confused with “Material handling (grammar: Handling)” because the grammars, “Traveling” and “Handling”, share similar voice feature.

Items		Prediction								Total
		Direct	Preparatory	Tools	Material	Waiting	Travel	Personal	Noise	
Ground Truth	Direct	341	0	0	0	0	0	0	4	345
	Preparatory	0	66	0	0	1	1	0	0	68
	Tools	0	0	41	0	0	0	0	0	41
	Material	0	0	0	64	0	0	0	0	64
	Waiting	0	1	1	0	83	1	0	1	87
	Travel	1	1	0	20	0	118	0	2	142
	Personal	0	0	0	3	0	6	65	6	80
	Noise	0	0	0	3	0	2	0	0	5
Total		342	68	42	90	84	128	65	13	832

Table 38: Confusion Matrix – Hospital – 2 (Day 1)

Table 39 shows confusion matrix per each category and their performance. “Direct Work” shows the best results. “Material Handling” shows the worst accuracy and precision & recall.

DIRECT ('D-WORK')		P	N	Total		PERFORMANCE	
	T	341	4	345		Accuracy	**99.40%**
	F	1	486	487		Precision	**99.71%**
	Total	342	490	832		Recall	**98.84%**
PREPARATORY ('READY')		P	N			PERFORMANCE	
	T	66	2	68		Accuracy	99.52%
	F	2	762	764		Precision	97.06%
		68	764	832		Recall	97.06%
TOOLS ('T-Q')		P	N			PERFORMANCE	
	T	41	0	41		Accuracy	99.88%
	F	1	790	791		Precision	97.62%
		42	790	832		Recall	100.00%
MATERIAL ('HANDLING')		P	N			PERFORMANCE	
	T	64	0	64		Accuracy	**96.88%**
	F	26	742	768		Precision	**71.11%**
		90	742	832		Recall	**100.00%**
WAITING ('WAITING')		P	N			PERFORMANCE	
	T	83	4	87		Accuracy	99.40%
	F	1	744	745		Precision	98.81%
		84	748	832		Recall	95.40%
TRAVEL ('TRAVELING')		P	N			PERFORMANCE	
	T	118	24	142		Accuracy	95.91%
	F	10	680	690		Precision	92.19%
		128	704	832		Recall	83.10%
PERSONAL ('PERSONAL')		P	N			PERFORMANCE	
	T	65	15	80		Accuracy	98.20%
	F	0	752	752		Precision	100.00%
		65	767	832		Recall	81.25%
NOISE		P	N			PERFORMANCE	
	T	0	5	5		Accuracy	-
	F	13	814	827		Precision	-
		13	819	832		Recall	-

Table 39: Confusion Matrix per Category – Hospital – 2 (Day 1)

<Day 2 >

The overall voice recognition accuracy was 90.8 %. This means that 1,300 activity categories out of 1,431 were correctly recognized. There were eight false-positives that the voice recognition engine recognized noises as activity categories. This is the reason why the total number of voice recognition accuracy analysis data (1432) is larger than the number of real observations (1423). Table 40 shows the confusion matrix of the results. In the confusion matrix, "Travel (grammar: Traveling)" was frequently confused with "Material handling (grammar: Handling)" because the grammars, "Traveling" and "Handling", share similar voice feature.

Items		Prediction								Total
		Direct	Preparatory	Tools	Material	Waiting	Travel	Personal	Noise	
Ground Truth	Direct	616	1	1	3	0	3	0	3	627
	Preparatory	0	126	0	0	1	0	1	3	131
	Tools	0	0	71	0	0	0	0	1	72
	Material	0	1	0	84	0	0	0	2	87
	Waiting	1	0	0	1	117	1	0	3	123
	Travel	0	1	2	43	4	192	1	24	267
	Personal	3	0	0	4	0	9	94	6	116
	Noise	3	0	1	3	0	1	0	0	8
Total		623	129	75	138	122	206	96	42	1431

Table 40: Confusion Matrix – Hospital – 2 (Day 2)

Table 41 shows confusion matrix per each category and their performance. "Direct Work" shows the best results. "Material Handling" shows the worst accuracy and precision & recall.

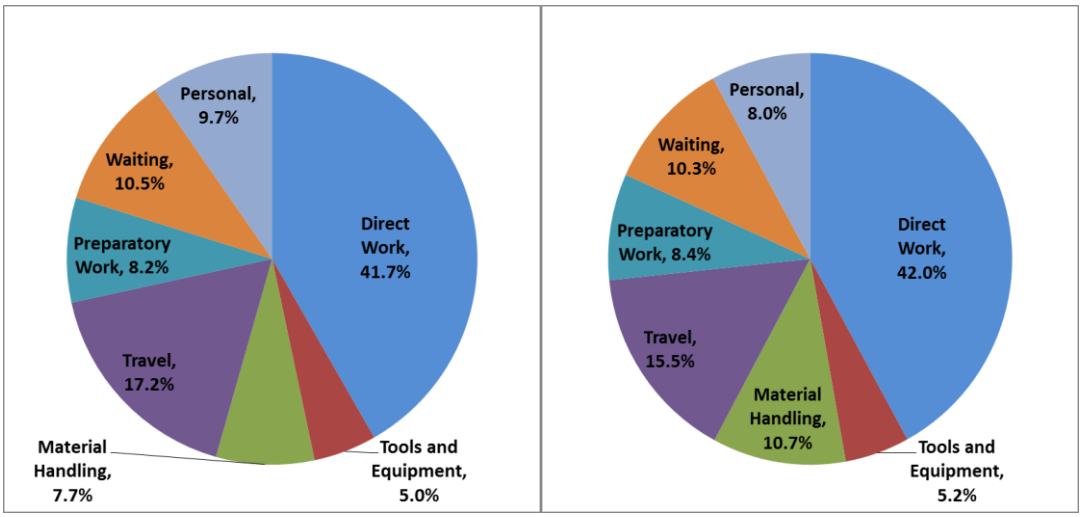
		P	N	Total		PERFORMANCE	
DIRECT ('D-WORK')	T	616	11	627		Accuracy	**98.74%**
	F	7	797	804		Precision	**98.88%**
	Total	623	808	1431		Recall	**98.25%**
PREPARATORY ('READY')		P	N			PERFORMANCE	
	T	126	5	131		Accuracy	99.44%
	F	3	1297	1300		Precision	97.67%
		129	1302	1431		Recall	96.18%
TOOLS ('T-Q')		P	N			PERFORMANCE	
	T	71	1	72		Accuracy	99.65%
	F	4	1355	1359		Precision	94.67%
		75	1356	1431		Recall	98.61%
MATERIAL ('HANDLING')		P	N			PERFORMANCE	
	T	84	3	87		Accuracy	**96.02%**
	F	54	1290	1344		Precision	**60.87%**
		138	1293	1431		Recall	**96.55%**
WAITING ('WAITING')		P	N			PERFORMANCE	
	T	117	6	123		Accuracy	99.23%
	F	5	1303	1308		Precision	95.90%
		122	1309	1431		Recall	95.12%
TRAVEL ('TRAVELING')		P	N			PERFORMANCE	
	T	192	75	267		Accuracy	93.78%
	F	14	1150	1164		Precision	93.20%
		206	1225	1431		Recall	71.91%
PERSONAL ('PERSONAL')		P	N			PERFORMANCE	
	T	94	22	116		Accuracy	98.32%
	F	2	1313	1315		Precision	97.92%
		96	1335	1431		Recall	81.03%
NOISE		P	N			PERFORMANCE	
	T	0	8	8		Accuracy	-
	F	42	1381	1423		Precision	-
		42	1389	1431		Recall	-

Table 41: Confusion Matrix per Category – Hospital – 2 (Day 2)

Work Rate Calculation Comparisons

<Day 1>

The comparisons of work rates calculations by manual method and proposed method were shown in the Figure 69 and Table 42. The "Preparatory work" shows small amount of difference (-0.1%). "Material Handling" and "Travel" are confused with each other. The "Material Handling" has the largest difference, 2.9 %.



(a) Manual Work Rates (b) Proposed Method's Work Rates

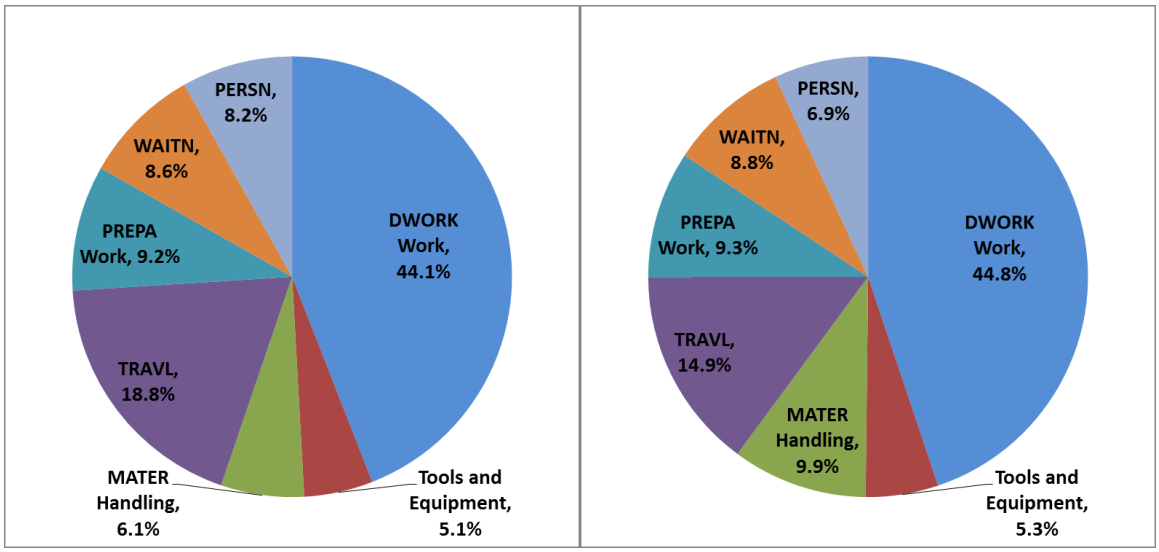
Figure 69: Work Rate Calculation Comparison – Pie Chart – Hospital – 2 (Day 1)

Category Type I	Category II	True Value (a)	Proposed Method (b)	Difference (a-b)
Productive	Direct Work	41.7%	42.0%	-0.3%
Supportive	Tools and Equipment	5.0%	5.2%	-0.2%
	Material Handling	7.7%	10.7%	-2.9%
	Travel	17.2%	15.5%	1.7%
	Preparatory Work	8.2%	8.4%	-0.1%
Idle	Waiting	10.5%	10.3%	0.2%
	Personal	9.7%	8.0%	1.7%
Total	Total	100.0%	100.0%	

Table 42: Work Rate Calculation Comparison – Table– Hospital – 2 (Day 1)

<Day 2>

The comparisons of work rates calculations by manual method and proposed method were shown in the Figure 70 and Table 43. The “Preparatory work” shows small amount of difference (-0.1%). “Material Handling” and “Travel” are confused each other. The “Travel” has the largest difference, 3.9 %.



(a) Manual Work Rates (b) Proposed Method′s Work Rates

Figure 70: Work Rate Calculation Comparison – Pie Chart – Hospital – 2 (Day 2)

Category Type I	Category II	True Value (a)	Proposed Method (b)	Difference (a-b)
Productive	Direct Work	44.1%	44.8%	-0.8%
Supportive	Tools and Equipment	5.1%	5.3%	-0.3%
	Material Handling	6.1%	9.9%	-3.8%
	Travel	18.8%	14.9%	3.9%
	Preparatory Work	9.2%	9.3%	-0.1%
Idle	Waiting	8.6%	8.8%	-0.2%
	Personal	8.2%	6.9%	1.2%
Total	Total	100.0%	100.0%	(rounded)

Table 43: Work Rate Calculation Comparison – Table– Hospital – 2 (Day 2)

4.1.7 Hospital Module Pre-fabrication

This site was a hospital module pre-fabrication facility. Most of the activities observed pertained to the pre-fabrication of headwall, bathroom, and ceiling modules. The weather, work types, and other details of the project and observations are shown in Table 44.

Items	Descriptions
Project Type	• Hospital module pre-fabrication
Weather	• Sunny; 75 ºF
Observation period	• 1 day (8 hours)
Work types	• Headwall, bathroom, and ceiling module pre-fab.
Work zones	• Two (Zone01 to Zone02)
Number of observations	• 848 observations • Number of workers: 45 ~ 50 • Minimum Observation Required: 46 per hour
Sound Noise Environment	• Grinding, drilling, hammering, and XY crane
Activity Categories and their Grammar Words	• 7 activity categories and grammar words o Direct work (D-Work) o Preparatory work (Already) o Tools and equipment (T-Q) o Material handling (M-R-H) o Travel (Traveling) o Waiting (Waiting) o Personal (Personal)

Table 44: Project and Observation Description – Pre-fabrication

Data Collection Results

Three sets of voice, location, and video data were successfully collected with standard time-stamps. The first set includes one voice file containing 167 activity category data, one location file containing 827 location points, and four video files recorded when activity category data was collected. The second set consists of one voice file containing 392 activity category data, one location file containing 1,590 location points, and eight video files recorded when the activity category data was collected. The third set consists of one voice file containing 289 activity category data, one location file containing 1,230 location points, and eight video files recorded when the activity category data was collected.

Synchronization of Voice and Videos

A manual method was applied to synchronize voices and videos because both of them contained standard time-stamps from GPS. From the three long source voice files, a total of 20 short voice clips were extracted. These clips were exactly matched with the 20 video files regarding the recording time, duration, and activity category data which they contained.

Zone Detection of Location Data

Zone detection results are shown in Figure 71. Observations were made in both Zone01 and Zone02, and no location points exist outside these zones. Zone detection was performed with a winding number counting algorithm and showed good results. Table 45 shows the accuracy of the zone detection results.

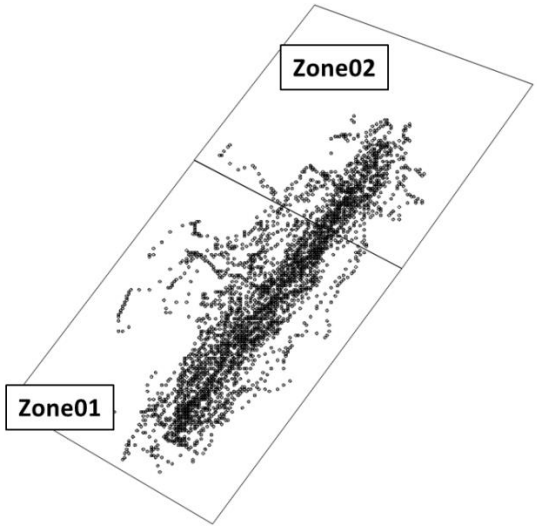


Figure 71: Zone Detection – Pre-fabrication

	Number of Actual Location Points in Each Zone (a)	Number of Detected Location Points in Each Zone (b)	Detection Accuracy (b / a * 100)
Zone01	2,737	2,737	100%
Zone02	910	910	100%
Out of Zones	0	0	-

Table 45: Zone Detection Accuracy – Pre-fabrication

Voice Recognition Results

The overall voice recognition accuracy was 85.03 %. This means that 727 activity categories out of 855 were correctly recognized. There were seven false-positives that the voice recognition engine recognized noises as activity categories (Table 46). This is the reason why the total number of voice recognition accuracy analysis data (855) is larger than the number of real observations (848).

Items		Prediction								Total
		Direct	Preparatory	Tools	Material	Waiting	Travel	Personal	Noise	
Ground Truth	Direct	420	3	4	0	2	5	0	20	454
	Preparatory	3	67	0	1	1	1	0	9	82
	Tools	1	1	49	0	0	0	0	1	52
	Material	0	3	1	24	2	0	0	0	30
	Waiting	5	2	0	0	63	1	1	13	85
	Travel	0	1	1	0	7	97	0	5	111
	Personal	3	4	0	0	2	11	7	7	34
	Noise	2	0	1	0	0	4	0	0	7
Total		434	81	56	25	77	119	8	55	855

Table 46: Confusion Matrix – Pre-fabrication

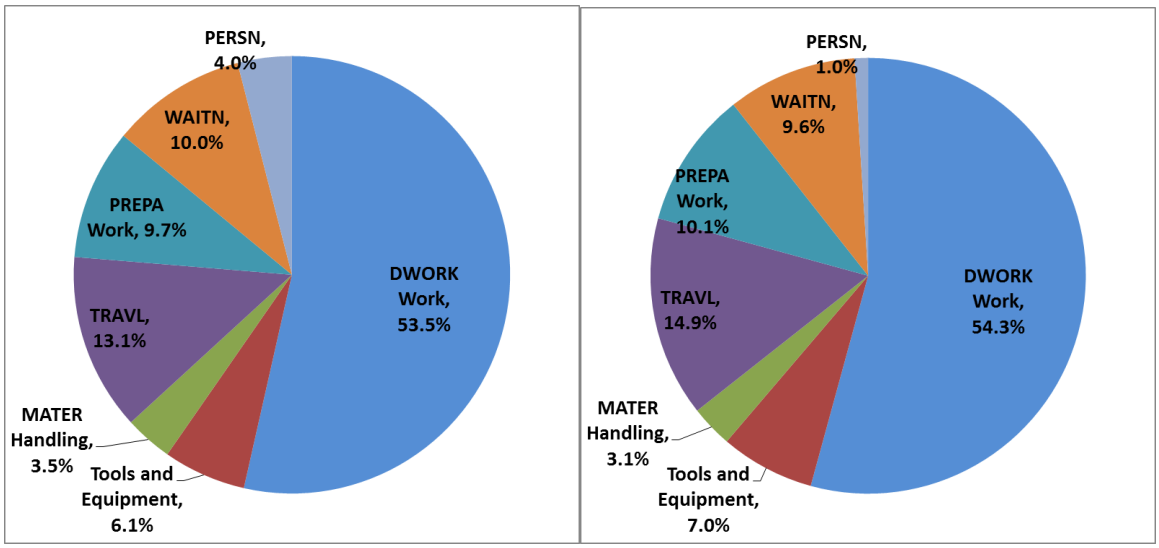
Table 47 shows confusion matrix per each category and their performance. “Material Handling” shows the best results. The most important category—“Direct Work”—also shows good performance while “Personal” shows the worst accuracy and precision and recall.

DIRECT ('D-WORK')		P	N	Total		PERFORMANCE	
	T	420	34	454		Accuracy	94.39%
	F	14	387	401		Precision	96.77%
	Total	434	421	855		Recall	92.51%
PREPARATORY ('ALREADY')		P	N			PERFORMANCE	
	T	67	15	82		Accuracy	96.61%
	F	14	759	773		Precision	82.72%
		81	774	855		Recall	81.71%
TOOLS ('T-Q')		P	N			PERFORMANCE	
	T	49	3	52		Accuracy	98.83%
	F	7	796	803		Precision	87.50%
		56	799	855		Recall	94.23%
MATERIAL ('M-R-H')		P	N			PERFORMANCE	
	T	24	6	30		Accuracy	**99.18%**
	F	1	824	825		Precision	**96.00%**
		25	830	855		Recall	**80.00%**
WAITING ('WAITING')		P	N			PERFORMANCE	
	T	63	22	85		Accuracy	95.79%
	F	14	756	770		Precision	81.82%
		77	778	855		Recall	74.12%
TRAVEL ('TRAVELING')		P	N			PERFORMANCE	
	T	97	14	111		Accuracy	95.79%
	F	22	722	744		Precision	81.51%
		119	736	855		Recall	87.39%
PERSONAL ('PERSONAL')		P	N			PERFORMANCE	
	T	7	27	34		Accuracy	96.73%
	F	1	820	821		Precision	87.50%
		8	847	855		Recall	20.59%
NOISE		P	N			PERFORMANCE	
	T	0	7	7		Accuracy	-
	F	55	793	848		Precision	-
		55	800	855		Recall	-

Table 47: Confusion Matrix per Category – Pre-fabrication

Work Rate Calculation Comparisons

Comparisons of work rate calculations by a manual method and the proposed method are shown in Figure 72 and Table 48. The "direct work" shows small amount of difference (-0.7%). "Personal" has the largest difference, 3.0 %, and "Material Handling" and "Waiting" shows the smallest difference, 0.4% each.



(a) Manual Work Rates (b) Proposed Method's Work Rates

Figure 72: Work Rate Calculation Comparison – Pre-fabrication

Category Type I	Category II	True Value (a)	Proposed Method (b)	Difference (a-b)
Productive	Direct Work	53.5%	54.3%	-0.7%
Supportive	Tools and Equipment	6.1%	7.0%	-0.9%
	Material Handling	3.5%	3.1%	0.4%
	Travel	13.1%	14.9%	-1.8%
	Preparatory Work	9.7%	10.1%	-0.5%
Idle	Waiting	10.0%	9.6%	0.4%
	Personal	4.0%	1.0%	3.0%
Total	Total	100.0%	100.0%	(Rounded)

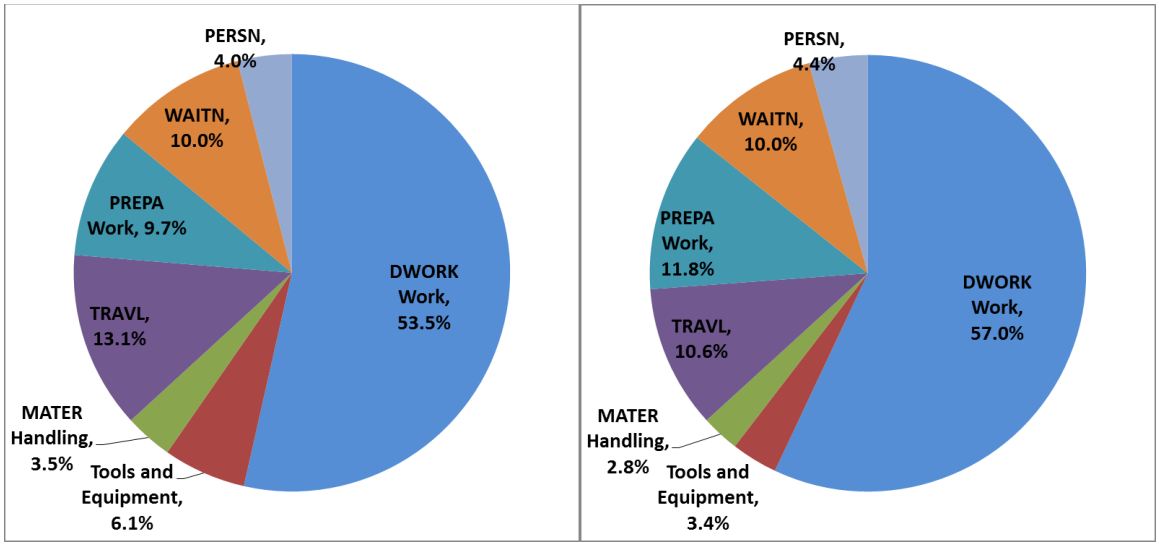
Table 48: Work Rate Calculation Comparison – Pre-fabrication

The direct work rate is higher (53.5%) than industry average (44%). It should be noted that there were several new workers who received man-to-man training at the site. This means that the new workers' and their trainers' activities could be categorized as "preparatory work" when they have discussions about certain work processes or "Travel" when they move from one place to the other place for the training of another work processes. This is the reason why the preparatory work rate (9.7%) and Travel rate (13.1%) are higher than industry averages (6% and 11%, respectively). If there was no training session, the direct work rate might be higher than the current results (53.5%).

Observation Results Comparison by Different Observers at the Same Site

During this case study, observation results by two different observers at the same site were compared to confirm the consistency of their observation results. Before starting the observation, the two observers shared clear definitions of activity categories and trained each other to be on the same page in terms of categorization of workers' activities. The results are shown in the Figure 73 and Table 49. Material handling and personal work rates show a small amount of differences (0.7% and -0.4%), and waiting shows no difference (0%). The difference between the two direct work rates seems acceptable (-3.5%) considering the large portion of direct work rates in each observation results. Tools and equipment, travel, and preparatory work show relatively large differences (2.7%, 2.5%, and -2.1%, respectively).

The on-site training mentioned in the previous sub-section can be one reason of the differences. The fact that there were man-to-man training sessions at the site was informed by a project manager after the observations were made. The observers could be confused to categorize the trainers and trainees into pre-defined activity categories.



(a) Manual Work Rates (Observer 1) (b) Manual Work Rates (Observer 2)

Figure 73: Work Rate Comparison by Different Observers – Pre-fabrication

Category Type I	Category II	Observer 1 (a)	Observer 2 (b)	Difference (a-b)
Productive	Direct Work	53.5%	57.0%	-3.5%
Supportive	Tools and Equipment	6.1%	3.4%	2.7%
	Material Handling	3.5%	2.8%	0.7%
	Travel	13.1%	10.6%	2.5%
	Preparatory Work	9.7%	11.8%	-2.1%
Idle	Waiting	10.0%	10.0%	0%
	Personal	4.0%	4.4%	-0.4%
Total	Total	100.0%	100.0%	(Rounded)

Table 49: Work Rate Comparison by Different Observers – Pre-fabrication

Historical Data for Comparison

Activity analysis results presented in the previous sections can be compared with historical data as shown in the Table 50. It provides average work rates in construction industry from 1985 to 2009. It contains six categories and their average values and standard deviation; however, it can be compared with the seven categories used in activity analysis. The "transport" of the six-category breakdown was divided into "tools and equipment" and "material handling" of activity analysis. Therefore, the simple summation of the two categories can be compared with the "transportation." Also, the "instruction" and "delay" of the six-category breakdown correspond to the "preparatory" and "waiting" of the seven-category breakdown of activity analysis, respectively. The Table 50 will be frequently referred in the following sections.

Historical Work Rates (1985-2009)			
Six Categories	Seven Categories	Average	Standard Deviation
Direct work	Direct work	44%	8.4%
Transport	Tools and Equipment	14%	4.4%
	Material Handling		
Travel	Travel	11%	3.9%
Instruction	Preparatory	6%	3.2%
Personal	Personal	5%	3.4%
Delay	Waiting	20%	5.3%

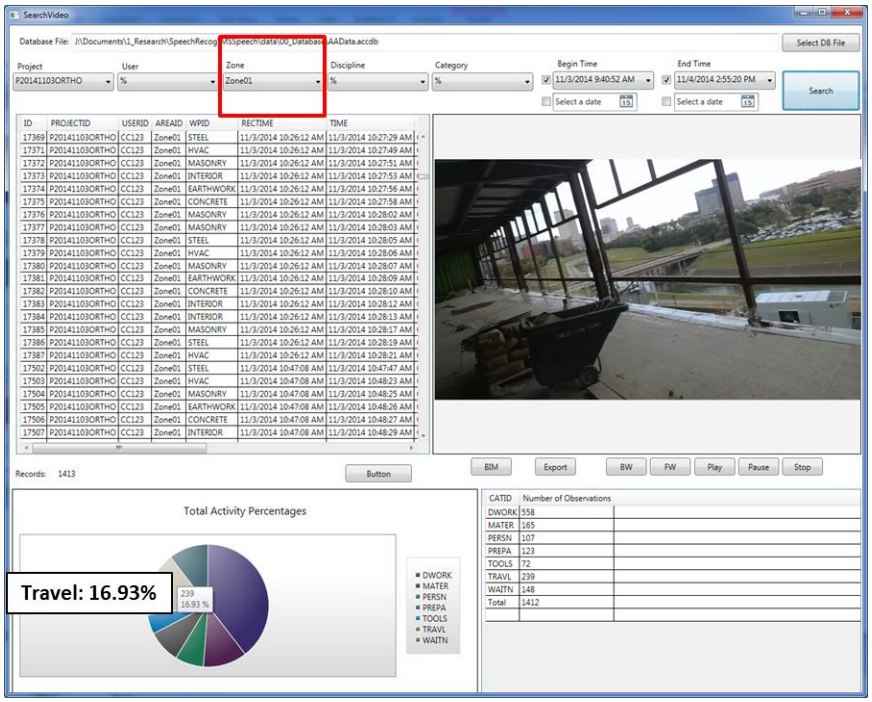
Table 50: Historical Work Rates (1985 – 2009, Gong et al. 2011a)

4.2 DYNAMIC ANALYSIS – OLTP MODULE

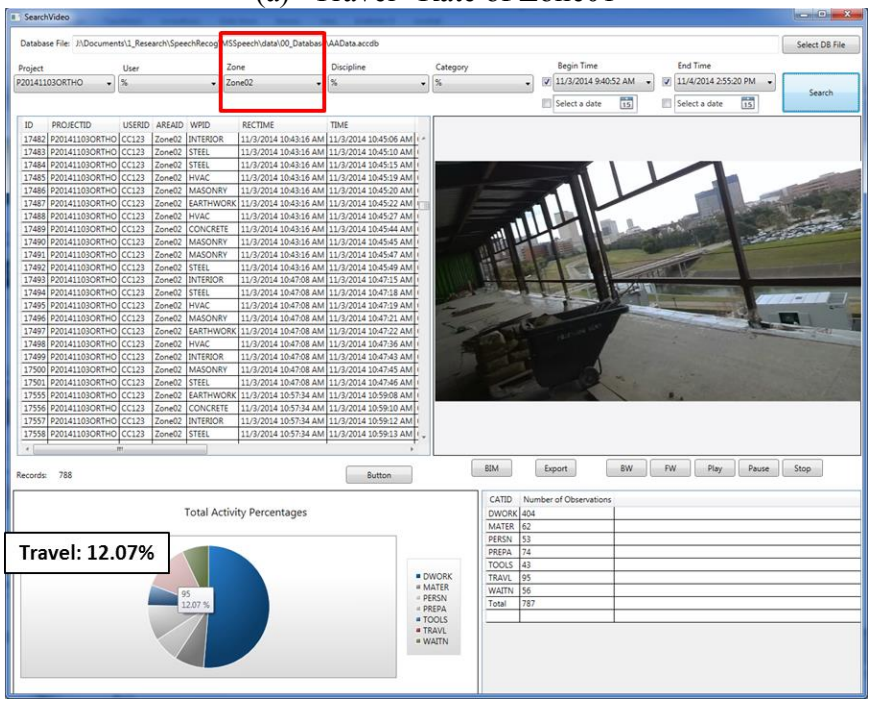
This operational/online transaction processing (OLTP) based dynamic data analysis module provides the following basic functions: search/comparison by zone, time, user (observer), location, and any other combinations of all the perspectives. This can be used for simple review of data but can be also used for deeper investigation.

The following scenario based example investigation uses this dynamic analysis module. The target project is "the Hospital-2." The investigation can start with the simple comparison of its work rates with the historical data shown in the Table 50. Both work rates of the hospital-2 project calculated by the manual method and proposed method indicate that the "Direct" (Day 1: 41.7% by manual and 42.0% by proposed methodology; Day 2: 44.1% by manual and 44.8 by proposed methodology) is close to the industry average (44%). However, the project shows higher "Travel" (Day 1: 17.2% by manual and 15.5% by proposed methodology; Day 2: 18.8% by manual and 14.9 by proposed methodology) rate than the industry average (11%). In this case, the OLTP module can focus on "Travel" category data, and review indexed videos related to the data.

It is frequently observed that many workers in the indexed videos are heading to or coming from the elevator which is the only vertical transportation equipment located in Zone01. It can be supported by Figure 74. It shows that Zone01 has higher "Travel" rate (16.93%) than Zone02 (12.07%). Also many workers are spending their time to wait for the elevator. For example, at 8:22 AM (Nov 4), at least 12 (8-10% of the total number of workers) workers are waiting for the elevator for several minutes (Figure 75). Observation paths in the Figure 76 show that the elevator has been a bottleneck of the construction site. More dense data points mean that the observer stayed longer time at the location. Based on this scenario, the vertical transportation plan failure can be identified.



(a) “Travel” Rate of Zone01



(b) “Travel” Rate of Zone02

Figure 74: “Travel” Rates of Zone01 and Zone02

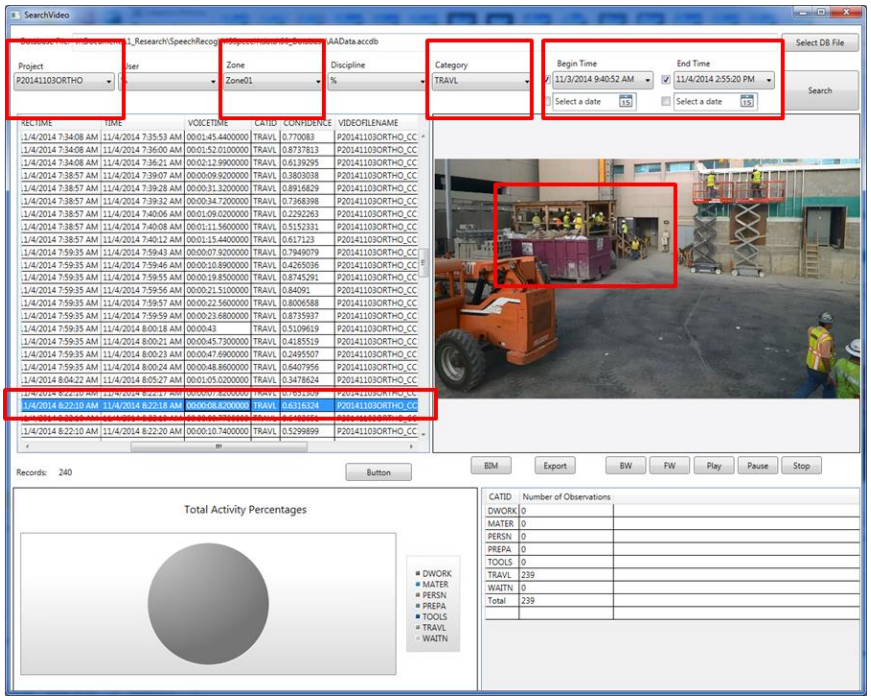
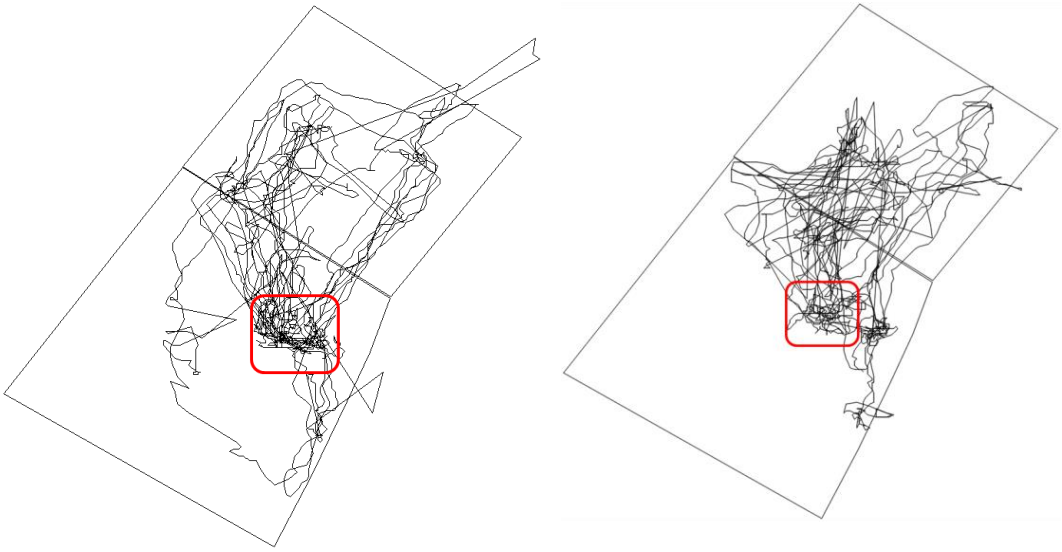


Figure 75: Waiting for Elevator



(a) Observation Path - Day 1 (b) Observation Path - Day 2

Figure 76: Bottleneck around the elevator

4.3 DYNAMIC ANALYSIS - OLAP

Different from the OLTP based analysis module developed for this research, OLAP analysis provides macro level analysis. Although all the construction sites used for validations were from different companies, it was assumed that all the construction sites used for validations belong to one virtual company for OLAP analysis. Then, one example of scenario based analysis (Nie et al. 2007) is as follows.

The analysis can start from the review of overall work rates of the company. Figure 77 shows the overall company level work rates. The overall direct work rate (DIRECT) is 43.44% and is within the industrial average because the range of the direct work rate is from 38% to 46.5% as shown in the Figure 78 and the previous Table 50 (Gong et al. 2011b). Therefore, it can be concluded that this company shows the average labor performance at the company level.

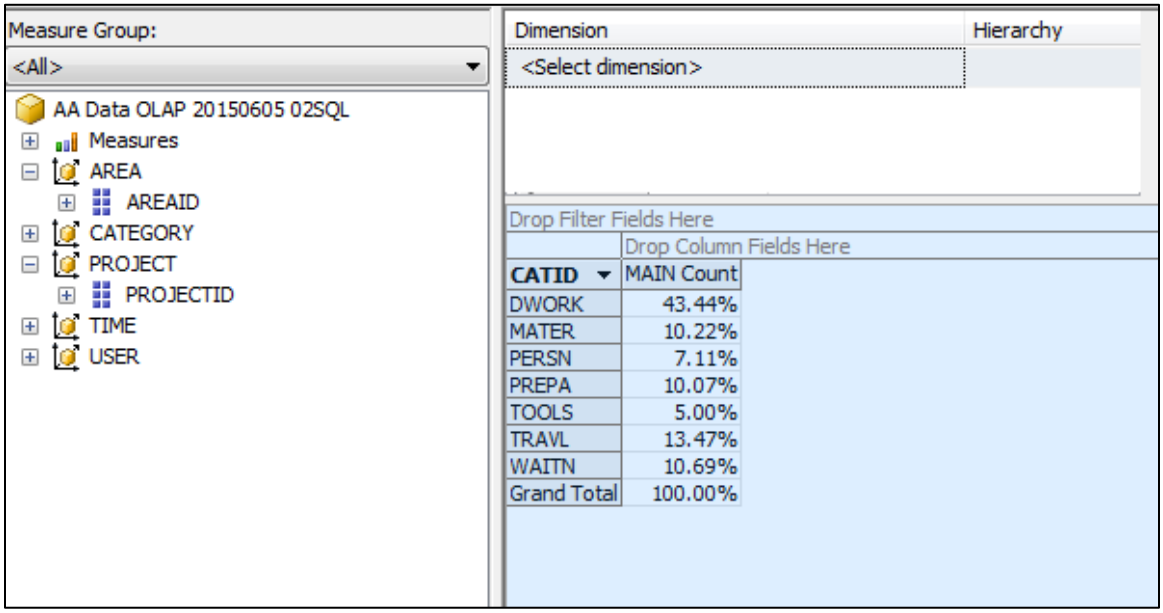


Figure 77: Company Level Work rates

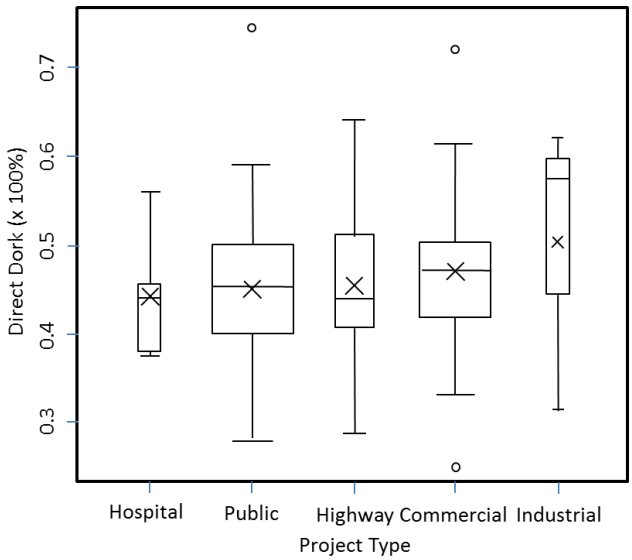
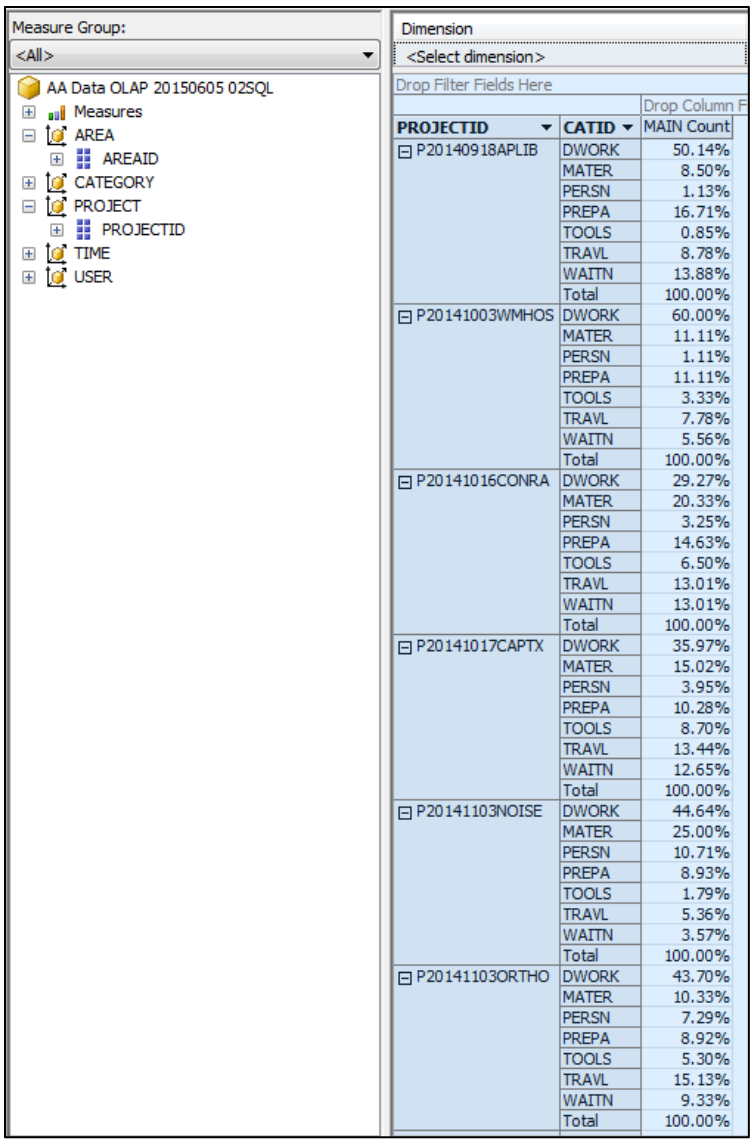


Figure 78: Direct Work Rates of Construction Industry by Project Type

Figure 79 shows the work rates by projects of the virtual company. The second project, 'P20141003WMHOS', shows the highest direct work rates while "P20141016CONRA" and "P201412071CAPTX" show the lower direct work rates than the other projects. The "P20141016CONRA" and "P201412071CAPTX" show higher "Material Handling (MATER - Material Handling)" rates than other projects. The "P20131103NOISE" can be ignored because it is not an actual project. Therefore, it might be a problem with material warehouse or unreasonable site layout.

In order to acquire better understandings about the projects' situation, the area (zone) dimension can be added in this analysis. For example, Figure 80 shows that the Zone01 and Zone02 of the "P201412071CAPTX" project have high "Transportation" work rates (i.e. the sum of MATER - Material Handling and TOOLS - Tools and Equipment). The transportation work rates of Zone01 and Zone02 are 29.42 % (14.71% +

14.71%) and 22.83% (15.07% + 7.76%) while the industry average is 14% (Table 50). Therefore, there might be issues with materials and tools/equipment. In order to acquire the more detailed information and understanding about this project's situation, project manager can use OLTP dynamic analysis module to review the details about the project such as the indexed video at that point.



PROJECTID	CATID	MAIN Count
P20140918APLIB	DWORK	50.14%
	MATER	8.50%
	PERSN	1.13%
	PREPA	16.71%
	TOOLS	0.85%
	TRAVL	8.78%
	WAITN	13.88%
	Total	100.00%
P20141003WMHOS	DWORK	60.00%
	MATER	11.11%
	PERSN	1.11%
	PREPA	11.11%
	TOOLS	3.33%
	TRAVL	7.78%
	WAITN	5.56%
	Total	100.00%
P20141016CONRA	DWORK	29.27%
	MATER	20.33%
	PERSN	3.25%
	PREPA	14.63%
	TOOLS	6.50%
	TRAVL	13.01%
	WAITN	13.01%
	Total	100.00%
P20141017CAPTX	DWORK	35.97%
	MATER	15.02%
	PERSN	3.95%
	PREPA	10.28%
	TOOLS	8.70%
	TRAVL	13.44%
	WAITN	12.65%
	Total	100.00%
P20141103NOISE	DWORK	44.64%
	MATER	25.00%
	PERSN	10.71%
	PREPA	8.93%
	TOOLS	1.79%
	TRAVL	5.36%
	WAITN	3.57%
	Total	100.00%
P20141103ORTHO	DWORK	43.70%
	MATER	10.33%
	PERSN	7.29%
	PREPA	8.92%
	TOOLS	5.30%
	TRAVL	15.13%
	WAITN	9.33%
	Total	100.00%

Figure 79: Work Rate Comparisons by Project

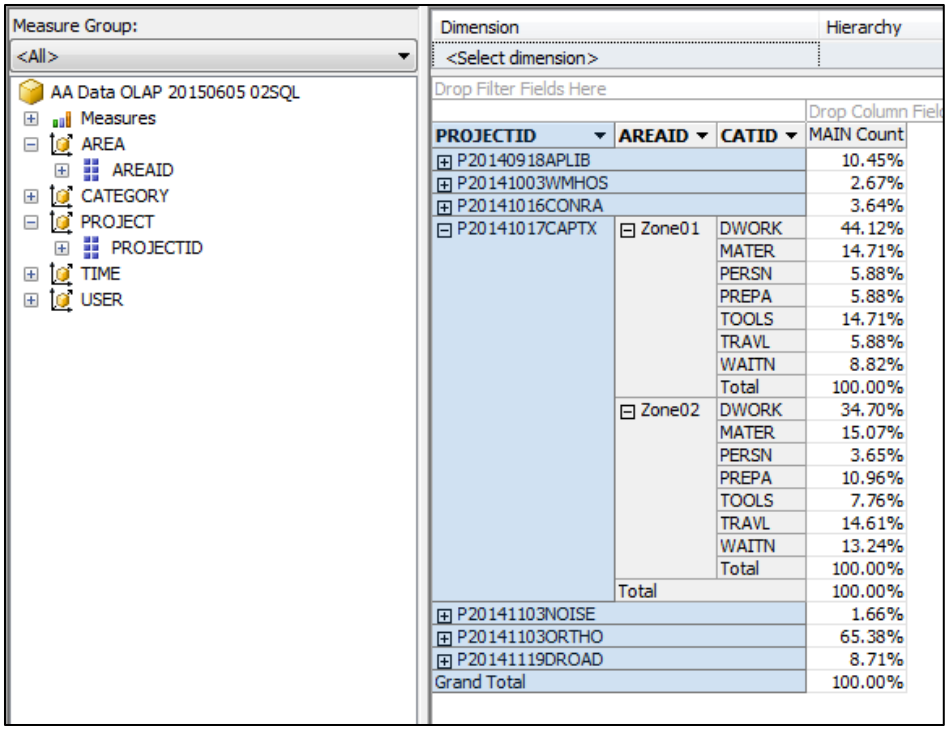


Figure 80: Work Rates by Focused Project and its Zones

Chapter 5 Conclusions

5.1 Summary of Research Contributions and Validation

The objective of this research was to develop an on-site data collection and analysis methodology to enable rapid and contextual activity analysis. This research focused on the semi-automation of on-site data collection and the automation of data analysis processes of activity analysis. The data analysis process consists of automated data integration and dynamic data analysis methods. The dynamic analysis can support effective interpretation of the activity analysis results for a labor productivity improvement study.

Based on the objective and research scope, this study has addressed the following two research questions.

- **Research Question I:** How can the activity category and its related time, location, and video data be effectively collected under realistic site conditions for activity analysis?
- **Research Question II:** How can the collected data be automatically integrated and analyzed to provide activity analysis results with context information for the study of productivity improvement?

Regarding the first research question, a semi-automated activity category data and its related time, location, and video data collection methodology was developed in this research. The semi-automation means man-machine-balanced data collection approach that a human observer classifies an activity category and records the category with the observer's voice. The remaining time, location, and video data can be collected in an automatic manner. Detailed process and methods have been developed and validated at actual construction sites.

Regarding the second research question, an automated data integration and dynamic analysis methodology was developed in this research. It uses voice recognition, time synchronization, operational/online transaction processing (OLTP), and online analytical processing (OLAP) to integrate and analysis collected data. With the integrated data, this methodology provides abundant contextual information on top of activity analysis results. The benefits of the contextual information have been validated via actual construction projects. By using the contextual information, project managers are able to understand actual working situations and the related environment. Based on the information, project managers can achieve a more reasonable productivity improvement plan and implementation.

5.2 INTELLECTUAL CONTRIBUTIONS

Development of a semi-automated activity category data and its related time, location, and video data collection methodology for labor productivity assessment and development of an automated activity analysis data integration and dynamic analysis methodology for contextual labor productivity improvement study are two major intellectual contribution of this study.

The man-machine balanced data collection methodology developed in this research enables to collect on-site activity analysis data from various types of projects and activities. Current automated on-site data collection methods using sensor and vision technologies reasonably work, but they are limited to specified activities under a controlled environment. However, the validation results show that those limitations of the current automated data collection methods can be overcome by the man-machine balanced methodology.

During the development and validation process, it was found and validated that the key information to integrating all three types of data (i.e., activity category, location, and video) is time. With the standard time-stamps, all the data can be meaningfully integrated with each other.

Activity category data integrated with time, location, and video data can provide abundant contextual information to interpret activity analysis results for labor productivity improvement study. The contextual information can support project managers or any other project participants to have a better understanding in terms of a productivity perspective. The information can also help to identify labor productivity related problems, plan failure and execution failure, to perform improvement study.

5.3 Expected Practical Implications

The methodology developed in this research can enable more frequent activity analysis during construction phase (Niebel and Freivalds 1999; Salvendy 2001). The manual data collection and analysis process of current activity analysis hinders more active application of it. However, this methodology can change this situation and provide more chances to improve labor productivity during construction phase. Furthermore, this methodology can be applied to any type of construction projects.

This methodology provides a way to integrate different data types with standard time-stamps and methods to dynamically analyze the integrated data.

This methodology provides abundant contextual information to interpret activity analysis results for labor productivity improvement study. This enables the establishment of rapid and appropriate improvement plan.

This methodology can be applied to any type of construction projects or works because of the semi-automated/man-machine balanced approach.

The dynamic analysis system using integrated data can be a good communication tool for productivity improvement study. Project participants can use the analysis system together to interpret the analysis results when they perform a productivity improvement study. This has been proved through the case studies. Project participants tends to more easily accept the results, find reasons of inefficiencies, and create improvement plan with the activity analysis results integrated with time, location, and video data.

This methodology provides a systematic way to store historical activity analysis data and offer easy access to them. These historical data can be a good source of information for current project and future productivity studies (Oglesby 1989).

The historical data (i.e. activity category, time, location, and video) can benefit dispute prevention and resolution between owners and contractors by enabling better documentation of productivity issues.

5.4 LIMITATIONS AND BARRIERS

One limitation of this methodology is that activity analysis results rely fundamentally on voice recognition accuracy. If voice recognition accuracy is not reasonable, collected data cannot be used for a productivity improvement study. This limitation can be overcome by adopting better noise-cancelling technologies, better voice recognition engines, and more distinct words for activity categories.

Another limitation is that this methodology requires training to use a noise reduction microphone, to understand the characteristics of a voice recognition engine,

and to select proper grammar. However, this training is simple, and most of the new methodologies or system requires no type of training.

5.6 FUTURE RESEARCH

A drone can be adopted as a carrier of data collection devices of this methodology. It can be remotely controlled to tour the construction site and collect the data. It can improve observation efficiency and minimize the chances that workers notice the data collection. Limitations of a drone such as short battery life have to be considered prior to its adoption.

Collecting voice comments or conversations with superintendents or workers during observations can be included to identify issues related to their current work: answers for "Why."

Vision recognition can be combined with this methodology. Fixed cameras at the construction site can monitor activity levels of workers in the areas of interests. If the activity level shows significant variations in a specified period, this methodology can be used to understand what issues occurred in the area.

Activity category data collection accuracy can be more improved with more active use of noise cancelling technologies and better voice recognition engines.

The integrated activity analysis results can be visualized with graphic data such as 2D drawings, 3D models, or BIM. Smaller zone definitions and additional data collection can be used to match the activity analysis results with the smaller zones. Observation direction can be additionally collected and improve the accuracy of matching zones. Also, point cloud data can be collected to identify physical construction objects in the project.

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