A RULE-BASED METHODOLOGY FOR AUTOMATED PROGRESS MONITORING OF CONSTRUCTION ACTIVITIES: A CASE FOR MASONRY WORK

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SUMMARY: *The conventional approach that is used to monitor construction projects is to collect progress data from the construction site through visual investigation. This results in deficient and sometimes erroneous data, and leads to inefficiencies in project control, delays and cost overruns. To address these problems in building construction projects, an approach was developed to automatically monitor activity progress by tracking major construction equipment and bulk materials using sensor-based technologies that are cost-effective and easy to deploy. In this approach data obtained from sensors (e.g., load sensor) and/or other sensor-based technologies (i.e., Radio Frequency Identification (RFID)), which were deployed on major construction resources, were fused using rule-based algorithms to determine the activity progress. This progress data was compared with human-generated site related data (e.g., schedules, site reports) to determine the activity performance. This paper presents the developed data fusion approach and rule-based data fusion algorithms that incorporate the domain-specific heuristic information for determining the activity's overall progress. To validate the proposed approach, a proof-of-concept prototype was deployed and tested at a construction site for monitoring the progress of masonry work. The results show that the developed approach achieved 95% average accuracy in identifying the progress of the masonry work that was monitored during the field tests. The main contributions of this study are the rule-based data fusion approach and the rules that were developed for processing data from equipment and bulk materials. These rules can be used to determine the progress of other activities that use similar resources.*

KEYWORDS: *Automated progress monitoring, equipment tracking, domain-heuristics, data fusion, sensor-based technologies.*

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1. INTRODUCTION

It is common for construction projects to fail achieving the planned project performance in terms of budget and schedule. Therefore, it is crucial to continuously monitor the progress at site and compare the as-built and as-planned performances. A frequently used method to collect progress data from a construction site is to assign a percentage of completion to each activity on a site visit based on personal experience. Manual collection of the progress data is a time-consuming process and the collected progress data is usually inaccurate, incomplete or unreliable since it is subjective and needs to be collected manually on a regular basis (Akinci et al., 2006; Son and Kim, 2010; Golparvar-Fard et al., 2012). This leads to inefficiencies in project control, delays and cost overruns. In double shift construction sites, collecting progress data and monitoring the progress of a project is even more problematic due to challenging site conditions (e.g., lighting) and lack of supervisors during the night shifts. Thus, there is a need for an approach to automatically track the progress at both day and night conditions by using advanced technologies.

In this study, it is proposed to track major resources (e.g., equipment and bulk materials) at site via sensor-based technologies to collect progress data. Various construction equipment and bulk materials are utilized at different stages of a project, and tracking these resources have the potential to provide information about the progress of the related activities. However, most of the previous studies on equipment tracking for progress monitoring focused on road construction, specifically earthmoving and excavation processes (Montaser and Moselhi, 2012; Pradhananga and Teizer, 2013; Heydarian et al., 2012; Pradhan and Akinci, 2012b; Rezazadeh et al., 2013; Vasenev et al., 2014). A few of the studies were conducted at building construction sites, either for tracking a piece of equipment, or for identifying the type of activity that is performed through analysis of the equipment movements (Sacks et al., 2005; 2006; Gong and Caldas, 2010; Costin et al., 2012; Yang et al., 2014). These studies were limited to track a particular equipment (e.g., tower crane) during a particular activity (e.g., concrete pouring). However, it is usually not sufficient to track a single equipment for progress monitoring of an activity, especially at building construction. This was also highlighted by other researchers stating that to enable informed decisions and assess the performance of projects, the fusion of a number of sources is needed because not all of the necessary information can be captured using a single data source (Shahandashti et al., 2011, McCabe et al., 2017). Therefore, it is proposed that a data fusion approach is needed to integrate the data related to multiple pieces of equipment involved in the successive steps of an activity to calculate its progress. The main objective of the study explained in this paper was to automatically determine the progress at site by tracking major resources (e.g., equipment and bulk materials) that are utilized in building construction activities via sensor-based technologies. An approach was developed to fuse the data obtained from the sensor-based technologies by considering the domain-specific heuristics, which include method used for completing a particular activity and precedence relation of the activity steps. A proof-of-concept prototype was developed and implemented at a construction site, and the performance of the developed approach for tracking the progress of masonry work was demonstrated. This paper presents the developed approach and rule-based data fusion algorithms for determining the progress of masonry work at a building construction. The main contribution of this study is the identification of the rules and development of the rule-based approach that can be used for data fusion. The rules that were developed in this study to analyse the data collected from the equipment and bulk material can be used to determine the progress of similar activities. The applicability of the rule-based approach developed in this study was also demonstrated in tracking the progress of rebar installation at a building construction (Guven and Ergen, 2017a).

2. BACKGROUND REVIEW

In this section, the studies that performed progress monitoring using advanced technologies were reviewed and data fusion approaches in construction management domain were reported.

Progress monitoring using advanced technologies

Researchers have performed various studies to monitor the progress of construction activities by using vision-based technologies, such as laser scanners, video cameras, and/or non-vision-based technologies, such as Radio Frequency Identification (RFID) and Global Positioning System (GPS) technologies. The main idea is to track the construction resources (i.e., building components and materials, workers, and equipment) and to capture the as-built status of building components to compare it with the as-planned Building Information Models (BIMs). In the recent years, the focus points of the researchers have been to use Unmanned Aerial Vehicles (UAVs) for autonomous data capturing to perform automated updates in BIMs, and to detect construction progress using images (McCabe et al., 2017).

The studies that utilize vision-based technologies for progress monitoring can be mainly grouped into three categories (Asadi and Han, 2018): (1) studies on 3D as-built model generation and alignment with BIM (Golparvar-Fard et al., 2009; Turkan et al., 2012; 2013; Kim et al., 2013a; Han and Golparvar-Fard 2015), (2) studies that use image processing and machine learning methods to monitor the construction progress (Golparvar-Fard et al. 2009; Kim et al. 2013a; Yang et al. 2014; Dimitrov and Golparvar-Fard 2014; Han and Golparvar-Fard 2015) and (3) studies that use UAV for autonomous data collection (Siebert and Teizer 2014; Youngjib et al. 2016; Ham and Golparvar-Fard 2017; McCabe et al., 2017). However, the vision-based technologies have some limitations. For example, they require registration of as-built data with the as-planned model and it is a time-consuming process that is mostly handled manually (Han and Golparvar-Fard, 2017; Asadi and Han, 2018). Also, suitable positioning and orientation are needed to minimize occlusions by foreground activities or other obstructions when cameras are used (Han and Golparvar-Fard, 2017). Similar applies to UAVs, as detail, coverage, and accuracy of the data captured is effected by manually planned inspections (Zhang et al. 2016). Moreover, they may not perform well at night and/or under varying lighting and shadow conditions (Yang et al. 2014; Teizer, 2015; Han and Golparvar-Fard, 2017). Finally, the other current challenges reported are the expensive costs of hardware, expensive processes of image-based 3D reconstruction and time-consuming laser scanning operations (Han and Golparvar-Fard, 2017).

Use of non-vision-based technologies for progress monitoring have a longer history in the literature, usually for tracking the IDs and/or location of resources related to construction activities (Song et al., 2006; Ergen et al., 2007a; 2007b; Chin et al. 2008; Grau and Caldas, 2009; Ju et al. 2012, Cheng et al., 2012; 2013a; 2013b; Shahi et al., 2013; 2014; Kim et al. 2013b; Pradhananga and Teizer, 2013, Cai et al. 2014; Chai et al., 2017). In the recent studies, the Smart Object (SO) concept has been applied in construction supply chains by using resources that are equipped with Auto-ID devices, such as RFID (Shin et al., 2011; Niu et al., 2016; 2017). In some studies, RFID technology has been integrated with BIM for creating cyber-physical systems to track the construction progress (Olatunji and Akanmu, 2015; Xue et al., 2018; Chen et al., 2018). A major limitation with these methods in tracking workers and materials can be costly if every item needed to be tagged, considering the high number of such resources in construction sites. Therefore, tracking equipment can be more cost-effective as there are less number of equipment at sites.

Most of the available equipment tracking studies is limited to earthmoving and excavation activities, road construction activities and concrete delivery (Heydarian et al., 2012; Montaser and Moselhi, 2012; Akhavian and Behzadan, 2012; Pradhan and Akinci, 2012b; Pradhananga and Teizer, 2013; Rezazadeh Azar et al., 2013). Being one of the most essential equipment at construction sites; several aspects of tower cranes have been studied in the literature generally by simulating the selection of the most appropriate tower crane, the optimal positioning and operation planning of tower cranes, and for measuring the productivity and enabling safety of tower cranes (Li and Liu, 2012; Roberts et al., 2017; Ji and Leite, 2018; Peng et al., 2018; Taghaddos et al., 2018; Zhou et al., 2019). Similar to tower cranes, construction hoists that are used for vertical transfer of material and personnel at high-rise buildings were examined in terms of their efficient usage and safety (Cho et al. 2011, Costin et al. 2012; Yang et al., 2012; Kim et al., 2016; 2018). However, a smaller number of studies tracked the lifting equipment used in the construction of superstructure at buildings for progress monitoring. The common focus of these studies was to track the tower crane during concrete pouring activity (Sacks et al., 2005; 2006; Gong and Caldas 2010; Yang et al. 2014). The main limitation of the studies on tracking the lifting equipment was that they tracked the progress of specific activity types (i.e., concrete pouring, material handling) by monitoring one particular piece of equipment (either a tower crane or a hoist). However, unlike the activities such as earthwork and excavation, most of which can be performed using a particular equipment; activities in the construction of building superstructure necessitate the use of different types of equipment at different stages. Therefore, a detailed data fusion approach is needed to integrate the data obtained from different pieces of equipment and other resources used in different stages of an activity at building constructions.

Data fusion approaches

Although a single-sensor model was adopted in the initial studies, the researchers started applying multisensory data fusion models in the following studies to achieve a more comprehensive understanding of the progress in construction projects. Data fusion studies in the construction management domain have a variety of purposes.

For example, tracking and locating construction materials and equipment (Song et al., 2006; Ergen et al., 2007a; 2007b; Grau and Caldas, 2009; Razavi and Haas, 2010; Vasenev et al., 2011; Ju et al. 2012, Cheng et al., 2012; 2013a; 2013b; Kim et al. 2013a; Pradhananga and Teizer, 2013, Cai et al. 2014; Chai et al., 2017), productivity monitoring (Weerasinghe and Ruwanpura, 2009; Gong and Caldas, 2010; Pradhan and Akinci, 2012b), progress monitoring (El-Omari and Moselhi, 2008; Bosche et al., 2009; Golparvar-Fard et al., 2009; Shahi et al., 2013; 2014; Han and Golparvar-Fard, 2015), quality control and safety (Cheng et al., 2012; 2013a; 2013b), and object recognition and reconstruction in construction by visual data fusion (Zhu and Brilakis, 2009; Kuipers et al., 2014). Since a generalized data fusion approach in the AEC domain does not exist in the literature, most of the researchers developed a data fusion approach that is specific to the problem at hand. A few of the researchers worked on adapting existing data fusion models developed for other domains (e.g., Joint Directors of Laboratories (JDL) and Dasarathy's model) to specific construction domain applications. For example, Razavi and Haas (2010) developed a modified data fusion model based on the JDL model to be used in location estimation in construction resource applications. On the other hand, Kiziltas et al. (2006) suggested using Dasarathy's model for defining the process of fusing data from multiple sources to generate integrated project histories for supporting estimator's decision making. These models are not utilized in this study as they do not cover the integration of domain specific data sources; and thus, are difficult to apply to other domains (Carvalho et al., 2003; Pradhan, 2009). Therefore, an approach for data fusion was proposed in this study. This approach uses rule-based algorithms to automate the progress monitoring of construction activities by using the data obtained through tracking of major resources in building construction sites.

The previous studies have not explored fusing different types of information obtained from multiple data sources at separate timeframes. Most of the data fusion applications in the literature fused data by using overlapping timeframes or overlapping location information of multiple data sources. By matching the identical timestamps, overlapping timeframes of multiple data sources were used to merge data (Weerasinghe and Ruwanpura, 2009; Pradhan and Akinci, 2012a; Cheng et al., 2013a; 2013b; Kuipers et al., 2014). For example, location data from GPS and ID data from RFID was fused by matching the timestamps of GPS readings and RFID readings when tracking construction material and other resources (Song et al., 2006; Ergen et al., 2007b; Grau and Caldas; 2009; Razavi and Haas, 2010). Besides identical timestamps, Pradhan and Akinci (2012a) used overlapping location information to fuse two spatial data sources (i.e., weather database and soil database) using the nearest neighbour approach.

In addition to matching overlapping timeframes or locations, some researchers used rule-based reasoning to fuse data (Ergen et al., 2007b; Grau and Caldas, 2009; Cheng et al., 2013a; 2013b). This is one of the most commonly used data fusion approach in the literature. For instance, Cheng et al., (2013a; 2013b) defined rules, and thresholds for heart rate and bending angle to determine ergonomically safe and unsafe conditions of workers while performing different activities. The type and location of a particular activity that a worker performs were identified by fusing the location data obtained from Ultra Wide Band (UWB) with the posture data obtained from the related sensors. Other reasoning mechanisms, such as reasoning based on expert knowledge, were also used in some of the data fusion studies (Vasenev et al., 2014). Shahi et al. (2014) defined case-specific rules to fuse the object recognition results obtained from a laser scanner with material tracking data (i.e., ID) obtained from UWB to monitor the progress of pipe installation in a pipeline project. In their approach, the location and ID information of the installed pipes were first extracted from the UWB system, and rules were defined to double-check these information items with the object recognition results obtained from the laser scanner (Shahi et al., 2014).

Pradhan and Akinci (2012b) followed a different approach and formulated data fusion as a planning problem, and developed a generalized method that was validated for construction productivity monitoring applications. They developed a taxonomy of reasoning mechanisms to fuse a pair of spatial and temporal data sources to support construction productivity monitoring in road excavation projects (Pradhan and Akinci; 2012a). The study explained in this paper extended this taxonomy of reasoning mechanisms for adapting it to building projects. The reasoning mechanisms are the data processing methods that describe the steps (i.e., extraction, transformation, interpretation and merging) that are required to be applied in a certain order to prepare the data obtained from different sources for data fusion. In this study, the developed reasoning algorithms work based on the identified rules that represent how tower cranes and hoists typically work at a site. This approach is preferred as it reflects the domain knowledge and can be easily modified by other researchers for data fusion in determining the progress of other activities that use tower cranes and hoists as a means of resource transfer.

3. PROPOSED APPROACH

The proposed approach aimed to be cost-effective and to have minimal interference with the existing workflows to enable fast adoption. Therefore, only one major equipment and bulk material that are relatively less in number were tracked. A rule-based approach was proposed to fusing the sensor-based data and human-generated data for progress monitoring of activities in building construction projects. The goal is to identify completion of each activity step and consequently to determine the activity progress. This study extended a taxonomy of reasoning mechanisms developed for data fusion (Pradhan and Akinci, 2012a) and adapted it to building projects. When fusing data, data extraction and data transformation steps that were defined in the taxonomy were followed and data interpretation step was introduced in this study. Also, a new data source, namely physical property data source was defined besides spatial and temporal data sources in the taxonomy.

Fig. 1 illustrates the proposed data fusion approach that was implemented for the masonry work in the case study. The first step is to identify domain-specific heuristics of the activity of interest through site observation. It includes information about: (1) the site layout, (2) the method of activity, and (3) the activity steps that are performed to complete that activity. Once this information is extracted from site, sensors are attached to related equipment or bulk material and rule-based algorithms are developed based on the domain-specific heuristics to fuse the raw sensor data and to identify the progress of activities. Raw data is obtained from the sensors that are either embedded in the equipment (e.g., position and load sensors) or that are deployed on the equipment or on bulk material (e.g., RFID). By using sensors, the following data types will be collected: (1) the trajectory of the equipment, (2) ID and other information (e.g., amount) related to the material that the equipment carries or handles, and (3) when and where the equipment and/or the bulk material are used.

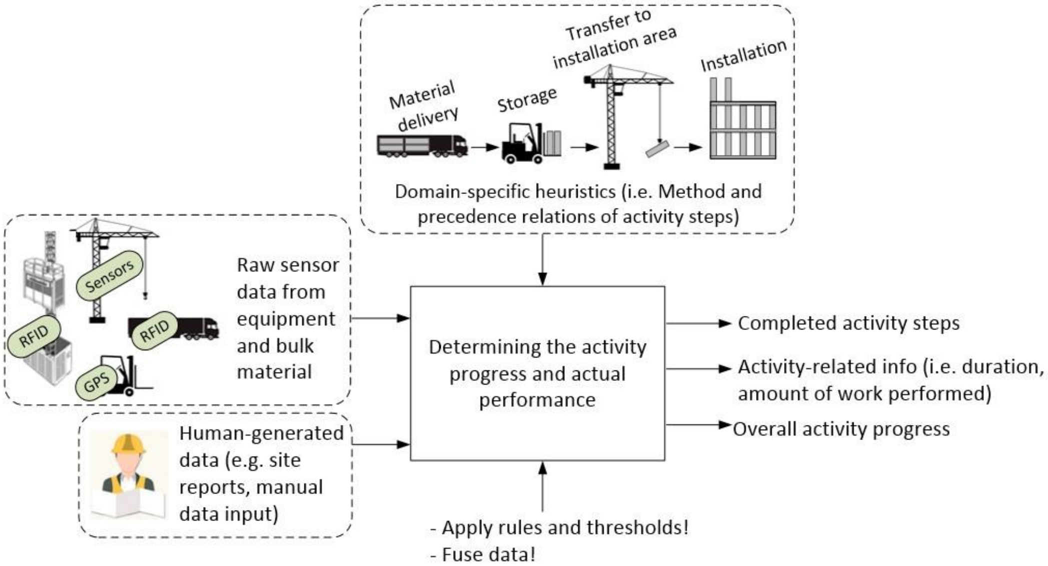

FIG. 1: Proposed data fusion approach.

As progress of each activity step is identified, the activity's overall progress is determined by integrating (1) the activity-related information obtained from each completed step with (2) the activity-related baseline data (i.e., budgeted material quantity and planned dates) that is manually extracted from the human-generated data sources (i.e., quantity take-offs and baseline schedule). The developed approach determines the overall activity progress based on: (1) physical completion, which is calculated by considering the contribution of the completed activity steps to the overall activity completion (i.e., relative percentage of activity step), or (2) material use. Moreover, the activity performance is determined by comparing the planned and actual activity parameters (i.e., start and end dates, quantity of work).

This approach was validated through the field experiments by using a proof-of-concept prototype that was implemented in a building construction. In the experiments, the major resources (i.e., tower crane and hoist) and bulk material (i.e., concrete masonry block pallets) were tracked to monitor the progress and the performance of the masonry work. The following sections elaborate the details of the developed rule-based data fusion algorithms, and the prototype development and implementation.

3.1 Overview of the test case

The developed data fusion approach was applied to a masonry work test case at a reinforced concrete residential project with 320.000 m2 total construction area. 24 apartment buildings were being constructed in the selected project and one building was selected as the test building. Data was collected at eight floors (i.e., from 20^{th} floor to 27th floor) of the building for three months.

The prototype that was implemented at the test site was designed to work under the current site conditions, considering the observed method of masonry work (Fig. 2). The masonry work that was monitored during the field tests included activity steps that are both performed during the day and night shifts. Usually the material delivery was performed during the night shift while the masonry installation was performed during the day. The tracked resources were the tower crane, construction hoist, and the reusable concrete masonry block pallets. Three main criteria used in selecting the sensor-based technologies were (1) cost-efficiency, (2) minimal interference with the existing workflows and (3) ability to work both day and night. The selected technologies were the existing embedded sensing technologies on the tower crane's anti-collision system and an RFID system. The anti-collision system is primarily deployed on tower cranes for remote monitoring of the crane movements and for automatically avoiding collision of cranes that are in close proximity to each other. Among various embedded sensing technologies that collect data in real-time, position sensors (i.e., angular position, trolley position, hook position) and load sensor were chosen to be included in the prototype. Tower crane sensors were used to monitor the material delivery during the night shift. An RFID system was deployed in the construction hoist and reusable concrete masonry pallets were tagged. The RFID system is used to track the masonry work installation step. It consists of one RFID reader (Motorola FX740), two antennas (MTI MT-242040), a notebook, a 12V 40Ah additional power supply and a modem used as a bridge in between the computer and the reader. The operating frequency of the reader is 902 MHz~928 MHz, 865 MHz~868 MHz, included in the UHF frequency. An "active reader - passive tag" system was designed and installed on the hoist that serves the test building. In the current version of the prototype, the data collected by the tower crane sensors and the RFID system are manually transferred to a database; however, both systems have local storage and wireless data transfer options to a central server to be used in the future. Details of the technologies utilized for data collection during the tests are provided in Guven and Ergen (2017b).

The next section explains the first step of the prototype development, where method used for masonry work and related activity steps were identified to extract domain-specific heuristics via site observations.

3.2 Identification of activity steps

Two activity steps that are commonly observed for masonry work were identified as: (1) transfer of concrete masonry block pallets from the laydown area to the installation area, and (2) installation of concrete masonry blocks and clean up of floor (Figs. 2(a) and 2(b)). The developed approach first identifies the start and finish dates of each of the activity step and the amount of work performed in each step. Then, the information obtained in each step is integrated to assess the overall progress of the activity and the baseline schedule and material information are compared with the actual values.

The sensors utilized in the prototype, and the data that were collected are summarized in the following paragraphs for the identified masonry activity steps:

- Transfer of concrete masonry block pallets from the laydown area to the installation area (Fig. 2(a)): In the first step, tower crane transfers the pallets that carry concrete masonry blocks from the laydown area to a building floor, where installation will be performed (Fig. 2(a)). The position sensors and load sensors that are embedded in tower crane's anti-collision system were used for tracking this activity step. The sensor data was used to (1) track the trajectory of the tower crane to determine the transfer of masonry blocks from the laydown area to the installation area at the building, and (2) determine the weight of the carried loads to quantify the masonry blocks transferred to the installation area. Hook position sensor data was used to identify the floor to which the masonry blocks were transferred.
- Installation of concrete masonry blocks and clean up of floor (Fig. 2(b)): In the second step, once the concrete masonry blocks are installed, the floor is cleaned up on a regular basis by removing the empty material pallets from the corresponding floor (Fig. 2(b)). This is typically performed via the hoist at construction sites since the tower cranes are more frequently occupied. The start date of the masonry

installation was identified based on when the transfer of material step was performed. Usually the material is transferred one day before the installation, and therefore, regardless of when the material was transferred (either during the day or night shift), installation starts the next day. The amount of progress made were determined by using the RFID technology. The concrete masonry block material pallets were tagged with RFID tags and an RFID system was deployed on the construction hoist. The goal was (1) to identify the floor at which the tagged material pallets were loaded on the hoist for removal from the floor during each clean up operation, and (2) to detect the number of pallets that were removed. The number of removed masonry block pallets were used to calculate the quantity of concrete masonry blocks utilized at the floor and consequently to calculate the activity progress. The end of installation step was identified when the percentage of utilized material reaches a certain level (i.e., 90%) as detected from the RFID readings.

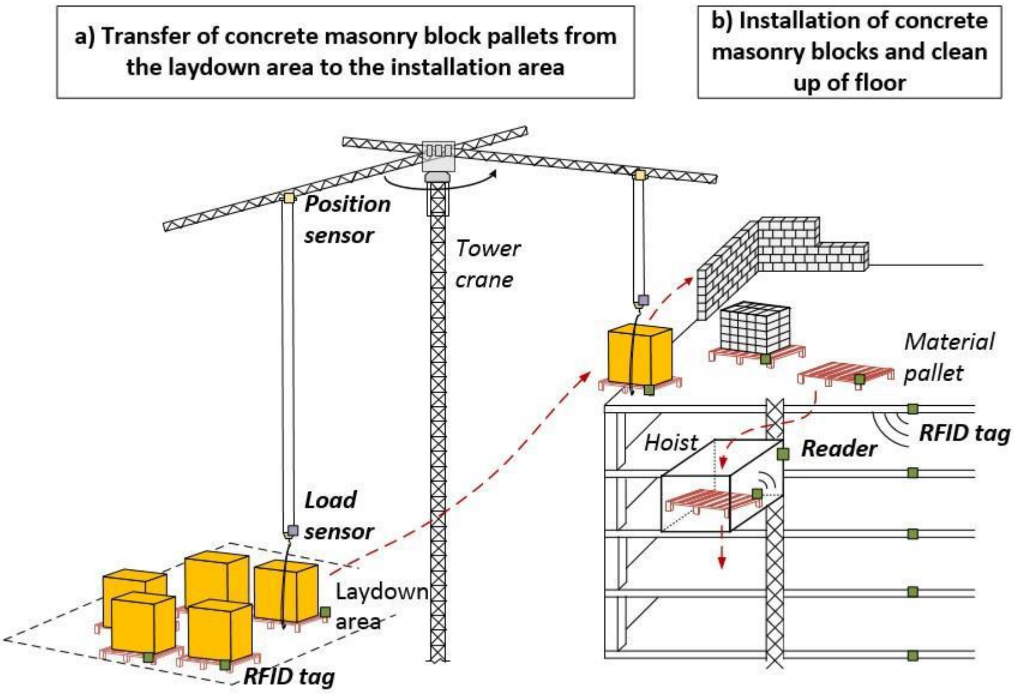

FIG. 2: Components of the prototype and the current method of masonry work.

The overall activity progress was calculated in terms of (1) physical completion (i.e., completion of activity steps), and (2) material use. When calculating progress based on physical completion, the completion of each activity step was defined as a milestone that represents some percentage of the activity's overall progress. These percentages were determined by experts, who are three project engineers that work at the site. The transfer of concrete masonry blocks to installation area represents 5% progress, while the installation and clean up step represents 95% progress of wall installation. Material use was used to determine the progress of the `installation and clean up step`, and it was calculated by comparing the quantity of material utilized at a floor with the quantity of material transferred to the floor. Finally, the actual dates and quantity information obtained from the sensor-based data sources were compared with the activity-related baseline data obtained from human-generated data sources to evaluate the activity performance.

Table 1 summarizes the method for collecting data from the equipment and bulk material (i.e., tower crane, hoist, and material pallets) by using sensor-based and human-generated data sources, and the how the collected data was fused. The results obtained for progress monitoring and performance evaluation of the masonry work are provided and the details are explained in the following sections.

3.3 Algorithms for data fusion

Fig. 3 presents the flowchart that explains application of the rule-based data fusion algorithms that were developed in this study. The basics steps of these algorithms were developed based on the taxonomy of data fusion reasoning mechanisms that was originally described by Pradhan and Akinci (2012a). Also, the domain-specific heuristics were integrated into the algorithms. The original taxonomy was based on the categorization of the data sources as: (1) spatial (e.g., design drawings, building information models) and (2) temporal (e.g., time-cards, schedule) (Pradhan and Akinci, 2012a). In this study, a new data source needed to be defined for activity progress monitoring and it is called the 'physical property' data source. It includes the measured or collected physical property values (e.g., weight, state of motion, volume) of entities (e.g., material, equipment). The physical property that need to be interpreted for tracking masonry work was identified as the weight of an object that is lifted by the tower crane. The taxonomy originally included the following reasoning mechanisms: (1) data extraction to extract relevant data from a data source, (2) data transformation to convert data from one state to another to make the data ready for data merging, and (3) data merging to combine or fuse two data sources. In addition to these, data interpretation step was introduced in this study to extract the physical data (e.g., weight) that is collected by activity monitoring applications.

Following paragraphs provide the details of how the related data fusion algorithms were applied during the test case implementation. These algorithms were applied on the data retrieved from the equipment and bulk material (i.e., tower crane, hoist and material pallets) for (1) identifying the specific steps of the masonry activity (i.e., transfer to installation area, installation and clean up of floor), and (2) collecting activity-related information for each step (i.e., dates and amount of work performed). The masonry work that was observed represents a typical masonry work methodology; and the rules that were developed based on this site observation is expected to be applicable to masonry work that is performed at other construction sites.

TABLE 1: Data collection and fusion method

<table>
<tr><th rowspan="2">Data collected from</th><th rowspan="2">Data collection method</th><th rowspan="2">Data collected from sensor-based and human-generated data sources</th><th rowspan="2">Information obtained from the collected data</th><th colspan="2">Results</th></tr>
<tr><th>Progress monitoring</th><th>Performance evaluation</th></tr>
<tr><td>Tower crane</td><td>- Position, depth and load sensors</td><td>(A) Load weight identified for each load transfer activity
(B) Angular position of the crane boom
(C) Trolley position
(D) Hook depth</td><td rowspan="3">(ΣA) = Total # of pallets transferred to the installation area

(E)= Floor to which the pallets are transferred

(E) = Floor from which the empty pallets are removed

(E) + (F) = # and sizes of pallets utilized at the floor calculated at each clean up</td><td rowspan="3">(B)+(C)+(D) = Completion of pallet transfer to floor (Progress % based on physical completion of transfer step)

(F) = Amount of installed masonry blocks (Progress % based on material use calculated after each clean up)

Date when (ΣF) reaches 90% = Completion date of wall installation at the floor (Progress % based on physical completion of installation step)

(ΣF) / (ΣA) = (Total # of pallets utilized) / (Total # of pallets delivered) (Overall activity completion %)</td><td rowspan="3">- Planned vs. actual start and end dates of masonry work

- Actual quantity of masonry work

- Budgeted vs. actual quantity of masonry work at the floor are compared</td></tr>
<tr><td>Hoist</td><td>-Passive RFID tags (on floors)
-Passive RFID tags (on pallets)
- RFID reader (on the hoist)
- Antennas (inside and outside hoist cabin)</td><td>(E) Floor ID

(F) Pallet IDs read at each clean up</td></tr>
<tr><td>Schedule and/or quantity takeoff spreadsheets</td><td>- Manual data extraction</td><td>- Budgeted quantity of masonry work (m²)

- Planned start and end dates</td></tr>
</table>

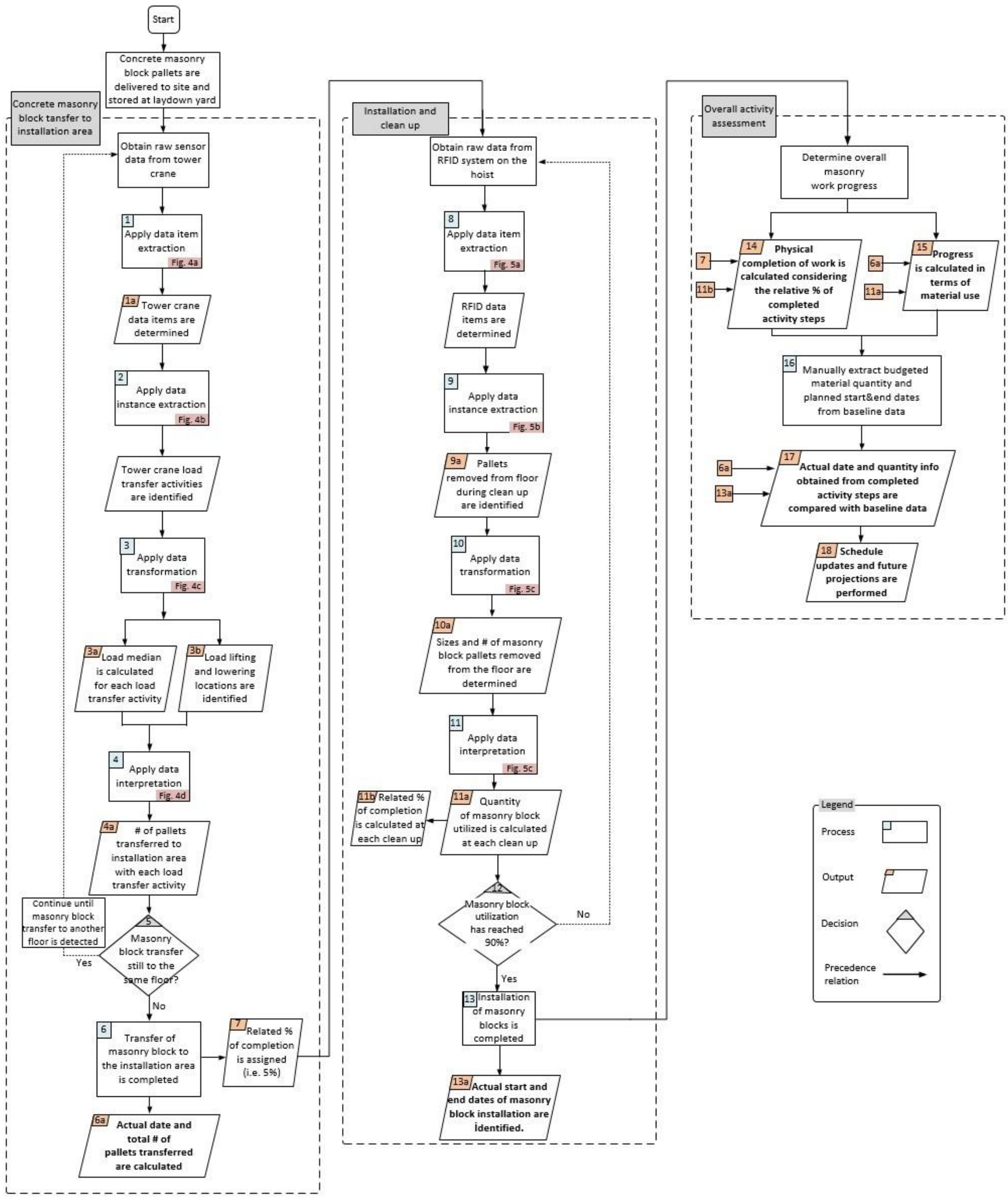

FIG. 3: Components of the prototype and the current method of masonry work.

3.3.1 Transfer of concrete masonry block pallets

Tower crane is used to transfer the concrete masonry block pallets from the laydown area to the installation area, which is at a floor of the building. Data from position and load sensors are analyzed to detect (1) the transfer of concrete masonry blocks to the installation floor by identifying the tower crane's activity, and (2) quantity of concrete masonry block transferred to the related floor via load weight (Table 1).

Tower crane sensor data - data item and data instance extraction (Figs. 3(1) and 3(2))

Data extraction is the process of extracting the relevant data from a given data source. As there may be various data items provided by a data source (e.g., date, time, location), only the data items that are relevant need to be extracted (i.e., data item extraction) (Fig. 3(1)). Similarly, only the data instances that represent a particular movement or behavior of the equipment is extracted from a dataset (i.e., data instance extraction) (Fig. 3(2)). Figs. 4a and 4b demonstrate how the data extraction algorithms are applied to the tower crane sensor data. The data items that are relevant for determining the tower crane activities and the data instances that represent certain tower crane activities (i.e., load transfer) are extracted (Fig. 4(a)): date, time, slewing position (angle), trolley position (distance), hook position (height), load weight (in tons) and power OFF (i.e., Boolean). Date and time indicate the timestamp of each record. The slewing angle (i.e., tower crane boom angle to a reference point), the trolley position (i.e., distance of the carriage from crane cabin) and the hook position (i.e., elevation of the crane hook from the ground level) are related to the 3D position of the tower crane boom, trolley and hook at the time of measurement. The load weight is the weight of the rebar measured during transfer. Finally, the power OFF value is equal to "0" when the tower crane is operating and is equal to "1" when it is not.

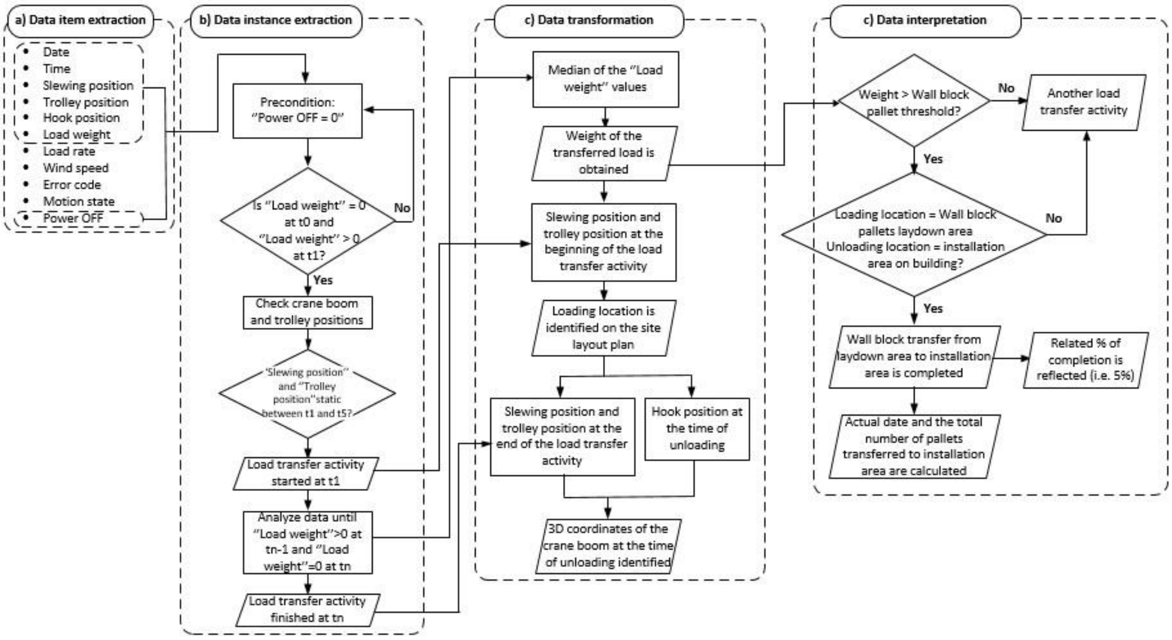

FIG. 4: Algorithms applied to the tower crane sensor data.

Data instance extraction is applied to the tower crane dataset to extract data that is collected during load transfer activities of the tower crane (Fig. 4(b)). A set of general rules that are applicable to other load lifting activities at construction sites were defined based on the weight variation pattern, and slewing and trolley position pattern. These parameters describe a tower crane's movement and the way the load on the hook changes when a load is lifted. These rules were determined through observations at site on how a tower crane is operated and by interpreting the related sensor data. The observations showed that the load weight value that is measured by the load sensor is zero at the beginning as if no load is on the hook. It then gradually increases in time and equals to zero again as the tower crane unloads the weight. In addition, the movement of the crane at the time of lifting and lowering is limited by safety regulations that prevent the operators to perform any sudden movements with the tower crane boom and trolley. This can be observed in the crane boom and trolley position sensor data as the boom and trolley remain relatively static at the beginning of a lifting activity before the operator turns the crane boom or moves the trolley back and forth.

Fig. 4(b) presents the rules that are used for extracting the data instances and Table 2 shows a data instance sample illustrating a single load transfer activity that was extracted among a daylong dataset recorded on a regular day. The first step in distinguishing the load transfer activities from other types of tower crane activities (e.g., the idle times) is to check whether the Power OFF value is equal to zero, as it shows that the tower crane is operating (Fig. 4(b)). Start of an activity is then determined with a change in the load weight value from zero to a value greater than zero (i.e., Load weight = 0 at t0 and Load weight > 0 at t1). In addition to the load weight change, the slewing position (i.e., tower crane boom angle for a reference point) and the trolley position (i.e., distance of the carriage from crane cabin) of the tower crane are checked, since these positions are distinctive in determining a load transfer activity. The characteristic movement of a tower crane at the beginning of a lifting activity (i.e., keeping the crane boom and trolley relatively static) to prevent struck-by hazards, is to not turn the crane boom right and left or move the trolley back and forth for a short period of time until the load is levitated from the ground to a safe height. It is observed that the crane boom and trolley were not moved more than 50 cm for 4 seconds at site and these were introduced as thresholds in the algorithm. These thresholds can be updated if needed at other sites. In summary, to classify a tower crane movement as a lifting activity; the load weight value should change as expected and both the boom and the trolley should be static for the defined time period. If not, this crane activity is ignored. The first three rows of Table 2 show how the slewing angle and the trolley position remained static as described. In the beginning (15:57:25) the slewing angle was 278 degrees and the trolley position was 38.7m. The third row that shows the measured values after four seconds (15:57:29), the slewing angle is still the same, while the trolley has moved to 38.6m, which is less than 50 cm (i.e., 10 cm) as described by the rules. Finally, the completion of a load transfer activity is detected when the load weight value decreases from a value greater than zero (i.e., load weight > 0 at tn-1) to zero (i.e., Load weight = 0 at tn).

TABLE 2: Sample extracted tower crane data for a load transfer activity

Date	**Time**	**Slewing position (^{o})**	**Trolley position (m)**	**Hook position (m)**	**Load weight (t)**	**Power OFF (Boolean)**
15.05.2015	15:57:25	278	38.7	0.0	0.0	0
15.05.2015	15:57:27	278	38.6	1.0	0.1	0
15.05.2015	15:57:29	278	38.6	2.5	0.5	0
15.05.2015	15:57:31	278	38.7	3.0	0.8	0
15.05.2015	15:57:33	278	38.6	3.0	1.1	0
15.05.2015	15:57:35	278	38.7	4.0	1.2	0
15.05.2015	15:57:37	278	38.6	5.5	1.4	0
…	…	…	…	…	…	…
15.05.2015	15:58:25	260	38.5	41.0	1.4	0
15.05.2015	15:58:27	259	38.6	41.5	1.3	0
15.05.2015	15:58:29	257	38.6	42.0	1.1	0
15.05.2015	15:58:31	257	38.6	42.0	1.1	0
15.05.2015	15:58:33	257	38.6	42.0	0.7	0
15.05.2015	15:58:35	257	38.6	42.0	0.0	0

Tower crane sensor data - Data transformation (Fig. 3(3))

Data transformation is performed to convert the data to another state or format to enable fusion of different forms of data. For example, level of detail or its coordinate system is changed. In the case of the tower crane, data transformation is applied once the relevant data items and data instances related to certain activities of the tower crane (i.e., load transfer activity) are extracted from the sensor data. The first step of data transformation is to determine weight of the load carried in each load transfer activity to identify the quantity of the concrete masonry blocks transferred to the installation area (Fig. 3(3)). Table 2 demonstrates how the load weight varies during a typical load transfer activity that can be measured by the load sensor on the tower crane. This is mainly caused by environmental factors that affect the load sensor measurements, such as windy weather. Also, the tower crane movement itself, such as turning and upwards and downwards movements, has an impact on the measured weight. To calculate a single value of the load weight, data aggregation (i.e., level of detail transformation) is applied to the load data that is determined through data instance extraction (Fig. 4(c)). Median of all the load weight values of a lifting activity is assumed to be the weight of the load being carried (Fig. 3(3a)).

The second step of data transformation determines the load lifting and lowering locations of each load transfer activity to identify the type of load that is being transferred (Fig. 4(c)). The tower crane is one of the equipment that is most frequently used by different trades throughout a regular work day at construction sites. Therefore, integrating the information about the site layout with the tower crane trajectory helps identifying for which construction activity the tower crane is used for. Since particular areas are designated for specific purposes on the site layout plan (e.g., installation area, laydown area), the loading and unloading areas of a load transfer activity can be identified. This is done by transforming the slewing angle and the trolley position at the start and end of a load transfer activity into the x and y coordinates in the local coordinate system of the construction site. While the slewing angle indicates the angular position of the tower crane boom based on a predefined reference point, the trolley position is the distance of the carriage from the crane cabin. Therefore, the loading and unloading location of a load transfer activity can be associated with the areas (e.g., laydown area, installation area) at a construction site. It should be noted that location of these areas on the site layout plan should be identified for each site and provided as an input. The final output of the data transformation is the weight of the transferred load, and the corresponding loading location (i.e., laydown area) and unloading location (i.e., installation area) on the site layout plan. The floor to which the concrete masonry blocks are transferred (i.e., the floor at which the transferred load is lowered) is identified by transforming the elevation of the hook obtained from the hook position sensor at the time of unloading (Fig. 3(3b)).

Tower crane sensor data - Data interpretation (Fig. 3(4))

Data interpretation is applied to identify the objects and states of objects from their physical properties that were obtained from tower crane sensors (i.e., weight) for tracking the masonry work. The weight of an object (e.g., carried by the tower crane) is a descriptive physical property that can be used to identify what the object is (i.e., rebar, wall block). To identify a wall material pallet by interpreting the weight of the load, a threshold value was used. This threshold value is specific to each site and it was determined as 700 kg for one concrete masonry block pallet during the field experiments. If the weight is above this threshold, and if the load is transferred from the laydown area to the installation area, it is determined that the load that is transferred is a concrete masonry block pallet (Fig. 4(d)). In the next step the number of concrete masonry block pallets transferred in a single load transfer activity is determined by using the measured weight value (Fig. 3(4a)).

Sensor recordings are interpreted to identify that the concrete masonry block transfer to installation area step continues at the same floor (Fig. 3(5)) until it is completed at the current floor (Fig. 3(6)). Then the algorithm starts to process the data related to the following step of the masonry work activity (i.e., installation and clean up). As the first step of the masonry work activity is determined to be complete, the progress of the masonry production activity at that floor is assigned as 5%, which is determined by the experts at site (Fig. 3(7)). Also, the actual date when the material transfer is performed, and the total number of material pallets transferred to the installation area is determined (Fig. 3(6a)).

3.3.2 Installation of concrete masonry blocks and clean up of floor

Material delivery from the laydown area to the installation area is followed by the installation of concrete masonry blocks. Wall installation starts on the next day following the transfer of masonry block pallets.

The floor at which the installation continues is cleaned up by removing the empty material pallets from the floor and it is performed via the hoist on a regular basis. The site engineers stated that this is a commonly used procedure in masonry work at high rise buildings. The hoist operates on the building façade, and the RFID system deployed on the hoist includes a reader, an antenna installed inside the hoist (i.e., antenna #1), another antenna installed on the outside of the hoist (i.e., antenna #2). Details on the experimental setup of the prototype can be found in Guven and Ergen (2017b). The antenna #1 detects the empty material pallets that are loaded in the hoist for removal from the building, while the antenna #2 detects the floor tags for identifying the floor from which the empty material pallets are removed (Fig. 5). By using the RFID system, each time the clean up operation is performed, the number of pallets, and thus, the quantity of concrete masonry blocks that are used at the installation are determined.

RFID data - data extraction (Figs. 3(8) and 3(9))

Fig. 5 presents the algorithms applied to the RFID system readings. To identify the material pallets being removed from a floor via the hoist, first steps are to perform data extraction (Fig. 5(a)) and data instance extraction (Fig. 5(b)) on the readings of the RFID system (Figs. 3(8) and 3(9)). Table 3 shows the summary of extracted data items: (1) timestamps of the readings, (2) unique tag IDs, (3) antenna number that detected the tags. When a tag is detected by an antenna, the algorithm checks the detected ID against a tag ID database that lists the pallet tags, the floor tags, and the size and type of concrete masonry block pallets that each tag represents. The rule-based reasoning methods are applied for processing the RFID readings to filter the tag IDs that need to be identified by each antenna. Antenna #1 is only used to detect the tags on the empty pallets and antenna #2 is used to read the floor IDs on the building façade. However, in some cases, tags are detected by both antennas and pallet tags are redundantly identified by antenna #2 and floor tags by antenna #1. The algorithm checks with the ID database and ignores the tags that entered the range of the other antenna by mistake and filters the duplicate reads (Fig. 5(b)).

Using this method, data instance extraction was performed on RFID data to identify the instances when the hoist is used to remove pallets from a floor. For example, Table 3 presents RFID data that is collected at the hoist during removal of pallets from 3rd floor, and the identified pallets and floors during the hoist movement (Fig. 3(9a)). The first row in Table 3 shows that the reading is performed by antenna #2 and the ID belongs to the 3rd floor. Next is followed by a reading performed by the antenna #1, and it is identified that the tag belongs to a 10 cm masonry block pallet. This is continued until the material pallets are brought to the ground floor.

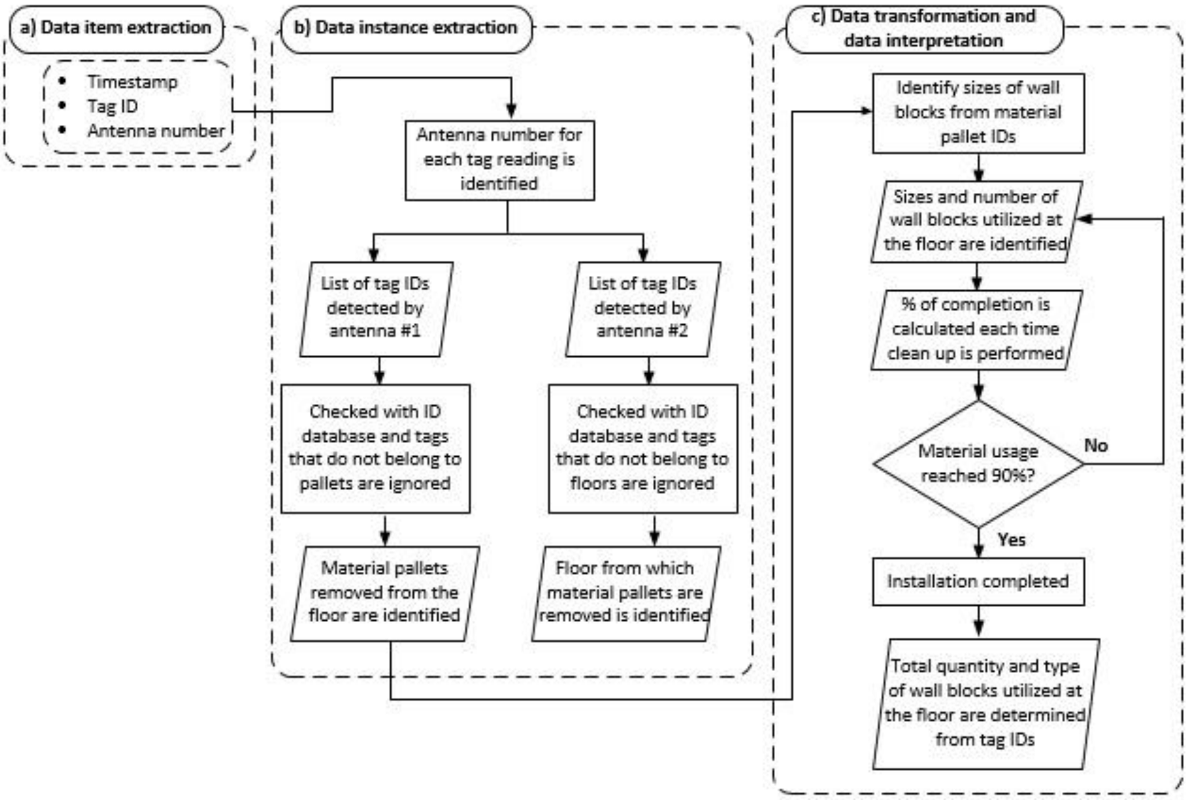

FIG. 5: Algorithms applied to the RFID data.

By matching the material tag IDs with the tag ID database, size and number of concrete masonry blocks utilized at a particular floor are identified (Figs. 3(10a) and 5(c)). The quantity of concrete masonry blocks utilized at the floor is calculated based on the size of concrete masonry blocks on a pallet (Figs. 3(11)). This process is applied on the RFID data each time the clean up of floor is performed throughout the installation; and consequently, the total quantity of utilized concrete masonry block is calculated (Fig. 3(11a)). The related completion percentage is calculated based on material use each time the clean up is performed and it is assigned to wall production activity at this floor (Fig. 3(11b)).

The installation is considered to be complete when the RFID readings indicate that the amount of utilized material at the floor has reached 90% (Figs. 3(12) and 3(13)), which was determined by the project engineers that worked at the site. It was stated that additional 5-10 % of the required material is delivered to the production area to cover the finishing work that will be performed later. The actual start and end dates of masonry block installation are identified (Fig. 3(13a)).

TABLE 3: Sample extracted RFID data and identified items

Timestamp	Tag ID	Antenna number	Item detected
2015-06-30 15:22:38.702	BDBD01FF1101000000020993	2	3rd Floor
2015-06-30 15:22:38.703	BDBD01FF1101000000020964	1	10 cm masonry block pallet
2015-06-30 15:22:38.718	BDBD01FF1101000000020913	1	15 cm masonry block pallet
2015-06-30 15:22:38.734	BDBD01FF1101000000020967	1	15 cm masonry block pallet
…	…	…	…
2015-06-30 15:45:37.921	BDBD01FF1101000000020939	1	10 cm masonry block pallet
2015-06-30 15:45:37.937	BDBD01FF1101000000020003	1	12.5 cm masonry block pallet
2015-06-30 15:45:37.953	BDBD01FF1101000000020891	1	12.5 cm masonry block pallet
2015-06-30 15:45:38.25	BDBD01FF1101000000020993	2	3rd Floor
2015-06-30 15:46:40.811	BDBD01FF1101000000020992	2	2nd Floor
2015-06-30 15:47:30.112	BDBD01FF1101000000020991	2	1st Floor
2015-06-30 15:47:30.828	BDBD01FF1101000000020990	2	Ground Floor

RFID data - data transformation (Fig. 3(10)) and data interpretation (Fig. 3(11)

3.3.3 Assessing the overall activity progress and performance

The overall activity progress was assessed individually for each floor that was monitored during the field experiments. The overall activity progress is determined by (1) considering the contribution of the each completed activity step to the overall activity completion (Fig. 3(14)), and (2) material usage percentage (Fig. 3(15)). Fig. 6 provides an example case that explains activity progress calculation in this approach.

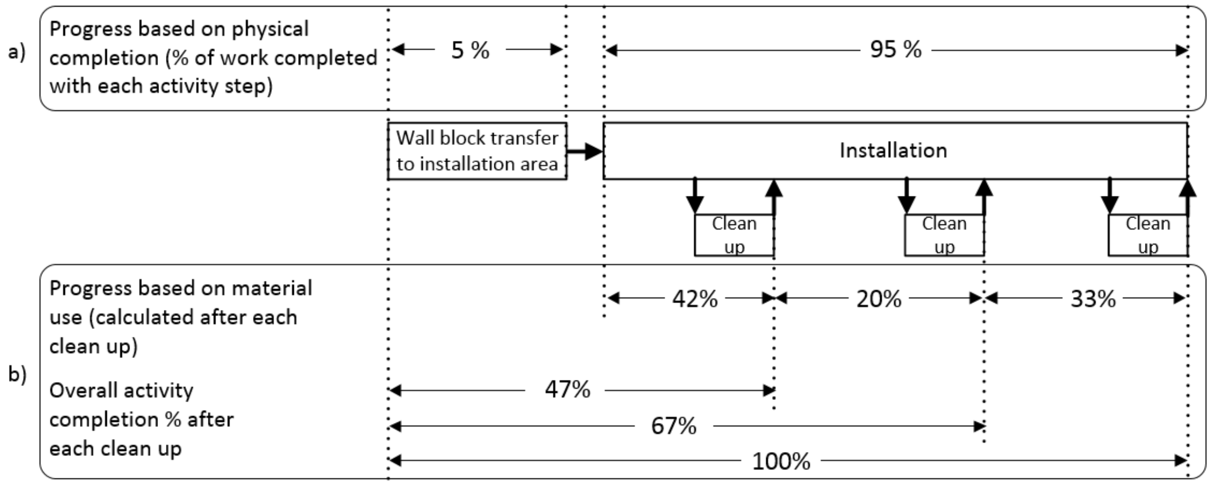

FIG. 6: Calculating the progress for a sample masonry case.

When the tower crane sensors identify that the transfer of concrete masonry block from the laydown area to the installation area was completed, 5% progress is assigned to the overall masonry work (Fig. 6(a)). The progress of the installation step is determined according to the material usage percentage, which is the proportion of the material utilized during wall production to the material transferred to the installation area. The amount of transferred material is determined by quantifying the amount of concrete masonry blocks transferred to a floor by crane (Fig. 3(7)). The utilized material is detected by tracking the empty pallets, which are carried to the ground floor via hoist during clean up of floor. The clean up was performed on a regular basis (e.g., three times in the example case) before the installation is fully completed (Fig. (6b)). During each clean up, the quantity of material utilized at the floor was determined via the RFID system on the hoist based on the number of identified pallets and wall block size, which are identified from the tag ID (Fig. 3(11b)). In the example case, the corresponding percentages of completed wall installation at each time the clean up was performed were calculated as 42%, 20% and 33%, respectively (Fig. (6b)). A cumulative percentage is also calculated for determining the completion of the masonry work at the end of each clean up as 47%, 67% and 100%, respectively.

The actual amount of work performed, and actual start and end dates for both the material transfer activity step, and the installation step are obtained through the processing of sensor-based data. The baseline data (i.e., budgeted quantity and planned dates) were obtained by manually extracting information from the human-generated documents, such as schedule and QTO spreadsheets (Fig. 3(16)). The actual dates and quantity information were compared with the baseline data (Fig. 3(17)) to evaluate the activity performance and to perform schedule updates and projections (Fig. 3(18)). Comparing the actual performance with the baseline data enables determining problems that might lead to delays.

3.4 Data fusion results

A physical prototype was developed and implemented at a construction site to track progress of masonry work by using the approach presented in this study. The test case conducted in this study faced some limitations regarding the implementation of the prototype. One limitation is that the hook position sensor that shows the depth of the crane hook was not available for data collection during the field tests. Therefore, the floor to which the concrete masonry blocks were transferred was obtained from the site reports. Another limitation of the prototype implementation was that during the construction of the related building, clean up of a floor was performed for once, at the end of the masonry work at each floor. Therefore, prototype was able to calculate a single progress percentage related to the installation work at each floor. Still, the results show that the percentage of completion identified was more accurate than the intuitive estimation that was being practiced at the experiment site. At the test site, it is assumed that masonry work at a floor will be completed within one week and 99% completion is assigned after a week unless there is a significant delay at the floor. In case of a delay, the site engineer enters a completion percentage, based on his/her own judgement.

For validation, the progress results retrieved from the field experiments were compared with the ground truth, which is based on on-site observations and daily site reports. Table 4 shows the results of progress estimation that are calculated for material delivery and wall installation steps of masonry work at eight floors of the test building. 5% progress, which indicates the completion of the material delivery step is correctly estimated at each floor. The average accuracy of the installation progress estimation is 95%. The accuracy of the overall progress estimation at each floor varies between 86-97%. For example, at the 20th floor, 87% of the installation is estimated to be complete, and the actual progress of the installation step (i.e., ground truth) is 90%. The overall progress estimation at the 20th floor is 92% while the actual progress (i.e., ground truth) is 95%, and the accuracy of the estimation is 97%. Some differences are observed between the estimated and actual progresses of installation since the progress is calculated based on material use (i.e., delivered vs. used). The utilized material includes waste during installation and also about 5-10% of the delivered material is used for finishing works that are performed later. Therefore, a slight difference between the estimated and actual progress was expected. Table 4 summarizes the results for all the building floors and details of the field experiments are provided in Guven (2016) and Guven and Ergen (2017a, 2017b).

By comparing the actual dates with the planned dates, the performance of the masonry work was detected. For example, the tower crane sensors correctly detected that the material delivery step was started and completed on the 13th of April. The planned date for this activity was 19th of March in the baseline schedule. By comparing the actual and planned dates, it is identified that there is almost one-month delay for the delivery of masonry block at the 20th floor, and the masonry work is completed in nine days instead of eight days, which was estimated productivity in the baseline schedule.

TABLE 4: Data fusion results for the actual progress of masonry work at the test building

Floor	Progress of material delivery step		Planned vs. actual dates of material delivery step		Progress of installation step			Planned vs. actual dates of installation step		Overall progress of masonry work		
	Est.	Actual	Planned	Actual	Est.	Actual	Accuracy	Planned	Actual	Est.	Actual	Accuracy
20	5%	5%	03/19	04/13	87%	90%	97%	03/21-29	04/15-24	92%	95%	97%
21	5%	5%	03/28	04/24	93%	94%	99%	03/30-04/07	04/25-05/01	98%	99%	99%
22	5%	5%	04/06	04/26	95%	90%	94%	04/08-16	05/02-05/10	100%	95%	95%
23	5%	5%	04/15	05/06	87%	89%	98%	04/17-25	05/11-20	92%	94%	98%
24	5%	5%	04/24	05/13	65%	76%	86%	04/26-05/04	05/21-28	70%	81%	86%
25	5%	5%	05/03	05/17	85%	91%	93%	05/05-13	05/29-06/06	90%	96%	94%
26	5%	5%	05/12	05/22	88%	90%	98%	05/14-22	06/07-17	93%	95%	98%
27	5%	5%	05/21	05/29	85%	89%	96%	05/23-31	06/18-28	90%	94%	96%
Ave.	-	-	-	-	86%	89%	95%	-	-	91%	94%	95%

4. CONCLUSIONS

This paper presents an automated data fusion approach that incorporates domain-specific heuristics for monitoring the progress of activities by tracking the construction equipment and bulk material in residential projects with sensor-based technologies. Domain-specific heuristics include method used for completing a particular activity and precedence relation of the activity steps. To address the fusion of data sources that provide data at succeeding time frames, initial observations were performed at site and domain-specific heuristics was incorporated in the developed approach. The developed approach aimed to be cost-effective and to have minimal interference with the existing workflows to enable fast adoption. Therefore, only the major equipment and bulk material that are relatively less in number were proposed to be tracked.

The main contribution of this study is the rule-based reasoning algorithms and data fusion approach, which includes data extraction, data transformation and data interpretation for identifying each activity step and for gathering information related to each step. The derived information from sensors throughout the consecutive steps of the activity were integrated to determine the overall progress of that activity and to evaluate its performance. Although the domain-specific information and rules were developed based on the observations at a site (e.g., how the crane operates, how the production is made); most of them are not specific to this construction site since they represent the typical practice at sites. Therefore, the defined rules can be used to determine the progress of masonry work or other types of work that use the same resources (i.e., crane and bulk materials) by incorporating some site specific details (e.g., thresholds) where necessary. The applicability of the developed rule-based approach was also demonstrated in tracking the progress of rebar installation at a residential building construction (Guven and Ergen, 2017a).

The results demonstrate that the developed approach is successful in monitoring progress of masonry work, which was performed during the day and night shifts. The developed approach enables automated and up-to-date progress estimation and eliminates the need for site observations and manual data collection from field for progress measuring and performance evaluation. The domain-specific heuristics defined for masonry work and the rules created based on crane and hoist operation approach represent the typical work practice and can be used to track other construction activities, in which similar major equipment are used. The developed approach can be applied to activity monitoring at prefabrication or steel construction sites since activities at such sites are performed in a repetitive manner, creating favourable conditions for tracking equipment.

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