Data-Fusion Approaches and Applications for Construction Engineering

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Abstract: Data fusion can be defined as the process of combining data or information for estimating the state of an entity. Data fusion is a multidisciplinary field that has several benefits, such as enhancing the confidence, improving reliability, and reducing ambiguity of measurements for estimating the state of entities in engineering systems. It can also enhance completeness of fused data that may be required for estimating the state of engineering systems. Data fusion has been applied to different fields, such as robotics, automation, and intelligent systems. This paper reviews some examples of recent applications of data fusion in civil engineering and presents some of the potential benefits of using data fusion in civil engineering. **DOI: 10.1061/(ASCE)CO.1943-7862.0000287.**

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Introduction

Data fusion is a multidisciplinary research area that borrows ideas from many diverse fields, such as signal processing, information theory, statistical estimation and inference, and artificial intelligence. Data fusion is the process of combining data or information to estimate the state of an entity (Steinberg and Bowman 2001). In most cases, the state of an entity refers to a physical state, such as identity, location, or motion over time (Khaleghi et al. 2009). The human brain is the best example of data fusion in action. The initial U.S. Joint Directors of Laboratories (JDL) Data Fusion Lexicon defines data fusion as

> A process dealing with the association, correlation, and combination of data and information from single and multiple sources to achieve refined position and identity estimates, and complete and timely assessments of situations and threats, and their significance. The process is characterized by continuous refinements of its estimates and assessments, and evaluation of the need for additional sources, or modification of the process itself, to achieve improved results (White 1987).

Performing data fusion has several general advantages, the most important of which are to enhance the confidence and therefore the reliability of measurements, improve detection by extending spatial and temporal coverage, and reduce data ambiguity (Waltz 1986). Data fusion can also provide specific benefits for certain application areas. For example, sensor networks are often composed of a large number of sensor nodes that pose a new scalability challenge caused by potential transmission and collisions of redundant data. Additionally, energy restrictions result from the fact that communication should be reduced to increase the lifetime of the sensor nodes. When data fusion is performed during the routing process—that is, sensor data is fused and only the result is forwarded—the number of messages is reduced, collisions are avoided, and energy is saved.

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Data-fusion systems can be studied from several perspectives. Forbes and Boudjemaa (2004) presented a taxonomy for fusion types according to which aspect of the system is fused:

- Sensor fusion: In this case, a number of sensors measure the same property that can be fused to form more reliable and accurate information about the phenomenon under observation.
- Attribute fusion: A number of sensors measure different attributes of the same experimental situation.
- Fusion across domains: A number of sensors measure the same attribute over a specific number of domains or ranges.
- Fusion across time: For a more accurate determination, historical information about the system from, for example, an earlier calibration, is fused with the current measurement.

Currently, data-fusion applications span a very wide domain, including military and nonmilitary applications. These applications attack a broad range of problems. The application domain can be categorized based on several aspects, such as data-fusion purpose, sensing environment, sensor platform, or primary observable data. In a classification by Yick et al. (2008) for application in wireless sensor networks, categories include monitoring and tracking. Monitoring applications comprise indoor/outdoor environmental monitoring, traffic monitoring, security systems, health and wellness monitoring, disaster prevention and relief, asset monitoring and management, power monitoring, inventory monitoring, medical diagnoses, factory and process automation, and condition monitoring and maintenance of infrastructure. Localization and target tracking applications include tracking objects, animals, people, and vehicles; disaster relief; law enforcement; and ocean surveillance.

This paper presents a review of some recent applications of data fusion in civil engineering. The first example is an automated materials tracking and locating tool for construction sites that aims to improve material distribution and project performance. Next, we present a hybrid data-fusion model for tracking on-site materials, and we present a methodology for automating the identification and localization of engineered components. Following that, we introduce an automated remote sensing technique developed to provide critical information for analyzing site operations and improving decision-making. Our fourth example presents a framework that applies visual data fusion for object recognition and reconstruction in construction venues. The fifth example introduces a data-fusion approach for rapid construction productivity analysis and continual assessment of construction productivity. Finally, we introduce Sensor Andrew as a possible approach for integrating isolated monitoring and control devices in a common infrastructure.

Data Fusion for On-Site Materials Tracking in Construction

Effective automated tracking and locating of thousands of materials on construction sites improves material distribution and project performance and thus has a significant positive impact on construction productivity. Many locating technologies and data sources have been developed (Caldas et al. 2006; Ergen et al. 2007; Goodrum et al. 2006; Grau and Caldas 2009; Jang et al. 2007; Razavi et al. 2008; Song et al. 2006; Teizer et al. 2008), and the deployment of a cost-effective, scalable, and easy-to-implement materials location sensing system at actual construction sites very recently has become both technically and economically feasible.

Using location sensing technologies such as radio-frequency identification (RFID), global positioning system (GPS), ultra-wideband (UWB), infrared, and others generally provides imperfect acquired data; that is, data that is uncertain, incomplete, imprecise, inconsistent, and ambiguous. A considerable opportunity still exists to solve this problem and improve the accuracy, precision, and robustness of such systems. In general, there are five major frameworks for dealing with the data imperfection: probabilistic, evidential belief reasoning, soft computing, optimization-based, and hybrid. In a research study by Razavi and Haas (2010, 2011), a data-fusion model is used on an integrated solution for automated identification, location estimation, and dislocation detection of construction materials. The developed model is a modified functional data-fusion model based on the JDL model (Fig. 1).

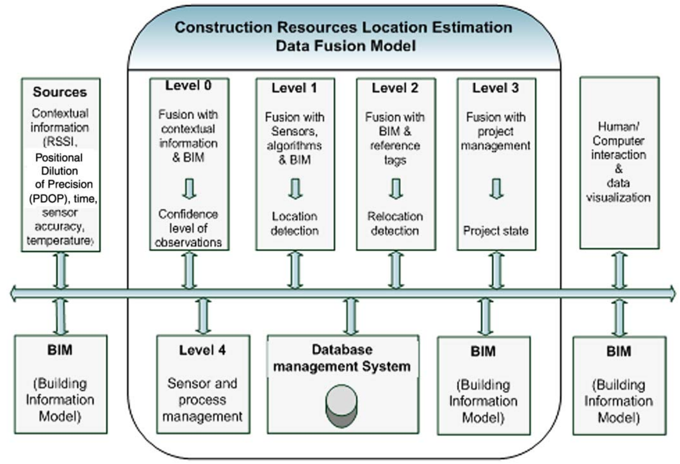

Fig. 1. Data-fusion model for construction resource location tracking

In this data-fusion model, attention is focused in particular on dislocation detection because it is closely coupled with location estimation and because it can be used to detect multihandling of materials. Multihandling is a key indicator of inefficiency. In this model, a hybrid data-fusion method was developed to incorporate other sources of information and to increase confidence, achieve more location estimation accuracy and precision, and add robustness to measurement estimates. This hybrid method leverages evidential belief reasoning and soft computing techniques. The experimental results show that the hybrid fusion method outperforms the traditional methods of data fusion for location estimation. The results presented in this study indicate a potential for the proposed method to improve location estimation and be robust to measurement noise and future advances in technology.

Methodology for Automating Identification and Localization of Engineered Components

The methodology for automating the identification and localization of engineered components proposed by Grau and Caldas (2009) includes a data collection and fusion module to manage and integrate the positioning and identification sensors. First, this module stores in a relational database the data collected by the GPS and RFID receivers. When used together, the receivers are synchronized so that their data can be fused based on identical time stamps. At a predefined interval—say, for instance, every 1 s—the GPS receiver determines its own position. Centered on this position, the RFID receiver simultaneously scans the surrounding area and detects the present tags. For a particular time frame, a new set of data is created for each unique tag code, along with the coordinates of the receivers. These time series of data records are stored in a relational database.

Second, this module provides basic GPS functions, such as differential correction, control on the satellite geometry, and coordinated transformation of the generated positions. To ensure

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the best positioning accuracy from the collected data, this module enables differential correction of the raw GPS positions, and it establishes the minimum geometric parameters among the relative position of the satellites above the receiver. Uncorrected GPS data have an intrinsic error usually greater than 10 m. This large deviation alone would introduce a high degree of inaccuracy within the location results. A wide area augmentation system (WAAS) type of differential correction was implemented to obtain precise GPS positions in real time. In addition to this differential correction, we established the definition of a minimum number and relative position of the emitting satellites to decrease the positioning error. Combining differential corrections with these requirements on the number and relative geometry of the satellites usually resulted in accuracies that were greater than 1 m. In any case, this module alternatively could limit the collection of GPS positions to those with an estimated accuracy greater than 1 m at all times.

The GPS receiver was also set up to transform the collected positions into a projected coordinate system. For the purposes of this study, the receiver-default longitude and latitude coordinates from the global World Geodetic System (WGS) 1984 were transformed into the Central Texas Projection of the State Plane Coordinate System, according to the North American Datum (NAD) 1983, in three Cartesian axes (x, y, and z). In this case, only the coordinates corresponding to the horizontal axes (x, y) were considered. This transformation from a global coordinated system into a local projected system simplified the implementation of the localization algorithms by providing coordinates in fundamental units of length, such as meters. Additionally, this transformation results in a more precise GPS position than those of a global reference because the local projected system was specifically designed for the region in which the framework was to be used.

Finally, this module also enabled the control of the RFID receiver functions. It modulates the emitting power of the RFID receiver, which reflects on the RFID communication range. Strong signals from the reader can activate remotely placed tags that can respond to the reader. Thus, strong reader signals can identify the maximum number of tagged components for a given time frame and roving pattern. For this reason, they are preferred because they minimize the time and effort required for collecting field data. Additionally, the scanning time of the RFID receiver can be adjusted to the maximum number of tagged components expected on a single scan; i.e., a great number of components require relatively long scanning times, whereas a lesser number of components require relatively short scanning times and will eventually result in more frequent scans.

Automated Remote Sensing Techniques for Site Operations Analysis

Research at the Real-time Automated Project Information and Decision Systems (RAPIDS) and Intelligent Vision and Automation Lab (IVA) laboratories at the Georgia Institute of Technology seeks to demonstrate and validate reliable localization of construction resources (personnel, equipment, and materials). One of the research plans consists of two major components: (1) the derivation of algorithms suited to tracking personnel, equipment, and machines; and (2) the validation and analysis of the algorithm outputs relating to activities or work packages.

The intent behind such monitoring and analysis is to automatically provide critical information on construction operations for improved decision making in construction engineering and management. The information obtained from such an automated system generates knowledge about worksite operations. In an information-based framework, much effort is spent acquiring and interpreting information. In a knowledge-based framework, efforts are allocated to making decisions based on the interpreted information. If successful, the transformation of the review of construction operations from information-based to knowledge-based can redirect significant human resources efforts and improve decision effectiveness.

Tracking techniques have been applied to document or track worksite operations in recent years. Existing and emerging (near) real-time location tracking technologies such as GPS, active or passive RFID, UWB, Robotic Total Station (RTS), laser and optical scanning, visual sensing, and other remote sensing technologies have distinct advantages, but they also carry limitations that prevent ubiquitous use in all construction engineering applications. Low-level data fusion and the tight integration of multiple raw data sets can yield more efficient and eventually more accurate raw data sets that can then be used to achieve inferences.

Most performance evaluation methods of raw data, however, are based on manually generated ground truth for relatively short sequences and for mostly single objects, thus excluding longer-term scenarios and spatially relevant evaluation methods for multiple objects as they relate to construction applications. A preliminary goal of this research was to examine the trajectories arising from a machine-learning–based visual tracking algorithm. Because vision tracking provides a cost-effective means to observe large construction environments, it is of interest to investigate its performance for tracking multiple objects (Teizer and Vela 2009).

We used two spatial tracking technologies to verify the visual tracking algorithm's accuracy. The zone of interest satisfies a ground plane assumption. The two technologies that form the ground truth for comparison are an RTS and a UWB system. For comparison, the visual tracking signal is projected to world coordinates with a calibrated camera model. RTS and UWB signals are filtered to remove outliers, and they are synchronized with the visual tracking signal.

A limited proof-of-concept study recorded the trajectories of five workers in a controlled construction setting using vision, UWB, and RTS sensing. A 1-in. reflectorless RTS was used to track a single resource (see Fig. 2). High-frequency [greater than 4 hertz (Hz)] time-of-flight distance measurements from the RTS to a small miniprism (installed on the target object) provided the ground truth measurement. Comparisons of time-stamped tracking locations generated by RTS and video were recorded. To track the ground truth of multiple resources in real time (at the same update

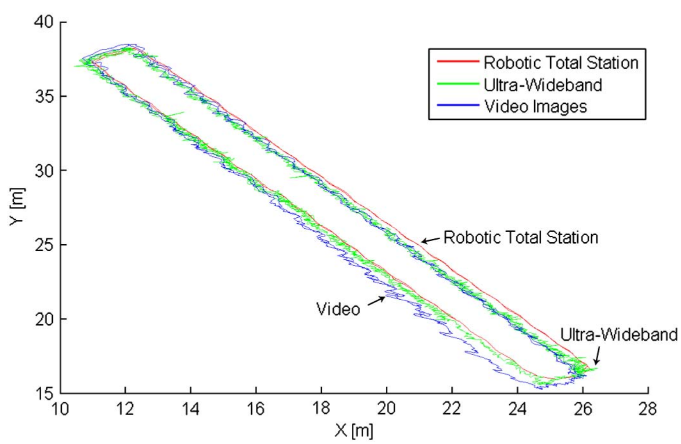

Fig. 2. Process of geospatially referencing trajectory data of Robotic Total Station (ground truth), ultra-wideband, and video

rate as the vision cameras), each construction person carried at least one UWB tag on his or her helmet, whereas pieces of construction equipment might carry a minimum of four UWB high-frequency tags to track position and orientation.

The error analysis of all tracking signals validates the hypothesis that a calibrated visual tracking system can be reliable and accurate when tracking multiple interacting people. Positioning errors of less than 0.5 m were achieved using a data-fusion approach that validates vision data. Many research questions remain to be addressed, for example, (1) what technologies can be used for ground truth measurements to validate vision-based algorithms, (2) what are underlying and standardized experimental characteristics to track multiple resources with low error rates, and (3) how are data sets from multiple emerging technologies fused and compared?

As these preliminary results indicate, existing barriers for implementing technology in construction, including data-fusion principles, are less a financial than a technical matter. Camera technology, like other remote sensing technology, comes with various benefits and barriers, but in recent years it has enjoyed more widespread application for the remote monitoring of construction site activities. The biggest barrier for many of these sensors typically is not their hardware, but the algorithms that process data efficiently and effectively. As many researchers and practitioners indicate, technology has an impact on industry practices only if it can demonstrate solutions to complex problems in an easy and understandable manner, so that people can use information rapidly rather than dealing with additional large data sets. Thus, sensor and data fusion plays a significant role in overcoming the shortcomings of individual hardware and data processing technology. As sophisticated data processing algorithms are being developed that link technology to specific construction applications, multiple engineering or management tasks—including progress monitoring, work sampling, safety, and security—can be semiautomatically or automatically assessed or controlled.

Visual Data Fusion for Object Recognition and Reconstruction in Construction

Visual data fusion can be performed at two levels. In the preliminary level, image features, such as color, texture, edge, and local scale/affine-invariant points, are extracted from single image/video frame and then combined for addressing the issues related to two-dimensional (2D) object recognition. In the second level, the image features are retrieved from multiple images/video frames, and they are matched to address the issues related to three-dimensional (3D) object reconstruction.

As for the combination of image features from single image/video frame, Brilakis et al. (2006) developed a method of retrieving material information in an image using the concept of material "signature." In this method, an image is first cropped into regions using bottom-up clustering methods. The signature of each image region is then calculated and is represented by a combination of the mean and the standard deviation of the region's color and texture values (i.e., intensity; normalized red, green, and blue; and six-response values to bank filters). This signature is compared with the signatures of material samples stored in a material knowledge database by measuring their Euclidean distances. If the distance of the region's signature compared to that of one material sample is smaller than a predefined threshold, that region is assumed to contain that material. For example, if the signature of one image region is matched to that of a concrete sample in the database, it assumes that the material contained in the region is concrete.

Extending from the material recognition, Zhu and Brilakis (2010) proposed a method of recognizing concrete columns in visual data by combining columns' boundary and material information. The method starts by extracting long vertical lines in visual data using edge-detection techniques and Hough transform. The bounding rectangle of each pair of long vertical lines is then formed. If the resulting rectangle resembles the shape of a column (i.e., the rectangle's width is smaller than its length), and if the color/texture contained in the rectangle are matched to that of concrete samples stored in a knowledge base, the region between the pair of lines is assumed to be a concrete column surface. In this way, a concrete column in an image/video frame can be detected.

The idea of combining material information and shape information can also be applied in other areas, such as defects detection. An example is in detecting potholes in a pavement image. First, a gray-scale pavement image is segmented into dark and brighter regions by using a histogram-based thresholding method. Assuming a dark curved region represents the shadow at the partial border of a pothole, it approximates the elliptic pothole shape using thinning and elliptic regression methods. Subsequently, the surface signature of the elliptic region is calculated and represented by a feature vector of color and texture information. This signature is then compared with the signatures of the outer neighboring regions. If the difference exceeds a predefined measure, it is assumed that the determined elliptic region represents a pothole.

When the features from multiple images/video frames are combined, the information related to camera parameters (e.g., position, orientation, and focal length) and 3D properties of an object can be retrieved. For example, the intrinsic and extrinsic properties of a camera can be determined from eight pairs of points when the 2D positions of these points in any two images captured by the camera are correspondingly matched.

Once the 2D positions of project-related entities (for example, workers or wheel loaders) are obtained and matched in different camera video frames, the real 3D coordinates of the entities in the scene can be calculated by triangulating those frames pairwise. Potentially, the method can automatically track a great number of entities at a construction site by using only a limited number of cameras. This facilitates construction management tasks such as productivity measurement, site safety enhancement, and activity sequence analysis. Moreover, when the 2D points are not limited to single objects in views but encompass the whole scene, a dense depth map of the scene can be calculated and represented as 3D point clouds.

Video Interpretation Methodology for Rapid Productivity Analysis

An essential component of the video interpretation methodology for rapid productivity analysis for construction operations proposed by Gong and Caldas (2009) is model-based reasoning. It is the essential process of converting observed information into productivity information that is of interest to site management. Humans, if trained, can conduct these information extraction tasks with remarkable ease. However, to expect such processes to be conducted autonomously by computers, humanlike reasoning must occur in explicit steps. Fusing video streams data and domain knowledge data is a critical component of the proposed methodology.

A three-step computer reasoning process was formally defined to imitate human reasoning processes, as if the videos were being analyzed by human experts. These steps are (1) state classification, (2) event detection, and (3) scenario recognition. These three core concepts must be clearly defined and understood. They involve

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domain-specific knowledge, requiring definitions within the domain context. In this study, they were defined in the following manner:

1. States: this refers to the object status in predetermined categories, such as "waiting," "idle," and "working."
2. Events: this refers to a significant change of states, such as "waiting → working" and "working → idle."
3. Scenarios: this refers to a semantically meaningful situation formed by a particular combination of states and events, such as "delay caused by working process violation" and "delay caused by waiting."

Using these definitions, the three reasoning steps were engineered to derive particular types of productivity information, whether that information was state classification for resource use, event detection for work flow, or scenario recognition for abnormal production scenarios.

The process of recognizing objects and inferring their properties for state classification is the backbone of the proposed methodology. Having a computer implement such a complex process is a great challenge. While we searched for a set of computer vision methods that would support this process, it was imperative that we understood the type of information needed for state classification, so that corresponding computer vision methods could be identified.

The working state of an object, which in this case is a particular type of construction resource, is often indicated by its position, moving trajectory, and kind of motion. These properties offer insights, at different levels of detail, into the working status of objects. However, extracting these properties also involves different layers of complexity. Determining the object's position can be accomplished using object detection. To determine the trajectory of objects, one needs to continuously track their positions. The tracking problem is trivial when only one object is tracked. However, in a scenario in which multiple objects require tracking—in particular when the objects are in the same category—tracking can become a very difficult problem. This is also true when detecting and representing the motion of objects. In most cases, though, motion is only meaningful for objects that can change shape, such as construction workers and certain types of construction equipment, so it is not always necessary to go beyond the level of trajectory to analyze the working state of every object. In some cases, the instantaneous position data of objects alone, without correspondence from frame to frame, can indicate their working status. This is particularly true in cases in which the aim of operation analysis is merely to acquire a quick appraisal of effective working time. In addition, explicit tracking of "objects" such as construction workers may cause ethical problems. Overall, the level of detail should conform to the specific objective of operation analysis.

Fig. 3 depicts the proposed classification structure. The methods include object detection (positional data), object tracking (trajectory data), and motion detection and analysis (motion data). In essence, a system of support algorithms in each of these categories was needed to compute video streams into an intermediate level of data (object layer) to support high-level reasoning steps.

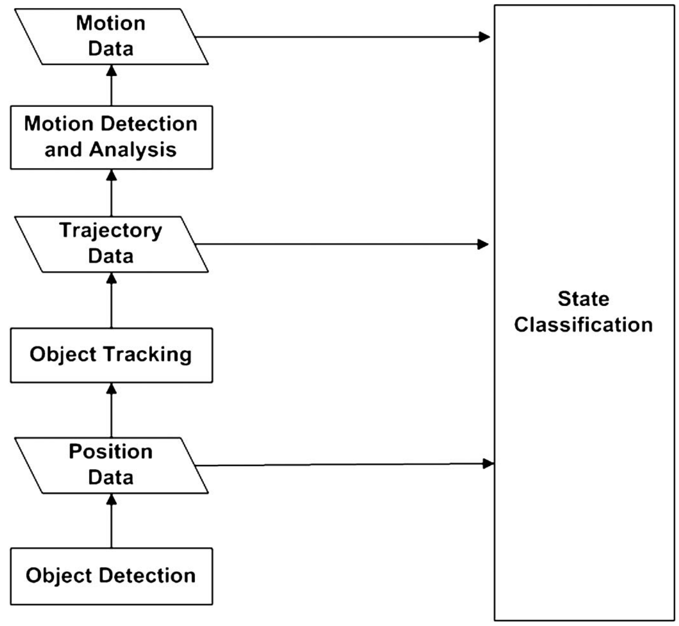

Fig. 3. State classification schema

Data Fusion and Integration for Supporting Continual Construction Productivity Assessment

The required information items for measuring and assessing construction productivity were identified by reviewing literature (Kannan 1999; Kiziltas 2008) and by applying different scenarios. Among the information requirements that were identified for assessing earth-moving productivity are observations of percentage complete for each task, expended labor hours, baseline labor hour budget for each task, average duration that a truck spends in different sections of the hauling road, soil characteristics (percentage of swell, soil density), average hauler waiting times, and weather conditions.

Different data-capture technologies were then selected to acquire the information items based on analysis of the different scenarios and the reviewed literature (Navon et al. 2004; El-Omari and Moselhi 2009; Kannan 1999; Oloufa et al. 2003). The selected data-capture technologies include GPS, on-board instrumentation (OBI), RFID, laser scanner, and video cameras, among others. We also took advantage of general data sources such as weather databases, soil databases, and industry standards (RSMeans).

To support continuous construction productivity assessment, the data should be continually collected and streamed for productivity assessment purposes. The selected data-capture technologies have different processing and communication requirements. Moreover, some of the selected data-capture technologies, such as video cameras and laser scanners, can produce great amounts of data.

IBM has created a large-scale distributed stream processing middleware (Gedik et al. 2008) called InfoSphere Streams/System S for real-time fusing, integrating, and analyzing large amounts of data. The focus on real-time analytic processing (compared with online analytical processing and online transaction processing) as the next generation of business intelligence solutions has led IBM to develop this platform. InfoSphere Streams is capable of processing structured and unstructured data streams (Gedik et al. 2008).

InfoSphere Streams/System S uses Stream Processing Application Declarative Engine (SPADE) as the front-end medium (Gedik 2008). SPADE is composed of an intermediate language, a toolkit of type-generic stream processing operators, and a set of adapters to digest data from different external sources and to publish data to various external sources (Gedik 2008). Reliability, scheduling optimization, distributed job management, and security are among the specifications of InfoSphere Streams (Gedik 2008).

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Data acquired from the selected data-capture technologies have different representations, quality, reference points, and levels of detail. The research team is currently developing the appropriate fusion plans to support construction productivity assessment based on work developed by Pradhan (2009). Pradhan identified transformation and merging operations for fusing data from multiple sources to support different queries of construction project team members. This is the framework used for the transformation and merging operations being developed to support construction productivity assessment.

Sensor Andrew: Integrating Isolated Monitoring and Control Devices in Common Infrastructure

Scaling technology has enabled computing devices to be embedded everywhere and in everything. As a collective, these devices promise unprecedented new abilities to observe and understand large-scale phenomena at a fine spatiotemporal resolution (Chen-Ritzo et al. 2009). Many problems in the building and construction industry benefit from this type of distributed monitoring approach, as shown in the previous sections of this paper. Managing our aging physical infrastructure (e.g., buildings, roadways, water/power distribution systems, and so on) requires that we continuously monitor and control different components distributed across large areas (e.g., neighborhoods, cities), and over a long period (e.g., years or decades). Similarly automated construction productivity analysis tasks require integrating different technologies (RFID, laser scanners, GPS, and so on).

To achieve this, a research team at Carnegie Mellon University has been developing Sensor Andrew (Rowe et al. 2011), a collection of hardware and software elements that together form a virtual instrument for large-scale sensing and actuation. This type of system enables engineers, operators, and facility managers to tap easily into an Internet-scale resource of sensors and actuators in a manner that is extensible, easy to use, and secure, but that maintains privacy.

Given the complexity of the system, it would not have been feasible to design every component of Sensor Andrew from scratch. The research team used existing technologies wherever possible, and it has innovated design whenever necessary. This allowed the team to develop a small-scale implementation of the system that provides basic functionality. Sensor Andrew provides the following five services: (1) uniform access to heterogeneous devices, (2) sharing of transducers across applications, (3) scaling to many devices, (4) integrating many currently isolated subsystems, and (5) protecting the security and privacy of data. Uniform access to devices is achieved using self-describing data objects defined by a transducer schema. Sharing transducer information across applications is achieved through a publish-subscribe software layer based on the Extensible Messaging and Presence Protocol (XMPP) (2010). Scalability is achieved through use of encapsulated addressing. Each device in the system is addressed with a unique name, server address, and namespace attribute. Integrating subsystems is possible through a standardized communication mechanism, with software adapters providing the last link of translation. Lastly, security and privacy are achieved through encryption, key management, access control, and policy.

The richness of sensors and actuators in the construction industry will only continue to increase with the convenience of emerging wireless sensor networks and low-cost embedded computers. Sensor Andrew leverages these technologies, then streamlines access to data and simplifies the process of adding, archiving, and discovering new sources of information. Rowe et al. (2011) describe additional details of an application built using the Sensor Andrew infrastructure, in this case for integrating different sensors and actuators in a residential building and for performing energy management tasks.

Conclusion

Data fusion is a multidisciplinary research field with a wide range of potential applications in areas such as robotics, automation, intelligent systems, and others. Interest in this field of research has steadily increased, driven by its resourcefulness and vast applications areas. This paper presents a review on some recent applications of data fusion in civil engineering. Civil engineering systems benefit from data fusion by enhancing confidence, improving system reliability, reducing ambiguity, improving detection, extending spatial and temporal coverage in sensing systems, and increasing dimensionality.

Some of the emerging research areas for data fusion in civil engineering include data fusion for large-scale sensor networks, data integrity and security, hybrid data-fusion methods to address different aspects of data imperfection, and data-fusion evaluation frameworks.

The challenges and barriers in bridging the gap between academic research and industry practices in this area include the following:

- Different fusion levels are not well-connected, fully understood, or well-integrated into conventional project management systems.
- The efforts of mobilizing and demobilizing the technology in real construction practices are underestimated.
- A need exists to clarify the distinction among the different viewpoints for data fusion in the new application area of construction engineering and management. Some of these viewpoints are:
  - *a.* knowledge-based studies that manage the information, algorithms, and databases;
  - *b.* fusion of different sources of data that covers the field data acquisition perspective; and
  - *c.* communication among different layers of data, data sources, people, and existing communication protocols (transferring the technology from conceptual ideas to marketable products is another challenge).
- Issues related to the data to be fused include data uncertainty, conflicting data, data correlation, spurious data, and information overload because of the large amount of input data. These types of challenges are even more in the multimodal nature of construction practices with the high ratio of noise and dynamics of such sites.
- We must deal with the reactions of a workforce to the intrusiveness of sensors (in multisensor data fusion) and with ethical issues.
- A growing volume of research in data fusion may lead to the reinvention of existing techniques or duplication of effort.

Implementing these technologies depends on aspects related to cost-benefit analysis, technical feasibility, technology usage, and technology impact. A cost-benefit analysis typically involves ensuring the following:

- Technology costs are within the project's budget;
- An economic analysis has been adequately performed;
- Potential exists for reducing project costs; improving safety, project quality, and quality of information; and/or reducing project duration;
- A documented case study of the technology's benefit exists; and

- Positive, statistical evidence of technology's benefit exists.

Technical feasibility examines criteria related to the technology's maturity, its compatibility with current technologies, and the risks associated with implementing it because of issues such as the technology vendor's standing in the industry and existing technological standards.

The technology usage issues relate to factors surrounding the likelihood that the technology will be used. Important aspects of these factors include:

- Perceived ease of use,
- Perceived usefulness,
- Incentive for using the technology,
- Goodness of fit between the project's needs and engineering's needs, and
- Goodness of fit between the project's needs and the workforce's needs.

Last, technology impact deals with specific technology characteristics that have been found to directly influence construction productivity, such as the capability of supporting the integration and automation of work functions.

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