A Review of Linear Transportation Construction Progress Monitoring Techniques

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Abstract:

Effective construction progress monitoring allows schedule and/or cost deviations to be identified early enough to implement corrective actions and avoid contract disputes. Current approaches are not accurate, consistent, reliable, or timely enough to enable effective project control decisions. This is, in part, the reason for an estimated $82.6 billion in global transportation project cost overruns each year. Recent studies have leveraged 4D Building Information Models (BIM) to automate the detection of as-planned components in as-built data; a crucial step in automating progress monitoring. However, the scope of these studies has been limited to mostly building construction components at the major activity level (e.g. columns, beams, foundations, walls, etc.). This paper presents a qualitative synthesis of the state-of-the-art in automated progress monitoring practice and research, focusing on approaches relevant to linear transportation projects. The literature is grouped into four broad categories: (1) image processing methods, (2) point cloud processing methods, (3) indirect methods, and (4) transportation and earthwork specific studies. Gaps in knowledge are identified for future research opportunities. It is concluded that more research is needed to propose feasible methods for automating progress monitoring on transportation projects.

Keywords: 4D, CIM, Progress Monitoring, Automation, Transportation.

1. INTRODUCTION

Transportation construction was a $370 billion industry in 2014 (Business Monitor International, 2014). Despite this huge capital investment, reliance on public funding and the social and economic importance of these projects, they consistently underperform in terms of cost and schedule. A global study (Flyvbjerg et al., 2003) of 258 transportation infrastructure projects in 20 nations found that almost 9 in 10 projects experience cost escalation. Twelve years later, (Salling & Leleur, 2015) analyzed transportation project data collected in Great Britain, Denmark, Sweden, and Norway and determined that 77% of road and rail projects experience cost overruns averaging 29%. Poor performance in this sector persists despite a number of technological advances in construction and equipment in the years between these studies. Analyzing the numbers, it can be argued that there is roughly $82.6 billion in annual cost overrun on transportation construction projects worldwide ($\$370\text{B} \times 77\% \times 29\%$). Over forty studies and audits (Siemiatycki, 2009) identified up to 83 different causes of construction cost and/or schedule overrun. Ultimately, core construction management functions like planning, control, and scheduling are the most important contributing factors (González et al., 2014).

Effective project control requires two pieces of information: (1) the plan, and (2) measurement of the actual performance (Del Pico, 2013). The overall process can be divided into four stages: (1) the collection of as-built data, (2) processing of the data into the form required for analysis, (3) comparison with the plan (or "as-planned") state of the project, and (4) implementation of management actions. Progress monitoring encompasses the first three steps, the automation of which is the best way to economically achieve effective real-time project control. This paper reviews the various methods currently used for accomplishing progress monitoring. Recent research efforts aimed at automating progress measurement are then summarized. Improvements to the state of practice are acknowledged, and further opportunities for improvement (gaps in knowledge) are highlighted.

2. CURRENT PRACTICE

Progress assessments can range from informal reviews, such as viewing photographs and notes in a field book, to highly detailed formal assessments, such as full topographic surveys depending on the contract requirements and project management style. The type of data collected to support these progress monitoring methods allows us to split the current practice into two broad categories: non-spatial and spatial.

2.1 Non-Spatial Progress Monitoring

Non-spatial progress monitoring is characterized by frequent manual checklist and text-based data collection methods that are time consuming and labor-intensive. There is no physical measurement of overall progress for the project; no spatial comparison of components that are supposed to be complete. This approach relies on the experience, training, and subjective assessment of the inspectors. Typically, non-spatial progress data collection is performed on a daily basis. Methods include paper or handheld-computer-based electronic checklists and reports, verbal updates from onsite personnel, site photographs, material delivery receipts, inventory reports, and contractor invoices (Del Pico, 2013). The raw data is then manually processed, typically by summarizing and entering the various forms of data into project management software and/or spreadsheets, and updating two-dimensional (2D) plans and work schedules. Regular coordination meetings involving key project participants help to facilitate the collection and processing of as-built data. Formal progress status reports are then prepared at regular intervals, most typically weekly. The result of the progress assessment process is a percent-complete determination for individual activities, work packages comprised of multiple activities, and/or the entire project using weighted ratios of the in-progress activities and work packages (Del Pico, 2013).

Non-spatial progress assessment methods are widespread but error-prone, inconsistent, and create a large workload for project managers. One study (Moore et al., 2001) documented error rates as high as 78% for visual inspection of transportation assets. Additionally, 30-50% of a project manager’s time is spent processing and analyzing progress data (Navon & Sacks, 2007). This excessive workload leads to further errors, as management teams rush to synthesize data and make effective project control decisions in a timely manner. Finally, the long data collection, processing, analysis, and reporting cycle (Del Pico, 2013) often means that project control measures are not implemented quickly enough to impact current operations. The need for more accurate, consistent, and timely progress monitoring methods is well-documented in literature and in practice.

2.2 Spatial Progress Monitoring

Spatial progress monitoring involves measuring physical objects readily observed on site. The volumes, areas and/or distances that form the basis of the analysis are then calculated and compared with the corresponding values in the schedule to determine project status. For linear transportation projects, the objects measured are most typically terrain and constructed surfaces (pavements, base courses, curbs, drainage ditches, etc.). Tools for collecting data can range from simple handheld tape measures to highly-accurate laser scanners that produce dense point clouds. The scale of most transportation projects dictates the use of methods capable of surveying large areas to a reasonable level of accuracy, depending on the design and quality control specifications. The most common tools used are Total Stations, Global Navigation Satellite System (GNSS) receivers, Light Detection and Ranging (LiDAR) scanners, and Photogrammetry. Additionally, new technologies like mobile LiDAR, airborne LiDAR, and drones are being tested and adopted by transportation agencies, contractors, and surveying professionals alike (NCHRP, 2013). The performance measures for spatial data collection are position accuracy (average distance error for a 3D point), and 3D data resolution (point cloud density). Table 1 compares the performance of spatial data collection technologies available in current practice, highlighting the strengths and weaknesses of each.

Raw data is processed into point cloud files that are then loaded into a computer-aided design (CAD) program where cross-sections are produced for the as-built versus as-planned comparison. The cross-section approach is the most widely used in linear transportation projects today (Kivimaki & Heikkila, 2015). Point coordinates are measured at regular intervals and at critical stations of interest perpendicular to the centerline of the road alignment along the length of the entire project. The CAD-plotted points defining the surface at each cross section are then superimposed with the design cross section, and deviations are manually observed and/or measured within the CAD software (Ghilani & Wolf, 2015). Figure 1 shows a typical cross-section view comparing existing and design surfaces. This method requires significant manual manipulation, and progress between measured cross-sections is left to best-guess interpretations of the data available at the known locations.

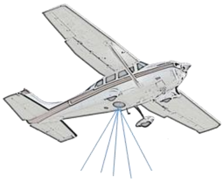
3. STATE OF RESEARCH

Many studies over the past 20 years have focused on automating or otherwise improving construction progress monitoring, with most focusing on identifying progress in building structural components. Kopsida et al., (2015) recently published a thorough review on this body of research. The following sections briefly highlight the different approaches in this field before looking more closely at transportation-specific research.

3.1 Image Processing Methods

A number of studies used image processing and computer vision techniques to reason about the presence of as-planned model objects in as-built photographs. Most use time-lapsed as-built imagery captured by a single stationary camera for recognition of structural components. Lukins & Trucco (2007) is a prime example of such an approach. The process begins by aligning a 3D BIM view with the camera view, and creating template masks for the 2D images from the 3D model components that should be visible in the scene. A derivative filter is then used on consecutive images to detect deviations in pixel intensity within the masked regions, identifying values that exceed a threshold as progress. Such approaches are susceptible to occlusions and changing light conditions, which are expected on a construction site. Additionally, it is impossible to recover 3D data from single 2D images, so progress occurring at different depths or in different regions of an object could go unrecognized.

Table 1. Spatial data collection method comparison*

Data Collection Technology	**Cost ($ ‘000s)**	**Delivery Time**	**Accuracy & Resolution**	**Strengths**	**Weaknesses**
 Manned Aerial Imagery	>10	Days - Weeks	**A**: 20-30 cm **R**: 10-20 pts/m^2	• Large area • Safe • Overhead view • Fast collection	• Costly • Long delivery • Low density • Low accuracy
 Manned Aerial LiDAR	>1,000	Days - Weeks	**A**: 10-15 cm **R**: 5-15 pts/m^2	• Day/night ops • Large area • Safe • Overhead view • Fast collection	• Costly • Long delivery • Low density • Low accuracy
 Unmanned Aerial Imagery	1 - 10	Day(s)	**A**: 3 mm – 5cm **R**: 100-500 pts/m^2	• Fast collection • Fast delivery • Safe • Accurate • High density • Low cost	• Low flight duration • Limited range • Limited payload
 Mobile LiDAR	300 - 1,000	Days	**A**: 2-6 cm **R**: 100s-1,000s pts/m^2	• Day/night ops • Large area • Fast collection • Safe • Accurate • Very high density	• Costly • Slow delivery • Ground view (occlusions)
 Terrestrial LiDAR	50 - 200	Day(s)	**A**: 1-2 mm **R**: 100s-1,000s pts/m^2	• Day/night ops • Fast collection • Very accurate • Very high density	• Costly • Ground view (occlusions)
 GNSS	10 - 30	Day(s)	**A**: 1-5 cm **R**: <1 pts/m^2	• Day/night ops • Accurate • Real-time kinematic tracking	• Costly • Sparse • Depends on satellite availability
 Total Station	5 - 15	Day(s)	**A**: 1-2 mm **R**: <1 pts/m^2	• Very accurate • Real-time kinematic tracking	• Sparse • Slow collection • Ground view (occlusions)

*Technical data compiled from multiple sources (Faro, 2015; Leica, 2015; NCHRP, 2013; Trimble, 2015)

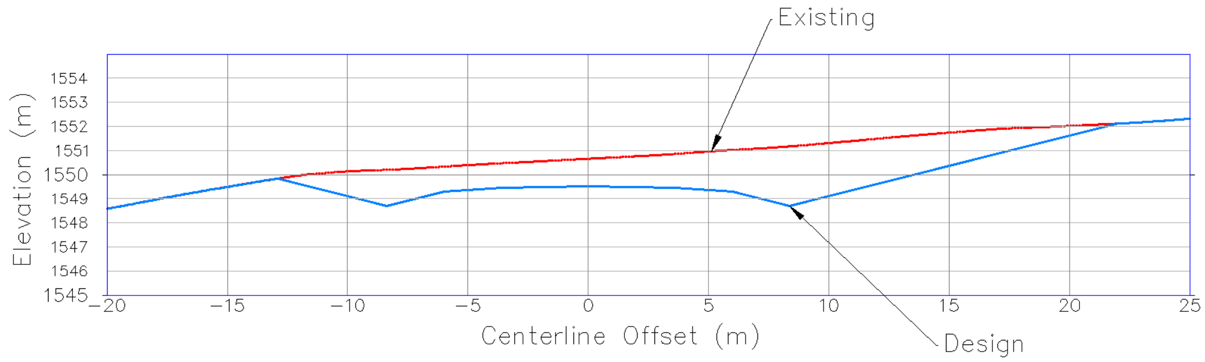


Figure 1. Cross section view for a typical road project

Despite these drawbacks, image-processing methods show promise for identifying materials in support of object recognition tasks. Most of these approaches use morphological filters, edge detectors, and/or statistical analysis to describe the texture and color/intensity within uniform image regions. Material identification is then accomplished by comparing the statistical descriptors produced by these processes with those produced by analyzing images of known materials (e.g. Brilakis et al., 2006). Machine-learning classifiers have also been used to improve and further automate the material identification decision (e.g. Dimitrov & Golparvar-Fard, 2014). These approaches rely on a database of labeled images with known materials. However, there can be significant variability in material texture and color from sample-to-sample and site-to-site, which is troublesome for such approaches. Extensive databases of labeled material images would be needed to reliably and consistently identify construction materials.

3.2 Point Cloud Processing Methods

A number of recent studies have aimed to capture the 3D aspect of progress by acquiring a dense point cloud of the as-built scene, registering and aligning it with a design model, and identifying points that correspond to planned objects. The majority of these studies used LiDAR for data collection (e.g. Bosché, 2010). Golparvar-Fard et al. (2015) and Tuttas et al. (2014) are recent examples of those using photogrammetric point clouds. Progress recognition was accomplished by comparing the as-built point cloud to either a sampled point cloud (point-to-point) or planar surface segments (point-to-plane) from the as-planned model. Point-to-point approaches like Bosché (2010) search for correspondences within a threshold distance to determine if an as-planned point is present in the as-built scene. Point-to-plane approaches like Tuttas et al. (2014) search for as-built points within orthogonal distance tolerances of the planar surface segments. Machine learning classifiers like decision trees (Tuttas et al., 2014) and support vector machines (Golparvar-Fard et al., 2015) have been used to learn complex boundaries for making the object recognition decision.

Again, most of the research in this area has focused on progress in building structural components. A few recent studies have addressed progress in mechanical, electrical, and plumbing (MEP) components with a circular cross-section (Bosché et al., 2015), secondary or temporary construction objects like formwork or scaffolding (Turkan et al., 2014), and operational level activities in building construction (e.g. reinforcing bar, insulation, etc.) (Han & Golparvar-Fard, 2015).

3.3 Indirect Methods

Other approaches sought to infer construction progress and productivity using an assortment of commercially available spatio-temporal sensors such as radio frequency identification (RFID) (e.g. Razavi & Moselhi, 2012) and ultra-wide band (UWB) (e.g. Shahi et al., 2012). A few studies like Razavi & Haas (2010) explored the combination of RFID and GPS sensors for real-time tracking of project resources in support of progress monitoring. Although these spatio-temporal sensors can be a useful source of information on construction sites, their implementation creates an additional work load for project management as tags and readers need to be systematically and repeatedly applied and repositioned as the project evolves. This is particularly troublesome for the types of large and continually-expanding construction sites expected on linear transportation projects.

3.4 Transportation and Earthwork Related Studies

There is very little past research on automating progress monitoring for transportation projects. The following review covers studies that are related to, or might be helpful for transportation progress monitoring research. The few studies that attempted to measure transportation progress are then discussed in further detail. A number of studies analyzed the use of technologies like LiDAR and photogrammetry for generating digital surface models (Hsiao et al., 2013; Johnson & Johnson, 2012) and calculating earthwork volumes (Bügler et al., 2013) in support of transportation project design and construction. While surface models and volumetric surveying can provide crucial information to project management, they cannot be used alone to measure actual versus planned construction progress. To address this limitation, volumetric measurements were recently used in conjunction with video-based construction equipment tracking and activity identification algorithms to produce detailed earthwork productivity estimates (Bügler et al., 2014). This study stopped short of delivering a true progress measurement, and integration of such information into a progress determination based on as-planned status remains unexamined in the literature.

Similar to building construction progress monitoring research, spatio-temporal sensors were evaluated for transportation and earthwork construction data collection. Specifically, GPS and RFID sensors were used in transportation and earthwork project management frameworks (Pradhananga & Teizer, 2013; Vasenev et al., 2014), and in support of transportation project performance measurement and control (Navon, 2005). One study (Navon & Shpatnitsky, 2005) attempted to identify progress and productivity on road construction projects using equipment-mounted GPS receivers and an object-oriented project management database. However, this approach only provides an indirect measure of progress, leaving much room for misinterpretation and error. This again highlights to limitations of using spatio-temporal sensors for progress monitoring, as they are not capable of physically measuring progress on site. Such approaches are better-suited to productivity measurement and tracking of critical project resources.

Automated detection of linear transportation assets and features can greatly increase the efficiency of data collection, processing, and interpretation. Methods were proposed for automatically identifying roads and smooth pavement surfaces in both high resolution imagery (Treash & Amaratunga, 2000) and point cloud data (Miraliakbari et al., 2015). Such approaches could be leveraged to identify regions of interest for construction progress determination. Automated detection and identification of transportation surface defects in imagery has also been accomplished (Ellenberg et al., 2014; Radopoulou & Brilakis, 2015). Although defect detection is primarily a quality control and maintenance/operation concern, methods for recognizing different regions in asphalt surfaces could be useful for identifying progress regions occurring in different layers during asphalt road construction.

The use of 3D and 4D civil information modeling (CIM) can make it possible to automate the third step of the progress monitoring cycle (as-built to as-planned comparison). Methods for creating 4D CIMs (Liapi, 2003) and integrating them into earned-value management systems (Yabuki & Shitani, 2005) were proposed. Others reviewed the use of CIM by contractors and transport departments, concluding that 4D models were most helpful for simulating construction and traffic control plans, and communicating design intent to project stakeholders and the public (Guo et al., 2014). The use of these models in supporting project control during the construction phase is neglected in the current body of research.

As observed in Table 1, unmanned aerial vehicles (UAVs) are capable of producing engineering surveying products to high levels of accuracy and data density at a comparatively low cost. This has been accomplished through photogrammetric post-processing, simultaneous localization and mapping (SLAM), and the use of lightweight LiDAR sensors. For these reasons, UAVs are an intriguing data collection platform for transportation and earthwork construction monitoring. Nex & Remondino (2013) published a thorough literature review on the use of UAV imagery for photogrammetric mapping and 3D modeling. A number of studies (Lin et al., 2011; Harwin & Lucieer, 2012; Mancini et al., 2013; Hugenholtz et al., 2015) evaluated the accuracy of DTMs produced by UAV-mounted sensors (LiDAR or camera) by comparing the results to other accepted methods. Acceptable accuracies for most engineering applications, defined as 5 cm and below according to Olsen et al. (2013), were reported in most cases. Methods for generating digital terrain models for large-scale earthwork projects have also been proposed (Kim et al., 2015; Uysal et al., 2015). The use of UAVs for quantitative infrastructure analysis and defect detection for both paved and unpaved road surfaces was also examined (Ellenberg et al., 2014; Zhang & Elaksher, 2012). One study (Siebert & Teizer, 2014) proposed a method for using UAV-produced photogrammetric terrain models in monitoring earthwork projects. Although this approach illustrates the capabilities of UAV-acquired photogrammetric DTMs in supporting construction operations, its scope was limited to earthwork tasks while focusing more on quality assurance than true progress assessment.

The most germane study to the topic of this paper (Kivimaki & Heikkila, 2015) proposed a real-time system that uses CIM surface models for cloud-based as-built comparisons on infrastructure projects. Their work represents the only study seen to date that makes use of the various CIM design surfaces available for comparison with the measured site surfaces. However, it is a pure quality assurance method that stops short of actual progress determination. It lacks any temporal consideration for what the elevation of the various project surfaces should be at a specific point in time. Additionally, manual matching of as-built data points to as-planned design surfaces is required for non-labeled data. The authors concede that this is a drawback on the efficiency of the overall approach. The ability to automatically assign non-labeled as-built data points to appropriate CIM design surfaces has not been explored in existing literature.

4. SYNTHESIS

Current progress monitoring approaches are not as accurate, consistent, reliable, or timely as they should be to enable effective control decisions aimed at keeping a project on schedule. The methods most often used rely heavily on manual non-spatial data collection processes such as checklists and daily reports. These fail to exploit the rich schedule and 3D spatial information available in 4D design models. Spatial data collection technologies exist, and they have great potential for increasing the accuracy, consistency, and reliability of progress measurement. However, they are used too infrequently in current practice due to the high cost, extended delivery times, and specialized equipment and labor requirements. Additionally, processing of the collected as-built data remains a largely manual and inefficient task, contributing further to the time and cost required to complete a progress monitoring cycle. Further automation in each of the three progress monitoring steps can address these issues. The studies reviewed in the previous section contributed to that goal, but there remains a need for a truly automated framework capable of monitoring progress information for all tasks and project types.

The vast majority of research in this field focused on the automated detection of structural assets like columns, beams, foundations, floors, and walls at the major activity level in building construction. Point cloud processing and image processing are the most prominent and promising approaches used to date. Each has specific strengths and limitations. Point cloud approaches combine dense and accurate data from 3D reconstruction technologies like LiDAR and photogrammetry with design model components for object recognition. This enables recognition of three-dimensional progress that may not be visible in 2D images alone. However, different stages of progress occurring in the same 3D space cannot be distinguished from one another using point data alone. For example, relying on point data alone a concrete column form might be misclassified as the completed column. Image processing approaches are good at construction material identification through the use of image texture analysis, but are susceptible to changing light conditions and occlusions. They are also incapable of capturing progress in three dimensions. The two approaches have remained largely segregated in the body of research. However, it is unlikely that either alone will provide a comprehensive and well-generalized solution. A combination of the two could, however, achieve synergistic results towards achieving truly automated progress monitoring. Han & Golparvar-Fard (2015) began looking into this, but the focus was limited to building elements.

The differences in site layout, construction techniques, and 3D modeling present challenges for the applicability of proposed building construction monitoring methods on transportation projects. The scale of transportation sites is usually orders of magnitude larger than building sites, restricting the data collection techniques that can feasibly be used in support of a rapidly-repeatable progress monitoring approach. Additionally, progress occurs iteratively in layers of different elevation occupying the same region of the site which presents challenges for pure point cloud processing approaches to object detection. The as-planned models are also different. Whereas BIMs are combinations of parametric 3D building components, CIMs are composed of various design surfaces interacting with an existing site surface and each other based on parametric object definitions (e.g. road alignments, profiles, grading slopes, etc.). The implication of these differences for existing automated progress monitoring methods has yet to be examined. The few transportation-related studies found by this review used either indirect measures of progress or focused on quality which fails to consider the temporal component of progress monitoring.

5. CONCLUSION

This paper reviewed the current practice and state of research in progress monitoring for linear transportation projects. The largely-manual and subjective current practice is too time consuming and inaccurate to enable effective project control decisions. Automating each step in the progress monitoring cycle can address these inefficiencies, and a number of academic studies have proposed methods for accomplishing that aim. However, the vast majority focused on structural components in building construction. The most significant knowledge gap identified is the lack of studies focused on progress monitoring for transportation projects. Indeed, none of the transportation-specific methods found by this review could be classified as true progress monitoring. The methods proposed for building construction are a promising start, but their applicability to transportation projects needs to be evaluated by further studies. A key question that needs to be answered is which sensor, or combination of sensors are most appropriate for as-built data collection on transportation construction sites. Additionally, the use of CIMs for gathering as-planned data and facilitating the necessary comparison needs to be evaluated. Finally, further studies are needed to propose methods for integrating point cloud and image processing approaches into a more holistic framework capable of identifying progress in multiple layers and at different stages of production.

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