An information fusion approach for filtering GNSS data sets collected during construction operations

A. Vasenev [a],*, N. Pradhananga [b], F.R. Bijleveld [a], D. Ionita [c,1], T. Hartmann [a], J. Teizer [d], A.G. Dorée [a]

[a] VISICO Center, Department of Engineering and Construction Management, Twente University, P.O. Box 217, 7500AE Enschede, The Netherlands
[b] School of Civil and Environmental Engineering, Georgia Institute of Technology, 790 Atlantic Dr. N.W., Atlanta, GA 30332-0355, USA
[c] Services, Cyber Security and Safety Research Group, Faculty of Electrical Engineering, Mathematics and Computer Science, Twente University, P.O. Box 217, 7500AE Enschede, The Netherlands
[d] RAPIDS Construction Safety and Technology Laboratory, Atlanta, GA 30318, USA

ARTICLE INFO	ABSTRACT
	Global Navigation Satellite Systems (GNSS) are widely used to document the on- and off-site trajectories of construction equipment. Before analyzing the collected data for better understanding and improving construction operations, the data need to be freed from outliers. Eliminating outliers is challenging. While manually identifying outliers is a time-consuming and error-prone process, automatic filtering is exposed to false positives errors, which can lead to eliminating accurate trajectory segments. This paper addresses this issue by proposing a hybrid filtering method, which integrates experts' decisions. The decisions are operationalized as parameters to search for next outliers and are based on visualization of sensor readings and the human-generated notes that describe specifics of the construction project. A specialized open-source software prototype was developed and applied by the authors to illustrate the proposed approach. The software was utilized to filter outliers in sensor readings collected during earthmoving and asphalt paving projects that involved five different types of common construction equipment. © 2014 Elsevier Ltd. All rights reserved.

1. Introduction

Documenting the movement of construction equipment during construction projects is helpful in controlling and continuously improving construction operations. Specifically, the documented trajectories of construction resources (personnel, equipment, and material) allows to analyze travel patterns of construction workers [1,2], assess equipment operators' work [3], labor activity [4], or study variability in construction processes [5,6].

Though available technologies such as GNSS (Global Navigation Satellite System), laser positioning, or ultra wideband (UWB) provide opportunities to track movement of the resources with high precision [7–9], any such data collection will yield erroneous measurements because of a multiplicity of external factors. Examples for these errors are outliers in documented readings that inaccurately represent equipment's location at specific time. For instance, GNSS measurements can show a position that cannot be realistic in

relation to the corresponding timeframe: a resource (e.g., construction equipment) moved into a new location rather too quickly or changed orientation in a manner that is physically impossible (e.g., an asphalt roller rapidly changes its direction by an angle larger than the one specified by the roller's manufacturer).

The described outliers occur because of the absence, poor strength, or reflections of navigation signals. In case of GNSS, such conditions are related to an absent or obscure line-of-sight between the GNSS tracker and the GNSS satellites. For instance, the line-of-sight can be affected by atmospheric effects and objects that obscure the satellites visibility, such as trees, overhead bridges, or other obstacles located on or next to a construction site.

To allow a sound understanding of the equipment's movement, all outliers should be filtered out before analyzing the collected data. Often, such filtering is performed by applying statistical techniques, such as moving average methods to smooth trajectory data or by relating the equipment movements to the expected moving trajectories [10]. Alternatively, simultaneously collected readings from different types of sensors can be fused to automatically cross-relate different readings and remove outliers. Examples of correcting equipment paths in such a way include fusing signals from GNSS devices and inertial measurement units [11], utilizing dead-reckoning sensors (including Doppler radar, encoder, and

* Corresponding author. Tel.: +31 53 4894828; fax: +31 53 4892511.
E-mail addresses: a.vasenev@utwente.nl (A. Vasenev), nipesh@gatech.edu (N. Pradhananga), f.r.bijleveld@ctw.utwente.nl (F.R. Bijleveld), d.ionita@utwente.nl (D. Ionita), t.hartmann@utwente.nl (T. Hartmann), teizer@gatech.edu (J. Teizer), a.g.doree@utwente.nl (A.G. Dorée).
[1] Tel.: +31 53 489 4283; fax: +31 53 4894571.

fiber-optical gyrometer) [12], and combining readings from different sensors by applying Kalman filtering [13,14].

Though such automated filtering methods can often significantly improve the accuracy of the documented equipment paths, such methods can also erroneously remove path segments related to specific movements of the equipment [15]. For instance, if a dump truck rapidly reverses its heading direction due to some events on site, the automated filtering methods can misinterpret the corresponding sensor readings as erroneous data and remove tracked points that do not represent outliers. In practice, filtering out such valuable data can result in an incorrect understanding of the construction equipment's trajectory and lead to erroneous data analysis, for example during safety assessment while evaluating near-misses. As quick unexpected direction changes are a common cause for near-miss accidents, the automated filtering mechanisms can negatively affect the search for such events. To avoid removing accurate but rather unexpected path segments, having additional information about equipment movements to inform GNSS data filtering process is needed.

To advise the process of filtering outliers in sensor readings the "hard" (sensor-based) data can be related to the "soft" data (human-generated records) that describe the project context and the conducted activities. These human-generated data can, for example, be collected in the form of a logbook, which describes how equipment moved on site as well as essential process events, and be collected in a formalized [16] or a standard- free format. Specifically, the events could be documented when a piece of equipment starts new activities, stops due to a breakdown, or alters its moving strategy can support the analysis of a particular trajectory segment, which may include an outlier. Alternative to maintaining a log-book during the construction project, a human observer can generate valuable soft data afterwards by retrospectively analyzing video recordings of the project.

Besides using additional soft data sources, the involvement of a human into the data analysis can additionally improve the filtering process. Specifically, human cognitive abilities can be related to fusing information from different sources, including sensor-originated and human-generated records. Among others, such abilities include recognizing visual and aural patterns, applying semantic reasoning [17], and interconnecting different elements and objects according to world models, physical laws, and geometric constraints [18]. Moreover, humans can also improve fusion processes by applying a priori knowledge about the environment and genuinely processing human-generated data [19]. In other words, the process of fusing information can directly benefits from human abilities "to gather and organize unstructured, a priori information about a problem and then mix that information with measured sensor data, making inferences that could not have been made using the sensor data alone" [20].

Because of theses advantages, it is not surprising that engaging humans into the processes of fusing information is strongly recommended in the information fusion literature [21–23].

To secure the benefits of employing a human expert into filtering trajectories of the construction equipment, it is essential to meaningfully organize interactions between the expert and the documented hard and soft data. In particular, the interactions should aim to assist experts in filtering equipment paths in a way that the experts can apply their a priori knowledge and expectations about how equipment can move during construction. At the same time, there is a necessity to structure the approach to reduce the human involvement to an acceptable level, because if the expert is overloaded with information, some outliers in larger data sets can easily be overlooked. A suitable approach to meet these requirements and integrate both "hard" sensor- and "soft" human-generated records could benefit from Information Fusion (IF) principles that aim at fusing any kind of data [19,24,16].

Based on the information fusion principles, this paper proposes a human-centered information fusion approach oriented to meaningfully utilize sensor readings and human-generated data that describe expected equipment movements. Within the approach a human expert is directly involved into filtering equipment trajectories: the expert defines the initial search parameters to identify potentially erroneous path segments and decides if the segment contains outliers. Additional information about the project specific conditions and its context inform the expert's decisions if path segments within spatial and temporally constrains are potentially prone to outliers. In summary, the approach structures how both hard and soft data are represented to an expert who analyses collected equipment trajectories and soft data in conjunction with personal knowledge and understanding how equipment is expected to move during specific time periods and at particular locations.

The following section of the paper introduces the major concepts related to information fusion in general. Then, the proposed human-centered approach to filter GNSS data follows. Later, the paper depicts how the implementation of the approach was embodied as open-source software and describes how the developed software was tested to filter paths of asphalt paving and earthmoving equipment. Results and findings are presented and discussed before the paper concludes.

2. Information sources beneficial for filtering documented trajectories of construction equipment

2.1. Overview of sensor-originated readings that constitute hard data

The most commonly used technologies to document equipment movements during construction include laser based positioning and GNSS sensors. For example, laser guided systems generally allow obtaining highly precise positioning data, providing an unobstructed direct line of view between the positioning station(s) and the tracking equipment can be maintained. However, additional stations to track equipment during large projects might be required in case buildings or trees are located on or next to the construction site. Alternatively, GNSS sensors can be utilized to track equipment over large distances but with less accuracy than laser guided systems. At the same time, the location accuracy of GNSS sensors can be improved by additional correction, e.g. by using a Differential GPS solution that transmits such data to multiple GNSS sensors in real time. Typically, global navigation tracking solutions can be particularly useful to track equipment that move on distance from the construction site, such as hauling trucks.

The choice between these systems should be made according to specifics of a construction project. As an example, for road paving processes GNSS solutions tend to be preferred to track these processes because the equipment continuously moves around on a construction site that also shifts. Nevertheless, both laser guided and global navigation systems are susceptible to a certain degree to the context of equipment tracking and can eventually include outliers in the documented equipment paths.

Compared to GNSS and laser based positioning, other technologies that document equipment movements are less adopted in practice. Examples of such less-utilized technologies include UWB sensors and computer vision tracking solutions. These technologies, similarly to the previously described, also do not guarantee outlier-free readings. In particular, UWB-based sensors can experience occlusion of tracking signals, while computer vision technologies additionally can suffer from other external factors, including dust and lighting conditions.

In summary, though several technologies provide opportunities to document equipment movements, the accuracy of the

documented paths is influenced by a construction project's specific context. Eventually, as every technology will yield outliers in the documented equipment paths, having additional data sources is desired.

2.2. Human-generated records: soft data

To support judgment of whether a particular segment of the documented trajectory paths corresponds to an outlier or not, additional descriptions about the equipment movements are useful. Particularly, human-generated notes ("soft data" as opposite to "hard" sensor readings) about the progress of the construction process could be of value, because humans can depict certain attributes of interest [22] and suggest specific inferences, such as specify relationships between entities [14].

Soft data can be related to hard data within both temporary and spatial domains. For example, the time stamp of a particular human-generated record might suggest to carefully examine the hard data collected at nearly the same time. Similarly, notes can indicate which locations of a specific project are particularly prone to inaccurate measurements, such as areas adjunct to high-rise buildings that can obscure navigation signals from satellites. From another perspective, parallel soft and hard data can support assessing uncertainty of soft data through the lens of the hard data [24]. This interrelation of soft and hard data within time and spatial domains confirms that the two types of data go hand-in-hand and complement each other.

As an example, a site manager involved in an asphalt paving project can produce soft data by making notes regarding how equipment operators intent to co-operate and what events took place on site. Such notes could include records when specific operations started, when trucks arrived, as well as any other relevant incidents, for example, if a roller discontinued operating due to breakdown or the need to refill its water tanks.

Once collected, the available soft and hard data need to be meaningfully processed according to some rules that will help to identify outliers. To demonstrate developments in the field of information fusion the next section depicts most common information fusion models. Later, the human-centered approach to combine hard and soft data related to filtering paths of construction equipment will be introduced.

3. Fusion of information

To benefit from the potential explanatory power of human-generated notes (soft data) that describe events and how entities on site were linked, soft data should be meaningfully related to the documented sensor readings. Ultimately, this relation might support making decisions about whether a particular segment of an equipment path contains outliers or not. The existing information fusion models allow systematic consideration of procedures to process data from different sources. This section briefly overviews such models.

Probably, the most widely accepted approach to categorize merging information from different sources started to develop with the introduction of the Joint Directors of Laboratories (JDL) data fusion model, proposed by the corresponding subpanel in 1991 [17]. The succeeding evolution of the model involved the introduction of two additional levels of fusion (data preprocessing and human–computer interaction) to depict the need for introducing the human into fusion processes.

While the JDL model was then employed in different research lines, including tailoring it to tasks of the civil engineering domain [25–27], the model has also been criticized because the active role of human users in fusion was not taken into account sufficiently

[28]. Specifically, as a functional model, the JDL aims "to facilitate understanding and communication among managers, theoreticians, designers, and evaluators as well as users of the data fusion systems" [27] and less concentrate on describing how the user can be incorporated into specific elements of the fusion systems.

For structuring the possibilities to involve humans into information fusion, the JDL model was extended by the fusion community to λJDL [29] and the visual data-fusion models (as described in [30]). A particularly noticeable upgrade to the JDL model was introduced by the Data Fusion Information Group's (DFIG) model [28]. The model (see Fig. 1) is constituted by several levels that are directly related to the elements of the aforementioned JDL model.

Essentially, the DFIG model proposes to perform human-centered fusion to estimate and predict relations among different objects in order to assess the situation in hands. In this way, the complicated fusion tasks are to be performed by humans due to their natural sense-making abilities related to estimating states and predicting relations among entities.

Altogether, the developments in the field of information fusion increasingly acknowledge the role of humans in information fusion processes. These considerations can be taken into account to develop approaches for filtering outliers in documented construction equipment trajectories. In this setting, human reasoning can support every aspect of the filtering process, including soft data processing, comprehending situations described by both hard and soft data, and deciding if a specific path segment is an outlier. The next section introduces the information fusion approach that benefits from the listed factors.

4. Information fusion approach to filter trajectories of construction equipment

The active involvement of the user is required to meaningfully perform numerous knowledge-intensive tasks, such as supervising complex systems [31] and applying context-sensitive knowledge for the needs of engineering tasks at hands [32]. In the civil engineering domain several information systems already rely on the decisions of human operators involved in the data processing loop (see for example [18,33]). Nevertheless, according to the best of the authors' knowledge, no approaches have been suggested on how to incorporate human reasoning in fusing hard and soft data in order to filter outliers in documented equipment paths.

To address the described gap related to filtering outliers in documented equipment paths this paper proposes a user-centered information fusion approach (Fig. 2). As central element the approach adopts the model of human decision making as introduced by Boyd in the mid-1950s [22]. The model organizes the decision making process as a loop formed by the four steps: Observe, Orient, Decide, Act (OODA). These steps aim to help differentiating information gathering, analysis and implementation activities by describing important aspects of decision making without excessive burden of details [34].

Within the here proposed approach, the OODA steps are laid out to govern interactions between the expert and the software to support data processing. In this set up, experts can make decisions if a path segment is an outlier based on available hard and soft data aligned with experts' understanding of how equipment can move in general, during a specific project, and within particular time and spatial boundaries.

The expert's knowledge can be outlined as a set of interdependent rules. This set of rules supports the expert during the "orient" and "decide" phases of the decision making loop. Within the proposed approach three interdependent groups of rules are outlined: general (how equipment can and cannot move), situated (equipment movements during different phases of the project with
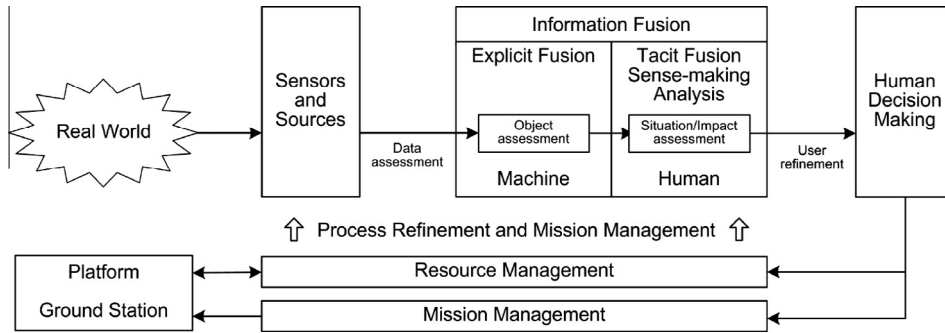
Fig. 1. Data Fusion Information Group (DFIG) 2004 model (reconstructed based on the model from [28]).
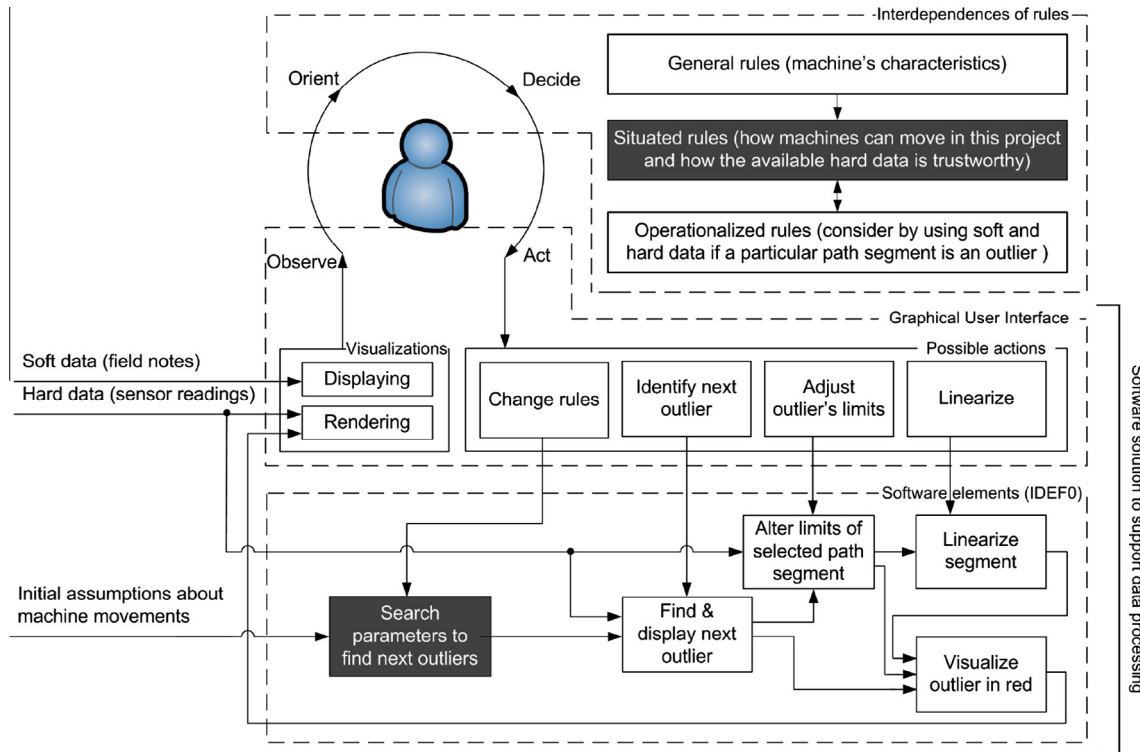

Fig. 2. Information fusion approach for retrospective analysis of the positional data by an expert.

respect to time or spatial limits), and operationalized (movements at specific time periods). According to the rules, an expert can deduce expectations on how equipment can move during specific periods of the project. The expert can then consider these expectations and judge whether sensor readings collected during those time periods include outliers.

The "general rules" are based on equipment characteristics and describe how particular construction equipment can move due to their specifications. For instance, different equipment can have specific limitations of the maximum speed or the turning angle. Also, certain behavior can be expected according to the equipment's purpose (for instance, a roller often reverse its traveling direction or an excavator might repeatedly turn around its axis). These equipment-specific rules describe how the equipment typically moves without considering specifics of a particular project. Consequently, the general rules supply an expert with an initial understanding about how specific equipment can move in general and during the examined project in particular.

The "situated rules" describe how construction equipment can move during the analyzed project. Such rules are related to general rules and to project-specific information, for instance to assumptions about the expected movement patterns in relation to particular projects. In these settings, the equipment's maximum speed during the project can be expected to remain considerably less than the maximum speed specified in the equipment's specifications. This assumption suggests to scrutinize specific elements of equipment paths, where (or when) the collected sensor readings can possibly include outliers. For example, the user can consider (1) a temporary period when an equipment is not expected to make rapid turns and move faster than a certain speed due to the geometry of the construction site; and (2) a spatial area where outliers can be grouped, thus if a single outlier was identified, the following documented equipment locations should be carefully analyzed as potentially prone to errors.

The situated rules are interrelated with the "operationalized rules". These rules exist in relation to a particular equipment path's segment. In this way, experts can judge whether the segment includes an outlier or if the sensor readings accurately describe equipment movements. Such judgments are rooted in situated rules and supported by visual representations of the documented

equipment's path and additional soft data. The operationalized rules can, in turn, influence the situated rules. For example, the existing expectations about the maximum equipment's speed during the analyzed project can be updated if that equipment had begun to move faster than expected. Similarly, if experts identify too many outliers within the project, they can adjust personal assumptions about how the collected sensor readings are reliable in general. Such assumptions can then be operationalized by changing the parameters to automatically search the next outlier. For instance, if experts identified that outliers tend to form groups, they can adjust parameters in a way that the software will critically analyze several consequent data points after one outlier will be identified.

Within the proposed classification of rules, the situated rules are central in describing how equipment can move during the analyzed project. These rules, if described as statements, can support the automated search for outliers the core of the expert's interactions with the supportive system. For instance, statements to support the search for outliers can have the following formats: (1) "the maximum angle between the previous and current heading of the equipment should not exceed '20' degrees"; (2) "the equipment's maximum speed should not exceed '2.7' m/s"; (3) or "after identifying an outlier the next path points should be automatically checked and the outlier limit should be extended until N consequent path points appear to be correct according to the expected equipment movements". Once the statements are formalized, they become a central element in the proposed IF approach to refine the documented equipment paths. The expert can use the statements as search parameters, requesting the software to find next outliers. The formalized statements to find the next outlier are related to the situated knowledge (these interrelated elements are shown with dark background in Fig. 2). After the next outlier is identified, the expert can change limits or eliminate the outlier. The expert can correct the path segment if the selection appears to be an outlier according to the available hard and soft data. These hard data corresponds to the documented elements of equipment paths right before and after the selection and soft data are related to the available human-generated information. The sequence of the possible actions is not predefined. For example, a user can find the next outlier and remove it without adjusting the outlier's limits. Similarly, the rules to search for next outliers can be changed at any time.

In addition to the described automated search for outliers, a possibility to manually define the beginning of an outlier without using an automated search should also be provided.

Overall, different sets of rules can characterize movements of construction equipment that correspond to different states such as those during which the equipment is idle, performs specific operations (such as paving, compacting, or excavating), or relocates to another position without carrying out specific operations. In this respect, the human-generated data about equipment activities with references to specific time periods can highly benefit the path filtering process as the expert can relate particular time-based on special-based segments of equipment paths to the expected equipment's behavior.

5. Procedure to validate the proposed approach

As mentioned, currently no method suggests a way to incorporate human reasoning to fuse hard and soft data for filtering outliers in documented equipment paths. To address the gap, the previous section proposed a human-centered fusion approach based on information fusion concepts. To validate the approach, the research strategy included the following procedure:

1. Based on the proposed approach the authors of this paper developed a software prototype that allows to import and visualize previously collected hard (GNSS sensor readings) and soft (specifically, a log of the construction project) data. The functional elements of the prototype were designed in direct correspondence to the components and the interconnection structure of the proposed information fusion approach (as demonstrated in Fig. 2). Thus, the functionality of the graphic user interface of the prototype allows experts to convey – during the "act" step of the OODA loop – decisions made during the "decide" step, while visualizations inform the "observe" step, which reinforces the "orient" step of the loop. The developed software prototype is described in more details in the next section.

2. The developed software was applied by the authors to examine paths of five different construction equipment (paver, roller, truck, excavator and dozer) that were involved in two distinct types of construction projects: asphalt paving and earthmoving. The purpose of the examination procedure was to inspect if the provided functionality can assist an expert in filtering outliers in documented (by using GNSS technologies) equipment paths according to the expert's understanding about expected movements of the equipment on site. The application of the developed prototype is described in Section 7.

6. Development of the software to filter and visualize outliers in equipment trajectories

The information fusion approach was operationalized in a software application to locate and eliminate outliers in documented equipment paths. This application was developed by the authors within the research track of the VISICO center of the University of Twente, The Netherlands, and is available as open-source software.

The graphical user interface (see Fig. 3) was developed according to the suggested information fusion approach and support an expert in steps "act" and "observe" of the described OODA loop. In particular, several interface elements simultaneously represent hard and soft data by displaying the overall path of the equipment and a selected path segment next to the log of the project. The demonstrated logbook represents an example of soft data and ultimately aims to inform the user regarding the details of the construction project in addition to the automatically collected data. Once informed about specifics of the process, the software user can relate them to elements of equipment paths and exercise expert judgment to decide if those elements correspond to outliers or reflect real equipment movements. The major part of the software interface visualizes hard sensor readings to support users in visual examination of the displayed path for evident outliers. Such analysis, rooted in human abilities to identify visual patterns, can naturally support rapidly filtering large groups of evident outliers.

In addition to providing opportunities for human exploration of the data, the software allows to search for the next outlier automatically. The user can choose between two means to detect outliers: *angle-based* search (by setting the maximum expected equipment's turning angle) and *speed-based* search (by defining the maximum expected speed of the equipment). Correspondingly, the next outlier will be identified either if the equipment direction significantly differs from the previous heading, or if the adjunct path points are located too distant from each other. After an outlier was identified, the program considers the next N data points. The user-entered value N – called the "intolerance level" – defines the amount of consequent points that should automatically be considered as being potentially incorrect. If another outlier is identified within the path between the next N location points, the limits of the selected outlier interval will be automatically
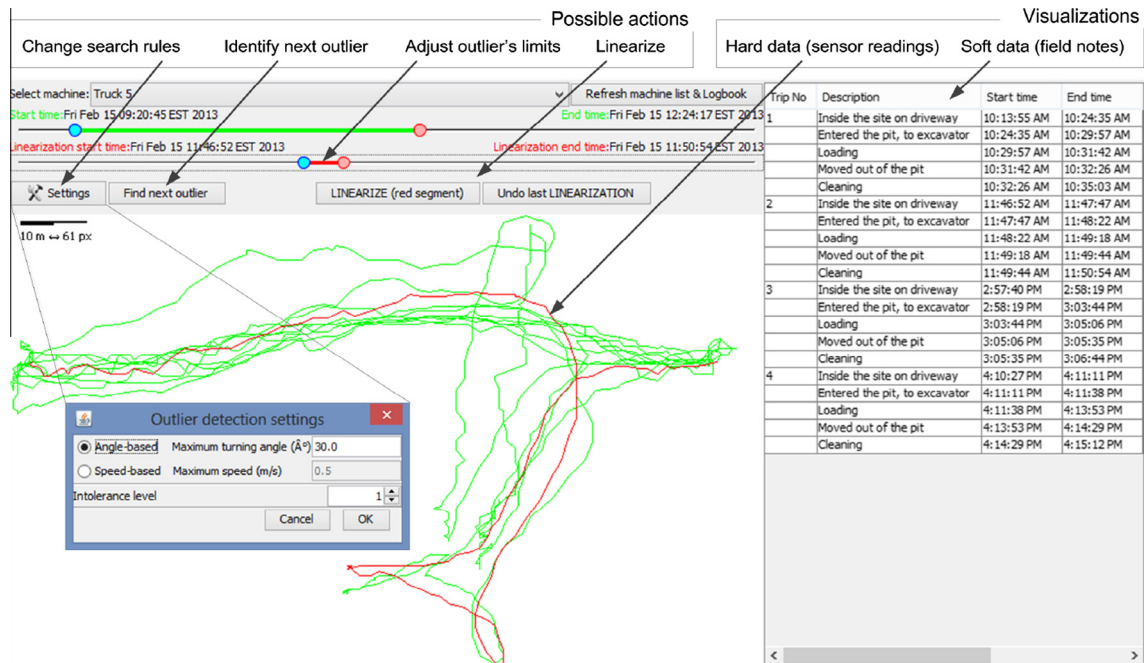
Fig. 3. Graphical user interface of the open-source application developed according to the suggested information fusion approach.

increased to include that outlier as well. This option allows identifying groups of outliers.

Users can (re-) define the limits that define an outlier by moving a dedicated horizontal slider. Then, the user can meaningfully relate the selected path with the soft data (logbook) that is displayed next to the path visualization. If the selected interval is considered as an outlier, the interval can be adjusted. While different interpolation techniques can be applied to eliminate outliers, in the developed software a linearization function was implemented by the authors, as it provides necessary functionality without introducing additional need to adjust specific parameters (and potentially communicate them with the user for fine-tuning). The last linearization can be undone, for example, if that action was performed by mistake.

In summary, removing an outlier is a three-step procedure. First, the expert can manually or automatically identify and select an untrustworthy path segment according to personal expectations on how specific equipment should move at a construction site. Then, the selected path segment can be related to human-generated data to justify decisions if the segment is an outlier. Finally, the expert can remove the outlier or search for the next doubtful path segments based on the same or different search parameters.

As indicated, the components of the developed software prototype naturally correspond to the elements of the proposed information fusion approach. As a result, the prototype provides the expert means to observe and act according to her/his decisions if a specific path segment is an outlier to be removed. As the purpose of the approach is related to filtering outliers in GNSS Data sets collected during construction operations, the prototype was applied to filter outliers in documented paths of earthmoving and asphalt paving equipment. The next section describes the details of these applications.

7. Application of software

To test the applicability of the proposed approach to filter outliers in paths of construction equipment the developed software was applied by the authors to analyze the paths of five different types of equipment involved in asphalt paving and earthmoving operations. The authors have had previous experience in processing GNSS data collected during construction operations.

The analyzed construction equipment trajectories were gathered by the authors by means of two different classes of GNSS devices. Each class was utilized to collect a separate dataset that corresponded to a specific type of construction operations. In particular, several inexpensive GPS devices (Wintec G-Rays 2) were used for tracking movements of earthmoving equipment and highly precise Differential GPS (Trimble SPS851 DGPS) to track asphalt paving operations. The latter high-end receivers estimated equipment positions based not only on transmission signals from GPS, but also from GLONASS navigation satellites. By employing different classes of GNSS devices, the conducted tests illustrate the applicability of the proposed approach to filter outliers without being limited to a particular device class, as sensor readings obtained by utilizing either highly or less precise sensors eventually include outliers.

This section is organized as follows: first, specifics of equipment movements on site are depicted. Then, the short description of the construction site context follows. Finally, examples of filtering particular segments of documented equipment paths are shown.

7.1. Data filtering in earthmoving operations

One of the most common ways to follow construction activities is to attach broadly available low-priced GNSS receivers to construction equipment. As this practice is being extensively adopted, eliminating outliers in equipment trajectories obtained by using these less precise tracking devices is essential before conducting further data analysis. The developed software to filter trajectories was applied to illustrated filtering outliers in paths of earthmoving equipment, documented by using such conventional sensors. The additional description of the utilized low-cost GPS data logging devices and their relative accuracy analysis can be found in [3].

As a part of validation of the proposed method an earthmoving project involving a number of dump trucks, two excavators, and a dozer was selected. Trajectories of the equipment were

documented during construction of the Engineered Biosystems Building (EBB) at the Georgia Institute of Technology, Atlanta, USA (see Fig. 4). The entire site was 120 m × 100 m in dimension with a total volume of excavation of 40,000 cubic yard (CY) (30,600 m³) of earth.

As in the scope of the proposed approach the understanding and expectations how equipment typically conduct their work is central, the next section depicts specifics of equipment movements.

7.1.1. Specifics of equipment movements in earthmoving projects

Dump trucks: Dump trucks are unique equipment that operate similar to automobiles on normal roads but exhibit different behavior at construction sites. In relation to the opportunities to filter outliers according to angle- and speed-based search options, the maximum turning angle and the maximum equipment' speed can be obtained from the equipment specifications (e.g. [35,36]). Additional information, such as suggested 16 km/h speed limit on site (e.g. according to [37]), could guide experts in making their decisions about suspicious path segments. Noticeable, though the speed limit can supply speed-based search, the human reasoning is still important to judge if a particular segment is an outlier or correspond to speeding on site.

Hence, soft data collected by a human observer can assist in making such decisions. The potentially valuable soft data in this case can include notes (as elements of the log of the project) when the truck enters and exits the construction site and how it moves from one specific zone on the construction site to another. As the operation sequence is known (typically a truck passes through a driveway, moves inside the pit and stops for loading and cleaning), the corresponding timestamps can help in path filtering by suggesting what search rules can be applied for different operations. For instance, to filter segments that correspond to the traveling along the driveway, an angle-based search can be used in connection to considering the geometry of the driveway. Then, during the travel, the truck's maximum allowed speed is limited due to presence of other construction equipment and workers, therefore a speed-based search can be utilized.

Excavators: Typical operations of the equipment include swinging movement for the most time and occasionally traveling from one working location to another. As the angle-based search could not be suggested to search outliers according to the specifics of equipment movements, the speed-based search can be of use, especially for filtering paths that correspond to the equipment travel paths. In this case, information about the equipment's maximum travel speed (e.g. 5.5 km/h for Komatsu PC 400 LC [38]) can

support automatic identification of segments that can refer to outliers.

Another type of earthmoving equipment – *Dozers* – typically move linearly to push the earth but also can rotate about its axis and change direction of movement from forward to backwards. Similar to other equipment, the maximum speed can be found in the equipment specifications (e.g. in [39] for John Deere Crawler Dozer 750C). As dozers can be idle or typically move in straight path during its operation, recording timestamps for when the equipment becomes idle or starts operating can advise an expert in applying the angle-based search for the linear movements that occurred during normal operating procedures.

All three types of the described construction equipment were involved in the construction project described earlier. The equipment trajectories were documented by the authors during the project and then processed using the developed software to filter outliers in equipment paths, as described next.

7.1.2. Description of data collection during the earthmoving project

GNSS paths of equipment involved in the chosen earthmoving project were collected during the entire work shift that lasted between 6:30 AM to 5:30 PM. The low cost portable GNSS devices gathered the equipment trajectories at the update rate of 1 Hz. To assist in identifying outliers manual observations were made and the timestamps when the working context of the equipment changed were noted down. The excerpt of the soft data for different equipment is presented in Table 1. Noticeable, the level of granularity of the soft data was not predefined. While the illustrative excerpt shows that the truck operations were tracked precisely; descriptions related to other equipment had fewer details. However, even the less detailed descriptions can also support the identification of activities on site and therefore inform the experts' filtering task, as described further.

7.1.3. Applying the developed software to filter outliers in equipment movements during earthmoving operations

Filtering paths of dump trucks: Trucks trajectories were documented only within the construction site, as the sensors were attached when trucks arrived on site and then removed at the exit gate. The left part of Fig. 5 shows trajectories on site collected by a tracking sensor throughout an entire workday. This figure similar to all figures presented later is a screenshot of the graphical user interface of the developed software and demonstrates the functionality of the developed program to overview equipment movements throughout a working shift along with selecting a segment that corresponds to a particular period of interest. The path

Fig. 4. GPS tags mounted on an excavator and a truck (left), data collection site (right).

Table 1
Sample of the human-generated data.

Type of equipment	Timestamp	Description
Dump Truck	2:57:40 PM	Entered the site
	2:59:36 PM	Entered the pit
	3:03:44 PM	Start loading
	3:05:06 PM	Loading complete
	3:06:01 PM	Cleaning
	3:06:44 PM	Exit
Excavator	6:03:44 AM	Moved inside the pit
	6:08:31 AM	Loading
	6:51:20 AM	Stopped (no trucks)
	7:02:33 AM	Loading
Dozer	6:45:45 AM	Started working
	7:15:42 AM	Stopped
	7:22:28 AM	Started working
	8:02:55 AM	Stopped

segment represents a single loading cycle of a truck highlighted in the figure by applying visualization limits that correspond to the timestamps obtained from the soft data. Since the truck paths differ across varying loads, the human involved into the filtering process can identify outliers by comparing a particular trajectory with trajectories corresponding to other loads. In this way, the understanding of how equipment moved during the entire work shift can support an expert in considering what parameters can be applied for the automated search for outliers. The regions 1, 2, 3 and 4 highlighted in the left part of the Fig. 5 are shown in more detail on the right side of the figure to demonstrate the identified outliers as well as how the path segments appear after eliminating these outliers.

Overall, Figs. 5, 6 and 7, 9 and 10 illustrate the way the proposed information fusion approach can be applied by showing (1) the initially collected sensor readings next to (2) several enlarged areas that show path segments before and after eliminating the outliers. As filtered GNSS paths normally appear largely similar to visualizations of the as-collected GNSS data and thus require enlarged areas similar to those demonstrated, the illustrations of filtered paths are not included in this paper.

In particular, to identify outliers in the documented GNSS data related to earthmoving operations, the authors applied the

developed software prototype in the following way. Some evident outliers were located manually, while others were found automatically by applying the angle-based search with the assumption that a turning angle should be less than 40°. The outlier selection and linearization were performed with respect to both hard and soft data at hand.

The manual selection was performed by the authors to filter out evident outliers according to the visualized sensor readings. Some visually obvious outliers that contained a large number of obviously erroneous points were identified and filtered out manually. Then, the software user applied automatic search for outliers to detect other (visually less noticeable) outliers that included relatively small number of erroneous points.

Filtering path of the excavator: The working shift of an excavator was documented as shown in Fig. 6. The figure particularly indicates large amounts of equipment's swing movements where operations were performed at particular spots. However, as the scope of this research was focused on equipment paths rather that equipment activities, only GNSS data related to relocating the equipment were analyzed and only the corresponding path segments were filtered. The soft data (as indicated in Table 1) was utilized to differentiate activities of the equipment.

The right part of Fig. 6 shows how filtering the equipment path was performed with the help of the developed software. Similar to the previous example, at first most evident outliers were removed manually and then less evident outliers were identified by using the parameter-based search. In this case the angle-based threshold for outlier identification was set as 30°.

Filtering paths of a dozer: The left part of Fig. 7 shows the dozer's moving trajectory within the documented work shift, while the selected section illustrated the equipment's typical moving pattern. These patterns represent the dozers' main activity of pushing soil towards the excavator. Thus, dozers have the capability to change their moving direction from forward to backward similar to trucks, but they travel shorter straight distances. Based on the visualized trajectories and existing soft data (such as presented in Table 1) the specific areas where the dozer traveled in a manner that corresponds to its typical activity (or was alternatively relocating) can be identified and the corresponding way of filtering can be performed. Several samples of manual and automated
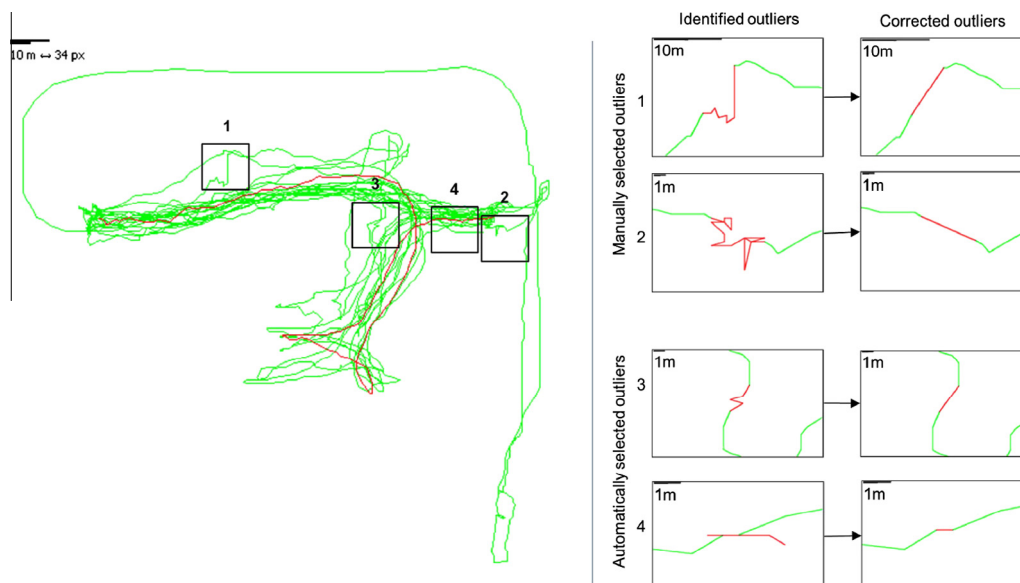

Fig. 5. Trajectories of trucks on the construction site collected by a GPS tag throughout the working day (on the left); path segments with outliers identified either manually or automatically and path segments after the outliers were removed (on the right).
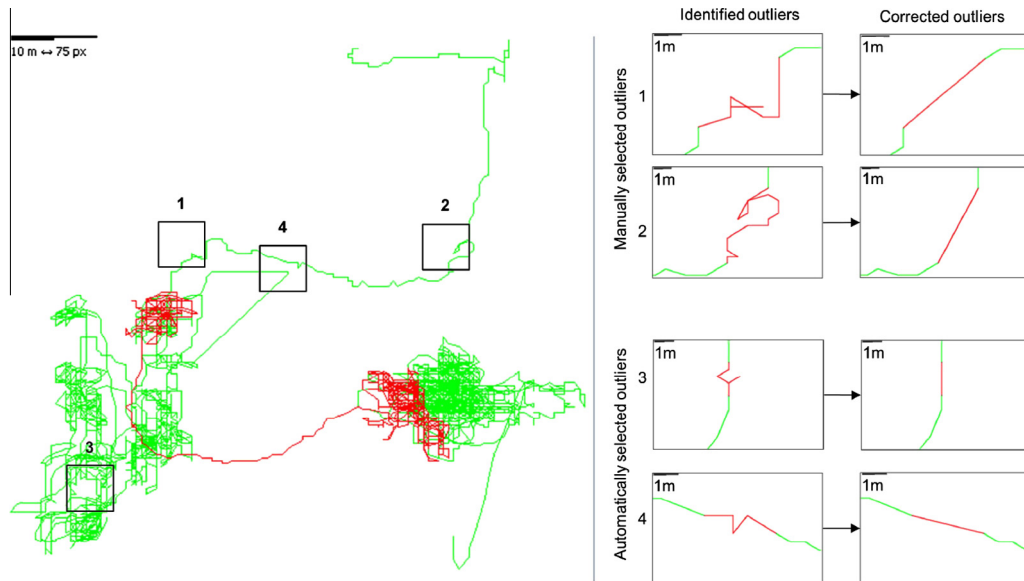
Fig. 6. Excavator's documented path with samples of filtering several manually and automatically identified outliers.
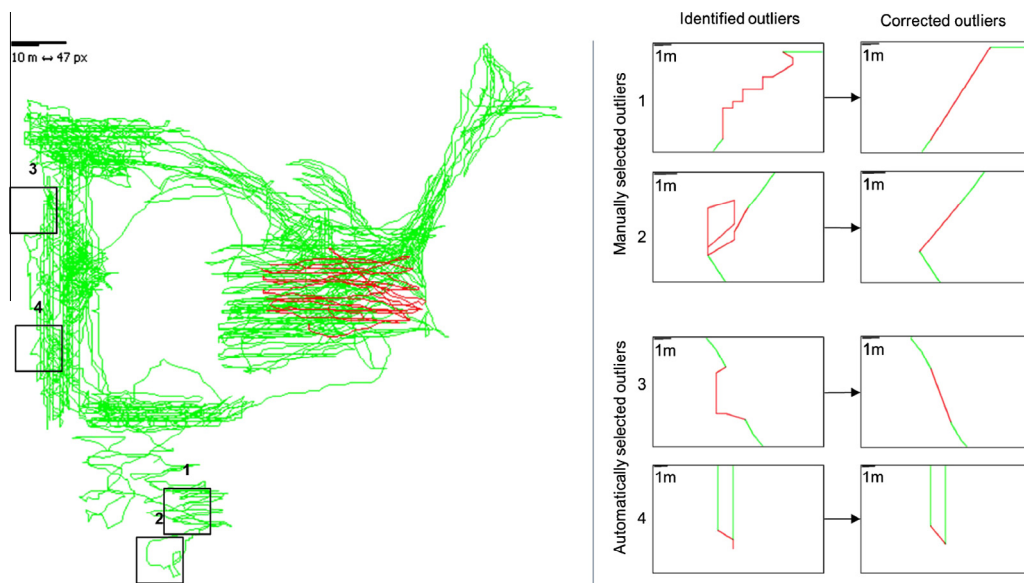

Fig. 7. Trajectory of a dozer and samples of filtering the documented dozer's path segments.

outlier identifications and filtering are shown within the right part of Fig. 7. Similarly to the previous examples, the angle-based search was found useful in identifying outliers.

7.2. Data filtering in asphalt paving operations

To examine the applicability of the approach to filter outliers without limitation to a particular technology class, such as inexpensive GPS receivers, the developed software was applied to filter outliers of equipment involved in paving operations whose paths were documented by means of highly precise GNSS sensors. The decision to utilize highly precise sensors was also motivated by typically high demands for accuracy to track paving activities. In particular, localization to track paving operations can be considered as accurate if it has the positioning accuracy of 10 cm in both transversal and longitudinal directions with the possible temporal degradation of the accuracy up to 20 cm [12].

Two essential differences between earthmoving and asphalt paving operations exemplify the different moving patterns of the corresponding equipment: (1) the material is continuously deployed during paving instead of removed during earthmoving; and (2) the continuity of the process is critical, as delays in deploying material that are caused by process interruptions influence the final quality of the road. Because of these characteristics of the asphalt paving operations, equipment movements during asphalt paving are largely differ from those entailed in earthmoving operations. Therefore, this second case validates the generality by illustrating how the proposed approach can be applied for different filtering needs originated from specifics of largely dissimilar construction domains.

Similar to earthmoving operations, movements of pavers and rollers highly depend on characteristics and functions of construction equipment, geometry of the construction site, and specifics of the paving process. Therefore, the additional information can

support anticipating and analyzing equipment movements. Such information can include descriptions of the construction process and site geometry, as well as depict paver's heading directions at specific locations.

7.2.1. Specifics of equipment movements during asphalt paving projects

Pavers: During road construction a paver normally changes its heading based on the site geometry while continue to move forward. At the end of a paved lane, it moves backwards to start another lane. Though the paver should, ideally, advance without stops to sustain the continuity of the paving process, in practice the continuity depends on project geometry, and also can be disturbed by external events or weather conditions. Thus, even if the maximum paver's speed is known (for instance it can be 25 m/min for a particular paver model [40]), the actual speed during road construction depends on the desired asphalt layer thickness, the continuity of asphalt delivery, and the movements of other equipment.

Besides constructing the asphalt layer, the paver sometimes needs to relocate to the beginning of the new paving lane and eventually has to stop and wait for the delivery of the asphalt mixture. In this setting, the information about delays of asphalt trucks, breaks, and other events that negatively influence the continuity of the paver movements can be easily documented as soft data. Therefore, collecting timestamps of the beginning and end of the paving lane, as well as describing on-site events (such as when or where equipment stops) can support experts in filtering outliers in equipment movements. Correspondingly, the choice of using an angle- or speed-based search to identify outliers can be justified by the experts according to their personal knowledge and the provided soft data in relation to the expected movements of the paver in particular moments of time. Overall, the equipment is not expected to make rapid turns and rapidly change speed during paving, but can perform so during relocating to the beginning of the next paving lane.

Rollers: The paver is closely followed by rollers. Rollers aim to achieve an optimum density and to provide a smooth surface by compacting the asphalt mat in specific patterns. In general, rollers move back and forth at slow but uniform speed, following a rolling pattern that progresses from the lower to the higher side of the asphalt lane. The roller's driving direction should not be suddenly changed or rapidly reversed, as these actions damage the road surface quality. Additionally, rollers should not stay still over the freshly paved asphalt mat and might avoid overusing stop/start sequences. The maximum speed and the maximum turning angle vary between different equipment models. For example, a specific three-drum roller can have the maximum steering angle of 40 degrees and can reach the speed of 10.2 km/h [41], and a tandem roller can perform 25 degree turn and can speed up to 12 km/h [42].

Though such information can already be used to filter outliers during equipment movements in relation to both relocating the roller to another lane and compacting operations, additional knowledge about the geometry of a particular project can also assist in searching for outliers. Beside compacting and relocating to the beginning of the next paved lane, the roller operator needs to perform other equipment-specific actions. For instance, the equipment eventually needs to travel longer distances to fill its water tank, as water needs to be continuously disposed during compaction to avoid sticking the mixture to the roller's drums. Such information about the equipment behavior can easily be documented by a human observer by means of project notes.

In summary, an expert can effectively filter documented paths of the construction equipment by considering the hard and soft data collected during asphalt paving projects in relation to the

expectations how the equipment can move on site. The next section illustrates such filtering based on the proposed information fusion approach.

7.2.2. Description of data collection during the paving project

The GNSS sensor readings as well as the project logbook used to validate the applicability of the approach to filter trajectories of asphalt paving equipment were gathered during a road construction project conducted near Alkmaar, a city in the Netherlands (Fig. 8). The structured data collection followed the methodology developed within the PQi (Process Quality improvement) framework developed at the University of Twente [5], which has the aim to improve process quality by structured monitoring construction work and making operational behavior explicit.

During the tracked 7 h work shift about 1200 tons of asphalt mixture was paved, which resulted in an 800 m long, 7 m wide, and 7 cm thick asphalt layer.

7.2.3. Applying the developed software to filter outliers in equipment trajectories collected during asphalt paving operations

Filtering path of the paver: The filtering of trajectories of equipment involved in the paving project was performed by utilizing the developed software. The user of the software first visually examined the path using the software, and then performed an automated search for outliers (Fig. 9).

Filtering path of the roller: The trajectory of a tandem roller was documented during a work shift between 4:56 AM and 11:42 AM. The equipment path highlighted in the left-top part of Fig. 10 corresponds to the time period between 8:05 and 10:11 when the equipment continuously compacted the asphalt layer. Before that period the roller went to the beginning of the paved lane and after that period the roller stood still.

Several outliers were identified in the documented equipment path. Similar to the paver's path's, both of the manually selected outliers were identified by visually examining the documented path using the interface of the developed software. One of these outliers was located at the beginning of the shift and another one was in the middle of the shift. The second of these outliers had a particularly large value that can be seen as the graph scale of the corresponding illustration extended up to 100 m. In addition to the manually identified outliers, several others were identified automatically.

Although the paths of asphalt paving equipment were collected using highly precise GNSS equipment, several significant outliers that had to be eliminated were still found. The proposed approach thus proved to be useful to identify outliers in equipment trajectories documented by highly precise GNSS sensors.

8. Discussion and future work

The proposed human-centered information fusion approach structures the way of identifying and filtering outliers in GNSS data while accounting for additional soft data characterizing construction processes. In addition, the approach allows incorporating human reasoning about how construction equipment can move during construction operations. The approach is constructed around the observe-orient-decide-act loop that characterizes human decision making and deals with both "hard" sensor readings and "soft" human generated data.

Documenting the site and taking notes during the process can provide specifics of the project's context as well as characterize relations between entities and events on site. Several examples of such descriptions include state of equipment within specific timeframes (if equipment stays idle or performs specific operations), geometry of and objects on the construction site (such as

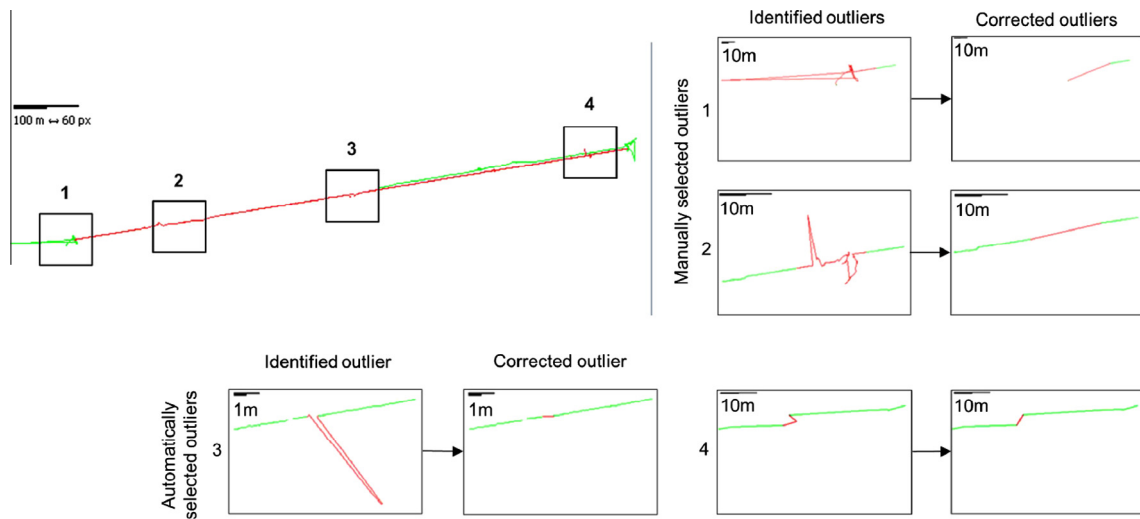**Fig. 8.** GPS tags mounted on a roller and a paver (left), data collection site (right).

Fig. 9. Overview of the paver's path with examples of identified and linearized sections of the paver's path.
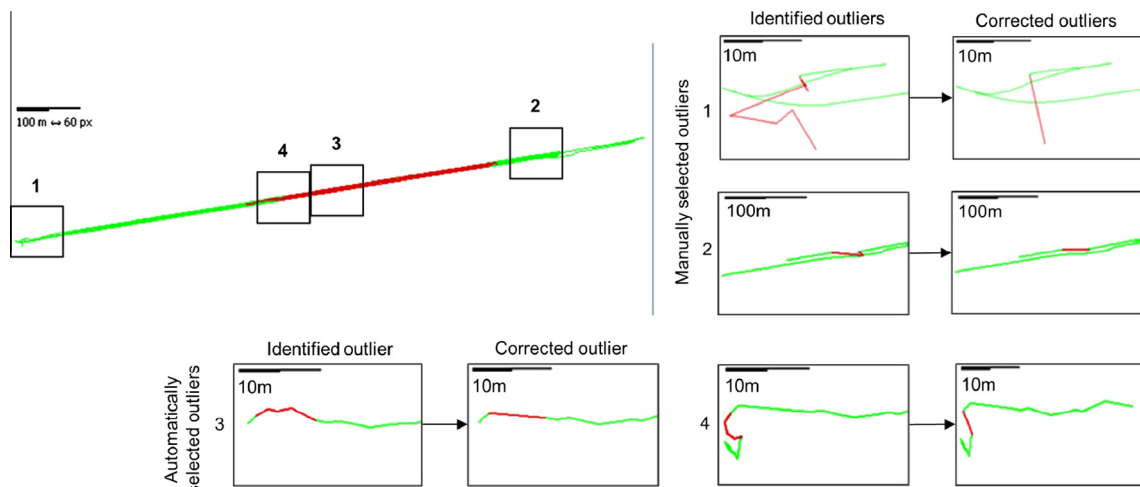

Fig. 10. Overview of the roller's path and examples of identified and linearized sections of the roller's path.

obstacles that could influence equipment movements) and unexpected events (e.g. delays in material delivery on site). Besides, using soft data can assist in capturing information that can hardly be obtained or require a large number of sophisticated sensors. Soft data can for instance describe locations of materials that were not tagged with positional sensors or markers, identify potential hazards, and characterize weather factors, including visibility, temperature, and rain that can potentially affect the construction

activities or sensor readings. In addition, some unquantifiable traits can be described using soft data, including equipment operator's fatigue, recent incidents on site that can influence worker's behavior, and performed impromptu temporary adjustments to the flow of work. As an additional value, the soft data can depict the intentions of equipment operators how to conduct their activities in a given context.

Based on the provided hard and soft data, the expert can identify outliers as visual anomalies in the data visualization or automatically find path segments where equipment moved in an unexpected manner. In this way, soft data can support the expert in making informed decisions whether particular segments of documented equipment paths are outliers.

The level of detail of soft data can ideally be just enough to support informed decisions, but according to the nature of human generated records such data granularity can hardly be predicted in advance. As the human-generated soft data aims to provide additional information about the progress of construction work, the amount of the supplied information can differ according to the observer's understanding of the needed data granularity, the person's available time and the needed amount of attention. These conditions particularly apply if multiple pieces of equipment should be tracked. Nevertheless, any amount of supplementary relevant information in addition to the hard data alone can potentially be helpful in identifying outliers. Once this data fusion approach is adopted experience and learning will shed more light on ways to deal with granularity and detail.

The conducted tests focused on refining GNSS paths of construction equipment as satellite-based navigation is probably the most common way to document equipment movements. To obtain paths that have different absolute error, both low and high precise equipment was used. Particularly, movements of equipment involved in earthmoving operations were recorded by using low-cost GPS receivers, while high-end DGPS sensors were employed during the asphalt paving project. The test outcomes indicated that sensor readings obtained by utilizing both classes of equipment paths included outliers that can be filtered according to the proposed approach. Therefore, the authors envision that equipment paths documented by using other technologies, such as laser-based positioning systems, could also be filtered likewise. However, additional tests for such technologies are desired.

Although the applicability of the information fusion approach was demonstrated by applying the specially developed software prototype to filter paths of different construction equipment, not all possibilities of utilizing different types of soft data were explored. In particular, the developed software only supports a particular type of soft data (a logbook of the construction project), therefore other potentially useful information sources, such as on-site photos and construction plans, were not presented to the user during tests. In other words, the potential surplus of utilizing specific types of soft data was not the subject of this research.

Additionally, the implementation of the approach as a prototype left space for possible improvements in terms of the graphical user interface. The developed interface can clearly be improved based on the tasks of the user and their specifics. For instance, the interface can be extended to encompass additional functionality to effectively handle extra-large datasets or filter paths that potentially contain large amounts of outliers.

In addition to the implementation process, several limitations also characterize the conducted tests. In particular, as the data collection was conducted not in experimental settings, but during real construction projects, the collected paths include absolute error, associated with the utilized equipment. Therefore, though the validation of the method was mainly concentrated on filtering outliers introduced by the environment, while aspects related to the in-depth discussion of the accuracy of the documented equipment itself were left aside.

Another characterization of the conducted tests is their purpose to demonstrate the potential applicability of the information fusion approach, rather than to provide evidence for advantages of using the proposed solution, for example by comparing it with the fully automated data analysis. This research design decision is related to the authors' consideration that the efficiency of software developed according to the proposed approach is a hardly generalizable characteristic because the demanded amount of human intervention into data processing highly depends on the accuracy of tracking technologies, ambient weather conditions, and the availability of unobstructed transmission signals from navigation satellites. Altogether, the amount of necessary corrections for hard data collected during a specific project can hardly be predicted beforehand, as construction processes are conducted within specific contexts that include particular site layouts as well as objects located on or next to the construction site that can introduce a different amount and type of outliers within collected data. Future research could include further justifications of the approach and evaluations of the desired degree of accuracy of the documented readings. In this way, the research can explore if the proposed information fusion approach can be related to particular data analysis tasks. For example, research could show whether filtering paths obtained by using low-cost equipment can effectively support precise process control and retrospective analysis of near-miss safety accidents. Another particularly promising future research direction is to develop machine learning algorithms that can automatically correct outlier detection settings, reducing the need to involve experts in the process. For instance, if GNSS data are found to be prone to outliers within a specific time or spatial constrains, the software could automatically adjust parameters and concentrate on searching potential outliers within those constrains. Also, additional research could study the benefits of incorporating additional sensor readings by utilizing other technologies, such as video tracking and dead-reckoning system, with respect to considering with the costs of adequately processing multiple input streams. Ultimately, these future research directions could lead to a computer-pull communication pattern when the input from the human could be requested "only when the expected value of their observation exceeded the cost of obtaining it" [43].

Future investigations into the nature of expert knowledge can also contribute to automating filtering equipment paths. Such investigations could involve careful analyses of how equipment and human operators can collaboratively perform information fusion tasks by applying frameworks for process analysis, based on distributed cognition [22]. Ultimately, this trajectory can support further development of information fusion approaches. Another way to improve path filtering can be to adopt structures for soft data based on particular domain-specific ontologies that unambiguously describe both possible events and project background conditions. Finally, better understanding of rules adopted and applied by an expert to filter equipment paths, can contribute to the more automated and even real-time filtering of equipment paths. In this case, a balance can potentially be found between reducing level of details to handle limitations pertinent to data transfer and processing during real-time tracking of construction activities, according to the scheme suggested in [44], and the robustness of data filtering algorithms. Apparently, a promising approach would be to apply qualitative reasoning methods to assess equipment movements at a construction site. As the major purpose of such methods is to support qualitatively reasoning about physical mechanisms, they provide a natural way to cope

with incomplete knowledge [45]. As the reasoning about equipment movements can be directly related to spatial qualitative reasoning the following three requirements to qualitative models (as listed in [46]) can guide the process of approaching filtering outliers in equipment paths: representation to describe relevant aspects of space by making only as many distinctions as necessary, domain theory to express partial knowledge available in the context and inference technologies to relate classes, such as spatial sizes and locations. Based on the potential value to structure and support interactions between human experts and equipment by adopting formalizing principles of qualitative reasoning, future research in this direction can be particularly fruitful.

9. Conclusions

This paper proposes a human-centered information fusion approach to support the interrelation of soft (human-generated notes) and hard (sensor readings) data with expert reasoning to filter equipment paths. This approach allows effective discrimination of outliers in an interactive way with the aim to increase accuracy of the collected GNSS path trajectories of construction equipment. The proposed approach in particular aspires to avoid cases when automated data filtering can misinterpret some path segments related to equipment-specific movements.

To illustrate the approach, the authors developed open-source software to refine documented paths of construction equipment and used it to filter path trajectories of five different construction equipment. The software demonstrated its functionality in supporting its users to easily identify and eliminate outliers based on expectations for how five different types of construction equipment move during asphalt paving and earthmoving projects. The source code of the software together with the compiled version and the description can be freely downloaded from a web-based source code repository [47] and could be applied to refine documented paths of construction equipment before further data processing.

Acknowledgments

References

[1] J. Teizer, U. Mantripragada, M. Venugopal, Analyzing the travel patterns of construction workers, in: 25th International Symposium on Automation and Robotics in Construction – Isarc-2008, 2008, pp. 391–396.

[2] J. Teizer, D. Lao, M. Sofer, Rapid automated monitoring of construction site activities using ultra-wideband, in: Proceedings of the 24th International Symposium on Automation and Robotics in Construction, Kochi, Kerala, India, 2007, pp. 19–21.

[3] N. Pradhananga, J. Teizer, Automatic spatio-temporal analysis of construction site equipment operations using gps data, Autom. Construct. 29 (2013) 107–122.

[4] T. Cheng, J. Teizer, G.C. Migliaccio, U.C. Gatti, Automated task-level activity analysis through fusion of real time location sensors and worker's thoracic posture data, Autom. Construct. 29 (2013) 24–39.

[5] S. Miller, Hot mix asphalt construction: towards a more professional approach, PhD thesis, University of Twente, 2010.

[6] S. Miller, T. Hartmann, A. Dorée, Measuring and visualizing hot mix asphalt concrete paving operations, Autom. Construct. (2011) 474–481.

[7] T. Cheng, J. Teizer, Real-time resource location data collection and visualization technology for construction safety and activity monitoring applications,

[8] T. Cheng, U. Mantripragada, J. Teizer, P. Vela, Automated trajectory and path planning analysis based on ultra wideband data, J. Comput. Civil Eng. 26 (2) (2012) 151–160.

[9] T. Cheng, M. Venugopal, J. Teizer, P. Vela, Performance evaluation of ultra wideband technology for construction resource location tracking in harsh environments, Autom. Construct. 20 (8) (2011) 1173–1184.

[10] M. Imran, Y. Hassan, D. Patterson, Gps-gis-based procedure for tracking vehicle path on horizontal alignments, Comput.-Aid. Civil Infrastruct. Eng. 21 (5) (2006) 383–394.

[11] F. Caron, E. Duflos, D. Pomorski, P. Vanheeghe, Gps/imu data fusion using multisensor kalman filtering: Introduction of contextual aspects, Inf. Fusion 7 (2) (2006) 221–230.

[12] F. Peyret, J. Jurasz, A. Carrel, E. Zekri, B. Gorham, The computer integrated road construction project, Autom. Construct. 9 (5–6) (2000) 447–461.

[13] E.P. Herrera, H. Kaufmann, J. Secue, R. Quirs, G. Fabregat, Improving data fusion in personal positioning systems for outdoor environments, Inform. Fusion 14 (1) (2013) 45–56.

[14] S. Rezaei, R. Sengupta, Kalman filter based integration of dgps and vehicle sensors for localization, in: 2005 IEEE International Conference on Mechatronics and Automation, vol. 1, 2005, pp. 455–460.

[15] F. Bijleveld, A. Vasenev, T. Hartmann, Smoothing gps data of rollers to visualize apshalt paving operations, in: Proceedings of European Group for Intelligent computing in Engineering (EG-ICE) workshop in June 2011, Twente University, The Netherlands, 2011, pp. 1–8.

[16] M. Pravia, O. Babko-Malaya, M. Schneider, J. White, C.-Y. Chong, A. Willsky, Lessons learned in the creation of a data set for hard/soft information fusion, in: 12th International Conference on Information Fusion, 2009 (FUSION '09), 2009, pp. 2114–2121.

[17] D. Hall, J. Jordan, Human-Centered Information Fusion, Artech House Electronic Warfare Library, Artech House, Incorporated, 2010.

[18] Y.-K. Cho, C.T. Haas, K. Liapi, S. Sreenivasan, A framework for rapid local area modeling for construction automation, Autom. Construct. 11 (6) (2002) 629–641.

[19] J. Raol, Multi-Sensor Data Fusion with MATLAB®, Taylor & Francis, 2009.

[20] W.G. Bath, C.M. Boswell, S. Sommerer, I.J. Wang, Detection systems information fusion, Johns Hopkins Apl. Tech. Digest 26 (4) (2005) 306–314.

[21] E.P. Blasch, S. Plano, Jdl level 5 fusion model user refinement issues and applications in group tracking, in: Signal Processing, Sensor Fusion, and Target Recognition Xi, vol. 4729, 2002, pp. 270–281.

[22] M. Nilsson, J. van Laere, T. Susi, T. Ziemke, Information fusion in practice: a distributed cognition perspective on the active role of users, Inform. Fusion 13 (1) (2012) 60–78.

[23] E.P. Blasch, S. Plano, Level 5: user refinement to aid the fusion process, in: Proc. SPIE, vol. 5099, 2003, pp. 288–297.

[24] B. Khaleghi, F. Karray, Human-centered multi-target tracking: a random set theoretic approach, in: 2012 IEEE 13th International Conference on Information Reuse and Integration (IRI), 2012, pp. 193–200.

[25] C. Haas, A model for data fusion in civil engineering, in: I. Smith (Ed.), Intelligent Computing in Engineering and Architecture, Lecture Notes in Computer Science, vol. 4200, Springer, Berlin Heidelberg, 2006, pp. 315–319.

[26] S. Shahandashti, S. Razavi, L. Soibelman, M. Berges, C. Caldas, I. Brilakis, J. Teizer, P. Vela, C. Haas, J. Garrett, B. Akinci, Z. Zhu, Data-fusion approaches and applications for construction engineering, J. Construct. Eng. Manage. 137 (10) (2011) 863–869.

[27] S.N. Razavi, C.T. Haas, Multisensor data fusion for on-site materials tracking in construction, Autom. Construct. 19 (8) (2010) 1037–1046. the role of VR and BIM to manage the construction and design processes.

[28] E. Blasch, Sensor, user, mission (sum) resource management and their interaction with level 2/3 fusion, in: 2006 9th International Conference on Information Fusion, 2006, pp. 1–4.

[29] D. Lambert, Grand challenges of information fusion, in: Proceedings of the Sixth International Conference of Information Fusion, 2003, vol. 1, 2003, pp. 213–220.

[30] É. Bossé, J. Roy, S. Wark, Concepts, Models, and Tools for Information Fusion, Artech House Intelligence and Information Operations Library, Artech House, Inc., 2007.

[31] S. Gentil, J. Montmain, Hierarchical representation of complex systems for supporting human decision making, Adv. Eng. Inform. 18 (3) (2004) 143–159.

[32] B. Song, Z. Jiang, Proactive search enabled context-sensitive knowledge supply situated in computer-aided engineering, Adv. Eng. Inform. 27 (1) (2013) 66–75. modeling, Extraction, and Transformation of Semantics in Computer Aided Engineering Systems.

[33] Y.-S. Kim, C.T. Haas, A model for automation of infrastructure maintenance using representational forms, Autom. Construct. 10 (1) (2000) 57–68.

[34] D. Bryant, Critique, explore, compare, and adapt (ceca): a new model for command decision making, Report DRDC-TORONTO-TR-2003-105, Defence R&D Canada – Toronto, Toronto ONT (CAN), July 2003.

[35] Hitachi eh-1100-3 specifications, <http://hitachiconstruction.com/assets/files/products/Mining/EH1100-3/EH1100-3_specs.pdf> (cited 04.04.14).

[36] S. Nunnally, Construction Methods and Management, Prentice Hall, 1998.

[37] Construction safety requirements, <http://www.flintco.com/uploads/cms_uploads/2013/12/safety-manual-subcontractor-re-1387396387.pdf> (cited 04.04.14).

[38] Komatsu pc400 lc, <http://www.komatsu.com/ce/products/pdfs/PC400_400LC-7_.pdf> (cited 04.04.14).

        A. Vasenev et al. / Advanced Engineering Informatics 28 (2014) 297–310

[39] John deere 750c, <http://www.deere.com/en_US/docs/construction/non_current_products/crawler_dozers/DKA750CII_0010.pdf> (cited 04.04.14).

[40] Vögele super 1900-3, <http://media.voegele.info/media/03_voegele/produkte/broschueren/02_raupenfertiger/layout_2013/super_1900_3/PB_SUPER_1900-3_EN.pdf> (cited 04.04.14).

[41] Hamm hw 90b/10 static three-wheel roller 10t, <http://www.hamm.eu/en/produkte/statische-walzen/serie-hw/hw-90b-10.227.php#!tab=technische-daten> (cited 04.04.14).

[42] Hamm dv 70 vv pivot steered tandem roller, double vibration roller, <http://www.hamm.eu/en/produkte/tandemwalzen/serie-dv/dv-70-vv.176.php#!tab=technische-daten> (cited 04.04.14).

[43] T. Kaupp, Probabilistic human-robot information fusion, PhD thesis, University of Sydney, 2008.

[44] A. Vasenev, T. Hartmann, A.G. Dorée, A distributed data collection and management framework for tracking construction operations, Adv. Eng. Inform. 28 (2) (2014) 127–137, http://dx.doi.org/10.1016/j.aei.2014.01.003.

[45] B. Kuipers, Qualitative reasoning: modeling and simulation with incomplete knowledge, Automatica 25 (4) (1989) 571–585.

[46] T. Escrig, F. Toledo, Qualitative Spatial Reasoning: Theory and Practice: Application to Robot Navigation, Frontiers in Artificial Intelligence and Applications, IOS Press, 1998.

[47] Data Import Wizard project, <http://asphaltopen.svn.sourceforge.net> (cited 04.04.14).