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Interactive Dashboards for Multi-Modal Data Analysis: Insights from Rail Construction Projects

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Abstract: The increasing volume and complexity of multimodal spatio-temporal data requires advanced approach for data exploration, integration and interpretation. This paper presents a flexible and extensible dashboard framework designed to support data-driven decision-making through interactive visualisation, exploration and analysis. The dashboard allows users to interpret structured data such as GNSS, IMU or temperature measurements as well as unstructured data types such as image files and contextual metadata. The dashboard follows the principle of combining data with reference data and display the process from raw to processed data. The concept is developed both for analysts and developers who need to identify suitable methods for analysing data and for subsequent debugging during the project. It supports analytical tasks such as pattern recognition, the integration of data sets and the validation of analysis results. By using InfluxDB for time series data management and Grafana for dynamic visualisation, the architecture ensures high scalability and responsiveness even with complex data sets. A use case from rail infrastructure monitoring shows how the dashboard facilitates data-driven insights and improves interpretability by linking multiple data perspectives. The integration of raw data, processed results and planned information enables users to align analysis results with operational objectives. This paper presents a reusable dashboard approach that improves decision-making and visual understanding of multimodal spatio-temporal data in applied cartographic and monitoring contexts.

Keywords: geospatial analytics, dashboard, exploratory spatial data analysis, decision support

1. Introduction

Interactive dashboards enable the visual presentation and exploration of complex datasets through coordinated maps, charts, and tabular views. Dashboards help to understand, evaluate and predict the development of data (Selby, 2009). Dashboards are used in many areas such as healthcare (Alhamadi et al., 2022; Bach et al., 2022; Davidson et al., 2022), education (Alhamadi et al., 2022; Bach et al., 2022) and urban development (Alhamadi et al., 2022; Bach et al., 2022).

Nowadays, vast amount of data can be captured very rapidly by different means, however, data analysis is not always straightforward and more often than not an iterative process. Especially with different data capturing methods such as positioning, capturing image or audio data, various data types result that require different processing methods for data analysis. An effective visualisation, an integrated view that links multiple data sources in their context and data processing stages, would better support the identification of relationships within multimodal data. Combined in a dashboard, the data can be utilised together and used for analytical purposes.

An important use and benefit of dashboards is that dashboards serve as important interfaces for data-driven decision-making (Park et al., 2010; Sarikaya et al., 2019). Despite an increasing number of case studies and general guidelines, there is surprisingly little design guidance for dashboards (Bach et al., 2022).

In cartography and geography, interactive dashboards are more than just a technical facilitator, as they are a means of conducting integrative geovisual analyses. Such tools provide a basis to combine traditional cartographic visualisations with modern data science workflows. Through dynamic linking, researchers can test spatial hypotheses, monitor urban phenomena or assess policy impacts in real time and under user control (Macenski et al., 2022).

This paper is intended as a flexible approach for data science and machine learning projects to link different datasets. This approach is applied to a case study of a railway construction site project for rail track replacement where a set of sensors, situated on key construction machines, are deployed to monitor and compare the construction process to the planned construction activities.

1.1 Requirements

Interactive dashboards appeal to different target audiences, including both development-oriented and management-oriented users (Selby, 2009). Development-focused users often require dashboards that support system monitoring, debugging, data processing validation, and iterative design, addressing metrics such as progress, reuse, or cycle time. In contrast, management-oriented users focus on strategic aspects such as process compliance, operational risks, and performance improvement. To meet both perspectives, dashboards must accommodate a wide range of types of visualisation and interaction functionalities that enable users to characterise system states, detect anomalies, assess risks, and forecast outcomes (Selby, 2009).

A critical requirement for modern dashboards is flexibility. As Davidson et al. (2022) observed during the COVID-19 pandemic during dashboard development, dashboards must adapt to evolving data sources and user needs. The adaptation and expansion of the data can be enhanced with raw sensor measurements, context data, processed data, labelled events, mapping, results and thresholds. Especially for analysis approaches based on exploratory visualisations, the analysis results should be embedded in the dashboard.

The most suitable form of visualisation for data analysis depends strongly on the specific data structure and the respective question of analysis, which is why adaptability is crucial. Therefore, multi-coordinate views (MCV) are beneficial (Roberts, 2007). MCV systems should be feature-rich and intuitive to use in order to visualise results quickly and enable simple investigations (Roberts, 2007). Each widget in an MCV setup represents a different aspect of the data set, such as a map for spatial analysis, a time series chart for temporal patterns, a bar chart for categorical distribution. Importantly, the views should be interactively linked so that users can explore relationships between the different data (Roberts, 2007).

In addition to analytical capabilities, interactive dashboards serve as powerful tools for communication, collaboration and troubleshooting workflows. This is particularly valuable in multimodal systems where complex pre-processing such as temporal alignment, spatial linking or normalisation of metadata can cause errors that are difficult to detect in tabular or code-based formats. As identified by Wongsuphasawat et al. (2016), visual interfaces that support step-by-step feedback help to detect inconsistencies, missing data or modelling assumptions early in the analysis process.

Analytical correctness in interactive dashboards requires not only accurate data processing, but also the use of standardised and formalised visual language (Bach et al., 2022). Inconsistent terminology, unclear visual coding or ambiguous interactions can undermine the interpretability and validity of results (Amar, Eagan and Stasko, 2005). Consistent scales, colour coding, units and naming schemes support both semantic clarity and analytical transparency and enable users to trust and reproduce the results (Schulz et al., 2013).

1.1.1 *Multi-Modal Data*

The data that flows into a dashboard can be of different data types. In addition to structured data such as temperature data, IMU data, GNSS points, log or analysis outputs (i.e. GNSS sensor is within a predefined zone), unstructured data such as audio and video data or digital elevation models may also be available. There is also process metadata, which can provide information about the quality of the data or the presence of missing measurement data. A multi-view design such as the MCV is particularly powerful for gaining insights from multimodal data (Roberts, 2007).

1.1.2 *Linking & Brushing*

Linking and brushing are foundational interaction techniques in visual analytics. They support both analytical goals, such as filtering based on specific attributes, and perceptual goals, such as identifying and localising elements across views (Roberts, 2007). Linking views means that selecting or highlighting data in one view automatically highlights the corresponding data in other views. For example, if you select a data point from one sensor, the time-corresponding points from the other sensors and the corresponding entries are highlighted. This allows users to recognise how patterns in one modality relate to patterns in others.

1.1.3 *Scalability*

Scalability in multimodal dashboards refers to the ability of the system to maintain responsive interaction as data volume and complexity increase. Multimodal datasets that combine time series, spatial data and categorical attributes can overwhelm standard interaction techniques such as brushing and linking, resulting in latency and visual clutter (Fekete et al., 2008). To solve this problem, scalable systems apply methods such as data aggregation, sampling and progressive rendering (Fekete and Primet, 2016). For time series, scalability can be improved by restricting the analysis to user-defined time windows that limit the displayed data and reduce the processing load by focusing only on relevant intervals.

1.2 Case Study

The proposed dashboard framework is adaptable across various domains, particularly in projects that begin with exploratory data visualisation as a foundation for deeper analysis. The case study for the proposed dashboard concept bases on developing a data capturing and analysis pipeline for monitoring rail construction sites. Rail infrastructure projects are subject to strict construction deadlines. Precise scheduling is critical for both maintenance and new construction of rail tracks. Rail infrastructure projects, depending on regulation and rail operators, face the seamless integration of the construction schedule in ongoing operation with synchronized timetables and face conventional penalties if deadlines are not met. In their literature, Hussain et al. (2023) emphasize the importance of a unified platform from planning to the site management in the construction phase to minimize cost overrun. The combination of the planned process and its mapping to the state of the construction site in near real time consolidates both views and supports decision-making and insights for future construction sites.

Real-time tracking of construction progress on rail construction sites, enabled by modern sensor technologies, aims to reduce waiting times and downtime. The use of data from IoT devices, such as Inertial Measurement Units (IMU), Global Positioning System (GPS), and cameras, on key construction machinery (crane, excavator, and tamping machine) enables the comparison of planned processes with executed processes. Mapping sensor data to the process plan is essential for this comparison. To identify which algorithm is suitable to analyse and map the captured data to the process plan, and to model the constraints imposed on the data, exploratory visualization is suitable for decision-making.

Another representative example could be its application in a behavioural observation station for meerkats. In this context, multiple data streams can be integrated, including spatial data (GNSS tracking of individuals), environmental sensor data (temperature, weight sensors at feeding stations, camera footage), structured planning data (locations of burrows of distinct subgroups), and experimental thresholds (call simulation of a bird of prey). By linking and visualising these heterogeneous data sources in a coordinated dashboard environment, researchers can monitor and analyse behavioural responses in real time like mapping behavioural patterns to environmental or contextual variables.

2. Methods

This section outlines the design and implementation of an interactive dashboard to support the development of an analysis pipeline with multi-modal spatial-temporal data. The goal is to create a flexible approach that can be applied to various fields, allowing users to explore understand and combine the data as well as make data-based decision

2.1 Design Concept

Our approach is designed to guide a variety of projects in creating a dashboard for data exploration, data-based decision-making for analysis methods and thresholds, and for debugging purposes. The dashboard enables exploratory data analysis, contextual conclusions and the discovery of patterns in heterogeneous data sources. This is achieved through a MCV setup, where each panel or widget represents a different aspect of the data.

The dashboard must be flexibly customisable to support various project needs. This means that the data can be continuously expanded or selected data can be displayed side-by-side within one panel. For example, combinations such as the temperature and with food intake metrics meerkats can be compared to identify potential behavioural patterns. The visualisation process is progressive. The data is presented at the beginning with raw data and allows for successive enrichment with processed information, contextual overlays, and derived analysis outputs, culminating in an integrated visual representation as exemplified Figure 1.

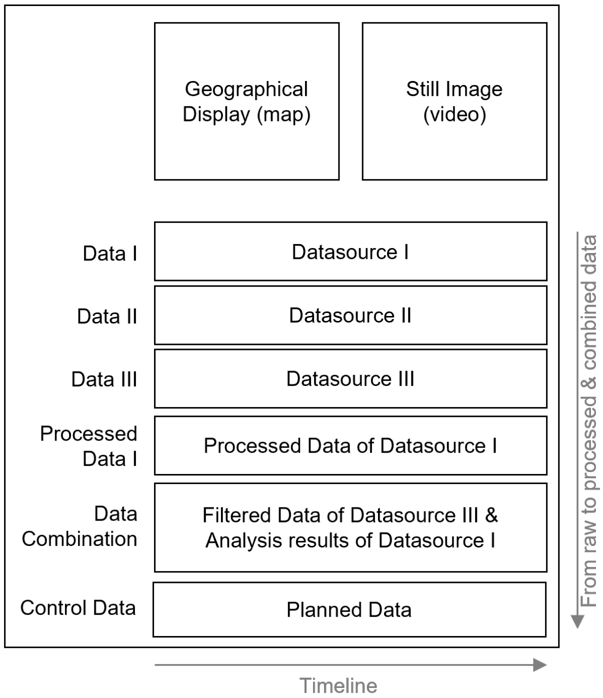

Figure 1. presents a schematic example of the dashboard architecture, illustrating how data from the various data sources as well as the processed data from data source I and the combination of data from the filtered data from data source III and the analysis results from data source I are displayed.

A core feature of the dashboard is its support for multimodal data, which may include spatial, temporal, categorical, and numerical information. Data elements are linked through shared attributes such as sensor ID, observed object, or temporal alignment. The raw data as well as the processed data and are relevant in the analysis process. The dashboard should provide an overview of all data at any given time. Planned data such as a process workflow or construction plans may be integrated to provide a comparative reference for interpreting real-world deviations. In this case study, planned activities and their activity area are integrated into a dashboard to enable a direct comparison between the observations by the sensors and scheduled activities.

In the context of time series, scalability can be improved by aggregating the data or restricting it to user-defined time windows. This reduces the amount of data displayed and reduces the processing load, as only relevant time ranges are considered.

2.2 Technical Implementation

2.2.1 *Data storage*

InfluxDB is a time series database designed to efficiently handle large amounts of time-stamped data of various types and enriching it with tags. It is particularly well-suited for applications where monitoring, analytics of time-stamped data is prevalent. InfluxDB can be used for the data management of multimodal data. In the exemplary case study time synchronisation plays a crucial role, as different sensors may operate in different time zones or are not properly synchronised. For instance,

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GNSS (Global Navigation Satellite System) data may be captured in GPS time, while temperature measurements could be recorded in local time. Ensuring time synchronisation before data storage is essential. Once the data is properly timestamped, it can be stored and used for analysis and processing. The data in the database can then also be used for analysis and processed directly.

Image and video data cannot be directly imported into the database in their original formats. Image data can be stored in binary form. Video data is not supported at the time of writing, but can added as individual images or frames.

2.2.2 *Dashboard*

Grafana is typically used for monitoring time series, but offers flexible panel configurations (as the boxes in figure 1) and supports data connections from various interfaces such as InfluxDB, allowing us to visualise real-time sensor data, derived metrics and system states within a single interface. This capability has been utilised to display the raw data, its processed results and analysis results. The various panels can also visualise information such as the completeness of the data (e.g. the number of missing values), the detection of outliers (e.g. statistical thresholds) and the consistency of the metadata (e.g. discrepancies in timestamps or sensor IDs).

With an established connection from InfluxDB to Grafana, the panels read and display the data from the Database. The reading flow of the panels from the top down starts with the display of the raw sensor data. Panels with the processed data or analysis results are added so the order makes sense for the user.

3. Results and Discussion

The developed dashboard integrates multimodal data sources such as time series, spatial data, and contextual metadata, into an interactive visual analytics environment. It enables users to perform exploratory data analysis using synchronised, linked views that support brushing, filtering, and the inspection of both raw and processed data. The system is structured around a multi-coordinate view setup, with visual components such as time series plots, spatial maps and images. Users are able to flexibly select, combine, and compare different types of data, which supports the identification of threshold or analysis methods.

This solution meets the needs of development-oriented and analysis-oriented tasks. It provides support for debugging, evaluating methods and data insights. The dashboard demonstrates a high degree of adaptability due to its modular design.

3.1 Design Concept

Our approach is intended to provide a conceptual framework for creating flexible, reusable dashboards that support exploratory data analysis, data-driven decision-making and debugging in the development phase. A key objective is to accommodate heterogeneous, multimodal data by enabling dynamically configurable views that combine raw inputs, derived metrics and analytical results. In line with the concept of MCV, the dashboard supports comparative analyses through linked panels that can be customised to the specific requirements of each project. For example, users can explore relationships between environmental variables and behavioural data such as temperature and food intake in meerkats by selecting relevant datasets and arranging them by time or entity. To ensure adaptability across different domains, the dashboard is designed for extensibility. New data sources can be added incrementally, and visualisations evolve from raw data representations to complex, customised views (see Figure 1). The link between the data sets is achieved through common identifiers such as sensor IDs, observation units or time intervals, that ensure semantic consistency between the views. In addition, scalability is achieved through aggregation and filtering. In this case study, as an example, this is achieved through aggregation of GNSS and IMU data, combined with temporal and categorical filtering for activity recognition such as “Standing” or “Driving”.

The approach is useful for understanding the data and making informed decisions about further processing steps and analysis methods. By comparing the raw data with the planned data, initial patterns can be identified that may guide the selection of appropriate analysis techniques. Further down the dashboard, the processed data and analysis results are presented, allowing for immediate validation of the outcomes. This structured approach not only aids in data analysis but also enhances system transparency, as all views are designed to facilitate debugging during the development of the analysis. It provides researchers with a comprehensive understanding of the data processing pipeline.

3.2 Technical Implementation

The import of the data to InfluxDB requires specific preparation, including the conversion of image data into binary form.

With the integration of various data sources such as InfluxDB, Grafana can import the data easily and offers a large number of visualisation elements, which can also be placed individually. In addition to time series data, tables or maps, the display of images is supported. This is particularly useful for debugging in the development process and cross checking the analysis results with reference data such as still images of video feeds or maps. There are certain limitations to the visualisations, such as a limited colour palette. For example, there are only 6 colours to choose from, but each with 5 different brightness levels. The key advantage for this use case is the ease of integration for new visualizations for visual exploration in the development of the analysis workflow.

3.3 Implemented Case Study

The dashboard in this project investigating several rail construction sites in Switzerland combines multimodal data, including spatial, temporal, and contextual data. Since the sensor box is mounted on the machine, the data can provide us insights to the movements and activities of the machine. For example, GPS data provides

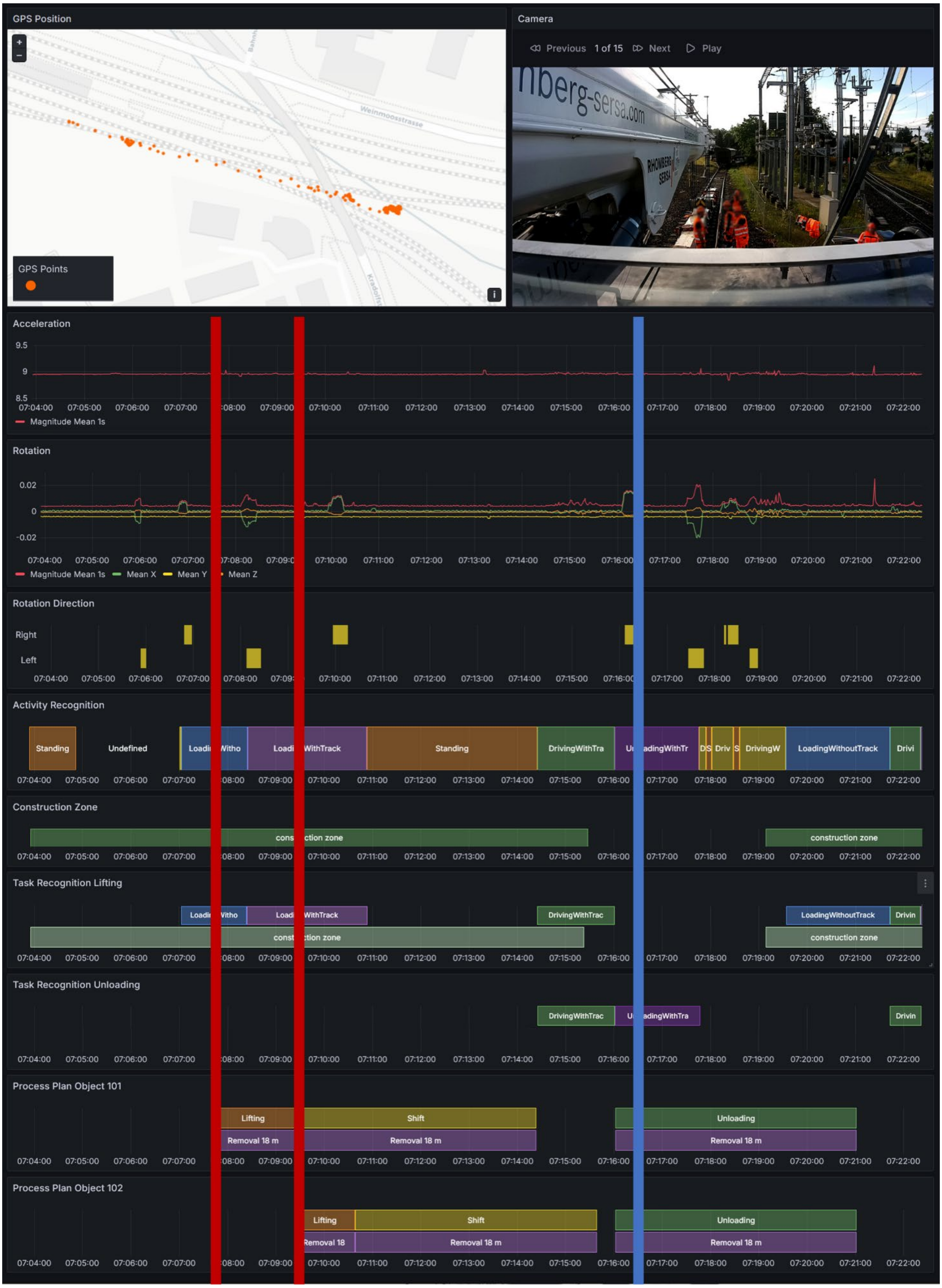

Figure 2. Dashboard in Grafana displayed the sensor data from raw to processed data with the process plan of the rail construction side. In red highlighted you find the process step of loading train tracks and in blue the unloading of a rail tracks

geographical information, IMU data offers insights into movement, and image data captures the environmental context. Image data are pre-processed and classified using machine learning (ML) algorithms to recognize movement patterns of construction machinery.

The dashboard for the case study is shown in Figure 2. The raw data such as the positions, the camera images and the IMU data (Rotation & Acceleration) can be found at the top. Derived from the IMU, movements of the machine such as rotation to the left or right are shown under the 'Rotation Direction' panel. Activity recognition processed from the video data with ML is shown in the 'Activity Recognition' panel. These are classified by colour for easy recognition. Then, in the 'Construction Zone' panel, a 2 metre buffer around the construction zone is used to check whether the machine position is within a predefined zone. In the 'Task Recognition Lifting' panel, the activity data filtered by 'Loading...' filtered activity recognition data is combined with the position in the construction zone. The aim of this combination is to investigate whether this combination is unique to the task of lifting off the track or not. The same is the aim of the 'Task Recognition Unloading' panel, where the combination of 'Unload...' and 'Drive...' combines filtered activity recognition data with the position in the designated deposit zone (which the machine not entered in this time period). The last two panels show the process plan per item (here the track units 101 and 102) as they were planned. This is helpful for categorising and comparing the key moments in the time series.

Exploratory visualizations enhance understanding of data dependencies and help uncover limitations in the dataset that may affect the outcome of the mapping process. The dashboard synchronizes all data and presents it in chronological order. The design principle of the dashboard follows the individual analysis steps of the workflow from the unprocessed data via the intermediate results and control methods to the mapping of the planning data from top to bottom in analogy to the reading flow. Such a layout supports intuitive data exploration, where users can trace the transformation process of the data. The dashboard implements various intermediate analysis steps that help to investigate the captured data and machine learning results of the sensor data. These encompass among other methods the cleaning and mapping of the GPS data of the construction machines to different zones of the construction site like construction zone of the single construction element or deposit zones, the video classification of machine movement data with purpose-trained machine learning methods or threshold-based identification of turns based on IMU data.

The use of the dashboard in our use case facilitates the visual exploration and insights of the analysis workflow combining temporally synchronized heterogeneous data streams. Analysis of the IMU data revealed that driving a curve produces output comparable to stationary rotation, suggesting potential improvements conclusions through integration with image data category outputs. Additionally, GPS data analysis identified a deviation from the planned process, as unloading of tracks occurred at an unintended location rather than the designated deposit zone (see red highlight in Figure 2). The inclusion of dependencies supports the detection and verification errors indicating classification errors or deviation from planned processes.

4. Conclusion

As more and more data is collected and processed, the need for structured analysis and visualisation will increase in the future, especially with complex projects. Having a tool in applied cartographic and monitoring contexts for the exploration, visualisation, presentation and debugging of multimodal data all in one saves time and resources.

The creation of dashboards for time-synchronized heterogeneous data streams along the analysis workflow supports the development process of spatial-temporal data analysis and data science workflows. The dashboard not only helps in gaining insights into the data but also facilitates data-driven decision-making and provides means to validate the results of the mapping process. An important aspect of the dashboard is its adaptability for future expansions and their linking with each other. This allows for the integration of additional data or further processed data, experimentation with new mapping methods, or the customization of visual components for specific use cases. The flexibility of the system is important for exploratory and decision-making tasks.

Our project benefited from the findings facilitated by exploratory data visualisation. It supported decisions on data-based analysis methods and helped defining threshold values. The continuous embedding of the analysis results also helps to compare the results with the raw data.

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