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Data-driven, sensor-based taxonomy for environmental life cycle assessment of pallets

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Pallets are one of the most important load carriers for international supply chains. Yet, continuously tracking activities such as *Driving*, *Lifting* or *Standing* along their life cycle is hardly possible. This contribution is the first to propose a taxonomy for sensor-based activity recognition of pallets. Different types of acceleration sensors are deployed in three logistical scenarios for creating a benchmark dataset. A random forest classifier is deployed for supervised learning. The results demonstrate that automated, sensor-based life cycle assessment based on the proposed taxonomy is feasible. All data and corresponding videos are published in the SPARL dataset [1].

[Keywords: logistics, warehousing, taxonomy, activity recognition, inertial measurement unit, life cycle]

1 Introduction

Studies assume a loss of millions of pallets every year in Europe alone [2]. Beyond that, an unknown number of pallets is destroyed or disposed. Furthermore, more than 100 million Euro pallets were produced in 2022, showing a growth of around 8 % more produced pallets compared to 2021. The production of new pallets is at an all-time high. The average lifespan of a Euro pallet is about seven years [3]. Both the number of recycled pallets and the average service life continue to increase [4]. Industry demands longevity of the pallets. Repairs have lower CO_2 emissions than newly produced units [5], making repairs the preferred option for the vision of a circular economy [6].

Tracking and analyzing pallets life cycles can help prolonging them, which in turn could help reducing the carbon footprint. Less pallets would need to be manufactured or disposed. However, the incomplete flow of information along a pallet's life cycle results in a lack of traceability of its processes and estimated duration of use. The lack of information within supply chains is due to the heterogeneity of deployed technologies, as well as missing data acquisition from the pallet as a source. Industry shifts towards smart objects within Industry 4.0, and companies seek to evolve their systems to record data along the entire life cycle of a product. [7] An automated sensor-based recognition of pallet activities is imperative to track activities along the supply chain. In the state of the art, there is no shared understanding of pallet activities in logistics and therefore no methodology for activity recognition. A taxonomy provides this understanding as it defines the set of activity categories to be recognized by a classifier.

The goal of this paper is to create a taxonomy of classes for sensor-based activity recognition of pallets. In this contribution, we focus on warehousing activities. We seek to evaluate the taxonomy's practical applicability by experimentation in real-world scenarios.

Apart from the taxonomy and experimentation with a classifier for sensor-based activity recognition, this paper contributes a new dataset. A previous version of the dataset can be found in [8] SPARL [1] includes recordings from three logistical scenarios. A total of 20 recordings with a total length of 50.5 minutes were created with five different accelerometers at sampling rates of 50 to 100,000 Hz. All recordings were documented with cameras from three angles and all frames were annotated with the corresponding activity labels. The SARA tool used for annotating the data is available online [9]. The automated recognition of the activities is performed using a random forest times series classification model.

The structure for the paper is as follows: The next section will discuss the related work, followed by a description of the methodology. The fourth section explains the experimental results which, followed by a discussion and a presentation of the resulting taxonomy of pallet activities. Finally, the results are discussed in the conclusion.

2 RELATED WORK

The related work is divided into the sub chapters of activity recognition in logistics and environmental aspects.

2.1 ACTIVITY RECOGNITION IN LOGISTICS

Activity Recognition (AR) describes the process of monitoring humans or objects, deriving information about their actions, analyzing it and classifying it into activities. A prominent sub domain is human activity recognition (HAR) which is relevant in many applications like logistics [10], healthcare [11] and sports [12]. The rising interest in HAR is based on recent technological advancements, in particular in sensor technology and machine learning. In logistics contexts environmental concerns, stress and strain of employees, increasing performance requirements as well as rising costs are dominant domain problems [13, 14].

In addition to HAR, another sub domain is object activity recognition. Sensors are placed on relevant objects that are being handled humans or machinery. The research domain of object activity recognition is significantly smaller than HAR. For pallets, research tends to focus on tracking in terms of temperature deviations or location [15, 16, 17, 18]. In [19] the authors work on sensor-based pallets and develop a system to monitor humidity and temperature in the surrounding environment to make assumptions about the state of the transported food. There are many commercially available sensors that can track objects, their temperature and impacts based on an event threshold, such as [20] and [21].

Regarding the sensors used for monitoring and deriving data, AR can be divided into two approaches: vision-based and sensor-based AR. To gather the relevant data in this field, humans or objects perform various tasks and actions while being monitored either via cameras, infrared, markers, inertial measurement units (IMUs), or other technological measurement systems or a combination of these different sensors [22]. The analysis process for this type of data includes movement segmentation, annotation or movement tracking c. f. [23].

The quality of AR is substantially influenced by the sensor configuration and the corresponding power supply. For the latter, research evaluated solar powered sensors, batteries and plug connections. [19]. Furthermore, [24] state that a sensor's characteristics and features, such as sensitivity, range or the integrated sensory system, need to be considered and tested, to facilitate replicability to develop a reliable and non-application-specific model. DIN EN 15433 [25] provides guidelines to achieve standardized data sets derived from sensor technology for mechanical-dynamic transportation load, which can enhance research in the field. It contains basic requirements for the sensors, such as being equipped with three accelerometers arranged at 90° to each other, as well as for data acquisition. Furthermore it contains instructions on recording and data analysis. Sensor data can have an influence on standards and test procedures in logistics, for example the DIN [26] and ista 3h [27].

To create activity classification models, research shows an extensive list of options such as random forest, decision trees, to name a few. Recently, deep learning architectures are increasingly being used for classification such as convolutional neural networks and transformer architectures [28] The selection of a suitable model depends on the recorded sensor data. In addition to the selection of the sensor and the model to be trained, the training material must be sufficiently good. The research community strives to achieve best practices in dataset creation for various applications. Yet, guidelines and tutorials for this aspect are sparse [29]. To address the problem of insufficient training material, transfer learning methods were used in [30, 31, 32]. Here, a model is first trained on data from a related problem and then transferred to the actual problem – possibly with an adaptation step.

Another approach to remedy insufficient training material is the use of experimental design. While efficient planning of experiments in relation to statistical modeling in the sense of classical statistical models is an established method [33], it has not yet been used for the precise adaptation of random forest classifiers or even neural networks in activity recognition. In general, the focus of neural network adaptation is on the best possible tuning parameters or importance sampling, which is more concerned with the skillful selection of subsets of the entire data set [34]. The determination of optimal test plans for neural networks was more of theoretical interest, c. f. [35]. On the whole, experimental design has received little attention in the field of machine learning, even though it can lead to better results, as explained in [36].

2.2 ENVIRONMENTAL ASPECTS

Logistics operations seek opportunities for savings and efficiency improvements in terms of CO_2 emissions. [37] Sustainable topics such as the circular economy are also widespread in research. The focus here is on closing the cycle of materials and resources in the product. [38] These movements towards sustainability are being driven not least by legal regulations such as the Packaging and Packaging Waste Regulation (PPWR) [39]. A neglected issue is the consideration of load carriers such as pallets. Nevertheless, the topic of pallet management has grown in published papers in recent years [40]. There is also a connection between economic and technical focal points, the focus here is also on the environmental aspects, in particular on life cycle assessment and carbon footprint estimations. Life cycle assessment or life cycle analysis according to

DIN EN ISO 14040 or 14044 is used to evaluate the potential environmental impacts of a product system over its entire life cycle. There are four stages: defining objectives and scope, inventorying, impact assessment and assessment. If there is no impact assessment, the study is called a life cycle inventory. [41] In logistics [5] and [42] e. g. assess the carbon footprints of wooden and plastic pallets, concluding that wooden pallets are more environmentally friendly than their artificial counterpart. Prolonging a plastic pallet's life by a more cautious usage can reduce the environmental impact of plastic pallets, as incineration has to be carried out less frequently. The carbon footprint for wooden pallets can be reduced through more frequent repairs that avoid increased production of pallets. Burning wooden pallets for energy production at the end of their life can reduce the resulting CO_2 balance. This creates a considerable advantage over plastic pallets. [5] A common concept among load carriers is pooling. A closed pooling system guarantees multiple use of the load carriers, as the users borrow them and the pooling company is responsible for their management. The multiple utilization approach is already sustainable, but data gaps and anomalies mean that not all movements, types of use or even misuse can be identified, which leaves room for improvement. [43, 44] The assessment of life cycles is depending on data, which is often unavailable when it comes to the movement and handling of pallets. The gap described, as well as the upcoming opportunity towards automated and dynamic life cycle assessments [45, 46], motivates our contribution.

3 METHOD

The following section describes the logistical scenarios considered in our experiments, the recording process and the description of the annotation. The approach is adopted from the tutorial as described in [29].

3.1 LOGISTICAL SCENARIOS

The scenarios are based on conventional processes from real-world facilities. To this end, three scenarios were created with domain experts from Fraunhofer IML. They represent common situations in a warehouse. The scenarios were recreated in the laboratory at Fraunhofer IML to create a representative environment. The following scenarios were set up:

1. Wrapping a pallet and handing it over to a conveyor system,
2. Putting various goods onto a pallet,
3. Load and unload a full pallet in a pallet rack.

The first scenario can occur in an outgoing goods department, for example, and is shown in Fig. 1. The fully loaded pallet is picked up by a forklift truck and moved onto the semi-automatic pallet wrapper (I). The pallet wrapper has a turntable with internal stretch foil carriage. The pallet is then prepared on the wrapper by attaching the stretch film to the pallet block. The pallet is then wrapped. The wrapped pallet is picked up by the forklift truck and placed on a transfer point (II), where the pallet is picked up by an electric pallet truck and placed on a conveyor (III). The pallet moves along this to the end of the conveyor where the scenario ends. The second scenario describes a picking process on a pallet, for example for a business to business delivery, see Fig. 2. In the initial state, the pallet is half-loaded and is picked up with a pallet truck and moved into a pallet rack. Goods are then picked from several pallets in the rack and loaded onto the pallet. The pallet is moved from picking station to picking station (I)-(IV). Finally, the loaded pallet is moved to its starting location, where the scenario ends. The last scenario shows a storage and retrieval process of a loaded pallet as it can happen between inbound and outbound. A fully loaded and wrapped pallet is moved into a pallet rack with a pallet truck and stored in an empty space on the first level (I). The forks are lowered and moved out so that the pallet truck no longer touches the pallet (II). After a short pause, the pallet is removed again and returned to its starting point. The process can be seen in Fig 3.

Table 1: Used sensors for recording sessions

Sensor	Manufacturer	Sampling rate
MSR 145	MSR Electronics	50 Hz
MetaMotionS	MBIENTLAB	100 Hz
MPU6000	Ivensense	1,000 Hz
LSM303D	STMicroelectronics	1,000 Hz
PCE-VDL 24I	PCE Instruments	1,600 Hz
8763B500	Kistler Instrumente	100,000 Hz

3.2 RECORDING SESSIONS

The recordings were created with five different acceleration sensors and documented with three different cameras. These were placed in a 3D printed pallet block. For this purpose, the existing middle wooden block was replaced with the sensor block. The following sensor configurations were used:

The MPU6000 and LSM303D sensors are build in a PX4FMU flight control board from Holybro. This board has also two gyroscopes (MPU6000 from Ivensense and the L3GD20 from STMicroelectronics) which are not considered further. Both recorded with 1,000 Hz. The 8763B500 from Kistler was used in combination with a 5512A module of the KiDAQ data acquisition system from Kistler. To start the recordings, it was necessary to ensure that access to the sensors was available. Four of the sensors had to be started by cable connection or by pressing a button. In addition, an external power supply had to be provided for two of the sensors. Only the MetaMotionS sensor could be started

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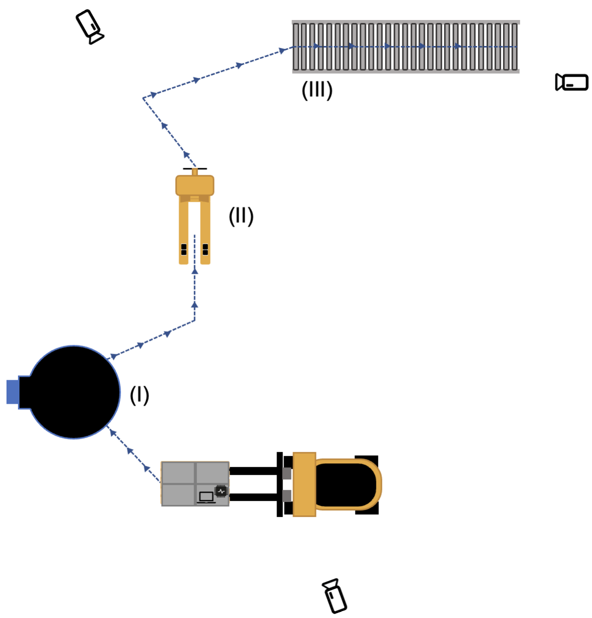

Figure 1: Sequence of the first scenario

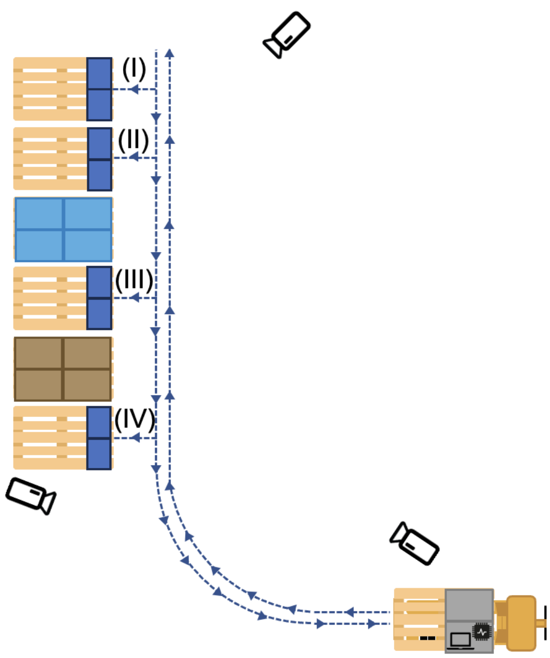

Figure 2: Sequence of the second scenario

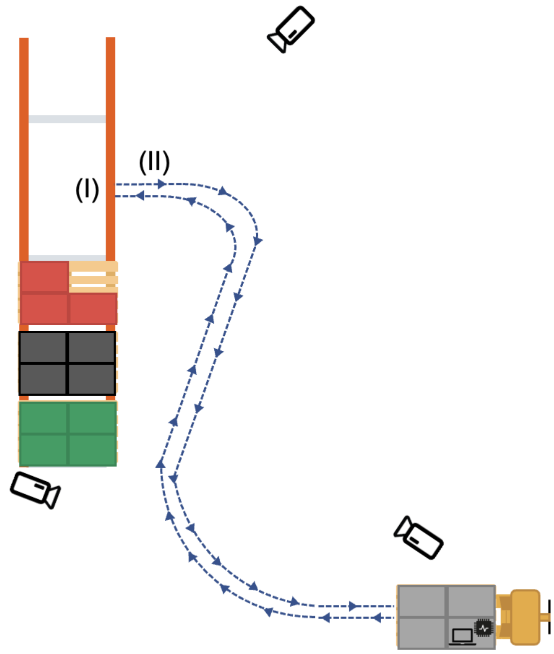

Figure 3: Sequence of the third scenario

Figure 4: 3D printed pallet block containing the sensors (left) and power supply container with cable management (right)

wirelessly via mobile app. The cable guides and power supply were stowed in a small load carrier on the pallet. This box was on the pallet at all times during the recording. The 3D printed pallet block and the sensor box can be seen in Fig. 4. The videos were recorded with three Logitech Mevo Start cameras, that were synchronized with each other via a mobile app. It should be noted that two recordings may be slightly out of sync for network reasons. The arrangement of the camera angles can be seen in Fig. 1, 2 and 3. The frames of the videos were then annotated and labeled with the Sequence Attribute Retrieval Annotator (SARA), which can be found under [9]. In order to synchronize the annotated frames with the time series of the sensors, a synchronization movement was performed in each recording. This was done by hitting a pallet block three times with a hammer at the beginning and the end of the record. The hammer hits are visible in the video recordings and in the time series of the sensor data. The following pipeline has

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been defined to start and end each recording according to the same sequence: In the first step, the pallet was lifted at the predetermined starting point of the scenario using the pallet truck so that the sensor installed in the pallet block could be started at the press of a button. The pallet is then lowered and the remaining sensors are started using a laptop. At the same time, the last sensor is started via app. When all the experimenters have left the viewing angle of the cameras, they are started. The person carrying out the test begins with the synchronization and then the actual sequence of the scenario is carried out as described in section 3.1. After the scenario, synchronization is repeated and the camera recordings and all sensor recordings are ended. Finally, the starting position is restored by returning the pallet to its starting point. In scenario 1, the wrapped film was removed and in scenario 2, the picked goods were put back in place. Scenario 1 was carried out at the Fraunhofer IML packaging laboratory. In total, it was repeated twice by two people, resulting in four recordings. The persons carrying out the test regularly operate a forklift truck or pallet truck. They did not know what the measurement was about and were only asked to perform the scenario. They were also asked to remain as constant as possible in their movements during the second recording. The pallet used had a total weight of 595 kg. This is made up of 24 containers with the dimensions 600 mm * 400 mm * 200 mm, each weighing 20.5 kg, and four containers with the dimensions 600 mm * 400 mm * 300 mm, which also weigh 20.5 kg. One of these containers contains the cable management and power supply. The weight of the other boxes is based on that of the sensor box. All load carriers used are standardized according to DIN 55423 [47]. The pallet used has a tare weight of 21 kg. Scenario 2 was carried out in the application hall of the Fraunhofer IML, which is characterized by having a single-aisle pallet rack. A total of 12 recordings were carried out by two other people. Eight full water crates were picked in the first four rounds, four crates measuring 600 mm * 400 mm * 200 mm were picked in rounds five to eight and four cartons measuring 370 mm * 370 mm * 370 mm were picked in the last four rounds. The water crates have a tare weight of 13.6 kg, the load carriers were brought to a weight of 10 kg with sacks and the cartons weigh 2 kg each. Each picking cycle was repeated twice and by two people. In the third scenario, four passes were also made at the pallet rack. The same people from scenario 2 stored and retrieved the pallet twice. As in scenario 1, the pallet weighed 595 kg.

3.3 Annotation

After completing the recordings, classes were defined for the annotation, which result from the sequence of scenarios. The classes were created as granular as possible so that a possible combination of different classes is possible in the future. The classes were defined semantically from the logistical application. The following classes were defined for the annotation:

Table 2: Class labels for annotation process

1	Wrapping	10	Docking
2	Wrapping (preparation)	11	Undocking
3	Driving (straight)	12	Standing
4	Driving (curve)	13	Loading
5	Lifting (raising)	14	Unloading
6	Lifting (lowering)	15	Rotation
7	Lifting (tilting)	16	Error
8	Lifting and Driving	17	Synchronization
9	Forks (entering or leaving the pallet)	18	None

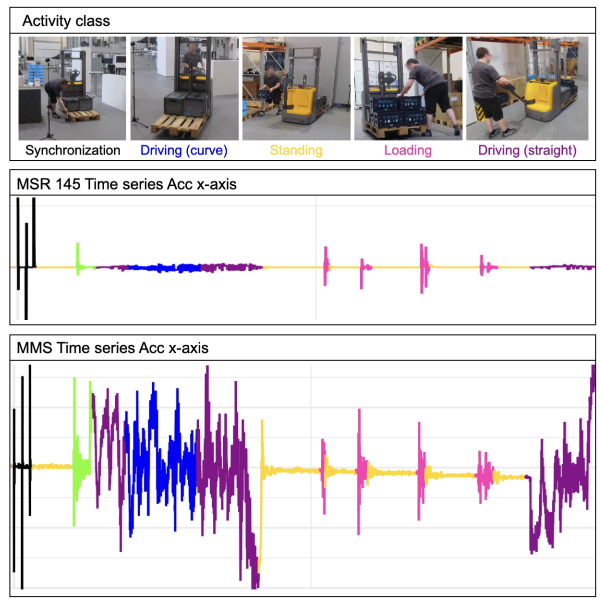

Figure 5: Excerpt of a scenario and comparison of the time series to video frames

The handling device and the item being used were labeled simultaneously. The following handling devices were labeled: High lift truck, low lift truck, forklift truck and roller conveyor. The list of items contains small load carrier, cardboard box, other container and no loading. The None class was used to mark segments outside the scenario. Error contains faulty images. The Rotation class was used for the initial scanning process of the pallet during the pallet wrapping in scenario 1. The manual marking of the video frames now makes it possible to analyze the IMU time series. A formal description of the pallet activities and thus a taxonomy is derived from this in section 5. Figure 5 shows an example of two labeled sensor time series in comparison to the video frame.

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4 EXPERIMENTAL ANALYSIS AND RESULTS

We have captured 20 recording units per sensor which we will refer to as data sets in this section. Each of these raw data sets contains the sensor measurements of one experiment in four attributes: a time stamp and acceleration information in x-, y- and z-direction. Each time point can be assigned to one activity class. Excluding the classes *Synchronization*, *None* and *Error* which are not considered for activity recognition and prediction, the data consists of more than 50 minutes of sensor measurements belonging to 13 activity classes. Table 3 displays information about the presence of the activity classes in each of the scenarios. Only the classes *Driving (curve)*, *Driving (straight)*, *Lifting (lowering)*, *Lifting (raising)* and *Standing* are present in all scenarios. The classes *Driving (curve)*, *Driving (straight)*, *Standing* and *Wrapping* are majority classes across all scenarios. The classes *Lifting and Driving*, *Lifting (tilting)*, *Docking*, *Wrapping (preparation)*, *Rotation* and *Loading* are minority classes across all scenarios.

As data reprocessing, the following operations were applied to each data set of each sensor. The acceleration data was transformed to have median value 0 across all time points of one experiment. To generate features for each time point t in the data set, the sensor measurements from 0.5 seconds before t until t were used. All sensor measurements within the time window $[t - 0.5, t]$ were used regardless of whether their activity class matches the activity class of time point t. In the time window, for each sensor component (x, y, z), quantiles of the original and the absolute sensor data were computed as measures of central and non-central tendency. Differences between these quantiles were calculated as measures of spread. Other popular measures of spread were also computed. In total, 210 features are created. For time points during the first 0.5 seconds of each experiment, the features could not be computed because there exists no complete 0.5-second time window. Therefore, these observations were only used for the computation of feature values for subsequent time points.

Random forest [48] was employed for predicting the activity classes. To account for class imbalance, the sampling of observations for tree creation was performed in a weighted fashion: each observation (corresponding to one time point) was drawn with a probability inverse proportional to the size of the respective activity class. To estimate the classification performance of the random forest unbiasedly, we combined 19 data sets to train a random forest model and evaluated this model's predictions on the left-out data set. For memory reasons, we maximally used 100,000 observations per class in the training data and selected these at random if applicable. We repeated this procedure 20 times so that each data set was used for predicting once.

First, we analyze if the activity classes are predicted correctly. Figure 7 presents confusion matrices aggregating the classification performance of the random forest models across all experiments and sensors. The diagonal in the left matrix displays the recall values, the diagonal in the right matrix the precision values. The majority classes *Driving (curve)*, *Driving (straight)*, *Standing* and *Wrapping* as well as the minority class *Loading* can be predicted well. The recall and precision values of the classes *Lifting (lowering)* and *Lifting (raising)* are acceptable. The two largest classes *Standing* and *Driving (straight)* are often obtained as predictions for observations of smaller classes. The classes describing activities applied to a standing pallet (e.g., *Docking*, *Forks entering or leaving the pallet*, *Wrapping (preparation)*) are often misclassified as *Standing*. All driving and lifting and classes have a notable frequency of being misclassified as *Driving (straight)*. Also, there exist confusions within the group of driving classes and within the group of lifting classes. This motivates combining groups of classes describing similar activities into super classes as presented in Figure 6.

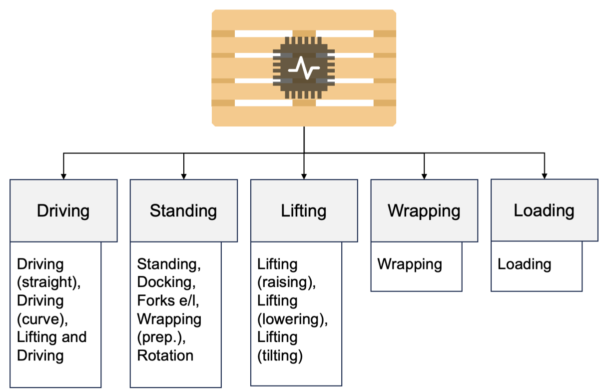

Figure 6: Proposed taxonomy and second annotation level for the description of pallet activities

The prediction results of the random forest models can be transformed into super class predictions. This means that the super class predictions are obtained from the models trained on the data with original classes labels. Figure 8 displays the classification performance of the random forest models comparing the predicted and true super classes analogously to Figure 7. Here, high recall and precision values can be observed for all super classes. Nevertheless, some confusions between *Lifting* and *Driving* as well as between *Standing* and *Loading* still exist.

The results presented in the confusion matrices were aggregated over all experiments and sensors. Figure 10 shows the F1 scores for predicting the activity super classes separately for each sensor and scenario. We observe that the classes *Driving* and *Standing* can be recognized very well based on all sensors and in all scenarios. Observations belonging to classes *Lifting* and *Driving* can be classified best for prediction data sets from scenario 2. This could be because there are more recordings for scenario 2 than for sce-

Table 3: For each scenario, the number of experiments, the total duration of all experiments (only the parts used for modeling later on) and the proportion of sensor measurements belonging to each of the activity classes is displayed. All values are rounded to integers.

Scenario	Number of experiments	Total duration (in seconds)	Driving (curve)	Driving (straight)	Lifting and Driving	Lifting (lowering)	Lifting (raising)	Lifting (tilting)	Standing	Docking	Forks entering or leaving the pallet	Wrapping (preparation)	Wrapping	Rotation	Loading
1	4	1591	10 %	15 %	1 %	3 %	4 %	2 %	20 %	1 %	9 %	6 %	27 %	3 %	–
2	12	872	12 %	30 %	–	3 %	2 %	–	45 %	–	–	–	–	–	8 %
3	4	568	11 %	30 %	10 %	8 %	14 %	–	13 %	–	14 %	–	–	–	–
All	20	3031	11 %	22 %	2 %	4 %	5 %	1 %	26 %	0 %	7 %	3 %	14 %	1 %	2 %

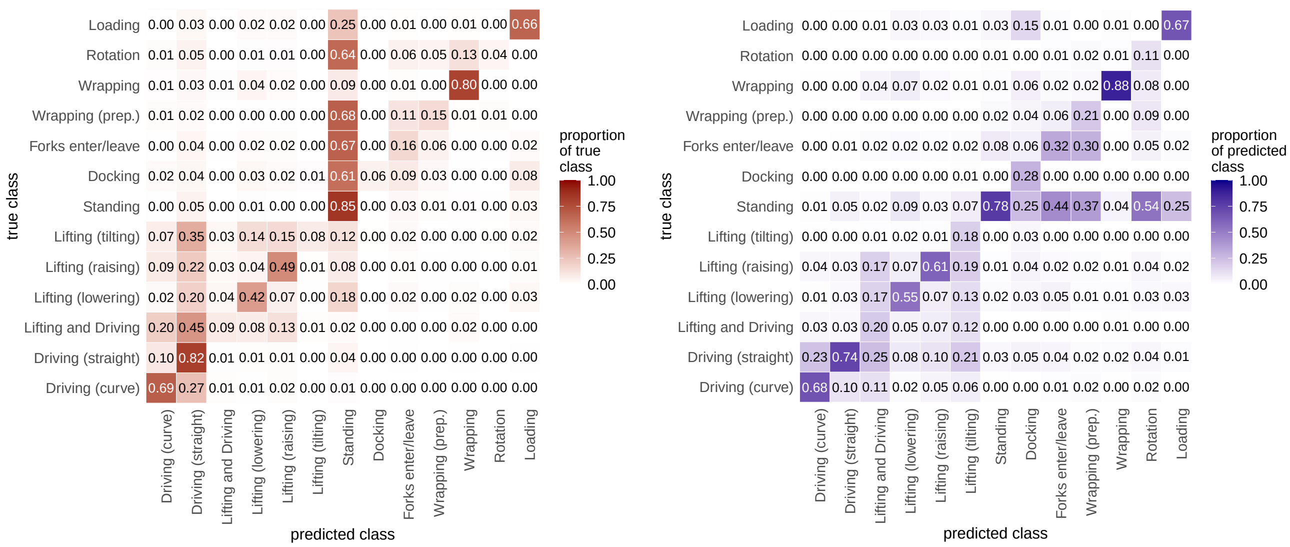

Figure 7: Confusion matrices for all activity classes averaged across all experiments and sensors. The entry in row i and column j represents
left: … the proportion (observations with true class i and predicted class j) / (observations with true class i).
right: … the proportion (observations with true class i and predicted class j) / (observations with predicted class j).

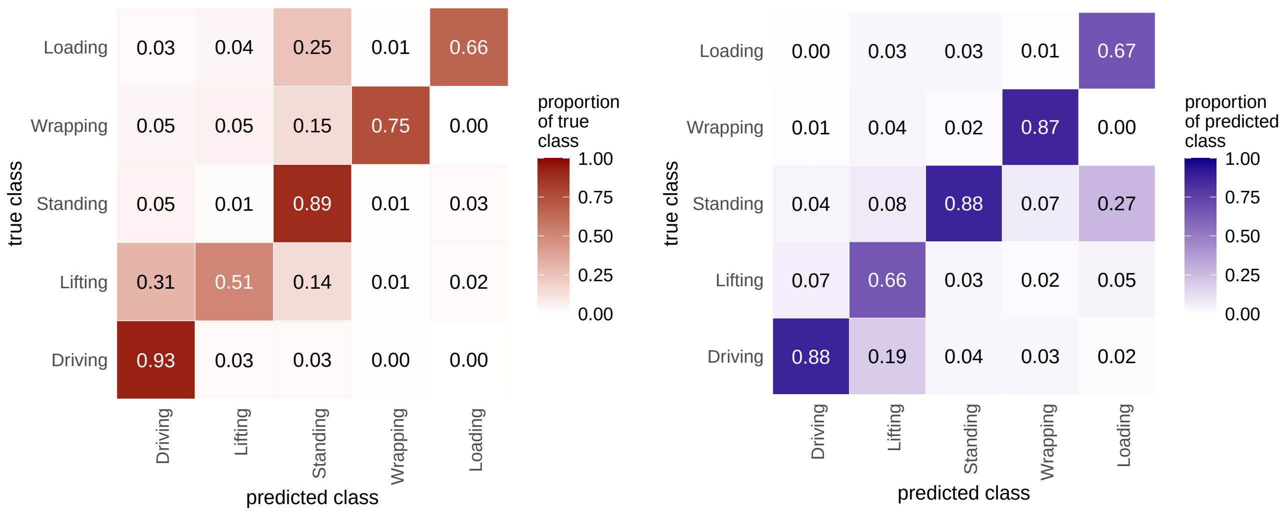

Figure 8: Confusion matrices for the super classes averaged across all experiments and sensors. The entry in row i and column j represents
left: . . . the proportion (observations with true class i and predicted class j) / (observations with true class i).
right: . . . the proportion (observations with true class i and predicted class j) / (observations with predicted class j).

narios 1 and 3. Hence, leaving out one of the recordings of scenario 2 for training takes away less information about the specific scenario. Also, the recordings of scenario 2 are much shorter than the other ones, resulting in a larger training data set when one recording of scenario 2 is left out for training. The classes *Wrapping* and *Loading* both only occur in one of the scenarios. Most sensors yield random forest models with similar performance for a certain class. The results achieved with sensor MSR 145 are always among the best.

Our last analysis focuses on the data used for training the random forest models. We compare our previously described approach of using all data sets except the prediction data set, that is, data sets obtained from different scenarios, for training the random forest model to an alternative approach where only the remaining data sets from the same scenario are used. Figure 9 presents the difference in F1 score between the two approaches when predicting on the same data set. We observe that the performance of the models trained on data from all scenarios is slightly lower than the performance of the models trained on the data of the same scenarios. The lower prediction accuracy for the cross-scenario model is expected here, because this model incorporates more classes (and therefore can predict classes that do not occur in a certain scenario). In particular, the cross-scenario model generalizes more and hence focuses less on the specifics of a certain scenario. The amount of predictive performance that is traded for a more generally applicable model is, however, very small. In some experiments, especially for the minority classes occurring in different scenarios, the classification performance of some classes can even be improved by incorporating data from different scenarios for specific sensors (e.g. LSM303D *Loading*).

5 Discussion of Experimental Results

When analyzing the sensor data, it was noticed that the majority of the data from the PCE sensor is incomplete or contains gaps. The sensor recordings were therefore not analyzed further. One recording from the MetaMotionS sensor also contains gaps. Accordingly, only 19 recordings could be considered for the analysis. The gyroscope data of the flight controller board was not taken into account. All data, with the exception of the PCE sensor recordings, can be found in [1]. In order to process the recordings of the Kistler sensor, which were recorded at 100 kHz, they were downsampled to 5 kHz and 20 kHz using a lowpass forward-backward filter according to [49]. The 5 kHz data from the sensor was used for the analyses. At higher sampling rates, the available resources reach their limits from a technical point of view. As a result, the data from the sensor is limited in the interpretation of the results and the full potential cannot be utilized at this point. An evaluation of the full 100 kHz will be carried out in the future.

When looking at the recognition performance across all classes, it is noticeable that low scores are achieved for the minority classes. Majority classes provide more reliable results, see section 4. In creating the annotation scheme, a conscious decision was made to use fine-grained classes. The classes were derived from the requirements of the logistics and from the observations of the video recordings.

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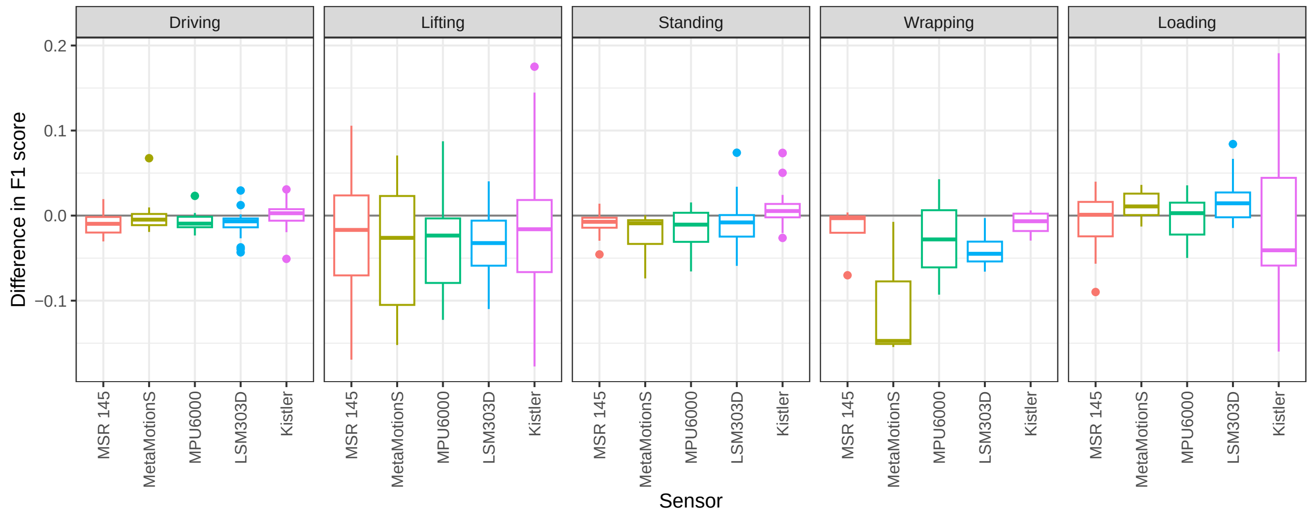

Figure 9: Boxplots of the F1 scores for predicting the activity super classes with a random forest model based on data belonging to the same scenario as the prediction data set or belonging to all scenarios. Positive values indicate that a model trained on all data sets (except the prediction data set) performs better on this data set than a model trained only on the other data sets from the same scenario.

For example, picking up and setting down the pallet is divided into the classes *Docking*, *Undocking* and *Forks entering or leaving the pallet*. This subdivision is used to see in retrospect whether recognition is possible. The results show that the classes achieve low performance or cannot even be annotated. Therefore, classes were merged to achieve better results. The classes presented here represent a first data-driven taxonomy and thus combine the requirements from the application and the results from the experiments Fig. 6 shows the merged classes.

This step enables higher recognition performance and is a proposal towards a taxonomy for the formal description of pallet activities. Despite summarizing the classes, fine-grained annotation will continue to make sense in the future, as better recognition rates can also be achieved for minority classes, depending on the data. Training across all scenarios for recognition as opposed to training adapted to the respective scenario lowers the recognition rate. However, this approach is more credible in the context of logistical activities and realistic validity. In the specific case, this would mean that it is assumed that the circumstances of the scenario would apply to all occurring warehouses. In logistics, there are many parameters that influence a warehouse and its processes, and each warehouse is adapted to its own use case. Therefore, a trained model must be combined with as much and as diverse data as possible to make a credible statement. The recordings and scenarios presented here indicate that it is possible to recognize activity classes even with little data. Nevertheless, more data must be recorded in the future, including a sufficient number of recordings containing minority classes. The goal is to improve the balance of classes in the training data set. For example, the classes Wrapping, Wrapping (preparation), Lifting (tilting) and Rotation only occur in Scenario 1, which consists of four recordings. For further results, these classes must appear in additional recordings in order to counteract misbalancing.

6 Conclusion

The results show that activity detection of pallet movements using acceleration sensors is feasible. Even lower sampling rates do not appear to yield worse results. It seems that the evaluation method of the random forest classifier is not the decisive factor for the quality of the results, since even the attempt to use a tuned model did not achieve any improvements. Rather, the data quality and quantity seem to be a decisive factor. Coming up with a conclusive taxonomy requires an iterative approach. Our results represent the first step in this direction. This is to be further enhanced in future experiments, bearing in mind that classes need to be semantically clear and relevant to the use case. Yet, the taxonomy has to be data-driven, meaning a sufficient classification must be achievable. The results show that this approach is feasible. This may imply changes to the taxonomy, as a relevant label is not necessarily easy to detect in a recording. We seek to tackle the issue of data balance is in the training data for future work. In the recordings presented here, some classes are only represented in one scenario, which does not produce meaningful results. Majority classes can already be recognized. Among other things, supervised learning requires a large number of balanced classes. However, a later aggregation of classes can be useful to achieve higher recognition rates. A fine-grained annotation of the videos is therefore very useful and should continue to be taken into account as long as they are labeled consistently. A combination of fine classes is possible, whereas a later splitting of the classes is not.

Industry transfer in terms of a commercial product based on our idea would require more data sets and further tests on a wide range of hardware. An industrial solution must be cost-effective, capable of real-time analysis and sustainable when it comes to the batteries and sensors. In summary, issues such as energy supply, data transmission, data evaluation and sensor attachment may also need to be clarified during operations. With more research resources, the realization of such a project is possible and contributes to sustainable logistics.

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APPENDIX

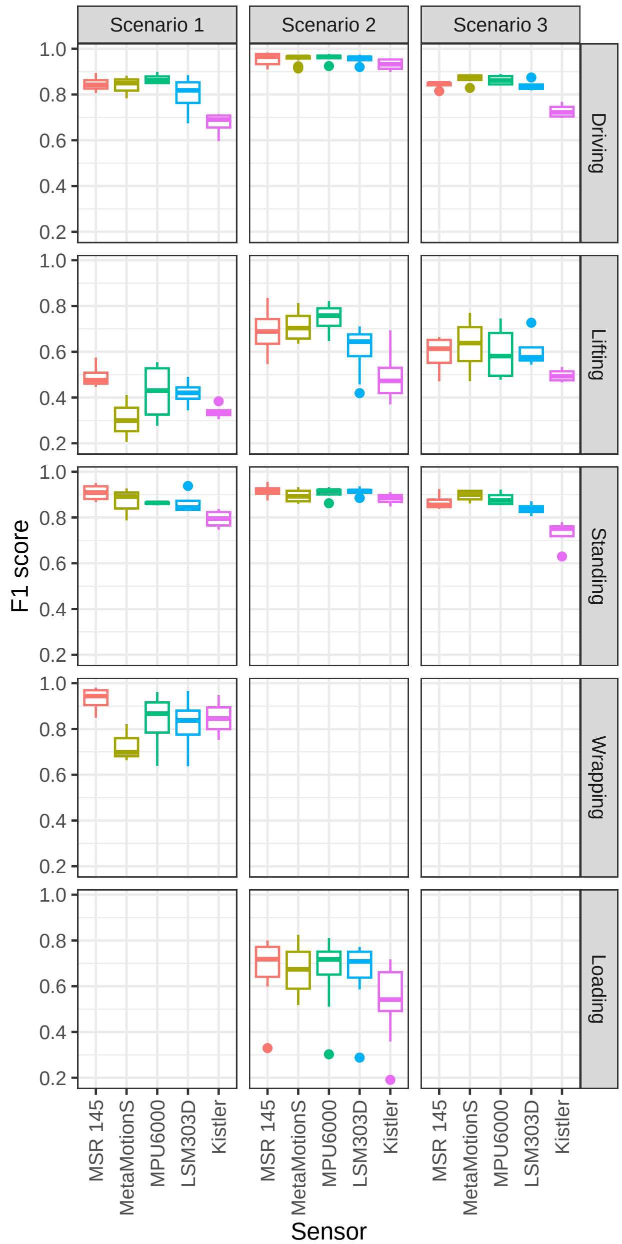

Figure 10: Boxplots of the F1 scores for predicting the activity super classes with a random forest model based on data provided by different sensors

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