# Motion Classification for Analyzing the Order Picking Process using Mobile Sensors

## *General Concepts, Case Studies and Empirical Evaluation*

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Abstract: This contribution introduces a new concept to analyze the manual order picking process which is a key task in the field of logistics. The approach relies on a sensor-based motion classification already used in other domains like sports or medical science. Thereby, different sensor data, e. g. acceleration or rotation rate, are continuously recorded during the order picking process. With help of this data, the process can be analyzed to identify different motion classes, like walking or picking, and the time a subject spends in each class. Moreover, relevant motion classes within the order picking process are defined which were identified during field studies in two different companies. These classes are recognized by a classification system working with methods from the field of statistical pattern recognition. The classification is done with a supervised learning approach for which promising results can be shown.

## 1 INTRODUCTION

Since 1999 e-commerce has been growing continuously especially in the retail sector. For instance in Germany, e-commerce companies have increased their sales for the last 5 years on average by 10 percent per year (HDE, 2014). It is forecasted that more than 40 billion euro will be spent online in 2015 alone. Due to this sustained growth, the relevance of industrial order picking has significantly changed for producers and retailers since the beginning of the e-commerce boom in 1999. Within the order picking process, stored articles are collected in a given quantity to satisfy customer orders. Today this process has a major impact on the customer service and consequently on the competitiveness (de Koster et al., 2006).

As manual work is one of the main cost drivers especially in high-wage countries, the duration of manual materials handling processes is crucially important for the operation and planing of industrial order picking systems. The knowledge of time quotas of manual tasks helps to find optimization potentials within the process, to estimate the performance and to determine the amount of staff required to fulfill the customer orders (Krengel et al., 2010, p.5). Currently, time measurement approaches like *REFA* or *Methods Time Measurement* (MTM) only allow for the quantification of average time values or the definition of standard times (Krengel et al., 2010, p.5). Thus, important process information like the travel or gripping time can only be estimated, but not automatically determined for a given system. Even modern *Warehouse Management Systems (WMS)* and corporate databases are not able to fill this lack of knowledge. For instance, a WMS usually saves how many order lines a worker acknowledged during a time period, but it is unknown how many picks were needed to process these order lines (ten Hompel and Schmidt, 2007).

Within this context, our goal is to develop a new way to analyze the order picking process and to gain new insights into this important part of corporate logistics. Therefore, we utilize mobile sensors and motion classification. Body-worn sensors collect physical data, like accelerations, rotation rates and changes in the magnitude of the surrounding magnetic field while the order picker is working. By identifying patterns in the data, executed motions and corresponding process steps can be recognized, quantified and analyzed. Therefore, multiple field studies were carried out, to identify relevant motions and to collect real process data for the development of a classification system. Two of these field studies with five different subjects are considered within this paper.



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The remainder of this article is organized as follows: After the introduction and related works, we present our overall approach as part of our ongoing research. Afterwards, the field studies and the derived classification method are described. This contribution closes with evaluation results of the proposed method.

## 2 RELATED WORK

In the field of logistics, different statistical and simulation-based approaches have been investigated during the last years to understand the characteristics of manual process steps and to identify the factors that affect the time consumption of these steps. For instance, in (Krengel et al., 2010) the process time is modeled with help of probability distributions. Further works in this area address the measurement of person specific performance metrics (Siepenkort, 2013) or the identification of factors that have impact on the performance of a worker (Stinson et al., 2014).

A non-statistical approach is presented in (Günthner and Steghafner, 2011) containing a virtual-reality-based planing tool which utilizes a simulation model of the planned system to estimate order picking time. For that, a head-mounted display, gloves with markers and a modified treadmill are used. In this paper, we are looking at the problem from a different perspective and try to gain insights into the order picking process by reducing the effort of measurements in existing systems. Consequently, we want to automate the measurement procedure and parts of the process analysis like the determination of the travel time. Thus, we investigate the possibilities of activity recognition and motion classification like being already employed in other domains, e. g. in medical science, sports or entertainment.

In medical science, sensor-based analysis of human movements and behavior is deployed especially for the detection and treatment of diseases which impact on the musculoskeletal system. This includes patients with strokes or neurodegenerations like Parkinson's disease (Bidargaddi et al., 2007), (Dobkin et al., 2011), (Zhu et al., 2012).

Another field of research related to the medical context is *Ambient Assisted Living* (AAL). AAL aims at the adaption of ICT-technologies helping elderly people living by themselves performing their daily activities and increasing their quality of life (Bravo et al., 2012, p.34). Therefore, the environment and the people are equipped with technical artifacts which among others detect anomalies, e. g. medical emergencies (Jeong et al., 2014), (Fernández-Llatas et al., 2013). The recognition of behavior and activities in AAL is summarized by the term *Activities of Daily Life Monitoring* (Zouba et al., 2008). As the focus of this application lies on the detection of anomalies, the deployed methodologies are not promising candidates for our goal, as we want to particularly understand the complete order picking process.

Many popular applications for motion classification and activity recognition were developed for sports and fitness. In this case consumer electronics devices like smartphones and wearables or even clothes which are equipped with inertial sensors are used to quantify the physical activities of a subject. This allows to monitor the health and training state (Long et al., 2009), (Toney et al., 2006), (Linz et al., 2006). Especially for professional athletes, sport-specific solutions are available to collect this data from daily training (Auvinet et al., 2002), (Bächlin et al., 2008), (Hardegger et al., 2015).

Within the production domain, different activity recognition approaches have been put forward to analyze manual manufacturing processes. For instance, (Hartmann, 2011) introduces a concept to measure and dissect the behavior of workers executing assembling tasks. Optical markers, cameras, IMUs and a multi-layer activity recognition are proposed there. A different approach can be found in (Koskimäki et al., 2013) and (Siirtola, 2015). Among others, the authors address the distinction of different tools the worker utilizes within the manufacturing process. While all mentioned works in this field separate data acquisition and data evaluation, (Stiefmeier, 2008) introduces an approach supporting activity recognition in real-time with the help of a string matching method. In summary, in production different activity recognition and motion classification approaches exist which address the special requirements of manual manufacturing tasks. As those tasks usually occur in a bounded area and mostly consist of upper limb movements, the existing methods do not meet the special requirements of the order picking process which includes many context-dependent motions and activities of the whole body (e. g. driving, walking).

## 3 APPROACH

To recognize human activities and motions in order picking, different levels of detail can be identified. These range from structured motions which are repeated periodically like walking or driving to more complex activities like packing. Especially the packing of orders consists of multiple sub tasks: setting up a shipping box, filling it, applying a shipping label and finally closing the box.

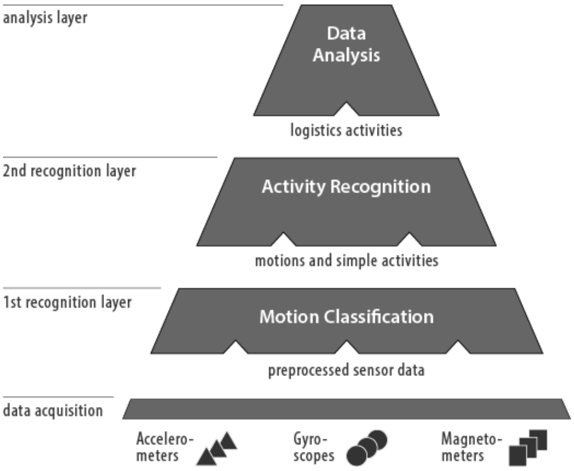


Figure 1: Layered architecture of our approach.

Hence, we decided to use a layered structure for the overall approach like it has already been done in other related works (Hartmann, 2011), (Siirtola, 2015). The resulting structure is shown in Figure 1. The inertial sensors provide the values for the motion classification on the data acquisition layer. Within the first recognition layer, recurring motions and simple activities (e. g. process order line) are identified which are inputs for the activity recognition. On the second recognition layer these inputs are composed to relevant order picking activities before they are automatically processed on the analysis layer.
As our research is still work in progress, this paper is solely addressing results of the motion classification layer. In future publications, we are planning to report on the other levels of our approach.

# 4 FIELD STUDIES

Based on the organization, material flow and technical equipment, order picking systems can be divided into different classes. For example, (Venn and Geißen, 2011) identify 8 classes of order picking systems by the way a source unit is transformed into a target unit with help of an order picker. However, in real-world systems members of the same class differ significantly in terms of motions and tasks that are executed by the pickers. As these differences are not well documented in the available literature, we decided to carry out multiple field studies to gain insights into the order picking process and to collect reliable motion data for the evaluation of our work.

In this paper, we consider two comparable order picking scenarios from different companies. Both systems are operated manually, meaning that the goods are stored in racks and the order picker travels through the storage to gather all lines from a given order list (cf. Fig. 2). Each article is stored inside a dedicated order box which is placed on a cart. In system A, the orders are provided on paper while workers in system B are using hand-held devices with a WiFi connection for this purpose. Both systems have a so called depot which is a dedicated place inside the system where every order begins and ends. Moreover, in the storage, all goods are assigned to static places.

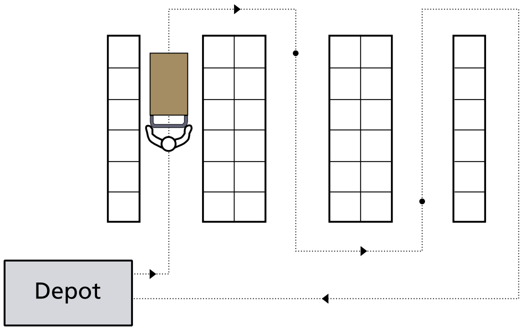


Figure 2: Example of a manual order picking system.

## 4.1 Measurement Equipment

In order to gather the motion data during our measurements, three dedicated *Intertial Measurement Units* (IMU) were used, mounted to the arms and torso of the subjects. Every IMU consists of an accelerometer, gyroscope and magnetometer whereby every single sensor provides values in three spatial dimensions. These sensors measure the linear acceleration $[m/s^2]$, the angular velocity $[rad/s]$ and the magnitude of the surrounding magnetic field $[\mu T]$. Additionally, we use a smartphone with an integrated IMU and a measurement app. This allows to compare the data retrieved from dedicated IMUs with data collected from consumer electronics devices. Beside raw sensor values, the dedicated IMUs provide data concerning the orientation of the unit related to an earth reference frame. The orientation is estimated in real-time using internal preprocessing based on Kalman filtering.

Currently, all sensors are controlled by means of *Bluetooth* and store the measurement results on the corresponding device. While the dedicated IMUs save values from all three sensors at a fixed rate (usually 100 Hz), the smartphone only provides a best effort service. This means, the operating system of the phone triggers events for every single sensor at different rates. While in the first case all 13 IMU values (9 raw sensor values and a unit quaternion) are stored together with the same timestamp, the phone creates separate entries for all sensors with different timestamps and varying rates.

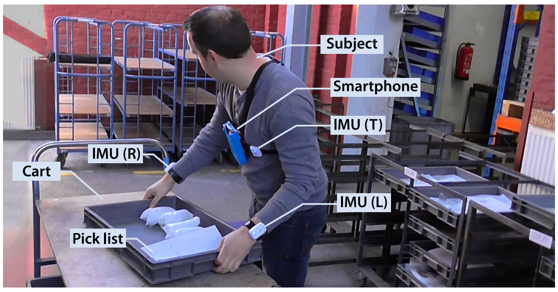

Figure 3: Measurements at the depot of system A.

For the annotation of the collected motion data, all measurement runs are recorded on video camera. To simplify the synchronization of sensor values and the camera recordings, an evident start/stop-motion was used. Figure 3 shows the utilized measurement equipment in a real scenario from system A.

## 4.2 Process and Motion Analysis

Order picking systems have two characteristics that are helpful when realizing activity recognitions and motion classifications. At first, from a process point of view, order picking is very structured compared to most every day activities. This means, it consists of distinguishable process steps which have a logical goal and occur in a system-specific sequence. In picker-to-parts order picking systems, the picker usually has to execute the following steps for every order line: proceed to next storage bin, identify storage bin, grap given amount of articles, place these in order box and acknowledge order line. Secondly, in materials handling many process steps occur in an specific environment or context. For instance, an order is started and stopped at the depot while an order line is picked inside the storage area. Thus, beside the identification of motion classes, another goal of our field studies was to learn more about the places where certain activities and motions are carried out.

During the video analysis, some observations were made which should be considered for the development of a motion classification in this field. For instance, the technical artifacts used to guide the order picker through the process like pick lists, handhelds, pick-by-light or pick-by-voice systems have a big impact on the motions occurring within the process. Furthermore, depending on the order lines, the executed motions can differ in terms of sequence and concurrency. Other results of this analysis and their implications will be addressed in a future publication.

However, from a logical point of view, the executed process steps were almost identical in both systems: First, every order was started at the depot. This included the retrieval of order information and box(es) which are used to carry the picked items. Then, every order line was processed like described above. The main difference between system A and B is how the order lists and acknowledgments are realized. While in system A pen and paper are used, in system B the picker carries a mobile terminal with an integrated barcode scanner. For every order line the picker needs to grab the item, scan its barcode as well as the barcode of the box, and finally place it in there.

As most of these process steps contribute to a certain part of the order picking time (e. g. travel or picking time), it seems reasonable for the future analysis to utilize these process steps for the definition of motion classes. Consequently, the following classes were defined: `START_ORDER`, `RETRIEVE_BOX`, `INFO`, `WALK`, `SEARCH`, `PICK`, `ACK` and `CLOSE_ORDER`. Even, if the scanning of a barcode belongs logically to the acknowledgment of an order line, we added a separate class `SCAN` to check if the classifiers are able to distinguish this motion from the others. Furthermore, we introduced additional classes to deal with the start/stop-motion, to omit certain parts of a measurement and to handle gaps in the annotations. These classes are called: `FLIP`, `NULL` and `UNKNOWN`.

# 5 METHOD

The proposed method works on time series data collected from the inertial sensors with a sampling rate $f$. We used classifiers from the field of statistical pattern recognition together with a supervised learning approach. With help of the classes identified during the process and motion analysis, the sensor data is labeled and prepared for the use within the method. To analyze the performance of standard classifiers on motion data from order picking processes, we chose *Support Vector Machines* (SVM), *Bayes* and *Random Forests* classifiers.

## 5.1 Features

For the classification of human motions, different statistical measures from the time domain have shown to work well (Bulling et al., 2014). This includes minimum, maximum, mean, standard deviation and the norm. Additionally, the magnitudes of the signal vectors are considered as features, because they are independent of the orientation of the sensors (Figo et al., 2010). Retrieving the six features mentioned before from the nine raw sensor values (three per IMU) yields 54 dimensional feature vectors which are classified by our method. Every feature vector is derived by means of a sliding window approach.

### 5.2 Windowing

The feature computation, classification and evaluation in this work are done based on a sliding time window approach dividing the sensor signals into equal-sized sequences which are called windows (Oppenheim and Schafer, 1999). In this process, the window length $w$ is usually significantly bigger than the time between two subsequent sensor measurements ($1/f$).

To recognize the motions of the order picker, the goal is actually to find the corresponding motion class for each inertial measurement. However, when working with the sliding window method, the sensor values are not mapped separately to the corresponding classes. Instead, each window is classified as a whole and labeled with a motion class.

Adjacent windows can be overlapping which usually results in a more accurate classification (Siirtola, 2015). Thus, the value of overlap is another parameter for the determination of windows. In our approach, a fixed step size $s$ is used to move windows forward at a constant time rate of $s$ seconds at a time. This was done to ease the implementation and to make it robust for sensor values with variable sampling rate like they are usually provided by smartphones.

### 5.3 Classification

As already mentioned before, our classification approach utilizes three classifiers from the field of statistical pattern recognition, being *SVMs*, *Bayes* and *Random Forest* classifiers. All of them were already used for motion classification and activity recognition and showed promising results. This was done, to learn more about their strength and weaknesses on motion data gathered from the order picking process. While currently every classifier works isolated, we are planning to use ensembles of these classifiers in the future.

## 6 EVALUATION

The proposed classification was evaluated in two steps. At first, three data sets from system A and system B were used, to carry out separate 3-fold cross validations. Further details concerning the data sets which were used during the evaluation can be seen in table 1 and an example plot of the sensor measurements in figure 4.

Then, cross-system experiments were done. During these experiments, models which were trained on system A were used to classify test data from system B and vice versa. This was done to gain first insights concerning the transferability of models between order picking systems from the same class referring to (Venn and Geißen, 2011) with differences in their technical realization (here: pick list vs. handheld).

Table 1: Details of the measurement data.

| Characteristics | System A | System B |
|---|---|---|
| *Subjects* | 3 Pers. | 2 Pers. |
| *Data sets* | 3 | 3 |
| *Total duration* | 10 min. | 23.5 min. |
| *Orders per data set* | 1 order | 3 - 5 orders |
| *Sensors* | 3 IMU | 3 IMU |
| *Sensor mounting*[1] | T, L, R | T, L, R |
| *Sampling rate* | 100 Hz | 100 Hz |

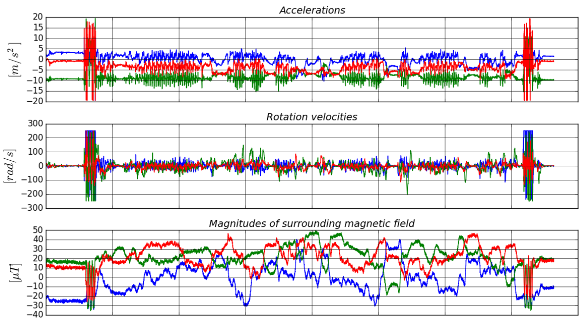


Figure 4: Plots from all inertial sensors of an IMU. The data was recorded in system A and the sensor was mounted to the subjects torso.

During all experimental runs, the window length $w$ and the step size $s$ were varied to derive the impact of these parameters on the classification rate whereas $w \in \{1.0, 1.5, 2.0, 2.5, 3.0\}$ and $s \in \{0.036, 0.125, 0.25, 0.5, 1.0\}$. The classification rate $c$ was determined from the error rate $e$ accounting for all misclassified windows of an experiment:

$$c = 1 - e$$

As mentioned before, the whole evaluation is based on overlapping time windows and for each window the features are calculated. Therefore, we started an evaluation run with labeled sensor values which were recorded every $t_s = 10\,ms$ (when $f = 100\,Hz$). These labels were generated with help of a manual video analysis. In order to use this data within an experiment, for every pair of $w$ and $s$ a new set of windows is required. Beside the features, for every window, a label must be chosen from the labels related to the corresponding sensor values. The window label is derived using a majority voting of all sensor values inside the window. In case of a tie, the label with the lowest index is used.

Due to the nature of the observed motions at the depots of both order picking systems, it was decided to omit these motions from the evaluation, because

[1]T=torso, L=left arm, R=right arm

annotation was rather complex. Thus, the `NULL` class was used during the annotation and all values in these time spans were set to zero. This reduced the classes to: `INFO`, `WALK`, `SEARCH`, `PICK`, `ACK`, `SCAN`, `FLIP`, `NULL` and `UNKNOWN`.

## 6.1 Single-system Experiments

Within the single system experiments, all data sets used for training and evaluation were taken from the same system. The results of the classifiers used for system A and system B with different subjects in the test set are shown in Tab. 2 and Tab. 3. Note that the *Random Forest* classifier shows the most stable performance in both systems over all three motion data sets with better results for system B. As SVM using RBF kernels performed rather poorly, linear kernels were used instead which achieved much better results on this time series analysis.

Table 2: Results of the three-fold cross validation for the motion classification using recordings from three different subjects P01, P02 and P03 (system A, $w = 2.0$, $s = 1.0$).

| Test | SVM | Bayes | RandForest |
|---|---|---|---|
| *P01* | 69.5 % | 67.6 % | 72.9 % |
| *P02* | 63.8 % | 62.3 % | 73.9 % |
| *P03* | 68.6 % | 73.3 % | 71.0 % |
| *Avg.* | **67.3 ± 3.1 %** | **67.7 ± 5.5 %** | **72.6 ± 1.5 %** |

Table 3: Results of the three-fold cross validation for the motion classification using recordings from two different subjects P01 and P02 (system B, $w = 3$, $s = 0.25$).

| Test | SVM | Bayes | RandForest |
|---|---|---|---|
| *P01* | 64.0 % | 64,5 % | 84.2 % |
| *P02 a* | 74.6 % | 73.2 % | 85.5 % |
| *P02 b* | 83.0 % | 83.9 % | 87.2 % |
| *Avg.* | **73.9 ± 9.5 %** | **73.9 ± 9.7%** | **85.6 ± 1.5 %** |

In figures 5 and 6 two *classes vs. time plots* can be seen. Those plots clearly show how the order picking process was executed and how much time the picker spent in each class. For instance, it can be seen that in system A the picker walked to a stored article, picked it and acknowledged the corresponding order line on his paper list. In system B on the other hand many articles were picked at the same place and the articles were stored close to each other. This becomes evident, since the time spent in the class `WALK` in this example is significantly shorter compared to system A. Here, it should be mentioned that system A and B were annotated in a slightly different way. While the difference between the classes `INFO` and `ACK` are obvious in a paper-based system, it was not easy to see the difference for system B using the handheld device. Thus, we decided to label every interaction with the handheld with the class `INFO`.

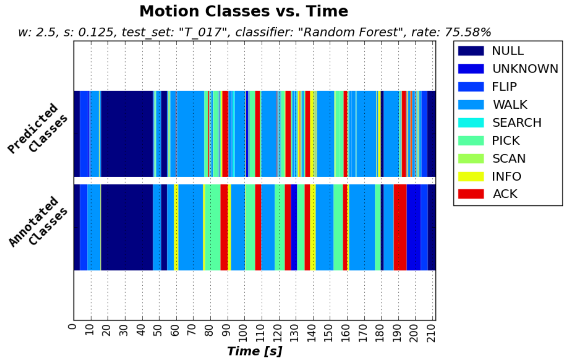


Figure 5: Example of a classes vs. time plot generated using a Random Forest classifier (system A).

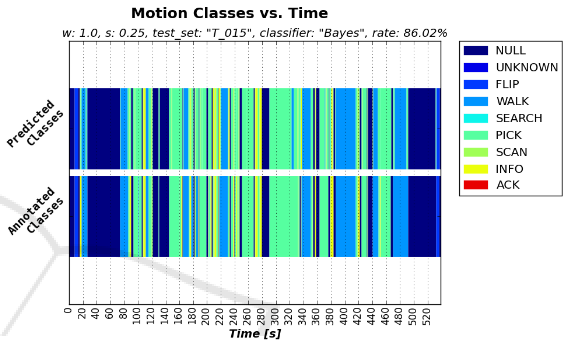


Figure 6: Example of a classes vs. time plot generated using a Bayes classifier (system B).

Figure 7 shows that the variation of $w$ and $s$ had no big impact on the classification quality which was the case for most experiments. This can be explained with the selection of the considered window lengths and step sizes, as those were chosen based on our experiences from manual time measurements.

## 6.2 Multi-system Experiments

During the multi-system experiments, the best performing models from one system and three test data sets from the other system were selected. Those test data sets were then classified and compared to the annotated data. The results of this transferability test show a reduced classification rate. This can be explained by the mismatch of training and testing conditions, the limited number of training samples and the differences between both systems in terms of picker guidance (pick list vs. handheld). We are planning to improve these results with help of adaption techniques and a scenario detection.

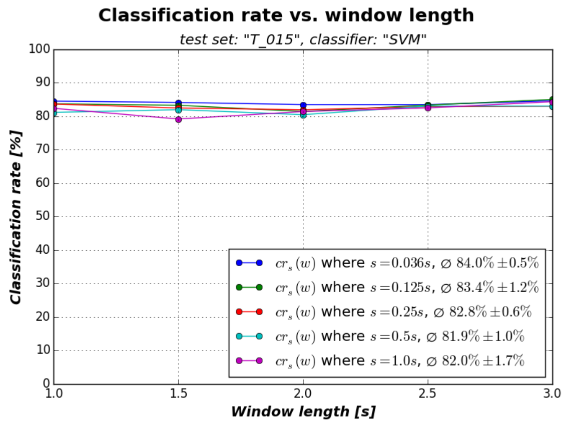


Figure 7: Impact of variation of $w$ and $s$ on $c$.

Table 4: Results of the multi-system experiments using the best performing models of the single-system experiments.

| *Classifier* | $w$ | $s$ | *Transfer* | $c$ |
|---|---|---|---|---|
| RandForest | 2.5 | 0.125 | $A \rightarrow B$ | 71.8 % |
| RandForest | 2.0 | 0.500 | $B \rightarrow A$ | 64.8 % |

## 7 CONCLUSION

In this paper a layered method for the analysis of manual order picking systems was introduced which automates the measurement procedure of different process aspects. Especially travel and picking times can be quantified with help of our approach. Therefore, a data acquisition based on inertial sensors (integrated in smartphones and dedicated devices) as well as a motion classification and activity recognition based on supervised machine learning methods are utilized. As part of our ongoing research, this paper focused on the motion classification being the first layer of the automated recognition. On this layer, classifiers from the field of statistical pattern recognition and an adopted sliding window approach are deployed. To identify motion classes and to learn about system characteristics affecting the motions of order pickers, field studies were carried out. Two of these were presented and used for the evaluation of our classification. The evaluation showed promising results with potential for further improvements. Beside single-system experiments, we also carried out multi-system experiments to test the transferability of the classification models.

Our future works will focus on the improvement of the classification as well as the development of the activity recognition and automated data analysis. Among others, we want to improve the preprocessing and introduce new features, like the orientation of the sensors and the context of the measured inertial data.

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Note that a significant part of research in the field of order picking is done in Germany and therefore some of the references are only available in German.