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A machine-learning method for classifying and analyzing foot placement: Application to manual material handling

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ABSTRACT

Foot placement strategy is an essential aspect in the study of movement involving full body displacement. To get beyond a qualitative analysis, this paper provides a foot placement classification and analysis method that can be used in sports, rehabilitation or ergonomics. The method is based on machine learning using a weighted k-nearest neighbors algorithm. The learning phase is performed by an observer who classifies a set of trials. The algorithm then automatically reproduces this classification on subsequent sets. The method also provides detailed analysis of foot placement strategy, such as estimating the average foot placements for each class or visualizing the variability of strategies. An example of applying the method to a manual material handling task demonstrates its usefulness. During the lifting phase, the foot placements were classified into four groups: front, contralateral foot behind, ipsilateral foot behind, and parallel. The accuracy of the classification, assessed with a holdout method, is about 97%. In this example, the classification method makes it possible to observe and analyze the handler's foot placement strategies with regards to the performed task.

1. Introduction

Foot placement strategy is an essential aspect in the study of movement involving full body displacement, and has been studied in various fields of biomechanics. In exercise science, studies have determined the influence of foot position on muscle activity during resistance training exercises (Signorile et al., 1995; Escamilla et al., 2001) or on the speed and power developed in fencing lunges (Gresham-Fiegel et al., 2013). In rehabilitation, the influence of turn strategies on patients with Parkinson's disease has been studied to reduce fall risks (Adamson et al., 2019) or minimize freezing of gait (Bhatt et al., 2013). In ergonomics, several studies have looked at the impact of footstep strategies on adopted postures and back loading in handling tasks (Delisle et al., 1996; Delisle et al., 1999), as well as the influence of working conditions on these strategies (Drury, 1985; Authier et al., 1995, 1996; Wagner et al., 2010). Additionally, foot placements of construction workers using stilts have been associated with the potential loss of postural stability (Pan et al., 2009).

Two different approaches to the study of foot placement strategy can be found in the literature. The first uses continuous variables, such as distance or angle between the feet, to describe foot placements (McIlroy and Maki, 1997; Mouzat et al., 2004). The second approach assigns foot placements to different groups defined according to the application. For example, to analyze characteristics that might contribute to freezing in Parkinson's disease, turning strategies were classified into three groups: crossover turn, step turn and mixed turn (Bhatt et al., 2013). For handling tasks, foot positions during the transfer were classified into three groups: open, forming an angle, and parallel (Authier et al., 1995).

In some studies, subjects were asked to perform a task by adopting one or more predefined foot placements (Kirby et al., 1987; Delisle et al., 1996, 1999; Zhou et al., 2016). Using this approach, it was possible to observe the influence of foot placements on biomechanical variables such as balance or back loading, but not to observe the strategy naturally adopted by a subject in a specific context. Other studies have focused on self-selected foot placement strategies. Based on digital video recordings, foot

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placements were classified a posteriori into predefined groups (Bhatt et al., 2013; Adamson et al., 2019). However, this approach is very time-intensive when the amount of data is large. To our knowledge, there have been two kinds of studies in which motion analysis data were used to automatically classify foot placement strategies. First, turning strategies in 90-degree turns were classified into step or spin turns (Fino et al., 2015; Golyski and Hendershot, 2017). In this case, the support foot during the turn was identified using the angular velocity of the pelvis and shanks or using the center-of-mass trajectory according to foot position. Second, in handling tasks (Wagner et al., 2009, 2010), each step was classified into one of four groups – progression, pivot, orient or move – using criteria defined according to foot location and spatio-temporal events. These criteria were based on thresholds for one or two variables such as foot rotation or position. Consequently, it was difficult to use a combination of all the available variables or to take into account the more subjective criteria used in observations. For example, a threshold based on ipsilateral foot orientation could be used to distinguish two groups; however, the position of the ipsilateral foot or the orientation of the contralateral foot could have added relevant information about the choice of group. Moreover, the criteria were developed for a given situation (in this case, transfers in the automotive assembly plant), and any change would require a new selection of criteria.

Machine learning techniques are becoming more widespread, especially in biomechanics (Halilaj et al., 2018). For example, they were used to predict ground reaction forces and moments (Johnson et al., 2018) or spinal forces (Hou et al., 2007) directly from kinematics data, to estimate body pose from two optical cameras (Mehrizi et al., 2019) or to detect surface- and age-related differences in walking from one inertial measurement unit (Hu et al., 2018). Machine learning makes it possible to handle multidimensional data and to take into account complex interactions between the various types of data. However, these latter studies were not interested in analyzing foot placement strategies.

The above aspects point to the need for an automatic foot placement classification method of foot placements with more flexibility than the previous methods based on thresholds. The objective of this paper is to use machine learning to classify foot placements. Based on motion analysis, the method is designed to learn a preclassification performed by an observer and then reproduce it on subsequent foot placements. The method is generic since it can be adapted to any groups, depending on the application. In addition, it allows for detailed observations such as variability in strategies or average foot placements for each group of trials or the variability of strategies. In this paper, we will describe the general concepts and illustrate how the method may be applied. The biomechanical risk factors most often associated with musculoskeletal disorders include lifting heavy objects (Kuiper et al., 1999; Nelson and Hughes, 2009; Costa and Vieira, 2010), and foot placements have been identified as a potential contributor in lifting tasks (Authier et al., 1996; Plamondon et al., 2006). In the application example, therefore, we will analyze aims at analyzing the foot placements of handlers during the lifting phase of a palletizing task.

2. Materials and methods

2.1. Application example

Experimental data were gathered from a previous study (Plamondon et al., 2014) involving 30 male subjects (mean ± SD, age of 31 ± 10 years old, height of 173 ± 6 cm, mass of 75 ± 11 kg). The study was approved by the local institution's research Ethics Committee, and each subject signed an informed consent form prior to the experiment.

An Optotrak optoelectronic system (Northern Digital Inc., Waterloo, Ontario, Canada) recorded at 30 Hz the 3D coordinates of markers located on the subject. Since the focus of the study was foot placement, only two clusters of four markers (one on each heel) were used. The locations of landmarks (medial and lateral malleoli and foot end) were identified in relation to their respective cluster.

The task consisted in transferring 24 boxes (four levels of six boxes) one by one from one pallet to another (Fig. 1). Four repetitions of this task resulted in 96 boxes handled by each subject. Subjects received no instructions or comments about lifting technique. All the boxes were of the same dimensions (26 cm × 35 cm × 32 cm) and had a mass of 15 kg.

Based on previous studies (Authier et al., 1995; Wagner et al., 2009), foot placements during the lifting phase were classified into four groups. The ipsilateral and contralateral feet were defined with regard to the turn direction. The groups were as follow:

1. front (F): both feet were in front of the lifting pallet and pointed towards it. They were not, or only slightly, oriented towards the deposit location;
2. contralateral foot behind (C): the ipsilateral foot was close to the lifting pallet and pointed towards it. The contralateral foot was set back and could be slightly rotated towards the deposit location;
3. ipsilateral foot behind (I): the contralateral foot was close to the lifting pallet and pointed towards it. The ipsilateral foot was set back and could be slightly rotated towards the deposit location;
4. parallel (P): the feet were not directly in front of the lifting pallet. They both pointed towards the transition area leading to the deposit location.

Figures in the Results section (Section 3) provide an example of foot placements for each group.

2.2. Input features

The foot locations serve as input for the classification algorithm. A global coordinate system $\mathcal{R}_0$ is associated with the environment and a local coordinate system is defined for each foot ($\mathcal{R}_f$, with

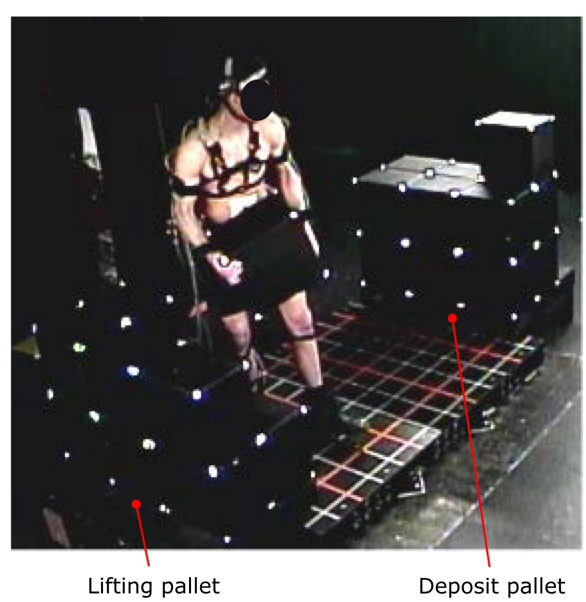


Fig. 1. Experiment set-up for transferring 24 boxes (four levels of six boxes) one by one from one pallet to another.

$f = ipsi$ or $contra$ for the ipsilateral or contralateral foot, respectively).

The definition of $\mathcal{R}_0$ depends on the context of the study. For example, in handling tasks, it could be based on the carried load, while in fencing it could be associated with the piste. The y_0 axis is determined for $\mathcal{R}_f$ and $\mathcal{R}_0$ has the same orientation when the subject is in a reference position. The z_0 axis is the vertical axis. Its orientation depends on the task performed and may vary within a study. Considering the example of a fencing lunge, a right-handed and a left-handed fencer having the same foot placement strategy will have symmetric local coordinate systems. The orientation of z_0 is used to compare the configurations. x_0 allows to define a direct orthogonal frame.

The origin of $\mathcal{R}_f$ is defined as the origin of the foot. The y_f axis points forward along the antero-posterior axis, the z_f axis is the vertical axis pointing upward, and x_f allows to define a direct orthogonal coordinate frame. The definition of the origin of the foot and the forward direction depend on the context and in particular on available motion capture data.

The proposed method classifies foot placements at a given time. Input features are the positions and orientations of $\mathcal{R}_f$ in relation to $\mathcal{R}_0$.

In the manual handling example, the origin of $\mathcal{R}_0$ was the center of the front side of the lifting pallet (Fig. 2). The y_0 axis pointed towards the back of the pallet so that $\mathcal{R}_f$ and $\mathcal{R}_0$ had relatively the same orientation when the subject was in front of the pallet. The orientation of the z_0 axis was adapted so that the rotation of the subject during his half turn corresponded to a rotation with a positive angle along the z_0 axis. Thus, regardless of the lifting pallet location and the turn direction, each foot placement was standardized according to the configuration shown in Fig. 2.

The local coordinate systems $\mathcal{R}_f$ were based on the experimental locations of the landmarks. The origin was estimated as the ground plane projection of the midpoint between the medial and lateral malleoli. The y_f axis was based on the line from the origin to the end foot, projected to the ground plane.

Between the lift (the instant when the handler starts to fully support the box) and the deposit (the instant when the box starts to come into contact with the deposit pallet), foot contacts were detected using foot kinematics. Fig. 2 shows the local coordinate systems location for each step of a handling task. $y_{contra/ipsi,s}$ corresponds to the y axis of the contralateral or ipsilateral foot of step s. Step 0 is associated with the lift and the last step with the deposit.

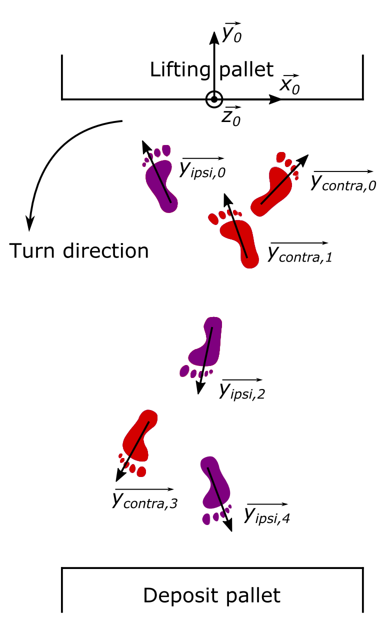


Fig. 2. Example of foot placements during a lifting task (between the lifting and deposit phase).

Foot placements were analyzed at the lift (step 0). The input features for the classification x_i were the orientation of the contralateral foot θ_{contra}, the orientation of the ipsilateral foot θ_{ipsi} and the position of the contralateral foot in relation to the ipsilateral foot $(x_{contra/ipsi}, y_{contra/ipsi})$ (Eq. (1)).

$$x_i = \left[\theta_{contra}\ \theta_{ipsi}\ x_{contra/ipsi}\ y_{contra/ipsi}\right] \tag{1}$$

2.3. Classification algorithm

The classification was performed with a weighted k-nearest neighbors (kNN) algorithm. The principle behind this method was as follows: given a set of training samples and a query, the query was labelled according to the label of the k-nearest neighbors in the training set. Details about the classification algorithm are provided in Appendix A.

2.4. Data analysis

The training set was randomly divided into two sets: a training set (used to learn model parameters and to select the hyper-parameter k) and a testing set (used to assess the model performance) (Fig. 3).

The hyper-parameter k was selected by using a k-fold cross-validation (referenced here by k_{cv} to distinguish it from the k of the k-nearest neighbors) on the training set. It corresponded to the k-value with the highest accuracy.

The model performance was assessed in terms of accuracy, sensitivity, specificity, and area under the curve (AUC) (Halilaj et al., 2018). The classification threshold of the curve (receiver operating characteristic curve) is the confidence index (Atiya, 2005) (see Appendix A).

The proposed method provided descriptive statistics and visual feedback about foot placements. The mean foot placements classified into each group could be estimated as the mean values of the features of each of that group's elements. The variability in each group could be estimated as the standard deviation of these features.

In the application example, the method was applied to only one of the 30 subjects. The data of this example subject were excluded from the learning and testing sets. The foot placements of the remaining 29 subjects were classified by a single observer (A.M.) according to the groups previously defined. 70% of these data from the 29 subjects (1949 handling tasks) constituted the training set and the remaining 30% (835 handling tasks) constituted the testing set (Fig. 3). The hyper-parameter tuning was performed with $k_{cv} = 10$ by varying k from 1 to 20.

Moreover, to assess the accuracy of the observer classification, an intra-observer reliability was conducted on 15% of the data randomly selected. The time between the two observations was four months. Percentage agreement, kappa coefficient (Cohen, 1960) and PABAK (Byrt et al., 1993) were computed.

3. Results

3.1. Intra-observer reliability

The percentage agreement of the intra-observer analysis was 97% and Kappa coefficient and PABAK was 0.95 and 0.94,

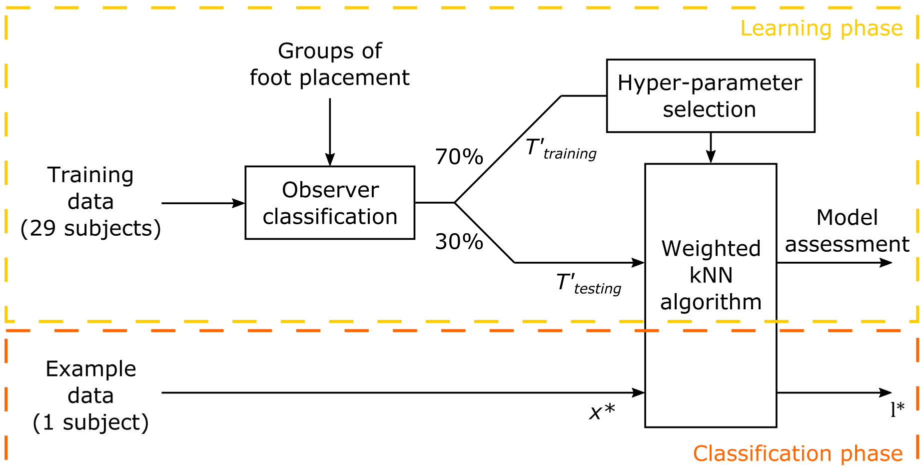


Fig. 3. Representation of the analysis architecture. $T'_{training}$ and $T'_{testing}$ are the standardized training and testing sets, respectively; x^* is the standardized query; l^* is the label of x^*.

respectively. A Kappa coefficient above 0.80 was considered as almost perfect agreement (Landis and Koch, 1977).

3.2. Classification model performance

The tuned hyper-parameter k was 8. Table 1 shows the classification method performance in terms of overall accuracy, as well as the accuracy, sensitivity, specificity and AUC for each group.

3.3. Analysis

Fig. 4 shows the 96 foot placements of the example single subject according to classification, along with the distribution in each group for that subject. The features of the average foot placements for each group are detailed in Table 2.

For group F, the feet were pointed toward the pallet. The rotation of the ipsilateral foot was slightly higher because the subject had prepared to turn towards the deposit location. For groups C and I, one of the feet was behind ($y_{c/i} = -28$ cm and $y_{c/i} = 33$ cm). The forward foot was pointed towards the lifting pallet. For group P, the feet pointed to the transition area leading to the deposit location. The rotation of the ipsilateral foot was greater than 90° while the contralateral foot was in an intermediate position.

Figs. 5 and 6 show the foot placement classifications when the boxes were on the top layer of the pile and close to the ground, respectively.

The frequency of foot placement patterns varied with the height of the lift. 83% were classified as F when the boxes were close to the ground and 42% when they were higher up. At the other end, only 4% were classified as P where boxes were close to the ground compared to 42% for the higher boxes. Within the same group, the position and orientation of the feet were influenced by the height of the lift. For example, within the front group, the contralateral foot was less turned towards the deposit location (−6° vs 31°) and the distance between the feet was greater (46 cm vs 30 cm) for the lower boxes. The distance between the feet increased for lower boxes in the other groups as well (46 cm vs 35 cm on average).

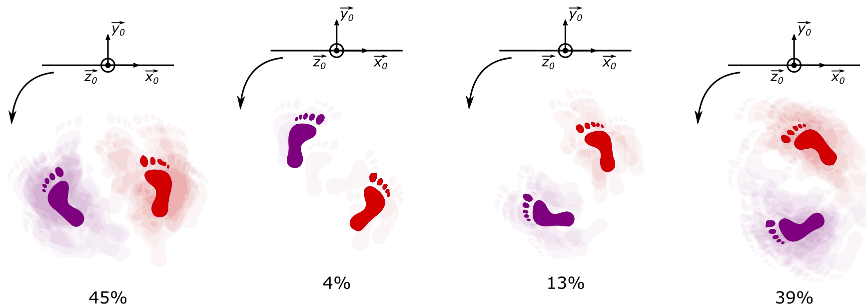
4. Discussion

This paper proposes a method for classifying foot placements based on a machine learning algorithm. This method could be adapted to any pre-defined classification and thus to applications in sports, rehabilitation or ergonomics. Instead of imposing a pre-defined foot placement (Kirby et al., 1987; Delisle et al., 1996, 1999; Zhou et al., 2016), an a posteriori classification method is used to analyze self-selected strategies and thus to observe the influence of the task on foot placements. Compared to observation techniques (Bhatt et al., 2013; Adamson et al., 2019), the processing time is much lower. In the application example, the computation time was about 10 ms per classification whereas an observation and a decision-making necessarily takes several seconds. In the case of analysing a complete database, the processing time becomes a major criterion. Moreover, once the learning phase has been completed, classification is automatic and not dependent on people processing the data. Moreover, the learning can be reused in other studies. With a machine-learning algorithm, all available foot location data can be taken into account simultaneously. Classification methods previously reported in the literature (Authier et al., 1995; Wagner et al., 2009, 2010) require criteria based on one variable such foot position or orientation. In the proposed method, the learning is based on a human observer classifying a set of examples. This makes it possible to take into account criteria that may be difficult to interpret in terms of equations.

Table 1
Assessment of the foot placement classification method in terms of accuracy, sensitivity, specificity, and area under the curve (AUC). The assessment was based on the testing set data.

[%]	Overall	F	C	I	P
Accuracy	96.9	98.5	99.0	98.1	98.1
Sensitivity	–	99.3	84.2	95.0	96.9
Specificity	–	98.1	99.7	98.6	99.1
AUC	–	99.8	99.8	99.4	99.7

F: front; C: contralateral foot behind; I: ipsilatéral foot behind; P: parallel.



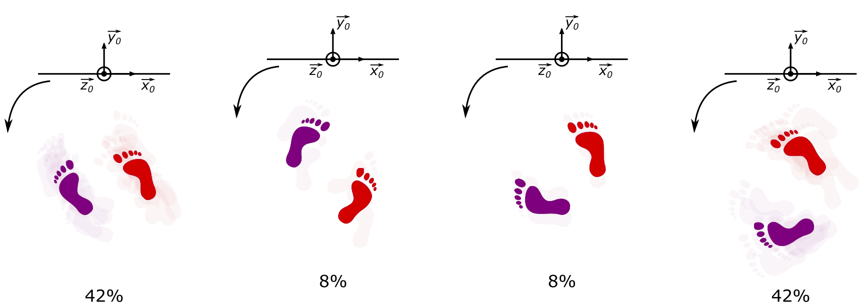
(a) Front (b) Contralateral foot behind (c) Ipsilateral foot behind (d) Parallel

Fig. 4. Illustration of all foot placement classifications. For each group, the dark footprint represents the average foot placement (centroid of the class). Lighter-colored footprints represent all the foot placements in the group. These are represented twice: the position and orientation of the ipsilateral foot is represented as a function of the mean contralateral foot, and the position and orientation of the contralateral foot is represented as a function of the mean ipsilateral foot. For each picture, the pallet location and turn direction were as indicated in Fig. 2. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 2
Average (standard deviation) features of foot placements of the example single subject in each group. This subject was previously excluded from the learning and the testing sets.

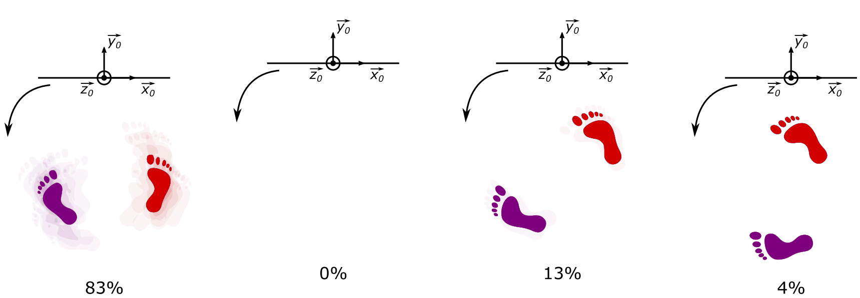
	F	C	I	P
θ_c [°]	9 (23)	−29 (29)	27 (11)	56 (13)
θ_i [°]	31 (17)	−21 (22)	73 (16)	105 (23)
$x_{c/i}$ [cm]	39 (8)	30 (6)	24 (8)	6 (9)
$y_{c/i}$ [cm]	6 (8)	−28 (8)	33 (8)	37 (8)

F: front; C: contralateral foot behind; I: ipsilatéral foot behind; P: parallel.



(a) Front (b) Contralateral foot behind (c) Ipsilateral foot behind (d) Parallel

Fig. 5. Foot placement classification when boxes were on top layer. The representation is the same as the one in Fig. 4.



(a) Front (b) Contralateral foot behind (c) Ipsilateral foot behind (d) Parallel

Fig. 6. Foot placement classification when boxes were close to the ground. The representation is the same as the one in Fig. 4.

The assessment of the model's performance may be interpreted differently depending on the application (Halilaj et al., 2018). In an ergonomics context, our method's accuracy is higher than the intra-observer reliability reported in the literature (Denis et al., 2000; Denis et al., 2002; Palm et al., 2016; Eliasson et al., 2017), considered excellent above 90%. This seems to validate the proposed method. In addition to the intra-observer reliability, these results indirectly validate the learning performance of the

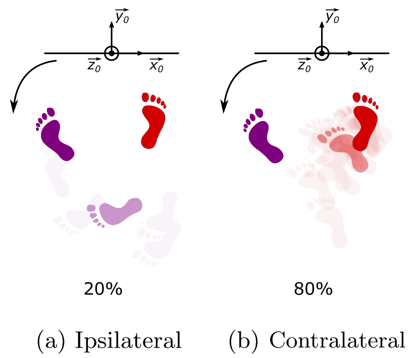


Fig. 7. Foot placements of the first step after the lift, when foot placements during this phase were in the first group (front). The dark footprint represents the average foot placement during the lifting phase. The footprint with intermediate transparency represents the average step performed after the lift (whether the step is performed by the contralateral foot, in which case the average placement is represented in red, or whether it is performed by the ipsilateral foot, in which case the average placement is represented in violet). All first steps are also represented with the highest transparency. The pallet locations and turn directions are as indicated in Fig. 2. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

observer. If the observer classification had been poor, then the classification algorithm would necessarily give poor results as well. Some foot placements appear to be at the boundary between several groups. For the example subject, the positions and orientations of some foot placements in group I and group P are quite close together (Fig. 4), which would have made classification using threshold-based criteria difficult. The performance results indicate that our model achieve good differentiation between groups by combining the data from all features.

The example of an application to handling tasks demonstrates the usefulness of such an approach. The data for the example subject show that he has two favorite patterns: front and parallel. In the first pattern, he tends to adopt a symmetrical motion during lifting. The second pattern implies an asymmetry during the lift, possibly to ensure a smooth transition to the deposit location and thus minimize loading time. For patterns belonging to the other groups, the orientation of the back foot was different. Indeed, when the ipsilateral foot was back, the body rotated in the direction of the deposit location, allowing the subject to initiate a more direct trajectory to the destination. Moreover, as previously reported in the literature (Authier et al., 1995), the subject adapted his foot placement strategy to the height of the lift. First, as boxes close to the ground pose a greater risk of injury (Plamondon et al., 2012), it would seem that the majority of the handlers adopted a symmetrical motion pattern. Second, for the same foot placement pattern, the subject increased the distance between his feet, probably to improve his stability with a larger base of support (Delisle et al., 1998) and to reduce asymmetrical loading.

The classification method focused on foot placement at a given time (when the handler started to fully support the box). Other phases of the task can be analyzed, such as events occurring before lifting or after deposit. Moreover, the proposed method could be extended to take into account a succession of steps. For instance, the next step performed after the lifting phase could be added to the analyses (step 1 in Fig. 2). Considering the data from the example subject in the application example, Fig. 7 shows the average foot placement and all the first steps performed when the foot placements were in group F. Two classes were used here, depending on the first step. Different sub-classes could be added to differentiate, for example, a reorientation step from a progression step (Wagner et al., 2009). Also, in the application example, the foot location was estimated as its projection on the ground. Subgroups could be defined to distinguish when a foot was on the ground and when it was not.

The application example was performed on handling tasks, but the machine-learning classification method can also be applied to other contexts such as sports or rehabilitation. For example, in sports, the classification of foot placement techniques during squat or leg press (Escamilla et al., 2001) can be based on machine learning techniques. Since, in this case, the variability of possible foot placements is relatively low, the amount of necessary data for training and testing can be reduced. In rehabilitation, machine learning techniques can be used to classify turn strategies (Bhatt et al., 2013; Adamson et al., 2019). In this case, the analysis requires to take into account several successive steps increasing the variability within each group. Thus, the number of necessary data for training and testing increases substantially.

Our method has several limitations. First, Second, foot placement depends on the anatomical characteristics of the subject (size or neutral orientation), which are not taken into account in the proposed method. However, as observed in the application example, variations in foot placements were observed in the same subject, depending on the task. Moreover, the quantity of data used for the learning phase was an important criterion for ensuring accurate classification (Halilaj et al., 2018): there has to be enough data to ensure complete learning but not so much as to result in overfitting. The quantity depends mainly on the variability of the inter-group data. In biomechanics, where input data are provided by motion capture, the number of subjects would be the limiting factor to ensure complete learning.

5. Conclusion

The proposed method automatically classifies and analyzes foot placements based on a pre-classification performed by an observer. It can be adapted to sports, rehabilitation and ergonomics applications. An application example using a manual material handling task has demonstrated the usefulness of classifying foot placements into groups to characterize average footstep strategies and variability for a given context.

Declaration of Competing Interest

Authors have no conflict of interest to disclose.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.jbiomech.2019.109410.

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