

A Pressure Plate-Based Method for the Automatic Assessment of Foot Strike Patterns During Running

ALESSANDRO SANTUZ,^{1,2} ANTONIS EKIZOS,^{1,2} and ADAMANTIOS ARAMPATZIS^{1,2}

¹Department of Training and Movement Sciences, Humboldt-Universität zu Berlin, Philippstraße 13, Haus 11, 10115 Berlin, Germany; and ²Berlin School of Movement Science, Humboldt-Universität zu Berlin, Philippstraße 13, Haus 11, 10115 Berlin, Germany

(Received 26 May 2015; accepted 7 October 2015; published online 15 October 2015)

Associate Editor Michael Torry oversaw the review of this article.

Abstract—The foot strike pattern (FSP, description of how the foot touches the ground at impact) is recognized to be a predictor of both performance and injury risk. The objective of the current investigation was to validate an original foot strike pattern assessment technique based on the numerical analysis of foot pressure distribution. We analyzed the strike patterns during running of 145 healthy men and women (85 male, 60 female). The participants ran on a treadmill with integrated pressure plate at three different speeds: preferred (shod and barefoot 2.8 ± 0.4 m/s), faster (shod 3.5 ± 0.6 m/s) and slower (shod 2.3 ± 0.3 m/s). A custom-designed algorithm allowed the automatic footprint recognition and FSP evaluation. Incomplete footprints were simultaneously identified and corrected from the software itself. The widely used technique of analyzing high-speed video recordings was checked for its reliability and has been used to validate the numerical technique. The automatic numerical approach showed a good conformity with the reference video-based technique (ICC = 0.93, $p < 0.01$). The great improvement in data throughput and the increased completeness of results allow the use of this software as a powerful feedback tool in a simple experimental setup.

Keywords—Locomotion, Gait analysis, Foot, Forefoot, Humans.

INTRODUCTION

For more than a century, scientists tried many ingenious ways to measure the distribution of pressure in the foot. The very first attempts with plaster-filled sacks^{[3](#page-8-0)} or spaded soil^{[36](#page-9-0)} at the turn of nineteenth century or the more sophisticated approaches using video recording^{[18](#page-9-0)} of the 1930s, had been as smart as difficult to apply and process. Since then, technology has made great strides leading, since the late 1970s, to a wide range of devices for the measurement of plantar pressure and ground reaction forces. $12,13$

The popularity of distance running has greatly increased over the last three decades.^{[11](#page-9-0)} An average runner usually strikes the ground around three times per second.^{[9](#page-8-0)} The description of how the foot touches the ground during running, called foot strike pattern (FSP), depends on the location of the first contact area with the ground^{[23](#page-9-0)} and rearfoot (RS) , midfoot (MS) and forefoot (FS) strike are the common classifications. If the FS is not followed by heel contact (as it is, instead, in the toe-heel-toe pattern), it is called toe strike (TS) .^{[30](#page-9-0)} FSPs during running have already been linked to injury risk^{[15,22,35,39,46](#page-9-0)} and perfor-mance.^{[17,21,23,27,30,31,34,37,45](#page-9-0)} Even if the conclusions are often contradictory and retrospective, it is clear that the study of FSPs is becoming increasingly connected not only to élite, but also to recreational sports.

The most used method to examine FSPs is the video analysis of the recorded landing.^{[5](#page-8-0)[,16,23,25,27](#page-9-0)} This approach, however, is time-consuming and observerdependent, since there is a need of trained people to manually scan the video recordings. Moreover, as it has been recently reported,^{[5](#page-8-0)} the reliability of the observations decreases when the analyzed foot is not the one in the foreground. Another possible approach would be to make a kinematic analysis using a video system. $\frac{2}{3}$ $\frac{2}{3}$ $\frac{2}{3}$ This solution can be a good asset when force plates are not available, but it certainly involves some preparation time to place the markers and calibrate the system. In addition, the compliance of the foot itself could produce some non-systematic errors.^{[2](#page-8-0)} Furthermore, the setup should include at least two cameras in order to include both feet in the analysis, thus adding

Address correspondence to Adamantios Arampatzis, Department of Training and Movement Sciences, Humboldt-Universität zu Berlin, Philippstraße 13, Haus 11, 10115 Berlin, Germany. Electronic mail: a.arampatzis@hu-berlin.de

some complexity to the experimental setup. These video-based methods, though, always rely on some level of manual preparation or elaboration and cannot be easily automated. Recently, also the use of inertial sensors has been proposed. 20 Given the inexpensive and lightweight nature of these devices, the approach is certainly appealing for in situ applications. A validation with a kinematic method, though, showed a low reliability for TS cases. 20 Moreover, the strict requirements for sensors' supports stiffness and the quite complex post-processing (i.e., filtering conditions), would require some experience and tuning before the proper application.

Other kinetic approaches, like the location of the center of pressure at impact, 13 13 13 are widely used by pressure plate companies in their built-in software. This analysis alternative seems to be a good candidate for automating the evaluation process and the reason is twofold. First, it allows not only for a categorical classification of the FSP, but also for a quantification of it through the foot strike index (distance from the heel to the center of pressure at impact relative to total foot length). Second, it appears to be an appropriate metric when searching for correlation with injury risks.^{[7](#page-8-0)[,35](#page-9-0)} Nevertheless, the analysis' boundary conditions must be clearly unfolded to the user, in order to: (a) correctly interpret and report the outcomes and (b) avoid inconsistencies like the presence of incomplete footprints when dealing with TS cases. The second point could be avoided by using pressure-sensitive insoles. 33 These devices, though, lack in reliability in presence of lightweight participants and need a refined algorithm in order to detect the toe-off.[33](#page-9-0)

The existing methods are either time-consuming, observer-dependent or lacking in accuracy when trying to give a real-time feedback to the participant during treadmill running. Therefore, it is clear that a substantial standardization of the methods employed to evaluate the FSPs is currently missing.

The development of an automatic numerical algorithm able to classify accurately FSPs during running would provide several benefits: first, it would avoid any observer dependence by automating the evaluation process. This characteristic can considerably enrich the analysis, potentially including in a single evaluation step a big number of step cycles at once. Another important advantage is the ease of use: the researcher does not need to be trained to identify the FSP. Finally yet importantly, the automatic nature of this evaluation model can speed up the throughput of the outcomes, thus giving the chance to give online-feedback information about the foot strike.

The objective of the current investigation was to validate an original FSP assessment technique based on the numerical analysis of foot pressure distribution. Further, we aimed to make the method completely reproducible and therefore the boundary conditions and the calculation process are explained step-by-step.

We validated our custom algorithm against one of the most used and accepted methods, the video analysis, $5,15,23,27,37,38$ $5,15,23,27,37,38$ using a large sample size. The investigation was conducted across a wide spectrum of submaximal speeds and two different conditions (barefoot and shod) in order to prevent the analysis of only very specific conditions. Finally, the treadmill approach ensures a consistent number of gait cycles to analyze and average. This significantly improves the impact of the method compared to others considering only one or two steps by using fixed cameras while running over ground or force plates.[2,5,](#page-8-0)[16,23–25,27,28,30,31,38,41](#page-9-0)

MATERIALS AND METHODS

Experimental Design

We recruited people of both genders and various ages ($n = 145$ $n = 145$ $n = 145$; 85 male, 60 female, see Table 1 for details). The criteria for assessing their running experience were defined as follows. Inexperienced ($n = 57$; 29 male, 28 female): people that were inactive, doing other sports^{[29](#page-9-0)} or that just took up running^{[5](#page-8-0)} (for a period \leq 1 year). Recreational (*n* = 67; 41 male, 26 female): people running more than 20 $km/$ week^{[30,32](#page-9-0)} and aver-aging three or more sessions/week in the past 5 years.^{[10](#page-9-0)} Competitive $(n = 21; 15 \text{ male}, 6 \text{ female})$: athletes running more than 40 km/week,^{29,34} registered in athletics or triathlon clubs and competing at the regional, national or international level in any event, except throwing and walking.[4](#page-8-0)

All of them gave informed consent for the experimental procedure, according to the rules of the local scientific board. None of the participants showed or reported any history of neuromuscular or musculoskeletal impairments at the time of the measurements. Moreover, in the 6 months prior to the measurements day, none of them has suffered any injury to the lower limbs and they all reported to be habitually shod during daily life and, if applicable, when running. No participant was an experienced barefoot runner.

The FSP assessment method was double: a video analysis using a high-speed camera and an automated evaluation using an algorithm to interpret pressure distribution data. After checking its reliability by comparing the outcomes of eight different observers, the video analysis was considered as a reference technique for validating the custom software.

			M	F
n	Total	145	85 (59%)	60 (41%)
	Inexperienced	57	29	28
	Recreational	67	41	26
	Competitive	21	15	6
Height (cm)	Total	175 ± 9	180 ± 7	168 ± 6
	Inexperienced	173 ± 9	178 ± 8	168 ± 6
	Recreational	176 ± 9	181 ± 6	169 ± 7
	Competitive	176 ± 7	180 ± 5	168 ± 5
Body mass (kg)	Total	69 ± 11	74 ± 9	62 ± 8
	Inexperienced	68 ± 11	74 ± 11	62 ± 8
	Recreational	70 ± 11	76 ± 9	62 ± 8
	Competitive	67 ± 9	71 ± 6	$57 + 5$
BMI ($kg/m2$)	Total	22 ± 2	23 ± 2	22 ± 3
	Inexperienced	23 ± 3	23 ± 3	22 ± 3
	Recreational	23 ± 2	23 ± 2	22 ± 3
	Competitive	21 ± 1	22 ± 1	20 ± 1
Age (years)	Total	30 ± 9	32 ± 9	27 ± 8
	Inexperienced	29 ± 10	30 ± 10	27 ± 10
	Recreational	32 ± 8	34 ± 8	29 ± 8
	Competitive	27 ± 6	28 ± 6	25 ± 5
Speed pref. (m/s)	Total	2.8 ± 0.4	3.0 ± 0.5	2.6 ± 0.3
	Inexperienced	2.6 ± 0.3	2.7 ± 0.3	2.5 ± 0.2
	Recreational	2.8 ± 0.3	3.0 ± 0.3	2.6 ± 0.2
	Competitive	3.5 ± 0.5	3.7 ± 0.4	3.0 ± 0.1
Speed faster (m/s)	Total	3.5 ± 0.6	3.7 ± 0.6	3.1 ± 0.3
	Inexperienced	3.1 ± 0.4	3.3 ± 0.4	3.0 ± 0.3
	Recreational	3.5 ± 0.4	3.7 ± 0.4	3.2 ± 0.2
	Competitive	4.4 ± 0.6	4.7 ± 0.3	3.6 ± 0.1
Speed slower (m/s)	Total	2.3 ± 0.3	2.4 ± 0.4	2.1 ± 0.2
	Inexperienced	2.1 ± 0.3	2.2 ± 0.3	2.0 ± 0.2
	Recreational	2.2 ± 0.3	2.4 ± 0.3	2.0 ± 0.2
	Competitive	2.7 ± 0.3	2.8 ± 0.3	2.4 ± 0.1

TABLE 1. Participants' anthropometric characteristics and running velocities.

Values reported as mean \pm SD.

Material

The foot strike videos were recorded using a highspeed video camera (Flare 4M180-CCL, IO Industries Inc., London, Canada) operating at 550 Hz, with dedicated recording software (Simi Grab 2.1.1, Simi Reality Motion Systems GmbH, Unterschleissheim, Germany). The resolution was set to 984 \times 400 pixels. Pressure distribution patterns were recorded at 120 Hz through a pressure plate (FDM-THM-S, zebris Medical GmbH, Isny im Allgäu, Germany) integrated in a treadmill (mercury, H-p-cosmos Sports & Medical GmbH, Nussdorf, Germany). The pressure plate data were acquired using the proprietary software (WinFDM-T v2.5.1, zebris Medical GmbH, Isny im Allgäu, Germany) and then extracted in a raw format for autonomous post-processing (R version 3.1.2, R Foundation for Statistical Computing, R Core Team, Vienna, Austria). Both the camera and the plate were synchronized using an analogue signal. The camera was set up 350 cm laterally to the left side of the treadmill, mounted on a tripod at a height of 29.5 cm

and angled perpendicular to the sagittal plane of the subjects.

Protocol

On the treadmill, the participants conducted a selfselected warm-up, $19,31$ in order to choose a comfortable running pace. The procedure to find the comfortable speed was implemented using the method of limits.^{[43](#page-9-0)} The speed was randomly increased with steps of 0.02 to 0.05 m/s at varying time intervals (around 5 to 10 s) until the participant was comfortable with a specific pace. Then the operation was repeated starting from a faster speed (around 0.5 to 1 m/s higher) and randomly decreasing it as previously done. If the comfortable value was not differing more than 10% from the previous, the average of the two values was taken as the preferred. Otherwise, the whole procedure was reiterated. The warm-up protocol typically lasted between 5 and 10 min, with an average of 6.8 ± 1.2 min.

After being instructed about the protocol, the participants ran for 90 s in four different conditions: preferred speed (shod, 2.8 ± 0.4 m/s), faster speed (shod, 3.5 ± 0.6 m/s) slower speed (shod, 2.3 ± 0.3 m/s), preferred speed (barefoot). For competitive and recreational runners, the faster speed was then determined calculating the average speed maintained during the personal best time effort over a 10 km race (mean $125 \pm 7\%$ of preferred speed). If no information was available (e.g. for inactive participants), the faster speed was set as the 125% of the preferred. The slower speed was set as the 75 to 85% of the preferred speed (mean $80 \pm 4\%$), accordingly to each participant's preference. As a guideline to identify the slower speed, the participants were asked to report a maximum value of 2 (i.e., weak, light effort) on the modified Borg Rating of Perceived Exertion scale.^{[6](#page-8-0)} Each condition was repeated, thus giving eight datasets for each subject. The order of the eight trials was completely randomized. Before every trial, each participant performed 60 s of familiarization running on the treadmill, in order to allow for accommodation.^{[44](#page-9-0)} Following, a dataset of 30 s was recorded. There were no stops between the trials, except the one or two necessary brakes to take the shoes off before running in the barefoot condition.

Analysis

Two main parts formed the FSP analysis: the video analysis as a well-accepted reference technique and the pressure plate data elaboration through a new numerical computation algorithm.

For the video analysis, eight observers were trained to identify the three FSPs (i.e., RS, MS and FS) by showing them ten trivial (clearly identifiable) and ten non-trivial videos taken outside the present study. A trivial video is namely a representation of an unambiguous FSP (e.g. a strong RS, where the rearfoot unequivocally touches the ground before any other part of the foot). On the contrary, a non-trivial video is a recording where the FSP is not clearly identifiable (e.g. a MS or a light FS or RS, where the gap between the outsole and the ground is not evenly assessed among different observers because of lighting conditions, superposition of similar colors, etc.). After becoming able to classify all the subjected data, the observers were asked to look at the study's videos and to recognize the RS, MS and FS cases. As reported from other studies,^{[5](#page-8-0)} there is indeed a decline in reliability of around 10% when making a video analysis of the foot in the background. To avoid this potential source of measurement uncertainty, only the data related to the left foot (foreground image) are presented.

A typical analysis scenario is shown in Fig. [1](#page-4-0). We report here only the data related to observations of the foreground foot (left), in order to avoid any additional measurement uncertainty^{[5](#page-8-0)} due to the difficult interpretation of a background image.

The pressure plate-data elaboration revolves around the concept of strike index (SI). The SI, as originally defined by Cavanagh and Lafortune^{[13](#page-9-0)} and then adopted from several other authors, $1,2,8,14,20,21,26,28,30,42$ $1,2,8,14,20,21,26,28,30,42$ $1,2,8,14,20,21,26,28,30,42$ $1,2,8,14,20,21,26,28,30,42$ $1,2,8,14,20,21,26,28,30,42$ $1,2,8,14,20,21,26,28,30,42$ is the distance from the heel to the center of pressure at impact relative to total foot length. However, the most important assumption made from this method is to know the foot (or shoe) length. The plate itself cannot measure this quantity accurately, since in cases like the TS the entire foot does not touch the treadmill. Therefore, for a clear identification of the FSPs from the pressure distribution data, the first step is to determine for each participant the footprint lengths. The measured lengths with and without shoes (for shod and barefoot trials, respectively) have been used as a reference to carry on the analyses. A custom-made caliper has been used for the measurements. The bare foot length has been considered as the distance from the pternion point to the most anterior point of the longest toe, measured parallel to the foot axis. In a similar way, the shoe length was measured as the distance between the perpendicular projection to the ground of the most posterior and the most anterior points of the outsole. These values constitute the foot and shoe measured lengths. The information regarding the footprint length is necessary especially when dealing with incomplete footprints during running (like in the case of TS, where the heel never touches the plate), since the pressure plate does not give any information about how long the original footprint should be.

To identify the forefoot, the midfoot and the rearfoot, the footprint is divided into three geometrically equal parts, each representing one third of the total length. Using the pressure values of the individual foot recorded from the plate, the code evaluates the footprint length (calculated length) along the treadmill's anterior–posterior axis. If the calculated value differs more than 5% from the measured one (e.g. for TS cases), the footprint is corrected with the ''real'' value, like shown in Fig. [2.](#page-5-0) The most important assumption underlying this step is that, during the toe-off phase, the tip of the shoe or of the foot always touches the ground. The width of the foot is considered as the widest footprint recorded. The footprint is thus localized within its real boundaries: this is done by expanding each pressure matrix in length and width with the appropriate number of zero elements in order to reach the correct length and width.

FIGURE 1. A typical video analysis scenario and the correspondent pressure distributions at impact. Pictures (a) and (b) represent the rearfoot strike, while (c) and (d) show the forefoot strike. Pictures (e) and (f) show the difficulty of assessing the FSP using the video analysis.

The calculation of the SI, then, automatically provides one of the three FSPs (RS, MS or FS, being the TS case included in the FS). To temporally locate the impact, the first recorded data after the swing phase has been taken as a reference, thus defining ''impact'' as "initial contact".^{[13](#page-9-0)} In the algorithm this is considered as the first non-zero pressure matrix after the last toe-off. In Fig. [3](#page-5-0), a flowchart shows the logic of the FSP determination algorithm, emphasizing the individual steps and their interconnections.

Statistics

We calculated a two-way Intraclass Correlation Coefficient (ICC) for single measurements to assess the agreement between eight different observers conducting the video analysis.

The 95% confidence interval of our sample's margin of error was estimated through a bootstrapping procedure, in order to have an indication about the uncertainty of our FSP estimate. The original data set was resampled 10,000 times with replacement, considering the FSP as the main parameter. Starting from a sample size of 41 in order to consider the sampling

distribution to be normal (central limit theorem), the procedure was repeated until the total sample size was reached, with increasing steps of 10. The minimum sample size was chosen since the central limit theorem states that the sampling distribution of the statistic is normal for sample sizes greater than 40. After elaborating the data, the agreement between the video analysis and the numerical approach was calculated, thus comparing our algorithm with a reference technique.

RESULTS

As shown in Table [2](#page-6-0), the agreement between the eight observers is usually higher for RS cases in all conditions (ICC values from 0.83 to 0.96, confidence level 0.99). The FS pattern assessment suffers a decrease in ICC value for the shod condition at faster and slower speeds (ICC values 0.65 and 0.73, respectively), while it produces higher agreement in the other conditions (ICC values 0.86 for the shod condition, preferred speed and 0.92 for the barefoot case). In evaluating MS cases, the observers never reach high agreement (ICC values 0.51

FIGURE 2. Graphical representation of the footprint's length correction. In this strong toe strike case, the participant never touched the ground with the rearfoot, as shown in the pressure distribution (a) and in the ground reaction forces (b) graphs. The identification of fore-, mid- and rearfoot is possible only after the footprint correction via software (a).

to 0.64). When joining the MS and FS strikes into a single pattern (MFS), thus identifying only two types of FSP, the ICC inevitably increases for all conditions (0.83 to 0.96). For this reason, the video analysis can be a proper reference method only when considering the RS and the joint MFS patterns.

As reported in Table [3](#page-6-0), the video analysis, averaged among eight observers, found 76.7% RS cases. The joint MFS pattern, accordingly, constitutes the 23.3% of the total 1160 observations (145 participants, five conditions, two trials for each condition). Being the measurement uncertainty of the numerical analysis independent on the foot considered, the results are presented for both the left and the right feet.

Combining all the results (preferred, faster and slower speed shod and preferred speed barefoot), the numerical analysis found 78.3% left and 77.8% right

FIGURE 3. Flow chart showing the logic of the FSP determination algorithm. Every fundamental step and interconnection are reported for reproducibility purposes.

RS cases (see Table [3\)](#page-6-0). Joining again the MS and FS patterns into a single one (MFS), makes the new pattern to contribute for 21.6% (left) and 22.2% (right) of the total observations. The computation times are 0.45 s for every second of recorded data on Intel $^{\circ}$ CoreTM i5-5250U @ 2.70 GHz with 8 GB RAM on Windows 7 64-bit and 0.15 s on Intel[®] Xeon[®] X5650 @ 2.66 GHz with 48 GB RAM on Windows 7 64-bit. To assess the validity of the numerical approach, the outcomes of the RS and MFS patterns

Condition	Speed	FSP	ICC	Lower bound	Upper bound	p value
Shod	Preferred	RS	0.83	0.77	0.87	< 0.01
		MS	0.58	0.50	0.67	< 0.01
		FS	0.86	0.82	0.90	< 0.01
		MFS	0.83	0.77	0.87	< 0.01
	Faster	RS	0.86	0.82	0.90	< 0.01
		MS	0.51	0.42	0.60	< 0.01
		FS	0.65	0.57	0.72	< 0.01
		MFS	0.86	0.82	0.90	< 0.01
	Slower	RS	0.89	0.86	0.92	< 0.01
		MS	0.64	0.56	0.72	< 0.01
		FS	0.73	0.66	0.79	< 0.01
		MFS	0.89	0.86	0.92	< 0.01
Barefoot	Preferred	RS	0.96	0.94	0.97	< 0.01
		MS	0.53	0.44	0.62	< 0.01
		FS	0.92	0.89	0.94	< 0.01
		MFS	0.96	0.94	0.97	< 0.01

TABLE 2. Intraclass correlation coefficient (ICC) calculated between the outcomes of eight observers' video analyses.

RS rearfoot strike, MS midfoot strike, FS forefoot strike, MFS midfoot and forefoot strike joint.

TABLE 3. Comparison of the video analysis' outcomes with the numerical results.

Video		Numerical					
FSP	Left	Left	Right	ICC (video vs. numerical)	Lower bound	Upper bound	p value
RS	890 (76.7%)	908 (78.3%)	903 (77.8%)	0.93	0.91	0.94	< 0.01
MFS	270 (23.3%)	252 (21.6%)	257 (22.2%)	0.93	0.91	0.94	< 0.01

The video analysis' results are an average of the eight observers' outcomes over all data (preferred, faster and slower speed shod and preferred speed barefoot). In the last two columns, the ICCs (and the relative p values) between the video and numerical results are reported. FSP foot strike pattern, RS rearfoot strike, MFS midfoot and forefoot strike joint.

were compared with the video analysis. The investigation of RS and MFS has been chosen because in these two FSP cases the reliability of the video analysis was very high. The ICCs, related to the left foot results, are calculated on the number of observations for each FSP. The RS and MFS cases return high values (0.93). All agreements are significant ($p < 0.01$).

The 95% confidence interval estimation of our dataset's standard errors gave the values reported in Fig. [4](#page-7-0). The margin of error was calculated in order to estimate the likelihood of obtaining results close to the whole population's. The following lines specify the values used to create the histogram in Fig. [4.](#page-7-0) The four conditions' video analysis presented the following FSPs: shod, preferred speed, 88.3% RS and 11.7% MFS; shod, faster speed, 87.6% RS and 12.4% MFS; shod, slower speed, 84.8% RS and 15.2% MFS; barefoot, preferred speed, 46.2% RS and 53.8% MFS. The numerical analysis of the left footprints produced: shod, preferred speed, 89.0% RS and 11.0% MFS; shod, faster speed, 89.0% RS and 11.0% MFS; shod, slower speed, 86.9% RS and 13.1% MFS; barefoot, preferred speed, 49.0% RS and 51.0% MFS. The numerical analysis of the right footprints produced:

shod, preferred speed, 88.3% RS and 11.7% MFS; shod, faster speed, 87.6% RS and 12.4% MFS; shod, slower speed, 86.2% RS and 13.8% MFS; barefoot, preferred speed, 49.0% RS and 51.0% MFS. The related margins of errors were 5.2, 5.4, 5.8 and 8.1% for the video analysis; 5.0, 5.0, 5.5 and 8.1% for the numerical analysis of the left footprints; 5.0, 5.1, 5.4 and 8.1% for the numerical analysis of the right footprints. The relative standard errors values are 2.6, 2.7, 3.0 and 4.1% (video analysis); 2.6, 2.6, 2.8 and 4.2% (numerical left); 2.6, 2.6, 2.8 and 4.2% (numerical right).

Table [4](#page-7-0) shows the FSP distribution during shod and barefoot running at a comfortable speed (here called ''preferred speed'').

DISCUSSION

This study aimed to create and validate an automatic method to evaluate FSPs during running. Using the plantar pressure distribution recorded by a pressure plate integrated in a treadmill, we created an algorithm able to detect the FSP during running. This provides the basis for the development of an onlinefeedback system. To validate the method, its agreement with a solid and often used reference technique—namely the analysis of the sagittal plane video of the striking foot—was checked. Among eight independent observers, the reference technique provided a very reliable RS and MFS patterns recognition. Therefore, it was considered an adequate gold standard for the evaluation of the new algorithm. The algorithm is able to quickly and accurately recognize the FSP and can therefore be easily used as a fast feedback tool. On a standard machine, the computation time is 45% of the recorded time (see results for details).

FSP assessment through video analysis showed a very high reliability in identifying RS cases. The rearfoot is most of the times easily located by the observers and the common strong dorsiflexion associated with a RS pat- tern^{30} tern^{30} tern^{30} helps in clearly defining the case. For similar reasons, also the FS case is often clearly isolated, espe-

FIGURE 4. Percentage of rearfoot strikes (RS) detected with the video analysis (averaged among eight observers) and by the numerical method (for both left and right foot). The error bars represent \pm se (standard error) values, calculated through a bootstrapping procedure.

cially when the plantar flexion right before the strike is substantial. There is, however, a low conformity among observers in determining MS cases. This is because the midfoot is often difficult to locate and often leads to the misinterpretation of the FSP. In addition, it is not always trivial to identify a gap or a contact between the outsole (or the bare foot) and the treadmill. These factors add an amount of uncertainty that translates in a lowered agreement between observers (low ICC). Joining, as we propose, the MS and FS cases into one single pattern called MFS solves most disagreeing cases. The decrease in ICC values for the shod condition at faster and slower speeds also suggests a dependence of the inter-rater reliability on the running speed. Since the foreground foot was the left, the image of the right foot was often difficult to interpret. A previously-reported decline in reliability when analyzing the foot in the background, $\frac{5}{2}$ $\frac{5}{2}$ $\frac{5}{2}$ convinced us to only present the data related to the image in the foreground, namely the left foot. Additionally, the video analysis is not adequate for giving online-feedback information about the FSP and proved to be extremely time-consuming, especially when the number of trials is not small. The video analysis, one of the most popular methods for FSP assessment, $5,15,23,27,37,38$ $5,15,23,27,37,38$ is anyhow solid enough to be considered as a reference technique for validating our algorithm. The uncommonly big sample size of 145 participants was chosen in order to reduce the chance of biases in our measurements. In these kinds of studies, it is very common to use small sample sizes.^{[2,](#page-8-0)[20,28,31,37,38,41,42](#page-9-0)} This is partly due to the complex structure of some experimental setups. The chosen sample size can be evaluated by estimating the margin of error. This quantity contains the information about the uncertainty with which one predicts to describe the whole population. This means that our sample estimate will not differ from the true population's by more than the margin of error values 95% of the time (the chosen confidence level). This is obviously a gross estimation that does not take into account all the underlying biases that might be present, but it is a starting point for evaluating the sample size.

In addition to what was previously done in other studies, $5,23,25,27,41$ $5,23,25,27,41$ we decided to widen the set of con-

TABLE 4. Foot strike patterns occurrences during shod and barefoot running at preferred speed.

FSP		Shod	Barefoot	
	Left $(\%)$	Right $(\%)$	Left $(\%)$	Right (%)
RS	89.0	88.3	49.0	49.0
MS	9.6	10.3	42.8	44.1
FS	1.4	1.4	8.2	6.9

FSP foot strike pattern, RS rearfoot strike, MS midfoot strike, FS forefoot strike.

ditions in order to test our automatic foot strike detection across various circumstances. Therefore, shod running data were recorded at three endurance running speeds. Further, barefoot running data (at preferred speed) were acquired. Moreover, using a treadmill allowed us to have a big number of gait cycles to analyze. This aspect is crucial for a task like running during which a certain amount of adaptation, albeit small, is needed before reaching the cyclicrepetitive state. For this reason, 30 s after at least 60 s $accommodation⁴⁴$ $accommodation⁴⁴$ $accommodation⁴⁴$ for each condition were recorded, excluding since the beginning the possibility of acquiring only single steps, thus minimizing the effects of artefacts in the assessment of the FSP for each participant and condition.

Since the video analysis (reference technique) is associated with a lack of reliability when dealing with MS cases, only the RS and the joint MFS patterns were used to validate our numerical approach against the reference. The agreement investigation between the two methods produced significantly high values. This will allow us, in the future, to conduct any treadmillbased study by using only our numerical approach for all FSPs (RS, MS, FS and TS). The numerical analysis, supported by a sample size of 145 participants, gave results that are consistent with previous findings. $23,24$ There is a clear dominance of RS patterns in the shod condition and MFS patterns in the barefoot condition. These numbers should be interpreted as referred to a sample of habitually shod runners that had no experience of barefoot running at the moment of the study. The fully automated process avoids any observer influence, thus producing objective results. The highthroughput nature of the numerical analysis helps to dramatically reduce the computation time and increase the efficiency of the FSP assessment.

With our approach, we introduced a foot length correction, which is key for producing accurate results. Peculiar cases can cause difficulties in analyzing data. The TS, for instance, produces a much shorter footprint than the original shoe (or foot). This would lead, without any additional information about the real length of the shoe or foot, to a wrong output. The algorithm would consider the footprint as complete even if only the forefoot and a portion of the midfoot (typical TS case) formed it. To avoid these singularities, the automatic algorithm needs the shoe (or foot) length as an initial input. A quick and easy measurement of the shoe length (for the shod condition analysis) and of the foot (for the barefoot cases) allows our algorithm to correctly locate the pressure information inside the real footprint. Therefore, every possible special case can be automatically analyzed. Furthermore, this method allows for within-person analysis, taking into account any possible asymmetries. This

feature would permit a higher level of online-feedback, increasing the amount of available information for both the researcher and the participant.

A potential limitation of this validation might be in its specificity to treadmill running. Even if there is evidence of similarity between overground and treadmill running, 40 40 40 most of the participants in this study run predominantly outdoors rather than on a treadmill. Also, the participants chose their own footwear and speed, thus not allowing for generalized conclusions on these parameters. Another possible limitation is undoubtedly given by the measurement system. The big size of the sensors $(8.47 \times 8.47 \text{ mm})$ and the relatively low sampling rate (120 Hz) of the pressure plate, may lead to accuracy issues when the requirements on the measurement uncertainty are particularly stringent.

ACKNOWLEDGMENTS

We are grateful to Arno Schroll for the precious suggestions in matter of statistics and to Sebastian Bohm, PhD and Falk Mersmann for the great help in collecting the participants.

REFERENCES

- ¹Almonroeder, T., J. D. Willson, and T. W. Kernozek. The effect of foot strike pattern on achilles tendon load during
- running. Ann. Biomed. Eng. 41:1758–1766, 2013.
²Altman, A. R., and I. S. Davis. A kinematic method for footstrike pattern detection in barefoot and shod runners. Gait Posture 35:298-300, 2012.
- ³Beely, F. Zur Mechanik des Stehens. Ueber die Bedeutung des Fussgewölbes beim Stehen. Arch. für Klin. Chir. 27:457–471, 1882.
- 4 Bennell, K. L., S. A. Malcolm, S. A. Thomas, P. R. Ebeling, P. R. McCrory, J. D. Wark, and P. D. Brukner. Risk factors for stress fractures in female track-and-field athletes: a retrospective analysis. Clin. J. Sport Med. 5:229– 235, 1995.
- 5 Bertelsen, M. L., J. F. Jensen, M. H. Nielsen, R. O. Nielsen, and S. Rasmussen. Footstrike patterns among novice runners wearing a conventional, neutral running shoe. Gait Posture 38:354-356, 2012.
- ⁶Borg, G. A. V. Psychophysical bases of perceived exertion. Med. Sci. Sports Exerc. 14:377–381, 1982. ⁷
- $7Bover$, E. R., and T. R. Derrick. Select injury-related variables are affected by stride length and foot strike style during running. Am. J. Sports Med. 43:2310-2317, 2015.
- ⁸Boyer, E. R., B. D. Rooney, and T. R. Derrick. Rearfoot and midfoot or forefoot impacts in habitually shod runners. Med. Sci. Sports Exerc. 46:1384-1391, 2014.
- $9B$ ramble, D. M., and D. E. Lieberman. Endurance running and the evolution of Homo. Nature 432:345–352, 2004.

- ¹⁰Braunstein, B., A. Arampatzis, P. Eysel, and G.-P. Brüggemann. Footwear affects the gearing at the ankle and knee joints during running. J. Biomech. 43:2120–2125,
- $^{12}_{1}$ Burfoot, A. The history of the marathon: 1976–present.
- Sport. Med. 37:284–287, 2007.
¹²Cavagna, G. A., L. Komarek, and S. Mazzoleni. The mechanics of sprint running. J. Neurosci. 217:709–721,
- 1971.
¹³Cavanagh, P. R., and M. A. Lafortune. Ground reaction forces in distance running. *J. Biomech*. 13:397–406, 1980.
- ¹⁴Chambon, N., N. Delattre, N. Guéguen, E. Berton, and G. Rao. Is midsole thickness a key parameter for the running pattern? *Gait Posture* $40(1):58–63$, 2014.
- ¹⁵Daoud, A. I., G. J. Geissler, F. Wang, J. Saretsky, Y. A. Daoud, and D. E. Lieberman. Foot strike and injury rates in endurance runners: a retrospective study. Med. Sci.
- Sports Exerc. 44:1325–1334, 2012. ¹⁶De Almeida, M. O., B. T. Saragiotto, T. P. Yamato, and A. D. Lopes. Is the rearfoot pattern the most frequently foot strike pattern among recreational shod distance runners?
- *Phys. Ther. Sport* 16(1):29–33, 2015. ¹⁷Di Michele, R., and F. Merni. The concurrent effects of strike pattern and ground-contact time on running econ-
- omy. J. Sci. Med. Sport 17:414–418, 2014.
¹⁸Elftman, H. A cinematic study of the distribution of pressure in the human foot. *Anat. Rec.* 59:481–491, 1934.
- ¹⁹Fletcher, J. R., S. P. Esau, and B. R. MacIntosh. Economy of running: beyond the measurement of oxygen uptake. J.
- Appl. Physiol. 107:1918–1922, 2009. 20Giandolini, M., T. Poupard, P. Gimenez, N. Horvais, G. Y. Millet, J.-B. Morin, and P. Samozino. A simple field method to identify foot strike pattern during running. J.
- Biomech. 47:1588–1593, 2014. 21Gruber, A. H., B. R. Umberger, B. Braun, and J. Hamill. Economy and rate of carbohydrate oxidation during running with rearfoot and forefoot strike patterns. J. Appl.
- Physiol. 115:194–201, 2013. 22Hamill, J., and A. H. Gruber. Running injuries: forefoot versus rearfoot and barefoot versus shod: a biomechanist's
- perspective. 2012. 23Hasegawa, H., T. Yamauchi, and W. J. Kraemer. Foot strike patterns of runners at the 15-km point during an elite-level half marathon. J. Strength Cond. Res. 21:888–
- $^{893, 2007.}$ ²⁴Hatala, K. G., H. L. Dingwall, R. E. Wunderlich, and B. G. Richmond. Variation in foot strike patterns during running among habitually barefoot populations. *PLoS One* 8:e52548, 2013.
- ²⁵Kasmer, M. E., X.-C. Liu, K. G. Roberts, and J. M. Valadao. Foot-strike pattern and performance in a marathon.
- Int. J. Sports Physiol. Perform. 8:286–292, 2013.
²⁶Kernozek, T. W., S. Meardon, and C. N. Vannatta. In-shoe loading in rearfoot and non-rearfoot strikers during running using minimalist footwear. Int. J. Sports Med.
- 35(13):1112–1117, 2014. 27Larson, P., E. Higgins, J. Kaminski, T. Decker, J. Preble, D. Lyons, K. McIntyre, and A. Normile. Foot strike patterns of recreational and sub-elite runners in a long-dis-
tance road race. J. Sports Sci. 29:1665-1673, 2011.
- ²⁸Laughton, C. A., I. M. Davis, and J. Hamill. Effect of strike pattern and orthotic intervention on tibial shock during running. J. Appl. Biomech. 19:153–168, 2003.
- ²⁹Lees, A., and J. Bouracier. The longitudinal variability of ground reaction forces in experienced and inexperienced
- runners. *Ergonomics* 37:197–206, 1994.
³⁰Lieberman, D. E., M. Venkadesan, W. A. Werbel, A. I. Daoud, S. D'Andrea, I. S. Davis, R. O. Mang'eni, and Y. Pitsiladis. Foot strike patterns and collision forces in habitually barefoot versus shod runners. Nature 463:531–
- 535, 2010.
 31 Logan, S., I. Hunter, J. T. Hopkins, J. B. Feland, and A. C. Parcell. Ground reaction force differences between running shoes, racing flats, and distance spikes in runners. J. Sport.
- Sci. Med. 9:147–153, 2010.
³²Lun, V., W. H. Meeuwisse, P. Stergiou, and D. Stefanyshyn. Relation between running injury and static lower limb alignment in recreational runners. Br. J. Sports Med.
- 38:576–580, 2004.
³³Mann, R., L. Malisoux, R. Brunner, P. Gette, A. Urhausen, A. Statham, K. Meijer, and D. Theisen. Reliability and validity of pressure and temporal parameters recorded using a pressure-sensitive insole during running. Gait Pos-
- ture 39:455–459, 2014.
³⁴McCallion, C., B. Donne, N. Fleming, and B. Blanksby. Acute differences in foot strike and spatiotemporal variables for shod, barefoot or minimalist male runners. J.
- Sport. Sci. Med. 13:280–286, 2014.
³⁵Milner, C. E., R. Ferber, C. D. Pollard, J. Hamill, and I. S. Davis. Biomechanical factors associated with tibial stress fracture in female runners. Med. Sci. Sports Exerc. 38:323–
- 328, 2006.
³⁶Momburg, F. Der Gang des Menschen und die Fuss-
- geschwulst. Berlin: Hirschwald, 1908; (87 pp).
³⁷Perl, D. P., A. I. Daoud, and D. E. Lieberman. Effects of footwear and strike type on running economy. Med. Sci.
- Sports Exerc. 44:1335–1343, 2012.
³⁸Pohl, M. B., and J. G. Buckley. Changes in foot and shank coupling due to alterations in foot strike pattern during
- running. Clin. Biomech. 23:334–341, 2008. 39Pohl, M. B., D. R. Mullineaux, C. E. Milner, J. Hamill, and I. S. Davis. Biomechanical predictors of retrospective tibial
- stress fractures in runners. *J. Biomech.* 41:1160–1165, 2008. ⁴⁰Riley, P. O., J. Dicharry, J. Franz, U. Della Croce, R. P. Wilder, and D. C. Kerrigan. A kinematics and kinetic comparison of overground and treadmill running. Med.
- Sci. Sports Exerc. 40:1093-1100, 2008.
⁴¹Scholten, S. D., N. Stergiou, A. Hreljac, J. Houser, D. Blanke, and L. R. Alberts. Foot strike patterns after obstacle clearance during running. Med. Sci. Sports Exerc.
- $34:123-129$, 2002.
⁴²Squadrone, R., and C. Gallozzi. Biomechanical and physiological comparison of barefoot and two shod conditions in experienced barefoot runners. J. Sports Med. Phys. Fit-
- ness 49(1):6–13, 2009.

⁴³Treutwein, B. Adaptive psychophysical procedures. *Vis* Res. 35:2503–2522, 1995.
- ⁴⁴White, S. C., L. A. Gilchrist, and K. A. Christina. Withinday accommodation effects on vertical reaction forces for
- treadmill running. *J. Appl. Biomech.* 18:74–82, 2002.
⁴⁵Williams, D. S., I. S. McClay, and K. T. Manal. Lower extremity mechanics in runners with a converted forefoot
- strike pattern. *J. Appl. Biomech*. 16:210–218, 2000.
⁴⁶Zifchock, R. A., I. Davis, and J. Hamill. Kinetic asymmetry in female runners with and without retrospective tibial stress fractures. J. Biomech. 39:2792–2797, 2006.

