Temporal Dynamics of Plantar Pressure Distribution using Parametric Mapping Techniques

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Abstract

Background: *Pedobarography produces large sets of plantar pressure samples that are routinely subsampled (e.g. using regions of interest) or aggregated (e.g. center of pressure trajectories, peak pressure images) in order to simplify statistical analysis and provide intuitive clinical measures.*

Research Question: *We hypothesize that these data reductions discard gait information that can be used to differentiate between groups or conditions.*

Methods: *To test the hypothesis of null information loss, we created an implementation of statistical parametric mapping (SPM) for dynamic plantar pressure datasets (i.e. plantar pressure videos). Our SPM software framework brings all plantar pressure videos into anatomical and temporal correspondence, then performs statistical tests at each sampling location in space and time. Novelly, we introduce non-linear temporal registration into the framework in order to normalize for timing differences within the stance phase. We refer to our software framework as STAPP: spatiotemporal analysis of plantar pressure measurements. Using STAPP, we tested our hypothesis on plantar pressure videos from 33 healthy subjects walking at different speeds.*

Results: *As walking speed increased, STAPP was able to identify significant decreases in plantar pressure at mid-stance from the heel through the lateral forefoot. The extent of these plantar pressure decreases have not previously been observed using existing plantar pressure analysis techniques.*

Significance: *We therefore conclude that the subsampling of plantar pressure videos - a task which led to the discarding of gait information in our study - can be avoided using STAPP.*

Keyterms— Pedobarography, Walking Speed, Statistical Parametric Mapping, Spatiotemporal Analysis

1 Introduction

Plantar pressure measurements (PPM) have the potential to objectively evaluate the impact of clinical interventions on foot and ankle function [1, 2, 3]. However, the potential of PPM has so far been restricted by the challenges involved in analyzing the large datasets that are produced [4]. A typical PPM examination generates a plantar pressure video: a sequence of plantar pressure images – known as frames – collected throughout a patient's stance phase. Such a video can contain hundreds of frames, each frame containing plantar pressures sampled at hundreds of spatial locations known as
pixels [5].

In an attempt to address the challenges involved in analyzing plantar pressure videos, the research community has proposed a wide variety of postprocessing and statistical analysis techniques [4], all of which involve subsampling or aggregation of the plantar pressure values. By far the most widely-used set of analysis techniques are region of interest (ROI) based, which subsample and aggregate pressure measurements within expert-defined anatomical foot regions [1, 6]. Also popular are centre of pressure (COP) trajectories which aggregate across the spatial dimensions [7, 8], and 2D pressure pattern images which aggregate across time [9, 10].

While these quantitative analysis techniques are simple and popular, they also clearly discard information present within the plantar pressure video [4]. This discarding of information can be justified in hypothesis-driven studies, specifically when the hypothesis has dictated that certain plantar pressure measurements can be safely ignored. However, for more exploratory – or data-driven – analyses, the discarding of plantar pressure measurements is not well motivated. At best, valuable information may go ignored. At worst, incorrect conclusions could be drawn from the reduced PPM dataset, as recent studies have shown [11, 12].

We hypothesize that subsampling the plantar pressure video discards gait information that can help differentiate between groups or conditions. To test this hypothesis, we first require an analysis technique that works with the plantar pressure video as a whole.

When performing a statistical analysis of plantar pressure datasets, statistical parametric mapping (SPM) is required in order to obtain statistically sound results [13]. SPM works by bringing the plantar pressure measurements from all subjects into anatomical correspondence, performing statistical tests at each sample location, then correcting for multiple comparisons. Different processing choices within SPM can lead to a variety of statistical results [14, 15, 16], suggesting that the SPM framework should be implemented with care. Established SPM implementations exist for COP trajectories [17] and 2D plantar pressure images [18], but SPM has been less frequently used on the full plantar pressure video. Pataky and Maiwald proposed using SPM to analyse for plantar pressure videos [5], but did so with a linear temporal registration.Since linear registration is unlikely to align key stance events (e.g. instants of vertical force extrema) [19, 20], nonlinear registration may be desirable when key event amplitudes are of interest. The work of Oliveira et al. [21, 22] performs such a non-linear temporal normalization, but has not been used in an SPM framework.

To address these limitations and to investigate our hypothesis, we propose *STAPP*: an SPM implementation for the spatiotemporal analysis of full plantar pressure videos.

STAPP implements SPM and applies a non-linear temporal normalization prior to statistical analysis. Furthermore, STAPP avoids subsampling the plantar pressure video and potentially discarding useful gait information.

The contributions of this article are twofold. First, we present the implementation details behind STAPP and show how it analyzes plantar pressure videos without performing any subsampling (Section 2). Second, we evaluate STAPP's ability to identify both where and when plantar pressure differences occur as a result of walking speed (Section 3). The results from this proof-of-concept are then compared to those from established SPM plantar pressure analysis techniques [17, 18] to evaluate if – and how – statistically significant plantar pressure results can be missed by subsampling the plantar pressure video. We discuss these results further in Section 4.

2 Materials and Methods

2.1 Data Collection and Preprocessing

Thirty-three healthy subjects (mean (SD) age: 46 (18) years; weight 74.2 (11.9) kg; height 174 (7.9) cm) participated in this study and gave written informed consent [8]. The study was approved by the internal review committee of the Sint Maartenskliniek and met the requirements for exemption from the Medical Ethics Committee review under the Dutch Medical Research Involving Human Subjects. The study was performed in accordance to the declaration of Helsinki.

Subjects walked at three walking speed conditions; slow, preferred, and fast. For the slow and fast, subjects had to walk 0.4 m/s slower and faster than their preferred speed, respectively. A minimum of five correct trials for each condition were collected. Correct trials were checked for each trial and were defined as trials with a speed deviations less than 0.05 m/s and without correcting steps such as lengthening or shortening the step or side step.

Plantar pressure was measured using a 0.5 m rs scan plate (rs scan, Paal, Belgium; dimensions: 48.8 × 32.5 cm) on top of a Kistler force plate (9286AA, Kistler, Wintherthur, Switzerland), which were synchronized with a rs scan foorscan® interface box. Walking speed was measured by an eight camera Vicon motion analysis system (Vicon, Oxford, United Kingdom) using a marker on the heel with additional markers on Metatarsal II and lateral Malleolus. Data was measured at a frequency of 200 Hz.

The rs scan footscan® pressure plate used for data collection has non-square sensor dimensions ($7.62\ mm \times 5.08\ mm$), resulting in video frames being compressed in the anterior-posterior direction. In order to recover the original foot geometry, each frame of the plantar pressure video was upsampled to a $1\ mm \times 1\ mm$ grid using cubic interpolation. Each frame of the plantar pressure video was then normalized by the total mean pressure to eliminate the influence of subject weight and walking speed on the magnitude – but not the distribution – of the plantar pressure values. This normalization, proposed and validated by Keijsers [23], involves dividing each plantar pressure sample by the sum of all pixel values in the 2D mean pressure image.

2.2 STAPP Analysis Pipeline

At a high level, STAPP implements the SPM framework by bringing datasets into anatomical - and in our case temporal - correspondence, then testing for significance at each measurement location [13]. The proposed STAPP implementation is shown in Figure 1 and consists of the five methods described below. In our descriptions, we will refer to a plantar pressure video V as a collection of plantar pressure samples indexed by pixel location x= [x, y] and time frame t.

2.2.1 Rigid Spatial Registration

To normalize each footstep with respect to rotation and position, we employed the image registration technique used in pSPM [18]. This technique relates two peak pressure images $I(\mathrm{x}) = \max_t (V(\mathrm{x},t))$ to each other by assuming that

$$I_{ref}(\mathrm{x}) \simeq I_k(\mathrm{Rx}+\mathrm{z}), \tag{1}$$

where I_{ref} is a reference peak pressure image to be aligned to, I_k is the peak pressure image being aligned, R is a 2D rotation matrix, and z = z_x, z_y is a translation vector. Equation 1 is solved for R and z simultaneously, and the resulting rotation and translation are applied to each frame of the corresponding video V_k. This algorithm is applied as the first step of the within- and between-subject registration tasks.

2.2.2 Deformable Spatial Registration

To normalize the shape and size of each footstep, we employed the image registration technique of Pataky et al. [24]. This technique relates two peak pressure silhouette images,

$$S(\mathrm{x}) = \begin{cases} 1 & \text{if } I(\mathrm{x}) > 5 \text{ kPa;} \\ 0 & \text{otherwise} \end{cases}$$

to each other by assuming that

$$S_{ref}(\mathrm{x}) \simeq S_k(\mathrm{x}+d(\mathrm{x})), \tag{2}$$

where S_{ref} is the silhouette image to be aligned to, S_k is the silhouette image being aligned, and *d* is a deformation vector field (i.e. an image comprised of translation vectors). Equation 2 is solved for *d* (under the constraint that the deformation field varies smoothly [24]) and the resulting deformation is applied to each frame of V_k. This algorithm is applied as the second step in the between-subject registration task.

2.2.3 Dynamic Time Warping

To normalize for footstep timing and duration, we employed the dynamic time warping algorithm of Zhou and de la Torre [25]. This technique relates two plantar pressure videos to each other by assuming that

$$V_{ref}(x, t) \simeq V_k(x, \phi(t)), \tag{3}$$

where V_{ref} is the plantar pressure video to be aligned to, V_k is the plantar pressure video being aligned, and ϕ is a non-decreasing function that warps the time dimension while keeping the video frames in order. Equation 3 is solved for and the resulting time warp is used to resample V_k along the time dimension. This algorithm is applied as the final step of the within- and between-subject registration tasks. Once this step has been performed in the within-subject registration, all videos from one subject are averaged to reduce the impact of both electrical and behavioural noise in further analysis [24].

2.2.4 Target Selection

SPM methods work best when an anatomically neutral dataset is chosen as a reference [24]. To create such a reference plantar pressure video, we employed the algorithm of Guimond et al. [26]:

1. Randomly select an initial reference $V_{ref} = V_i$.
2. Align V_{ref} to all videos $V_1, \cdots, V_N$ in the study using (1), (2), and (3).
3. Average the transformations calculated in step 2 to obtain $\bar{R}$, $\bar{z}$, $\bar{d}$, and $\bar{\phi}$. These transformations capture how V_{ref} differs from the population average.
4. Apply the transformations $\bar{R}$, $\bar{z}$, $\bar{d}$, and $\bar{\phi}$, to V_{ref}. This step transforms V_{ref} towards the population average.
5. Repeat from step 2 until no change in V_{ref} is seen.

Once this algorithm has been run, all plantar pressure videos were aligned to V_{ref} using (1), (2), and (3).

2.2.5 Statistical Analysis

Our statistical analysis consisted of two steps. First, 1-way ANOVA tests were performed at each pixel to determine if there were any significantly different plantar pressures between walking speeds. The result of these 1-way ANOVA tests was a statistical parametric mapped, SPM{F}, video similar to our plantar pressure videos, but containing F-statistics instead of pressure values. The 1-way ANOVA is followed up with post-hoc paired t-tests between each pair of walking speeds. The result of these paired t-tests were SPM{t} videos containing a t-statistic at each pixel of each frame. Random field theory was then used to identify pixels, and clusters of pixels, that show statistically significant plantar pressure differences [27].

3 Results

STAPP was used to examine plantar pressure differences as a result of walking speed in a cohort of 33 healthy adults. To evaluate the effect of subsampling, we compare our STAPP results to two other types of SPM analyses on subsampled plantar pressure data: the 2D pSPM technique of Pataky and Goulermas [18] on mean pressure images, and the 1D centre of pressure analysis technique that has been used in previous studies [7, 8]. The centre of pressure analysis was performed using SPM1D TOOLBOX created by Todd Pataky [17] while pSPM was implemented in MATLAB, version 2015b (The MathWorks, Natuck, USA).

Note that STAPP produces SPM{t} and SPM{F} videos that are not amenable for presentation in print. Therefore, we present here results sampled from the SPM{t} and SPM{F} videos STAPP produces. The full STAPP videos for our results, as well as additional statistical results, are provided as supplementary material.

3.1 STAPP Results

Figure 2 shows, at each time point, the percentage of the footprint that had significant differences in our 1-way ANOVA analysis between the walking speed groups. From this graph, we identified three notable time periods to further illustrate these plantar pressure differences: during heel strike (sampled at 7% of the stance phase), mid-stance (sampled at 50% of the stance phase), and forefoot push-off (sampled at 80% of the stance phase). The post-hoc paired t-test results for those time points are shown in Figure 3.

At 7% into the stance phase, significant differences can be observed. A faster walking speed leads to increased pressure under the heel and our STAPP analysis captures that effect for all walking speed comparisons. Around mid-stance (50% into the stance phase), STAPP reported significantly lower plantar pressure across the majority of the foot as walking speed increases. In particular, this decrease in plantar pressure was seen extending under the lateral forefoot and heel. The results at 80% into the stance phase showed increased walking speed leading to decreased plantar pressure on the lateral forefoot, but also increased plantar pressure under the toes. The extent of these statistical differences also decreases as walking speeds decreases.

Figure 4 shows the duration of statistically significant plantar pressure differences detected in our post-hoc paired t-tests. As walking speed increased, the majority of pressure sensors recorded a decrease in plantar pressure in at least 10% of the stance phase. At some time points, plantar pressure in the heel either increased (e.g. heel strike) or decreased (e.g. mid-stance).

3.2 Comparison to pSPM

Figure 5 shows the pSPM results for the mean plantar pressure images at different walking speeds. Some consistent patterns can be seen across these pSPM test results. Similar to the STAPP results, significant increases in mean pressure were observed in the heel and toe areas, with significant decreases in the midfoot and lateral part of the forefoot. Also, fewer foot regions showed significant pressure differences with pSPM than in the STAPP results, and the quantity of pressure differences was dependant on walking speed. For example, almost no significant differences were found between the preferred and slow walking speed conditions (Figure 5d).

3.3 Comparison to Centre of Pressure

Figure 6 shows the 95% confidence intervals for the centre of pressure (COP) trajectories at different walking speeds. Intervals where COP differs with walking speed, according to our 1-way ANOVA analysis, are highlighted in grey. A noticeable difference in the anterior-posterior COP location was observed following mid-stance (Figure 6a) as the faster the walking speed, the sooner the transition to the forefoot. The COP differences in the medial-lateral direction was also noticeable between 30% and 80% of the stance phase (Figure 6b). The faster the walking speed, the more the COP location moves to the medial side of the foot. The timing of these COP differences corresponds with the differences highlighted by STAPP with the exception that STAPP also shows significant differences at the heel strike.

4 Discussion

We hypothesized that subsampling PPM discards gait information useful for differentiating between groups or conditions, but the lack of a proper statistical analysis framework for plantar pressure videos hindered our ability to validate this hypothesis. As a result, we presented herein STAPP: a software framework for analysing plantar pressure videos using SPM. As an SPM implementation, STAPP works by bringing datasets into anatomical - and in our case temporal - correspondence, then testing for significance at each sample location [13].

We applied STAPP to the plantar pressure videos of 33 subjects walking at three different speeds. Our STAPP analysis agrees with centre of pressure results reported here and elsewhere [8, 28], in the sense that both techniques identified significant gait differences at mid-stance and in the forefoot roll-off phase. However, previous studies were unable to identify what part of the foot was responsible for these differences, or whether they were the result of plantar pressure increases or decreases. STAPP is able to show *for the first time* that these differences in centre of pressure were the result of decreased pressure under the heel and forefoot at mid-stance, and increased pressure under the toes during the forefoot roll-off phase. STAPP was also able to identify differences at the heel strike that were not found in the centre of pressure results. This discrepancy is due to the fact that the pressure magnitude at heel strike changed but not how that pressure was distributed under the heel. Therefore no changes were seen in the centre of pressure. Given the role a harder heel strike plays in repetitive stress injuries [29], STAPP's ability to identify increased pressure at heel strike could yield advantages in future biomechanics research.

Similarly, the STAPP results agreed with pSPM to the extent that pressure increased with faster walking speed in the heel and toe areas, while pressure in the midfoot decreased with faster walking speed [10]. However, pSPM was unable to show when these pressure differences occurred, specifically that the increased pressure was seen under the heel during heel strike and under the toes during the forefoot roll-off phase. Moreover, pSPM was unable to show that the decreased pressure in the midfoot actually extends to include the heel and the lateral forefoot, and that this decrease in plantar pressure occurs around mid-stance. The impact of pSPM's under-reporting was most noticeable in the heel where both significant increases and decreases in plantar pressure went unreported. These results show that, while some time points may show significant differences in plantar pressure, averaging over all time points – as is done when computing 2D mean pressure images – can smooth out those differences, making the resulting mean pressure differences statistically insignificant. In creating the mean pressure images, two significant results (increased pressure at heel strike and decreased pressure at mid-stance) were averaged together and, to a noticeable extent, cancelled each other out. The extent to which this cancelling effect can impact clinical biomechanics research is something we will examine in our future work.

While STAPP benefits by retaining the whole PPM, there are clinical situations where STAPP's use may not be well advised. If a patient group has a severe pathological condition, the registration and time warping algorithms used by STAPP may not be sufficient to establish anatomical correspondence across subjects. In that case, the subsequent statistical tests would not include comparable pressure samples, thereby producing unreliable results. Also, the within-subject registration and averaging performed by STAPP discards within-subject variability. There are certain clinical cases where that information is necessary. Our future work will evaluate the effect of, and potentially remove, these limitations.

The present study shows that while analysis techniques can identify statistically significant results when subsampling PPMs, they cannot provide a full description of how groups or conditions differ. Their subsampling steps remove information either on the spatial location of plantar pressure differences (e.g. centre of pressure), or on their timing (e.g. pSPM). In the context of a data-driven experiment, where no assumptions are made on which plantar pressure measurements are relevant to a research question, this loss of information through subsampling is counter-productive. We have also shown that subsampling can cause statistically significant results to cancel each other out (e.g. pSPM in the heel area), potentially leading one to draw incorrect conclusions from the plantar pressure data. STAPP avoids this subsampling and, as a result, provides a unified, spatiotemporal analysis of full plantar pressure videos.

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