

1 **Pedobarographic Statistical Parametric Mapping of plantar pressure data in new and**
2 **confident walking infants: a preliminary analysis**

3 Eleonora Montagnani^{A*}, Stewart C Morrison^A, Matyas Varga^A, Carina Price^B

4

5 ^A School of Health Sciences, University of Brighton, Darley Road, Eastbourne, United Kingdom

6 ^B Centre for Health Sciences Research, University of Salford, Frederick Road, Salford, United

7 Kingdom

8

9 ***Corresponding author:**

10 Eleonora Montagnani

11 Email: e.montagnani@brighton.ac.uk

12 Address: 204 Aldro Building, 49 Darley Road, Eastbourne, BN20 7UR, UK

13

14 **Word count of the manuscript (without reference list): 3163 words**

15

16

17

18

19

20

21

22 **Abstract**

23 In infancy, plantar pressure data during walking has been investigated through regional approaches,
24 whilst the use pedobarographic Statistical Parametric Mapping (pSPM) has not been reported. Analysis
25 of pressure data using pSPM is higher in resolution and can enhance understanding of foot function
26 development, providing novel insights into plantar pressure changes. This work aims to detail the
27 implementation of the pSPM data processing framework on infants' pressure data, comparing plantar
28 pressure patterns between new and confident walking steps. Twelve infants walked across an EMED-
29 xl platform. Steps were extracted and imported into MATLAB for analysis. Maximum pressure pictures
30 were transformed to point clouds and registered within and between participants with iterative closest
31 point and coherent point drift algorithms, respectively. Root mean square error (RMSE) was calculated
32 within both registrations as a quality measure. Pressure patterns were compared between new and
33 confident walking using nonparametric-paired sample SPM1D t-test. RMSEs were under 1 mm for both
34 registration algorithms. In the transition to confident walking, significantly increasing pressure was
35 detected in the left central forefoot. Implementing pSPM to infants' pressure data was non-trivial, as
36 several phases of data processing were required to ensure a robust approach. Our analysis highlighted
37 the presence of significant changes in pressure in central left forefoot after 2.2 months of walking, which
38 have not been reported before. This can be explained as previous regional approaches in infancy
39 considered the forefoot as whole, preventing detection of changes in discrete anatomical regions.

40

41 **Keywords:** pSPM, foot, plantar pressure, infants, gait

42

43

44

45

46

47

48

49 **1. Introduction**

50 Quantifying plantar pressure data as infants learn and master walking skills enhances knowledge of the
51 typical biomechanics of the foot throughout development, providing information related to foot function
52 changes. The conventional approach to analysis and reporting infants' pressure data is regional analysis,
53 which has been adopted using three, five, six or seven regions of interest (ROIs) (Montagnani et al.,
54 2021, in press). Traditional regional analysis software have been developed to be accessible without the
55 need to understand programming languages (e.g., MATLAB, Python), making it easy to implement for
56 pressure data processing. This ease in processing data comes with certain disadvantages, notably
57 assumptions relating to the statistical treatment of regional data as discrete, treating the regions of the
58 foot independently (Pataky and Goulermas, 2008). Furthermore, the use of regional analysis in infancy
59 presents limitations due to the ongoing foot development, which causes lack of clear anatomical
60 definition on the plantar surface and hypotheses relating to the ROIs typically analyzed in the plantar
61 pressure field.

62 Pedobarographic Statistical Parametric Mapping (pSPM) conducts statistical inference at the pixel level
63 in the spatial domain (Pataky and Goulermas, 2008), and it has been adopted in adults (McClymont et
64 al., 2016; Oliveira et al., 2010; Pataky et al., 2008) and children (Phethean et al., 2014). However, the
65 use of pSPM in infants' pressure analysis has not been reported. Adopting pSPM could be non-trivial
66 in infancy, as foot placement on the pressure platform could be influenced by the combination of high
67 variability in gait, the testing protocol adopted, and the developmental characteristics of the infant's
68 feet. These factors lead to capturing steps highly irregular in shape and spatial orientation (Price et al.,
69 2017) that could make data processing challenging. Therefore, this study aimed to detail the
70 implementation of the pSPM processing framework on pressure data captured in infants. By
71 undertaking this work, we also aimed to compare pressure patterns of new and confident walking
72 infants, providing a preliminary set of novel information about plantar pressure patterns that could direct
73 future research in the field.

74

75 **2. Methods**

76 This work emerges from a longitudinal study, which is part of the Great Foundation Initiative (Price et
77 al., 2018). Ethical approval was obtained from the ethics committees of the Schools of Health Sciences
78 at the University of Brighton (LHPSCREC 17-11) and the University of Salford (HSCR161779).

79 *2.1 Participants*

80 Twelve infants (5 female, 7 males) were recruited via social media and local communities in the South
81 East (Brighton) and North West (Salford) of England. Infants were born full-term, without neurological
82 and/or musculoskeletal conditions, impairment in attaining walking stages or gross motor development
83 deficiency. For data collection, infants came to the Human Movement Laboratory of the respective
84 Universities at the attainment of two stages of foot loading (Price et al., 2018):

- 85 • New walking: infants able to take 3 to 5 steps independently: mean age (SD): 13.2 months (1.0);
86 weight: 10.8 (1.1) kg; foot length: 11.4 (0.8) cm; foot width: 5.4 (0.4).
- 87 • Confident walking: infants able to take 10-15 steps independently and confidently, interacting
88 with others, carrying toys while walking, navigating around objects: mean age (SD): 15.1
89 months (1.3); weight: 11.3 (1.2) kg; foot length: 12.0 (0.8) cm; foot width: 5.4 (0.5).

90 Once infants reached each stage, parents were asked to book the visit within 21 days. At each stage,
91 written informed consent was given by parents.

92 *2.2 Testing procedure*

93 Plantar pressure data were collected using the EMED xl platform (4 sensors per cm², 100Hz; Novel,
94 Munich, Germany), embedded in a nursery-style environment (Price et al., 2018). After familiarizing
95 with the space, infants walked freely, in self-selected directions and speed, across the space, while HD
96 video was collected (Vicon Bonita 720c; Oxford, U.K/Logitech HD Pro Webcam).

97

98

99

100 2.3 Data pre-processing pSPM framework

101 Steps were extracted from the pressure trials in the EMED software and processed if the feet were
102 within the platform borders and did not miss extensive anatomical parts. Visual inspection of the stance
103 phases was also performed to ensure processing of steps from full gait cycles. This was necessary due
104 to the diverse nature of foot contact of new and confident walking steps. Left feet (LF) and right feet
105 (RF) were processed and analyzed separately, assuming population-level asymmetry. Three steps for
106 each foot, for each participant at each stage were used for this work (n=144). Maximum pressure
107 pictures (MPPs) of the steps were exported as ASCII text files (Novel Emascii software), and imported
108 into MATLAB 2019a (The Mathworks Inc, Natick, USA) as 2-dimensional (2D) numeric matrices for
109 data processing and analysis. Each MPP was then positioned in a grid of 36x25 pixels, to standardize
110 matrix dimensions of each MPP. Non-zero entries of the MPP matrices corresponded to pixels
111 containing pressure values.

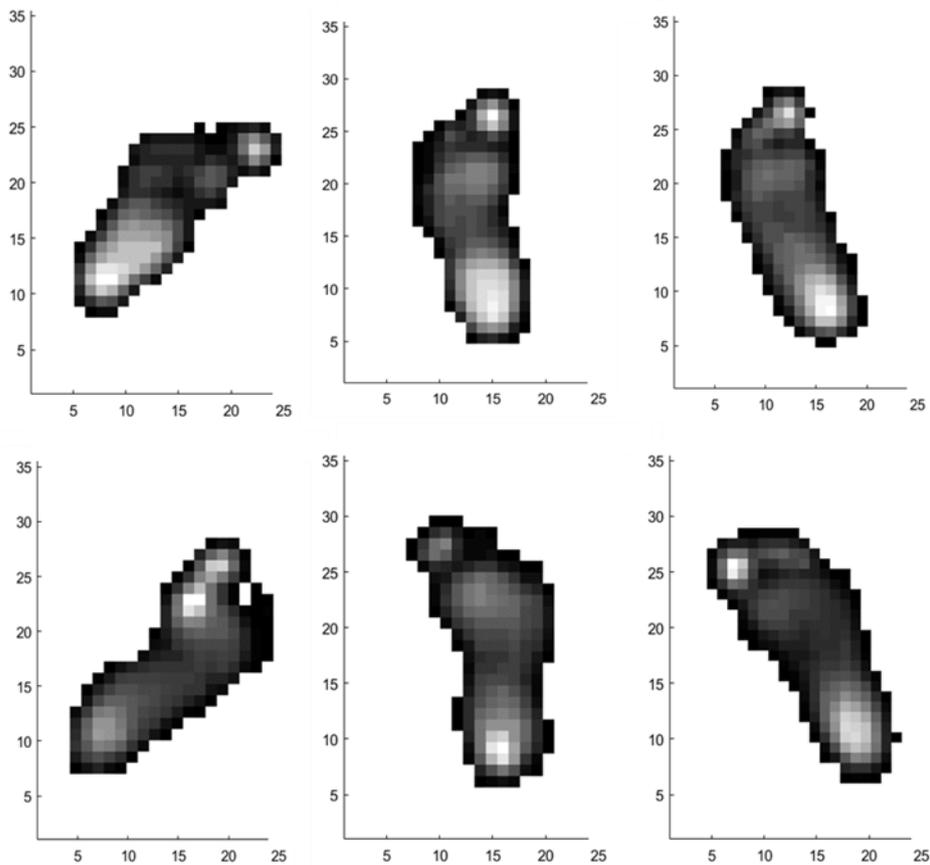
112 2.3.1 Transformation to point clouds

113 The coordinates of the pixels in the matrices' reference system were used to represent the pixels in the
114 3-dimensional (3D) Euclidian space. We used such representation to convert MPPs into point clouds
115 using a built-in MATLAB function that transformed each pixel into a point, whilst pressure values
116 within each pixel were stored in separate vectors.

117 2.3.2 Within-subjects registration

118 Point clouds were registered within subject (WS) to a chosen template, defined as the point cloud with
119 the highest number of points. Point clouds that were subject to registration will be referred to as sources.
120 To perform WS registration, a rigid iterative closest point (ICP) algorithm for point cloud registration
121 was used (Besl and McKay, 1992), in the form of a built in MATLAB function. However, the visual
122 inspection of the data highlighted highly variable shape and spatial orientation of the steps (Fig. 1). The
123 ICP algorithm is highly susceptible to local minima and its performance relies on the quality of the
124 initial pose of the point clouds with respect to the template (Yang et al., 2015). For this reason, previous
125 works has tried to improve its implementation by performing initial coarse alignment of the data

126 (Makadia et al., 2006; Rusu et al., 2009). Therefore, an additional data processing passage was required
127 prior to WS registration, to yield optimal points overlap. This was obtain by vertically aligning the
128 original MPPs using principal component analysis (PCA), similarly to Kim et al. (2013).



129

130 **Fig. 1.** Example of the spatial orientation of left and right MPPs positioned in a common reference
131 system of 36x25 pixels.

132

133 2.3.3 Computing axes of MPPs using principal component analysis (PCA)

134 Binary MPPs were created and matrices of each MPP were put in two vectors (a and b) as coordinates.
135 The means of a and b were calculated and subtracted from each index of the respective coordinates,
136 creating new vectors: A and B . This enabled to find the centroid of the MPP. Vectors were positioned
137 in a matrix, defining its columns. Covariance matrix was then calculated as:

138

$$C = \begin{pmatrix} cov(A, A) & cov(A, B) \\ cov(B, A) & cov(B, B) \end{pmatrix}$$

139 (1)

140 Eigenvectors and eigenvalues of the covariance matrix were found and plotted as the principal axes of
141 the MPPs (Fig.2). To perform a counterclockwise rotation of the MPPs, θ was calculated as the angle
142 forming between the longest eigenvector (x_1) and the vector parallel (black dashed line) to the y-axis
143 passing through the centroid (y_1) (Fig.2), according to:

144

$$\theta = atan(x_1, y_1)$$

145 (2)

146 Where *atan* is a built-in MATLAB function returning the inverse tangent (\tan^{-1}) of the ratio of x_1 and
147 y_1 in radians. Once θ was calculated (2), it was applied in the rotational transformation matrix (3),
148 having the general form:

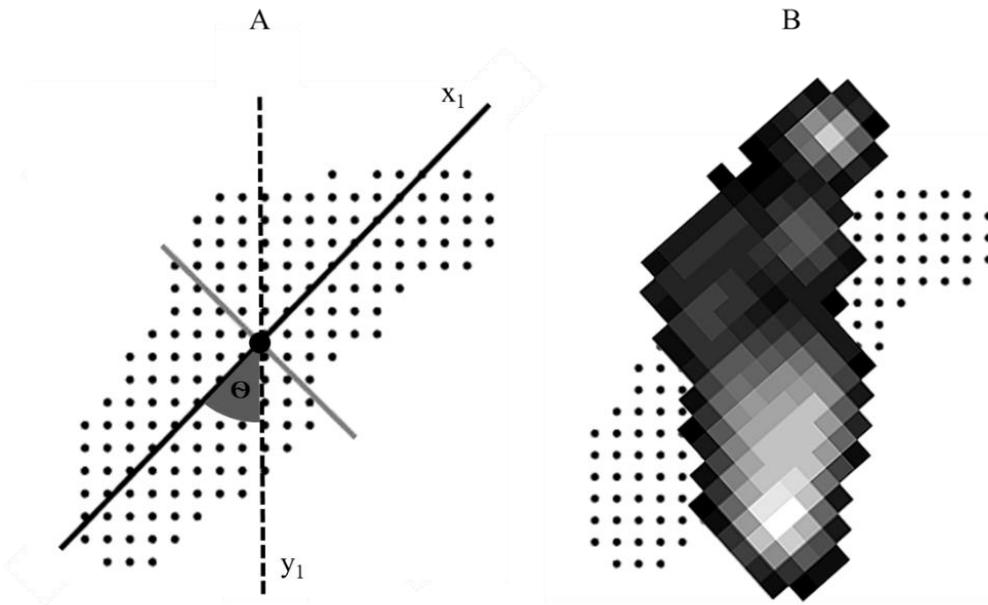
149

$$\begin{pmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{pmatrix}$$

150 (3)

151 to enable counterclockwise rotation of the MPPs to vertical. Coordinates were then multiplied by the
152 resulting transformation matrix, obtaining vertically aligned MPPs (Fig.2).

153
154
155
156
157
158



159

160 **Fig. 2.** (A) non-aligned MPP (black dots), principal axes are identified as black (x_1) and grey lines intersecting
 161 at the image centroid, where the vector parallel to the y-axis passes through (y_1); x_1 and y_1 were used to
 162 calculate Θ . The grey, shorter axis was reported for display purposes, enabling to visualize the centroid of the
 163 MPP, thus the intersecting point of y_1 . (B) Non-aligned binary MPP (black dots) and vertically aligned MPP
 164 (greyscale, pixel-image).

165

166 Once PCA was performed, the rotated MPPs were re-transformed to point clouds, and WS registration
 167 was achieved through the rigid ICP algorithm. Quality of WS registration pre and post PCA is also
 168 reported (Fig.S1)

169 After WS registration, for each vertex of the template a built-in MATLAB function was used (based on
 170 Euclidean distances) that returns the nearest neighbors of a query point in the input point cloud, to find
 171 corresponding points between the sources and the WS template.

172 *2.3.4 Averaging*

173 Once aligned and registered, corresponding coordinates of point clouds were averaged, resulting in one
 174 mean point cloud per participant per foot (Phethean et al., 2014). This was performed to reduce the

175 impact of differences in shape and dimensions of the point clouds (Fig. 1), and to enhance further steps
176 of data processing.

177 *2.3.5 Between-subjects template computation and registration*

178 To perform between subjects (BS) registration, an unbiased BS template was chosen as the foot with
179 length and width closest to the mean length and width of all the feet analyzed (Pataky et al., 2011). The
180 non-rigid coherent point drift (CPD) algorithm for point cloud registration was performed through a
181 built-in MATLAB function, to allow the shape of the point clouds to change using a displacement field
182 as transformation. Next, the nearest neighbors of each vertex in the source point clouds were found in
183 the unbiased BS template to establish points' correspondences.

184 *2.4 Statistical analysis*

185 To determine registration quality, the root-mean-square error (RMSE) was calculated between the
186 source and the template (Pataky, 2012) for each step. RMSE values were transformed to mm and mean
187 and standard deviation (SD) were reported. Graphic representations of the registration quality were also
188 reported for both WS and BS registrations.

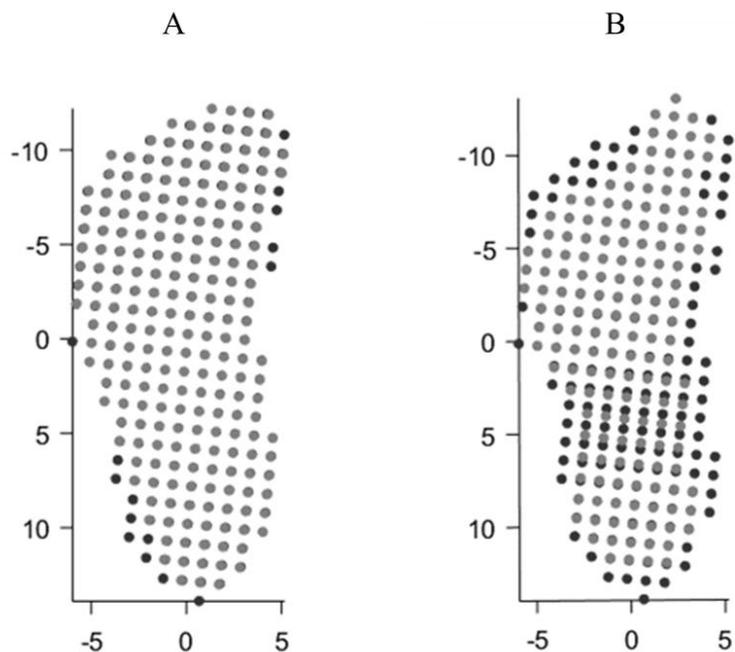
189 Analysis with SPM1D was conducted between sets of point clouds of new and confident walking steps.
190 This was possible as pressure data was spatially aligned and nonparametric inference used (Pataky and
191 Goulermas, 2008). Analysis was conducted using a two-tailed, nonparametric paired sample SPM1D t-
192 test (<http://www.spm1d.org/>), with significance set as $\alpha=0.05$. A t-value was calculated at each point of
193 the point clouds, defining an SPM t curve. As nonparametric inference was used, multiple comparison
194 corrections was performed using nonparametric permutation test, where the critical threshold was based
195 on the maximum test statistic value across the entire domain (Pataky, 2012). If the SPM t-curve crossed
196 this critical threshold (t critical) at any point, significant points were located (Pataky, 2012), reflecting
197 that pressure in those points is significantly different between new and confident walking steps.
198 However, SPM1D only supports critical test statistic calculation, thus cluster-specific p values were not
199 available. Nonparametric linear regression was also performed between body weight (confounding
200 variable) and plantar pressure at pixel level using SPM1D (Fig.S2).

201 **3. Results**

202 *3.1 Within and between subject registration quality*

203 With respect to registration accuracy, the mean (SD) RMSEs in the LF were 0.36 mm (0.09) and 0.39
204 mm (0.08) for WS and BS registration, respectively. In the RF, the mean (SD) RMSEs were 0.38 mm
205 (0.06) and 0.37 mm (0.05) for WS and BS registration, respectively. Visual representation of the
206 registration performances was also presented in Fig. 3.

207 Fig. 3 (A) demonstrated minimal non-overlapping points found on the lateral border of the heel and the
208 medial border of the hallux. Considering the BS registration, non-overlapping points were present
209 around the apex of the toes, around the foot periphery and between the heel and the midfoot (Fig. 3, B).



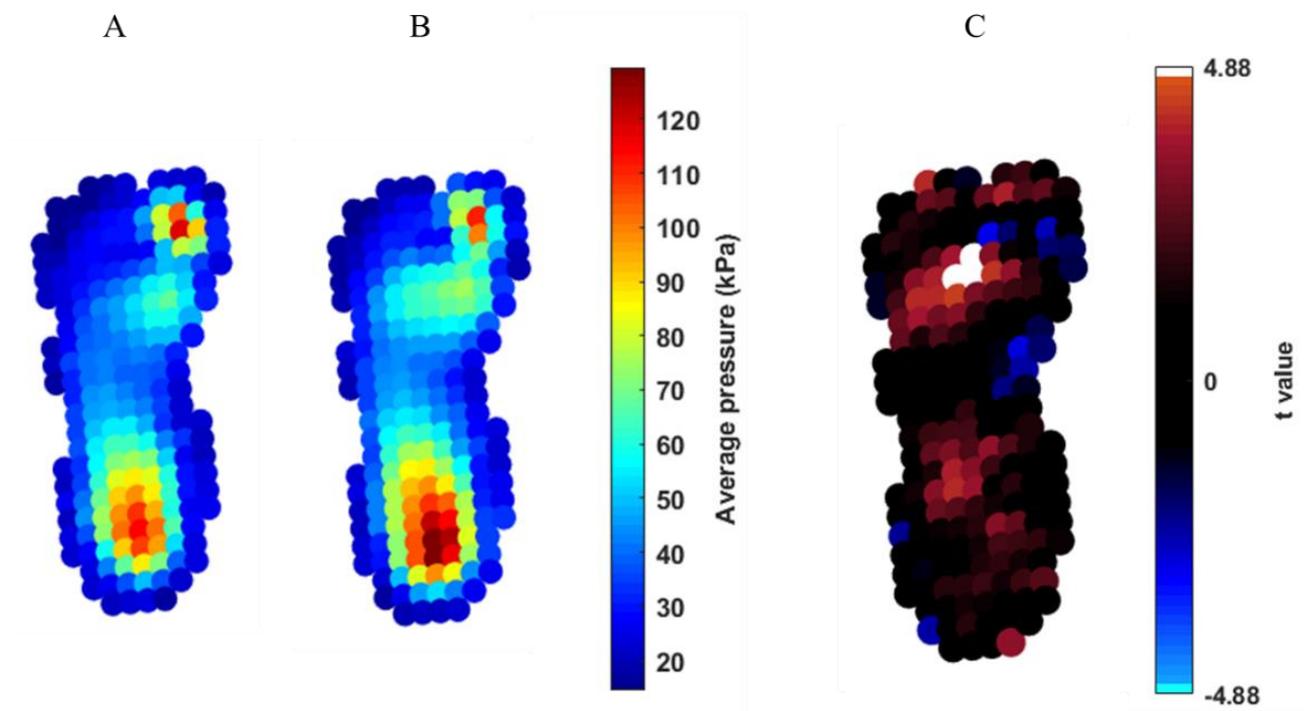
210

211 **Fig. 3.** Visual representation of the source (grey points) and template (black points) overlap during WS
212 registration (A) and BS registration (B).

213 *3.2 Plantar pressure inference*

214 In the transition from new to confident walking, pSPM detected an area of significantly increasing
215 pressure in the central forefoot of the LF (Fig. 4). Significant differences in pressures were not identified

216 in the RF; however, the qualitative trends suggested the presence of increased pressure in the central
217 heel, medial to lateral forefoot and decreased in the hallux in both LF and RF (Fig. 4 and 5).



218

219 **Fig. 4.** Nonparametric pSPM paired t test on left feet for comparison between new and confident walking steps.

220 From left to right: average pressure distribution of new walking (A), average pressure distribution of confident

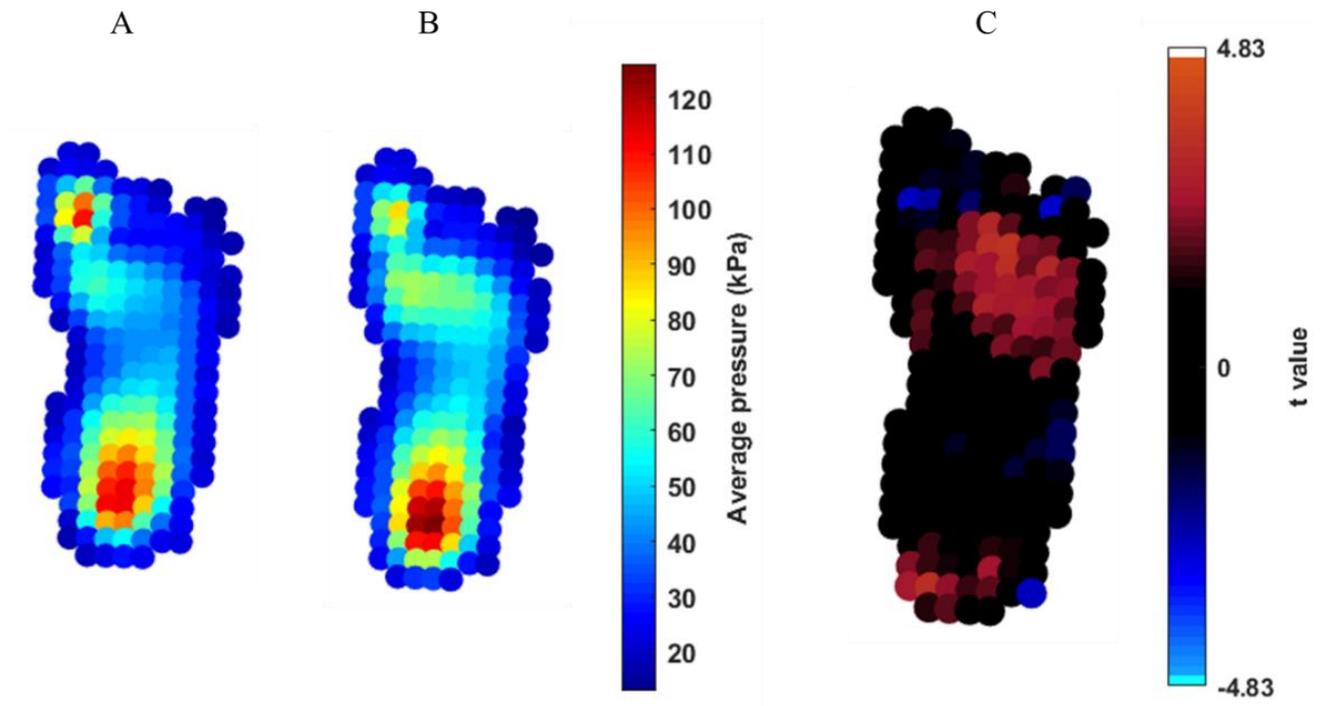
221 walking (B), and raw t value of statistical analysis (C), where the extremes of the colourbar reflects t-values

222 needed to reach statistical significance, with alpha set at 0.05. The colourbar for A and B presented different min

223 and max kPa values that were adjusted by the overall max and min values to allow for comparison. Cool and

224 warm colours identify where confident walking steps had lower and higher peak pressure than new walking

225 steps, respectively (C).



226

227 **Fig. 5.** Nonparametric pSPM paired t test on the right feet for comparison between new and confident walking
 228 steps. From left to right: average pressure distribution of new walking (A), average pressure distribution of
 229 confident walking (B), and raw t value of statistical analysis (C), where the extremes of the colourbar reflects t-
 230 values needed to reach statistical significance, with alpha set at 0.05. The colourbar for A and B presented
 231 different min and max kPa values that were adjusted by the overall max and min values to allow for comparison.
 232 Cool and warm colours identify where confident walking steps had lower and higher peak pressure than new
 233 walking steps, respectively (C).

234

235 Regression analysis of the pixel-level data revealed the absence of statistically significant correlation
 236 between the increasing body weight and plantar pressure in both feet (Fig.S2).

237 **4. Discussion**

238 This work reported details of the implementation of the pSPM approach to infants' pressure data, also
 239 investigating changes in plantar pressure as walking experience increases.

240 *4.1 Methodological considerations*

241 The use of pSPM in infancy is important to provide clear and unbiased insights into foot development.
242 Traditional software for pressure data processing rely on the assumption that analysis is carried out on
243 data presenting geometrical and/or pressure gradient patterns of adults' feet (Ellis et al., 2011). Although
244 regional analysis is advantageous under certain circumstances (e.g., offloading specific foot regions),
245 its use is debatable in the context of development, due to the ongoing anatomical and structural changes
246 of the infants' feet. These changes prevent the foot from acting as a typically functional unit and
247 therefore undermine the relevance of common ROI boundaries implemented in typically developed
248 feet. Therefore, by selecting a methodology that divides the foot into ROIs according to adults' feet
249 features, researchers imply that the infant foot is a well-developed functional unit, ignoring its
250 anatomical and functional characteristics.

251 Another important methodological aspect of this study is the testing protocol and its effect on pressure
252 data in infancy. Infants were able to walk freely and uninstructed as opposed to being restricted to a
253 straight line, causing inconsistent directions of foot progression and contact patterns. Therefore, we
254 anticipated the presence of a high intra, inter individual variability, and assumed the presence of
255 population-level asymmetry in gait and related pressure patterns, which is why both feet were analyzed
256 in this study.

257 The presence of intra and inter subject variability associated with the unrestrained testing protocol could
258 also contribute to reduced registration quality. However, the rigid ICP algorithm, enhanced by PCA
259 (Fig.S1), yielded low RMSEs in both LF and RF. This can be due to the closer intra-individual
260 correspondences in feet dimensions. The quality of the WS registration was also shown in Fig. 3 (A),
261 where the optimal overlap of points suggests a satisfying performance of the ICP algorithm to the
262 present data set. Performance of CPD algorithm was slightly less accurate, considering the RMSE
263 values and the visual representation of the registration (Fig. 3, B). This could be explained by the high
264 inter-individual differences in foot dimensions and profile on the pressure platform. Nevertheless,
265 RMSEs were under 0.4 mm for both WS and BS registration, which, considering the mean foot length
266 and width, indicates good fit of the sources to the template. Moreover, the low SD reported in both
267 registrations suggested that the ICP and CPD algorithms performed consistently on the point clouds,

268 without high between registration variations. These results suggest that the proposed methodology
269 provided an effective, high quality, and solid framework to implement pSPM to free walking pressure
270 data in infancy.

271 *4.2 Functional considerations*

272 This study suggests that after 2.2 months of independent walking experience, pressure significantly
273 increases in the central left forefoot during gait. This has also been previously identified between 4 and
274 7 years, and authors argued about anatomical foot changes taking place (Phethean et al., 2014). In this
275 work, anatomical foot development is unlikely to occur at a rate that would cause significant differences
276 in pressure to happen, due to the short period between stages of foot loading (2.2 months). Furthermore,
277 our analysis revealed that the increasing body weight did not influence plantar pressure data (Fig.S2).
278 This could be due to the minimal increase in weight between new and confident walking stages (+0.5
279 kg; ~ 5% of initial body weight), which occurred alongside a corresponding ~5% increase in foot length.
280 A previous comparison of infants (mean age: 23.5 (5.7) months) identified statistically increasing
281 pressure in the central forefoot between trials of walking and running (Hennig and Rosenbaum, 1991).
282 This could suggest that significant pressure changes in the central left forefoot could be attributed to
283 the increasing walking speed, as infants become more experienced in walking. However, this was not
284 quantified and reported as part of this research and would require further exploration.

285 Significant increase in pressure in the central forefoot between these stages of foot loading has not been
286 reported in the literature before, and it could be due to different methodological approaches. Bertsch et
287 al. (2004) found that during the first year of independent walking, the whole forefoot demonstrated
288 significantly increasing pressure. However, the exact anatomical location of such change was unknown
289 due to the application of a whole forefoot region. This implies that differences in pressure distribution
290 could have been anywhere within the boundaries of the forefoot, limiting considerations regarding
291 plantar pressure changes in the transition to confident walking. Increasing the resolution of the forefoot
292 mask (e.g., lateral, central, and medial forefoot) might lead to the detection of significant differences in
293 the central forefoot. However, statistical outcomes would be highly dependent on the ROI selected

294 (definition and number of ROIs), which causes arbitrary and inconsistent exploration of infants' pressure
295 data, as reported elsewhere (Montagnani et al., 2021, in press).

296 Other changes in pressure were identified also qualitatively in both feet, and specifically in the central
297 heel, medial to lateral forefoot and hallux (Fig. 4 and 5, A, B). Previous works demonstrated that
298 pressure in the hallux is the highest during the first few months of independent walking but decreases
299 after three to six months of walking (Bertsch et al., 2004; Bosch et al., 2010; Hennig and Rosenbaum,
300 1991). The literature also report significant increasing heel pressure during the first year of independent
301 walking (Bertsch et al., 2004), as initial heel contact occurs as opposed to forefoot contact (Hallemans
302 et al., 2003; Hallemans et al., 2006). Findings from our work agree with previous studies and suggest
303 that changes in pressure occur rapidly, as infants become confident in walking. As opposed to previous
304 works reporting data in infancy for either LF, RF, or mixed (Alvarez et al., 2008; Bertsch et al., 2004;
305 Bosch et al., 2010), our work showed different statistical results in LF and RF. This could be related
306 to the presence of high inter-limb asymmetry during the first months of walking (Ledebt et al., 2004),
307 which could lead to different pressure changes in the RF and LF between early and confident walking.
308 However, because a large area of non-significant pressure increase is visible in the RF (Fig. 5),
309 differences in statistical outcomes might in-fact be due to the small sample size analyzed, in terms of
310 both the number of participants and steps included in the analysis. This could also explain why we were
311 not able to detect larger areas of significant changes in pressure in either foot during the transition to
312 confident walking. Combining pressure data from LF and RF by mirroring would have provided a larger
313 sample size, but this would have assumed population-level symmetry in gait and related pressure
314 patterns within the loading stages.

315 Thus, additional work should be undertaken to investigate whether differences in pressure are present
316 between LF and RF within foot loading stages, which would illuminate population-level symmetry in
317 plantar pressure patterns. Future research analyzing a larger sample with pSPM may have the capability
318 to detect the presence of plantar pressure changes that have not been reported before. Therefore, further
319 investigations with the present methodology are warranted, to increase resolution of data analysis and
320 ensure clearer understanding of foot function development, as infants become confident in walking.

321 **Acknowledgment**

322 Dr. Stewart Morrison held the grant provided by The Dr William M Scholl Unit of Podiatric
323 Development, which funded Dr. Carina Price, Matyas Varga and Eleonora Montagnani. At the time this
324 article was written, Eleonora Montagnani and Matyas Varga were PhD students at the Department of
325 Health Sciences at the University of Brighton, England.

326 **References**

327 Alvarez, C., De Vera, M., Chhina, H., Black, A., 2008. Normative data for the dynamic
328 pedobarographic profiles of children. *Gait Posture* 28, 309-315.

329 Bertsch, C., Unger, H., Winkelmann, W., Rosenbaum, D., 2004. Evaluation of early walking patterns
330 from plantar pressure distribution measurements. First year results of 42 children. *Gait & Posture* 19,
331 235-242.

332 Besl, P.J., McKay, N.D., Year Method for registration of 3-D shapes. In *Sensor fusion IV: control*
333 *paradigms and data structures*.

334 Bosch, K., Gerss, J., Rosenbaum, D., 2010. Development of healthy children's feet--nine-year results
335 of a longitudinal investigation of plantar loading patterns. *Gait Posture* 32, 564-571.

336 Ellis, S.J., Stoecklein, H., Yu, J.C., Syrkin, G., Hillstrom, H., Deland, J.T., 2011. The accuracy of an
337 automasking algorithm in plantar pressure measurements. *HSS Journal* 7, 57-63.

338 Hallemans, A., D'Août, K., De Clercq, D., Aerts, P., 2003. Pressure distribution patterns under the feet
339 of new walkers: the first two months of independent walking. *Foot & ankle international* 24, 444-453.

340 Hallemans, A., De Clercq, D., Van Dongen, S., Aerts, P., 2006. Changes in foot-function parameters
341 during the first 5 months after the onset of independent walking: a longitudinal follow-up study. *Gait*
342 *Posture* 23, 142-148.

343 Hennig, E.M., Rosenbaum, D., 1991. Pressure distribution patterns under the feet of children in
344 comparison with adults. *Foot & ankle* 11, 306-311.

345 Kim, C., Son, H., Kim, C., 2013. Fully automated registration of 3D data to a 3D CAD model for project
346 progress monitoring. *Automation in Construction* 35, 587-594.

347 Ledebt, A., van Wieringen, P.C., Savelsbergh, G.J., 2004. Functional significance of foot rotation
348 asymmetry in early walking. *Infant Behavior and Development* 27, 163-172.

349 Makadia, A., Patterson, A., Daniilidis, K., Year Fully automatic registration of 3D point clouds. In 2006
350 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'06).

351 Montagnani, E., Price, C., Nester, C., Morrison, SC., 2021. Dynamic Characteristics of Foot
352 Development: A Narrative Synthesis of Plantar Pressure Data During Infancy and Childhood. *Pediatric*
353 *Physical Therapy*, doi: 10.1097/PEP.0000000000000819

354 McClymont, J., Pataky, T.C., Crompton, R.H., Savage, R., Bates, K.T., 2016. The nature of functional
355 variability in plantar pressure during a range of controlled walking speeds. *Royal Society open science*
356 3, 160369.

357 Oliveira, F.P., Pataky, T.C., Tavares, J.M.R., 2010. Registration of pedobarographic image data in the
358 frequency domain. *Computer methods in biomechanics and biomedical engineering* 13, 731-740.

359 Pataky, T.C., 2012. Spatial resolution in plantar pressure measurement revisited. *Journal of*
360 *biomechanics* 45, 2116-2124.

361 Pataky, T.C., Bosch, K., Mu, T., Keijsers, N.L., Segers, V., Rosenbaum, D., Goulermas, J.Y., 2011. An
362 anatomically unbiased foot template for inter-subject plantar pressure evaluation. *Gait Posture* 33, 418-
363 422.

364 Pataky, T.C., Caravaggi, P., Savage, R., Parker, D., Goulermas, J.Y., Sellers, W.I., Crompton, R.H.,
365 2008. New insights into the plantar pressure correlates of walking speed using pedobarographic
366 statistical parametric mapping (pSPM). *Journal of biomechanics* 41, 1987-1994.

367 Pataky, T.C., Goulermas, J.Y., 2008. Pedobarographic statistical parametric mapping (pSPM): a pixel-
368 level approach to foot pressure image analysis. *Journal of biomechanics* 41, 2136-2143.

369 Phethean, J., Pataky, T.C., Nester, C.J., Findlow, A.H., 2014. A cross-sectional study of age-related
370 changes in plantar pressure distribution between 4 and 7 years: a comparison of regional and pixel-level
371 analyses. *Gait Posture* 39, 154-160.

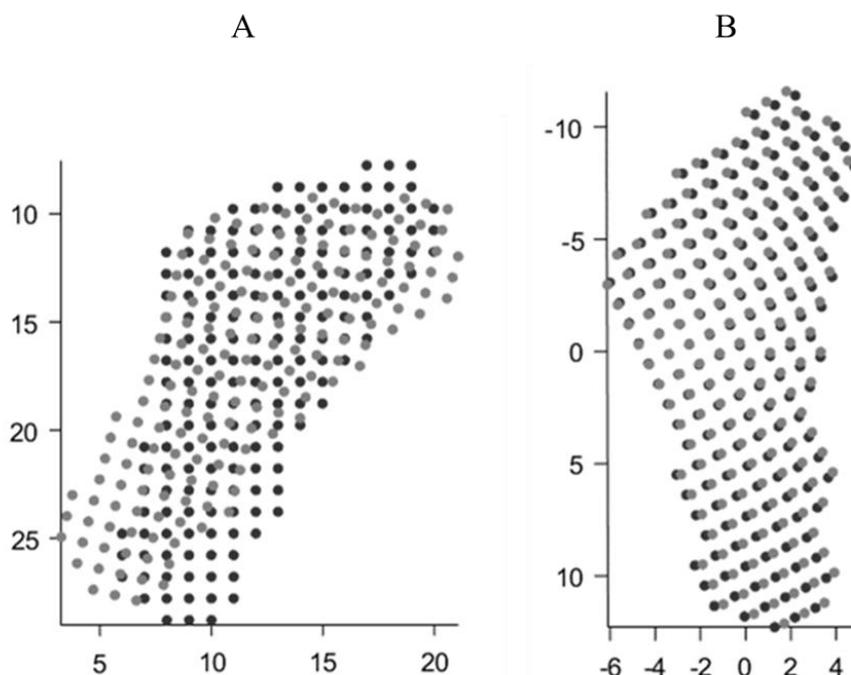
372 Price, C., McClymont, J., Hashmi, F., Morrison, S.C., Nester, C., 2018. Development of the infant foot
373 as a load bearing structure: study protocol for a longitudinal evaluation (the Small Steps study). *J Foot
374 Ankle Res* 11, 33.

375 Price, C., Morrison, S.C., Nester, C., 2017. Variability in foot contact patterns in independent walking
376 in infants. *Footwear Science* 9, S47-S49.

377 Rusu, R.B., Blodow, N., Beetz, M., Year Fast point feature histograms (FPFH) for 3D registration. In
378 2009 IEEE international conference on robotics and automation.

379 Yang, J., Li, H., Campbell, D., Jia, Y., 2015. Go-ICP: A globally optimal solution to 3D ICP point-set
380 registration. *IEEE transactions on pattern analysis and machine intelligence* 38, 2241-2254.

381 **Supplementary figures**

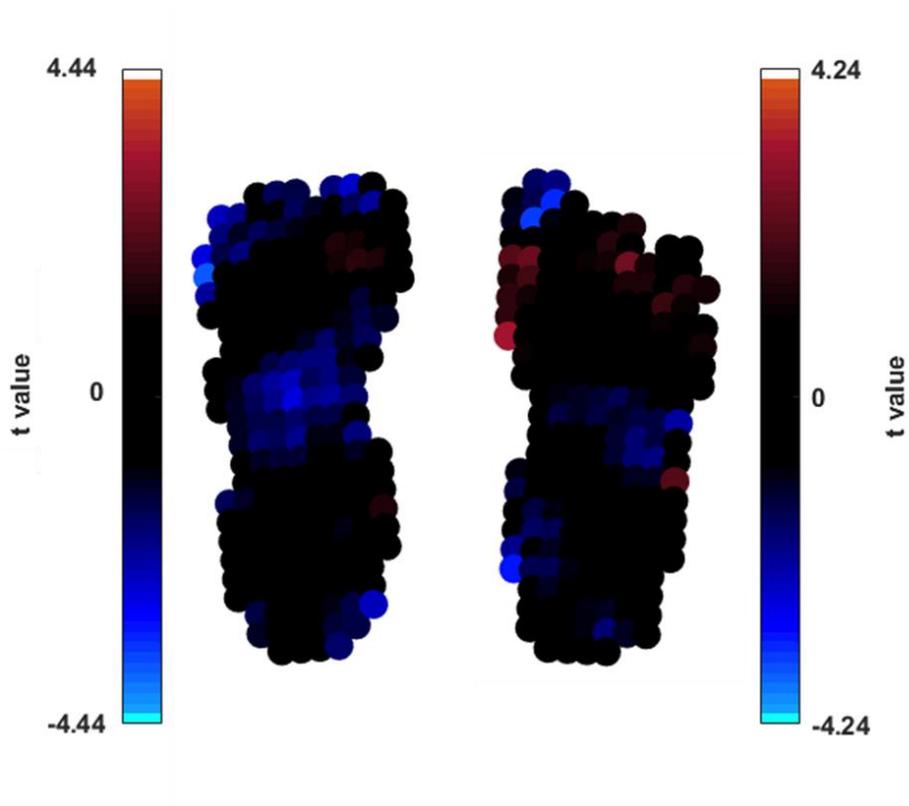


382

383 **Fig. S1.** Visual representation of WS registration performed without PCA (A) and with PCA (B).

384

385



386

387 **Fig. S2.** Nonparametric linear regression analysis at pixel level, computed in both LF and RF. T-values indicates
388 the strength of linear regression between increasing body weight and plantar pressure data.

389