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1 **High-precision scanning system for complete 3D cow body shape imaging and**  
2 **analysis of morphological traits**

3  
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9  
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11  
12 **Abstract**

13 Monitoring the growth and body condition of cows is essential for optimal  
14 management of modern dairy farms. However, monitoring is rarely performed on  
15 commercial farms. Modern technologies based on three-dimensional (3D) shape  
16 analysis could address this problem. The objective of the present study was to test  
17 and validate tools that can record and analyze 3D body shapes of animals. On 30  
18 Holstein dairy cows, wither height (WH), heart girth (HG), chest depth (CD), hip width  
19 (HW), backside width (BaW) and ischial width (IW) were manually measured. These  
20 manual measurements were compared to those measured with a scanner  
21 (Morpho3D) that provided 3D images of the entire cow body. Correlations between  
22 manual and Morpho3D measurements were high: 0.89 for CD, 0.82 for HW, 0.78 for  
23 HG, 0.76 for BaW, 0.63 for IW and 0.62 for WH. The mean coefficient of variation of  
24 reproducibility for Morpho3D was 2.8%. Future development can provide new  
25 opportunities for dairy herd management based on determining animal body volume  
26 and surface area.

27 **Keywords:** body measurement; cows; sensors; 3D images

28

## 29 **1. Introduction**

30 Body weight (BW), morphological traits and body condition score (BCS) are important  
31 parameters traditionally used in dairy cattle production. They are essential for  
32 accurately monitoring growth rate or changes in growth and thus for adapting animal  
33 nutrition to increase efficiency or maintain productivity. Currently, except for BW, most  
34 measurements are performed manually (e.g. measuring tape, ruler) or visually  
35 (Heinrichs and Hardgrove, 1987). These measurements are time consuming and  
36 could result in injury to livestock farmers. They are also a source of stress for animals  
37 and, in many cases, observer-dependent. As a result, such information during the  
38 growing period is rare on many commercial farms, and when available in France, is  
39 reduced to 4-6 BW measurements during the growing period. Developing accurate  
40 and automatic technologies that do not depend on humans could help address these  
41 issues. Developing automatic measurement methods to study phenotypic traits,  
42 however, is considered a bottleneck in biology, particularly for large live and moving  
43 animals such as dairy cows (Chéné et al., 2012).

44 Techniques based on optical detection devices are interesting alternatives to manual  
45 measurements or more costly methods (Pezzuolo et al., 2018). Technologies have  
46 been developed to detect lameness in cows (van Hertem et al., 2014; Zhao et al.,  
47 2018) and to measure body parameters such as BCS (Halachmi et al., 2008; Fischer  
48 et al., 2015; Sploliansky et al., 2016). Two-dimensional (2D) image approaches have  
49 been used for pigs with a certain degree of success (Marchant et al., 1993; Schofield  
50 et al., 1998). Their effectiveness is decreased, however, by the lack of a third  
51 dimension, distortion problems, the calibration procedure, and the need for multiple  
52 cameras and three-dimensional (3D) reconstruction models. The development and  
53 marketing of relatively inexpensive 3D cameras has decreased interest in 2D

54 technology in favor of 3D approaches. Recently, new imaging technologies have  
55 been successfully developed and used to analyze body condition in dairy cattle,  
56 using either a fixed (Fischer et al., 2015) or mobile (Kuzuhara et al., 2015) device.  
57 Others (Negretti et al., 2008; Buranakarl et al., 2012; Guo et al., 2017; Pezzuolo et  
58 al., 2018) have developed and used 3D imaging technologies for a wider variety of  
59 livestock. In most cases, animals were measured under laboratory conditions (heavy  
60 equipment and landmarks on animals to guide computer measurement), providing  
61 either images of the entire body of restrained animals or of part of the body of  
62 unrestrained animals. In most cases, equipment can adapt to farm conditions; recent  
63 literature describes devices used to estimate weight of pigs in barns (Pezzuolo et al.,  
64 2018; Wang et al., 2018) and broilers in houses (Mortensen et al., 2016). Pezzuolo et  
65 al. (2018) used inexpensive and portable equipment based on the Microsoft Kinect®  
66 v1 sensor but concluded that the method needed additional technical development to  
67 acquire and extract data automatically.

68 The present study presents a new, more accurate scanner – Morpho3D – that was  
69 developed in an eponymous study to easily capture the full shape of cow bodies and  
70 to precisely accurately measure their morphological traits in the 3D imaging space.  
71 Its measurements were compared to direct measurements of the live cows. To  
72 validate the method, repeatability and reproducibility, which are important criteria  
73 when applying methods, were estimated.

74

## 75 **2. Materials and methods**

76

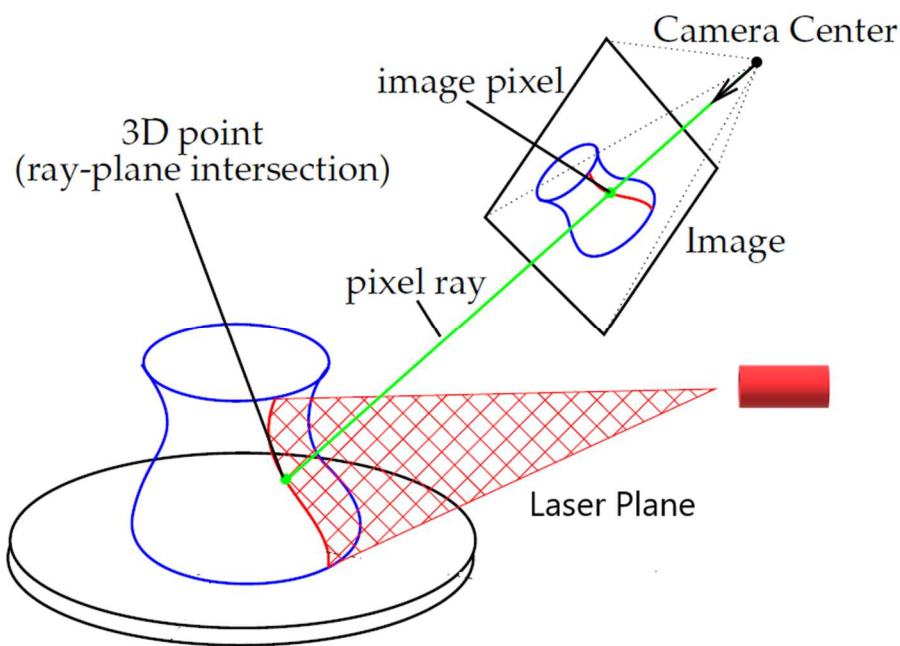
77 **2.1. Animals:** Data were obtained from the INRA-UMR PEGASE experimental dairy  
78 station at Mejusseume, Le Rheu, in western France (48°11'N; 1°71'W; elevation 35

79 m). Data were collected from May-June 2017. The study involved 30 dairy cows, with  
80 a mean ( $\pm 1$  standard deviation (SD)) age of 3.0 ( $\pm 1.2$ ) years and milk production of  
81 25.5 ( $\pm 3.6$ ) kg milk per day. After each milking (twice a day), cows were individually  
82 and automatically weighed on a static weighing station (DeLaval France, Elancourt,  
83 France) at the milking parlor's exit. Their mean ( $\pm 1$  SD) weight was 674 ( $\pm 66$ ) kg.  
84 Mean BCS ( $\pm 1$  SD), based on the French scoring scale of 0-5 (Bazin et al., 1984),  
85 was 2.1 ( $\pm 1.2$ ). Data from the 30 cows were used to estimate the accuracy of the  
86 measurements extracted from images from the new scanner and calculate  
87 correlations between these estimates and manual measurements of the cows.

88

89 **2.2. Morphological acquisition system:** 3D images of the cows were acquired  
90 automatically using the sliding acquisition system, Morpho3D, located near the  
91 weighing station. The system has 5 cameras, each paired with a laser projector. **The**  
92 **laser has a wavelength of 650 nm, which is shorter than those of infrared lasers (750-**  
93 **2000 nm), to make it visible to humans and animals. This decreases risks to them,**  
94 **since the visible laser, unlike an infrared laser, triggers a blink reflex in humans. The**  
95 **laser is turned on only when the system's portal is moving. With a power of**  
96 **approximately 80 mW, it is a class 3B laser (CDRH, 2018). Looking directly at the**  
97 **beam is dangerous. The risk was low in the present study, however, because the**  
98 **beams are emitted on the sides of the animal, and looking at diffuse reflections of the**  
99 **laser is not considered dangerous. In addition, full power is distributed over a stripe**  
100 **and not concentrated on a single point. Also, the laser moves at a mean speed of 0.5**  
101 **m.s<sup>-1</sup>, so it spends little time on the eye.**  
102 The VGA image resolution of each camera was 640 × 480 pixels. **Reconstructing an**  
103 **animal in 3D is a generalization of laser triangulation. Traditionally, triangulation is**

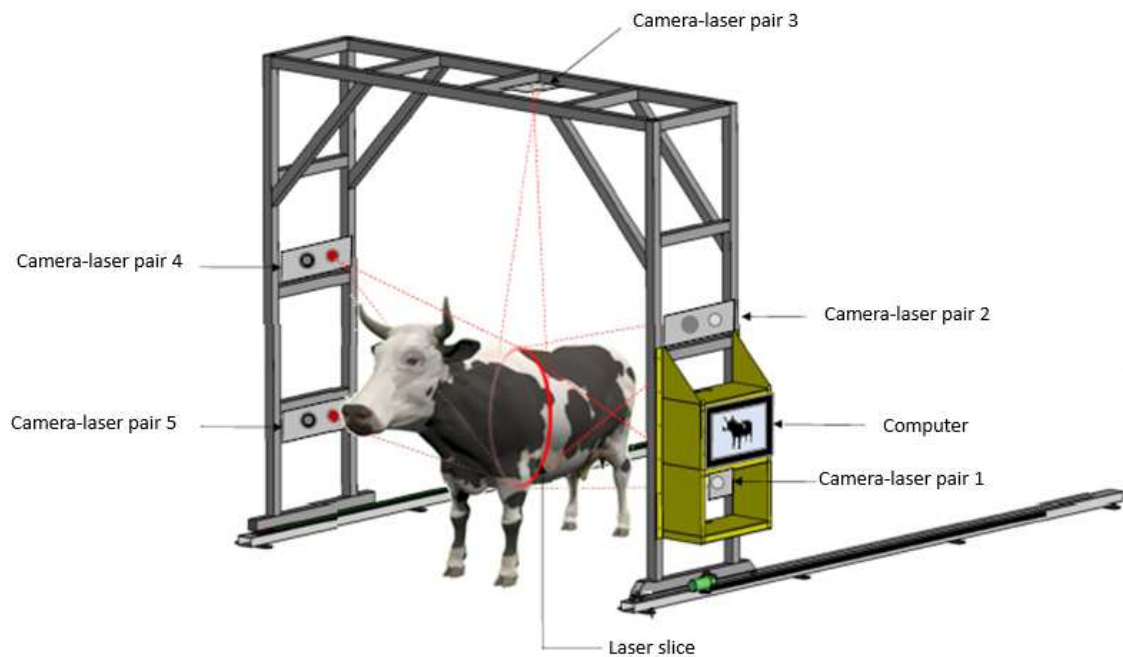
104 based on the triangle formed by a camera, a laser and the single point the laser  
 105 projects on an object. In contrast, each Morpho3D laser generates a vertical plane,  
 106 whose intersection with the object appears as a stripe in each image yielding more  
 107 points per image. Knowing the equation of the plane in the camera frame allows the  
 108 3D position of the points in each stripe in the camera frame to be determined by  
 109 intersecting the plane with the radius passing through the origin of the camera and  
 110 the points observed in the image plane (Fig. 1).



111  
 112 **Fig. 1.** Diagram of the triangulation process (adapted from Taubin, 2018)

113  
 114 Sliding the system's portal horizontally scans the laser plane over the entire object,  
 115 yielding a cloud of points consisting of several "slices" of 3D points (1 slice = 1  
 116 image). These point slices are aggregated based on the location of the system's  
 117 portal.

118 Since the cameras are sensitive to light, excessive direct sunshine was avoided in  
 119 the stable. The cameras were attached to the sliding portal ( $l = 5.00$  m;  $l = 2.58$  m;  $h$   
 120  $= 3.00$  m; Fig. 2).



121

122 **Fig. 2.** Design of the Morpho3D scanner

123

124 Two cameras were fixed at 0.40 and 1.77 m above ground level, respectively, on  
 125 each side of the portal. A fifth camera was fixed to the middle of the top of the portal  
 126 (3.00 m above ground level). The portal moved at a mean speed of  $0.5 \text{ m}\cdot\text{s}^{-1}$  from  
 127 back to front (phase 1) and returned to its initial position at a mean speed of  $0.3 \text{ m}\cdot\text{s}^{-1}$   
 128 (phase 2). Each camera took 80 images per second and did so only during phase 1,  
 129 yielding a total of 2,000 images. **Images are used only to extract laser stripes; 90% of**  
 130 **each image is not used, like in many triangulation systems that use laser planes.**

131 Four stainless steel cables were used within the Morpho3D Scanner, on both side of  
 132 cow, to secure the scanner and restrict cow movement. Cows could also be  
 133 restrained by a self-locking head gate if necessary.

134

135 **2.3. Calibration.** Calibration consisted of finding the position of the laser plane in  
136 each camera space and the relative positions of the cameras. The cameras were  
137 calibrated in three ways:

- 138 1. Calibration of each camera to determine its intrinsic parameters and to correct  
139 distortions;
- 140 2. Calibration of the laser plane in each camera frame for triangulation and  
141 reconstruction of 3D points;
- 142 3. Calibration of all five cameras to place their point clouds in the same frame

143 The cameras were calibrated using a black-and-white checkerboard placed in  
144 different locations in the Morpho3D. Each camera-laser pair was calibrated  
145 individually and then two-by-two to calibrate all five cameras collectively.

146  
147 Calibration determined the relative position of a camera to its corresponding laser  
148 plane, which is required to triangulate 3D data. It also determined the positions of the  
149 cameras relative to each other in order to merge their clouds. For Morpho3D, a black-  
150 and-white checkerboard of known dimensions was used. The technique corresponds  
151 to a "model" type of calibration (the model is the target). The camera is calibrated by  
152 capturing at least ten images of the target with laser stripes. A program then analyzes  
153 these images and determines the required parameters and also provides a  
154 confidence value. Calibration was performed twice, first in the laboratory and then  
155 after installation on the farm.

156  
157 **2.3. Image capture and reconstruction.** When a cow entered the Morpho3D, image  
158 capture did not begin until it stopped moving. If the cow moved during recording, the  
159 record was deleted and another was started. Two or three attempts were usually

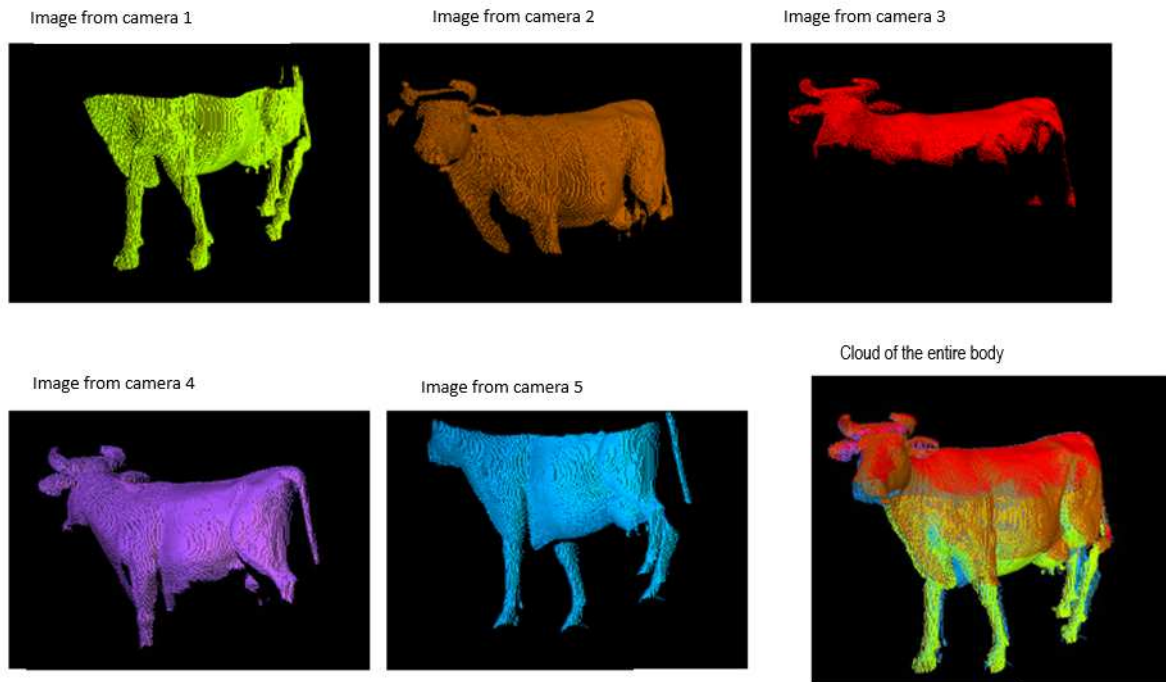


160 required the first time, but since images were recorded once a month for the entire  
161 lactation period, cows became accustomed to the process and usually required only  
162 one attempt afterwards, though some cows required more.

163

164 Images of the laser stripes projected onto the cow were captured by their  
165 corresponding camera and sent to a computer to reconstruct the cows' 3D  
166 information. First, images from each camera were processed to build separate point  
167 clouds using calibration information and the speed of the portal. A 3D reconstruction  
168 of the entire cow was generated by recording and merging the multiple 3D point  
169 clouds from the five camera-laser pairs. This resulted in a single point cloud  
170 representation of the entire cow (Fig. 3). Two camera filters were used during image  
171 capture. The first was a physical filter centered on the laser wavelength to reduce  
172 ambient light and increase the contrast of laser stripes in each image. The second  
173 was a software filter. For this filter, since each camera-laser pair was fixed at a  
174 specific height on the structure, the distance between the ground and the camera  
175 was known. The depth of field of each camera varied from 0.3-3.5 m. A maximum  
176 depth was determined for each individual camera to prevent recording undesirable  
177 points that were too far from the camera and did not belong to the cows, such as  
178 walls. Other undesired objects (e.g. a cable) were easily deleted (Fig. 4) during a  
179 cleaning process, using Metrux2α® software (3DOuest company, Lannion, France).  
180 This step ensures that the point cloud is a sampling of a smooth surface on which  
181 surface normal vectors can be estimated. An example of using Morpho3D with a live  
182 cow is available online (<https://vimeo.com/219370900>).

183



184

185 **Fig. 3.** The process of reconstructing 3D clouds of cows from the five camera-laser pairs, as  
 186 a function of the speed of the scanner's portal (to generate a cloud of the entire body)

187

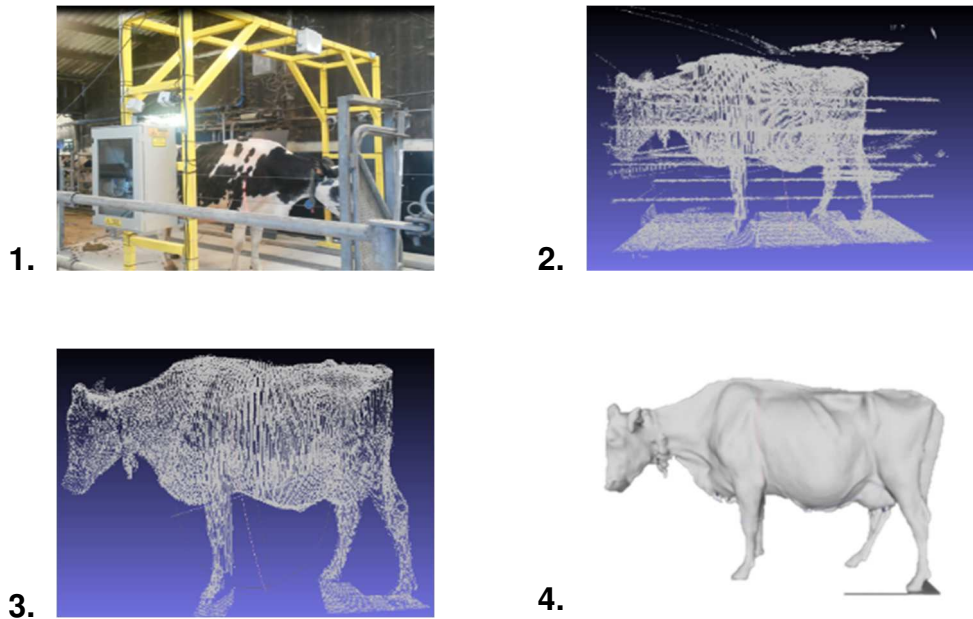
188 Finally, surface normals were estimated from the point cloud, and a screened  
 189 Poisson surface reconstruction algorithm was applied to build a triangulated mesh  
 190 (Kazhdan and Hoppe, 2013) using Meshlab open-source software (Cignoni et al.,  
 191 2008). Image-processing steps are shown in Fig. 4.

192

193

194

195



196 **Fig. 4.** Steps from data acquisition to final 3D image: (1) data acquisition; (2) raw point cloud;  
 197 (3) point cloud after cleaning and (4) final 3D image after Poisson reconstruction.

198

199 It took 5 s to record the entire body and 2 minutes to acquire the point cloud  
 200 automatically, which was then saved. The final mesh used for analysis required 10-12  
 201 minutes to generate.

202

203 **2.5. Nomenclature of body traits and measurements:** The two measurement  
 204 methods were compared for the 30 cows. Six of the 30 cows underwent a series of  
 205 repeated manual measurements of the same body traits (six times each) to estimate  
 206 reproducibility (see next section). Since reference measurements for animal  
 207 development are always measured on live animals, qualified and experienced  
 208 technicians trained us how to find where to measure cow body traits, using a group of  
 209 non-experimental live cows. The next step consisted of comparing body traits  
 210 measured by the trained technicians (hereafter “reference measurements”) to those  
 211 that we measured, using another group of non-experimental cows. Differences

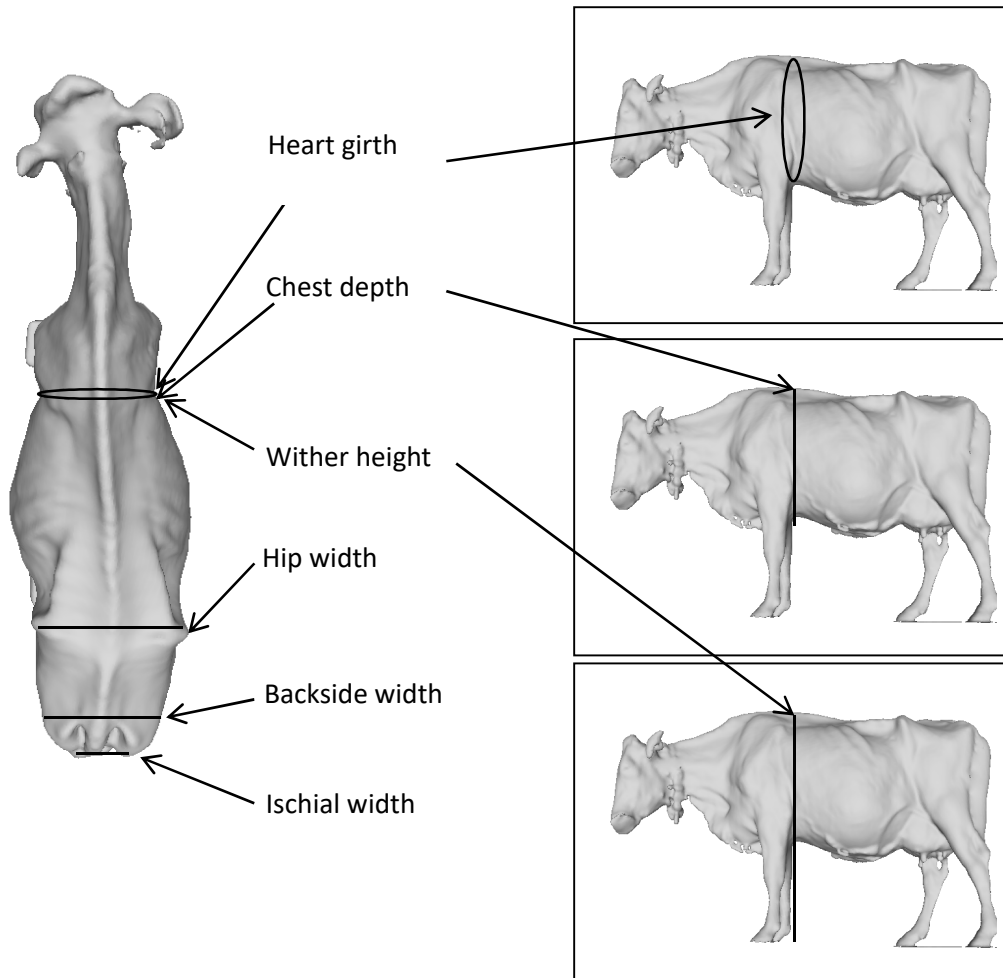
212 between the two sets of measurements were similar among body traits, even for  
213 several traits that are usually difficult to detect (e.g. ischial width).

214 Measurements were then taken of experimental cows. A plastic model cow was used  
215 to estimate repeatability (see next section). For manual measurements, we used  
216 permanent ink to identify measurement locations on the plastic model. For  
217 measurements extracted from 3D images, we first fixed small balls on the plastic  
218 model to precisely locate where to perform measurements. We then used a 3D  
219 image without the balls to extract reference measurements of the model.

220 Six measurements were taken of live animals and extracted from images: heart girth  
221 (HG), chest depth (CD), wither height (WH), hip width (HW), backside width (BaW)  
222 and ischial width (IW) (Fig. 6). For live animals, a tape measure was used to measure  
223 HG, while a height gauge was used for the other measurements. For images, the  
224 relevant measuring location was determined visually, and measurements were  
225 extracted using Metrux2α® software.

226

227



228  
229  
230

231 **Fig. 6.** Body traits measured on live animals and extracted from 3D images

232

233 **2.6. Validation:** Developing a scanning method for high-throughput use first required  
 234 characterizing properties of this new technology and then validating them. To this  
 235 end, validation consisted of comparing the values measured on the live animals to  
 236 those extracted from the 3D images. Repeatability and reproducibility of the two  
 237 methods were also estimated. Repeatability assesses the error generated when  
 238 estimating an indicator several times from the same sample using the same method  
 239 in the same environment in a short period of time. Thus, repeatability was estimated  
 240 by extracting measurements six times on the same day from the same 3D scan of the  
 241 same reference animal (the plastic cow). Reproducibility assesses the same error but  
 242 under variable environmental conditions. Reproducibility was estimated by scanning

243 six live cows six times each on the same day. Two individuals extracted  
244 measurements from each 3D image. In total, each body trait of each live cow was  
245 measured six times by each method i.e., a total of 12 times. For repeatability and  
246 reproducibility, we estimated the error associated with each body trait for each  
247 measurement method independent of that associated with the measurers. Extracting  
248 body trait measurements from each 3D image six times (on six cows) meant that the  
249 six extraction processes had the same body measurement, and the landmarking was  
250 repeated six times. Similarly, scanning cows six times on the same day meant that  
251 the error associated with extracting measurements was the same for a given image,  
252 but the error associated with image acquisition and processing differed for each scan.  
253 Thus, the reproducibility error included the repeatability error in its variability.

254 Variability in measurements extracted from 3D images was corrected for the effect of  
255 individual cows by extracting residuals from an ANOVA model. Coefficients of  
256 variation for repeatability and reproducibility ( $CV_r$  and  $CV_R$ , respectively) were  
257 estimated from their respective means ( $\mu_r$  and  $\mu_R$ , respectively) and standard  
258 deviations ( $\sigma_r$  and  $\sigma_R$ , respectively). Likewise, variability in the repeatability and  
259 reproducibility of manual measurements was corrected for the effects of individual  
260 cows and individual measurers by extracting residuals from two ANOVA models. The  
261 first included cow identity as a factor to explain repeatability, while the second  
262 included cow identity and measurer identity as factors to explain reproducibility. The  
263 more repeatable (or reproducible) the 3D measurement was, the smaller was its  $CV_r$   
264 (or  $CV_R$ ).

265

266 **2.7. Statistical analysis:** Correlations between measurements extracted from 3D  
267 images and reference values of repeatability and reproducibility were calculated  
268 using SAS software (SAS institute, 2016).

269

### 270 **3. Results**

#### 271 **3.1. Comparison of body traits measured manually and with the 3D scanner**

272 Most manual measurements were smaller than those extracted from the 3D images  
273 (Table 1). The largest difference between the two sets of measurements (11.2%) was  
274 observed for IW, while the smallest difference (1.3%) was observed for WH.

275

276 **Table 1.** Mean measurements (cm) of body traits of 30 live Holstein cows performed  
277 manually and extracted from images from a new 3D scanner (Morpho3D) and P values of the  
278 difference between them (Student's t-test)

<b>Body trait</b>	<b>Manual</b>	<b>Morpho3D</b>	<b>P value</b>
<b>Heart girth</b>	207.5	221.5	< 0.0001
<b>Chest depth</b>	79.4	83.8	< 0.0001
<b>Wither height</b>	146.9	148.8	< 0.003
<b>Hip width</b>	55.5	54.4	< 0.02
<b>Backside width</b>	51.9	54.4	< 0.008
<b>Ischial width</b>	17.4	19.6	< 0.02

279

280 The correlation between manual and Morpho3D measurements was also high,  
281 ranging from 0.63 for IW to 0.89 for CD (Table 2).

282

283 **Table 2.** Correlation coefficients (r) and their P values between mean values of body traits  
284 manually measured and those estimated from images from a new 3D scanner (Morpho3D)  
285 for 30 live Holstein cows

<b>Body trait</b>	<b>r</b>	<b>P value</b>
<b>Heart girth</b>	0.78	< 0.001
<b>Chest depth</b>	0.89	< 0.001
<b>Wither height</b>	0.62	< 0.001
<b>Hip width</b>	0.80	< 0.001
<b>Backside width</b>	0.76	< 0.01
<b>Ischial width</b>	0.63	< 0.01

286

### 287 **3.2. Repeatability and reproducibility**

288 Repeatability and reproducibility were generally similar between methods, but the  
289 method with higher value varied among body traits (Table 3). For Morpho3D  
290 measurements,  $\sigma_r$  ranged from 0.34-1.89 cm (CV = 0.26-9.81%) and  $\sigma_R$  from 0.55-  
291 5.87 cm (CV = 0.94-7.34%). For manual measurements,  $\sigma_r$  ranged from 0.21-1.32  
292 cm (CV = 0.11-10.30%) and  $\sigma_R$  from 0.49-1.19 cm (CV = 0.42-4.46%).

293



294 **Table 3.** Mean ( $\mu$ ), standard deviation ( $\sigma$ ) and coefficient of variation (CV) of repeatability and  
 295 reproducibility of manual measurements and those extracted from images from a new 3D  
 296 scanner (Morpho3D) of body traits of cows. A model cow was used to estimate repeatability,  
 297 while six live cows were used to estimate reproducibility.

Body trait	Method	Repeatability			Reproducibility		
		$\mu_r$ (cm)	$\sigma_r$ (cm)	CV <sub>r</sub> (%)	$\mu_R$ (cm)	$\sigma_R$ (cm)	CV <sub>R</sub>
Heart girth	Manual	194.2	0.21	0.11	204.2	0.86	0.42
	Morpho3D	195.8	1.89	0.97	221.1	5.87	2.63
Chest depth	Manual	75.1	0.42	0.56	79.1	0.49	0.62
	Morpho3D	76.5	0.44	0.58	84.4	0.92	1.09
Wither height	Manual	129.1	1.04	0.80	148.9	1.07	0.72
	Morpho3D	131.1	0.34	0.26	148.6	2.12	1.42
Hip width	Manual	39.8	0.35	0.88	55.5	1.01	1.82
	Morpho3D	39.9	0.67	1.68	58.6	0.55	0.94
Backside width	Manual	50.9	0.36	0.71	50.8	1.19	1.82
	Morpho3	52.6	0.34	0.64	55.5	1.82	3.28
Ischial width	Manual	12.8	1.32	10.30	17.3	0.77	4.46
	Morpho3D	17.5	1.78	9.81	15.4	1.13	7.34

298

#### 299 4. Discussion

300 It is unknown why manual measurements were usually smaller than those extracted  
 301 from the 3D images. With additional effort, the point clouds behind the final mesh  
 302 were also analyzed; they yielded similar results, indicating that the scanning  
 303 equipment probably overestimated certain measurements (by 2-7%). In particular, IW  
 304 (11.2% difference between manual and mesh measurements) is extremely difficult to  
 305 measure accurately on live animals, even for trained technicians. The prominence of  
 306 bones used to measure HW explained the small differences observed between

307 manual and Morpho3D measurements, as Pezzuolo et al. (2018) observed.  
308 Conversely, no prominent bones are available for measuring SW. In addition, HG and  
309 CD were overestimated because the cow's front leg often obscured its chest in the  
310 image. Correlations between measurements of both methods were generally lower in  
311 the present study than those reported by Buranarkal et al. (2012) and Pezzuolo et al.  
312 (2018). Buranarkal et al. (2012) measured animals under laboratory conditions and  
313 placed landmarks on them, but this approach would be difficult to implement under  
314 commercial conditions. Pezzuolo et al. (2018) used a method based on a suitable  
315 low-cost depth camera (Microsoft Kinect v1), which allowed to take measurements  
316 without contacts on pigs and extract body dimension and calculate then, body weight.  
317 This method can detect and identify anatomical landmarks that could be of interest  
318 for further development, but authors concluded that proposed models need to be  
319 adapted and calibrated to specific breed.

320 According to Fischer et al. (2015), measurement methods whose repeatability and  
321 reproducibility have a CV less than 4%, as in the present study, are considered  
322 promising. The difference in measurements between the plastic model and live cows  
323 was initially attributed to the latter's movement and long hair. However, 3D images  
324 were deleted if cows moved during image acquisition, and the cows' hair had been  
325 clipped; thus, these were not the source of the differences.

326 Research in the field of animal imaging, first 2D and now 3D, is increasing due to  
327 improvements in costs, ergonomics, maintenance, etc. This research has identified  
328 several objectives for high-speed acquisition of phenotypic traits, such as  
329 measurement of morphological traits, body condition traits and, indirectly, BW of  
330 animals (to be published). However, Tschärke and Banhazi (2013) identified limits to  
331 these approaches and suggested ways to improve them. The first recommendation

332 was to automate measuring and image processing. Brandl and Jorgensen (1996)  
333 and Arias et al. (2004) identified the need for further research to facilitate complete  
334 automation of the often semi-automatic scanners. Two completely automatic systems  
335 for weighing and sorting pigs and for measuring body condition of dairy cows have  
336 been marketed (Hölscher+Leuschner, Emsbüren, Germany), but they were only  
337 moderately accurate (Bergfeld et al., 2013). The second recommendation was to  
338 maximize repeatability of the measurements. Many authors highlight the strong  
339 influence of animal position on measurement variability and the importance of  
340 selecting, often manually, the best images in order to decrease undesirable variations  
341 (Kmet et al., 2000; Stajniko et al., 2008). Fischer et al. (2015) showed that only a few  
342 of the studies that estimated BCS from images evaluated their method (e.g.  
343 determination of repeatability and reproducibility). Spolianski et al. (2016) extracted  
344 BCS from images and evaluated the repeatability and accuracy of the method, as did  
345 Viazzi et al. (2013). Other authors studies have evaluated methods for studying cow  
346 problems (Beiderman et al., 2014) or measuring BCS (Bercovich et al., 2013) by  
347 calculating correlations with measurements from other methods (manual, or those  
348 extracted from images) or calculating classification accuracy (Beidermann et al.,  
349 2014). All authors, however, emphasized the importance of evaluating each method  
350 accurately.

351 According to Tscharke and Banhazi (2013), controlling the environment is also  
352 important. Since most technologies are sensitive to daylight, they are used under  
353 controlled light conditions. Similarly, restricting animal movement to obtain usable  
354 images is also crucial. Animal color or lack of cleanliness can sometimes cause  
355 problems acquiring images. Further studies are needed so that scanners developed  
356 under controlled conditions can be used in the “aggressive” environment of a

357 commercial, or at least an experimental, farm. Tschärke and Banhazi (2013)  
358 indicated that bias and modeling are also important when working with images. Many  
359 potential biases exist when estimating BW or BCS. Optimizing models and equations  
360 that consider parameters such as age or sex will increase accuracy.

361

## 362 **5. Conclusion and future studies**

363 **This new scanning technology provides new perspectives for assessing animal**  
364 **morphology.** The time required to measure all six body traits was estimated as 2.5  
365 and 15 min for the manual and Morpho3D methods, respectively. Image acquisition is  
366 rapid for the latter (mean = 6 seconds), but the time required to analyze and obtain  
367 the final results was approximately 14 minutes. The prototype was not designed to  
368 minimize image processing times, however, so it is possible to reduce them in the  
369 future. A valuable advantage of 3D images is that they remain available for additional  
370 or new analyses if necessary.

371 The risk of human injury when acquiring images is reduced to nearly zero, which  
372 could be of interest to types of production in which animal measurements are  
373 necessary and risky, such as beef production. A major concern, currently under  
374 review, is to automate the steps of image analysis: cleaning, reconstruction and  
375 extraction of measurements. This is clearly a major point when using this method at a  
376 large scale and when developing new technology based on “one-shot” technology, in  
377 which animal movement is no longer a problem. In the latter case, image definition  
378 will probably decrease, but based on developments in the Morpho3D project,  
379 accurate equations and algorithms should be available to optimize analysis. The  
380 ability to capture a 3D image of an entire animal will allow for many potential  
381 improvements in the near future. Automatic estimation of visual BCS, morphological

382 scoring for selection purposes, BW, surface area and volume will be developed and  
383 implemented in Metrux2α® software and compared to manual measurements. Body  
384 surface area, for example, has been demonstrated as useful for determining precise  
385 doses of medication for large animals. Moreover, it is likely that calibrating carcass  
386 characteristics from slaughterhouse data with these animal shapes will help estimate  
387 the quality of meat of live animals.

388

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