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2 **Early and non-intrusive lameness detection in dairy cows using 3-dimensional video**

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16 **ABSTRACT**

17 Lameness is a major issue in dairy herds and its early and automated detection offers animal
18 welfare benefits together with high potential commercial savings for farmers. Current
19 advancements in automated detection have not achieved a sensitive measure for classifying
20 early lameness. A novel proxy for lameness using 3-dimensional (3D) depth video data to
21 analyse the animal's gait asymmetry is introduced. This dynamic proxy is derived from the
22 height variations in the hip joint during walking. The video capture setup is completely covert
23 and it facilitates an automated process. The animals are recorded using an overhead 3D depth
24 camera as they walk freely in single file after the milking session. A 3D depth image of the
25 cow's body is used to automatically track key regions such as the hooks and the spine. The
26 height movements are calculated from these regions to form the locomotion signals of this
27 study, which are analysed using a Hilbert transform. Our results using a 1-5 locomotion
28 scoring (LS) system on 22 Holstein Friesian dairy cows, a threshold could be identified
29 between LS 1 and 2 (and above). This boundary is important as it represents the earliest point
30 in time at which a cow is considered lame, and its early detection could improve intervention
31 outcome thereby minimising losses and reducing animal suffering. Using a linear Support
32 Vector Machine (SVM) binary classification model, the threshold achieved an accuracy of
33 95.7% with a 100% sensitivity (detecting lame cows) and 75% specificity (detecting non-
34 lame cows).

35 **Key words:** 3D computer vision, early lameness detection, gait asymmetry, locomotion
36 analysis

37 **1. Introduction**

38 Lameness in dairy cows is acknowledged as being one of the most serious problems that
39 affect an animal's welfare and thus, farm productivity (De Mol et al., 2013). Willshire & Bell
40 (2009) reported that lameness in the UK's national herd accounted for financial losses of up
41 to £127.8 million in the year 2009. Regardless of its causes, early detection and prompt
42 treatment minimises losses and reduces animal suffering (Cha, Hertl, Bar, & Gröhn, 2010;
43 Leach, Tisdall, Bell, Main, & Green, 2012). Until now, measurement and analysis of weight
44 distribution or walking pattern as the animal walks on force plates or the use of body sensors
45 (accelerometers) are the most established conventional gait analysis methods. However, due
46 to high expense, implementation complexity (Chapinal, de Passillé, Rushen, & Wagner,
47 2010; Maertens et al., 2011) and high vulnerability to damage and loss of the recording
48 equipment while collecting the data; such systems have never been implemented on a large
49 scale, or on a regular basis, in dairy farming. Automated vision based methods for lameness
50 detection are in their infancy and are based almost entirely on a single static measurable trait
51 (i.e. estimating the animal's back curvature/posture to predict gait soundness, Poursaberi,
52 Bahr, Pluk, Van Nuffel, & Berckmans, 2010). However, although well established in the
53 literature, there is unreliability in using back arching, as reported by Poursaberi et al. (2011),
54 whereby some lame cows do not present an arched back, while conversely some healthy
55 cows do show an arched back. Both Viazzi et al. (2014) and Van Hertem et al. (2014)
56 developed automated lameness detection systems based on the measurements of the back
57 arch, using 3-dimensional (3D) video. Although such systems are applicable for commercial
58 farm implementations, no published research has shown a method that focused on early
59 lameness classification that is suitable for daily use on a commercial farm, as we present
60 here.

61 **2.0 Method**

62 Because many quadrupeds (including cows) walk in a symmetrical manner, gait symmetry
63 has been the principal indicator in many conventional methods. However, it has been
64 reported that gait asymmetry may occur for reasons other than lameness (e.g. udder fill;
65 Flower, Sanderson, & Weary (2006) or a slippery floor causing the cows to take short and
66 careful steps; van der Tol et al. (2005)). For similar reasons, a levelled concrete surface (with
67 micro-grooves to improve the grip as the animals walk) was used while recording the data
68 after the milking session. However, from a wider perspective, monitoring locomotion is
69 generally useful for the farmers because it may reveal other well-being issues (Van Nuffel et
70 al., 2015) - e.g. mastitis; Van Nuffel et al. (2015) or sole ulcers; Flower et al. (2006).

71 In a symmetrical (healthy) gait, the animal's feet are expected to be on the ground for the
72 same amount of time and the footfalls within each pair of legs are evenly spaced in time. As a
73 consequence, the left and right side of the body perform the same motion half a stride out of
74 phase (Hildebrand et al., 1985; Remy, Buffinton, & Siegwart, 2009). However, in the case of
75 a lame animal, the limbs tend to exhibit a certain asymmetry as the animal walks, which
76 could be used as an indicator for a certain lameness stage. In dairy cows it is known that
77 lameness significantly worsens the vertical symmetry (i.e. symmetry of the weight
78 distribution between the right and left legs) as the animals walk on force plates (Thorup et al.,
79 2014). Thus, the contralateral limb movements of lame animals are expected to show
80 asymmetry as the animal walks. However, prior investigations have mainly focused on
81 measuring the kinematic differences of these limbs on force plates, which is -as mentioned
82 earlier- a complex method to implement on commercial dairy farms. Instead, by using 3D
83 video from the top of the herd, here we investigate the height movement variations of the hip
84 joints to study gait asymmetry.

85 It is hypothesized that a dynamic measure over a full gait cycle, observing the regular
86 movements of each footfall, will assist in detecting early stage lameness. Standard 2-

87 dimensional (2D) video imagery when used in this way presents numerous problems which
88 are difficult to overcome (Van Hertem et al., 2014). These include segmentation of the
89 foreground from the background, occlusions and sensitivity to lighting variance. Recent
90 advances in acquisition technology have allowed deployment of cheap and accurate 3D
91 sensors, capable of video recording, which helps overcome those issues associated with 2D
92 capture, and assists in the extraction of robust features. By incorporating Hildebrand's work
93 on locomotion and results from force plate methods, a novel extrapolation from 3D video
94 data was developed to extract motion in terms of height variation symmetry, thus, objectively
95 analysing an animal's locomotion.

96 From an implementation perspective, dairy farmers tend to prefer any system offering the
97 least possible interference in the daily routine of the herd. Farmers also prefer a capturing
98 setup where minimal human involvement is required to achieve maximum accuracy and this
99 points to the need for an automated mechanism. One of the major subjectivity concerns in
100 many conventional and manual methods is the presence of a human observer, which is known
101 to affect the cow's behaviour (Breuer, Hemsworth, Barnett, Matthews, & Coleman, 2000;
102 Grandin, 2010; Reader, Green, Kaler, Mason, & Green, 2011). The accuracy of the lameness
103 scoring is highly contingent on the animal's behaviour, which in cows is liable to variation in
104 the presence of observers. Therefore, in order to be able to study pain-related behaviour in the
105 most reliable manner; the data capturing system has to be completely covert (human
106 involvement during the procedure should not be required). By using an overhead view (i.e.
107 from above the herd), our capturing system is completely covert, thus, enabling objective
108 results to be obtained. Our approach also facilitates full automation and provides a hardware
109 configuration which is less prone to damage and the presence of complex and noisy image
110 backgrounds.

111 The locomotion data presented here is an initial part of a large ongoing data collection project
112 at Bridge Farm, Glastonbury, United Kingdom, where more than 200 Holstein Friesian dairy
113 cows are housed. All cows were milked twice a day. A custom race has been built next to the
114 milking parlour which forces the cows to walk unconstrained in single file underneath the 3D
115 camera. This race was in regular use as an exit from the milking parlour for several months to
116 allow the animals to adapt to the changes, before collecting the data. The data consists of 23
117 3D recorded sessions from 22 cows, using a standard depth-sensor camera (ASUS Xtion PRO
118 LIVE, ASUSTeK Computer Inc., Taipei, Taiwan). All cows have visible brand numbers and
119 are tagged with standard Half Duplex (HDX) electronic tags for identification purposes. A
120 Radio Frequency Identification (RFID) reader (Agrident ASR700 Controller, Agrident B.V.,
121 Meterik, Limburg, Netherlands) was used to read the tags as the cows walked in the race. A
122 single camera was used through-out the entire data collection to capture the animals from an
123 overhead position. Both the camera and the RFID reader were connected to a computer
124 (Windows 7, i5, 8GB RAM). As we are studying a sensitive lameness stage, it is important
125 that we observe as many possible cycles of the locomotion's resulting signals. Following
126 several tests at different Field of Views (FOVs); the 3D data presented here is captured at a
127 height of 3.69 m off the ground. This was the maximum height achieved to acquire as many
128 footfalls as possible without causing heavy distortions in the depth data (pixel resolution at
129 this setting is 3.6 mm × 3.6 mm). The horizontal FOV was around 6 m. This has allowed the
130 capture of at least two full gait cycles i.e. eight footfalls on average. The average acquired
131 frames for one cow's locomotion was 70. This also means that we were able to perform the
132 analysis as the cow's body leaves the frame (i.e. when the hooks are still visible). The camera
133 operated at 30 frames s⁻¹.

134 To provide conventional manual scoring, an experienced local observer has scored each cow
135 using the locomotion/lameness score (LS) system provided by (Sprecher, Hostetler, &
136 Kaneene, 1997).

137 **3. Results & Discussion**

138 As presented in Table 1, the animals were scored in an open field as they walked freely from
139 the cow race. This was performed immediately after (~5-7 min) the evening milking session
140 when the 3D recordings were made, in order to minimise any variations that might occur
141 given a longer time frame (e.g. injury). At the time of scoring, two additional standard 2D
142 digital video cameras (one looking to the side, the other looking at the rear of the animals)
143 were used to assist with reviewing the manual locomotion scores and identifying the cows
144 using the brand number. The observer watched the recorded 2D videos and gave a final score
145 for each cow with a clear brand number. The data was organised manually; the desired
146 (manually scored with a brand number) cows were located in the RFID logs, and the
147 timestamps of these readings were then used to locate the cows in the 3D recorded data. Each
148 cow used in this data has been scored at least three times over the period of three weeks (with
149 the exception of the severely lame cows i.e. LS 4 and 5 in Table 1), from the 20th May 2015
150 to the 2nd June 2015. Because early lameness is being investigated, only cows that repeatedly
151 received manual scores of either 1, 2 or 3 across the three sessions were used. This provides a
152 reliable data-set of cows scored at LS 1, 2 and 3 that can be used confidently to establish a
153 sensitive early lameness threshold. The scored cows were extracted from the recorded 3D
154 data as separate ONI files (labelled with the unique brand number), each cow's locomotion
155 represents a single ONI file which was then processed in MATLAB (R2015b, The
156 MathWorks Inc., MA, USA).

157 The pre-processing steps of the 3D data involve subtracting the background (an image of the
 158 cow race when there is no cow present) and applying a height threshold to eliminate
 159 surrounding object pixels and discarding extraneous information by filtering-out the noisy
 160 areas from the subtracted depth image. The resulting image was then smoothed using a
 161 symmetric Gaussian low-pass filter to remove quantization artefacts in the raw image. This
 162 processed 3D image is used to extract the height measurements from key Regions of Interests
 163 (ROIs), to compare the changes in the 3D surface as the cow progresses under the camera.
 164 Our algorithm is able to extract high curvedness (convex) features of the animal's hooks and
 165 spine from the processed 3D image, by applying the curvedness measure as first proposed by
 166 Koenderink & van Doorn (1992):

$$167 \quad C_{(x,y)} = \sqrt{\frac{\kappa_1^2(x,y) + \kappa_2^2(x,y)}{2}} \quad (1)$$

$$168 \quad C_{\max} = \max(C) \quad (2)$$

$$169 \quad \bar{C}_{(x,y)} = \frac{C_{(x,y)}}{C_{\max}} \quad (3)$$

170 where \bar{C} is the curvedness measure of the 3D shape. It represents the normalised magnitude
 171 of the combined principle curvatures ($\kappa_1 + \kappa_2$). The principal curvatures (in differential
 172 geometry) are calculated from the Gaussian and mean curvatures of the surface. They
 173 correspond to the orthogonal axes which reflect a point on the object's surface. By
 174 thresholding the curvedness, the most prominent convex features (which corresponds to
 175 peaks) are visible - as shown in Fig. 1. The scapula or shoulders are very difficult to extract at
 176 the current camera height. However, we found that the peaks were a reliable feature to extract
 177 the hooks in order to track the hind limb movements. These peaks are typically represented
 178 by a region of 10-20 pixels allowing the local maxima of this region to be located. For

179 increased robustness to noise, the algorithm calculated a weighted average using a 2D
180 Gaussian convolution window over each thresholded region to find the pixel with the highest
181 curvedness value. Thus, we are able to robustly locate the hooks' ROIs by tracking the
182 outermost peak points as the animal walks. Using this approach, it was found that the spine
183 represents the largest connected object given in a binary converted image of the curvedness
184 threshold. Figure 1 illustrates the image processing pipeline described above. This process
185 was repeated for each frame in the data. An overall detection rate (number of successfully
186 processed frames where all features were correctly tracked /all frames) of 85.7% on the first
187 attempt for the automated features extraction algorithm, for both the hooks and the spine
188 features. All frames were manually observed to ensure correct features extraction. An
189 interactive tool for manual intervention allowed the correction of any obvious misdetections,
190 in order to correct ROIs for accurate feature points. This test allowed us to identify some of
191 the most common problems in our data (i.e. changes in the spine's curvedness which leads to
192 a separated spine ROI or the pins been identified as hooks when the whole body alignment
193 changes). Upon modifying the algorithm, a better automatic performance is achieved for
194 hooks and spine features (96.1% and 100%, respectively).

195 A dynamic measure of height changes for each ROI was applied by calculating the median
196 and maximum variations. It was found that maximum height variations were more suitable
197 for this analysis as they are more sensitive to small changes, especially in cows with early
198 stage lameness. These measures are normalised by removing the global locomotion variations
199 from the surface of the cow. A middle ROI (near the sacrum bone) was located between the
200 right and left hook to remove the effect of the cow's overall movement towards and away
201 from the camera by subtracting the sacrum ROI variations from both hooks' ROIs. The
202 resulting signals were then filtered using a moving-average digital filter to remove noise
203 (mainly due to the high distance of the camera position) and a sine wave was fitted (using a

204 least-squares cost function) to the mean in each estimated period. In a healthy cow, as shown
205 in Fig. 2, the right-left locomotion signals may not start equally out of phase but shift to
206 become equally out of phase for the right-left hooks (i.e. the movements of the right-left hind
207 limbs) at a certain time in the locomotion, representing a full cycle of footfalls. This is mainly
208 because the animals enter the FOV freely, i.e. the starting footfall (limb) is unknown and it
209 varies across the data. Because of their lateral sequenced gait (hind-left, fore-right, hind-right,
210 fore-left) as they walk, the phase difference given one full cycle between the out of phase
211 maxima and minima peaks (from the locomotion signals) usefully indicates how symmetrical
212 the height variations are. Thus, it is a key proxy that can be used to track, measure and rank
213 the symmetry between the movement of the right and left hind limbs and to subsequently,
214 establish distinguished patterns between locomotion scores. Because of the nature of these
215 sinusoidal signals, i.e. single cycle sinusoids (mono-components), the Hilbert transform is a
216 suitable technique to estimate the instantaneous varied frequency between right and left
217 signals. This transform converts the locomotion signals from the time-domain into analytic
218 signals in which the phase and magnitude of the original data can be analysed directly. Here
219 the magnitude and phase will change in synchronization with the original sinusoidal signal
220 and the differences between right and left can be calculated. Figure 2 shows the signal
221 processing steps of this study, as described above. Figure 3 shows examples of various
222 locomotion signals from our data for LS 1-3. The difference in the amplitude changes are
223 noticeably in lame cows, indicating either hook has moved higher/lower as compared to the
224 other. This supports the previous findings, that cows standing with discomfort in one limb,
225 remove weight from that limb and shift it primarily to the contralateral limb (Neveux, Weary,
226 Rushen, von Keyserlingk, & de Passillé, 2006), resulting in significantly higher height
227 variations (maxima peak) in the contralateral limb as compared to the lame limb (minima

228 peak) in a given cycle. Thus, a smaller phase difference is observed in a lame as compared to
 229 a healthy cow.

230 The resulting locomotion signals of this study correlate well with the manual locomotion
 231 scores which are heavily reliant on the limb movements, even though the limbs themselves
 232 are not visible from the view point of the 3D camera. Subsequently, we were able to extract a
 233 novel proxy by measuring the resulting symmetry from the height movements as we are
 234 closely observing the dynamics of each hind limb across all frames, as the animals walk
 235 freely. This has allowed us to anticipate objective lameness trends at early stages.

236 The symmetry patterns derived from the phase difference of close locomotion scores i.e. LS
 237 1, 2 and 3 are noticeably changing across the majority of the examined data. Our results in
 238 Table 1 show a clear difference in the overall mean phase difference of the right-left signals
 239 in LS 1, 2 and 3. Here lameness reduces the overall mean difference due to uneven peaks in
 240 the locomotion signals resulting from asymmetric height movements. However, in severe
 241 lameness scores, due to very limited data (only two cows in locomotion scores 4 and 5),
 242 although the mean differences sit within the early lameness threshold, they fall outside the
 243 trend observed in scores when more data and sessions are available. It is important to mention
 244 that collecting more data in LS 4 and 5 is very difficult.

245 **Table 1** Manual and algorithm locomotion scores.

Manual locomotion scores ¹			Algorithm scores	
Cows ²	N ³	Locomotion Score	Mean phase difference (SD)	Significance ⁴
4	3	1	0.1520 (0.0614)	-
7	3	2	0.0785 (0.0516)	Y
10	3	3	0.0493 (0.0361)	Y
2	1	4	0.0507 (0.0486)	Y
		5	0.0523 (0.0386)	Y

- 1 Scored manually by the in-house observer using Sprecher et al. (1997) 1-5 scoring method.
- 2 Number of cows in each LS.
- 3 Number of times each cow is manually scored.
- 4 Y=Yes indicating a significance difference of less than $P < 0.05$ from LS1, using a Student t-test.

246 However, this does not affect the main purpose of this study, as we are able to observe a
 247 sensitive trend for early lameness. A significant statistical difference is shown using one-way
 248 ANOVA between all five groups ($P < 0.05$). Student t-tests (unpaired two-sample t-tests,
 249 given unknown variance) reveal a significant difference between the data in LS 1 and each
 250 other level, as shown in Table 1. The same test shows a significant difference for LS 1 vs LS
 251 2 and 3 combined, LS1 vs all other levels ($P < 0.0004$, $P < 0.000009$ respectively). Thus, a
 252 sensitive pattern was observed in the mean phase differences as the lameness level increases.
 253 We suggest a threshold from this data at a mean phase difference of 0.09 (by subtracting the
 254 full standard deviation from the mean phase difference of LS 1). However, this could result in
 255 a small overlap between LS 1 and 2 which could be further refined given more data. At this
 256 early stage lameness threshold (i.e. LS 1 vs. all lameness levels), we used a supervised
 257 learning (linear SVM) classification model to assess the system’s sensitivity (100%),
 258 specificity (75%) and overall accuracy (95.7%). The sensitivity represents the ability to detect
 259 lame cows from LS 2 to 5, and the specificity represents the ability to detect the non-lame
 260 cows in LS 1. The binary classification model’s confusion matrix is shown in Table 2.

261 **Table 2** Confusion matrix for the early lameness threshold for all cows using a linear SVM classification. This strict binary
 262 classification is established between LS 1 (Healthy) and LS 2, 3, 4 and 5 (Lame). An accuracy of 0.95 is achieved using this
 263 classification at a very sensitive lameness stage, $n = 23$.

		True class	
		Lame	Healthy
Predicted class	Lame	19	
	Healthy	1	3

264 **4. Conclusions:**

265 Preliminary results of a non-intrusive 3D video data capturing setup have been presented that
 266 allow regular daily data capture on a large scale in commercial dairy farms. Our algorithm is

267 able to detect lameness trends at early stages. The extracted novel proxy from the 3D data is a
268 dynamic symmetry measure which reflects the locomotion soundness by tracking the
269 movements of the spine and hind limbs. The presented results show patterns that enable us to
270 distinguish between close locomotion scores; i.e. LS 1, 2 and 3 on 22 dairy cows. Based on
271 these results, we are able to identify an early lameness threshold on a 1-5 scoring system. We
272 believe that our study strides towards an accurate, automated and objective locomotion
273 assessment without the need for human involvement. One of the major advantages of our
274 system is that we are able to capture data after each milking session on a daily basis, thus,
275 small developing lameness trends could be incorporated and detected potentially even before
276 a human observer could. Future work will focus on improving the robustness of the
277 algorithms using further captured data and by analysing the individual cow's variation.

278

279

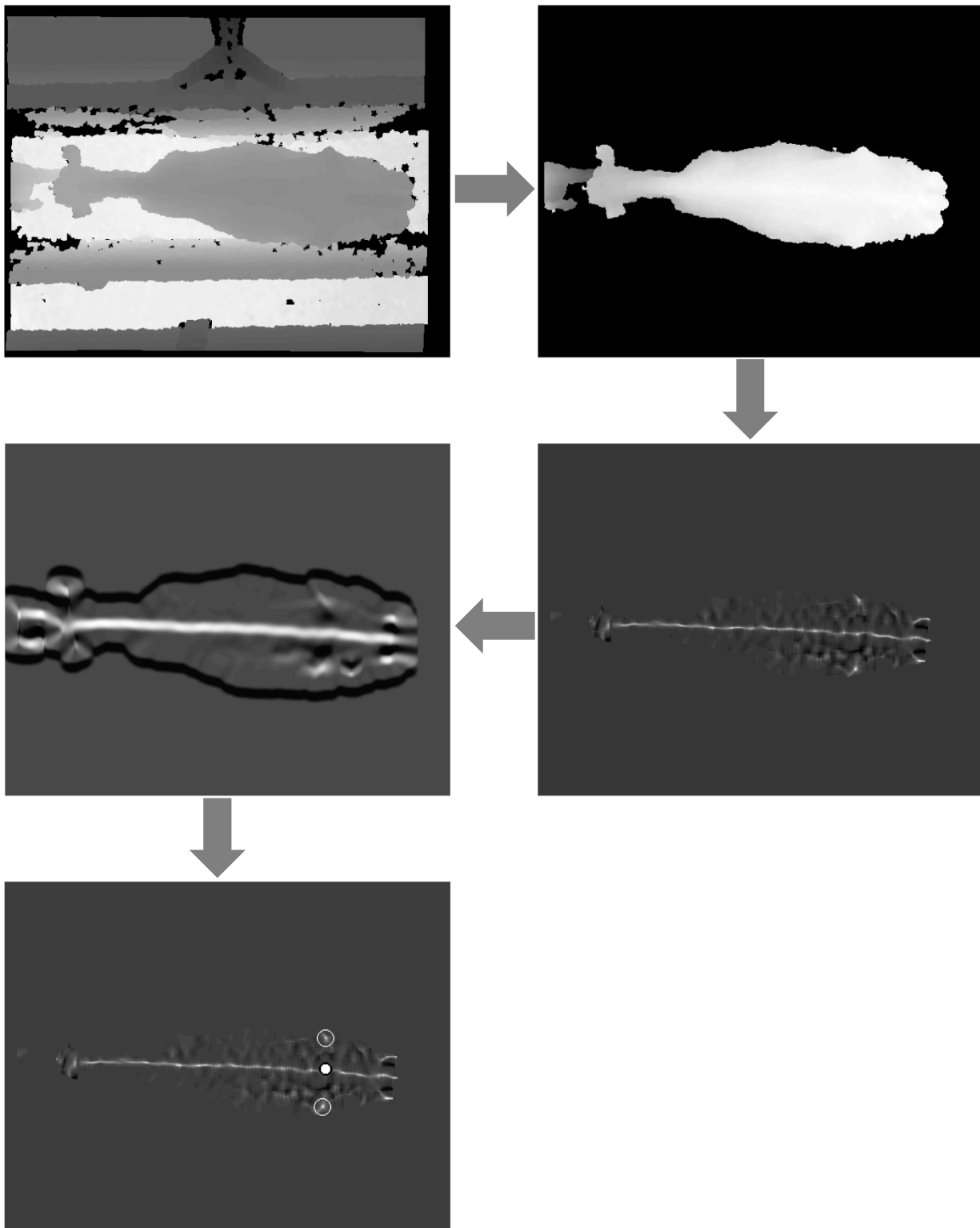
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282 and Bridge Farm (Glastonbury, UK); for their extensive help and input during data collection
283 at the farm.

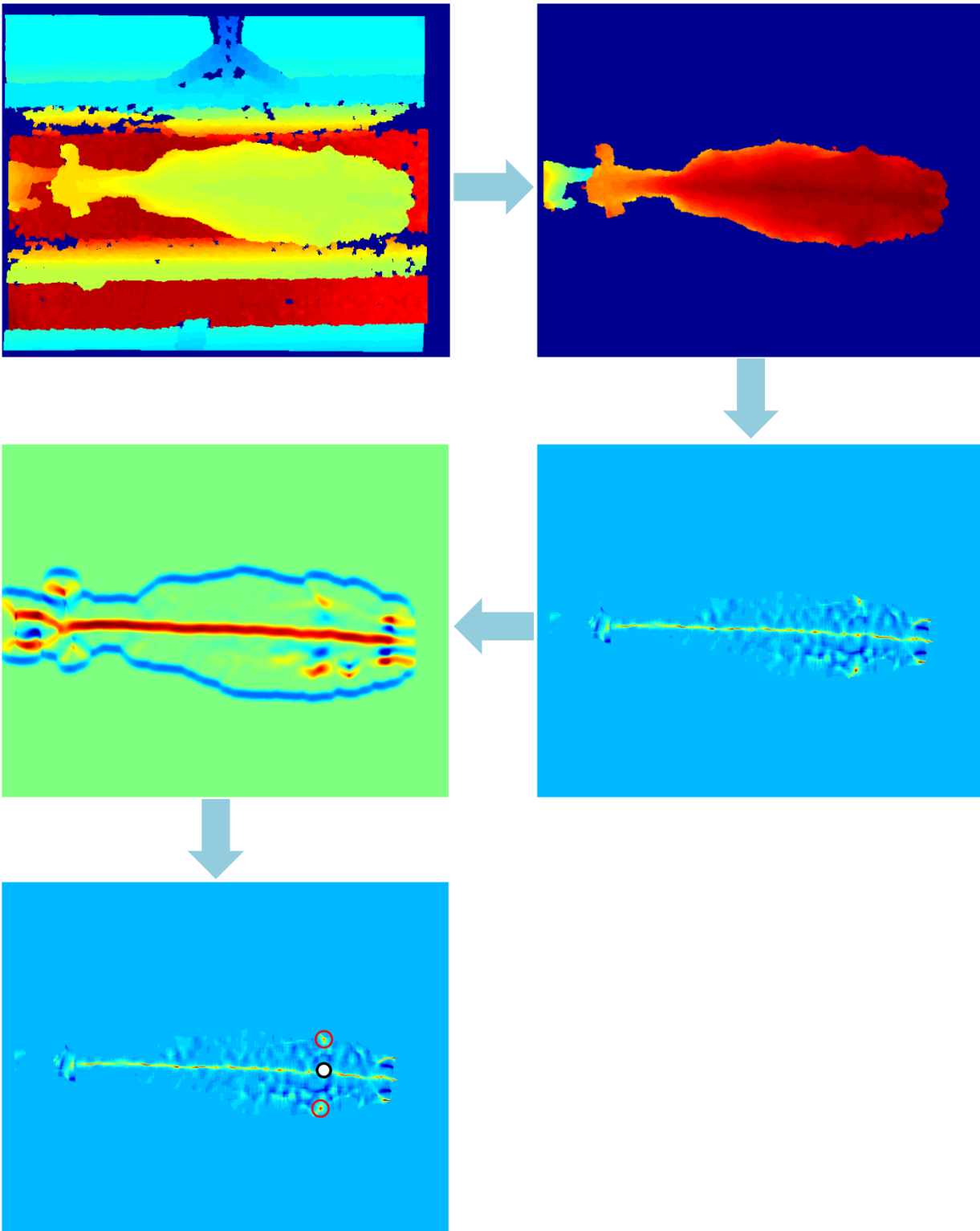
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- 335

336 Fig. 1 (greyscale)

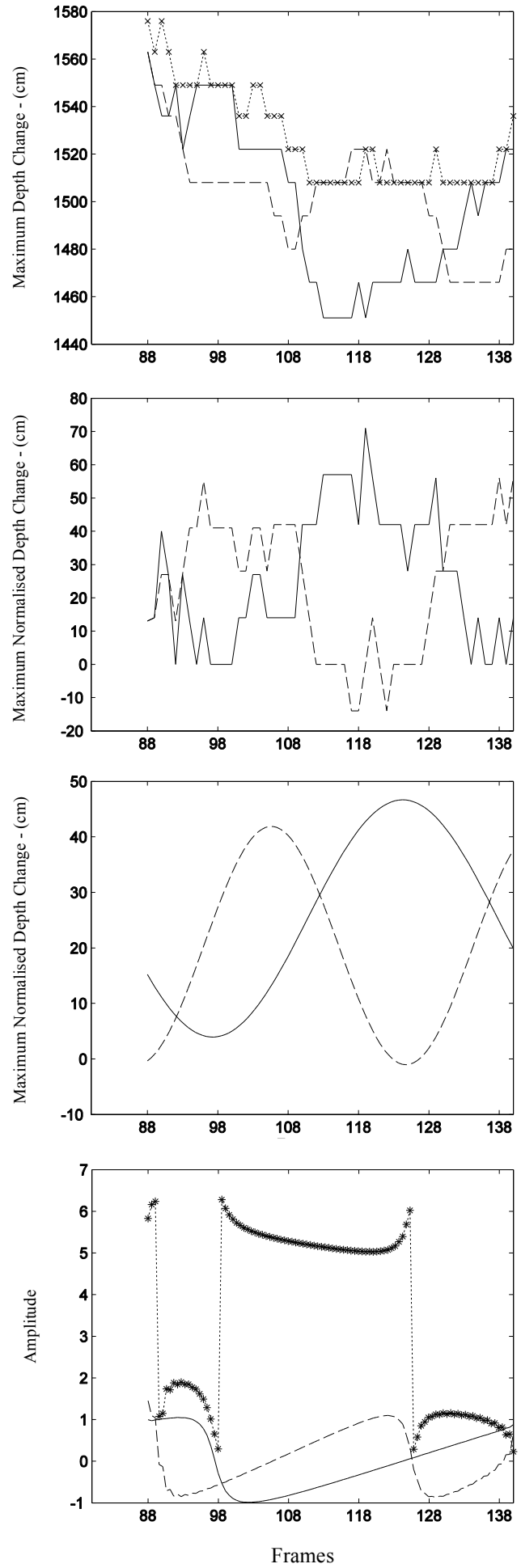


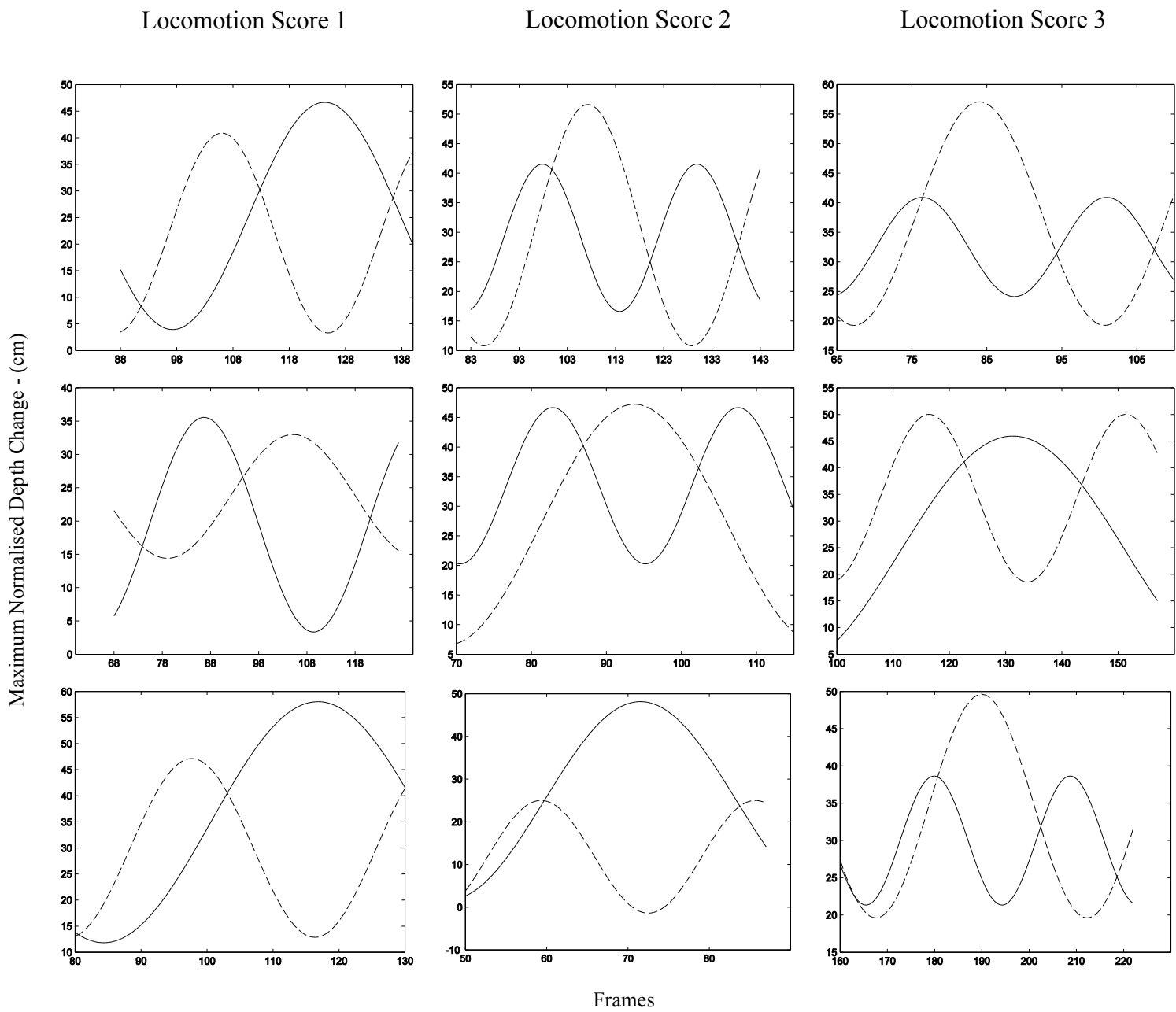
337 Fig. 1 (online color)



338 Fig. 2

339





341 Fig. 1. Automated 3D depth image processing pipeline and features extraction for the hooks
342 and the spine from a single 3D cow image. The first image is a raw depth image from the
343 camera in the race; followed by the same image with the background removed, height
344 threshold applied and smoothed to prevent limiting any curvature information; followed by
345 the curvedness data calculation image with high peaks shown; followed by a binary
346 converted image of the curvedness threshold to track the spine; followed by the features
347 (ROIs) selection image. The distinctly curved (highest convex regions i.e. spine, hooks and
348 pins) are clearly visible. This data is used to extract the ROIs in each frame.

349

350 Fig. 2. Locomotion signals and their Hilbert transform derived from height variation
351 measurements. This figure shows the signal processing steps in a descending order. The
352 measurements are taken at 30 frames per second. The first figure represents raw maximum
353 depth changes in cm in each ROI across all frames, right hook ROI (solid), left hook ROI
354 (dashed), sacrum ROI (x-dotted); followed by normalized measurements for the right and left
355 hooks ROIs after subtracting the sacrum ROI measurements from each hook ROI; followed
356 by a filtered, smoothed sinusoidal fitted signals which represent the locomotion signals of this
357 study; followed by the wrapped Hilbert transform (*-dotted) for the difference between the
358 right hook ROI and the left hook ROI.

359

360 Fig. 3. Examples of filtered sinusoidal locomotion signals for three different lameness scores.
361 Right hook ROI (solid) and left hook ROI (dashed). The left column represents cows with
362 locomotion score 1 (healthy); the middle column represents cows with locomotion score 2;
363 the right column represents cows with locomotion score 3. All locomotion scores presented in
364 this figure are according to Sprecher et al. (1997) scoring system.