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3   Discriminating spontaneous locomotor play of dairy calves using accelerometers

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15   INTERPRETIVE SUMMARY

16   Title: Discriminating spontaneous locomotor play of dairy calves using accelerometers

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18   In calves, play behavior is a promising indicator to assess both compromised and

19   enhanced welfare. However, quantifying play is difficult due to its rare and irregular

20   occurrence. We aimed to validate 1 Hz accelerometer recordings to measure locomotor play

21   of dairy calves in their home-pens. Accelerometer data were combined into 10 s periods and

22   periods were categorized as PLAY/NOPLAY using quadratic discriminant analysis.

23   Comparing these periods with behavior recorded from video, play was correctly classified in

24   79% of cases. Based on a correlation of $r_P=0.87$ with observed play intervals, it may be used

25   as a proxy to replace behavior observations.

ABSTRACT

Play behavior is a promising welfare indicator in dairy calves as it decreases in negative situations such as pain or hunger and increases in positive contexts such as in appropriate social environment. Directly measuring play is time consuming as it is performed in irregular bouts and can be inconsistent over days. To facilitate automatic recording of play, previous studies fitted tri-axial accelerometers to the hind legs of calves, measuring the velocity of movements in large arenas, and reported high correlations between vertical axis peak duration and the duration of locomotor play. The current study aimed at validating accelerometers for recording spontaneous locomotor play in the calves' home-pens over longer periods of time. Data were collected from 48 Holstein Friesian calves at either four or eight weeks of age, housed in groups of three in pens of 10 m^2. Acceleration at the vertical axis of the hind leg was recorded at a rate of 1 Hz. One active time period for each calf was randomly selected (mean duration $\pm$ SD = 34 $\pm$ 9 min). From video of the corresponding time period, frequency of locomotor play events consisting of run, turn and buck/buck-kick was recorded using behavior sampling. Combined counts of play events were highly correlated ($r_p = 0.91$) with counts of peaks in acceleration. However, for calves with higher levels of locomotor play, this method underestimated the extent of play. Alternatively, run, turn and buck events obtained from video were transformed into a binary response by creating intervals of 10s and then classifying each 10s interval as comprising events of play (PLAY) or not comprising events of play (NOPLAY). The corresponding accelerometer data for all 10s periods, equaling 10 consecutive readings each, were classified into PLAY or NOPLAY with quadratic discriminant analysis. 79% of periods with locomotor play were correctly classified. Counts of observed play intervals correlated with the counts of play periods from accelerometers at $r_p = 0.87$, but the discriminant analysis consistently overestimated play. In conclusion, accelerometer measurements at 1 Hz (in 1 s intervals) and at the vertical axis alone cannot be used to exactly quantify absolute levels of locomotor play in the home-pen. However, counts of peak accelerations can provide a rough

52 estimate of inter-individual differences in play events and discriminant analysis can be used as

53 a proxy for one-zero sampling of inter-individual differences in locomotor play.

54 **Key words:** automated measuring, acceleration, behavior classification, dairy calf

INTRODUCTION

56 In the past decade, accelerometers have found increasing application in farm animal research.

57 The use of accelerometers facilitates data collection as automatic recording can circumvent

58 time and resource intensive behavior observations. In calves, accelerometers have been

59 primarily employed to record general activities. For example lying, standing or locomotion of

60 dairy calves have been recorded using accelerometers to detect early behavioral signs of

61 respiratory diseases (Swartz et al., 2017) and of neonatal diarrhea (Sutherland et al., 2018b).

62 Moreover acceleration measurements have been used to quantify lying and standing when

63 studying effects of social housing on weaning (Overvest et al., 2018) and determining effects

64 of different disbudding methods on lying behavior (Sutherland et al., 2018a). While the

65 accuracy of recording general activities from accelerometers is high, the validation of

66 recording specific behaviors such as feeding and ruminating is still in progress (e.g. Roland et

67 al., 2018).

68 In calves, play behavior is a promising indicator to assess both compromised welfare, e.g.

69 pain after disbudding (Mintline et al., 2013) or hunger after weaning off milk reduced play

70 (Krachun et al., 2010, Miguel-Pacheco et al., 2015), and enhanced welfare, e.g. group housing

71 increased play (Valníčková et al., 2015). However, calves perform spontaneous play for only

72 a few minutes per day (Jensen et al., 2015) at irregular intervals (Fraser and Duncan, 1998).

73 Thereby quantification of play from observation is usually accomplished either through

74 continuous recording of durations or events (e.g. Jensen et al., 2015, Miguel-Pacheco et al.,

75 2015) or through one-zero sampling of the presence of play in certain sample intervals (e.g.

76 Valníčková et al., 2015). These challenges associated with measuring play behavior raise the

77 interest in automatic recording techniques. In previous studies, accelerometers were used to

78 automatically record locomotor play of calves, however the recordings were conducted in

79 large arenas and for a short time only. Rushen and de Passillé (2012) found correlations of up

80 to $r_s = 0.88$ between the duration of running and the sum of total acceleration in all three axes

81 and Luu et al. (2013) found correlations of up to $r_p = 0.98$ between the duration of locomotor

82 play (running plus jumping/kicking) and the sum of the percent of peaks (3 g or higher) of all

83 axes. In both studies acceleration was recorded at a high rate of 33 Hz and in all three axes,

84 limiting the recording duration to 10 min due to the memory capacity of the accelerometers

85 (HOBO Pendant G Acceleration Data Logger, Onset Computer Corporation, Pocasset, MA,

86 USA). With the intention of assessing a longer recording duration, Luu et al. (2013) simulated

87 a sampling frequency of 1 Hz by taking every 33rd acceleration reading on one axis only and

88 found a correlation of $r_p = 0.92$ between the percent of peaks on the vertical axis and the

89 duration of locomotor play. In order to test the practical application of measuring spontaneous

90 locomotor play over the duration of many hours, the current study aimed to validate the use of

91 accelerometers to measure play behavior in the home-pens of calves at low recording rates.

92 Specifically, our objectives were using recordings at 1 Hz on the vertical axis (1) to test

93 whether counts of peak accelerations can accurately estimate events of locomotor play and (2)

94 to determine whether classifying periods of acceleration readings into PLAY/NOPLAY can

95 reliably measure play behavior recorded by one-zero sampling from video.

96

97 **MATERIAL AND METHODS**

98 All data were collected at the Netluky Research Station at the Institute of Animal Science in

99 Prague/Czech Republic between August 2016 and April 2017. The study was approved by the

100 Institutional Animal Care and Use Committee of the Institute of Animal Science in Prague

101 and the Czech Central Committee for Protection of Animals, Ministry of Agriculture (permit

102 number 27356/2016-MZE-17214).

103

104 *Animals and Housing*

105 The 48 Holstein Friesian-calves (20 female, 28 male) reported on here were a subset of a

106 larger study using 72 calves. They were housed in an uninsulated barn with wind-shields in 24

107   groups of three. Pens were 10.1 m^2 with a straw-bedded lying area of 4.2 x 1.4 m and a

108   concrete activity and feeding area of 3.5 x 1.2 m. Calves entered group-housing at an average

109   age of 13.3 ± 3.1 days (mean ± SD) with groups entering the experiment consecutively. Calf

110   allocation to groups was balanced for sex, age and weight. For the purpose of another

111   experiment calves were fed either 6 liters of milk daily throughout the experiment or they

112   received 9 liters per day at week 4 and the provision continuously increased to 12 liters at

113   week 6. All calves received three milk meals per day in teat buckets. All calves received 3

114   liters of milk in the morning. Calves with a low milk allowance received 1.5 liters of milk per

115   meal at midday and in the evening. Calves with a high milk allowance received 3 liters

116   continually increasing to 4.5 liters of milk per meal at midday and in the evening. Calves had

117   ad libitum access to water, concentrates and hay offered in buckets. Among the 72 calves, two

118   focal calves per group were randomly selected with observations of one calf taking place at 4

119   weeks and the other at 8 weeks of age. Calves weighed 57.5 ± 5.7 kg (mean ± SD) at 4 weeks

120   and 88.3 ± 12.4 kg at 8 weeks.

121

122   *Acceleration measurements*

123   Accelerometers (HOBO Pendant G Acceleration Data Logger, Onset Computer Corporation,

124   Pocasset, MA, USA; product specifications are described in detail in Luu et al. (2013)) were

125   fitted to the rear side of both hind legs of calves using elastic cohesive bandages.

126   Accelerometers were attached vertically to the leg such that the x-axis was perpendicular to

127   the ground. The accelerometers were set to measure readings on the vertical axis at a rate of 1

128   Hz (1 sample/s), allowing recording of acceleration every second for 18.1 hours. Acceleration

129   was recorded from 05.00 until 23.04 on two consecutive days per testing week with the

130   accelerometer on the right leg recording day 1 and on the left leg recording day 2. Calves

131   wore accelerometers for approximately 66 hours per testing week (from the evening before

132   until the morning after the testing days). Programming of accelerometers was performed using

133   an optical infrared base station with USB interface and the HOBOware Pro Software (Version

134   3.7.8; Onset Computer Corporation, Pocasset, MA, USA) with the starting time set in

135   advance.

136

137   ***Behavior observation***

138   Behavior of calves was video recorded for 48 hours per testing week using one camera per

139   pen (VCC-HD2300P, Sanyo, Japan; FW2220R-Z, Dahua Technology Co., China; HDC-

140   SD99, Panasonic, Japan) and infrared radiators (RM50-AI-50, Raytec, UK; LIR-T80 and

141   LIR-T60, IR LAB Surveillance Tech, Taiwan). Based on the graphic display of downloaded

142   acceleration values, using the plot-function of the HOBOware Pro Software, lying and active

143   phases could be clearly distinguished. Therewith one activity bout of approx. 30 min was

144   selected for each calf. Activity bouts were selected in a time span between 05.00 and 20.00

145   when accelerometer recordings were available and video recordings allowed easy distinction

146   of behaviors due to daylight hours. The week and day of the selected activity bout was

147   randomized for each focal calf. Selection of activity bouts was balanced across different times

148   of the day and start time of selected bouts ranged from 06.04 until 19.23. The duration of

149   selected activity bouts was 34.3 ± 9.2 min (mean $\pm$ SD). For individual recognition calves

150   were marked across their backs and sides with animal marking sticks. Behaviors categorized

151   as locomotor play are described in Table 1. The criterion interval for halts in between running

152   events was set to 1 second based on visual assessment of a log survivorship plot. Events of

153   locomotor play behavior were continuously recorded by one person using the Mangold

154   INTERACT video analysis software (Version 16.1.5.8). Intra-observer-reliability was

155   measured from 3 randomly selected activity bouts of 41.7 ± 8.0 min each (mean $\pm$ SD)

156   assessed two times. A Wexler's ratio was calculated from the number of agreements (i.e. the

157   number of locomotor play events that were correctly scored within one second in both

158   recording sessions x 2) divided by the number of possible agreements (i.e. the total number of

159   locomotor play events scored in both sessions; e.g. used in Wathan et al. 2015). Wexler's ratio

160   was assessed for each activity bout individually, with an average agreement ratio of 0.84.

161   Continuous recording was transformed into one-zero sampling by creating sample intervals of

162   10 s and classifying them according to presence or absence of locomotor play events within

163   the interval.

164

165   *Data analysis*

166   All statistical analyses were performed in SAS 9.4. We analyzed the acceleration data

167   according to two methodologies:

168

169   *Peak acceleration method (PEAK).* We used Pearson correlations to assess the strength of

170   association between counts of peak measurements of acceleration and counts of observed

171   locomotor play events. Counts of peak accelerations were calculated for different upper and

172   lower thresholds of acceleration values in steps of 0.1 g (e.g. counts of values $\geq$ 3.2 g, 3.1 g,

173   3.0 g,… and $\leq$ -3.2 g, -3.1 g, -3.0 g,…). Pearson correlations of all 1056 combinations (32

174   thresholds of ≥ 0 g times 31 thresholds of < 0 g) of counts of peaks applying different upper

175   and lower thresholds with counts of locomotor play were calculated. Therewith, the best

176   combination of threshold values of acceleration to predict locomotor play was identified as

177   counts of peaks of $\geq + 1.6$ g and $\leq - 3.0$ g. While the distribution of data was right-skewed and

178   did not visually conform to the assumption of normality for parametric measures of

179   association, the data distribution was unimodal. Three outliers were visually detected using a

180   Cook's Distance plot, though no outlier with leverage was visually identified in the outlier

181   and leverage diagnostics (leverage and studentized residuals).

182

183   *Classifier method (CLASS).* We used quadratic discriminant analysis to predict a categorical

184   response (Kuhlenkasper and Handl, 2017), i.e. the occurrence of locomotor play in each

8

185   period (10 s fragment of observations) based on classifiers (predictor variables describing

186   acceleration values in each period (James et al., 2015)). As discriminant analysis requires two

187   sets of data, one set to train the discriminant function and one set to test its predictions, we

188   divided the recorded activity bouts in half. Therefore the accelerometer data were combined

189   to 10 s periods, resulting in 10 measurements per period. Subsequently the periods were

190   alternately allocated to a training data set or a testing data set (testing data set: n=48, mean

191   number of periods $\pm$ SD = 102.3 $\pm$ 26.9). The presence (PLAY) or absence (NOPLAY) of

192   locomotor play in each period was identified from video observation and used as the gold

193   standard. For each period the following metrics were calculated as classifiers derived from the

194   original value (OV) or change in values (CV = $x_i - x_{i-1}$) e.g. minimum, maximum, mean,

195   median, quartiles, variance, total sum; a full list is provided in Supplemental Table S1.

196   Relevant classifiers were then visually preselected from boxplots of PLAY and NOPLAY

197   from the training data set when the interquartile range of NOPLAY was low with little to no

198   overlap with PLAY and when outliers were not widely dispersed. A quadratic discriminant

199   function was then developed with classification probabilities based on the proportional

200   occurrences of how often PLAY and NOPLAY were scored in the training data set, i.e. 97%

201   of periods displaying NOPLAY and 3% of periods displaying PLAY. With the testing data set

202   the predictive abilities of the discriminant function were assessed. Discriminant functions

203   with different combinations of classifiers were tested and the combination of classifiers with

204   the highest sensitivity and specificity was selected. The relevant classifiers included in the

205   final discriminant function are displayed in Table 2. Discriminant analysis assumes a

206   Gaussian distribution from observations of each class (James et al., 2015). The present data of

207   the values of classifiers could not be assumed to be normally distributed nor could data be

208   transformed to fit the underlying assumptions of normality. We were able to circumvent this

209   issue by dividing the data set into two halves, a training data set and a testing data set.

210   Therewith the performance of the discriminant function was not contingent on the data

211   distribution and could be independently verified.

212

213   ***Comparison of PEAK and CLASS.*** In order to directly contrast the outcome of the two

214   methodologies on the basis of the same set of data, we calculated PEAK and CLASS with the

215   testing data set only (n = 48; mean duration ± SD = 17.1 ± 4.6 min). To assess the strength of

216   association between the measures of acceleration and the observed locomotor play, a Pearson

217   correlation of counts of peaks resulting from the PEAK method and counts of observed

218   locomotor play events was calculated. Likewise, a Pearson correlation of counts of PLAY

219   periods resulting from the CLASS method with counts of observed locomotor play intervals

220   from one-zero sampling was calculated. In order to assess the magnitude of disagreement and

221   facilitate the detection of trends, we produced Bland-Altman plots. The plots depict the

222   average of the acceleration measure and the observation on the x-axis and the difference

223   between the acceleration measure and the observation on the y-axis (Altman and Bland,

224   1983). Bland-Altman plots were produced for both methodologies of analysis and compared

225   visually.

226

227   **RESULTS**

228   When assessing play by continuous recording of frequencies, calves performed 5.3 events of

229   locomotor play per 30 min observation period (SD = 7.3; range = 0 - 27). The Pearson

230   correlation with counts of peaks of $\geq + 3.0$ g and $\leq - 3.0$ g from the corresponding

231   accelerometer data, as described by Luu et al. (2013), was 0.83 (P<0.01). However, we

232   attained the highest correlation with counts of locomotor play when using counts of peaks of

233     $\geq + 1.6$ g and $\leq - 3.0$ g (r_p = 0.91, P > 0.01; Figure 1). The respective scatter plot (Figure 1)

234   illustrates a strong linear relationship of both measurements, but an unequal rate of increase of

235   counts of peaks with counts of play is noticeable. The Bland-Altman plot (Figure 2) further

236   emphasizes the uneven distribution across the range of locomotor play as higher counts of

237   locomotor play events were increasingly underestimated by the peak acceleration method,

238   demonstrating that the number of play events and the number of accelerometer peaks did not

239   directly correspond to each other, i.e., they are not on the same scale. The mean deviation of

240   peak measurements from observed play events amounted to - 1.90 ± 4.42.

241   Alternatively, when recording locomotor play with one-zero sampling, calves performed play

242   in 2.7 periods per observation (SD = 3.5; range = 0 - 16). From the accelerometer data, we

243   estimated the number of play periods using the classifier method with the outcome displayed

244   as contingency table (Table 3). It follows that CLASS overestimates the number of PLAY

245   periods. CLASS achieved a precision of 0.95 (= proportion of correctly classified periods), a

246   sensitivity of 0.79 (= proportion of correctly classified true positives) and a specificity of 0.96

247   (= proportion of correctly classified true negatives). Counts of PLAY periods identified with

248   CLASS highly correlated with counts of observed PLAY periods recorded from video (r_p =

249   0.87; P < 0.01; Figure 3). The scatter plot (Figure 3) illustrates a strong linear relationship of

250   both measurements but indicates an intercept and concomitant overestimation of PLAY

251   periods by the CLASS method. The number of accelerometer-identified PLAY periods

252   surpasses the number recorded visually by 3.65 ± 2.42 periods; nonetheless the Bland-Altman

253   plot (Figure 4) shows an evenly distributed deviation of the two measurements across the

254   range of counts of PLAY periods.

255

256   **DISCUSSION**

257   With this study we aimed at providing an approach to automatically record locomotor play of

258   calves in their home-pen and for long durations using acceleration measurements. In previous

259   studies accelerometers have been validly used to record durations of lying and standing in

260   calves (Bonk et al., 2013, Swartz et al., 2016). Similarly in the current study we were able to

261   easily distinguish between lying and standing on the vertical axis, with values of lying

262 fluctuating around 0 *g* and values of standing around - 1 *g*, depending on the position of the

263 hind leg. Therefore with - 1 *g* as the center of fluctuation, measuring play with peaks of ≥ +

264 1.6 *g* and ≤ - 3.0 *g* is sensible. We reason that peaks had not reached + 3.0 *g*, as reported by

265 Luu et al. (2013), because the smaller dimensions of the home-pens in comparison with a

266 large arena did not permit calves to consistently reach accelerations of a similarly high level.

267 Thus small spaces can restrict the magnitude of movement and also fragment the occurrence

268 of play (Jensen et al. 1998). Nevertheless we cannot draw conclusions on any space allowance

269 between our home-pen and the arena of Luu et al. (2013) as this was not part of our

270 investigation. Moreover locomotor play consists of rapid motions of the hind legs for short

271 durations and is often nested within short time intervals. Therefore recordings at 1 Hz and on

272 one axis may be too infrequent to accurately capture locomotor play events in the home-pen,

273 resulting in the unequal increase and accretive underestimation of higher frequencies of play

274 events of the PEAK-method, as visualized in the Scatter plot and Bland-Altman plot.

275 Nevertheless, the high correlation of peak accelerations and observed play events elucidates a

276 strong link between the two recording methods. Thus, while the PEAK-method cannot record

277 the duration of play in absolute terms, it can produce an approximate estimation of play levels

278 and allows the comparison of relative differences between calves in standard housing

279 conditions.

280 In the CLASS method, we used the accelerometer data to simulate the one-zero observational

281 method by merging the recordings to 10 s periods, thus ensuring the use of repeated measures

282 and circumventing the need to count individual peaks above/below a certain threshold. This

283 allowed us to view acceleration values in context, integrated with the values preceding and

284 following them. We derived classifiers from combined values e.g. mean of two highest values

285 or variance to mathematically describe the 10 acceleration measures per period and highlight

286 the differences between PLAY and NOPLAY. Thereby we classified brief time spans

287 according to the presence or absence of locomotor play within these 10 seconds. The use of

12

288　original individual acceleration values e.g. the mere minimum or maximum value would have

289　resulted in a lower sensitivity to correctly identify PLAY periods. Such an approach has been

290　previously successfully implemented in accelerometer validation regarding sheep gait,

291　describing periods with relative frequencies of integers e.g. the number of high frequency

292　acceleration readings between - 4 and - 3 per period divided by all readings of the period

293　(Radeski and Ilieski, 2017). Other studies described periods using movement metrics e.g.

294　mean, variance and inverse coefficient of variation (Watanabe et al., 2008) or signal

295　magnitude area, average intensity and average entropy (Barwick et al., 2018). However, in

296　these studies acceleration was recorded at a higher rate. Recording at a higher rate would have

297　also allowed for classifying shorter periods. For example Radeski and Ilieski (2017) recorded

298　at 33 Hz and classified periods of three seconds.

299　CLASS correctly discriminated 79% of periods with an occurrence of locomotor play, but at

300　the same time overestimated play by approximately 200% (out of 304 play periods identified

301　by CLASS, 102 periods were true positives and 202 periods were false positives). Similarly

302　other accelerometer models consistently overestimated locomotor behavior e.g. Swartz et al.

303　(2016) overestimated stepping by 18% and Trénel et al. (2009) consistently overestimated

304　moving activity with a ratio of probability of correct negatives to correct positives of 7.57

305　(PV- = 0.98, PV+ = 0.13). Thus while the number of classified play periods is strongly

306　associated with counts of observed play intervals, overall the classifier method overestimates

307　locomotor play in absolute terms and produces an intercept by adding 3.7 play periods to each

308　observation. However, the Bland-Altmann plot shows a rather consistent and evenly

309　distributed deviation across the range of number of play intervals observed without indication

310　of a directed effect. Hence, while CLASS cannot accurately measure locomotor play, it can be

311　used as a proxy. After factoring in the consistent overestimation, it assesses the number of

312　play periods close to the scale of one-zero sampling and thus allows comparing absolute

313　differences between individuals. With these results we offer a feasible approach to assess

314 spontaneous locomotor play in home-pens of calves using an affordable and commercially

315 available accelerometer model for durations of many hours or perhaps even days.

316 Nevertheless these results may only be valid for the housing conditions investigated and

317 further studies are needed to validate this approach under e.g. different space allowances. A

318 prerequisite to classify periods with discriminant analysis is to use shorter subsets of behavior

319 recordings as a training data set. In the current study only active periods of animals were

320 included in the analysis. In order to apply the classifier method to the full data set it is

321 necessary to either preselect only active periods or to include lying bouts in the training data

322 set. Therewith it is feasible to train the discriminant function with the selected classifiers and

323 thereafter to apply it to the entire recordings of acceleration.

324 We must stress that our proposed approach with recording at a frequency of 1 Hz can only be

325 used as an approximate estimation of locomotor play. A higher level of accuracy could be

326 achieved by increasing the rate of recording. Measuring acceleration at the highest rate (33

327 Hz) allowed de Passillé et al. (2010) to measure the interstep interval and accurately

328 distinguish between different gait patterns. Radeski and Ilieski (2017) were able to achieve

329 high accuracy in classifying 3 s periods of walking, trotting and galloping in sheep with

330 discriminant analysis, when recorded at a rate of 33 Hz. In the current study the recording rate

331 was limited by its data storage capacity, however Le Roux et al. (2018) achieved a 469-fold

332 reduction in memory requirement when classifying lying, standing and walking on the

333 accelerometer rather than storing raw data. Thus, the proposed approach is easily applicable

334 and inexpensive with the available resources, however there are numerous options to improve

335 the accuracy of recording by availing technical advancements.

336

337 **CONCLUSION**

338 Using the peak acceleration method, the acceleration of calves' hind legs measured at a rate of

339 1 Hz can be used to obtain an approximate estimation of inter-individual differences in the

340   occurrence of locomotor play events. Quadratic discriminant analysis can replace

341   observational one-zero sampling, when based on indirect movement metrics obtained from

342   10-second-periods of raw accelerometer data. This alternative method may be more accurate

343   in quantifying the inter-individual differences in locomotor play of dairy calves in their home-

344   pens as it reveals less biased estimates across different levels of play. If the accurate

345   measurement of absolute levels of behavior is the ultimate aim of automatic recording, a

346   sensor with higher memory capacity must be found.

347

352

353   **REFERENCES**

354   Altman, D. G. and J. M. Bland. 1983. Measurement in Medicine: the Analysis of Method Comparison

355   Studies. Statistician 32:307-317.

356   Barwick, J., D. W. Lamb, R. Dobos, M. Welch, and M. Trotter. 2018. Categorising sheep activity

357   using a tri-axial accelerometer. Comput Electron Agric 145:289-297.

358   https://doi.org/10.1016/j.compag.2018.01.007

359   Bonk, S., O. Burfeind, V. S. Suthar, and W. Heuwieser. 2013. Technical note: Evaluation of data

360   loggers for measuring lying behavior in dairy calves. J. Dairy Sci. 96:3265-3271.

361   https://doi.org/10.3168/jds.2012-6003

362   de Passillé, A. M., M. B. Jensen, N. Chapinal, and J. Rushen. 2010. Technical note: Use of

363   accelerometers to describe gait patterns in dairy calves. J. Dairy Sci. 93:3287-3293.

364   https://doi.org/10.3168/jds.2009-2758

365   Fraser, D. and I. J. H. Duncan. 1998. 'Pleasures', 'pains' and animal welfare: Toward a natural history

366   of affect. Anim. Welfare 7:383-396.

367 James, G., D. Witten, T. Hastie, and R. Tibshirani. 2015. An Introduction to Statistical Learning with

368 Applications in R. Springer Science+Business Media, New York. https://doi.org/10.1007/978-1-4614-

369 7138-7

370 Jensen, M. B., L. R. Duve, and D. M. Weary. 2015. Pair housing and enhanced milk allowance

371 increase play behavior and improve performance in dairy calves. J. Dairy Sci. 98:2568-2575.

372 https://doi.org/10.3168/jds.2014-8272

373 Jensen, M. B. and R. Kyhn. 2000. Play behaviour in group-housed dairy calves, the effect of space

374 allowance. Appl. Anim. Behav. Sci. 67:35-46. https://doi.org/10.1016/S0168-1591(99)00113-6

375 Jensen, M. B., K. S. Vestergaard, and C. C. Krohn. 1998. Play behaviour in dairy calves kept in pens:

376 the effect of social contact and space allowance. Appl. Anim. Behav. Sci. 56:97-108.

377 https://doi.org/10.1016/S0168-1591(97)00106-8

378 Krachun, C., J. Rushen, and A. M. de Passillé. 2010. Play behaviour in dairy calves is reduced by

379 weaning and by a low energy intake. Appl. Anim. Behav. Sci. 122:71-76.

380 https://doi.org/10.1016/j.applanim.2009.12.002

381 Kuhlenkasper, T. and A. Handl. 2017. Diskriminanzanalyse. Pages 363-413 in Multivariate

382 Analysemethoden. Theorie und Praxis mit R. 3rd ed. Springer Spektrum, Berlin, Heidelberg.

383 https://doi.org/10.1007/978-3-662-54754-0_12

384 Le Roux, S. P., R. Wolhuter, N. Stevens, and T. Niesler. 2018. Reduced Energy and Memory

385 Requirements by On-Board Behavior Classification for Animal-Borne Sensor Applications. IEEE

386 Sens J 18:4261-4268. https://doi.org/10.1109/jsen.2018.2816965

387 Luu, J., J. F. Johnsen, A. M. d. Passillé, and J. Rushen. 2013. Which measures of acceleration best

388 estimate the duration of locomotor play by dairy calves? Appl. Anim. Behav. Sci. 148:21-27.

389 https://doi.org/10.1016/j.applanim.2013.07.004

390 Miguel-Pacheco, G. G., A. Vaughan, A. M. de Passille, and J. Rushen. 2015. Relationship between

391 locomotor play of dairy calves and their weight gains and energy intakes around weaning. Animal

392 9:1038-1044. https://doi.org/10.1017/S1751731115000063

393   Mintline, E. M., M. Stewart, A. R. Rogers, N. R. Cox, G. A. Verkerk, J. M. Stookey, J. R. Webster,

394   and C. B. Tucker. 2013. Play behavior as an indicator of animal welfare: Disbudding in dairy calves.

395   Appl. Anim. Behav. Sci. 144:22-30. https://doi.org/10.1016/j.applanim.2012.12.008

396   Overvest, M. A., R. E. Crossley, E. K. Miller-Cushon, and T. J. DeVries. 2018. Social housing

397   influences the behavior and feed intake of dairy calves during weaning. J. Dairy Sci. 101:8123-8134.

398   https://doi.org/10.3168/jds.2018-14465

399   Radeski, M. and V. Ilieski. 2017. Gait and posture discrimination in sheep using a tri-axial

400   accelerometer. Animal 11:1249-1257. https://doi.org/10.1017/s175173111600255x

401   Roland, L., V. Schweinzer, P. Kanz, G. Sattlecker, F. Kickinger, L. Lidauer, A. Berger, W. Auer, J.

402   Mayer, V. Sturm, D. Efrosinin, S. Breitenberger, M. Drillich, and M. Iwersen. 2018. Technical note:

403   Evaluation of a triaxial accelerometer for monitoring selected behaviors in dairy calves. J. Dairy Sci.

404   101:10421-10427. https://doi.org/10.3168/jds.2018-14720

405   Rushen, J. and A. M. de Passillé. 2012. Automated measurement of acceleration can detect effects of

406   age, dehorning and weaning on locomotor play of calves. Appl. Anim. Behav. Sci. 139:169-174.

407   https://doi.org/10.1016/j.applanim.2012.04.011

408   SAS Institute. 2012. User's Guide: Statistics, Version 9.4 Edition. SAS Institute, Inc., Cary, NC.

409   Sutherland, M. A., J. Larive, V. Cave, and G. Zobel. 2018a. Behavioural and physiological responses

410   to clove oil injected under the horn bud of calves. Appl. Anim. Behav. Sci. 204:29-36.

411   https://doi.org/10.1016/j.applanim.2018.03.004

412   Sutherland, M. A., G. L. Lowe, F. J. Huddart, J. R. Waas, and M. Stewart. 2018b. Measurement of

413   dairy calf behavior prior to onset of clinical disease and in response to disbudding using automated

414   calf feeders and accelerometers. J. Dairy Sci. 101:8208-8216. https://doi.org/10.3168/jds.2017-14207

415   Swartz, T. H., A. N. Findlay, and C. S. Petersson-Wolfe. 2017. Short communication: Automated

416   detection of behavioral changes from respiratory disease in pre-weaned calves. J. Dairy Sci. 100:9273-

417   9278. https://doi.org/10.3168/jds.2016-12280

418   Swartz, T. H., M. L. McGilliard, and C. S. Petersson-Wolfe. 2016. Technical note: The use of an

419   accelerometer for measuring step activity and lying behaviors in dairy calves. J. Dairy Sci. 99:9109-

420   9113. https://doi.org/10.3168/jds.2016-11297

17

421 Trénel, P., M. B. Jensen, E. L. Decker, and F. Skjøth. 2009. Technical note: Quantifying and

422 characterizing behavior in dairy calves using the IceTag automatic recording device. J. Dairy Sci.

423 92:3397-3401. https://doi.org/10.3168/jds.2009-2040

424 Valníčková, B., I. Stěhulová, R. Šárová, and M. Špinka. 2015. The effect of age at separation from the

425 dam and presence of social companions on play behavior and weight gain in dairy calves. J. Dairy Sci.

426 98:5545-5556. https://doi.org/10.3168/jds.2014-9109

427 Watanabe, N., S. Sakanoue, K. Kawamura, and T. Kozakai. 2008. Development of an automatic

428 classification system for eating, ruminating and resting behavior of cattle using an accelerometer.

429 Grassl. Sci. 54:231-237. https://doi.org/10.1111/j.1744-697X.2008.00126.x

430 Wathan, J., A. M. Burrows, B. M. Waller, and K. McComb. 2015. EquiFACS: The Equine Facial

431 Action Coding System. PLoS ONE 10:e01317318. https://doi.org/10.1371/journal.pone.0137818

432   **Table 1.** Ethogram of locomotor play derived from Jensen et al. (1998) and Jensen and Kyhn
433   (2000)

Type of locomotor play	Description
Running	Rapid gait with phase of suspension in the air. Minimum of 2 consecutive suspension movements in a forward direction. Running is counted as a new event after 1 second break.
Turning	The two forelegs are lifted from the ground and stretched forward, as the forepart of the body is elevated and turned to one side. Movement upwards and sideward for a minimum of 90 degrees. Occurrence is scored during running bouts.
Bucking/Buck-kicking	Simultaneous lifting of hind legs, claws are raised to a level as high as, or higher than tarsal joints in a standing position. One or both hind legs may be kicked in a posterior or lateral direction. Occurrence is scored during running bouts.

434

435 **Table 2.** Descriptions and equations of the classifiers included in the final discriminant
436 function. Means ± standard deviation of the classifiers are shown for the periods of the testing
437 data set identified as PLAY or NOPLAY from video. OV = original values, CV = change in
438 values, PLAY = period with presence of locomotor play, NOPLAY = period with absence of
439 locomotor play

| Classifier	Equation	NOPLAY	PLAY
OV: Mean of two highest acceleration measurements	$\dfrac{\max(x) + \ \max2(x)}{2}$	-0.89 ± 0.21	0.04 ± 0.99
OV: Mean of two lowest acceleration measurements	$\dfrac{\min(x) + \ \min2(x)}{2}$	-1.06 ± 0.20	-1.85 ± 0.70
OV: Variance	$\dfrac{\sum(x - \mu)^2}{10}$	0.03 ± 0.10	0.74 ± 0.80
CV: Maximum of absolute value of change in acceleration measurements	$\max(\|\Delta x\|)$	0.26 ± 0.48	2.41 ± 1.45
CV: Mean of change in acceleration measurements	$\dfrac{1}{10}\sum \Delta x_i$	-0.00 ± 0.03	-0.01 ± 0.12
CV: Total sum of absolute values of change in acceleration measurements	$\sum \|\Delta x_i\|$	0.66 ± 1.15	6.96 ± 4.78

440

441   **Table 3.** Contingency table with number of periods identified with the classifier method
442   (CLASS) as PLAY (event of locomotor play occurring in this period) and NOPLAY (no
443   event of locomotor play occurring in this period)

Observed behavior	Predicted behavior		
(Video)	**(CLASS)**		
	NO PLAY	**PLAY**	**Sum**
NOPLAY	4591	202	4793
PLAY	27	102	129
Sum	4618	304	4922

444

445 **Figure 1.** Relationship between counts of peak accelerations (≥ 1.6 *g* and ≤ 3.0 *g*; PEAK) and

446 counts of locomotor play events observed from video (n = 48 calves). Jitter function was used

447 in the graph to make multiple identical values more visible
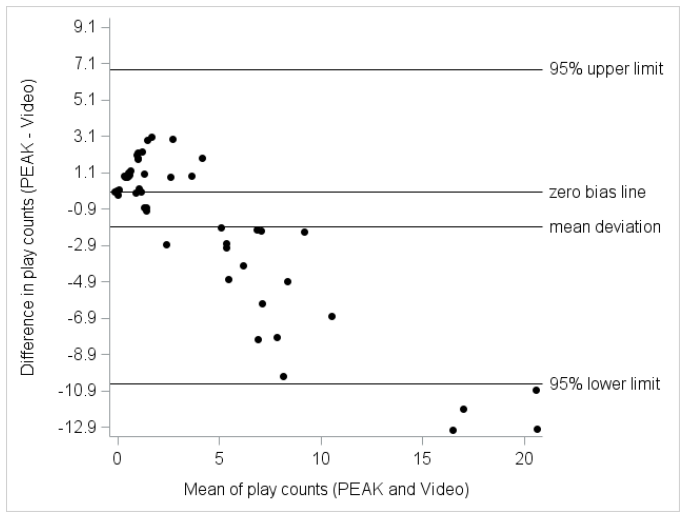
448   Größbacher Figure 1
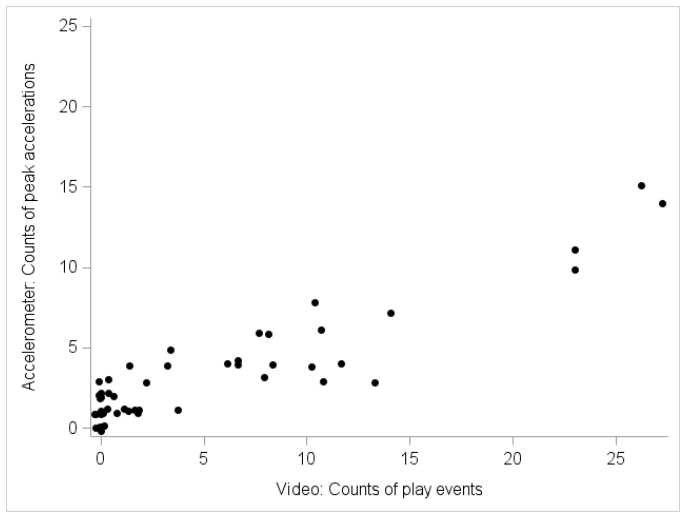
449

450 Figure 2. Bland-Altman Plot of the difference in the assessment of locomotor play recorded

451 with accelerometers and video observation compared with the mean of both assessments

452 (PEAK = Peak acceleration method; n = 48 calves). Confidence intervals were estimated at

453 6.8 at the 95% upper limit and - 10.6 at the 95% lower limit. Jitter function was used in the

454 graph to make multiple identical values more visible

455   Größbacher Figure 2

456

457   Figure 3. Relationship between counts of periods with locomotor play identified with

458   accelerometers (CLASS = classifier method) and counts of sample intervals with locomotor

459   play observed from video (n = 48 calves). Jitter function was used in the graph to make

460   multiple identical values more visible

461   Größbacher Figure 3
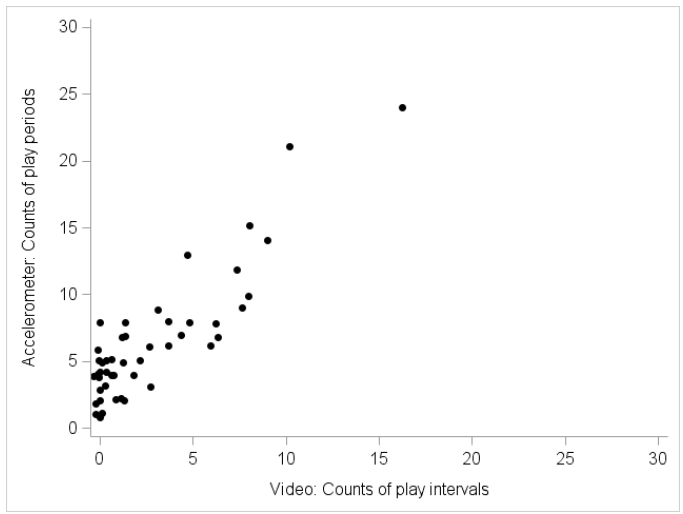
462

463   Figure 4. Bland-Altman Plot of the difference in the assessment of locomotor play periods

464   identified with accelerometers and locomotor play intervals from video observation compared

465   with the mean of both assessments (CLASS = Classifier method; n = 48 calves). Confidence

466   intervals were estimated at 8.4 at the 95% upper limit and - 1.1 at the 95% lower limit. Jitter

467   function was used in the graph to make multiple identical values more visible

468   Größbacher Figure 4
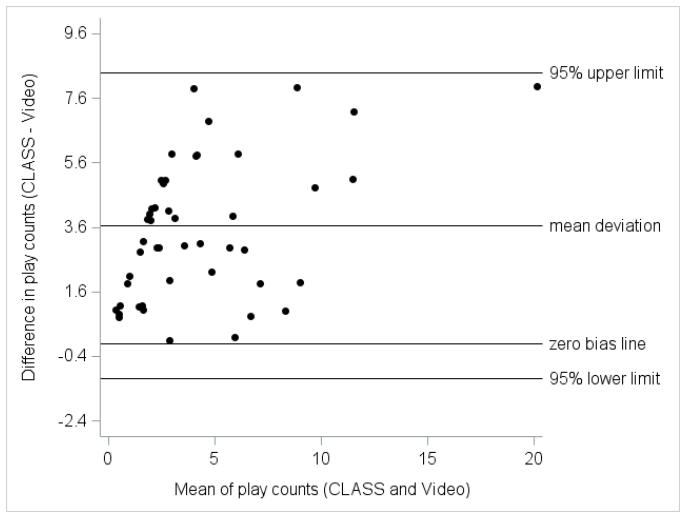
469

470 **Supplemental Table S1.** Descriptions and equations of all potential classifiers not included in the final discriminant function. Means ± standard
471 deviation of the classifiers are shown for the periods of the testing data set identified as PLAY or NOPLAY from video. OV = original values, CV =
472 change in values, PLAY = period with presence of locomotor play, NOPLAY = period with absence of locomotor play. Potential classifiers that
473 were preselected and tested but not included in the final discriminant function are marked with 'Yes'

Classifier	Equation	NOPLAY	PLAY	Preselection
OV: Highest acceleration measurement	$\max(x)$	-0.84 ± 0.33	0.44 ± 1.30	Yes
OV: Second highest acceleration measurement	$\max2(x)$	-0.94 ± 0.12	-0.37 ± 0.84	Yes
OV: Mean of two highest acceleration measurements	$\dfrac{\max(x) + \max2(x)}{2}$	-0.89 ± 0.21	0.04 ± 0.99	Yes
OV: Third quartile of acceleration measurements	$x_{Q0.75}$	-0.96 ± 0.08	-0.64 ± 0.50	No
OV: Mean of acceleration measurements	$\dfrac{1}{10}\sum x_i$	-0.98 ± 0.07	-0.93 ± 0.29	No
OV: First quartile of acceleration measurements	$x_{Q0.25}$	-1.00 ± 0.07	-1.24 ± 0.41	No
OV: Mean of two lowest acceleration measurements	$\dfrac{\min(x) + \min2(x)}{2}$	-1.06 ± 0.20	-1.85 ± 0.70	Yes
OV: Second lowest acceleration measurement	$\min2(x)$	-1.02 ± 0.10	-1.52 ± 0.69	Yes
OV: Lowest acceleration measurement	$\min(x)$	-1.11 ± 0.33	-2.19 ± 0.86	Yes
OV: Variance	$\dfrac{\sum(x - \mu)^2}{10}$	0.03 ± 0.10	0.74 ± 0.80	Yes
OV: Total sum of absolute values of acceleration measurements	$\sum |x_i|$	9.84 ± 0.63	11.32 ± 2.20	Yes

CV: Highest change in acceleration measurements	$\max(\Delta x)$	0.22 ± 0.43	2.01 ± 1.34	No
CV: Second highest change in acceleration measurements	$\max 2(\Delta x)$	0.07 ± 0.14	0.86 ± 0.81	No
CV: Third quartile of change in acceleration measurements	$\Delta x_{Q0.75}$	0.04 ± 0.07	0.50 ± 0.55	No
CV: Mean of change in acceleration measurements	$\frac{1}{10}\sum \Delta x_i$	-0.00 ± 0.03	-0.01 ± 0.12	Yes
CV: First quartile of change in acceleration measurements	$\Delta x_{Q0.25}$	-0.04 ± 0.08	-0.49 ± 0.53	No
CV: Second lowest change in acceleration measurement	$\min 2(\Delta x)$	-0.07 ± 0.15	-0.88 ± 0.82	Yes
CV: Minimum of change in acceleration measurement	$\min(\Delta x)$	-0.23 ± 0.44	-2.07 ± 1.33	Yes
CV: Variance of change in acceleration measurements	$\frac{\sum(\Delta x - \mu)^2}{10}$	0.05 ± 0.21	1.56 ± 1.75	Yes
CV: Maximum of absolute value of change in acceleration measurements	$\max(|\Delta x|)$	0.26 ± 0.48	2.41 ± 1.45	Yes
CV: Total sum of absolute values of change in acceleration measurements	$\sum |\Delta x_i|$	0.66 ± 1.15	6.96 ± 4.78	Yes

474