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Validity of the Microsoft Kinect sensor for assessment of normal walking patterns in pigs

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Abstract

Lameness is a major problem affecting pigs and its detection is subjective and challenging on large farms. Previous research using advanced kinematic gait analysis (Vicon) has established that abnormality in the movement of the axial body during walking is associated with lameness in pigs. Vertical excursion of head and neck was most affected, and increased by +15-58 mm in lame compared to normal pigs. However, simpler technology is required to automate lameness detection. In this experiment, walking trajectories of mid-line dorsal body regions of seven normal pigs varying in size were filmed repeatedly within day and between days on two or three occasions within one week. Trajectories were tracked simultaneously using both a 6-camera Vicon system, set up in an array flanking a walkway and detecting reflective markers, and a Microsoft Kinect motion sensor, mounted above the walkway. Four pigs wore a large (height 30 mm) reflective marker in the mid-neck region, detectable by both Kinect and Vicon during two days. Two custom-written computer algorithms using the

Kinect developer toolkit were produced to (1) follow the large neck marker and (2) enable marker-free tracking of other body regions. Reversed depth data from the Kinect and vertical position data from the Vicon were compared to assess agreement. There was a high positive correlation between the Kinect and Vicon trajectory means of the large neck marker ($P<0.001$; $r=0.994$). The Kinect neck marker trajectory mean was generally higher than the Vicon trajectory mean, therefore a positive difference of 4 mm ± 4.2 mm (LoA) was noted. There was no pig effect on trajectory differences, but a pig effect on trajectory mean which reflected the size of the pig ($P<0.001$). The mean±SD of continuous differences between corresponding Kinect and Vicon neck marker trajectories amounted to 5 ± 1.5 mm. The mean of vertical displacement amplitudes was 5 ± 2.8 mm, and hence the minimum difference of +15 mm in lame animals should be detectable in more than 99% of cases. Trajectories of neck, back and pelvis generated by a marker-free Kinect application showed less similarity to corresponding Vicon trajectories. It was concluded that the Kinect device could distinguish sound from lame pigs by tracking neck region elevation during walking; however, markerfree tracking algorithms need refinement and further development to become sensitive and reliable.

Keywords: Kinect; Lameness; Pigs; Automated detection; Motion capture

1. Introduction

Lameness is a major problem afflicting 10-20% of the pigs within the modern pig industry (Kilbride et al., 2009). To date, lameness detection in livestock is largely subjective, potentially delayed and insensitive to early or mild problems (Dalmau et al., 2010). Subjective lameness scoring often has a low to moderate repeatability between observers, and estimates of true lameness prevalence on a farm require the examination of all animals, which makes the monitoring of animal mobility a challenging and expensive task (Mullan et al., 2009).

There are various lameness indicators in different farm animal species. Arching of the back is a common indicator of lameness in cows (Poursaberi et al., 2010; Sprecher et al., 1997), head bobbing is characteristic in sheep and horses (Kaler et al., 2009; Buchner et al., 1996) and in pigs (Stavrakakis et al., 2013; Mustonen et al., 2011). Other qualitative lameness indicators which have been used by observers of cows include 'tenderness', 'irregular gait' and 'increased abduction' (van Nuffel et al., 2009). Generally, most lameness scoring systems across species include concepts such as “changes in weightbearing of affected limb(s)”, “irregular or assymmetric gait” and “discomfort and reluctance in moving”. Visual mobility scoring requires a high level of training and assessment of individual animals. However, this is often difficult to implement on farms with multiple animals in a pen and other factors, such as dirty floors, potentially influencing the subjective outcome (Mullan et al., 2009).

In an attempt to achieve objectivity and to automate lameness detection, various researchers have recently used biomechanical and computer vision techniques to assess lameness in a range of species including horses (Pfau et al., 2007), cattle (Viazzi et al., 2014a; van Hertem et al., 2013) and pigs (Meijer et al., 2014; Pluym et al., 2013). Temporal gait variables (stance times), measures of asymmetry between left and right limbs and the arching of the back are the most widely used gait variables for automated lameness detection in cows (Viazzi et al., 2014a; van Nuffel et al., 2009). However, there are differences between species in gait alteration and compensation strategies and also in farming routines, therefore suitable species-specific gait variables and detection algorithms need to be identified and developed (Stavrakakis et al., 2015; Neveux et al., 2006). Using a specialised marker-based Vicon system for kinematic gait analysis, abnormality in the movement of axial body regions during walking has been associated with lameness in pigs. Stavrakakis et al., (2015; 2013) reported that vertical excursion of the head and neck was most affected in lame pigs and increased by +15-58 mm compared to normal pigs.

Extensive attempts are now being made within the field of clinical biomechanics to utilise the Microsoft Kinect sensor as a cheaper alternative to conventional expensive and laborious gait analysis technologies, such as the Vicon system (Sandau et al., 2014). Good agreement between the Kinect and specialised motion analysis systems has already been established for some clinical purposes, such as assessment of postural control, functional activity and spatiotemporal gait assessment in humans (Bonnechere et al., 2014; Clark et al., 2013). Kinect studies of gait assessment in humans currently use the full skeletal tracking ability of the Kinect (Seer et al., 2014), whereas this study used only the depth sensor since the skeletal tracking was not designed to work with quadrupeds. If developed further, however, the Kinect sensor could provide a new, cheap and portable movement monitoring device for quadrupeds and may allow early and consistent identification of lame pigs. Furthermore, continuous monitoring could enable assessment of changes in pen- and farm based lameness prevalence over time, for example when changes occur in management, genetics, nutrition and behaviour of pigs (Viazzi et al., 2014b).

The aim of this study was to evaluate the validity of the Microsoft Kinect sensor for assessment of normal walking in pigs, by comparing its depth data measurements with the "gold standard" provided by the Vicon system. Pigs of varied size were used to identify potential sensitivity of the Kinect sensor to differences in depth, i.e distance from the body surface to the sensor. It was hypothesised that the Kinect depth data could reproduce Vicon-derived trajectories both in terms of absolute and relative values, and that pigs could be correctly identified as having a normal walking pattern based on relevant Kinect-derived measurements. Correlation of both single values derived from Kinect and Vicon trajectories and continuous differences along trajectories were assessed. A reference marker tracked by both systems on the neck gave the ground truth estimate for the difference between the Kinect and Vicon; a markerfree tracking within the Kinect depth data was performed to evaluate the potential "unaided" performance of the sensor.

2. Materials and Methods

2.1.1 Experimental design and data collection

All procedures on animals were in accordance with institutional and UK animal welfare regulations (http://www.ncl.ac.uk/research/ethics/animal/animalpolicy.htm). From the commercially-run pig unit at Cockle Park, Newcastle University, seven clinically healthy pigs (Hermitage Genetics, Kilkenny, Ireland) were randomly selected at a mean liveweight of 52 kg (SD 9.5, range 39-63kg) and housed in a partly-slatted concrete pen (9 m^2) in a controlled environment building. One week of habituation to close human contact and short isolation from pen mates followed.

Subsequently, over a period of seven days, data were collected on liveweight and selected gait parameters on two (N=3 pigs) or three (N=4 pigs) separate days. Not all seven pigs were cooperative on all three days or their data were not usable due to marker occlusion or very irregular movement. Motion capture took place in an adjacent building, a modified finisher pig building which had been adapted to provide a waiting area, a handling area and a motion capture arena. Hemispherical, reflective markers (19Lx19Wx10H mm; The Vibration Solution, Burlington) were attached at the central nasal bone, the mid-neck proximal to shoulders (frontal to the shoulder widening), the posterior mid-thorax (back), anterior mid-pelvis (narrowest width between abdomen and pelvis) and tail base of one pig at a time (Figure 1, B), using double-sided, adhesive tape (Supa Brands, Worsley, Manchester). Next, the pig was moved into the motion capture area, where it proceeded to walk along a concrete walkway measuring 3.5 m long and 2.0 m wide. Movement was captured simultaneously by the Vicon 3D optoelectronic motion analysis system and the Kinect motion sensor.

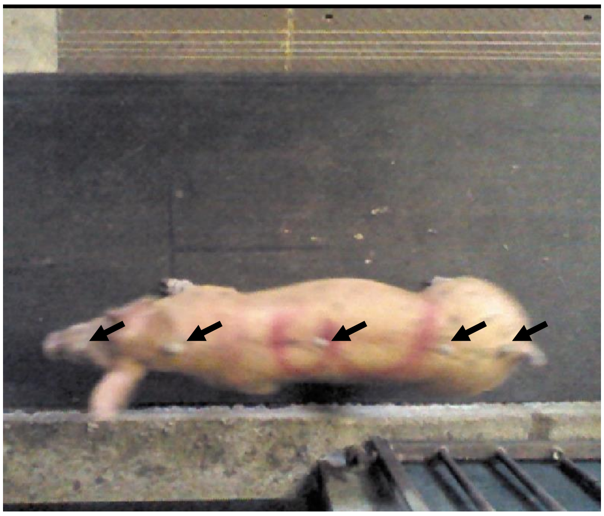
The Vicon system (Vicon T20, Oxford, UK) included six infrared cameras set up in an array to one side of the walkway and connected to a PC featuring Nexus software (v1.7.1, Vicon, Oxford, UK). Frames were sampled at 125 Hz and subsequently interpolated to match the sampling rate of the Kinect. The Kinect motion sensor (v1, Kinect for Windows, Microsoft, USA) was mounted 1.8 m above the walkway (Figure 1, A). Filming was triggered manually when pigs approached the field of view of the Kinect camera. Cooperative pigs followed a human guide at a regular and continuous walking pace along the walkway.

Since, during the process of filming, it transpired that the hemispherical markers were too flat for extraction by the Kinect sensor, the marker on the neck was replaced by a larger spherical, reflective marker (25x25x30 mm) on the second and third days for four out of the seven pigs. This large marker served as a reference marker for the true difference between Kinect and Vicon, since it could be tracked by both motion capture systems. The remaining three pigs were fitted with only hemispherical markers for collection of Vicon data and constituted the dataset for marker-free Kinect tracking.

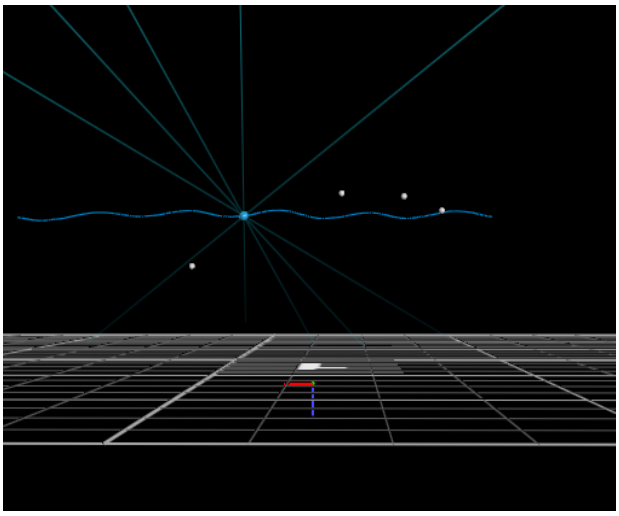
Figure 1 A-D:

A)

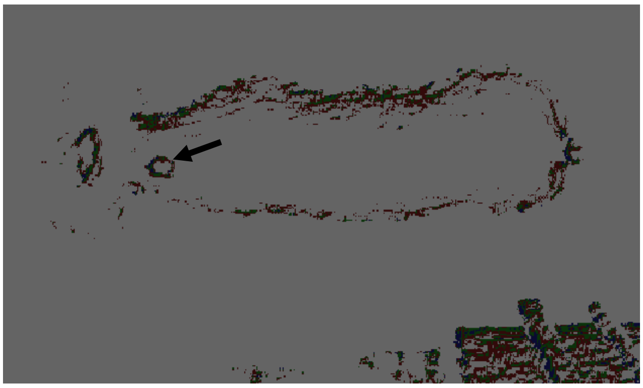
Gait lab set-up showing the Vicon cameras with infrared strobe around each lens, and the Kinect camera mounted above the walkway (arrow).



B) Pig on walkway with five reflective Vicon markers (arrows) visible on the Kinect RGB camera.



C) Reflective markers visible on the Vicon Nexus software motion capture screen. In this image the trajectory of the neck marker is displayed.



D) The 30mm neck marker (arrow) extracted by a custom-written Kinect algorithm.

2.1.2 Data processing and analysis

Two custom-written computer algorithms using the Kinect developer toolkit were produced. Kinect algorithm (1) identified and followed the large neck marker, placed on four of the pigs on two occasions, by finding regional points along the pig spine with the least distance to the sensor (referred to as depth). This was achieved by a programme which identified the pig outline, derived a band area along the longitudinal axis of the pig and compared the least distant values within the band on a frame-by-frame and frame-aligned region-by-region basis. Kinect algorithm (2) enabled a marker-free tracking of neck, back and pelvic sampling points, approximating the position of Vicon reflective markers on those three pigs without the large marker. Sampling points of nasal bone and tail base were discontinued due to inconsistencies of head and tail movement and therefore inconsistent tracking within the Kinect depth data.

Kinect sampling point depth data generated by both algorithms were converted into distance-from-floor for comparison with Vicon's vertical position data. To account for the fact that the floor of the walkway was not completely even, two different approaches were taken to adjust the depth data. Three empty frames at the beginning of a film selected immediately before entry of a pig onto the screen were used to generate a floor distance-to-sensor pixel map, so that the coordinates of pig body sampling points could subsequently be subtracted from the corresponding floor positions (dynamic floor inverse). A second reversion technique assumed a constant floor distance value for the generation of a Kinect-independent inverse of the sampling point data (constant floor inverse). The latter method enabled assessment of the true differences between both systems after normalising each value by subtracting the mean of the entire trajectory, but this method was not suitable for comparing absolute values. For the marker-free Kinect assessment, the second technique was also used, since only relative measures were compared.

Vicon marker trajectory data were collected from Nexus software and imported into Matlab (R2010b, Mathworks©, Natick, USA) for resampling at 30 Hz and corresponding Vicon and Kinect video footages were identified. Vertical excursions (amplitudes) of Kinect and Vicon trajectories were calculated as the difference between local extremes on curves and averaged. Overall, 3-5 films per pig and per capture day were processed.

After checking for normality of the data, the correlation between Kinect and Vicon trajectory means and effect of pig and capture date on trajectory means and differences were assessed using Minitab statistical software (v16, Minitab Inc., State College, USA).

3. Results

3.1.1 Large neck marker dataset (N = 4 pigs)

Differences between absolute Kinect and Vicon trajectories (dynamic floor inverse). The mean ± SD of continuous differences between corresponding absolute Kinect and Vicon neck marker trajectories amounted to 8 ± 1.1 mm. A high positive correlation between the Kinect and Vicon trajectory means of the large neck marker ($P<0.001$; $r=0.994$) was found. This relationship became stronger when observations within pig were averaged by day or over the entire data collection (Figure 2 A-C). Average neck marker height was greater in all Kinect-derived observations compared to the Vicon data and this positive difference was 4 ± 4.2 mm (Limits of Agreement, LoA; Figure 3). Pig effect on neck marker trajectory mean was significant ($P<0.001$), reflecting the size of the pig. Pig height, based on large neck marker trajectory means obtained by Vicon, ranged from 540-580 mm.

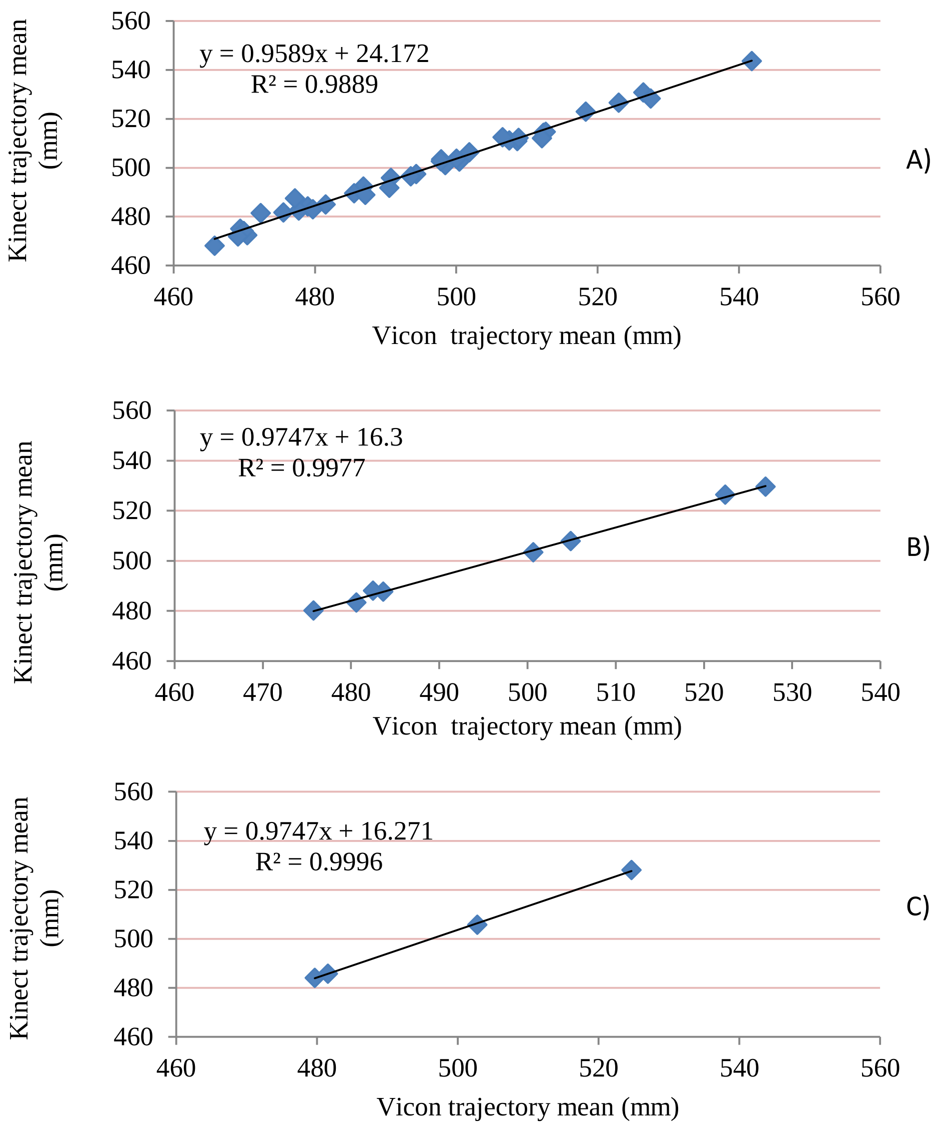


Figure 2 A-C: Correlation of Kinect and Vicon neck marker vertical position showing means from 4 pigs x 2 days with a total of 40 observations (a), pig mean within day (b) and total pig mean (c).

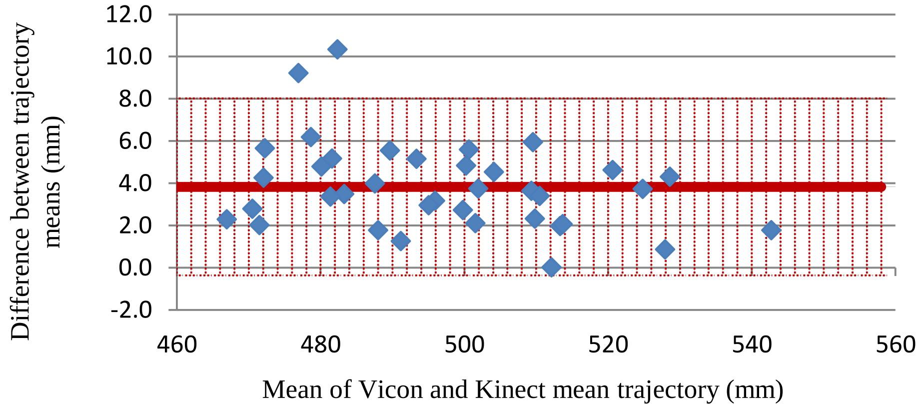


Figure 3: Limits of agreement between Kinect and Vicon neck marker vertical position trajectory means. Red line is at 3.8 mm mean difference ± 4.2 mm, representing the limits of agreement as SD (2.1 mm) x 2.

Differences between normalised Kinect and Vicon trajectories and vertical amplitudes (constant floor inverse). The mean ± SD of continuous differences between corresponding Kinect and Vicon neck marker trajectories amounted to 5 ± 1.5 mm. Similarly, the mean of vertical displacement amplitudes was 5 ± 2.8 mm, suggesting that differences were not exaggerated around trajectory extremes. There was no effect of pig on the differences between Vicon and Kinect trajectories, but there was a day effect (P=0.048). Mean difference on day 3 (5.8 mm) was higher compared to day 2 (4.7 mm). Absolute values (mean ± SD) of the average vertical amplitude of the neck marker trajectories were 16 ± 7.0 mm and 14 ± 5 mm for the Vicon and Kinect measurement, respectively, which correspond to neck elevation values observed in normal pigs. Corresponding Vicon and Kinect neck marker trajectories of three pigs, performing a range of head movements are presented in Figure 4. Pig A shows the typical regular head bobbing at a quicker walking speed, whereas Pig B lifted its head and Pig C dipped its head whilst walking past the cameras. Corresponding Vicon and Kinect neck marker trajectories of one pig, with two different floor corrections methods applied, are presented in Figure 5.

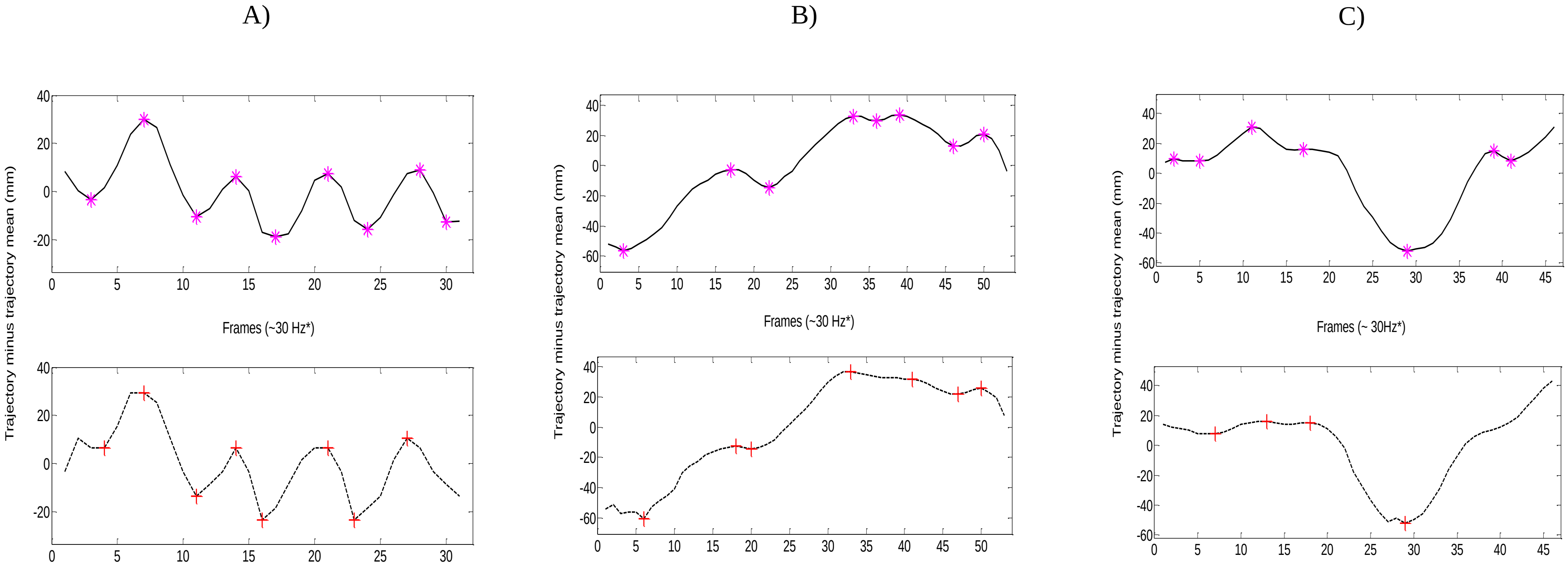


Figure 4 A-C: Neck marker trajectory of three pigs (A, B, C) tracked by Vicon (continuous) and Kinect (dashed). Local maxima and minima are identified on each trajectory. *The Kinect sampling rate may vary depending on the instantaneous processing capacity

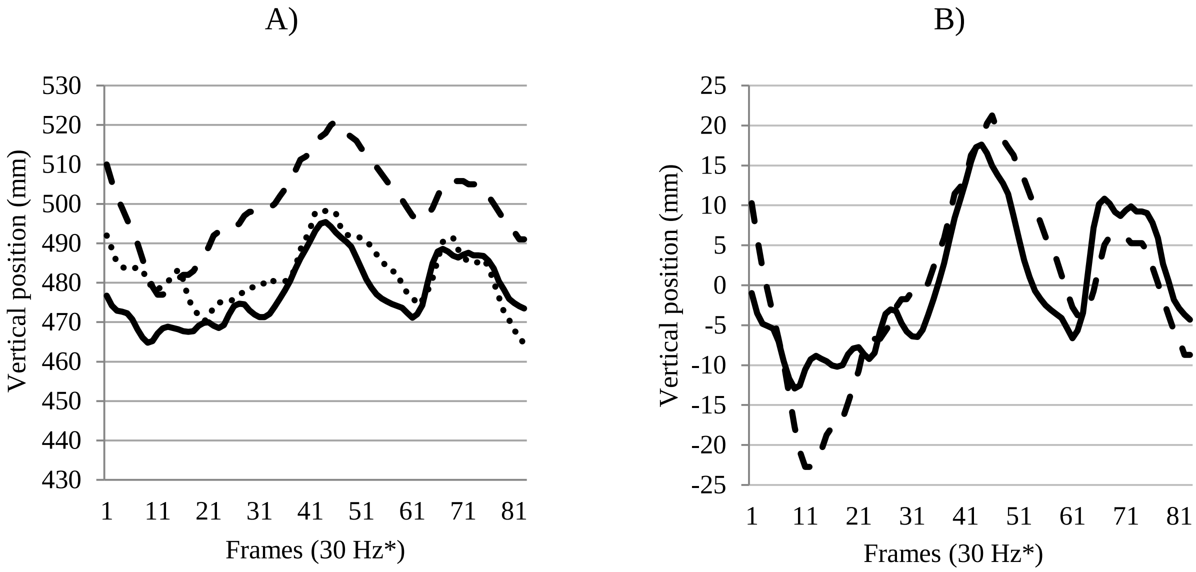


Figure 5 A-B: (A) Neck marker trajectory of one pig tracked by Vicon (continuous), Kinect, assuming a constant floor (dashed), and Kinect with a dynamic floor correction (dotted). B) shows the previous Vicon (continuous) and Kinect (dashed), assuming a constant floor, trajectories normalised to the trajectory mean for the assessment of absolute differences along the entire trajectories. * The Kinect sampling rate may vary depending on the instantaneous processing

3.1.2 Marker-free Kinect tracking method of neck, back and pelvic region (N = 3 pigs)

Trajectories of neck, back and pelvis generated by a marker-free Kinect application generally showed less similarity to the corresponding Vicon trajectories. This was mainly reflected in a greater mean ± SD of the continuous differences between corresponding Kinect and Vicon trajectories, specifically 11 ± 2.2 mm. Mean differences between vertical amplitudes of neck, back and pelvic region trajectories were 6 ± 5.9 mm; 5 ± 3.7 mm and 4 ± 3.6 mm, respectively. Absolute values (mean ± SD) of the vertical amplitudes of neck trajectories were 19 ± 7.6 mm and 18 ± 8 mm for Vicon and Kinect measurements, respectively. Back vertical position amplitudes were 15 ± 10.7 mm and 18 ± 13 and pelvic amplitudes were 16 ± 10.6 and 16 ± 8.7 according to Vicon and Kinect measurements, respectively.

4. Discussion

This study evaluated the validity of the Microsoft Kinect sensor for the identification of normal walking patterns in pigs, by comparing Kinect depth data measurements to data derived from the "gold standard" Vicon motion analysis system. It was hypothesised that the Kinect depth data could reproduce Vicon-derived trajectories in terms of both absolute and relative values and thus that pigs could be correctly identified as having a normal walking pattern based on relevant Kinect-derived measurements. A reference marker on the neck tracked by both motion capture systems gave the ground truth estimate for differences in marker position measured by the Kinect and Vicon systems, whilst marker-free tracking within the Kinect depth data was undertaken to evaluate the potential "unaided" performance of the sensor. Since this was a proof-of-concept study, the number of animals used was relatively low, but the replication of data collection was nevertheless sufficient to confirm reproducibility of the technology.

In previous reports by Stavrakakis et al. (2015; 2013), lame pigs have been shown to have a characteristic head bob arising from altered head and neck movement, particularly a rise in the vertical displacement amplitudes of the head and neck during walking. This movement alteration was regarded as one of the most suitable gait parameters to be incorporated into automated detection of lameness in pigs. Other gait parameters relating to hoof placements in space and the timing of these, particularly asymmetries in temporospatial gait, were also strongly associated with lameness in groups of pigs (Stavrakakis et al., 2015). Nonetheless, these gait parameters are likely to be more difficult to exploit and integrate within a motion analysis system suitable for pig farms, because of the necessary sensor proximity to legs. In these previous studies, all data were collected by a Vicon motion capture system which enabled an accurate and steady tracking of both head and neck regions by means of reflective markers. However, using the Kinect in the present study, sampling points of nasal bone and tail base had to be discontinued due to inconsistencies of head and tail movement and therefore inconsistent tracking within the Kinect depth data. Additionally, the Kinect sensor was mounted in a bird's eye-view perspective above the walkway, since this position was considered to be the most suitable perspective for an on-farm mobility monitoring device. A large marker on the nasal bone, therefore, would not have provided a large difference to surrounding surfaces within the depth data of the Kinect, whose x-and y-planes were almost parallel to the frontal plane of the pig walking underneath. Consequently, when using the Kinect sensor filming from a bird's eye perspective, neck elevation was considered to be the best proxy measure for the characteristic lameness-related head bob.

In this study, tracking both the absolute depth and the relative depth trajectory of an object were of interest to test the general performance of the Kinect sensor in a farm environment. However, only the relative measures are subsequently required for the detection of lameness. Therefore, two techniques were applied to calculate distance-from-floor for comparisons between Vicon and Kinect data and thus enable assessment of absolute and relative differences. The technique which used the specific floor distance corresponding to the pixel(s) in which the neck marker was identified was expected to lead to greater differences between the two motion capture systems. Firstly, since the Kinect data is known to contain an uncertainty of up to 10 mm (Koshelham and Elberkink, 2012), then two measures based on Kinect data will theoretically contain twice the inherent Kinect uncertainty. Secondly, the walkway on which the pigs were walking had a minor inclination of approximately 5-10mm. Hence, using the floor distance to correct the neck marker distance from the sensor levelled the marker trajectory. No such correction was performed using the Vicon trajectories and hence differences between both systems became greater. The finding that absolute Kinect-derived trajectory heights were overestimated compared with Vicon is not surprising if taken into account that Vicon tracks the centroid of a marker, whereas the Kinect algorithm identified the nearest pixel(s) of the large marker. However, another possible explanation is that within the recommended tracking range for the Kinect, namely 0.8 - 4 m - a range which was never exceeded in this study, accuracy of the Kinect decreases with increasing distance of an object from the sensor (Koshelham and Elberkink, 2012). This could be an additional error introduced by the dynamic floor correction. The technique which assumed a constant floor height generated data which corresponded directly to the Vicon data, since Vicon data also assumed a level floor. Consequentially, comparing the results of the two techniques, levelling the marker trajectory with the dynamic floor inverse generated an additional mean error of at least 3 mm.

Due to differences in pig size, pig effect on absolute trajectory means was expected to be significant. However, there was no pig effect on differences between trajectories, suggesting that the same sensor mounting height could be recommended over walkways or pens containing pigs at different ages or sizes. Moreover, the absence of a pig effect on differences between Kinect and Vicon systems encourages the conclusion that greater within-pig neck elevation due to lameness should be detectable by the Kinect. Interestingly, there was a day effect on differences between trajectories measured by the two systems, with results between two days deteriorating by 1.1 mm on average. Pigs generally became more habituated and cooperative with the process of motion capture and hence it might have been expected that differences between the two sensors would have reduced over time due to more regular movements by the pigs. Also, the equipment was not changed or handled differently and therefore an inferior performance of the Kinect would not be expected for reasons related to electronics. However, although this was not systematically quantified, the lighting conditions in the experimental building may have varied between the two days due to the prevailing weather conditions outside the building. The Kinect sensor is known to be influenced by lighting conditions (Koshelham and Elberkink, 2012; Hernandez-Lopez et al., 2012), which can decrease accuracy of the device's output. Thus the recently released Kinect version (v2) has been improved to be less sensitive to variations in lighting (Breuer et al., 2014; Smisek et al., 2013). Future studies aiming to develop an on-farm automated lameness system based on the Kinect sensor should use the improved version to test whether differences compared to reliable systems, such as the Vicon, can be minimised. Furthermore, whilst in this study the Kinect and Vicon systems were manually synchronised, improvements in synchronisation between the two systems could be made to minimise differences even further. Finally, direct comparisons of normal and lame pigs should be made to confirm that normal and abnormal trajectories can be detected by the Kinect sensor independently.

Overall, as a proof-of-concept study, the presented results have shown that the Kinect is a promising alternative device for tracking neck elevation in walking pigs, and even the marker-free tracking was surprisingly good despite imperfections in the methodology.

However, tracking algorithms need improvement to accommodate for pigs walking at angles to the direction of movement and adjustments should also be made to the bending movements of body parts during walking with respect to the longitudinal body axis. Equally, for a reliable extraction of geometric points within body parts, machine learning classifiers should be trained to identify local image features corresponding to body parts of pigs, similar to the skeletal tracking tool used for humans (Henrickson et al., 2014).

Conclusion

Vertical position trajectories of a dorsal neck marker on pigs produced by the Kinect motion sensor and the "gold standard" Vicon system showed a high level of agreement. It is therefore concluded that the Kinect sensor is suitable to track characteristics of sound walking in pigs based on neck elevation and shows considerable potential to track abnormalities in walking patterns caused by lameness. Thus fully automated and marker-free tracking of relevant dorsal mid-line point trajectories for a relatively modest cost appears to be feasible, but the technology requires refinement and further software development before it can be recommended for commercial use.

Conflict of interest

None of the authors of this paper has a financial or personal relationship with other people or organizations that could inappropriately influence or bias the content of the paper.

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