Animal Lameness Detection with Radar Sensing

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***Abstract*—Lameness is a significant problem for performance horses and farmed animals, with severe impact on animal welfare and treatment costs. Lameness is commonly diagnosed through subjective scoring methods performed by trained veterinary clinicians, but automatic methods using suitable sensors would improve efficiency and reliability. In this paper, we propose the use of radar micro-Doppler signatures for contactless and automatic identification of lameness, and present preliminary results for dairy cows, sheep, and horses. These proof-of-concept results are promising, with classification accuracy above 85% for dairy cows, around 92% for horses, and close to 99% for sheep.**

***Index Terms*— Radar sensing, radar applications, micro-Doppler signatures, feature extraction, machine learning**

I. Introduction

LAMENESS is a very significant problem for farmed animals and performance horses. It has a negative impact on animal welfare and economically, both in terms of lost production and treatment costs. In dairy cattle, lameness is widely regarded as a major welfare problem. Difficulties with early identification of lameness in dairy cattle is a well-recognized issue [1]. Overall economic losses resulting from lameness have been estimated to be around $75 per cow per year [2]. The true extent of lameness in the UK dairy herds is unknown, but the herd level incidence has been estimated at 50 limb cases per 100 cows-years [3]. Sheep farmers are faced with a similar problem, with prevalence as high as 10% of the flock [4] and an estimated cost to the UK sheep industry of £24 million, for the most common cause of lameness in sheep [5]. For horses, the most frequent disease syndrome recorded in the UK in the 2016 was lameness, accounting for 33% of the reported issues [6].

The most common form of lameness identification is by subjective scoring method. While subjective gait assessment methods provide an immediate, on-site recognition and require no technical equipment, they show variation in reliability and repeatability of and between observers [7-8]. More objective kinetic and kinematic methods to identify both lameness and limb abnormalities have been studied, such as force plate systems, 3D-accelerometers, infrared thermography and tracking mixed with modelling from vision-based and optoelectronic systems; these show promise when compared with more traditional methods [9-10].

In this context, radar sensing can potentially enable contactless and automatic detection of lameness, with no additional sensors attached to the body of the animals under test, and sensing capabilities provided in any weather or lighting conditions, including outdoor farm environments. Extensive literature exists on the use of radar signatures to analyze human gait and activities in the assisted living context and security/surveillance [11-12]. However, there is very limited work on radar for lameness detection of animals, to the best of our knowledge (with the exception of a few papers where the signature of quadrupeds is treated as a potential "confuser" for human detection [13-14]). In this paper, we expand the preliminary results on our previous work [15] by providing an initial validation of the use of radar sensing to detect lameness in dairy cows, sheep, and horses. Experimental data were collected at the facilities of the Veterinary School at the University of Glasgow, and analyzed with techniques inspired from radar automatic target recognition (micro-Doppler signatures, feature extraction and supervised learning for classification). Promising results were achieved using very simple features (mean and standard deviation of the center of mass and bandwidth of the micro-Doppler signatures) and classifiers (such as SVM, Support Vector Machine, and KNN, K Nearest Neighbor), with 85% accuracy obtained for dairy cows, approximately 92% for horses, and 99% for sheep. The choice of features appears to have greater impact than the classifier, as similar accuracy is achieved with the same combinations of features for SVM and KNN.

The rest of this letter describes in more detail the experimental setup, data collection, and results, and proposes some conclusions and future work on this topic.

II. Experimental setup and data collection

The data analyzed in this paper were collected using a commercial Ancortek FMCW radar operating at 5.8 GHz [16]. The radar signal had 400 MHz bandwidth and 1ms duration, providing an unambiguous Doppler range of ±500 Hz. This is equivalent to a maximum recordable velocity of approximately 12.9 m/s (46 km/h), sufficient to capture the movements of the

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animals under test. The transmitted power was approximately 19dBm, and Yagi antennas with 17dBi gain were used for the transmitter and receiver, in a monostatic radar configuration. The range resolution of the radar was 37.5 cm (related to 400 MHz bandwidth), and the 3dB beam-width of the antennas was approximately 24° in azimuth and elevation. The data were collected in three different environments at the Cochno Farm and Weipers Equine Hospital at the University of Glasgow as shown in Fig. 1, one for each species of animals. Dairy cows were walked individually along a narrow corridor adjacent to the milking parlor, with radar recordings collected for both the anterior view (conducted first) and the posterior view (conducted second, after re-configuration of the equipment) of each cow. For sheep, individual animals were gathered in a small fenced area near the radar, and allowed to walk away along the narrow fenced corridor visible in Fig. 1 to rejoin the rest of their flock while recording with the radar. Horses were led by a groom back and forth along the corridor shown in Fig. 1, with radar recordings taken at both walking and trotting pace, and for both anterior and posterior view on the horses under test. During each recording, the animals were scored for lameness by veterinary clinicians to provide ground truth for comparison with the radar data. A binary scenario of detecting lame vs non-lame animals is considered in this paper, treating mild lameness cases as part of the "non-lame class" and medium and severe lameness cases as "lame class". This is done for sheep and cows to match the empirical assessment provided by veterinary clinicians during the data collection. For horses, a more elaborate scenario with 3 classes (lame, non-lame, mildly lame) is considered, to take into account the borderline cases when some signs of lameness were present, but difficult to confirm definitively.

Micro-Doppler signatures were generated by Short Time Fourier Transform (STFT) with 0.3 s Hamming window and 95% overlap. The data were pre-filtered to remove static clutter at 0 Hz. Three examples of micro-Doppler signatures are shown in Fig. 2 for the animals considered here, namely a healthy dairy cow walking towards the radar (Fig. 2a), a lame sheep walking away from the radar (Fig. 2b), and a mildly lame horse trotting (Fig. 2c). One can see that the signatures appear similar to those recorded for humans [11-12]. The main contribution from the body of the animal occupies the middle of the signature (for example at about 75-80 Hz at 5 seconds in Fig. 2a), and periodic contributions from the legs at higher Doppler/velocity around the main component (clearly visible above 100 Hz and up to about 200 Hz for Fig. 2a, for example). The signatures for sheep present more frequent limb movements compared with the cow signature, as expected because they were moving much faster during the data collection. Fig. 3 presents the signatures for two dairy cows, one which was healthy and one severely lame, showing both anterior view (when the animals were walking towards the radar) and posterior view (when the animals were walking away from the radar). Although an empirical visual comparison is not straightforward, one can see that the main Doppler contribution tends to have lower values for the lame animal, corresponding to slower walking pace (at approximately 30-40 Hz compared with the 70-80 Hz of the healthy cow). Furthermore, the pattern of Doppler contribution from the legs appear to be less intense for the lame animal.

Each micro-Doppler signature was divided into segments of 1.5-2s for the time intervals when the animals were present in the radar beam, and numerical features were extracted from each segment. In this letter, we mostly considered four simple features previously used for human micro-Doppler analysis [17]. These are the mean and standard deviation of the Doppler centroid f_c and bandwidth B_c, as calculated in equations 1 and 2 below. The former is an estimate of the center of mass of the micro-Doppler signature $M(d,t)$ as a function of Doppler bin d and time bin t, and the latter an estimate of the intensity of the signature around the centroid. In practical terms, the centroid can be related to average Doppler component in the signature, i.e. the bulk velocity of the animal body, and the bandwidth can be considered as a measure of the signature spread due to the patterns of leg motions.

$$f_c(t) = \frac{\sum_d f(d) M(d,t)}{\sum_d M(d,t)} \tag{1}$$

$$B_c(t) = \sqrt{\frac{\sum_d \left(f(d) - f_c(t)\right)^2 M(d,t)}{\sum_d M(d,t)}} \tag{2}$$

For classification, several classifiers based on supervised learning have been considered, but only results for Support Vector Machine (SVM) and Nearest Neighbour with 3 neighbours (KNN-3) are presented. KNN is a simple classifier, chosen for ease of understanding and implementation; SVM is a classic classifier used in this domain, in this case used with non-linear kernel (quadratic kernel).

Classification results were cross-validated using 80% of the samples for training and 20% for testing, repeating the process 20 times with randomly selected subsets for training and testing and providing the average accuracy across all the tests. This process was repeated for each combination of features considered.

Fig. 1 View of the three experimental setups, namely the dairy cows area (top) and sheep pen (bottom) at the University of Glasgow Cochno Farm, and the test corridor at the University Weipers Equine Hospital (right)

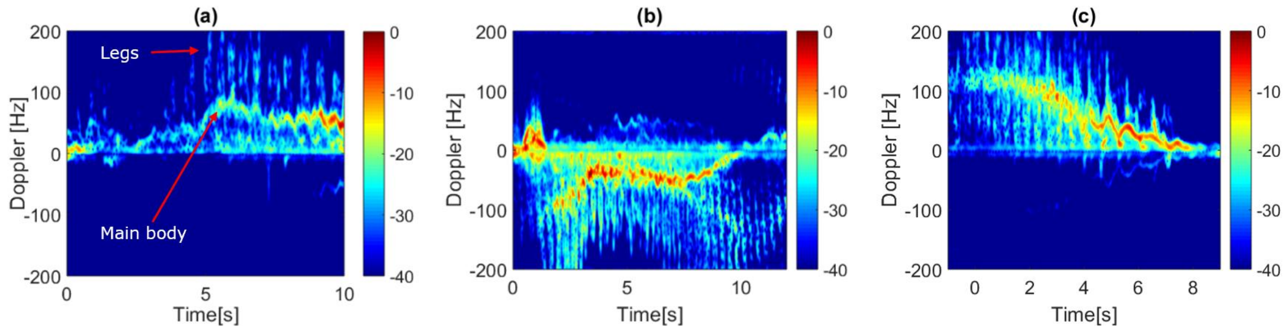

Fig. 2 Examples of micro-Doppler signatures of farm animals: (a) healthy dairy cow, (b) lame sheep, and (c) mildly lame horse

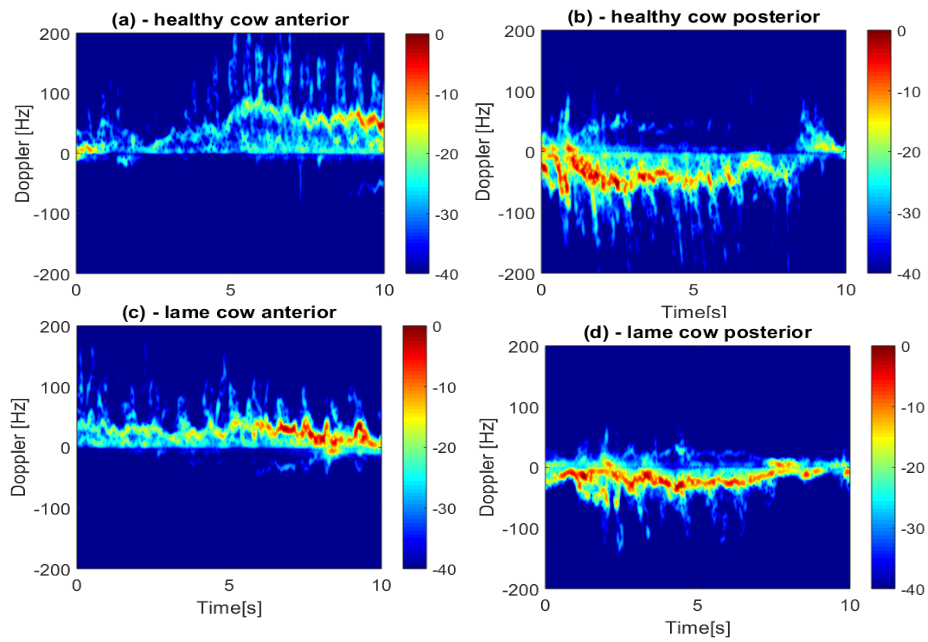

Fig. 3 Micro-Doppler signatures of dairy cows: (a) healthy cow walking towards the radar, (b) healthy cow walking away from the radar, (c) lame cow walking towards the radar, and (d) lame cow walking away from the radar

III. Discussion of the Results

A. Dairy Cows

Five dairy cows were considered for this test, with radar recordings taken looking at the posterior and anterior view of each cow. The cows were scored for lameness on a 0 (no lameness) to 3 (severe lameness) by two veterinary clinicians while walking, independently for the anterior and posterior test [18]. This scoring system is a standard approach used in veterinary practice in the UK, although there exist multiple scoring methods worldwide [19]. Three of the five cows were classified as lame (scores of 3, 2.5, and 2 on average), and two as healthy (scored 0.5 and 1) using a binary classification. As mentioned in section II, grouping the 0 to 3 scoring system into a binary non-lame (score 0-1) vs lame (2-3) classification was done to match the overall empirical assessment of the veterinary clinician who assisted with the data collection, and is a possible approach in veterinary literature [20].

A total of 53 samples were obtained, with 18 samples for the “non-lame class” and 35 for the “lame class”. This class imbalance depends on the time each cow was visible to the radar sensor, as their speed cannot be controlled while recording data.

Fig. 4 shows the classification accuracy obtained for SVM quadratic and KNN for both anterior and posterior view as a function of the feature combinations used as input to the classifiers. The combinations indicated on the X-axis of Fig. 4 and following figures in this section include:

- #1-4, individual features where 1 and 2 are the mean and standard deviation of the centroid respectively, and 3 and 4 the mean and standard deviation of the bandwidth
- #5-10, 6 possible pairs of features combining the aforementioned four individual features
- #11-14, triplets of features (combinations of 3 features)
- #15 all four features used jointly

SVM-Q and KNN appear to provide similar trends of accuracy as a function of features, at least for the posterior view. This appears to suggest that the choice of features has a great impact on the final performance, more than the type of classifier, at least for the classification problem considered here. Accuracy of 80% is achieved with only two features, mean of centroid and bandwidth, up to a peak of 85% adding the standard deviation of the centroid as a feature. Accuracy for the anterior view appears to be systematically lower than for the posterior view, and this is somewhat expected as lameness in dairy cows tend to be more significant in the hind limbs, which are less visible from an anterior perspective. An example of confusion matrix for the highest accuracy case in posterior perspective (SVM-Q classifier with 3 features as input) is shown in Table I. There are more “false positives” (healthy cows predicted as lame) than “false negatives” (lame cows predicted as healthy); this trend is also seen in the anterior perspective (confusion matrix not shown here for conciseness). Evaluating what is more penalizing in practical and economic terms between false positives and false negatives depends on the context and implications of the lameness diagnosis for the affected cows. Predicting a healthy cow as lame can have a significant logistic/economic impact, if the animal is taken away from the herd and removed from the dairy production cycle for treatment. Furthermore, if we assume that a veterinary clinician will check every case flagged as lame by the automatic radar system, then false positives can increase time and cost of the procedure. The counter-argument is that false negatives are also undesirable for the long-term wellbeing of the animals and the overall effectiveness of the proposed system, especially if lameness cases are systematically missed until the health of the animals affected are seriously compromised.

B. Sheep

Measuring sheep is more challenging, as they generally dislike being separated from other sheep and prefer to walk in groups, nose to tail with other sheep. For this test, we used 6 sheep, 3 of them presenting healthy/normal gait and 3 of them presenting some form of lameness (sheep are normally marked on a binary 0/1, non-lame/lame scale by veterinary clinicians). A total of 42 samples were considered for classification, 19 samples for the “non-lame class” and 23 for the “lame class”. The radar was deployed to look at the hind limbs of the sheep. Fig. 5 presents accuracy as a function of feature combinations, for both SVM-Q and KNN classifiers. Very high classification accuracy approaching 100% is achieved, even with just a single feature (mean of centroid) using SVM-Q, and also using simpler KNN with a pair of features. Essentially, in this case the classification appears to be strongly related to the mean velocity of the sheep (i.e. mean of the main body velocity from the micro-Doppler signature). In this case, average velocity can be considered in first instance a good proxy for lameness in sheep, as lame animals cannot move as fast as healthy ones although they all try to run to rejoin their flock.

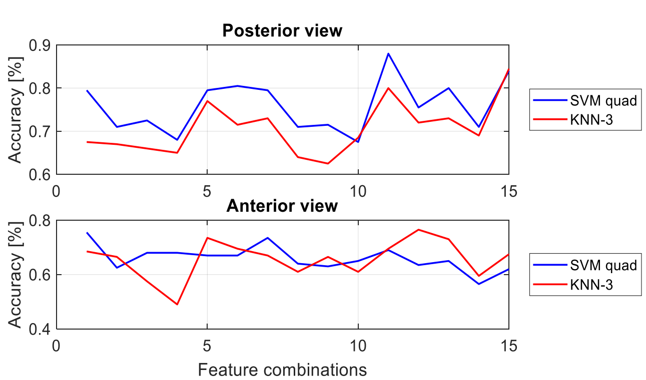

Fig. 4 Classification accuracy as a function of feature combinations for dairy cows, anterior and posterior view

TABLE I
CONFUSION MATRIX FOR BEST ACCURACY IN DAIRY COWS (POSTERIOR VIEW)

Accuracy [%]	Predicted Healthy	Predicted Lame
True Healthy	70%	30%
True Lame	8.6%	91.4%

C. Horses

For this test, 4 horses were recorded for both walking and trotting gait patterns. Of the four horses, one had no visible lameness; one had severe lameness in the anterior, and two had mild lameness in the proximal front limb. These horses were labelled into three groups: “healthy”, “lame” and “minimally lame”. Overall, 162 samples were obtained from the four horses with 54 samples for the ‘healthy’, 36 samples for ‘lame’ and 72 samples for ‘min. lame’ classes; this considered both walking and trotting recordings together.

The classification results from this three-class set are shown in Fig 6 and Table II. The trend here is similar to the previous sections, in which there is no distinct difference between the performances of the classification algorithms. The only change from the previous sections was a difference with the SVM, where we used a cubic kernel, which provided improved results compared with the quadratic kernel (approximately 12% higher on average). This may be due to the more complex distribution of features, the problem being a 3-class classification. The suitability of centroid-based features remains significant even in this case, with peaks of accuracy shown in Fig. 6 when centroid-based features are added to the feature set while testing all the possible combinations, similarly to what was recorded for sheep in Fig. 5. With the most suitable combination, classification accuracy of up to approximately 92 % can be attained. While the classifier correctly identifies the ‘healthy’ and ‘minimal lame’ to very high rates in Table II, there is a relatively high false negative for the ‘lame’ class, as roughly one in ten ‘lame’ horses are incorrectly classified as ‘healthy’. Further work is needed to identify the limitations of this approach causing these false negatives; one possible cause can be related to the presence of time snapshots when the horses were turning while walking or trotting back and forth, or stopping and standing still for short time while following the groom.

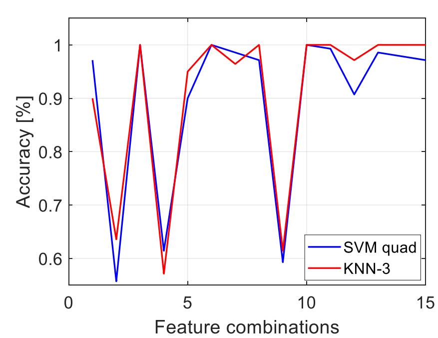

Fig. 5 Classification accuracy as a function of feature combinations for sheep, posterior view

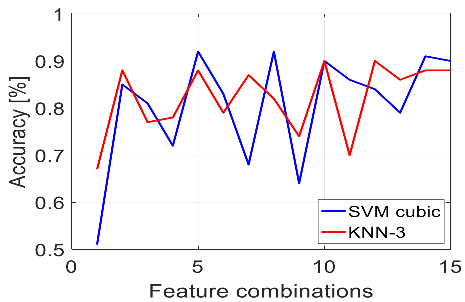

Fig. 6 Classification accuracy as a function of feature combinations for horses

TABLE II
CONFUSION MATRIX FOR HORSES TESTS

Accuracy[%]	Predicted Healthy	Predicted Lame	Predicted Min. Lame
True Healthy	94.2	5.8	0
True Lame	11.6	87.7	0.7
True Min. Lame	1.4	3.4	95.2

IV. CONCLUSIONS AND FUTURE WORK

In this letter, we presented preliminary results for detecting lameness for farmed animals and horses using radar micro-Doppler signatures, where promising classification rates have been achieved with simple features and classifiers. Specifically, lameness in dairy cows can be identified to 80%, up to almost 100% in sheep, and up to 92% in horses for a 3-class problem of classifying severe, mild, and absence of lameness.

Features based on centroid and bandwidth of the micro-Doppler signature appeared to be able to capture the signs of lameness, considering the average velocity of the animal (linked to the center of mass of the signature, the centroid), in conjunction with potential irregularities in the legs' patterns of movement (related to the spread of the signature, i.e. the bandwidth). In the case of sheep, the correlation between good accuracy in detecting lameness and usage of features related to the bulk velocity was better than for cows and horses. However, basing lameness detection on velocity only can be an oversimplification and one needs to take into account the intricacies of the limb patterns in the micro-Doppler signature to achieve a more comprehensive analysis. To achieve this aim, further work will consider higher order moments such as skewness and kurtosis, as well as other possible metrics to expand the feature space for improved and more robust performance.

Additional work will seek to expand and validate these initial results with a larger sample of animals, and investigate the effect on classification performance of changes in the setup (e.g. distance of the radar, height from ground, anterior or posterior view of the animal under test). The deployment environments on different farms or horse training grounds can differ substantially. Given the simple features and classification algorithms used here, work to transition towards real-time classification and monitoring appears feasible. Furthermore, the possibility of achieving finer classification for different severity levels of lameness and different affected limbs will be considered, moving from binary to multiclass scenarios also for the case of cows (normally scored on a 0 to 3 scale in the UK), and exploiting hierarchical classification and fusing information from multiple views on the animal under test. Finally, one could consider modifications to the classification algorithm to reduce 'false positives' or 'false negatives'. The threshold to consider these acceptable will depend on the animal under test (for example higher-end animals such as horses compared to individual sheep in large farms), and the end users' requirements and regulations on animal welfare (for example in very large industrial farms as opposed to small family-managed businesses).

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