Evaluation of lameness detection using radar sensing in ruminants

Valentina Busin DVM DipECSRHM PhD MRCVS [1]*, Lorenzo Viora DVM DipECBHM FHEA MRCVS [2], George King BVMS Cert VC MRCVS [2], Martin Tomlinson BVMS DipECBHM MRCVS [2], Julien Le Kernec PhD Associate FHEA CEng MIET SMIEEE MCF 63 [3], Nicholas N Jonsson BVSc PhD MRCVS [4], Francesco Fioranelli PhD FHEA CEng MIET MIEEE [3]

[1]Division of Pathology, Public Health and Disease Investigation; School of Veterinary Medicine; University of Glasgow; 464 Bearsden Road; Glasgow; G611QH; UK

[2]Farm Animal Clinical Sciences; School of Veterinary Medicine; University of Glasgow; 464 Bearsden Road; Glasgow; G611QH; UK

[3]School of Engineering; University Avenue; University of Glasgow; Glasgow; G128QQ; UK

[4]Institute of Biodiversity, Animal Health & Comparative Medicine; University of Glasgow; Glasgow; UK

* corresponding author: valentina.busin@glasgow.ac.uk

Abstract

Lameness is a major health, welfare and production-limiting condition for the livestock industries. The current “gold-standard” method of assessing lameness by visual locomotion scoring is subjective and time-consuming, whereas recent technological advancements have enabled the development of alternative and more objective methods for its detection. This study evaluated a novel lameness detection method using micro-Doppler radar signatures to categorize animals as lame or non-lame. Animals were visually scored by veterinarian and radar data were collected for the same animals. A machine learning algorithm was developed to interpret the radar signatures and provide automatic classification of the animals. Using veterinary scoring as a standard method, the classification by radar signature provided 85% sensitivity and 81% specificity for cattle and 96% sensitivity and 94% specificity

for sheep. This radar sensing method shows promise for the development of a highly functional, rapid, and reliable recognition tool of lame animals, which could be integrated into automatic, on-farm systems for sheep and cattle.

Introduction

Lameness is an important health, welfare and production-limiting problem for the sheep and cattle industries in the UK. The overall mean prevalence of lameness in ewes has been estimated at 4.9%,[1] whilst a recent review of the current state of lameness in UK dairy cows reports an expected herd level prevalence of lameness that lies between 25 and 37%,[2] which represents a substantial cost to both industries[3, 4] and a significant welfare concern.[5]

The prompt identification of affected sheep and cattle is essential to provide effective treatment of individual animals[6-8] and improve animal welfare. However, rapid and reliable recognition of lame animals is not always achievable. Farmers may consider the identification and handling of affected animals to be a considerable barrier to lameness control.[9, 10] Moreover, previous studies suggest that many dairy farmers cannot effectively detect lameness in their cattle.[11] More worryingly, one study suggested that some farmers may not perceive lameness to be a problem, even when as many as one in three cows was determined to be lame on their farm[12]. The current "gold-standard" method to quantify the occurrence of lameness is by whole herd/flock visual locomotion, or mobility scoring, which, in both species, is subjective, requiring training to be sufficiently reliable,[13, 14] and is labour-intensive. [9, 12]

Recent technological advancements[15, 16] have, with varying degrees of success, enabled the development of objective methods for detection of lameness,[17] such as infra-red technologies,[18, 19] intra-ruminal boluses,[20] force-plate systems,[21] 3D-accelerometers and tracking combined with modelling from vision-based and optoelectronic systems.[22] Although providing alternative detection methods, they require the individual provision of potentially costly devices or for animals to be restrained.

We have previously shown the potential of micro-Doppler radar signatures for lameness detection in a small number of animals.[23] Radar sensing has the advantages of providing contactless and automatic detection of lameness, with no requirement for additional on-animal sensors, and its sensors are suitable for outdoor, farm environments. The working principle of radar is to send electromagnetic pulses in free space (air) and to measure the time required by the pulses to return from scatterers (or targets, in this case, the moving animals). Since we know electromagnetic waves travel at the speed of light, the time for the signal to travel between the radar and the scatterers can be used to calculate the range separating them, or in practice the distance of the targets.[24] Observing the evolution of ranges over time allows the extrapolation of the speed of the scatterers (radar signatures), as their distance changes over time. Lameness is abnormal motility, so it is reasonable to expect that lame animals will have a different pattern of movement from normal animals and that the different movement patterns of their limbs will be reflected in distinct radar signatures.

This study aimed to take the micro-Doppler radar sensing method for which there was previously established technical proof of concept and quantify its performance for lameness detection in dairy cows and sheep on farm.

Materials and methods

Dairy cows

54 Holstein Friesian dairy cows from a farm in Central Scotland were assessed. The cows were observed walking individually along a 30 m long and 1 m wide corridor at the exit of the milking parlour, following afternoon milking. They were mobility scored as they moved along a corridor away from the observer using a modified ordinal scale based on Whay and others: [25]

- score 0 = non-lame

- score 1 = steps uneven or strides shortened with affected limb(s) not immediately identifiable
- score 2 = uneven weight bearing on a limb that is immediately identifiable and/or obviously shortened strides
- score 3 = severely lame, unable to walk as fast as a brisk human pace and lame leg easy to identify

The mobility score was carried out by the same observer (the same qualified veterinary surgeon, experienced in cattle mobility scoring). The radar recordings were collected simultaneously.

Sheep

80 Easycare sheep from a farm in Central Scotland were assessed as per routine lameness detection and treatment. The sheep were gathered in an outdoor prebuilt handling area. After gathering within the collecting pens, each sheep was admitted to a race 7 m long and 0.4 m wide via a lifting gate and made to walk through. Mobility was scored by observing the animal moving along the race to the collecting yard at the end. Visual mobility scoring for sheep was based on an ordinall scale adapted from Angell and others: [26]

- score 0 = non-lame
- score 1 = mild lameness with uneven gait but weight bearing
- score 2 = moderate lameness with occasional non-weight bearing
- score 3 = severe lameness with constant non-weight bearing

The mobility score was carried out by the same observer (the same qualified veterinarian surgeon, experienced in sheep mobility scoring). The radar recordings were collected simultaneously.

Radar sensing and processing

The measurements were performed with a commercial off-the-shelf radar sensor, Ancortek SDR 580-B, operating at 5.8 GHz in C-band. The radar transmits approximately 100 mW of power, a harmless exposure of non-ionizing electromagnetic radiation, with an operating frequency similar to those used by common Wi-Fi routers. The system operates with two antennas (Yagi antennas, similar to scaled versions of television antennas), one for the transmitter and one for the receiver, placed close to each other at approximately 30-50 cm distance. The antennas were placed on tripods and directed towards the areas where the animals were moving (Figure 1).

The data collected by the radar were processed to extract spectrograms (velocity-time representations), which display the velocity of the animal (body) and moving parts (i.e. limbs, head) at different instants in time in a continuum (Figure 2). This is done assuming lameness can be detected by identifying abnormal patterns of movements in comparison with normal, non-lame animals. The processing steps of the proposed algorithm include:

- Collection of raw radar data (Figure 2A), which appear as complex In-phase and Quadrature (I&Q) numbers.
- Transformation into Range-Time domain using a Fast Fourier Transform (FFT) algorithm (Figure 2A-B), which is the standard algorithm used in this type of radar systems.[27] The output of this stage is a series of range profiles (Figure 2B top) that display the distance of a possible target, in this case, the animal under test. By stacking multiple range profiles, one next to each other, a range-time-intensity (RTI) bi-dimensional plot can be generated (Figure 2B bottom), which can display the temporal evolution of the distance of all targets during a radar recording.
- A further FFT algorithm is applied to the RTI plot to form range-Doppler plots (Figure 2C), which display the ranges (distances from the radar) at which movement was recorded, i.e. ranges at which there was a moving target. It should be noted that radar systems measure velocities through the Doppler effect, essentially a change in phase of the electromagnetic waves similar to what also happens for sound waves; hence, range-velocity plots can also be denoted as range-Doppler plots.
- Finally, range-Doppler plots are summed together to generate spectrograms (Figure 2D), which, as mentioned above, display the temporal evolution of the velocity of body and limbs and can be used to detect lameness. Essentially, a range-Doppler plot displays if and where something is

moving but not how, whereas a spectrogram display how something is moving over time, which is the required information for lameness detection. Spectrograms are the representation in images of the radar micro-Doppler signatures.

After generation, each spectrogram was divided into segments of a given duration, namely 1.5 seconds, 3 seconds, and 5 seconds, from which features are extracted. Features are statistical numerical parameters (e.g. the mean and the variance) that can represent the relevant information in the micro-Doppler signature, as shown in the sketch of Figure 2E. The values of these features were then used as samples in a supervised learning framework to train a classification algorithm able to automatically distinguish between the signatures of healthy and lame animals.[28]

It should be noted that the radar signal processing steps prior to feature extraction are rather common in research on micro-Doppler signatures. The innovative content of the proposed work is in the extraction and selection of suitable features (i.e. the most appropriate information derived from the radar micro-Doppler signatures) that can distinguish between lame and healthy (not-lame) animals. In this work, 20 features (Table 1) were selected, based on their good performance as identified in previous research for applications to micro-Doppler signatures of human mobility.[29] These feature samples are labelled as belonging to one of the classes of interest, “lame” or “healthy”, depending on the lameness score assigned by the observer during the data collection.

Lameness classification

After extracting samples for all 20 considered features from each spectrogram segment, each feature was ranked using the T-test[27] to identify the most significant feature samples in relation to lameness detection. The T-test considers the intra-class and the inter-class variability of the samples for each feature, accounting for both healthy and lame animals, and provides a metric of quality for each that is independent of specific classification algorithms. Feature selection is commonly applied in micro-Doppler based classification problems to reduce the dimensionality of the feature space, with the primary aim of removing features that may provide redundant or confusing information.[30]

Furthermore, feature selection reduces the computer data loading, which can be beneficial in case of a portable, low computational in-field device ("on-the-edge" processing).

Animals were labelled as "lame" if they were scored 1, 2, or 3 and labelled as "healthy" if scored with 0. Although in the dairy industry it is common to refer to animals as lame if they score 2 or 3, we selected 1 as the most appropriate threshold for our work for two reasons. Firstly, only 9 cattle scored greater than 1, so setting the threshold at 1 provided considerably greater statistical power. Secondly, there is a distinct difference between the roles of an automated lameness detection system and of a veterinary examination. Assuming that close examination and treatment after initial automated detection is the goal of the system, then the system has a screening function, ideally with the capacity to detect early cases, enabling early veterinary examination and treatment. The classification was performed using a "leave-one-out-cross-validation" approach. Data from each individual animal were removed from the rest of the dataset and used only to test the classification algorithm, and not used in the supervised learning framework for the training of the algorithm. This process was repeated for all available animals, allowing to test the classifiers' performances in the presence of unseen data, i.e. data related to an animal that was not part of the training pool, where this training pool contained data for all other animals, lame or not-lame.

The two classifiers used are a Naïve Bayesian classifier (NB) and a Nearest Neighbour (KNN) with three neighbours.[30] The NB classifier assumes that feature samples for each class of interest (lame and healthy in this case) can be represented by a multivariate Gaussian distribution, with mean and variance estimated at the training phase; at the testing phase, a sample is assigned to one of the classes based on minimisation of a cost function calculated on the basis of those Gaussian distributions. The KNN classifier considers the distance of each testing sample in the feature space from the three closest neighbours; the sample is assigned to the class of the majority of the neighbours (in our case to lame if there are 2 or 3 neighbours belonging to the lame class, or the opposite for the healthy class).

Radar sensing performances

Sensitivity and specificity of the radar sensing in classifying animals as “lame” or “healthy” were calculated by comparing the visual lameness scoring with the classification given by the analysis of the radar data. They were calculated independently for each species (dairy cows and sheep) and each combination of the algorithm (NB and KNN) and time segment duration (1.5s, 3s, and 5s), using the veterinary diagnosis as the true status. Sensitivity was the proportion of all true lameness cases that were predicted by the micro-Doppler sensor system. Specificity was the proportion of all animals considered to be normal by the veterinarian that was predicted to be normal by the micro-Doppler sensor system.

Results

Based on the T-test, eight out of the 20 features were selected for each scenario in terms of animal species considered, along with the duration of the segment of radar data and type of classifier. This enabled the optimisation of the selection of features and the adaptation of the processing algorithm to the specific scenario under test.

A total of 51 dairy cows (31 “lame” and 20 “healthy”) were included in the evaluation. The total time to collect the lameness records at the farm was approximately 2 hours. A total of 75 sheep (25 “lame” and 50 “healthy”) were included in the evaluation. The total time to collect the lameness records at the farm was approximately 1.30 hours. Three cows and five sheep were not included because of inconclusive or incomplete visual assessment of lameness by the veterinarian.

Sensitivity and specificity of the radar sensing in classifying animals as “lame” or “healthy” are reported in Table 2. For each cow, the analysis included five segments of 5 seconds duration, seven segments of 3 seconds duration and 14 segments of 1.5 seconds duration. For each sheep, there were two segments of 5 seconds, three segments of 3 seconds and six segments of 1.5 seconds.

The highest performances of the novel method for evaluation of lameness were Naïve Bayes at 3 seconds for cattle, which gave 85% sensitivity and 81% specificity and Naïve Bayes at 1.5 s for sheep, which gave 96% sensitivity and 94% specificity. The full classification results for cows and sheep are available as supplementary material.

Discussion

We have demonstrated that this novel lameness detection method using radar has the potential for automatic discrimination between non-lame animals and lame animals, even of mild degree (score 1). The radar signatures were captured with a commercial off-the-shelf radar sensor and two antennas, while a supervised machine learning framework was developed to classify the animals. There was minimal setting-up time for the technology (radar and antennas), which worked well within normal farm settings. Short radar segment duration (3 seconds for cattle and 1.5 seconds for sheep) provided the best results, where rapid assessment is an important feature for the application of this technology on-farm. The selection of the minimum duration, indeed, could have a substantial operational impact because the time available for the radar to observe the animals is limited by the length of the passage in which the equipment is installed (milk parlour vs sheep race).

The overall performance of the proposed method for lameness detection was heavily influenced by operational parameters including the temporal duration of the spectrogram segment, and the implementation of the classification algorithm, both in terms of feature extraction and selection (e.g. what characteristics of the radar signatures are more suitable to capture the presence of lameness), as well as the classifier itself (as many different classifiers exist based on the supervised learning approach discussed here). Hence, considerable variation is reported in our results for the different segment durations, features, and classifier types, evidenced by the high range of performance between the best and worst classifier. The selection of the most suitable combination of features and classification algorithms to optimise performance across a range of conditions and environments remains a research challenge.

The “leave-one-out-cross-validation” approach was used in the supervised machine learning framework for training and testing, to mimic the situation where the algorithm is presented with an animal with an unknown status, as is expected to be the case in the field. The two classifiers used (NB and KNN) are rather simple classifiers compared to other available in the literature,[27, 30] e.g. classification trees, support vector machines, random forest, neural networks of various topologies (convolutional, recurrent, hybrid). They were selected for their simplicity and the reduced computational complexity that they require, in view of the implementation of the algorithm in the farm environment, where large computational power may not be easily provided or be too expensive. Although the proposed radar sensing method has only been tested in one farm, it has already shown considerable flexibility, as the same technology and machine learning training were used successfully for two completely different systems (dairy cattle vs sheep). The field of observation was 30 m for cattle and 7 m for sheep, so sheep yielded fewer segments than cattle. Work is in progress to develop radar signal processing and machine learning techniques to optimise sensitivity and specificity, with the validated pre-trained algorithm deployed in different farming scenarios for sorting lame vs non-lame animals.

Sensitivity (85% for cattle and 96% for sheep) and specificity (81% for cattle and 94% for sheep) estimates for this novel system are encouraging. When compared to the “gold standard” of locomotion scoring, studies in dairy cattle have shown that lameness detection based on a series of lameness indicators in tied cows[31] or free-stall barns[32] can provide a sensitivity of around 50% and specificity of 86 to 93%. Similarly, when compared to other automated systems, such as infra-red technologies (sensitivity 74% and specificity 68%)[19] or force plate system (sensitivity 24-35% and specificity 85-95%),[21] our proposed method has either comparable or higher analytical performances to other potential alternative lameness detection methods. Similarly, in sheep, the performance was considerably better than obtained using infra-red technologies (sensitivity of 83% and specificity of 78%).[18]

This method of lameness detection has the potential to be implemented as an automatic diagnostic tool for use in "precision farming" applications. Detection of lame animals would be by continuous, contactless and labour-free monitoring by placing the radar at strategic places (e.g. gates within adjacent fields for grazing animals or passageways for indoor systems). Coupled with electronic identification of individual animals, it would enable identification of lame individuals for treatment, also enabling the efficient reporting and robotic drafting out of animals for examination and treatment. Without individual animal identification, it would enable estimation of lameness prevalence within farms, which is increasingly important to livestock producers operating under quality-assurance programmes. The radar system would be expected to be cost-effective relative to accelerometer-based approaches because it does not require instrumentation of each animal. The initial capital cost might be high, but the cost per animal will be reasonable, and integration within automatic settings (precision farming) will considerably reduce labour requirements.

It is possible that the radar-based method of assessment was already an improvement over the visual locomotion scoring, which was used as the "gold standard" in this and other studies. The availability of well-labelled data for training of the algorithm is crucial at the testing stage and significantly affects the final performance of the algorithm. This had proven to be a challenge during our study because there were occasions when the veterinary surgeon was unable to confidently assign a lameness score. This is not unexpected, as the limitations of visual assessment are well described in the literature, even for experienced observers.[11, 13] These uncertain classifications can have a significant cascade influence. In particular, for cases labelled as 1, they could have been erroneously misclassified by the observer as mildly lame, where the signatures of individual animals within this class would be more similar to 0-labelled cases or 2-labelled cases, with bias in the training and further result in erroneous classification by the algorithm. To overcome this issue, a panel of experts could be recruited to allow for uniform classification of lameness and reducing errors in the algorithm training. Once the algorithm has been provided with well-labelled and verified data, a more objective, reliable and repeatable system would be available.

In conclusion, there was a high average true classification for all combinations of features and algorithms (over 70% for cattle and over 80% for sheep) in the farm under study, which improved substantially on random-selection — selecting the best analytical methods for sheep and cattle improved on this substantially (85% sensitivity and 81% specificity for cattle; 96% sensitivity and 94% specificity for sheep). Additional work is being undertaken to evaluate this method on over farms, to develop the algorithms further and to implement this method as an automatic diagnostic tool on-farm.

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Table 1 – Features used to train the classification algorithm; in particular each feature is representing a statistical moment (such as mean or standard deviation) of parameters extracted from the spectrograms (such as centroid and bandwidth) or their SVD decomposition. *The SVD generates three matrices: U, S, and V from the initial matrix with the pixel values of the spectrogram

segment. U and V contain the eigenvectors of the original matrix, ranked in order of relevance in terms of information contained.

Parameters	Features extracted			
Centroid (centre of mass) of the signature	mean	standard deviation	skewness	kurtosis
Bandwidth (extent of the signature around its centroid) of the signature	mean	standard deviation	skewness	kurtosis
Whole spectrogram segment (matrix of pixels)	mean	standard deviation	skewness	kurtosis
First right and first left eigenvector of the Singular Value Decomposition (SVD)* of the spectrogram segment	mean	standard deviation	sum of pixel (for matrices U and V)	mean of the diagonal of the left and right matrices, U and V, containing eigenvectors of the spectrogram segment

Table 2 –Estimation of sensitivity, specificity and accuracy for Naïve Bayesian (NB) and k-Nearest Neighbour (KNN) and using three segment durations: 1.5 seconds (1.5 s), 3 seconds (3 s) and 5 seconds (5 s) for dairy cows and sheep.

	Naïve Bayesian algorithm			**k-nearest neighbour algorithm**		
	5 s	3 s	1.5 s	5 s	3 s	1.5 s
Dairy Cows						
True Positives	71.6	79.3	82.5	73.6	70.9	69.6
False Positives	28.4	20.7	17.5	26.4	29.1	30.4
True Negatives	72	86.4	73.9	43	72.9	72.1
False Negatives	28	13.6	26.1	57	27.1	27.9
Sensitivity[1]	0.72	0.85	0.76	0.56	0.72	0.71
Specificity[2]	0.72	0.81	0.81	0.62	0.71	0.70
Accuracy[3]	0.72	0.83	0.78	0.58	0.72	0.71
Sheep						
True Positives	84	94.7	94	84	81.3	79.3
False Positives	16	5.3	6	16	18.7	20.7
True Negatives	74	92	96.3	86	83.3	79
False Negatives	26	8	3.7	14	16.7	21
Sensitivity[1]	0.76	0.92	0.96	0.86	0.83	0.79
Specificity[2]	0.82	0.95	0.94	0.84	0.82	0.79
Accuracy[3]	0.79	0.93	0.95	0.85	0.82	0.79

[1] Sensitivity = True Positives/(True Positives + False Negatives)

[2] Specificity = True Negatives/(True Negatives + False Positives)

[3] Accuracy = (True Positives + True Negatives)/Count Of All Observations

Figure 1. Radar sensing system set up at the farm. 1A Dairy cows set up showing the two antennas and the corridor at the exit of the milking parlour (1A). Sheep set up showing the radar sensor and the two antennas placed at the side of the running race next to the lifting gate (1B).

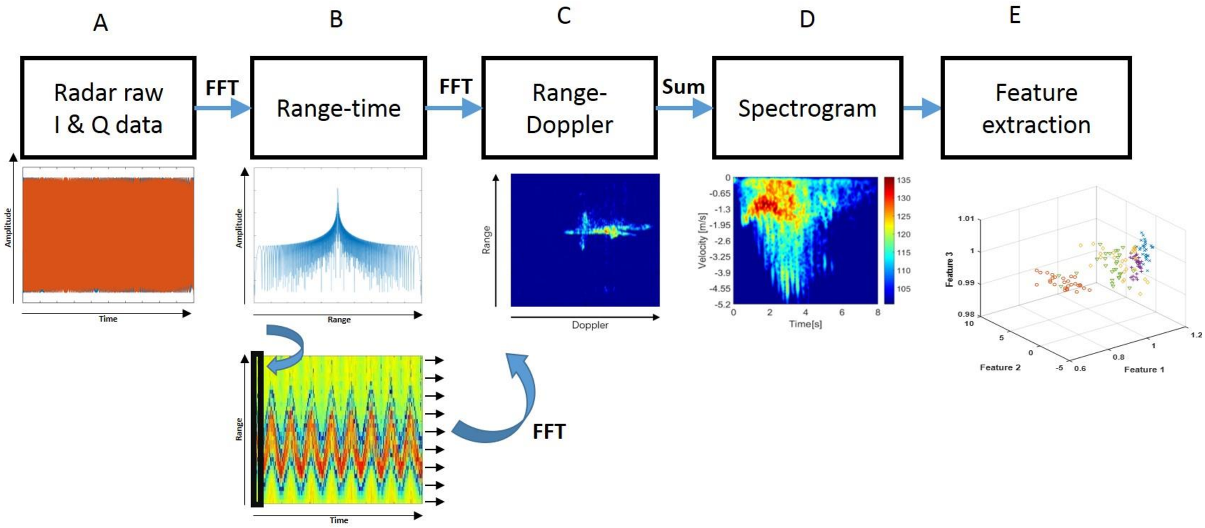

Figure 2. Radar signal processing chain from raw data to numerical features for classification: radar raw data (2A) transformed into range-time data (2B) and range-Doppler data (2C) with two consecutive Fast Fourier Transform (FFT) operations, followed by addition over range dimension to generate spectrograms (2D) and feature extraction from them (2E).