# Gait analysis of horses for lameness detection with radar sensors

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## Abstract

This paper presents the preliminary investigation of the use of radar signatures to detect and assess lameness of horses and its severity. Radar sensors in this context can provide attractive contactless sensing capabilities, as a complementary or alternative technology to the current techniques for lameness assessment using video-graphics and inertial sensors attached to the horses' body. The paper presents several examples of experimental data collected at the Weipers Centre Equine Hospital at the University of Glasgow, showing the micro-Doppler signatures of horses and initial results of their analysis.

## 1 Introduction

In 2016 the most frequent disease syndrome recorded for horses in the UK was lameness, which accounted for 33% of all reported issues according to the National Equine Health Survey (NEHS) [1]. This report appeared to link the majority of lameness cases to problems in the limbs (proximal limb degenerative disease), and in general lameness has a very severe impact on horses' welfare through pain and suffering, often leading to loss of use and euthanasia.

To address this problem, different methods to detect and assess lameness have been developed by veterinary clinicians, an important feature of which must be the repeatability and objectivity of the assessment. In [2], a case study on the repeatability of subjective, empirical evaluation of lameness between 2-5 veterinary clinicians with 18-years experience was carried out. Depending on the severity of lameness and the standard test used, agreement varied from 51.6% to 93%, where the lowest score was linked to mild lameness.

This shows the importance of developing objective methods for lameness detection and proper diagnosis and treatment. Gait evaluation techniques [3] for kinematic analysis include video-graphic combined with commercial software (e.g. *Centaur Biomechanics* [4]) or optoelectronics systems (e.g. *Qualisys* [5]), as well as a variety of sensors such as electro-goniometers, force plates or shoes, strain gauges, accelerometers. A review of commercial existing technology is available in [6].

Video-graphic analysis can provide good results and its performance has been improving in the past few years in terms of higher frame rates and higher image resolution. However, this method can be severely affected by weather and light conditions, as well as by errors in the calibration stage.

Inertial sensor-based systems for lameness detection and quantification are available. A commercially system consisting of two single-axis accelerometers and a gyroscope fitted to the horse's poll, pelvis and right forelimb pastern respectively is available for clinical use (*Equinosis, LLC)*. The use of this system has been validated for the detection of lameness and quantification of the response to diagnostic tests [7-10]. However, the use of these systems is limited to the examination of the horse during trotting only and are unsuitable for slower e.g. walk or faster e.g. gallop gaits.

Radar sensors can provide useful information in the process of detecting and assessing lameness of horses, leveraging on the extensive research work and established techniques developed for the analysis of human radar signatures. These techniques exploit generally the micro-Doppler signatures, i.e. the additional Doppler components on the signatures of moving targets, which are caused by the swinging of limbs and movements of torso [11]. These have been extensively used for a variety of applications [12], such as detecting humans against possible false targets (vehicles, animals), classifying different activities performed by people, discriminating armed versus unarmed personnel, and identifying specific individuals from their walking gait.

In the context of assessment of horses' lameness, radar sensors can be attractive for their contactless and non-invasive sensing capabilities, with no need to attach to the horses' body devices such as accelerometers and inertial sensors, with the potential of making the assessment procedure easier to carry out and faster. Furthermore, radar systems are expected to be capable of assessing horses' gait at any speed (walk, trot, canter and gallop) and under any weather or lighting condition. This can address the limitation of video-graphic and inertial/accelerometers systems, whereby their accuracy can be severely limited for high-speed velocity of galloping horses.

This paper presents preliminary results on the investigation of the use of radar sensors to identify signs of lameness or other irregularities in horses' gait. The long-term aim of this work is to explore the suitability of radar-based techniques for lameness assessment of horses, as alternative and/or complementary technologies to kinematics techniques based on inertial sensors. In particular, micro-Doppler signature analysis and suitable feature extraction and classification techniques will be explored, with the objective of discriminating between radar signatures of healthy horses and horses exhibiting fore or hind limb lameness, and quantify its severity. There is rather limited literature describing and presenting the micro-Doppler radar signatures of animals [13, 14], especially with the purpose of performing diagnosis on the animals' gait rather than for automatic target recognition purposes animals versus humans.

This project is an interdisciplinary collaboration between the School of Engineering and the Weipers Centre Equine Hospital at the University of Glasgow, where the experimental trials will take place building on the experience of the veterinary clinicians in lameness assessment. The authors have previously demonstrated the use of inertial sensors to objectively assess flexion tests [10] and diagnostic anaesthesia [8], as well as providing valuable insight into compensatory load redistribution [7, 9].

The paper is organized as follows. Section 2 presents a preliminary example of a simulated spectrogram of a walking horse based on Motion capture data. Section 3 describes the preliminary experimental trials and results of the data analysis. Finally, section 4 concludes the paper and outlines future work.

## 2 Simulation of horse gait radar signature

The generation of reliable simulated data describing radar signatures of horses' gait can be very valuable to have a benchmark to compare experimental data with, and to obtain the required volume of data to achieve the necessary statistical significance when applying machine learning based classification techniques. Research work on simulated data with these objectives is also reported for human radar data [15].

Using examples of motion-captured data of walking horses, provided by courtesy of the Swedish University of Agriculture Sciences and Qualisys, radar signatures of horses walking towards the radar have been simulated with ranges varying from 30 down to 5 m. The data was acquired in Strömsholm, Sweden, in a sand school fitted with 60 cameras from Qualisys running at 200 frames per second. The horse was fitted with 39 optical markers (4 on the head, 1 on withers, 7 markers on each forelimb, 4 markers on the pelvis and 8 markers on each hind limb) for the automatic extraction of motion capture data, as shown in Figure 1a).

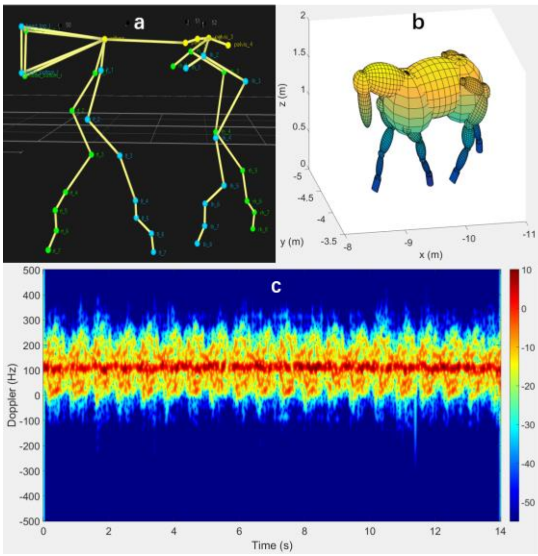


Figure 1: a) Motion capture data of the optical markers on a walking horse from the 39 markers [5], b) 3D model of horse c) spectrogram of walking horse (carrier frequency 5.8 GHz, PRF 1 kHz)

The centre of the sand school is the centre of the Cartesian coordinate reference system. Using MATLAB basic fitting tool based on 'shape-preserving interpolant', the movements were up-sampled to 1000 fps to match the experimental pulse repetition frequency (PRF) of 1 kHz). The data was simulated at 5.8 GHz using an adapted approach based on the simulation in V. Chen's book [16] and the radar cross section (RCS) model was superimposed on the optical data. The RCS has been modelled with spheres and ellipsoids as shown in Figure 1b) that have analytical equations taking into consideration incident angles (azimuth, elevation) therefore resulting in more lifelike micro-Doppler signature as seen in Figure 1c) for the abovementioned scenario and also it matches the experimental radar parameters presented in section 3.

## 3 Experimental setup and data analysis of horse gait radar signatures

### 3.1 Experimental setup and data collection.

Experimental data were collected at the Weipers Centre Equine Hospital of University of Glasgow, involving two horses, one exhibiting a sound, healthy gait, and another one (8 years old Warmblood gelding) with consistent right forelimb lameness at a trot in a straight line (AAEP Grade 3/5) in a relatively clutter free environment. The horses were led by a groom to walk and trot back and forth along a corridor space shown in Figure 2, with the radar located at the extremity of the corridor as indicated in Figure 2. Multiple radar captures were collected changing parameters such as the polarisation (vertical co-polarised VV, horizontal co-polarised HH, and cross-polarised VH) and the range resolution of the radar waveform to investigate their effect on the signatures. Effort was made to collect repeated measurements of the same type of movement (walk or trot) for the two horses under test, but some differences must be expected for the non-cooperative nature of the targets of interest.

The radar system is a commercial, off-the-shelf Frequency Modulated Continuous Wave (FMCW) radar system operating at a carrier frequency of 5.8GHz. The bandwidth of the linear frequency modulation was 400 MHz and 100 MHz (corresponding to range resolution of between 38 cm and 150 cm). The duration of the chirp waveform was 1 ms, providing an unambiguous Doppler frequency range of ±500 Hz. The recorded datasets were between 25s and 40s long, each containing at least two captures of the horse micro-Doppler signature, one for the horse walking away from the radar and one with the horse walking towards it. Trotting sequences were also recorded in a similar manner. 28 datasets were recorded as a whole. The transmitted power of the radar was approximately +19 dBm, and the gain of the transmitter and receiver antennas was 17 dBi. The antennas were commercial off-the-shelf Yagi antennas with a beam-width of 24° in elevation and 24° in azimuth respectively.

### 3.2 Micro-Doppler signatures and feature extraction.

The data recorded from the radar system was passed through a moving target indicator (MTI) filter then processed using Short Time Fourier Transform (STFT), and the absolute value of the result was then squared to create spectrograms of each activity set. The sliding window of the STFT had an overlap factor of 95% and duration of 0.2 s. An example of the resulting spectrograms can be seen in figure 3, which shows the micro-Doppler signature of a healthy and lame horse.

Features were then extracted from the spectrograms to be used as input parameters for automatic classification. The spectrograms were segmented into 3s images, with 0.5 second shift to generate multiple images from the same spectrogram, in order to increase the number of available samples given the limited set of experimental data. A total number of images equal to 165 were generated, with each image being used to derive 3 feature samples, giving a total of 495 predictors within the feature set.

The three features considered here were the mean of the centroid or centre of mass, the entropy of the image, and the 3$^{rd}$ order moment of the histogram containing pixel intensity values. These are explained in more detail below.

Prior to feature extraction, the spectrograms were limited within the Doppler bins containing the horses' signatures, discarding the Doppler bins with no signature at the highest positive and negative Doppler values. The positive parts of the spectrograms were mirrored in the negative Doppler region, in order to apply the same processing for both cases when the horses were moving towards the radar and away from it.

The centre of mass of the spectrograms (known as centroid) is the estimated centre of the gravity of the micro-Doppler signature. This feature has previously been applied for personnel recognition [17]. The mathematical expression is reported in equation 1, where *S(i,j)* is the spectrogram at the i$^{th}$ Doppler bin and the j$^{th}$ time bin and *f(i)* is the Doppler frequency of the i$^{th}$ Doppler bin. The mean value of centroid appears to provide good separation between the healthy and lame horses' data, as shown in Figure 4, with reduced values for the lame horses as they are expected to have reduced movement due to their condition.

$$f_c(j) = \frac{\sum_i f(i)S(i,j)}{\sum_i S(i,j)} \qquad (1)$$

Regarding the second feature, in information theory entropy is described as the average information within a medium along with its complexity. Image entropy is a measure of the randomness of data within an image, which can be used to define the texture of an input image. It also represents the distribution and the concentration of energy within the image texture [14]. It is defined as:

$$E = -\sum_n \boldsymbol{p}(n) log\, \boldsymbol{p}(n) \qquad (3)$$

Where ***p(n)*** is the energy distribution of the spectrogram, i.e. the grey levels of the spectrogram. Larger values of entropy are indicative of a complex texture, which suggests high overall movement. Lame horses by nature are expected to have more limited movements (thus, simpler texture) which translates to lower overall movement.

Figure 2: Weipers centre equine hospital corridor and experimental setup with radar system.

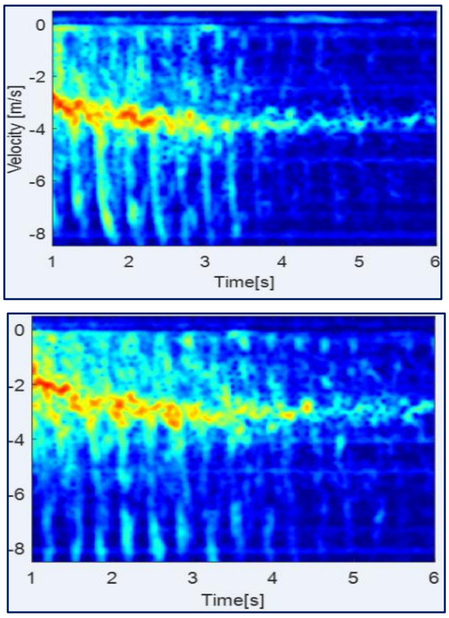


Figure 3: Spectrogram of a healthy (top) and lame (bottom) trotting horses

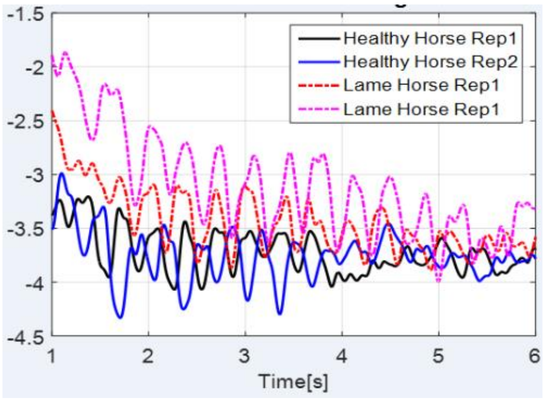


Figure 4: Centre of mass of the radar micro-Doppler signature for healthy and lame horses

The 3rd order moment of statistical histogram represents the skewness of the data and the symmetry of the curve of the histogram's envelope, as well as the fluctuations of the grey scale within the image [14]. The nth order moment is defined in [18] as in equations 4-5, where *p(r)* is the envelope of the histogram representing the probability of *r* being a certain grey level between 0 and L, i.e. the envelope of the spectrogram, and $r_i$ is the variable representing greyness of a pixel. A skewness equal to zero is related to a symmetric histogram, and therefore a very regular movement. As the lame horse is expected to exhibit more irregular, less symmetric movement than the healthy horse, the expectation is that the skewness parameter will be lower and closer to zero for healthy horse data.

$$fm = mean[p(r)] \tag{4}$$

$$M_n = \sum_{i=0}^{L-1} (r_i - fm)^n p(r_i) \tag{5}$$

Figure 5 shows feature space plots for the three considered features, using together samples related to both healthy and lame horses, walking and trotting. The entropy and the 3rd order moment or skewness appears to provide good separation between the two classes of lame horses and healthy horses.

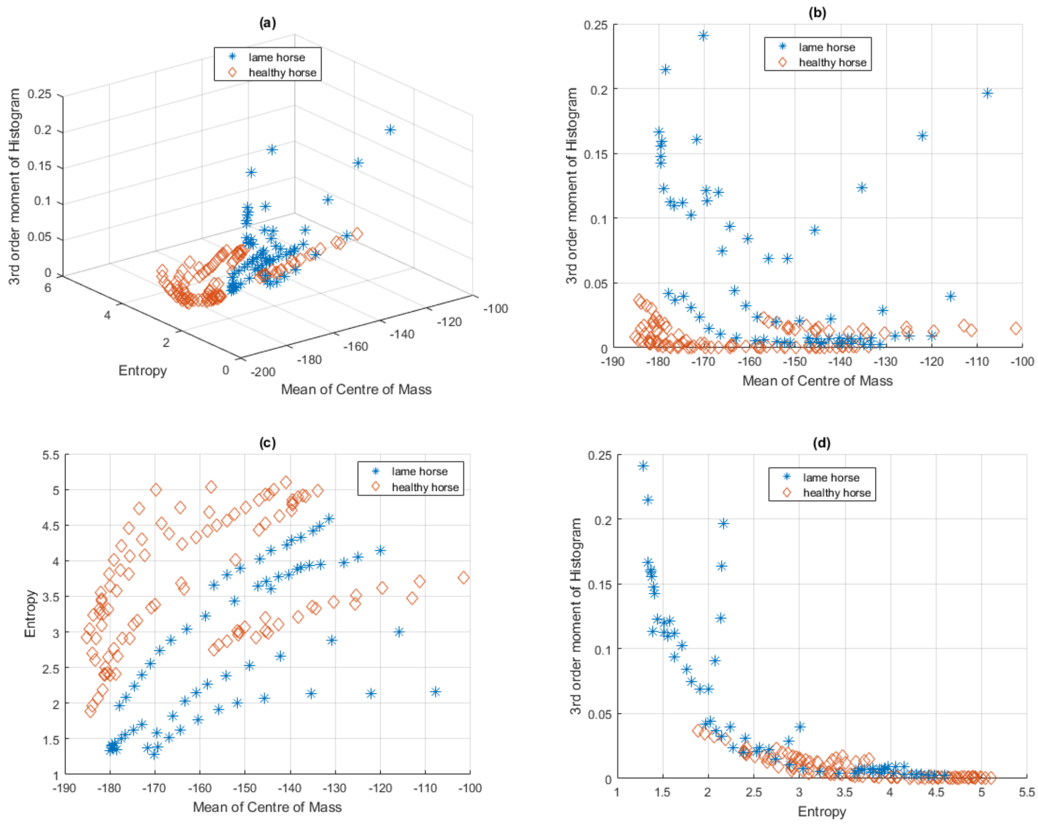


Figure 5: Feature space scatter plots for different features: (a) skewness, entropy and centroid, (b) entropy and centroid, (c) skewness and entropy, and (d) skewness and centroid

### 3.2 Classifiers and Results

A Support Vector Machine (SVM) with Gaussian radial basis functions and a Nearest Neighbour (kNN) classifier with 5 neighbours were used to classify the horse data into two classes: "lame horse" and "healthy horse". A detailed description of the classifiers can be found in [19].

The feature set was partitioned into four equal groups of data; three were then used to train the classifier (75%), with the fourth one used for testing (25%). This was repeated four times, with random changes of the samples chosen for training and testing to test the robustness of the proposed approach (4-fold cross-validation).

The results are shown in the confusion matrices in table I and II, for the two different classifiers. 15 out of 165 predictions were incorrectly classified for the SVM classifier, providing an accuracy of approximately 90%. The k-NN classifier presented similar performance, with 16 misclassification events out of 165. It can be seen that the majority of the errors implies classifying a lame horse as a healthy one, which is an element to address to improve the robustness and the applicability of the proposed method. The results are nevertheless encouraging, showing that differences in horses' gait can be correctly inferred from the radar signatures.

| TRUE/PREDICTED | LAME HORSE | REGULAR HORSE |
|---|---|---|
| LAME HORSE | 52 | 14 |
| REGULAR HORSE | 1 | 98 |

**Table 1** Confusion matrix for SVM classifier

| TRUE/PREDICTED | LAME HORSE | REGULAR HORSE |
|---|---|---|
| LAME HORSE | 54 | 12 |
| REGULAR HORSE | 4 | 95 |

**Table 2** Confusion matrix for k-NN classifier

## 4 Conclusion and future work

This paper has presented preliminary results of the investigation of radar sensors and micro-Doppler signatures to assess horses' lameness. Three features have been extracted from experimental radar signatures and used as inputs to two classifiers, achieving accuracy in the region of 90%.

Radar micro-Doppler signatures are more challenging to analyse than human signatures. This is likely to be related to the different kinematics of the horses' gait on 4 limbs rather than on 2 limbs as for humans. For the data considered here, there is also an additional complexity factor to collect reliable large amount of experimental data, as horses are non-cooperative targets, and maintaining exactly the same trajectories and aspect angles for all the recorded datasets was not possible. Furthermore, the generation of multiple images from the same spectrogram to increase artificially the number of available feature samples can affect the data and introduce correlation that has an impact on the final classification results.

Additional work will be performed by addressing these issues in further data collection, including different horses and where possible horses with different levels of lameness. This will enable a more accurate investigation of possible features to improve the detection of lameness in horses, as a function of the many radar and operational parameters. The exploitation of simulated data to be combined and compared with the experimental data will be also explored. The influence of clutter levels in the experimental environment will be also characterised, for example indoor vs outdoor environments where the horse can move, as well as the presence of objects around. In this current work, static clutter has been filtered from the micro-Doppler signatures by using a MTI filter, but it is expected that slow moving clutter (for example foliage outdoor or other animals nearby) can have an effect on the accuracy of the proposed method.

Finally, it would be recommended that the horses be classified separately, i.e. without mixing data referring to the trotting and walking movements. These not only exhibit different velocities, where trotting is a faster movement, but also different kinematics of the limb position, where walking is a 4-beat gait and trotting a 2-beat gait. Figure 6 shows the feature space plot for walking and trotting movements, and the separation between healthy horses and lame horses is much clearer than in the previous case (Figure 6), when samples related to both types of movements were mixed together.

Furthermore, the simulated micro-Doppler signatures presented in section 2 will allow a parametric study on the effects on the classification performance depending geometry configuration (azimuth, elevation, monostatic, multistatic) and parameters (frequency, bandwidth).


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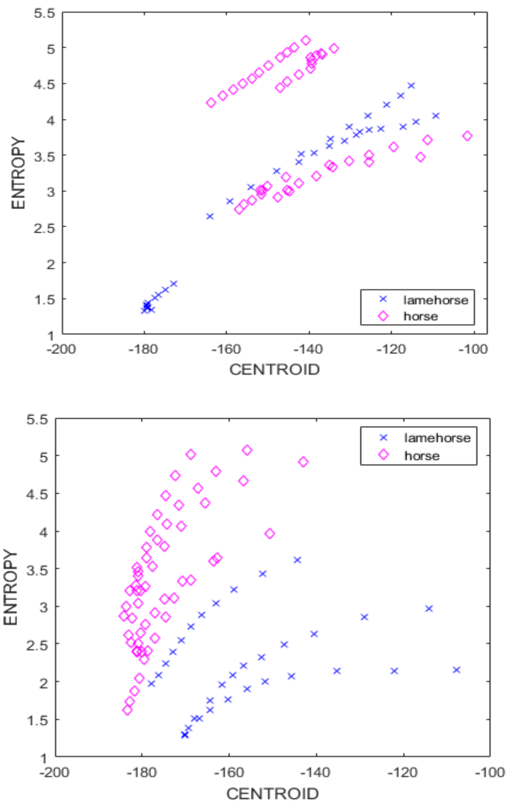

Figure 6: Feature space plot for walking (top) and trotting (bottom)

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