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# Cattle Urination Behaviour Remote Monitoring using mmWave FMCW RADAR

Yanhua Zhao[1,3], Vladica Sark[1], Markus Ulbricht[1], David Janke[4], Sabrina Hempel[4], Gundula Hoffmann[4]
Thomas Amon[4,5], Barbara Amon[4], Milos Krstic[1,2], Eckhard Grass[1,3]
[1]IHP - Leibniz-Institut für innovative Mikroelektronik
Frankfurt(Oder), Germany
[2]University of Potsdam, Germany
[3]Humboldt-University Berlin, Institute of Computer Science, Berlin, Germany
[4]Leibniz Institute for Agricultural Engineering and Bioeconomy, Germany
[5]Institut of Animal Hygiene and Environmental Health Department of Veterinary Medicine Freie Universität Berlin, Germany
{zhao,sark,ulbricht,krstic,grass}@ihp-microelectronics.com
{DJanke,SHempel,ghoffmann,tamon,bamon}@atb-potsdam.de

***Abstract*—Summers have been getting hotter in recent years. This is a warning for us that fighting against climate change requires our participation. On dairy farms, there are large numbers of cows. Their urine contains ammonia, which is harmful to the environment. To neutralise these harmful gases in time, the urination of cattle needs to be detected so that countermeasures can be enacted correspondingly. Frequency-Modulated Continuous-Wave (FMCW) RADAR and deep learning methods will be combined to detect and recognize cattle urination events in this work.**

***Index Terms*—FMCW, RADAR, mmWave, ammonia, deep learning, urination detection**

## I. Introduction

RADAR technology has attracted a lot of attention in recent years. There are many applications regarding RADAR. In the medical field, RADAR can be used to detect physiological signals [1], such as breathing rate and heartbeat rate or even blood pressure. In addition to this, RADAR plays a crucial role in gesture recognition [3], [8] and gait recognition [2].

In this work, RADAR will be used to detect the urinary behaviour of cattle. Cattle urine contains ammonia, which can pollute the environment. It is essential to detect urination events from cattle as their urine tends to evaporate rapidly at normal temperatures. When a single urination event is detected, measures can be taken to effectively remove the contaminant. Information about the health of cattle can also be obtained from the frequency and duration of urination.

Ammonia sensors can detect ammonia. However, it is not capable of locating the exact position of the cow's urine.

Devices that can detect cow urination include cameras, RADAR, etc. Cameras cannot protect the farmer's privacy and their performance is affected by lighting conditions. In contrast, RADAR offers better protection of the farmer's privacy and works well in all light conditions.

From the many types of RADAR, the Frequency-Modulated Continuous-Wave (FMCW) RADAR [5] was chosen to implement the experiment. This is because the FMCW RADAR can detect the range and velocity of multiple targets.

In this work, we carried out pre-experiments indoors to select suitable features for the urine fall and conducted the first experiments on the farm.

The size of the RADAR raw data is large. If it is fed directly into the neural network, the neural network will be under a lot of computational pressure. The FMCW RADAR raw data can be pre-processed to obtain a range-Doppler heat map and a range-angle heat map. Its size is smaller compared to the raw data and the range, Doppler and angular features of the target are highlighted.

There is a water falling process in cow urination and therefore a corresponding change in range and Doppler, but not much in angle. The results of the pre-experiments in the indoor environment indicate that the water falling changes more significantly on the range Doppler heat map because of its higher range and velocity resolution. Range-Doppler heat map for each frame will be fed into the convolutional neural network as input data for further feature extraction, which will then be learned by the long short-term memory (LSTM) [10] neural network in temporal and eventually classified in the classifier.

The rest of the paper is organised as follows. In Section II, the FMCW RADAR system will be explained, followed by a description of the event detection and recognition methodology in Section III. In Section IV, the experimental setup and analysis of the results will be presented. Section V will conclude the paper.

## II. FMCW RADAR system

The waveform of the FMCW RADAR employed in this work is an upward sawtooth wave, as illustrated in the Figure 2. The parameter B on the Figure 2 is the bandwidth. $T_c$ is the time duration of a Chirp. $\tau$ is the time of flight for the waveform to travel from the transmitter to the target object and be bounced back to the receiver. $f_b$ is the beat frequency. $T_f$ represents the duration of a frame. One frame has multiple chirps.

Fig. 1. Example of Cattle Urination [4]

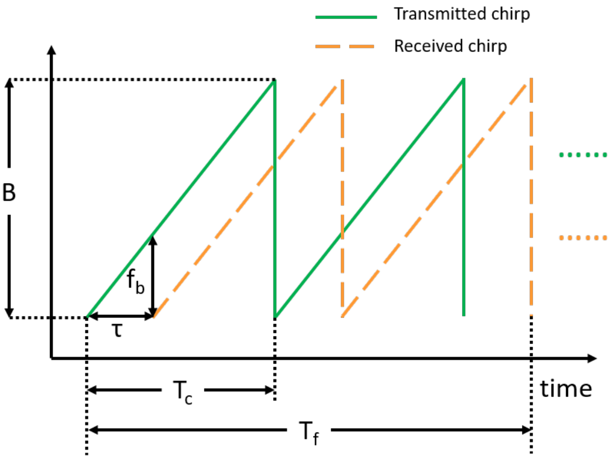



Fig. 2. Waveform

A typical transmitter wave is represented as follows:

$$T(t) = A\cos\left(2\pi f_c t + \pi \frac{B}{T_c} t^2\right) \tag{1}$$

Where $A$ is the amplitude factor, $f_c$ represents the starting frequency.

Chirp is transmitted into space and bounced back to the receiver by the object, the expression for the waveform at the receiver is:

$$R(t) = \alpha A\cos\left(2\pi f_c (t-\tau) + \pi \frac{B}{T_c} (t-\tau)^2\right) \tag{2}$$

Where $\alpha$ is the amplitude attenuation factor.

The received signal will be mixed with the transmitted signal and passed through a low pass filter to filter out the high frequency signal. Afterwards the beat signal will be obtained.

$$B(t) = \alpha A^2 e^{j(2\pi f_b t + \phi(t))} \tag{3}$$

The $\phi(t)$ can be written as:

$$\phi(t) = \frac{4\pi R(t)}{\lambda} \tag{4}$$

Where $R(t)$ is the distance between the target and the RADAR and $\lambda$ denotes the wavelength.

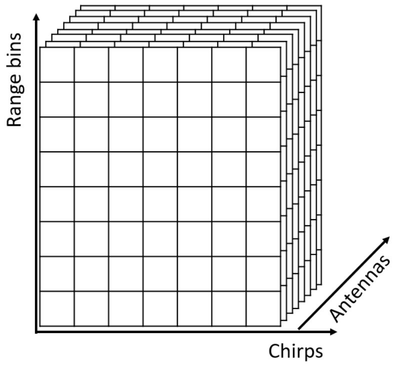



Fig. 3. Raw data structure

Then the beat frequency can be expressed as:

$$f_b = S\tau \tag{5}$$

$S$ is the slope of the chirp.

## III. Proposed Event Detection and Recognition Methodology

### A. Feature selection

The raw data from the FMCW RADAR has three dimensions, as depicted in Figure 3, namely range bins, chirps and antennas. A chirp has multiple range bins. There are multiple chirps per frame. The experimental RADAR uses one transmitting antenna and 16 receiving antennas, so there are 16 antenna channels per frame. From these the range, speed and angle of the target can be extracted by performing a fast Fourier transform (FFT) along those three dimensions.

After performing the 2DFFT, a range-Doppler heat map (RDM) can be constructed. Similarly range-angle heat maps (RAM) can be obtained after 3DFFT. More information on the processing of RADAR data can be found in [3].

Before the formal experiments start, a simple pre-experiment is carried out in an indoor environment to find suitable features. In the pre-experiment, tap water is used to mimic the process of urine falling. Tap water has similar reflective properties to urine as there are some dissolved substances in it. As shown in Figure 5, two snapshots capture the water's fall.

Because the water fall is continuous, this special feature can also be observed in the RDM map in Figure 5a. Similar to RDM, there are similar features in RAM map, but they are not as clear as those in RDM.

The range-Doppler map is therefore selected as the target feature and will be further fed into the neural network for training and recognition.

### B. Recognition pipeline

The recognition pipeline is displayed in Figure 4. The LSTM neural network will be used together with a convolutional neural network (CNN) [8] to learn and recognise the characteristics of the falling urine, as the dynamic characteristics of the falling water can be learned and remembered due to its

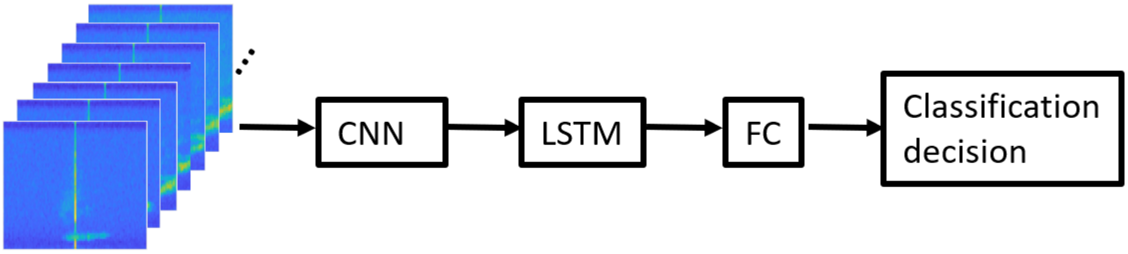
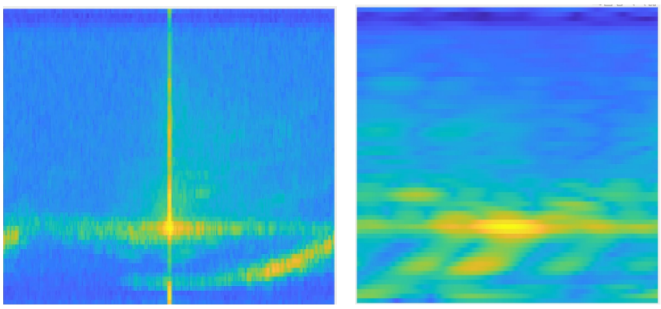



Fig. 4. Recognition pipeline



(a) RDM (b) RAM

Fig. 5. Features of water falling

feedback mechanism and memory module. The range-Doppler map is fed sequentially into the CNN to extract features. Next these features will be passed to the LSTM unit. In the final stage, classification decisions will be made.

## IV. Experiment and Evaluation

A Radarbook2 microwave RADAR evaluation platform [6], a Raspberry Pi [7] and a camera are utilized in the experiment. The RADAR has a starting frequency of 76 GHz, a bandwidth of 4 GHz and a chirp duration of 200 microseconds. The recordings from the camera will be used as ground truth. The experimenter will be able to manipulate and adjust the data collection process remotely. The layout of the specific equipment system is illustrated in Figure 6. The experimental site is the barn of the Leibniz-Innovationshof [9] in Brandenburg. Our experimental equipment is mounted to a beam above the

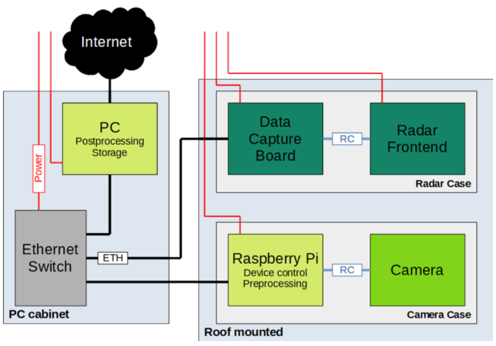



Fig. 6. Experimental system

Fig. 7. Experimental set-up

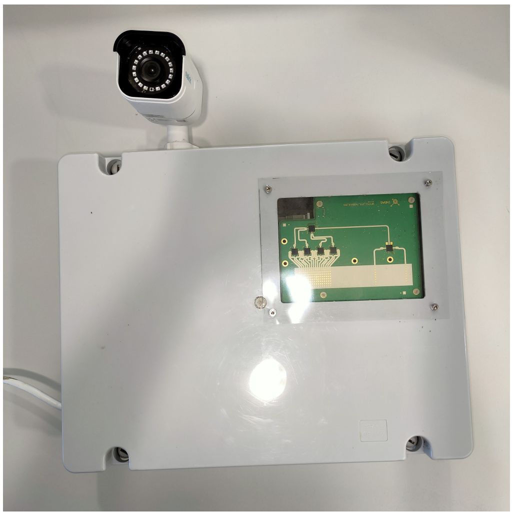


Fig. 8. Near-view of experimental equipment

animals in the cattle barn and is marked in blue in Figure 7, and the cattle often walk along this corridor. Figure 8 presents a near view of the experimental equipment. The RADAR and Raspberry Pi are packed in a box with holes. The camera is positioned on the outside of the box and is connected to the Raspberry Pi via a cable.

As the urinary behaviour of cattle is not under human control, a cow urinates approximately 5-10 times per day, and the size of the RADAR monitoring area is limited. Sufficient events for neural network training require a longer time to collect. It is good to have as much training data as possible so that a wide variety of peeing patterns will be included. The trained model will perform better in the test set. The ratio of the training and test sets in the plan is 70% to 30%.

In the future, when sufficient valid data is collected, this work can be moved further forward.

## V. Conclusion and Future Work

In this paper, RADAR is used for the first time to monitor the urinary behaviour of cattle, for the sake of environmental protection. This ongoing work will aim to collect sufficient and valid data to validate the recognition pipeline in this paper and to eventually achieve the goal of protecting the environment and mitigating global warming.

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