Animal activity recognition using a FMCW Millimeter Wave Radar

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ABSTRACT
Most people consider their own well-being, as well as the well-being of the people and animals around them, to be a vital part of their lives. Monitoring the well-being of pets, in particular, is a difficult task. Therefore, it is wise to monitor the pet's activities and behavior frequently when no one is present.

Activity recognition and tracking behavior of both human and animals is a field of research which could entail interesting insights concerning their physical and mental well-being. Most modern techniques to monitor individuals require either physical sensors and tags or are made available by using cameras. By using a system which is based on Frequency modulated continuous millimeter wave radars (FMCW) it is possible to make the research to activity and behavior recognition remote and non-invasive. The goal of this paper is to research the possibilities of animal activity and posture recognition using a FMCW Millimeter wave radar.

Keywords
Activity and posture recognition, Millimeter wave radar, FMCW, point cloud.

1. INTRODUCTION
Monitoring human activities provides an insight in the behavior and patterns of people in their daily life's. These insights play a vital role in keeping people healthy. Monitoring human activities can be of assist in various sectors, like healthcare, sports, and security. This field of research already has some major contributions, all of which help improving or introducing methods to achieve human activity recognition (HAR). Next to the importance of human activity recognition is the field of research focusing on animal activity recognition (AAR).
Since the beginning of the corona pandemic the amount of people adopting a dog has increased significantly. Taking care of a dog includes making sure the dog feels well in its environment. Keeping a close watch on a dog makes it easier to ensure its well-being, however it is rather impossible for a person to monitor a dog all the time. Monitoring a dog while it is alone or sleeping could reveal interesting details in its activities and sleeping patterns. These aspects of a dog's life could indirectly be used to determine a dog's well-being. Furthermore, it can give an early alarm to the dog owner in case of emergency. Tracking a dog and recognizing their posture and activities is assumably the most useful way of monitoring them. There already are various kind of sensors serving the purpose of monitoring animals. These sensors are mainly wearable sensors, which makes them less animal-friendly to use. Therefore, it is more interesting to apply remote sensing methods as they are contactless and non-invasive. FMCW Millimeter wave radars are particularly useful for this purpose.

The Millimeter wave radar transmits electromagnetic wave signals, which get reflected by objects in their path. This reflection is captured by the receivers on the radar and can be used by researchers to gather relevant data from their test subjects. After this data is gathered Machine- and Deep learning methods will be used to detect and recognize animal- and human activities.

There already are studies researching activity and posture recognition of both humans and animals, using Millimeter wave radar techniques. However, the limited number of studies about animals focus mainly on livestock and how to track their behavior and movements with regards to further breeding of these animals.

Furthermore, the animal focused studies only consider a limited number of activities and postures of a larger group of animals. Activities these papers extract are mostly based on differences in walking pace.

In this paper, the possibility of animal activity recognition using a millimeter wave radar will be researched. This is done by first exploring the possibilities concerning human activity recognition, after which the same procedure will be applied on animals. This will give insights in the level of accuracy a millimeter wave radar provides in animal activity recognition. This paper answers the following sub research questions:

- How can raw millimeter wave data be gathered and processed in order to be useful for activity recognition?
- What challenges arise when dealing with animal activity recognition in comparison to human activity recognition?
- What classifiers are appropriate for animal activity recognition?

Finally, the paper will conclude to what extent it is possible to accurately detect animal activities using a millimeter wave radar.

The paper will elaborate on related work in this field of research. After that, an explanation on some relevant technical details is given, in order to provide enough information about the methods used during this research. Finally, the paper will discuss the experimental setup, challenges, classifiers, results, and potential possibilities for further research.

2. RELATED WORK
Since this field of research is rather novel, not a lot of research on this specific topic has been done yet. The research was gathered using google scholar and IEEE. The research can be divided in a couple of categories: The first categorial division can be made between the research on humans and animals. These two categories can then be divided in 'Activity and posture recognition' and 'Tracking' [13, 4, 12, 11]. As mentioned before the Millimeter wave radar transmits electromagnetic waves and records reflections from the objects in the environment [10]. Then the radar computes point clouds, and it removes the points that belong to the static background. The point clouds generated are used by Machine learning

classifier algorithms in order to recognize activities and postures. Most articles found use these point cloud-based methods to either recognize the activity/posture or to track the subjects. Although most articles are focused on either activity recognition or the tracking of humans, both can be a sound basis for further research on animals. Human activity and posture recognition (HAR) is the focus of the papers by Singh et al. and Cui et al. [8, 1]. Most important is the paper by Singh et al. [8], since it uses the point cloud-based methods mentioned before. The techniques discussed in this article are the main reference for the research performed in this paper. However, since these papers are focused on humans, they only apply to a certain extend to the contents of this paper. The articles by Henry et al. and Dore et al. [3, 2] are focused on behavioral tracking of animals, sheep in particular. In their research they try to track the movements and behavior of herds of sheep using a FMCW Millimeter wave radar. The paper of Henry et al. [3] solely focusses on the use of the Millimeter wave radar, while the paper by Dore et al. [2] also compares the use of the Millimeter wave radar to tracking by video and infrared cells. These papers use a more suiting test subject, since it is focused on animals. However, their focus is on the tracking of animal herds outdoor, which makes these papers deviate from the goal of this paper. The feature extraction and classification to label activities of individuals is a part of the Machine- and Deep learning part of this paper. In the papers listed in the Reference various ways of training classifiers are mentioned using different Machine- and Deep learning techniques [7, 5].

3. TECHNICAL DETAILS

3.1 Millimeter wave radar

In this research the Texas Instrument's IWR1443BOOST FMCW Millimeter wave radar was used to gather data form the test subjects. The Millimeter wave radar transmits an electromagnetic wave signal that objects in their path then reflect. By capturing the reflected signals, features like range, velocity and the angle of an object can be determined [10]. These features can be used to generate a so-called point cloud. The point clouds consist of clustered points each containing x, y, and z coordinates. These points are displayed in a three-dimensional grid.

3.2 Software

In order to visualize and record the aforementioned point clouds a software package called ROS (Robot Operating system) was used. ROS is a collection of software frameworks used for development of robotics. The relevant services ROS provides are generating point cloud data, visualizing these point clouds and finally storing them. Since ROS is only compatible with a Linux based Operating System, a Ubuntu Virtual Machine was used to install and use the ROS packages. VirtualBox provided the Virtual Machine.

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3.3 Data processing

In the paper by Singh et al. [8] a specific set of data processing steps are introduced. The data pre-processing techniques used in this research are based on the ones introduced in their paper.

3.3.1 Storing data

Rosbags are a part of the ROS packages and are used to store raw point cloud data. The rosbag files are stored in the '.bag' format. The data stored in this format is not suitable for direct further utilization. Therefore, the rosbags first must be converted to text files. ROS has built in functionalities to convert rosbags to text files, using terminal commands. By Using a python script all rosbags are converted to text files automatically.

3.3.2 Voxelization

Next the gathered data was voxelized according to the voxelization script from the repositories implemented by Singh et al. [8]. This voxelized data is ready to be used by the classifiers. Voxalization is a data processing technique which transforms three dimensional data into a voxelized grid. This means that in non voxelized data each point in a 3D grid has its own x, y, and z coordinate. Whereas the voxelized representation of this same data is represented as cubic elements which can contain none, one or multiple points. The size of each voxel in our grid is 10 * 32 * 32. To create workable samples, the data is divided in sets of 60 frames. This results in a shape of 60 * 10 * 32 * 32 for each sample in the voxelized representation.

4. EXPERIMENT

In this section the experimental setup is discussed. In table 2 and 3 the amount of data records, and seconds per activity are displayed. The amount of data acquired from human activities is larger than from animal activities. The cause for this difference is discussed in section 7.
First, the experimental setup for human activity recognition will be described, then the experimental setup for animal activity recognition will follow. This is also the order in which the experiments were executed during the research. In table 1 the configurations for the Millimeter wave radar are summarized.

Table 1 Radar configurations

Parameter	Value
Number of range samples	240
Number of chirps	16
Frequency	79.210 GHz
Bandwidth	2439.803 MHz
PRI	64.140 us
Frame time	33.33 ms
Max range	10 meter
Range resolution	0.044 meter
Max Doppler	+-4.197m/s
Doppler resolution	0.615 m/s

4.1 Data collection

4.1.1 HAR

The radar was mounted on a tripod at a height of 0.90 meters, the activities were executed at 1.30 meters distance from the radar. The data was gathered using two subjects. To make sure each activity is clearly separated the activities are recorded one by one. Each activity was performed for 20 second continuously by the two test subjects. This time frame is based on earlier research performed by Singh et al. [8]. To reassure the activities are performed consequently and at a constant pace, each subject performed the activities for only five trials in a row. After these five trials, each trial being 20 seconds long, it is possible that the activity will not be performed with the same intensity anymore, most likely due to fatigue of the subjects. The activities measured can be found in the table below, together with the amount of data each activity has. The data was stored and processed as described in section 2.

Table 2 HAR activities

Activity	Records	Seconds
Sitting	31	780
Walking	32	800
Waving	30	600
Kicking	30	600
Slapping	30	600

4.1.2 AAR

To record animal activity data the same principle is applied as with the human activity dataset. A dog is used to record four different activities, displayed in table 3. The dog is approximately 45kg, 0.75 meters high and 1.10 meters long. These attributes make it necessary to change the height of the radar. Therefore, the radar is set at a height of 0.50 meters, instead of the 0.90 meters used during the human activity recognition. The activities are performed at approximately 1.30 meters distance from the radar. The activities 'sitting' and 'lying down' are recorded in trials of 10 seconds, instead of the 20 second trials used in human activity recognition. This is because it is more difficult to keep a dog in the same position for longer than 10 seconds. To record a walking motion the dog was recorded walking towards the radar. The path to the radar took the dog about 5 seconds, therefore this is the timespan of the trials used to record the walking activity. The last activity mentioned in table 3 is 'eating'. An attempt to record this activity was made, as it could be useful in terms of animal well-being. However, the quantity of this dataset is lower than the rest of the activities recorded, this was due to the short amount of time the test subject spent eating in a day.

Table 3 AAR activities

Activity	Records	Seconds
Sitting	50	500
Walking	72	400
Lying down	50	500
Standing	100	500
Eating	25	250

5. MACHINE LEARNING METHODS

Both the human and animal data has been split in a train-test ratio of approximately 5:1.
To classify the activities several Machine- and Deep learning models are trained and compared. The basics of these models will be explained in this section.

The following classifiers are used: SVM, KNN, MLP and LSTM. The SVM, MLP and LSTM are also trained in the paper by Singh et al. [8], therefore the comparing their accuracies with the ones from this paper can give interesting insights.

The SVM is trained after applying principal component analysis (PCA) on the input data. The PCA reduces the number of dimensions in the training data. PCA requires a lot of computational performance from a computer, therefore the number of components the PCA uses on the data is set at 300.

The K-nearest neighbors (k-NN) determines the class of a data sample based on k number of features which are very similar or close to the data sample. If the parameter 'k' in k-NN is for example 1, it will classify an unknown set as the training set that is the closest to the unknown set.

The multilayer perceptron (MLP) is a class of Artificial Neural Networks (ANN). ANN models are inspired from the human brain, and according to Subasi et al. [9] they have some extraordinary abilities that are useful for current research in biomedical signal analysis. The MLP consists of three layer nodes, an input, hidden and output layer.

A bi-directional LSTM consists of two layers operating in parallel. The two layers run the input two ways, one time from past to future, and one time from future to past. Using a bi-directional LSTM over a unidirectional LSTM provides a faster and better learning process on a certain problem. [8]

6. CHALLENGES

As mentioned in the introduction one of the goals of performing data collection on both humans and animals was to research what challenges would arise when collecting this type of data on Animals. The first problem, and the problem causing the most limitations, was the data retrieval method. As mentioned in the experimental setup the way the data was gathered is by performing a certain activity continuously in front of the radar for a certain amount of time. For human activity recognition this method forms no obstacle, since the subjects can be clearly instructed on the activities they have to perform. On animals however this opposes a problem, for most dogs it is impossible to perform the same activity in front of a radar for a long period of time. This makes the method of data retrieval on animals inefficient and time intensive.
Secondly, the quality of the data collected is mostly based on the density of the point clouds. Human subjects provided more dense point clouds than the animal subject. The first reason for the difference in point cloud density are the type of activities. During the data collection it became clear that the density of the point clouds became higher when an activity had much variation in velocity. The activities performed by the human subjects contained more distinguishable and fast movements, resulting in a denser point cloud. The second reason is the size of the test subjects. The body of a human subject has a larger area which can be detected by the radar. This research used a relatively large animal, however the difference in size could still be causing a less dense point cloud. Figures 1 and 2 contain an image of the ROS visualizer displaying the generated point clouds on both a human and a dog.

Next to these challenges concerning data collection, there were some other challenges. The radar and software setup required numerous steps. These steps on general were lacking documentation and were not specifically designed for the radar used in this research. This resulted in a setup process which took more time than it should have. Releasing better documentation on this topic could increase the efficiency on this type of research.

Lastly, a challenge was the training of the classifiers. The data files gathered, mainly the human activity data files, were relatively large. The data processing itself took a lot of time and storage. Loading the training data and using this data to train the models takes a lot of computational capacity of a computer. This made the training of the models time intensive, and due to this the model parameters could not be changed easily.

Figure 1 Human point cloud

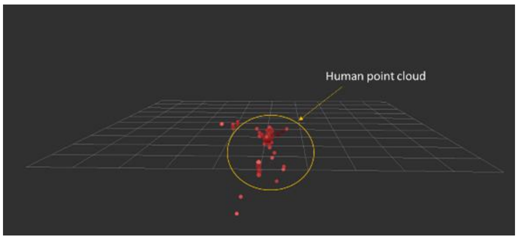
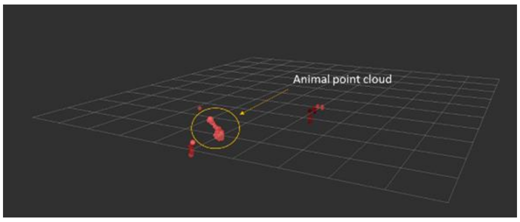


Figure 2 Animal point cloud



7. DISCUSSION

Although it was possible to record animal data, there were some limitations. Firstly, the difference in point cloud density between human and animal activity data was significant. The paper by Cui et al. [1] hypothesizes that the radar fails to detect movements close to the ground. In their research, focused on human posture recognition, this results in failing to distinguish lower body parts from each other. To apply their hypothesis on the research in this paper, the animal activity recognition could be less clear because an animal is closer to the ground, and the radar therefore has more trouble generating a dense point cloud. The difference between the point clouds can be seen in figures 1 and 2, containing human and animal point cloud data, respectively.

Secondly, the data gathering method used in this research limits the number of activities detected and the amount of data each activity set contains. The initial cause for this lack of quantity is that it is more difficult to instruct an animal on certain tasks than it is for humans. The paper by Labdha et al. [6] researches animal activity recognition using a wearable device. The data gathering method used in their paper monitors the animals in their natural habitat, while labeling the data afterwards. This way of acquiring data seems to be more effective and makes it possible to gather a larger data set on, more importantly, a larger number of different activities.

The accuracies of the classifiers are displayed in table 4. As is displayed in this table the highest accuracies on both human and animal data originate from the MLP and LSTM. On human data the models performed well with an accuracy of 95% for the MLP and an accuracy of 96% for the LSTM. These two models performed with accuracies of 71% and 72% respectively on animal data. The other two classifiers perform poorly on both human and animal data. This makes the two neural networks (MLP and LSTM) more suitable to use for this type of data.

The accuracies of the trained models on animal data are in general lower than the models trained on human data. One reason for this difference could be the amount of training data used during the training and testing of the models. As mentioned above, one of the limitations affected the amount of data we were able to gather on animal activities. This lack of data quantity could lead to lower accuracies. Finally, the difference in point cloud density between human and animal point cloud data could also be an indicator for the worse performance of the classifiers on animal data. The details on the differences in point cloud density are more extensively discussed in section 6.

Table 4 Classifiers

CLASSIFIER	HAR ACCURACY	AAR ACCURACY
SVM	63.05%	55.00%
KNN	28.15%	18.25%
MLP	95.40%	71.29%
LSTM	96.70%	72.45%

8. CONCLUSION

This paper researched to what extent animal activities can be recognized using a Millimeter wave radar. This was researched by performing experiments on both humans and animals. The paper designed an experimental setup in which the data was gathered, stored, and processed. Furthermore, the paper addressed challenges and limitations which occurred during research. The machine- and deep learning models trained in the research determined the accuracy with which the activities can be classified. This research concluded that although it is possible to use a millimeter wave radar to detect animal activities, it is has a lower accuracy than human activity recognition. This makes the millimeter wave radar not yet an optimal replacement for wearable solutions serving the same purpose. This is mainly due to the fact that the raw point cloud data provided by animal activities is of lesser quality than those provided by human activities. Furthermore, the data gathering process is inefficient and time intensive, which leads to a limited number of activities that can be recorded. Further research is needed to address these problems, this will increase the amount of usable data and the number of detectable activities. This can result in a better performance of the machine- and deep learning models, and therefore in a more accurate activity recognition.

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