Novel Radar based In-Vehicle Occupant Detection Using Convolutional Neural Networks

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***Abstract*—Vehicle Occupant Detection has gathered attention with the advancement of Connected Automated Vehicles (CAVs) since it enhances vehicular safety features and contributes to Vehicle-to-Everything (V2X) communication features. In this paper, a novel Frequency Modulated Continuous Wave (FMCW) radar-based occupancy detection utilizing Convolutional Neural Networks (CNN) is introduced. The proposed methodology tackles disadvantages posed by visual and sensor-based methods when privacy, computational complexity, line-of-sight requirements, and robustness are concerned. The system uses time-domain raw radar data signals to form visual heatmaps based on signal intensity variation caused by presence of a target. The heatmaps developed for each data frame acts as an input to the neural network. Visually generated signal based heatmaps differentiate three classes of vehicle occupancy: vacant, driver seat and rear passenger occupancy. The adapted CNN architecture is an implementation of transfer learning where a version of the VGG-16 pretrained model consisting of 16 convolutional layers is used. A validation accuracy of 96.88% is achieved with a dataset containing 1000 heatmap images for each class. The results conclude that radar generated time domain heatmaps efficiently detect vehicle occupancy employing transfer learning even with smaller datasets.**

Keywords—FMCW, CNN, Radar, Transfer Learning, Classification, Vehicle safety, Vehicle Occupancy.

I. INTRODUCTION

Successfully determining vehicle occupancy has been an area of interest for auto-manufacturers and transport regulatory boards. As the industry is moving towards highly automated vehicles, active and passive safety systems in vehicles are of major concern. While active safety systems try to avoid catastrophic accidents and crashes, passive safety systems try to protect passengers or occupants during or after the crash [1]. Seat belt warning (SB), Airbag deployment (AB) and Child Safety Systems (CSS) are some examples of passive safety systems in vehicles. Statistics have suggested that the use of seat belts and airbags have saved thousands of lives and have decreased accident fatality by nearly 12% [2]. On similar grounds, child presence system installation has been strongly recommended by the European New Car Evaluation Program (NCAP) in new cars starting from 2020 [3]. At the base level, vehicle occupant detection was initially implemented to provide passive safety features such as seat belt reminders [4]. Recent advancements in the automotive domain have given rise to several modern applications of occupancy detection. The passenger operation of electric vehicles and futuristic autonomous vehicles depend highly on vehicle occupancy to provide better user experience [5] or effective use of Driver State Monitoring (DSM) systems [6].

In literature, various attempts have been made to detect occupants in vehicles. Early implementations involved pressure sensors embedded in seats to enhance occupant protection [7] [8]. These methods pose disadvantages when dynamic observations are required. Capacitive seat sensors were developed to solve this issue as they determine the electric field distribution to capture information of mass distribution. The principle of capacitive sensing has been improved and developed to work on low electric field radiation systems [9] and multiple transmitting and receiving electrodes [10]. However, systems developed based on electric fields, capacitive or inductive methods have posed high false alarm rates which led to users often disabling these features [11]. On-board motion sensors that depend on the opening and closing of doors have also been used for occupant detection and counting which pose similar false positive issues [12].

Vision based methods using optical devices such as cameras have proven to be a feasible solution for occupant detection. External image data obtained through cameras set along roadways have been often used for vehicle occupant counting in high occupancy vehicles lanes [13] [14]. Such methods seem impractical when off roadway occupancy sensing in concerned. Detection and localization of passengers have been implemented efficiently with image data obtained from in-vehicle cameras in combination with machine learning and deep learning algorithms such as SVM (Support Vector Machine) [15], AdaBoost [16], CNN (Convolutional Neural Networks) [17], Clustering and Linear Regression based classifiers [18]. Although vision-based methods provide promising results, they invade users' privacy and do not perform well in occluded scenarios. The issue of user privacy has been attempted to be resolved using thermal cameras [19] but are sensitive to external temperature conditions and occupant clothing.

In recent times, radar systems have gained attention due their reliability in detecting targets under different conditions and their ability of seamless hardware and software integration [20]. Human sensing with UWB (Ultra-Wideband) radar technologies have been utilized for in-room applications for several applications such as vital sign monitoring [21] and gesture recognition [22]. Currently, classes of Ultra-Wideband (UWB) radars such as IR-UWB (Impulse Radio Ultra-Wideband), CW (Continuous Wave) and FMCW (Frequency Modulated Continuous Wave) radars have become popular choices for such applications. The feasibility and robustness of UWB radar for human occupancy detection in indoor applications can be extended to other confined environments such as vehicle cabins. The IR-UWB radars have been used in vehicle cabins to detect passenger vital signs [23] but has difficulty in classifying stationary and moving objects. CW radars are another popular choice due to their simple architecture and ease of use. Applications such as human life detection have been implemented using CW radars [24], however, these radars have only been able to detect moving targets and not their range [25]. At present, FMCW radars are employed in applications such as adaptive cruise control as they are capable of detecting range, angle and the velocity of objects [26]. Previous FMCW literature in the automotive domain suggests limited use of the radar for in-vehicle applications.

Machine learning and Deep learning has been incorporated with FMCW signals for various applications. The time domain FMCW signals have been effectively used for target range estimation using ANN (Artificial Neural Networks) [27] with synthetically generated radar data signals. Some other implementations focused on phase-based characteristics of reflected FMCW signals from pedestrians and vehicles to classify respective targets [28]. Deep CNN image based architectures such as YOLO [29] has been used for external target detection in cars using 2D images created in the range-angle (RA) domain from raw FMCW signals. VGG-16 [30] which is another image based CNN architecture has also been used on range-angle images generated from FMCW signals for human detection and classification in indoor environments. Range-azimuth estimation have also been implemented for in-vehicle occupant detection using FMCW features and Support Vector Machines (SVM) but suffered resolution issues [31].

In this paper, the method of transfer learning is applied where the VGG-16 [32] based CNN network is modified for vehicle occupant detection on visual heatmaps created with time-domain FMCW radar signals. The system poses several advantages over previously discussed implementations:

1. Contactless, non-intrusive system that is robust to slight movements in targets.
2. Secures users' privacy as it eliminates the concept of in-cabin images.
3. Performs well in occluded scenarios due to FMCW radar signals' ability to penetrate through objects.
4. Low-cost implementation that can be performed with a single transmitter and receiver based FMCW antenna.
5. The transfer learning approach avoids overfitting issues when working with smaller datasets.

The remainder of the paper is organized as follows: Section II of the paper outlines the methodology, working of FMCW systems and the system setup. Section III outlines CNN architecture and software details of the implementation. Section IV presents the results, discussion on performance.

II. Methodology, Hardware Specifications and System Setup

A. *Methodology*

The detailed methodology is summarized in figure 1. The received FMCW reflected off targets are further processed to eliminate effects of static clutter. The method of background subtraction where an array of average signal values collected in the absence of the target is subtracted from the acquired signal is employed. Signal intensities of each frame is calculated to form heatmaps that correspond to target detection. The heatmaps form the input to the CNN where classification takes place.

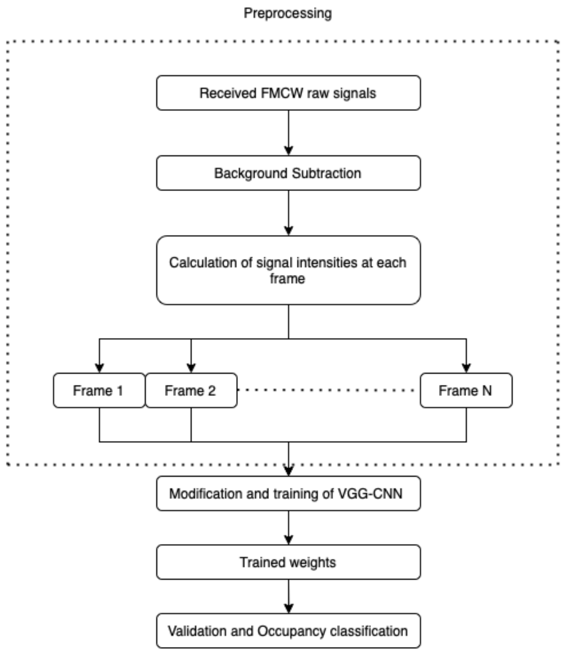

Figure 1. Block diagram of the proposed algorithm

B. *FMCW - Hardware specifications*

The basic working of radars involves the emission of EM (Electromagnetic) waves into surrounding environment where an identical echo of the transmitted wave is reflected at the receiver. The FMCW radar emits waves that are commonly called "chirps". Chirps emitted by FMCW are either sinusoidal or sawtooth waveforms whose frequency linearly increases and is swept between the start (fmin) and end (fmax) frequency bands. The relation between increasing frequency and time can be observed in figure 2. It is notable that the extent of linearity with respect to time depends on the start and end frequencies.

Multiple chirps can be emitted in certain modules that are reflected to the receiver from the targets in the radar arena. The received and transmitted chirps are mixed to generate an IF (Intermediate Frequency) signal or Beat signal that has a constant frequency. Multiple tones of IF signals are produced when multiple targets are present in the arena. The range of the target from the radar can be calculated as frequencies of IF signals are directly proportional to distance. Lower frequencies correspond to targets present close to the radar and vice versa.

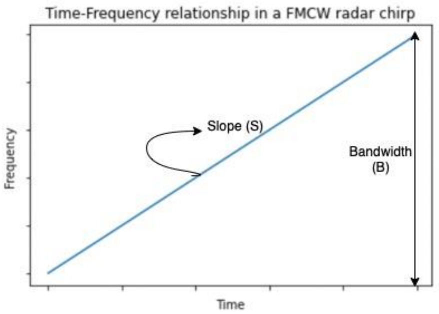

Figure 2. FMCW signal and Time-Frequency relationship

The FMCW radar module selected in this paper is the off-shelf commercially available Walabot Developer Kit [32] that is an integrated radar and signal processing unit. The module consists of 18 pairs of transmit/receive antennas that are used for 2-dimensional object detection. The version selected in this paper can output both raw radar data as well as processed data that is accessed through the Walabot software development kit. The Walabot emits a single chirp per frame and has a frequency sweep of 3.3-10GHz. Each frame captured by the module consists of 8192 samples classified as range bins. The sampling rate of the module is 4Hz.

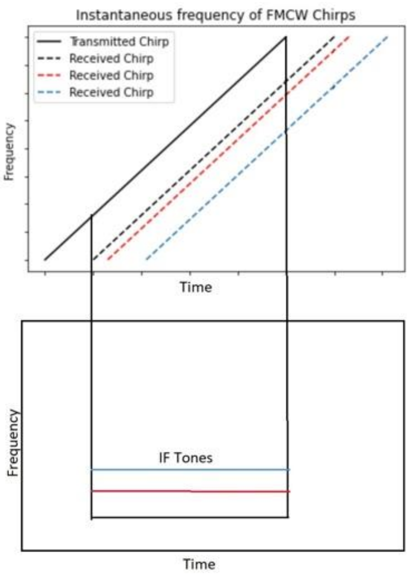

Figure 3. Multiple FMCW chirps and frequency relationship

C. System setup and Data Acquisition

The radar data obtained from the Walabot contains received signal voltage in a matrix form whose dimension depends on the number of active antennas. The code used for data acquisition is a modified version of the open-source python code for a project called ‘People and Fall detection’ available on the Walabot Community website [33]. The proposed system uses four pairs of active antennas for data collection out of which the data representing horizonal plane is selected. It was observed that the AntennaPair-2 (txAntenna=1, rxAntenna=3) represents strong signal strength in the horizontal plane [33]. Hence, further signal processing and heatmap generation is done using the signal obtained from AntennaPair-2. To replicate the vehicle environment, the radar was placed in a Driver-in-loop simulator as shown in the figure 5. Position of the radar remained fixed throughout the data collection experiment.

Figure 4. Walabot hardware antenna array

Clutter suppression is an important step in processing radar data. In this case, signal reflections from seats and other in-vehicle objects are considered static clutter interference. The raw data acquisition code including a background subtraction function is applied to eliminate signal energy from static clutter and other objects. The target arena for the radar is specified in spherical coordinates where Phi and Theta are measured in degrees with a resolution of 4.5 degrees per pixel whereas R is measured in centimeters with a resolution of 5cm per pixel. The Walabot arena setting for occupant sensing is as follows:

- Phi = (-60,60,4.5)
- Theta = (-45,45,4.5)
- R = (10,400,5.0)

Figure 5. Hardware positioning and setup

FMCW data has been captured for 3 occupant scenarios:

1. Driver seat occupancy
2. Rear passenger seat occupancy
3. No vehicle occupancy

Equal number of data points have been collected for all the three scenarios with two participants ensuring at least 1000 frames in each class for training and 200 images for validation with the neural network. The participants in the driver seat performed a brief driving activity during data acquisition whereas participants in the rear passenger seat performed non-driving activities. The vehicle accommodated one participant at a time for data collection ensuring single occupancy for each scenario described. The raw data recorded has been processed to generate horizontal plane heatmaps based on reflected signal intensities. The band representing highest signal intensity in each case indicates the presence of a target. The comparison of heatmaps produced for each class is represented in the figure 6. The heatmaps produced act as input to the CNN.

III. CNN ARCHITECTURE AND TRAINING

The proposed CNN model is designed to work efficiently with smaller datasets as it has been pretrained on larger datasets for different problem statements. The architecture used in this paper is a modified version of the VGG-16 [32] CNN model trained on a subset of the ImageNet dataset consisting of over 14 million images belonging to 22000 classes. The subset of the ImageNet dataset contains different images of vehicles and contains 1000 output labels.

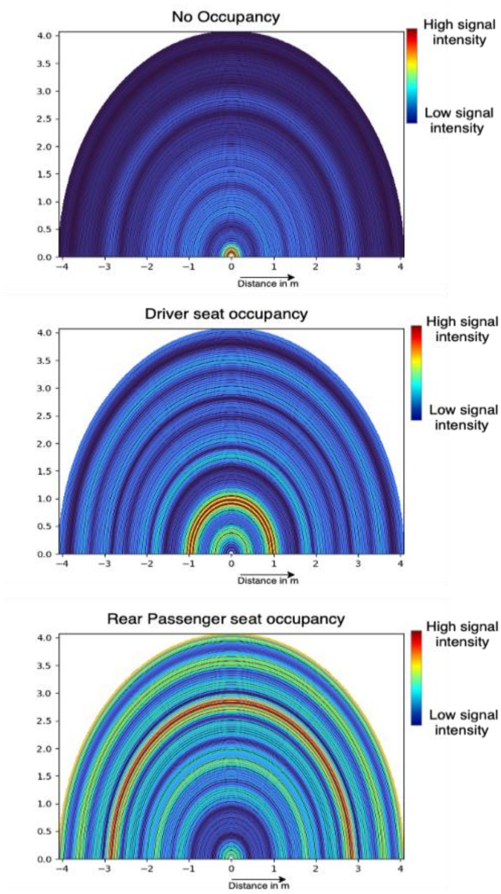

Figure 6. FMCW heatmaps for occupant detection

The model contains 16 convolutional and max pooling layers and three fully connected dense layers. Each convolution layer filter has kernel size of 3*3 and pooling region of 2*2. The input layer and the final layer has been modified to perform classification on the three classes of vehicle occupancy defined in the section above. The activation function at the final layer is set to Softmax with a three-class output. The CNN architecture is shown in the figure 7. The implementation of the VGG-16 CNN network has been done with 3000 input images and 600 validation images. In this paper, the all the pre-trained convolutional layers are frozen for training except the last two layers for fine-tuning purposes. The final fully connected layer has been modified to output three occupancy classes in the architecture as shown in figure 7.

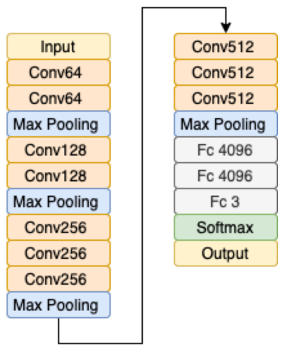

Figure 7. VGG-16-CNN Architecture

IV. RESULTS

The CNN model defined in the previous section has been trained with radar signal heatmaps produced for each frame in the preprocessing stage with 119,558,147 parameters. The model was trained for 75 epochs to attain a maximum training accuracy of 98.96% and a maximum validation accuracy of 96.88%. Figure 8 depicts the model performance in terms of accuracy and loss function. As observed, the loss decreases 0.0708 at maximum validation accuracy. The issue of overfitting which is often the case when smaller datasets are concerned has been solved by transfer learning in the proposed algorithm.

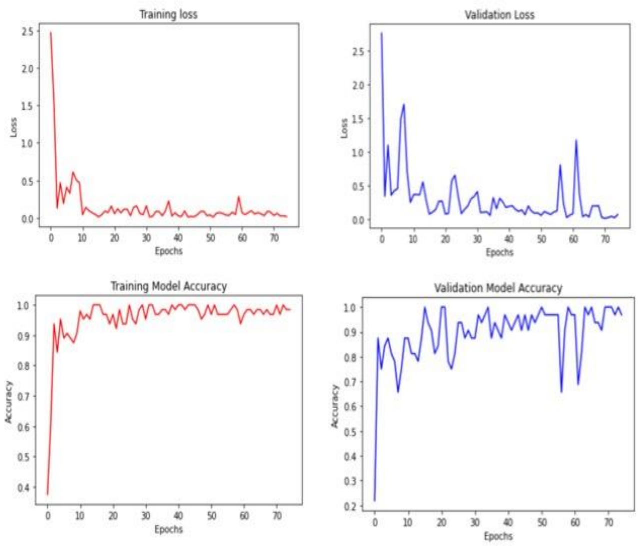

Figure 8. CNN results

Along with the validation results the model has been tested on several test image heatmaps generated which were not used for training and validation to test the performance on unseen data. A group of 120 images consisting of 40 images from each class that constitutes to 10 seconds of data in each class has been selected.

TABLE I. CNN CLASSIFICATION TEST RESULTS

Class	No. of true predictions
No Occupancy	37/40
Driver seat occupancy	34/40
Passenger seat occupancy	31/40

It was observed that some heatmaps contained severe passenger motion which causes disruptions in the heatmap distributing peak signal energy to several other range bins. In such cases, the maximum intensity ring is not observed in specific frames. Some examples of energy intensity distributions caused by motion is shown in the figure 9. As observed in the driver occupancy heatmap, the signal intensity (according to the scale) is spread across several bins below 1m.

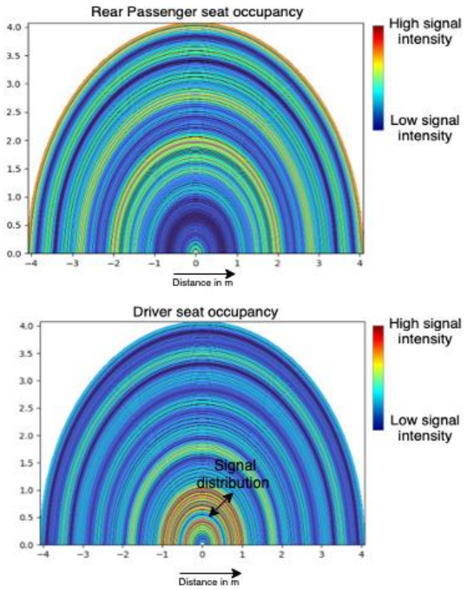

Figure 9. Energy distribution cause by target motion

The issue of signal intensity distribution can be solved by employing movement cancelling pre-processing steps with raw radar signals. However, practical implementation of occupant detection is a real-time application that requires the detection over a span of seconds. The overall accuracy of the system would not be affected as the algorithm can be improved to classify occupants based on probabilistic methods considering the high sampling rate of 4frames/second if the adjacent frames detect occupants successfully. Alternatively, the neural network can be trained with a larger dataset fine-tuned to avoid false negatives.

V. Conclusion and future work

In this paper, an efficient vehicle occupant detecting system employing Frequency Modulated Continuous Wave (FMCW) radars and Convolutional Neural Networks (CNN) in the form of transfer learning has been investigated. The results suggest that the system can successfully detect occupants in driver and rear passenger seats with a validation accuracy of 96.88%. The proposed algorithm is a computationally less complex, cost effective and non-line-of-sight implementation that overcomes drawbacks posed by sensor based and vision-based occupant detection methods. The drawbacks of the system proposed in this paper include signal intensity distribution in the heatmaps when quick target motion is identified. However, it was observed that the overall accuracy of the system does not degrade as the module has a good sampling rate of 4 frames/second and the system would not be affected by minimal number of false negative frames in real-time applications. The error rate of the system remains within 5% even if two wrong predictions occur in every interval of 10 seconds.

The proposed system is based on horizontal plane data obtained from a specific radar antenna pair from the Walabot module. It can be further improved for multiple occupant detection and localization systems by processing radar data in the horizontal and vertical planes. The applications of vehicle occupant detection fall beyond vehicle safety with the current advancements in the automotive industry as user interaction and experience has gained attention. The scope of the proposed system can be further broadened to in-vehicle physiological sensing applications as FMCW radars are efficient in measuring signals such as heartrate and respiratory rate with frequency domain analysis of raw radar signals.

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