mmWave Testbed for Data Collection and Model Sharing in Contactless Concentration Monitoring System

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CCS Concepts

• **Human-centered computing → Ubiquitous and mobile computing systems and tools**; • **Computing methodologies → Neural networks**.

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1 Introduction

Maintaining concentration is essential for productivity, learning, and safety, yet it remains difficult to assess objectively in everyday settings. Traditional methods such as self-reporting and observational studies are subjective and labor-intensive. Wearable sensors can provide physiological data but require constant contact with the user, while camera-based systems raise privacy concerns and are sensitive to illumination and occlusion.

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Millimeter-wave (mmWave) sensing offers a contactless and privacy-preserving alternative by capturing micro-movements of the human body through radar reflections. With the growing integration of mmWave technology in WiGig and 5G systems [2, 3], such sensing approaches are increasingly practical. We present a system that detects concentration-related behaviors—eye blinking, nodding, yawning, and leg shaking—using reflected mmWave signals to infer attention levels.

Our system integrates signal preprocessing, beamforming-based spatial decomposition, frequency-domain analysis, and deep learning with domain adaptation [5]. The approach achieves accurate classification using a single Commercial-Off-The-Shelf (COTS) radar, offering a low-cost solution for contactless concentration monitoring in classrooms, offices, and healthcare environments.

2 System Design

The system comprises four key components: signal preprocessing, spatial decomposition, activity separation, and activity recognition.

Signal Preprocessing: Raw intermediate-frequency (IF) radar data include environmental noise and static reflections. We apply a two-stage filter: a finite impulse response (FIR) low-pass filter and Savitzky–Golay smoothing to suppress noise while retaining fine-grained motion features. The processed phase signal captures millimeter-level displacements essential for subtle activity detection [6].

Spatial Decomposition: To overcome the limited 120° field of view of COTS mmWave devices, Delay-and-Sum (DAS) beamforming is employed to enhance reflections from specific body regions. Upper-body reflections (30°–90°) capture head and facial motions such as blinking and nodding, while lower angles (0°–30°) indirectly capture leg shaking through torso vibrations. This decomposition allows multiple concurrent activities to be spatially isolated even when partially occluded.

Activity Separation: We use Short-Time Fourier Transform (STFT) to analyze the spectral distribution of motion signals. Each activity exhibits distinct frequency characteristics—eye blinking (0.5–2 Hz), nodding (0.5–2 Hz), yawning (0.1–0.5 Hz), and leg shaking (4–8 Hz) [4, 7]. Combining spectral and spatial features enables robust separation of overlapping activities.

Activity Recognition: A one-dimensional convolutional neural network (CNN) processes the segmented phase data for multi-label classification. The CNN learns temporal and spatial features to recognize multiple activities concurrently. To maintain robust performance across environments, we adopt adversarial domain adaptation and reconstruction-based regularization following [5].

3 Methodology

3.1 Feature Extraction and Segmentation

After beamforming and frequency analysis, phase data from selected range–angle bins are normalized and divided into fixed-length windows. Each segment represents a potential micro-activity. Dominant frequency peaks and temporal gradients are extracted as discriminative features for classification.

3.2 Learning Architecture and Adaptation

The CNN architecture consists of two convolutional and pooling layers followed by dense layers with sigmoid activation to enable multi-activity detection. An adversarial adaptation network aligns feature distributions between environments following the domain generalization approach in [5]. This ensures reliable inference even under domain shifts caused by different furniture or layout configurations.

3.3 Implementation Details

The radar operates at 77 GHz with 4 GHz bandwidth, offering a range resolution of 3.85 cm and angular resolution of 14.3°. The model is trained in PyTorch and deployed on an embedded GPU platform for real-time operation at 25 Hz sampling rate.

4 Testbed Evaluation

We evaluate the proposed system using our developed mmWave testbed built on the Texas Instruments AWR1642 FMCW radar with a DCA1000EVM data acquisition module. The testbed provides synchronized data collection, configurable device placement, and reproducible experiments, supporting cross-environment evaluation for reliable sensing research.

Ten volunteers (eight males, two females, aged 24–31) participated in experiments across three indoor environments with varying layouts and reflective surfaces. Each subject performed four concentration-related activities—eye blinking, nodding, yawning, and leg shaking—for 60 s each at distances of 0.5 m, 1.0 m, and 1.5 m. Additional non-concentration behaviors such as talking and casual gestures were recorded as baseline samples.

The system achieved an overall classification accuracy of 95.3% across four concentration-related activities, maintaining above 78% accuracy at 1.5 m. Cross-environment evaluation achieved an average accuracy of 87.7%, improving to 91% with domain adaptation. These results validate that the developed mmWave testbed enables reliable and privacy-preserving concentration monitoring across diverse conditions [1, 6].

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