Poster: ZigZagCam: Pushing the Limits of Hand-held Millimeter-Wave Imaging

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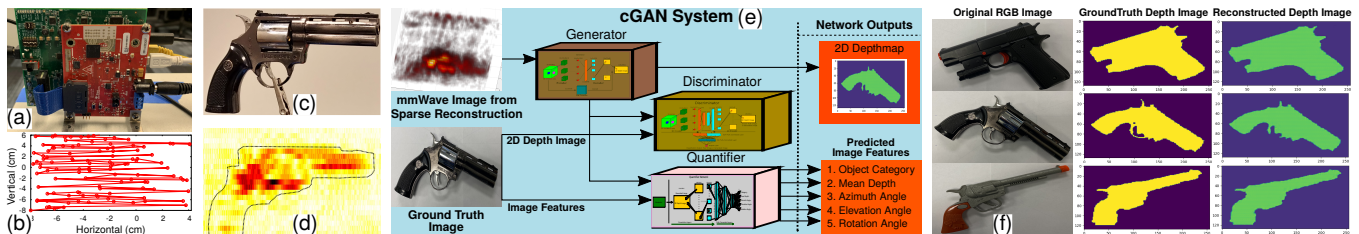{hregmi,msaadat}@email.sc.edu;sur@cse.sc.edu;srihari@sc.edu

Figure 1: (a) Millimeter-wave device; (b) An example of handheld *zigzag* motion; (c) RGB image of a toy gun; (d) Its mmWave image from sparse reconstruction; (e) cGAN system overview; and (f) Three different shape reconstructions.

CCS CONCEPTS

• **Human-centered computing** → **Ubiquitous and mobile computing systems and tools**; • **Computing methodologies** → **Machine learning approaches**.

KEYWORDS

Millimeter-Wave, See-through Imaging, Generative Adversarial Networks

HAND-HELD MMWAVE IMAGING

The ubiquity of millimeter-wave (mmWave) technology in 5G-and-beyond devices enable opportunities to bring through-obstruction imaging in hand-held, ad-hoc settings. This imaging technique will require manually scanning the scene to emulate a Synthetic Aperture Radar (SAR) [4] and measure back-scattered signals. Appropriate signal focusing can reveal hidden items and can be used to detect and classify shapes automatically. Such hidden object detection and classification could enable multiple applications, such as in-situ security check without pat-down search, baggage discrimination without opening the baggage, packaged inventory item counting without intrusions, *etc.*

Emulating SAR on a hand-held mmWave device, however, is challenging for three reasons: (1) the hand-held device moves in a non-linear trajectory; (2) the back-scattered signal shows localized sparsity due to non-uniform scanning; and (3) the specular reflectivity from some of the objects and its improper orientation *w.r.t.* scan plane may only allow for a partial shape reconstruction (see Fig. 1[d]). In this work, we propose *ZigZagCam* that aims to solve the above challenges.

SPARSE RECONSTRUCTION AND MACHINE LEARNING

To solve the challenges (1) and (2) above, we apply two well-known techniques. *First*, to compensate for the non-linearity of the hand-held trajectory, we add phase correction in the back-scattered signals to estimate the equivalent samples which would fall on the closest point in the ideal, linear trajectory [4]. *Next*, to recover the samples in sparsely sampled area, we apply a Compressed Sensing (CS) based recovery framework [2]. Figs. 1(a) & (b) show our 77 GHz platform and an example hand-held *zigzag* trajectory. Figs. 1(c) & (d) show an example toy gun and its corresponding mmWave image that we reconstructed at 1 m. stand-off distance.

The reconstructed image not only has a poor resolution but also is missing majority of the edges and parts due to specularity and low reflectivity: Only a rough silhouette is visible (Fig. 1[d]). Clearly, the resultant image would also lack important features for automatic detection or classification. To improve the image quality, we are inspired by the existing work in enhancing low resolution visual images to high resolution using conditional Generative Adversarial Networks (cGAN) [1, 3]. We propose to use cGAN to not only improve the mmWave image resolution but also restore the missing parts in it.

The high-level idea is intuitive. *First*, *ZigZagCam* trains a cGAN framework by showing several examples of mmWave images from sparse reconstruction and its corresponding ground-truth RGB

images. *Next*, cGAN uses a "Generator" to learn the association between the mmWave image to the ground-truth shape, and a "Discriminator" that helps to teach better association at each epoch [3]. *Finally*, during run-time, when cGAN has been trained appropriately, the "Generator" can estimate accurate 2D depthmap outlining the shape without the ground-truth. In addition to the shape, we also use a "Quantifier" framework that extracts other features of the hidden object, like its orientation, depth, types, *etc.*

ZigZagCam's cGAN is trained in dual stages: *First*, we train for 1000 epochs using a synthesized dataset of 8000 mmWave images of various objects. *Next*, we fine-tune the model for additional 1000 epochs using 150 real mmWave images. Post training, we test several real mmWave images without training their ground-truth shapes. Fig. 1(f) shows three example shapes accurately predicted by *ZigZagCam* under testing. Besides, our results indicate that *ZigZagCam* can estimate objects' depth and orientation with less than 5% error in more than 90th percentile. In the future, we will train

and evaluate *ZigZagCam* for shape reconstruction, classification, features identification for more types of objects across different environmental and hidden conditions.

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