Original Review

Review #114A

Overall Merit: 3 (Weak Accept)

Reviewer Expertise: 3 (Knowledgeable)

Paper Summary:

This paper introduces mmDefender, an innovative mmWave radar-based system for non-invasive walk-through detection and localization of on-body concealed weapons. This work notably contributes to enhancing security protocols while ensuring efficiency and non-invasiveness.

Strengths:

The authors properly contrast mmDefender with traditional security methods like visual inspections, metal detectors, and physical pat-downs, which often compromise efficiency and privacy. By leveraging mmWave technology, mmDefender can penetrate clothing and accurately identify concealed objects, significantly reducing physical intrusion.

The paper thoroughly addresses the challenges of using mmWave radar, such as real-time data processing and interpretation amidst varying walking speeds, clothing materials, and environmental conditions.

One of the standout aspects of this paper is its detailed discussion of the technical hurdles overcome in developing mmDefender. These include understanding hardware limitations, efficiently transferring mmWave data, and creating algorithms for real-time processing and classification. Achieving a 90.96% F1 score in detecting concealed weapons in various positions, including the chest, waist, pocket, and ankle, underscores the system's effectiveness and robustness.

Weaknesses:

While the 90.96% F1 score is impressive, the paper does not delve deeply into the scenarios where the system might fail or produce false positives/negatives, which are critical for understanding its real-world applicability. Finally, the discussion on the system's scalability for high-traffic areas could be more extensive, and further exploration in this area would be beneficial.

Comments:

N/A

Review #114B

Overall Merit: 3 (Weak Accept)

Reviewer Expertise: 3 (Knowledgeable)

Paper Summary:

The paper presents a mmWave based sensing system that detects concealed weapons on walking persons. The paper includes the system design and its evaluation.

Strengths:

1. Important, interesting and challenging problem
2. Thorough description of the system

Weaknesses:

1. While the design decisions are presented, the reasoning behind them are missing. Why did they make these decisions and what other options have they looked at?
2. While the evaluations seems thorough, it misses a few important aspects.

Comments:

Major concerns:

The data used to train the neural net seems limited. Only six different people are used and there is a single setup only. What if the sensor placement is somewhat different as is likely in different deployment scenarios?

A related problem is that the evaluation uses a subset of the collected data of the same six people. In a practical deployment there will be hundreds or thousands of different people being scanned. Six people does not begin to cover the space. A good test would be to have a few people not in the training set to see whether the approach generalizes at all.

There is no much justification of the design decisions taken. Were there other alternatives looked at? For example, section 4.2 presents the design of the neural net with a lot of detail. Why is this the best architecture?

The system only looks at the front of the people. Handguns are kept in the back stuck in the waistband in many cases.

The actual test object is not a gun at all. There are only two non-gun test objects.

Minor comments:

The training data is imbalanced. In real life, true positive cases will be few and far between. Yet, the training data has 83% positive cases.

Why not a binary classifier: positive/negative? Having the locations on the body is nice to have **once** the system works well enough in practical cases.

In the related works section, it is not clear how/why some of the existing works are not as good as the presented system. Based on the short summary in the paper, [20] seems better than this work (I have not read [20]).

Is Table 1 missing?

Since the people have to walk through a constrained space (e.g., an entrance to a building) in the presented setup, would a metal detector gate work better? The promise of mmWave is exactly to remove such a constraint. How could this approach improve to address this in the future?

Section 2, the mmWave background section, could be clearer. "The distance to the object is proportional to the IF signal" What property of the signal? The formula to R seems to contain only constants. Speed of light, bandwidth of chirp, frequency of the IF signal. I am surely missing something. If it is the frequency that is changing, how do we know what part of that change is due to distance and what is to Doppler shift?

Review #114C

Overall Merit: 1 (Reject)

Reviewer Expertise: 4 (Expert)

Paper Summary:

This paper presents mmDefender, a mmWave-based system to detect concealed metallic objects on human bodies when the passes by. The core idea is to explore the range-azimuth profiles to figure out additional radar reflections caused by the metallic objects. The authors have performed a thorough evaluation of the proposed framework.

Strengths:

- An interesting problem of good importance and having relevance with the EWSN community
- The paper presents a thorough evaluation of the proposed system
- The idea of using range-azimuth profiles for searching the reflections from additional metallic objets is interesting

Weaknesses:

- The authors claim to be the "first" in proposing such a solution; however, that is not true
- The solution setup is questionable (check my detailed comments below)
- Comparison with existing solutions are missing (possibly the authors are not aware of the existing works)
- The generalizability of the proposed solution is not very clear

Comments:

While I appreciate the authors for developing a practical system and testing it thoroughly under different scenarios (I must admit that I liked the thoroughness of evaluation section of the paper, although with some concerns as explained later on), there are some major criticisms that I have on the overall problem space and authors' claims.

(1) The authors have claimed that they are the first to develop a mmWave-based solution for identifying concealed metallic objects using mmWave radars; unfortunately, this is not true. Please check the following work by Regmi et al. published in IMWUT 2021:

[a] Regmi, Hem, et al. "Squigglemilli: Approximating sar imaging on mobile millimeter-wave devices." Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies 5.3 (2021): 1-26.

Although the above work uses a handheld mmWave radar rather than a fixed one, but the broad objective is the same (detecting concealed objects), and the method is robust. I would expect the authors to at least cite this work and compare their proposed solutions qualitatively, if not quantitatively. Indeed, the authors should argue why such a solution may not work when the radar is fixed but the subjects are mobile.

(2) My next major criticism about the mmDefender is that I feel that the problem statement is rather limited, as the proposed solution will detect ANY concealed metallic objects, may it be a metallic necklace, the metallic belt buckle or a metallic logo on the purse at the back-pocket of the subject, and there is no way to differentiate them. Indeed, it will keep on giving such false alarms for any metallic objects that the subject might have. Indeed, if you have a general environment, like a shopping mall or a train station, the people will have many such metallic objects on them, which mmDefender will alarm falsely. Indeed, I would argue that Squigglemilli (as referenced above) will work better under such scenarios, as they tried to detect the shape of the objects. Therefore, the problem space needs better justifications and arguments.

While I liked the overall idea of using the range-azimuth profile for concealed object detection, I think the work needs to be much matured considering the above factors; and the paper needs thorough analysis, discussion and comparison with the existing works. Indeed, there are works on object detection based on reflection patterns from mmWave radars, which the authors have not cited. [b] Kosuge, Atsutake, et al. "mmWave-YOLO: A mmWave imaging radar-based real-time multiclass object recognition system for ADAS applications." IEEE Transactions on

Instrumentation and Measurement 71 (2022): 1-10. [c] Shuai, Xian, et al. "millieye: A lightweight mmwave radar and camera fusion system for robust object detection." Proceedings of the International Conference on Internet-of-Things Design and Implementation. 2021. [d] Cheng, Yuwei, Hu Xu, and Yimin Liu. "Robust small object detection on the water surface through fusion of camera and millimeter wave radar." Proceedings of the IEEE/CVF international conference on computer vision. 2021. Although these works does not directly detect concealed objects, but they propose approaches for accurate object detection; so I feel such works must be cited and compared with the proposed solution.

(3) Finally, there might be a general issue regarding evaluation, which is a concern for me. The authors have used the data from same set of peoples for training their model and evaluating. However, what if the data is trained on one set of people and tested on a different set, having different types of objects. That raises the question about generalizability of the proposed solution, which the authors need to address by performing leave-one-out experiments with both subjects and the objects used for evaluation.

NB: This work have used human subjects for evaluation; so I feel an ethical approval is required, although the ethical concerns can be minor (as mmWave radars also captured personal information about human subjects, like their physiological statistics as discussed in several existing literature).

Review #114D

Overall Merit: 4 (Accept)

Reviewer Expertise: 3 (Knowledgeable)

Paper Summary:

This paper presents mmDefender, a novel system for the real-time detection and localization of concealed weapons on individuals as they walk through entry points using mmWave radar. The system's design is grounded in an empirical study that informed radar placement and processing algorithms, leading to the development of a two-stage neural network and a bandwidth-efficient data transport algorithm. The system achieves a weight-averaged F1 score of 90.96% and an end-to-end processing time of 3.7 seconds.

Strengths:

- Thorough evaluation
- Novel neural architecture combines modalities effectively
- Detects concealed objects on moving individuals
- Real-world applicability

Weaknesses:

- Lacks baseline comparison
- Limited details on system calibration

Comments:

The paper's evaluation is thorough and well-executed. Figure 14 demonstrates the system's inference efficiency. While the work has some shortcomings, the system was thoroughly tested, and its design was well justified.

The experiment was run on very few people (only six) but many configurations and scenarios. While I initially thought this might not be enough, I don't think the human body is the limiting factor. The factors affecting the system's ability to detect the weapon were properly accounted for in the experiments.

I wonder if there's a way to further reduce download time—could sparse subsampling of the input help and still maintain high detection accuracy?

The baseline comparison with existing weapon detection systems could be clearer. How does mmDefender compare to other systems in terms of accuracy, TP/FP rates, latency, and cost? There are several other work in the literature that have similar goals. How do you compare against them?

Regarding system calibration, more information on how to adapt the system for different environments (e.g., airports, concerts, schools) would be valuable. The 3.7 seconds per person might be too slow for large venues—how could this be addressed? I also couldn't help but think of how sensitive the system was the shape of the object and noticed that you don't evaluate that part of it. Again, this is a part of the evaluation that's missing. Still, if you were to put it in a broader context of security system and the security detection tolerance for those systems it would properly contextualize your design choices and evaluation choices.

While the system is promising, it does need a large amount of data for pretraining, and the potential requirement for fine-tuning in different environments is a drawback. If weapons with different physical properties are involved, could this require a system redesign? It would be helpful to discuss strategies for overcoming these challenges.