# Comparative Study of Passive and Active Acoustic Sensing for Indoor Room Recognition

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## 1. Introduction

GPS is a widely used service around the world and is now an indispensable feature of mobile devices. However, for indoor use they leave much to be desired [1]. In such situations specialized Indoor Positioning Systems (IPS) are used instead. An emerging method to achieve such localization is by using sound with machine learning models. As every smartphone possesses acoustic systems this method is very accessible and infrastructure-free.

## 2. Research Background

The focus of this research will be the recognition of rooms within a building using acoustic systems. This can be achieved through two different ways:

- **Passive Sensing**: listens to existing background audio.
- **Active Sensing**: sends signals and listens to the echo data.

## 3. Research Question

How does passive acoustic sensing compare to active acoustic sensing?

- What are the prerequisites of the two sensing models?
- What is the accuracy of both sensing models in silent conditions?
- How robust is the passive sensing model against interference?

## 4. Method

A java front-end application is used with the two sensing modes. In active sensing mode it emits 20kHz signals for 2ms every 100 ms. In passive sensing mode only audio is recorded. Both sensing modes use a sampling frequency of 44100hz. The data is sent to a server hosted on a laptop for preprocessing, training and classification. On the server the audio data is split into samples, with active sensing samples having a duration of 100ms and passive sensing samples of 1 second. The samples are then converted into spectrograms using Fourier Transform and the irrelevant frequencies are discarded. Active sensing considers in the [19.5-20.5] kHz range. Passive sensing only considers frequencies in the [0-1] kHz range. These samples are then used in a convolutional neural network (CNN) for classification. Data collection is done separately for the two sensing modes in a residential building with 6 different rooms. 50 seconds worth of data is collected in each room for training. For testing 100 samples of new data is collected per room for each experiment. A total of 4 testing experiments were performed in which the testing conditions were changed:

- A baseline in an optimal condition which is most similar to the condition in which the training data was collected in. This implies a silent condition a single person in the room with the phone located in the same position and orientation.
- A condition in which constant acoustic background noise is present. With everything else being consistent with the baseline condition.
- A condition in which multiple people are present at the same time in the room, including one person standing between the microphone and the wall. With everything else being consistent with the baseline condition.
- A condition in which the orientation of the phone is turned 90 degrees around the vertical axis. With everything else being consistent with the baseline condition.

## 5. Results

| Testing Environment | Active Sensing | Passive Sensing |
|---|---|---|
| Baseline | 0.6350 | 0.7367 |
| Noisy Environment | 0.5967 | 0.2167 |
| Orientation Change | 0.4550 | 0.7100 |
| Presence of people | 0.4417 | 0.7218 |

Table 1. Accuracy of active and passive sensing in the classification of 6 different rooms.

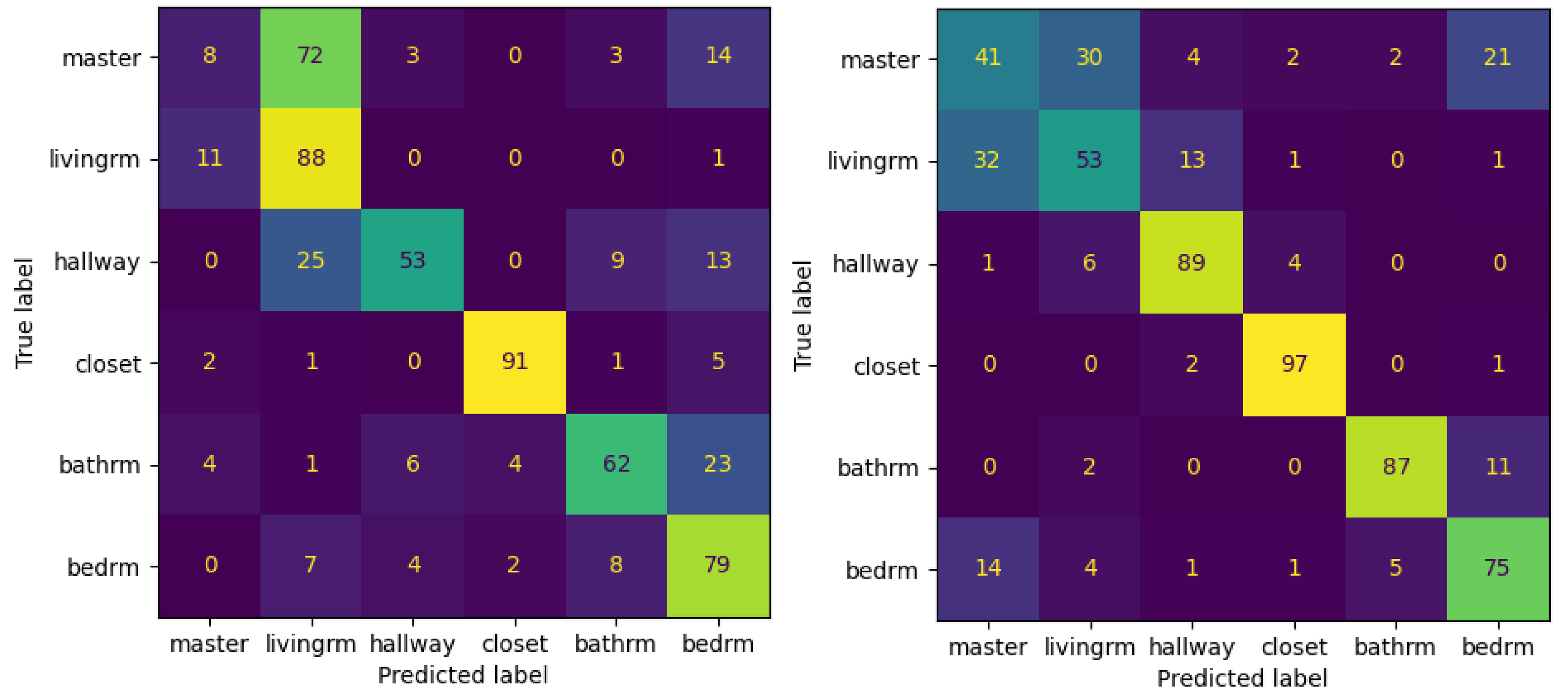


Figure 1. Confusion matrix of active (Left) and passive (Right) sensing baselines

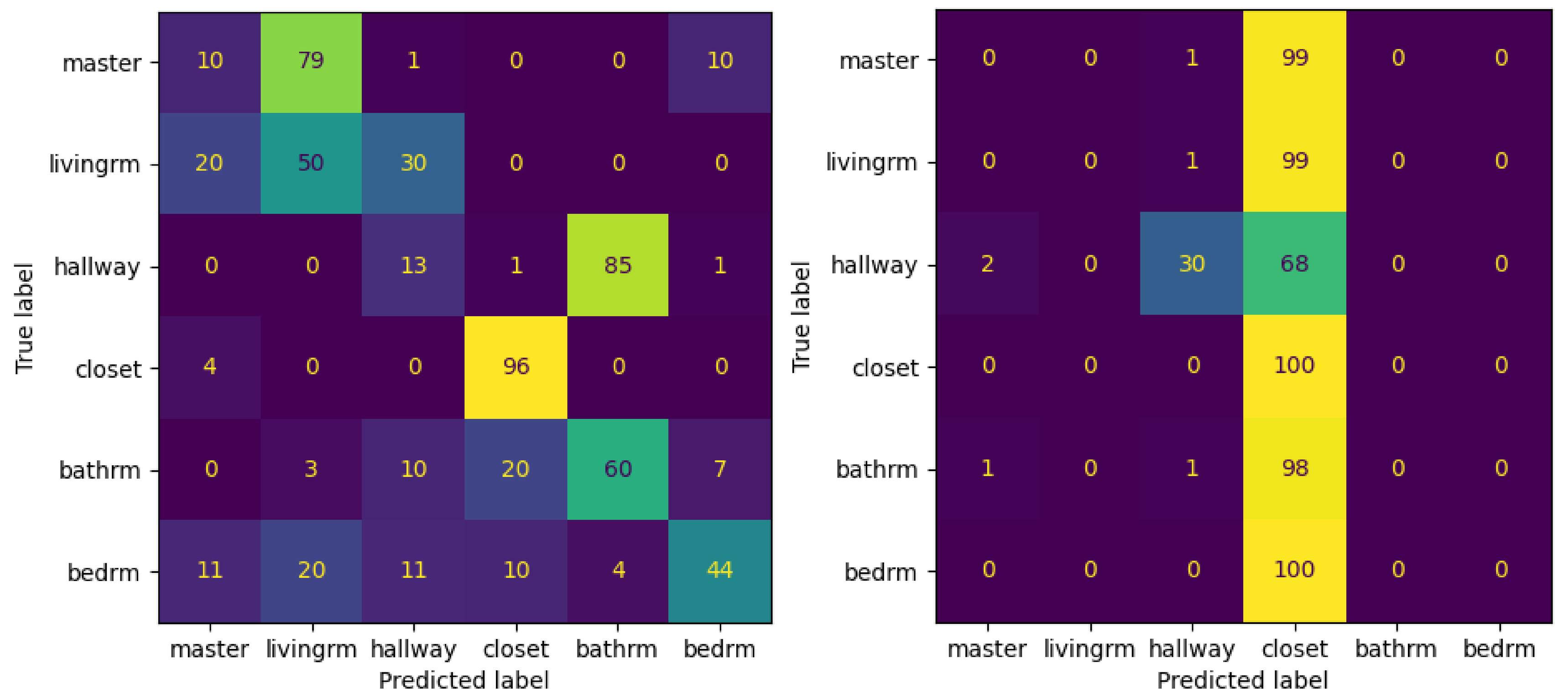


Figure 2. Confusion matrix of active sensing rotated (Left) passive sensing noisy (Right)

## 6. Discussion

In the experiments is is visible that noise had a significant impact on passive sensing performance while active sensing was much more resilient. This is likely due to the difference in frequency bands used for the sensing methods. As most noise is of lower frequencies, they tend to be filtered during the preprocessing for active sensing.

The effect of rotation and the presence of people in the room had a sizeable effect on active sensing. Both of these experiments alter the trajectory of the echoes. As the passive sensing method does not rely on any echoes, the overall performance drop was limited. The effect of rotation was especially apparent in the hallway, likely due to the shape. The rotation significantly alters the distance the echo has to travel.

While the overall accuracy of active sensing was found to be less accurate than passive sensing in baseline conditions, this can potentially be attributed to data collection flaws. Active sensing was also able to classify rooms using much shorter samples, lowering the response time significantly. Additionally there are still other conditions that have yet to be explored, such as time-invariance. Which is something that passive sensing was shown to be susceptible to [2], [3].

## 7. Conclusion

Both models were shown to respond differently to changes in environment, with active sensing being more sensitive to geometrical changes but noise robust and passive sensing being highly susceptible to noise but robust to any geometrical changes. This makes the potential fusion of the two modalities especially promising, as both methods would be able to compensate for each others shortcomings. Additionally both methods do not require any additional infrastructure and data collection can occur simultaneously.

## References

[1] Mikkel Kjærgaard, Henrik Blunck, Torben Godsk, Thomas Toftkjær, Dan Lund, and Kaj Grønbæk. Indoor positioning using gps revisited. pages 38–56, 05 2010.

[2] Ricardo Leonardo, Marilia Barandas, and Hugo Gamboa. A framework for infrastructure-free indoor localization based on pervasive sound analysis. *IEEE Sensors Journal*, 18(10):4136–4144, 2018.

[3] Stephen Tarzia, Peter Dinda, Robert Dick, and Gokhan Memik. Indoor localization without infrastructure using the acoustic background spectrum. pages 155–168, 06 2011.

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