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Improving Indoor Localization by Fusing Active Acoustic Location Sensing and WiFi Localization

3. Objective

Combining active acoustic location sensing and WiFi localization to further increase the accuracy of classifying rooms or positions in open indoor spaces.

4. Methodology

- Implement acoustic localization according to RoomRecognize [3]
- Implement WiFi localization by using received signal strength (RSSI) as fingerprints
- Fusing the localization methods together with weighted averaging, two-step localization, and ensemble stacking

5. Experimental setup

- This building provides:
 - Many rooms that do not require
 - employee access
 - An abundance of WiFi access
 - points

6. Results

- Confusion matrices of individual classifiers can be seen in Figure 2 and
- can be compared to combined classifiers in Figure 3
- Combinations are able to reduce certain classification errors
- Combinations can introduce completely new misclassification errors
- The correct label was almost always
- present in the top 3 predictions

7. Conclusion and Future work

- It is possible to improve indoor localization accuracy by combining active acoustic sensing and WiFi localization
- Combined classifier misclassification tends to overlap with individual classifier mistakes But can introduce new errors
- A larger dataset should be taken to determine the improved accuracy
- Can add additional classifier to the fusion

1. Introduction

- Navigating office spaces or museums Locating patients within a hospital
- Navigating robotic units within a building [1]
- underperform under certain conditions changing room environment [3] reliance on infrastructure [4]

 The measurements were taken in the university building Pulse.

A small amount of human traffic

Accuracies of all classifiers and

- combinations can be seen in Figure 1

Classifier	Split 1	Split 2
WiFi	88%	90%
Acoustic	82%	88%
Weighted average	98%	90%
2-step localization	89%	92%
Stacking	92%	81%
WiFi top 3	100%	100%
Acoustic top 3	100%	98%

Figure 1: Test set localization obtained from 3 different tro

Figure 3: Confusion matrices of combined classifiers

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Indoor localization can have a multitude of use cases

• GPS is the most widely used method for localization but underperforms indoors due to signal blocking [2]

Many indoor localization approaches exist, but they

• A combination of localization methods enables more unique feature extraction from the environment

2.	Bc
•	ndoo

• There are multiple ways that classifiers can be fused together to improve accuracy

Confusion matrix, Acoustic localization											
	pulse: 2nd-floor-kitchen	4	0	0	0	1	0	0	0	0	
7	pulse: 1st-floor-printer	0	7	0	0	0	0	0	0	0	
	pulse: above-bathroom-2029	0	0	5	0	0	0	0	0	0	
	pulse: 1st-floor-kitchen	1	0	0	3	1	0	1	0	0	
pel	pulse: couches	0	1	0	1	3	0	0	1	0	
ne la	-	0	0	0	0	0	2	0	0	0	
			0	0					0		
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	pulse: behind-bathroom	0	0	0	0	0	0	0	5	0	
	pulse: locker-2079	0	0	0	0	0	0	0	1	4	
	pulse: map	0	0	0	0	0	0	0	0	0	
		pulse: 2nd-floor-kitchen	pulse: 1st-floor-printer	pulse: above-bathroom-2029-	bulse: 1st-floor-kitchen	bulse: couches	pulse: above-bathroom-window-	pulse: 1st-floor-couches-	pulse: behind-bathroom-	pulse: locker-2079	
		pulse: 1st-floor-printer pulse: above-bathroom-2029 pulse: 1st-floor-kitchen pulse: couches pulse: above-bathroom-window pulse: 1st-floor-couches pulse: behind-bathroom pulse: locker-2079	pulse: 1st-floor-printer pulse: above-bathroom-2029 pulse: 1st-floor-kitchen pulse: couches pulse: couches pulse: above-bathroom-window pulse: 1st-floor-couches pulse: behind-bathroom pulse: locker-2079 0	pulse: 1st-floor-printer 0 7 pulse: above-bathroom-2029 0 0 pulse: 1st-floor-kitchen 1 0 pulse: couches 0 1 pulse: above-bathroom-window 0 0 pulse: 1st-floor-couches 0 0 pulse: behind-bathroom 0 0 pulse: locker-2079 0 0 pulse: map 0 0	 Pulse: 2nd-floor-kitchen Q Q	Pulse: 2nd-floor-kitchen4070pulse: 1st-floor-printer0700pulse: above-bathroom-20290001pulse: 1st-floor-kitchen1010pulse: above-bathroom-window0000pulse: 1st-floor-couches0000pulse: behind-bathroom0000pulse: locker-20790000pulse: range, service0000pulse: si strefloor-kitchen000pulse: locker-2079000pulse: locker-2079000pulse: nape, service000pulse: istrefloor-kitchen000pulse: solote-bathroom-window000pulse: locker-2079000pulse: solote-bathroom-window00pulse: solote-bathroom-window00pulse: locker-207900pulse: solote-bathroom-window00pulse: solote-bathroom-window00pulse: solote-bathroom-window00pulse: solote-bathroom-window00pulse: solote-bathroom-window00pulse: solote-bathroom-window00pulse: solote-bathroom-window00pulse: solote-bathroom-window00pulse: solote-bathroom-window00pulse: solote	pulse: 2nd-floor-kitchen 4 0 0 0 0 pulse: 1st-floor-printer 0 7 0 0 0 pulse: above-bathroom-2029 0 0 1 0 1 pulse: 1st-floor-kitchen 1 0 0 1 3 pulse: above-bathroom-window 0 0 0 0 0 pulse: 1st-floor-couches 0 0 0 0 0 pulse: behind-bathroom 0 0 0 0 0 pulse: locker-2079 0 0 0 0 0 pulse: ist-floor-kittrher, ising, ising ising ising ising ising pulse: locker-2079 0 0 0 0 ising ising ising ising ising ising ising	pulse: 2nd-floor-kitchen 4 0 </td <td>pulse: 2nd-floor-kitchen 4 0 0 1 0 0 pulse: 1st-floor-printer 0 7 0</td> <td>pulse: 2nd-floor-kitchen 4 0 0 0 1 0 0 0 pulse: 1st-floor-printer 0 7 0</td> <td>pulse: 2nd-floor-kitchen 4 0<!--</td--></td>	pulse: 2nd-floor-kitchen 4 0 0 1 0 0 pulse: 1st-floor-printer 0 7 0	pulse: 2nd-floor-kitchen 4 0 0 0 1 0 0 0 pulse: 1st-floor-printer 0 7 0	pulse: 2nd-floor-kitchen 4 0 </td

Figure 2: Confusion matrices of individual classifiers







pulse: above-bathroom-2029 0 0 5 pulse: behind-bathroom 0 0

> References [1] Weipeng Guan, Shihuan Chen, Shangsheng Wen, Zequn Tan, Hongzhan Song, and Wenyuan Hou. Highaccuracy robot indoor localization scheme based on robot operating system using visible light positioning IEEE Photonics Journal, 12(2):1–16, 2020

ackground

or localization methods can be split into two

- broad categories
- Infrastructure-dependant
 - WiFi
 - Bluetooth
 - FM-based
- infrastructure-free
 - Barometric pressure patterns
 - Geomagnetism
 - Acoustic (Passive and Active)

Weighted averaging

- Multi-step localization
- Ensemble stacking



Predicted labe

[2] Nabil Drawil, Haitham Amar, and Otman Basir. Gps localization accuracy classification: A context-based approach. Intelligent Transportation Systems, IEEE Transactions on, 14:262–273, 03 2013

[3] Qun Song, Chaojie Gu, and Rui Tan. Deep room recognition using inaudible echos, 2018

[4] Practical robust localization over large-scale 802.11 wireless networks. 2004