

A Machine Learning & Fingerprinting Wi-Fi-Lora Signal based Indoor Positioning System reducing time-to-market



 Width

 9.5m

 Width

 Y=0.5m

 Image: Second second

Context and Goal

Why Indoor Positioning System?
-hard to develop and deploy due to : too many
HW/SW, data, signals
Why Fingerprinting?
- allows to eliminate the embedded development
on radio emitter, to limitate the radio networks



Fig.1: Indoor localization test area made in Egypt, in 2020, 700 PoR/PoT of fingerprints observed with WIP@, with various ratio (for example here 25% training PoR and 75% testing PoT)

Methodology and Contributions

Blanchmark with reguler repartition tanining/training for reproductable experiments :*RSS,XGB,MMSE,CSI* -RF,XGB,ML ,MMSE for Wi-Fi based indoor Positioning, algorithm, Fingerprint

-In progress: application

fingerpritn,wifi+Lora,posture+AOA,

,accelerometer/relative displacements relatifs, CNN+multi Channel signals (Numerica, France)

(In progress): pragmatic fingerprint mobile application based on inertial navigation and on taking into account realistic postures of the user with his mobile phone. knowledge and programming,Why Machine-Learning (ML) ?-Learn from observations without codingcomplexed and secured network protocols



Fig. 2: Architecture of our ML-Fingerprinting based IPS using WiFi+Lora signals and RF+XGb+CNN+RN+LSTM ML-algorithms and either WIPS@ or our fingerprinting@ to treat user's posture, AoA, RSSi

 Table 2: Comparison of state of the art of previous and our work.

Systems	Duration in man.month	Lines of code and data
IPS based on mobile-centric Wi-Fi with statistical fingerprint	6	12K
IPS based on infrastructure- centric Wi-Fi and secure with dynamic fingerprint	12	30K

Results

Table 1 Representation of positioning errors for the Egypt room from the data of a composition of elements						
96	Scenario	RF.(m)	XGB. (m)	RF.(MMSE)	XGB. (MMSE)	
10 % T= A=	T=70	2.26	2.36	1.60	1.88	
	A=630	2.33	2.38	152	1.75	
		2.21	2.31	1.55	1.78	
		2.28	2.35	1.59	1.86	
		2.23	2.30	1.61	1.80	
		2.25	2.37	1.50	1.84	
		2.24	2.39	1.57	1.79	
		2.32	2.41	1.54	1.77	
		2.34	2.40	1.56	1.73	
	I _{ct} at 95 %	[2.19;2.35]	[2.27;2.45]	[1.50;1.62]	[1.72;1.90]	
33 %	A=233	2.01	2.17	1.22	1.37	
	T=467	2.09	2.20	1.19	1.40	
		2.02	2.19	1.17	1.35	
	$I_{\rm ct}$ at 90 %	[2;2.09]	[2.16;2.20]	[1.12;1.26]	[1.29;1.45]	
66 %	A=467	1.25	1.30	1.03	1.08	
	T=233	1.22	1.33	1.01	1.05	
	I _{ct} at 97 %	[1.20;1.25]	[1.28;1.33]	[1;1.04]	[1.04;1.08]	
80 %	A=560	1	1.11	0.73	0.82	
	T=140	1.02	1.13	0.70	0.79	
		1.01	1.15	0.71	0.81	
		1.03	1.12	0.72	0.80	
	I _{ct} at 97 %	[1;1.04]	[1.10;1.15]	[0.70;0.74]	[0.80;0.83]	





Figure1 :CDF RF. (m), XGB.(m), RF.(MMSE), XGB.(MMSE) at 10% Figure2: CDF RF.(m), XGB.(m), RF.(MMSE), XGB.(MMSE) at

ML + fingerprint +Wi-Fibased IPS

2K





Figure3:CDF RF.(m), XGB.(m), RF.(MMSE), XGB.(MMSE) at 66% Figure4/CDF RF.(m), XGB.(m), RF.(MMSE), XGB.(MMSE) at 80%

Our ML+fingerpint based IPS reduce with a fector twelve to six the time to conceive, develop and benchmark the indoor positioning evaluation of a WiFi or Lora mobile device.

The proposed algorithms still achieve good positioning effect even in environmental changes compared to other algorithms What seems more reasonable is the results we obtain today rather than in the initial test which according to the non-reproducible tests we have a bias which is very important of 2 % compared to the previous paper. **Mariame Niang, Philippe Canalda, Massa Ndong, Ibra Dioum, Idy Diop, François Spies**







