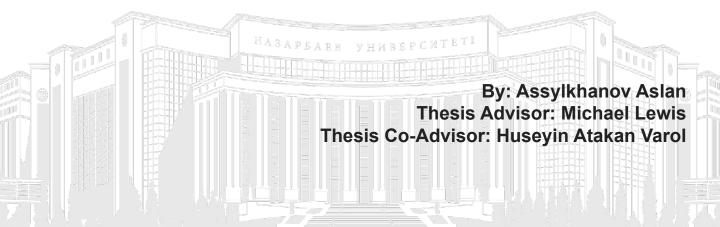


Transformer-Based Multimodel Indoor Localization Using Wireless and Inertial Sensors



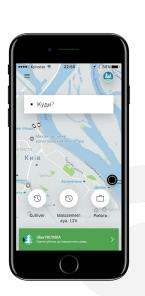
Outline



- Introduction
- Related Work
- Methodology
- Dataset
- Results
- Discussion

Introduction

- What is Localization?
- Localization services are used in a number of application types (Health, Transportation, Emergency etc.)



Localization-based app



Introduction



- One can separate the localization into two categories:
 - Indoor
 - Outdoor
- Outdoor can be considered as an already solved issue (GPS, GLONASS, Galileo)
- Indoor localization still remains an open problem



Weird indoor localization mistakes

Related Work



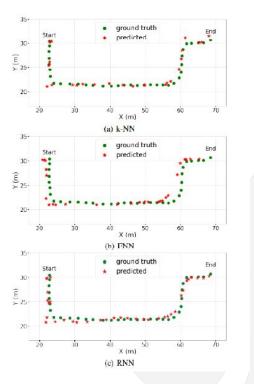
- Started poorly
- Many different solutions
 - Deep Neural Network (DNN) with a Hidden Markov Model (HMM)
 - two separate module
 - Convolutional Neural Network (CNN) with two dimension map
 - data collected arbitrarily
 - RNN solutions
 - both real and simulated data
 - generated trajectories
 - employed a roving robot

Classifiers	Without PCA	With PCA	Enhanced
$\mathrm{K}=1$	7.24m	4.24m	41.44%
$\mathrm{K}=2$	6m	4.24m	29.33%
K = 20	6.24m	4.24m	32.05%
Linear SVM	7.24m	5.24m	27.62%
Random Forest	9.12m	6.12m	<u>32.9%</u>

Localization results at 2016

Related Work

- IPIN 2018 & 2019 competition have winners with results of 0.5m and 1.9m respectively
 - However, no explanation of the algorithm used
- NU ISSAI Work
- No solution employing the Transformer neural network



Illustrated comparisons between different algorithms





Methodology

- This work is an extension to the research that has been done by the ISSAI team of Nazarbayev University
- My work is dependent on the testbed setup that has been prearranged by the ISSAI team

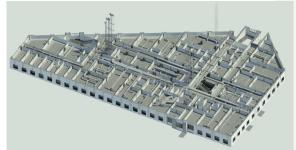


ISSAI team setting up the Testbed environment

Methodology. Testbed



- The testbed environment
 - C4 block of NU: 4-6 floor, including transition spaces (stairs, elevators)
 - \circ The area covered: 9564 m²



The layout of the fourth floor in C4 building

Methodology. Testbed Setup

- The testbed environment has been setup with ArUco markers whose position was calibrated via Leica TS06 plus total station
- Overall, 654 *14cm x 14 cm* markers were attached all over the testbed



ArUco markers calibrated



Methodology. Data collection setup



- To collect the WiFi, IMU and Position information we have created data collecting Android application
- The application was installed on Samsung Galaxy A21
 & Oppo A5, both running Android 10

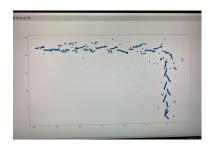


ISSAI Data Collection app

Methodology. Data collection setup



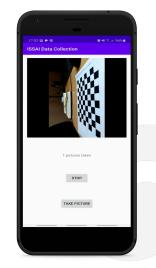
- During the first run the following steps should be made
 - Calibrate the camera
 - Set the focus and record it



Before the focus is set



After the focus is set



Camera calibration process

Methodology. Data collection

- As the operator starts the data collection process the IMU calibration routine should be performed. This is a required step for every trajectory
- While the operator is moving at random, sometimes changes floors, the app collects the sensors data and estimates the position using ArUco markers



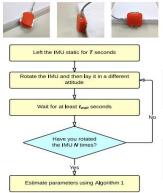
Position estimation on ArUco marker



Methodology. Data processing



- After the trajectories are collected they are run through alignment and calibration algorithms
- Calibration: reduces bias that can lead to drift of the estimated orientation
- Alignment: sort data, label WAPs, identify undetected WAPs, map data to the timestamp



IMU calibration routine

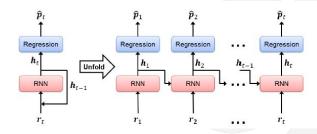


Methodology. Data analytics

- Task definition
 - position vector: $p = (x; y; z) \in \mathbb{R}^3$
 - sensors vector:

 $r = (r_1; r_2; ;; r_n; ;a_x; a_y; a_z; g_x; g_y; g_z; m_x; m_y; m_z) \in \mathbb{R}^{n+9}$

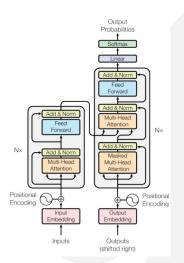
- RNN structure
 - $\circ \quad h_t = RNN(r_t; h_{t-1})$
 - $\circ \quad \hat{p}_t = Wh_t + b$
 - where
 - W weight matrix
 - b bias vector



Baseline RNN structure

Methodology. Data analysis

- Previous work, baseline RNN, was focusing on the the sequential data
- In this work we try using the Transformer neural network
 - It can "pay attention" to the various data before it
 - Our idea is that it can not only look at h_{t-1}, but also at the h_{t-2}; h_{t-3}; h_{t-4};;;h_{t-n}



Transformer structure



Methodology. Data analysis



 When the models provides the prediction of the position p̂_i we estimate its accuracy using the Mean Error Distance (MED) formula

$$\text{MED} = \frac{\sum_{i} dist(\mathbf{p}_{i}, \mathbf{\hat{p}}_{i})}{N}$$

Mean Error Distance formula

Dataset



We have collected 113 trajectories

- via Samsung A21 79
- o via Oppo A5 34
- Trajectories are collected at random path and represents the real human walking path
- Data stored in separate .csv files

Column	Description
1	Timestamp of recorded sample (μs)
2	Acceleration value on X-axis (m/s^2)
3	Acceleration value on Y-axis (m/s^2)
4	Acceleration value on Z-axis (m/s^2)
5	Gyroscope value on X-axis (rad/s)
6	Gyroscope value on Y-axis (rad/s)
7	Gyroscope value on Z-axis (rad/s)
8	Magnetic field value on X-axis (μT)
9	Magnetic field value on Y-axis ((μT)
10	Magnetic field value on Z-axis ((μT)
11	Position on X-axis (m)
12	Position on Y-axis (m)
13	Position on Z-axis (m)
14-449	RSS values of WAPs (dBm)

Dataset column description

Dataset



• The data is split into:

- Training
- Validation
- Test

Dataset	Subsets	Total length (m)	Total duration (s)
IPIN 2016	Training	$\approx 8,470$	13,908
	Test	$\approx 4,400$	8,605
	Total	pprox 12,860	22,513
IPIN 2017	Training	$\approx 10,940$	18,411
	Validation	$\approx 3,725$	7,930
	Test	$\approx 3,220$	6,518
	Total	pprox 17,890	32,859
WiFine	Training	$\approx 31,843$	112,330
	Validation	$\approx 4,786$	17,273
	Test	$\approx 6,149$	21,911
	Total	pprox 42,778	$151,\!514$
Current work	Training	$\approx 21,628$	76,682
	Validation	$\approx 4,374$	15,849
	Test	$\approx 3,830$	13,133
	Total	pprox 29,832	105,664

Comparison of dataset statistics

Dataset



• 436 WAPs

Reference points estimation error

- 2-3mm on average
- max 5cm at furthest locations

Dataset	N_B	N_F	N_{RP}	N_S	N_W	N_T	Area
UJIIndorLoc	3	4-5	933	21,049	520	n/a	108,703
XJTLUIndoorLoc	1	2	969	n/a	515	n/a	306
UTSIndoorLoc	1	16	1,840	9,494	589	n/a	44,000
Tampere	1	5	4,648	4,648	991	n/a	22,570
Library	1	2	n/a	63,504	448	n/a	308
JUIndoorLoc	1	3	1,000	25,364	172	n/a	2,646
IPIN2016	4	1-6	2,007	n/a	n/a	26	n/a
IPIN2017	3	1-6	2,697	n/a	n/a	38	n/a
IPIN2018	1	3	n/a	n/a	n/a	38	9,000
WiFine	1	3	26,418	26,418	436	290	9,564
Current work	1	3	5,146	10,283	436	113	9,564

The open-source datasets for WiFi-based indoor localization. N_B - number of buildings, N_F - number of floors, N_{RP} - number of reference points, N_S - number of samples, N_W - number of WAPs, N_T number of trajectories, Area (m²) - over buildings and floors, n/a - not available

Results



- Ran RNN and Transformer models with both Wi-Fi only and Wi-Fi + IMU data
- 4 prepended rectified linear activation unit (ReLU) layers with 64 hidden units to all models

The model	Result
RNN (Wi-Fi only)	2.6m
RNN (Wi-Fi + IMU)	2.54m
Transformer (Wi-Fi only)	2.4m
Transformer (Wi-Fi $+$ IMU)	2.3m

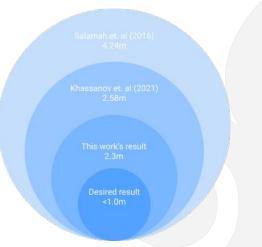
Mean Error Distance (MED) results of different model variations

Localization results compared

• Our aim was to

Discussion

- Collect data from Wi-Fi & IMU sensors
 within the C4 Testbed ✓
- Replicate the previous results & improve on them
 - 3.05m -> 2.45m
- \circ Achieve accuracy within 1m or less X
- Try new neural network model for the task of indoor localization ✓





Discussion. Future work



- Collect more data.Especially using Oppo phone
- Regularize the Wi-Fi data [ref: regularization]
- Different Wi-Fi representation
- Leveraging building layout as an additional source of information
- Using other sensors. Barometers for floor change [ref: barometer]



THE END

Thank you for your attention

