Smartphone Sensors Based Indoor Localization Using Deep Neural Networks

Imran Ashraf[1][0000-0002-8271-6496], Soojung Hur[1], and Yongwan Park[1] *

Department of Information & Communication Engineering, Yeungnam University, 38541, Republic of Korea
ashrafimran@live.com, sjheo@ynu.ac.kr, ywpark@yu.ac.kr

Abstract. This research presents the use of deep learning based ensemble classifier to perform indoor localization with heterogeneous devices. Features extracted from magnetic data of Galaxy S8 are fed into neural networks (NNs) for training. The experiments are performed with S8 and G6 smartphones to find out the impact of device dependence on localization accuracy. Results demonstrate that NNs can play a potential role for precise indoor localization. The proposed approach is able to achieve a localization accuracy of 2.5 m at 50% on two different devices. Mean error for S8 and G6 is 2.61 m and 2.95 m, respectively.

Keywords: Indoor localization · magnetic field · smartphone sensors · deep neural networks.

1 Introduction and Background

Indoor localization has attracted a huge interest in industry and academia during the last decade. The inception and penetration of location based services (LBS) further accelerated this research. The success of global positioning system (GPS) made it the most reliable localization technology for the outdoor environments. However, GPS sensitivity to occlusions including ceilings and walls makes it inappropriate and inefficient for indoor localization. This lead researchers to investigate alternative technologies which could potentially overcome such limitations and work efficiently for indoor environments. A large body of work has been presented on such technologies including ultra-wideband (UWB), radio frequency identification (RFID), infrared (IR), etc. Such technologies are however limited by their dependence on additional hardware which needs to be installed in the area intended for localization. The proliferation and wide use of modern smartphone presenst a potential solution to this limitation. Today smartphones are equipped with a variety of sensors which can be leveraged for indoor localization. Smarthone sensors including Wi-Fi, Bluetooth, and camera lead to the development of many localization techniques.

Wi-Fi and Bluetooth based localization systems are limited by inherent limitations of wireless communication [1, 2]. The problems of multipath shadowing, fading and impact of other dynamic factors on signal fluctuation may occasionally lead to very high localization error. The geomagnetic field based localization has been the center of many research works and got an exponential attention during the last few years [3, 4]. The geomagnetic field (referred to as magnetic field in the rest of the paper) is the natural phenomenon and pervasive in nature. The magnetic field

* This work was supported by the Brain Korea 21 Plus Program (No.22A20130012814) funded by the National Research Foundation of Korea (NRF). This research was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Science, ICT and Future Planning (2017R1E1A1A01074345).

strength varies from 25 μTesla to 65 μTesla over the globe. On the other hand, man made construction obstruct the magnetic field and alter it to cause anomalies. Such magnetic anomalies are observed to exhibit unique behavior and used as fingerprint in many research works [5, 6]. Despite that the techniques which utilize magnetic field fingerprints have two major limitations. First is the change in magnetic behavior due to heterogeneity of the smartphones. Smartphones use the magnetometer built by various companies which lead to different magnetic field intensity even for the same place [3]. This limits the wide applicability of magnetic field based localization systems as various smartphones show different localization error with the same approach. Second limitation is the similarity of magnetic field intensity at multiple locations, especially when the localization space is large. We aim to solve these problems using deep neural networks (DNN).

Deep learning has recently been utilized to solve many problems and indoor localization is no exception. DNN and convolution neural networks (CNN) have been used for indoor scene recognition, object detection, etc. We make the use of ensemble learning wherein more than one DNN are trained and each DNN serves as a location classifier. The prediction from each of these classifiers is then employed to find the final location of the user. Deep learning is a data intensive technique and requires a large amount of data for training. We have collected thousands of magnetic samples for this purpose. The key contribution of this research is the proposal of a smartphone sensors base indoor localization approach which works with multiple neural networks (NN) to predict user's current location. The proposed approach is tested with heterogeneous devices including Galaxy S8 and LG G6 to evaluate the localization accuracy.

The rest of the paper is organized in the following manner. Section 2 overviews few works related to this research. Section 3 describes the proposed approach while Section 4 details the experiment setup and analyzes the results. Finally, conclusion is given in Section 5.

2 Related Work

The application of magnetic field data for indoor localization has been investigated by many research works . Such research include the analysis of properties of magnetic field data that can be used for localization, as well as, the impact of various devices usage, and the orientations of these devices [5-8]. Li et al., investigated the use of smartphone magnetometer based fingerprinting approach to perform indoor localization in [9]. The localization error is low if more elements of magnetic field are used. However, the error may become higher up to 20 m when the localization area is large and complex. Zhang et al., reduces the survey time of building the fingerprint database with crowd sourcing approach in [10]. Later, a revised Monte Carlo technique is used to locate a pedestrian indoor. The proposed approach is able to converge to a 5 m area by using 30 sec data. The research suggests the use of assistive technologies to reduce the localization error.

An indoor localization system is presented in [11] which combines Wi-Fi signal with magnetic field data to build the fingerprint database. The search space restriction using Wi-Fi access points help in reducing the localization error to 4.5 m which is 16.6 m with magnetic field data. Recently the use of deep learning is reported to perform localization with smartphone sensors in [12]. The research uses smartphone camera, motion sensors, compass, magnetometer and Wi-Fi to do the localization. CNN is used to identify indoor scene which helps to narrow down the search space in magnetic database. The reported localization error is 1.32 at 95%. Similary the research [13] proposes a multi-story localization approach based on smartphone sensors and makes the use of deep learning. The CNN based scene recognition is used to identify a specific floor which increases the localization accuracy as well. The reported localization error is 1.04 m at 50 percent.

The above mentioned research works are limited by two factors in essence. First problem is the use of Wi-Fi signals which are vulnerable to dynamic factors. Secondly the impact of device heterogeneity is not studied very well. Additionally the use of smartphone camera consumes

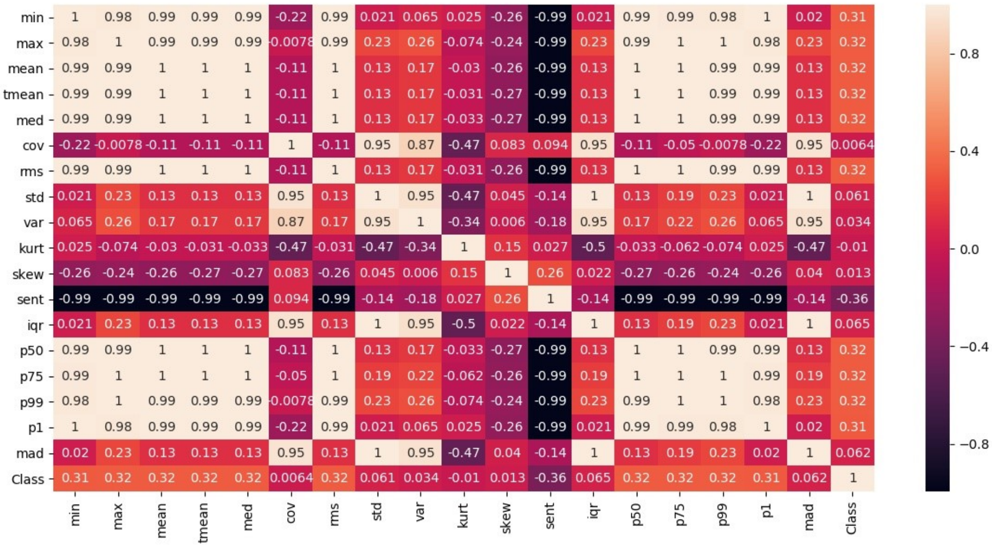

Fig. 1. Correlation of selected features to predict a specific class. 'Class' weight in rows shows the importance of features.

the battery very fast and is not an efficient solution. It is noteworthy to point out that deep learning has been utilized on smartphone camera images alone. We aim to use deep learning on the magnetic field data to perform indoor localization.

3 Materials and Methods

This section provides the details of the proposed approach. The first task is to find suitable features which are fed into the NNs.

3.1 Features Selection

The major limitation of using the magnetic field is the device dependence. The intensity of collected magnetic data may be different depending on the sensitivity of the installed magnetometer in various smartphones. Another shortcoming of magnetic data is its low dimensionality. We can use only magnetic x, y, and z data as a fingerprint. These values may be very similar at multiple locations, especially in large space. So, contrary to using the magnetic field data, we aim to work with important features of this data.

We initially shortlisted a total of 18 features including '*minimum*', '*maximum*', '*mean*', '*trimmed mean*', '*median*', '*root mean square*', '*standard deviation*', '*interquartile*', '*percentile (1, 50, 75, 99)*', '*mean absolute deviation*', '*coefficient of variance*', '*kurtosis*', '*Shanon's entropy*', and '*skewness*' for this purpose. Features including '*coefficient of variance*', '*kurtosis*', '*Shanon's entropy*', and '*skewness*' are dropped due to their little correlation to the classification label. The correlation of the features is shown in Figure 1.

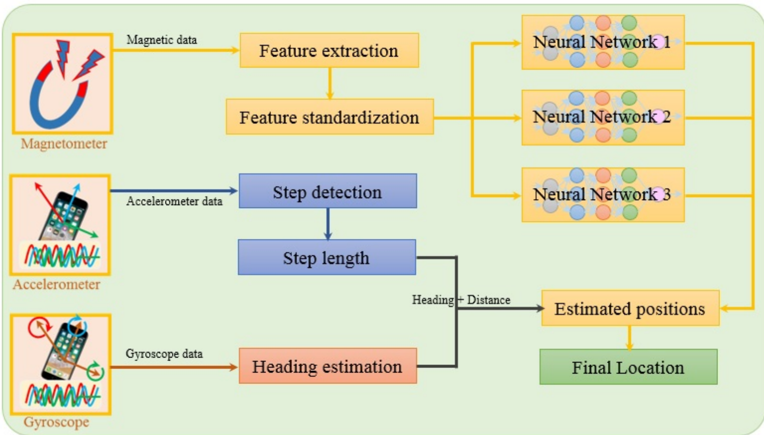

Fig. 2. Architecture of proposed approach.

3.2 Proposed Approach

The architecture of the proposed approach is shown in Figure 2. The features extracted from the magnetic data are standardized and fed into neural networks. We train three different NN to make the ensemble.

Every NN has different number of layers, as well as, the containing neurons. Similarly, the internal structure of fully connected layers is different. The structure of NNs is shown in Figure 3. During the localization phase, the features extracted from user collected magnetic data are used by trained NNs to predict user current location. For this purpose, we use three consecutive frames of 2 sec each which are considered as T_1, T_2, and T_3. For T_1, the predictions from three NNs are taken to form the location candidates (L_c).

$$L_c = \exists(P_{NN1_{T1}} \cup P_{NN2_{T1}}) \cup (P_{NN1_{T1}} \cup P_{NN3_{T1}}) \cup (P_{NN2_{T1}} \cup P_{NN3_{T1}}) \tag{1}$$

where P shows the prediction made by NN and $\exists$ shows that unique predictions are considered alone. We take top 10 predicted locations from each NN to formulate L_c. NNs predictions at T_2 and T_3 help to refine L_c. So, if the predictions for T_2 are in the area as shown in Figure 4, they are added in L_c for T_3, else, they are discarded. The encircled area is estimated user traveled distance at a medium speed.

Algorithm 1 Find user location

$L_c \longleftarrow findLocCandidates(P_{NN1_{T_1}}, P_{NN2_{T_1}}, P_{NN3_{T_1}})$
for $T \longleftarrow 2$ *to* 3 **do**
  $L_c \longleftarrow refineLocCandidates(L_c, P_{NN1_T}, P_{NN2_T}, P_{NN3_T})$;
  $(x_T, y_T) \longleftarrow calApproxPos(S_{l_T}, \psi_T)$;
end for
$L_p \longleftarrow calCenteroid(L_c)$;

With each T, L_c are updated as user moves to another location. We use accelerometer and gyroscope data for this purpose. Step detection is performed using the algorithm proposed in [4], while step length estimation is done with Weigberg model [14]:

$$S_l = k\sqrt[4]{a_{max} - a_{min}} \tag{2}$$

where a_{max}, and a_{min} shows the maximum and minimum acceleration.

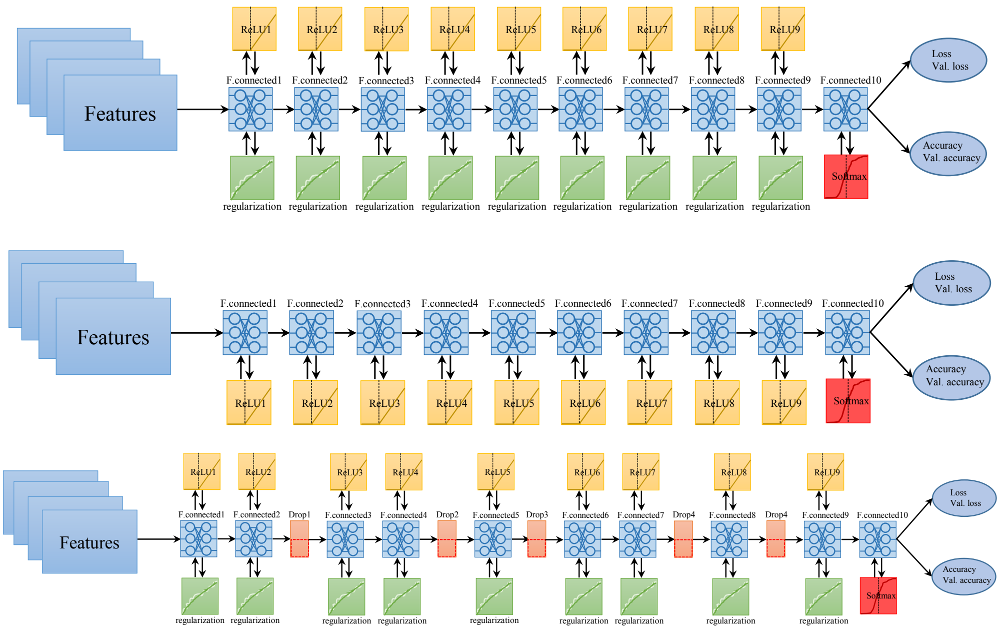

Fig. 3. Structure of NN-1 (top), NN-2 (middle), and NN-3 (bottom).

x_T and y_T are calculated using S_{l_T} and heading estimation ψ_T as follows:

$$x_i = x_{i-1} + S_{l_{i-1}} \times cos(\psi_{i-1}) \tag{3}$$
$$y_i = y_{i-1} + S_{l_{i-1}} \times sin(\psi_{i-1}) \tag{4}$$

The same process is repeated for T_2 and T_3. During this process, the predicted locations converge to a small area. We calculate the centroid of these refined locations which represent the user's predicted location L_p.

4 Experiment and Results

The experiments are conducted using Samsung Galaxy S8 (SM-G950N), and LG G6 (LGM-G600L) devices. The features for training are extracted using Galaxy S8 collected data, while testing is done with two smartphones. The path used for the experiments is shown in Figure 5. The area of experiment building is 92 $\times$36 m^2. Experiments are performed with people of different heights to evaluate the proposed approach.

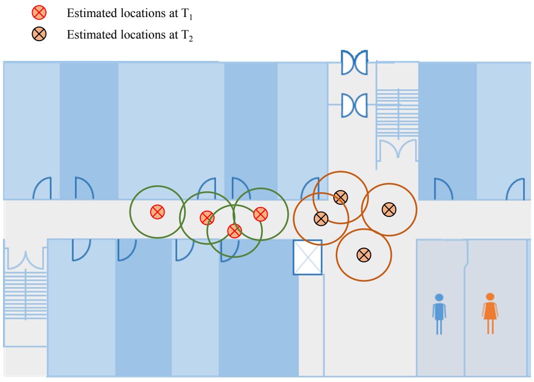

Fig. 4. Outlier selection criteria.

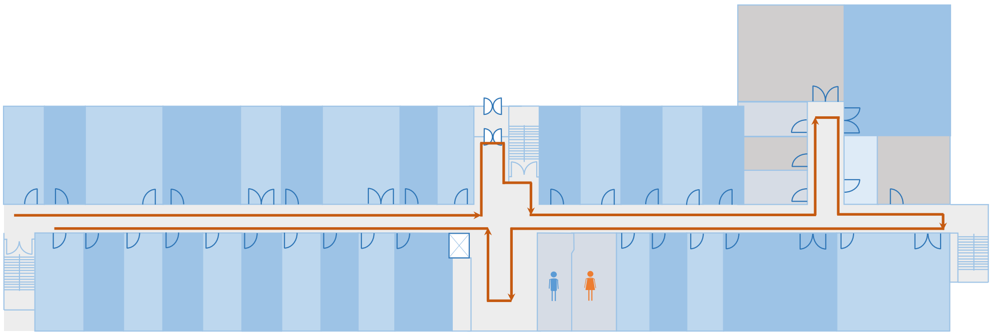

Fig. 5. The path used for experiments.

Results are shown in Figure 6. Results demonstrate that the proposed approach can locate a person within 2.5 m, irrespective of the used device. Maximum errors are 13.33 m and 13.57 m for S8 and G6, respectively. However, the cumulative probability of maximum error is only 0.02. The mean error at 75% is 3.7 m and 4.1 m for S8 and G6. Even though the training is performed with S8 data, the localization errors are very similar for two smartphones. The underlying reason is the usage of features extracted from magnetic data than the magnetic data themselves. It also shows the usefulness of deep learning to assist in reliable indoor localization. We conducted additional experiments with less features also excluding *'interquartile'*, *'standard deviation'*, and *'mean absolute deviation'*. Removing these features degrades the localization performance.

5 Conclusion

This research aims at using deep learning based ensemble classifier to solve indoor localization with heterogeneous devices. Three NNs are trained on magnetic data features from S8 smartphone. The experiments are performed with S8 and G6 smartphones. Results demonstrate that the use of features extracted from magnetic data are very fruitful to train NN. The localization accuracy is 2.5 m at 50% on two different devices. Mean error for S8 and G6 is 2.61 m and 2.95 m, respectively. Data collection is a laborious task which we intend to overcome with crowd

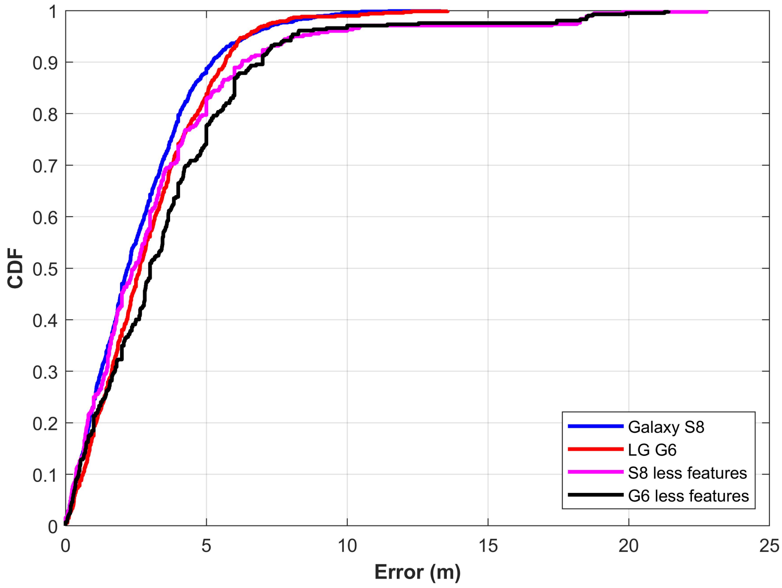

Fig. 6. Localization results using S8 and G6.

sourcing data collection in future. How the larger indoor area may affect the performance of the proposed approach is an intended future work.

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