On the RSS biases in WLAN-based indoor positioning

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***Abstract*—Fluctuations in the Received Signal Strength, caused for example by temporal propagation dynamics or various mobile types, can decrease the positioning accuracy in WLAN-based indoor fingerprinting. In this paper, the effect of an offset between Received Signal Strength values in the training and estimation phases is investigated. Our study is based on a huge measurement campaign that covers in total eight different buildings with several floors each, in two countries. Different offset types and offset values are studied on a large scale, in terms of 3D positioning accuracy and floor detection probability. We will show that biases between -20 dB and $+10$ dB do not affect the positioning results in a significant way and that such biases could be also tolerated without calibration.**

I. Introduction

WLAN-based positioning is becoming more and more popular in indoor areas, where the traditional Global Navigation Satellite Systems (GNSS) often fail to offer a position estimate due to the multipath propagation and weak signal powers [1], [2], [3]. A wide area of Location-Based Services (LBS) and location-based business models are envisioned for the future, once the barrier of indoor location is crossed [4]. The underlying multiple access schemes for WLANs are both Direct Sequence-Code Division Multiple Access (DS-CDMA) and Orthogonal Frequency Division Multiplexing (OFDM) techniques and the underlying modulations range from Binary Phase Shift Keying (BPSK) to higher order Quadrature Amplitude Modulation (QAM). Thus, Time-Of-Arrival (TOA) or Round-Trip-Time (RTT)-based estimations for WLAN location are still not widespread, due to the many different underlying physical layer features of WLANs on the market. Alternatively, the Received Signal Strength (RSS) or the Received Signal Strength Indicator (RSSI) of the signal can be used for the positioning purposes. RSS-based positioning methods have the advantage of easy accessibility, availability in almost every device and cost effectiveness due to the ability to utilize the current wireless infrastructures.

Many RSS-based positioning methods involve two stages: an initial off-line training phase and an on-line estimation phase, where the actual mobile position estimation is done [1], [5], [6]. It is generally known that since the positioning process is divided into two phases, the RSS fluctuations may decrease the positioning accuracy. In the training phase, models and databases are built based on collected information about the indoor environment. The information can be collected in a dedicated mode (where the samples are collected in advance, usually with one device only) or a crowd-sourced mode (where the mobiles collect the samples continuously). Typically, this information includes data samples such as measurement point coordinates and RSS values that have been collected with the help of indoor maps of the particular building. These location-sensitive samples are usually called fingerprints (FPs). In the estimation phase, that involves real-time processing, the unknown position of a mobile station (MS) is estimated based on the information saved in the training phase. Now, if the RSS that is saved to the database in the training phase differs significantly from the RSS of the user device in the real-time localization phase, the positioning accuracy may be degraded. An offset in RSS values can be caused for example, by different equipment type, which is especially true in crowd-sourced data collection (this is most likely seen as a constant positive or negative bias), temporal propagation dynamics such as user orientation, body losses in more or less crowded period during the training phase compared with the estimation phase (random bias) or environmental changes between the two phases.

Due to the possible biases between the RSS values in the training and estimation phases, both calibration techniques and different calibration-free positioning algorithms have been proposed, e.g. in [7], [8] and [9]. There are studies that present how different equipment measures the RSSI, e.g. [10] and [11]. In [12], the effect of three dynamic factors (relative humidity level, people presence and movements, and open/closed doors) to the positioning accuracy was studied shortly, but the study was limited into one corridor only with very few Access Points (APs) and the amount of the RSS offset is not specified or studied at all. Also in [13], where the positioning performance of different devices in the same environment was studied, the indoor environment was limited to two corridors of one-floor only. Thus, as far as the authors know, there are not any publications or research on the effect of the different types of a bias: how much a constant or a random bias affects the positioning results? What is the amount of bias that is still reasonable in terms of positioning accuracy? How about a bias that occurs only in some regions of a building? Our study aims at giving an answer to these questions. Indeed, many papers rely on some measurements, but they address only one floor and/or one building. Our measurements cover in total eight different buildings in two different countries, all of them with several floors (between 3-9 floors).

This paper is a comprehensive study of the effect of a bias between the RSS values in training and estimation phases. This kind of analysis has not been done before on a such a large scale. We address fingerprinting estimation method and will show the effect of different bias types and values, based on a huge indoor measurement data campaign. The data is collected with two different tablets, a Windows tablet and an Android Nexus tablet, in several buildings in Tampere, Finland and Berlin, Germany (university buildings, office buildings and shopping centers). Exactly the same device was used to collect the training and estimation data for one particular building, but the devices may have been different from one building to another. In our study, we show that biases between -20 dB to $+10$ dB are easily tolerated in indoor environments. This finding is an important one for the purpose of future indoor WLAN-based positioning which will rely on crowd-sourced data collected with various mobile devices.

II. Positioning Principle

A. Training Phase

In the FP-based positioning method, the main idea is to first create a database in the training phase using pre-measured samples with known locations in the building of interest and then use only this database and the current real-time measurements in the estimation phase. The measurement points (i.e., grid points or FPs) are formed as (x_i, y_i z_i, $P_{i,k}$), where x_i, y_i z_i are the 3D coordinates of the FP i ($i = 1, ..., N_{fp}$, where N_{fp} is the total number of FPs) and $P_{i,k}$ denotes the measured RSS from kth AP in the FP i. Since in this paper, a bias b is artificially added to the original measured RSS $P_{i,k}$, the FPs are formed as (x_i, y_i z_i, $\hat{P_{i,k}}$), where $\hat{P_{i,k}} = P_{i,k}+b$. Our artificial added bias tries to model the effect of a bias coming e.g. from various mobile devices, from different device orientations, and from different level of crowdiness in the measurement areas (influencing the body absorption levels). We will adopt two models of such a bias: either a constant one (which may happen when the training data was collected with a single mobile device different from the device used in the training) or a random one (which may happen when the training data was collected in a crowd-sourced mode, with many different devices).

In the training phase, we use so-called synthetic grids, where the grid resolution is fixed. The grid points (i.e., FPs) have some pre-defined size (e.g., 1 m x 1 m, or 5 m x 5 m, building dependent) and all samples measured in this area are fixed to the same grid point. Since the training phase process consists of several different measurement collections at different time instants (and can be collected also continuously, e.g., by using crowd-sourcing), several measurements can occur in the same grid point. Therefore, when a new sample occurs to a grid point that already has a sample, all hearable APs are examined. If a new AP has been detected in the incoming sample, the AP is saved to the grid point data. If an AP is detected both in the old and incoming sample, the old RSS value is replaced with mean over the old and new RSS values. The architecture of the positioning system used in this paper is mobile-based. This means that the user device, e.g., a mobile station (MS), makes the necessary measurements (here, RSSs of the heard APs) and calculates the position estimate. The training phase data are saved and continuously maintained and updated on a database (i.e., server) and transferred to the MS when requested.

B. Estimation Phase

When comparing currently measured RSS levels (in dBm) by the MS to the RSS levels of the FPs, the most typical optimization criteria are

1) to minimize the power difference between the observed RSS O_k and the RSS of the FP $\hat{P_{i,k}}$ [14] or

2) to maximize the number of commonly heard APs N_{AP} in the current measurement and in the FP (test rank based method) [9] or

3) to take into account both of the previous criteria as well as possible, e.g., by computing a Gaussian likelihood function $\mathcal{L}_i$ for each FP i. This is a special case of the criterion 1 and the most widely used optimization criterion in fingerprinting [15].

The Gaussian likelihood function $\mathcal{L}_i$ is calculated for each FP i as a sum of logaritmic likelihoods:

$$\mathcal{L}_i = \sum_{k=1}^{N_{AP}} log\left(\frac{1}{\sqrt{2\pi\sigma_{ap}^2}}exp\left(-\frac{(O_k-\hat{P_{i,k}})^2}{2\sigma_{ap}^2}\right)\right), \quad (1)$$

where σ_{ap} is a noise variance that represents both shadowing and measurement error effects. Now, if no nearest neighbour (NN) method is used, the FP $\hat{i}$ with highest Gaussian likelihood $\mathcal{L}_{\hat{i}}$ is selected, and the location of this FP $[x_{\hat{i}}, y_{\hat{i}}, z_{\hat{i}}]$ is returned as MS location ($[x_{\hat{i}}, y_{\hat{i}}, z_{\hat{i}}] = [x_{\hat{MS}}, y_{\hat{MS}}, z_{\hat{MS}}]$). When the NN method is used, FPs with highest Gaussian likelihoods are selected, and the position of the MS is calculated as an average over the corresponding locations of N_n nearest neighbours

$$[x_{\hat{MS}}, y_{\hat{MS}}, z_{\hat{MS}}] = \frac{1}{N_n}\left(\left[\sum_{n=1}^{N_n} x_{\hat{i}}, \sum_{n=1}^{N_n} y_{\hat{i}}, \sum_{n=1}^{N_n} z_{\hat{i}}\right]\right). \quad (2)$$

III. Measurement Analysis

A. Measurement scenarios

The measurement data was collected in 8 different buildings (two university buildings, two office buildings and four shopping malls) in Tampere, Finland and in Berlin, Germany. Since the AP infrastructure was renewed for one university building after the first measurement collection, the collection was performed again to have one measurement scenario more. Measurements for both training and estimation phase were collected manually with two different tablets, a Windows tablet and an Android Nexus tablet, that included detailed indoor maps for each building. The same device was used in one building, but the device may have changed from one building to another. After the training phase, the user tracks used for the positioning analysis here were collected separately during different days and covering several floors in each building. All measurement scenarios, with building descriptions and main characteristics, are detailed in Table I, showing the number of FPs (i.e., the number of synthetic grid points in the traning database), the number of user measurements in the user track, the number of detected APs, the number of floors, the rough estimate of the building size and the AP density of the particular building. We remark that an AP stands for a MAC address; several APs can transmit from exactly the same location (e.g., as it is the case in WLAN with multiple BSSID).

B. Adding a bias to the original FPs

When studying the effect of a bias between the RSS values in training and estimation phases, a bias b is added to the original measured RSS $P_{i,k}$ (in dBm) in the FPs. Both constant and random bias are examined, as well as a case of localized constant bias, where a bias occurs just for a certain part of the FPs for every floor. A constant bias (negative or positive) can be caused e.g. by different mobile types in training data collection. Temporal propagation dynamics such as user orientation, or body losses in more or less crowded period during

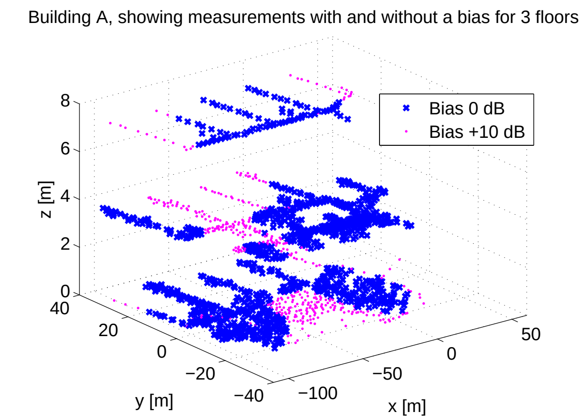

Fig. 1. Illustration of a localized bias for 3-floors of the building A.

the training phase compared with the estimation phase can instead cause randomizity to the RSS values in the FPs. Same holds for manual mode in the training phase or on-going training phase in a crowd-sourced manner, where several different types of mobile devices are used. A localized bias can be caused e.g. by environmental changes between the training and estimation phase or by only partly updated FP database. A localized bias is illustrated in Fig. 1, where all of the FPs are shown for three floors of Building A. The blue crosses represent the positions of the FPs without a bias and magenta dots represent the positions of the FPs with a bias. In this example, a bias occurs for 30% of the FPs. The areas with a bias are created by choosing first randomly one FP and then adding a bias to this FP and every neighboring FP within 20 m range [16]. Then, the next FP is chosen randomly and a new area with the bias is created. This is continued as long as the chosen percentage (e.g., 30%) of the FPs with a bias is filled.

C. Positioning results

In what follows, the positioning results are presented as Mean Distance Error in 3D (MDE), Floor Detection Probability (FDP) and Percentage of Distance Errors (PDE) of less than 5 m. The MDE is computed by averaging the Euclidean distances between the estimated location and true location in a three-dimensional Cartesian coordinate system (x,y,z). Floor detection is estimated separately, by looking at the z-coordinate of the position estimate and choosing the closest floor. In our analysis, both constant and random bias were analyzed by varying the amount of a bias between -50 dB and $+50$ dB. In the position estimation, NN-method is used, with $N_n = 5$. The noise variance σ_{ap}, that represents both shadowing and measurement error effects, was assumed to be equal for all APs and was chosen to be $\sigma_{ap} = 10$ dB, which showed consistently good results in all of

TABLE I
MEASUREMENT SCENARIOS.

	Building (measurement device)	Location	No. of FPs	No. of user meas.	No. of APs [a]	No. of floors	Building size [m]	AP density per m^2
A	University building 1 (Windows)	Tampere, Finland	1476	158	309	4	163×58	0.0029
B	University building 1, renewed (Nexus)	Tampere, Finland	505	181	238	4	135×55	0.0033
C	University building 2 (Windows)	Tampere, Finland	584	176	353	3	152×93	0.0051
D	Office building 1 (Nexus)	Berlin, Germany	624	850	333	9	75×65	0.0133
E	Office building 2 (Nexus)	Tampere, Finland	844	143	994	7	59×61	0.0408
F	Shopping mall 1 (Nexus)	Berlin, Germany	1633	520	405	6	205×235	0.0019
G	Shopping mall 2 (Windows)	Tampere, Finland	1789	205	326	6	160×139	0.0021
H	Shopping mall 3 (Nexus)	Berlin, Germany	306	776	503	3	175×160	0.0062
I	Shopping mall 4 (Windows)	Tampere, Finland	274	215	69	3	152×123	0.0010

[a]Each AP is identified by an individual MAC-address, but since some WLAN transmitters may have multiple MAC-addresses, some of the APs here can be at the same physical location.

the buildings, and according to the average shadowing variance observed in WLAN indoor channels [17]. For the cases of random bias and localized bias, all of the results are averaged over 1000 random iterations.

MDE, FDP and PDE are shown in Tables II, III and IV, respectively. In each table, the first row (bias $b = 0$) shows the results without any bias and it is kept as a reference. All of the data scenarios are included, and the results are shown with various constant bias values, with two different scenarios of random bias and with two different scenarios of localized bias. For the random bias, the amount of a bias was varied between -10 dB and $+10$ dB (case 1) and between -50 dB and $+50$ dB (case 2). In the localized bias case 1, the bias is set up to be -10 dB for 50% of the FP database and $+10$ dB for the rest 50%. In the localized bias case 2, $+10$ dB bias occurs in 70% of the FPs, and 30% of the FPs are without any bias. When studying the tables II, III and IV, it can be seen that the constant bias $b = -10$ dB affects the results very little, if any. The averaged MDE over all of the data scenarios remains totally the same than in the reference case (bias $b = 0$) and both FDP and PDE decrease only slightly (-0.5% and -0.2%, respectively). Almost as good results are obtained for a posivite constant bias $b = +10$ dB. In this case, MDE deteriorates less than 1 m in four buildings and less than 2 m in seven buildings. Same holds for FDP (4% decrease on average) and PDE (4.3% decrease on average). The same conclusion can be drawn also based on Fig. 2 showing the Cumulative Distribution Function (CDF) of absolute distance error for building A (upper plot of Fig. 2) and building F (lower plot of Fig. 2) for random bias case 2 and constant biases of $b = +/-10$ dB, $b = +/-30$ dB and $b = +/-50$ dB. As good results as for the constant bias of $+/-10$ dB are obtained also for the two localized bias cases, where either two different biases ($+/-10$ dB) are covering the whole building (i.e., localized bias, case 1) or a bias of 10 dB occurs in some part of the building only (i.e., localized bias, case 2).

For constant bias $b = -20$ dB, the results are around the same level than for $b = +10$ dB. After this, i.e. $b = -30$ dB or less and $b = +20$ dB or more, the results start to deteriorate slightly more. However, based on [13] and [18], it seems that the offset between different mobile types is usually less than $+/-20$ dB. It can also be seen that in some cases, the results seem to improve with a bias (e.g., MDE and FDP with $b = -10$ dB, for buildings C and E). This however can be explained by the fact that due to the manual data collection, we assume an error of appr. $0.5-1$ m both for the training phase data and for the user measurement locations. The difference between the results for buildings A (University building 1) and B (University building 1 with renewed AP infrastructure) is caused by the number of the FPs and APs (see Table I). After the AP infrastructure was renewed, the measurement collection phase was not as wide as previously, and the number of FPs in the renewed case is just around one third of the FPs in the original case. Indeed, also the number of heard APs is less.

In the case of random bias, a different uniformly distributed random bias either between -10 dB and $+10$ dB (case 1) or between -50 dB and $+50$ dB (case 2) was added for every heard AP in every FP. As it can be seen in Tables II, III and IV, the smaller random bias (i.e., case 1) affects the results very slightly, if any. Both MDE and FDP are at the same level for every building, and also PDE is decreased only by ca. 2 meters on average. In most buildings, also the random bias with higher variation (i.e., case 2) affects the MDE with less than 3 meters and to the FDP with less than 10%, as can be seen in Tables II and III. However, the PDE is clearly affected more, as noticed both in Table IV and in Fig. 2. One reason for this pretty good performance of a random bias may be the APs with multiple MAC-addresses, since the AP locations are not known or estimated and since

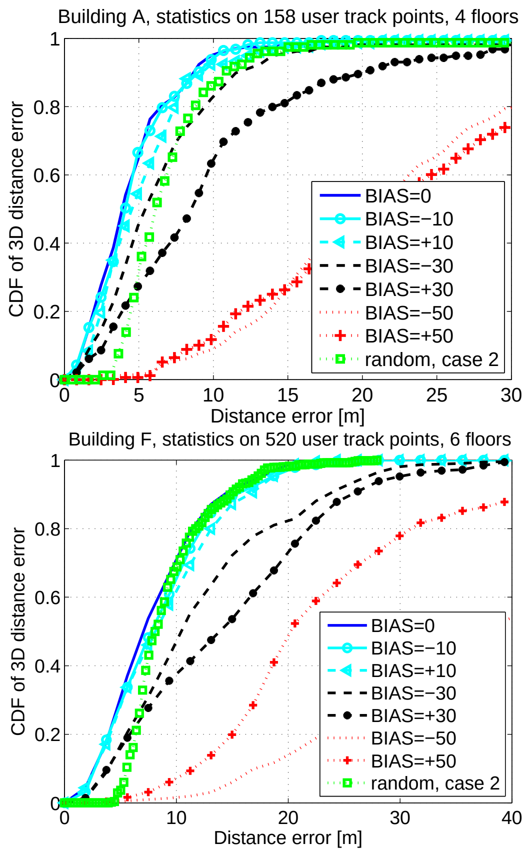

Fig. 2. CDF of absolute distance error for building A (upper plot) and building F (lower plot).

the bias for each AP (i.e., for each MAC-address) is chosen randomly.

Based both on the Fig. 2 and Tables II, III and IV, we can conclude that both constant or random biases between -20 dB to $+10$ dB covering either the whole building or only parts of it, can be easily tolerated in indoor environments. Indeed, in most cases a positive bias affects more than a negative. This is also intuitively clear, since a negative bias in the FPs actually means that the measured RSS by the mobile are relatively higher. Thus, since high RSS values occur in smaller areas in the AP coverage area than lower values, the positioning accuracy is also better.

IV. Conclusion

In this paper, we have shown the effects of offsets between the RSS values in the training and estimation phases of fingerprinting. Both constant and random biases were investigated, covering either the whole building or only parts of it. The results are presented in terms of positioning accyracy and floor detection probability. Based on a huge measurement campaign, it has been shown that either constant or random biases between -20 dB and $+10$ dB do not increase the positioning errors as much as it is generally believed. This holds both for a bias in whole building and for localized bias, that occurs only in some parts of the building. Thus, these amounts of biases can be easily tolerated without any calibration. Indeed, a random bias with relatively high variation between -50 dB and $+50$ dB did not affect significantly the MDE and FDP, but the decrease can be seen mostly in PDE.

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TABLE II

MEAN DISTANCE ERROR [M] IN 3D.

Bias b [dB]	Building A	Building B	Building C	Building D	Building E	Building F	Building G	Building H	Building I	mean
0	4.7	6.0	10.1	4.0	3.5	7.9	10.7	9.2	17.7	8.2
-10	4.9	6.2	9.8	4.9	3.3	8.5	10.5	9.7	16.0	8.2
$+10$	5.4	7.8	12.8	3.6	3.9	8.8	12.6	10.9	25.3	10.1
-20	5.9	6.9	9.6	6.0	3.3	9.9	12.1	10.9	17.4	9.1
$+20$	6.9	9.8	18.1	3.6	4.5	11.2	15.7	12.6	29.7	12.5
-30	7.2	7.5	9.9	6.8	3.5	12.2	14.6	12.4	24.2	10.9
$+30$	9.9	11.0	25.5	4.4	5.3	14.5	20.5	14.9	34.5	15.6
-40	12.1	12.3	12.7	8.9	5.1	16.6	18.5	15.7	34.7	15.2
$+40$	15.4	15.5	34.3	6.9	7.4	16.3	23.3	19.2	41.7	20.0
Random, case 1	4.8	6.2	10.5	4.0	3.4	8.0	10.9	9.5	18.6	8.4
Random, case 2	7.2	8.8	11.2	5.5	3.9	9.3	14.3	13.0	21.5	10.5
Localized, case 1	5.4	7.1	11.6	4.6	3.6	8.6	11.4	10.6	20.8	9.3
Localized, case 2	5.1	7.3	11.9	4.0	3.8	8.4	12.1	10.3	22.2	9.5

TABLE III

FLOOR DETECTION PROBABILITY [%].

Bias b [dB]	Building A	Building B	Building C	Building D	Building E	Building F	Building G	Building H	Building I	mean
0	89.9	97.2	86.9	92.7	79.7	88.1	84.4	84.0	91.6	88.3
-10	90.5	96.7	92.6	92.0	82.5	88.3	79.5	84.4	92.6	88.8
$+10$	84.8	92.3	75.0	92.0	79.7	85.2	77.1	80.8	91.6	84.3
-20	87.3	96.7	90.3	92.5	79.0	90.0	67.8	82.1	94.4	86.7
$+20$	82.3	86.7	66.5	89.6	73.4	81.2	58.5	78.0	91.6	78.6
-30	81.6	94.5	86.9	88.2	78.3	91.2	60.0	76.7	92.6	83.3
$+30$	74.1	75.5	46.6	84.8	73.4	82.7	47.3	72.9	95.8	72.6
-40	70.9	77.9	68.8	76.0	59.4	80.0	51.7	63.0	94.0	71.3
$+40$	61.4	61.3	33.0	72.9	59.4	82.5	37.6	54.3	94.4	61.9
Random, case 1	89.7	97.2	87.6	92.9	80.6	86.9	82.7	84.3	90.2	88.0
Random, case 2	80.8	86.8	74.2	86.2	78.9	84.7	61.9	76.0	92.4	80.2
Localized, case 1	87.1	94.4	83.6	90.6	79.8	86.9	76.5	82.3	92.2	85.9
Localized, case 2	86.7	93.6	78.2	91.8	78.7	85.5	79.0	81.9	90.4	85.1

TABLE IV

PERCENTAGE OF DISTANCE ERRORS LESS THAN 5 M [%].

Bias b [dB]	Building A	Building B	Building C	Building D	Building E	Building F	Building G	Building H	Building I	mean
0	64.4	47.5	24.4	69.8	75.8	30.0	15.9	23.6	10.0	40.2
-10	66.6	46.0	32.0	56.5	79.1	29.1	17.5	22.3	11.3	40.0
$+10$	54.4	37.2	21.2	77.6	71.6	28.4	13.1	16.1	3.5	35.9
-20	54.9	43.9	29.3	37.3	82.0	25.9	12.2	18.9	10.6	35.0
$+20$	41.0	29.4	10.1	77.1	66.4	21.2	9.0	12.5	4.0	30.1
-30	44.9	41.6	26.7	26.3	77.0	17.0	6.7	17.7	7.7	29.5
$+30$	27.3	17.7	5.7	64.4	53.6	15.0	5.6	7.2	4.0	22.3
-40	17.1	21.2	16.8	11.8	58.9	4.4	4.6	13.9	0.2	16.5
$+40$	10.8	6.4	2.5	35.6	36.1	6.5	2.4	6.4	0.6	11.9
Random, case 1	66.1	44.2	22.2	70.9	76.9	29.3	13.2	18.2	5.9	38.5
Random, case 2	31.3	23.5	1.1	40.3	77.6	3.5	0.8	0.3	0	19.8
Localized, case 1	55.2	40.3	13.5	62.8	75.5	21.4	8.0	11.8	3.3	32.4
Localized, case 2	60.3	35.5	15.8	72.7	73.7	23.9	9.4	11.9	2.3	33.9

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