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Localization in 5G Ecosystem with Wi-Fi

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***Abstract*—Location awareness is essential in 5th generation (5G) ecosystem to enable location-based services and to efficiently manage the network. This paper presents a method for efficient localization based on the fusion of heterogeneous observations gathered with different technologies in the 5G ecosystem. In particular, a soft information (SI)-based approach is developed for hybrid localization fusing 5G and Wi-Fi measurements. Results obtained in an indoor environment compliant with 3rd Generation Partnership Project standards quantify the benefits of hybrid localization via SI with respect to the case of a single technology.**

***Index Terms*—Location awareness, 5G, Wi-Fi, machine learning, wireless networks.**

I. Introduction

Accurate location information is a key enabler for a variety of location-based services (LBSs) and efficient management in 5th generation (5G) networks [1]–[6]. LBSs in the 5G ecosystem include autonomy [7], smart environments [8], crowdsensing [9], and Internet-of-Things [10]. Localization-of-Things (LoT) [11] can be achieved in 5G ecosystem via observations that are both radio access technology (RAT)-dependent (i.e., related to 3rd Generation Partnership Project (3GPP) technologies) and RAT-independent (i.e., related to non-3GPP technologies such as Wi-Fi, Bluetooth, ultra-wideband, and global navigation satellite system). However, LoT in 5G ecosystem is challenging due to the complex wireless environments and the LBSs tight requirements [12]. Therefore, it is important to develop algorithms able to efficiently exploit and fuse heterogeneous observations.

Localization techniques typically rely on single-value estimates (SVEs) of power-, time-, or angle-based metrics, to serve as a input to a localization algorithm [13]. In particular for 5G networks, such SVEs are obtained through the exchange of specific reference signals between the next generation NodeBs (gNBs) and the user equipment (UE) to be localized. Example of SVE is the downlink time difference of arrival (DL-TDOA) obtained from the positioning reference signal (PRS) [14]. In a 5G ecosystem, SVEs from RAT-independent observations can also be exploited to increase the localization accuracy via hybrid localization and data fusion. However, the accuracy of SVE-based localization techniques degrade in challenging wireless environments due to biases in SVEs caused by multipath propagation and non-line-of-sight conditions [15]. This can undermine the capabilities of meeting the performance constraints defined by the 3GPP for most demanding LBSs. Moreover, data fusion techniques typically require the knowledge of models to account for the relationship among the different types of observations [16]; such models may be difficult to obtain in complex environments. Therefore, there is a growing interest in conceiving localization algorithms that are able to cope with the wireless environment and at the same time allow for seamless fusion of different types of observations.

Recently, soft information (SI)-based localization has been proposed, which shows a significant performance gain compared to classical SVE-based localization [11]. SI-based approach shows several advantages compared to classical SVE-based localization: it is more robust to detrimental effects caused by the wireless propagation conditions and uses probabilistic models which allows for ease integration of different types of observations. Such models can be tailored to the environment via unsupervised machine learning techniques.

This paper explores the use of SI-based methods for LoT in 5G ecosystem. We advocate the exploitation of SI for localization in 5G ecosystem, which allows to improve localization accuracy and provides an unified framework for fusing heterogeneous measurements. In order to validate the proposed approach, hybrid localization in an indoor environment is considered. In particular, the fusion of DL-TDOA measurements from 5G network and time-of-flight (TOF) measurements from Wi-Fi is carried out via SI. The key contributions of this paper include:

- development of SI-based techniques for LoT in 5G ecosystem;
- quantification of SI-based localization performance gain over classical SVE-based techniques.

Results in terms of empirical cumulative distribution function (ECDF) for the horizontal localization error are obtained via rigorous simulation in a 3GPP standardized scenario, namely indoor open office (IOO) [17].

The remaining sections are organized as follows: Section II gives a brief overview of DL-TDOA localization in 5G networks, Section III describes SI-based localization for 5G ecosystem, and Section IV presents the simulation settings and performance results. Finally, our conclusions are given in Section V.

Notations: Random variables are displayed in sans serif, upright fonts; their realizations in serif, italic fonts. Vectors are

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denoted by bold lowercase and uppercase letters, respectively. For example, a random variable and its realization are denoted by x and x; a random vector and its realization are denoted by $\mathbf{x}$ and $\boldsymbol{x}$, respectively. $||\cdot||_2$ denotes the norm 2 operator.

II. DL-TDOA Localization in 5G Networks

DL-TDOA measurements are obtained via the exchange of the PRS between gNBs and UEs. The PRS is used exclusively for localization purposes and is obtained starting from a pseudo-random Gold sequence long 31 bits, where the sequence seed is initialized according to the ID of the transmitting gNB [18]. The sequence is modulated according to quadrature phase-shift keying (QPSK) and mapped into the time-frequency grid of a 5G slot.[1] In time, the PRS occupies L, with $L \in \{2, 4, 6, 12\}$, consecutive symbols within a 5G slot. In frequency, the PRS shows a comb-like structure where the QPSK symbols are mapped into only one subcarrier every K, with $K \in \{2, 4, 6, 12\}$, while the others are padded to zero. The periodicity K of the occupied subcarrier is referred to as comb size. This particular time-frequency structure helps avoiding collisions with neighbor transmitting gNBs. The detailed procedure describing the mapping process of the QPSK symbols into the resource elements $a_{l,k}$, i.e., the k-th subcarrier for the l-th symbol, composing the slot grid is described in [18]. The n-th sample of the l-th orthogonal frequency division multiplexing (OFDM) baseband symbol allocated for PRS transmission is obtained via inverse fast Fourier transform (IFFT) as

$$s_l[n] = \sqrt{\frac{P_{\rm tx}}{N_{\rm FT}}} \sum_{k=0}^{N_{\rm FT}-1} a_{k,l} \exp\left\{2\pi \frac{nk}{N_{\rm FT}}\right\} \tag{1}$$

where $P_{\rm tx}$ is the transmitted power and $N_{\rm FT}$ is the number of IFFT points, i.e., the total number of subcarriers allocated for transmission. The OFDM symbols $s_l[n]$ with $l = \{1, 2, \ldots, L\}$ are then pulse-shaped and up-converted to obtain $s(t)$. The value of $N_{\rm FT}$ is determined by the allocated PRS bandwidth. In particular, the number of subcarriers allocated for PRS is quantified in terms of resource blocks (RBs), where each RB represents 12 contiguous subcarriers. Hence, the number of IFFT points is $N_{\rm FT} = 12N_{\rm RB}$, where $N_{\rm RB}$ takes value between 24 and 272, with a granularity of 4. The actual PRS bandwidth is calculated as $B = 2^{\mu}\Delta f N_{\rm FT}$, where μ is the numerology, with $\mu \in \{0, 1, 2, 3, 4\}$ and $\Delta f = 15\,$KHz is the smaller subcarrier spacing allowed in 5G.

In order to obtain DL-TDOA measurements, an UE first estimates the time-of-arrivals (TOAs) of the PRSs transmitted by a set of gNBs satisfying constraints on the received signal quality (e.g., signal-to-noise ratio greater than a predefined threshold) [19]. The TOA is typically estimated evaluating the crosscorrelation between the transmitted and received signals as

$$R[n] = \sum_{m=0}^{N_{\rm s}-1} z[m] s^*[n-m] \tag{2}$$

[1]A 5G slot is composed by 14 consecutive symbols and a varying number of subcarriers, depending on the allocated transmission bandwidth.

where $N_{\rm s}$ is the number of received signal samples, $z[n] = z(nT_{\rm s})$ is the sampled version of the received signal at the UE, $T_{\rm s}$ is the sampling time, $s[m]$ represents the L-symbol long transmitted PRS, and $N_{\rm s}$ is chosen such that $N_{\rm s} = LN_{\rm FT}$.[2] Several criteria can be employed to estimate the TOA from (2), including maximum peak search or maximum likelihood algorithms used to estimate the channel impulse response [20]–[22]. Once TOAs are estimated, the UE computes the DL-TDOA and transmits the values back to the network. Consider $N_{\rm BS}$ gNBs, indexed by $i = 1, 2, \ldots, N_{\rm BS}$, as involved in the localization process with gNB 1 serving as reference gNB without loss of generality. The DL-TDOA relative to the gNBs pair $(i, 1)$ can be written as

$$\hat{\tau}_{i,1} = \hat{\tau}_i - \hat{\tau}_1 \tag{3}$$

for $i = 2, 3, \ldots, N_{\rm BS}$, where $\hat{\tau}_i$ and $\hat{\tau}_1$ are the estimated TOA of the PRSs transmitted by the gNBs i and 1, respectively. Based on the DL-TDOA measurements, the UE position $\boldsymbol{p} \in \mathbb{R}^2$ can be estimated via a least squares (LS) approach. In particular, define the vectors

$$\hat{\boldsymbol{d}} = c_0[\hat{\tau}_{2,1}, \hat{\tau}_{3,1}, \ldots, \hat{\tau}_{N_{\rm BS},1}]^{\rm T} \tag{4a}$$

$$\boldsymbol{d}(\boldsymbol{p}) = [d_{2,1}(\boldsymbol{p}), d_{3,1}(\boldsymbol{p}), \ldots, d_{N_{\rm BS},1}(\boldsymbol{p})]^{\rm T} \tag{4b}$$

where c_0 is the signal propagation speed, $d_{i,1}(\boldsymbol{p}) = ||\boldsymbol{p} - \boldsymbol{p}_{\rm BS}^{(i)}||_2 - ||\boldsymbol{p} - \boldsymbol{p}_{\rm BS}^{(1)}||_2$, and $\boldsymbol{p}_{\rm BS}^{(i)}$ the i-th gNB position. Then, an estimate of the UE position $\hat{\boldsymbol{p}}$ can be obtained as

$$\hat{\boldsymbol{p}} = \arg\min_{\tilde{\boldsymbol{p}}} \left(\hat{\boldsymbol{d}} - \boldsymbol{d}(\tilde{\boldsymbol{p}})\right)^{\rm T} \left(\hat{\boldsymbol{d}} - \boldsymbol{d}(\tilde{\boldsymbol{p}})\right). \tag{5}$$

Different strategies can be adopted to solve (5) depending on the accuracy and computational constraints. An exhaustive search of the minimum can be carried out on a discretized version of the monitored area. Alternatively, iterative algorithms aiming at finding an approximate solution can be employed, such as Levenberg-Marquardt algorithm [23].

III. SI for 5G Ecosystem

SI is composed by soft feature information (SFI) related to the measurements data, and soft context information related to contextual data (e.g., mobility model and environmental map) [11]. This work will focus on SFI that can be extracted directly from RAT-dependent and RAT-independent observations. In particular, DL-TDOA measurements $\hat{\tau}_{i,j}$ and range estimates $\hat{r}$ based on Wi-Fi TOF measurements are considered.

In non-Bayesian settings, given a generic measurement vector (MV) $\boldsymbol{y}$ and a feature vector (FV) $\boldsymbol{\theta}$, the associated SFI can be written as $\mathcal{L}_{\boldsymbol{y}}(\boldsymbol{\theta}) \propto f_{\mathbf{y}}(\boldsymbol{y}; \boldsymbol{\theta})$, i.e., the SFI is proportional to the likelihood function of $\boldsymbol{\theta}$ given $\boldsymbol{y}$. The MV $\boldsymbol{y}$ represents any type of position-related measurements (e.g., DL-TDOA, TOF, or received waveform samples), while the FV $\boldsymbol{\theta}$ is a function of the UE position $\boldsymbol{p}$ (e.g., distance, angle, or other quantities which depends on the UE position). For DL-TDOA measurements in 5G networks, the SFI can be written as $\mathcal{L}_{\hat{\tau}_{i,j}}(d_{i,j}(\boldsymbol{p}))$ and it is referred to as soft range

[2]The sampling time $T_{\rm s}$ is related to the bandiwidth of the transmitted PRS.

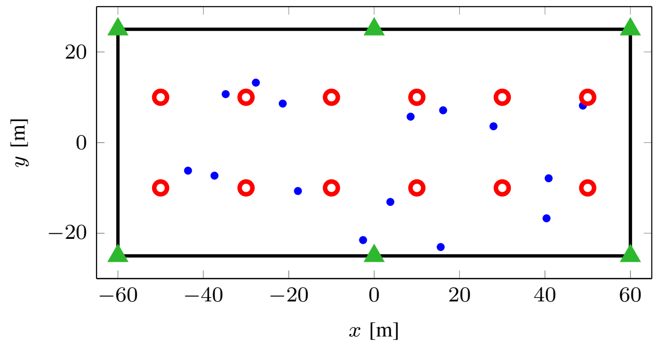

Fig. 1. IOO scenario with gNBs (red annolous), Wi-Fi APs (green triangles), and a particular instantiation of the UEs (blue dots).

information (SRI) [11], [24] as the FV is related to the distance. Given the SRI, the UE position $\boldsymbol{p}$ can be estimated as

$$\hat{\boldsymbol{p}} = \arg\max_{\boldsymbol{p}} \prod_{i=2}^{N_{\mathrm{BS}}} \mathcal{L}_{\hat{\tau}_{i,1}}(d_{i,1}(\boldsymbol{p})) \tag{6}$$

where the MVs from different gNBs are assumed statistically independent for a given the UE position. Similarly, SRI for Wi-Fi range measurements is given by $\mathcal{L}_{\hat{r}}(d(\boldsymbol{p}))$, where $\hat{r}$ and $d(\boldsymbol{p})$ represent the estimated range and true distance between the UE and Wi-Fi access point (AP), respectively. The characterization of the relation between the MV and FV via a probabilistic model provides a richer information compared to SVE and an efficient way to fuse heterogeneous measurements. In particular, as long as MVs obtained from different technologies can be considered statistically independent given the UE position, thus the resulting SFI can be obtained via simple multiplication of individual SFIs.[3] For hybrid localization in 5G ecosystem, consider a 5G network composed of N_{BS} gNBs and a UE measuring DL-TDOAs as in (3). In addition to performing measurements with 5G gNBs, the UE is able to acquire TOF measurements from N_{AP} Wi-Fi APs deployed in the same monitored environment. Thus, the UE position can be efficiently estimated via SI-based approach as

$$\hat{\boldsymbol{p}} = \arg\max_{\boldsymbol{p}} \left\{ \prod_{i=2}^{N_{\mathrm{BS}}} \mathcal{L}_{\hat{\tau}_{i,1}}(d_{i,1}(\boldsymbol{p})) \prod_{n=1}^{N_{\mathrm{AP}}} \mathcal{L}_{\hat{r}_n}(d_n(\boldsymbol{p})) \right\} . \tag{7}$$

The SFI can be determined based on prior knowledge of the relation between MV and FV, or it can be directly learned from the environment via unsupervised machine learning techniques. In particular, SFI can be obtained using a Bayesian formulation and considering the joint probability distribution $f_{\mathsf{y},\boldsymbol{\theta}}(\boldsymbol{y},\boldsymbol{\theta})$ referred to as generative model for the MV and FV. If no prior information is available for the FV $\boldsymbol{\theta}$, the SFI is proportional to the generative model, i.e., $\mathcal{L}_{\boldsymbol{y}}(\boldsymbol{\theta}) \propto f_{\mathsf{y},\boldsymbol{\theta}}(\boldsymbol{y},\boldsymbol{\theta})$.

[3]RAT-dependent and RAT-independent observations can be reasonably assumed statistically independent given the UE position regardless of the specific technology.

An estimate $\hat{f}_{\mathsf{y},\boldsymbol{\theta}}(\boldsymbol{y},\boldsymbol{\theta})$ of the generative model can be inferred employing density estimation techniques based on measurements and features $\boldsymbol{x}^{(m)} = [\boldsymbol{y}^{(m)}, \boldsymbol{\theta}^{(m)}]$ collected in the environment of interest, where $m \in \mathcal{N}_{\mathrm{D}} = \{1, 2, \ldots, N_{\mathrm{D}}\}$ and N_{D} is the number of collected data. A well-known and widely adopted density estimation technique is Gaussian mixture model (GMM) fitting [25]. In GMM fitting, the generative model can be written as

$$\hat{f}_{\mathsf{x}}(\boldsymbol{x}) = \sum_{i=1}^{N_{\mathrm{GM}}} \pi_i \varphi(\boldsymbol{x}; \boldsymbol{\mu}_i, \boldsymbol{\Sigma}_i) \tag{8}$$

where N_{GM} is the number of Gaussian distributions composing the mixture, π_i the weight of the i-th distribution (satisfying the constraint $\sum_{i=1}^{N_{\mathrm{GM}}} \pi_i = 1$), and $\varphi(\boldsymbol{x}; \boldsymbol{\mu}_i, \boldsymbol{\Sigma}_i)$ represents a multidimensional Gaussian distribution with mean vector $\boldsymbol{\mu}_i$ and covariance matrix $\boldsymbol{\Sigma}_i$. The optimal values in maximum likelihood sense for π_i, $\boldsymbol{\mu}_i$, and $\boldsymbol{\Sigma}_i$ can be obtained applying expectation-maximization algorithm on the measured data $\{\boldsymbol{x}^{(m)}\}_{m \in \mathcal{N}_{\mathrm{D}}}$ [25].[4] Once the generative model is estimated from the collected data, it can be used to estimate the UE position. In particular, every time a new MV $\tilde{\boldsymbol{y}}$ is available, the generative model is evaluated in order to determine the associated SFI, i.e., $\mathcal{L}_{\tilde{\boldsymbol{y}}}(\boldsymbol{\theta}) \propto \hat{f}_{\mathsf{y},\boldsymbol{\theta}}(\tilde{\boldsymbol{y}},\boldsymbol{\theta})$, and then used in (6) and (7).

IV. Case Study

Consider an IOO area of 120 meters by 50 meters according to [17] in which a varying number of UEs are randomly located and where $N_{\mathrm{BS}} = 12$ 5G gNBs and $N_{\mathrm{AP}} = 6$ Wi-Fi APs are deployed as in Fig. 1. In such a scenario, results in terms of ECDF of the horizontal localization error for hybrid localization in 5G ecosystem are presented. In particular, the performance of SVE-based methods for individual 5G and Wi-Fi measurements, SI-based methods for individual 5G and Wi-Fi measurements, as well as results fusing of such measurements via SI framework, are compared.

For 5G network, DL-TDOA measurements obtained from the PRS are considered. The PRS is simulated at waveform sample level according to the details given in Sec. II following [17]. The gNBs transmitting power is 24 dBm and the localization performance is evaluated considering two different PRS bandwidths and carrier frequencies: i) 50 MHz at 2 GHz; and ii) 100 MHz at 4 GHz. DL-TDOA measurements are obtained via crosscorrelation between the transmitted and the received PRS as in [22]. In order to improve the accuracy, the received PRS is averaged over three different transmissions, each composed of $L = 12$ symbols with comb size $K = 6$. The noise figure at the UE side is of 5 dB. The propagation channel between the gNBs and the UEs is simulated using Quadriga channel simulator for the IOO channel model parameters [26], [27]. On the other hand, Wi-Fi related measurements consist of range estimates for the distance between the UEs and the APs. The range estimates are obtained considering the true

[4]Pre-processing can also be applied to the data $\{\boldsymbol{x}^{(m)}\}_{m \in \mathcal{N}_{\mathrm{D}}}$ in order to obtain better density estimates, e.g., data sphering [24].

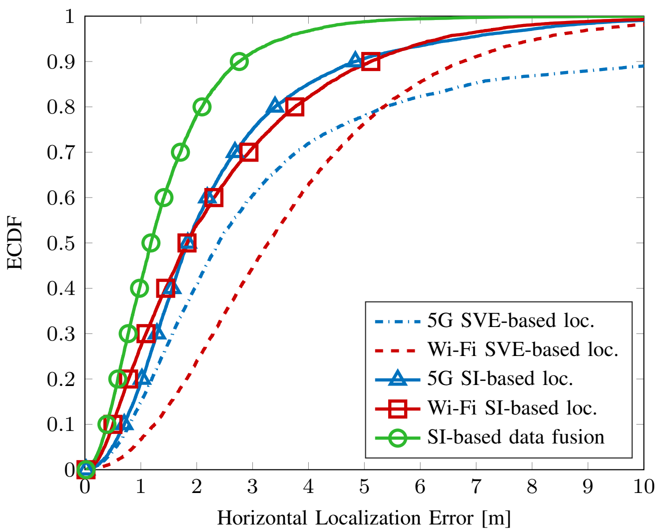

Fig. 2. ECDF of the horizontal localization error for the different SVE-based and SI-based localization techniques considered in the case of 50 MHz PRS bandwidth at 2 GHz.

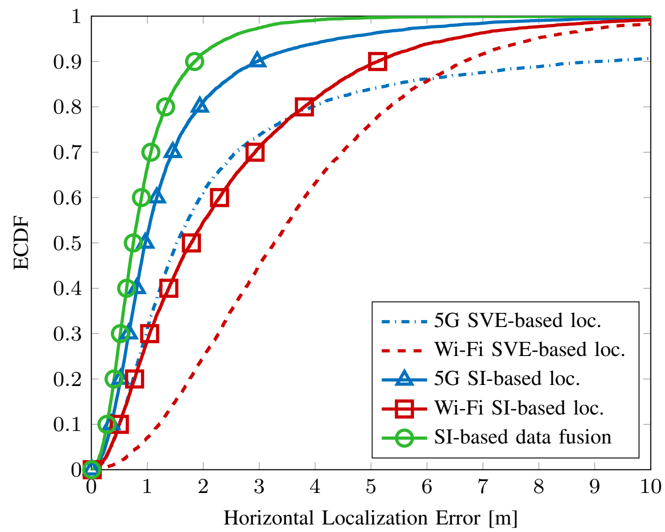

Fig. 3. ECDF of the horizontal localization error for the different SVE-based and SI-based localization techniques considered in the case of 100 MHz PRS bandwidth at 4 GHz.

distance between the UE and AP plus a range estimation error. Such range estimation error is modeled according to the experimental results in [28] which are based on TOF measurements. The measurements are obtained using off-the-shelf components operating on a fixed channel of the 2.4 GHz ISM band and running a 802.11 b/g custom firmware. In particular, the measurements gathered in the scenario referred to as Testbed I in [28] are used to generate range errors for the AP-UEs distances. Testbed I in [28] presents similar characteristics in terms of dimensions and mix of line-of-sight and non-line-of-sight conditions with the considered IOO scenario. The fitting distribution is chosen as a Gamma distribution with parameters $\alpha = 1.1$ and $\beta = 3.35$.[5] The ranging based on TOF measurements presents a median error of 2.4 meters and an 80-percentile error of 5.3 meters.

For SVE-based approach, LS algorithm is employed to infer the UE location based on 5G DL-TDOA measurements and Wi-Fi range measurements [23]. LS algorithm represents a good baseline to perform performance comparison as reported in 3GPP technical report [17]. For SI-based approach, the DL-TDOA measurements and distance differences are considered as MV and FV for 5G technology, respectively, while range estimates based on TOF measurements and distances are considered as MV and FV for Wi-Fi technology, respectively, as described in Sec. III. A GMM as in (8) with $N_{\mathrm{GM}} = 5$ mixture components is used as generative model for both DL-TDOA and ranging measurements. The model is validated, i.e., GMM parameters are learned and the localization performance evaluated, via a k-fold cross-validation procedure [29], where $k = 10$, over 1000 different UEs and channel instantiations. For SI-based localization employing a single technology, UE location is inferred via (6), while hybrid localization is carried out via (7), where the maximum value is obtained via an exhaustive search over the monitored area with a step size of 0.05 meters.[6]

Fig. 2 shows the ECDF of the horizontal localization error for the different localization techniques considered in the case of 50 MHz PRS bandwidth at 2 GHz: 5G SVE-based localization; Wi-Fi SVE-based localization; 5G SI-based localization; Wi-Fi SI-based localization; and SI-based localization with data fusion between 5G and Wi-Fi measurements. It can be observed that SI-based localization offers a significant performance improvement with respect to SVE-based localization. In particular, at the 90-th percentile the SI-based approach shows an improvement of approximatively 6 meters and 2 meters compared to SVE-based approach for the individual 5G and Wi-Fi localization, respectively. It can also be observed that, the fusion of 5G DL-TDOA measurements and WI-Fi TOF measurements using the SI-based approach further improves the localization accuracy. In particular, at the 90-th percentile data fusion provides an improvement of approximatively 2 meters with respect to the single technology localizations. At the same percentile, the improvement offered by data fusion compared to 5G and Wi-Fi SVE-based localization is approximatively 8 meters and 4 meters, respectively.

Fig. 3 shows the ECDF of the horizontal localization error for the different localization techniques considered in the case of 100 MHz PRS bandwidth at 4 GHz: 5G SVE-based localization; Wi-Fi SVE-based localization; 5G SI-based localization; Wi-Fi SI-based localization; and SI-based localization with data fusion between 5G and Wi-Fi measurements. It can be observed that, SI-based localization for 5G further improves

[5] A Gamma distribution with shape parameter α and scale parameter β for a random variable x is defined as $f(x;\alpha,\beta) = (\beta^{\alpha}\Gamma(\alpha))^{-1}x^{\alpha-1}\exp\{-x/\beta\}$, where $\Gamma(\cdot)$ is the Gamma function.

[6] A smaller step size would increase the localization accuracy at the cost of a higher latency and simulation time. Depending on the accuracy and latency constraints, the step size parameter can be optimized.

the localization accuracy compared to SVE-based approach. At the 90-th percentiles, SI-based localization provides an improvement of approximatively 5 meters compared to the SVE-based approach. It can also be observed that the data fusion of 5G and Wi-Fi measurements still provides a performance improvement compared to the single technology case despite 5G SI-based localization performs significantly better compared to Wi-Fi SI-based localization. At the 90-th percentile, the improvement provided by the data fusion is approximatively 1 meter compared to individual 5G SI-based localization.

V. Final Remark

This paper developed a soft information (SI)-based approach for accurate localization in the 5th generation (5G) ecosystem. In particular, the fusion of 3rd Generation Partnership Project (3GPP) and non-3GPP measurements through SI framework is presented. Results are shown for a case study in a 3GPP indoor environment where downlink time difference of arrival measurements obtained from 5G technology and range measurements obtained from Wi-Fi technology are considered. It is shown that data fusion via SI significantly outperforms single-value estimate (SVE)-based localization for both technologies and improves the performance compared to SI-based localization with single technology. SI-based localization provides better performance compared to classical SVE-based localization, especially in harsh wireless environments, and provides an unified framework to efficiently fuse heterogeneous measurements. Therefore, SI-based localization is a promising solution to provide accurate localization in 5G ecosystem.

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