PARAMETER ESTIMATION OF IN-CITY FRONTAL RAINFALL PROPAGATION

Mor Hadar, Jonatan Ostrometzky†, Senior Member, IEEE, and Hagit Messer*, Life Fellow, IEEE*

*School of Electrical Engineering, Tel Aviv University, Israel
†Dept. of Electrical Engineering, Columbia University in the City of New York, NY, USA

ABSTRACT

Modern infrastructures support smart-city operations, which are based on short millimeter-waves wireless links connected by a dense network. These links are sensitive to hydrometeors, and their signals attenuated by rain. In this study, we demonstrate that standard signal-level measurements being collected by the network can be used to estimate the movement of an ongoing storm. Parameters characterizing the movements of the frontal rain cell, as its velocity and direction, can be accurately estimated. We first estimate the differential time of arrival of the attenuated signals between pairs of links, from which we extract the parameters of interest. We demonstrate our results using actual measurements from an operating system in the city of Rehovot, Israel.

Index Terms— Smart-City, mmWave, Storm Direction Estimation, TDE, Array Processing

I. INTRODUCTION

Attenuation of transmitted power of an electromagnetic wave occurs when energy is scattered or absorbed by diffusers in the path of propagation. For Commercial Microwave Links (CMLs), this is described by the International Telecommunication Union (ITU) recommendation [1]. The common approach for modelling attenuation due to rain is described by the power-law model [2], [3]:

$$A = aR^b \tag{1}$$

where A (in dB/km) is the signal attenuation caused by rain, R (in mm/h) is the path-integrated rain rate (i.e., the rain intensity) along the link and a, b are coefficients depending on the link's frequency, polarization and rain's drop size distribution. It was first suggested in 2006 to use CMLs' susceptibility to rain as opportunistic sensors for measuring rain rate near ground [4]. Since then, the research field of environmental monitoring using CMLs, has been greatly developed, focusing on deeper research [5].

Recently, many cities, on their way to become smart cities, established an in-city communication network based on millimeter-waves, as relevant applications are based upon access to a high-capacity communication infrastructure [6].

In this paper, we aim to demonstrate for the first time the potential of using smart city CMLs' measurements as opportunistic sensors for environmental parameters estimation in a street-level scale by using operational smart city network measurements on a use case of estimating direction and velocity of in-city frontal rain cells. Previous work, exploiting CMLs for frontal rain observation [7], was done in a large scale rain. Other works used rain gauges spread in the city [8], [9]. In-city meteorology is different and not well studied. In-city environmental parameters, especially real-time rain intensity monitoring and long period statistics, can greatly benefit for in-city hydrological application such as urban watershed, urban drainage planning, flood warning system, adaptive irrigation system and more.

The rest of the paper is as follows: *Section II* describes the data and shows measurements' example from a city in the center of Israel. *Section III* presents the theory and methodology of our estimation approach. *Section IV* details a real-world demonstration of our suggested approach. *Section V* discusses sources of errors and concludes this paper.

II. THE DATA

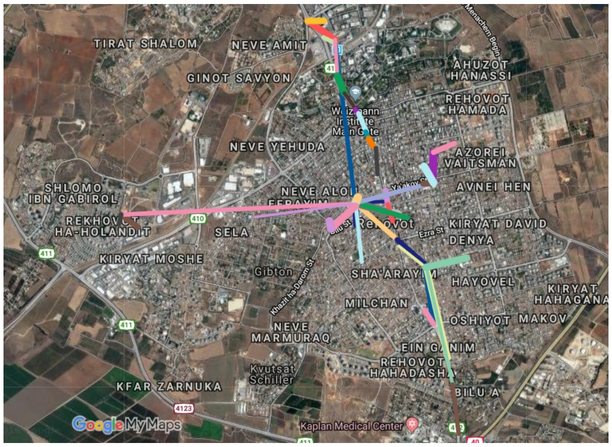
The measurements discussed are Received Signal Level (RSL) recorded regularly from all network's hops by its operator for management purposes. We received RSL measurements from Rehovot municipality network (see Table I and **Fig 1**) [10], with the courtesy of the operator company SMBIT Ltd [11]

Table I. Rehovot's network characteristics

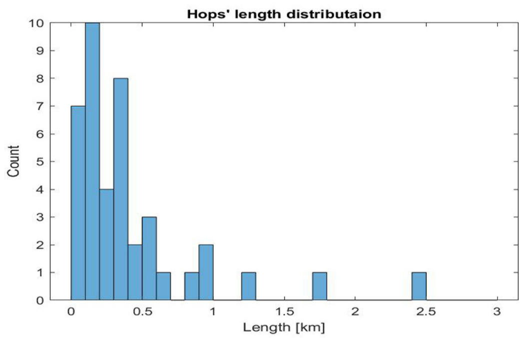
No. of Hops	41
City Area	5×5 km ^{2}
Hops' Lengths	$66 - 2042$ m (see **Fig 1(b)**)
Equipment supplier	Siklu Ltd [12]
Frequency	74.85 GHz* (TDD)**
Time Sampling Resolutions	30 sec
Power (RSL) Resolution	1 dB

*Except two links operating in 84.37 GHz
**TDD - Time Division Duplex

RSLs recorded during storm events can be used to estimate frontal rain cell movement velocity and direction in a city scale. **Fig 2** presents attenuation of RSLs during two (separated) stormy events. In both figures, the RSLs time-series are presented in the left panels, arranged as follows:

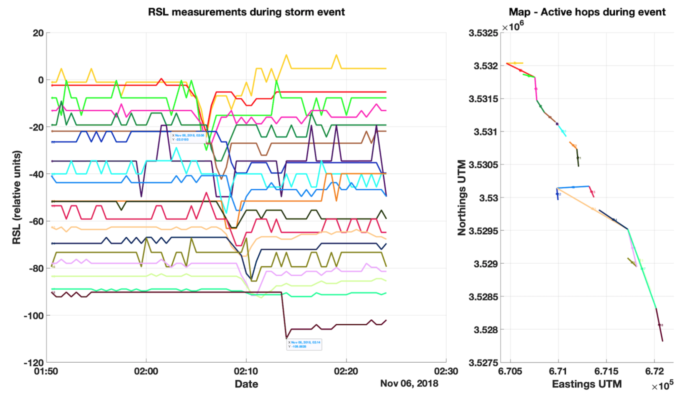


(a)

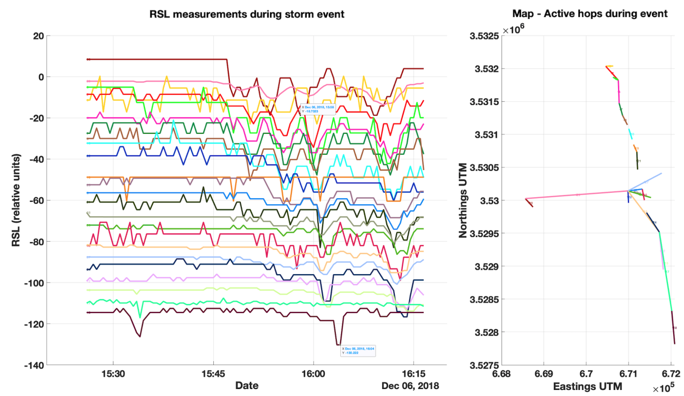


(b)

Fig. 1. (a) Hops in Rehovot. Google Maps, 2019, [13]. (b) Hops' length distribution



(a)



(b)

Fig. 2. RSLs time-series and a map (UTM zone 36R) of active hops during two storms in Rehovot. (a) Storm during Nov. 6^{th} 2018, crossing the city roughly from north to south; and (b) Storm during Dec. 6^{th} 2018, crossing the city roughly from west to east

The upper time-series belongs to the first hop attenuated by the storm. Beneath it, the time-series depicted belongs to the hop attenuated secondly and so on. The illustrative-maps on the right panels present the active hops' location during the events. In **Fig 2a**, the frontal rain cell arrived from north and we can clearly see its progress south as the hops' signal attenuated once the rain cell reaches the hop's locations. In **Fig 2b** the storm arrived from west-north and headed east.

III. THEORY AND METHODOLOGY

As described above, we are facing a tempo-spatial estimating problem, and as such, sensor array processing tools are naturally examined [14]. A common approach is to estimate the Time Difference of Arrival (TDOA) between pairs of sensors [15], followed by source's spatial parameters from the noisy TDOAs estimation. Here, the source is the frontal rain cell approaching the city, where the sensors are the hops signals attenuated by the rain (see (1)). The first step of calculating TDOA uses cross-correlation tool and is described in III-A. The second step of estimating frontal rain cell position assumes a parametric model, solved by a Non-linear least square (NLS) technique. The deterministic parameters to be estimated are the in-city frontal rain cell moving-velocity, v, and its moving-direction, θ. The suggested method, is obviously sub-optimal, and its limitations are discussed in *Section V*. However, it demonstrates the potential of in-city rainfall monitoring using smart city infrastructures. In particular, we show that actual signal level measurements from smart-city network hold valuable information about tempo-spatial characteristic of an environmental phenomenon. We demonstrate it by using basic tools from sensor array processing framework, while making the following restrictive assumptions:

1) The rain is caused by a single rain cell.
2) During the observation time, the in-city rain cell is moving in constant velocity and constant direction.
3) The rain cell is big enough to cover all hops used for estimation.

4) During the observation time, the RSL signals are assumed stationary and ergodic processes.
5) Each hop (or link), is modeled as a point sensor located in its center.

Here, we demonstrate the feasibility by solving a simplistic case, which corresponds to the strict assumptions made. Indeed, considering the general case using relaxed and more realistic assumptions is important and is being investigated by us currently, and will be presented in a future work.

III-A. Time Difference of Arrivals

Estimating the TDOA between frontal rain cell attenuating each pair of hop's RSLs, is followed by the concept suggested in [16], using correlation method. The RSL (in dB) of a link is combined from the following components:

$$\text{RSL}(t) = \text{round}(\text{TSL} - A_r(t) - A_w(t) - A_e(t) - A_0 + N(t)) \tag{2}$$

Where TSL is the assumed constant Transmitted Signal Level. The total attenuation consists of several components: A_0 is the constant attenuation caused by the path-loss, $A_r(t)$ is the attenuation caused by rain, $A_w(t)$ is the attenuation caused by the wet-antenna effect [17] (in the sequel we will treat the wet antenna attenuation as part of the rain attenuation $A_r(t)$, this assumption is discussed in *Section V-A*), and $A_e(t)$ is the attenuation caused by other environmental phenomena which can be neglected during storms. $N(t)$ is an additive measurement noise assumed independent (among all links). Lastly, the rounding describes the quantization effect caused by hardware limitations. The attenuation factors are described in [18]. Each hop is combined from two links operating at the same frequency (for bi-directional communication). For simplicity, we used the measurements from one arbitrary link per hop. Therefore, the cross-correlation between hops i and j, for the time difference k, $R_{ij}[k]$, can be calculated by:

$$R_{ij}[k] = \begin{cases} \sum_{n=0}^{N-k-1} RSL_i[n+k]RSL_j[n] & ;k \geq 0 \\ R_{ji}(-k) & ;k < 0 \end{cases} \tag{3}$$

To increase the Signal-to-Noise Ratio, before calculating the cross-correlation, the baseline ($TSL - A_0$) is estimated by a moving-average filter over 10 days, assuming 10 days has more dry days than wet. There are complex methods for calculating the baseline [19] but this is beyond the scope of this paper. The baseline is then subtracted from the RSL measurements. In addition, the RSL is normalized by each hop's length. The arguments k that maximize (3) for each pair of $\{i, j\}$ are converted to actual time via multiplication with the time sampling resolution (30 sec), and are then used as the dependent variables in *Section III-B*. Hence, the dependent variables, the estimated TDOA for each pair, $\hat{\tau}_{ij}$, in the time domain is given by:

$$\hat{\tau}_{ij} = (\arg\max_k\{R_{ij}[k]\}) \cdot 30 \tag{4}$$

III-B. Non-Linear Least Square Estimator

Let I denote the full set of N sensors pairs (i, j). This includes all $M(M-1)/2$ sensors pairs [15]. Thus, $I = \{(i, j)|1 \leq i < j \leq M\}$. $\hat{\tau}_{ij}$ is an element in the Nx1 vector $\underline{\hat{\tau}}$ which consists of all available TDOA pairs. Under setting of sensor array processing, each link is a sensor in our problem, assumed to be located at the center of the link as described in assumption 5. The relation between v, θ and the dependent variable, $\hat{\tau}_{ij}$, is given by the following model:

$$\hat{\tau}_{ij} = \frac{d_{ij}cos(\phi_{ij} - \theta)}{v} + n_{ij} = \tau_{ij}(v, \theta) + n_{ij} \tag{5}$$

ϕ_{ij} is the angle of the line between each pair of sensors with x-axis. Thereby $d_{ij}cos(\phi_{ij} - \theta)$ is the distance projection between each pair of sensors on the frontal rain cell moving-direction θ. n_{ij} represents the estimation errors which are similar among all hops due to the hop's length normalization (which is, however, dependent). We solve the over-determined equations system (5) using a non-linear least square (NLS) technique [20]. The simplified cost function to be minimized is the sum of residual:

$$J = (\underline{\hat{\tau}} - \underline{\tau}(v, \theta))^T(\underline{\hat{\tau}} - \underline{\tau}(v, \theta)) \tag{6}$$

The estimated parameters are therefore:

$$(\hat{v}, \hat{\theta}) = \underset{v,\theta}{\text{argmin}}\{J(v, \theta)\} \tag{7}$$

We used Matlab function $lsqnonlin$ [21] to solve (7), based on the optimization algorithm 'trust-region-reflective' which requires an initial guess for the parameters that we arbitrarily set to $v_0 = 20\ \frac{\text{m}}{\text{s}}$; $\theta_0 = 360°$.

IV. RESULTS

The method described in *Section III* was first tested on the measurements depicted in *Section II*. In both cases one can identify, from the raw RSL measurements, the rain induced attenuation and the delay in which it accrues at the different links, as summarized in table II. $\hat{v}$,$\hat{\theta}$ are the results of the method described in *Section III*. v_{naive} and θ_{naive} are a simple calculation done by taking only the two extreme hops (sensors), the first and last one to be attenuated by the frontal rain cell. The naive calculation is based on picking the most distinguishable point of the RSL at both links, which yields the angle between center of the hops relative to the x-axis, θ_{naive}, and the velocity, v_{naive}, which is calculated by v_{naive} = distance/time, where "distance" is the length between the centers of the extreme hops, and "time" is the lag between the distinguishable picks. "Storm strength" is a metric, defined as the maximal attenuation recorded among all hops during the storm (after normalization by the hops' length).

As shown, the naive calculation estimation are close to the NLS estimated parameters, providing a sanity check for our procedure. Unfortunately, our results cannot be compared

Table II. Results for two storms

Storm Event	Event1	Event2
Date	Nov 6, 2018	Dec 6, 2018
Starting Time	02:04	15:47
Duration	30 min	45 min
Storm Strength	15.6 dB	18.8 dB
$\hat{v}$	8.66 m/s	10.23 m/s
v_{naive}	8.79 m/s	9.25 m/s
$\hat{\theta}$	339°	356°
θ_{naive}	291°	331°

with other sources of measurements since near ground in-city direct meteorological measurements are, in general, not available. In particular, there are no weather stations in Rehovot with the closest one being 3.64 km far. Its measurements cannot be used as a reference since urbanization has its own affect on rain characteristics [22] and therefore, in-city rain cannot be considered the same as that measured outside. Moreover, there is lack of knowledge about characteristic of weather in a city scale. After demonstrating the validity of our approach on two specific events, we have applied it on measurements taken over 16 months. 405 rainy period, each of 10 minutes $-$ 90 minutes in length, were analysed from February 2018 to June 2019. The histogram of **Fig 3** illustrates the distribution of the velocity estimates $\hat{v}$ over all these cases. Exponential distribution of the tail of $\hat{v}$, commonly used to describe various natural phenomena, can be identified. Moreover, the resulting mean velocity is $19.8\ \frac{\mathrm{m}}{\mathrm{s}}$, which is in the range of typical measurements ([23], which finds the expected value to be $21.1\ \frac{\mathrm{m}}{\mathrm{s}}$ (based on the log-normal distribution)).

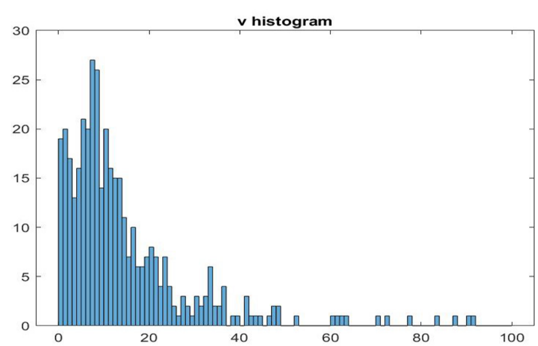


Fig. 3. Moving-velocity $\hat{v}$ distribution over 405 rain periods, collected between Feb. 2018 and June 2019, each of 10 minutes $-$ 90 minutes.

V. DISCUSSION AND CONCLUSION

This paper presented a new approach that uses signal level measurements taken by CMLs deployed in a smart-city communication network to estimate the propagation of the frontal rainfall. By treating CMLs as a sensor array, and taking pairs of CMLs-based attenuation values, we first extract the TDOA of the frontal rain cell hitting each of the CMLs paths (i.e., hops). Next, we use the extracted TDOA values to estimate the rain cell velocity and moving direction. We presented an experimental setup in which we show the feasibility of our methodology to estimate the tempo-spatial properties of the rain cell, using actual-world measurements.

V-A. Sources of Errors

The restrictive assumptions, specified in *Section III*, might introduce errors into the estimation process due to mis-modelling, and can be divided into two types: 1) Assumptions concerning urban rain cell characteristics - Single rain cell in an event, constant velocity and direction and a large rain-cell size (compared with the hops' length); 2) Assumptions concerning the methodology - Modeling the sensors to be point sensors whereas in practice, these are path-integrated sensors, and treating the wet antenna effect as part of the rain.

V-B. Future Work

Even-though the demonstration presented herein is promising, we presented preliminary feasibility study. Our future work will focus on generalizing the presented methodology. We aim to face the 'point sensor' model assumption which might cause errors when working with long links, as well as the 'wet antenna' assumption - as this phenomenon causes signals to be attenuated slightly after the storm is over, and thus, distorts the 'storm's fingerprint' in the RSLs.

We believe that our presented methodology contributes to meteorological research, as "small scale rainfall" study is currently challenged by the too wide scales [24], which the proposed opportunistic sensors tools might solve, especially in city-scale weather studies. Moreover, the problem discussed above is advantageous to the future development of IoT applications, which are based on city-scale fast communication.

VI. ACKNOWLEDGMENT

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