Opportunistic use of GNSS Signals to Characterize the Environment by Means of Machine Learning Based Processing

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OPPORTUNISTIC USE OF GNSS SIGNALS TO CHARACTERIZE THE ENVIRONMENT BY MEANS OF MACHINE LEARNING BASED PROCESSING

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ABSTRACT

GNSS is widely used to provide positions in an absolute reference frame in Unmanned Aerial Vehicles (UAV) and Unmanned Ground Vehicles (UGV), where GNSS is merged with the information provided by other sensors. Even if the main goal of GNSS signal processing is the positioning, multifrequency signals are a rich source of information about the propagation environment surrounding the mobile vehicle. In urban and harsh environment, situational awareness is essential to tailor the operations and take proper countermeasure to harsh propagation conditions. Given this framework the present paper will describe the use of GNSS as signals of opportunity for the characterization of the operative environment by processing the GNSS observables through Machine Learning (ML) algorithms that can be used as efficient features extractors. The paper will present some case studies of operational scenarios for UGVs and for a static monitoring station, showing how through combining DSP techniques with both unsupervised and supervised ML algorithms (K-means classes, Support Vector Machines) it is possible to retrieve the information about the propagation scenario for multipath, interference and atmospheric limitations.

***Index Terms*—** Multipath, interference, scintillation, K-means clustering, support vector machines.

1. INTRODUCTION

Global Navigation Satellite Systems (GNSS) play a central role in many applications that necessitate high accuracy and precision positioning. However, the satellite signals are prone to suffer from many error sources, such as multipath, ionospheric anomalies, and interference.

While multipath is the reception of reflected or diffracted replicas of the desired signal due to the physical surrounding environment [1], GNSS signals can also undergo refraction and diffraction effects while propagating through the ionosphere because of the ionospheric irregularities. These ionospheric effects are gathered under the name of scintillation [2]. Both multipath interference and scintillation cause carrier phase tracking errors and reduction in the signal amplitude, leading to loss of lock and large degradation in the accuracy [3, 4]. Strong scintillation events are a threat not only for GNSS operations but they can severely affect communication systems and other infrastructures, making the modeling and the early detection of the events significant importance. Moreover, the interference sources from intentional and unintentional anthropogenic activities can bring severe effects to the signal processing stages of GNSS receivers, leading to outliers in the Position, Velocity and Time (PVT) estimation [5]. Therefore, in order to reach a satisfactory accuracy in many applications, detecting the outliers caused by multipath, scintillation, and interference is obviously of paramount importance not only for positioning services.

In the literature, in order to cope with the multipath effect diverse methods have been developed at either signal processing level or measurement level [6]. In addition, the problem of operating under the signal outages and abrupt phase changes caused by scintillation have led to the development of advanced Kalman Filter (KF) based carrier tracking structures at the receiver level [7]. On the other hand, observing the effects on the GNSS signals, the format of which is well known, it is possible to retrieve information on the propagation channel, making them Signal of Opportunity (SoP) for the modeling of the channel itself. GNSS signals are placed in the low-GHz frequency band, and a large number of signals and satellites now available allows to obtain a good span of both the frequency and spatial domain for the channel modeling. However, even with this large and diverse set of information sources, it is necessary to distinguish and classify threats, observing the distortion of the GNSS signal [8].

With the flourishing artificial intelligence world, different machine learning algorithms (ML) have started to be applied for scintillation and multipath detection. The proposed methods for scintillation [9] and multipath detection are mainly based on the Support Vector Machines (SVM) algorithm [10, 11, 12, 13]. SVM algorithm belongs to the class of supervised machine learning algorithms which require large data sets to properly train the algorithm to recognize the multipath and scintillation presence in the new measurements [14]. How-

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ever, in the unsupervised learning methods (e.g. K-means) the limitation of the availability of the a-priori obtained training sets has been overcome for multipath detection in [15]. For interference detection, apart from the traditional detection methods based on the Digital Signal Processing (DSP) theories, the use of machine learning is also an evolution and it can be implemented based on the raw measurements of the GNSS receivers [16].

The aim of this paper is to use machine learning algorithms to retrieve information about the propagation environment. The work presented here has focused on the implementation of two machine learning algorithms, namely K-means and SVM, and their performance analysis on the real data to characterize the environment. The collected real data during a road test in The Hague, The Netherlands, and a real scintillation data in Hanoi, Vietnam have been exploited in this paper.

The paper is organized as in the following. In Section 2, the effects of the propagation environment on GNSS signal processing and measurements are summarized. The overview of the implemented machine learning algorithms, namely, K-means and SVM, are presented in Section 3. In Section 4, the performance of the implemented algorithms to characterize the environment through the collected real GNSS data is discussed. Eventually, conclusions are drawn in Section 5.

2. THE EFFECTS OF THE PROPAGATION ENVIRONMENT ON GNSS POSITIONING

After GNSS signals are captured by an antenna, the signals are downconverted to an intermediate frequency (f_{IF}) and sampled in the radio front-end (RFE). At the output of the RFE, the received GNSS signal from one satellite is modeled as:

$$\begin{aligned} r[n] = \sqrt{2A}\, c(nT_s - \tau_0)\, d(nT_s - \tau_0) \\ \cos(2\pi(f_{IF} + f_0)nT_s - \varphi_0) \\ + \eta_{IF}(nT_s). \end{aligned} \tag{1}$$

where T_s is the sampling period of the front-end. A is the received signal power. While c is the pseudorandom noise code (PRN) code, d is the navigation data message of the transmitted signal. η_{IF} is the Gaussian noise term. τ_0, f_0, and φ_0 are the code delay, Doppler frequency offset, and carrier phase, respectively. The delay and attenuation of each transmitted satellite signal are different from each other and the sampled signal is the combination of the captured visible satellite signals. Through a two-stage architecture of signal acquisition and tracking, the estimations on code phase (τ_0), carrier phase (φ_0), and Doppler frequency (f_0) are to be made to demodulate the navigation data (d) correctly.

Under multipath conditions, the received direct line-of-signal (LOS) signal ($r[n]$) is superimposed by N multipath signals in which the actual number is unknown. Received multipath signal can be modeled as [17]:

$$\begin{aligned} r_m[n] = \sqrt{2A} \sum_{k=1}^{N} \alpha_k\, c(nT_s - \tau_0 - \tau_k)\, d(nT_s - \tau_0 - \tau_k) \\ \cos(2\pi(f_{IF} + f_0 + (\Delta f_k - \Delta f_0))nT_s - \varphi_0 - \Delta\phi_{M,k}) \\ + \eta_{IF,k}(nT_s). \end{aligned} \tag{2}$$

where α_k is the signal attenuation, τ_k is the time difference between the direct signal and k^{th} multipath signal. $\Delta\phi_{M,k}$ is the phase shift due to multipath. ($\Delta f_k - \Delta f_0$) is the fading frequency that corresponds to the Doppler difference between direct and k^{th} multipath signals [18]. As it can be seen in (2), multipath propagation heavily influences code and phase observations [17].

In the case of the scintillation effect, modeling the occurrence of an event is not easy due to its quasi-random nature [19]. Amplitude scintillation causes power fades leading to fluctuating carrier-to-noise ratio (C/N_0) due to the fact that the diffracted signals are constructively and destructively added to the actual signal [20]. In the case of strong amplitude scintillation events, tracking of the GNSS signal is challenging and even it is observed that acquisition of the signals can be prevented [21]. Moreover, abrupt phase changes occurred due to the phase scintillation event can also cause cycle slips and loss of lock by adding error to the carrier phase (φ_0) estimations.

Under the interference disturbance, the useful GNSS signals are affected by an additional interference component at the signal processing stages of the GNSS receiver. A complete description on the signal models of different interference sources can be found in [5].

Summarizing, multipath, scintillation and interference lead to degradation in the carrier amplitude and errors in the pseudorange and carrier phase that degrade the overall navigation performance. Pseudorange measurement (p_r^s) that is computed for the visible satellite k by the receiver can be expressed by including the different error sources that corrupt the accuracy as:

$$p_r^s = x_r^s + c\,dt^s - c\,dt_r + \Delta T_r^s + \Delta I_r^s + \Delta M_r^s + \varepsilon_i + \varepsilon_r^s \tag{3}$$

where r and s represent a GNSS receiver and satellite, respectively. x_r^s corresponds to the actual distance between the receiver and satellite. While dt_r is the receiver clock offset, dt^s is the satellite clock offset. c is the speed of light. T_r^s, I_r^s, M_r^s, and ε_i are tropospheric delay, ionospheric delay, multipath delay and interference effect in meters, respectively. ε_r^s is the receiver dependent noise.

3. MACHINE LEARNING ALGORITHMS

In the case of using GPS signals, by comparing the computed scintillation indices for the satellites on consecutive days, repeated multipath effects can be distinguished from scintillation for a static data collection, because there is a periodicity of the events due to the periodicity of the satellite constellation. However, in a kinematic scenario, it is not efficient and also it does not work due to the fact that multipath errors inflate the scintillation indices leading to a false indication for scintillation activity [15]. Therefore, here we implement two ML algorithms: one for dynamic scenarios with K-means clustering and the other for static scenarios with SVM.

In the K-means clustering algorithm, the data is divided into two clusters, namely, multipath and no-multipath cases [15]. The algorithm is fed by the measurement sets computed for each satellite. In order to detect the satellite signals suffering from the multipath error, the dimension of the data set is set to three by including the standard deviations of the measurements, namely, pseudorange, carrier phase and C/N_0 in a sliding time window.

In the SVM ML algorithm, multipath is distinguished from scintillation using correlator level observables. Two features are extracted from these observables: the variance of the signal intensity, and the covariance between In-phase and Quadrature-phase (I and Q) components.

4. IMPLEMENTATION AND TEST RESULTS OF THE ALGORITHMS

The road test was conducted in The Hague, The Netherlands, with a data recording system based on a Universal Software Radio Peripheral (USRP) N210 front-end for collecting GPS L1 C/A signals [22]. The urban testing environment allowed for collecting data sets that contain multipath, unintentional interference and probably intentional interference. The digital samples collected at IF were further processed by a Software Defined Radio (SDR) GNSS receiver which enabled to have full control of the parameter settings in order to obtain raw measurements and PVT values. Fig. 1 shows the computed trajectory by processing the samples in the receiver.

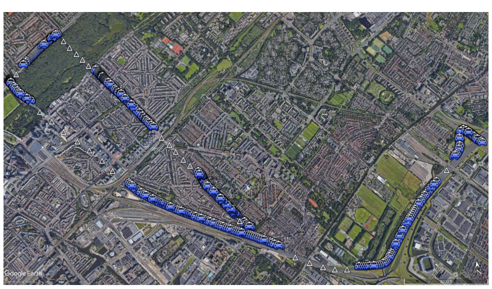

Fig. 1. The trajectory of the collected GNSS raw data using a car equipped with GNSS antenna and front-end in The Hague, The Netherlands.

The blue car symbols in Fig. 1 indicate the points at which the navigation solution was computed successfully by tracking only GPS L1 C/A signals. On the other hand, the triangle symbols point out the intervals at which the number of tracked satellites was less than four, mostly three. These results could give an idea to infer that the propagation environment surrounding the car was harsh from time to time.

4.1. Multipath Detection

Fig. 2 shows a portion of the trajectory during which the multipath effect is quite visible in the PVT estimations. The red cars are the solution using all the tracked signals, while the blue cars indicate the solution after excluding the multipath signals. 2D positioning difference between the blue car and red car symbols is around 13-15 meters. Fig. 3 shows the sky plot of the acquired satellite signals.

Fig. 2. Biased navigation solution due to the multipath.

Among the successfully tracked satellite signals (PRN 8-27-21-20-16-10), the K-means algorithm creates two clusters, by separating PRN 8 and 27 into the same group for the multipath signals. In this portion of the trajectory, a direct satellite signal which belongs to the satellite at the highest elevation (PRN-27) attenuated and diffracted, and the refracted signals have a higher amplitude compared to the others. This is mostly because of the big buildings on the both side of the roads.

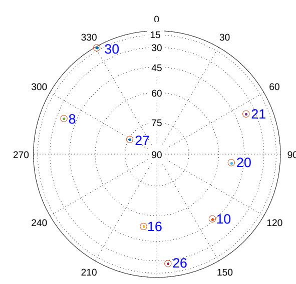

Fig. 3. Sky plot of the visible satellites.

However, in the test scenario shown in Fig. 4, only PRN-8 is detected to be affected by multipath. Here, the multipath effect is arising due to the existence of the high building visible on the left side of Fig. 4, and the exclusion of PRN-8 from the PVT computation improves the navigation solution. In Fig. 4, while white square symbols show the PVT solutions obtained by processing all the tracked satellites, blue square symbols show the PVT solution after satellite signal PRN-8 is excluded from the PVT estimation as a cross-check on the presence of the reflected signals affecting the quality of PRN-8.

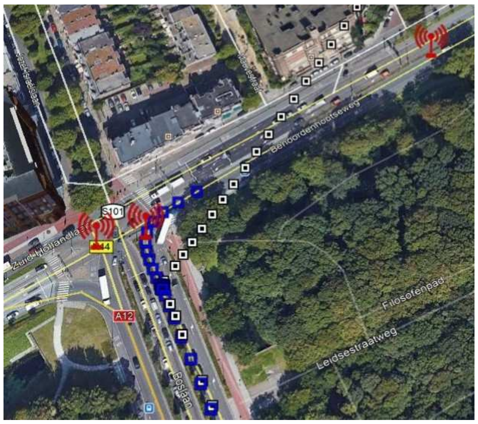

Fig. 4. Biased navigation solution due to the inteference and multipath effect.

4.2. Interference Evaluation

The interference detection is first implemented based on the DSP techniques to find the potential interference along the trajectory shown as the red mark in Fig. 4. In order to detect and characterize the interference, the raw samples are analyzed in time domain and frequency domain, with an additional histogram of the samples which can reflect the relative strength of the interference. Fig. 5 shows an example of a detected continuous wave interference (CWI) within the GPS L1 bandwidth, represented as a spectral line in the frequency domain. However, this CWI is relatively weak due to the fact that the histogram keeps a Gaussian shape, showing that the noise is still the dominant component.

In the test scenario shown in Fig. 4, although interference effects still remain due to the fact that the signals from all satellites are affected by the interference and the exclusion of one satellite measurements would not mitigate all the effects, the overall position performance is still improved by excluding the outliers classified.

4.3. Scintillation Detection

An SVM model was trained to distinguish between scintillation and multipath for a scintillation monitoring station in Hanoi, Vietnam. The training and testing sets were manually labeled. The training accuracy reached 100 % using the proposed features. Fig. 6 shows the labeling results obtained from the model when applied to a new data set that was not

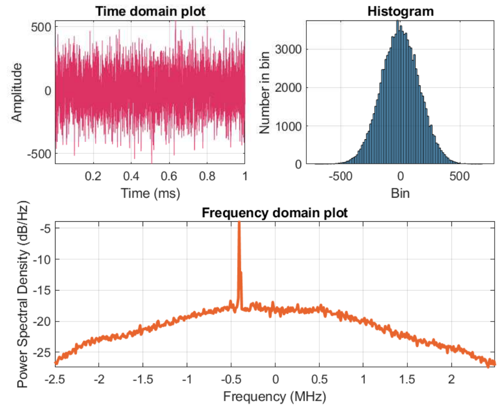

Fig. 5. Interference detection and characterization based on DSP techniques.

used during the training phase. The proposed methodology was able to distinguish multipath from scintillation with 100 % accuracy too.

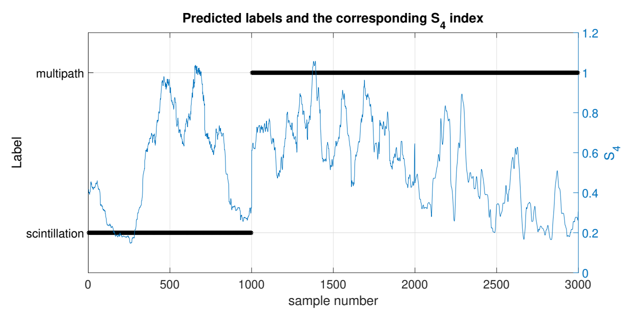

Fig. 6. Multipath and scintillation labels.

5. CONCLUSIONS

In this paper, we reviewed and analyzed the detection of multipath, interference and scintillation using machine learning algorithms to characterize the environment surrounding a receiver. Two machine learning models were trained and then utilized for characterizing the environment. The first model, based on unsupervised k-means clustering was able to identify the GNSS signals suffering from multipath, and by excluding these signals from the PVT computation, the position was improved. Moreover, the interference effects were analyzed and it was found that the model is able to mitigate multipath effects despite of the weak interference. Also, a model to distinguish scintillation from multipath was trained using supervised SVM algorithm. The model was able to distinguish between scintillation and multipath. By further analysis of the multipath class it is possible to characterize the environment around the receiver and identify if there are obstacles that contaminate the scintillation monitoring activity.

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