A machine learning approach to GNSS scintillation detection: automatic soft inspection of the events

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ABSTRACT

Classical approaches for the automatic detection of ionospheric scintillation events in Global Navigation Satellite System (GNSS) receivers are based on the observation of indices (e.g. S4) that are obtained by processing parameters assessed at the signal processing stages of the receiver. Such values are the result of algorithms that imply specific processing choices (such as detrending, averaging and threshold operations) which influence the final performance of the detection. To reach good levels of accuracy and generalization for the identification and classification of the physical phenomenon, these approaches may require an additional human effort to refine the detection results by means of a manual inspection of the events, which is expensive and time consuming. This paper proposes a new methodology for the detection of ionospheric scintillation events based on Machine Learning techniques applied to GNSS data. This method, based on Decision Trees algorithms, aims at overcoming the limitation of the classical approaches by identifying scintillation events “as if” done by a human operator through visual inspection. This approach is automatic, unbound from traditional scintillation indices and features improved detection, false alarm, and missed detection rates when compared to standard methods.

INTRODUCTION

Ionospheric scintillations are fluctuations of the Global Navigation Satellite System (GNSS) signal amplitude and phase, caused by the irregular electron content distributions in the upper layers of the atmosphere, which may determine a disruptive impact on the receiver performances. Despite being more frequent at Equatorial and Polar latitudes [1]–[3], they can also be observed at mid-latitudes [4] in case of severe ionospheric activity.

For this reason, GNSS receivers tailored to the monitoring and detection of scintillation events are often deployed in areas where scintillation may occur. The purpose is indeed twofold: on one side, observation of the signals themselves, which are a source of information for understanding and modelling the upper layers of the atmosphere; on the other side, they can be used as detectors

and triggers to raise warning and take countermeasures for GNSS-based operations. It is important to design receivers robust to the presence of scintillations, but also to have proper algorithms for the detection of events which may induce phase errors, cycle slips, increased carrier Doppler jitter and losses of lock, resulting in positioning errors of the order of tens of meters, and, in the most severe cases, even in the complete receiver outage [5].
Recent approaches for scintillations studies are based on the software defined radio paradigm. Such techniques aim at collecting digital raw samples of the received GNSS signal during relevant ionospheric storm. In fact, the availability of raw digital samples allows for post-processing of GNSS signals by using GNSS software receivers. Different algorithms and processing strategies can be tested on the same data-set, thus enabling valuable comparisons and proper tuning of the algorithms themselves. A side effect is that the huge quantity of GNSS data, grabbed generally in remote, harsh geographical areas, makes hard to store and to transfer the data, thus limiting the possibility of conducting extensive analyses [6].
This makes particularly relevant the detection task. A continuous data recording is clearly unaffordable, and proper *detection rules* have to be set, to trigger the storage of raw IF samples. The presence of scintillations is assessed relying on the computation of two indices: $S4$ for amplitude scintillation and σ_ϕ for phase scintillation [7, 8]. The detection is performed comparing such indexes to predefined thresholds, the values of which are set to roughly classify the presence of moderate and strong events. However, such *hard* approaches may cause loss of transient phases of the phenomenon (then delaying the raise of possible warning flags), loss weak events with high variance, or induce false alarms due to signal distortions, caused by other propagation phenomena, such as multipath or interference [5]. There is indeed an increasing need of automatic and reliable detection techniques, for atmospheric modelling or for mitigation of the GNSS errors within the receiver.
In this paper we propose a new detection strategy, based on a supervised machine learning approach [9]. The tool is able to perform an automatic, highly accurate detection of ionospheric scintillation events in GNSS data collections. The proposed solution aims at performing a more accurate remote on-site analysis, dropping useless data while properly storing scintillation-affected data, thus reducing the total storage usage. Previous works on the topic aim at the same objective; however, they focus on different machine learning algorithms and on different input data [10, 11, 12].

TRADITIONAL APPROACHES FOR IONOSPHERIC SCINTILLATION DETECTION

In this paper, we focus on equatorial scintillation events, that are characterized by fast variations of amplitude and phase of the GNSS signals. In particular, we only focus on amplitude scintillations, and thus on the analysis of the value of the $S4$ index. $S4$ corresponds to the normalized standard deviation of the detrended Signal Intensity (SI) computed from the in-phase (I) and quadrature-phase (Q) prompt correlation samples [7]. The computation of the $S4$ is cumbersome and computationally demanding. It requires complex averaging and detrending operations on the received signal, in order to reduce noise and to remove the slow variations due to the signal dynamics. The definition of detrending is not trivial: several approaches, based on the use of high-order Butterworth filters, of wavelet transformations and on simple averaging have been described [13, 14, 15]. Nevertheless, it has been proven that different methods lead to different results [16]. It has also been proven that a different detrending shall be chosen for different geographical areas [17]. Nevertheless, it has also been shown that detrending operations could introduce post-processing artifacts [10].

Manual human-based visual inspection

The presence of scintillation is normally evaluated through manual visual inspection of $S4$ time series. This approach is extremely reliable, being based on the experience of the person who analyses data. The possibility of considering also boundary conditions (such as satellites elevation, azimuth, C/N_0), as well as historical data, is a great added value. However, this technique is extremely time consuming, and cannot be implemented in real time. The high number of monitoring stations deployed around the world, as well as their remote location, make this approach unfeasible.

Hard detection rule

An automatic detection rule is often used. Scintillation at time n is declared present if the $S4$ index at time n exceeds a predefined threshold, T_{S4}, typically set to the value 0.4 [18]:

$$S4[n] > T_{S4}.$$

This very simple detection technique is called *Hard detection rule*. It is characterized by a low computational burden, and can work in real time.

Semi-hard detection rule

As the $S4$ index is a measure of the variation of the amplitude of the GNSS signal, it is not unlikely that events other than ionospheric scintillation cause it to raise above the threshold. The task of distinguishing scintillation from other error sources, thus reducing the probability of false alarms, is not trivial. In order to better characterize the scintillation phenomenon, more parameters can be observed. For example, it is quite common to filter data applying an elevation threshold. As low elevation satellites are more subject to multipath reflections, most of the false alarms can be removed by considering only values of satellites above a certain elevation, say $T_{el} = 30°$. Further conditions can be defined on the C/N_0 value, or on the satellites' azimuth. On the basis of these considerations, a second detection scheme, called *Semi-hard detection rule*, is often considered. Scintillation at time n is declared present if:

$$S4[n] > T_{S4} \ \wedge \ el[n] > T_{el} \ \wedge \ C/N_0\,[n] > T_{C/N_0}.$$

This second rule has a slightly higher computational burden, but features an overall higher accuracy, thanks to its higher robustness to false alarms due to multipath.

Examples of detection based on traditional techniques

The Hard and Semi-hard rules are the traditional techniques employed in scintillation monitoring. Figure 1 provides three examples of scintillation detection results, comparing the performance of the two traditional rules to the manual visual based annotation.

The case studies reported refer to a data collection performed on spring 2015 at the Navis Centre (Hanoi, Vietnam), during moderate Equatorial amplitude scintillation events. The three case studies considered are representative of common problematic situations. The cases in which scintillation can be easily declared present or absent are trivial and have been omitted.

The figure shows $S4$, elevation and C/N_0 estimates provided by a GNSS ionospheric monitoring receiver, relative to GPS L1 C/A signals. For each plot, the top figure depicts:

- the $S4$ estimate (black curve);
- an orange line, in correspondence of the threshold of the detection rules ($T_{S4} = 0.4$).
- the events detected according to manual annotation (blue box);
- the events detected according to the Hard rule (cyan dots);
- the events detected according to the Semi-hard rule (purple dots).

To assist the interpretation of the results, the middle and the lower box report respectively the elevation of the satellite and the C/N_0 estimate, along with the thresholds used for the Semi-hard rule, plotted in orange ($T_{el} = 30°$, $T_{C/N_0} = 37$ dBHz).

In order to quantify the correct detection, false alarm and missed detection rates of the Hard and Semi-hard rules, the manual annotation is considered as the *ground truth*. Although not being scientifically rigorous, it is the only possible approach, and has been considered in other works on the topic [12].

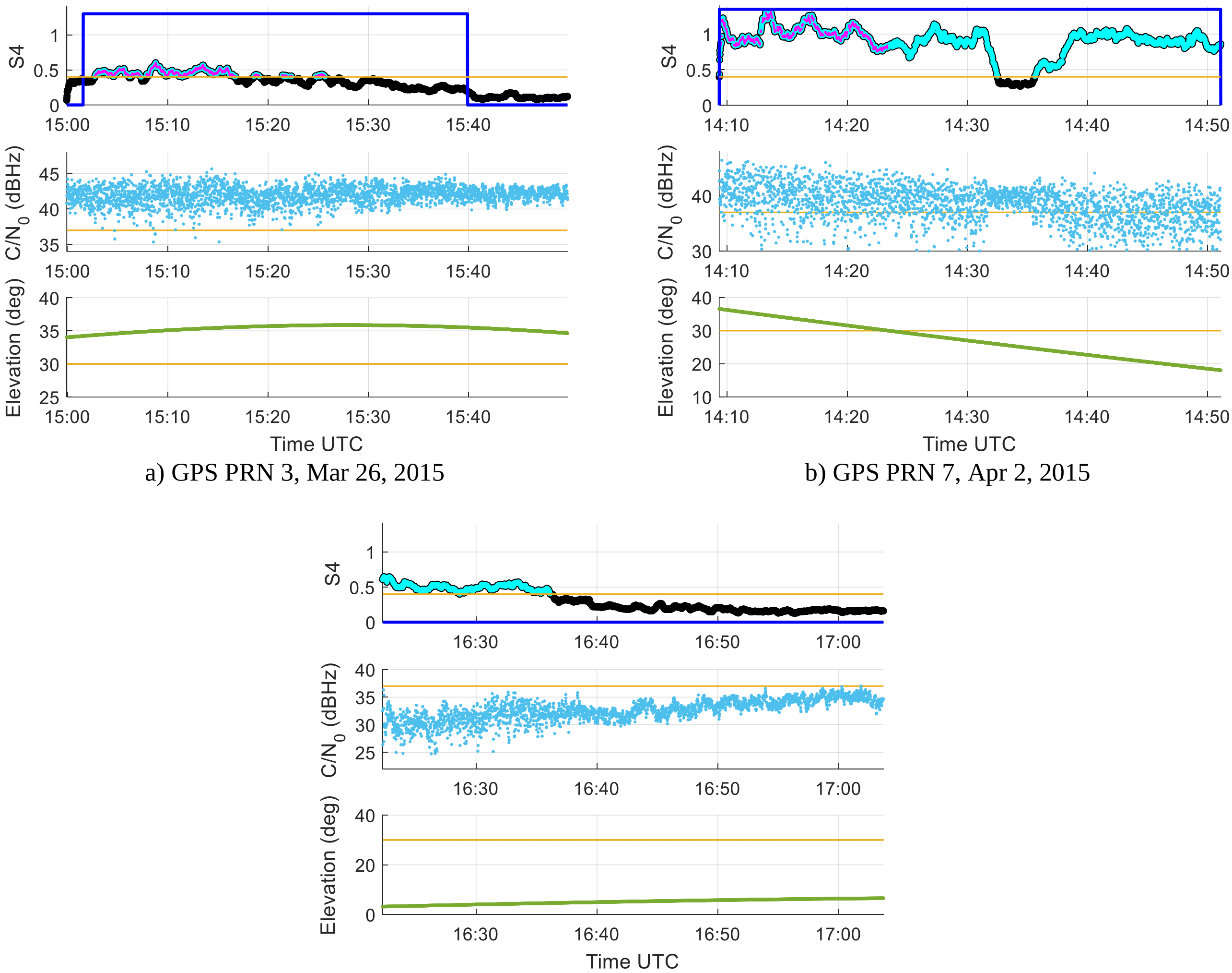
Case study 1, PRN 3, Mar 26

In the first case (Figure 1a), a moderate scintillation event is reported ($0.3 < S4 < 0.6$). According to the manual annotation, scintillation is detected in the interval between 15:02 and 15:40. Both the rules are able to identify the scintillation event; however, since the value of S4 is low, they are not able to catch the full event. Event though some points are characterized by a S4 lower than the threshold, they are still part of the same scintillation event, so they should be classified as scintillation. As a consequence, the missed detection rate is high.

Table 1a reports the detection probabilities of this case study, in terms of confusion matrix. The true positives rate is reported in the bottom right box, and is around 23 % for both the rules. This means that in 23 % of the cases the Hard and Semi-hard rules correctly identify a scintillation event. Similarly, the true negative rate is reported in the top left box. It is about 30 % for both the rules, meaning that in 30 % of the cases the two rules correctly identify a non-scintillation event. The overall correct detection rate is the sum of the true negatives and true positives, and it is equal to about 54 %. The bottom left box reports the false negatives rate, i.e. the missed detections. The perccentage is high for both rules, due to the fact that the S4 is lower than the threshold even though there is moderate scintillation acvtivity. The top right box reports the fasle negatives rate, i.e. the false alarms. No false alarms are present in this case study. The small difference between Hard and Semi-hard detections is due to the fact that, in some situation, the C/N_0 goes below the threshold defined for the Semi-Hard rule, resulting in a slightly increased missed detection rate.

Case study 2, PRN 7, Apr 2

The second case (Figure 1b) reports a strong scintillation event ($S4 > 0.6$). According to the manual annotatoin, all the points are marked as scintillation (from 14:09 to 14:51). The hard rule correctly identifies as scintillation most of the points, except for the interval in which the S4 goes below the threshold 0.4. However, from visual inspection, it is clear that these points, between 13:33 and 13:36 are still part of the same scintillation event, so they should be marked as scintillation. As a consequence, the missed detection rate for the hard rule, reported in Table 1b, amounts to 7.43 %. All the other points are correctly marked as scintillation, hence the overall correct detection rate amounts to 92.57 %. On the contrary, the Semi-Hard rules fails in detecting most of the scintillation events, because of the hard threshold on the elevation. In order to reduce the false detections due to multipath reflections, T_{el} has been set to 30°; however, in this situation a real scintillation event is going through, despite the low satellite evelation. Consequently, the Semi-hard rule filters all the points for which elevation is lower than 30°, resulting in a very high missed detection rate (72.9 %), and in a reduced correct detection rate (27.2 %). This example highlights the fact that traditional rules could be too conservative and therefore could mask interesting scintillation events.



a) GPS PRN 3, Mar 26, 2015

b) GPS PRN 7, Apr 2, 2015

c) GPS PRN 23, Apr 2, 2015

Figure 1. Examples of scintillation detection using Hard and Semi-hard rule, compared with the manual annotation and with $\boldsymbol{C/N_0}$ and elevation trend for three different satellites.

Case study 3, PRN 23, Apr 2

The third case study reports a common situation, in which no scintillation is going on (the manual annotation reports no scintillation for the full length of the observation), but the S4 exhibits oscillations due to multipath reflections (the satellite is at low elevation). Therefore, the Hard rule, based on S4 only, erroneously marks as scintillation all the points from 16:22 to 16:36, resulting in a false alarm rate equal to 33.36 % (Table 1c). All the other points are correctly marked as non-scintillation events (overall correct detection rate equal to 66.64 %). The Semi-hard rule solves this issue, by applying the elevation mask. The overall correct detection rate for the Semi-hard case amount to 100 %.

As a summary, we can say that both the rules exhibit high missed detection rates, and that the Hard rule is also subject to false alarms. A clear remark derived from this analysis is that it is very difficult to automatically detect scintillation by applying thresholds, without taking into account both the physics of the event and the environmental conditions. The presence of multipath reflections makes more difficult the design of a general rule based on thresholds. Moreover, manual annotation can assure higher accuracy in the event classification (e.g. in terms of duration and continuity), but it comes at a higher cost in term of time needed for the annotation and skills needed to understand the outputs of the monitoring.

Table 1. Confusion matrices for the Hard and Semi-Hard case.

a) GPS PRN 3, Mar 26, 2015

Manual annotation	Hard rule 0	Hard rule 1
0	30.84 %	0 %
1	45.88 %	23.27 %

Manual annotation	Semi-hard rule 0	Semi-hard rule 1
0	30.61 %	0 %
1	46.12 %	23.27 %

b) GPS PRN 7, Apr 2, 2015

Manual annotation	Hard rule 0	Hard rule 1
0	0 %	0 %
1	7.43 %	92.57 %

Manual annotation	Semi-hard rule 0	Semi-hard rule 1
0	0 %	0 %
1	72.9 %	27.1 %

c) GPS PRN 23, Apr 2, 2015

Manual annotation	Hard rule 0	Hard rule 1
0	66.64 %	33.36 %
1	0 %	0 %

Manual annotation	Semi-hard rule 0	Semi-hard rule 1
0	100 %	0 %
1	0 %	0 %

MACHINE LEARNING FOR AUTOMATIC SCINTILLATION DETECTION

The limitations of the aforementioned approaches can be reduced exploiting machine learning techniques, able to learn from human processes to produce automatic high accuracy detection and classification (measured with respect to the human visual inspection). The goal of machine learning algorithms is to replicate the performances of the manual detection, without introducing additional human effort to manually classify the datasets. As a result, we will obtain a system that incorporates intelligence handled by a machine able to perform scintillation detection along with learning capabilities, producing a better phenomenon understanding and thus a possible improvement of receivers robustness to scintillation events. The machine learning detection algorithm, once trained on big datasets labelled by the manual annotation, is able to improve the detection properties with respect to the Hard and Semi-hard approaches. In addition, such approach overtakes the problem of computing the scintillation indexes, by relying on intermediate signal measures, as the correlation outputs and phase measurements.

Machine learning is the systematic study of intelligent algorithms and systems that improve their knowledge or performances by experience [19]. Despite its roots in theories developed several years ago, machine learning has recently become quite popular in the big data analytics field, thanks to the improved computational capabilities of the processing units. Nowadays, it is used to address a number of different threats, such as the detection of financial services [20] where the processing of real-time and historical big dataset enable to automatically detect transaction frauds events. Recent studies, are demonstrating that these methodologies can be adopted also to solve GNSS signal processing issues such as scintillation events detection [11] [12].
In this work, a specific machine learning class of algorithms based on decision trees in investigated. Decision trees [21] are able to classify data leveraging graph structures that represent all the possible solutions of a given problem. The goal of such algorithms is to find a path through the tree that corresponds to the best possible solution, thus the best classification for objects in the dataset.

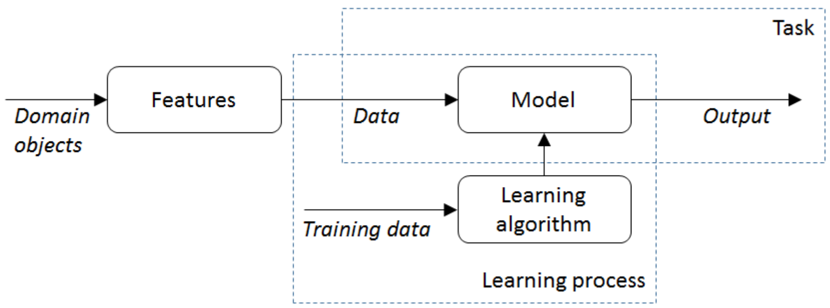


Figure 2. Machine learning process diagram.

Figure 2 shows the steps of a standard Machine Learning supervised approach.

The process starts from the studied domain and must be described through objects and dimensions. In the proper case, the studied domain is related to the acquisition of a signal. The definition for 'object' in the signal domain could be a sample in a specific time *t*, which is described by different dimensions. The set of all the dimensions used for describing a sample are named Features and all samples are called Data. Finally, the dataset is the group of all samples, each one described by different features.
Once the dataset has been determined, it can be processed by a machine learning algorithm. Its purpose is to build a model that could map a set of features of each sample to an output, that in this case is the decision whether this sample is part of the signal in which scintillation is occurring. In order to create this type of mapping it is necessary to perform what is called a "learning process". The algorithm needs to be trained to build a proper model to classify the output. This process begins with taking a subset that must be representative of the entire dataset in order to let the learning algorithm to know and understand the trend of the data. It is important to specify that the analyzed subset must be annotated with the desired output. When the training phase is done, the Model is complete and it can be used to classify new data.
A detailed description of the decision tree algorithm is out of the scope of this paper and can be found in [21].

Identification of the set of features

The standard set of features is composed by the 1 Hz observables provided by any GNSS scintillation monitoring receiver: S4, σ_ϕ, C/N_0, elevation and azimuth.
However, using quantities such as elevation and azimuth is discouraged, as they are location and time dependent. Similarly, also the use of the scintillation index S4 should be avoided, as it already represents the output of the traditional approach for amplitude scintillation detection. In addition, its computation involves complex averaging and detrending operations, which could introduce post-processing artefacts and location dependent solutions. Even the use of C/N_0 could lead to misleading results: the C/N_0 estimator suffers scintillation events. In particular cases of fading and lock failure, the C/N_0 estimate might be affected by a bias or even provide completely wrong results, thus fooling the detection rule [8].
In this paper the raw GNSS signal measurements at the correlator output of the receiver tracking stage are used as features. The rationale is to detect scintillation by exploiting, as features, not the final scintillation index, but its components. For this reason, the following set of features has been selected:

- $\langle I^2 \rangle$, the in-phase correlator output squared and averaged over the observation window;
- $\langle Q^2 \rangle$, the quadra-phase correlator output squared averaged over the observation window;
- $\langle SI^2 \rangle$, the signal intensity squared and averaged over the observation window;
- σ_ϕ, the phase scintillation index.

RESULTS

The entire dataset includes a total of 172124 entries, for which the percentage of scintillation event is approximately 25,77 %.
In order to conduct a deep analysis on the ability of a machine learning model to learn from the manual annotation, the cross-validation has been performed. The cross-validation [22] is a test methodology that assures a more stable validation of the performance. It is an iterative approach with the purpose to test every part of the dataset. Initially, the dataset gets randomly shuffled, and then it is split in 10 equal-sized-folds. The shuffling stage is accurately performed in order to guarantee for each fold the same distribution of scintillation and non-scintillation elements. Finally, 10 different trainings and tests are performed, each time using nine folds as training set and one fold as test set. It is important to underline that the test fold is changed on every iteration and that it is not part of the training set.

Table 2. Results obtained from each cross-validation fold

Test fold	1	2	3	4	5	6	7	8	9	10
Training set size	154911	154912	154912	154911	154912	154912	154911	154912	154912	154911
F-Score	0.9658	0.9687	0.9676	0.9700	0.9642	0.9679	0.9659	0.9644	0.9725	0.9668

Table 2 reports the results for each fold used as test, in terms of different parameters [23]. The training set size is the number of elements contained in the nine folds used as training set. The F-score is a measure of a test's accuracy. It takes into account both false positives and false negatives and is weighted by the number of scintillation events.

The complete confusion matrix, relative to the overall dataset, is shown in Table 3. It is obtained by taking the prediction result for each fold during the cross-validation, and by comparing them to the manual annotation.

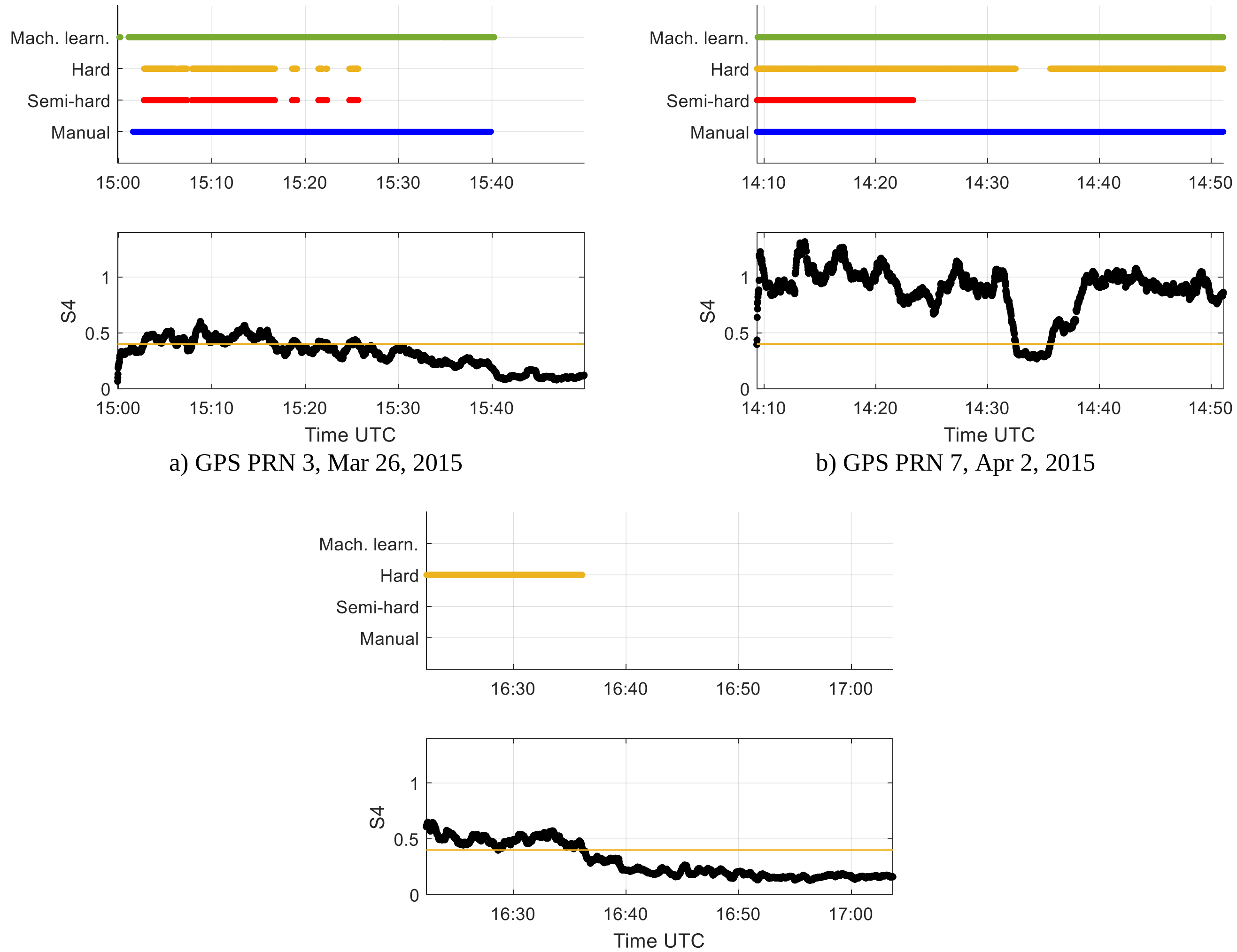
Table 3. Confusion matrix of the entire dataset

		Machine learning	
		0	**1**
Manual annotation	**0**	73.48 %	0.93 %
	1	0.75 %	24.84 %

Case Studies analysis

Figure 3 shows the results of the detection performed by the machine learning based approach, compared to the results of the traditional Hard and Semi-hard rules already discussed above, for the same case studies considered above.

The blue line represents the human-driven manual detection, which is assumed as the ground truth. The results of the Hard and Semi-hard rules are reported in orange and red respectively. The green line on the top represents the detection results of the machine learning algorithm. The bottom box reports the S4 scintillation index and the threshold ($T_{S4} = 0.4$), as a reference. The confusion matrixes are reported in Table 4.



a) GPS PRN 3, Mar 26, 2015

b) GPS PRN 7, Apr 2, 2015

c) GPS PRN 23, Apr 2, 2015

Figure 3. Scintillation detection performed by machine learning compared with traditional Hard, Semi-hard and Manual approaches

Case study 1, PRN 3, Mar 26

In this case, machine learning is able to correctly identify the scintillation event. Almost all the points marked as scintillation by the manual annotation are also marked by machine learning (Figure 3a). The detection of the event is also slightly anticipated. The overall correct detection rate is 96.33 %. The missed detection and false alarms (1.33 % and 2.33 % respectively) are concentrated on at the edges of the event. Their impact on the overall performance is negligible.

Case study 2, PRN 7, Apr 2

This case was characterized by very high missed detection rates. Figure 3b shows the excellent detection performance of the machine learning compared to traditional methods. In particular, the false negatives are reduced from more than 70 % (Semi-hard rule) to 2.16 %. The overall success rate amounts to 97.84 %, and as in the previous case, the missed detections are concentrated at the edges of the event.

Case study 3, PRN 23, Apr 2

The last case is reported in Figure 3c. Also in this case, machine learning detection perfectly matches the manual annotation, and the false alarms detected by the Hard rule, and due to multipath reflections, are completely eliminated. The overall detection rate amounts to 100%. This result shows the good potentialities of machine learning to solve the problem of S4 variations due to non-ionospheric nuisances, such as multipath. Moreover, it shows the potential of this approach to solve the problem of useless GNSS samples data storage [6]. Differently from the traditional approach, which would maintain this dataset by classifying it as affected by scintillation, the machine learning algorithm is able to identify the lack of scintillation in data avoiding keeping them and saving GB of storage resources.

The overall detection performance, when compared to the traditional rules, considerably improves in all the case studies analyzed.

Table 4. Confusion matrices for the machine learning approach.

Manual annotation	Machine learning 0	Machine learning 1
0	21.94 %	1.33 %
1	2.33 %	74.39 %

a) GPS PRN 3, Mar 26, 2015

Manual annotation	Machine learning 0	Machine learning 1
0	0 %	0 %
1	2.16 %	97.84 %

b) GPS PRN 7, Apr 2, 2015

Manual annotation	Machine learning 0	Machine learning 1
0	100 %	0 %
1	0 %	0 %

c) GPS PRN 23, Apr 2, 2015

CONCLUSIONS

In this paper a novel approach for scintillation detection based on machine learning algorithms has been presented. Several experimental tests, have been performed showing that the performances of the soft approach based on machine learning can reach the level of accuracy of manual annotation, with the added value of being based on a generalized, location independent rule. This result can demonstrate that machine learning can facilitate the work of researchers of analyzing big sets of GNSS data affected by scintillation, leading to a better understanding of the physical phenomenon with a potential impact on the improvement of robustness of GNSS receiver to such ionospheric events. Moreover, the results show that a real-world application of this techniques is effective in remote areas where saving computing and storage resources is necessary.
Future works will include a deeper analysis of the best criteria for the feature selection, the investigation of alternative machine learning models and algorithms (e.g., Random Forest, Support Vector machines and Neural Networks) and an extension of the results considering other data collection.

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