Exploration of machine learning tools developed for the study of space weather and its impact on position approximation in GNSS systems.

G. Fajardo [1], E. Pacheco [1]

[1] **Instituto Geofísico del Perú, Jicamarca Radio Observatory**

Abstract

The equatorial ionosphere has been extensively studied using purely physical models, however in recent years, with a large amount of data, it has been possible to improve these models using machine learning techniques. In this paper, we share the research results aimed to evaluate the influence of space weather parameters on GPS position approximation. We evaluated data from the Huancayo GPS station between 2016 and 2020 and we have taken into account the space weather data from the OMNI website, scintillation index (S4) and position data obtained from the GPS of the LISN network to perform our model. In addition, we use tropospheric conditions provided by the Geophysical Institute of Peru (IGP). The final result is a reliability matrix obtained with an XG Boost algorithm that will allow us to evaluate if a GPS signal given the conditions is indeed reliable or not.

1. Introduction

Several studies mention that the GPS positioning error contributed by the ionosphere reaches tens of meters for certain conditions, which can be a threat for the correct operation of various devices that depend on GNSS.
Therefore, it is useful to have a model that relates the ionospheric phenomena at the magnetic equator with the impact for a GPS end-user.
However, the data collection performed by the GNSS (GPS Novatel) in Huancayo give us a mixed information (Figure 1), the position approach contains error of Ionospheric source but from tropospheric source as well.
The present work explores the possibility of using ionospheric and lower atmosphere information to predict the degree of reliability (error) when using GNSS and as a first step to build a more complex forecasting model.

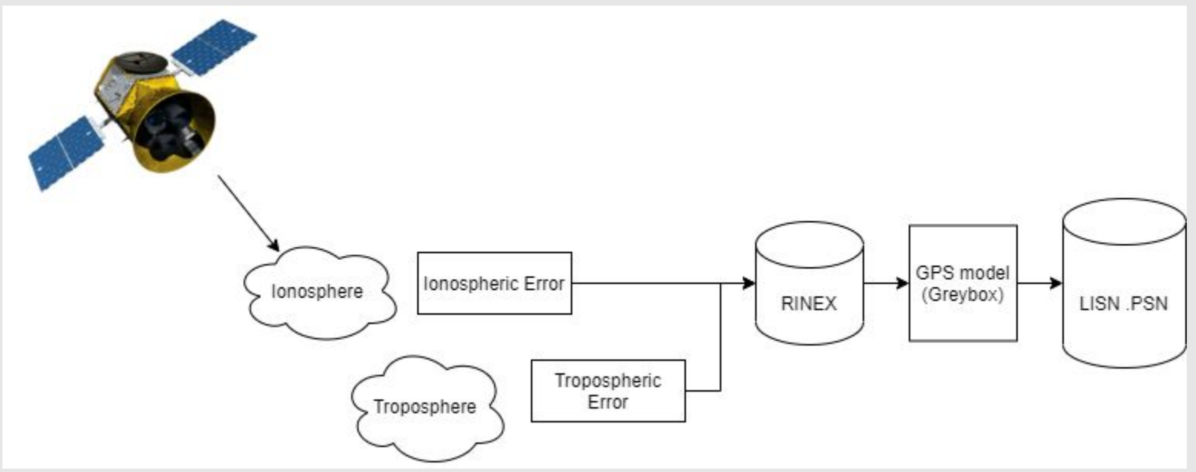

Figure 1: Schematic model of the relationship between the sources of error in the signals used by GNSS and the files that make up our databases.

2. Description

As described in the introduction it is important to take into account also the tropospheric conditions, since our information is mixed. This must be done unless there is more accurate information of the solution that the GPS takes in each approach or if the solution includes the pseudoranges (evitar escribir "you" en textos formales). For this reason we have considered on this occasion the atmospheric conditions of air pressure and temperature for the station of Huancayo.
In this new model we are also taking into account the delay of space weather parameters that can affect the result, adding to the model main Space Weather conditions (Figure 2) : S4, Kp, F10.7, Bx, By, Bz, SW_plasma, not only under current conditions but also with delays of -30 min, -60 min and -90 min (Figure 3). A database containing all these variables for each time unit was built in order to be used in training of XGBoost and Support Vector Machine models that can predict continuously or in binary format, the expected error in the GPS calculated approach for certain conditions.
We decided to label the error in binary form, since after analyzing the approximations we obtained a statistical distribution with little dispersion. Then we separate the absolute error of length in binary form taking as threshold the upper quartile (3 meters error), therefore if the absolute error is less than 3 meters then the label will be: "null", otherwise it will be: "error".

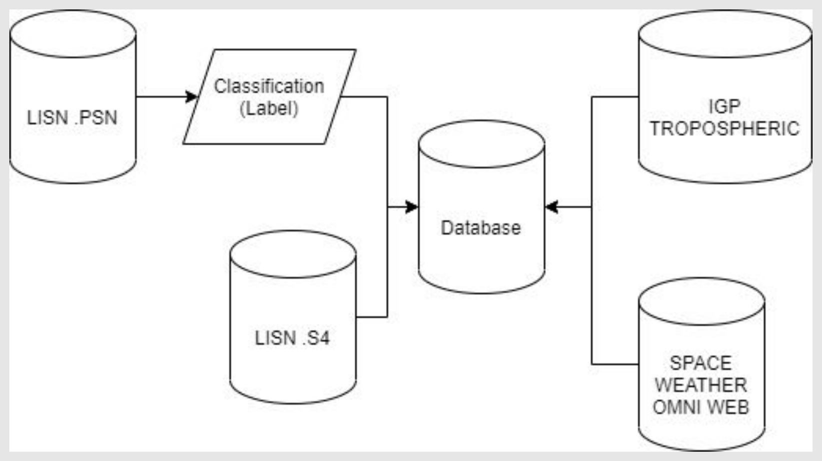

Figure 2: Databases used in the project.

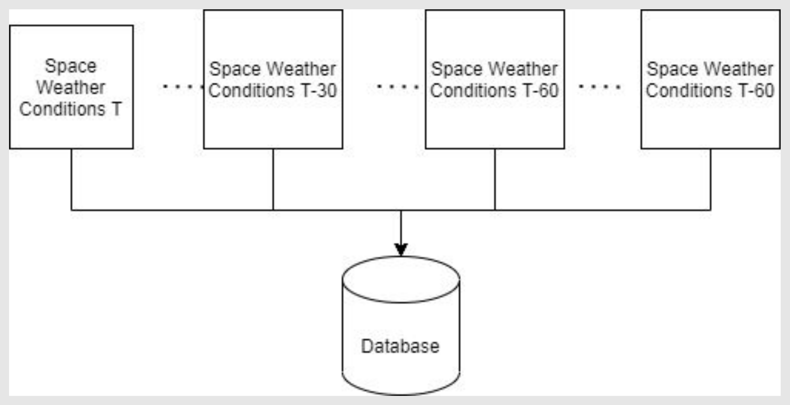

Figure 3: Data from space weather conditions used with delay.

3. Results

In the image we can see the variables (actual) used for each day in which the training is performed: S4, Kp, F10.7, Vector_B, Bx, By, Bz, SW_plasma, atmospheric pressure and air temperature (Figure 4).
In the figure below we can see the result of the parametrization for the Support Vector Classification and XGBoost models with data from summer 2015 and 2016, where the height that the GPS should measure was defined as 3325 meters above sea level.
The results (Figure 5) show a slightly better performance (average accuracy) of the XGBoost algorithm (0.91) over the Vector Support Classification (0.87), the metrics are obtained with 20% of the data (validation), in both models it is observed that if the model indicates that the error is zero, the result can be trusted, however, if the model indicates that the data is reliable, the result cannot be trusted.
Therefore the results of the XGBoost model can be provided to GPS end users so that they can know if given the conditions in the area the position they get from the GPS is likely to be accurate (less than 3 meters error) or not.

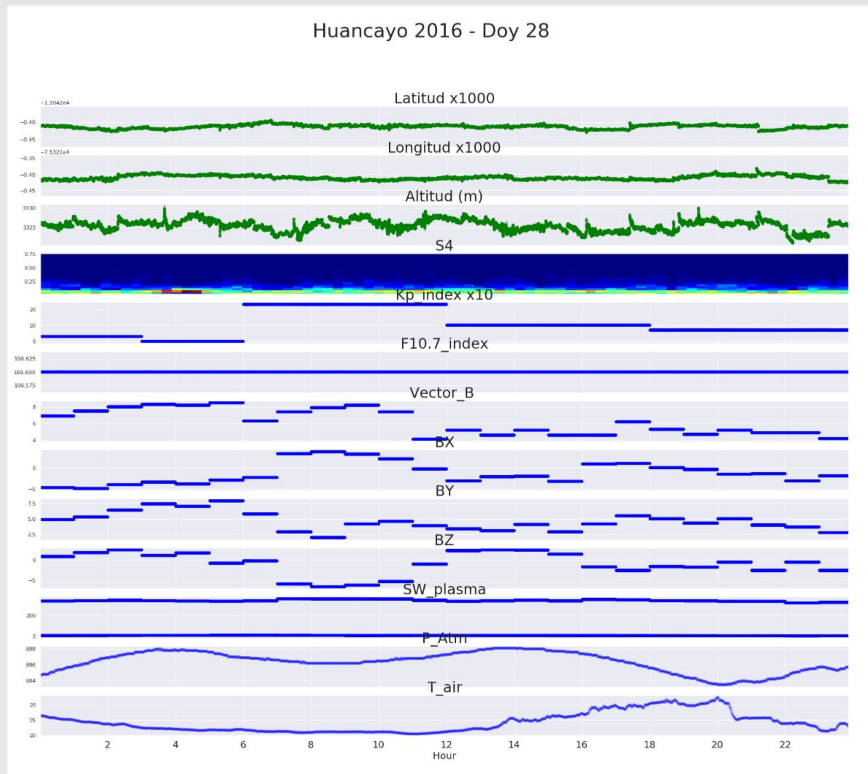

Figure 4: View of the data used for day 28 of 2016 from the Huancayo station.

	precision	recall	f1-score	support
Bajo	0.67	0.63	0.65	949
Nulo	0.91	0.93	0.92	4043
accuracy			0.87	4992
macro avg	0.79	0.78	0.79	4992
weighted avg	0.87	0.87	0.87	4992

	precision	recall	f1-score	support
Bajo	0.68	0.47	0.55	267
Nulo	0.94	0.97	0.96	2301
accuracy			0.92	2568
macro avg	0.81	0.72	0.76	2568
weighted avg	0.91	0.92	0.92	2568

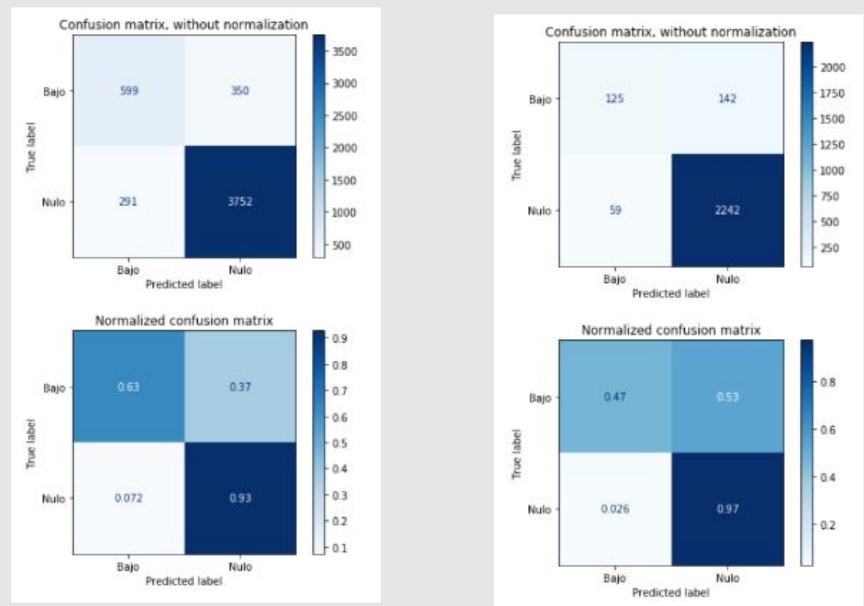

Figure 5: In the left column metrics and confusion matrix with the validation data for Support Vector machine, in the right column metrics and confusion matrix with the validation data for Support Vector machine.

4. Future Work

For future work, we plan to add correlations with low latitude phenomena, such as spread F, implement a tropospheric model to complement our machine learning model and finally extract GPS information directly from the RINEX files.

5. Acknowledgments

We gratefully acknowledge the thesis program of the Geophysical Institute of Peru and the Jicamarca Radio Observatory staff for their support. We also thank Cesar Valladares, Cesar De La Jara for the LISN data.

6. References

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2021 CEDAR Virtual Meeting, June 22-26

email: george.fajardo@jro.igp.gob.pe