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RELACIONES INSTITUCIONALES



PRODUCCIÓN



GEODESIA



Ministerio
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DESCARGA DE MAPAS

Monitoreo automático de parámetros de relojes atómicos

Bettachini, V.A.

14 de julio de 2025

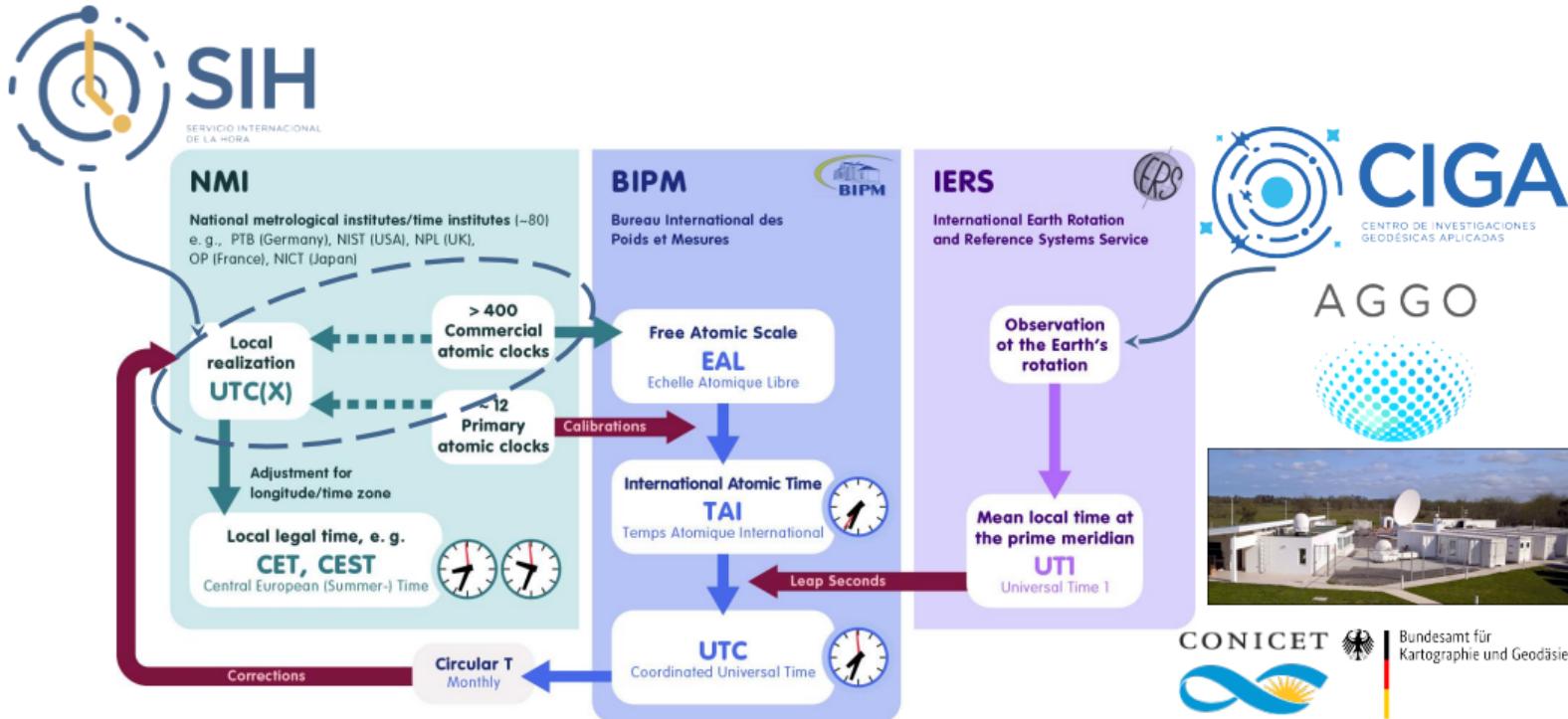


Ministerio de Defensa
República Argentina



- ▶ Servicio Internacional de la Hora
- ▶ Anomalías en serie de tiempo
- ▶ Detección de anomalías
- ▶ Registro de series

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Microsemi Precise Time-Scale System

- ▶ Varios módulos de electrónica



Microsemi Precise Time-Scale System

- ▶ Varios módulos de electrónica
- ▶ Receptor GNSS



Microsemi Precise Time-Scale System

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- ▶ Receptor GNSS
- ▶ Cuatro computadoras

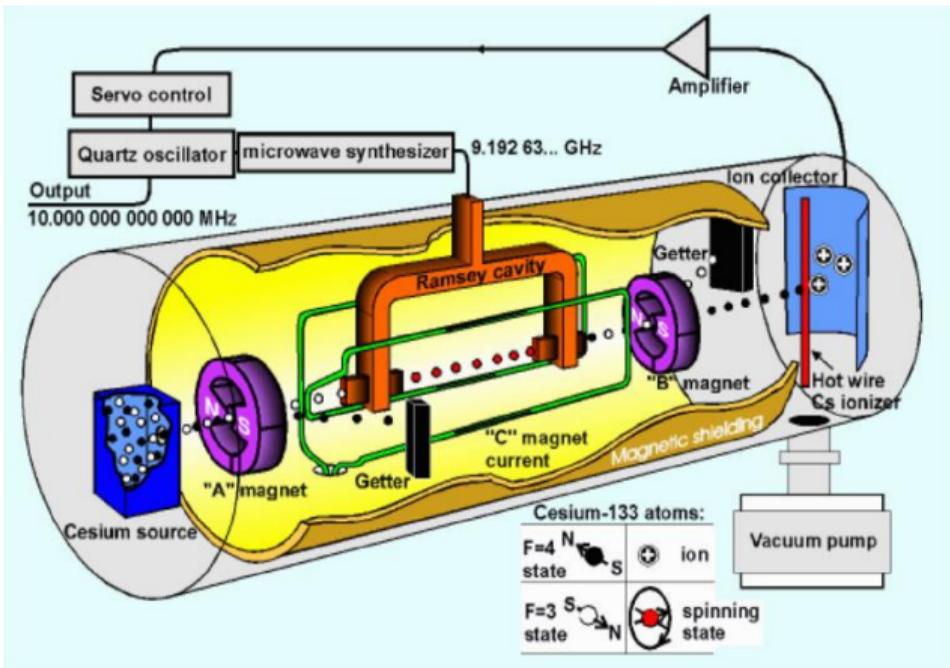


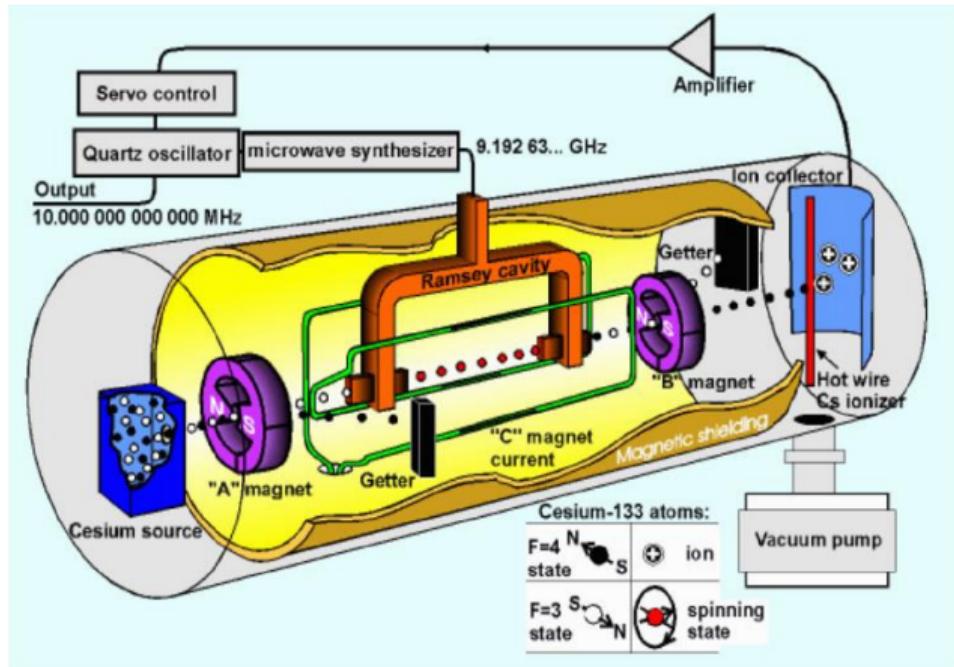
Microsemi Precise Time-Scale System

- ▶ Varios módulos de electrónica
- ▶ Receptor GNSS
- ▶ Cuatro computadoras
- ▶ Patrón de frecuencia de ^{133}Cs

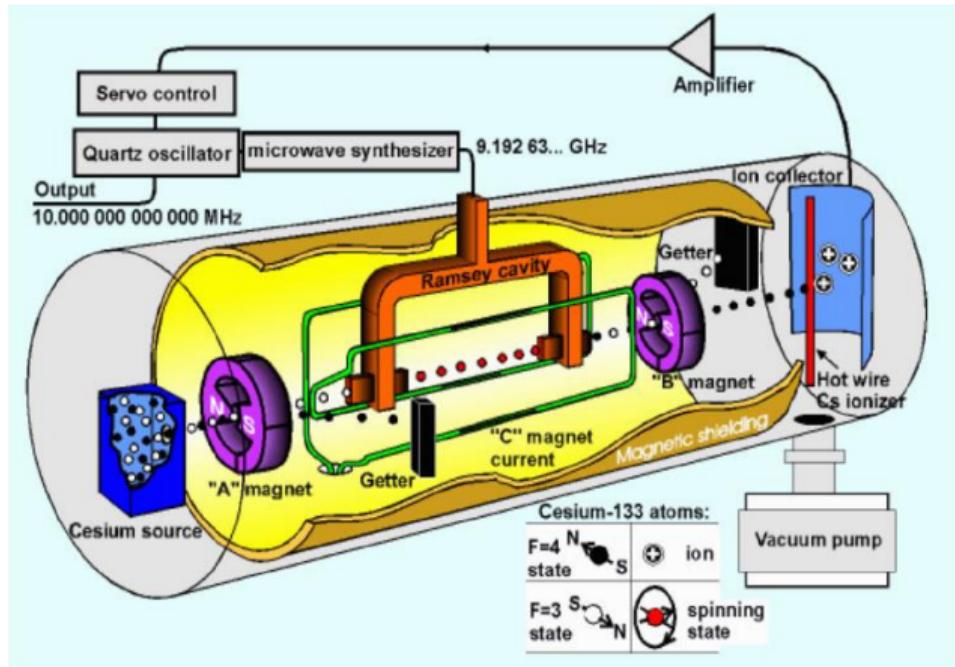


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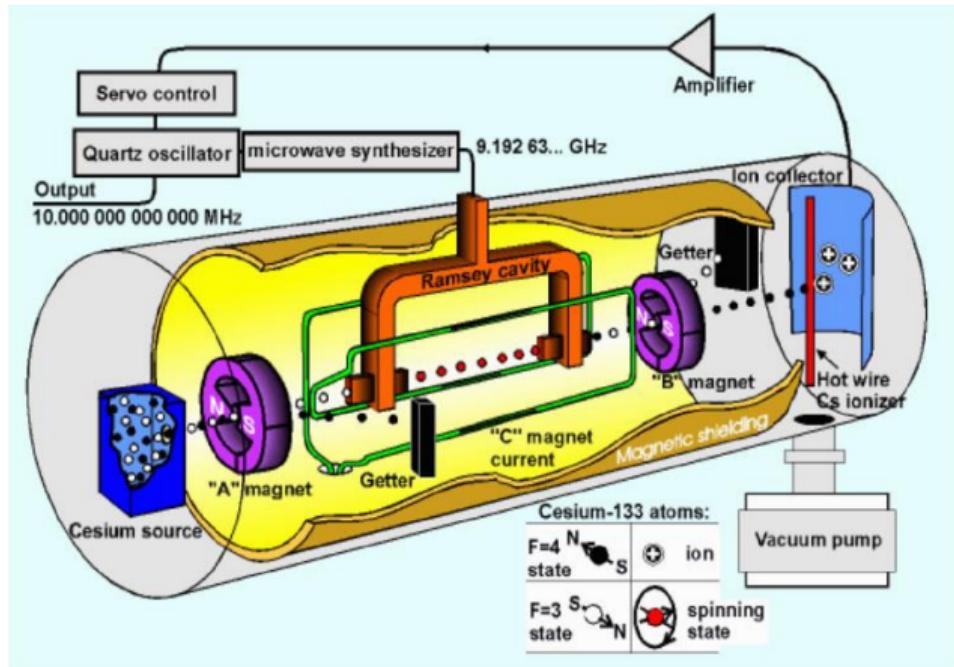


Sensibilidad ante
 ► Campos magnéticos



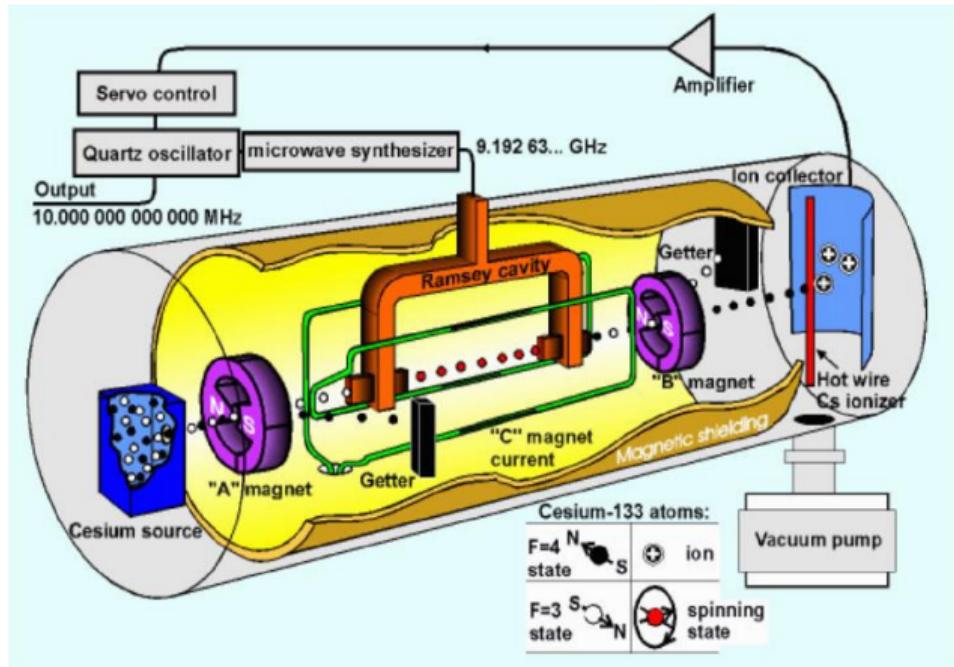
Sensibilidad ante

- ▶ Campos magnéticos
- ▶ Campos eléctricos



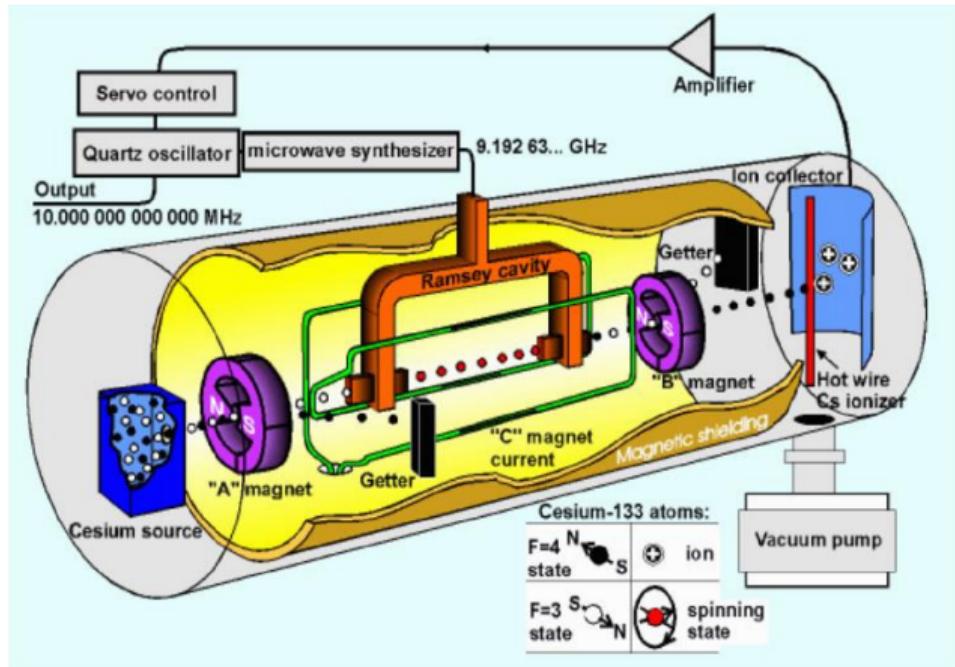
Sensibilidad ante

- ▶ Campos magnéticos
- ▶ Campos eléctricos
- ▶ Temperatura



Sensibilidad ante

- ▶ Campos magnéticos
- ▶ Campos eléctricos
- ▶ Temperatura
- ▶ Vibraciones

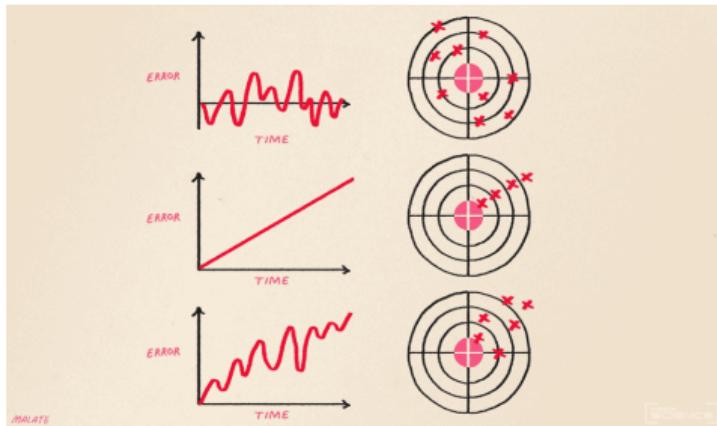


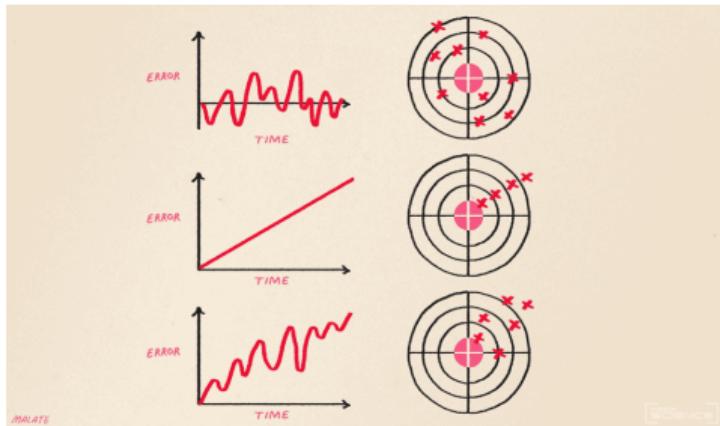
Sensibilidad ante

- ▶ Campos magnéticos
- ▶ Campos eléctricos
- ▶ Temperatura
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- ▶ Presión atmosférica

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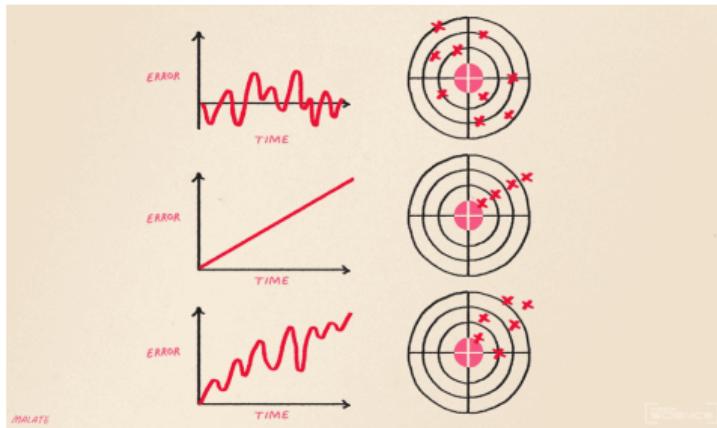
Procesos no estacionarios en serie de tiempo



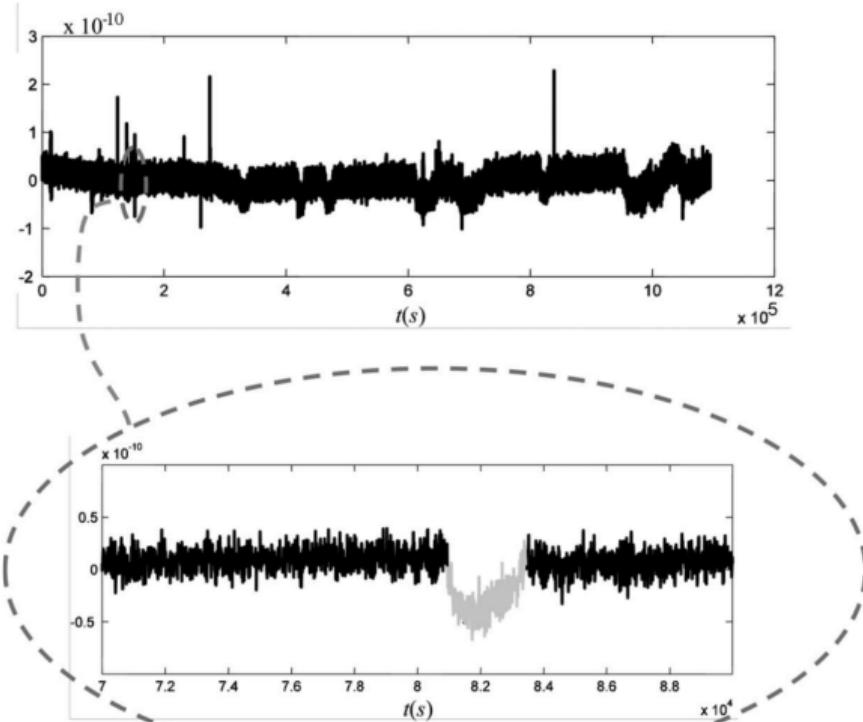


$$\sigma_y^2(\tau) = \frac{1}{2(N-1)\tau^2} \sum_{i=1}^{N-2} (x_{i+2} - 2x_{i+1} + x_i)^2$$

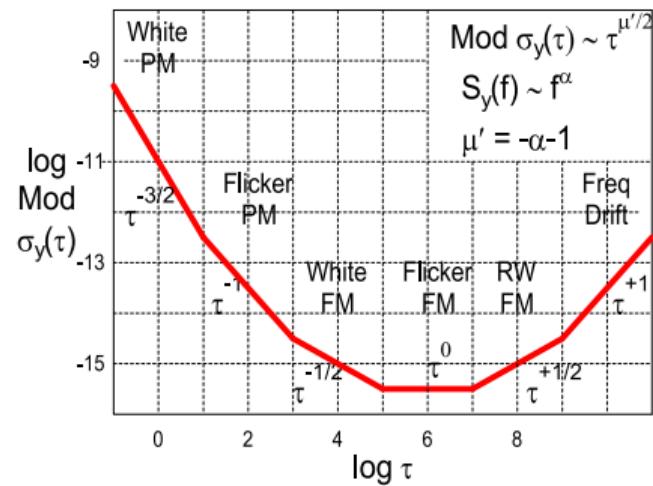
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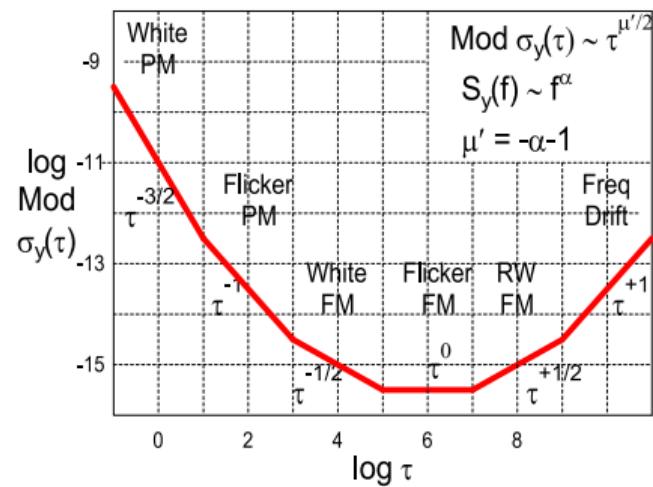
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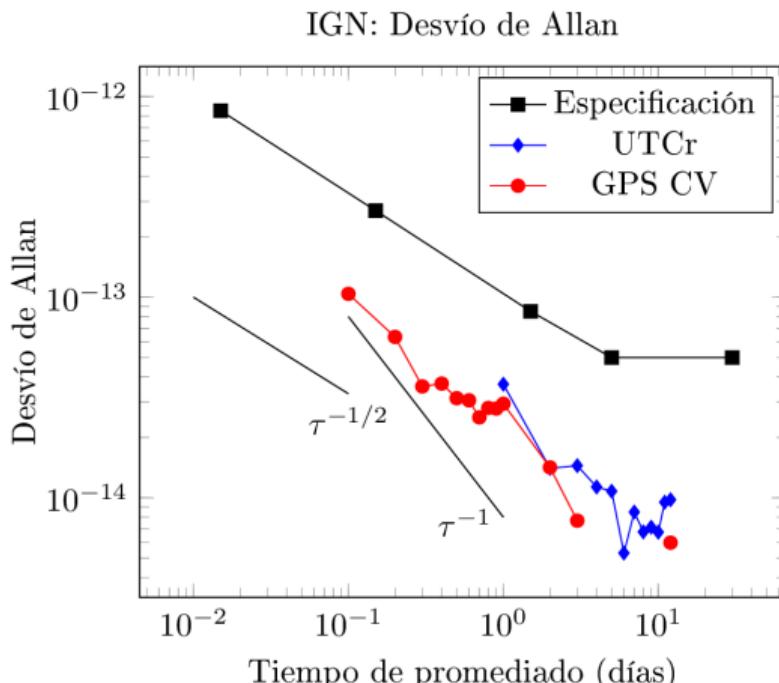
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Pendiente → proceso



Pendiente → proceso



¿Qué quisiéramos? ¡Alerta automática!





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Metrologia

<https://doi.org/10.1088/1681-7575/ea9b30>

Anomaly detection for atomic clocks using unsupervised machine learning algorithms

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Abstract

Atomic clocks are the most accurate timekeeping instruments in the world and play a crucial role in numerous applications, notably in satellite navigation. Nonetheless, the accuracy of these clock signals is subject to anomalies, highlighting the importance of anomaly characterization and detection. In our study, we identify three types of anomalies in the phase data of atomic clocks—outliers, phase jumps and inflection points, and also frequency jumps in the frequency data, which corresponds to the inflection points. The novelty of our work lies in the application of machine learning methods for atomic clock anomaly detection (AD), as opposed to traditional algorithms. We introduce a variety of unsupervised AD and change point detection (CPD) algorithms from the realms of statistics and machine learning, propose a customized thresholding function for AD, and evaluate AD and CPD algorithms on both synthetic and real-world atomic clock data. Our experiments reveal that the subsequence local outlier factor algorithm achieves excellent performance in detecting outliers and phase jumps, but struggles with inflection points. Crucially, we found that the application of a CPD algorithm specifically for detecting the frequency jumps in frequency data substantially improves performance. Our study adopts unsupervised machine learning methods for AD provides robust detection strategies, thereby contributing an expanded understanding of the use of machine learning for clock data monitoring.

Keywords: atomic clock, phase jumps, frequency jumps, anomaly detection, change point detection, machine learning



- ▶ Anomalías en la serie temporal
 - ▶ Valores estadísticos extremos (*outliers*)
 - ▶ Saltos de fase
 - ▶ Puntos de inflexión en la tendencia

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 - ▶ Factorización de *outliers* locales en subsecuencia (Sub-LOF)
 - ▶ *outliers* y saltos de fase
 - ▶ Paquete Python TimeEval

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 - ▶ Registrar series temporales de parámetros internos y ambientales





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 - ▶ Evaluar algoritmos de correlación temporal de sucesos entre series

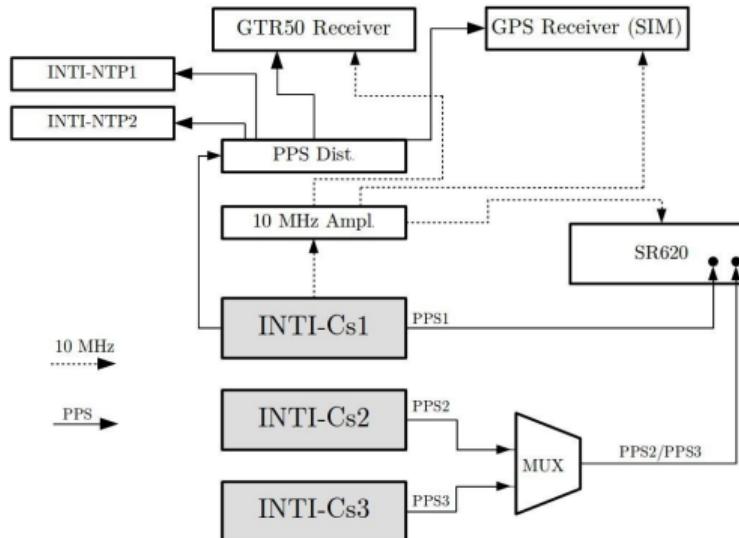
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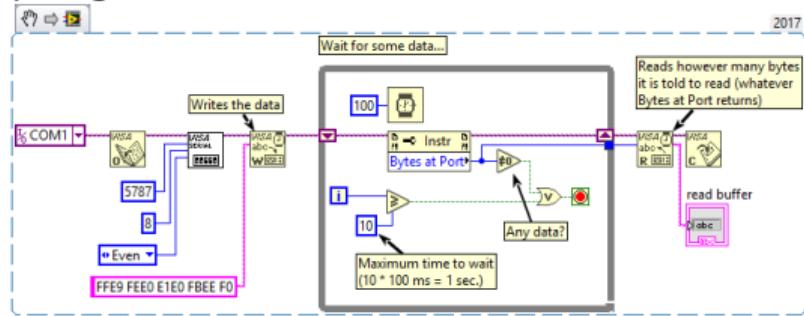


El patrón informa parámetros internos



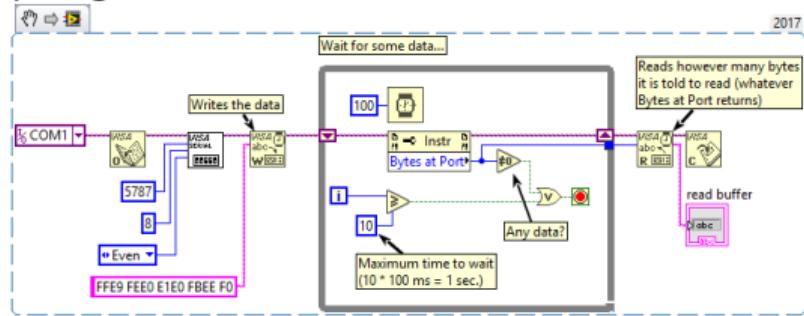


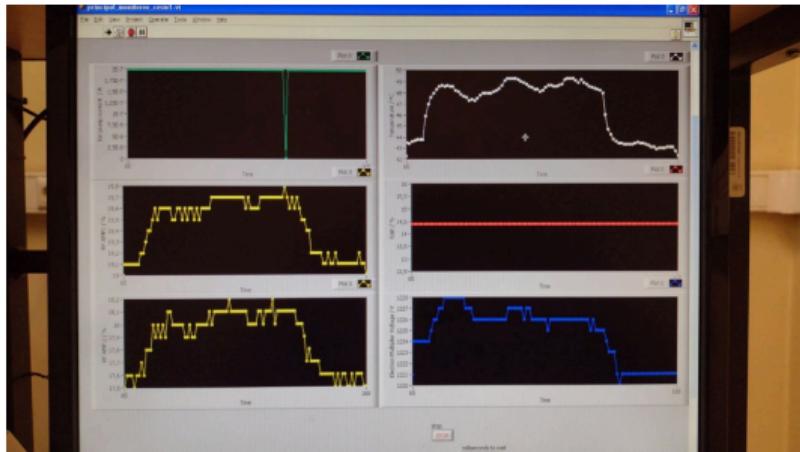
Consultado vía RS-232 por un programa en LabView





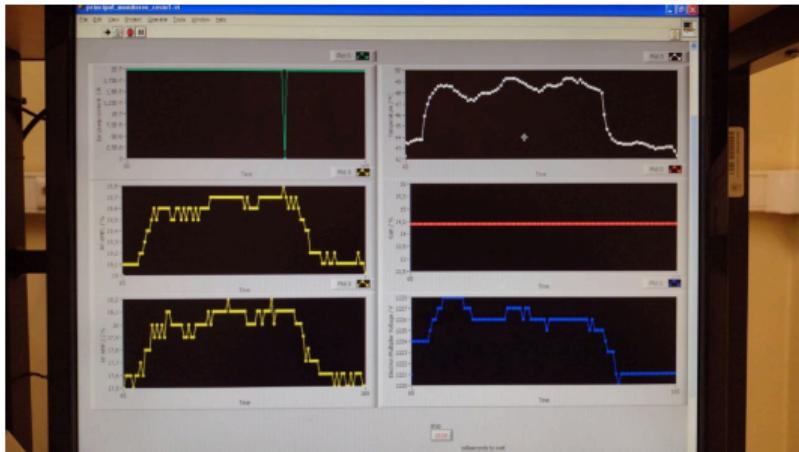
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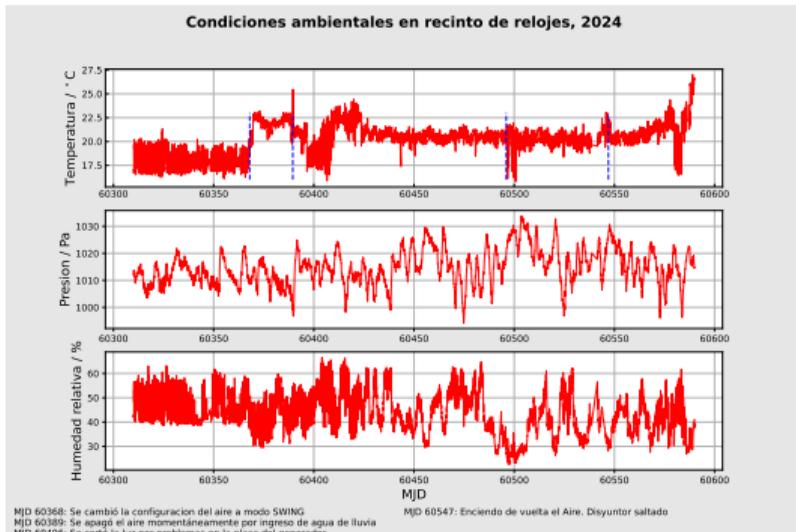


Parámetros internos 5071A INTI
registrados por programa LabView

Registro de parámetros en INTI



Parámetros internos 5071A INTI
registrados por programa LabView



Parámetros ambientales en
sala relojes INTI



BIPM, Sèvres, October 10, 2018.

In order to fulfill Recommendation CCTF 4 (2017) to collect and make available meteo data, the WG on GNSS and the WG on TWSTFT have defined a meteo format named CCTF V1.0 (see description here after). A single daily file should report all available meteo measurements at the time laboratory: interior and exterior measurements of temperature, humidity, atmospheric pressure. The data sampling is left to the laboratory appreciation and ability, but as minimum hourly measurements are recommended. The data accuracy depends on each station sensor, and is also left to the laboratory appreciation and ability.

The format proposed is compatible with what is already provided if the ITU-format TW files; a script can be used to transfer the ITU data in the more complete meteo file covering both GNSS and TW, interior and exterior measurements.

The BIPM Time department has set-up a directory structure:

- * to collect the meteo files in the BIPM ftp server in /data/UTC/LABO/meteo
- * to make them available in yearly directories e.g. <ftp://ftp2.bipm.org/pub/tai/data/2018/meteo/>

The FileName to be used for the daily meteo files is

metLLMJ.DAY with

LL = 2-character BIPM code of the LAB

MJ = 2 first characters of the mjd

DAY = 3 last characters of the mjd



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Recomienda informar:

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- ▶ En el laboratorio
- ▶ Exterior (meteorología)

In order to fulfill Recommendation CCTF 4 (2017) to collect and make available meteo data, the WG on GNSS and the WG on TWSTFT have defined a meteo format named CCTF V1.0 (see description here after). A single daily file should report all available meteo measurements at the time laboratory: interior and exterior measurements of temperature, humidity, atmospheric pressure. The data sampling is left to the laboratory appreciation and ability, but as minimum hourly measurements are recommended. The data accuracy depends on each station sensor, and is also left to the laboratory appreciation and ability.

The format proposed is compatible with what is already provided if the ITU-format TW files; a script can be used to transfer the ITU data in the more complete meteo file covering both GNSS and TW, interior and exterior measurements.

The BIPM Time department has set-up a directory structure:

- * to collect the meteo files in the BIPM ftp server in /data/UTC/LABO/meteo
- * to make them available in yearly directories e.g. <ftp://ftp2.bipm.org/pub/tai/data/2018/meteo/>

The FileName to be used for the daily meteo files is

metLLMJ.DAY with

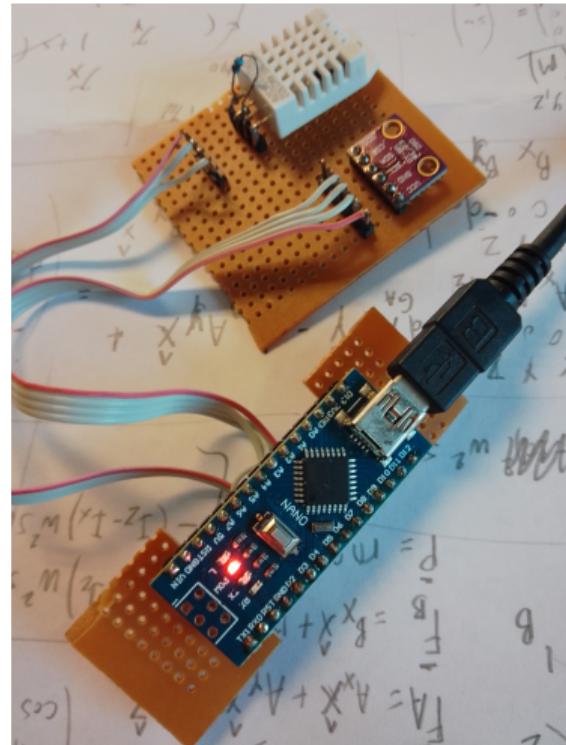
LL = 2-character BIPM code of the LAB

MJ = 2 first characters of the mjd

DAY = 3 last characters of the mjd

En la sala de servidores

- ▶ Arduino Nano: adquisición
- ▶ BMP280: temperatura, presión
- ▶ AHT10: temperatura, humedad

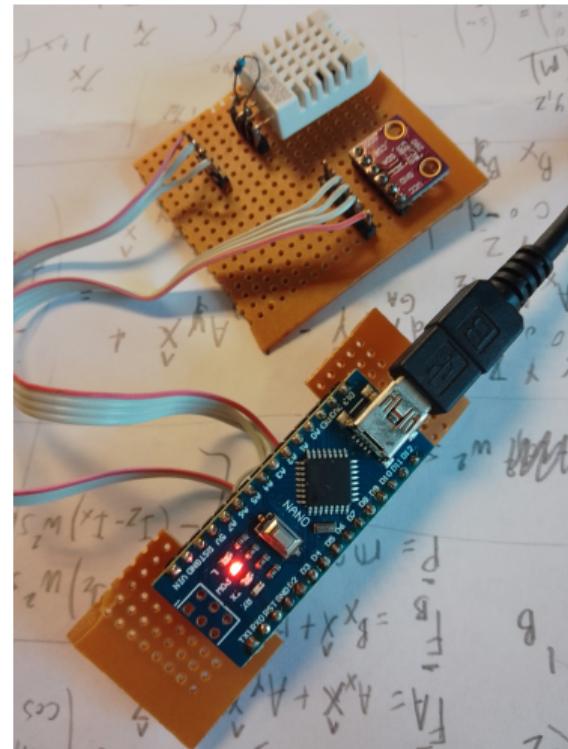


En la sala de servidores

- ▶ Arduino Nano: adquisición
- ▶ BMP280: temperatura, presión
- ▶ AHT10: temperatura, humedad

En la terraza del edificio técnico

- ▶ Sensores meteorológicos





- ▶ Identificación temprana de anomalías en serie de tiempo





- ▶ Identificación temprana de anomalías en serie de tiempo
 - ▶ Más rápido monitoreo del estado del patrón de frecuencia





- ▶ Identificación temprana de anomalías en serie de tiempo
 - ▶ Más rápido monitoreo del estado del patrón de frecuencia
- ▶ Registro de parámetros ambientales





- ▶ Identificación temprana de anomalías en serie de tiempo
 - ▶ Más rápido monitoreo del estado del patrón de frecuencia
- ▶ Registro de parámetros ambientales
 - ▶ Seguir recomendación CCTF 4 del BIPM e informales regularmente



- ▶ Identificación temprana de anomalías en serie de tiempo
 - ▶ Más rápido monitoreo del estado del patrón de frecuencia
- ▶ Registro de parámetros ambientales
 - ▶ Seguir recomendación CCTF 4 del BIPM e informales regularmente
 - ▶ Intentar correlacionar anomalías tiempo/ambientales



- ▶ Identificación temprana de anomalías en serie de tiempo
 - ▶ Más rápido monitoreo del estado del patrón de frecuencia
- ▶ Registro de parámetros ambientales
 - ▶ Seguir recomendación CCTF 4 del BIPM e informales regularmente
 - ▶ Intentar correlacionar anomalías tiempo/ambientales
 - ▶ ¿Puede controlarse algo del ambiente para mejorar la precisión?



SIH
SERVICIO INTERNACIONAL
DE LA HORA



GEOGRAFÍA



PUNTOS DE VISTA



CARTA TOPOGRÁFICA



GRACIAS POR SU ATENCIÓN



Ministerio
de Defensa
República Argentina