IGN
Instituto Geográfico Nacional
REPÚBLICA ARGENTINA

GEOGRAFÍA

PUNTOS DE VISTA

CARTA TOPOGRÁFICA

TALLERES GRÁFICOS

FOTOGRAMETRÍA

DESCARGA DE MAPAS

RELACIONES INSTITUCIONALES

PRODUCCIÓN

GEODESIA

Ministerio de Defensa
República Argentina

Monitoreo automático de parámetros de relojes atómicos

Bettachini, V.A.

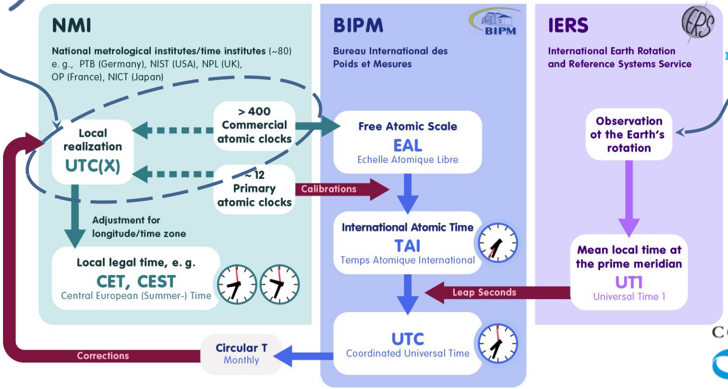
14 de julio de 2025

Ministerio de Defensa
República Argentina

Instituto Geográfico Nacional
REPÚBLICA ARGENTINA

Sinopsis

SIH
SERVICIO INTERNACIONAL DE LA HORA



CIGA
CENTRO DE INVESTIGACIONES GEODÉSICAS APLICADAS

AGGO

CONICET

Bundesamt für Kartographie und Geodäsie

Microsemi Precise Time-Scale System

- Varios módulos de electrónica

Microsemi Precise Time-Scale System

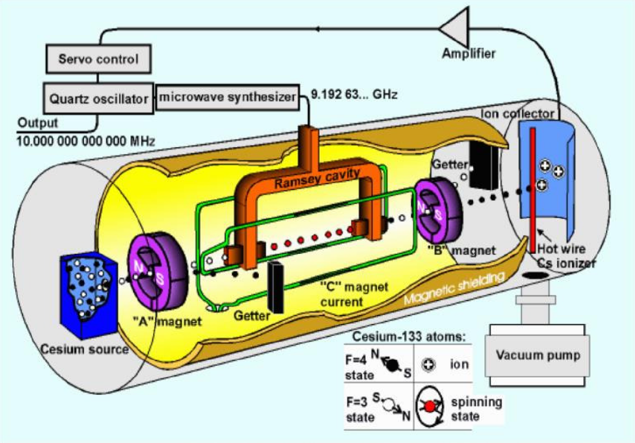
- Varios módulos de electrónica
- Receptor GNSS

Microsemi Precise Time-Scale System

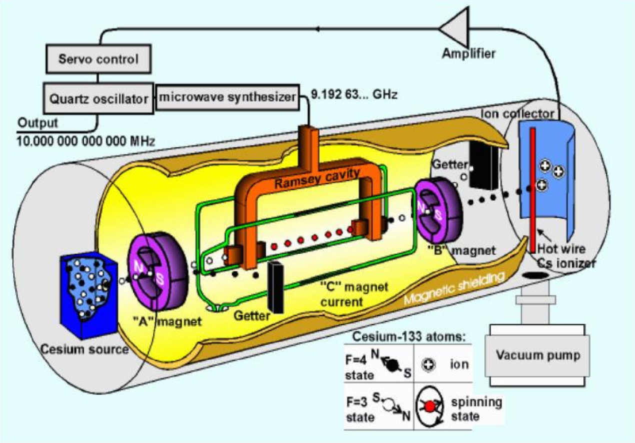
- Varios módulos de electrónica
- Receptor GNSS
- Cuatro computadoras

Microsemi Precise Time-Scale System

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



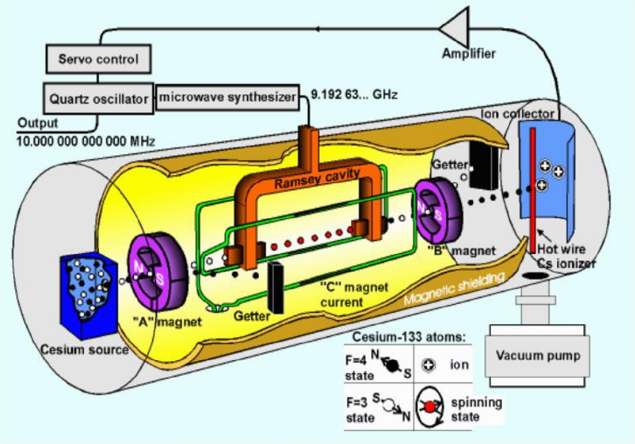
Servo control
Amplifier
Quartz oscillator
microwave synthesizer
9.192 63... GHz
Output
10.000 000 000 000 MHz
Ion collector
Ramsey cavity
Getter
"B" magnet
Hot wire
Cs ionizer
"C" magnet
current
Magnetic shielding
"A" magnet
Getter
Cesium source
Cesium-133 atoms:
F=4 state
ion
F=3 state
spinning state
Vacuum pump



Sensibilidad ante

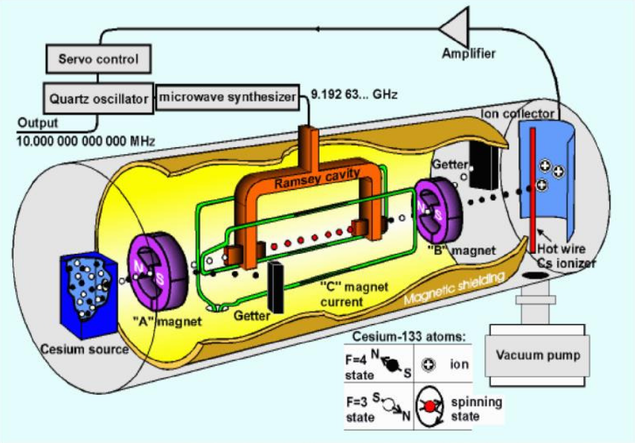
- Campos magnéticos

Patrón de frecuencia de ^{133}Cs



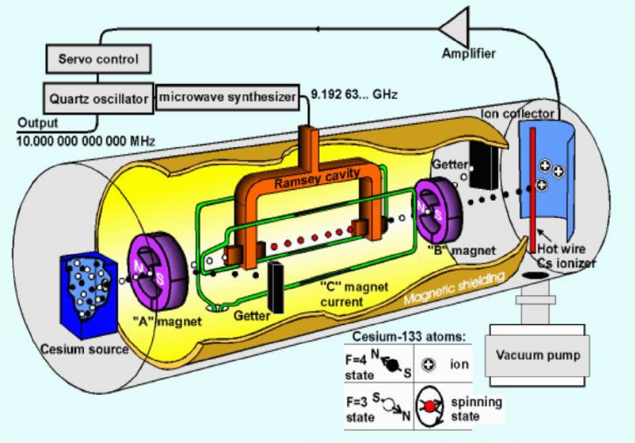
Sensibilidad ante

- Campos magnéticos
- Campos eléctricos



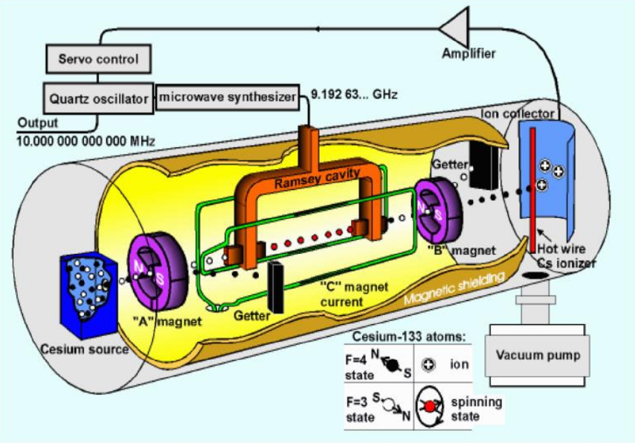
Sensibilidad ante

- Campos magnéticos
- Campos eléctricos
- Temperatura



Sensibilidad ante

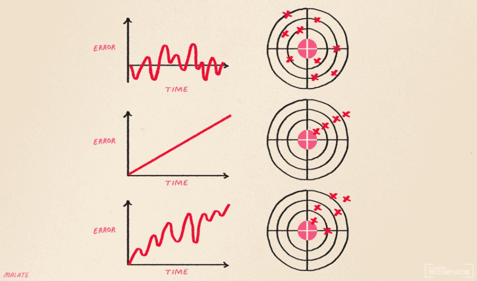
- Campos magnéticos
- Campos eléctricos
- Temperatura
- Vibraciones

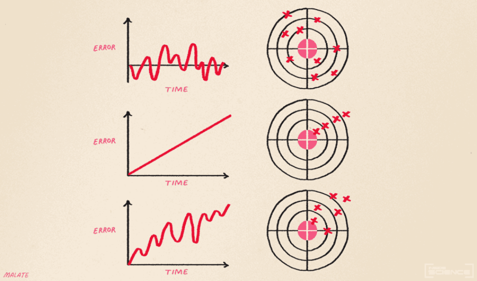


Sensibilidad ante

- Campos magnéticos
- Campos eléctricos
- Temperatura
- Vibraciones
- Presión atmosférica

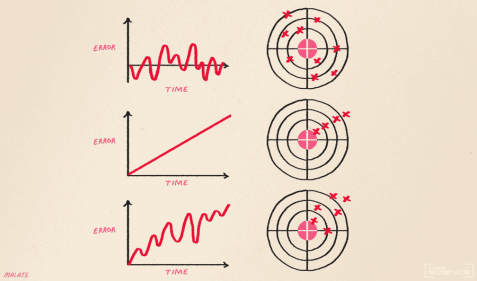
Procesos no estacionarios en serie de tiempo



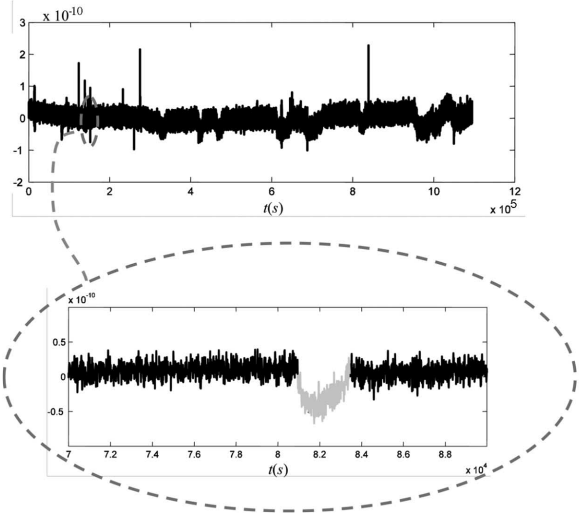


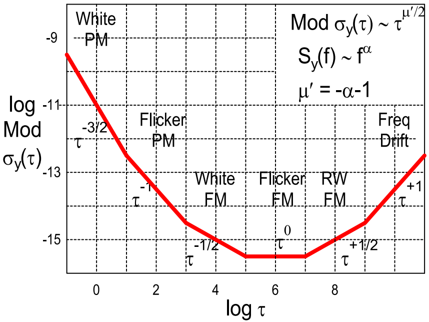
$$\sigma_y^2(\tau) = \frac{1}{2(N-1)\tau^2} \sum_{i=1}^{N-2} \left(x_{i+2} - 2x_{i+1} + x_i\right)^2$$

Procesos no estacionarios en serie de tiempo

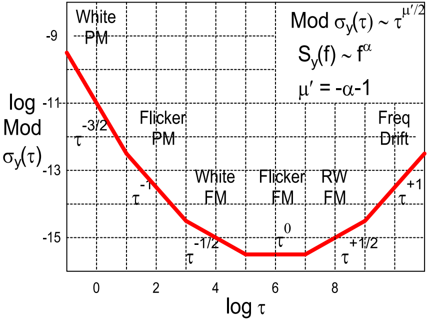


$$\sigma_y^2(\tau)=\frac{1}{2(N-1)\tau^2}\sum_{i=1}^{N-2}\left(x_{i+2}-2x_{i+1}+x_i\right)^2$$

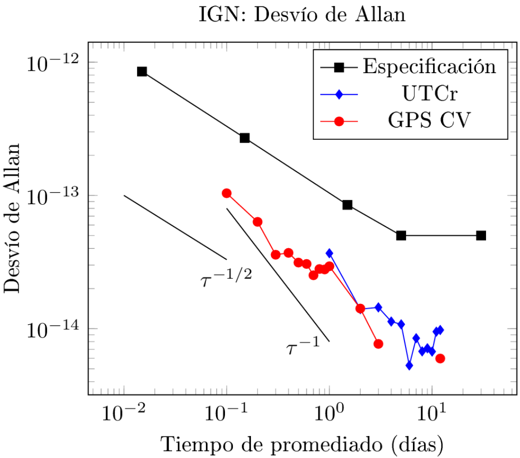




Pendiente $\rightarrow$ proceso



Pendiente → proceso



¿Qué quisiéramos? ¡Alerta automática!

OPEN ACCESS
IOP Publishing | Bureau International des Poids et Mesures
Metrologia
Metrologia **61** (2024) 055005 (13pp)
https://doi.org/10.1088/1681-7575/ad6b30

Anomaly detection for atomic clocks using unsupervised machine learning algorithms

Edwin Chen[1,3], André Charbonneau[2], Marina Gertsvolf[2] and Yunli Wang[2,*]

[1] University of Toronto, Toronto, ON M5S 1A1, Canada
[2] National Research Council Canada, Ottawa, ON K1A 0R6, Canada

E-mail: yunli.wang@nrc-cnrc.gc.ca

Received 19 October 2023, revised 29 June 2024
Accepted for publication 5 August 2024
Published 14 August 2024

CrossMark

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

¿Qué quisiéramos? ¡Alerta automática!

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

OPEN ACCESS
IOP Publishing | Bureau International des Poids et Mesures — Metrologia
Metrologia **61** (2024) 055005 (13pp) https://doi.org/10.1088/1681-7575/ad6b30

Anomaly detection for atomic clocks using unsupervised machine learning algorithms

Edwin Chen[1,3], André Charbonneau[2], Marina Gertsvolf[2] and Yunli Wang[2,*]

[1] University of Toronto, Toronto, ON M5S 1A1, Canada
[2] National Research Council Canada, Ottawa, ON K1A 0R6, Canada

E-mail: yunli.wang@nrc-cnrc.gc.ca

Received 19 October 2023, revised 29 June 2024
Accepted for publication 5 August 2024
Published 14 August 2024

CrossMark

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

¿Qué quisiéramos? ¡Alerta automática!

- Anomalías en la serie temporal
  - Valores estadísticos extremos (*outliers*)
  - Saltos de fase
  - Puntos de inflexión en la tendencia
- Algoritmos de mayor desempeño (F1)

OPEN ACCESS
IOP Publishing | Bureau International des Poids et Mesures   Metrologia
Metrologia **61** (2024) 055005 (13pp)   https://doi.org/10.1088/1681-7575/ad6b30

Anomaly detection for atomic clocks using unsupervised machine learning algorithms

Edwin Chen[1,3], André Charbonneau[2], Marina Gertsvolf[2] and Yunli Wang[2,*]

[1] University of Toronto, Toronto, ON M5S 1A1, Canada
[2] National Research Council Canada, Ottawa, ON K1A 0R6, Canada

E-mail: yunli.wang@nrc-cnrc.gc.ca

Received 19 October 2023, revised 29 June 2024
Accepted for publication 5 August 2024
Published 14 August 2024

CrossMark

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

¿Qué quisiéramos? ¡Alerta automática!

- Anomalías en la serie temporal
  - Valores estadísticos extremos (*outliers*)
  - Saltos de fase
  - Puntos de inflexión en la tendencia
- Algoritmos de mayor desempeño (F1)
  - Factorización de *outliers* locales en subsecuencia (Sub-LOF)
    - *outliers* y saltos de fase
    - Paquete Python TimeEval

OPEN ACCESS
IOP Publishing | Bureau International des Poids et Mesures
Metrologia
Metrologia 61 (2024) 055005 (13pp)
https://doi.org/10.1088/1681-7575/ad6b30

Anomaly detection for atomic clocks using unsupervised machine learning algorithms

Edwin Chen[1,3], **André Charbonneau**[2], **Marina Gertsvolf**[2] and **Yunli Wang**[2,*]

[1] University of Toronto, Toronto, ON M5S 1A1, Canada
[2] National Research Council Canada, Ottawa, ON K1A 0R6, Canada

E-mail: yunli.wang@nrc-cnrc.gc.ca

Received 19 October 2023, revised 29 June 2024
Accepted for publication 5 August 2024
Published 14 August 2024

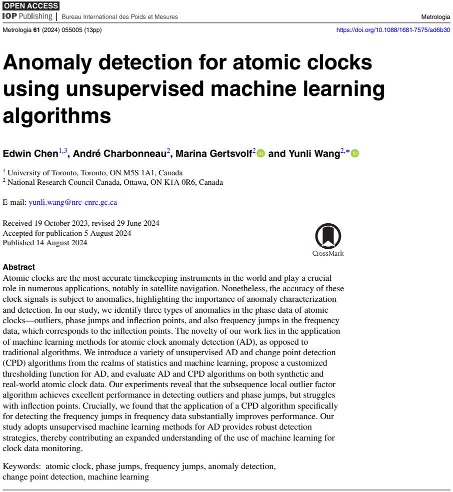
CrossMark

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

¿Qué quisiéramos? ¡Alerta automática!

- Anomalías en la serie temporal
  - Valores estadísticos extremos (*outliers*)
  - Saltos de fase
  - Puntos de inflexión en la tendencia
- Algoritmos de mayor desempeño (F1)
  - Factorización de *outliers* locales en subsecuencia (Sub-LOF)
    - *outliers* y saltos de fase
    - Paquete Python TimeEval
  - Detección de cambio puntual (CPD)
    - Inflexiones en serie de frecuencias
    - Paquete Python Raptures


OPEN ACCESS
IOP Publishing | Bureau International des Poids et Mesures
Metrologia
Metrologia 61 (2024) 055005 (13pp)
https://doi.org/10.1088/1681-7575/ad6b30

Anomaly detection for atomic clocks using unsupervised machine learning algorithms

Edwin Chen[1,3], **André Charbonneau**[2], **Marina Gertsvolf**[2] and **Yunli Wang**[2,*]

[1] University of Toronto, Toronto, ON M5S 1A1, Canada
[2] National Research Council Canada, Ottawa, ON K1A 0R6, Canada

E-mail: yunli.wang@nrc-cnrc.gc.ca

Received 19 October 2023, revised 29 June 2024
Accepted for publication 5 August 2024
Published 14 August 2024

CrossMark

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

1. Contar con muchos ejemplos de anomalías

1. Contar con muchos ejemplos de anomalías
    - Solicitar series usadas en Chen et al. (2024) al NRC de Canadá

1. Contar con muchos ejemplos de anomalías
   - Solicitar series usadas en Chen et al. (2024) al NRC de Canadá
2. Implementación local de algoritmos Sub-LOF y CPD

Etapas hacia una implementación

1. Contar con muchos ejemplos de anomalías
   - Solicitar series usadas en Chen et al. (2024) al NRC de Canadá
2. Implementación local de algoritmos Sub-LOF y CPD
   - Reproducir resultados de Chen et al. (2024) con series provistas

1. Contar con muchos ejemplos de anomalías
   - Solicitar series usadas en Chen et al. (2024) al NRC de Canadá
2. Implementación local de algoritmos Sub-LOF y CPD
   - Reproducir resultados de Chen et al. (2024) con series provistas
3. Minar series de tiempo propias en búsqueda de anomalías

1. Contar con muchos ejemplos de anomalías
   - Solicitar series usadas en Chen et al. (2024) al NRC de Canadá
2. Implementación local de algoritmos Sub-LOF y CPD
   - Reproducir resultados de Chen et al. (2024) con series provistas
3. Minar series de tiempo propias en búsqueda de anomalías
   - Evaluar número de anomalías detectadas con Sub-LOF y CPD

Etapas hacia una implementación

1. Contar con muchos ejemplos de anomalías
   - Solicitar series usadas en Chen et al. (2024) al NRC de Canadá
2. Implementación local de algoritmos Sub-LOF y CPD
   - Reproducir resultados de Chen et al. (2024) con series provistas
3. Minar series de tiempo propias en búsqueda de anomalías
   - Evaluar número de anomalías detectadas con Sub-LOF y CPD
4. Correlacionar anomalías en tiempo con las de parámetros

1. Contar con muchos ejemplos de anomalías
   - Solicitar series usadas en Chen et al. (2024) al NRC de Canadá
2. Implementación local de algoritmos Sub-LOF y CPD
   - Reproducir resultados de Chen et al. (2024) con series provistas
3. Minar series de tiempo propias en búsqueda de anomalías
   - Evaluar número de anomalías detectadas con Sub-LOF y CPD
4. Correlacionar anomalías en tiempo con las de parámetros
   - Registrar series temporales de parámetros internos y ambientales

Etapas hacia una implementación

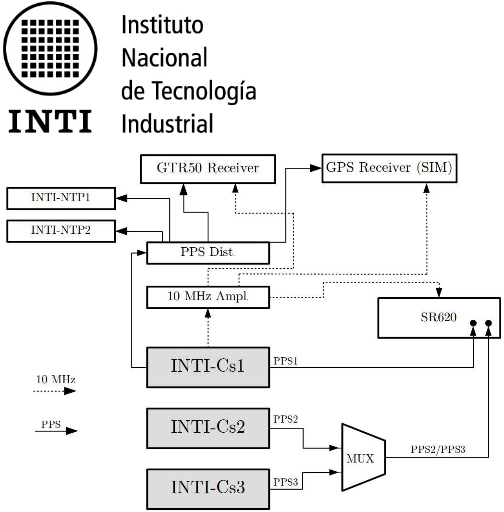
1. Contar con muchos ejemplos de anomalías
   - Solicitar series usadas en Chen et al. (2024) al NRC de Canadá
2. Implementación local de algoritmos Sub-LOF y CPD
   - Reproducir resultados de Chen et al. (2024) con series provistas
3. Minar series de tiempo propias en búsqueda de anomalías
   - Evaluar número de anomalías detectadas con Sub-LOF y CPD
4. Correlacionar anomalías en tiempo con las de parámetros
   - Registrar series temporales de parámetros internos y ambientales
   - Detección *clásica* (Z-score, ARIMA) o con ML (autoencoder)

Etapas hacia una implementación

1. Contar con muchos ejemplos de anomalías
   - Solicitar series usadas en Chen et al. (2024) al NRC de Canadá
2. Implementación local de algoritmos Sub-LOF y CPD
   - Reproducir resultados de Chen et al. (2024) con series provistas
3. Minar series de tiempo propias en búsqueda de anomalías
   - Evaluar número de anomalías detectadas con Sub-LOF y CPD
4. Correlacionar anomalías en tiempo con las de parámetros
   - Registrar series temporales de parámetros internos y ambientales
   - Detección *clásica* (Z-score, ARIMA) o con ML (autoencoder)
   - Evaluar algoritmos de correlación temporal de sucesos entre series

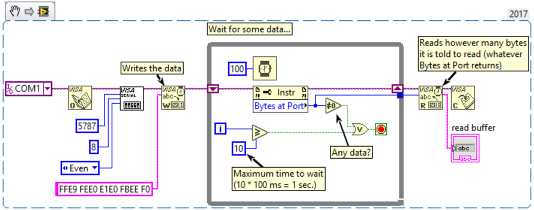
Serie de tiempo en INTI

INTI
Instituto
Nacional
de Tecnología
Industrial

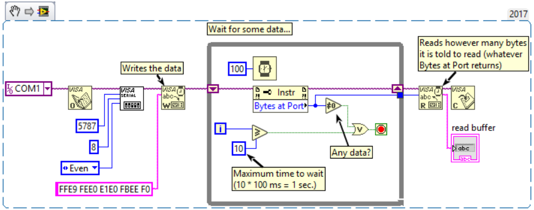

INTI
Instituto
Nacional
de Tecnología
Industrial
GTR50 Receiver
GPS Receiver (SIM)
INTI-NTP1
INTI-NTP2
PPS Dist.
10 MHz Ampl.
SR620
INTI-Cs1
PPS1
10 MHz
PPS
INTI-Cs2
PPS2
MUX
PPS2/PPS3
INTI-Cs3
PPS3

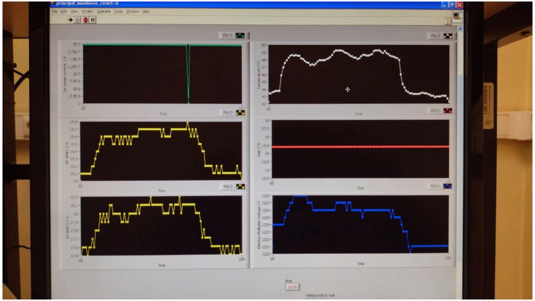

21 39 18
Operating normally
STATUS PUMP OVENS CTRL C-FIELD

Consultado vía RS-232 por un programa en LabView



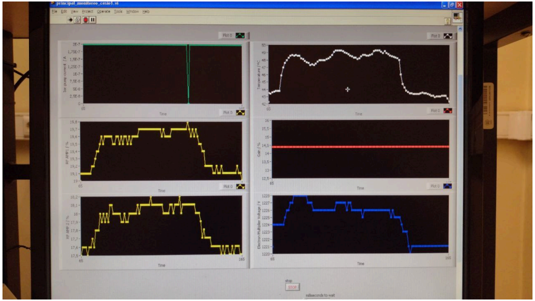
Consultado vía RS-232 por un programa en LabView



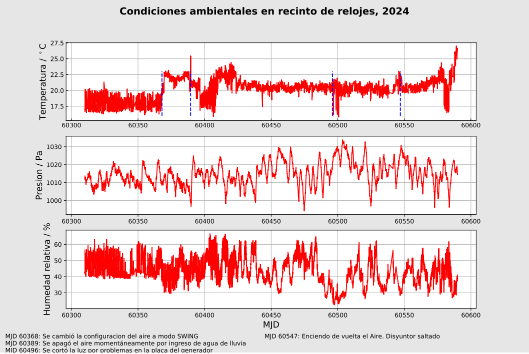


Parámetros internos 5071A INTI registrados por programa LabView

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

Recomienda informar:

- Temperatura
- Presión atmosférica
- Humedad

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

Recomienda informar:

- Temperatura
- Presión atmosférica
- Humedad
- En el laboratorio

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

Recomienda informar:

- Temperatura
- Presión atmosférica
- Humedad
- En el laboratorio
- Exterior (meteorología)

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.

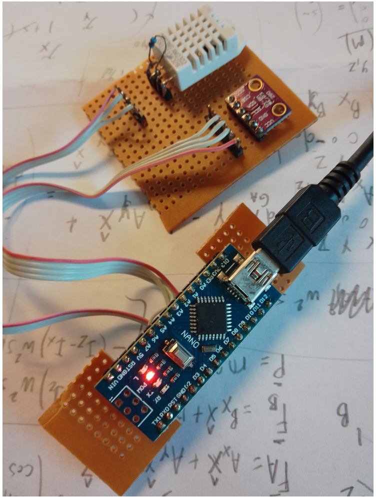
The format proposed is compatible with what is already provided if the ITU-format TW files; a script can be used to transfer the ITU data in the more complete meteo file covering both GNSS and TW, interior and exterior measurements.

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

En la sala de servidores

- Arduino Nano: adquisición
- BPM280: temperatura, presión
- AHT10: temperatura, humedad

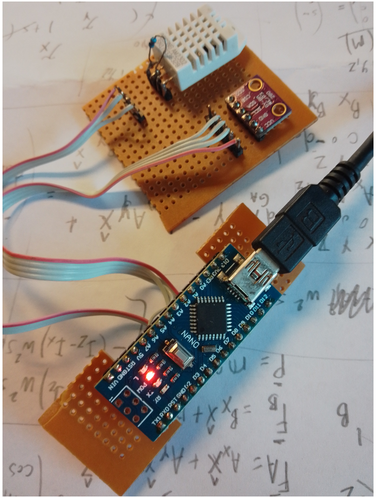


En la sala de servidores

- Arduino Nano: adquisición
- BPM280: temperatura, presión
- AHT10: temperatura, humedad

En la terraza del edificio técnico

- Sensores meteorológicos



- Identificación temprana de anomalías en serie de tiempo

Para concluir

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

Para concluir

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

- Identificación temprana de anomalías en serie de tiempo
  - Más rapído 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 rapído 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 rapido 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?

Sus preguntas

SIH

SERVICIO INTERNACIONAL
DE LA HORA

GEOGRAFÍA

PUNTOS DE VISTA

CARTA TOPOGRÁFICA

IGN Instituto Geográfico Nacional REPÚBLICA ARGENTINA

GRACIAS POR SU ATENCIÓN

Ministerio de Defensa República Argentina