Enhancing Ring Laser Gyroscope data analysis through Neural Networks for Earthquake detection and Phenomenon identification

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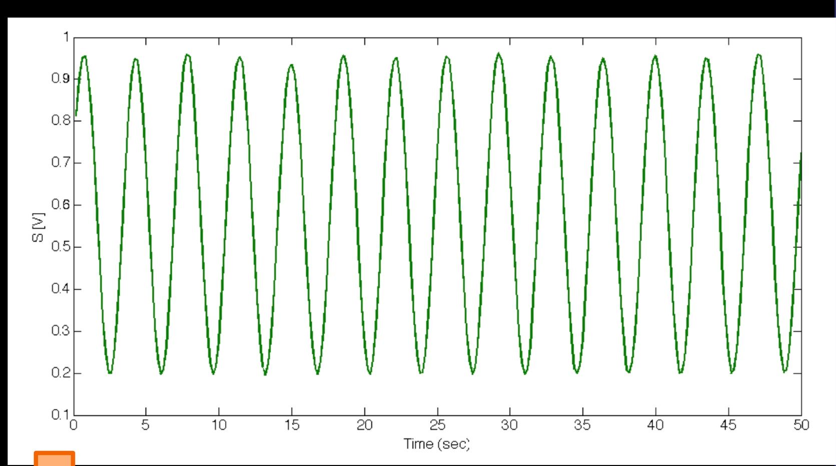
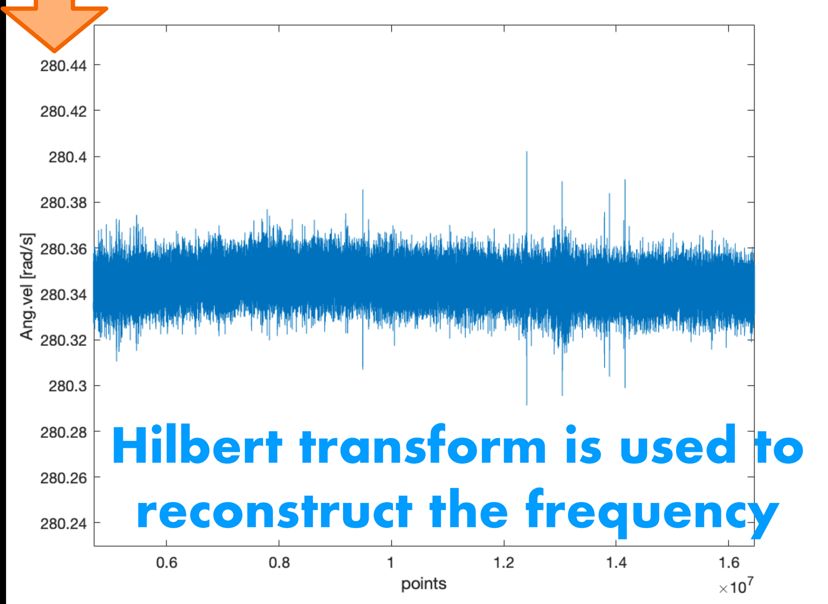
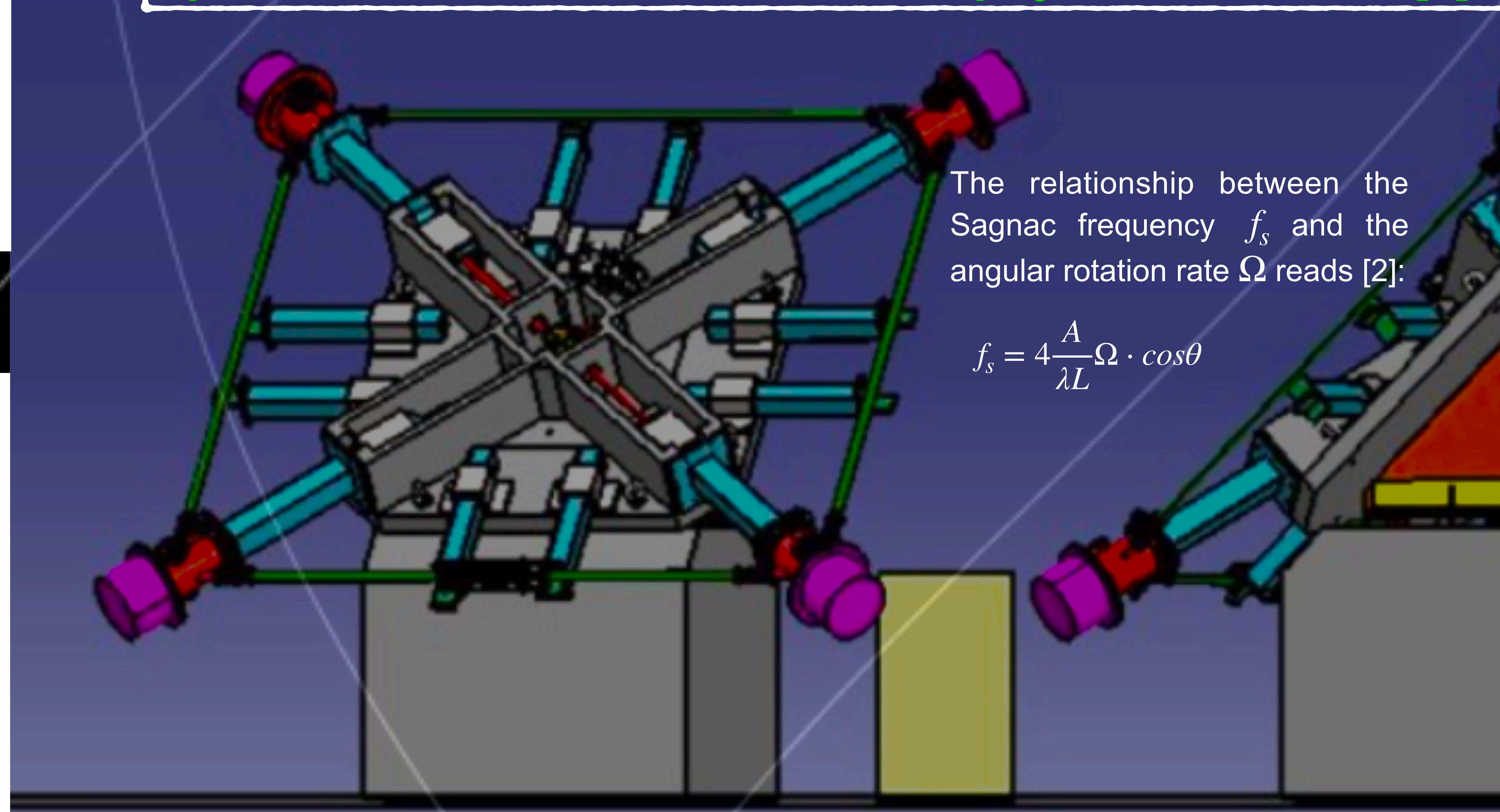
Interferogram of the two clockwise and counterclockwise beams



The **beat note** detected by GINGERINO in 50 secs

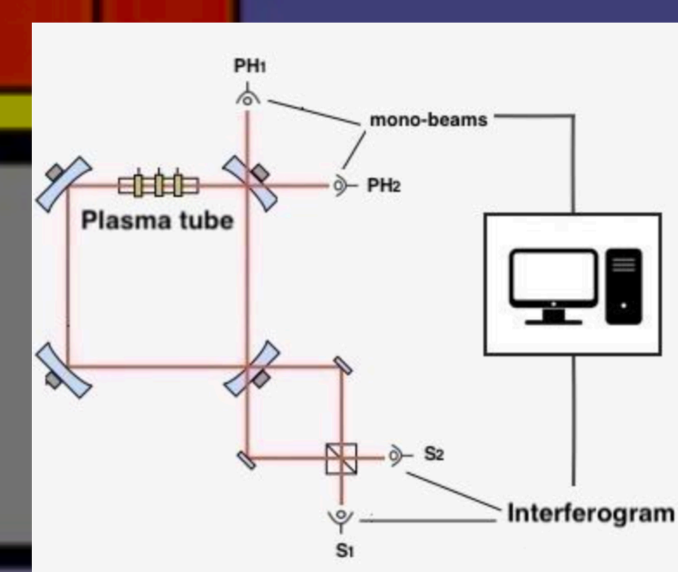


GINGER sensitivity targets: 1 part out of 10^9 - 10^{11} of the Earth's rotation
1 part out of 10^9 is the fundamental physics watershed [1]



The relationship between the Sagnac frequency f_s and the angular rotation rate Ω reads [2]:

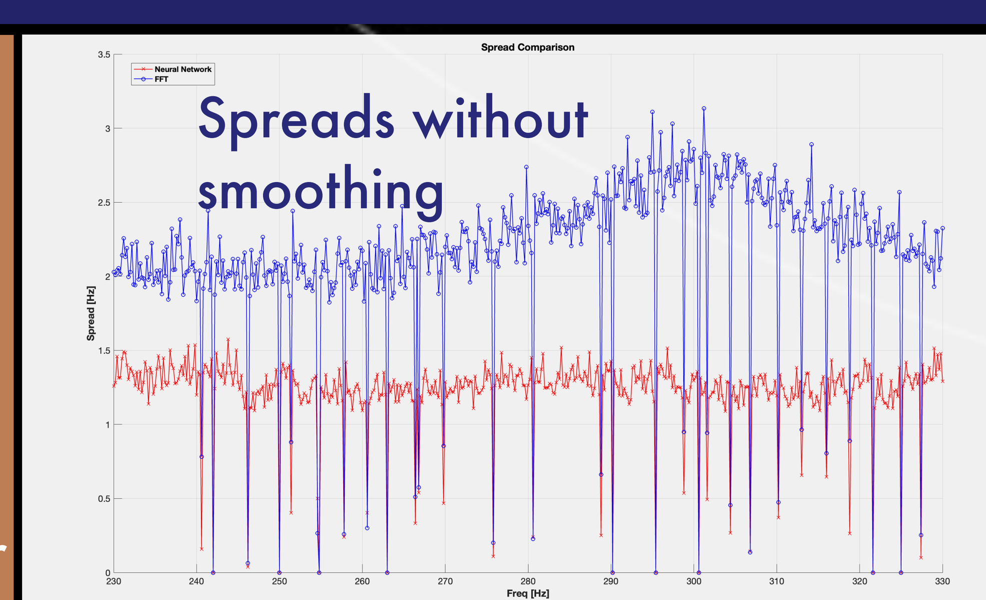
$$f_s = 4\frac{A}{\lambda L}\Omega \cdot cos\theta$$

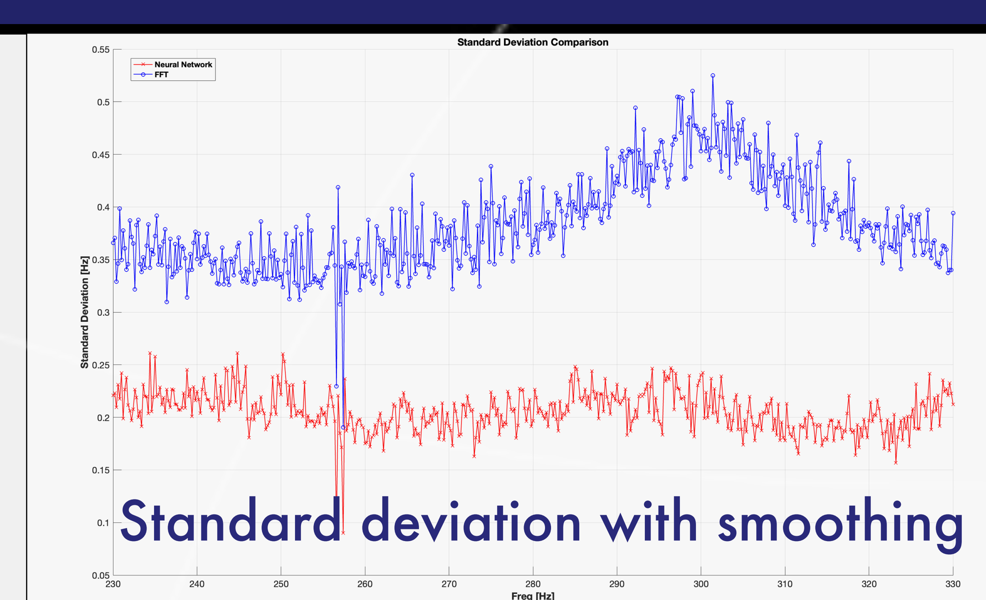


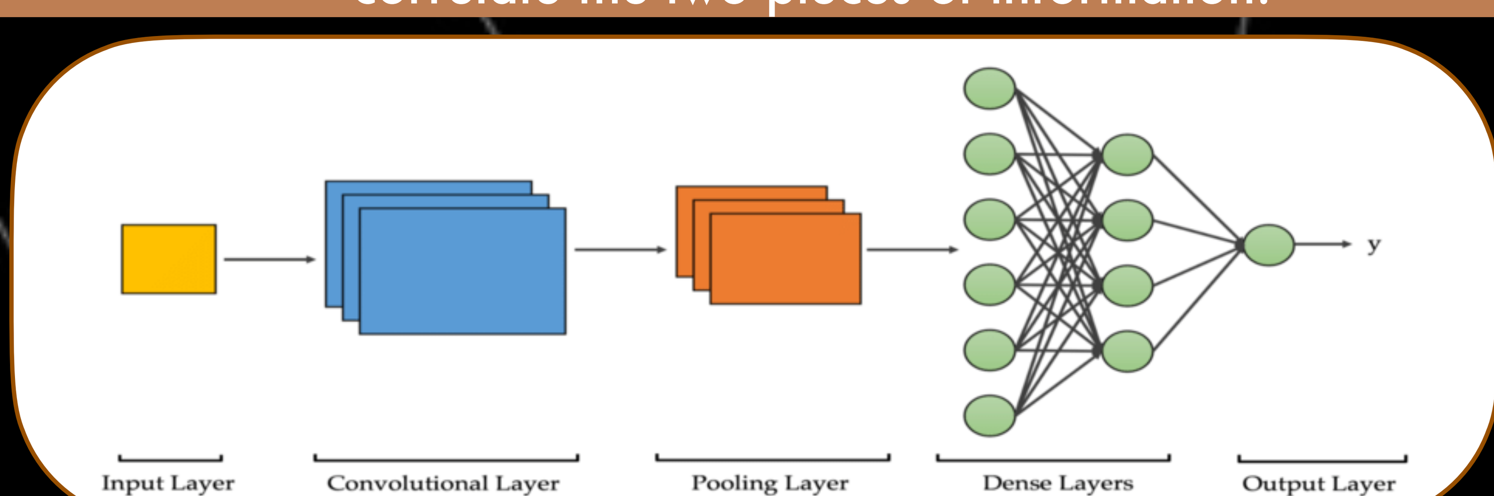
Real time for seismology, triggers and feedback controls

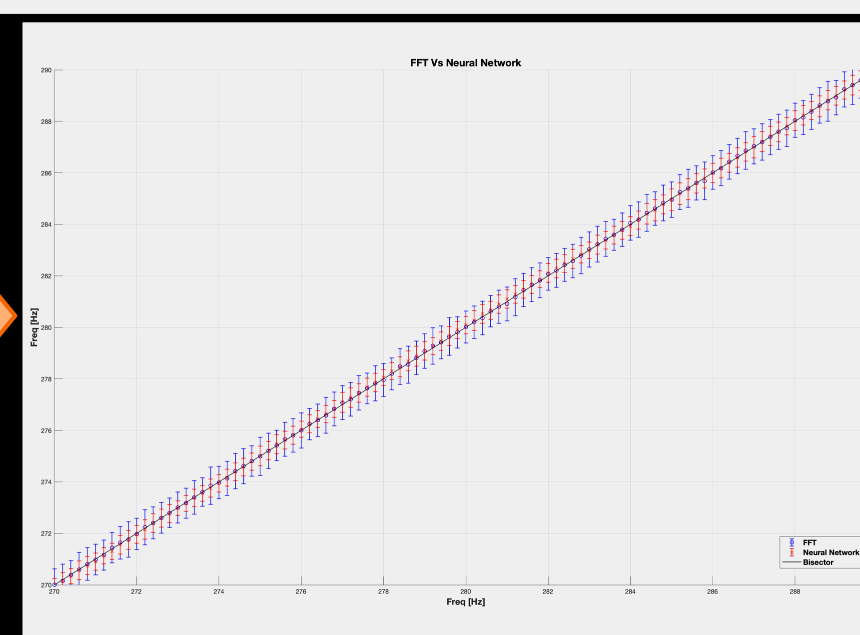
The analysis using the Hilbert method requires an interferogram with a sufficient number of periods, this does not allow us to provide the signal in real time. Therefore, we have developed a Neural Network (NN) capable of extracting the frequency from a window of one hundredth of a second, which corresponds to a 50-point sinusoid. We compared this NN with a tool implemented in Labview based on FFT. We applied these two methods to recover frequency from simulated signal with Gaussian noise and a frequency range between 150 Hz and 350 Hz. Across the entire range, the NN is twice as accurate as the FFT in terms of both the standard deviation of the reconstructed frequency signal and the spread.

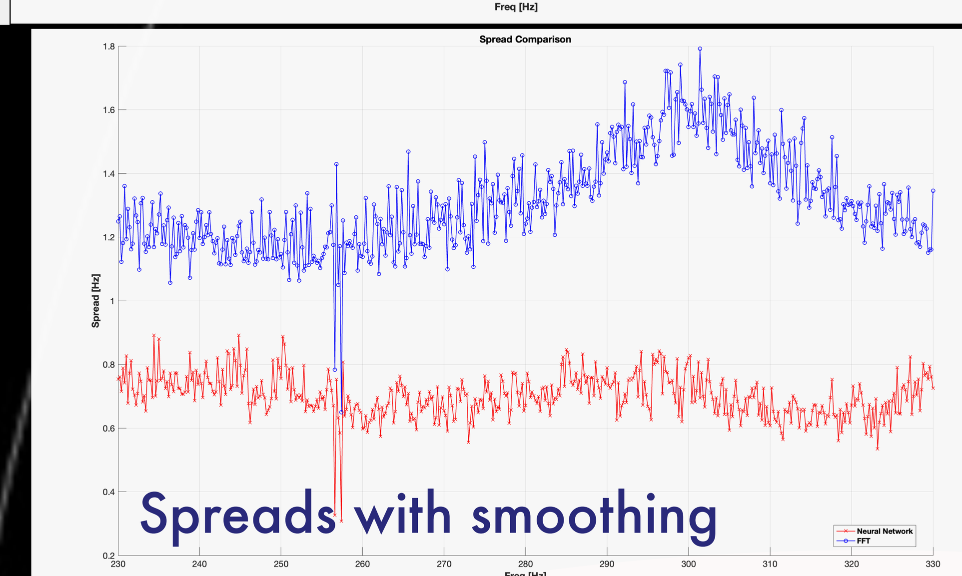
We used synthetic sinusoids with different frequencies and starting phases; we also varied their amplitude and mean value, or adding Gaussian noise to avoid overfitting; since the real signal always has the same average frequency, the network memorizes without generalizing and loses its robustness. Additionally, the network that achieved the best results was the one that output both the frequency and the cleaned sinusoid. This strategy ensures that by reconstructing both the clean sinusoid and the frequency, the network learns to better correlate the two pieces of information.



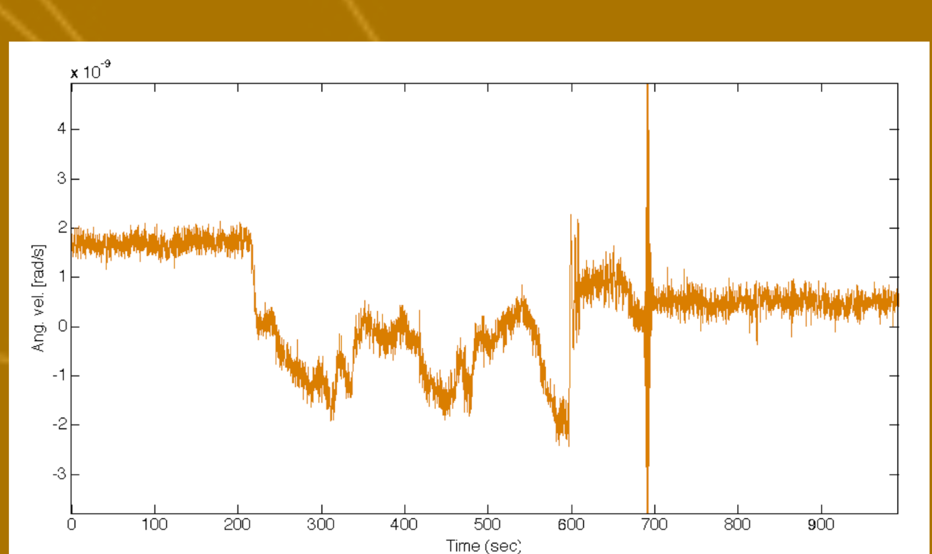




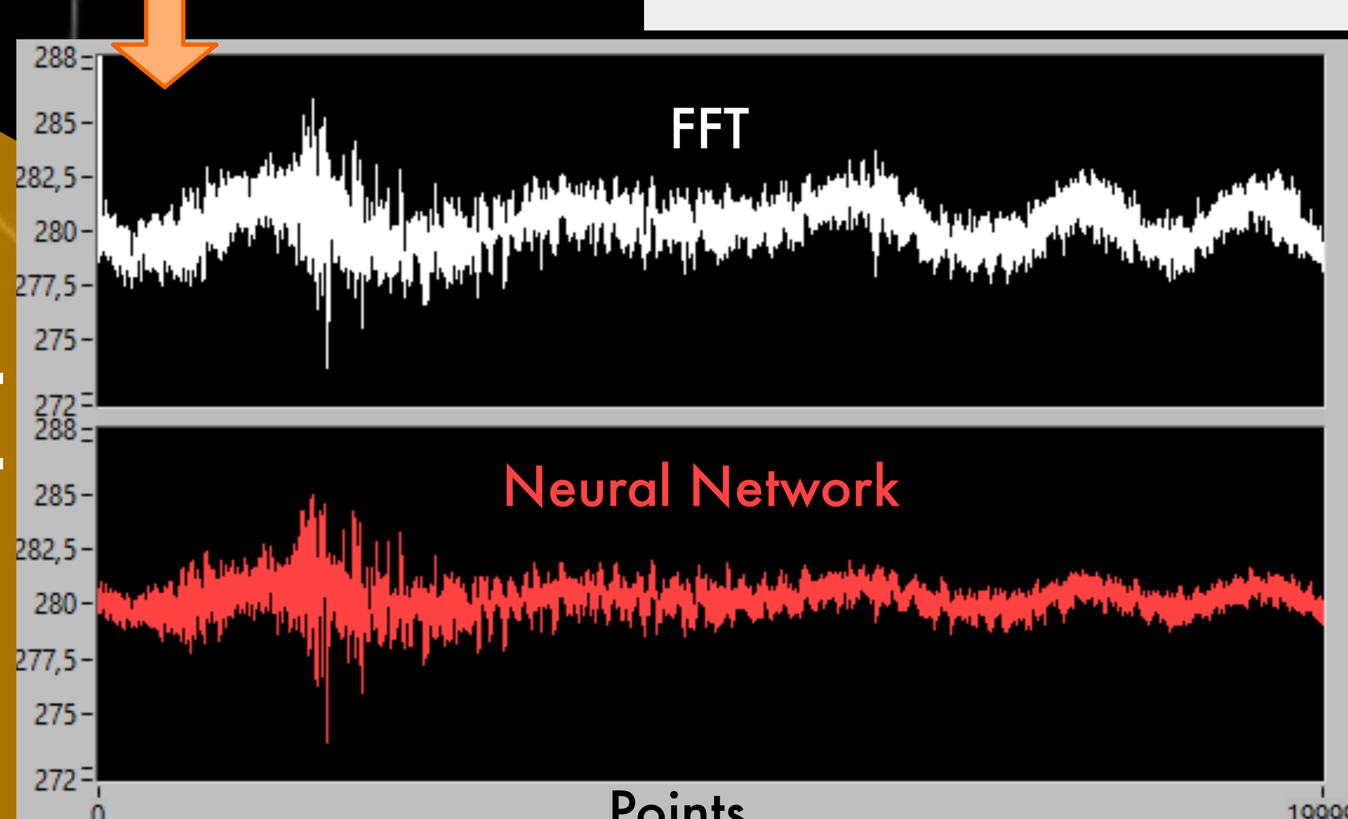




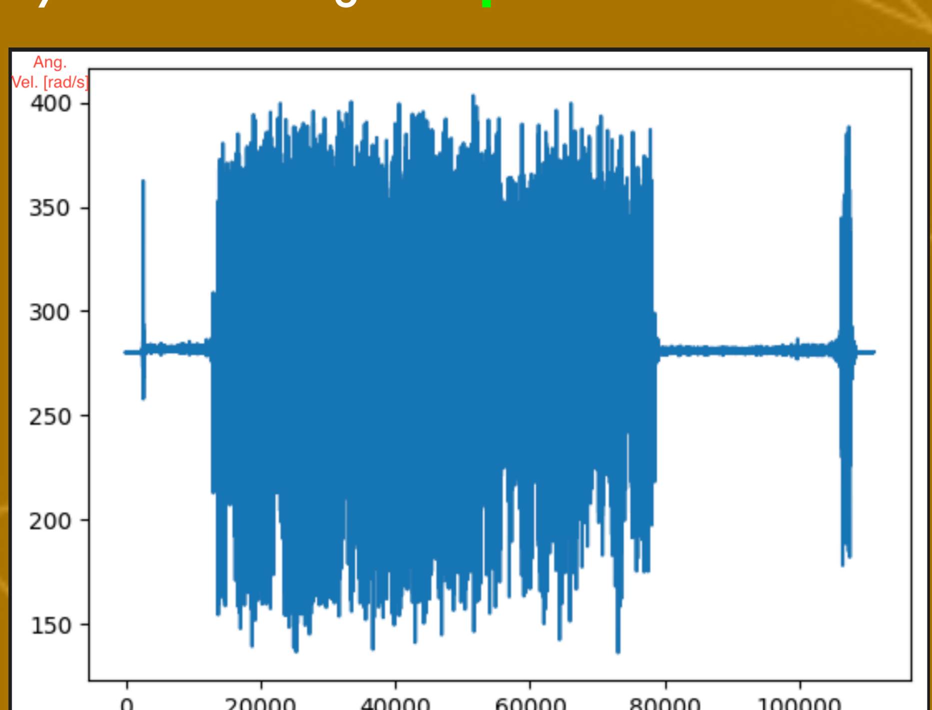
Typical disturbance due to laser dynamics during the **mode jump**



Earthquake

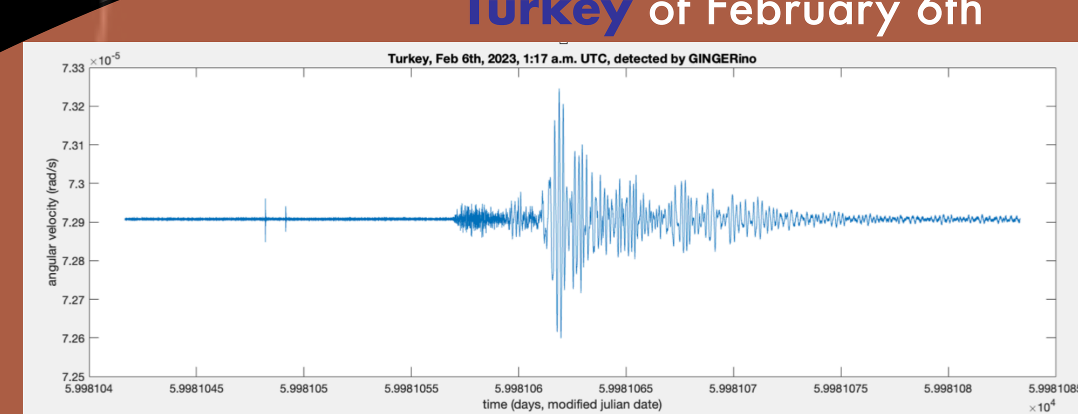


Typical disturbance due to laser dynamics during the **split mode**



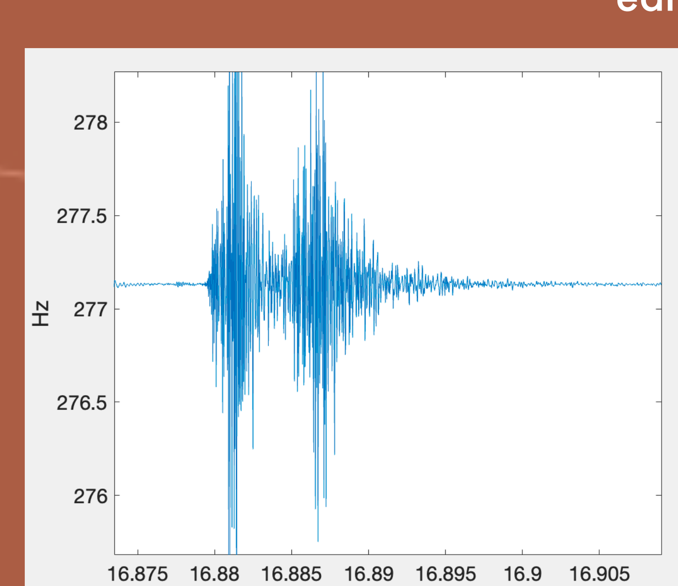
Although GINGERINO already has systems to classify the goodness of the signal and currently has a duty cycle of more than 90%, we are building NNs that identify disturbances from the laser. To do this we have as input the time series containing these disturbances and as output the mask that distinguishes between: 0 the good signal and 1 the anomalies. It might seem like a classification problem instead it is a regression problem, needing a seq2seq translator.

Contribution of the **earthquake** of **Turkey** of February 6th

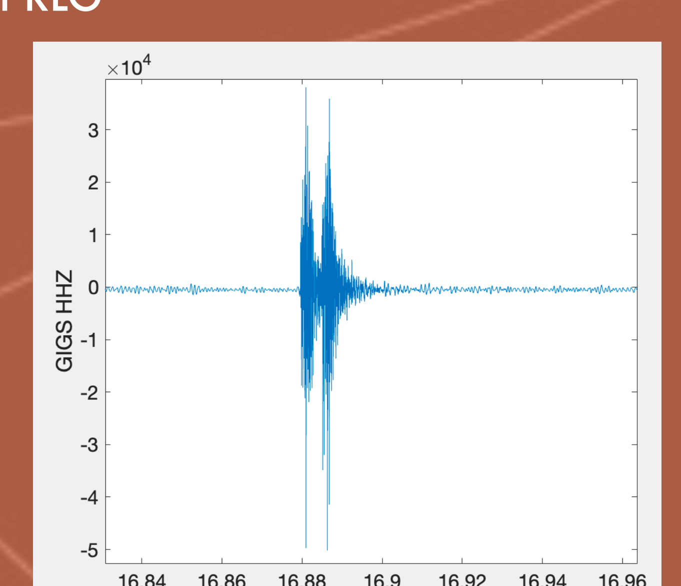


To have enough examples of earthquakes to train a network to recognize them, we create a network that generates the earthquakes seen by a Ring Laser Gyroscope (RLG), starting from the earthquakes revealed by GIGS. This is possible because we have a GIGS station co-located with GINGERINO.

This NN is later applied to other stations similar to GIGS to obtain new examples of earthquakes seen by an RLG



Map from GIGS to GINGERINO



References

[1] Possible Tests of Fundamental Physics with GINGER, Giuseppe Di Somma (Pisa U.) et al.DOI: 10.3390/astronomy3010003,Published in: Astronomy 3 (2024) 1, 21-28
[2] GINGER, Carlo Altucci et al., e-Print: 2209.09328 [gr-qc], DOI: 10.2140/memocs.2023.11.203 , Published in: Math. Mech. Compl. Sys. 11 (2023) 203-234

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