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INTERIM REPORT 1

Improving earthquake monitoring for gravitational-waves detectors with historical seismic data

Sky Soltero

ABSTRACT

A remarkable level of isolation from the ground is required for Advanced gravitational-wave detectors such as the Laser Interferometer Gravitational-Wave Observatory (LIGO) to function at peak performance. These ground based detectors are susceptible to high magnitude teleseismic events such as earthquakes, which can disrupt proper functioning, operation and significantly reduce their duty cycle. As a result, data is lost and it can take several hours for a detector to stabilize and return to the proper state for scientific observations. With advanced warning of impeding tremors, the impact can be suppressed in the isolation system and the down time can be reduced at the expense of increased instrumental noise. An earthquake early- warning system has been developed relying on near real-time earthquake alerts provided by the U.S. Geological Survey (USGS) and the National Oceanic and Atmospheric Administration (NOAA). The alerts can be used to estimate arrival times and ground velocities at the gravitational-wave detectors. By using machine learning algorithms, a prediction model and control strategy has been developed to reduce LIGO downtime by 30%. This paper presents further improvements under consideration to better develop that prediction model and decrease interruptions during LIGO operation.

INTRODUCTION

The two detectors that compose the Laser Interferometer Gravitational-Wave Observatory (LIGO) along with Virgo, and GEO600 detectors form a global network of gravitational wave interferometers. Keeping the detectors in operating mode requires an exceptional level of isolation from the ground so that the cavities can be held in optical resonance and be capable of observing displacements in space-time of less than one thousandth of the diameter of a proton. Environmental disturbances such as earthquakes can disrupt operating mode, destabilize detectors and cause the detectors to fall out of lock despite seismic isolation systems already in place to minimize interfering effects. When the detectors have fallen out of lock, where the control system cannot maintain optics at their stabilized positions, it can take many hours to return to the locked state and normal operation. During the observation run (referred as O1), from January 18, 2015 to January 12, 2016 operation was disrupted 62 times at LIGO Hanford and 83 times at LIGO Livingston due to earthquakes. Previous studies have shown that by using an early-warning earthquake system, relying on alerts provided by the U.S. Geological Survey (USGS) and the National Oceanic and Atmospheric Administration (NOAA), arrival times and ground velocities could be predicted which have a direct correlation with the operation status of the interferometers (Coughlin et al. 2017). The higher the incoming seismic velocities the more unstable the interferometer. A strategy intended to maintain lock and suppress these seismic disturbances early in the isolation system, at the expense of sensitivity and increased noise, would notably increase the interferometers' duty cycle (Biscans et al. 2018). Consequently, an earthquake early warning application named Seismon has been created to process real-time alerts from the USGS containing specific characteristic information about the earthquakes to provide estimated arrival times of the seismic phases and seismic amplitudes of the surface waves at the detector sites. By implementing detector control configurations, it is predicted that 40 to 100 earthquake operation interruptions could be prevented in a 6-month period.

OBJECTIVES

We aim to improve the algorithms of Seismon and as a result reduce LIGO downtime and increase the time the detectors are in observing mode. The alerts received from USGS contain information on time, location, depth, and magnitude of a specific earthquake which is then used to predict ground velocities, arrival time and amplitude of the various seismic phases at the detector sites. Seismon initially relies on earthquake notifications from a worldwide network of seismometers. P-waves (primary) traveling twice as fast as S-waves (secondary) reach the seismic stations first, thus providing the initial earthquake character estimations. As more and more data is acquired solutions to the hypocenter and magnitude of the earthquake are estimated and the solutions are sent to USGS's Product Distribution Layer (PDL). This ensures Seismon receives the most pertinent notifications. From there the notifications are processed to predict the seismic wave arrival time and the amplitude of the ground motion at the detectors. Past earthquake records and the seismic data at the detectors are also examined to predict how the ground motion will affect the observatories. The predicted amplitude and past earthquake data are compared, with the difference being minimized by adaptive simulated annealing algorithms to obtain solutions close to the global minima. Lastly, the predictions are used to create warnings delivered to the detectors containing the amplitude prediction, lockloss probability and the anticipated earthquake arrival time at the observatories. Seismon performance can be evaluated by recording and analyzing the notification duration, accuracy of predicted ground-motion amplitude, time-of-arrival predictions and the detector lockloss predictions. Current evaluations with the LIGO Observing Run 1 from September 2015 to January 2016, show about 90% of seismic events are within a factor of 5 of the predicted ground velocity and within 3s of the final predicted arrival time (Coughlin et al. 2017). Examining the times lockloss occurred, it can be said that the detectors generally fall out of lock at ground velocities greater than 5 μm/s but at lower velocities the data is more complex. Therefore, incorporating more ways of determining better lockloss predictions are of interest and would demonstrate success in this project. We purpose to improve the Seismon algorithm by incorporating more machine learning methods, broadening ground motion parameters and collecting more accurate data to enrich the prediction models.

APPROACH

We intend on advancing the Seismon application by improving predictions and acquiring more data of various parameters of incoming teleseismic events. We will test if the arrival time predictions can be improved by machine learning algorithms. To enhance ground velocity predictions, we will explore broadening our data resources and determine if we can acquire more data from hundreds of other seismic stations around the United States and the world. In addition, we would like to discover if we can use moment tensor data to further improve velocity predictions.

PROJECT SCHEDULE

I propose the following analysis and timeline for improving the code base: **1.** (week 1-3) Understanding how magnitude and location play a role in different velocity estimations. Running and understanding existing machine learning infrastructure. **2.** (week 4-6) Applying existing methods to broader seismic datasets. Creating a world grid with approximate earthquake velocities at various sections of the earth's surface based on historic data. **3.** (week 7-10) Employing machine learning algorithms to improve on the existing algorithms.

1. RESULTS (IN PROGRESS)

To better understand the effects of earthquake magnitude and global location on arriving earthquake surface velocities at the detectors, multiple plots using historical data have been made. In Figure 1, earthquake velocities are determined by dividing the distance from earthquake origin to detector by the difference of P-surface wave prediction times and earthquake times. These earthquake velocity magnitudes are then plotted at their origin in regards to latitude and longitude.

These plots show velocities reaching up to 16,000 m/s, which is higher than expected for simple P-waves. To explore the contributions of reflections internal to the Earth, in Figure 2, the effective velocities of the paths that include reflections (left) and those that do not (right). These velocities are shown on a grid of depth and degrees. While the plot on the right is in line with expectations for P-wave velocities, the plot on the left shows the contributions from reflections, leading to much higher effective velocities (and therefore faster arrivals). This result shows that the first arrivals of the P-waves shown in Figure 1 derive from P-waves reflecting in the Earth.

We now explore the velocities in real data measured from seismometers at the Hanford and Livingston sites. Figure 3 show the effective earthquake velocity, measured as the distance of the earthquake divided by the difference of the peak ground velocity time and earthquake time. It shows a range of velocities from 2000 to 5000 m/s which is appropriate for surface wave velocities dominating the time-series, as expected. We include only the historical data with peak ground velocities greater than 1 μ/s.

To understand the frequency of earthquakes at certain velocities, Figure 4 shows a histogram corresponding to the data used for Figure 3. These plots show that the majority of earthquakes have effective velocities between 2000 and 4000 m/s, as expected for surface waves. The outliers are likely either body wave contributions or contamination from other earthquakes.

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MOTIVATION

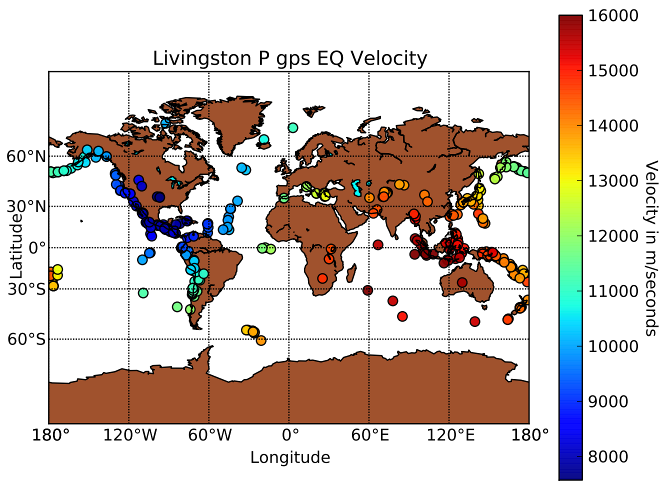

Figure 1. Magnitude of earthquake (EQ) velocities based on data using P-wave arrival times plotted at corresponding latitude and longitude points. Data with peak ground velocities less than 1 μ/s have been omitted. Displayed on the left is the plot for Livingston data and on the right is the plot for Hanford data.

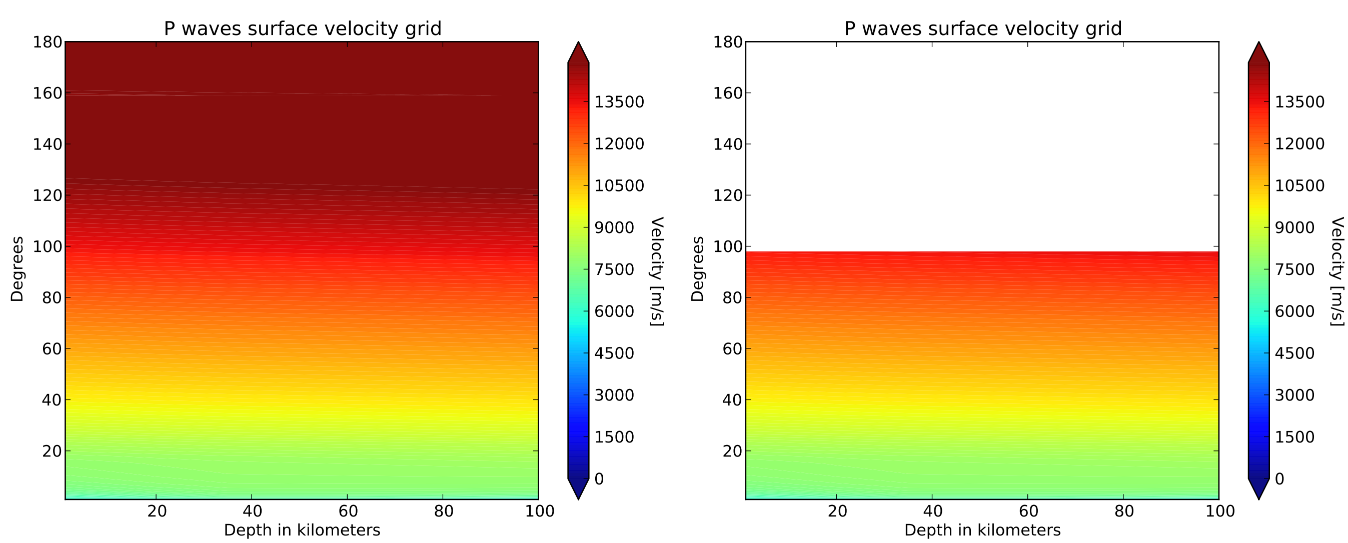

Figure 2. Magnitude of Earthquake velocities based on data using P-wave arrival times plotted in accord to degrees and dept of earthquake origin. Displayed on the left plot is the velocity without taking into account reflections. On the right plot reflections are taken into account and more expected P-wave velocities are shown.

Gravitational-wave detectors such as the Laser Interferometer Gravitational-Wave Observatory (LIGO) require exceptional isolation from the ground, yet are still susceptible to disrupting seismic events such as earthquakes. As a result proper functioning is disrupted, detectors fall out of lock and observing mode may be stalled for several hours, which decreases the opportunity of a gravitational-wave being observed. Previous studies have shown that by using an early-warning earthquake system known as Seismon, relying on alerts provided by the U.S. Geological Survey (USGS) and the National Oceanic and Atmospheric Administration (NOAA), arrival times and ground velocities could be predicted which have a direct correlation with the operation status of the interferometers (Coughlin et al. 2017).A strategy intended to maintain lock and suppress these seismic disturbances early in the isolation system, at the expense of sensitivity and increased noise, would notably increase the interferometers' duty cycle (Biscans et al. 2018). The motivation for this project is to ultimately increase the amount of time the LIGO detectors are in observing mode to increase the amount of gravitational waves detected. More specifically, we aim to decrease detector lockloss by improving arrival time, velocity and lockloss predictions so that a control strategy to stabilize the detectors may be utilized more effectively.

PROGRESS

The problem I am working on is increasing the accuracy of arrival time and velocity predictions. The more accurate the predictions are the more effective the detectors can implement a control strategy to combat the arriving earthquakes and keep the detectors running at the expense of added noise. Arrival time and velocity predictions are currently used in the Seismon application already with positive results on decreasing LIGO downtime. My project assumes by improving these arrival time and velocity predictions with machine learning we can further decrease the amount of downtime the detectors experience due to seismic disturbances. My approach so far is to understand how earthquake magnitude and origin position play a role in the velocity of the different seismic phases. I have done this by constructing different plots that can be referred to in the Results section above. My approach now is to try and implement the machine learning algorithm used for ground motion and lockloss predictions on earthquake velocity predictions. Additionally, I would like to construct a global grid using hundreds of thousands of historical earthquake data and try to map the typical earthquake velocity through approximate sections of the earth's surface. In the future we might take a look at incorporating more data resources and using moment tensor data to further improve velocity predictions. Some of progress I have made so far are plots displaying arrival times and velocity magnitudes in accord to their coordinate position on earth. Histograms showing us the occurrence of the various peak ground wave velocities have also been created. Also, I have created some plots displaying P wave surface velocities as a function of degrees and dept and have consulted with a seismologist the likelihood of certain high velocities. Additionally, I have started to understand and edit the machine learning algorithm we will be experimenting with on velocity predictions. Lastly, I have started to experiment with creating a global grid of velocities at different sections of the earth.

CHALLENGES

Some of the challenges I have met so far are conceptually understanding the data for different seismic phases and how they affect the earthquake velocity that we are concerned about and the detectors. Additionally, understanding the machine learning algorithm and what parts are needed for our arrival time and velocity predictions is also a bit confusing. Some of the challenges I anticipate are understanding how the predictions tie into the rest of the Seismon application since there are many scripts and files that construct it. I also anticipate some challenges in code due to my lack of experience with Matlab but know it will get easier as more progress is made.

REFERENCES

Biscans, S., Warner, J., Mittleman, R., et al. 2018, Classical and Quantum Gravity

Coughlin, M., Earle, P., Harms, J., et al. 2017, Classical and Quantum Gravity, 34, 044004

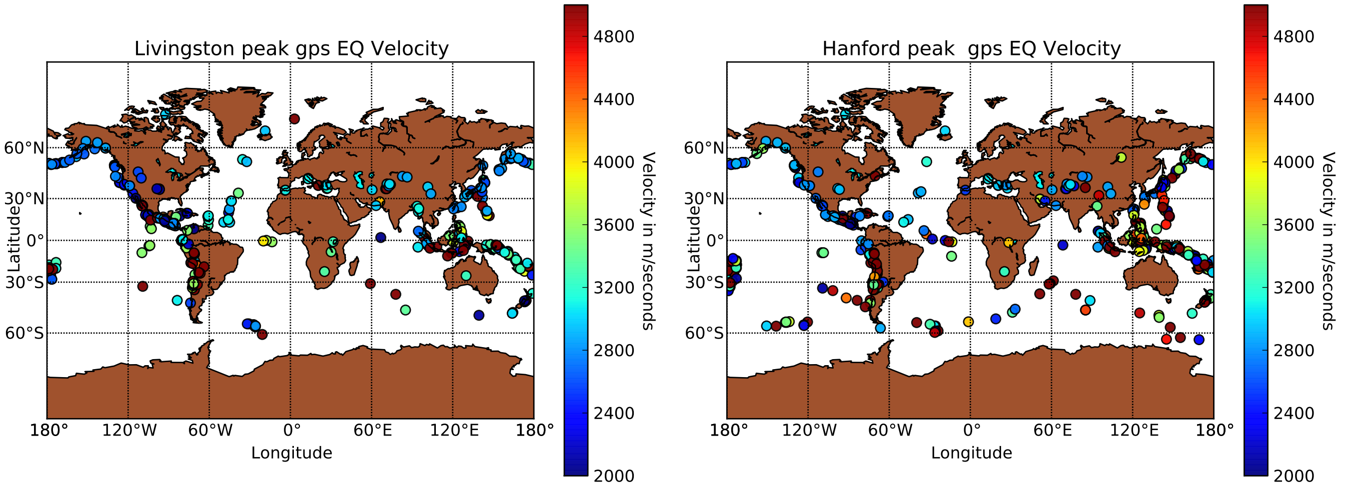

Figure 3. Magnitude of earthquake (EQ) velocities based on data using peak ground velocity gps time plotted at corresponding latitude and longitude points. Data with peak ground velocities under 1e-6 have been omitted. Displayed on the left is the plot for Livingston data and on the right is the plot for Hanford data.

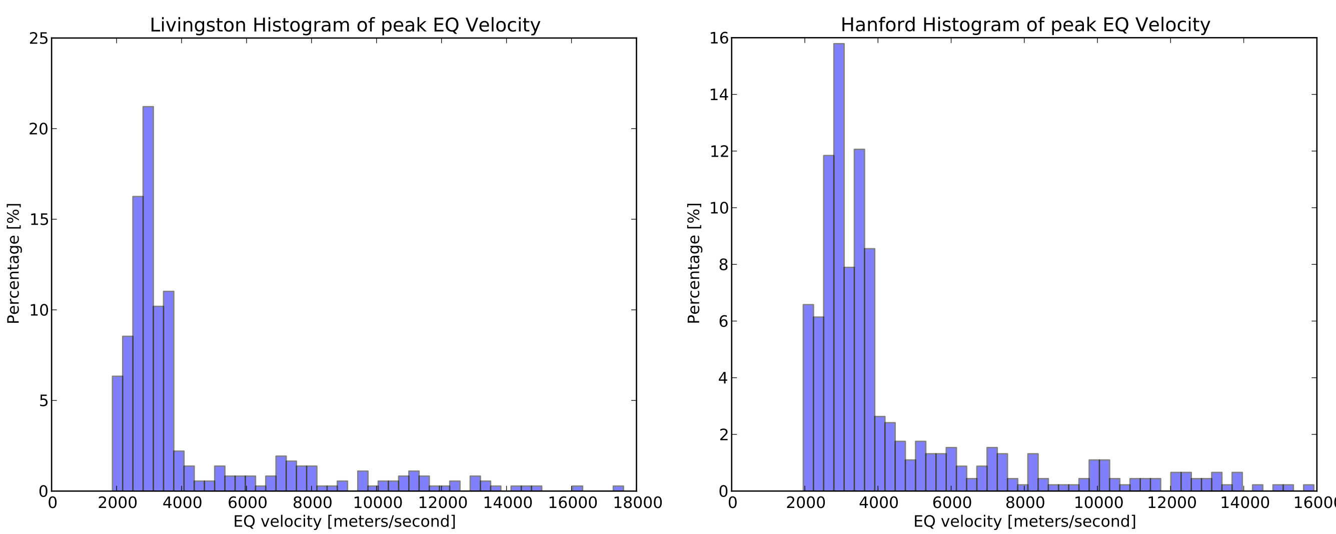

Figure 4. Percentage of different earthquake (EQ) velocities based on data using peak ground velocity gps time divided by the distance from the detectors. In association with the above Figure 2 plots. Data with peak ground velocities less than 1 μ/s have been omitted. Displayed on the left is the plot for Livingston data and on the right is the plot for Hanford data.