Case Study: Skymap Data Analysis

Leonidas Deligiannidis, Chen-Hsiang Yu, Mira Yun, and Hongsheng Wu

Department of Computer Science and Networking
Wentworth Institute of Technology, Boston, MA, USA
{deligiannidisl | yuj6 | yunm | wuh}@wit.edu

Abstract - We studied the similarities among sky localization maps corresponding to Gravitational Wave (GW) transients. Instead of using images for this study, we now use the sky-maps as two-dimensional signals for the analysis. The proposed method enabled us to train a Support Vector Machine (SVM) to classify GWs as events or background noise, with better accuracy than with our previous study. First, we use two morphologies of the skymaps where each morphology is derived from two different algorithms. Second, we compare the skymaps directly as signals and apply image processing techniques for the analysis. Third, based on the dataset and chosen features, an SVM machine learning model is trained to perform predictions for future signals. The current result shows that the proposed method not only improves background rejection in searches of gravitational-wave transients, but it also performs better than our previous study.

Keywords: Machine Learning, Signal Processing

1 INTRODUCTION

While the upgrades to the Advanced Laser Interferometer Gravitational wave Observatory (LIGO) are being implemented, we are obligated to develop and test new algorithms and methods for detecting Gravitational Waves (GWs) with high confidence. As advanced GW detectors are likely to produce multiple skymaps for the same event, new methods and algorithms are necessary to be developed. Here, we will try to quantify how similar these skymaps are, on an event-by-event basis in this paper.

Since Sep. 2015, when the first GW was observed (but announced later in 2016), we are in a new era in astronomy. The first observed GW was originated from the collision of Binary Black Holes (BBHs) [1-3]. This new messenger of the Cosmos will revolutionize the way we observe the Universe, probing parts and processes that are inaccessible by electromagnetic waves or neutrinos. Two of the detection and sky-localization methods involved in the search for GW transients are coherent-WaveBurst (cWB) [4] and omicron-LAL-Inference-Burst (oLIB) [5]. Both cWB and oLIB rely on excess power methods followed by a coherent analysis of the signals from the two Advanced LIGO detectors to identify transient events. Once the events are identified, constrained likelihood analysis and Bayesian methods are used to perform localization of the source in the sky. Such localization in the sky for GW sources is essential for understanding their populations, as well as for connecting GW and traditional astronomy with electromagnetic waves.

In this paper, we use skymaps produced by [6] for the first ever event-by-event comparison of cWB and oLIB in their ability to localize GW transients. In their study, they used as a proxy for their candidate (astrophysical) signals sine-Gaussian and Gaussian signals of multiple signal duration and frequency content. In addition, astrophysically motivated BBH approximants were also used. In general, the Advanced LIGO detectors and the search methods we invoked in this study are sensitive to transient signals with durations up to few seconds and frequency content between 40Hz and 1000Hz.

Sky localization as performed by the above study [6] establishes the probability of the GW source to lie in each of the 250,000 equal-area pixels over which the full sky is discretized. In their 2015-2016 observing run and with the two advanced LIGO detectors (one in Livingston, LA and another one in Hanford, WA), the sky localization accuracy is limited by the fact that the measurement of the arrival times of the GW plane wave is performed over a single baseline (defined by the locations of the two Advanced LIGOs). Typical 50% error areas are hundreds of square degrees [6]. This ability to localize is expected to improve with the addition of a third GW detector close to Pisa, Italy, which started some time in 2017

[7], and some of the detected events were accurately localized with its addition. In this paper, six detected and confirmed events are used to verify the functionality of our model trained by using Support Vector Machine (SVM) machine learning. We analysed simulated events and real background noise and then we trained of ML. We then used as input the real and confirmed GW events to verify our analytics approach to classify a signal as an event of background noise.

The rest of this paper is organized as follows. We introduce the dataset and the used analysis algorithms in Sections 2 and 3. Sections 4 and 5 present implementation details, statistical test results, and verification with machine learning algorithm. Finally, Sections 6 and 7 summarize the paper and outlines ideas for future work.

2 THE DATASET

The authors in [6] made publicly available the raw data corresponding to the sky maps they obtained through their extensive simulation work prior to the start of Advanced LIGO's first observing run in 2015 and 2016. A total of 5530 maps of simulated GW and 607 maps of real background noise were used in our study. The signal-to-noise ratio of the data was above 8. All intrinsic and extrinsic parameters of the sources have been chosen randomly. A sample set of skymaps showing background noise and a real event rendered using Mollweide projection is shown in Figure 1 and 2 respectively.

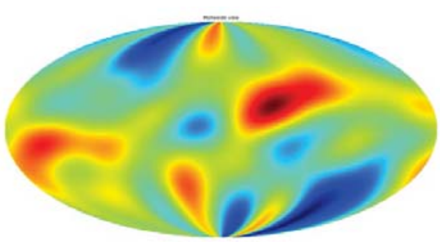

Figure 1: Background noise rendered using Mollweide projection.

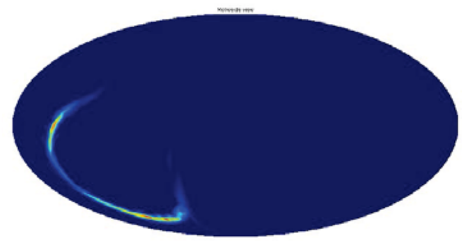

Figure 2: The first real event (GW150914) directly observed; rendered using Mollweide projection. GV first observed in September 14th, 2015 at 09:50:45UTC. https://losc.ligo.org/events/GW150914.

3 ANALYSIS ALGORITHMS

We used several algorithms for the analysis and classification of signals that contain potential GW events. The results of this analysis were later used to define features for our SVM classifier. For every simulated event, two skymaps were presented for comparison on an event-by-event basis to the following statistical tests. The maps were produced from the same signal utilizing a different technique [6]. The goal is to establish the centricity and overall statistical properties of the distribution for typical GW events. We chose four features for training an SVM model. These four features are explained below:

1. Mean Square Error (MSE) computes the difference between two sample signals:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(p_i - q_i)^2$$

   where N is the total number of pixels in an image (when the signal is represented as a 2-dimentional visualization) and p_i and q_i are the pixel values from the two signals.

2. Structural Similarity Index (SSI) [8] measures the structural similarity between two images as they are detected by the human eye. Images that appear indistinguishable to the human eye have an SSI value near 1 where images that are very distinguishable have an SSI value near 0. The SSI is calculated as:

ISBN: 1-60132-501-0, CSREA Press ©

$$SSI(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$

where μ_x and μ_y are the averages of the pixel values of the two input signals, σ_x^2 and σ_y^2 are the variances, and σ_{xy} is their covariance. c_1 and c_2 are two variables to stabilize the division with weak denominator.

3. Fidelity: as defined in information theory, measures the similarity between two distributions. It is calculated as:

$$Fidelity = \sum_{i=1}^{N} \sqrt{p_i * q_i}$$

The Fidelity assumes that the samples are probabilities with values ranging from 0 to 1.

4. Fast Fourier Transform (FFT) cross correlation: cross correlation can be performed to measure how similar two signals are; this is a fast operation if it is performed in the frequency domain. It can also indicate how much a template image/signal needs to be shifted to map in onto the comparing image/signal; this however, as it will be shown later, did not produce any useful information and we did not include it as an indicator. This can be done by transforming both signals to the frequency domain, taking the complex conjugate of one of them, and then multiplying the two. The value of 1 implies identical signals and 0 means that they are totally different.

4 RESULTS

We implemented and ran the algorithms presented in the previous section, using the Python packages SciPy and Healpy on a Lenovo laptop running 64-bit Ubuntu 14.04LTS, with a quad-core i7 Intel processor @2GHz and 8GB of RAM; each event was processed on average in 0.8 seconds. In Figures 3, 4 and 5, we show the outcome of the statistical tests.

As shown in Figure 3, there is a clear separation between event and noise. In general, noise has lower MSE and SSI values but higher Fidelity. All three features (MSE, SSI, Fidelity) show a difference between noise and events and this difference is statistically significant as we will show below. We found that the FFT cross-correlation algorithm did not produce any useful information in this study. In our previous study [9], where rendered images of the skymaps were used, we found that the FFT cross-correlation could be used as an additional feature.

One key question to ask is if any of these statistical tests can be used as a measurement to separate noise and signal in a search for GWs. This goes beyond the ability of individual searches for GWs and relies on what we have observed earlier, namely on the fact that multiple searches and sky-localization methods show strong correlations when processing GW signals (i.e., signals coherent in the Advanced LIGO detector sites) vs. how they behave on background (random) events.

We used the sample of events that we analysed above with their corresponding statistical tests values to construct Receiver-Operator-Characteristic (ROC) curves. Such curves allow us to assess the ability of the corresponding test to enhance the noise vs. signal discrimination using the skymap information. From this study, and as we can read off Figure 4, most of the methods perform comparably. All methods performed very well with area under the graph being over 0.85, 0.952 and 0.902, for SSI, MSE and Fidelity respectively.

We also tested our hypothesis that there is a significant difference in population means of the different types of events (signals and noise). Our independent variable was the type of signal (event, and noise) and our dependent variables were the scores of each algorithm (MSE, SSI, and Fidelity). Using Analysis of Variance (ANOVA), we found that there is a difference in performance of all the algorithms between noise and signals and this difference is statistically significant. Specifically, for MSE $F_{1,6135}$=257.8, SSI $F_{1,6135}$=480.9 and Fidelity $F_{1,6135}$=893.7, the *p* value is significant at 5% level (<0.001).

Figure 5 shows the mean values/distributions for each of algorithm (MSE, SSI, Fidelity). Each graph shows the distributions of our independent variable (TYPE) which is “EVENT” and “NOISE”.

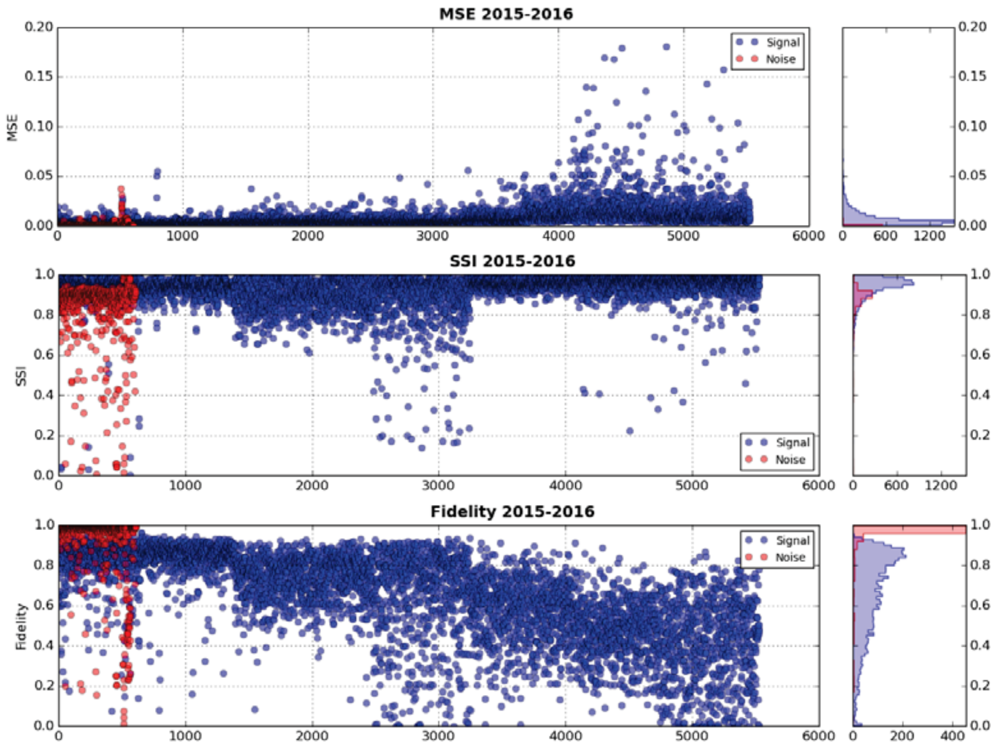

Figure 3: Plots of the raw MSE, SSI, and Fidelity values for all 5530 simulated events and 607 background noise signals [6]. The left-hand-side panels show these values on an event-by-event basis, while the right-hand-side panels are histograms of the corresponding quantities. We use blue markers for skymaps corresponding to GW signal and red markers for noise.

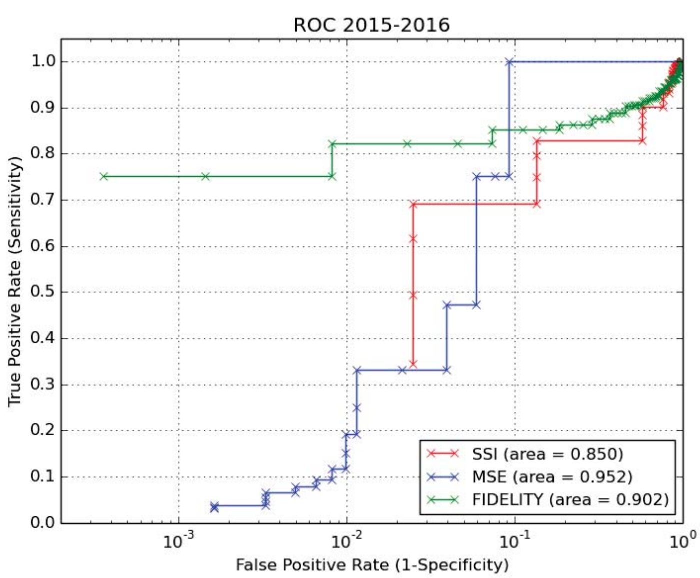

Figure 4: ROC curve for SSI, MSE, and Fidelity.

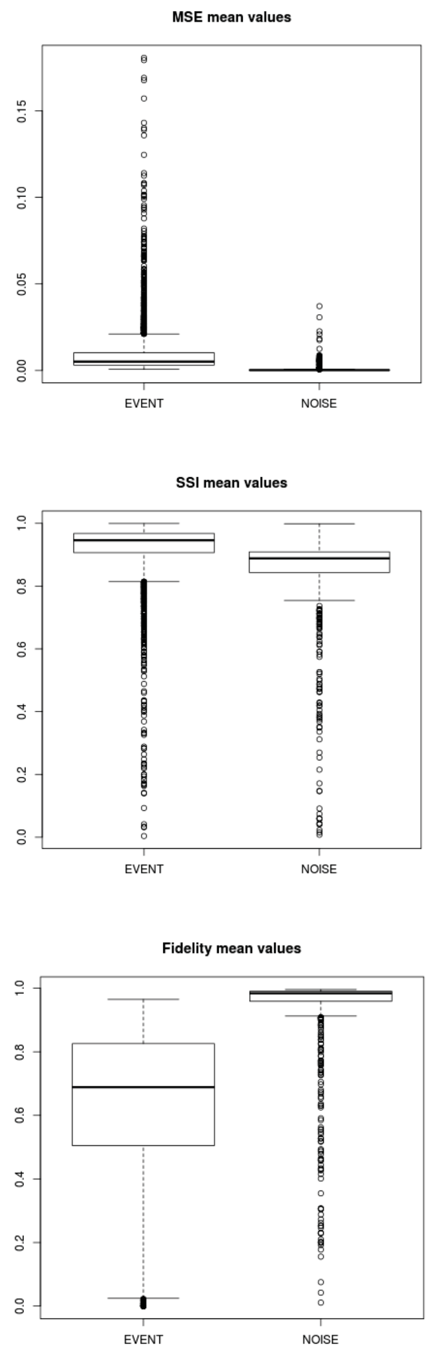

Figure 5: Three plots showing the mean distributions of the Events and Background Noise for the three algorithms (MSE, SSI, and Fidelity).

5 PREDICTIONS AND VERIFICATION UNSING MACHINE LEARNING

Based on the dataset and the selected features, we trained our SVM model in python. In training our model, the grid search [10] was performed to find the hyperparameter (C) for the SVM. For each search, 5-fold cross validation was performed 5 times and its average was calculated. The size of our dataset was 6137 points; 5530 simulated events and 607 of background noise. About a third of the data (2026 points) was reserved for testing and validation; (196 background samples, and 1830 simulated event samples). Table 1 shows the results of our classifier with accuracy of 0.99 (+/- 0.02).

Table 1: Performance of SVM.

	precision	recall	f1-score	support
Noise	0.96	0.93	0.94	607
Signal	0.99	1.00	0.99	5530
Avg./total	0.99	0.99	0.99	6137

The Confusion Matrix, shown in Table 2, indicates that out of the 196 background samples, 11 were classified falsely as events and the 185 correctly as noise. From the 1830 simulated events, only 4 were classified falsely as noise.

Table 2: Confusion Matrix on the Test dataset.

	Noise	Signal
Noise	185	11
Signal	4	1826

To validate our model and analysis, we used the trained SVM for predictions. We used the publicly available GW signals as an input to conduct the prediction and validation. This includes the first six confirmed GW signals. The trained SVM model predicted correctly that the inputs were all events with confidence of 89% to 99%.

6 DISCUSSION

We have performed a statistical analysis on sky localization maps for GW events as simulated and analysed by GW transient-finding methods for quantifying their similarities. As one would expect intuitively, such methods produce maps that our statistical tests deem to be very similar. Among the tests that we performed, the MSE and Fidelity are the ones with the sharpest cut off (followed by the SSI), indicating their potential ability to perform better when involved in a method-consistency-test. A key quantity we have not presented in this paper is the corresponding distribution of our statistic when performed on noise events, i.e. detector artefacts not corresponding to astrophysical sources. Due to proprietary access to such data by the LIGO Scientific Collaboration, we have submitted a request for the public release of a representative sample of such noise data for completing this analysis.

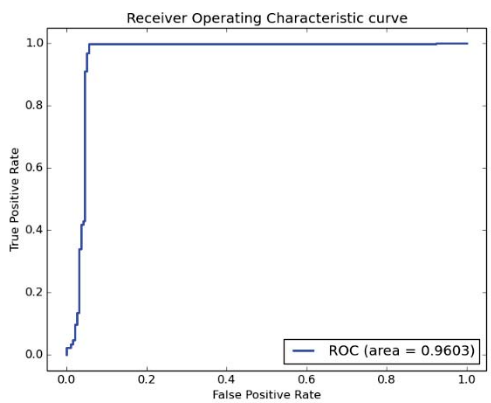

Figure 6: ROC curve for the SVM.

To assess the ability of the SVM and test the classifier using the three features (MSE, SSI, Fidelity) of the skymaps information, we constructed a ROC curve. This ROC curve, shown in Figure 6, indicates that the trained SVM model can perform very well and the area under the curve is 0.96.

7. CONCLUSION AND FUTURE WORK

The observation of gravitational waves has become one of the most important events in Astrophysics. The gravitational waves are ripples in space generated in certain gravitational interactions and propagate as waves. The collected data are huge, complex and difficult to manipulate. In this paper, we presented a methodology involving an SVM to classify skymaps as containing signals or background noise. The current results show that the proposed method not only improves background rejection in searches of gravitational-wave transients, but it also performs better than our previous study.

For future work, we will extend our current project to implement a new mobile framework for researchers to access and investigate this data. The research problems include: (1) How to extend existing mobile technologies (front-end User Interface and back-end) to provide a scalable mobile framework for accessing huge data-sets and (2) how to design a proper authentication model to access sensitive LIGO data that is stored in a distributed environment maintained by different authority entities.

REFERENCES

[1] LIGO Scientific and Virgo Collaboration, *Phys. Rev. Lett.* **116**, 241103 (2016)

[2] LIGO Scientific and Virgo Collaboration, *Phys. Rev. Lett.* **116**, 061102 (2016)

[3] LIGO Scientific and Virgo Collaboration, *Phys. Rev. Lett.* **116**, 131103 (2016)

[4] S. Klimenko et al., *Phys. Rev. D* **92**, 042004 (2016)

[5] R.Lynch, S. Vitale, R Essick, E. Katsavounidis, F Robinet, arXiv:1511.05955

[6] R. Essick, S. Vitale, E. Katsavounidis, G. Vedovado, S. Klimenko, Astrop J, 800:81 (2015); public data release at http://www.ligo.org/scientists/burst-first2years/

[7] LIGO Scientific and Virgo Collaboration, arXiv:1304.0670 / Living Reviews: 10.1007/lrr-2016-1

[8] Z. Wang, A. C. Bovik, H. R. Sheikh and E. P. Simoncelli, IEEE Transactions on Image Processing, vol. 13, no. 4, pp. 600-612, Apr. 2004.

[9] Leon Deligiannidis, "An Image Analysis of Sky-Localization Maps of Gravitational-Wave Transients", 2016 International Conference on Computational Science and Computational Intelligence (CSCI), Las Vegas, NV, 2016, pp. 698-702.

[10] Chih-Wei Hsu, Chih-Chung Chang, Chih-Jen Lin, et al. 2003. A practical guide to support vector classification. (2003).