ESTIMASI PARAMETER FISIS SISTEM LUBANG HITAM GANDA BERDASARKAN DATA GELOMBANG GRAVITASI DENGAN *CONVOLUTIONAL NEURAL NETWORK*

Diajukan untuk memenuhi salah satu syarat untuk memperoleh gelar sarjana sains program studi fisika kelompok bidang kajian fisika antariksa dan energi tinggi

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Estimasi Parameter Fisis Sistem Lubang Hitam Berdasarkan Data Gelombang Gravitasi Dengan *Convolutional Neural Network*

ABSTRAK

Selama 10 tahun terakhir dunia astronomi mengalami revolusi setelah ditemukannya gelombang gravitasi oleh dua detektor LIGO yang bersumber dari tumbukan spiral komponen-komponen sebuah sistem lubang hitam ganda. Salah satu tantangan yang dihadapi dalam studi berkaitan dengan estimasi parameter fisis yang dapat memakan waktu berjam-jam bahkan berhari hari menggunakan inferensi Bayesian sebagai metode standarnya. Penelitian ini bertujuan untuk melakukan estimasi tiga parameter fisis utama di antaranya ialah massa primer dan sekunder, serta jarak sistem lubang hitam ganda dengan memanfaatkan model *Convolutional neural network* (CNN). Untuk melatih model ini, data simulasi dibangkitkan dengan pendekatan numerik *SEOBNRv4_opt* dan gangguan *transient* dalam bentuk deret waktu (*time series*) yang dikonversi menjadi spektogram. Uji statistik-t Welch dilakukan terhadap distribusi PSD (*power spectral density*) untuk memastikan data simulasi ini sesuai dengan data yang didapatkan oleh LIGO sehingga dapat merepresentasikan sinyal gelombang gravitasi nyata. Hasil implementasi model CNN terhadap data nyata untuk estimasi massa primer memberikan nilai MAE sebesar 0,036, RMSE sebesar 0,067, dan R^2-score sebesar 0,942. Sedangkan, untuk estimasi massa sekunder diperoleh MAE sebesar 0,031, RMSE sebesar 0,056, dan R^2-score sebesar 0,926. Sementara itu, dalam estimasi jarak diperoleh MAE sebesar 0,053, RMSE sebesar 0,099, dan R^2-score sebesar 0,752. Dalam melakukan komparasi distribusi hasil estimasi dengan data nyata dilakukan uji statistik Cramér-von Mises yang memberikan nilai statistik sebagai indikator kemiripan. Nilai statistik yang diperoleh untuk massa primer sebesar 0,042 dengan signifikansi (*p-value*) 0,939 yang jauh lebih besar dari taraf nyata 0,05. Sedangkan, untuk massa sekunder diperoleh nilai statistik sebesar 0,136 dengan signifikansi 0,444. Sementara itu, untuk jarak diperoleh nilai statistik sebesar 0,032 dengan signifikansi 0,979. Model ini dapat mengestimasi tiga parameter fisis utama secara akurat dan efisien dengan waktu komputasi hanya beberapa detik sehingga dapat menjadi metode alternatif yang cepat tanpa sumber daya komputasi yang tinggi.

Kata Kunci : *Convolutional Neural Network,* Gelombang Gravitasi, Sistem Lubang Hitam Ganda

Physical Parameter Estimation Of Binary Black Hole Systems Based On Gravitational Wave Data Using Convolutional Neural Network

ABSTRACT

Over the past 10 years, the world of astronomy has been revolutionized after the discovery of gravitational waves by two LIGO detectors originating compact binary coalescences such as binary black hole system. One of the challenges faced in this study is the physical parameter estimation which can take hours or even days using Bayesian inference as the standard method. This study aims to estimate three main physical parameters, including the primary and secondary masses, and the distance of the double black hole system using the Convolutional neural network (CNN) model. Simulation data using the SEOBNRv4_opt approach with additional noise in the form of time series converted into spectrograms are generated as training data. A Welch's t-statistic test was performed on the PSD (power spectral density) distribution to ensure that the simulation data matches the data obtained by LIGO so that it can represent real gravitational wave signals. The implementation of the model resulted an MAE of 0.036, RMSE of 0.067, and R^2-score *of 0.942 for the primary mass. On the other hand, it yielded an MAE of 0.031, RMSE of 0.056, and* R^2-score *of 0.926 for the secondary mass. Meanwhile, for distance estimation, we obtained an MAE of 0.053, RMSE of 0.099, and* R^2-score *of 0.752. In comparing the distribution of the estimated results with real data, the Cramér-von Mises statistical test was carried out which provided a statistic value as an indicator of similarity. For the primary mass the statistical value of 0.042 obtained with a significance (p-value) of 0.939 which is much greater than the lower limit of 0.05. Meanwhile, for the secondary mass, a statistic value of 0.136 was obtained with a significance of 0.444. On the other hand, for the distance, a statistic value of 0.032 was obtained with a significance of 0.979. This model can estimate three main physical parameters accurately and efficiently with a computing time of only a few seconds, making it a fast alternative method without high computing resources.*

Keywords : *Binary Black Hole Systems, Convolutional Neural Network, Gravitational Waves*

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DAFTAR GAMBAR

DAFTAR TABEL

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