

Multi-scale searching machine to detect the cosmic strings network

A. Vafaei Sadr^{1,2,3}, S. M. S. Movahed^{*1}, M. Farhang¹, C. Ringeval⁴, F. R. Bouchet⁵, B. Bassett^{3,6,7,8} and M. Kunz²

¹*Department of Physics, Shahid Beheshti University, Velenjak, Tehran 19839, Iran*
**E-mail: m.s.movahed@ipm.ir*

²*Département de Physique Théorique and Center for Astroparticle Physics, Université de Genève, 24 Quai Ernest Ansermet, 1211 Genève 4, Switzerland*

³*African Institute for Mathematical Sciences, 6 Melrose Road, Muizenberg, 7945, South Africa*

⁴*Centre for Cosmology, Particle Physics and Phenomenology, Université Catholique de Louvain, Louvain-la-Neuve B-1348, Belgium*

⁵*Institut d'Astrophysique de Paris (UMR7095: CNRS & UPMC-Sorbonne Universities), F-75014, Paris, France*

⁶*South African Astronomical Observatory, Observatory, Cape Town, 7925, South Africa*

⁷*SKA South Africa, The Park, Park Road, Pinelands, Cape Town 7405, South Africa*

⁸*Department of Maths and Applied Maths, University of Cape Town, Cape Town, South Africa*

Cosmic topological defects formed during phase transition in the very early universe are theoretically well-motivated. The cosmic string (CS) can leave the imprint on the CMB stochastic field leading to emerge additional stochasticity behavior. We will rely on the stochasticity nature of CMB superimposed by Cs network and therefore some topological and geometrical measures accompanying multi-scale edge-detection algorithm to examine the capability of Cs detection, will be introduced and utilized. On the noiseless sky maps with an angular resolution of $0.9'$, we show that our pipeline detects cosmic string with $G\mu$ as low as $G\mu > 4.3 \times 10^{-10}$. We also explore two powerful tree-based machine learning algorithms to exploit the feature importance. Such approach opens new insight into utilizing prior information for detecting exotic features in a cosmological stochastic field. Machine learning method enables us to detect Cs with $G\mu > 2.1 \times 10^{-10}$ at 3σ level.

Keywords: cosmic background radiation - cosmology; theory - early Universe - large-scale structure of Universe, methods: data analysis

1. Introduction

The line-like version of topological defects called cosmic strings (CSs) are theoretically expected to be produced in the early Universe (see ^{8,9} and references therein). A lot of effort has been put into developing powerful statistical tools for cosmic string network detection and putting tight upper and lower bounds on the CS tension, parameterized by $G\mu$, where G and μ represent Newton's constant and the string's tension, respectively. Mathematical description of the string tension is intimately related to the energy of the phase transition epoch as $\frac{G\mu}{c^2} = \mathcal{O}(\varpi^2/M_{\text{Planck}}^2)$, with the symmetry breaking energy scale, ϖ . The CS network can left imprints on the CMB anisotropies according to different mechanisms such as ordinary and integrated Sachs-Wolfe effect ⁴, lensing and polarization. The Gott-Kaiser-Stebbins effect produces line-like discontinuities on the CMB temperature anisotropies of the form: $\frac{\delta T}{T} \sim 8\pi G\mu v_s$ ^{4,7}. Here v_s is the transverse velocity of the string. CMB-based approaches to search for CS have been conducted to wide range of constraint on the $G\mu$. This range covers the lower value form $G\mu \gtrsim 6.3 \times 10^{-11}$ for noise less

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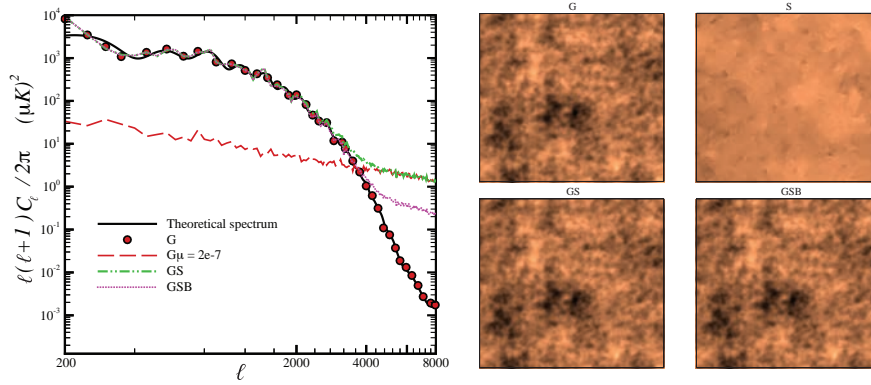


Fig. 1. Left panel: The CMB power spectrum for different components. Right panel includes the Gaussian CMB, CS-induced anisotropies, the combination of the Gaussian and string, smeared by the beam named by G, S, GS and GSB maps, respectively⁹.

map³ to upper limit with $G\mu < 8.8 \times 10^{-7}$ ^{1,8,9}. Here, we propose a multi-scale edge-detection algorithm to search for the CS network on the CMB anisotropies. In order to deduce a systematic method to examine the most relevant method in recognizing CS network on the CMB map, we use machine learning (ML)-based algorithms to search for CS network on CMB data.

2. Simulation the components

Our pipeline for simulation mock CMB map consists of three components: (1) the Gaussian inflation-induced contribution denoted by G , as well as the secondary lensing signal, (2) the CS contribution, $G\mu \times S$, where S represents the normalized simulated template for the string signal and $G\mu$ sets its amplitude, and (3) the experimental noise indicated by N . The full simulated map $T(x, y)$, with x and y representing pixel coordinates, would then be $T(x, y) = B[G(x, y) + G\mu \times S(x, y)] + N(x, y)$, where B characterizes the beam function⁹. For the CS-induced CMB anisotropies, we use high-resolution flat-sky CMB maps obtained from numerical simulations of Nambu-Goto string networks using the Bennett-Bouchet-Ringeval code. They are also produced by stacking maps from various redshifts^{2,5,6}. Our simulated map is in the flat sky limit with 100 square maps of side $\Theta = 7.2^\circ$, with 1024×1024 pixels with the resolution of $R = 0.42'$ before convolution with an experimental beam. Figure 1 indicates the power spectrum of various components together the corresponding real space fluctuations.

3. Image processing based methods

Our goal in this work is to evaluate the performance of various sequences of image-processing and statistical tools in the detection of the trace of a possible CS network

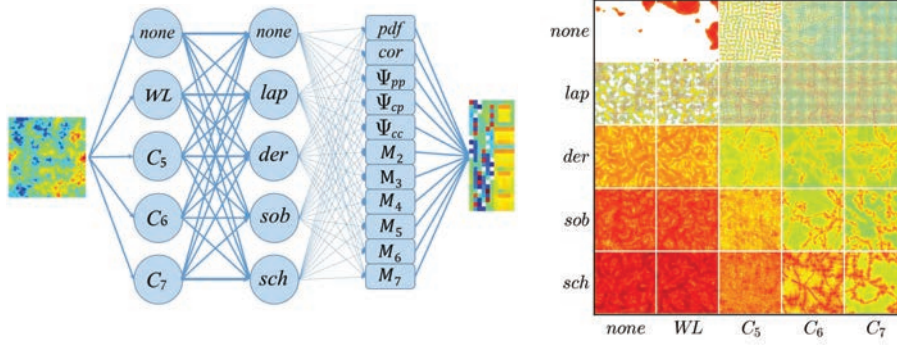


Fig. 2. Left panel: A schematic view of the feature vector generation. For a CMB map including a 275-dimensional feature vector, here presented as a 25×11 array (right side). Right panel: All of the 25 outputs of the image processing layers of the algorithm applied to a map with $G\mu = 1.0 \times 10^{-7}$. The color scale is logarithmic. These are then passed to the 11 statistical measures, yielding the full set of 275 features⁸.

on CMB maps. Our proposed pipeline comprises two major steps: (1) Processing CMB maps: here we apply several image-processors with the aim to isolate or/and enhance the CSs imprint on CMB maps. The two pillars of this step are a multi-scaling analysis through curvelet-decomposition of the input maps and the generation of filtered maps through extended Canny algorithm. (2) Using various statistical analysis of CMB map to quantify the detectability of CSs signature on the filtered maps from the first step. Curvelet decomposition and extended Canny algorithm are used to enhance the string detectability as indicated in Figure 2. The one-point probability density function, the weighted two-point correlation function (TPCF) of the anisotropies, the unweighted TPCF of the peaks and of the up-crossing map, as well as their cross-correlation are among statistical tools used here. On noiseless sky maps with an angular resolution of $0.9'$, we show that our pipeline detects CSs with $G\mu$ as low as $G\mu \gtrsim 4.3 \times 10^{-10}$. At the same resolution, but with a noise level typical to a CMB-S4 phase II experiment, the detection threshold would be to $G\mu \gtrsim 1.2 \times 10^{-7.9}$.

4. Machine learning approach

The purpose is to develop a detection strategy through optimally exploiting the available information accessible to the multi-scale pipeline of⁹. We use two tree-based supervised classifiers: random forest (RF) and gradient boosting (GB)⁸. The information in the maps is compressed into feature vectors before being passed to the learning units. The feature vectors contain various statistical measures of the processed CMB maps that boost cosmic string detectability (see Figure 2). Our proposed classifiers, after training, give results similar to or better than claimed detectability levels from other methods for string tension. Our results confirm that the the minimum detectable $G\mu$ for a noise-free experiment is 2.1×10^{-10} . This

bound is, to the best of our knowledge, below the claimed detectability levels by other methods on noise-less maps. The minimum detectable tension in this work for a CMB-S4-like (II) experiment, $G\mu \gtrsim 3.0 \times 10^{-8}$, is a major improvement over the claimed detectability level by the above multi-scale pipeline, $G\mu \gtrsim 1.2 \times 10^{-7}$. For a Planck-like case, the minimum detectable $G\mu$ is 5×10^{-7} , comparable to the current upper bounds from Planck data¹. Final remark is that, the scale of curvelet components should be matched to the effective resolution of experiments in the presence of experimental noise, larger-scale curvelet components are the more important decomposers. For filters it is difficult to make a definite recommendation, while the second moment is the most important statistical measure in the classification process.

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