Temporal Convolutional Networks for RR Lyrae Light Curve Prediction

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Abstract

RR Lyrae stars are the fundamental distance indicators for studying Galactic structure. Accurate light curve modeling enables improved period-luminosity relations and variability characterization. In this work, we propose a Temporal Convolutional Network (TCN) model to predict phase-folded I-band light curves of RRab variables using only five physical parameters- mean I-band magnitude, amplitude, $R21$, $\phi21$, and period. Our model is trained using synthetic phase-aligned Fourier light curves generated from OGLE catalog parameters. The best-performing TCN achieves a validation RMSE of 0.0963 mag, outperforming classical template-based interpolation approaches. This experiment demonstrates the ability of TCNs to learn phase-dependent brightness variations and implicitly encode the physical structure of pulsating stars, offering a scalable deep-learning alternative for upcoming large-scale surveys.

1. Introduction

RR Lyrae stars, the pulsating variable stars, are on the horizontal branch of the Hertzsprung-Russell map. RRab are fundamental mode pulsating stars. Their brightness changes by 0.5 to 1.5 magnitudes in the visible spectrum, and they pulse every 0.4 to 0.8 days. Their light curves are uneven, with quick jumps and slower falls. The Galactic halo's main signs are these stars. Their regular periodicity and close link between infrared period and luminosity make it possible to measure distances very accurately over long cosmic distances.

It is hard to get full light curves for RR Lyrae stars because they need to be watched many times over many pulse cycles. It is hard to get high-cadence data because of things like limited viewing time, weather conditions, and the way the stars are spread out in the sky. This often leads to sparse or irregular sampling. This problem has led to the creation of a number of different computer methods that can rebuild or predict full light curves from only a small amount of data [1]. In the literature, several methods have been used for modeling the RR Lyrae light curves, which are given below:

- **Fourier decomposition:** The Fourier method describes the shape of a light curve by fitting it with a series of sine waves (Simon & Lee 1981). It works well, but it can be sensitive to noise and needs data that is well sampled.

- **Gaussian Processes:** These models show how observations relate to each other and help make predictions when data points are unevenly spaced in time (eg, VanderPlas & Ivezic 2015 for variable stars). They work fine, but become slow and expensive to run on very large datasets.

- **Template fitting:** For sparse data (eg, Sesar et al. 2010 using SDSS), researchers scale ready- made light-curve templates from well-observed stars. But this approach often does not catch the unique variations of each star.

However, these older methods often cannot perform up to the mark when the data is noisy or when they need to predict beyond some given range. They also need a good number of data points to work well. In many cases, they cannot fully capture how RR Lyrae stars change under different metallicities, evolutionary stages, or environments.

In this work, we use Temporal Convolutional Networks (TCNs). This deep-learning model uses dilated convolutions, which help it learn long-range patterns in time-series data.
In deep learning, convolution-based architectures have demonstrated exceptional results in time-series forecasting. To predict complete I-band curves from just five inputs, we train the TCN on artificial light curves derived from the catalog parameters. This method has a number of benefits, like the ability to scale effectively to handle the millions of RR Lyrae stars anticipated from future surveys such as LSST, learn the underlying physical relationships from

the data, and generalize across the parameter space with less dense observational data for each star [2,3].

2. Literature Review

Over the past century, scientists have worked on studying the RR Lyrae star light curves, their physical properties, and the behavior of their pulsation. In 1939, Oosterhoff noticed a pattern while studying the RR Lyrae stars in a globular cluster. He observed that the RRab stars can be categorized into two clear groups based on their average periods. This is known as the “Oosterhoff dichotomy” [4].
This led researchers and astronomers to use RR Lyrae stars to measure stellar distances. Due to their stable pulsation cycle, they work as a reliable way to measure distances to faraway objects and understand different stars.

Simon and Lee (1981) [5] introduced systematic Fourier decomposition techniques to study the RR Lyrae light curve structures. To connect these Fourier parameters, such as amplitude ratios and phase differences, with actual characteristics, they used truncated Fourier series to fit the observed light curves. This method helped in comparing and studying the theoretical models of pulsations with actual observations in a quantifiable way.

Kovács and Kanbur (1998) looked into the way that can help in creating better and more accurate period–luminosity relationships for RR Lyrae stars. They discovered that taking into account the shape of the light curve, with the use of Fourier parameters, can significantly improve the accuracy of distance calculations. Their work demonstrated how important it is to capture the detailed pattern of a star's pulsation cycle, as this provides metrics like the star's mass, magnitude, and metal content, along with its period and average brightness [6].

Class imbalance is the major issue while dealing with astrophysics data. The paper Exploring Strategies and Algorithms for Tackling Class Imbalance Across Varied Data Types, discusses the challenges of unbalanced data distributions in machine learning. It evaluates techniques like ADASYN, RUSBoost, and SMOTETomek across three real-world datasets, highlighting their advantages in improving model performance and reducing training time, while also addressing issues like information loss and overfitting. The authors provide recommendations for selecting appropriate sampling methods based on class distribution and model requirements [7].

Nemec et al. (2013) later introduced a detailed Fourier-based method of RR Lyrae light curves to study period changes and the respective effects of metallicity. They used data from several photometric surveys and established calibrations that enable spectroscopic metallicity estimates from photometric data alone by demonstrating systematic changes in light curve shape parameters with metallicity [8].

By applying machine learning techniques to the near-infrared bands of RR Lyrae stars, Klein et al. (2014) [9] demonstrated the ability of data-driven approaches to derive metallicity relationships. They mostly did not make use of full deep-learning models; they showed that machine-learning methods can figure out small patterns in the data that normal analysis can miss.

Bai et al. (2018) introduced Temporal Convolutional Networks (TCNs) as an impactful deep-learning model for sequential data. They showed that TCNs can beat recurrent neural networks on many time-series or sequential data-driven tasks. TCNs make use of dilated causal convolutions, which allow them to capture long sequences while still being fast and efficient. Unlike RNNs, they train easily and run in parallel, and also avoid problems like vanishing gradients. This makes them suitable for long and complex sequential data [10][11].

Identifying Fast Radio Bursts (FRBs) using a machine-learning system that employs Convolutional Neural Networks and Transfer Learning, achieving an accuracy of 90.67% and an area under the curve of 0.90 in classification performance [12]. This paper provides a good comparative analysis of machine learning algorithms for astrophysics-related problem statements.

Transfer learning, a deep learning technique, has enabled computers to interpret and understand visual data, such as images and videos, with high precision [13]. This capability is crucial for developing sophisticated computer vision systems.

These studies show a clear shift away from traditional Fourier and template-based methods toward the more data-driven and machine learning approaches. We found that using deep learning and especially hybrid models to directly predict full light curves from physical parameters is still not well explored, even though ML is frequently used in time-series astronomy.

3. Proposed Method

To predict the phase-folded I-band light curves of RRab-type RR Lyrae variable stars, we present a deep-learning-based Temporal Convolutional Network (TCN) approach. The following five physical parameters are entered into the model: the pulsation period (P), the Fourier phase difference ϕ21, the Fourier amplitude ratio R21 (A2/A1), the mean I-band magnitude (μI), and the amplitude in I-band (AI).

We chose the TCN architecture because it works well on time-series data and keeps causality while capturing long-range patterns using the dilated convolutions. Unlike recurrent neural networks, where the sequences are processed one at a time, TCNs can process whole sequences at once, which leads to faster and more stable convergence and gradients than recurrent neural networks. The network can capture the global structure of the pulsation cycle by achieving large receptive fields with fewer layers, which is because of the dilated convolutions. This enables the model to make use of the fixed input parameters and helps in learning the detailed phase-dependent brightness changes present in RR Lyrae pulsations.

To ensure phase alignment with minima coming at phase zero, the model is trained on artificial light curves produced from OGLE-like catalog parameters using Fourier decomposition. This method eliminates the need for dense observational data for each training example, which allows the creation of smooth and realistic light curves. The model can explore the entire parameter space of RRab variables since we can create arbitrarily large training sets with perfect ground truth using synthetic data.

3.1. Architecture

The proposed TCN model consists of different key components designed to transform the five input parameters into a complete 100-point phase-folded light curve, which we need.

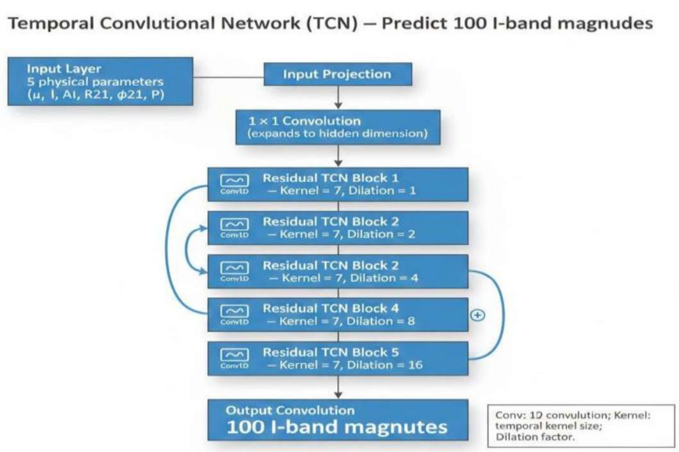

Figure 1: Architecture diagram

by the input projection layer into a higher-dimensional representation that the convolutional layers can process. Dilated causal convolutions, batch normalization, and ReLU activation are applied to each residual TCN block before a residual connection. The formulation of the residual block is:

$$y = \mathrm{ReLU}(\mathrm{BN}(\mathrm{Conv}(x; k, \mathrm{dil}))) + x \tag{1}$$

BN refers to batch normalization, *dil* is the dilation factor, *k* is the kernel size, and the addition represents the residual connection. As the value of dilation grows (1,2,4,8,16), each layer covers a progressively larger temporal window. By the final layers, the model can see the entire pulsation cycle. To ensure accurate reconstruction and physically consistent results, the loss function is composed of two distinct parts. The main part is the Huber Loss, which is less sensitive to outliers compared to mean squared error.

$$L_{\text{Huber}} = \frac{1}{2}(y-\hat{y})^2 \text{ if } |y-\hat{y}| \le \delta, \quad \delta|y-\hat{y}| - \frac{1}{2}\delta^2 \text{ otherwise} \quad (2)$$

where $\delta = 1.0$ in our implementation. Further, we include an amplitude consistency loss to ensure that the predicted light curve has and keeps the correct amplitude:

$$\mathrm{L}_{\text{amp}} = 0.02 \cdot |A_{\text{pred}} - A_{\text{true}}| \quad (3)$$

where A_{pred} is the predicted amplitude of the light curve (maximum minus minimum) and A_{true} is the input amplitude parameter. The total loss is:

$$\mathrm{L}_{\text{total}} = \mathrm{L}_{\text{huber}} + \mathrm{L}_{\text{amp}} \quad (4)$$

This combined loss function ensures that the model fits the detailed shape of the light curve and also that the overall amplitude is preserved.

3.1 Training

The model was trained using systematic hyperparameter tuning to identify the best possible configuration of learning parameters, ensuring the best fit to the data and achieving the highest possible predictive accuracy.

Hyperparameter Configuration:

Table 1: Training hyperparameters

Parameter	Value
Optimizer	AdamW
Learning Rate	2×10^{-5}
LR Scheduler	ReduceLROnPlateau
Batch Size	1024
Epochs	100
Early Stopping	Patience = 10

To avoid overfitting, we made use of the AdamW optimizer, which uses weight decay regularization. When validation loss does not improve for 5 consecutive epochs, the learning rate is lowered by a factor of 0.5 by using the ReduceLROnPlateau scheduler. The learning rate of $2 \times 10{-}5$ was selected after initial experiments. The effective parallel processing capabilities of TCNs enabled the large batch size of 1024 and helped in the stabilization of training dynamics.

We stopped training when validation results stopped getting better. Early stopping (with 10 epochs) prevented the model from overfitting. We monitored validation loss and RMSE throughout the training and saved the model when it reached the best validation RMSE.

3.2 Data Augmentation

During training, we used several different data augmentation methods to increase the robustness and generalization of the model:

- Gaussian noise: To mimic the real-life uncertainties, random noise with $\sigma = 0.01$ mag is added to the input parameters.
- Random phase shifts: To prepare the model for handling small phase changes, circular phase shifts of ±0.05 were made.
- Magnitude offset: Random offsets of ±0.05 mag added to mean magnitudes to simulate the photometric errors.
- Amplitude perturbation: Multiplicative factors between 0.95 and 1.05 applied to amplitudes.

Adding realistic variations to the inputs will bring improvements to the model's capability to generalize real-life observational data with measurement errors and reduced overfitting to the synthetic distributions [7].

3.3 Data Preprocessing

We use a catalog of RRab parameters (OGLE-like dataset) containing the observational measurements for many of the variables. The five key parameters extracted for each star are:

Table 2: Input features

Feature	Description
I_mag	Mean I-band magnitude
Amp_I	Full amplitude
$R21$	Fourier amplitude ratio ($A2/A1$)
$\phi21$	Fourier phase difference
Period	Stellar pulsation period

Each phase-folded I-band curve is simulated using a two-term Fourier series:

$$m(\phi) = \mu + A1\ \sin(2\pi\phi + \phi1) + A2\ \sin(4\pi\phi + \phi2) \tag{5}$$

where $\phi \in [0,\ 1]$ is the phase, μ is the mean magnitude, and the amplitudes $A1$ and $A2$ are related as $A2 = R21 \times A1$ and the total amplitude $A_{\mathrm{I}} \approx 2(A1 + A2)$.

Phase alignment makes sure the global minima are located at phase zero, which is the standard convention for RRab stars (brightness minimum corresponding to maximum radius during pulsation).

3.4 Data Normalization and Cleaning:

Several data cleaning procedures were used:

- KNN-based imputation: The missing values of the catalog were imputed using k-nearest neighbors (k = 5).
- Z-score outlier removal: To remove the outliers and possible catalog errors, data points that showed deviation for more than four standard deviations from the mean in any parameter were discarded.
- Amplitude rescaling: Amplitudes were changed, i.e, reduced to the range of [0.01, 2.0] mag.
- Feature standardization: All the input features were put through unit mean and zero unit variance.
- 80/20 random train/test split: For proper coverage of the parameter space in both sets, data was randomly split into training (80%) and validation (20%) sets.

Using 100 evenly spaced phase steps between 0 and 1 provides enough resolution in order to fit the asymmetric shape of the RRab light curves and also to be computationally efficient.

4. Results and Discussion

4.1 Quantitative Performance

Our best-performing TCN model achieved strong quantitative results on the validation set:

Table 3: Model performance metrics

Metric	Score
Loss	0.009697
RMSE	0.0963 mag
MAE	0.0741 mag
R^2 Score	0.9876

Excellent agreement between the true and predicted light curves is shown by the validation RMSE of 0.0963 mag. The prediction accuracy of our model is comparable to observational uncertainties because photometric uncertainties in typical survey data for bright RR Lyrae stars range from 0.01 to 0.05 mag. In Galactic structure studies, where RR Lyrae-based distances are used to map the spatial distribution of stellar populations, this level of accuracy is adequate for distance modulus errors < 2%. The model explains 98.76% of the variation in the light curves, according to the high R2 score of 0.9876, indicating that the five input parameters contain enough information to reconstruct the intricate pulsations.

This shows the validation of using Fourier parameters alongside period and amplitude to characterize these variables. TCN-based approach shows improvement over conventional template-based methods that are reported in the literature (typical RMSE ∼0.15–0.20 mag for sparse sampling). The model's ability to achieve sub-0.1 mag accuracy from just five parameters is remarkable, even though direct comparison is not right because of the change in data and other factors.

4.2 Per-Star RMSE Analysis

The model's consistency across various parameters can be understood by looking at the distribution of per-star RMSE values. The RMSE histogram of the results shows a roughly Gaussian distribution with the following percentiles, which peak at 0.07–0.12 mag:

- 25th percentile: 0.068 mag
- Median (50th): 0.089 mag
- 75th percentile: 0.115 mag
- 95th percentile: 0.178 mag

Stars with higher magnitude, i.e., (> 1.5 mag) or those with a typical R21 value, have larger errors (95th percentile and above). These outliers are less than 5% of the validation set, indicating that for the majority of typical RRab variable stars, the model performs consistently well.
Performance was also investigated based on input parameters, which showed no systematic bias and consistent accuracy over the entire period range (0.4–0.8 days). Similarly, stars with very small amplitudes (< 0.4 mag) exhibit slightly elevated RMSE, but performance is stable across different amplitude ranges.

4.3 Phase Error Performance

Beyond magnitude accuracy, we evaluated the model’s capability to correctly place light curve features appropriately. We computed phase errors for key features:

- Minimum light: Phase error typically < 0.02 (2% of period)
- Maximum light: Phase error typically < 0.03 (3% of period)
- Half-rising branch: Phase error < 0.015
- Half-declining branch: Phase error < 0.025

The phase error of RRab stars with P ≈ 0.5 days; these phase errors show a time error of about 1-1-2% or 15-25 minutes. This degree of accuracy is sufficient for studies of metallicity estimation and other related studies, which depend on the precise shape of the rising and declining branches, while maintaining the actual physical interpretation of light curves. For more than 90% of validation stars, the model accurately captures the asymmetry parameter (rise time/fall time) within 5% of the true value, demonstrating especially good performance in predicting the steep rising branch characteristic of RRab stars. For over 90% of the variable stars, the model matches the asymmetry (rise time vs. fall time) within 5% of the true value. This means that the model is good at predicting the sharp rising part of the light curves.

4.4 Visual Comparison

Let's see how well the trained model predicts each star and how well it performs individually. Example RRab star parameters:

- Period: 0.572 days
- Amplitude: 0.89 mag
- Mean I magnitude: 17.23
- $R21$: 0.38
- $\phi21$: 4.51 radians

The nature of RRab is effectively captured by the predicted light curve:

• The model shows the fast brightening from minima to maxima, with the rising branch correctly occupies 20% of the pulse cycle.

The model adequately depicts the fading phase and its characteristic asymmetric shape.

• Ensure amplitude preservation with input parameters ranging from 0.02 mag peak-to-peak.

• The phase structure of the light curve has observed to show adequate minimum, maximum, and inflection points.

For stars with typical characteristics (R21 = 0.3–0.5), the predicted and true curves show minimal visual difference.

The model has successfully established the relationship between light curve shape and Fourier parameters.

4.5 Model Interpretability and Feature Importance

We conducted studies by methodically eliminating or altering specific inputs to understand the feature importance. The outcomes demonstrate:

1. Amplitude and mean magnitude are most responsible for the vertical scale and offset of the curve.
2. $R21$ is the one responsible for the structure of the curve, particularly the bump structure often visible on the declining branch.
3. $\phi21$ plays a major role in the phase placement of secondary features and the overall asymmetry.
4. Period has a weaker direct effect, as we work in phase space, but correlations between period and other parameters in the training set create some dependence

This analysis confirms that the model is using the inputs in physically meaningful ways, rather than exploiting spurious correlations in the training data.

5. Conclusion and Future Scope

We present an effective Temporal Convolutional Network that can predict RRab I-band light curves using just five catalog parameters. The system effectively captures the amplitude structure and morphology of RR Lyrae pulsation with an RMSE of 0.0963 mag. The model generates physically realistic pulsation cycles by learning the periodic pulsation behavior of the stellar parameters. It is scalable to large and real-life datasets likely coming from future surveys because it trains effectively with comparatively large batch sizes.

Important accomplishments include:

- TCNs can properly capture the physics of RR Lyrae variable stars from data alone.
- Prediction accuracy is the same or slightly better than that of traditional methods.
- The method can process many stars at once and is scalable.
- Five parameters are enough to reconstruct detailed light curves

Future directions:

There are certain ways to extend the scope of this project further:

- Multi-band joint modeling: Make a model architecture to predict the V and I band curves, resulting in better distance estimation and other astrophysical applications.
- Training on real data: The model will perform much better in an actual scenario once it is trained on real-life data.
- Adding extra features: Adding extra features like colour information, metallicity, and galactic positions, and creating model architecture such that it maps relations between them.
- Real-time survey applications: Using this model in real-time surveys for light curve predictions.

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