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Identification and Analysis of Non-Stationary Time Series Signals Based on Data Preprocessing and Deep Learning

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ABSTRACT

Deep learning is not the most accurate way for recognizing time series signals, and it is unable to identify non-stationary time series signals with numerous chaotic classes. Moreover, the signal detection benefits from data preprocessing have gone unnoticed. Therefore, this paper investigates the detection and analysis of non-stationary time series signals using deep learning and data preprocessing. The fitting model of the historical stationarity index is built based on the Gaussian mixture model of single Gaussian models, and the change point of the non-stationary time series signal is detected. To further increase the signal's recognition rate, the non-stationary time series signal is preprocessed using the truncated migration algorithm. The main classification task and the auxiliary classification tasks are constructed to identify non-stationary time series signals characterized by huge chaotic classes through multi-task learning. The efficiency of the suggested method and model is validated by experimental data.

1. INTRODUCTION

Time series signals can illustrate how things or phenomena change over time in terms of their state or intensity. This energizes ongoing studies into these signals [1-6]. One of the key study areas is the identification and analysis of non-stationary time series signals, which has been applied in a variety of industries and fields, including streaming media, meteorology, medicine, and business [7-17]. Researchers both domestically and internationally have been using deep learning techniques with significant self-learning capabilities to detect time series signals in recent years, but the signal recognition rate is still suboptimal [18-23]. With change point monitoring as a representative application scenario, the extraction of time series signal stationarity indicators and the development of deep learning techniques to enhance signal recognition accuracy represent an unavoidable trend and have significant practical implications.

It is well known that research has been done on non-stationary acoustic signal filtering techniques based on wavelet threshold denoising. This method calls for the usage of a significant amount of CPU resources for processing huge volumes of data. A different method for building CF based on the McCulloch-Pitts neuron model was proposed by Khobotov et al. [24]. This neuron-like CF relies exclusively on logical processes, which employ fewer CPU resources, and is based on particular nonlinear transformations of input and test signals. The results are thought to be applicable to a wide range of real-world scenarios involving long-range sonar, seafloor detection, and non-stationary environments. Empirical Fourier Decomposition (EFD), a method that combines the improved Fourier spectral segmentation methodology and the usage of zero-phase filter banks, was proposed by Zhou et al. [25] as a precise adaptive signal decomposition tool. A numerical analysis was done to look at the reliability and accuracy of EFD. The results demonstrate that for signals with several non-stationary modes and closely spaced modes, EFD can yield accurate and reliable decomposition results. Ding et al. [26] created the Kernel Ridge Regression-based Chirp Transform (KRR-CT) to precisely identify the TF features of non-stationary signals and build energy-concentrated TF flats since the solution of the polynomial approximation is easily influenced by noise or interference. Even with significant noise present, a stable solution can be produced in the KRR-CT approximation stage. Wang et al. [27] addressed a number of frequently employed time-frequency analysis techniques for non-stationary signals, examined these techniques with mixed signals and noise, and then went into great depth into the benefits and drawbacks of each technique. The study of the time-frequency of the continuous wave radio Doppler signal produced when the missile strikes the target using an enhanced time-frequency analysis approach based on STFT is proposed. The aforementioned technique is used to process real experimental data, and positive results are obtained. This validates that the method is feasible and effective, and will significantly support any further information processing or calculation.

Research on various non-stationary signal identification and analysis techniques based on signal processing theory has been extensive both domestically and internationally. While neglecting the positive impact of data preprocessing on signal identification, there is currently no solution that can address the issue of recognizing non-stationary time series signals of vast chaotic classes. Therefore, this work investigates the detection and analysis of non-stationary time series signals using deep learning and data preprocessing. Chapter 2 completes the identification of the change point of the non-stationary time series signal and builds the fitting model of the historical stationarity index based on the Gaussian mixture model of single Gaussian models. To further increase the signal's recognition rate, the non-stationary time series signal is preprocessed in Chapter 3 using the truncated migration algorithm. The main classification goal and an auxiliary classification assignment are designed in Chapter 4 to identify non-stationary time series signals characterized by vast chaotic classes. The efficiency of the suggested method and model is validated by experimental data.

2. CHANGE POINT DETECTION

Time series signal stationarity can be dynamically defined via stationarity indicators. The amplitude of the stationarity index will quickly grow or drop for non-stationary time series signals as the signal transitions from a stationary to a non-stationary state. It is evident that the change in the condition of the time series signal occurs at the same time as the stationarity index begins to fluctuate. It is required to find the non-stationary time series signal's transition point before recognizing the non-stationary time series signal itself.

Building a fitting model of the historical stationarity index first, then determining if the present stationarity index complies with the model, is the typical method for detecting changes in the stationarity index. The historical stationarity index fitting model in this study is built using the Gaussian mixture model of single Gaussian models. The probability distribution formula for the single Gaussian model is given by the expression $\omega=(r^*, \varepsilon^2)$, where r^* and ε are the mean and standard deviation of the estimated Gaussian distribution, respectively:

$$h(r \mid \omega)=\frac{1}{\sqrt{2\pi\varepsilon^2}}\exp\left(-\frac{(r-r^*)^2}{2\varepsilon^2}\right) \tag{1}$$

r^* and ε can be respectively calculated by:

$$r^*=\frac{1}{m}\sum_{j=1}^{m} r_j \tag{2}$$

$$\varepsilon=\sqrt{\frac{1}{m}\sum_{j=1}^{m}\left(r_j-r^*\right)^2} \tag{3}$$

Let β_h be the mixture coefficient of each Gaussian model, and $\beta_h \geq 0$, $\sum^{H}{}_{h}=1\ \beta_h=1$. The probability distribution of the Gaussian mixture model composed of h single Gaussian models can be expressed as:

$$h(r \mid \omega)=\sum_{h}^{H}=1\beta_h\psi(r \mid \omega_h) \tag{4}$$

The distribution density $\psi(r|\omega_h)$ of the *h-th* Gaussian model can be given by:

$$\psi(r \mid \omega_h)=\frac{1}{\sqrt{2\pi\varepsilon_h^2}}\exp\left(-\frac{(r-r_h^*)^2}{2\varepsilon_h^2}\right) \tag{5}$$

Let $\omega_h=(r_h^*,\varepsilon^2{}_h)$ be the *h-th* Gaussian model, whose mean and standard deviation are similar to Eq. (2) and Eq. (3), respectively. Then, the Beta distribution is defined in the (0, 1) interval. Assume that the hyperparameters of the Beta distribution are represented by β and γ, and the Beta function is represented by $Y(\beta, \gamma)$. The probability distribution of the Beta distribution can be expressed as:

$$h(r \mid \beta,\gamma)=\frac{1}{Y(\beta,\gamma)}r^{\beta-1}(1-r)^{\omega-1} \tag{6}$$

The Beta function $Y(\beta, \gamma)$ can be expressed as:

$$Y(\beta,\gamma)=\int_0^1 b^{\beta-1}(1-b)^{\gamma-1}\,db \tag{7}$$

The single Gaussian model constructed in this way is suitable for any random time series signal data. ITo detect whether the abnormality of the time series signal occurs at the $(m+1)$-*th* time, this paper conducts a hypothesis test on the model based on the PauTa criterion. Assuming that $|r_{m+1}-r_m^*|<l\varepsilon$ is satisfied, then the time series signal state does not change at the $(m+1)$-*th* moment, represented by F_0; when $|r_{m+1}-r_m^*| \geq l\varepsilon$, the signal state changes, denoted by F_1, means that the following process:

$$\begin{aligned} F_0 &: \left|r_{m+1}-\overline{r}_m\right|<l\varepsilon \\ F_1 &: \left|r_{n+1}-\overline{r}_n\right| \geq l\varepsilon \end{aligned} \tag{8}$$

3. SYMBOL RECOGNITION

The traditional signal recognition model usually has the problem of a limited receptive field, which makes the extracted signal timing features not objective enough. To further improve the recognition rate of non-stationary time series signals, this paper uses the truncated migration algorithm to preprocess the signals, and constructs a new sampling matrix, which enables the signal recognition model to extract more sampling points and signal symbols. Figure 1 shows the processing flow of the non-stationary time series signals.

The information features of non-stationary time series signals can be generated by fusing the space and channel information in the local receptive field. Suppose the convolution operation is represented by $\otimes$, the input is represented by A, the feature is represented by G, the convolution kernel is represented by L, $L \in R^{l\times l}$, the size of the convolution kernel is represented by l. Then, the convolutional operation can be expressed as:

$$G=A\otimes L \tag{9}$$

The receptive field of G is limited by L and A. Changes in the sign of a signal are characteristic for non-stationary time series signal identification. Traditional signal recognition models are difficult to capture long-term dependencies, and can only classify non-stationary time series signals by comparing the signal signs of each sampling point. In this paper, the data truncation migration algorithm is used to enable the signal recognition model to compare more symbolic information. The specific steps of the algorithm are as follows:

Step 1: Assuming that the length is represented by k, and the width and channel dimensions are 2 and 1, respectively. Then, the sampling matrix BC can be reshaped as (2, k, 1).

Step 2: Set the distance R to be moved to describe a truncation and the number of truncation movement times B_P.

Step 3. Let B_0 be the original sampling matrix i. Migrate the 1×R truncation at the right end of B_0 to the leftmost of that matrix to produce matrix B_1. Then migrate the 2×R truncation at the right end of B_1 to the leftmost of B_1 to produce matrix B_2. Perform similar migration P times to produce matrix B_P.

The combination of B_0 and B_1 makes $\{b_k\}$, $k\in[1, R]$ close to $\{b_k\}$, $k\in[k-R+1, k]$ in the horizontal direction, and close to $\{b_k\}$, $k\in[R, 2R]$ in the vertical direction. The combination of B_1 and B_2 makes $\{b_k\}k\in[R, 3R]$ close to $\{b_k\}$, $k\in[1, R]$ and $\{b_k\}$, $k\in[k-R-1, k\}$ in the horizontal direction, and close to $\{b_k\}$, $k\in[3R, 5R]$ in the vertical direction, and so on.

Step 4. After moving P times, if the following formula is established, return to Step 3. Otherwise, go to Step 5.

$$\frac{P\times(P+1)\times R}{2}<k \tag{10}$$

Step 5: Merge the sampling matrices B_0 to B_P through the "Concatenate" operation (Figure 2), and denote the generated new sampling matrix by B_{IW}. The size of B_{IW} is (2P+2, k, 1), and the "Concatenate" operation is represented by "$\oplus$". Then, B_{IW} can be formed by the following formula:

$$B_{IW}=B_0\oplus B_1\oplus\ldots\oplus B_P \tag{11}$$

Step 6: Convert B_{IW} into a sampling matrix B_{XT} based on amplitude X and phase T:

$$\begin{aligned}X&=\sqrt{I^2+W^2}\\T&=\arctan\left(I/W\right)\end{aligned} \tag{12}$$

Step 7: Merge B_{IW} and B_{XT} in the channel dimension through feature concatenation. Take the formed new matrix as the input of the classifier B'_C, then:

$$B'_C=B_{IW}\oplus B_{XT} \tag{13}$$

To enhance the extracted non-stationary time series signal features, the conversion result of the sampling matrix is transformed into the form of polar coordinates through Steps 6 and 7. The final output is matrix B'_C of the size (2P+2, k, 2).

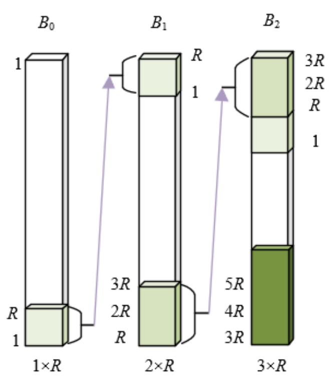

Figure 1. Processing flow of the non-stationary time series signal

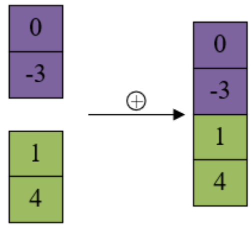

Figure 2. Operation principle of feature concatenation

4. MODEL CONSTRUCTION

Confusion can easily result from non-stationary time series signals whose distribution law is time-dependent. In order to recognize non-stationary time series signals defined by significant chaotic classes, this paper introduces multi-task learning. In this study, the network that can discriminate between two non-stationary time series signals is employed for auxiliary classification tasks, with the multi-task learning network's primary task being the identification of all non-stationary time series signals. On this basis, this paper connects gated recurrent unit (GRU), responsible for the auxiliary tasks, with convolutional neural network (CNN), responsible for the primary task, in series into a model (Figure 3).

The GRU model contains two gates, the update gate c_p and the reset gate s_p. The state f_p at time p depends on how much information is inherited from state f_{p-1} at time p-1, and how much new information is extracted from the candidate state $\dot{f}_p$ at time p. Both of the information volumes are decided by the update gate c_p. The value of c_p increases with the importance of the state at the previous moment to the state at the current moment. Let a_p be the input vector at the current moment, Q_c be the weight matrix of the update gate, $\varepsilon(.)$ be the sigmoid function, and y_c be the bias of the update gate. Then, c_p can be calculated by:

$$c_p=\varepsilon\left(Q_c a_p+Q_c f_{p-1}+y_c\right) \tag{14}$$

Whether the candidate state $\dot{f}_p$ at time p depends on the state f_{p-1} at time p-1 depends on the reset gate s_p. The less important the state at the previous moment to the state at the current moment, the smaller the s_p. Let Q_s and y_s be the weight and bias of the reset gate, respectively. Then, s_p can be calculated by:

$$s_p=\varepsilon\left(Q_s a_p+Q_s f_{p-1}+y_s\right) \tag{15}$$

Let Q_f, y_f and $\circ$ be weight, bias, and Hadamard product, respectively. Then, the candidate state $\dot{f}_p$ can be calculated by:

$$\dot{f}_p=\mathrm{Tanh}\left(Q_f a_p+Q_f\left(s_p\circ f_{p-1}\right)+y_f\right) \tag{16}$$

The output of the GRU model can be expressed as:

$$f_p=\left(1-c_p\right)\circ f_{p-1}+c_p\circ\dot{f}_p \tag{17}$$

Since this article sets up several auxiliary task models for the non-stationary time series signal identification model, it is vital to thoroughly analyze the over-fitting phenomenon of the model, even though the performance of the GRU model will improve as the number of layers grows. In this study, a 3-layer GRU model is constructed.

The primary classification job model for non-stationary time series signals accepts input in the one-dimensional time series A/P format. In order to increase the rate at which non-stationary time series signals are recognized, this study builds a model for the primary task classification using CNN and GRU in series. It also realizes the merging of the spatial and temporal aspects of the signal. The model training process is shown in Figure 4.

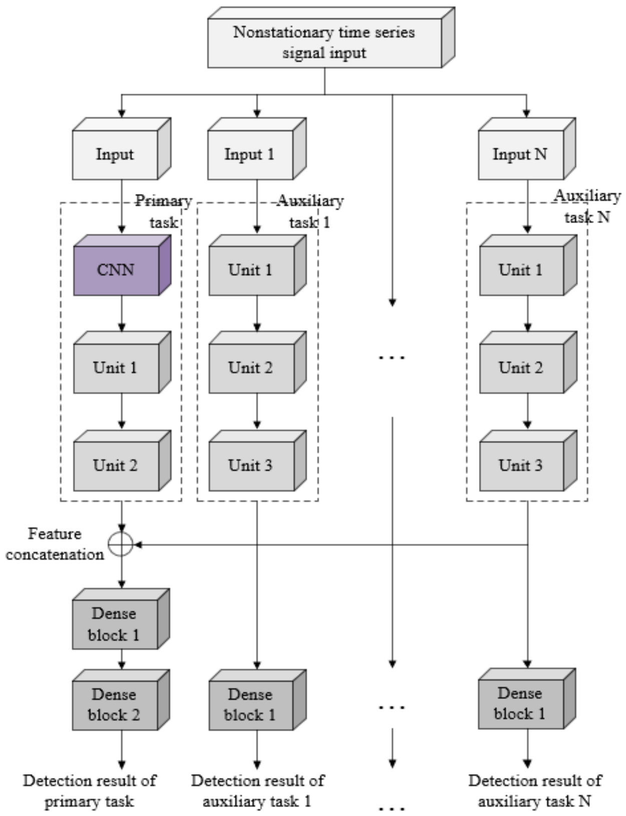

Figure 3. Structure of the detection model

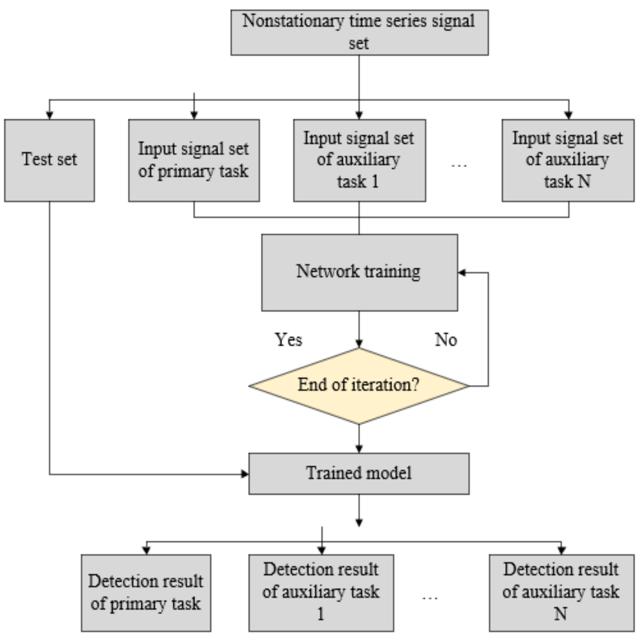

Figure 4. Flow of model training

5. EXPERIMENTS AND RESULTS ANALYSIS

The results of data preprocessing using various numbers of single Gaussian models are shown in Figure 5. The algorithms in this work correspond to algorithms 1 through 5, with 2, 3, 4, 5, and 6 being the number of single Gaussian models, respectively. The figure shows that the error value of the non-stationary time series signal change point detection is lowest when the number of single Gaussian models is 4. Thus, it is determined that there should be exactly four single Gaussian models.

Figure 6 displays the recognition model's training and validation losses. The figure shows that the model's convergence occurs quickly, there is no over-fitting after 80 iterations, and both the training set's and the test set's performance are satisfactory. Table 1 displays, for various values of the distance R to be shifted by a truncation, the accuracy of non-stationary time series signal detection. The average value and maximum value of the non-stationary time series signal recognition rate are at their highest when the distance to be moved for a truncation is 4. Currently, less than 1 second is needed for one iteration, which is also within the allowed range of less than 1 minute.

Figure 7 compares the detection accuracies of different signal recognition models. It is observed that, with the growth of the signal to noise ratio (SNR), the signal recognition effect of five detection models all improves, including the envelope feature-based model, the double spectra feature-based model, the wavelet transform feature-based model, the multilayer perceptron (MLP), and long short-term memory (LSTM) model. The envelope feature-based model, the double spectra feature-based model, the wavelet transform feature-based model cannot extract more time series features of nonstationary time series signals, or fuse the spatial and temporal features of the signals. Their highest detection accuracy is around 70%. Despite capable of extracting spatial and temporal features, the MLP cannot connect adjacent time domain signals, and its accuracy is about 80%. Our model fuses the spatial and temporal features of the signals, and differentiates the signals with confusion phenomenon. The highest accuracy is around 90%.

The detection accuracies with different input formats were compared to further verify the effectiveness of our model on nonstationary time series signals. As shown in Table 2 and Figure 8, the detection accuracies with the two formats (image format and time series format) are similar. It is verified that the one-dimensional time-series format input, which has certain advantages in theory, also has ideal recognition performance in the actual process of signal recognition with confusion. Compared with the other five models, our model boasts high mean accuracies with both two input formats. Whether the SNR is low, medium or high, our model can recognize nonstationary time series signals better than the image format. This further verifies the effectiveness of our model.

Table 1. Detection accuracies at different R values

R	Maximum accuracy	Mean accuracy	Matrix shape	Iterative time
1	95.27%	63.58%	(36,114,6)	142*s*
2	93.24%	67.42%	(25,174,1)	85*s*
3	93.52%	69.18%	(11,196,5)	61*s*
4	98.31%	70.54%	(18,142,1)	59*s*
5	96.47%	66.37%	(16,195,4)	51*s*
6	94.18%	51.24%	(13,127,6)	57*s*

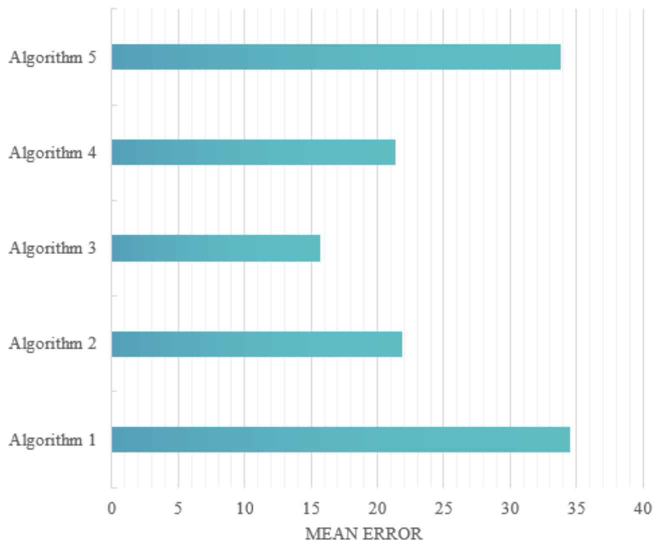

Figure 5. Change point detection errors of different signal Gaussian models

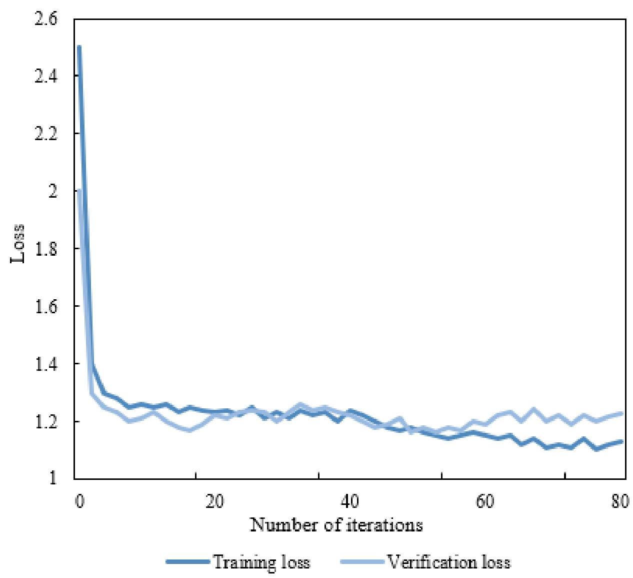

Figure 6. Training and verification losses of the identification model

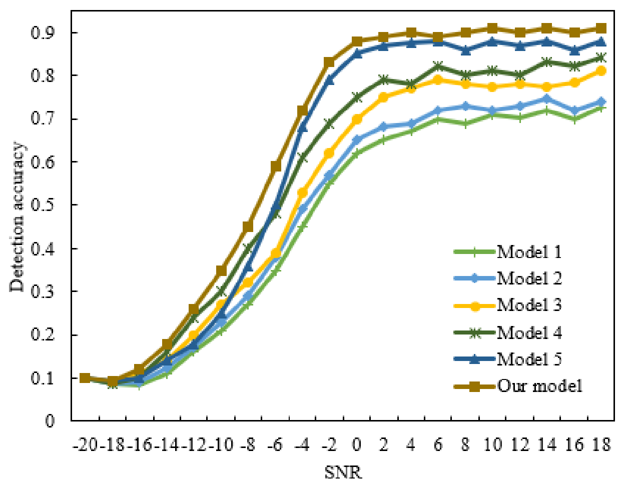

Figure 7. Detection accuracies of different signal recognition models

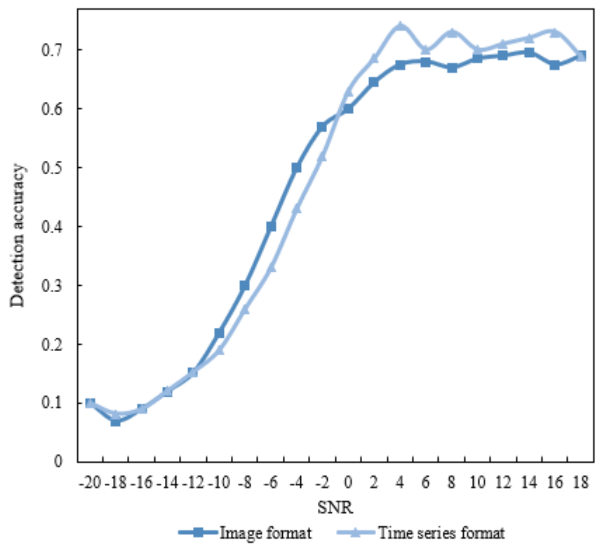

Figure 8. Detection accuracies of input formats

Table 2. Mean detection accuracies with different input formats

Model number	Input format	Mean detection accuracy			
		SNR interval	Low SNR	Medium SNR	High SNR
1	Image	62.14	21.62	50.81	80.92
	Time series	59.82	19.85	59.27	84.26
2	Image	52.65	17.34	50.61	68.04
	Time series	44.96	18.51	42.78	76.92
3	Image	59.81	19.14	63.61	85.37
	Time series	63.47	19.39	57.41	80.69
4	Image	65.23	27.52	60.81	88.92
	Time series	64.58	20.45	61.21	89.24
5	Image	72.68	21.04	68.61	88.09
	Time series	81.49	24.91	70.74	89.96
Our model	Image	80.47	29.34	73.69	91.32
	Time series	89.22	31.76	77.61	95.62

6. CONCLUSIONS

This paper investigates the detection and analysis of non-stationary time series signals using deep learning and data preprocessing. The fitting model of the historical stationarity index is built based on the Gaussian mixture model of single Gaussian models, and the change point of the non-stationary time series signal is detected. To further increase the signal's recognition rate, the non-stationary time series signal is preprocessed using the truncated migration algorithm. The main classification task and the auxiliary classification tasks are constructed, and coupled with multi-task learning, to identify non-stationary time series signals characterized by huge chaotic classes through multi-task learning. Through experiments, the change point detection errors of different number of single Gaussian models are compared, indicating that the best number is 4. Then, the training and validation looses of the recognition model were presented, which confirm that the model converges quickly. In addition, the detection accuracies at different R values and of different models were contrasted. The results show that the one-dimensional time-series format input, which has certain advantages in theory, also has ideal recognition performance in the actual process of signal recognition with confusion. Finally, the mean recognition accuracies of models with different input formats are compared, suggesting the effectiveness of our algorithm and model.

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