Harnessing Vision Models for Time Series Analysis: A Survey

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Abstract

Time series analysis has witnessed the inspiring development from traditional autoregressive models. deep learning models, to recent Transformers and Large Language Models (LLMs). Efforts in leveraging vision models for time series analysis have also been made along the way but are less visible to the community due to the predominant research on sequence modeling in this domain. However, the discrepancy between continuous time series and the discrete token space of LLMs, and the challenges in explicitly modeling the correlations of variates in multivariate time series have shifted some research attentions to the equally successful Large Vision Models (LVMs) and Vision Language Models (VLMs). To fill the blank in the existing literature, this survey discusses the advantages of vision models over LLMs in time series analysis. It provides a comprehensive and in-depth overview of the existing methods, with dual views of detailed taxonomy that answer the key research questions including how to encode time series as images and how to model the imaged time series for various tasks. Additionally, we address the challenges in the pre- and post-processing steps involved in this framework and outline future directions to further advance time series analysis with vision models.

1 Introduction

Vision models have historically been used for time series analysis. Since 1-dimensional (1D) convolutional neural networks (CNNs), such as WaveNet [Van Den Oord *et al.*, 2016], were found effective in sequence modeling [Bai *et al.*, 2018], they have been extensively adapted to various time series tasks [Koprinska *et al.*, 2018; Zhang *et al.*, 2020]. Recently, with the significant advances of sequence modeling in the language domain, growing research attentions on time series have been drawn to methods ranging from Transformers [Wen *et al.*, 2023] to Large Language Models (LLMs) [Zhang *et al.*, 2024]. Meanwhile, the demands for universal modeling have spurred on an explosion of works on time series foundation models, such as TimesFM [Das *et al.*, 2024], Chronos [Ansari *et al.*, 2024] and Time-MoE [Shi *et al.*, 2024].



Figure 1: The general process of leveraging vision models for time series analysis. The red boxes are two views of taxonomy used in this survey. The dashed boxes denote optional, task-dependent steps.

As Large Vision Models (LVMs), such as ViT [Dosovitskiy *et al.*, 2021], BEiT [Bao *et al.*, 2022] and MAE [He *et al.*, 2022], become achieving a similar success as LLMs (but in vision domain), a great deal of emergent efforts has been invested to explore the potential of LVMs in time series modeling [Chen *et al.*, 2024]. This is inspired by the plenty of ways for visualizing time series as images such as line plots of univariate time series (UTS) and heatmaps of multivariate time series (MTS). Such images provide a more straightforward view of time series than the counterpart textual representations to humans and, presumably, AI bots.

Taking a closer inspection reveals more advantages favoring LVMs over LLMs: (1) There is an inherent relationship between images and time series – each row/column in an image (per channel) is a sequence of *continuous* pixel values. By pre-training on massive images, LVMs may have learned important sequential patterns such as trends, periods, and spikes [Chen *et al.*, 2024]. In contrast, LLMs are pre-trained on *discrete* tokens, thus are less aligned with continuous time series. In fact, LLMs' effectiveness on time series modeling is in question [Tan *et al.*, 2024]; (2) Instead of using channelindependence assumption [Nie *et al.*, 2023] to individually model each variate in an MTS, some imaging methods (§3.7) can naturally represent MTS, enabling explicit correlation encoding; (3) When prompting LLMs, existing methods often struggle with properly verbalizing a long sequence (or a matrix) of floating numbers in a UTS (or MTS), which may be limited by the context length or induce high API costs. In contrast, existing works find that using LVMs on imaged time series is more prompt-friendly and less API-costly [Daswani *et al.*, 2024]; (4) Some imaging methods can encode long time series in a compact manner [Naiman *et al.*, 2024], thus have a great potential in modeling long-term dependency.

Also, the concurrent developments of LLMs and LVMs for time series pave the way for a confluence, *i.e.*, leveraging Large Multimodal Models (LMMs), such as LLaVA [Liu *et al.*, 2023], Gemini [Team, 2023] and Claude-3 [Anthropic, 2024], to consolidate the two complementary modalities, which may revolutionize the way (*e.g.*, visually, linguistically, *etc.*) that users interact with time series.

Despite the significance, a thorough review of relevant works is absent in the existing literature to the best of our knowledge. The survey [Zhang et al., 2024] discusses a few vision models, but its focus is LLMs for time series. In light of this, in this survey, we comprehensively investigate the traditional and the state-of-the-art (SOTA) methods. Fig. 1 identifies the general process of applying vision models for time series analysis, which also serves as the structure of this survey. Our taxonomy has a dual view: (1) in Time Series to Image Transformation (§3), we review 5 primary *imaging meth*ods including Line Plot, Heatmap, Spectrogram, Gramian Angular Field (GAF), Recurrence Plot (RP), and some other methods; (2) in Imaged Time Series Modeling ($\S4$), we discuss conventional vision models, LVMs and the initial efforts in LMMs. To highlight the taxonomy, we defer the discussion on the desiderata of pre- and post-processing to the end of this survey ($\S5$). For comparison, we provide Table 1 to summarize the existing methods. Finally, we discuss future directions in this promising field (§6). A Github repository¹ is also maintained to provide up-to-date resources including our code of the imaging methods in $\S3$. We hope this survey could be an orthogonal complement to the existing surveys on Transformer [Wen et al., 2023], LLMs [Zhang et al., 2024; Jiang et al., 2024] and foundation models [Liang et al., 2024] for time series, and provide a complete view on the process of using vision models for time series analysis, so as to be an insightful guidebook to the developers in this area.

2 Preliminaries and Taxonomy

In this paper, a UTS is represented by $\mathbf{x} = [x_1, ..., x_T] \in \mathbb{R}^{1 \times T}$ where *T* is the length of the UTS, $x_t (1 \le t \le T)$ is the value at time step *t*. Suppose there are *d* variates (or features), let $\mathbf{x}_i \in \mathbb{R}^{1 \times T}$ $(1 \le i \le d)$ be a UTS of the *i*-th variate, an MTS can be represented by $\mathbf{X} = [\mathbf{x}_1^{\top}, ..., \mathbf{x}_d^{\top}]^{\top} \in \mathbb{R}^{d \times T}$.

As illustrated in Fig. 1, this survey focuses on methods that transform time series to images, namely *imaged time series*, and then apply vision models on the imaged time series for tackling time series tasks, such as classification, forecasting and anomaly detection. It is noteworthy that methods on videos or sequential images (*a.k.a.* image time series [Tarasiou *et al.*, 2023]) do not belong to this category because they don't transform time series to images. Similarly, methods for spaciotemporal traffic data are out of our scope if the meth-

ods focus on streams of images (*e.g.*, traffic flows in a stream of grid maps [Zhang *et al.*, 2017]), but methods on imaging time-space matrices [Ma *et al.*, 2017] that resemble MTSs are included. For vision models on audios, this survey only discusses some representative works in §3.3 due to space limit. The focus of the survey will remain on general time series.

2.1 Taxonomy

We propose a taxonomy from the two views of *Time Series to Image Transformation* (§3) and *Imaged Time Series Modeling* (§4) as illustrated in Fig. 1. For the former, we discuss 5 primary methods for imaging UTS or MTS, and remark on their pros and cons. For the latter, we classify the existing methods by conventional vision models, LVMs and LMMs. We discuss their strategies on pre-training, fine-tuning, prompting, and the deigns of task-specific heads. We also discuss the challenges and solutions in pre-/post-processing in §5. Table 1 presents a summary. In the following two sections, we will delve into the existing methods from the two views.

3 Time Series To Image Transformation

This section summarizes the methods for imaging time series $(\S3.1-\S3.6)$ and their extensions to encode MTSs $(\S3.7)$.

3.1 Line Plot

Line Plot is a straightforward way for visualizing UTSs for human analysis (e.g., stocks, power consumption, etc.). As illustrated by Fig. 2(a), the simplest approach is to draw a 2D image with x-axis representing time steps and y-axis representing time-wise values, with a line connecting all values of the series over time. This image can be either three-channel (*i.e.*, RGB) or single-channel as the colors may not be informative [Cohen et al., 2020; Sood et al., 2021; Jin et al., 2023; Zhang et al., 2023]. ForCNN [Semenoglou et al., 2023] even uses a single 8-bit integer to represent each pixel for blackwhite images. So far, there is no consensus on whether other graphical components, such as legend, grids and tick labels, could provide extra benefits in any task. For example, ViTST [Li et al., 2023b] finds these components are superfluous in a classification task, while TAMA [Zhuang et al., 2024] finds grid-like auxiliary lines help enhance anomaly detection.

In addition to the regular Line Plot, MV-DTSA [Yang *et al.*, 2023] and ViTime [Yang *et al.*, 2024] divide an image into $h \times L$ grids, and define a function to map each time step of a UTS to a grid, producing a grid-like Line Plot. Also, we include methods that use Scatter Plot [Daswani *et al.*, 2024; Prithyani *et al.*, 2024] in this category because a Scatter Plot resembles a Line Plot but doesn't connect data points with a line. By comparing them, [Prithyani *et al.*, 2024] finds a Line Plot could induce better time series classification.

For MTSs, we defer the discussion on Line Plot to $\S3.7$.

3.2 Heatmap

As shown in Fig. 2(b), Heatmap is a 2D visualization of the magnitude of the values in a matrix using color. It has been used to represent the matrix of an MTS, *i.e.*, $\mathbf{X} \in \mathbb{R}^{d \times T}$, as a one-channel $d \times T$ image [Li *et al.*, 2022; Yazdanbakhsh and Dick, 2019]. Similarly, TimEHR [Karami *et al.*, 2024] represents an *irregular* MTS, where the intervals

¹https://github.com/D2I-Group/awesome-vision-time-series



Figure 2: An illustration of different methods for imaging time series with a sample (length=336) from the *Electricity* benchmark dataset [Nie *et al.*, 2023]. (a)(c)(d)(e)(f) visualize the same variate. (b) visualizes all 321 variates. Filterbank is omitted due to its similarity to STFT.

between time steps are uneven, as a $d \times H$ Heatmap image by grouping the uneven time steps into H even time bins. In [Zeng *et al.*, 2021], a different method is used for visualizing a 9-variate financial MTS. It reshapes the 9 variates at each time step to a 3×3 Heatmap image, and uses the sequence of images to forecast future frames, achieving time series forecasting. In contrast, VisionTS [Chen *et al.*, 2024] uses Heatmap to visualize UTSs. Similar to TimesNet [Wu *et al.*, 2023], it first segments a length-T UTS into $\lfloor T/P \rfloor$ length-P subsequences, where P is a parameter representing a periodicity of the UTS. Then the subsequences are stacked into a $P \times \lfloor T/P \rfloor$ matrix, with 3 duplicated channels, to produce a grayscale image input to an LVM. To encode MTSs, VisionTS adopts the channel independence assumption [Nie *et al.*, 2023] and individually models each variate in an MTS.

Remark. Heatmap can be used to visualize matrices of various forms. It is also used for matrices generated by the subsequent methods (*e.g.*, Spectrogram, GAF, RP) in this section. In this paper, the name Heatmap refers specifically to images that use color to visualize the (normalized) values in UTS \mathbf{x} or MTS \mathbf{X} without performing other transformations.

3.3 Spectrogram

A *spectrogram* is a visual representation of the spectrum of frequencies of a signal as it varies with time, which are extensively used for analyzing audio signals [Gong *et al.*, 2021]. Since audio signals are a type of UTS, spectrogram can be considered as a method for imaging a UTS. As shown in Fig. 2(c), a common format is a 2D heatmap image with x-axis representing time steps and y-axis representing frequency, *a.k.a.* a time-frequency space. Each pixel in the image represents the (logarithmic) amplitude of a specific frequency at a specific time point. Typical methods for producing a spectrogram include **Short-Time Fourier Transform (STFT)** [Griffin and Lim, 1984], **Wavelet Transform** [Daubechies, 1990], and **Filterbank** [Vetterli and Herley, 1992].

STFT. Discrete Fourier transform (DFT) can be used to describe the intensity f(w) of each constituent frequency w of a UTS signal $\mathbf{x} \in \mathbb{R}^{1 \times T}$. However, f(w) has no time dependency. It cannot provide dynamic information such as when a specific frequency appear in the UTS. STFT addresses this deficiency by sliding a window function g(t) over the time steps in \mathbf{x} , and computing the DFT within each window by

$$f(w,\tau) = \sum_{t=1}^{T} x_t g(t-\tau) e^{-iwt}$$
(1)

where w is frequency, τ is the position of the window, $f(w, \tau)$ describes the intensity of frequency w at time step τ .

By selecting a proper window function $g(\cdot)$ (e.g., Gaussian/Hamming/Bartlett window), a 2D spectrogram (e.g., Fig. 2(c)) can be drawn via a heatmap on the squared values $|f(w, \tau)|^2$, with w as the y-axis, and τ as the x-axis. For example, [Dixit *et al.*, 2024] uses STFT based spectrogram as an input to LMMs for time series classification.

Wavelet Transform. Continuous Wavelet Transform (CWT) uses the inner product to measure the similarity between a signal function x(t) and an analyzing function. The analyzing function is a *wavelet* $\psi(t)$, where the typical choices include Morse wavelet, Morlet wavelet, *etc.* CWT compares x(t) to the shifted and scaled (*i.e.*, stretched or shrunk) versions of the wavelet, and output a CWT coefficient by

$$c(s,\tau) = \int_{-\infty}^{\infty} x(t) \frac{1}{s} \psi^*(\frac{t-\tau}{s}) dt$$
(2)

where * denotes complex conjugate, τ is the time step to shift, and s represents the scale. In practice, a discretized version of CWT in Eq. (2) is implemented for UTS $[x_1, ..., x_T]$.

It is noteworthy that the scale *s* controls the frequency encoded in a wavelet – a larger *s* leads to a stretched wavelet with a lower frequency, and vice versa. As such, by varying *s* and τ , a 2D spectrogram (*e.g.*, Fig. 2(d)) can be drawn on $|c(s,\tau)|$, where *s* is the y-axis and τ is the x-axis. Compared to STFT, which uses a fixed window size, Wavelet Transform allows variable wavelet sizes – a larger size for more precise low frequency information. Thus, the methods in [Du *et al.*, 2020; Namura *et al.*, 2024; Zeng *et al.*, 2023] choose CWT (with Morlet wavelet) to generate the spectrogram.

Filterbank. This method resembles STFT and is often used in processing audio signals. Given an audio signal, it firstly goes through a *pre-emphasis filter* to boost high frequencies, which helps improve the clarity of the signal. Then, STFT is applied on the signal. Finally, multiple "triangle-shaped" filters spaced on a Mel-scale are applied to the STFT power spectrum $|f(w, \tau)|^2$ to extract frequency bands. The outcome filterbank features $\hat{f}(w, \tau)$ can be used to yield a spectrogram with w as the y-axis, and τ as the x-axis.

Filterbank was adopted in AST [Gong *et al.*, 2021] with a 25ms Hamming window that shifts every 10ms for classifying audio signals using Vision Transformer (ViT). It then becomes widely used in the follow-up works such as SSAST [Gong *et al.*, 2022], MAE-AST [Baade *et al.*, 2022], and AST-SED [Li *et al.*, 2023a], as summarized in Table 1.

3.4 Gramian Angular Field (GAF)

GAF was introduced for classifying UTSs using CNNs by [Wang and Oates, 2015a]. It was then extended to an impu-

Method	TS-Type	Imaging	Imaged Time Series Modeling				TS-Recover	Task	Domain	Code	
noulou			Multi-modal	Model	Pre-trained	Fine-tune	Prompt	15-100000	TUSK	Domaill	Couc
[Silva et al., 2013]	UTS	RP	X	K-NN	X	X	×	×	Classification	General	X
[Wang and Oates, 2015a]	UTS	GAF	×	CNN	×	✓ Þ	×	1	Classification	General	X
[Wang and Oates, 2015b]	UTS	GAF	×	CNN	×	✓ Þ	×	1	Multiple	General	X
[Ma et al., 2017]	MTS	Heatmap	×	CNN	×	✓ ⁶	×	1	Forecasting	Traffic	x
[Hatami et al., 2018]	UTS	RP	×	CNN	×	✓ ⁶	×	×	Classification	General	x
[Yazdanbakhsh and Dick, 2019]	MTS	Heatmap	X	CNN	×	✓ Þ	X	×	Classification	General	$\checkmark^{[1]}$
MSCRED [Zhang et al., 2019]	MTS	Other (§3.6)	x	ConvLSTM	×	✓ [♭]	X	×	Anomaly	General	$\checkmark^{[2]}$
[Li et al., 2020]	UTS	RP	x	CNN	1	1	X	×	Forecasting	General	✓ ^[3]
[Cohen et al., 2020]	UTS	LinePlot	x	Ensemble	×	✓ [♭]	X	×	Classification	Finance	X
[Barra et al., 2020]	UTS	GAF	×	CNN	×	✓ ^b	×	×	Classification	Finance	x
VisualAE [Sood et al., 2021]	UTS	LinePlot	×	CNN	×	✓ ^b	×	1	Forecasting	Finance	x
[Zeng et al., 2021]	MTS	Heatmap	×	CNN,LSTM	×	✓ ^b	×	1	Forecasting	Finance	x
AST [Gong et al., 2021]	UTS	Spectrogram	×	DeiT	1	1	×	×	Classification	Audio	✓ ^[4]
TTS-GAN [Li et al., 2022]	MTS	Heatmap	×	ViT	×	✓ ^b	×	1	Ts-Generation	Health	✓ ^[5]
SSAST [Gong et al., 2022]	UTS	Spectrogram	×	ViT	✓ 4	1	×	×	Classification	Audio	√ ^[6]
MAE-AST [Baade et al., 2022]	UTS	Spectrogram	×	MAE	✓ ⁴	1	×	×	Classification	Audio	√ ^[7]
AST-SED [Li et al., 2023a]	UTS	Spectrogram	×	SSAST, GRU	1	1	×	×	EventDetection	Audio	x
[Jin et al., 2023]	UTS	LinePlot	×	CNN	1	1	×	×	Classification	Physics	x
ForCNN [Semenoglou et al., 2023]	UTS	LinePlot	×	CNN	×	✓⁵	×	×	Forecasting	General	x
Vit-num-spec [Zeng et al., 2023]	UTS	Spectrogram	×	ViT	×	✓ Þ	×	×	Forecasting	Finance	X
ViTST [Li et al., 2023b]	MTS	LinePlot	×	Swin	1	1	×	×	Classification	General	✓ ^[8]
MV-DTSA [Yang et al., 2023]	UTS^*	LinePlot	×	CNN	×	✓ Þ	×	1	Forecasting	General	✓ ^[9]
TimesNet [Wu et al., 2023]	MTS	Heatmap	×	CNN	×	✓ Þ	×	1	Multiple	General	$\checkmark^{[10]}$
ITF-TAD [Namura et al., 2024]	UTS	Spectrogram	×	CNN	1	X	×	×	Anomaly	General	x
[Kaewrakmuk et al., 2024]	UTS	GAF	×	CNN	1	1	×	×	Classification	Sensing	x
HCR-AdaAD [Lin et al., 2024]	MTS	RP	×	CNN, GNN	×	✓ ▷	×	×	Anomaly	General	×
FIRTS [Costa et al., 2024]	UTS	Other (§3.6)	×	CNN	×	✓ ▷	×	×	Classification	General	✓ ^[11]
CAFO [Kim et al., 2024]	MTS	RP	×	CNN,ViT	×	✓ ^b	×	×	Explanation	General	✓ ^[12]
ViTime [Yang et al., 2024]	UTS^*	LinePlot	×	ViT	✓ 4	1	×	1	Forecasting	General	✓ ^[13]
ImagenTime [Naiman et al., 2024]	MTS	Other (§3.6)	×	CNN	×	✓ ^b	×	1	Ts-Generation	General	$\checkmark^{[14]}$
TimEHR [Karami et al., 2024]	MTS	Heatmap	×	CNN	×	✓ Þ	×	1	Ts-Generation	Health	✓ ^[15]
VisionTS [Chen et al., 2024]	UTS^*	Heatmap	×	MAE	1	1	×	1	Forecasting	General	✓ ^[16]
InsightMiner [Zhang et al., 2023]	UTS	LinePlot	1	LLaVA	1	1	1	×	Txt-Generation	General	x
[Wimmer and Rekabsaz, 2023]	MTS	LinePlot	1	CLIP,LSTM	1	1	×	×	Classification	Finance	X
[Dixit et al., 2024]	UTS	Spectrogram	1	GPT40,Gemini & Claude3	1	×	1	×	Classification	Audio	×
[Daswani et al., 2024]	MTS	LinePlot	1	GPT40,Gemini	✓	×	1	×	Multiple	General	x
TAMA [Zhuang et al., 2024]	UTS	LinePlot	1	GPT40	✓	×	1	×	Anomaly	General	X
[Prithyani et al., 2024]	MTS	LinePlot	1	LLaVA	1	1	1	×	Classification	General	✓ ^[17]

Table 1: Taxonomy of vision models on time series. The top panel includes single-modal models. The bottom panel includes multi-modal models. **TS-Type** denotes type of time series. **TS-Recover** denotes recovering time series from predicted images (\S 5). *: the method has been used to model the individual UTSs of an MTS. [‡]: a new pre-trained model was proposed in the work. [‡]: when pre-trained models were unused, "Fine-tune" refers to train a task-specific model from scratch. **Model** column: CNN could be regular CNN, ResNet, VGG-Net, *etc.*

tation task in [Wang and Oates, 2015b]. Similarly, [Barra *et al.*, 2020] applied GAF for financial time series forecasting.

Given a UTS $\mathbf{x} \in \mathbb{R}^{1 \times T}$, the first step is to rescale each x_t to a value \tilde{x}_t within [0, 1] (or [-1, 1]). This range enables mapping \tilde{x}_t to polar coordinates by $\phi_t = \arccos(\tilde{x}_i)$, with a radius r = t/N encoding the time stamp, where N is a constant factor to regularize the span of the polar coordinates. Two types of GAF, Gramian Sum Angular Field (GASF) and Gramian Difference Angular Field (GADF) are defined as

GASF:
$$\cos(\phi_t + \phi_{t'}) = x_t x_{t'} - \sqrt{1 - x_t^2} \sqrt{1 - x_{t'}^2}$$

GADF: $\sin(\phi_t - \phi_{t'}) = x_{t'} \sqrt{1 - x_t^2} - x_t \sqrt{1 - x_{t'}^2}$ (3)

which exploits the pairwise temporal correlations in the UTS. Thus, the outcome is a $T \times T$ matrix **G** with $\mathbf{G}_{t,t'}$ specified by either type in Eq. (3). A GAF image is a heatmap on **G** with both axes representing time, as illustrated by Fig. 2(e).

3.5 Recurrence Plot (RP)

RP [Eckmann *et al.*, 1987] encodes a UTS into an image that captures its periodic patterns by using its reconstructed *phase*

space. The phase space of $\mathbf{x} \in \mathbb{R}^{1 \times T}$ can be reconstructed by *time delay embedding* – a set of new vectors $\mathbf{v}_1, ..., \mathbf{v}_l$ with

 $\mathbf{v}_t = [x_t, x_{t+\tau}, x_{t+2\tau}, ..., x_{t+(m-1)\tau}] \in \mathbb{R}^{m\tau}, \quad 1 \le t \le l$ (4) where τ is the time delay, m is the dimension of the phase space, both are hyperparameters. Hence, $l = T - (m-1)\tau$. With vectors $\mathbf{v}_1, ..., \mathbf{v}_l$, an RP image measures their pairwise distances, results in an $l \times l$ image whose element

$$\mathbf{RP}_{i,j} = \Theta(\varepsilon - \|\mathbf{v}_i - \mathbf{v}_j\|), \quad 1 \le i, j \le l$$
(5)

where $\Theta(\cdot)$ is the Heaviside step function, ε is a threshold, and $\|\cdot\|$ is a norm function such as ℓ_2 norm. Eq. (5) generates a binary matrix with $\operatorname{RP}_{i,j} = 1$ if \mathbf{v}_i and \mathbf{v}_j are sufficiently similar, producing a black-white image (*e.g.*, Fig. 2(f)).

An advantage of RP is its flexibility in image size by tuning m and τ . Thus it has been used for time series classification [Silva *et al.*, 2013; Hatami *et al.*, 2018], forecasting [Li *et al.*, 2020], anomaly detection [Lin *et al.*, 2024] and explanation [Kim *et al.*, 2024]. Moreover, the method in [Hatami *et al.*, 2018], and similarly in HCR-AdaAD [Lin *et al.*, 2024], omit the thresholding in Eq. (5) and uses $||\mathbf{v}_i - \mathbf{v}_j||$ to produce continuously valued images to avoid information loss.

Method	TS-Type	Advantages	Limitations
Line Plot (§3.1)	UTS, MTS	matches human perception of time series	limited to MTSs with a small number of variates
Heatmap (§3.2)	UTS, MTS	straightforward for both UTSs and MTSs	the order of variates may affect their correlation learning
Spectrogram (§3.3)	UTS	encodes the time-frequency space	limited to UTSs; needs a proper choice of window/wavelet
GAF (§3.4)	UTS	encodes the temporal correlations in a UTS	limited to UTSs; $O(T^2)$ time and space complexity
RP (§3.5)	UTS	flexibility in image size by tuning m and τ	limited to UTSs; information loss after thresholding

Table 2: Summary of the five primary methods for transforming time series to images. **TS-Type** denotes type of time series.

3.6 Other Methods

Additionally, [Wang and Oates, 2015a] introduces Markov Transition Field (MTF) for imaging a UTS. MTF is a matrix $\mathbf{M} \in \mathbb{R}^{Q \times Q}$ encoding the transition probabilities over time segments, where Q is the number of segments. ImagenTime [Naiman *et al.*, 2024] stacks the delay embeddings $\mathbf{v}_1, ..., \mathbf{v}_l$ in Eq. (4) to an $l \times m\tau$ matrix for visualizing UTSs. MS-CRED [Zhang *et al.*, 2019] uses heatmaps on the $d \times d$ correlation matrices of MTSs with d variates for anomaly detection. Furthermore, some methods use a mixture of imaging methods by stacking different transformations. [Wang and Oates, 2015b] stacks GASF, GADF, MTF to a 3-channel image. FIRTS [Costa *et al.*, 2024] builds a 3-channel image by stacking GASF, MTF and RP. The mixture methods encode a UTS with multiple views and were found more robust than single-view images in these works for classification tasks.

3.7 How to Model MTS

In the above methods, Heatmap ($\S3.2$) can be used to visualize the variate-time matrices, \mathbf{X} , of MTSs (e.g., Fig. 1(b)), where correlated variates should be spatially close to each other. Line Plot (§3.1) can be used to visualize MTSs by plotting all variates in the same image [Wimmer and Rekabsaz, 2023; Daswani et al., 2024] or combining all univariate images to compose a bigger image [Li *et al.*, 2023b], but these methods only work for a small number of variates. Spectrogram ($\S3.3$), GAF ($\S3.4$), and RP ($\S3.5$) were designed specifically for UTSs. For these methods and Line Plot, which are not straightforward in imaging MTSs, the general approaches include using channel independence assumption to model each variate individually [Nie et al., 2023], or stacking the images of d variates to form a d-channel image [Naiman et al., 2024; Kim et al., 2024]. However, the latter does not fit some vision models pre-trained on RGB images which requires 3-channel inputs (more discussions are deferred to $\S5$).

Remark. As a summary, Table 2 recaps the salient advantages and limitations of the five primary imaging methods that are introduced in this section.

4 Imaged Time Series Modeling

With image representations, time series analysis can be readily performed with vision models. This section discusses such solutions from the traditional models to the SOTA models.

4.1 Conventional Vision Models

Following traditional image classification, [Silva *et al.*, 2013] applies a K-NN classifier on the RPs of time series, [Cohen *et al.*, 2020] applies an ensemble of fundamental classifiers such as SVM and AdaBoost on the Line Plots for time series

classification. As an image encoder, CNNs have been widely used for learning image representations. Different from using 1D CNNs on sequences [Bai et al., 2018], 2D or 3D CNNs can be applied on imaged time series as shown in Fig. 3(a). For example, regular CNNs have been used on Spectrograms [Du et al., 2020], tiled CNNs have been used on GAF images [Wang and Oates, 2015a; Wang and Oates, 2015b], dilated CNNs have been used on Heatmap images [Yazdanbakhsh and Dick, 2019]. More frequently, ResNet [He et al., 2016], Inception-v1 [Szegedy et al., 2015], and VGG-Net [Simonyan and Zisserman, 2015] have been used on Line Plots [Jin et al., 2023; Semenoglou et al., 2023], Heatmap images [Zeng et al., 2021], RP images [Li et al., 2020; Kim et al., 2024], GAF images [Barra et al., 2020; Kaewrakmuk et al., 2024], and even a mixture of GAF, MTF and RP images [Costa et al., 2024]. In particular, for time series generation tasks, GAN frameworks of CNNs [Li et al., 2022; Karami et al., 2024] and a diffusion model with U-Nets [Naiman et al., 2024] have also been explored.

Due to their small to medium sizes, these models are often trained from scratch using task-specific training data. Mean-while, fine-tuning *pre-trained vision models* have already been found promising in cross-modality knowledge transfer for time series anomaly detection [Namura *et al.*, 2024], fore-casting [Li *et al.*, 2020] and classification [Jin *et al.*, 2023].

4.2 Large Vision Models (LVMs)

Vision Transformer (ViT) [Dosovitskiy et al., 2021] has inspired the development of modern LVMs such as Swin [Liu et al., 2021], BEiT [Bao et al., 2022], and MAE [He et al., 2022]. As Fig. 3(b) shows, ViT splits an image into patches of fixed size, then embeds each patch and augments it with a positional embedding. The vectors of patches are processed by a Transformer as if they were token embeddings. Compared to CNNs, ViTs are less data-efficient, but have higher capacity. Thus, pre-trained ViTs have been explored for modeling imaged time series. For example, AST [Gong et al., 2021] fine-tunes DeiT [Touvron et al., 2021] on the filterbank spetrogram of audios for classification tasks and finds ImageNet-pretrained DeiT is remarkably effective in knowledge transfer. The fine-tuning paradigm has also been adopted in [Zeng et al., 2023; Li et al., 2023b] but with different pre-trained models such as Swin by [Li et al., 2023b]. VisionTS [Chen et al., 2024] attributes LVMs' superiority over LLMs in knowledge transfer to the small gap between the pre-trained images and imaged time series. It finds that with one-epoch fine-tuning, MAE becomes the SOTA time series forecasters on some benchmark datasets.

Similar to time series foundation models such as TimesFM [Das *et al.*, 2024], there are some initial efforts in pre-training ViT architectures with imaged time series. Following AST,



Figure 3: An illustration of different modeling strategies on imaged time series in (a)(b)(c) and task-specific heads in (d).

SSAST [Gong *et al.*, 2022] introduced a masked spectrogram patch prediction framework for pre-training ViT on a large dataset – AudioSet-2M. Then it becomes a backbone of some follow-up works such as AST-SED [Li *et al.*, 2023a] for sound event detection. For UTSs, ViTime [Yang *et al.*, 2024] generates a large set of Line Plots of synthetic UTSs for pre-training ViT, which was found superior over TimesFM in zero-shot forecasting tasks on benchmark datasets.

4.3 Large Multimodal Models (LMMs)

As LMMs get growing attentions, some notable LMMs, such as LLaVA [Liu *et al.*, 2023], Gemini [Team, 2023], GPT-4o [Achiam *et al.*, 2023] and Claude-3 [Anthropic, 2024], have been explored to consolidate the power of LLMs and LVMs in time series analysis. Since LMMs support multimodal input via prompts, methods in this thread typically prompt LMMs with the textual and imaged representations of time series, and instructions on what tasks to perform (*e.g.*, Fig. 3(c)).

InsightMiner [Zhang *et al.*, 2023] is a pioneer work that uses the LLaVA architecture to generate texts describing the trend of each input UTS. It extracts the trend of a UTS by Seasonal-Trend decomposition, encodes the Line Plot of the trend, and concatenates the embedding of the Line Plot with the embeddings of a textual instruction, which includes a sequence of numbers representing the UTS, *e.g.*, "[1.1, 1.7, ..., 0.3]". The concatenated embeddings are taken by a language model for generating trend descriptions. Similarly, [Prithyani *et al.*, 2024] adopts the LLaVA architecture, but for MTS classification. An MTS is encoded by the visual embeddings of the stacked Line Plots of all variates. The matrix of the MTS is also verbalized in a prompt as the textual modality. By integrating token embeddings, both methods fine-tune some layers of the LMMs with some synthetic data.

Moreover, zero-shot and in-context learning performance of several commercial LMMs have been evaluated for audio classification [Dixit *et al.*, 2024], anomaly detection [Zhuang *et al.*, 2024], and some synthetic tasks [Daswani *et al.*, 2024], where the image and textual representations of a query time series are integrated into a prompt. For in-context learning, these methods inject the images of a few example time series and their labels (*e.g.*, classes) into an instruction to prompt LMMs for assisting the prediction of the query time series.

4.4 Task-Specific Heads

For classification tasks, most of the methods in Table 1 adopt a fully connected (FC) layer or multilayer perceptron (MLP) to transform an embedding into a probability distribution over all classes. For forecasting tasks, there are two approaches: (1) using a $d_e \times W$ MLP/FC layer to directly predict (from the d_e -dimensional embedding) the time series values in a future time window of size W [Li et al., 2020; Semenoglou et al., 2023]; (2) predicting the pixel values that represent the future part of the time series and then recovering the time series from the predicted image [Yang et al., 2023; Chen et al., 2024; Yang et al., 2024] (§5 discusses the recovery methods). Imputation and generation tasks resemble forecasting as they also predict time series values. Thus approach (2) has been used for imputation [Wang and Oates, 2015b] and generation [Naiman et al., 2024; Karami et al., 2024]. When using LMMs for classification, text generation, and anomaly detection, most of the methods prompt LMMs to produce the desired outputs in textual answers, circumventing task-specific heads [Zhang et al., 2023; Dixit et al., 2024; Zhuang et al., 2024].

5 Pre-Processing and Post-Processing

To be successful in using vision models, some subtle design desiderata include **time series normalization**, **image alignment** and **time series recovery**.

Time Series Normalization. Vision models are usually trained on standardized images. To be aligned, the images introduced in §3 should be normalized with a controlled mean and standard deviation, as did by [Gong et al., 2021] on spectrograms. In particular, as Heatmap is built on raw time series values, the commonly used Instance Normalization (IN) [Kim et al., 2022] can be applied on the time series as suggested by VisionTS [Chen et al., 2024] since IN share similar merits as Standardization. Using Line Plot requires a proper range of y-axis. In addition to rescaling time series [Zhuang et al., 2024], ViTST [Li et al., 2023b] introduced several methods to remove extreme values from the plot. GAF requires min-max normalization on its input, as it transforms time series values withtin [0, 1] to polar coordinates (*i.e.*, arccos). In contrast, input to RP is usually normalization-free as an ℓ_2 norm is involved in Eq. (5) before thresholding.

Image Alignment. When using pre-trained models, it is imperative to fit the image size to the input requirement of the models. This is especially true for Transformer based models as they use a fixed number of positional embeddings to encode the spacial information of image patches. For 3-channel RGB images such as Line Plot, it is straightforward to meet a pre-defined size by adjusting the resolution when producing the image. For images built upon matrices such as Heatmap, Spectrogram, GAF, RP, the number of channels and matrix size need adjustment. For the channels, one method is to duplicate a matrix to 3 channels [Chen *et al.*, 2024], another way

is to average the weights of the 3-channel patch embedding layer into a 1-channel layer [Gong *et al.*, 2021]. For the image size, bilinear interpolation is a common method to resize input images [Chen *et al.*, 2024]. Alternatively, AST [Gong *et al.*, 2021] resizes the positional embeddings instead of the images to fit the model to a desired input size. However, the interpolation in these methods may either alter the time series or the spacial information in positional embeddings.

Time Series Recovery. As stated in §4.4, tasks such as forecasting, imputation and generation requires predicting time series values. For models that predict pixel values of images, post-processing involves recovering time series from the predicted images. Recovery from Line Plots is tricky, it requires locating pixels that represent time series and mapping them back to the original values. This can be done by manipulating a grid-like Line Plot as introduced in [Yang et al., 2023; Yang et al., 2024], which has a recovery function. In contrast, recovery from Heatmap is straightforward as it directly stores the predicted time series values [Zeng et al., 2021; Chen et al., 2024]. Spectrogram is underexplored in these tasks and it remains open on how to recover time series from it. The existing work [Zeng et al., 2023] uses Spectrogram for forecasting only with an MLP head that directly predicts time series. GAF supports accurate recovery by an inverse mapping from polar coordinates to normalized time series [Wang and Oates, 2015b]. However, RP lost time series information during thresholding (Eq. 5), thus may not fit recoverydemanded tasks without using an *ad-hoc* prediction head.

6 Challenges and Future Directions

Fundamental Understanding. Given the multiple methods for imaging time series, the existing works usually pick their own choice by intuition. There remains a gap in both theoretical and empirical understanding of research questions such as which imaging methods fit what tasks and whether LVMs truly learn patterns from the images that make them more suitable than LLMs in time series modeling. Some existing works evaluate multiple imaging methods, but in limited tasks. For example, ImagenTime [Naiman et al., 2024] compares the representation abilities of GAF, STFT, and delay embedding ($\S3.6$) in a time series generation task. However, a thorough understanding that can guide future developments of LVMs and LMMs on top of different imaging methods is absent. This survey provides an initial comparative discussion of these methods in §3. Further investigations with empirical validation and theoretical justification is essential to the synergy between LVMs/LMMs and time series analysis.

Modeling the Correlation of Variates in MTS. In §3.7, we discussed the existing methods for imaging MTSs. However, each of them has its limitation. For example, when visualizing a variate-time matrix by a Heatmap image (*e.g.*, Fig. 2(b)), the row a variate locates at matters to the downstream modeling of correlations. This is because vision models only encode the spatial relationships of pixels thus correlated variates should be spatially close to each other. Similarly, Line Plots does not enable explicit modeling of correlated variates by vision models. Stacking *d* images, one per variate, into

a *d*-channel input may disable the chance to use pre-trained LVMs due to their fixed 3-channel RGB input. As such, effective methods at either the imaging step or the modeling step (*e.g.*, leveraging graph neural networks (GNNs) on variates) that allow correlation learning from MTSs are in demand.

Advanced Imaging for Time Series. In addition to the basic methods introduced in §3, it is promising to explore more advanced image representations. For example, InsightMiner [Zhang et al., 2023] adopts Seasonal-Trend decomposition, which is often used to extract components that can serve as inductive bias for time series models. Generalizing it to decompose images such as Spectrogram, GAF, RP into fine-grained representations may further boost vision models' ability in time series analysis. Moreover, mixture of imaging may enable encoding of information from different views, such as frequency (Spectrogram), temporal relationships (GAF) and recurrence patterns (RP). FIRTS [Costa et al., 2024] stacks a mixture of images in multiple channels for a classification task, but it is limited to images of the same size. Modeling a mixture of arbitrary images by methods such as multi-view learning may enable more flexibility.

Multimodal Time Series Models and Agents. As can be seen from Table 1, the existing research on multimodal analysis (with vision modality) is much less than unimodal analysis, with a limited scope of time series tasks. Given the existing LLMs for time series such as Time-LLM [Jin *et al.*, 2024] and S²IP [Pan *et al.*, 2024], it is appealing to introduce vision modality to further boost the performance in wide tasks such as forecasting, classification and anomaly detection. Furthermore, the visual representation of time series provides the foundation for exploring multimodal AI agents [Xie *et al.*, 2024] for more intricate and nuanced tasks that requires reasoning and interactions with environments, such as root cause analysis in AI for IT Operations (AIOps).

Vision-based Time Series Foundation Models. A foundation model (FM) is a deep learning model trained on vast datasets that is applicable to a wide range of tasks. Recent time series FMs, such as TimesFM [Das *et al.*, 2024], MO-MENT [Goswami *et al.*, 2024], Chronos [Ansari *et al.*, 2024] and Time-MoE [Shi *et al.*, 2024], are mostly built upon LLM architectures and trained on raw time series. Given the potential of image representation, it is promising to explore vision models as a new architecture to revolutionize time series FMs. This research direction not only leverages the advantages of LVMs as introduced in §1 (*e.g.*, the prior knowledge extracted from the vast pre-training images), but also enables future development of vision-language FMs for time series.

7 Conclusion

In this paper, we present the first survey on leveraging vision models for time series analysis, whose general process structures the survey. We propose a new taxonomy consisting of imaging and modeling methods for time series. We discuss the pre- and post-processing steps as well. Each category encompasses representative methods and relevant remarks. The survey also highlights the challenges and future directions for further advancing time series analysis with vision models.

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