

Novel Approach for Imaging Time Series for the Improvement of Classification Results “Grayscale Fingerprint Features Field Imaging (G3FI)”

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ABSTRACT

The remarkable successes achieved by Deep Learning (DL) in computer vision drew the attention of researchers to exploit this capability to apply it for the processing of time series and multivariate data. Thus, researcher began the development of suitable methods to transform time series signals into, images to enable the use of DL techniques to improve the classification of time series data. The most state-of-art techniques are Recurrence Plot (RP), Gramian Angular Field (GAF), or Markov Transition Field (MTF). These techniques transform each time series into RGB image. In this paper, a new transformation technique of time series and multivariate data to images technique is proposed. This technique is called “Grayscale Fingerprint Features Field Imaging” (G3FI). The main differences between this technique and state-of-art techniques are: a) the resulted image is a grayscale; b) the size of the resulted image is much smaller than the size of resulted images using state-of-art techniques. These differences provide the proposed technique with several advantages over the prior art, as it (a) results in avoiding redundant information and (b) noise, and (c) leads to a significant reduction in the required computational power. For the proof of concept, a dataset "Sonar, Mines vs. Rocks" is investigated and individually transformed using RP, GAF, and MTF, and the new developed technique "G3FI". The resulted images from each transformer are individually used to train and test Convolutional Neural Networks (CNN). The proposed method leads to competitive results in comparison to RP, GAF, and MTF.

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INTRODUCTION

The remarkable successes achieved by Deep Learning (DL) in Computer Vision (CV) for image classification, drew the attention of researchers to exploit this capability apply it for the processing of time series [1]. Thus, researcher began to develop suitable methods for transformation time series format dataset into images to enable the use of DL techniques to improve classification performance [2], [3], [4], [5].

The state-of-art transformation techniques, so-called Imaging Time Series, are Recurrence Plot (RP), Gramian Angular Field (GAF), and Markov Transition Field (MTF) [5]. The operating principle of imaging time series techniques is based on the transformation of the descriptive features of each time series sample in the given dataset into a 2D texture coded image [2], [3], [4], [5]. Each of the state-of-art imaging time series techniques consist of a sequence of complex mathematical transformation and further processing steps to perform the transformation and to prepare the transformed images for the classification. The applied mathematical transformation matrices are 1) Recurrence matrix (RP technique), 2) Gram matrix (GAF technique) and 3) Markov Transition matrix (MTF technique) [2], [5]. Generally, the resolution of the resulting images of state-of-art techniques depends essentially on the number of descriptive features of the time series format dataset, where this resolution is square of feature number of transformed sample [2], [3], [4], [5]. Thus, the higher the number of features of a sample, the higher the resolution of the resulting image. This, in turn, leads to a significant increase of computational power.

This paper introduces a newly developed imaging time series technique called "Grayscale Fingerprint Features Field Imaging (G3FI)". In this technique, the transformation process of each sample of the time series format dataset into a 2D image requires only two simple steps, and the resolution of resulted image is equal to the number of the descriptive features of transformed sample. Thus, required computational power for further image processing (classification) should be less than required computational power of resulted image by the state-of-art techniques.

STATE-OF-ART IMAGING TIME SERIES TECHNIQUES

In this section, state-of-art imaging time series techniques will be shortly introduced.

Recurrence Plot (RP)

The RP has been developed by J. P. Eckmann, et al. [6] to visualize the recurrence of state \vec{x}_i in 2D or 3D phase/state space. The RP aims to trace and analysis the trajectory of m –dimensional phase space through a two-dimensional representation of its repetitions. The application of RP analysis as an imaging time series technique aims to extract the trajectories of time series and to calculate the

binarized pairwise distance matrix between them as a recurrence representation in the phase/state space; this matrix is denoted as R to build the recurrence diagram (RP) as follows [5]:

$$R_{i,j} = \theta(\varepsilon - \|\vec{x}_i - \vec{x}_j\|) = \begin{cases} 1 & \text{if } \|\vec{x}_i - \vec{x}_j\| \leq \varepsilon \\ 0 & \text{otherwise} \end{cases}, \forall i, j \in \{1, \dots, n - (m - 1)\tau\} \quad (1)$$

Where:

$R_{i,j}$ is the trajectory of the recurrence of a state \vec{x}_i between the initial time point (i) and the time point (j) over time in the m – dimensional phase space, n is length of the trajectory through the phase space/number of the future states resulting from a given initial state in phase space, θ is Heaviside function, ε is Recurrence threshold, and $\|\cdot\|$ is Norm.

Gramian Angular Field (GAF)

The GAF is used to represent the temporal correlation between each pair of values of the time series in order to obtain a relevant image [5]. The core of GAF is the Gram matrix, denoted by (G), which is a useful tool in linear algebra and geometry to calculate the linear dependence of a set of vectors. The steps of GAF method are introduced in Figure 1.

Markov Transition Field (MTF)

The MTF is used to represent the transition probabilities between each pair of values in the discretized time series in order to obtain a relevant image [5]. The Markov transition, also known as stochastic or probability matrix is the core of the MTF. The transition matrix is the square matrix that represents the transition probabilities of a state to another in the phase/state space of a dynamical system during one time step/unit of motion. The steps of MTF method are introduced in Figure 2.

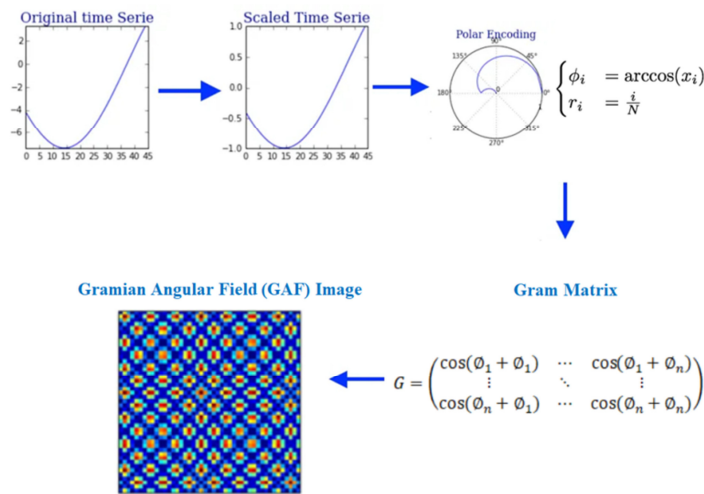


Figure 1. Illustration of the GAF technique-based encoding procedure

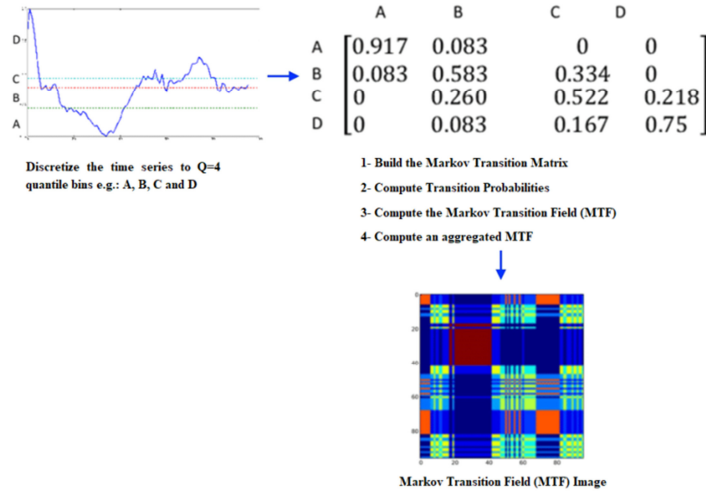


Figure 2. Illustration of the MTF technique-based encoding procedure

GRAYSCALE FINGERPRINT FEATURES FIELD IMAGING (G3FI) TECHNIQUE

The novel G3FI technique aims to generate the grayscale fingerprint of the descriptive features of each sample of the time series format dataset. Here, the term "fingerprint" refers to the ability of each feature to distinguish between the different states of the dataset under consideration.

The vector of the descriptive features of each considered sample can be defined as:

$$F = \{f_1, f_2, \dots, f_i, \dots, f_n\} \forall i \in \{1, 2, \dots, n\} \quad (2)$$

where:

1. f_i : The i^{th} descriptive feature and
2. n : The number of the used descriptive features.

The proposed process of generation the corresponding grayscale fingerprint is as follows:

- Grayscale-based normalizing process of descriptive features of each considered sample by using equation 3, which leads to new feature values between zero (black) and 255 (White):

$$F' = 255 * \left(\frac{f_i - F_{min}}{F_{max} - F_{min}} \right) \quad (3)$$

where:

1. F' : The normalized/scaled vector of the descriptive features of each considered sample,

2. F_{min} : The minimum value of the descriptive features of each considered sample
 3. F_{max} : The maximum value of the descriptive features of each considered sample
 4. 255: The scalar of grayscale processing
- Generation process of G3FI image ($Image_{G3FI}$) by reshaping (Re) the grayscale normalized vector F' of each considered sample into the $(K * L)$ matrix as follows:

$$Image_{G3FI} = Re_{K,L}(F') \quad (4)$$

where:

1. $Re_{K,L}$: The reshaping process of the grayscale normalized/scaled vector F' into $(K * L)$ matrix to generate G3FI Image
2. K : The number of rows in the G3FI image matrix ($1 \leq K \leq (n/2)$)
3. L : The number of columns in the G3FI image matrix ($1 \leq L \leq (n/2)$)

PROOF OF CONCEPT

To prove the efficiency the new proposed technique, a time series data set is investigated. Time series samples in this data set are individually transformed using state-of-art techniques and new proposed techniques. The resulted images from each transformer are individually used to train and test Convolutional Neural Networks (CNN). The overall proof of concept method will be introduced in the following subsections.

Sonar Dataset

The benchmark dataset (Sonar, Mines vs. Rocks) as a time series format dataset is used. It consists of multivariate samples (60 features in time series format) obtained by processing sonar signals, which were bounced off a metal cylinder and a rock at various angles and under various conditions [7].

Convolutional Neural Network (CNN)

The CNN is the type of the Artificial Neural Network (ANNs) [8], which consists of a sequence of input layer, the (N) hidden layers (feature extraction blocks) followed by a classification block and the output layer (Figure 3). Each feature extraction block consists of sequence of the (convolutional, nonlinear activation such as Rectified Linear Unit (ReLU) and pooling, respectively) layers. The classification block consists of the sequence of the layers of flatten, fully connected network, and SoftMax, which is the output layer [1].

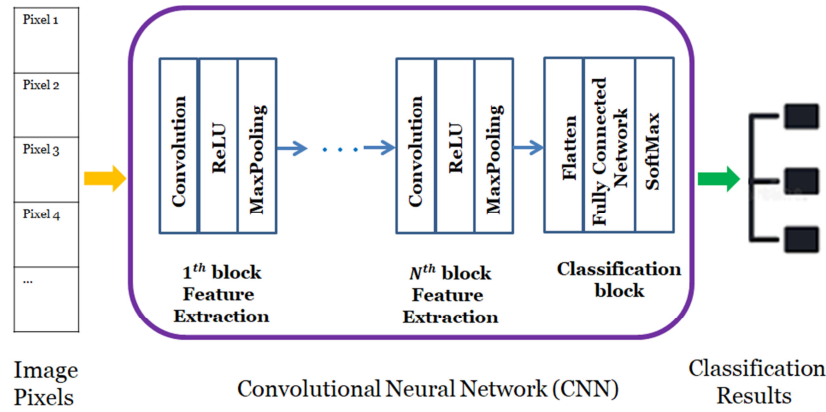


Figure 3. CNN structure with the N hidden layers as the feature extraction blocks and one classification block

Experimental Setup

A CNN-Model-based classification system consisting of two hidden layers ($N = 2$ feature extraction blocks with 32 neurons in the first layer and 64 neurons in the second block) and one classification block (with 128 neurons fully connected network and 2 neurons SoftMax function as output layer) is realized to classify the resulted image each individual transformer. In order to generate the RP, GAF and MTF images of the 207 samples Sonar dataset, the "RecurrencePlot", "GramianAngularField" and "MarkovTransitionField" methods of the pyts (Python Package for Time Series Classification) module [5] are respectively applied. Figure. 4, shows a time series sample of the sonar dataset and the related transformation results using RP, GAF, MTF, and G3FI techniques.

To achieve a fair comparison between these four imaging methods, ensure that the classification/prediction process is performed for the same images of the sonar time series format set in both the training phase of the CNN model and the evaluation phase; therefore the proposed experimental setup uses the 10-times random shuffling and the 10-fold cross-validation techniques to complete the Proof of Concept (PoC) of the novel G3FI technique as well for the comparison between G3FI and state-of-the-art techniques as illustrated in Figure 5.

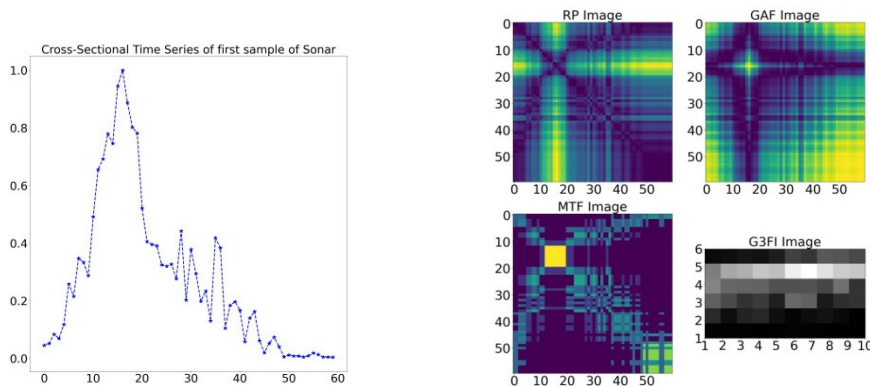


Figure 4. A sample of the time series sonar dataset (left) and the related time series images using RP, GAF, MTF and G3FI techniques (right).

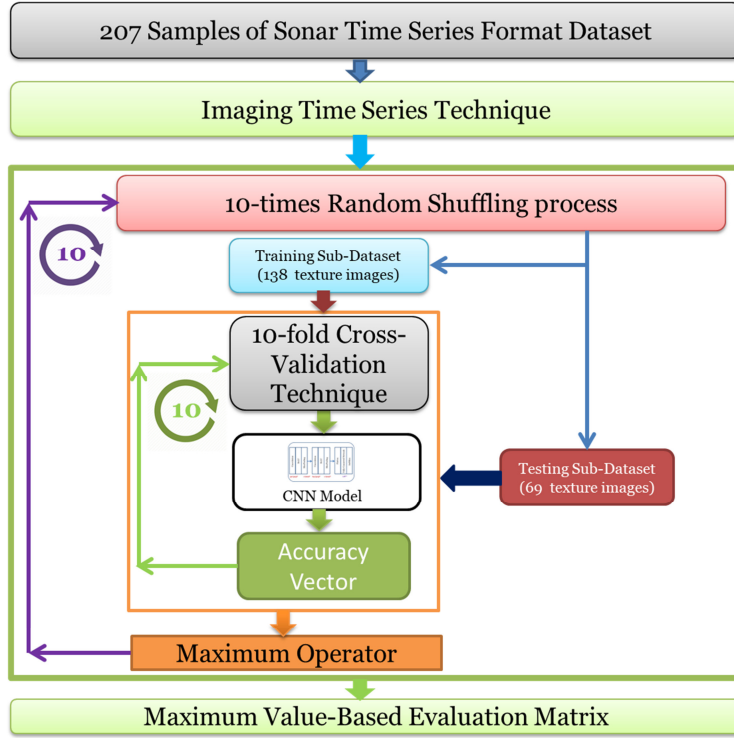


Figure 5. Illustration of experimental setup

RESULTS AND DISCUSSION

The results of the applied experimental test are presented of the four image time series techniques in Table I. It can be seen that the G3FI method provides competitive results compared to state-of-art imaging time series techniques. The best performance, i.e., the accuracy value, is 95.65217495% (green rectangles in Table I). This best performance can be achieved by using low resolution image (60 pixels) resulted by using G3FI image, while stat-of-art techniques should use high resolution images (e.g.: 3600 pixels of RP image) to achieve the same performance. As it is shown in Table I (bold numbers), G3FI leads to the best classification results of the ten performed iteration.

Table I. Maximum Value-based Evaluation Matrix of the four considered imaging time series

	RP	GAF	MTF	G3FI
1.	88,40579987	91,3043499	73,91304374	85,50724387
2.	89,85507488	89,85507488	84,05796885	91,3043499
3.	86,95651889	86,95651889	79,7101438	88,40579987
4.	86,95651889	82,60869384	79,7101438	86,95651889
5.	89,85507488	92,75362492	78,26086879	92,75362492
6.	92,75362492	91,3043499	82,60869384	95.65217495
7.	89,85507488	89,85507488	81,15941882	89,85507488
8.	95,65217495	91,3043499	78,26086879	95,65217495
9.	91,3043499	92,75362492	89,85507488	92,75362492
10.	82,60869384	88,40579987	81,15941882	84,05796885

CONCLUSION

The imaging time series (such as RP, GAF, or MTF) methods have significantly contributed to consolidate the application of DL technology to improve classification results of tasks consisting of time series data. In this paper, the “Grayscale Fingerprint Features Field Imaging (G3FI)” is proposed as imaging time series technique. The resolution of the resulted G3FI image is equal to the number of used descriptive features in the time series format dataset, while in the state-of-art techniques the resolution of the resulted images is square of number of used descriptive features. The G3FI technique introduces strong and competitive classification performance in comparison to state-of-art techniques.

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