International Conference on Applied Energy 2021
Nov. 29 - Dec. 2, 2021, in Bangkok, Thailand
Paper ID: xxxx

Elevating Energy Data Analysis with M^{2}GAF: Micro-Moment Driven Gramian Angular Field Visualizations

Abdullah Alsalemi[a], Abbes Amira[b,a], Hossein Malekmohamadi[a], Kegong Diao[c], Faycal Bensaali[d]*

[a] *Institute of Artificial Intelligence, De Montfort University, Leicester, UK*
[b] *Department of Computer Science, University of Sharjah, Sharjah, UAE*
[c] *Institute of Energy and Sustainable Development, De Montfort University, Leicester, UK*
[d] *Department of Electrical Engineering, College of Engineering, Qatar University, Doha, Qatar*
**Correspondence email: P2621877@my365.dmu.ac.uk*

ABSTRACT

With global pollution and buildings power consumption on the rise, energy efficiency research has never been more necessary. Accordingly, data visualization is one of the most sought challenges in data analysis, especially in energy efficiency applications. In this paper, a novel micro-moment Gramian angular fields time-series transformation of energy signals and ambient conditions, abbreviated as M^{2}GAF, is described. The proposed tool can be used by energy efficiency researchers to yield deeper understanding of building energy consumption data and its environmental conditions. Current results show sample G^{2}GAF representation for three power consumption datasets. In summary, the proposed tool can unveil novel energy time-series analysis possibilities as well as original data visualization that can yield deeper insights, and in turn, improved energy efficiency.

Keywords: Gramian angular fields, energy efficiency, artificial intelligence, data visualization, micro-moments, internet of energy.

NONMENCLATURE

Abbreviations	
GAF	Gramian Angular Field
GADF	Gramian Angular Difference Field
GASF	Gramian Angular Summation Field
M^{2}GAF	Micro-Moment Gramian Angular Field

Symbols	
x	Time-series vector
R	Regularizing constant factor
N	Number of samples in x
$\emptyset$	Angular cosine of x

1. INTRODUCTION

On grounds of resurging global pollution and skyrocketing expenses involving heating, ventilation, and air-conditioning and other energy systems in buildings, energy efficiency has arisen as a major issue [1].

Accordingly, data visualization is one of the most sought challenges in data analysis. Particularly in energy efficiency applications, distilling meaning from extensive power consumption series via visual aids can be an instrumental tool in obtaining useful insights. On top, visualization can bring new levels of understanding that algorithms cannot achieve. In fact, a plethora of research contributions have uncovered tools and methods for power consumption data visualization, including interactive studies [2]. It has been signified that contextually effective graphing of time-series consumption can be powerful tool not only for discerning patterns, but for motivating positive behavioral change.

For instance, eco-feedback systems have been extensively adopted with the aim of encouraging sustainable behavioral adjustments on the premise that occupants are ignorant of the energy used as a result of their day-to-day activities [3].

Compellingly, data visualization can be a powerful tool to understand that programmatically. Therefore, Machine Learning (ML) can be used hand in hand what is specific data visualizations to yield more useful results and insights [2], [3]. Also, data visualization can be a tool to convert 1-Dimensional (1D) data and to higher dimensional realms that can enable using more complex ML algorithms suitable for multidimensional data.

Henceforth, in this paper, a novel transformation tool is introduced to convert 1D time-series energy data into 2D graphical representations using Gramian Angular Fields (GAF). From this work, the following contributions can be revealed:

1. Novel conversion of 1D time-series energy consumption data to 2D GAF image representations;
2. Introduction of a novel tool for GAF transformations of micro-moments, which are time-based encapsulations of energy data coupled with ambient environmental conditions, abbreviated as M^2GAF; and
3. Shed light on the applications of the produced representations in both data visualization and analytics.

The remainder of this paper is organized as follows. Section 2 discusses related work to the area of GAF representations, while Section 3 describes basic GAF theory. The proposed transformation tool is devised in Section 4 with preliminary results discussed in Section 5. The paper is concluded in Section 6.

2. RELATED WORK

In recent literature, GAF-related contributions have mainly focused on seizure classification [4], speech recognition [5], fault detection [6], study blood flow patterns [7], among others. Emphasis on energy efficiency application did not receive much attention.

As an example, Yang et al. [8] have introduced a Convolutional Neural Network (CNN) based sensor classification solution by encoding multivariate time series into 2D colored images using three different transformation methods: Gramian Angular Summation Field (GASF), Gramian Angular Difference Field (GADF), and Markov Transition Field (MTF). These methods were chosen to observe their impact of concatenation sequence complexity of images on the classification accuracy. As per the results, it was shown that there was no interconnection between the selection of these transformation methods and the prediction outcome.

In renewable power generation, Hong et al. [9] proposed a study that utilizes GAF for the improvement of power system operation by forecasting accurate day-ahead solar irradiation. By converting 1D time-series data into a sequential set of images, GAF, along with a Convolutional Long Short-term Memory (LSTM) network was used as a novel method to overcome the LSTM constraint encountered in 1D forecasting problems, as well as to reduce uncertainties while managing the balance between the load and generation.

On the other hand, Lee et al. [10] have addressed the prediction of Work-Related Musculoskeletal Disorders (WMSDs) while excessive load carrying during various construction tasks. In this study, the GAF transform was employed to convert data coming from the inertial measurement unit sensors to into images before performing a hybrid CNN-LSTM to classify load-carrying modes. The results have shown high prediction accuracies.

Moreover, Damasevicius et al. [11] have addressed the challenges encountered when interpreting information carried by the biomedical signals, such as their large amount, high complexity, and high-dimensionality. Therefore, a GAF representation was proposed for the visualization of physiological time series signals, of which was demonstrated on the arrhythmia case classification task using the K-Nearest Neighbor (KNN) classifier.

Also in building energy management, on the other hand, Ulyanin et al. [12] have encoded the feature extraction and clustering of building energy profiles as images using GAF for visualization. Sensor data of daily energy profiles are collected for enhanced monitoring and analysis of the building energy systems. A well-known simple algorithm deployed for this purpose is K-means, nevertheless, the system is able to overcome its challenges including its algorithm rigidity and lack of insight on the most valuable data, such as the hidden non-linear features.

Based on the above literature, this work aims to specialize in transforming time-series energy signals along with contextual environmental data into GAF representation to enable further data analysis and visualization.

3. GRAMIAN ANGULAR FIELDS (GAF)

As described earlier, GAF representation are graphical tools to visualize time series data into 2D images, providing a higher dimension for further data analysis and interpretation.

As illustrated in **Error! Reference source not found.**, the process involving the conversion of a micro-moment dataset into a 2D image using a GAF transformation program, producing 2D M²GAF image that is then input into a 2D classifier for further analysis.

Fig. 1. Overview of the M²GAF transformation.

In theory, the GAF transformation was suggested to represent time-series data as pictures, allowing image-based Deep Learning (DL) techniques to be used [9], [13].

First, a time-series vector $x = \{x_1, x_2, x_3, \ldots, x_N\}$ with *N* samples is normalized to [0, 1] using Eq. (1).

$$\tilde{x}_i = \frac{(x_i - \max(x)) + (x_i + \max(x))}{\max(x) - \min(x)} \tag{1}$$

To obtain the polar coordinates, the value of each series element is then encoded as angular cosine, and the timestamps are divided by a regularizing constant factor, *R*, as shown in Eq. (2).

$$\begin{cases} \emptyset = \arccos(\tilde{x}_i)\,, & 0 < \tilde{x}_i < 1 \in x \\ r = \dfrac{t}{R}\,, & t \in R \end{cases} \tag{2}$$

Two images can be generated from two GAF equations: the Gramian Angular Summation Field (GASF), defined by Eq. (3) and Eq. (4), and the Gramian Angular Difference Field (GADF), defined by Eq. (5) and Eq. (6) [14]. The Gramian field is determined after the rescaled time series has been converted by defining the angular perspective as the trigonometric sum of each point in the interval. As noted from the equations, GASF is based on cosine functions, whereas GADF is based on sine functions making the trigonometric functions the only difference between the two GAF equations:

$$GASF = \begin{pmatrix} \cos(\emptyset_1 + \emptyset_1) & \cdots & \cos(\emptyset_1 + \emptyset_N) \\ \vdots & \ddots & \vdots \\ \cos(\emptyset_N + \emptyset_1) & \cdots & \cos(\emptyset_N + \emptyset_N) \end{pmatrix} \tag{3}$$

$$GASF = \tilde{x}'.\tilde{x} - \sqrt{I - \tilde{x}^2}'.\sqrt{I - \tilde{x}^2} \tag{4}$$

$$GADF = \begin{pmatrix} \sin(\emptyset_1 + \emptyset_1) & \cdots & \sin(\emptyset_1 + \emptyset_N) \\ \vdots & \ddots & \vdots \\ \sin(\emptyset_N + \emptyset_1) & \cdots & \sin(\emptyset_N + \emptyset_N) \end{pmatrix} \tag{5}$$

$$GADF = \sqrt{I - \tilde{x}^2}'.\tilde{x} - \tilde{x}'.\sqrt{I - \tilde{x}^2} \tag{6}$$

Due to the superposition of directions with regard to the time interval, the transformation maintains the temporal dependency between values while also giving temporal correlations. The bijective matrix that arises is the outcome of this process. As a result of the inverse function, an absolute reconstruction of the original data can be obtained.

4. MICRO-MOMENT GRAMIAN ANGULAR FIELD REPRESENTATIONS (M²GAF)

After describing the core concept of GAF representation, a novel derived postulation is described that aims to transform energy consumption data, both aggregated and appliance-level, as well as contextual environmental data into 2D GAF images. In other words, the GAF notion is employed to elevate the 1D micro-moment data into 2D GAF representations, or M²GAF.

Before diving into the details of the process, it is prudent to define the concept of micro-moments, which is popularized by Google as an internet tool for targeted marketed. The concept has evolved into a more mature encapsulation of both energy data (i.e. electric current, voltage, and power) and contextual ambient conditions (i.e. indoor/outdoor temperature humidity, light level, and barometric pressure as well as space occupancy).

Table 1 lists five Energy Micro-Moment (EMM) indexes, from healthy (EMM 0) to extremely excessive (EMM 5). They range from normal consumption, to identifying appliance status change, and also classifying unhealthy consumption into environment-based, no-presence based consumption, and extreme consumption levels in terms power magnitude.

Table 1. The EMM index.

Index	Label
0	Normal consumption
1	Switch appliance on/off
2	No-presence normal consumption
3	Context-based excessive consumption
4	Extremely excessive consumption

The direction progression of a GAF image is shown in Fig. 2, where the 4 sub-plots indicate the evolution of a GAF representation as a time-series signal develops over time. It can be noticed that the direction of progression is diagonal in GAF images and blue values represent the lowest values of the original signal, while red indicates maximum values.

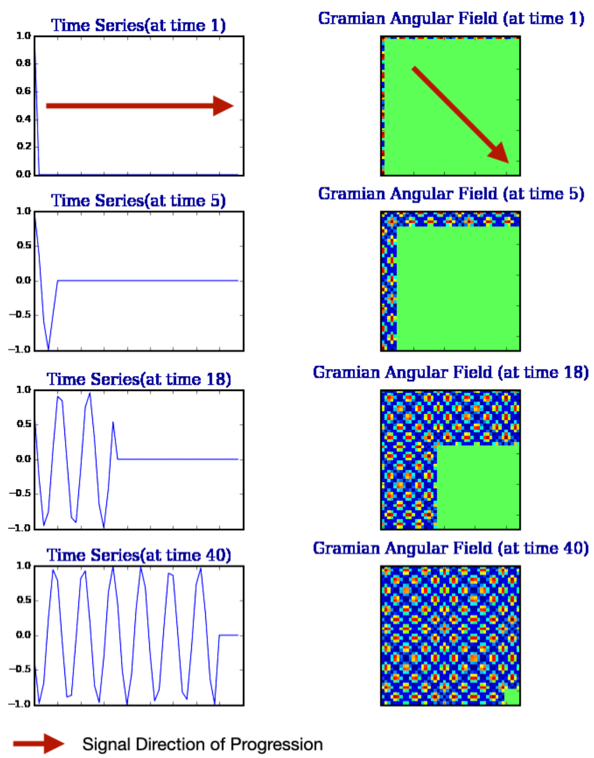

Fig. 2. Evolution of a GAF image over time . Adapted from [15].

5. PRELIMINARY RESULTS & DISCUSSION

In this section, introductory findings on the M^{2}GAF transformation are unveiled to prove the concept, explore conversion performance, and shed light on potential data visualization and analysis. In this work, three datasets are examined:

1. Micro-moment dataset collected by the authors at De Montfort University (DMU) that includes energy (W) and ambient environmental data (°C, RH%, KPa, Lux), abbreviated as DMUD in short;
2. Qatar University Dataset (QUD)[1] that includes micro-moments power consumption footprints (W) of different appliances; and
3. UK Domestic Appliance-Level Electricity (UK-DALE)[2] dataset that includes aggregated and disaggregated power consumption data (W) from five UK houses.

The process described in Section 4 is realized via a Python program using the *pandas* library for manipulating time-series data and *pyts* and *matplotlib* *libraries* for creating GAF images using the GASF algorithm. The code can be found as an open-source repository in GitHub[3]. Hence, as illustrated in Fig. 3, three M^{2}GAF visualizations are produced for DMUD, QUD, and UK-DALE datasets, respectively.

In terms of potential applications for the produced M^{2}GAF representation, this work provides a novel opportunity for energy efficiency researchers with the ability to utilize 2D classifiers such as 2D-CNNs, 2D deep neural networks (2D-DNNs), time-frequency analysis, genetic algorithms, etc. in the following applications:

1. Power consumption anomaly detection;
2. Non-intrusive load monitoring;
3. Energy-saving recommender systems;
4. Load-balancing systems;
5. Edge-based energy efficiency systems;
6. Blockchain-based energy efficiency systems; and

Moreover, the produced visualization can be further improved to succinctly condense power consumption data in a single or multiple images, resembling QR-codes for energy efficiency applications.

6. CONCLUSIONS

In this paper, a novel time-series transformation of micro-moment based energy signals and ambient conditions, abbreviated as M^{2}GAF, is described. The tool can be used by energy efficiency researchers to yield deeper understanding of building energy consumption data and its environmental conditions. It also opens new possibilities of utilizing 2D algorithms for time-series data as well as original data visualization that can yield deeper insights into consumption patterns, and in turn, lead to improved energy efficiency.

[1] https://github.com/YassineHimeur/QUD-dataset
[2] https://jack-kelly.com/data
[3] https://github.com/Abdol/GAF-Energy

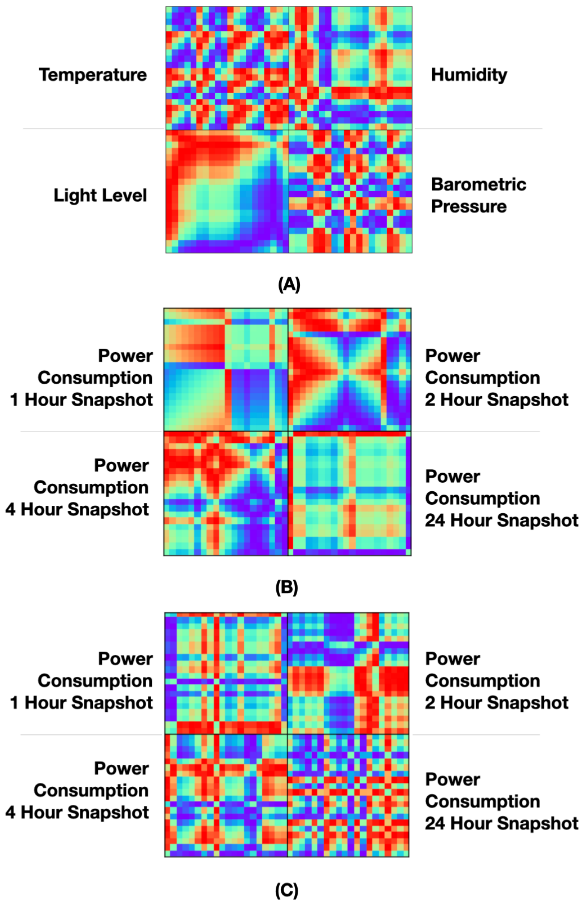

Fig. 3. M^{2}GAF results for (A) Ambient environmental data from DMUD, (B) power consumption data of a computer from QUD, and (C) aggregated power consumption data from UK-DALE.

REFERENCES

[1] L. G. B. Ruiz, M. C. Pegalajar, M. Molina-Solana, and Y.-K. Guo, "A case study on understanding energy consumption through prediction and visualization (VIMOEN)," *Journal of Building Engineering*, vol. 30, p. 101315, Jul. 2020, doi: 10.1016/j.jobe.2020.101315.

[2] A. Al-Kababji *et al.*, "Energy Data Visualizations on Smartphones for Triggering Behavioral Change: Novel Vs. Conventional," in *2020 2nd Global Power, Energy and Communication Conference (GPECOM)*, Oct. 2020, pp. 312–317. doi: 10.1109/GPECOM49333.2020.9247901.

[3] L. Xu, A. Francisco, J. E. Taylor, and N. Mohammadi, "Urban Energy Data Visualization and Management: Evaluating Community-Scale Eco-Feedback Approaches," *Journal of Management in Engineering*, vol. 37, no. 2, p. 04020111, Mar. 2021, doi: 10.1061/(ASCE)ME.1943-5479.0000879.

[4] A. Shankar, H. K. Khaing, S. Dandapat, and S. Barma, "Epileptic Seizure Classification Based on Gramian Angular Field Transformation and Deep Learning," in *2020 IEEE Applied Signal Processing Conference (ASPCON)*, Oct. 2020, pp. 147–151. doi: 10.1109/ASPCON49795.2020.9276717.

[5] Md. M. Islam and Md. M. H. Shuvo, "DenseNet Based Speech Imagery EEG Signal Classification using Gramian Angular Field," in *2019 5th International Conference on Advances in Electrical Engineering (ICAEE)*, Sep. 2019, pp. 149–154. doi: 10.1109/ICAEE48663.2019.8975572.

[6] M. Ganesan and R. Lavanya, "A deep learning approach to fault detection in a satellite power system using Gramian angular field," *International Journal of Engineering Systems Modelling and Simulation*, vol. 12, no. 2–3, pp. 195–201, Jan. 2021, doi: 10.1504/IJESMS.2021.115538.

[7] S. D. Wickramaratne and M. S. Mahmud, "A Deep Learning Based Ternary Task Classification System Using Gramian Angular Summation Field in fNIRS Neuroimaging Data," in *2020 IEEE International Conference on E-health Networking, Application Services (HEALTHCOM)*, Mar. 2021, pp. 1–4. doi: 10.1109/HEALTHCOM49281.2021.9398993.

[8] C.-L. Yang, Z.-X. Chen, and C.-Y. Yang, "Sensor Classification Using Convolutional Neural Network by Encoding Multivariate Time Series as Two-Dimensional Colored Images," *Sensors*, vol. 20, no. 1, Art. no. 1, Jan. 2020, doi: 10.3390/s20010168.

[9] Y.-Y. Hong, J. J. F. Martinez, and A. C. Fajardo, "Day-Ahead Solar Irradiation Forecasting Utilizing Gramian Angular Field and Convolutional Long Short-Term Memory," *IEEE Access*, vol. 8, pp. 18741–18753, 2020, doi: 10.1109/ACCESS.2020.2967900.

[10] H. Lee, K. Yang, N. Kim, and C. R. Ahn, "Detecting excessive load-carrying tasks using a deep learning network with a Gramian Angular Field," *Automation in Construction*, vol. 120, p. 103390, Dec. 2020, doi: 10.1016/j.autcon.2020.103390.

[11] R. Damaševičius, R. Maskeliūnas, M. Woźniak, and D. Połap, "Visualization of physiologic signals based on Hjorth parameters and Gramian Angular Fields," in *2018 IEEE 16th World Symposium on Applied Machine Intelligence and Informatics (SAMI)*, Feb. 2018, pp. 000091–000096. doi: 10.1109/SAMI.2018.8323992.

[12] S. Ulyanin, J. Vazquez-Canteli, J. Y. Park, and Z. Nagy, "SCAFE: Automated simultaneous clustering and non-linear feature extraction of building energy

profiles," *J. Phys.: Conf. Ser.*, vol. 1343, p. 012037, Nov. 2019, doi: 10.1088/1742-6596/1343/1/012037.

[13] K. P. Thanaraj, B. Parvathavarthini, U. J. Tanik, V. Rajinikanth, S. Kadry, and K. Kamalanand, "Implementation of Deep Neural Networks to Classify EEG Signals using Gramian Angular Summation Field for Epilepsy Diagnosis," *arXiv:2003.04534 [cs, eess]*, Mar. 2020, Accessed: Sep. 22, 2021. [Online]. Available: http://arxiv.org/abs/2003.04534

[14] Z. Wang and T. Oates, "Imaging Time-Series to Improve Classification and Imputation," presented at the Twenty-Fourth International Joint Conference on Artificial Intelligence, Jun. 2015. Accessed: Sep. 22, 2021. [Online]. Available: https://www.aaai.org/ocs/index.php/IJCAI/IJCAI15/paper/view/11082

[15] L. de Vitry, "Encoding time series as images," *Analytics Vidhya*, Oct. 16, 2018. https://medium.com/analytics-vidhya/encoding-time-series-as-images-b043becbdbf3 (accessed Sep. 22, 2021).

[16] Y. Himeur, A. Alsalemi, F. Bensaali, and A. Amira, "Building power consumption datasets: Survey, taxonomy and future directions," *Energy and Buildings*, vol. 227, p. 110404, Nov. 2020, doi: 10.1016/j.enbuild.2020.110404.