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DATA ARTICLE

Time-domain spectra of ultrasonic wave transmitted through granite and gypsum samples containing artificial defects

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Abstract

The internal defects in rock masses can significantly impact the quality and safety of geotechnical projects. Mechanical waves, as a common nondestructive testing (NDT) method, can reflect the external and internal structures of rock or rock masses. Analyses on the reflected and transmitted waves enable nondestructive identification and assessment of potential defects within rocks. Previous studies mainly focused on the variation of single or limited wave features like main frequency, amplitude and energy between the intact and non-intact samples. In fact, most information contained in the waveforms is neglected. Techniques of data mining can provide a powerful tool to reveal this information and therefore a more accurate determination of the internal structures. In this study, 995,412 NDT data from 14 types of granite and gypsum samples with different cross-section shapes and different types of defects are recorded by an ultrasonic wave generation and collection system. This dataset can be used not only as the training data for defect classification in NDT but also as a good reference for conventional NDT analyses. Besides, time-series data analysis is an opportunity and challenging issue, this dataset holds great potential for broader application in general time-series classification analysis.

KEYWORDS

artificial defects, nondestructive testing, rock defects, stress wave, time-domain spectra, time-series data, ultrasonic wave

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1 | INTRODUCTION

As a natural material, rocks generally contain defects with various sizes created in the formation and the following weathering processes. In the past two centuries after the Industrial Revolution, intensive constructions became a significant force affecting the near-surface earth. Some presenting underground infrastructures can be seen as artificial defects in rocks for a new project. These defects are great threats to the stability and safety. The defects in rocks therefore contain two categories: (1) natural defects, like microcracks (Kranz, 1983), fractures (Wong & Xiong, 2018; Zhao, 2000), joints (Zhao, 1997), voids or cavities (Hao & Azzam, 2005; Huang et al., 2021; Tao et al., 2017), discontinuities (Zou, Wong, et al., 2016) and faults (Doan & d'Hour, 2012) from microscopic to macroscopic dimensions; (2) artificial defects, like caverns (Wang, Cao, et al., 2021; Zhao et al., 1999), tunnels (Grøv & Trinh, 2022; Medina et al., 2022) and shafts (Neupane et al., 2021; Xie et al., 2022). These defects can influence the evolution of the terrain in geology and the safety of infrastructures in engineering. Hence, techniques to detect these defects are crucial to designing safe underground structures with reasonable costs.

The non-destructive testing (NDT) methods of detecting these defects in rocks are always challenging due to the diversity of defects and geological conditions. NDT is a method that uses the change of the physical quantities (such as deformation, displacement, conductivity, resonance, temperature, magnetic fields, etc.) of the testing objectives to determine the integrity, defects or other conditions without affecting the structure or normal use (Gupta et al., 2022; Zhu et al., 2011). In recent years, researchers have conducted extensive in-depth research on the detection of internal defects using a number of NDT solutions (Dwivedi et al., 2018; Wang et al., 2020; Xiong et al., 2024), for example, ultrasonic wave (Basu & Aydin, 2006; Shrifan et al., 2019), microwave (Ida, 2012; Wahab et al., 2019), impact-Echo (Zou et al., 2023; Zou, Chen, et al., 2016), GPR (Gao et al., 2018; Sansalone & Streett, 1997), X-ray (Takano et al., 2006) and acoustic emission (AE) (Cheon et al., 2014; Jia et al., 2021; Pan et al., 2018). Most research mainly concentrated on the testing of structure members, like the anchor rods (Beard & Lowe, 2003; Li et al., 2022), bolts (Shi et al., 2018; Wang, Gao, et al., 2021), slabs (Li et al., 2017; Zou, Chen, et al., 2016) and structural body (Farahani et al., 2023; Lu et al., 2024). However, these investigations are relatively few.

NDT methods based on mechanical waves have extensive applications in structural engineering (Xie et al., 2018), geotechnical engineering (Soga et al., 2019) and geological surveys (Pileggi et al., 2011). In rock engineering, the sizes of defects showing significance to the construction are usually larger than 1 cm ~10 cm which requires a wavelength of a similar dimension for the wave-based NDT methods. In rocks, the frequency of this kind of wave is about 0.5 MHz for mechanical waves in case of the wave velocity of about 5000 m/s. Ultrasonic waves wavelength <2 cm, which are suitable for this goal.

On the other hand, with the development of AI and computing units (CPU, GPU and APU), data-driven research has become a prominent trend. Data, as the cornerstone in the fields of information science and computer science, serves not only as a carrier of information but also as the pivotal force propelling algorithmic evolution. Among various challenges encountered in data science, time-series classification (TSC) has consistently stood out as one of the most demanding and challenging problems in data mining (Bagnall et al., 2015; Ismail Fawaz et al., 2019; Kaushik et al., 2020; Susto et al., 2018).

Over the past decade, the development of TSC has been facilitated by advancements in computer performance (Feremans et al., 2022; Ismail Fawaz et al., 2019). Time-series data, characterized by the sequence of data over time, exists in nearly every task requiring human cognition. More broadly, any classification or recognition problem involving temporally ordered data can be considered a TSC issue (Bai et al., 2021; Längkvist et al., 2014; Li & Jung, 2023). Applications based on the features of time-series data have found widespread application across various fields, including health sciences (Hasselgren et al., 2020; Rajkomar et al., 2018), human activity identification (Gupta, 2021), audio identification and classification (Barchiesi et al., 2015), system security (Susto et al., 2018), etc. Furthermore, TSC has been implemented in numerous fields, with organized public competitions and openly available datasets. For instance, Nweke et al. utilized sensors to collect time-series data on human physiological activities, applying it to medical applications such as motion injury detection and elderly care (Nweke et al., 2018). Bai et al. conducted data mining on time-series data, proposing a symbolic aggregate approximation algorithm that enhanced TSC classifier performance through ensemble classifier construction, successfully applied to the recognition of speech signal data (Bai et al., 2021). Moreover, Farahani et al. applied TSC algorithms, including Machine Learning (ML) and Deep Learning (DL) models, to a large number of different data in the manufacturing industry to achieve an intelligent assessment of the state of machinery and prompt the development of Industry 4.0 (Farahani et al., 2023).

Considering the above NDT and TSC recent research status, to fill the gap of a lack of dataset about the waveforms transmitted rock with defects and AI-based NDT method in rock mechanics, the authors introduced a NDT method powered by a machine learning technique

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to evaluate the conditions of artificial defects in rock-like gypsums through the time-series ultrasonic waves passing through the samples (Tian et al., 2024). In this process, a total of 259,595 sets of data were collected by a high-frequency data collection system. In the machine learning model, 70% and 30% of the data are used for the training dataset and the testing dataset, respectively. The test result shows that a high accuracy (>97%) of determining these defects can be provided by this NDT method with the assistance of the K-nearest neighbour (KNN) and support vector machine (SVM) supervised algorithms. After getting the expected result in this primary process, the authors collect more data and form a reusable dataset. Therefore, this paper aims to share this dataset to make it open-source to more researchers who are interested in the application of artificial intelligence methods in NDT and TSC problems. The data acquisition method, structure of the data, raw data and data will be stated in detail in the following sections. This dataset can be used to train more advanced and effective models. Furthermore, this dataset can be used not only for NDT data classification but also for stress wave analysis in rock mechanics.

2 | DATA ACQUISITION METHOD

The data are a series of wave spectra in the time domain with a total number of 995,412 sets. The variable with time is the voltage transduced by a high-sensitive piezoceramics sensor which can respond to extremely tiny acoustic vibration produced by microcracks. The mechanical wave in the form of pulse is generated continuously by a transducer of an ultrasonic-wave emission instrument. Since there are intrinsic changes in interface condition, electro-magnetic oscillation, sensory attenuation, slight displacement, alignment of sensors, platform vibration, environmental interferences and human operation, though the pulses are produced continuously by the same instrument, each pulse generated is different from others. The generated pulses go through samples containing various types of defects and then are collected by the aforesaid acquisition system. The samples are fabricated by granite and moulded gypsum, and flaws are cast to simulate different defect conditions. This section introduces the preparation of the samples, wave generation and collection subsystems.

2.1 | Sample preparation

Natural granite exhibits minimal internal defects and possesses high compressive strength attributed to its formation conditions. Therefore, it is frequently used in rock mechanics research (Zhao & Li, 2000; Zou, Wong, et al., 2016). However, due to its elevated strength and brittleness, it is challenging to fabricate artificial defects inside the rock. To avoid local damage that influences the rock's mechanical properties, gypsum, chosen for its comparable mechanical properties, is utilized as a substitution. Gypsum is a type of rock-like material which frequently used for the study of rock mechanical properties and failure processes (Deng et al., 2022; Li et al., 2016; Li & Ma, 2009; Zhao et al., 2023; Zou, Wong, et al., 2016). According to the literature (Park & Bobet, 2009; Zou et al., 2012; Zou & Wong, 2016), when mixing the gypsum paste, the proportion of gypsum powder: water: diatomaceous earth is advised to be 175:70:2 to obtain good strength. The addition of diatomaceous earth can prevent the separation of water from the paste.

Considering the dimensions of the ultrasonic transducer, the sample size is designed to be 35 mm in length, 35 mm in width and 40 mm in height. The mould for fabricating gypsum samples is manufactured by a 3D printer (Anycubic MONOX) that can provide accurate positions for the steel shims to create flaws. The fabrication of gypsum samples includes four steps: mould design and production, mould assembly, sample casting and sample drying, as shown in Figure 1 (Tian et al., 2023). Based on the materials and the flaw geometry, the samples are divided into 14 types, as summarized in Table 1, and their dimensions are shown in Figure 2. To better understand the materials, the basic physical and mechanical properties of the intact samples are tested through a series of tests, as shown in Table 2.

2.2 | Data collection

The mechanical wave is generated by an ultrasonic testing instrument and collected by a high-sensitivity transducer and a high-frequency recording instrument. The ultrasonic testing instrument RSM-SY6 emits continuous ultrasonic pulses on the sample surface, naming the incident pulse (Pile Integrity Tester, 2023; Sinorock, 2022). Simultaneously, a wave-detection instrument Vallen AMSY-6 with a high-sensitivity transducer is used to receive the transmitted wave pulse passing through the sample at the opposite surface. The process of data collection is illustrated in Figure 3 (GmbH, 2022; Group, 2022). The main technical parameters of the RSM-SY6 and Vallen AMSY-6 can be obtained in Table 3.

The ultrasonic pulse is generated by a transducer with a size (40 mm diameter circle) covering one end of the sample. The typical incident wave is a time-voltage pulse representing a single trigger. The Vallen AMSY-6

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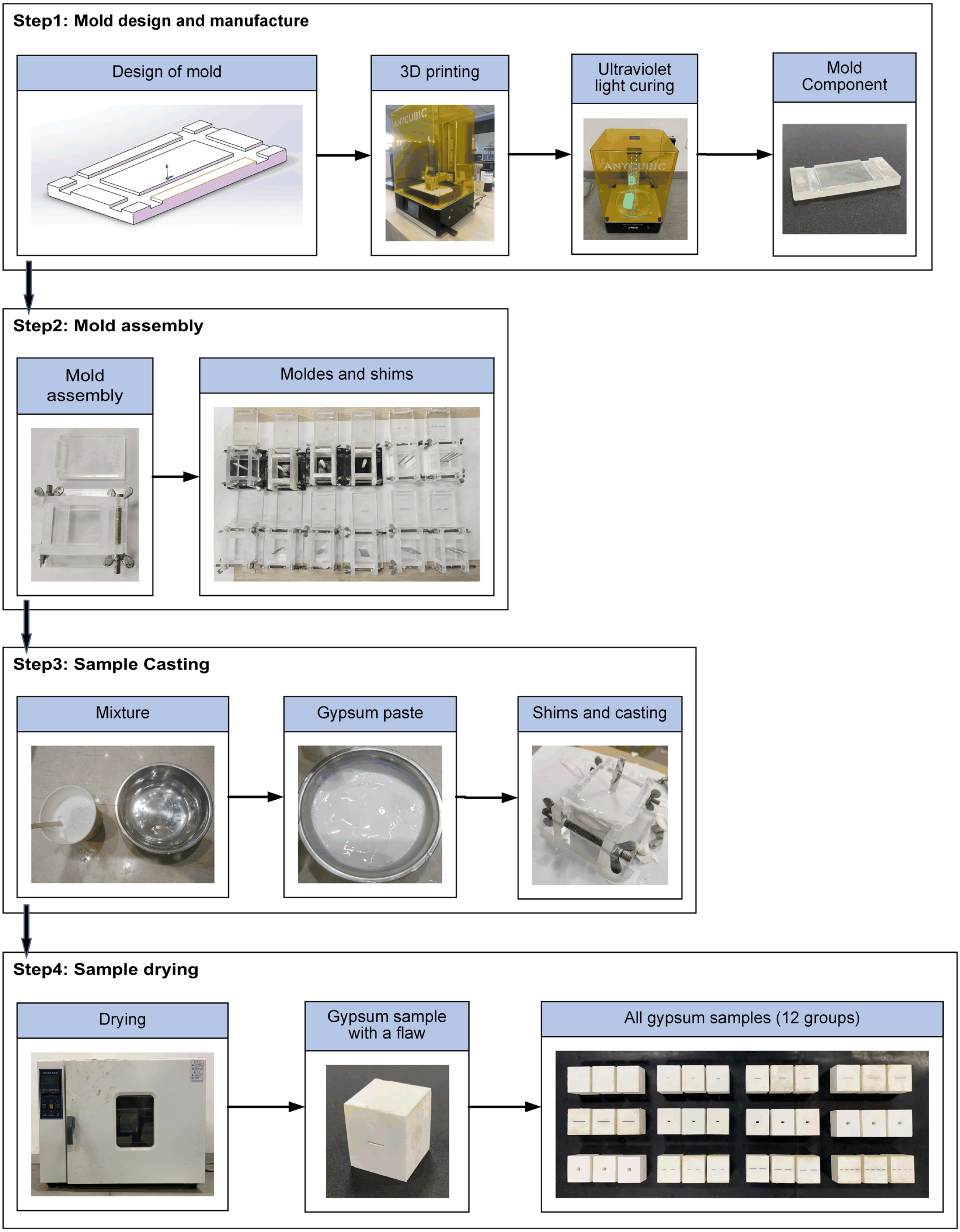

FIGURE 1 Casting process of moulded gypsum samples (Tian et al., 2023).

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TABLE 1 Summary of samples.

				Flaw properties		
Sample number	Material	Cross-section shape	Integrity	Flaw numbers	Flaw width (x)	Flaw length (y)
R-S-0-0-0	Granite	Square	Intact	0	—	—
R-C-0-0-0		Circular		0	—	—
G-I-0-0-0	Gypsum	Square	Intact	0	—	—
G-N-1-1-5			Non-intact	1	1 mm	5 mm
G-N-1-1-10				1	1 mm	10 mm
G-N-1-1-15				1	1 mm	15 mm
G-N-1-1-20				1	1 mm	20 mm
G-N-1-2-5				1	2 mm	5 mm
G-N-1-3-5				1	3 mm	5 mm
G-N-1-4-5				1	4 mm	5 mm
G-N-1-5-5				1	5 mm	5 mm
G-N-2-1-5				2	1 mm	5 mm
G-N-2-1-10				2	1 mm	10 mm
G-N-4-1-5				4	1 mm	5 mm
Total	14 types					

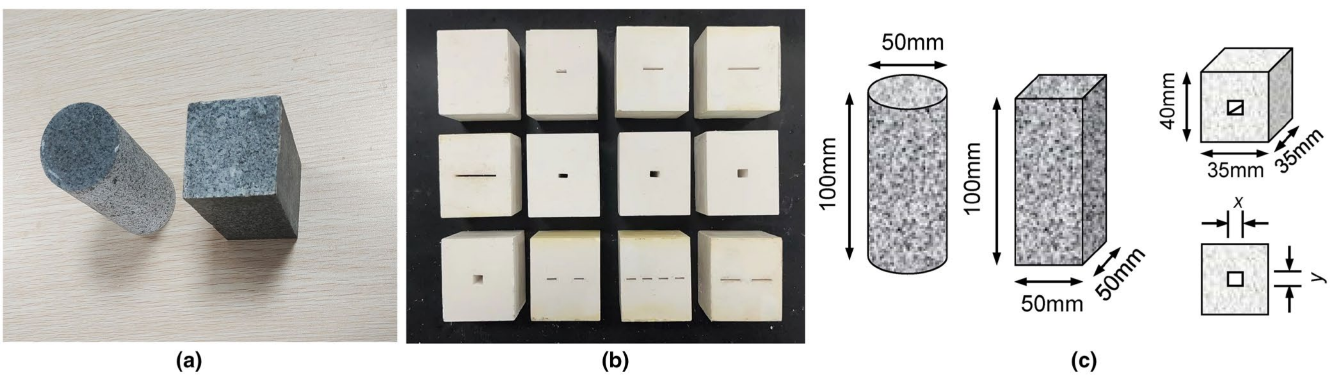

FIGURE 2 (a) Granite samples (top view), (b) prismatic gypsum samples (top view) and (c) dimensions of samples (side view).

TABLE 2 Physical and mechanical properties of the present granite and gypsum (Zou et al., 2023).

Material type	Wave velocity (m/s)	UCS (MPa)	Density (g/cm^3)	Elastic modulus (GPa)	Poisson's ratio
Granite	4436	165	2.8	50	0.27
Gypsum	4300	63.6	1.55	8	0.12

instrument uses a high-sensitive transducer, which is also a piezoelectric ceramic, to record the vibration at the other end. The transmitted signal is also a time-voltage pulse, different from the incident pulse, containing the information of the sample and the defects in it. Due to the randomness of the incident pulse, the transmitted pulse is also different from each other, even in the same group of pluses.

3 | AN OVERVIEW OF DATASETS

Through continuous emission and collection of ultrasonic pulses, a large number of time-series signals are obtained for analysis. During data collection, the Vallen AMSY-6 threshold is set at 34 dB (default value) to filter useless signals. The Vallen AMSY-6 captures a single signal pulse with a length of 1638.4 μs. Simultaneously, the dataset

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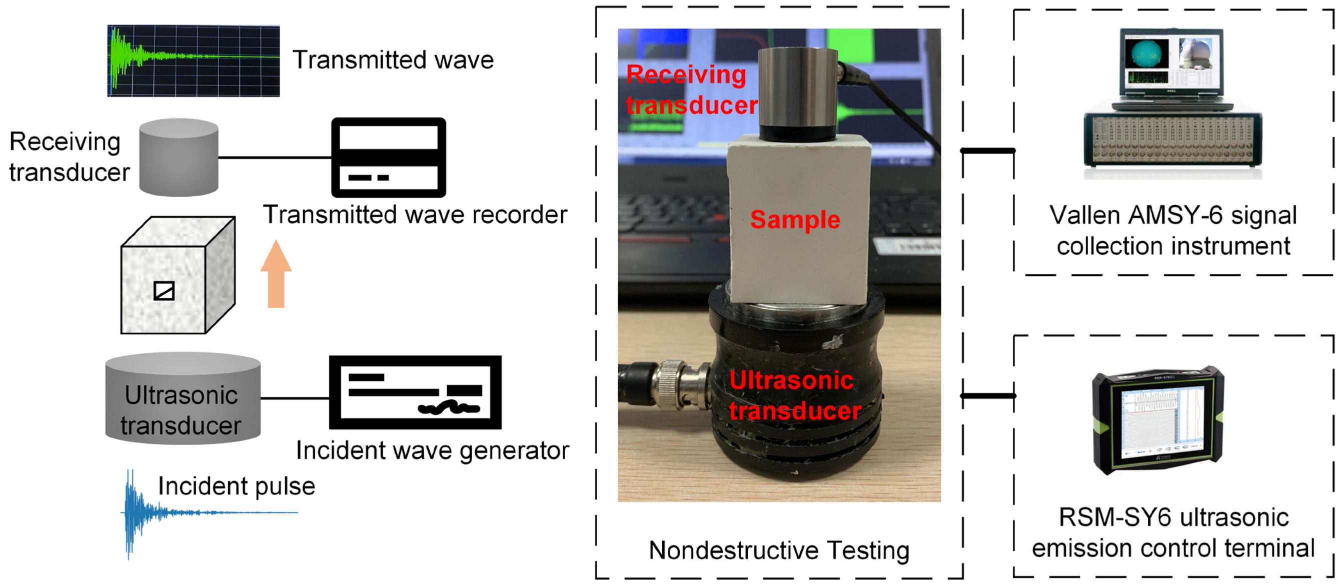

FIGURE 3 Diagram of the data collection system.

TABLE 3 Specifications of the data collection system.

Instrument	Specification	Value
RSM-SY6	Frequency bandwidth	2 kHz ~ 2 MHz
	Period	1 μs ~ 0.5 ms
	Acoustic time accuracy	$\leq$ 0.5 %
	Acoustic amplitude accuracy	$\leq$ 3 %
Vallen AMSY-6	Sampling rate (interval)	5 MHz (0.2 μs)
	Sensor type	VS45-H (with shield crosstalk <−80 dB)
	Frequency range	500 Hz ~ 2.4 MHz
	RMS resolution	<1 μV
	Average noise	<1 μV
	Receiving sensitivity	<1 μV

is manually labelled at each stage for the corresponding sample number. The original database file of Vallen AMSY-6 constitutes a large time-series set, with a '*tridb*' suffix, and is a proprietary format. The data structure of the database is key-value, specifically *index* - *data*. The database contains all signals, each signal can be extracted via its *index* using the official Python module pyVallenAE (Berbuer, 2023). After the Python extract, the file format is single text, containing all original information and can open with any text processing software (like Notepad, Vim, Excel, etc.) to do further analysis. According to sample rate 0.2 μs, each signal data is in the form of a vector with dimensions 8192. After all the data are extracted, the dataset is organized into 14 subdirectories as illustrated in Figure 4, each named after the respective classes. Inside each folder is waveform signal data, and the amount of data in each category is summarized in Table 4. The

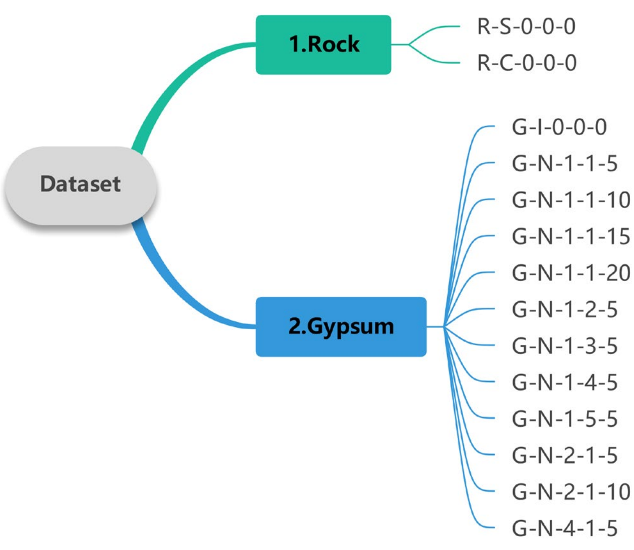

FIGURE 4 Dataset subdirectory structure.

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TABLE 4 Data distribution of the dataset.

Subdirectory	Number of data (unit: Unit)	Subdirectory	Number of data (unit: Unit)	Subdirectory	Number of data (unit: Unit)
R-S-0-0-0	82,930	G-N-1-1-15	59,227	G-N-1-5-5	58,696
R-C-0-0-0	109,217	G-N-1-1-20	90,721	G-N-2-1-5	61,088
G-I-0-0-0	112,596	G-N-1-2-5	53,833	G-N-2-1-10	61,340
G-N-1-1-5	31,814	G-N-1-3-5	57,700	G-N-4-1-5	81,908
G-N-1-1-10	56,403	G-N-1-4-5	77,939	Total	995,412

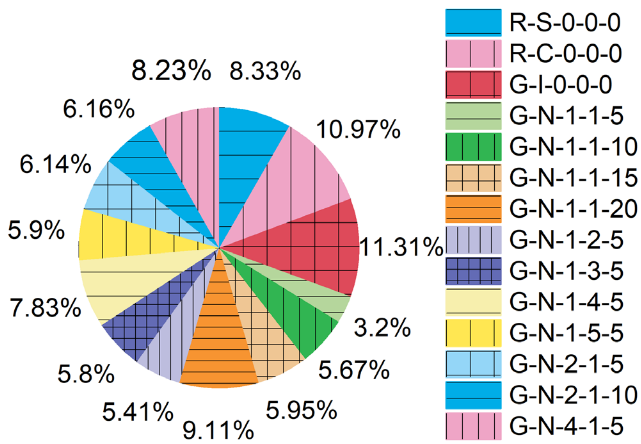

FIGURE 5 Proportion of each type of data group.

proportions of each data group are shown in Figure 5. Besides, typical waveforms of each type are plotted in Figures 6 and 7.

4 | PERSPECTIVES ON TIME-SERIES DATASETS

4.1 | Current efforts of time-series datasets

With the increment of TSC applications, the algorithm for TSC problems has been developed by scientists (Faouzi, 2022; Li & Jung, 2023; Ruiz et al., 2021). These algorithms encompass not only the extraction of features from time-series, used as inputs for standard machine learning classifiers but also direct processing of raw time-series data (like deep learning). Main time-series algorithms include nearest-neighbour classification with dynamic time warping (Kate, 2016), kernel methods (Patle & Chouhan, 2013), shapelet-based algorithms (Ji et al., 2019), tree-based algorithms (Mienye et al., 2019), Bag-of-words (dictionary-based) methods (Large et al., 2019), imaging time-series (Wang & Oates, 2015), deep learning (Ismail Fawaz et al., 2019), random convolutions (Dempster et al., 2020) and ensemble models (Wichard & Ogorzalek, 2004). These algorithms have great contributions to the exploration of time-series data mining.

Many scientists dedicate time-series datasets and make significant devotion. Regarding dataset collection for benchmarking TSC algorithms, the primary resources include the UCR TSC datasets archive (Bagnall, Lines, et al., 2018; Dau et al., 2019). This archive offers open-source datasets about univariate TSC which have been pre-divided into training and testing sets. Moreover, those TSC datasets have been standardized for better reuse. The current version of this archive consists of 128 datasets from various domains such as audio, medicine, kinesiology, sensors, simulation, spectroscopy, etc. For algorithms dealing with multivariate TSC, the main resources include the UEA multivariate TSC archive (Bagnall, Dau, et al., 2018) and a public access TSC archive (Baydogan, 2015), both containing several time-series datasets.

4.2 | Opportunities and challenges

Over the past decade, extensive research on TSC has made significant progress in prediction accuracy, generalization and robustness (Bai et al., 2021; Faouzi, 2022; Guo et al., 2021; Ismail Fawaz et al., 2019). Numerous methods have been investigated, encompassing specific metrics of simple and multiple complex feature extraction (including transformation), as well as deep learning feature mining (Faouzi, 2022; Guo et al., 2021). Time-series data, as a distinct form of data, has garnered widespread attention in contemporary science and engineering (Hamilton, 2020). Possessing dynamic, continuous and ordered characteristics, time-series data finds extensive applications in various fields such as finance (Sezer et al., 2020), meteorology (Duchon & Hale, 2012), healthcare (Kaushik et al., 2020) and industry (Mehdiyev et al., 2017).

Time-series data provides people with an opportunity to more accurately capture the evolution of systems. Through the analysis of time-series data, scientists can uncover patterns and trends inherent in historical changes, facilitating effective prediction and decision-making. For

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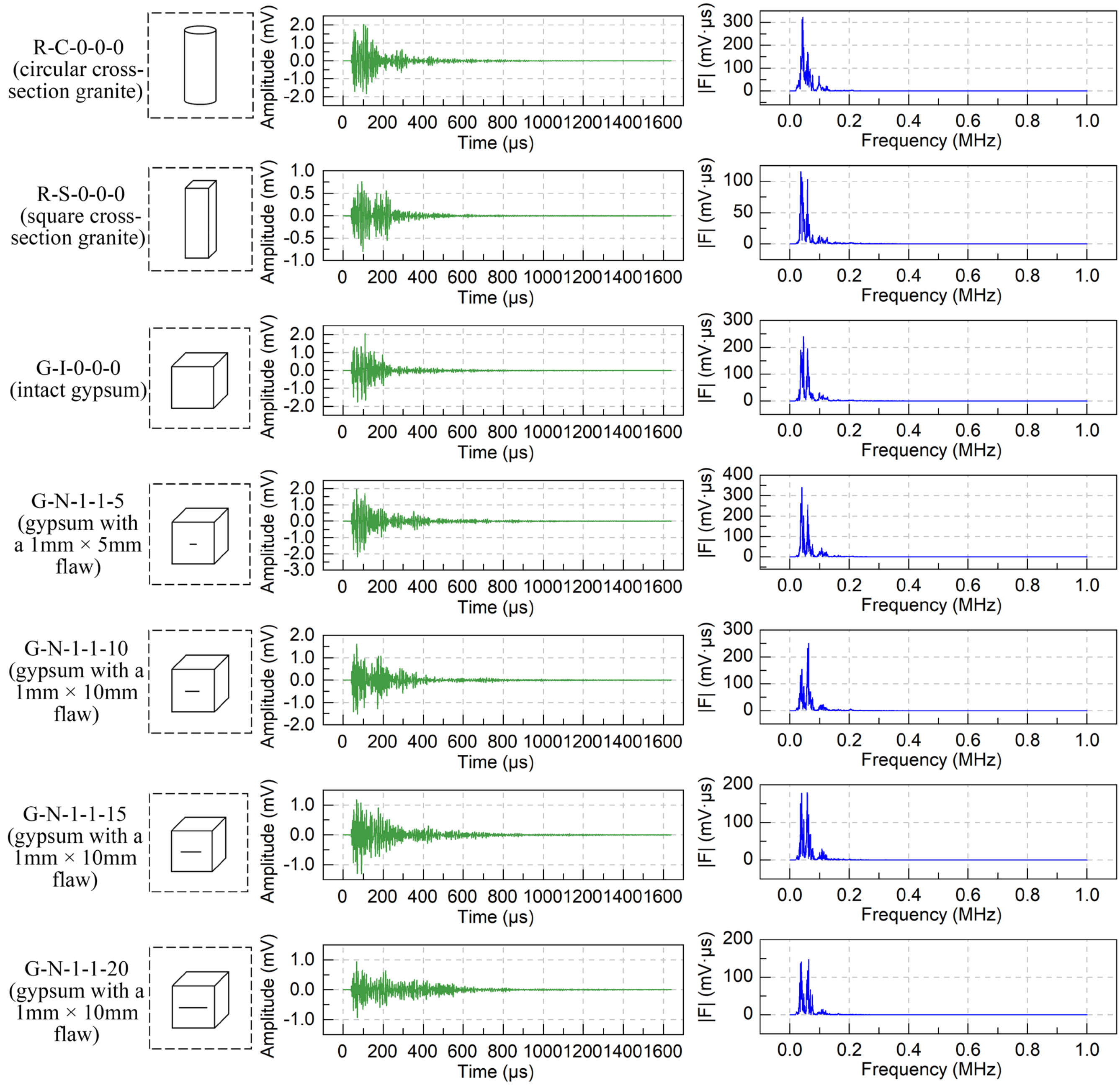

FIGURE 6 Typical waveform plot of sample R-C-0-0-0, R-S-0-0-0, G-I-0-0-0, G-N-1-1-5, G-N-1-1-10, G-N-1-1-15 and G-N-1-1-20.

example, in finance, time-series analysis aids in predicting stock market trends (Sezer et al., 2020). In meteorology, it contributes to more accurate weather forecasts (Duchon & Hale, 2012). Furthermore, the widespread application of time-series data has propelled developments in related fields, sparking a series of data-driven innovations. Therefore, the dataset in this paper can give scientists more opportunities for wave propagation analysis, stress wave analysis, TSC analysis and even rock mechanical behaviour prediction.

However, the study of time-series data not only presents vast opportunities but also comes with a series of challenges. Firstly, time-series data is sensitive to the environment (Ismail Fawaz et al., 2019), making it contain much noise and interference. Secondly, time-series data often displays non-stationary characteristics that contain much information, whereas traditional statistical methods appear limited in the interpretation of the data (Li & Jung, 2023). Additionally, the physical meaning of analysing results is hard to explain and visualize. Finally, time-series data always appear larger, making the analysis algorithm have higher time and space complexity (Read et al., 2020). Similarly, the dataset in this paper is very large and contains much implicit information, which is a challenge for high-performance algorithm applications. In a word, the challenges and

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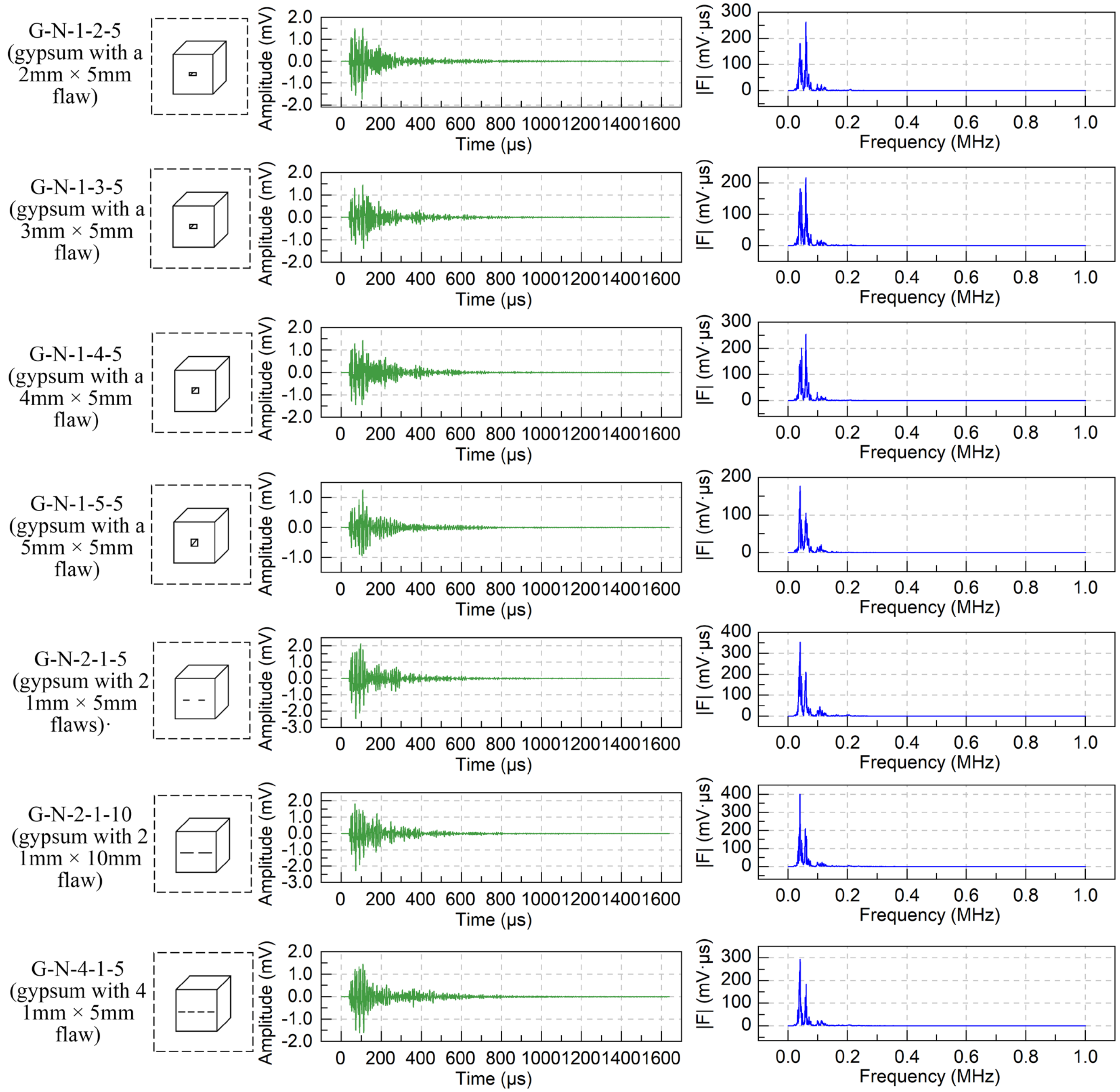

FIGURE 7 Typical waveform plot of sample G-N-1-2-5, G-N-1-3-5, G-N-1-4-5, G-N-1-5-5, G-N-2-1-5, G-N-2-1-10 and G-N-4-1-5.

opportunities of time-series analysis coexist, which has great research value.

5 | CONCLUSION

The detection and localization of complicated defects in rocks present significant challenges in NDT. While there have been numerous applications of TSC, standardized open-source datasets remain scarce. Building upon the authors' previous work demonstrating the efficacy of combining ML with NDT for classifying defect types in rocks, this paper addresses the deficiency in high-quality datasets related to mechanical wave propagation. We fabricated 14 types of rock samples with varying cross-sectional shapes and flaws, generating a dataset comprising 995,412 discrete nondestructive testing data points through a combination of ultrasonic and mechanical wave detection technologies. This dataset cannot only be used for accurate nondestructive testing signal classification but also can be used as a valuable dataset for general time-series data analysis. Besides, the complexities of time-series data analysis remain challenging and can be analysed by AI-powered methods, including ML (such as

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KNN and SVM model) and DL (such as CNN and LSTM model) methods, which can be effectively applied to enhance our understanding of mechanical wave behaviours in rocks. Furthermore, the authors want these data can be good study material for the exploration of AI-powered NDT methods in construction or survey in geotechnical engineering.

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CONFLICT OF INTEREST STATEMENT

All authors disclosed no relevant relationships.

OPEN RESEARCH BADGES

This article has been awarded Open Data Badge for making publicly available the digitally-shareable data necessary to reproduce the reported results. Data is available at https://doi.org/10.6084/m9.figshare.24954945.

DATA AVAILABILITY STATEMENT

The dataset is open-source via FigShare: https://doi.org/10.6084/m9.figshare.24954945. We welcome researchers to use this dataset for their research.

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