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Vectorized dataset of roadside noise barriers in China using street view imagery

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Abstract. Roadside noise barriers (RNBs) are important urban infrastructures to ensure that cities remain liveable. However, the absence of accurate and large-scale geospatial data on RNBs has impeded the increasing progress of rational urban planning, sustainable cities, and healthy environments. To address this problem, this study creates a vectorized RNB dataset in China using street view imagery and a geospatial artificial intelligence framework. First, intensive sampling is performed on the road network of each city based on OpenStreetMap, which is used as the georeference for downloading 6×10^6 Baidu Street View (BSV) images. Furthermore, considering the prior geographic knowledge contained in street view images, convolutional neural networks incorporating image context information (IC-CNNs) based on an ensemble learning strategy are developed to detect RNBs from the BSV images. The RNB dataset presented by polylines is generated based on the identified RNB locations, with a total length of 2667.02 km in 222 cities. Last, the quality of the RNB dataset is evaluated from two perspectives, i.e., the detection accuracy and the completeness and positional accuracy. Specifically, based on a set of randomly selected samples containing 10 000 BSV images, four quantitative metrics are calculated, with an overall accuracy of 98.61 %, recall of 87.14 %, precision of 76.44 %, and F_1 score of 81.44 %. A total length of 254.45 km of roads in different cities are manually surveyed using BSV images to evaluate the mileage deviation and overlap level between the generated and surveyed RNBs. The root mean squared error for the mileage deviation is 0.08 km, and the intersection over union for overlay level is 88.08 % ± 2.95 %. The evaluation results suggest that the generated RNB dataset is of high quality and can be applied as an accurate and reliable dataset for a variety of large-scale urban studies, such as estimating the regional solar photovoltaic potential, developing 3D urban models, and designing rational urban layouts. Besides that, the benchmark dataset of the labeled BSV images can also support more work on RNB detection, such as developing more advanced deep learning algorithms, fine-tuning the existing computer vision models, and analyzing geospatial scenes in

BSV. The generated vectorized RNB dataset and the benchmark dataset of labeled BSV imagery are publicly available at https://doi.org/10.11888/Others.tpdc.271914 (Chen, 2021).

1 Introduction

In recent years, several studies have documented the substantial impact of traffic noise problems in cities (Apparicio et al., 2016; Begou et al., 2020). Roadside noise barriers (RNBs) are a vital urban infrastructure that contribute significantly to mitigate undesirable traffic noise in communities (Abdulkareem et al., 2021; Ning et al., 2010). Additionally, RNBs contribute to the development of sustainable cities in many ways. For example, with the emphasis on new energy, RNBs are being used to install solar photovoltaic panels, thereby increasing the utility of new energy sources (Gu et al., 2012; Zhong et al., 2021). The reasonable presence of RNBs also enables the airflow in the urban canyon region to be adjusted, thereby improving the roadside air quality (Huang et al., 2021; Zhao et al., 2021). Because of the importance of RNBs in building sustainable cities, the demand for RNBs has increased alongside traffic growth in recent decades (Den Boer and Schroten, 2007; Oltean-Dumbrava and Miah, 2016). There are bottom-up benefits from establishing an accurate and standardized large-scale RNB dataset with detailed geospatial information about RNBs, including their mileage, location, and distribution (Liu et al., 2020; Wang and Wang, 2021). Specifically, precise RNB locations enable traffic departments to effectively manage and maintain this type of infrastructure (Sainju and Jiang, 2020), urban research can simulate dynamic cities based on accurate RNB geospatial information (Wang and Wang, 2021; Zhao et al., 2017), and governments can rely on the RNB maps to examine urban layouts and create green and sustainable cities (Song et al., 2021; Song and Wu, 2021).

Over the past few years, extensive geospatial databases have been established to store data on many aspects of urban infrastructure (Griffiths and Boehm, 2019; Perkins and Xiang, 2006). However, the sharing and exchange of RNB data in these databases are restricted, and the data only cover a limited geographic area (Wang et al., 2019; K. Zhang et al., 2022). These challenges to data acquisition are because databases have to adhere to various standards related to geographic data (e.g., file format and geographic coordination reference; Lafia et al., 2018). On the other hand, the RNB data are often created and updated manually through road inspections and investigations which are costly and time consuming, especially on a large scale (Potvin et al., 2019; Ranasinghe et al., 2019). The RNB geospatial dataset must be generated, and kept up to date, as soon as possible using alternative, efficient methods.

Street view imagery is georeferenced data densely covering the road network of cities. As a new geospatial data source, it provides depictions of real-world surroundings, including natural landscapes and the built environment, and enables users to recognize physical objects, urban dynamics features, and geographic scenes on a large scale (Zhang et al., 2018). In addition, as part of the data sharing movement, an increasing number of community-based organizations and corporations, such as Baidu Maps, Tencent Maps, and Google Maps, are regularly generating and updating open-access street view imagery (Qin et al., 2020; Zhang et al., 2019). Such big data bring great prospects for acquiring urban infrastructure information (e.g., RNBs), with benefits such as broad coverage, a rapid update speed, and low acquisition costs (Kang et al., 2020). However, manual interpretation is a tedious task, and conventional computer vision algorithms struggle when confronted with large amounts of data and complex image features (Zhang et al., 2018).

With the advancement of computing hardware and frameworks, deep learning methods now have an increased capacity for extracting semantic features from a large amount of data (Lecun et al., 2015; Liu et al., 2022). The emerging approaches are increasingly being used to interpret physical objects and detect interior patterns from Earth observation data (Z. Zhang et al., 2022; Qian et al., 2022). Meanwhile, image classification based on deep learning has been used to identify RNBs using street view imagery (Zhong et al., 2021). However, for the purposes of identifying RNBs, prior geographic knowledge, which is essential, is frequently overlooked, such as the fact that RNBs are frequently located between roads and densely populated regions (e.g., residential, educational, and medical areas; Arenas, 2008; Wang et al., 2018; K. Zhang et al., 2022). In recent years, a new framework of data-driven research based on geospatial artificial intelligence (GeoAI) and machine learning has resulted in multiple notable improvements in the discovery of geographic scene knowledge (Goodchild and Li, 2021; Li, 2020). When empirical and prior spatial information are included into deep learning approaches, they can help to develop a more holistic understanding of a research subject and mitigate the effects of data scarcity or representational bias (Janowicz et al., 2019; Qian et al., 2020). As a result, it is possible to enhance the effectiveness of deep learning methods in identifying RNBs by incorporating some prior geographic knowledge from street view imagery. Additionally, Wolpert and Macready (1997) introduced the “no free lunch” theory, demonstrating that a single model must pay for some accuracy by degrading its generalizability. This is acceptable, as it is challenging to construct a perfect solution for all scenarios using a single model, particularly when dealing with vast volumes of data and large-scale areas (Wang and Li, 2021).

The purpose of this study is to build an accurate and nationwide vectorized RNB dataset utilizing Baidu Street View (BSV) imagery. To improve the performance for the detection of RNBs, this work proposes a GeoAI framework. Concretely, an ensemble of convolutional neural networks incorporating image context information (IC-CNNs) is developed, which considers the prior geographic knowledge contained in street view images. Subsequently, a post-processing method is applied to generate the vectorized RNB dataset based on the identified RNB locations. Last, the RNB dataset quality is quantitatively evaluated from two perspectives, i.e., the detection accuracy and the completeness and positional accuracy. The main contributions of this study can be summarized as follows:

1. This study provides the first reliable and nationwide vectorized RNB dataset in China and provides labeled BSV images which can be used as a benchmark dataset.
2. A GeoAI framework is presented for the processing of numerous BSV images in order to generate the RNB mapping and for the comprehensively evaluation of the generated results.
3. This study presents multiple IC-CNNs based on prior geographic knowledge and an ensemble learning strategy to achieve high-performance object identification from street view imagery.

The remainder of this paper is organized as follows. Section 2 briefly describes the data and methods used to generate and evaluate the RNB dataset. Section 3 presents the results of the RNB mapping and an evaluation and analysis for the RNB dataset. Section 4 discusses the capability of proposed methods, as well as the challenges and limitations of this work. The last section provides the conclusions of this study.

2 Data and methods

2.1 The GeoAI framework

The GeoAI framework's workflow is divided into three stages: data preparation, modeling, and evaluation, as shown in Fig. 1. To begin with, BSV images are gathered during the data preparation stage using OpenStreetMap (OSM) road data and the BSV application programming interface (API). Subsequently, BSV images are used to generate various samples for modeling and evaluation. During the modeling stage, deep learning approaches are used to detect RNBs from the BSV imagery. Using the vectorization post-processing method, the identified and scattered RNB locations are subsequently processed into a vectorized dataset. During the evaluation stage, the quality of the created dataset is quantitatively assessed in two aspects, i.e., the detection accuracy and completeness and positional accuracy.

2.2 Data preparation

There are three types of data are acquired for this study, i.e., the road networks, administrative boundary, and street view imagery. Afterwards, training, validation, and test samples are collected based on these data. The data from Taiwan Province are scarce.

2.2.1 Road networks

The road networks were downloaded from OSM (https://www.openstreetmap.org/, last access: 16 May 2021) in May 2021, which are polyline-based and include a variety of road types, including motorways, trunk roads, primary roads, and secondary roads. According to previous findings, the quality of OSM road networks in China is high in terms of completeness and positional accuracy (Liu and Long, 2015). In addition, RNBs have a high probability of being installed on motorways and trunk roads (K. Zhang et al., 2022). Therefore, given the expense of acquiring and computing BSV images, in this study, samples on motorways and trunk roads are only considered for downloading BSV images. Figure 2a depicts the spatial distribution of these two types of roads.

2.2.2 Administrative boundary

The city boundary was acquired from http://bzdt.ch.mnr.gov.cn/ (last access: 21 April 2021) in April 2021. According to the urban management hierarchy established by the Chinese government, cities in China are divided into four tiers (Guan and Rowe, 2018; Jia et al., 2020), including municipalities, sub-provincial cities, and prefecture-level cities, and their locations are shown in Fig. 2b. Specifically, tier 1 is centrally administered cities and municipalities. Tier 2 is primarily sub-provincial cities, whereas tier 3 is province capitals and large prefecture-level cities. Tier 4 is ordinary prefecture cities. Cities with varying administrative levels have varying authorities over resource allocation and jurisdiction (Guan et al., 2018).

2.2.3 Street view imagery

With their high-resolution and detailed information on Chinese streets, BSV images are of comparable quality to Google Street View images, which are not available in China (H. Zhou et al., 2019). Numerous sample points along OSM roads are collected, and the BSV API is utilized to obtain street view images at those locations. Following the work of K. Zhang et al. (2022), a sampling interval of around 25 m is utilized to account for the tradeoff between data granularity and the expense of downloading imagery. As a result, the total number of sample points is 24 871 839. As shown in Fig. 3, an illustration of the BSV images, with photographs showing different directions, shows that a BSV image with a 90° viewing angle is more appropriate for the present work because it provides a comprehensive roadside view. Hence,