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Data Article

Non-central panorama indoor dataset

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A R T I C L E I N F O

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A B S T R A C T

Omnidirectional images are one of the main sources of information for learning-based scene understanding algorithms. However, annotated datasets of omnidirectional images cannot keep the pace of these learning-based algorithms development. Among the different panoramas and in contrast to standard central ones, non-central panoramas provide geometrical information in the distortion of the image from which we can retrieve 3D information of the environment. However, due to the lack of commercial non-central devices, up until now there was no dataset of these kind of panoramas. In this data paper, we present the first dataset of non-central panoramas for indoor scene understanding. The dataset is composed of **2574** RGB non-central panoramas taken in around 650 different rooms. Each panorama has associated a depth map and annotations to obtain the layout of the room from the image as a structural edge map, list of corners in the image, the 3D corners of the room and the camera pose. The images are taken from photorealistic virtual environments and pixel-wise automatically annotated.

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Specifications Table

Subject	Computer Science: Computer Vision and Pattern Recognition
Specific subject area	Non-central circular panoramas for indoor scene understanding.
Type of data	RGB Image (.png) Color code depth maps (.png) Layout annotations (.png, .npy, .txt, .mat)
How the data were acquired	Random generation of virtual environments. Ad-hoc programmable camera projection model for image rendering via ray tracing. The RGB images are rendered with POV-Ray[1] and the depth maps with Mega-POV[2]. Layout annotations are obtained from the 3D model of the virtual environment.
Data format	Raw Filtered
Description of data collection	From the generated virtual environments, we randomly place the non-central acquisition system in different locations inside the environment. The radius of acquisition is 1 meter. The size of the panoramas is 1024 × 512 pixels. Once acquired the non-central panoramas, we exclude those that will be physically impossible to acquire in a real situation (i.e. the non-central acquisition system goes through an object or a wall, creating a black hole in the image).
Data source location	• Institution: University of Zaragoza, Department of Computer Science and Systems Engineering • City/Town/Region: Zaragoza, Aragon • Country: Spain • Location: Data acquired synthetically
Data accessibility	Repository name*: Github and Mendeley Data* *URL to Github repository:* https://github.com/jesusbermudezcameo/NonCentralIndoorDataset *URL to Mendeley Data:* https://data.mendeley.com/datasets/jsxkzsknv3/1
Related research article	*B. Berenguel-Baeta, J. Bermudez-Cameo and J.J. Guerrero, Atlanta Scaled Layouts from Non-central Panoramas. Pattern Recognition (2022).* *DOI:* https://doi.org/10.1016/j.patcog.2022.108740

[1] The Persistence of Vision Raytracer. http://www.povray.org (accessed May 2022)
[2] MegaPOV. http://megapov.inertart.net (accessed May 2022)

Value of the data

- The presented dataset is the first existing dataset with non-central panoramas. It includes annotations for different purposes as layout recovery, line extraction and depth estimation.
- Since it is the first non-central dataset, it can be used to adapt existing algorithms for omnidirectional central images to the non-central case.
- In the related research [1], only the RGB images and layout annotations were used. Future research topics will include monocular depth estimation and other geometry and learning-based methods.
- Researchers who want to take advantage of the geometrical properties of non-central systems [2] can find in this dataset a perfect source of information for evaluation of previous proposals and the development of new solutions and algorithms to recover the scale and metrics of different environments directly from panoramic images.

1. Data Description

The dataset contains a set of gravity-oriented panoramas. We make this specification since non-central panoramas cannot be rotated artificially in a different axis that the revolution axis of the non-central system (i.e. during data augmentation). The dataset includes the following folders in this distribution:

- ***NonCentralIndoorDataset***
  - **img:** contains the RGB non-central panoramas.
  - **depth_coded:** contains depth maps coded in 3 channels (RGB channels) associated with the RGB panoramas.
  - **EM_gt:** contains 1-channel images with the structural lines of the environment.
  - **DataPython:** contains ground truth information used to evaluate the work presented in [1].
    - *3D_gt:* 3D position of the corners of the room in meters.
    - *cam_pose:* camera location.
    - *label_ang:* labelling for the floor-wall and ceiling-wall intersections as spherical coordinates of the projecting rays.
    - *label_cor:* pixel coordinates of the 3D corners in the panoramas.
  - **DataMatlab:** contains ground truth information used to evaluate the work presented in [1].
    - *mat_gt:* same labelling as in DataPython but in MatLab format.
- ***Tools:***
  - *DepthCodification.py:* provides the code to encode depth in a 3-channel image and to decode the 3-channel image into a matrix with distance values.
  - *Matlab2Python.py:* takes as input Matlab data in the format of *DataMatlab/mat_gt* and outputs the information in Python-friendly files as *DataPython.*
  - *Python2Matlab.py:* takes as input the information in the format of *DataPython* and outputs **.mat* files to be used in MatLab.

2. Experimental Design, Materials and Methods

The data of this dataset is obtained from environments randomly and synthetically generated. We first generate a random layout constrained by different structural limits (see Table 1). These limits include minimum and maximum: area of the room, number of walls, wall length, angle between walls (if non-Manhattan), room height and Manhattan ratio.

The first version of each layout is a Manhattan layout constrained by the previous limits. Then, depending on the Manhattan ratio, a set of random vertical planes clip the layout introducing oblique walls in angles with respect to the previous walls in the range of the walls angle limit. After the layout clip, we evaluate the final layout, checking if it meets the constraints. If any of the constraints is not satisfied, the layout is deleted and a new one is generated.

Once the structure of the room is obtained, we randomly set different kinds of walls containing doors, windows, colors and textures. These characteristics of the walls are randomly selected from different pools (e.g. we have different models of doors and windows to select). At this point we select the colors and textures of the ceiling and floor of the room.

Once defined the 3D structure of the room, we include objects in it. For that purpose, we build a free space map where we can place different kinds of objects. First, we consider the kind of objects that are placed next to a wall in a fixed orientation (beds, wardrobes, desks). Then, we place objects in the room in a random position and orientation (chairs, sofas, carpets). Finally,

Table 1
Layout limits for randomized generation.

Parameter	Min	Max
Area (m^2)	25	110
Number of walls	4	14
Wall length (m)	0,5	8
Walls angle (degs)	25	100
Room height (m)	2,5	4,25
Manhattan ratio	0,7	

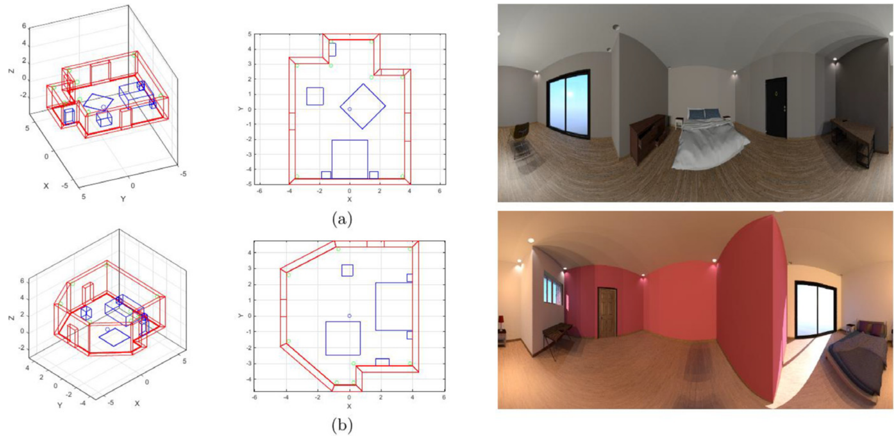

Fig. 1. Layout generation and non-central panorama rendering examples. (a) Manhattan random room. (b) Atlanta random room.

we place objects that are placed on top of other objects (cups, clocks, clothes) and we also place lighting sources for a more realistic rendering. All of these objects are randomly picked from different pools depending on the object class. Besides, the ambient illumination conditions are also randomly picked from 3 different configurations.

Once defined our room, we have all the necesary information to generate the ground truth and the labelling of the dataset (see Fig. 1). The next step is to render the RGB non-central panoramas and generate the depth maps. The color images are rendered with the ray tracing software POV-Ray while the depth maps are obtained with the use of MegaPOV. The non-central panoramic camera is modeled by using an ad-hoc programmable camera projection model included in last versions of POV-Ray. For each scene we can render different acquisitions modifying the position and the orientation of the camera. In the case of the proposed dataset, the camera is always oriented with the gravity direction. Notice that, by contrast with central panoramas (e.g. equirectangular images), we can not post-process a single render for obtaining different panoramas with different orientations.

Ethics Statements

The work did not involve any human or animal subjects, nor data from social media platforms.

CRediT Author Statement

Bruno Berenguel-Baeta: Investigation, Resources, Visualization, Writing – original draft; **Jesus Bermudez-Cameo:** Conceptualization, Methodology, Software, Resources, Data Curation, Writing – review & editing; **Jose J. Guerrero:** Supervision, Writing – review & editing, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Non-Central panorama Indoor Dataset (Original data) (https://drive.google.com).

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References

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[2] J. Bermudez-Cameo, O. Saurer, G. Lopez-Nicolas, J.J. Guerrero, M. Pollefeys, Exploiting line metric reconstruction from non-central circular panoramas, Pattern Recognit. Lett. 94 (2017) 30–37, doi:10.1016/j.patrec.2017.05.006.