Proceedings of the 33rd European Safety and Reliability Conference (ESREL 2023)
Edited by Mário P. Brito, Terje Aven, Piero Baraldi, Marko Čepin and Enrico Zio
 Published by Research Publishing, Singapore.
doi: 10.3850/978-981-18-8071-1_P242-cd

An automatic live load survey method based on multi-source Internet data and computer vision

Chi Xu

College of civil engineering, Tongji University, China. E-mail: tjxuchi@126.com

Jun Chen

College of civil engineering, Tongji University, China. E-mail: cejchen@tongji.edu.cn

Jie Li (Corresponding author)

College of civil engineering, Tongji University, China. E-mail: lijie@tongji.edu.cn

The measured live load forms the data basis for the reliability analyses. This study focuses on the amplitude measurement of the sustained load, which is an essential component of the live load. Traditional survey methods are characterized by manual and on-site operation, which can lead to a series of problems including the high cost, low efficiency and occupant resistance. Taking full advantages of the unlimited Internet resources and computer vision technology, a new survey method is proposed to realize an automatic and online investigation into the load amplitude. The amplitude statistics are derived from the survey data on the object weights, room areas and object quantities. Specifically, the object weights and room areas are directly acquired from the product information on e-commerce websites and the residence information on real estate websites, respectively. The object quantities are identified from the room photos on real estate websites. Therefore, an object detection model based on the YOLOv4 algorithm is developed. The load investigation into living rooms is used for illustrating the implementation process of the proposed method. The result of a previous survey covering 20040 m^2 suggests that 6 types of indoor objects contribute the majority of the load statistics and require to be considered in the detection model. The training, validation and test dataset include 5979, 1000 and 1000 room photos, respectively. The detection model has mean average precision (mAP) of 62% on the test dataset. For comparison, object quantities in 343 living rooms are obtained by both the manual counting and computer vision. The difference between the manual and automatic survey results is smaller than 20%, which verifies the feasibility and accuracy of the proposed method.

Keywords: live load, multi-source data, computer vision, automatic survey, online method.

1. Introduction

Rational load determination is the basis for the structural design and reliability analyses. Being a basic structural load, the live load is of interest in this study.

The live load is induced by the use and occupancy of structures ASCE (2022). Based on the temporal behaviour, the live load is classified into the sustained load and extraordinary load Corotis and Jaria (1979). This study focused on the sustained load, which is produced by the indoor furniture and normal living or working personnel Chalk and Corotis (1980). The amplitude of the sustained load between occupancy changes is generally considered as a constant.

The survey data of the sustained load facilitate the development of the probabilistic modelling and form the data basis for the design load determination. Based on theoretical analyses, the statistical properties of the load amplitude and change interval are required to describe a sustained load process Peir and Cornell (1973); McGuire and Cornell (1974). The data acquisition of the load amplitude is of interest in this study.

Traditional survey methods of the sustained load amplitude are mainly based on manual and on-site investigation. The room area and indoor object weights of all the surveyed regions require to be measured on site. Therefore, the occupant resistance, high manpower requirement and long implementation period frequently emerge in previous surveys. The inventory technique is proposed to solve the above problems Culver (1976); Harris and Corotis (1978). The piece weight of an object is approximately estimated based on its type, material and dimensions. The inventory technique avoids the direct weighing and is followed by subsequent load investigators Andam (1986); Kumar (2002). In addition, the piece weight of indoor objects can also be assessed by volumetric measurements and using standard furniture records Choi (1992). However, load investigators still require to enter the surveyed regions and infer the object weight from limited information.

Taking full advantages of the unlimited data on the Internet and computer vision technology, this study proposes a new survey method for determining the sustained load amplitude. An online and automatic survey process can be realized by using the proposed method.

The remainder of this paper is organized as follows. Section 2 introduces the theoretical model and survey objectives of the sustained load amplitude. Section 3 proposes the framework of the new survey method and develops an object detection model. Section 4 validates the accuracy of the proposed method through a real load investigation.

2. Theoretical load model

The sustained load is typically modelled as a Poisson square process, which is given as Peir and Cornell (1973); McGuire and Cornell (1974):

$$S(t)=\sum_{i=0}^{N(t)}\eta_i I_i\left(t,T_i,T_{i+1}\right) \tag{1}$$

in which $N(t)$ is the total number of occupancy changes from 0 to t, T_i stands for the time of the i th occupancy change and $T_0=0$, η_i denotes the load amplitude between the i th and $(i+1)$ th occupancy changes, $I_i\left(t,T_i,T_{i+1}\right)$ satisfies:

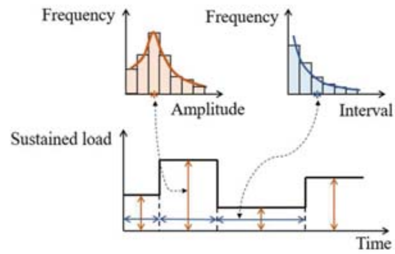

Fig. 1.The random variables required to describe a sustained load process.

$$I_i\left(t,T_i,T_{i+1}\right)=\begin{cases}1 & t\in\left[T_i,T_{i+1}\right]\\ 0 & t\notin\left[T_i,T_{i+1}\right]\end{cases} \tag{2}$$

Figure 1 presents a typical sustained load process and the two random variables required to describe such a process Li and Wang (2021). As mentioned above, this study focused on the amplitude.

The load amplitude can be expressed based on the unit load or equivalent uniformly distributed load ($EUDL$). For an interested area A , the live load intensity at point (x,y) is denoted by $w(x,y)$. The unit load is defined by:

$$U=\frac{\iint_A w(x,y)\mathrm{d}x\mathrm{d}y}{A} \tag{3}$$

The $EUDL$ is given by:

$$EUDL=\frac{\iint_A w(x,y)I(x,y)\mathrm{d}x\mathrm{d}y}{\iint_A I(x,y)\mathrm{d}x\mathrm{d}y} \tag{4}$$

in which $I(x,y)$ is the influence surface function over A .

Based on theoretical analyses McGuire and Cornell (1974), the mean of U is expressed as:

$$\mu_U=m \tag{5}$$

The variance of U is given by:

$$\sigma_U{}^2=\sigma^2+\frac{\sigma_s{}^2}{A} \tag{6}$$

in which m,σ and σ_s are three parameters required to be determined from survey data.

The mean of $EUDL$ is equal to the mean of U . The variance of $EUDL$ is:

$$\sigma_{EUDL}{}^2=\sigma^2+\frac{\sigma_s{}^2}{A}k \tag{7}$$

where k is determined by $I(x,y)$ over A and is generally taken to be 2.2 in load investigations Kumar (2002).

In live load investigations, the mean and area-dependent variance of U are required to estimate the m, σ and σ_s.

3. New survey method

3.1. *Framework*

The unit load can be expressed as:

$$U = \frac{\sum_{j=1}^{R} W_{j,1} + W_{j,2} + \cdots + W_{j,M_j(A)}}{A} \tag{8}$$

in which R is the total number of indoor object types, A is the area of the surveyed region, $W_{j,m\left[m=1,2,\cdots,M_j(A)\right]}$ is the weight of the m th object in the j th type, $M_j(A)$ is the total number of objects in the j th type over the surveyed region.

Some basic assumptions are established first: the piece weights of the object in the same type are independent and identically distributed, the piece weight and total number of the objects in the same type are independent, and the total weight of the objects in different types are independent.

The mean of U is given by:

$$\mu_U = \sum_{j=1}^{R} \frac{\mu_{M_j(A)} \mu_{W_j}}{A} \tag{9}$$

in which W_j represents the piece weight of an object in the j th type, $\mu_{M_j(A)}$ and μ_{W_j} are the means of $M_j(A)$ and W_j, respectively.

The variance of U is:

$$\sigma_U^{\,2} = \sum_{j=1}^{R} \frac{\mu_{M_j(A)} \sigma_{W_j}^{\,2} + \sigma_{M_j(A)}^{\,2} \mu_{W_j}^{\,2}}{A^2} \tag{10}$$

where $\sigma_{M_j(A)}^{\,2}$ and $\sigma_{W_j}^{\,2}$ stand for the variances of $M_j(A)$ and W_j, respectively.

A room is generally employed as a basic survey unit. Based on Eq. (9) and Eq. (10), the object quantities, object piece weights and room areas are required to derive the mean and variance of U.

The schematic diagram of the new survey method is presented in Figure 2.

The room area and object weight are easy to access. The room area is extracted from the residence information on the real estate website. The object weight is obtained from the product information on the e-commerce website.

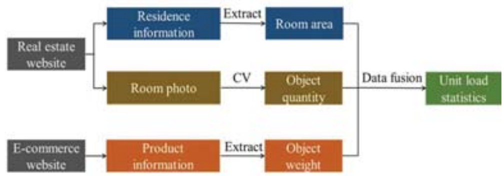

Fig. 2.The schematic diagram of the new survey method.

The object quantity requires to be recognized from the room photos on real estate websites based on the computer vision (CV). Specifically, an object detection model is developed.

3.2. *Object detection model*

The object detection is an important CV task, which aims to locate the objects and assign a category to each object Wu et al. (2020). In this study, the object detection based on YOLOv4 algorithm is employed for the automatic counting of the objects in room photos Bochkovskiy et al. (2020).

The living room in residential buildings is employed for illustrating the investigation process.

3.2.1. *Object type determination*

The types of objects that require to be detected are determined first. Eq. (9) and Eq. (10) suggest that the mean and variance of U are both the sum of R items. Each item represents the contribution of a particular object type. A previous survey covering more than 20000 m^2 of living rooms indicates that 6 types of objects contribute around 75% of the mean and 70% of the variance. These 6 predominant types including the sofa, dining table, TV cabinet, tea table, fridge and air conditioner are considered here.

3.2.2. *Dataset*

A dataset containing 7979 room photos and the above 6 types is established. The room photos are obtained from the open-access data on a real estate website (www.lianjia.com). The training, validation and test dataset includes 5979, 1000 and 1000 photos, respectively. The resolution is 400×710 (height × width) and the annotation data are organized in an XML format.

3.2.3. *Training*

The object detection model is mainly based on the YOLOv4 algorithm. However, it is found that the CIOU (Complete Intersection over Union) loss function has unsatisfied performance on the present dataset and detection task. The loss function of YOLOv3 algorithm is employed Zheng et al. (2020); Redmon and Farhadi (2018).

The momentum optimizer is used and the variation of the learning rate with iterations is shown in Figure 3. Some other training parameters are listed in Table 1.

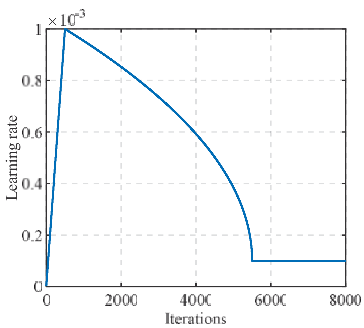

Fig. 3.The variation of the learning rate with iterations.

Table 1. Training parameters of the object detection model.

Parameter	Value
Input size	736×736
Momentum	0.9
Weight decay	0.0005
Batch size	8
Max epoch	25

The weight statistics of the tea table and TV cabinet are very close, therefore these two types are combined in the detection process. A similar processing is conducted on the fridge and air conditioner.

The variation of the loss function with iterations on the training dataset is presented in Figure 4.

3.2.4. *Performance evaluation*

The performance of the model on the validation dataset is analysed. The variation of the average precision (AP) with epochs at a given IOU threshold is presented in Figure 5.

The mAP (mean average precision) of all types after 10 epochs is the most satisfactory, therefore the model after 10 epochs is selected and tested on the test dataset. The precision of the model on the test dataset at a given IOU threshold is presented in Figure 6. Figure 6 suggests that the mAP on the test dataset is 62%. Some detection results are shown in Figure 7.

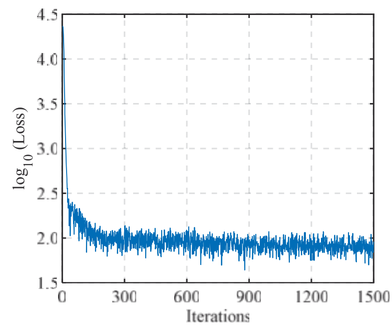

Fig. 4.The variation of the loss function on the training dataset with iterations.

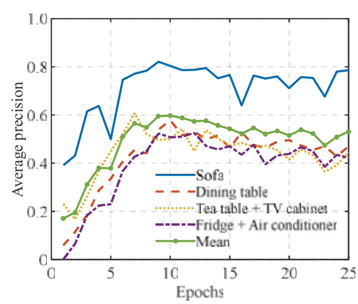

Fig. 5.The variation of the average precision with epochs on the validation dataset.

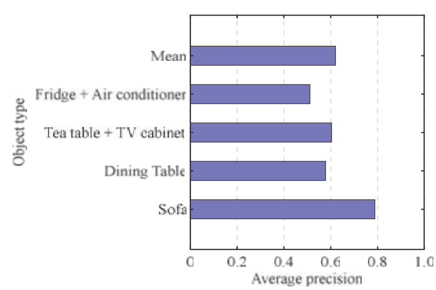

Fig. 6.The precision of the model on the test dataset.

4. Case study

A live load investigation is conducted on 334 living rooms covering more than 6000 m^2. The quantities of 4 types of indoor objects (after combining) are investigated by both manual counting and the computer vision. The survey results are compared to verify the accuracy of the proposed method, as shown in Figure 8. The manual counting is conducted through the virtual reality views of the living rooms.

(a)

(b)

Fig. 7.The detection results on the test dataset.

In the application of the object detection model, the confidence threshold of each type is determined by achieving the highest F1-score on the validation dataset.

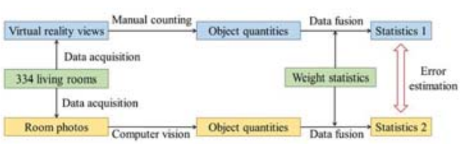

Fig. 8. The process of verifying the accuracy of the proposed method.

The survey results obtained by manual counting is regarded as the benchmark data. Subsequently, the relative error of the proposed method is defined by:

$$\varepsilon = \frac{\theta_{\mathrm{cv}} - \theta_{\mathrm{ma}}}{\theta_{\mathrm{ma}}} \tag{11}$$

in which θ_{cv} represents the statistical result obtained by the computer vision and θ_{ma} stands for the statistical result obtained by manual counting.

The mean amplitudes obtained by two different methods are shown in Figure 9. The mean derived from the computer vision is smaller than that derived from manual counting. The relative error of the mean amplitude is -10.5%.

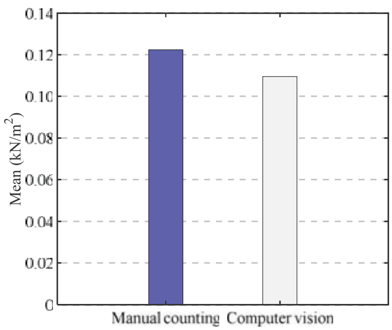

Fig. 9. The mean amplitudes obtained by two different methods.

Based on Eq. (10), the variance of the unit load is area dependent. Therefore, the surveyed rooms are grouped according to their areas and the variance is obtained for each group. The area range and room quantity of each group are listed in Table 2.

Table 2. The area range, room quantity and relative error of each group.

Area (m^2)	Group number	Room quantity	Relative error
<10	1	45	10.9%
$[10,15)$	2	98	17.6%
$[15,20)$	3	76	19.3%
$[20,25)$	4	53	17.9%
$[25,30)$	5	28	17.7%
≥ 30	6	43	14.2%

The standard deviations (SD) obtained through manual counting and the computer vision are compared in Figure 10. The SD through the computer vision is larger than the corresponding result through manual counting. The relative errors of the SD are calculated and provided in Table 2. Table 2 illustrates that the relative error of the SD is smaller than 20%.

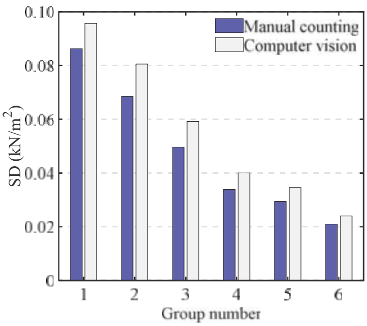

Fig. 10. The standard deviations of the load amplitude obtained by two different methods.

5. Conclusions

A new survey method for determining live loads is proposed by using the multi-source online data and computer vision, which realizes automatic acquisition and processing of the survey data.

A dataset containing 7979 room photos and 6 object types is established. The object detection model after 10 epochs of training has the best performance on the validation dataset and achieves 62% mAP on the test dataset.

A real live load survey is conducted to verify the accuracy of the proposed method, in which both manual counting and the computer vision are used to obtain the object quantities. The relative errors of the mean and standard deviation are around 10% and smaller than 20%, respectively.

The proposed method allows automatic load investigations without entering the surveyed regions. The object detection model for other room types can be developed in a similar manner to this study.

References

American Society of Civil Engineers (ASCE). (2022). *Minimum Design Loads and Associated Criteria for Buildings and Other Structures*. American Society of Civil Engineers.

Andam K. A. (1986). Floor live loads for office buildings. *Building and Environment, 21(3-4)*, 211-219.

Bochkovskiy A., C. Y. Wang and H. Y. M. Liao (2020). Yolov4: Optimal speed and accuracy of object detection. *arXiv preprint arXiv:2004.10934*.

Chalk P. L. and R. B. Corotis (1980). Probability model for design live loads. *Journal of the Structural Division, 106(10)*, 2017-2033.

Choi E. C. C. (1992). Live load in office buildings. Point-in-time load intensity of rooms. *Proceedings of the Institution of Civil Engineers-Structures and Buildings, 94(3)*, 299-306.

Corotis R. B. and V. A. Jaria (1979). Stochastic nature of building live loads. *Journal of the Structural Division, 105(3)*, 493-510.

Culver C. G. (1976). Live-load survey results for office buildings. *Journal of the Structural division, 102(12)*, 2269-2284.

Harris J. C. and R. B. Corotis (1978). Hospital inventory load survey. *Journal of the Structural Division, 104(12)*, 1859-1868.

Kumar S. (2002). Live loads in office buildings: point-in-time load intensity. *Building and environment, 37(1)*, 79-89.

Li J. and D. Wang (2021). On the principle of load combination of structures. *Structural Safety, 89*, 102046.

McGuire R. K. and C. A. Cornell (1974). *Live load effects in office buildings. Journal of the Structural division, 100(7)*, 1351-1366.

Peir J. C. and C. A. Cornell (1973). Spatial and temporal variability of live loads. *Journal of the Structural Division, 99(5)*, 903-922.

Redmon J. and A. Farhadi (2018). Yolov3: An incremental improvement. *arXiv preprint arXiv:1804.02767*.

Wu X., D. Sahoo, and S. C. Hoi (2020). Recent advances in deep learning for object detection. *Neurocomputing, 396*, 39-64.

Zheng Z., Wang P., Liu W., Li J., Ye R. and D. Ren (2020). Distance-IoU loss: Faster and better learning for bounding box regression. *In Proceedings of the AAAI conference on artificial intelligence, 34(07)*, 12993-13000.