IoPT: A Concept of Internet of Perception-aware Things

Yuki Matsuda
yukimat@is.naist.jp
Nara Institute of Science and Technology
Ikoma, Nara, Japan

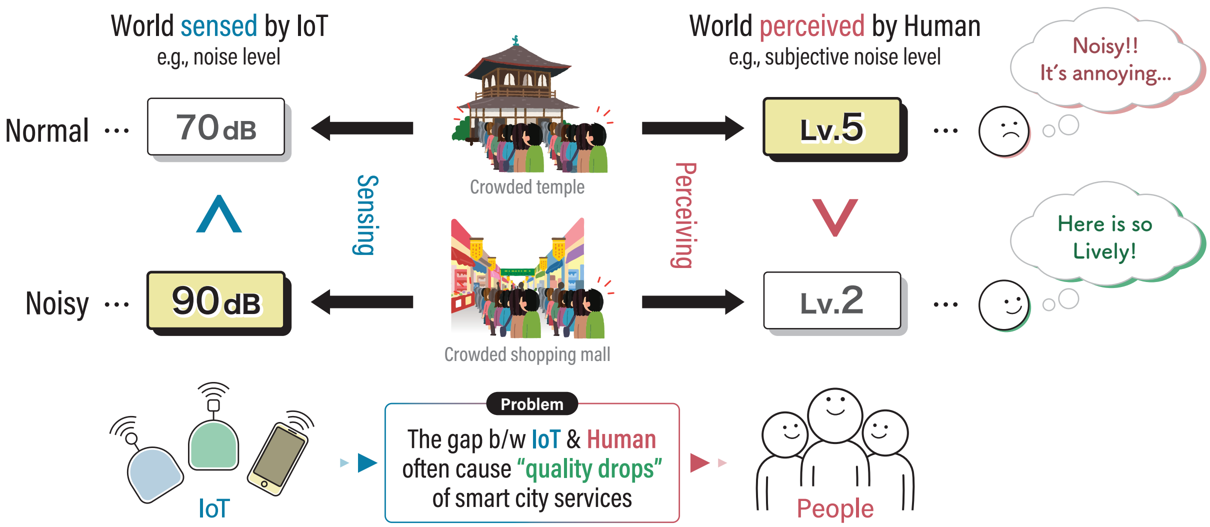


Figure 1: The difference between the worlds sensed by IoT and perceived by human

ABSTRACT

The Internet of Things (IoT) is undergoing remarkable technological innovation, it is expected uncountable number of IoT devices will be installed everywhere and enrich our daily life in near future. There is a technical challenge that is the physically accurate data does not always match the "experience" of people, because the "perception" of people will be easily biased by various stimulations from surrounding environments. This paper presents a concept of Internet of Perception-aware Things (IoPT), which aims to fill the gap in perception between IoT and human. Through the case study targeting subjective crowdedness, we have confirmed perception data have huge deviations though there are correlations between sensor data and perception data, and perception will be biased due to the environmental conditions.

CCS CONCEPTS

• **Human-centered computing → Ubiquitous computing**.

KEYWORDS

Internet of Things, Perception, Human-in-the-loop System.

ACM Reference Format:
Yuki Matsuda. 2022. IoPT: A Concept of Internet of Perception-aware Things. In *Proceedings of the 12th International Conference on the Internet of Things (IoT '22), November 7–10, 2022, Delft, Netherlands.* ACM, New York, NY, USA, 4 pages. https://doi.org/10.1145/3567445.3571108

1 INTRODUCTION

The Internet of Things (IoT) is undergoing remarkable technological innovation, and it is expected that countless IoT devices will be installed in our living environment and carried by the general people in the near future. This will be even more pronounced in urban environments where large numbers of people live, and where mass IoT devices will be installed, continuously generating data about cities. In providing smart city services (e.g., sightseeing navigation) utilizing data obtained from such various IoT devices, how can we provide services that are compassionate to the "people" who actually use them? This is an important question in gaining acceptance of the smart city concepts among general people. Until today, several researches for realizing compassionate smart city services are proposed, such as the psychologically safe road sensing using a wearable device and social media [8], the memorable route recommendation by detecting effective landmarks [9], the tourists' satisfaction level estimation in sightseeing spots [5], and mapping of the smellscapes using social media [7].

IoT '22, November 7–10, 2022, Delft, Netherlands

ACM ISBN 978-1-4503-9665-3/22/11...$15.00
https://doi.org/10.1145/3567445.3571108

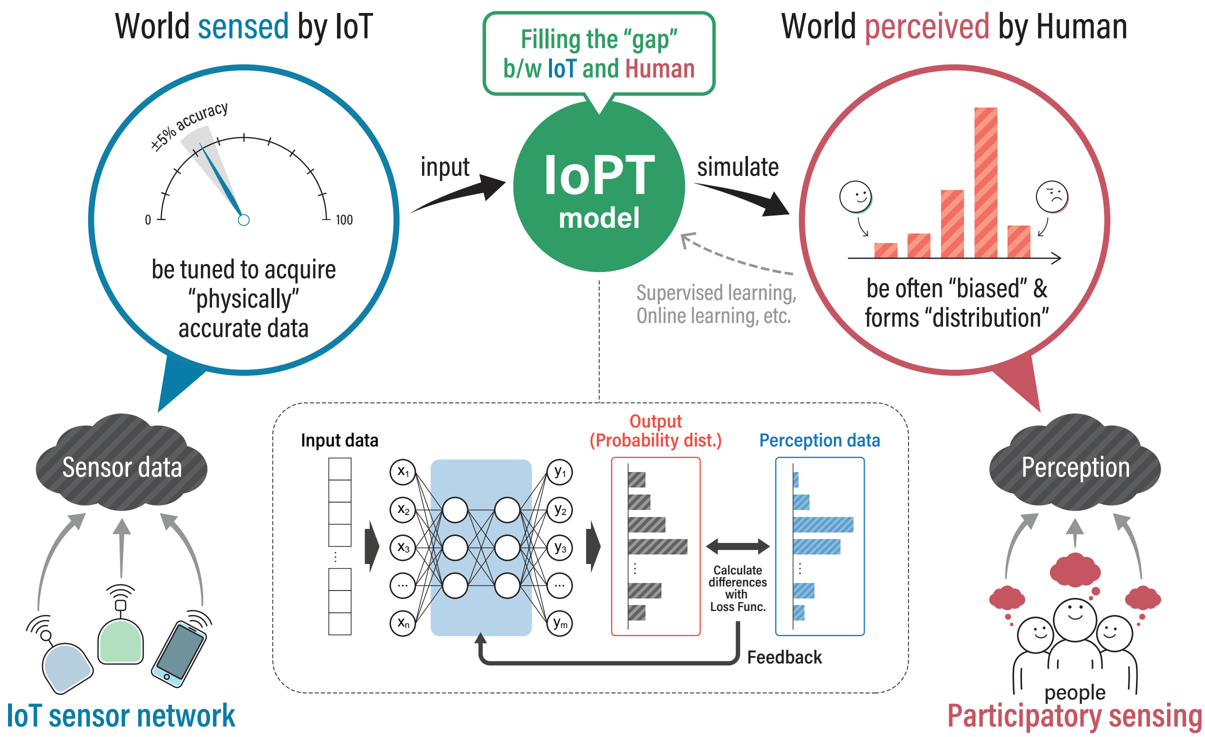


Figure 2: A concept of Internet of Perception-aware Things (IoPT)

Here, the challenge is the physically accurate data does not always match the "experience" of people, because the "perception" of people will be easily biased by various stimulations from surrounding environments. Figure 1 shows the typical example of mismatch between IoT and human. Simply comparing noise level (dB) between a crowded temple and a crowded shopping mall, the latter is absolutely noisier, however, people sometime perceive the other way round depends on the situation. This situation might cause the deterioration in the subjective quality of context-aware services, e.g., the recommendation without considering time, place, and occasion (TPO) will be much further from our expectations. This paper presents a concept of Internet of Perception-aware Things (IoPT), which aims to fill the gap in perception between IoT and human.

2 INTERNET OF PERCEPTION-AWARE THINGS (IOPT)

In this section, we design the Internet of Perception-aware Things (IoPT), a concept for filling the gap in perception between IoT and human. Figure 2 shows the overview of the IoPT concept. The key idea is that we employ participatory sensing [1], not as a method to collect input data for direct analysis of urban environments, but as a method to collect data for training models of IoT.

The IoPT consists of three core components: (1) participatory sensing, (2) IoT sensor network, and (3) IoPT model.

Participatory sensing The data about the world perceived by human (*perception data*) will be collected by using a participatory sensing framework, e.g., requesting general people to report their current feelings/perspectives via smartphone apps. The perception data will be represented as a distribution form because people might perceive in different ways even environment is the same completely.

IoT sensor network The data about the world sensed by IoT (*sensor data*) will be collected by using a IoT sensor network. The various IoT, including IoT installed in certain places and mobile IoT carried by general people or vehicles etc., can be utilized as the sensing node.

IoPT model The model which allows the IoT sensor network to simulate the perception of human (*IoPT model*), will be trained with perception data as ground-truth and sensor data as input.

Eventually, the IoT sensor network, which was tuned to acquire physically accurate data at first, can be equipped with the capability to understand the "experience" of people. It means that smart city services considering people's perceptions can be provided without relying on continuous participatory sensing.

3 CASE STUDY AND DISCUSSION

As the preliminary case study to confirm the IoPT concept, we surveyed how the world is perceived by human by recruiting 2,200 general people on the Yahoo! Crowdsourcing platform in May 2021.

The overview of the case study is shown in Figure 3. As the target which can be investigated with an online questionnaire, we selected the *subjective crowdedness* of the city. To collect perceptions from people, we showed photos of cityscape including various numbers

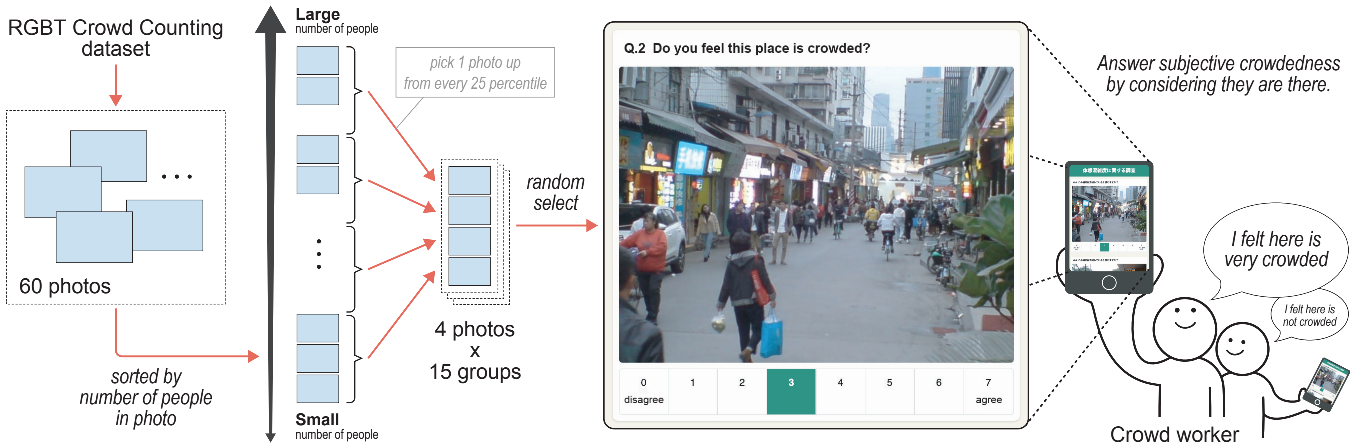


Figure 3: Procedure of case study

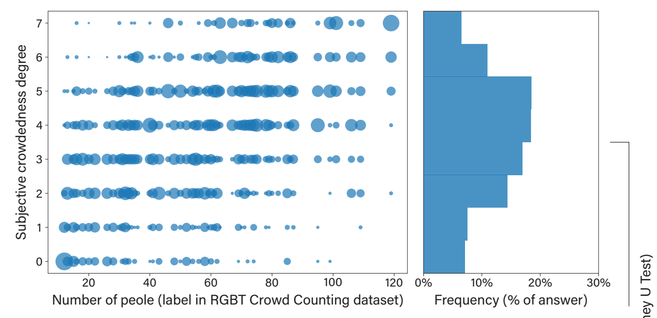
of pedestrians (10–120 people), and asked them to answer subjective crowdedness degree on an 8-level Likert Scale (not crowded: 0 – very crowded: 7) by considering that they are there. We selected 60 photos of the first-person views from the RGBT Crowd Counting dataset [3], and sorted them by the number of people in the photo. Then, pick one photo up from every 25 percentiles randomly, and create 15 groups with 4 photos. One of these groups will be provided to one person, and the answer will be collected. To exclude careless responses, the screening process of checking straightlining (selecting the same options) will be applied.

In addition, we divided people into two groups and requested them to imagine different situations: the before-COVID-19 situation and the after-COVID-19 situation. In total, we got valid answers from 834 people (3,336 samples), and 603 people (2,412 samples) respectively.

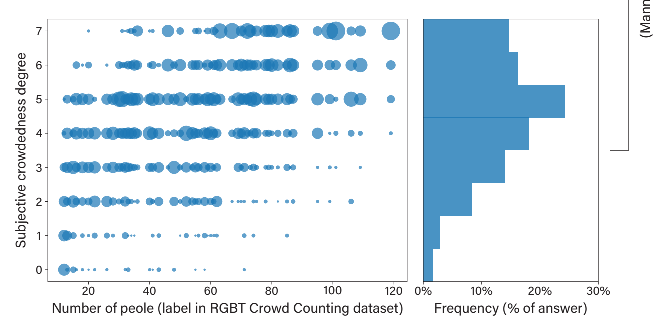
The result is shown in Figure 4. Bubble charts and Histograms show the relationship between the actual number of people in photos and the perceived crowdedness degree, and frequency of the latter, respectively. To confirm whether the perception significantly changes depending on the situation of the before- and after-COVID-19 situations (Figure 4(a) and (b)), we conducted statistical testing. First, random sampling is applied to both datasets for arranging the number of samples, consequently, 2,412 samples are acquired for each. We applied the Kolmogorov-Smirnov Test with a 5% significance level, then it is confirmed that both distributions are not following a normal distribution. Finally, we have confirmed a significant difference between the distribution of both conditions with the Mann-Whitney U Test with a 5% significance level. From the result, we have confirmed:

- the sensor data and perception data have correlations however perception contains huge deviations,
- the surrounding environment (e.g., COVID-19 situation) gives significant effects on the perception of people.

It suggests there is a use-case that our IoPT concept could apply. Also, it suggests that the perception of people might be changed over time affected by the alteration in customs, changes in population distributions, the happening of historic crises, etc. This change



(a) A case of "before" COVID-19 situation



(b) A case of "after" COVID-19 situation

Figure 4: Result of experiment focusing crowdedness of the city

will cause a performance decrement in the IoPT model, i.e., concept drift [4]. To adjust the IoPT model with these changes, we might need to employ online learning and incremental learning.

4 CONCLUSION AND FUTURE PERSPECTIVE

In this paper, we proposed the IoPT concept, and designed architecture to fill the gap in perception between IoT and human. Through the case study, we confirmed there is a case in which the IoPT concept might be applied. Also, we confirmed the technical challenges to realizing this concept. As a next step, we will build the IoPT model by collecting data with a participatory sensing framework [6] and a crowdedness estimation system for fixed-routed buses [2], and evaluate whether the IoT sensor can simulate the perception of people.

ACKNOWLEDGMENTS

This study was supported in part by JST PRESTO under Grant No. JPMJPR2039.

REFERENCES

[1] Jeffrey A. Burke, Deborah Estrin, Mark Hansen, Andrew Parker, Nithya Ramanathan, Sasank Reddy, and Mani B. Srivastava. 2006. Participatory sensing. In *First Workshop on World-Sensor-Web (WSW '06)*. ACM, 1–5.

[2] Yuji Kanamitsu, Eigo Taya, Koki Tachibana, Yugo Nakamura, Yuki Matsuda, Hirohiko Suwa, and Keiichi Yasumoto. 2022. Estimating Congestion in a Fixed-Route Bus by Using BLE Signals. *Sensors* 22, 3 (2022), 1–15. https://doi.org/10.3390/s22030881

[3] Lingbo Liu, Jiaqi Chen, Hefeng Wu, Guanbin Li, Chenglong Li, and Liang Lin. 2021. Cross-Modal Collaborative Representation Learning and a Large-Scale RGBT Benchmark for Crowd Counting. In *2021 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR '21)*. IEEE/CVF, 4821–4831. https://doi.org/10.1109/CVPR46437.2021.00479

[4] Jie Lu, Anjin Liu, Fan Dong, Feng Gu, João Gama, and Guangquan Zhang. 2019. Learning under Concept Drift: A Review. *IEEE Transactions on Knowledge and Data Engineering* 31 (2019), 2346–2363.

[5] Yuki Matsuda, Dmitrii Fedotov, Yuta Takahashi, Yutaka Arakawa, Keiichi Yasumoto, and Wolfgang Minker. 2018. EmoTour: Estimating Emotion and Satisfaction of Users Based on Behavioral Cues and Audiovisual Data. *Sensors* 18, 11 (2018), 1–19. https://doi.org/10.3390/s18113978

[6] Yuki Matsuda, Shogo Kawanaka, Hirohiko Suwa, Yutaka Arakawa, and Keiichi Yasumoto. 2022. ParmoSense: Scenario-based Participatory Mobile Urban Sensing Platform with User Motivation Engine. *Sensors and Materials* 34, 8 (2022), 3063–3091. https://doi.org/10.18494/SAM3961

[7] Daniele Quercia, Rossano Schifanella, Luca Maria Aiello, and Kate McLean. 2015. Smelly Maps: The Digital Life of Urban Smellscapes. In *Proceedings of the International AAAI Conference on Web and Social Media (ICWSM '15)*. AAAI, 327–336.

[8] Bernd Resch, Anja Summa, Günther Sagl, Peter Zeile, and Jan-Philipp Exner. 2015. Urban Emotions—Geo-Semantic Emotion Extraction from Technical Sensors, Human Sensors and Crowdsourced Data. In *Progress in Location-Based Services 2014*. Springer, 199–212. https://doi.org/10.1007/978-3-319-11879-6_14

[9] Shoko Wakamiya, Hiroshi Kawasaki, Yukiko Kawai, Adam Jatowt, Eiji Aramaki, and Toyokazu Akiyama. 2016. Lets Not Stare at Smartphones While Walking: Memorable Route Recommendation by Detecting Effective Landmarks. In *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp '16)*. ACM, 1136–1146. https://doi.org/10.1145/2971648.2971758