# Multimodal Object Recognition Using Bayesian Attractor Model For 2D and 3D Data

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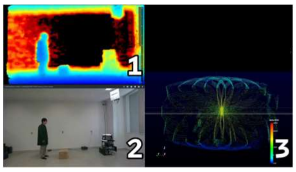
## Background



- **Developing 6G technologies**[1]
  - Connecting various types of sensors[2,3,4]
    - RGB Camera, LiDAR sensor, Infrared sensor
    - Analysis at edge and cloud
  - ➢ **Exploring 6G Use Case**
- **Robot control with digital twin**
  - Humans and robots cooperate in logistics warehouse
  - Stochastic robot control for safety and efficiency
  - ➢ **Stochastic recognition techniques are essential**




**Example of co-operative working**

[1] H. Viswanathan and P. E. Mogensen, "Communications in the 6g era," IEEE Access, vol. 8, pp. 57 063–57 074, 2020.
[2] X. Ding, J. Guo, Z. Ren, and P. Deng, "State-of-the-art in perception technologies for collaborative robots," IEEE Sensors Journal, vol. 22, no. 18, pp. 17 635–17 645, 2022.
[3] Wu, Hai, et al. "Virtual Sparse Convolution for Multimodal 3D Object Detection." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2023.
[4]Jiao, Yang, et al. "MSMDfusion: Fusing lidar and camera at multiple scales with multi-depth seeds for 3d object detection." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2023.

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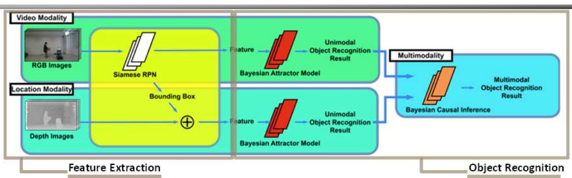
## Our Previous Work: Overview






- **Object recognition method inspired by brain information processing mechanism**[5]
  - Calculates Posterior probability density (**Confidence**) about the observed object
  - Realizes **Uncertainty-aware object recognition** using confidence levels and enable risk assessment
- **Remaining Issue: Dependencies between modalities**
  - **Dependencies** arise between recognition results before integration **due to shared feature extraction parts**

[5]R. Seki, D. Kominami, H. Shimonishi, M. Murata, and M. Fujiwaka, "Multi-object recognition method inspired by multimodal information processing in the human brain," in 2022 IEEE Globecom Workshops.

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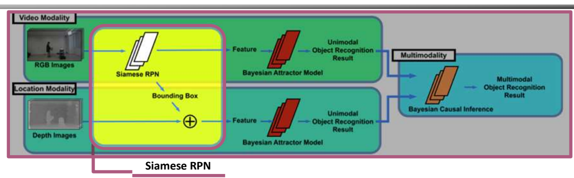
## Feature Extraction by Siamese-RPN






- **One-shot object detection method**[6]
  - **Video features** : Extract features **by CNN-based extraction** as the region (Bounding Box) where an object exists
  - **Location features** : Extract features **by combining position of Bounding Box and depth images**
    - **Center of Bounding Box (x, y) and depth (z)**
    - **Dependencies** arise in the assumptions of Siamese RPN feature extraction **before integration**

[6]B. Li, J. Yan, W. Wu, Z. Zhu, and X. Hu, "High Performance Visual Tracking With Siamese Region ProposalNetwork," Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2018

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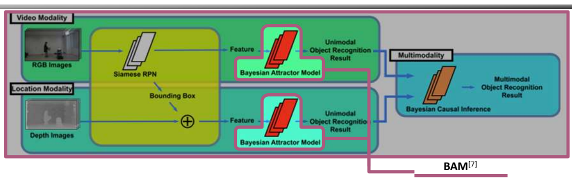
## Unimodal Object Recognition by Bayesian Attractor Model






- **Unimodal Object Recognition using Brain-inspired model considering uncertainty**
  - Represents human decision state using state-space model that has fixed points called **attractors**
    - Attractors store the characteristics of each object
  - **Updates its state** according to the observation and recognize objects stochastically
    - Posterior probability density (**confidence**) on each attractor is derived as the certainty of recognition
  - ➢ **Construction of risk-aware systems** is made possible by recognition with confidence

[7] S. Bitzer, J. Bruineberg, and S.J. Kiebel, "A Bayesian Attractor Model for Perceptual Decision Making," PLOS Computational Biology, 2015

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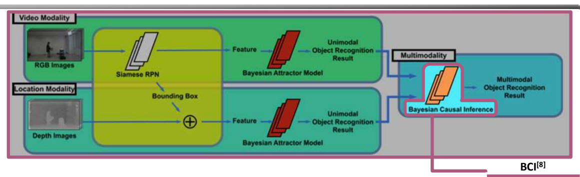
## Multimodal Object Recognition by Bayesian Causal Inference






- **Multimodal object recognition using BCI Model that integrates different modalities**
  - **Reduces recognition error** by leveraging different modalities
    - Assesses if the observation is focused on the same object and establish the weights accordingly
    - Calculates confidence by integrating the probability distributions obtained from each modality
  - ➢ Support decision-making by **considering uncertainties** associated with modalities

[8] K.P. K¨ording, U. Beierholm, W.J. Ma, S. Quartz, J.B. Tenenbaum, and L. Shams, "Causal Inference in Multisensory Perception," PLOS ONE, 2007.

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## Contribution in Present Work



- **Problem：Dependencies before multimodal integration**
  - Use the information extracted from RGB images by Siamese RPN when processing depth images
    - **Dependencies** arise between recognition results before the integration of multimodal data
  - ➢ The reduction in recognition in the video modality results in decreased recognition in the location modality
    - ➢ Deterioration of dependability
- **Contribution：Resolve dependencies in the feature extraction**
  - **Employ point clouds** as a modality capable of standalone analysis, independent from video modality
    - **Adopt PointNet**[9] for semantic segmentation
  - ➢ Construct to merge video and location modalities following their separate recognition
    - ➢ Improvement of dependability

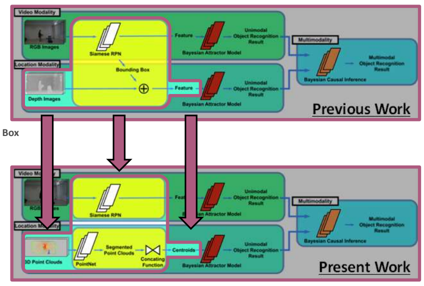
[9] C.R. Qi, H. Su, K. Mo, and L.J. Guibas, "Pointnet: Deep learning on point sets for 3d classification and segmentation," Proceedings of the IEEE conference on computer vision and pattern recognition, 2017



## Difference Between Previous and Present Work



- **Previous Work**
  - Video Modality
    - RGB images
    - Siamese RPN[6]
  - **Location Modality**
    - **Depth images**
    - **Combining with Bounding Box**
- **Present Work**
  - Video Modality
    - RGB images
    - Siamese RPN[6]
  - **Location Modality**
    - **3D Point Clouds**
    - **PointNet**[9]

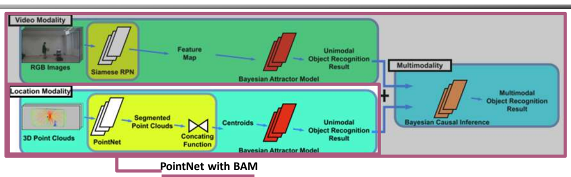



**Comparing Two Methods**



## Present Work: Unimodal Object Recognition by PointNet






**Our present work using Bayesian Attractor Model for RGB and Point Clouds**

- **Recognition model combining BAM [7] and PointNet [9]**
  - Utilize **3D centroids** of objects instead of location based on depth images and Bounding Box
    1. **Performs semantic segmentation** of point clouds using PointNet
    2. Acquires labelled point clouds and calculates centroids of objects
  - Recognition with 3D centroids using BAM
    - Memorize the centroids at 1st frame in BAM, compare observation with them, and recognize an object with confidence

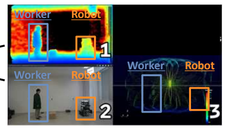


## Evaluation Settings



- **Create dataset using an RGB-D camera and a LiDAR sensor**
  - Time-series data consisting of **RGB-D images** and **3D point clouds** with labels
  - A scene where **a human and a robot** are performing cooperative work indoors
- **Tasks for object recognition from multimodal sources**
  - Targets : Worker / Robot
  - Task : Estimate what given feature corresponding to each object represents

**Intel® RealSense™ Depth Camera D455**[10]




**Task**

**Livox Avia**[11]

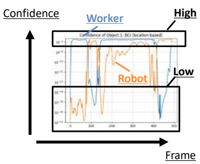
[10] https://www.intelrealsense.com/depth-camera-d455/
[11]https://www.livoxtech.com/jp/avia



## Evaluation Metrics



- **Inputs and outputs**
  - **Input (video)** : image features representing each object per frame
  - **Input (location)** : position features representing each object per frame
  - **Output** : confidence for each object
    - Example of output where **worker features** are given as input
    - **Horizontal axis**: Time [frames], **Vertical axis**: Confidence
    - **Blue:** Worker confidence, **Orange:** Robot confidence
- **Quantitative and qualitative evaluation**
  - **Quantitative evaluation : Transition of confidence**
    - **How recognize** the objects in each modality and integrated one
  - **Qualitative evaluation : Precision**
    - Percentage of objects that are truly correct when an object is recognized
    - Calculated by assuming that the object with **the highest confidence as recognized**

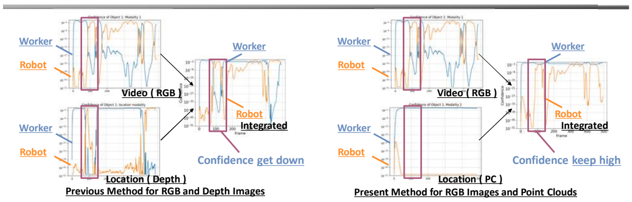



**Example of output when observing Worker**



## Quantitative Evaluation: Misprediction of Bounding Box






**Transition of Confidence (Target: Worker)**

- **Integration when one modality's recognition is high and the other's is low.**
  - **A decrease in recognition in the video modality leads to a decline in recognition in the location modality as well**. previous method **does not improve** the recognition by integration
  - When the confidence of the worker is **low** in the video modality and **high** in the location modality, present method **keeps the confidence of the worker in integrated result high**, even if robots are also recognized

## Qualitative Evaluation: Multimodal Object Recognition



Result on Precision

| Modality | Worker | Robot |
|---|---|---|
| Single modality (video) | 1.000 | 0.594 |
| Single modality (depth) | 1.000 | 0.806 |
| Single modality (location) | 0.788 | 1.000 |
| Video-based Multi-modalities (with depth) | 1.000 | 0.784 |
| Video-based Multi-modalities (with location) | 0.936 | 0.869 |

- **The precision for both targets are improved by multimodal integration**
  - **Single modality** reduces the certainty of one side
  - **Multimodal integration** results in high precision score for both targets



## Conclusion



- **Proposed method**
  - Multimodal object recognition method for 6G use case
    - Develop unimodal object recognition using point clouds with confidence
    - Improve our previous multimodal object recognition method using brain mechanisms
- **Experimental results**
  - Capture and test the environment for our use case using an RGB-D camera and a LiDAR sensor
  - Observe improvement of recognition by integrating recognition results
- **Future work**
  - Expand recognition targets
    - 2-class classification and one object in each class, assuming both exist in the frame in current experiments
    - For practical use, it is necessary to support multi-class multi-objects.
  - Propose a method to associate results from different modalities
    - Association of recognition results is given In current work



## Appendix







## Bayesian Attractor Model (BAM)[7]



- **A model combining Attractor model with Bayesian theory**
  - A model inspired by the process through which the brain makes decisions based on sensory organ information
    - Fusion of the attractor model for memory and the Bayesian estimation model for state updating
  - Produce recognition outcomes along with confidence based on continuous observations of what is being observed
- **Attractor model**
  - A model of recognition grounded in the brain's mechanisms of memory and cognition
    - Place fixed points (attractors) on the state space that correspond one-to-one with the objects of observation
    - Internal state changes in response to input
  - If inputs for the same target are sustained, it converges to the attractor that represents that target
- **Bayesian theory**
  - Calculate the posterior probability using prior probabilities and observations
  - Compile information continually upon receiving new inputs to revise decisions



## Bayesian Causal Inference (BCI)[8]

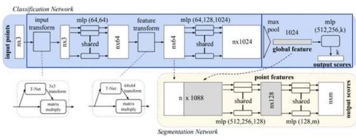


- **A statistical model combining Bayesian theory and causal inference**
  - A model inspired by the process through which the brain makes decisions based on multimodal information
    - Infer whether objects recognized by two different modalities are the same and integrate
  - Combine modalities with different advantages to provide more accurate predictions
    - Evaluate the likelihood that inputs from various modalities stem from a single external occurrence
    - Based on evaluated causal links, determine if sensory inputs should be merged or regarded independently
- **Formula for generating confidence**
  - $c_V, c_L$ : Confidence in video and location modalities
  - $P(c_V, c_L \mid C = 1) = \begin{cases} 0.5 + \sigma_{c=1} & \text{if } L_V = L_L, \\ \sigma_{c=1} & \text{otherwise,} \end{cases}$
  - $P(c_V, c_L \mid C = 2) = \begin{cases} 1 & \text{if } L_V \neq L_L \\ 0 & \text{otherwise} \end{cases}$
  - $\sigma_{c=1} = 0.5\sigma(\max(c_V)) + 0.5\sigma(\max(c_L))$
  - $\sigma = 1/(1 + \exp(-x - \lambda_{bci}))$
  - $L_V = \mathrm{argmax}(c_V)$
  - $L_L = \mathrm{argmax}(c_L)$



## PointNet[9]

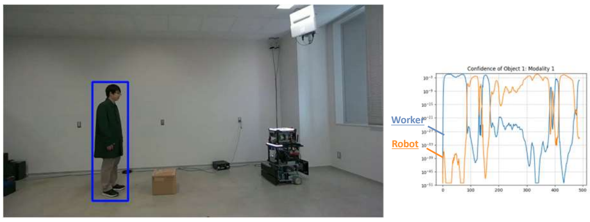





PointNet Architecture[9]

- **Deep learning framework for processing 3D point clouds**
  - Apply the same **Multilayer Perceptron (MLP)** to each point, followed by the application of **Max-Pooling**
    - Produces the same output, **independent of the order in which the point cloud is inputted**
  - Utilize a subnet called T-Net
    - Produces an affine transformation matrix for the input, allowing for adjustments such as rotation and shifting
  - **Utilizing global features**
    - **Integrate local and global features** and apply MLP for the realization of **semantic segmentation**

## Example of Bounding Box Detection Employing Siamese RPN 19

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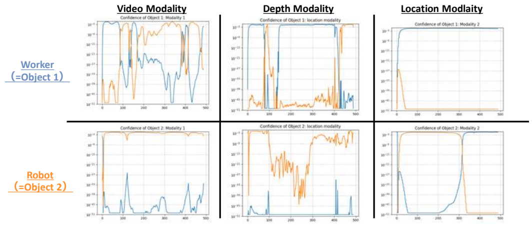
## Evaluation Results: Unimodal Object Recognition 20

- **Unimodal Object Recognition**
  - Use the term "**depth modality**" to distinguish the location modality using point clouds that employs depth images
  - Observe the correlation between video and depth modalities, which is a challenge in previous work




Evaluation results of unimodal object recognition

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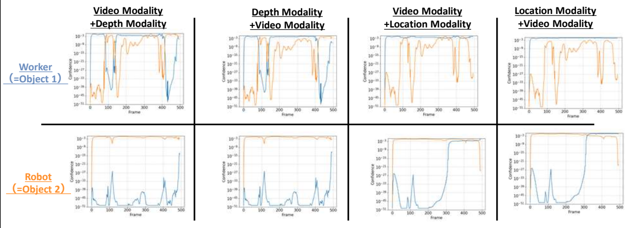
## Evaluation Results: Multimodal Object Recognition 21

- **Multimodal Object Recognition**
  - When using **depth images**, the parts where correlation was observed have not been corrected
  - When using **point clouds**, the problem has been resolved




Evaluation results of multimodal object recognition

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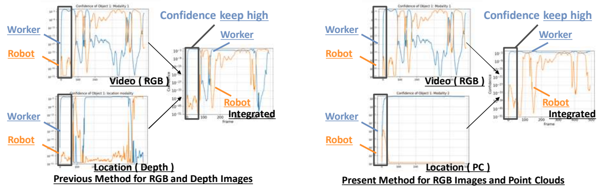
## Quantitative Evaluation 22




Transition of Confidence (Target: Worker)

- **Integration when both modalities produce recognition results with the same trend**
  - When the confidence of the worker in the video and location modalities are **high**, the confidence of the worker in integrated result is also **high**
  - When the confidence of the robot in the video and location modalities are **low**, the confidence of the worker in integrated result is also **low**

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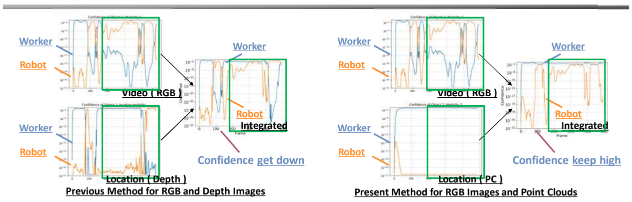
## Quantitative Evaluation: Misrecognition in Previous Method 23




Transition of Confidence (Target: Worker)

- **Integration when both modalities confidently provide different recognition results**
  - Bounding Box is right in the video modality, but the perception **continues to be wrong**
  - **Misrecognition occur** in the depth modality where they pass each other in the latter part of the scene
  - It is **clearly recognizable** by using centroids in location modality

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