Ecological Approach for Object Relationship Extraction in Elderly Care Robot

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***Abstract*— This paper proposes an ecological approach for object relationship extraction. First, we explain the ecological approach used to develop our previous works in the perception of a partner robot. Second, we developed a framework for finding the relation of objects based on scenarios of daily human activities. We represent the relationships among objects in a graph consisting of nodes and edges. Graph Convolutional Networks (GCN) is used to train the graph and perform semi-supervised classification. Third, we generate and prepare the datasets and then train the GCN. Finally, we present training visualization in two different scenarios. The proposed methods allow the system to identify the object based on its relationship. This approach is then used as a starting point to implement the ecological factors in elderly care robot applications.**

Keywords— object relationship extraction, ecological approach, graph convolutional networks, elderly care robot

I. Introduction

The COVID-19 pandemic has increased the risks to physical and mental health among people. The social restrictions imposed worldwide have had an economic impact, and the government has provided various social assistance programs to vulnerable and affected populations [1]. The elderly are a part of the community that is vulnerable when this pandemic occurs. Almost every day, the elderly are active at home as a place to live. They feel lonely throughout the day because they are left behind by working families or live alone because their husbands or wives have died. Family members, health-care professionals, or communities around the elderly cannot adequately accompany the elderly. Therefore they are required to be able to live independently in their loneliness [2].

There is much technology that can help the elderly to do activities at home. Smart home technology [3] can automate household appliances and monitor home security. Telehealth technology [4] can monitor the physiological of the elderly and report it to health-care facilities. There are currently many Internet of things applications connecting people with the device and their surrounding communities [5]. However, the issue of elderly loneliness at home is still gaining much attention. Many studies provide the solution for a robot capable of supporting and taking care of the elderly in their home [6].

The elderly care robot's application still leaves ethical problems [7] because it cannot replace humans' roles in accompanying the elderly. Many demands in this type of robot so that they get to know the elderly personally. Companion robot technology for the elderly is currently quite widely developed [6], [8]. In its development, the personal intelligent robot system is not enough to solve all the problems of the elderly who live alone at home. It occurs because home issues are very complex and challenging for robots to understand. Many factors indirectly affect the activities of the elderly at home [9]. Many activities take place between the individual with surrounding environments and objects. It is, therefore, essential to describe all these interactions into the representation of the ecological approach.

The ecological approach is an analysis method that emphasizes the relationship between humans and their environmental activities [10]. Humans and their various activities are always the focus of analysis concerning their abiotic, biotic, social, economic, and cultural environments. This approach is essential for the robot to provide the best service [11] according to the object and environment related to human behavior. This research aims to enhance the elderly's quality of life. This approach looks at the problem from the perspectives of interactions in the home as an ecosystem. We use object detection as an initial step to this approach.

Previous studies have shown the relationship between objects in graph data structures [12], [13]. This data structure comprises many object nodes and numerous edges that represent the relationships of objects. To identify and visualize the interaction of items in many contexts, we have used Graph Convolutional Networks [14]. By identifying the relationships between objects, we can recognize groups of objects in supporting human activities.

This research aims to represent the ecological approach for object relationship extraction in our elderly care robots development [15]. The method developed is based on our previous Informationally Structured Space (ISS) [8]. This paper also contributes mainly to the formulation of the framework for representing the relationships between the elderly and objects as ecological factors. This understanding is essential for robots to provide the best possible service following the ecological based on the current conditions. Therefore, this study is also expected to enhance quality of life of the elderly, especially in this pandemic.

This paper is structured in several stages as follows. Section 2 discusses why we use the ecological approach in the development of elderly care robots. Section 3 proposes a methodology in the development of object relationship

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extraction-based robot visual perceptions using GCN. Section 4 shows the training results of the GCN and discusses the effectiveness of the proposed method. Finally, section 5 presents the conclusions and future works of the research.

II. Ecological Approach

Ecology is not directly linked to robotics, but various robotics applications are being developed under these principles. The ecology terms in the robotics field were first used by Arkin (1996) from his article on the schema-theoretic approach to ecological robotics [16]. And then continued by Duchon (1998) that described the principles of this approach [17]. The most important rule of the ecological approach in robots is the relationship between perception and action. An agent-environment system considers as a unit of analysis. The function is learning about affordance as objects of perception, combined with learning techniques and perceptual development. However, this will require adaptation and learning processes as with ecosystems in nature.

In the concept of ecology, home is an ecosystem consisting of several interrelated things [18]: living things such as humans, pets, plants; non-living things such as furniture, tools; and other environmental factors such as outdoor weather. All connect and build harmonious relationships. However, new problems will arise when robots enter the home ecosystem. Robots may be considered foreign-factors that can threaten the ecosystem as foreign-factors may damage the ecosystem's natural balance. This problem is a challenge in developing companion robots [19]. Robots that act as agents must have the ability to capture all information from the environment. Such information is like the relationship between objects around the robot, human activities, and other variables. This view is the first step in building the cognitive concept that robots need to grasp the scene.

The elderly have several daily living activities (ADL) such as eating, bathing, dressing, toileting, moving, and continence, involving several or many living things and objects. Robots need to understand the relationship between ADLs and entity objects in the ecosystem [20]. We proposed an ecological approach to develop an understanding of the robot of the object relationship. There are two types of parameters on the objects, namely system and environmental parameters. System parameters may be able to adjust according to the desired target.

An example is an object in the house. We can define the objects that we want to use for certain activities. For example, glass is an object used for drinking s. However, some items may have more than one function. For example, the function of glass may be for drinking and medication activities. It is challenging to change environmental parameters since those parameters naturally exist-for example, ambient, temporal, and spatial factors. Including health factors, we cannot control them directly, but habits can change health. Fig. 1. illustrates how robots perceive humans from an ecological point of view.

Technological developments such as robotics currently aim to help the elderly, emphasizing their independence as a principal objective. We highlight how robots enter the field of human experience with objects around them [21]. This approach is the basis for robots to behave or provide the best service according to the current situation of the elderly. The ability to understand this ecosystem allows robots as agents to behave adaptively in various situations and conditions. We used a system parameter as a learning input for the robot. The robot will see how humans interact with objects in the house. The robot can then classify the objects used according to the context of human activity. We present a methodology for developing object relations based on the visual perception of robots using learning algorithms in the following section.

III. Proposed Method

This section will discuss the proposed method used in the ecological approach to the elderly care robot. The system consists of four parts: generating datasets, data preprocessing,

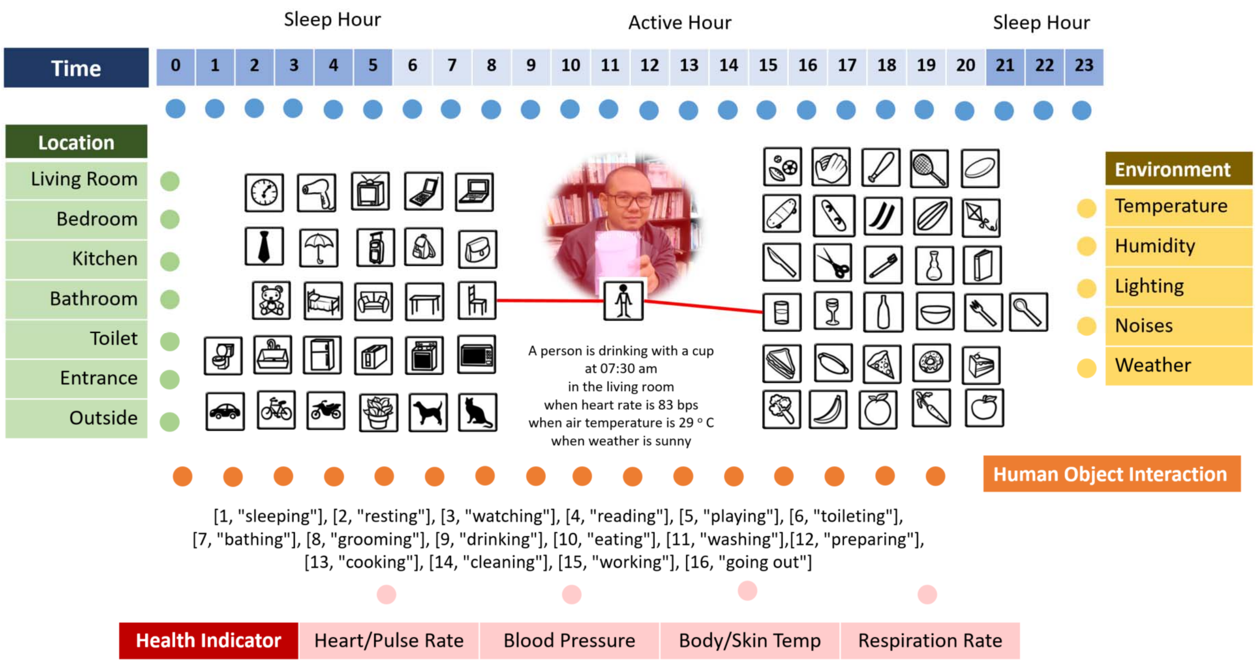


Fig 1. The robot views of human activity from ecological approach.

defining the Graph Convolutional Networks (GCN), training, and visualization.

A. Generating datasets

To generate the datasets, we use vision-based data acquisition that consists of an object detection algorithm. This experiment used an object detection algorithm with the MobileNetV2 architecture [22] and using the COCO Label dataset [23] because the architecture has diverse data set and has high accuracy. The goal is to obtain captured objects list at a particular time. This system used Logicool HD 1080 pixel web-camera to grab the image. The computer that we used is NVIDIA Jetson TX2 [24], which is an embedded AI computing device with JetPack 4.3 that provides Ubuntu 18.04.3 LTS (Bionic Beaver) as the operating system. These hardware systems will determine the interaction between humans and the object. This system will use two necessary AI components, namely cuDNN 7.6.3 and TensorRT 6.0.1. NVIDIA CUDA Deep Neural Network Library (cuDNN) offers highly tuned implementations for regular routines such as forward and reverse convolution, pooling, normalization, and activation layers [25]. Although TensorRT is an SDK for deep learning inference to high performance. This hardware includes a deep learning inference optimizer and runtime which delivers low latency and high-throughput for app lications with deep learning inferences.

We use two scenarios to show human activities related to objects in daily activities. The scenario chosen is on-table activities, including lunch and work. We have conducted experiments using ten items, namely: (0) person, (1) bottle, (2) bowl, (3) spoon, (4) fork, (5) keyboard, (6) cup, (7) laptop, (8) mouse, and (9) cellphone. We choose one person as a human object to perform these activities sequentially for approximately 10 minutes every scenario. The camera captures human activity with these objects every second and stores them in the datalog in CSV-file format. A program we created to read the file and generate a graph consisting of nodes and the relationships between nodes. The program calculates the appearance frequency of each object and associates it with other items [26]. The program then determines the relationship between these objects and insert them into the edge elements in the graph. The next section discusses how to prepare data for further processing.

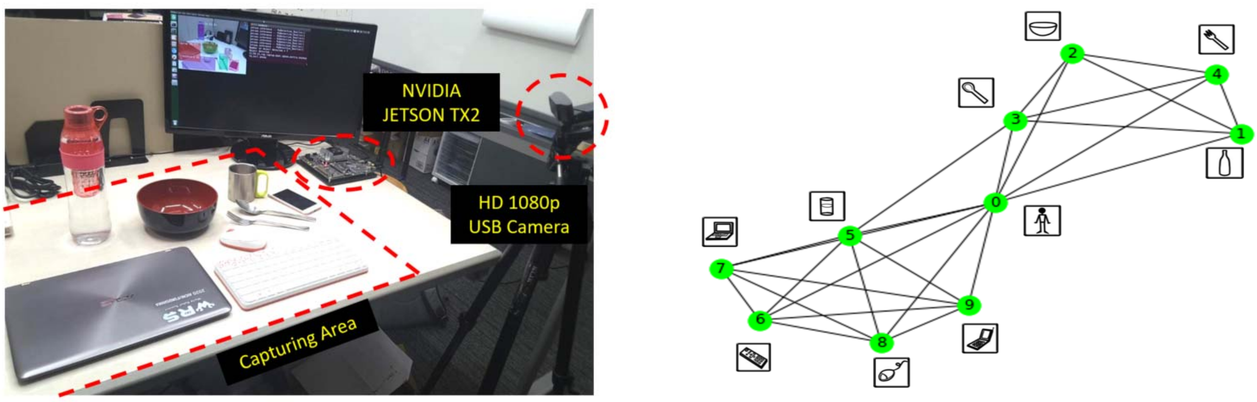
B. Data preprocessing

The data preparation consists of several stages: data filtering, data aggregation, and graph representation. Data filtering is the stage where the system evaluates collected data to indicate whether the object data is valid or not. Invalid information typically produces noise or object detection errors. For example, the error object detection typically occurs rarely and can be ignored. Then the data aggregation is performed to handle a large amount of data [27]. Data acquisition is generally performed per unit of seconds to generate data that does not vary much. Not all data is processed, and it is possible to simplify these data. The simplifications here are generalizations for large amounts of data. For example, data getting in every frame-rate can be generalized for every second so that one data can represent several data.

The data collected will be formed into a graph that represents ecology. A graph data structure is currently widely used as a natural framework to find interactions among elements represented as graph nodes. Each node may represent data related to the features it has, while the edges mean the relationship between one object and another object. A graph is a computational logic-based representation. Information conveyed in this model can be manipulated by computer programs and simplified in data structures for further processing. These data are built into a graph structure using the spring model NetworkX [28]. Next, we can assign the features to nodes and edges in the networks. Then, we stored all nodes and edges are in NumPy arrays. One for the source and the other for the destination. The edges are directional in the default system, so we must make the edges bi-directional before constructing the graph structure. Fig. 2 shows the experimental setup, including the equipment (a) and object numbering for graph representation (Fb). The next section discusses how to define Graph Convolutional Networks further.

C. Define the Graph Convolutional Networks

Most of the graph data were built from real-world interactions such as social networks and the World Wide Web. Several researchers have processed graph using classical techniques such as kernel methods [29] and graph regularizations [30]. Recently, a neural network has been used to generalize datasets using graph structures [31]. This period is the beginning of the rising Graph Convolutional Networks (GCN). The architecture is similar to a traditional CNN, but it takes graphs as input. Also, the convolution and pooling operations are different in principle. We use Deep Graph



(a) (b)

Fig 2. Experimental setup : (a) equipment; (b) object numbering with graph representation.

Library (DGL), a Python package dedicated to deep learning on the graph structure [32]. These tools built-in existing tensor Deep Learning frameworks (Pytorch or MXNet) and simplifying the implementation of graph-based neural networks. This experiment will learn scene understanding by using DGL enables computation on graphs from a high level. We then train our graph dataset with GCN in DGL to classify nodes in a graph.

This research focused on object detection related to our daily activity. The scenario is a network that includes ten objects and pairwise links between objects which interact in everyday activity. The object later divides into two classes led by the person (node 0) and the selected item. To perform node classification, we use the simplest definition of the GCN framework developed by Kipf and Welling (2017) [14]. At layer l, each node v_i^l carries a feature vector h_i^l. Each GCN layer tries to aggregate the features from u_i^l where u_i are neighborhood nodes to v into the next layer representation at v_i^{l+1}. An affine transformation with some non-linearity follows this. The definition of GCN describes as a message-passing paradigm. Each node will update its feature with information sent from neighboring nodes. Fig. 3 shows the illustration of message passing in Graph Neural Networks.

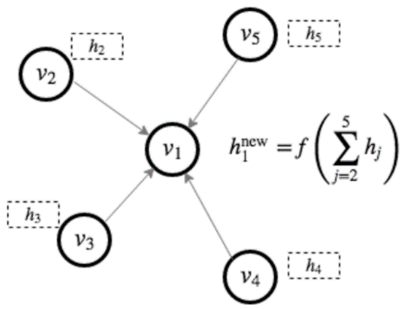


Fig.3 Message passing in Graph Neural Networks [14]

We define a model that contains two GCN layers. The first layer transforms input features of a size of 5 to a hidden dimension of 5. The second layer transforms the hidden layer and produces output features of length 2, corresponding to the two classes of the objects. We use learnable embeddings to initialize the node features. Since this is semi-supervised learning, only the person (node 0) and the object selected are assigned labels. Fig. 4 shows the system design of the ecological approach with GCN.

D. *Training GCN and Visualization*

The final phase is testing, wherein this phase, the GCN structure, has completed training and validation and will be tested with the new graph. The system will use necessary AI components, namely Deep Graph Library (DGL), for processing the graph integrated with Pytorch. We use a training loop that is the same as other PyTorch models: create an optimizer, feed the inputs to the model, calculate the loss, and use the *autograd* function to optimize it. We can use any computer with or without GPU capability in the implementation of GCN training. We choose the required data sampling to speed up the learning process, even though the graph structure is relatively simple compared to the image data, which is usually used as input for deep learning.

The training data steps as follows: (a) normalize the graph structure to be accepted as a GCN input with node and weight properties. (b) Graph convolution layer filters and extracts essential features. (c) Rectifier Linear Unit (ReLU) performs pooling/ down-sampling during the convolution process. (d) The graph convolution layer performs downsampling the graph information. (e) The softmax layer produces the final classification and makes a decision. The task is to predict which side of each object tends to join, given the network itself. The model produced an output feature of size 2 for each node; we can visualize by plotting the output feature in a 2D space.

IV. RESULTS AND DISCUSSION

In this section, we will present the results of the learning phase. We can see the results after the program reads the graph, enters it as GCN input, and carries out the learning process. As the number of nodes and edges in the graph is small, the number of epochs selected is 100. The loss decreases with the rising number of epochs. After the 70th epoch, a slight loos reduction occurred, and the loss value is less than 0.1. We do the learning process on each object to become the initial to compare to the person [13]. After that, two poles attract each other between the selected object and the person. The experiment showed that the GCN learning method succeeded in a semi-supervised classification before 100 epochs. Fig. 5 shows the decrement of GCN training loss until 100 epochs for the semi-supervised classification of each object as initial.

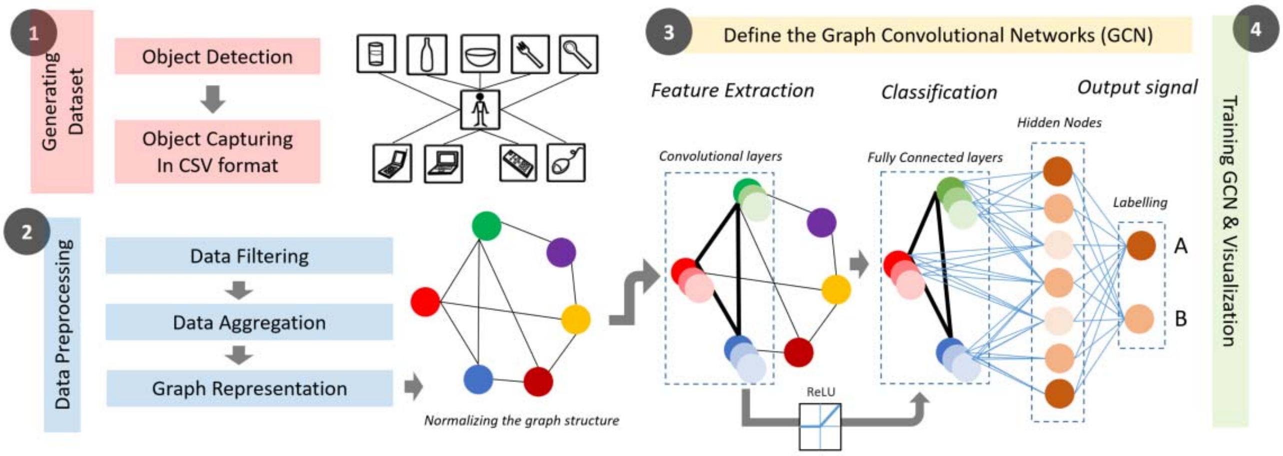


Fig 4. System design of ecological approach with Graph Convolutional Networks.

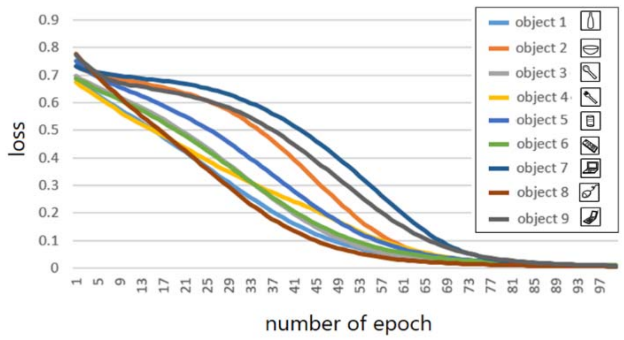


Fig 5. The loss of training every object the GCN.

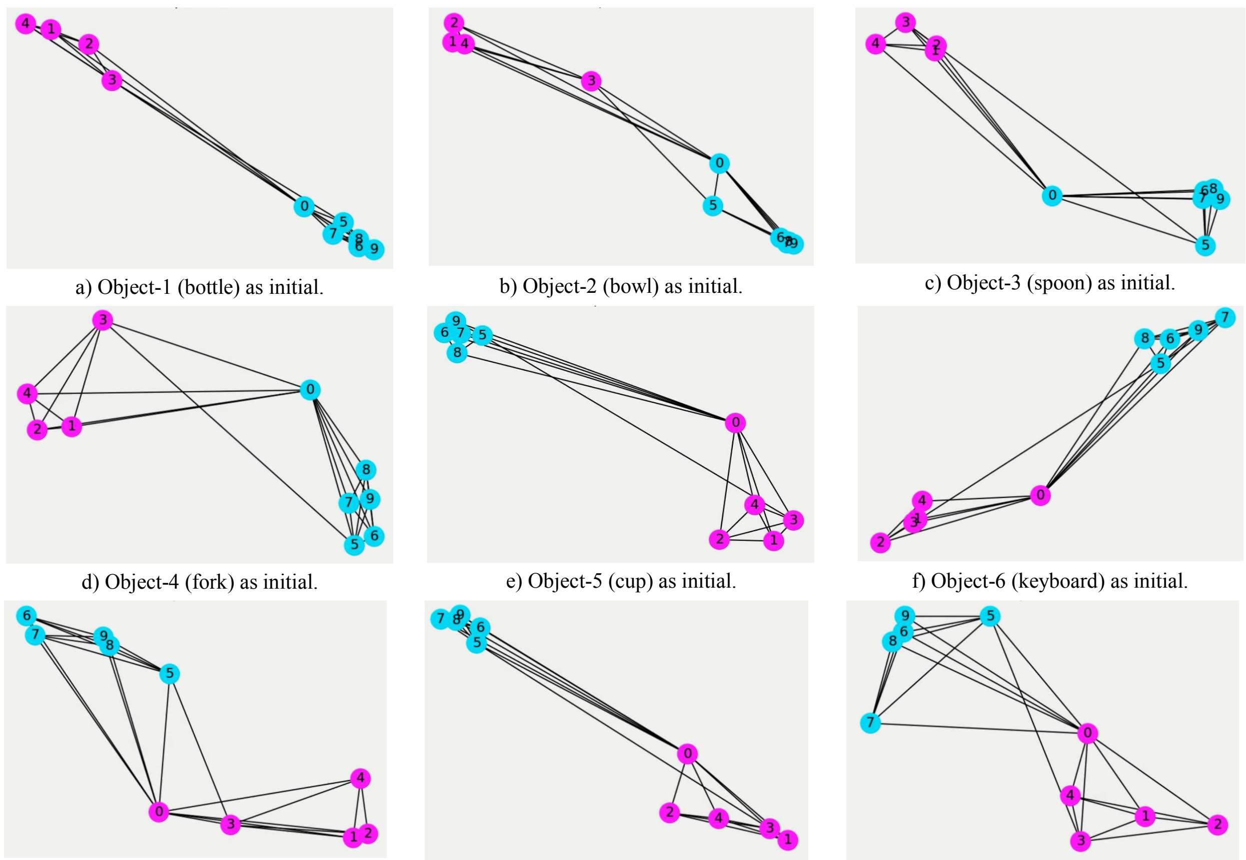
From the graphic representation, then we analyze the distance of the relationship between objects. Fig. 6 shows the result of the GCN training result for each object's semi-supervised classification as initial. During the lunch scenario, we can see that object-1 (bottle), object-2 (bowl), object-3 (spoon), and object-4 (fork) appear together frequently. However, only object 1, 2, and 4 have a strong relation in the lunch scenario (Fig. 6b and 6d). Object-3 looks quite far away from another object in the lunch scenario. Object-3 close to the lunch item occurs when used as the classification's initial (Fig. 6c). This is because object-3 also has a relation with object-5 (cup) in the working scenario. We may infer that the spoon follows the cup object since it is also used for stirring the drink in the cup (Fig. 6b).

In the working scenario, we can see that object-5 (cup), object-6 (keyboard), object-7 (laptop), object-8 (mouse), and object-9 (cellphone) appear together frequently. Objects-6, object-7, and object-8 attract each other. This is because these objects are often used together in a work scenario. Object-9 also has closeness, although it is used less frequently than work scenario objects. It is different for object-5, which is quite far from other objects in the working scenario (Fig. 6b, 6c, 6g, and 7i). This happens because object-5 is close to object-3 in the lunch scenario. We can see the effect of the relationship from one object to another from this result.

These results indicate that the relationship between one object and another object affects the position of an object in a class [12]. The intended position is the distance between an object and the object that is the initial of the class. This approach can be used in many elderly care robot applications. First, the robot can provide recommendations for what objects are needed in an activity scenario. Second, the robot can serve to remind what items are left behind in an activity scenario. For example, during a work scenario, the elderly are usually accompanied by a cup of coffee, but there is no object on the table. Robots can offer assistance to prepare a cup of coffee for the elderly. This requires a long interaction to understand the activities of the elderly to meet their needs.

V. Conclusion and Future Works

This paper discussed a study on ecological representation for object classification in elderly care robot applications. The model is obtained by observing object detection in two daily activity scenarios. All of these data are taken simultaneously, then represented in the field of experience that can be learned from all interactions that occur from ecological perspectives. GCN application for input graphs



a) Object-1 (bottle) as initial.
b) Object-2 (bowl) as initial.
c) Object-3 (spoon) as initial.
d) Object-4 (fork) as initial.
e) Object-5 (cup) as initial.
f) Object-6 (keyboard) as initial.
g) Object-7 (laptop) as initial.
h) Object-8 (mouse) as initial.
i) Object-9 (cellphone) as initial.

Fig 6. Experimental result of semi-supervised classification using GCN for 9 objects (cyan is lunch scenario and magenta is work scenario).

with multiple contexts is needed. The objectives of this method are for semi-supervised classification in daily activity related to the objects. This system needs to be supported by more distributed personal datasets for real-world applications. Furthermore, this study will describe the ecological constraints for the application of elderly care robots in more specific problems. This approach will be evaluated with input data from human-object interaction, environment, and health sensors in real-time. We can see what the robot can respond based on the information learned from these inputs. It will be the basis for developing a context-aware system in the elderly care robot application.

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REFERENCES

[1] I. Ali and O. M. L. Alharbi, "COVID-19: Disease, management, treatment, and social impact," *Science of The Total Environment*, vol. 728, p. 138861, Aug. 2020, DOI: 10.1016/j.scitotenv.2020.138861.

[2] B. McAdams, M. von Massow, and M. Gallant, "Food Waste and Quality of Life in Elderly Populations Living in Retirement Living Communities," *Journal of Housing For the Elderly*, vol. 33, no. 1, pp. 72–84, Jan. 2019, DOI: 10.1080/02763893.2018.1451801.

[3] N. N. W. Tay, J. Botzheim, and N. Kubota, "Human-Centric Automation and Optimization for Smart Homes," *IEEE Trans. Automat. Sci. Eng.*, vol. 15, no. 4, pp. 1759–1771, Oct. 2018, DOI: 10.1109/TASE.2018.2789658.

[4] K. Kurnianingsih, L. E. Nugroho, W. Widyawan, L. Lazuardi, A. S. Prabuwono, and T. Mantoro, "Personalized adaptive system for elderly care in smart home using fuzzy inference system," *Int J of Pervasive Comp & Comm*, vol. 14, no. 3/4, pp. 210–232, Sep. 2018, DOI: 10.1108/IJPCC-D-18-00002.

[5] A. R. Anom Besari, I. K. Wobowo, S. Sukaridhoto, R. Setiawan, and Muh. R. Rizqullah, "Preliminary design of mobile visual programming apps for Internet of Things applications based on Raspberry Pi 3 platform," in *2017 International Electronics Symposium on Knowledge Creation and Intelligent Computing (IES-KCIC)*, Surabaya, Sep. 2017, pp. 50–54, DOI: 10.1109/KCIC.2017.8228460.

[6] J. Woo, J. Botzheim, and N. Kubota, "A Socially Interactive Robot Partner Using Content-Based Conversation System for Information Support," *JACIII*, vol. 22, no. 6, pp. 989–997, Oct. 2018, DOI: 10.20965/jaciii.2018.p0989.

[7] M. Niemelä, L. van Aerschot, A. Tammela, I. Aaltonen, and H. Lammi, "Towards Ethical Guidelines of Using Telepresence Robots in Residential Care," *Int J of Soc Robotics*, Feb. 2019, DOI: 10.1007/s12369-019-00529-8.

[8] S. Yamamoto, J. Woo, W. H. Chin, K. Matsumura, and N. Kubota, "Interactive Information Support by Robot Partners Based on Informationally Structured Space," *Journal of Robotics and Mechatronics*, vol. 32, no. 1, pp. 236–243, 2020, DOI: 10.20965/jrm.2020.p0236.

[9] K. S. Gayathri, K. S. Easwarakumar, and S. Elias, "Fuzzy Ontology Based Activity Recognition for Assistive Health Care Using Smart Home:" *International Journal of Intelligent Information Technologies*, vol. 16, no. 1, pp. 17–31, Jan. 2020, DOI: 10.4018/IJIIT.2020010102.

[10] K. J. Vicente and J. Rasmussen, "Ecological interface design: theoretical foundations," *IEEE Trans. Syst., Man, Cybern.*, vol. 22, no. 4, pp. 589–606, Aug. 1992, DOI: 10.1109/21.156574.

[11] M. Yani, A. R. A. Besari, N. Yamada, and N. Kubota, "Ecological-Inspired System Design for Safety Manipulation Strategy in Home-care Robot," in *2020 International Symposium on Community-centric Systems (CcS)*, Hachioji, Tokyo, Japan, Sep. 2020, pp. 1–6, DOI: 10.1109/CcS49175.2020.9231354.

[12] N. Kubota, Dalai Tang, and Hiroyuki Kojima, "Visualization of perceptual information of a partner robot," in *2007 IEEE International Conference on Robotics and Biomimetics (ROBIO)*, Sanya, China, Dec. 2007, pp. 628–633, DOI: 10.1109/ROBIO.2007.4522235.

[13] R. Tanaka, J. Woo, and N. Kubota, "Action Acquisition Method for Constructing Cognitive Development System Through Instructed Learning," in *2019 International Joint Conference on Neural Networks (IJCNN)*, Budapest, Hungary, Jul. 2019, pp. 1–6, DOI: 10.1109/IJCNN.2019.8852180.

[14] T. N. Kipf and M. Welling, "Semi-Supervised Classification with Graph Convolutional Networks," *arXiv:1609.02907 [cs, stat]*, Feb. 2017, Accessed: Feb. 16, 2020. [Online]. Available: http://arxiv.org/abs/1609.02907.

[15] F. Ardilla, A. A. Saputra, W. Chin, and N. Kubota, "Integrated Intelligent Robotics Platform for Elderly Care," p. 5, 2020.

[16] R. C. Arkin, F. Cervantes-Pérez, and A. Weitzenfeld, "Ecological Robotics: A Schema-theoretic Approach," in *Series in Machine Perception and Artificial Intelligence*, vol. 27, WORLD SCIENTIFIC, 1997, pp. 377–393.

[17] A. P. Duchon, L. P. Kaelbling, and W. H. Warren, "Ecological Robotics," *Adaptive Behavior*, vol. 6, no. 3–4, pp. 473–507, Jan. 1998, DOI: 10.1177/105971239800600306.

[18] C. A. Lopez and L. F. Castillo, "Value creation system in the connected home ecosystem," *J Ambient Intell Human Comput*, Feb. 2020, DOI: 10.1007/s12652-020-01805-6.

[19] A. Yorita, S. Egerton, J. Oakman, C. Chan, and N. Kubota, "Self-Adapting Chatbot Personalities for Better Peer Support," in *2019 IEEE International Conference on Systems, Man and Cybernetics (SMC)*, Bari, Italy, Oct. 2019, pp. 4094–4100, DOI: 10.1109/SMC.2019.8914583.

[20] C. Debes, A. Merentitis, S. Sukhanov, M. Niessen, N. Frangiadakis, and A. Bauer, "Monitoring Activities of Daily Living in Smart Homes: Understanding human behavior," *IEEE Signal Process. Mag.*, vol. 33, no. 2, pp. 81–94, Mar. 2016, DOI: 10.1109/MSP.2015.2503881.

[21] A. R. A. Besari *et al.*, "Preliminary design of interactive visual mobile programming on educational robot ADROIT V1," in *2016 International Electronics Symposium (IES)*, Denpasar, Indonesia, Sep. 2016, pp. 499–503, DOI: 10.1109/ELECSYM.2016.7861057.

[22] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L.-C. Chen, "MobileNetV2: Inverted Residuals and Linear Bottlenecks," in *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*, Salt Lake City, UT, Jun. 2018, pp. 4510–4520, DOI: 10.1109/CVPR.2018.00474.

[23] T.-Y. Lin *et al.*, "Microsoft COCO: Common Objects in Context," *arXiv:1405.0312 [cs]*, Feb. 2015, Accessed: Feb. 16, 2020. [Online]. Available: http://arxiv.org/abs/1405.0312.

[24] S. Mittal, "A Survey on optimized implementation of deep learning models on the NVIDIA Jetson platform," *Journal of Systems Architecture*, p. 15, 2019.

[25] S. Chetlur *et al.*, "cuDNN: Efficient Primitives for Deep Learning," *arXiv:1410.0759 [cs]*, Dec. 2014, Accessed: Nov. 23, 2020. [Online]. Available: http://arxiv.org/abs/1410.0759.

[26] A. R. A. Besari, R. Zamri, K. A. A. Rahman, Md. D. Md. Palil, and A. S. Prabuwono, "Surface Defect Characterization in Polishing Process Using Contour Dispersion," in *2009 International Conference of Soft Computing and Pattern Recognition*, Malacca, Malaysia, 2009, pp. 707–710, DOI: 10.1109/SoCPaR.2009.142.

[27] S. Randhawa and S. Jain, "Data Aggregation in Wireless Sensor Networks: Previous Research, Current Status and Future Directions," *Wireless Pers Commun*, vol. 97, no. 3, pp. 3355–3425, Dec. 2017, DOI: 10.1007/s11277-017-4674-5.

[28] A. Hagberg, D. Schult, and P. Swart, "NetworkX Reference," p. 776.

[29] Y. Tian, L. Zhao, X. Peng, and D. Metaxas, "Rethinking Kernel Methods for Node Representation Learning on Graphs," p. 12.

[30] Y. Pei, N. Chakraborty, and K. Sycara, "Nonnegative Matrix Tri-Factorization with Graph Regularization for Community Detection in Social Networks," p. 7.

[31] M. Gori, G. Monfardini, and F. Scarselli, "A New Model for earning in," p. 6.

[32] M. Wang *et al.*, "Deep Graph Library: A Graph-Centric, Highly-Performant Package for Graph Neural Networks," *arXiv:1909.01315 [cs, stat]*, Aug. 2020, Accessed: Nov. 23, 2020. [Online]. Available: http://arxiv.org/abs/1909.01315.