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Social Media Agency Robot for Elderly People

Toru Kobayashi[1,a) Taishi Miyazaki[1] Rinsuke Uchida[1] Hiroe Tanaka[1] Kenichi Arai[1]

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Abstract: We suggest a Social Media Agency Robot that can be used for interactive communication between elderly people and the younger generation via existing Social Media. This robot system has been implemented on a cloud service and a single board computer embedded in a human-type robot, which is equipped with a microphone, camera, speaker, sensors, and network access function, so that elderly people can transmit and receive information by voice via Social Media without using smartphones. We employed LINE which is a proprietary application for instant communications on electronic devices such as smartphones. In LINE, we need to select a message destination address before sending messages. On the other hand, our developed robot is basically operated by voice due to realizing the simple user interface. Therefore, we suggested a message exchange learning-type destination estimation method that enables elderly people not to express a message destination address explicitly. We also designed the Social Media Agency Robot based on the service-oriented architecture that enables us easily to use open innovation such as external cloud-based services. We developed the prototype system including the message exchange learning-type destination estimation method. Then, we did an experiment to evaluate our prototype system at a house for the elderly with the care service and detached houses in the Nagasaki prefecture. We confirmed the effectiveness of the message destination estimation through the real message exchange experiment by the elderly. We also evaluated the usability of the prototype system through the interview with the experiment subject.

Keywords: social media, elderly people watching services, IoT, service-oriented architecture, user interface, robot

1. Introduction

The current situation and trends concerning the elderly and their environment in Japan is really serious. According to the Annual Report on the Aging Society (2014) issued by the Cabinet Office [1], the number of households with elderly people aged 65 and over is increasing. As of 2012, the number was 20.93 million, making up 43.4% of all households (48.17 million). The number of elderly people living alone is on the rise. The increase in elderly people living alone is remarkable among both males and females. The percentage of elderly people living alone against the total population of elderly people was 4.3% for males and 11.2% for females in 1980. However, in 2010, these numbers were 11.1% for males and 20.3% for females.

On account of this current situation, an elderly people watching system has become important. However, most of the existing elderly people watching services are belonging to the service category of a confirmation of elderly people's safety based on one-way communication from elderly people [2], [3], [4]. Therefore, current services are not enough for elderly people who want to have a closer connection with society. On the other hand, Social Media like Twitter has already become popular. However, people need to use smart devices like smartphones efficiently to access Social Media. This fact might cause obstacles for elderly people in using Social Media. Therefore, we have developed a Social Media Mediation System that can be used for interactive communication between elderly people and the younger generation via existing Social Media like Twitter or Google Calendar [5], [6], [7]. We have implemented this suggested system on a single board computer embedded in a human-type robot, which is equipped with a microphone, camera, speaker, sensors and network access function. Elderly people can transmit and receive information by voice via Twitter. From the younger generation's point of view, they can communicate with elderly people at any time through their accustomed Social Media using smartphones without a special system.

On the other hand, currently here in Japan, LINE has become a popular messaging service that we can use to exchange texts, images, video and audio, and conduct free VoIP conversations and video conferences [8]. LINE also provides the Messaging API [9], so we decided to employ LINE as Social Media for our robot system. In LINE, we need to select a message destination address before sending a message. However, our developed robot is basically operated only by voice due to realizing the simple user interface. Therefore, we suggested a message exchange learning-type destination estimation method that enables elderly people not to express a message destination address explicitly [10]. This method is based on the machine learning algorithm that performs the message destination estimation according to message contents of elderly people. We need a right message destination address as training data to increase the machine learning performance. However, if we asked elderly people to express a right message destination address to gather training data for machine learning, it would not make sense. Therefore, we designed the method that uses a response against a message from elderly people as training data. In this method, a message receiver's response against a

1 Nagasaki University, Nagasaki 852–8521, Japan
a) toru@cis.nagasaki-u.ac.jp

message from elderly people would be applied to machine learning as training data, so that we could increase the machine learning performance without any effort on the part of elderly people. However, in our previous work [10], we had not evaluated the effectiveness of the suggested method using the real message exchange results by the elderly.

We also re-designed the Social Media Agency Robot based on the service-oriented architecture that enables us easily to use open innovation such as external cloud-based services [11]. For example, we used Google Cloud Speech API as speech recognition and IBM Watson Natural Language Classifier (NLC) as the message destination estimation machine learning engine. We could expect that this feature allows us to launch a new communication system quickly at low cost. We developed the main functionality on Amazon Web Services as the prototype system. In our previous work [5], [6], [7], [10], the main functionality had been implemented on a single board computer embedded in a robot installed at the elderly people's house, so that serviceability has been increased.

We confirmed the effectiveness of the message destination estimation through the real message exchange experiment by the elderly. In order to evaluate the message destination estimation, we asked 6 subjects who are from 78 to 94 years old to use the prototype system at the house for the elderly with the care service at Togitsu-machi in the Nagasaki prefecture and detached houses in Nagasaki city in Japan. We also evaluated the usability of the prototype system through the interview with the experiment subject. We show the related work in Section 2. In Sections 3 and 4, we explain the Social Media Agency Robot in detail. We show the experiment results and discussion in Section 5. Then, we conclude in Section 6.

2. Related Work

Recently, we can see many elderly people watching services or systems. We could extract 32 relating services or systems through Web search investigation among Japanese internal commercial services and international research systems. We show the research results in terms of the relationship between elderly people and watchers in **Table 1**. For example, Zojirushi I-Pot [12], which is a water heater, can send an e-mail message to relatives when a single-living elderly person turns on the I-Pot in the morning. In this service, the relationship between elderly people and watchers is one-to-one. The information sending direction is one-way that is from elderly people to watchers. We found out that one-way communication like Zojirushi I-Pot was 26 of 32 (81%). This means that existing relating services are focusing on a confirmation of elderly people's safety. Murase developed the distance communication environment using activities in daily life like a setting action of an alarm clock as a trigger [13]. This research has been involved in the category of interactive and many-to-many communication. However, he implemented this system as an original communication application. Therefore, in order to use this system, watchers need to install the special application and learn how to use it.

We also show the research results concerning implementation methods for an elderly people watching system in **Table 2**. The use of Social Media as an implementation method was only 5%. AWARE–Ageing Workforce towards an Active Retirement [14] is the Social Media for retired people to keep in touch with the younger generation. This is using the original Social Media platform, so that the younger generation cannot communicate with elderly people by using accustomed Social Media like Twitter or LINE. We are focusing on the interactive communication between elderly people and the younger generation via existing Social Media. From a viewpoint of purpose and implementation method, our approach is completely different from the related work.

On the other hand, we have some communication robot studies for elderly people. Inoue developed a communication robot for elderly people and their families to support their daily lives [15]. He tried to analyze how families living with seniors feel about using the human-type communication robot. Sasama reported an experiment for motivating elderly people with robot-guided interaction [16]. He built a framework for encouraging elderly people to participate in more activities by providing local news. Kanoh executed an examination of the practicability of communication by means of a robot-assisted activity program for elderly people [17]. He has developed a Robot Assisted Activity (RAA) program for recreational use in health care facilities for elderly people. These relating studies are focusing on encouraging elderly people to have more communication with closed people, so that remote communication functionality is not enough. We are focusing on remote communication using Social Media. This point is the different point.

We have also voice operation robots such as Amazon Echo [18], Google Home [19], and Pepper [20]. They are robots with artificial intelligence, so that people can operate them by voice to search information or control house appliances. However, we cannot communicate with the other persons via social media by using them. The different point is that our developed robot enables us to communicate with the other persons via social media.

With regard to a message filtering mechanism like Bayesian

Table 1 Relationship between elderly people and watchers.

Direction \ Target	One-to-one	One-to-many	Many-to-one	Many-to-many
One-way [Elderly people ↓ Watchers]	16	9	0	1
Interactive way [Elderly people ↕ Watchers]	3	2	0	1

Table 2 Relationship between elderly people and watchers (number of relevant work, double count allowed).

Device \ Method	Original	Phone	E-mail	Web	SNS
Original devices (robot, sensor)	6	4	0	5	1
Smartphones	3	1	1	6	1
Consumer devices	1	3	3	2	0

Filter, as a spam filter for e-mail messages this one is famous [21], [22]. In this case, an e-mail receiver needs to decide whether received an e-mail message would be spam e-mail or not. However, in our method, we use the response from people who get messages from elderly people, so that elderly people do not have to do anything for increasing machine learning performance. This point is completely different from a spam filter mechanism.

3. Use Case and Message Destination Estimation

3.1 Use Case

Figure 1 shows the use of the Social Media Agency Robot. After setting this robot at an elderly person's house, for example, an elderly person can send a granddaughter a message like "Happy birthday, Hanako! I sent you the present." just by speaking to the Social Media Agency Robot. This message will be sent to the granddaughter's LINE account automatically, so that she can see these messages using her accustomed LINE and a smartphone during her spare time. Then, the replied text message using LINE like "Thanks Grandpa!" by the granddaughter will be sent to the elderly person as voice by the Social Media Agency Robot. In the same way, when the elderly person speaks to the robot like "Ms. Yamada, when will you come here?", this message will be sent to the care manager's LINE account automatically. The elderly person can also hear the response from the care manager like "I will go there at three pm!".

Using the Social Media Agency Robot, elderly people can communicate with the younger generation interactively via LINE using neither smartphones nor personal computers. The younger generation can also communicate with elderly people interactively using their accustomed LINE and smartphones during their spare time.

3.2 Message Destination Estimation Method

We need to prepare a classification model in advance to realize the message destination estimation according to message contents. We also need to make a classification model against each elderly person. However, it would be difficult to collect the necessary training data for making a classification model in advance. Therefore, we introduce the message exchange learning-type classification model making method. In this method, we do not have to gather all needed training data in advance. Machine learning performance will be increased gradually by exchanging a message frequently. In this situation, we could not put the responsibility on elderly people. Therefore, we designed the method that uses a response against a message from elderly people as training data.

Figure 2 shows the message exchange learning-type classification model making method. Firstly, we try to calculate the message destination address probability against the message, "Ms. Yamada, when will you come here?" that is sent by the elderly person. We call this function the Destination Estimation. In the case of Fig. 2, the destination address probability is under a predefined threshold value, so that this message will be distributed to all registered persons (①). As a result, only a care manager responded such as "I will go there at three pm!" (②). In this case, we decide that the message from the elderly person might be for the care manager, then we register the destination address and the message contents into the classification model (③). In this method, the correspondence determination between the messages is the most important issue. In this issue, we employed the chronological order method by which we evaluate the closeness of the response time according to managing the messages in chronological order.

We show the detail of the message destination estimation method consisting of the Destination Estimation and the Classification Model Making in **Fig. 3**. In the Destination Estimation, we give the message from the elderly person to Natural Language Classifier (NLC) of IBM Watson API series. Then, NLC calculates the message destination address probability for each registered person such as a Net Super, a Granddaughter, and a Care Manager. If each destination address probability were lower than a predefined threshold value, the message would be distributed to all registered persons (①). If one of the destination address probabilities were higher than a predefined threshold value, the message would be sent to only that correspondent. NLC is one of the Watson API, which covers 16 kinds. This API enables us to classify text using the classifier trained by the data which a

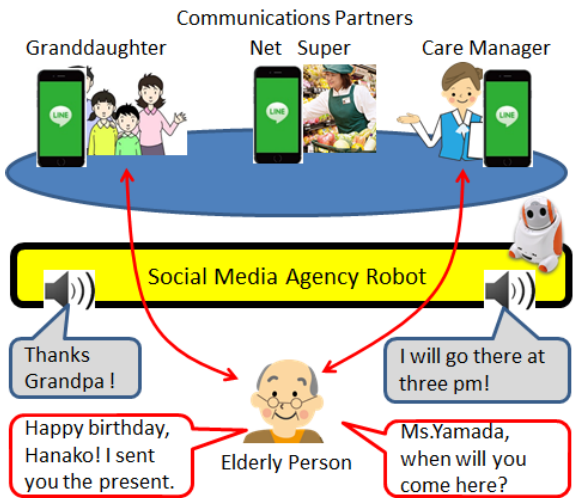


Fig. 1 Use case of Social Media Agency Robot.

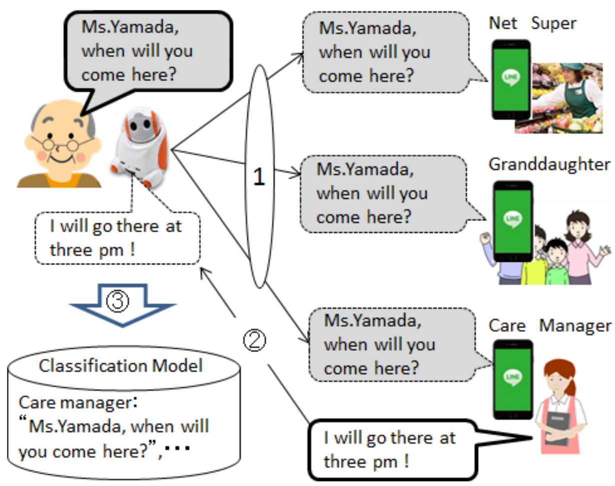


Fig. 2 Message exchange learning-type classification model making method.

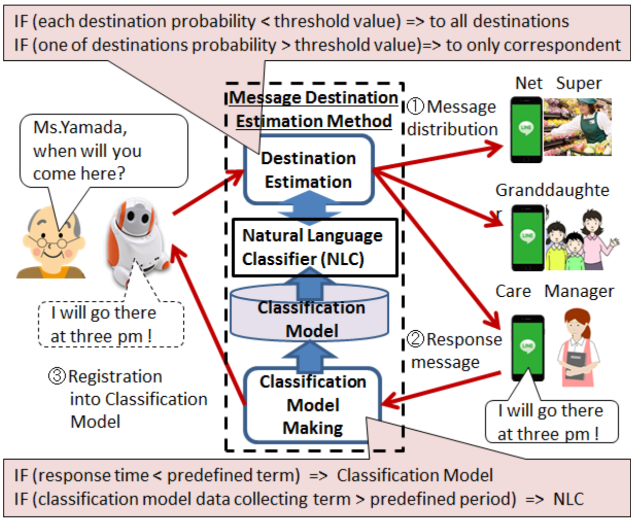


Fig. 3 Detail of message destination estimation method.

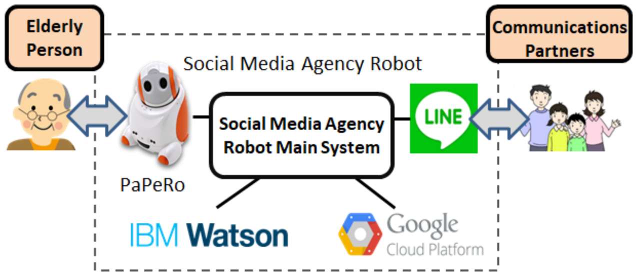


Fig. 4 Social Media Agency Robot architecture.

user gave. The question-answering system that was realized in a quiz show, "Jeopardy!", classified question texts by a rule-based system. NLC has been developed based on "Jeopardy!" using a deep learning technique and opened as open-API. Though the details are not shown, it enables us to make a natural language classifier in adding the knowledge model that was constructed based on knowledge such as Wikipedia and our domain knowledge model [23]. The domain knowledge model means the Classification Model in Figs. 2, 3. NLC can acquire the classification information of enormous words from Wikipedia. Therefore, even if the volume of the Classification Model is small, NLC can classify given text with high precision. In this sense, the quantity of characteristic used for a classification might be the association between words embedded in the text and defined classes. The class of the text message comes back when we input a text message. We regarded this class as a destination address and implemented the Destination Estimation. In the Classification Model Making, if we would have a response (②) within a predefined term against the message from an elderly person, we recognized such a responder as a destination person of the previous message from an elderly person (①). Then, we register the responder's address and the message contents from an elderly person with the Classification Model. If the data collecting term of the classification model would exceed a predefined term, we transmitted the stored data in the Classification Model to NLC as training data. In this way, we can get a learning effect whenever we repeat message exchanging.

4. Social Media Agency Robot

4.1 System Architecture

We designed the Social Media Agency Robot based on the service-oriented architecture. **Figure 4** shows the Social Media Agency Robot architecture. In external cloud-based services, we employed LINE as Social Media, Google Cloud Speech API of Google Cloud Platform as speech recognition, and Natural Language Classifier of IBM Watson as message destination estimation. In a human-type robot, we used PaPeRo, which stands for "Partner-type-Personal-Robot", is a personal robot developed by the Japanese firm NEC Corporation [24]. It is noted for its cute appearance and facial recognition system. We implemented the Social Media Agency Robot Main System on the cloud service. This Main System controls all external cloud-based services and PaPeRo. Thanks to this architecture, the external cloud-based service adaptation is very easy because it is enough for us to modify only the application interface part.

4.2 System Configuration

We show the Social Media Agency Robot system configuration in **Fig. 5**. We assigned the Social Media Agency Robot Main System to Amazon Web Services, and also assigned the Social Media Agency Robot Subsystem to Raspberry Pi, which is a single board computer embedded in PaPeRo. These Main System and Subsystem are communicating with each other to execute all functionalities. The Main System provides mainly the LINE message exchange function and message destination estimation function. The Subsystem offers mainly the interface function between the Main System and PaPeRo, which has user interface devices like a speaker, camera, proximity sensor, and operation button.

4.3 Message Exchange Sequence

In this section, we show the message exchange sequences in both directions between an elderly person and a communications partner. We show the message exchange sequence started from an elderly person in **Fig. 6**. To start this sequence, the elderly person just pushes the button located in front of PaPeRo, then PaPeRo starts to record voice messages and take a picture for the elderly person (Recording /Photographing). The Message Transmit/Receive of the Main System reduces the picture image coming from PaPeRo to adapt to message exchange using LINE. Voice messages are sent to Google Cloud Speech API to convert speech to a text message. Then, the text message is sent to Natural Language Classifier to calculate the class probability that means message destination address probability against each communications partner. According to the rule described in Section 3.2, the message destination candidate will be determined. Finally, whole information such as text message, voice, image, and message destination address will be sent to the LINE message API to distribute all the information to the determined communications partner.

We also show the message exchange sequence started from the communications partner in **Fig. 7**. A new message coming from the communications partner through the LINE messaging API is processed by the Classification Model Making and the Message Transmit/Receive of the Main System simultaneously. In the

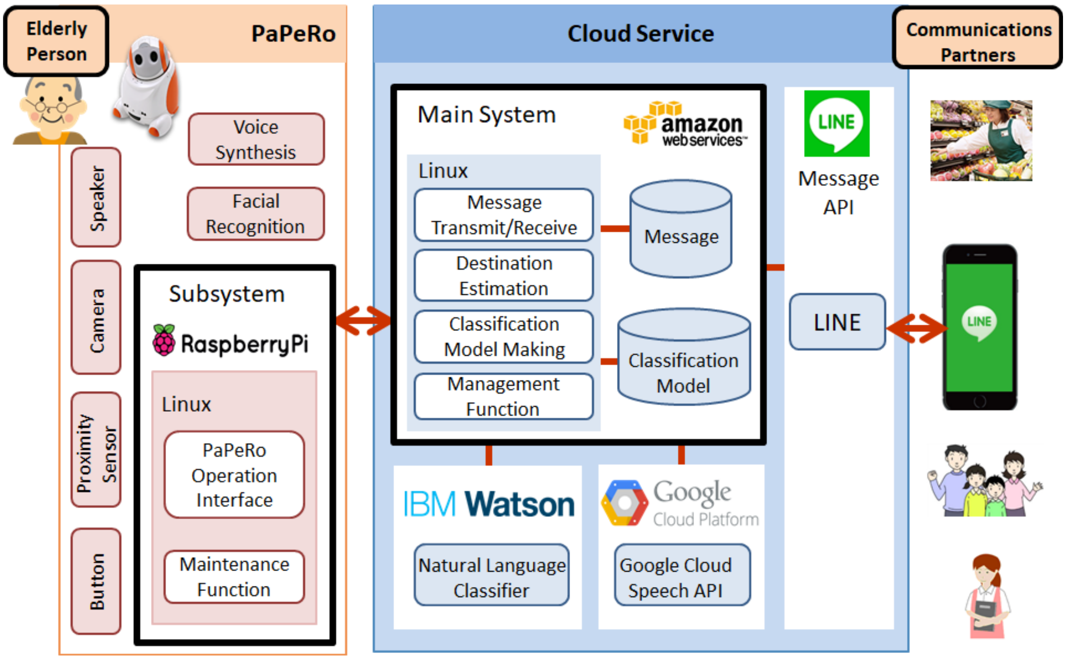


Fig. 5 Social Media Agency Robot configuration.

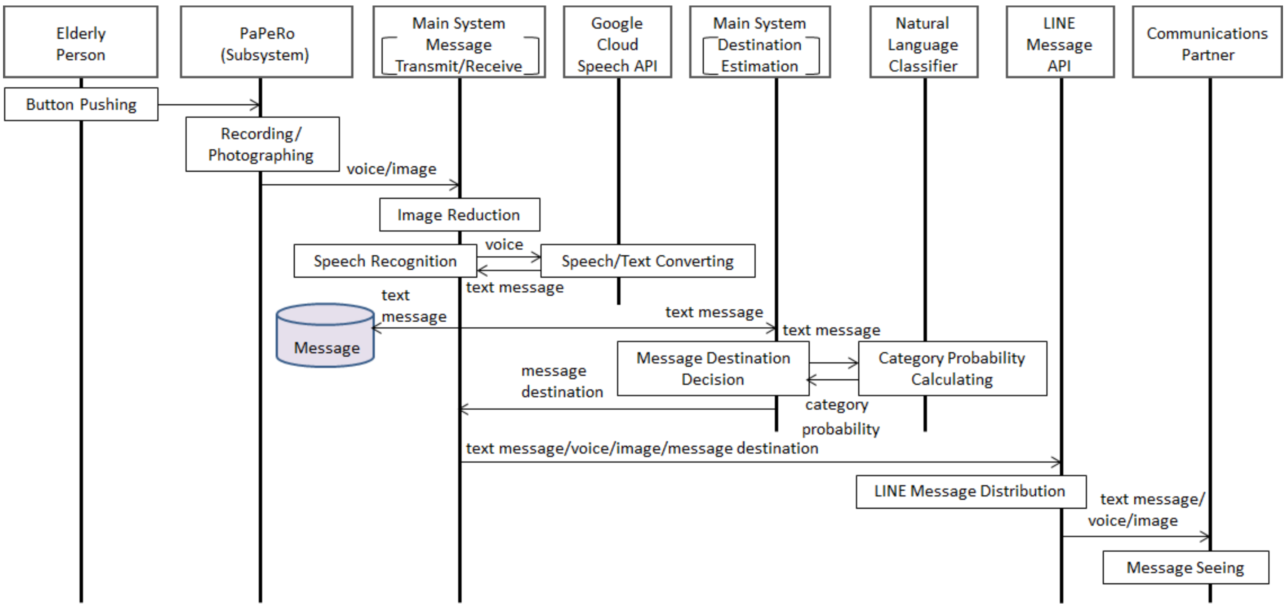


Fig. 6 Message exchange sequence from elderly person to communications partner.

Classification Model Making, the classification model rebuilding and transferring will be executed by the way described in Section 3.2. On the other hand, the Message Transmit/Receive will inform the elderly person of arriving new messages in what can make PaPeRo's LED shine. When the elderly person accesses PaPeRo, new messages will be spoken by PaPeRo. Then, the confirmation message like "Message has been heard" will be automatically sent back to the communications partner.

4.4 Prototype System Specification

We show the hardware configuration (**Fig. 8**) and software architecture (**Fig. 9**) of PaPeRo i, which is one of the PaPeRo product series. User interface devices and sensors are equipped with PaPeRo i. In terms of software architecture, PaPeRo i is constructed on an open platform, so that we can implement a flexible application. Raspberry Pi 3 and PaPeRo i are connected with robot internal LAN. The Subsystem of our prototype system has been implemented on the application layer of Raspberry Pi 3 and controls preinstalled functions and devices on PaPeRo i.

We show the hardware and software specification of the environment for the Subsystem and the Main System (**Table 3**). We implemented all systems using PHP and Python. For communication between the Main System and LINE, Google, and IBM Watson, we used each external cloud service's REST API protected by HTTPS. For communication between the Main System and the Subsystem, we used HTTP POST requests.

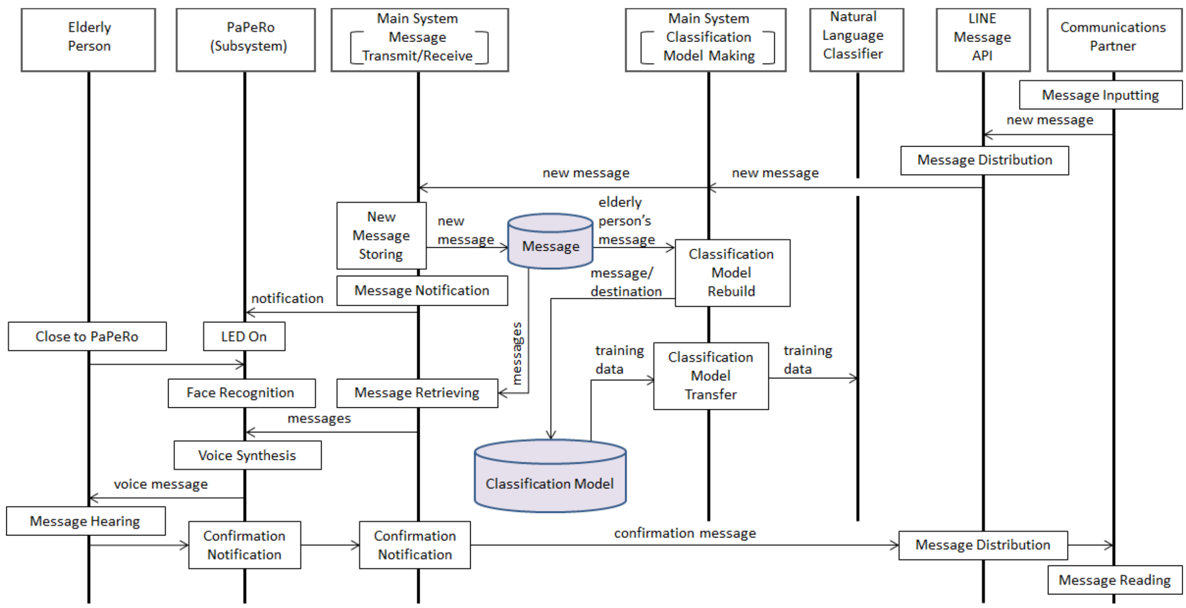


Fig. 7 Message exchange sequence from communications partner to elderly person.

Device	Explanation
Camera×2	VGA camera for face recognition, SXGA camera for still image
Microphone ×2	Directional microphone for speech recognition, Non-directional microphone for noise canceling
Speaker	For voice synthesis
Sensor	infrared sensor, temperature sensor, humidity sensor, illuminance sensor, acceleration sensor
Volume	Hardware/software volume

Fig. 8 PaPeRo i hardware configuration.

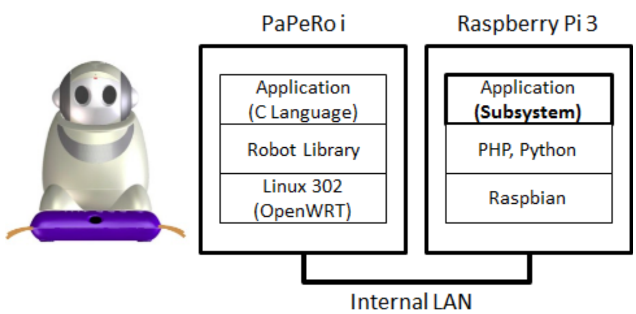


Fig. 9 PaPeRo i software architecture.

4.5 Use Case of Prototype System

We show the use of the prototype system according to the case described in Fig. 1. When an elderly person says "Happy birthday, Hanako! I sent you the present." in front of PaPeRo i, a still image, a voice message, and a text message of an elderly person will be shown on the screen of a granddaughter's smartphone as LINE messages (**Fig. 10** (a)). Then, the replied text message using LINE like "Thanks Grandpa!" by the granddaughter will be sent to the elderly person by the Social Media Agency Robot (Fig. 10 (b)). Then, the ears of PaPeRo i will shine (**Fig. 11**), so that the elderly person can know that a new message has arrived. When the elderly person comes close to PaPeRo i, PaPeRo i starts to speak automatically "Thanks Grandpa!". Then, the confirmation message will be sent back to the granddaughter, so that the granddaughter can confirm whether the elderly person has heard her message or not.

Table 3 Specification of subsystem and main system.

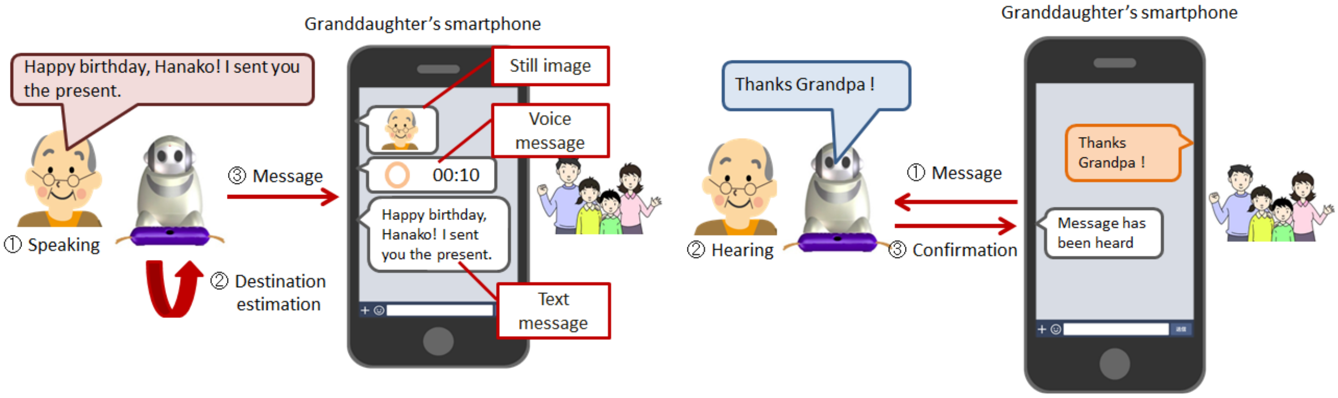
	Subsystem (PaPeRo)	Main System (Amazon Web Services)
Hardware	**Raspberry Pi 3 Model B**	**Amazon EC2 t2.small** ・CPU: Intel(R) Xeon(R) CPU E5-2676 v3 @ 2.40GHz ・Memory: 2GB
Software	・Raspbian GNU/Linux 8.0 (jessie) ・PHP 5.6.24 ・Python 3.4.2	・CentOS 6.9 ・Apache 2.2.15 ・PHP 5.6 ・MySQL 5.1 ・Python 2.6.6

5. Experiments and Discussion

5.1 Experiment Outline

We did an experiment to evaluate our prototype system from Nov. 14, 2016 to Nov. 30, 2017 at the house for the elderly with the care service and detached houses in Nagasaki prefecture. We show the detail of the experiment conditions in **Table 4**. All subjects could not use smartphones. Before starting the experiment, we did some tasks listed in the bellow as experiment preparation.

- We registered LINE messaging API bot accounts for each test subject's PaPeRo i with LINE server.
- We sent communications partners an instruction and a QR code to register a LINE account for PaPeRo i with LINE application of their smartphones, so that communications partners could register a LINE account for PaPeRo i easily as LINE friend just by taking a picture of a QR code.
- We installed PaPeRo i in the living room of each of the test subjects and connected PaPeRo i with the Internet through Wi-Fi router.
- We explained PaPeRo i usage to subjects by showing a demonstration. The PaPeRo i usage includes two actions such as coming close to PaPeRo i to hear messages com-



(a) Elderly person to granddaughter (b) Granddaughter to elderly person

Fig. 10 Use case of prototype system.

Fig. 11 PaPeRo i's action when arriving new messages.

Table 4 Experiment condition.

Subject Number	Experiment Period	Age	Gender	Family Living Together	Communications Partner
1	Nov.14,2016-Dec.24,2016	78	Female	Single	Eldest daughter, Care worker, Research staff
2	Aug.22,2017-Sep.27,2017	82	Female	Single	Eldest daughter, Grandsons, Research staff
3	Aug.28, 2017-Nov. 30,2017	84	Male	Couple	Eldest daughter, Care worker, Granddaughters, Research staff
4	Aug.28,2017-Nov. 30,2017	78	Female	Couple	Eldest daughter, Care worker, Granddaughters, Research staff
5	Sep.20,2017-Nov.30,2017	80	Female	Single	Eldest daughter, Research staff
6	Nov.11,2017-Nov.26,2017	94	Female	Single	Second son, Wife of the second son, Third son, Research staff

ing from communications partners and pushing the button in front of PaPeRo i to send a message to communications partners.

In the case of subject number 1, we asked her eldest daughter who lived in a different prefecture, a care worker, and our research staff to register the LINE account for PaPeRo i. Her eldest daughter did not have any trouble in registering the LINE account for PaPeRo i. On the other hand, PaPeRo i usage is very simple, so that we needed only 10 or 15 minutes to explain the usage to subjects. After that, they could start to use PaPeRo i smoothly. We show the usage scene between a subject and a care worker in **Fig. 12**. We set the message recording time for 10 seconds at first. However, we had the comment that 10 seconds were too short to say something during the usage explanation. Therefore, we set it for 20 seconds. Just after starting the experiment, all subjects enjoyed using PaPeRo i.

Fig. 12 Usage scene between a subject and a care worker.

Table 5 Special comments extracted by the interview.

Subject Number	Message Total Number	Special Comments
1	126	She learned how to use robot in a day. She enjoyed message exchanges with the family and the research staff very much. She had an attachment to the robot.
2	92	She enjoyed message exchanges with the grandchild who lived in Brazil very much. The family of the subject was satisfied because everyday message exchanges led to security for the family.
3	67	He did not have a feeling of resistance to using the robot. However, he did not feel the need to use the robot for communication with others because he lived together with his wife who is the subject number 4.
4	31	She felt uneasiness in using the robot first. However, she sent messages with a robot more positively than her husband who is the subject number 3.
5	51	She had little use frequency of the robot. We thought that the need of the robot was low because she always communicates on thetelephone frequently.
6	76	She was able to do the communication using the robot in spite of advanced age of 94 years old. During an experiment period, her physical condition turned worse. Thanks to a robot, a family was able to notice a change in the physical condition.

5.2 Evaluation Results

We carried out an interview for all subjects after the experiment based on free talking. We show the special comments extracted by the interview and the exchange message total number during the experience in **Table 5**. From the interview, we generally understood that the following characteristics could be an important evaluation for our robot system.

- All subjects were able to use the robot every day. The reason is because the subjects were attached to the cute robot with some human characteristics.
- A female subject was uneasy about to a robot which appeared to have male characteristics. However, when a female

subject had got used to the robot, a female subject sent the message using a robot with male characteristics positively.

- The use frequency of the robot depends whether there is a family who lives together. The elderly who lived alone used more robots.
- The result was good for not only for the elderly but also for the family who was living separately from the elderly. The reason is because the family can confirm the safety of the elderly who lived alone.

The subject number 1 had the highest message exchange number according to Table 5. Therefore, we decided to use the communication history of the subject number 1 for the message destination estimation accuracy evaluation. In this paper, the elderly person's message destination estimation method is the main issue. Therefore, we evaluated the speech recognition accuracy that became a premise of the elderly person's message destination estimation method and message destination estimation accuracy. We show the results in the next section.

5.3 Message Destination Estimation Accuracy

At first, we evaluated the speech recognition accuracy. The experiment conditions are shown in the following.

- Target data is the messages from the subject number 1.
- Data collection period is from Nov. 14, 2016 to Dec. 22, 2016.
- Target message number is 126.

We made the correct data manually by hearing all voice messages. In advance of calculating speech recognition accuracy, we divided each message into every word by using morphological analysis. Calculating formula of the speech recognition accuracy is described in formula (1).

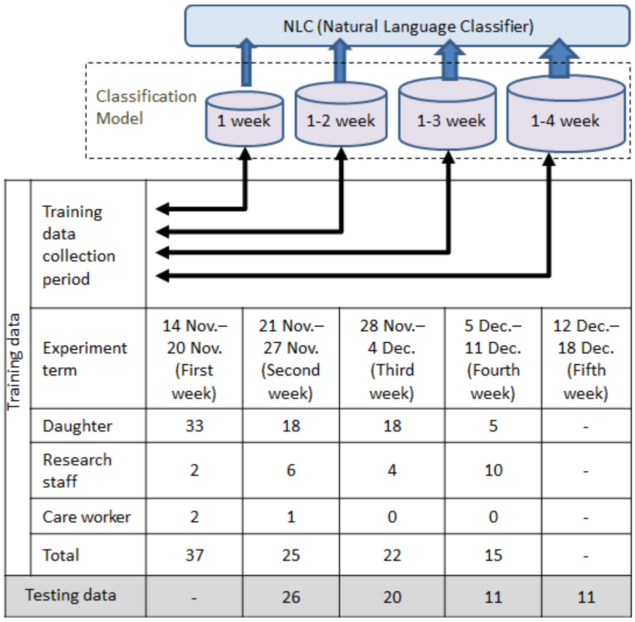
$$\text{Speech Recognition Accuracy} = \frac{\#C - \#I}{\#C + \#S + \#D} \qquad (1)$$

#C: Correct word number, #S: Substituted error number,
#I: Insertion error number, #D: Deletion error number

In the results, #C was 2,161, #S was 74, #I was 6, and #D was 147. The total word number was 2,388, so that speech recognition accuracy was 90.5%. This accuracy is for Google Speech Recognition API, it is not for our own original function. However, this accuracy affects the precision of the elderly person's message destination estimation method because this method is based on the speech recognition results. Therefore, we evaluated this accuracy in advance of evaluating the message destination estimation accuracy. We judged that 90.5% accuracy is good enough to proceed to execute the next step, because if we could execute the elderly person's message destination training for the long term, we could make the occurrence of miss speech recognition minimized.

Secondly, we evaluated the elderly person's message destination estimation method. The experiment conditions are shown in the following.

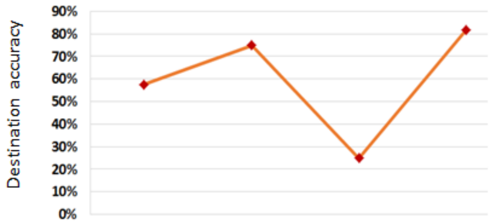
- Target data is the messages from the subject number 1
- Data collection period is from Nov. 14, 2016 to Dec. 18, 2016.
- The predefined term of the response time against the subject number 1's message (described in Fig. 3) is 24 hours. If a communications partner responded to the subject number 1's message within 24 hours, the first responder would be registered into the Classification Model.



Training data	Experiment term	14 Nov.– 20 Nov. (First week)	21 Nov.– 27 Nov. (Second week)	28 Nov.– 4 Dec. (Third week)	5 Dec.– 11 Dec. (Fourth week)	12 Dec.– 18 Dec. (Fifth week)
	Daughter	33	18	18	5	-
	Research staff	2	6	4	10	-
	Care worker	2	1	0	0	-
	Total	37	25	22	15	-
Testing data		-	26	20	11	11

Fig. 13 Training data and classification model.

- The predefined period of the classification model data collecting term (described in Fig. 3) is one week. At every week-end, the stored data in the Classification Model is transmitted to NLC as training data (**Fig. 13**). In this mean, at the end of the fourth week, NLC should grow wise.
- We used the exchange messages from the second week to the fifth week as testing data (at the gray part of Fig. 13). For example, the destination address of the second week messages will be calculated by NLC using the classification model made by the first week training data. The destination address of the fifth week messages will be also calculated by NLC using the classification model made by the first-fourth week training data.
- We could get the destination probability of each destination address from NLC. The probability of total destination address becomes 100% without depending on the number of destination addresses. When the number of destination addresses is two in the lowest case, if we relatively evaluated the estimated probability of two destination addresses, 50% become a turning point of the superiority and inferiority. The number of destination addresses is more than two in the normal use case. If the estimated probability of one destination address exceeded 50%, the estimated probabilities of other destination addresses become all less than 50%. Therefore, we set the threshold with 50% to be relatively decided the superiority and inferiority, regardless of the number of destination addresses. However, we should consider the adjustment of the threshold more than 50% through the evaluation of the user for future practical use.
- We made the correct data that means the destination address of the subject number 1's message manually by checking all message contents and the message exchange context. We



		21 Nov.– 27 Nov. (Second week)	28 Nov.– 4 Dec. (Third week)	5 Dec.– 11 Dec. (Fourth week)	12 Dec.– 18 Dec. (Fifth week)
Estimation Results	Experiment term				
	Daughter	15/15= 100%	15/15= 100%	4/4= 100%	7/7= 100%
	Research staff	0/8=0%	0/3=0%	0/10=0%	2/2=100 %
	Care worker	0/8=0%	0/2=0%	0/2=0%	0/2=0%
	Total	15/26= 57.6%	15/20= 75.0%	4/16= 25.0%	9/11= 81.8%
Correct data	Daughter	15	15	4	7
	Research staff	8	3	10	2
	Care worker	3	2	2	2
	Total	26	20	16	11

Fig. 14 Correct data and destination estimation results.

show the correct data at the lower column of **Fig. 14**.

According to these conditions, we evaluated the message destination estimation accuracy (Fig. 14). We calculated the ratio that we were able to estimate for the correct data definitely (at the gray part of Fig. 14). We show the time transient graph of the destination estimation accuracy in the upper part of Fig. 14. In this graph, we can see that the fourth week accuracy is temporarily down. We had many messages to our research staff in this week compared with the previous weeks. Therefore, we thought that the learning effect of the past message exchange had not been provided yet. There is evidence that the destination estimation accuracy rises again in the fifth week. About the estimation result of every destination, the destination estimation to the daughter is always high. That is why about 75% were addressed to the daughter among all transmission messages. From these results, it could be said that our suggested method in this paper is effective for message destination estimation.

5.4 Evaluation of Superiority

In this section, we indicate the evaluation of the superiority by comparing our previous work results [10] with this paper's experiment results. In our previous work, we inspected whether we could classify Japanese sentences by machine learning as a first step for the message exchange learning-type destination estimation method. In order to achieve this purpose, we used "Kente-gokko" corpus as a Japanese corpus. "Kente-gokko" corpus is classified into four categories such as "music", "game", "anime", and "idol". The text data causing "Kente-gokko" corpus are quizzes contributed to quiz site "Kente-gokko". It is the biggest quiz site in Japan. The number of the corpus is all 19,000 cases. The length of each quiz sentence was around 30 characters on the average. In terms of the machine learning algorithm, Two-class Boosted Decision Tree, Two-class Locally-Deep Support Vector Machine, and Multi Logistic Regression had been applied. Then, we confirmed that the average accuracy rate was 81%.

On the other hand, in this study, we used the real message exchange results by the elderly for the message exchange learning-type destination estimation method evaluation. The number of exchanged messages was 443 for all subjects. The length of each exchanged messages was 52 characters on the average. In terms of the machine learning algorithm, we used Natural Language Classifier of IBM Watson API series based on a deep learning technique. Then, we confirmed that the accuracy rate of the fifth experiment week (final experiment week) was 81.8% (Fig. 14).

Comparing the average accuracy rate of our previous work with the accuracy rate of the fifth experiment week of this study, they are the almost same. This means that our suggested message exchange learning-type destination estimation method functions effectively. Because if our suggested method did not function, the accuracy rate should worsen even if Natural Language Classifier was superior rather than our previous work algorithm. However, the accuracy rate of the second experiment week and the fourth experiment week were lower than the average accuracy rate of our previous work (Fig. 14). The reasons that the accuracy rate decreases are listed below.

- In the case of not having enough training data, especially in the initial phase like the second experiment week in Fig. 14.
- In the case of joining a new communication partner, especially in the middle phase like the fourth experiment week in Fig. 14.

5.5 Other Applied Examples of the Message Exchange Learning-type Destination Estimation Method

The advantage of the message exchange learning-type destination estimation method is that the system can estimate the most suitable message destination address. This method is based on learning the exchange message results between a sender and a receiver. This suggested method has mainly two features. The first is that the training data can be created based on the message receiver's response against a message from the sender. The second is that the message sender does not have to express the message destination address explicitly after learning was completed.

Therefore, we could introduce this method into the marketing activity example or the car driver assistant example as well as the Social Media Agency Robot, if we would apply it. In the case of the marketing activity example, a marketing research company first distributes some promotion messages to all consumers. Then, the company will create the training data based on the consumer's response against a promotion message. After learning was completed, the company can send the promotion message only to the active consumers who respond many times. In this way, the effectiveness of advertising may be increased by using our suggested method. In the case of the car driver assistant example, our suggested method enables hands-free driving without expressing the message destination address. It is enough for a driver to speak only the message that he/she wants to send by using our suggested method. This use case may increase the driver's capability in terms of information exchange while driving the car.

6. Conclusion

We developed the Social Media Agency Robot that can be used for the interactive communication between elderly people and the younger generation via LINE. In our robot system, elderly people can communicate only by voice due to realizing the simple user interface. In order to determine a LINE message destination address only by voice, we suggested the message exchange learning-type destination estimation method. We also designed the Social Media Agency Robot based on the service-oriented architecture that enables us easily to use external cloud-based services such as LINE messaging API, Google Cloud Speech API, and IBM Watson Natural Language Classifier.

We developed the prototype system including the message exchange learning-type destination estimation method on Amazon Web Services. Then, we had the demonstration experiment to evaluate our prototype system at the house for the elderly with the care service and detached houses in the Nagasaki prefecture. In the results of the demonstration experiment, we confirmed that the reputation of the robot was good for not only the elderly but also the family living separately from the elderly. We also confirmed that we were able to achieve a message destination estimation probability of more than 80% at the last period of the demonstration experiment. This result proves the effectiveness of our suggested method.

Furthermore, we will perform the proof experiment for more subjects and inspect the precision of the message estimation method in the near future. We will also improve quality, security, and scalability of the system for practical use.

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Toru Kobayashi is a professor at the Division of Electrical Engineering and Computer Science, Graduate School of Engineering, Nagasaki University. He received Ph.D. (2011) in engineering from the University of Electro-Communications. He has worked for NTT (1987–2013). He is a senior member of the IEEE Computer Society, and a senior member of IEICE.

Taishi Miyazaki was a master degree student of Division of Electrical Engineering and Computer Science Graduate School of Engineering, Nagasaki University. Currently, we works for Mitsubishi Electric Information Network by Digital Technology.

Rinsuke Uchida is a master degree student of Division of Electrical Engineering and Computer Science Graduate School of Engineering, Nagasaki University.

Hiroe Tanaka graduated from Nagasaki Junshin Catholic University. She was a project researcher of Division of Electrical Engineering and Computer Science Graduate School of Engineering, Nagasaki University.

Kenichi Arai graduated from Shinshu University, Japan where he received his B.E., M.E., and Dr.E. degrees in 2004, 2006, and 2010, respectively. He is currently an assistant professor at the Division of Electrical Engineering and Computer Science, Graduate School of Engineering, Nagasaki University. He is a member of IEICE and a member of IPSJ.