Abstract—In this paper, we propose a novel video summarization system which captures images via a social robot’s camera but processes images on a server. The system helps remote family members easily be aware of their seniors’ daily activities via summaries. The system utilizes two vision-based algorithms, one for pose estimation and the other for human detection, to locate people in frames to guide the robot through people tracking and filter out improper frames including the ones without a person or blurred, or with a person but too small or not at the center of the frame. The system utilizes a video summarization method to select keyframes by balancing the representativeness and diversity. We conduct experiments of the system through three in-the-wild studies and evaluate the performance through human subject studies. Experimental results show that the users of the system think the system is promising and useful for their needs.

I. INTRODUCTION

With a large portion of the population becoming aged, we aim to investigate the feasibility of applying video summarization techniques using a social robot to help family members look after seniors living alone. The setting is a home where an elderly person lives alone, whose family members are willing to care for the person but too busy to assist every day. A household robot will help if it can follow the senior, continuously pay attention to its master, notify family members in an emergency, and create a brief video summary of the senior’s daily activities. However, in reality, such features are currently unavailable. Since social robots will enter many families’ houses in the near future, we believe those features will be developed soon. Thus, we investigate the hardware and software limitations to perform those high-level intellectual actions and the users’ real experience. The hardware issues include limited battery capacity and cost considerations. Most commercial social robots are equipped with ultra-low-voltage CPUs (central processing units) for long use duration, which result in insufficient computing power to process complex calculations on enormous amounts of data, such as those gathered for video analysis. Regarding the software issue, although human detection and video summarization algorithms have been rapidly improved, most state-of-the-art methods are based on CNNs (convolutional neural networks) and require powerful processors, particularly GPUs (graphics processing units) to speed up computation. However, social robots usually have no GPU for the cost and battery concerns.

In this study, we propose a prototype of computing in client-server architecture to address the problem of limited computing resources available on a social robot. We implement a client-side program running on a social robot to capture videos and control the robot’s behaviors. We also implement two server-side program running on a high-performance machine. One analyzes video frames received from the robot and sends back real-time analyzed results and the other screens frames and generates summaries. Our contributions are twofold:

- To the best of our knowledge, this is the first paper addressing the summarization problem of robot-centric videos for human subjects.
- We propose a practical system which generates favorable summaries for users in the wild.

II. RELATED WORK

The topic addressed in this paper are covered by four research fields and we discuss each of them as following.

Camera-based Indoor Monitoring System There are many ways of using cameras to help the elderly for their indoor life and one of them is multi-camera surveillance systems [1], [2], [3], [4], [5]. Those systems have shown that they are capable of effectively localizing humans, identifying subjects, and monitoring activities, but it is an open question whether seniors are willing to install such a system at home. There is a lack of friendly interactions provided by those systems and their users cannot have a choice of not being monitored. In contrast, the proposed method is user-friendly since a user can easily notice the robot and order it around.

Video Summarization. Video summarization is the process of analyzing a video, in order to create a summary with the major points of the original video. Numerous methods [6], [7], [8], [9], [10], [11], [12], [13], [14] and datasets [15], [16], [17], [18] have been proposed in the literature. Since our output data are also video summaries, all existing methods are useful references for us. However, it appears that we cannot simply apply any developed method because we do not find any existing dataset similar to our setting. The videos collected by our robot are domain-specific and video summarization algorithms are highly data-dependent.

Vision-based Human Detection. Finding humans in images is an essential and significant task in any intelligent systems, as it provides the semantic information of an image. It has a wide range of applications including autonomous machines and surveillance. Numerous methods have been proposed in the literature using shape [19], appearance [20], motion [21], depth [22], background subtraction [23], and stereo data [24], [25]. The problem is reduced to a special case of object detection while only 2D visual data are used and the person...
Control the robot’s actions. Our robot will capture videos, run computationally intensive programs for fast response to capture images and transmit them to a server which can localize different parts of human bodies. The problem has been studied for a long time [31], [32], [33]. With the advance of high-performance GPUs and CPUs, methods with real-time response have been available in the literature [34].

Social Robots. Among various robots designed for numerous purposes, social robots focus on providing a practical and interactive robotic solution to improve the quality of users’ life. Many studies have shown that social robots are good tools to meet the elderly individual needs and requirements [35], [36], [37]. With the advance of technology, social robots have been extended from zoomorphic robots to humanoid moving robots equipped with multiple sensors and advanced intelligence [38], [39], [40], [41]. The developed features and used robot reported in this paper follow the same trend of social robot development.

### III. Proposed Method

The proposed system consists of two hardware devices and four software algorithms. The former are a moving robot equipped with a camera and a remote server with sufficient computing power as shown in Fig. 1. The latter are the ones for pose estimation, object detection, image removal, and video summarization as shown in Fig. 2.

**System Design.** We use a movable social robot equipped with a camera and a wireless communication module to capture images and transmit them to a server which can run computationally intensive programs for fast response to control the robot’s actions. Our robot will capture videos of the daily activities of participants, and our system will generate video summaries which will be viewed by their family members.

To guide the robot towards a proper location to capture videos, we need to know where people are in captured frames at first. We utilize OpenPose [34] and YOLOv3 [42] to perform the tasks of pose estimation and human detection. We need both of them because YOLOv3 cannot tell the body parts and OpenPose easily generates false positives as shown in Fig. 3. We use YOLOv3 to filter out false positives generated by OpenPose by the rule that the detected landmark points of OpenPose should be ignored if they are not contained in any bounding boxes of the human class.

**Rule-based Robot Movement Control.** For the case that multiple sets of effective human body keypoints are available, we pick the largest one in terms of size as our target person because of its closest physical location to the robot. According to the detected keypoints of the target person, we determine 1 out of 8 exclusive cases as $d_1$ to $d_8$ will be determined. Depending on the robot’s mobility state as active ($s_1$) or idle ($s_2$), 1 out of 10 robot’s movements ($m_1$ to $m_{10}$) will be selected and recorded into a history. The mobility state will switch to idea if the robot cannot find any person after turning around twice. The active state will be triggered if a person is detected.

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**Table 1: Keypoint set and detection cases.**

| Keypoint set | Detection cases | Mobility states | Movements | Movement History |
|--------------|----------------|----------------|-----------|-----------------|
| $\{p_k\}$   | $d_1$ to $d_8$ | $m_1$ to $m_{10}$ | $h_{n-1}$ to $h_{n-24}$ |

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**Fig. 1.** Hardware devices. Due to the limited computational resources available on a robot, we extend them by a powerful computer equipped with large storage and a high-performance CPU and GPU. We transmit data between the robot and the computer via the wireless connection to ensure the robots moving capability.

**Fig. 2.** Flowchart of the proposed method. Input frames are analyzed by four different algorithms. OpenPose and YOLOv3 are used to detect people in frames to guide the robot towards a proper location to follow a user. A content filter removes improper images from the input for summarization. A summarization method using GoogLeNet and K-means extracts keyframes.

**Fig. 3.** Landmark keypoints and bounding boxes. (a) 18 landmark points estimated by OpenPose. (b) A false positive generated by OpenPose, which finds a human body from a chair. (c) We only accept the results of OpenPose which are contained in bounding boxes reported by YOLOv3.
state will be triggered if the robot still cannot find a person after turning around twice, i.e. the latest 25 movement history elements match one of two predefined patterns. We use the mobility states to determine the robot’s movement when no person is detected. In the idle state, we keep the robot still ($m_0$). In the active state, we turn the robot left or right $30^\circ$ ($m_7, m_8$) depending on the position of a detected person at the left or right side of the latest frame available. We set the robot’s neck angle to $15^\circ$ vertically ($m_9$) if the robot fails in detecting a person around because the degree adjustment enables the camera to capture a person at a farther distance.

When a person is detected in a distance ($d_1$), the robot will approach the person and adjust its neck angle ($m_1$) until the person’s figure is large enough. We measure the size using the mean of two keypoint distances $\overline{p_1p_8}$ and $\overline{p_1p_{11}}$ (as shown in Fig. 3(a)) since they are the most significant lengths on a torso. We stop the robot when it is close to the person in an approximate distance of 2 meters because we found the distance is practical to capture images. We then only rotate the robot and adjust its neck angle to keep the person’s head at the center of captured frames at the 3/4 height depending on available facial keypoints ($m_2$ to $m_6$).

**Content Filter.** We capture images as the robot is moving and thus get many blurred images. In addition, captured images may contain no person or a captured person is very small in the images because the robot takes time to approach the person. The robot needs to adjust its neck and rotate its body to put the person at the center of a frame, and thus must capture many images in which the person is cut by the frame boundary. We set the criteria of unwanted images as the ones blurred or containing no person, and the ones containing a person who is too small, out of the center of the frame, or does not show at least one eye. We use an existing blur-detection algorithm variance-of-the-Laplacian [43] due to its simplicity and effectiveness [44] and set a low threshold to ensure all of the remaining images being sharp.

**Video Summarization.** We set our summary format as keyframes due to its efficiency to consume information by allowing users to look at all images at a glance. We adopt the manner of state-of-the-art video summarization methods [6], [7], [10] to extract image features using a GoogLeNet [45] model pre-trained on ImageNet [46] for 1000 classes. We use K-means clustering [47] to group the extracted features and select the image closest to a cluster center as a keyframe. We use clustering rather than LSTM-based methods [6], [7], [10] because our input/output data are different from theirs. Our input videos are long and contain many unwanted frames, and the proposed content filter breaks a video into numerous discontinuous pieces. In contrast, their input videos are short and ready to watch. Their algorithms are designed to generate further condensed videos, which are still videos, but our expected output data are keyframes. We present all of our video summarization code in the supplementary material since it is short and easy to understand.
During an experiment, we hide our engineer UI and show Zenbo’s face, as shown in Fig. 5(a)(b), to provide intuitive interaction experiences for the participants. We show expressions AWARE_LEFT and AWARE_RIGHT when the robot is going to turn left and right, HAPPY when the user is looking at the robot, i.e. the user’s nose and eyes are detected, ACTIVE when the robot is moving, EXPECTING when the robot is in the user’s back, and DEFAULT_STILL when the robot’s mobility state is idle.

Our collected user opinions about the experience of interacting with the robot and the feeling regarding the generated keyframes are shown in Table II. Their feelings are measured in a range between 1 to 5. The study shows that our participants think that our robot application is highly acceptable (Q1 and Q4) except for privacy concern (Q3). The female participants in our experiments 1 and 3 both express their worry whether the robot will take pictures if they have nothing on. It indicates a great demand for the improvement of our content filter which should be capable of protecting participants’ privacy.

The study also shows that our users think the application is practical (Q7) and the image quality is good (Q6), but we find that there is still space to improve the summaries. As shown in Fig. 6(1e)(1f)(1g) and (2c)(2d) look repeated but we think summaries should be diversified. We check the extracted features of those frames and found the problem is caused by the extracted feature vectors, which should be similar but in fact highly dissimilar, and thus results in different cluster centers. It suggests that our feature extractor—a GoogLeNet model pre-trained on ImageNet, used by several state-of-the-art video summarization algorithms—may not fit our application because of our domain-specific source images—domestic and human dominant. Since the image content is significantly different from those evaluated by generic summarization methods, it is still an open question to investigate which image features work best for our application.

V. CONCLUSION AND FUTURE STUDY
The paper presents an effective method to generate video summaries for family members of seniors living alone using a social robot. Based on an existing pose estimation and an object detection method, the proposed method integrates a content filter, a robot action control, and a video summarization method. Experimental results show that our participants highly accept the interaction with a robot for this application but require an advanced content filter to protect their privacy. Experimental results also show that our summary users are satisfied with the quality of generated keyframes, but expect more diversified activities. Our users also express strong demand for fall detection and they want to receive an immediate notification rather than a summary.

In addition to the study topics driven by users’ experience, we also have several technical topics for future study including how to reduce the hardware requirement, how to reduce computational load, and how to expand the application’s features. We observe that it is expensive to use a high-performance GPU to achieve the human detection task and will investigate low-cost substitutes such as Intel OpenVINO library [48]. We find that we need neither all keypoints nor very accurate coordinates provided by OpenPose. Thus it will be an improvement to find or develop a lightweight pose estimation algorithm as a substitute. Since a social robot owns multi-type sensors like microphones and depth cameras, it will be a very interesting study to integrate audio and depth data to generate high-quality summaries.
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