Robust Object Recognition Through Symbiotic Deep Learning In Mobile Robots

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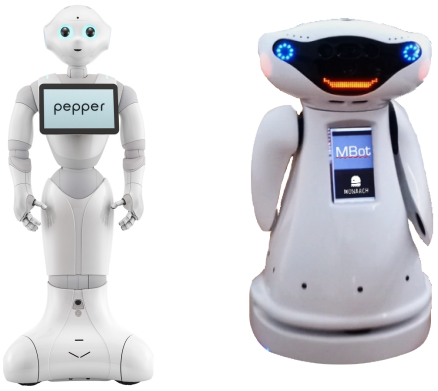
***Abstract*— Despite the recent success of state-of-the-art deep learning algorithms in object recognition, when these are deployed as-is on a mobile service robot, we observed that they failed to recognize many objects in real human environments. In this paper, we introduce a learning algorithm in which robots address this flaw by asking humans for help, also known as a symbiotic autonomy approach. In particular, we bootstrap YOLOv2, a state-of-the-art deep neural network and train a new neural network, that we call HUMAN, using only collected data. Using an RGB camera and an on-board tablet, the robot proactively seeks human input to assist it in labeling surrounding objects. Pepper, located at CMU, and Monarch Mbot, located at ISR-Lisbon, were the service robots that we used to validate the proposed approach. We conducted a study in a realistic domestic environment over the course of 20 days with 6 research participants. To improve object detection, we used the two neural nets, YOLOv2 + HUMAN, in parallel. Following this methodology, the robot was able to detect twice the number of objects compared to the initial YOLOv2 neural net, and achieved a higher mAP (mean Average Precision) score. Using the learning algorithm the robot also collected data about where an object was located and to whom it belonged to by asking humans. This enabled us to explore a future use case where robots can search for a specific person's object. We view the contribution of this work to be relevant for service robots in general, in addition to Pepper, and Mbot.**

I. INTRODUCTION

Human-robot symbiotic learning is an increasingly active area of research [1], [2], [3], [4]. Anthropomorphic robots are being increasingly deployed in real-world scenarios, such as homes, offices, and hospitals [5], [6], [7]. However, exposure to real human environments raises multiple challenges often overlooked in controlled laboratory experiments. For instance, robots equipped with state-of-the-art neural nets trained for object recognition still fail to provide accurate descriptions for the majority of the objects surrounding them outside controlled environments.

This thesis tackles the aforementioned problem using a symbiotic interaction approach, in which the robot seeks human assistance in order to improve its object recognition skills (our primary aim of this work).

This is achieved by deploying a learning algorithm that empowers the robot to ask humans for help. Over time, it can be measured that the human input increases the robot's effectiveness. The learning process is bootstrapped by an external state-of-the-art neural net — YOLOv2 — for real-time object detection [8].



(a) Pepper the robot (b) Mbot the robot

Fig. 1: The mobile robots used for the evaluation of the proposed method. Photos: SoftBank/Aldebaran and IDMind Robotics

The robot, using its RGB camera, in conjunction with its on-board tablet, explores its environment whilst labeling objects. The robot then confirms these labels by interacting with humans, asking them to respond to simple Yes/No questions and/or requesting that they adjust a selection rectangle positioned around an object in the tablet.

With the learning algorithm the robot also collects information about where the objects were seen in the map of the scenario and to whom they belong, if they are personal objects. Providing accurate information will equip the robot with the means to do other tasks like actively seek a personal object, on request. This task was made possible due to our realization of the wide applications that can be derived from the data that the robot collected.

The social robots used to test our approach were Pepper (shown in Figure 1a), a service robot developed by Softbank/Aldebaran Robotics and specifically designed for social interaction [9], and Monarch Mbot (shown in Figure 1b). In addition, the two robotic platforms were located in separate working environments: Pepper was located at CMU, USA, and Mbot at ISRobotNet@Home[1], Test Bed of ISR-Lisbon, Portugal. The experiments were conducted in a realistic domestic scenario. By having many research participants interact and modify the test environment, the unpredictability of object placement and arrangement was

[1]More info can be found at http://isrobonet_athome.isr.tecnico.ulisboa.pt/

ensured.

At the end of our experiment, the robot was able to detect twice the number of objects compared to the initial YOLOv2, with an improved mean Average Precision (mAP) score.

This paper is structured as follows: Section II reviews the state-of-the-art, Section III describes the learning algorithm, Section IV presents the YOLOv2 + HUMAN approach, Section V describes the experimental setup, Section VI analyzes the results, and Section VII presents our conclusions.

II. RELATED WORK

The complexity of indoor environments grows exponentially due to a various number of factors, increasing the difficulty for robots to complete tasks successfully. The particular task of learning and recognizing useful representations of places (such as a multi-floor building) and manipulating objects has been a subject of active research namely, in a symbiotic interaction with humans [10].

In this paper, we aim to detect objects coupled with their bounding-box. A few works have explored a human-based active learning method specifically for training object class detectors. Some of them focus on human verification of bounding-boxes [11] or rely on a large amount of data corrected by annotators [12]. Others explore how people teach or are influenced by the robot [13].

It is worth mentioning that symbiotic autonomy has been actively pursued in the past [14], [15]. Some interesting approaches are focused on improving the robot's perception with remote human assistance [16]. Research groups have also worked on developing autonomous service robots such as the CoBots [2], the PR2 [17] and many others.

Considering spatial information analysis and mapping, studies using ultrasonic imaging with neural networks [18], 3D convolutional neural networks with RGB-D [19] and a combination of the RANSAC and Mean Shift algorithm [20] have been in development for several decades, which demonstrates a clear evolutionary trajectory that enable the developments of the present.

Other works using scene understanding and image recognition show a strong affinity with this paper. Works such as: using saliency mapping plus neural nets to tackle scene understanding [21]; full pose estimation of relevant objects relying on algorithmic processing and comparison of a dataset of images [20]; feature-matching technique implemented by a Hopfield neural network [22]; and data augmentation [23].

When it comes to showing an object located in the real world to the robot, previous work has investigated alternative ways of intuitively and unambiguously selecting objects, using a green laser pointer [24]. In our approach, we took advantage of the robot's tablet purposely inbuilt for interacting with humans.

Finally, there has been work done in the area of getting robots to navigate in a realistic setting and detecting objects in order to place them on a map [25]. In our case, using input from human interaction allows the robot to generate this information. This enables the robot to store where each object was seen and how many times it was seen at each location.

Fig. 2: Mbot (top) and Pepper (bottom) learning

III. LEARNING ALGORITHM

The goal of this algorithm is to create a neural net, called HUMAN, that is able to detect objects within a scenario that the robot is deployed into.

The algorithm consists of three parts: First (A), the robot captures images to learn and predict what and where the objects are located in the images. Then (B), the robot asks the humans questions while confirming its previous predictions and collecting additional information. Finally (C), the robot re-trains its detector using the collected information to improve its future predictions.

A. Predicting the objects

The robot starts by navigating to a location it hasn't visited before and captures different images. These are the images that the robot will learn about for that day.

Before requesting help from a human, the robot predicts what the objects are and where they are located in each of the images.

To make these predictions the robot uses YOLOv2 [8], a neural net trained in COCO dataset[26], able to detect up to 80 classes of objects[2]. From "person" to "bed" or "bicycle" this neural net includes generic classes that apply to a vast number of different scenarios.

B. Interacting with Humans

When interacting with humans the robot will be asking questions: (1) Labeling the objects and (2) Identifying to whom an object belongs.

1) Labeling the objects: For labeling the objects the robot will first confirm the previous predictions and then ask the human if all the objects in the image are labeled.

[2]The 80 COCO class labels can be found at http://cocodataset.org

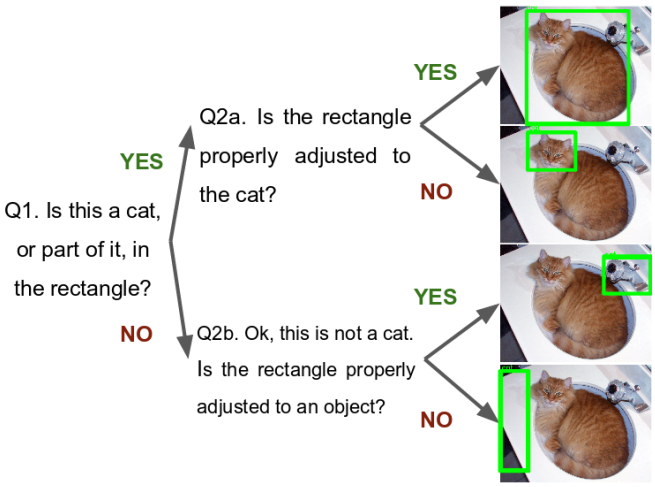


Fig. 3: E.g. Outcomes from Q1 and Q2.

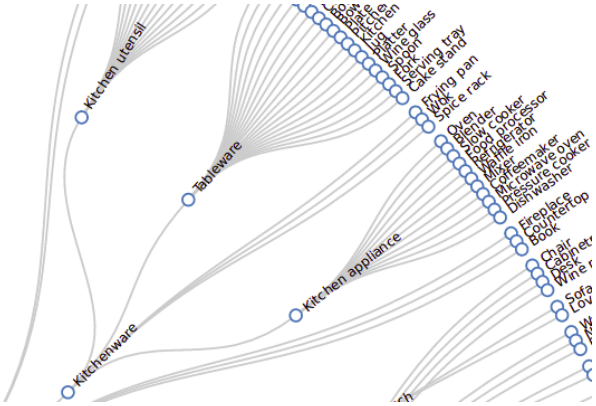


Fig. 4: Some classes that can be added to the robot using the labels from OpenImages dataset.[27]

To confirm the predictions the robot asks two Yes/No questions. Given a prediction, for example, the object "cat", the robot asks:

- Q1: Is this a cat, or part of it, in the rectangle?
- (if Yes to Q1) - Q2a: Is the rectangle properly adjusted to the cat?
- (if No to Q1) - Q2b: Ok, this is not a cat. Is the rectangle properly adjusted to an object?

The robot provides instructions to the human explaining that the properly adjusted rectangle refers to a rectangle that is specifying the extent of the object visible in the image.

These first two questions (Q1 and Q2) return 4 possible outcomes (see Figure 3). If the human says No to Q2a the robot asks for an adjustment of the bounding-box. If the human says Yes to Q2b the robot asks for a relabeling.

After confirming and correcting the predictions the robot then asks:

- Q3: Are all the objects in this image labeled?
- (if Yes to Q3): The image is ready for part (C) - Training.
- (if No to Q3): The robots ask for the human to adjust the rectangle to an object and label it.

When labeling, a list of the previously labeled objects shows up. If the person does not find the object in this list, a new class can be added from a predefined dictionary of classes. This dictionary restrains the lexical redundancies within a language, for example "waste bin" and "trash can" are categorized as only the "waste container" class.

When adding a new class, the robot shows the person the zoomable diagram (Figure 4), organized by categories from the OpenImages dataset [27]. This diagram includes 600 classes, in an organized structure. The robot only accepts new classes from this list.

We tagged the objects in this list as personal or not (e.g. classes like "mobile phone" and "backpack" are tagged as personal objects and classes like "oven" and "table" as not personal). This is used to ask the second type of questions:

2) To whom an object belongs: After labeling all the objects in the image, the robot then asks to whom each of these objects belong (if they are tagged as personal objects). This way the robot also stores information that will be useful when searching for an object belonging to a specific person.

C. Training

The interaction with humans results in a set of labeled images. Every time the robot collects a multiple of 50 images it trains a neural net, HUMAN50, HUMAN100, HUMAN150 and so on, using all the human labeled images. From these images 70% is used for training and 30% is used for testing.

The HUMAN neural net uses the same structure and algorithm as YOLOv2 but is trained using only the images labeled by humans. The reason why we train the HUMAN neural net using only the images labeled by humans is due to the fact that YOLOv2 uses the full images when training . So if we wanted to add a new class to YOLOv2, trained with the COCO dataset, for example "lamp" we would need to label all the lamps in thousands of images of that dataset.

After training, the HUMAN neural net is also used in part (A) - Predicting the objects. Using the predictions from both neural nets, the robot is able to predict more objects present in an image.

1) Filtering labels used for training: We remove repeating labels (of the same class) over the same area in the image.

If a person answers Yes to Q1 (correct label), and No to Q2a (bounding-box poorly adjusted), reffering to two different predictions pertaining to the same object, then we get two repeated labels. To avoid this problem, if in an image, an IoU (Intersection over Union) larger than 0.5 is detected between the same labels, we only use one of them (the one with a larger area) for training.

The IoU is a measure of how close two bounding-boxes match. To calculate the IoU we divide the intersection area by the union (total area) of the bounding-boxes.

In practice, an IoU score below 50% is probably an incorrect match. This value was set in the PASCAL VOC

Fig. 5: Domestic scenario where we ran the experiments.

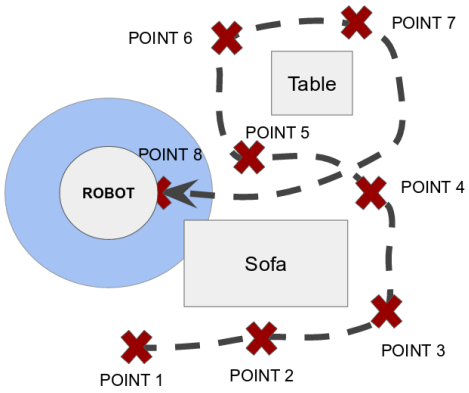


Fig. 6: Points of reference comprising the surrounding area.

competition [28], humans tend to be slightly more lenient than the IoU larger than the 50% criterion [11].

IV. YOLOv2 + HUMAN

In a real human scenario robots will need to interact with an unpredictable set of classes.

We used an approach that combines two neural nets (YOLOv2 and HUMAN), running simultaneously. The HUMAN neural net serves as an auxiliary one to the one that was trained with thousands of images in a global effort.

When the two neural nets detect the same object class in the same area in the picture (IoU larger than 50%), we use the prediction with higher confidence. By default, a confidence from 0.0 to 1.0 is given by the YOLOv2 algorithm, associated to each prediction [8].

V. EXPERIMENTAL SETUP

Using our current computational resources, running the two neural nets as separate processes requires an external computer with a GPU. In our trails we ran the computations and trained the neural nets in this external computer[3]. The average time it took to train the neural nets was 6 hours while YOLOv2 [29] is able to detect the objects in real-time (our bottleneck was the robot's WiFi connection).

A. Domestic Environment

Using a realistic domestic scenario (Figure 5) composed of one bedroom, one living room, one dining room and a kitchen. The experience was conducted over the course of 20 days, taking a total of 5 hours. Six research participants acted as the human input for the robot, answering questions about objects in order to evaluate if the robot could train the HUMAN neural net when confined to a small-scale environment. We also tested the applicability of using the two neural nets in parallel: YOLOv2 + HUMAN and evaluated the correctness of the robot's predictions.

1) Generating Points of Reference: The robot should be able to detect the surrounding objects independently of its current pose (location + orientation), relative to a fixed world frame. There are infinite poses within a confined environment but the robot can't feasibly ask infinite questions to fulfill its objective. To solve this, it starts by defining a set of sparse points. When the distance between the robot and all the existing reference points is greater than a fixed distance it creates a new reference point (Figure 6).

2) Using the Points of Reference: The robot should also be able to detect the objects in different light conditions (related to various hours of the day), and at different positions, angles and perspectives. We defined that each day the robot will navigate to 1 point of reference per day, at a random time and capture a total of 8 images at different orientations relative to the world frame. This way it captures different exposures and the implicit unpredictability of day-to-day objects.

B. Looking for a specific's person object

When the robot asks a human a question about an object associated with a certain Point of Reference, it gathers the spacial information of that object.

If the robot registers, for example a "doll", as being 1 time in the living room and 10 times in the bedroom, if asked to search for that same object it will hierarchically search by divisions with greater number of occurrences of that object. This somewhat emulates the thought process of humans when they are looking for a misplaced object, wherein they will look for the most common places where they see or use said object.

Furthermore when a user asks where his or hers object is, the robot, using the neural nets (YOLOv2 + HUMAN150), starts by detecting the objects. When the searched personal object class is detected, e.g. "backpack", the robot compares the part of the image inside the bounding-box with all the previous instances of "backpack's it has recorded and associates it to the one with the highest amount of features in common (using OpenCV's SIFT code[4]).

VI. RESULTS

To evaluate the proposed system, we compared the neural nets using an external ground-truth composed of 100 pictures. These images were captured by the robot in different places of the experience scenario without the constraint of

[3]GPU:NVIDIA's GeForce GTX 1080 Ti; CPU: Intel(R) Core(TM) i7-8700K CPU @ 3.70GHz

[4]The code can be found at https://opencv.org/

being in a Point of Reference. They also included different lightning conditions and 10 blurred pictures (robot moving).

A. Average Precision

The neural nets predictions were judged by the precision/recall (PR) curve. The quantitative measure used was the average precision (AP) [30], [31], [32], [28].

It was computed as follows:

- First, we computed a version of the measured precision/recall curve with precision monotonically decreasing, by setting the precision for recall r to the maximum precision obtained for any recall $r' > r$.
- Then, we computed the AP as the area under this curve by numerical integration. No approximation was involved since the curve is piecewise constant.

First, we map each detection to a ground-truth object instance. There is a match if the labels are the same and the IoU (Intersection over Union) is larger than 50% (value established in the PASCAL VOC competitions [31]), by the formula:

$$IoU = \frac{Area(B_p \cap B_g)}{Area(B_p \cup B_g)}, \quad (1)$$

where $B_p \cap B_g$ and $B_p \cup B_g$ respectively denotes the intersection and union of the predicted and ground-truth bounding-boxes.

In the case of multiple detections of the same object, only 1 (one) is set as a correct detection and the repeated ones are set as false detections [28].

B. Correctness of Predictions

During the 20 day experiment the robot trained 3 different neural nets: HUMAN50, HUMAN100 and HUMAN150. In the first week (less than 50 images), the robot was using only YOLOv2 to generate the predictions. In the second week the robot used YOLOv2 and HUMAN50. And finally, during the last week it used YOLOv2 and HUMAN100.

Looking at Table I, II and III we can see the results from the Yes or No questions (Q1 and Q2).

For both the neural networks, over 50% off all the predictions were true positives (Label ✓and Bounding Box ✓), while less than 15% were false negatives (Label × and Bounding Box ×).

We also observed that although the HUMAN neural net generated a smaller amount of predictions, those had a comparative performance versus YOLOv2, even when trained only with 50 images.

TABLE I: Predictions - **Week 1 - Image 0 to 50.**

YOLOv2 - total number of predictions: 190

(values in %)	Bounding Box ✓	Bounding Box ×
Label ✓	60.0	13.7
Label ×	14.2	12.1

TABLE II: Predictions - **Week 2 - Image 50 to 100.**

YOLOv2 - total number of predictions: 162

(values in %)	Bounding Box ✓	Bounding Box ×
Label ✓	61.7	16.7
Label ×	9.3	12.3

HUMAN50 - total number of predictions: 122

(values in %)	Bounding Box ✓	Bounding Box ×
Label ✓	54.1	33.6
Label ×	4.1	8.2

TABLE III: Predictions - **Week 3 - Image 100 to 150.**

YOLOv2 - total number of predictions: 210

(values in %)	Bounding Box ✓	Bounding Box ×
Label ✓	58.0	14.3
Label ×	16.7	11.0

HUMAN100 - total number of predictions: 107

(values in %)	Bounding Box ✓	Bounding Box ×
Label ✓	52.3	24.3
Label ×	13.1	10.3

C. Evaluation of the neural nets

Table IV shows the AP for each of the classes and finally the mAP (mean Average Precision). We can also see that YOLOv2 could only possibly detect a total of 20 of the classes present in the ground-truth, while HUMAN50 could detect 36, HUMAN100 40 and HUMAN150 41.

In this experiment, we verified the improvement of the HUMAN neural net with an increasing mAP, from 22.1% to 30.3% and finally 36.9%. On average the mAP value significantly increased by 7.5% between the different stages.

Even more impressive was the final score obtained with the neural nets in parallel achieving a total of 44.3%, which was almost 10% higher than the YOLOv2 score.

D. Human mistakes

We identified two primary categories of human error in labelling images: (a) unlabeled objects (happens when objects are difficult to label, e.g. small objects, or when people couldn't find the object in the list, e.g. "fire extinguisher" was not in included in the OpenImages labels); (b) wrong label (e.g. human clicks Yes when should have clicked No).

Despite the human error, we observed that the mean average precision and the total of correct predictions increased, suggesting the improvement of the neural net.

E. Looking for a specific's person object

In Figure7, we can see the results of this experiment, where we simulated the misplacement of a backpack and remotley requested the robot to search for it (using Telegram bot API[5]). As the figure suggests, the robot searched the surrounding environment and after approximately 2 minutes he

[5]More info can be found at https://core.telegram.org/

TABLE IV: Average Precision using an external ground-truth composed of 100 images in different poses. Values are in percentage (%) and the largest one per row marked in **bold**.

values in %	YOLOv2	H50	H100	H150	YOLOv2 + H150
apple	**25.0**	0	**25.0**	12.5	**25.0**
backpack	6.3	39.9	**79.1**	53.1	57.6
banana	20.0	0	20.0	20.0	**40.0**
bed	66.7	16.7	48.8	41.7	**89.6**
bicyclehelmet	-	**0**	**0**	**0**	**0**
book	13.2	23.7	24.0	26.2	**28.8**
bookcase	-	22.2	30.6	**33.3**	**33.3**
bottle	31.3	-	6.7	6.7	**39.6**
bowl	48.1	0	15.8	28.6	**54.7**
cabinetry	-	36.4	44.8	**55.2**	**55.2**
candle	-	-	0	**16.7**	**16.7**
chair	55.5	27.0	39.0	45.0	**56.4**
coffeetable	-	24.8	35.1	**57.1**	**57.1**
countertop	-	46.5	76.2	**85.7**	**85.7**
cup	25.5	1.0	32.8	32.3	**43.1**
diningtable	40.6	35.2	51.1	46.6	**52.1**
doll	-	-	-	**0**	**0**
door	0	58.1	**70.6**	61.8	61.8
doorhandle	-	0	0	**16.3**	**16.3**
envelope	-	-	0	**3.9**	**3.9**
glasses	0	**56.9**	31.3	53.1	53.1
heater	-	28.6	**40.8**	35.7	35.7
lamp	-	0	0	**18.3**	**18.3**
nightstand	-	**62.5**	50.0	50.0	50.0
orange	20.0	0	20.0	**40.0**	**40.0**
person	**50.0**	0	37.5	25.0	47.5
pictureframe	-	**35.8**	35.0	34.6	34.6
pillow	-	25.9	22.9	**36.2**	**36.2**
pottedplant	**70.7**	41.9	45.9	66.7	63.6
remote	**65.1**	0	0	0	**65.1**
shelf	-	0	0	**41.7**	**41.7**
shirt	-	0	**50.0**	**50.0**	**50.0**
sink	15.8	-	6.7	13.3	**20.8**
sofa	88.0	7.7	38.5	61.3	**92.3**
tap	-	0	5.6	**36.9**	**36.9**
tincan	-	9.5	**34.2**	26.6	26.6
tvmonitor	38.2	36.4	55.6	**74.0**	67.8
vase	20.8	20.0	6.7	11.1	**24.0**
wardrobe	-	12.5	0	**50.0**	**50.0**
wastecontainer	-	90.9	98.6	**99.2**	**99.2**
windowblind	-	35.3	35.3	**47.1**	**47.1**
# total of classes	20	36	40	**41**	**41**
mAP	35.0	22.1	30.3	36.9	**44.3**

had a positive match on the subject's backpack. Pertinently there were two more backpacks present at the scene and Pepper was able to identify the desired one.

VII. CONCLUSIONS

This paper presents an approach to address the object detection limitations of service robots. In particular, we bootstrap YOLOv2, a state-of-the-art neural, based on the teaching provided by the humans in close proximity. The robot then trains a neural net with the collected knowledge and uses two neural nets in parallel: YOLOv2 + HUMAN. By using the two neural nets, the robot gets the ability to adapt to a new environment without losing its previous knowledge. We implemented our learning algorithm in two different robots, Pepper and Mbot, and conducted experiments to test the performance of these neural nets in a domestic scenario. Potential future work includes further

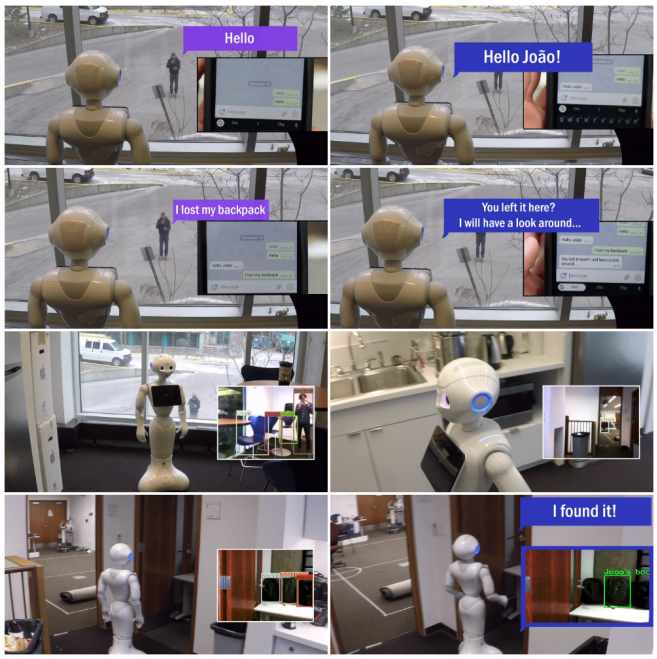


Fig. 7: Pepper looking for João's backpack demo.

enhancing the object detection capabilities with a focus on sharing information between the robots (located in different places/countries). We view the contribution of this paper to be relevant for service robots in general, in addition to Pepper and Mbot.

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