Validation of a Mobile Robot-Integrated RFID and Machine Vision System for Elderly Care Environments

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***Abstract*— In this article, by combining mobile robots, passive RFID, and machine vision in a unique way, we create a system that can take actions in preventing potential accidents by identifying, alerting, and helping a care home client at risk. We validated a laboratory version of the system, in which an RFID reader and machine vision equipped mobile robot identifies and greets a person wandering in the care environment at night, and gently guides the person back to the room for a safe night. According to our results, both RFID and machine vision systems integrated into a mobile robot were technically functional in a lit room, while the functionality of the machine vision system in a dark room needs further development. The main added value of this research was to bring together all this commercial equipment to validate the idea as proof-of-concept.**

Keywords*— *RFID applications, RFID in healthcare, mobile robot, machine vision

I. Introduction

Autonomous mobile robots (AMR) can be utilized in a variety of routine logistical tasks, but also additional tasks could be designed for them. In healthcare environments, they could free professionals from, e.g., transport [1], disinfection [2], and patient data collection [3] tasks, and allow people to focus on their core work [4][5]. AMR can navigate independently on their maps, plan the fastest or the most practical routes, and redesign the route if necessary. They can avoid and bypass collisions and contamination with humans and other moving, stationary, or contaminant objects, obey calls from different operators, give spoken instructions, and reorganize their actions according to the signals from the environment [6]-[9].

Passive RFID (radiofrequency identification) technology provides automatic identification of products and items [10][11], but also people [12][13], achieved with energy source-free and wirelessly addressable electronic tags. As each tag has a unique identification number (ID), it is possible to identify tagged people from a distance with an RFID reader, which can be attached for example to an AMR. The use of UHF (ultra-high frequency) enables working distances of several meters.

This paper is based on an earlier conference publication [14], in which we described a use scenario concerning the above-mentioned technologies for improving elderly care nighttime safety. In the scenario, a wandering resident is identified by an RFID reader integrated into a mobile robot and guided back to the person's room by the mobile robot. The focus of this paper is to also integrate machine vision to the system as an alternative solution to detect people without RFID tags but also enable the future use cases. The machine vision system detects if any untagged persons are near the robot, in the direction specified by the RFID reader. Based on the machine vision data the decisions on how to guide the person identified by the RFID reader are made. The untagged people detected by the machine vision system can be e.g., visitors, relatives or paramedics already guiding the identified person and thus no further guidance is given by the robot. The additional features of the machine vision system will also be used in future scenarios. Based on all this info, the data fusion system communicates with the database to figure out how all this information will affect the actions in this case.

II. Practical Implementation

In practice, when an RFID reader integrated in a mobile robot detects a lost or otherwise at the wrong time wandering person on the robot's normal route, the robot can speak to ask the person to follow the robot back to their room while constantly monitoring, if the person follows.

The RFID reader equipment consisted of CAENRFID Proton R4320P Long Range RAIN RFID Reader and 4 x LAIRD S8658PRJ RFID reader antennas. The reader used frequency of ETSI EN 302 208 v3.1.1 865.600-867.600 MHz. The antennas were mounted one to each side of a wooden cabinet and the cabinet was mounted on top of a MiR250 mobile robot, as illustrated in Fig. 1. The mounting height of each antenna's middle point was 0,63 m from the floor level.

The research has been funded by the Academy of Finland (decisions 337863 and 337861).

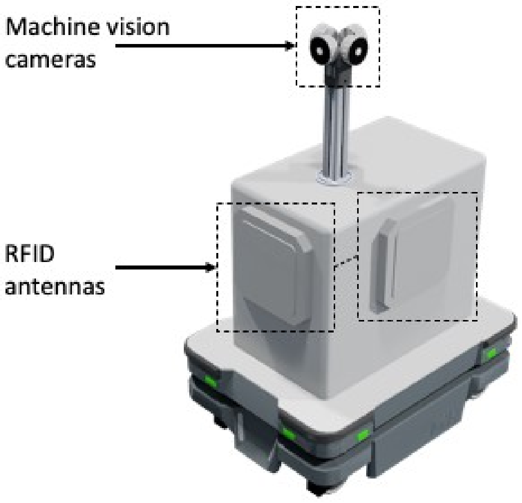

Fig. 1. The RFID reader antennas and machine vision cameras integrated into the mobile robot cabinet.

Machine vision cameras were basic security cameras with integrated infrared illumination and solenoid-driven infrared filters. The solenoid-driven infrared filters gave the cameras the ability to image normal visible wavelength light when the environment is well lit, but they can also see on infrared wavelength when it is pitch-dark. These cameras are connected via a network switch to the data fusion computer that is aboard the mobile robot. There are a total of four cameras that are fastened 90 degrees apart from each other, as shown in Fig. 1. This gives a 360-degree field of view (FOV) to the system; hence one camera can see over 90 degrees horizontally. Through this arrangement, the computer gets four 1920x1080 images, and stitches them as one wide picture that covers the whole 360 degrees FOV. After that, the mentioned image is uploaded to the OpenCV-based program that recognizes human figures.

The created machine vision system works by initially receiving a stream of images from the security cameras by OBS studio software. Four image streams from the four cameras are arranged side by side to create a panoramic view of the 360-angle area. These four image streams stitched together are then formed as an output of a virtual camera. This stream is used as an input of the machine vision algorithm. The algorithm used in this test version of the machine vision system was YOLO version 5, which is available in GitHub. YOLO is described as a collection of different object detection architectures and models that are pretrained using the COCO (Common Objects in Context) dataset. The MS COCO is a dataset to be used in detection and segmentation of objects seen in our daily, natural environments [15]. When using the YOLO in these preliminary tests, a dataset called Crowd Human with images of human characters was configured to be used instead of the COCO dataset. In these tests, one example (detect.py) of YOLO was utilized by configuring it to the purposes of our tests.

III. Validation measurements

A. Mobile Robot-Integrated RFID System

The purpose of the RFID system validation measurements was a) to validate the mobile robot-integrated RFID system's reading performance in the use scenario and b) to initially test different placement for basic commercial RFID tags on human body. The measurements were performed in a corridor with commercial passive UHF RFID tags (Avery Dennison Shortdipole Monza 4D) placed in various places on the human body, as illustrated in Fig. 2. The chest was chosen to be one of the attachment points, as in this context tags could be hanging in a keychain, attached to a name tag, or integrated into clothing. A front pocket was taken as another placement, as it is also a potential place in case the tag is a key ring, for instance. Collar and shoe were selected as well, as they are further away from the lossy human body, and potentially readable from various directions. Upper back and calf were selected as potential places to clothing-integrated tags, as they can easily be made unnoticeable for the user (memory impaired users may be willing to detach tags from clothing). One tag was placed on the hem of the shirt, as it was only loosely on the body. The distances of the tags from the floor were: shoe 4 cm, calf 30 cm, pocket 70 cm, hem 80 cm, chest 120 cm, and collar 135 cm. The test subject was female.

In this preliminary experiment, the purpose was to test general, commercial tags in this setup in a real, lossy environment and with several tags in near proximity to each other ("the worst-case scenario"). The RFID system validation measurements were taken from distances of 1.2 m and 3 m and from four directions (0° = front, 90° = left, 180°= back and 270°= right). Each measurement was taken with the following protocol: Reading started at 7.15 dBm ERP (Efficient Radiating Power) and the power was raised in steps of 2 dBm up to maximum allowed transmit power. On each power step, RFID tags were queried once, and all obtained results were written to a database. On each tag the written result contained values of tag ID, Received Signal Strength Indicator, tag placement on body, antenna number, reading power, read step index, the orientation of the person, and read time. Each measurement was taken five times to be able to identify unreliable measurement results, which occasionally occur in real use environment due to reflections and other disturbances.

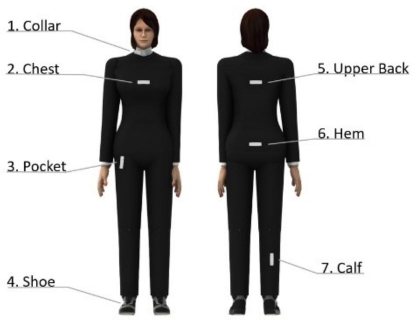

Fig. 2. Passive UHF RFID tag placements on human body.

B. Mobile Robot-Integrated Machine Vision System

The purpose of the machine vision system validation measurements was to verify and confirm the functionalities of the machine vision system in the detection of human figures. The measurements were performed using three different procedures.

The first procedure tested the detection of a human figure from three different distances. The distances between the test subjects and the machine vision system integrated in the mobile robot were 3 m, 5 m and 8 m. Each test subject in turn went 3 m from the machine vision system, first looking in the direction of the robot, then always turning 90 degrees to the right so that the human was imaged from the front, left, back and right. The same imaging was repeated for each test subject also at a distance of 5 m and 8 m. At the end of the test procedure, the same imaging was performed by one of the test persons with the support of a rollator, in which case the person turned the direction of travel of the rollator according to their own direction of travel each time they turned 90 degrees.

In the second procedure, the tests of the first procedure were repeated, but under dark conditions. Lights were turned off from the lab room, but some light was glimmering from the hallway through the window.

The third procedure further tested how the machine vision system recognizes people in different directions simultaneously. In the measurement situation, there were six different people on different sides of the robot, five of whom were standing, and one was sitting. All test subjects were 2-4 m away from the robot. Program outputs, where the human figures are marked in the image with red dot, are shown in Fig. 3. From this information, the system also calculates where the identified person is with respect to the mobile robot.

Seven people participated in the tests, three of whom were men, two women, and two children, as presented in Fig. 4. By repeating the tests with different test subjects, the aim was to ensure that the functioning of the system was not affected by the gender, size or age of the person being detected. Because the mobile robot, the integrated RFID reader, and the integrated machine vision system are also designed to work in crisis situations, the test subjects kept face masks on their faces throughout the validation measurements. This ensured that the use of a face mask would not prevent the detection of the human figure.

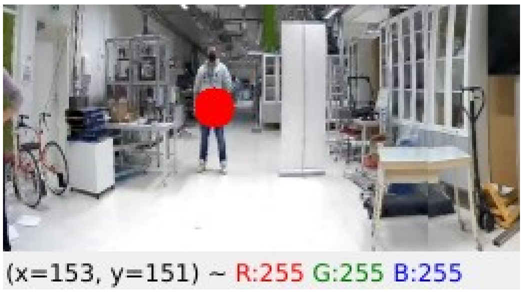

Fig. 3. Detected human figure output with red dot.

Fig. 4. Test subjects who participated in the validation measurements of the machine vision system.

IV. Results and Discussion

A. Mobile Robot-Integrated RFID System

The validation measurement results of the mobile robot-integrated RFID system are presented in Table I, which presents the threshold power (minimum power required to read the RFID tag) for different RFID tag placements on body, in different orientations (the person is measured directly from front, back and both sides), and from different distances (1.2 m and 3 m). Red color without any measurement result indicates the tag was not readable.

As can be seen from Table I, the RFID tags, which were placed on the chest and on the upper back were the easiest to detect. Similarly, the collar tag was easily detected in all other directions except from the opposite side of the body, as the collar tag was only added on the right side of the body.

The shoe tag, the pocket tag, as well as the calf tag were also placed on this side, but they were not readable from all directions. The pocket tag as well as the calf tag were very tight on the body, which affects the losses and shortens the read range. Additionally, the shoe tag did not perform well, which may be caused by lossy shoe sole material, or its very close position related to the floor. Surprisingly, the hem tag also performed poorly. The potential tag placements for this use case on the human body were chest, upper back, and collar. To be able to detect the person from all directions, it would be advisable to attach tags on opposite sides of the body (back and front or right and left side).

These measurement results do not reveal which reader antenna was detecting the RFID tag, as from the measurement purpose of this study, it was only relevant, if the tag was read. However, it is our future topic to study, as it affects the functioning of the total system and system integration with the machine vision system.

TABLE I. The Tag's Threshold Power on Human Body

1.2 m	3183 Collar	3191 Chest	3189 Pocket	3181 Shoe	3190 Upper Back	3186 Hem	3185 Calf
Front	29	17			29		
Back	29				13	25	29
Right	23	25	29	31	27	27	
Left		25			19		
3.0 m	**3183 Collar**	**3191 Chest**	**3189 Pocket**	**3181 Shoe**	**3190 Upper Back**	**3186 Hem**	**3185 Calf**
Front	29	23			31		
Back		31			17		
Right	25	29			31		
Left		31			27		

B. Mobile Robot-Integrated Machine Vision System

The validation measurement results of the mobile robot-integrated machine vision system are shown in Table II and Table III. Partial detection in the table means that the subject is detected as a human figure from some but not from all directions (from front, left, back and right). As can be seen, in a fully lit room, at distances of 3 m and 5 m, the machine vision system detected all test subjects as humans when viewed from all four directions. The detection of a test subject dressed in dark clothing from 8 m was uncertain against a distant, uneven background, but all other test subjects were identified from 8 m from all directions.

TABLE II. MACHINE VISION VALIDATION RESULTS IN A LIT ROOM

Distance [m]	Identification [persons]	Partial identification [persons]	No identification [persons]	Person with the rollator
3	7	0	0	Identified
5	7	0	0	Partial
8	6	1	0	Partial

TABLE III. MACHINE VISION VALIDATION RESULTS IN A DARK ROOM

Distance [m]	Identification [persons]	Partial identification [persons]	No identification [persons]
3	3	3	1
5	0	5	2
8	0	0	7

Detection of the test subject with a rollator was uncertain at distances of 5 m and 8 m, when the subject and the rollator were imaged from the side. The front and back of the subject were detected in these situations as well.

In a dark room, detection was not as certain. The undetectable test subject at 3 m was the subject dressed in dark clothing, who was only partially detected in a fully lit room at 8 m. In the darker environment, the detection seems to be more clearly influenced by the clothing. At 3 m from each direction, the detected test subjects were those wearing the brightest colored shirts. Regarding partial detection, it was found that the system best detects a subject from a frontal image. The position of the legs was also found to be important for detection. If the subject was standing with legs apart, the system detected the subject as a human figure more easily than when standing legs together. This emerged in situations where detection was more uncertain. Finally, in a multisubject validation, all the test subjects positioned in different directions, 2-4 m away from the robot, were correctly detected.

The validation measurement results showed that detection of human figures works. As the system also gives the direction in which the detected people are and since the size of a human figure gives a rough estimate of how far the detected subject is, the system has even more potential than presented in this first laboratory version. According to these initial results, detection of human figures in a dark environment is the most important target for further development.

V. CONCLUSION

Based on the validation measurements in the laboratory environment, it is concluded that both RFID and machine vision system integrated on a mobile robot were operating well, though further development is needed, for example, to improve the RFID tag readability at different situations and to develop machine vision-based detection of a person in a dark room by integrating a near infrared lighting to it. Our future work also includes further development of the data fusion protocol for seamless integration and interactions of the different sub-systems for this specific use case, as well as testing the system in a real use environment. Further, on-body RFID tags suitable especially for this purpose will be designed and detailed performance measurements will be carried out for individual tag placements. The results of this study form the basis for these next development steps.

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