2014 IEEE International Conference on Robotics & Automation (ICRA)
Hong Kong Convention and Exhibition Center
May 31 - June 7, 2014. Hong Kong, China

Human-Robot Collaboration in a Mobile Visual Sensor Network

Ha Manh Do, Craig Mouser, Meiqin Liu, and Weihua Sheng

Abstract—**This paper proposes and implements a framework for human-robot collaboration in a Mobile Visual Sensor Network (MVSN). A collaborative architecture for the proposed human-integrated MVSN was developed to allow the human operator and robots to collaborate to perform surveillance tasks. We successfully implemented the MVSN so the user can control the deployment of the mobile sensors through his head movement. We also explored using computer vision techniques and navigation techniques on the robot nodes to conduct active human target detection. The robot nodes, therefore, are able to detect human faces while exploring the unknown environment, and then relay the face images to the operator for target recognition. In this way, humans and robots can complement each other to accomplish surveillance tasks. Our experimental results validated the proposed framework.**

I. Introduction

In recent years, Mobile Visual Sensor Networks (MVSNs) which consist of multiple robots equipped with visual sensors have been used for numerous applications, such as surveillance for security, reconnaissance for military or police operations, or search and rescue in emergency response. While stationary visual sensor networks (VSNs) have limited sensing ability and coverage, MVSNs have some advantages, such as adaptation to environmental changes, re-configurability for better sensing performance, and larger coverage compared with a single robot or a stationary sensor network. MVSNs enable users to explore dangerous areas or areas that do not support human life, such as the ocean or outer space. Furthermore, a user can team up with multiple robots, which can greatly reduce the time it takes to explore an area and gather intelligence or locate the desired object.

In traditional surveillance applications, the mobile visual sensor nodes independently and continuously send video streams to a central processing server, where the video could be analyzed by software or human operators. In this work we propose that humans and mobile robots can work together to accomplish a task. In other words, humans and robots can form a team with each having complementary skills and being committed to a common goal through collaboration [1]. Our work focuses on the application of detecting and recognizing a human target through human-robot collaboration.

This work is partially supported by the NSF grant CISE/IIS 1231671 and National Natural Science Foundation of China under Grants 61328302 and 61222310.

Ha Manh Do, Craig Mouser, and Weihua Sheng are with the Laboratory for Advanced Sensing, Computation and Control (ASCC Lab), School of Electrical and Computer Engineering, Oklahoma State University, Stillwater, OK, 74078, USA (e-mails: ha.do@okstate.edu, cmouser@okstate.edu, weihua.sheng@okstate.edu); Meiqiu Liu is with the College of Electrical Engineering, Zhejiang University, Hangzhou 310027, China (e-mail: liumeiqin@zju.edu.cn).

Fong and Nourbakhsh [2] pointed out that to reduce human workload, fatigue induced error and risk, intelligent robotic systems need to be a significant part of mission design. It is relatively easy for robot sensors to detect targets. However, current mobile robots have poor performance of target recognition in changing and unstructured environments. Furthermore, dealing with the variability in shape, texture, color, and size of natural objects leads to more complicated algorithms for robust target recognition and results in an MVSN that is more difficult and expensive to develop and operate [3]. On the other hand, humans have superior recognition capabilities, can easily adapt to changing environments [4], and are good at sensor deployment. However, human operators are inconsistent, suffer from distraction [5], and quickly become tired and overloaded in stressful conditions. By combining the advantages of human perception and recognition skills with the autonomous robots' accuracy and consistency, a human–robot team can increase the performance of target recognition and reduce the complexity of the algorithms, even in unpredictable conditions that autonomous systems are incompetent to deal with [6].

This paper proposes and implements a framework for human-robot collaboration in an MVSN, in which humans and mobile robots work together in surveillance tasks to explore an area as well as to detect and recognize a target. This paper is organized as follows. Section II covers previous work done in this field. Section III presents the design of the human-integrated MVSN and its implementation as an open platform. Section IV describes human-robot collaboration for surveillance. Section V gives the experimental results. Section VI concludes the paper and also discusses the potential future work.

II. Previous Work

This section presents related works in the field of human-robot collaboration in surveillance. Burke *et al.* [7] used wearable arm trackers and a tablet to immerse a human node in a multiple-robot team for remote exploration and surveillance. They focused on the development of a multimodal interaction system including naturalistic human gestures, voice commands, and a tablet interface to provide the human operator with multiple interaction modes given the situational demands. However, their surveillance system did not send video back to the operator and the robots did not share detection and recognition task with the operator. While Lewis *et al.* [8] stated that beside human-robots interaction the robots need to be equipped with autonomous algorithms to mitigate some of the challenges and complexity the operators face in controlling multiple robots. Iocchi *et al.* [9] proposed a system including human security operators carrying sensors, mobile robots and network of fixed cameras to collaboratively monitor public environments. However, the paper mainly discussed the system architecture and the data

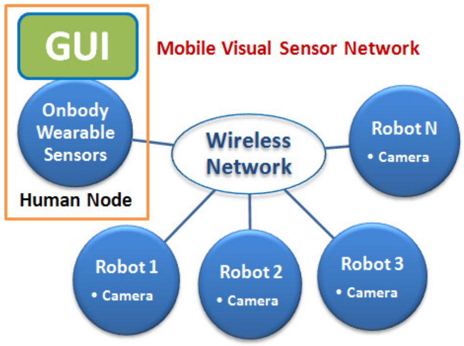


Figure 1. Human-Robot Team Configuration in the Mobile Visual Sensor Network.

fusion approach for future development to locate and track targets through cooperation between sensor nodes. Tkach *et al.* [10] presented four human–robot collaboration levels for target recognition tasks in unstructured environments. They proposed algorithms that are developed for real-time dynamic switching between collaboration levels in a human–robot target recognition task. Their algorithms can increase the target identification rate and reduce the complexity of the robotic system. Those examples also provide an empirical proof of the advantages of such collaborations in a target recognition task.

MVSNs were deployed for urban search and rescue response at the World Trade Center [11]. During that mission, it is found that the most pressing concern is to allow humans to efficiently control more robots when the robot-to-human ratio is high. Another concern is to create intelligent and intuitive human-robot interfaces. In subsequent research, Nourbakhsh *et al.* [12] developed a multirobot search and rescue system. They used a multi-agent architecture to create a scalable system that could integrate multiple types of robots as well as humans into a network. By creating separate nodes in their multi-agent system for information gathering, communication, exploration, and human interaction, their system becomes scalable to a level that allows a human to efficiently manage multiple agents.

The above works mainly focused on solving separate problems, such as human-robot interaction, human-robot cooperation or coordination, and adjustable-autonomy for multiple robots, human-robot collaboration in exploration or target detection/ recognition, etc. In this paper, we aim to develop an open platform of a human-integrated MVSN based on a new collaborative architecture that efficiently allows a human and multiple robotic sensors to collaborate in a surveillance task. This platform mainly addresses two issues: human-assisted robot deployment and human-robot collaborative target recognition. Our platform allows the robots and a human to perform the work in which they are best suited. This makes our framework scalable and simple, which leads to increased robot-to-human ratio without increasing the complexity of the interface.

III. Human-Integrated Mobile Visual Sensor Network

The proposed human-integrated MVSN consists of two parts: the robot nodes and the human node. The robot nodes are essentially mobile robots equipped with cameras. Human wearing on-body devices and a minicomputer with a multimedia graphical user interface (GUI) acts as a human node in the MVSN. Those nodes are wirelessly connected in a configuration as shown in Fig. 1. This configuration allows the human to act as one additional node connected to the wireless network as the robots do and to collaborate with the robots on surveillance tasks. Human-robot collaboration in MVSN requires significant researches to address principal challenges such as human-robot communication of intention, action planning and coordination. Efficient solutions to these problems require communication and collaborative models which has been partially addressed by existing multiagent system (MAS) architectures such as RETSINA [13]. In the human-integrated MVSN, two essential tasks, remote deployment of robots and target search and recognition, need to be implemented based on mobile robot service such as SLAM (Simultaneous Localization and Mapping), navigation, and object detection.

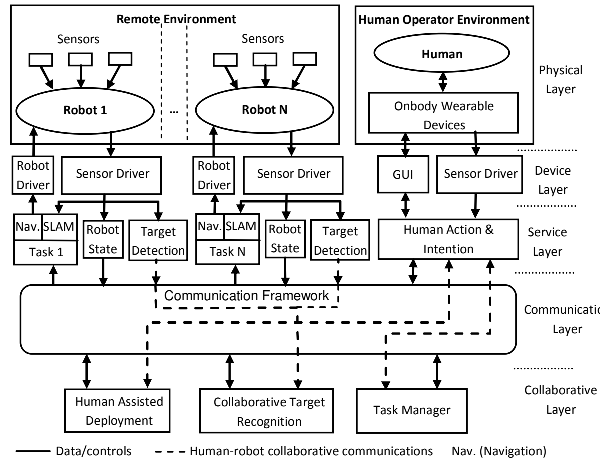


Figure 2. Collaborative Architecture of the Human-integrated MVSN

A. *Collaborative Architecture of Human-integrated MVSN*

As shown in Fig. 2, the five-layer collaborative architecture of human-integrated MVSN includes physical layer, device layer, service layer, communication layer, and collaborative layer. The physical layer consists of the hardware of the nodes. The robot nodes are built based on mobile robots equipped with sensors such as a RGB camera or RGB-D camera, a laser range finder (LRF), and encoders. The human operator wears on-body devices and a mini-computer with graphical user interface. The device layer provides the device drivers for the sensors and actuators. The service layer contains basic services each node provides. The collaborative layer contains high level functions for human-robot collaboration and robot-robot cooperation. Based on the Robot Operating System (ROS) network [14], the communication layer provides a seamless connection between the different modules in the service layer and the collaborative layer.

The collaborative layer is developed for human-robot collaboration and robot-robot cooperation in the MVSN. Currently, this layer is proposed with three main functions including human-assisted deployment, collaborative target

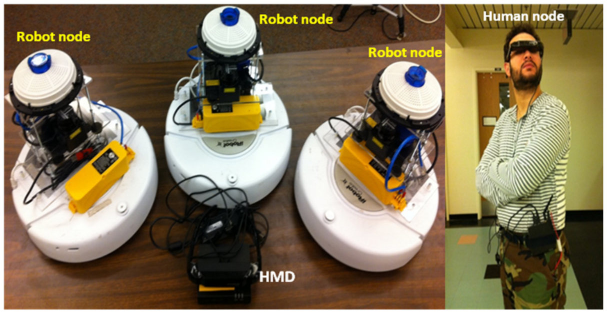


Figure 3. A network of three mobile sensors and the human node.

recognition, and task manager. Human-assisted deployment provides methods to enable the human operator to actively guide multiple robots to explore the unknown environment while searching for targets and to assist the robots to solve problems during autonomous exploration and search. Collaborative target recognition enables the human operator and robots to work together to detect and identify a target. Task manager coordinates the different functions and dispatches the right tasks to each individual robot.

The above architecture was applied to implement the software of the proposed MVSN. In this paper, we focus on human-assisted deployment and collaborative target recognition. As we mentioned, human is good at deploying the robots at a higher level while the robots are good at detecting targets through vision sensors. Based on commands estimated from the head motion and a GUI, the robots are easily deployed to explore the remote location. While exploring the remote location, the robots can detect the targets and send the image of the target to the human operator for recognition.

B. *Open Platform for Human-Integrated MVSN*

The open platform built for testing the proposed human-integrated MVSN consists of multiple mobile robot nodes and the human node, which are shown in Fig. 3. This section describes the hardware and software structure of this platform.

1) Hardware

a) Robot node

The robot node, an ASCCBot [15] developed in our lab, is a mobile visual sensor platform built on an iRobot Create base. Mounted on it are an omnidirectional camera, a laser range finder (LRF), and a fit-pc2 minicomputer. It also has batteries on board to power these devices. The omnidirectional camera is a Mobotix Q24 360° IP camera. It can display the images in various modes from a full 360° view to a simple pinhole camera style view. The LRF is a Hokuyo URG-04LX-UG01. It is a low-power laser rangefinder with a wide range up to 5600mm x 240°, and an accuracy of ±30mm.

b) Human node

As shown in Fig. 3, an operator wearing a head-mounted display (HMD), the Vuzix iWear VR920, acts as a human node in the MVSN. In this node, the HMD is connected to a fit-pc2 minicomputer running Windows 7. The HMD is capable of sensing head rotation using built-in 3 degree of freedom head-tracker. Therefore it can be used for the deployment of robots through human head motion. It can send rotational feedback to allow the operator to control the mobile visual network with the rotations of his head. For instance, looking left can cause the robot to turn left. Moreover, the HMD allows the operator to have both see-through mode and immersive mode when navigating the robots. In the immersive mode, this HMD can allow the user to remain more focused. The video from the cameras on the robots can be streamed back to the user and displayed on the HMD. Therefore the user can locate and recognize targets of interest by collaborating with multiple robot nodes.

2) Software

The software consists of two main parts: the robot node software and the human node software. They were both developed based on ROS.

a) Robot node software

ROS Electric [14] was installed on Ubuntu 10.04 for running the robot node's software. For the basic functions in the robot node, we utilized exiting packages from ROS repositories to develop the device layer for interfacing with the robot base, and Hokuyo LRF. In service layer, two main services including SLAM and navigation were developed based on existing ROS packages. SLAM was based on Rao-Blackwellized particle filters [16]. Motion planning and autonomous navigation were based on the particle filter based localization method [17], and the adaptive (or KLD-sampling) Monte Carlo localization approach [18]. We implemented the driver to receive the images from the Q24 camera.

b) Human Node Software

The software of the human node allows a human node to be integrated into the network. This node can publish and subscribe message through ROS network, read data from Yaw, Pitch, and Roll sensors on the HMD. Those data were fused by Human Action & Intention function to recognize the operator's commands through his head motion. The GUI developed based on OpenCV allows the operator to view the map and the image from each robot node on the HMD.

IV. HUMAN-ROBOT COLLABORATION IN SURVEILLANCE

A. *Human-assisted deployment*

Using head motions, the human operator can deploy the robot nodes in different environments. First, the operator determines the initial locations of robots and assigns each robot a goal point on the 2D map. The operator can also drive any robot by watching what the robot sees through the HMD, while the other robots autonomously move to their goal points. After the timeout, if any robot cannot reach the goal point, it sends a request to the operator for assistance. Therefore by assistance provided by the operator, the robots can be deployed in complex environments. In the future, the robot-robot cooperative SLAM, collaborative navigation, and autonomous exploration and search would be fully developed for faster and more efficient exploration of the unknown environments.

B. *Collaborative Target Recognition*

The surveillance task consists of target detection and target recognition. In particular, in the proposed MVSN, human detection was conducted by robot nodes, and human recognition was performed by the human node.

1) *Active Human Target Detection (AHTD)*

In human target detection, body parts such as head, face, legs, arms, upper body, lower body, etc. can provide cues for human detection, but a face usually plays a major role in human recognition. Face detection is the first step to all facial analysis algorithms and it is easier than detection of other body parts because the human face has a distinct structure. Face detection proposed by Viola and Jones [19] is the most popular approach. We adopted this approach for face detection. In general, a frontal view of the human face can make it easier for the operator to recognize. In this sense, a good viewpoint should be found to obtain a frontal face image. Therefore, active human target detection (AHTD) was implemented on our system.

The OpenCV's HaarDetectObjects function was first utilized with different trained classifiers to get the initial face region, then the *Good Features to Track* [20] function was applied to compute the feature points in the face region for tracking and evaluating the face. To find a better viewpoint, we need define a measure to assess its suitability for face detection. The viewpoint was evaluated by a confidence measure based on the distribution of feature points in the face region as follows:

$$confidence = 2\min\left(\frac{N_R}{N_R+N_L}, \frac{N_L}{N_R+N_L}\right) \tag{1}$$

Here N_R is the number of feature points in the right half of the face region. N_L is the number of feature points in the left one. If it is a profile face, the feature points mostly locate on the left half or the right half, so the confidence is much less than 1.0. While the frontal face gives a high confidence of close to 1. As shown in Fig. 4, the profile face obtained from the viewpoint (b) gives a *confidence* of 0.67, while the frontal face obtained from the viewpoint (d) gives a *confidence* of 0.94.

The robot runs the AHTD method according to the following steps:

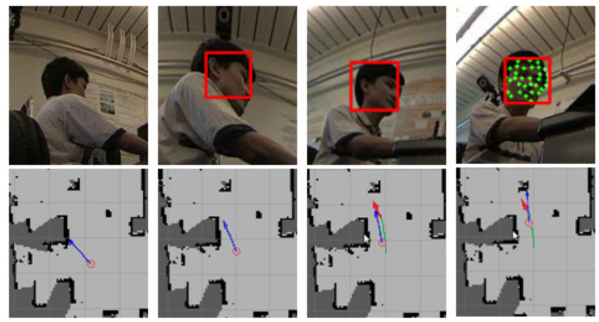
Step 1 - Face detection: The robot performs face detection on the whole image with deferent cascades of frontal faces and profile faces.

Step 2 - Face evaluation: We compute the feature points in the face region using *Good Features To Track* function and then the *confidence* measure according to (1). If the confidence is above certain threshold (0.85), the face region is highlighted and sent to the human node, otherwise the robot is guided to a new position to achieve a better viewpoint in next steps.

Step 3 - Goal point prediction: The goal point with the best viewpoint is predicted through the angle of face (AOF) from the camera, the angle of human (AOH) in the panorama image, and the distance (D) between the human target and the robot.

confidence : a) 0.0 b) 0.67 c) 0.73 d) 0.94

Figure 4. Shapshots from different viewpoints with different confidences.



(a) (b) (c) (d)

Figure 5. Sequence of robot motion shown in the map and face detection results of AHTD in corresponding frames

Step 4 - Robot navigation and face tracking: Move the robot and predict the new IROI based on robot motion. The face detection is done on this IROI to reduce computation. The *confidence* and the new goal point are updated for each image frame. If the *confidence* is above certain threshold, the face region is highlighted and sent to the human node**.** If the face is lost in two consecutive frames, go back Step 1.

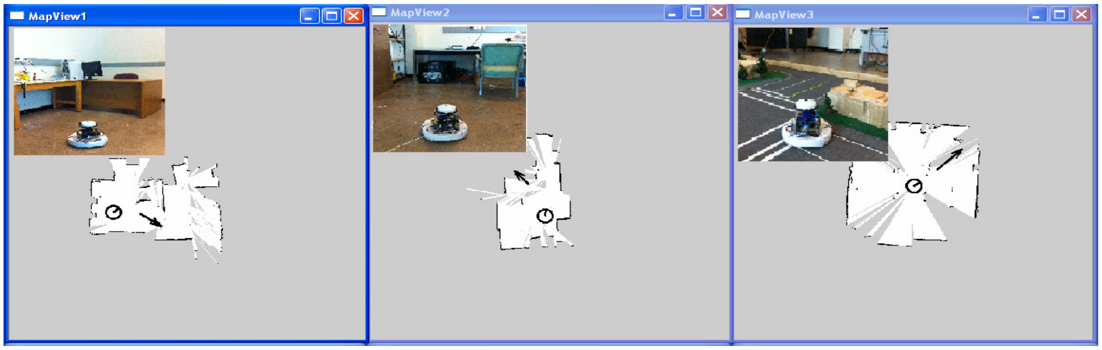
Fig. 5 presents the sequence of robot motion shown in the map and face detection results of AHTD in corresponding frames. In the map, the robot and its moving direction are represented by a red circle and a blue arrow, respectively. A profile face was detected in frame (b). As shown in Fig. 5-c, a new goal point (represented by a red arrow) and a path (represented by a green curve) were generated to navigate the robot to the location with the best viewpoint. The robot stopped at frame (d) when the *confidence* reached 0.94 at the position very close to the goal point.

2) *Collaborative target recognition*

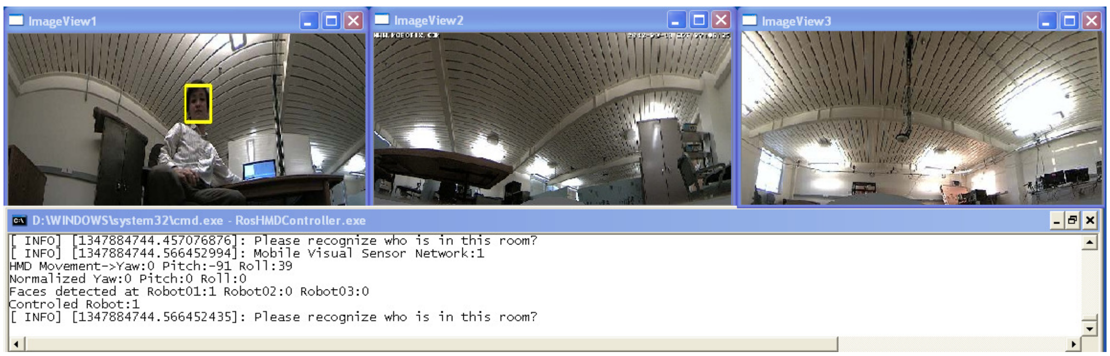
Once a face is detected, the robot can autonomously send the image to the HMD and ask the human node to recognize the face. The operator is usually able to recognize the highlighted faces sent from the robot. In case the image is not clear, the operator could drive the robot around the human target to get a better viewpoint for recognition. After that the operator could assign a new goal point to the robot and get back to the previous task of collaborating with other robots.

C. *Task Manager*

The task manager was developed as a state machine. It allows the human operator to control the network, to assign tasks to robot nodes, to switch the map view and the image view. The system mainly works in two phases including: deployment phase and recognition phase. The task manager monitors not only the whole MVSN but also each node in autonomous tasks. It allows the system to smoothly switch



a) Human can deploy robot nodes in different rooms and select the goal points in the maps.



b) Robot node can autonomously transmit the face image to the HMD and ask the operator to recognize the detected face.

Figure 6. Shapshots from the graphical user interface of the software on the human node.

between those phases. It also ensures the robot navigates to the goal point.

V. Experiments and Results

In this section, we present our experimental results. Through the experiments, the network was configured with three robot nodes and a human node as our human-integrated MVSN. Each of these robot nodes could detect faces, stream images, publish the number of faces detected, create a 2D map using SLAM, autonomously navigate to a goal point, and autonomously reach the best viewpoint to detect faces. Working as a master node in the network, the human operator wearing the HMD could see what robots were seeing, deploy and control the network, and collaborate with robot nodes to recognize human targets. The graphical user interface of the software on the human node is shown in Fig. 6.

In our testing, we were able to successfully deploy the robots in a lab environment. These nodes were connected to a wireless network though a Wi-Fi router, which provides sufficient bandwidth. The MVSN was tested for both human-assisted deployment and collaborative surveillance.

A. Robot Deployment

There are three different modes of operation during robot deployment.

• *Mode 1*: A user can view images from all 3 robot nodes and can switch display mode: double panorama (360^0 view) mode which is good for exploring a remote location; panorama (180^0) mode which is good for face detection.

• *Mode 2*: A user can view maps from all 3 robot nodes. The robot's position was updated on the map and the operator can select the goal point by selecting the goal position they want the robot to reach. The robots can then automatically move to that location.

• *Mode3*: The human node controls an active robot, subscribes to both the map and the image of this robot, and drives the robot to explore the environment. Meanwhile, other robots can autonomously navigate to their goal points as shown in Fig. 6-a.

The robots correctly built and displayed a 2D map. The map is streamed at 480x480 at more than 6 frames per second with a delay less than 0.5 s. The video was also successfully streamed at 640x480 at more than 3 frames per second. There is also a slight delay of approximately 0.6 s between the robot video and the map feed when it is displayed on the HMD, resulting in Table I.

B. Collaborative Target Recognition

The operator could listen to requests for help from other robots while controlling one robot to explore the remote location. The robot nodes were able to successfully and accurately detect faces and draw a rectangle around them. They then sent the detected faces back to the human node where the operator recognizes them. The robot that has a higher number of detected faces is autonomously switched into the HMD. The operator can recognize the faces and send back the results to the robot as shown in Fig. 6-b.

TABLE I
TRANSMISSION DELAY BETWEEN ROBOTS AND HUMAN NODE

Mode	Image	Map
Mode 1	2.2 s	x
Mode 2	x	0.5 s
Mode 3	0.6 s	0.15 s

TABLE II
ACCURACY OF THE FACE DETECTION

Viewing Angle	4 feet	6 feet	8 feet	10 feet
0°	98%	67%	5%	0%
30°	95%	47%	2%	0%
45°	93%	43%	3%	0%
90°	98%	67%	5%	0%
100°	35%	21%	0%	0%
110°	0%	0%	0%	0%

The face detection was able to detect all faces within 4 feet of the robot when the face was looking at 90° or less angle from the camera. At 6 feet we saw a significant drop in performance, only detecting faces correctly in 67% of the frames. By the time we reached 10 feet, the algorithm could no longer detect faces. These results can be seen in Table II. It was also able to detect faces from only 0° to 90° off the horizontal plane of the camera.

VI. CONCLUSION AND FUTURE WORK

In this research, we proposed the collaborative architecture to develope a human-integrated mobile visual sensor network for surveillance applications. Three aspects of the system architecture were implemented: human-assisted robot deployment, human-robot collaborative surveillance based on the AHTD, and task manager. This case study of human-robot collaboration proves that it is possible to develop an MVSN that combines the complementary capacities of human and robots. The collaborative architecture was validated in a lab environment for human target recognition. Overall, this system could be deployed into the real world and have impact on applications such as surveillance, reconnaissance, search and rescue, and exploration. The future work will improve the following two aspects. First, the software should be able to detect other objects, depending on the application at hand. Second, in order to enhance the efficiency of collaboration, robot nodes should be able to understand and predict the human intentions through multimodal interaction that incorporates gestures, and gazes.

REFERENCES

[1] A. Bauer, D. Wollherr, and M. Buss, "Human-Robot Collaboration: A Survey," *International Journal of Humanoid Robotics*, vol. 05, no. 01, p. 47, 2007.

[2] T.W. Fong and I. Nourbakhsh, "Interaction Challenges in Human-Robot Space Exploration," *Interactions*, Vol. 12, No. 2, March 2005, pp. 42-45.

[3] R. Kleihorst, B. Schueler, A. Danilin, and M. Heijligers, "Smart camera mote with high performance vision system", *Proceedings of ACM SenSys Workshop on Distributed Smart Cameras (DSC '06),* 2006.

[4] G. Rodriguez and C. R. Weisbin, "A new method to evaluate human-robot system performance.," *Autonomous robots*, vol. 14, no. 2–3, pp. 165-78, 2003.

[5] J. B. F. Van Erp and H. a. H. C. Van Veen, "Vibrotactile in-vehicle navigation system," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 7, no. 4–5, pp. 247-256, Jul. 2004.

[6] A. Bechar and Y. Edan, "Human–robot collaboration for improved target recognition of agricultural robots," Ind. Robot, vol. 30, no. 5, pp. 432–436, 2003.

[7] D. Burke, N. Schurr, J. Ayers, J. Rousseau, J. Fertitta, A. Carlin, and D. Dumond, "Multimodal interaction for human-robot teams," *SPIE Defense, Secur. Sens.*, vol. 8741, no. International Society for Optics and Photonics, p. 87410E, May 2013.

[8] M. Lewis, M. Goodrich, K. Sycara, and M. Steinberg, "Human Factors issues for Interaction with Bio-Inspired Swarms," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, 2012, vol. 56, no. 1, pp. 61–64.

[9] L. Iocchi, D. N. Monekosso, D. Nardi, M. Nicolescu, P. Remagnino, and M. V. Espina, "Smart Monitoring of Complex Public Scenes Collaboration between Human Guards , Security Network and Robotic Platforms," in *2011 AAAI Fall Symposium*, 2011, pp. 14–19.

[10] I. Tkach, A. Bechar, and Y. Edan, "Switching Between Collaboration Levels in a Human--Robot Target Recognition System," *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews and*, vol. 41, no. 6, pp. 955-967, 2011.

[11] J. Casper and R. R. Murphy, "Human-robot interactions during the robot-assisted urban search and rescue response at the World Trade Center.," *IEEE transactions on systems, man, and cybernetics. Part B, Cybernetics*, vol. 33, no. 3, pp. 367-85, Jan. 2003.

[12] Nourbakhsh, I.R., K. Sycara, M. Koes, M. Yong, M. Lewis, and S. Burion. "Human-Robot Teaming for Search and Rescue." *IEEE Pervasive Computing* 4.1 (2005): 72-78. Print.

[13] K. Sycara, J. A. Giampapa, B. Langley, and M. Paolucci, "The RETSINA MAS , a Case Study," *Spinger-Verlag*, pp. 232–250, 2003.

[14] "ROS wiki," Webpage, http://www.ros.org/wiki/, accessed Jun. 2012.

[15] Gang Li, Jianhao Du, Chun Zhu and Weihua Sheng, "A cost-effective and open mobile sensor *platform for n*etworked surveillance", Proc. SPIE 8137, 813713 (2011).

[16] G. Grisetti, C. Stachniss, W. Burgard, "Improved Techniques for Grid Mapping With Rao-Blackwellized Particle Filters," *Robotics, IEEE Transactions on* , vol.23, no.1, pp.34-46, Feb. 2007.

[17] S. Thrun, D. Fox, W. Burgard, and F. Dellaert, "Robust monte carlo localization for mobile robots," *Artificial Intelligence,* 128(1-2):99–141, 2000.

[18] D. Fox, "Adapting the Sample Size in Particle Filters Through KLD-Sampling," *International Journal of Robotics Research*, 22, 2003.

[19] P. Viola and M. Jones, "Robust real-time object detection," International Journal of Computer Vision, 57(2), 137-154, 2004.

[20] Shi, J.; Tomasi, C., "Good features to track," *Computer Vision and Pattern Recognition, 1994. Proceedings CVPR '94., 1994 IEEE Computer Society Conference on*, vol., no., pp.593,600, 21-23 Jun 1994.