Sensor- and Plausibility-based Surveillance of Human/Robot-Workspaces

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Abstract

We introduce an approach of multi-view based surveillance of human/robot workspaces. Unknown objects within a robot workcell as e.g. humans are to be detected to avoid accidents with the robot. Therefore, two aspects are to be discussed: First, the reconstruction of regions within the robot workcell which are potentially occupied by unknown objects based on sensor data and additional plausibility criterions. Second, since the quality of reconstruction mainly depends on the placement of the sensors, objective functions and optimal values for this purpose are presented.

1 Introduction

Today there is a great demand in opening robot workspaces to humans. The latter are to work together with/parallel to robots, in order to ensure an ergonomic working environment, and to increase economic efficieny, still.

In contrast to preceding robot workspaces, the human resembles an object with apriori unknown movement, here. Despite this unknown object, accidents are to be avoided. Therefore, the region which could be occupied by the unknown objects needs to be sensed, e.g. by artificial skins, cameras and other sensors. To use each sensor's advantage, we focus on applying several sensors in a network. We are given a multi-perspective view of the work cell, identifying the regions occupied by unknown objects despite static and dynamic obstacles. This can also be seen as an approximation of the unknown object. An appropriate reaction for the robot is to avoid the occupied region or reducing the speed when approaching.

Next to the state of the art (Section 2), the remainder of this paper discusses two reconstruction methods (Section 3): The first one incorporates the reconstruction into an enclosed plausibility based approach and the second one utilizes a network of depth cameras. Of course, the quality of the approximation mainly depends on the placement of the sensors (Section 4).

2 Related Work

Human/Robot -Coexistence and -Cooperation While different sensor types and methods have been applied to enable human robot coexistence and cooperation, camera-based systems are appropriate for this application and a prominent field of reasearch, as in [26, 19, 8, 10].

Multi-View Reconstruction Multi view reconstruction has been considered for several years. At first, the primary goal was to create a three-dimensional geometric model of one or a few objects within the camera views. This goal allows to setup an optimal reconstruction environment, e.g. with only one single object to reconstruct and none occluding objects. In contrast, the robot workspace contains occluding objects and several objects to reconstruct.

For grayscale/color cameras, the visual hull [9] and the photo hull [18, 24] are – depending on the used information – the most accurate reconstruction consistent to all views. The depth hull concept [2] is the generalization of the visual hull concept for depth cameras.

Reconstruction algorithms use several data structures like voxels [18, 19], octrees [25, 19], conexels [3, 17], polyhedrons [9, 8] and occupancy grids [11, 14]. Todays GPU processing capabilities are integrated in those algorithms where possible [19, 23].

The problem of occlusions induced by statical objects in the reconstruction environment when using multi color-camera setups in conjunction with background subtraction approaches have been firstly tackled by so called occlusion masks [19]. These occlusion masks represent the projection of statical occluders and are interpreted as foreground additional to the foreground determined by the background subtraction. A more accurate consideration of occlusions, also of dynamical occluders and additional plausibility information about connected regions of humans has been utilized to improve the quality of the reconstruction [13, 16].

Sensor Placement/Optimization Optimization of sensors in a network, e.g. cameras, can usually be divided into two groups, one of the two is generally optimizing visibility or costs: There have been investigations about how to position and orient cameras subject to observing a maximal number of surfaces [15], and different courses of action [1, 7], as well as maximizing the volume of the surveillance area [21], or the number of objects [20]. Another common goal belonging to the first group is to be able to observe all items of a given set, but minimize the amount of cameras (including their positions), f.e. the "Art Gallery Problem" in [6, 20].

The other group of sensor network optimization is minimizing the error that is made regarding a special purpose of the network: The phrase 'Photogrammetric Network Design' is used to express minimizing the reconstruction error for several (three-dimensional) points by cameras for distances smaller than a few hundred meters (*close range photogrammetry*). The default assumption in this context, however, is that no occlusions occur, for details cf. [12, 22]. Optimally localizing an entire object which is not occluded is a task treated in [5].

In this paper we focus on evaluating the quality of sensor placement of a fixed amount of sensors according to the difference between target and its approximation made by a change-detection as a fusion method. This problem has been discussed in [27], but the author does not consider obstacles. In [4], static obstacles are considered, but a subset of cameras is chosen out of a preinstalled set instead of rearranging the whole set. In the section about quality, the attention is given to different types of objective functions, only restricted to a changed-detection system, followed by their optimal value.

3 Reconstruction

This section contains the description of two reconstruction methods. The first approach incorporates sensor data and environmental knowledge into the reconstruction, followed by plausibility checks. The second one describes a fusion technique utilizing a network of depth cameras to determine an approximation of the human.

The following definitions are fundamental to this (Section 3) and the next section (Section 4).

Definitions The region Z is the work cell of the robot. A *target* t is an object which is being approximated, we are approximating unknown objects, like humans, here. When speaking of the approximation R, a conservative reconstruction $t \subset R$ of the target is ment. I is the number of sensors being applied. A point $p \in Z$ is called *target-free*, if a sensor states the absence of the target. The region $F^{(i)} \subset Z$ are all the points being tagged as target-free by a chosen sensor $i \in \{1, ..., I\}$. The region $F = \bigcup_{i \in \{1,...,I\}} F^{(i)}$ are all the points being tagged as target-free at least once. The region $C^{(i)} = Z \setminus F^{(i)}$ is assigned as *possibly containing targets* by sensor $i \in \{1, ..., I\}$.

3.1 Plausibility Based

In this section one way to generate a high-quality approximation R is described. The process starts with a basic approximation R and improves that basic approximation step-wise, whereby each resulting improved approximation R_1, R_2 and R_3 represents an approximation R. R_3 will be the most accurate approximation R.

Without any precautions humans have to be assumed inside the entire robot workspace Z. Sensors can be used to detect the presence of humans, but also their absence. Common examples of sensors are grayscale/color-, infrared- and depth-cameras but also proximity sensors and sensor skins. More intelligent and complex sensors which consist of several basic sensors are also imaginable. In order to map sensor data to the robot workspace, these sensors must be calibrated and registered in a common coordinate system. Since sensors can be used to detect the absence of humans, the previously assumption that humans may reside inside the entire robot workspace can be reduced step-wise by applying the exclusion principle. Occlusions induced by non-human objects residing inside the robot workspace are handled implicitly since only those regions of the robot workspace $F^{(i)}$ may be assumed to be target-free (i. e. "human-free"), where a sensor $i \in \{1, ..., I\}$ is able to guarantee it. This is only possible if the sensor is able to detect the targets. After applying all sensor data regarding the absence of humans, only a region of the entire robot workspace $R_1 = Z \setminus \bigcup_i F^{(i)}$ is still assumed to potentially contain targets. R_1 is the first approximation of the target, achived only by applying sensor information.

Another step can be performed to enhance the reconstruction: It can be assumed that humans cannot enter a solid or an inaccessible object volume, such as a table, a rack or the robot. Thus these object volumes $O^{(j)}$, $j \in \{1, ..., J\}$ can be subtracted from the previously determined region $R_2 = R_1 \setminus \bigcup_j O^{(j)}$. R_2 is the second, more accurate approximation of the target.

A third step utilizes properties about connected regions of targets. Typically it can be assumed that humans cannot fly, so connected regions of R_2 which do not have contact to an object in direction of the gravity must be artifacts which can be excluded. Furthermore, humans have a minimum volume, so that connected regions of R_2 which have a lower volume can be excluded, too. As another example, humans have a certain minimal thickness, so that connected regions of R_2 which completely reside in a thinner hull around known objects like tables, racks or the robot could not contain a human and therefore must be artifacts. Further examples base on aspects like color, connection to the boundary of the considered reconstruction zone or on the distance between connected regions of two consecutive timestamps. Utilizing such kind of information about the targets (here the humans) allow to check the plausibility of connected regions and the identification and elimination of artifacts $A^{(k)}$, $k \in \{1, ..., K\}$. Thus the most accurate approximation is achived by removing identified artifacts $R_3 = R_2 \setminus \bigcup_k A^{(k)}$.

A current implementation of the system is based on a voxel representation. In a concrete setup, which is illustrated in Figure 1, in a human/robot-context of the size $6\,\mathrm{m} \times 6\,\mathrm{m} \times 3,5\,\mathrm{m}$ the system consists of eight color cameras, nine up-to-date computers (CPU: Quad-Core, 2.1-2.6 GHz; Mem: 2-8 GB) and a voxelspace-resolution of $126 \times 90 \times 66$ and has a performance of about 3 to 4 Hz.

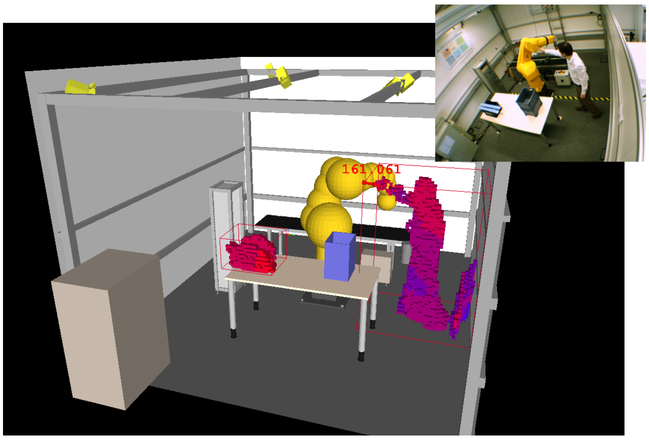

Figure 1: Image of example setup (upper right) and resulting reconstruction (red voxels) of one surveillance cycle.

3.2 Depth Image Based

Depth Images Depth-cameras like ToF-cameras or Kinect sensors directly provide depth images at a sufficient high resolution and framerate for real time surveillance tasks. As those cameras use an active measurement principle, interferences between multiple cameras in the common part of their visible volumes have to be considered regarding the placement of the cameras and the measurement errors while processing the surveillance. Grayscale/color- or infrared-cameras can be treated as depth-cameras with binary depth measurement using an applied change detection method. Their depth images results of the three dimensional projection of the segmentation images provided by the change detection method [8].
The main advantage of depth-cameras is, that a single depth image already provides 2,5D geometrical data to divide the camera's visible volume into a free region $F^{(i)}$ in between the camera center and the measured surface and an occluded region O else.

Object Detection and Data Fusion Since no information of t within O is derivable of the depth image itself, complete O within Z is to be approximated. A CAD model of the geometry of Z is assumed to be known, thus for all depth-cameras in the sensor network depth images of the empty robot workcell can be generated as reference images for a background subtraction method. The differences within the segmentation image of the background subtraction method are directly providing O as the possibly target-containing region within Z: $C^{(i)} = O \cap Z$. A lossless representation of $C^{(i)}$ can be achieved by using its bounding surface using i.e. polyhedrons or by its volume using i.e. an occupancy grid.
Depending on the position, orientation and aperture angle of a depth-camera, only a part of Z is within the visible volume. For a better coverage of Z and a more accurate approximation of the targets within and a decrease of their occlusions, the segmented depth image data of multiple depth-cameras is to be fused, leading to an approximation of the depth hulls, denoted as C.

Detected Object Classification The robot and its occlusion in all depth images are also part of C. Since the robot model is known the robot occlusion M can be calculated. Assuming that no t is within M at the start of the surveillance, no t can approach and enter this occlusion undetected while the surveillance is operating. The part of C outside M now is the most accurate conservative approximation of depth image data: $R = C \backslash M$
Depending on the application the minimum distance between R and the robot model for an arbitrary robot configuration or predefined safety zones can be calculated.
The setup for an example application is described above and used with four PMD cameras instead of the color cameras. A distance velocity control of the robot is performed using polyhedral representation of C [8]. The performance of the surveillance cycle is about 3 to 5 fps.

4 Quality of Sensor Placement

In order to utilize a sensor network optimally, the sensors' positions or other parameters need to be chosen carefully. Here is an approach in evaluating the quality of a surveillance system with a changed-detection method, such as the two background-subtraction methods in Section 3.
Therefore, the sensor data fusion is adressed, shortly. After that the quality is formulated in several objective functions. In the end, we introduce optimal values of this quality which can further be used as stopping criteria for an optimization.
We will use the general term "sensor" instead of one particular device, e.g. "depth camera". The quality of the sensor placement discussed here does not consider interferences of active sensors' signals, however.

Sensor data processing and Fusion In a change detection method with every sensor data the sensor divides the surveillance area entirely into the following regions: An undetectable one, where no information can be derived by the sensor (this could be the room behind a wall in a background-subtraction-method); An identical region, where nothing has changed (e.g. according to a prechosen reference state), also called "target-free" in the beginning of Section 3 (notation F^i, being the i-th sensor); and a changed region, something must have come up, here.
For this optimization to work, we need to be given the following three combined sections of the work-cell: Next to the section F, where one of the sensors $1, ..., I$ states the description "target-free", the other significant section is "the over-all undetectable section" U where all of the sensors state "undetectable". The last section is called the "changed section", elsewhere. A target with unknown movement, as a human happens to be, will be included in these last two sections, as it moves either in detectable

range and is mapped to "changed" or moves out of this range into the "undetectable section". So the remaining sections apart from F are considered as the approximation $R := Z \setminus F$ of the target t.
Obstacles are objects that are no targets. The consideration of obstacles lies in the implementation of this mapping (the change-detection-system).

Quality of Sensor Placement The quality of sensor placement can be formulated as an objective function. We have implemented the objective function f as a simulation of the work-cell with a voxel representation. There, each voxel $V_{(n)} \subset Z$, $n \in \{1, ..., N\}$ in a 3-dimensional voxelspace consisting of N voxels is being tagged as part of one of the sections "target-free", "changed" or "undetectable", which is illustrated in Figure 2. After such a fusion, the following objective functions appear as reasonable:

1. Maximizing visibility is a common request. This comes along with minimizing the over-all undetectable section. Thus, the quality of the system needs to be measured by the volume of such an undetectable section. The objective function, here, could be the sum of voxels which are marked as over-all undetectable.

$$f^{(1)} = \sum_n \begin{cases} 1, & V_n \hat{=} \text{“undetectable”} \\ 0, & \text{else} \end{cases}$$

2. Also, every voxel could be weighted by its importance $\omega(n), \quad n \in \{1, ..., N\}$ instead of weighted by a constant parameter like 1.

3. Minimizing the error of the system of surveillance is another significant goal. We want to reconstruct the target, represented by the non-target-free approximation R, here, so in case of an optimization, the difference between the approximation and the target needs to be minimized. Furthermore, having constructed R as an all times conservative approximation of the target $t \subset R$, it suffices to minimize the approximation. Here, the quality of the system is measured by the volume of changed and undetectable sections. Both the tags "changed" and "undetectable" are worth distinguishing, as, e.g., an emphasis could be put on not leaving as many points undetectable as changed.

$$f^{(3)} = \sum_n \begin{cases} \omega_1, & V_n \hat{=} \text{“changed”} \\ \omega_2, & V_n \hat{=} \text{“undetectable”} \\ 0, & \text{else} \end{cases}$$

4. As this is a safety issue, is it not too blue-eyed to assume a point is target-free (and belongs to F) if only one sensor states it? Since the definition of the target-free section F seems not conservative enough this definition can be restricted. In order to measure the quality of the change-detection-method the same definition of the target-free section F and thus the approximation R should be used in both the reconstruction and the evaluation, however.

Say, instead of just one, at least two sensors need to state "target-free" at one point so that it belongs to an over-all target-free section F. The more sensors the definition requires, the smaller the target-free section becomes, and the larger the approximation of the target $R = Z \setminus F$. Thus, the approximaton will be better in the sense of "more conservative" than the one with only one sensor in the previous approach. But it will be worse in accuracy.
Let us assume that we have used the one-sensor-definition of F, called F_1, for the evaluation of the system. But we have used the two sensor-definition $F_2 \subset F_1$ for the approximation $R := Z \setminus F_2$. Then, the inclusion $Z \setminus F_1 \subset R$ holds true. In the sense of an accurate approximation of the target we have overestimated the reconstruction.

Optimization Shifting one of the sensors a little bit, could cause a different target-free section. Not only altering position is causing changes of the sections, but also altering orientation, zoom, opening angle, etc. Thus, all the sections, and thereby the approximation of the target, also, can be parameterized by a vector of parameters v:

$$R = R(v), \quad F = F(v), \quad U = U(v)$$

The parameters in the vector v, which we have specified to parametrize the approximation, allow us to be the degrees of freedom in an optimization. Such an optimization is built from two parts, an optimization algorithm and an objective function. In sensor network optimization, the implementation of the objective function is more complex, by far. Above, we have put some thought into this objective function in terms of the quality of the change-detection-method. The parameter vectors of the best quality – according to the objective function – are used to generate a new parameter vector, afresh, by a technique specified in the optimization algorithm. The algorithm continues until stopping criteria are met. In the next paragraph, we consider criteria which correspond to the chosen objective functions.

Stopping Criteria Stopping criteria tell the optimization algorithm when to stop. Next to limiting the length of time or the amount of iteration cycles, the intrinsic hope is to reach the optimum. Alternativly, a value, that is in an ϵ-neighbourhood of the optimum. But what could an optimum f_{opt} of the discussed objective functions be like? Each objective function results in a different optimal value:
1. When minimizing the undetectable section, first, suppose there are no objects in the work cell. The optimal value that can be reached is zero, as it would be best to distinguish the whole undetectable section. The inside of static objects cannot be eliminated by sensors utilizing a change-detection method. It is always undetectable. Thus, the optimal value has to be chosen as the inside volume ϵ_s of static objects.

$$f^{(1)}_{opt} = \epsilon_s = \sum_n \delta_s(n)$$

As a preperation step for the second objective function, the *static indicator* δ_s is introduced for a given voxel $n \in \{1, ..., N\}$ with:

$$\delta_s(n) := \begin{cases} 1 & \text{voxel } n \text{ in obj.} \\ 0 & \text{else} \end{cases}$$

2. If these voxels are weighted by $\omega(n), \quad n \in \{1, ..., N\}$ the optimal value would be

$$f_{opt}^{(2)} = \sum_n \omega(n) \cdot \delta_s(n)$$

3. When minimizing the difference between approximation and targets, the inside of targets cannot be eliminated as it is always changed or undetectable, no matter how many sensors there might be placed. Thus, the optimal value has to be chosen according to their volume and the volume of possible static occluders. Thus, we define the static indicator δ_s as above and the target indicator δ_t, accordingly.

The changed section is weighted by ω_1 and the over-all undetectable section by ω_2. Static objects only cause undetectable voxels $\delta_s \cdot \omega_2$, targets cause both changed and undetectable voxels. But what is it weighted with, if the weights ω_1, ω_2 depend on the arrangement of sensor, static occluders and targets, and therefore on the sensor parameters in v? In a minimization, the optimal weight would be $\min\{\omega_1, \omega_2\}$. This leaves us the optimal value of

$$f_{opt}^{(3)} = \sum_n \omega_2 \cdot \delta_s + \min\{\omega_1, \omega_2\} \cdot \delta_t(n)$$

4. When retaining the same weights, the fourth objective function can be stopped with the same stopping criteria as the privious one.

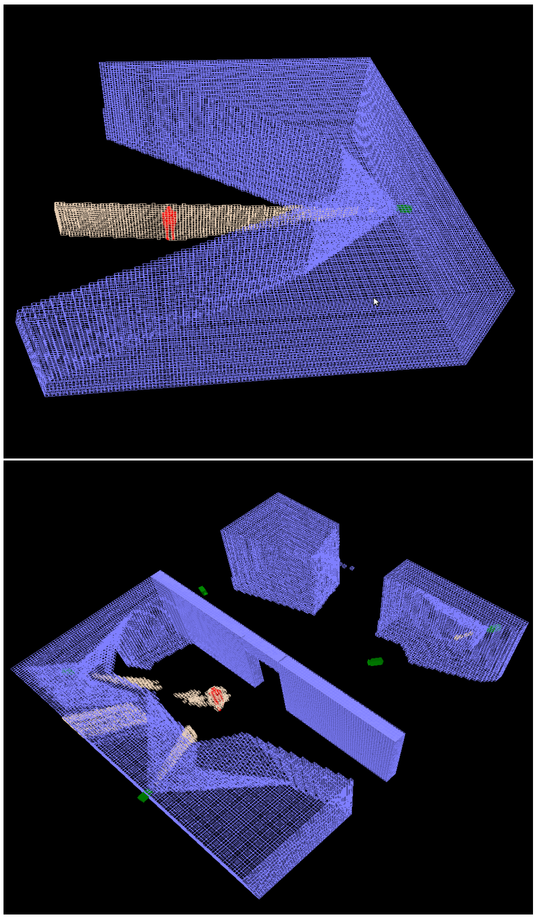

Figure 2: Each voxel in a 3-dimensional voxelspace is being tagged as part of one of the sections "target-free" (free space), "changed" (beige) or "undetectable"(blue). The unknown target is the red human figure. A static obstacle is the grey wall. First picture: One camera (green). Second picture: five cameras.

5 Conclusions and Future Work

The paper introduces a surveillance approach for Human/Robot-Workspaces using a camera network. In order to safeguard the robot, all unknown objects within the workspace are to be detected and the region possibly occupied by them is to be reconstructed of the camera data. In contrast to traditional camera-based multi-view-reconstruction methods, here, environmental occlusions within human/robot workspaces have to be considered. Two methods for reconstruction are presented for this purpose. Optimal placement of the cameras is crucial for a good quality of approximation in the reconstruction. Therefore, an optimization is introduced and applied to get a good configuration of the camera network.

As future work for the optimization, a native desire also could be "minimizing the false alarms of a system but still ensuring safty". How can an error be minimized, that is made by the system regarding such a purpose? The first approach is to integrate the cause of such an error, in a change-detection-system the obstacles to the target. The second approach is simulating not only the sensor system, but the purpose action, as well.

References

[1] R. Bodor, A. Drenner, P. Schrater, and N. Papanikolopoulos. Optimal camera placement for automated surveillance tasks. *Journal of Intelligent and Robotic Systems*, 50(3):257–295, 2007.

[2] Alexander Bogomjakov and Craig Gotsman. Reduced depth and visual hulls of complex 3d scenes. *Comput. Graph. Forum*, 27(2):175–182, 2008.

[3] Josep R. Casas and Jordi Salvador. Image-based multi-view scene analysis using 'conexels'. In *Proceedings of the HCSNet workshop on Use of vision in human-computer interaction - Volume 56*, 2006.

[4] A.O. Ercan, A.E. Gamal, and L.J. Guibas. Camera network node selection for target localization in the presence of occlusions. In *In SenSys Workshop on Distributed Cameras*, 2006.

[5] A.O. Ercan, D.B. Yang, and A.E. Gamal et al. Optimal placement and selection of camera network nodes for target localization. *Distributed Computing in Sensor Systems*, pages 389–404, 2006.

[6] U.M. Erdem and S. Sclaroff. Optimal placement of cameras in floorplans to satisfy task requirements and cost constraints. In *OMNIVIS Workshop*. Citeseer, 2004.

[7] L. Fiore, G. Somasundaram, and A. Drenner et al. Optimal camera placement with adaptation to dynamic scenes. In *IEEE International Conference on Robotics and Automation*, 2008.

[8] M. Fischer and D. Henrich. Surveillance of robots using multiple colour or depth cameras with distributed processing. In *ACM/IEEE International Conference on Distributed Smart Cameras*, 2009.

[9] Jean-Sebastien Franco and Edmond Boyer. Efficient polyhedral modeling from silhouettes. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 31:414–427, 2009.

[10] Thorsten Gecks. *Sensorbasierte, echtzeitfähige Online-Bahnplanung für die Mensch-Roboter-Koexistenz*. PhD thesis, Universität Bayreuth, März 2011.

[11] Li Guan, J.-S. Franco, and M. Pollefeys. 3d object reconstruction with heterogeneous sensor data. In *International Symposium on 3D Data Processing, Visualization and Transmission*, 2008.

[12] R.I. Hartley. Estimation of relative camera positions for uncalibrated cameras. In *Computer Vision-ECCV'92*, 1992.

[13] Dominik Henrich, Markus Fischer, Thorsten Gecks, and Stefan Kuhn. Sichere mensch/roboter-koexistenz und kooperation. In *ROBOTIK 2008*, München, Germany, Juni 2008.

[14] Martin Hofmann, Moritz Kaiser, and Hadi Aliakbarpour et al. Fusion of multi-modal sensors in a voxel occupancy grid for tracking and behaviour analysis. In *12th International Workshop on Image Analysis for Multimedia Interactive Services (WIAMIS)*, 2011.

[15] R.J. Holt, M. Hong, R. Martini, I. Mukherjee, R. Netravali, and J. Wang. Summary of results on optimal camera placement for boundary monitoring. In *Proceedings of SPIE*, volume 6570, 2007.

[16] S. Kuhn and D. Henrich. Multi-view reconstruction of unknown objects within a known environment. In *5th International Symposium on Advances in Visual Computing*, ISVC '09, 2009.

[17] S. Kuhn and D. Henrich. Multi-view reconstruction in-between known environments. Technical report, Lehrstuhl für Angewandte Informatik III, Universität Bayreuth, 2010.

[18] Kiriakos N. Kutulakos and S. M. Seitz. A theory of shape by space carving. *International Journal of Computer Vision*, 38, 2000.

[19] A. Ladikos, S. Benhimane, and N. Navab. Efficient visual hull computation for real-time 3d reconstruction using cuda. In *Conference on Computer Vision and Pattern Recognition Workshops*, 2008.

[20] A. Mittal and L.S. Davis. A general method for sensor planning in multi-sensor systems: Extension to random occlusion. *International Journal of Computer Vision*, 76(1):31–52, 2008.

[21] A.T. Murray, K. Kim, J.W. Davis, R. Machiraju, and R. Parent. Coverage optimization to support security monitoring. *Computers, Environment and Urban Systems*, 31(2):133–147, 2007.

[22] G. Olague and E. Dunn. Developement of a practical photogrammetric network design using evolutionary computing. *The Photogrammetric Record*, 22:22–38, 2007.

[23] A. Schick and R. Stiefelhagen. Real-time gpu-based voxel carving with systematic occlusion handling. In Joachim Denzler, Gunther Notni, and Herbert Süsse, editors, *Pattern Recognition*, volume 5748 of *Lecture Notes in Computer Science*, pages 372–381. 2009.

[24] S. M. Seitz, B. Curless, and J. Diebel et al. A comparison and evaluation of multi-view stereo reconstruction algorithms. *Computer Vision and Pattern Recognition*, 1:519–528, 2006.

[25] Richard Szeliski. Rapid octree construction from image sequences. *CVGIP: Image Understanding*, 58(1):23 – 32, 1993.

[26] Stefan Thiemermann. *Direkte Mensch-Roboter-Kooperation in der Kleinteilmontage mit einem SCARA-Roboter*. PhD thesis, Universität Stuttgart, 2005.

[27] D.B. Yang, J. Shin, and L.J. Guibas et al. Sensor tasking for occupancy reasoning in a network of cameras. In *Int. Conf. on Broadband Communications, Networks and Systems (BaseNets)*, 2004.