Model Guided Multimodal Imaging and Visualization for Computer Assisted Interventions

Nassir Navab
Computer Aided Medical Procedures (CAMP), Technical University Munich
Boltzmannstr. 3, 85748 Garching b. Muenchen, Germany
navab@cs.tum.edu

Abstract

In this short paper, we[1] try to present a summary of some of our activities relevant to computer assisted interventions and computer vision. References to published work in major journals and conferences allow the reader to get access to more detailed information on each subject. It was not possible to cover all aspects of our research within this paper, but we hope to provide an overview on some of these within this short paper. The readers are also invited to visit our web-site at (http://campar.in.tum.de) to get more information on aspects of our work, which are not presented here.

1 Introduction

Since the discovery of X-ray imaging at the end of 19th century medical images have played crucial role in patient diagnosis and treatment. Last decades of twentieth cen-tury gave birth to a large number technologies and devices for physiological sensing and imaging. However in the absence of well-established scientific models of diagnosis and treatment, and in an environment where no concept and solution integrating patient specific models and process modeling was available, the sensing and imaging modalities where developed as general tools. This of course translates into sensing and imaging systems, which are not optimized and cause unnecessary side effects. For example, the medical imaging devices often provide images of the anatomy without giving the option to their users to specify a particular diagnostic or treatment objective. Even if the physician is interested only in particular qualitative or quantitative information in regard to a particular anatomy or progress of a particular disease, the imaging and sensing modalities are often only providing general anatomical or functional information.

Our objective is to create strong partnerships between clinicians, scientists and industry to define the path towards revolutionizing the design and development of physiological sensing and imaging devices in order for them to be based on and to contribute to the patient's physiological models as well as complex modelling of diagnostic and therapeutic procedures. We also focus on design of novel sensory and imaging technologies, which consider the acquisition and modelling of information across scales and close the loop between diagnosis and therapy. The automatic generation of customized detailed view of the sensory and imaging information as well as diagnosis and therapeutic procedure to physicians as well as patients is also within our focus.

[1]The author would like to thank Stefanie Demirci, Stefan Hinterstoisser, Diana Mateus, Tobias Blum, Lejing Wang, Tobias Lasser, Darko Zikic, Ben Glocker, Christian Wachinger, and Alexander Ladikos for their valuable input to different sections of this overview paper.

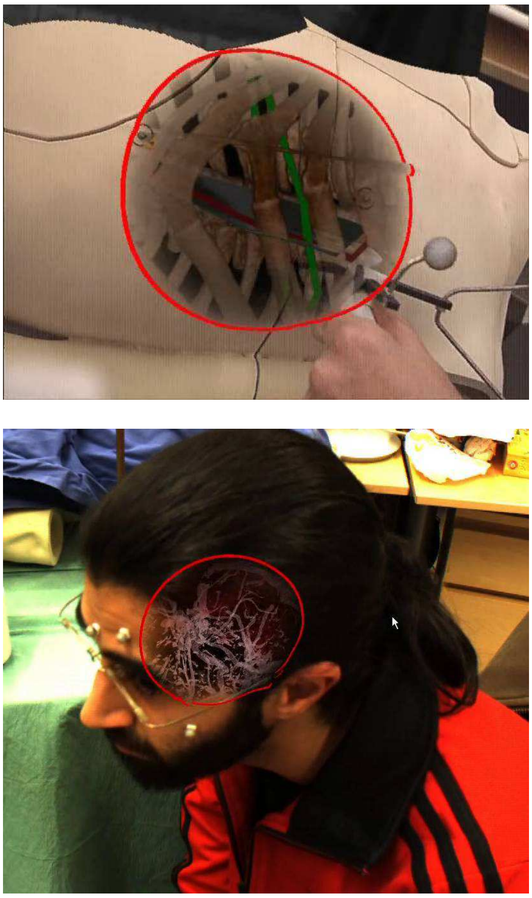


Figure 1. Medical Augmented Reality in Abdominal (left) and Brain (right) Applications

In this short overview paper we present a summary of some of our activities in the medical field as well as some of our research in computer vision. We believe in a strong synergy between computer vision and computer assisted inteventions. By focusing our active research in both fields, we are able to directly benefit from and transfer new results.

2 Surgical workflow recovery and analysis

Computers can aid the surgeon during a running surgery in many ways. However, one crucial point for using e.g. navigation systems, intra-operative imaging, augmented reality visualization or other computer aided solutions is to optimally integrate them into the workflow. When a novel technology is not well integrated into the surgical workflow and when using it complicates and lengthens the surgery it will not be used. Therefore such technologies have to be well integrated and have to provide the right information at the right time. One important issue in order to do this is the recovery an modeling of surgical workflow. We then need systems that can automatically recognize workflow steps. If we continuously detect the workflow step of a running surgery, we will be able to provide the right information at the right moment with appropriate visualization. We have developed methods to automatically generate temporal models of the workflow of a minimally-invasive surgery based on the instruments that are used during the surgery [2, 41]. We have shown that when using such a model, we can detect the current phase of a running surgery based on the instruments that are used. Another application of such a model would be to predict the remaining time of a running surgery in order to call the next patient automatically. Furthermore such methods can be used to automatically generate human-understandable statistical representations of the workflow [11] for training or analysis of surgical procedures. Such methods can also be used when other information than instrument usage is available in the operating room. For exmaple, we have shown that it is possible to model surgeries and detect the current phase based on images from multiple external video cameras [42], accelerometers that are attached to the arms of the surgeon [1] and/or laparoscopic video [9].

3 Medical Augmented Reality

Medical augmented reality (AR) has been an active subject of research in the last two decades. In the beginning, the focus was mainly on technical issues like tracking, calibration and display devices. These technologies matured in the last years and recent research focuses more on topics like usability for specific applications, user acceptance and perceptual issues. We have presented different methods to improve usability of medical AR systems, especially for systems using a head-mounted display (HMD). The virtual mirror [6] is a new interaction paradigm that allows a surgeon to take an additional viewpoint on critical structures. The user can freely move the virtual mirror inside the patient to obtain a second view of important structures, while preserving the necessary alignment between real and virtual. Regarding issues related to depth perception, when simply augmenting virtual information onto the human body, the user does not have a proper depth perception as this visualization suggest that the virtual object is in front of real objects. Contextual in-situ visualization [7, 5] significantly improves the depth perception of surgeons by superimposing augmented objects as if the user would see them through a kind of window into the body. Furthermore we have shown that missing out-of-focus blur reduces the viewing comfort in AR system and have presented a first system that can add artificial out-of-focus blur [12].

Based on this basic research we have been able to develop AR systems that are more intuitive and less stressful to use, providing additional information than traditional visualization methods. We have presented a HMD-based AR system for trajectory planning in neurosurgery [47], a very delicate task as no important structures must be injured. AR can help by providing intuitive visualization during the planning. Also for training we see a great potential of AR and have developed an AR system to teach the use of ultrasound (US) [10]. Learning how to correctly use US is very difficult as it is user dependent and US images are hard to interpret. The AR system allows seeing the US slice in-situ and provides a review environment for trainees where their own performance can be compare visually with the performance of an expert.

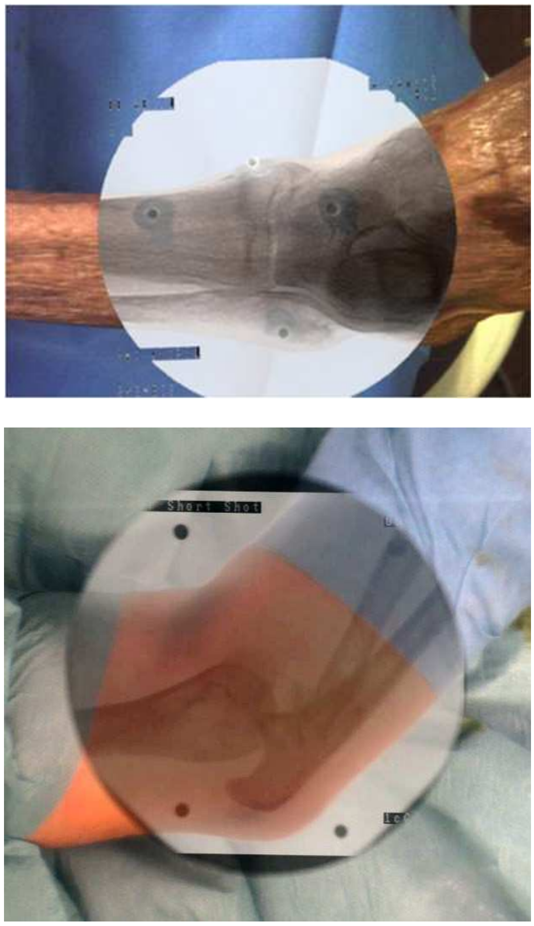
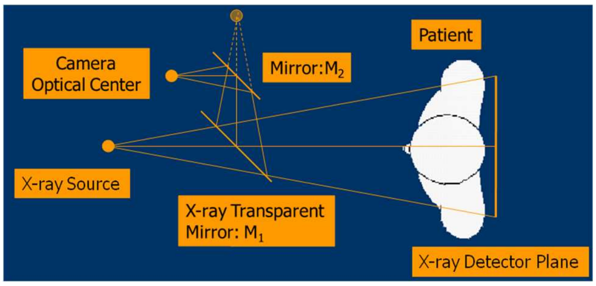


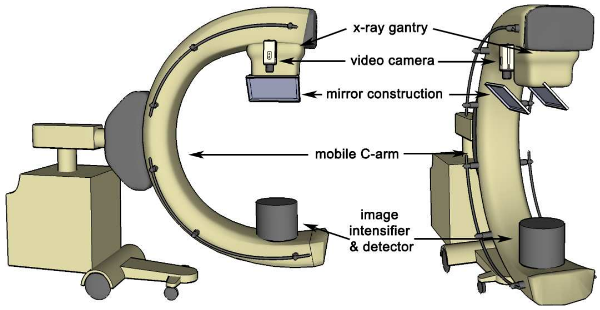
Figure 2. CamC imaging provides significant benefits for orthopaedic and trauma surgery.

4 CAMC

The Camera Augmented Mobile C-arm (CamC) system extends a standard mobile C-arm by a video camera and mirror construction [38, 39]. Thanks to the mirror construction and a one-time calibration of the CamC system, the acquired fluoroscopy images are co-registered with the video images without any further calibration or registration during the intervention, providing a geometrically correct overlay. The design and imaging concept of CamC are visualized in Fig. 3. This allows the CamC system to provide a real-time intra-operative visualization of patient skin surface together with underlying bone structures, i.e. an X-ray and video image overlay. A workflow based method has been applied to evaluate the clinical impact of the CamC system by comparing its performance with a conventional system, i.e. standard mobile C-arm [62]. Interlocking of intramedullary nails on animal cadaver is chosen as a simulated clinical model for the evaluation study. Experimental results show that it takes significantly less radiation exposure whereas operation time for the whole interlocking procedure and quality of the drilling result are similar, using the CamC system compared to using the standard mobile C-arm. The X-ray and video image overlay of the CamC system enables many novel solutions for advanced C-arm X-ray imaging and surgical navigation. The problem of positioning mobile C-arms repositioning during surgical procedures currently requires time, skill and additional radiation. A visual servoing based method proposed by Navab



(a)



(b)

Figure 3. Design (a) and imaging concept (b) of CamC

et al. [40] uses a CamC system to speed up the procedure, simplify its execution and reduce the necessary radiation for C-arm positioning. The CamC system provides an accurate positioning and guidance of instruments in 2D. However, no depth control was possible. As an extension to the CamC system, Traub et al. [48] presented a multi-view opto-xray imaging system that is also capable of depth control during trauma surgery and orthopedic procedures using only one additional X-ray image and a second video camera that is rigidly attached to the C-arm. Multiple C-arm X-ray images are acquired in order to help clinicians evaluate long bone geometry. However, impromptu and accurate intra-operative evaluation based on separated individual images remains challenging. It would be desirable to present clinicians with an X-ray panorama by stitching the individual X-ray images. Wang et al. developed a method [59, 60, 61] to create parallax-free panoramic X-ray images without the requirement of overlapping X-ray regions using the CamC system.

5 freehandSPECT

Patient tailored surgery and quality assurance is prompting the development of intra-operative imaging systems. In the particular case of radio-guided surgery, 3D nuclear imaging systems could enable navigated image-guided resection of radioactively labelled lymph nodes, tumors and metastases. This would allow the precise transfer of the unique information of nuclear imaging into surgery. Freehand SPECT is a novel imaging modality that enables 3D nuclear imaging in the operating room [64]. In Freehand SPECT, hand-held 1D gamma detectors are tracked with spatial positioning systems in order to reconstruct localized 3D SPECT images using series expansion methods adapted to ad-hoc random detector geometries and sparse, limited-angle and irregularly sampled data.

A first prototype of Freehand SPECT was introduced in 2007 [63]. Development since then has focused on guiding the freehand acquisitions to ensure reproducibility [35], on the reconstruction method to improve accuracy and sensitivity [36, 65] as well as on hardware developments to enable the translation of the technology into actual clinical practice [64]. Current research is focusing on substituting the 1D gamma detectors with hand-held, miniaturized 2D gamma cameras, as well as investigating the potential of high-energy gamma probes to visualize common high-energy tracers like F18-FDG intra-operatively in 3D.

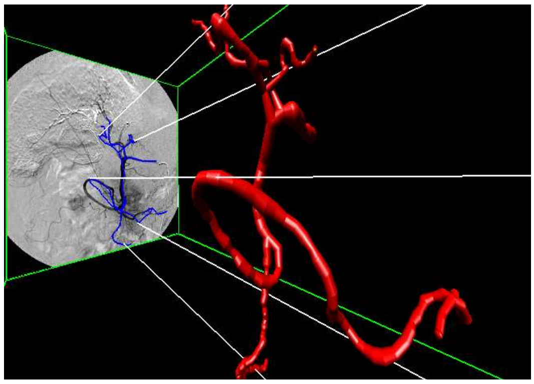
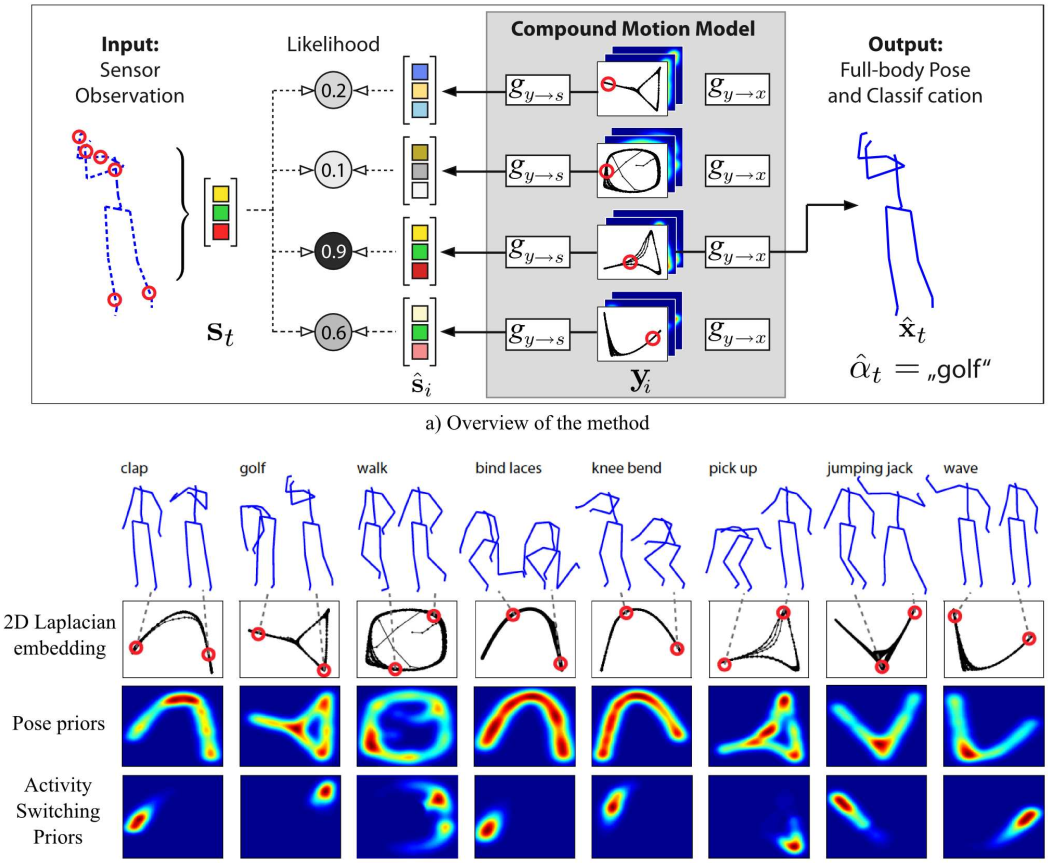


Figure 5. Visualization of the 2D/3D scenario: Our approach estimates the 3D deformation based on the 2D projection image.

6 Deformable Medical Image Registration

Deformable registration seeks to estimate the transformation which relates the corresponding structures in two given images. This is one of the most important pre-processing steps for a large number of medical applications. Examples range from the fusion of information from different modalities for diagnosis and treatment, to construction of anatomical atlases in the field of computational anatomy. Especially the multi-modal registration problem is still an active and challenging research topic due to the complex structure of the associated optimization problem.

An important aspect in image registration algorithms is the optimization of the objective function. Accurate, reliable, and robust registration demands powerful optimization strategies due to the inherent challenging problem of automatically finding correspondences between images. We have exploited discrete labeling of Markov random fields (MRF) as a novel optimization paradigm for solving registration. Discrete MRFs have been widely used in computer vision for image denoising or segmentation. The big challenge, however, in using MRFs for the task of registration is the gap between the discrete nature of labeling problems and the continuous transformation parameters to be estimated in registration. Our general framework bridges this gap and allows to represent both linear [16, 69] and non-linear [15] registration as graph labeling problems based on iterative label space refinement strategies. Our dervied algorithms are computationally efficient, avoid local minima through large neighborhood search, and yield high-accurate and robust registration results. We have



a) Overview of the method

b) Motion Models for 8 activities

Figure 4. Human Motion Analysis via Manuifold Learning

applied our methods to various applications such as multi-modal registration [14, 68], atlas-based segmentation via registration [17], or deformable stitching for whole-body MRI [49].

Besides the derivative-free MRF-based methods, we have also proposed a number of modifications to differential methods which considerably improve the efficiency compared to the standard approaches. In the initial work on this subject, we observed and analyzed the behavior that some derivative-based methods do not perform evenly in the whole image domain [73], and achieve a much faster convergence locally in image parts with strong intensity gradients (local gradient bias). In further work, we proposed a number of optimization schemes, which reduce this unwanted effect for arbitrary similarity measures. In [71], we propose an optimization based on the concept of *natural gradients*, inspired by approaches from the machine learning community. In [67], we propose a scheme based on a heuristically derived preconditioning term, and a generalizing framework unifying a large number of different registration methods. By providing a connection to preconditioning in [67], we demonstrate that the negative local gradient bias is related to the condition of the registration problem. In consequence, optimization methods which employ a preconditioning, such as Newton-type methods will suffer less from the local gradient bias. This provides further insight into the performance of existing registration methods, such as the classical method of Horn and Schunck [72].

The registration of 3D vasculature to 2D projections is the key for providing advanced systems for image-based navigation and guidance. Building upon our original work on 2D-3D registration of vascular structures in [18, 19], which perform a linear registration, we developed the first system capable of deformable 2D-3D registration of vascular structures [70, 20]. Due to the addition of regularization terms in 3D, our approach was capable of approximating the correct 3D transformation even in the challenging single-view scenario (see Fig. 5). We further improved the original deformable approach in by eliminating the need for manual interaction during the medical treatment and improving the performance [21]. This is achieved by a novel data term, which avoids does not require a segmentation of the 2D vasculature.

7 Ultrasound Mosaicing & Motion Modeling

Ultrasound mosaicing adresses the combination of multiple ultrasound frames. The usage of ultrasound mosaicing provides the sonographers not just with a compounded volume of higher quality; recent studies also state a couple of other clinical advantages that come along with the extended FOV. First, the spatial relationship among structures that are too large for a single volume is easier to understand. Second, sonographers have the flexibility to visualize anatomical structures from a variety of different angles. Third, size and distance measurements of large organs are possible. Fourth, individual structures within a broader context can be identified by having an image of the whole examination area. And last, because of the increased features in the compounded view, specialists that are used to other modalities than ultrasound can better understand the spatial relationships of anatomical structures; helping to bridge the gap between the modalities and making it easier to convey sonographic findings to other experts.

We propose to apply simultaneous registration techniques to find the correct alignment of the images [56, 57]. We derive a novel extension for multivariate similarity measures and deduce efficient optimization techniques [53]. Moreover, we devise ultrasound specific similarity measures that deal with the particularities of ultrasound: viewing-angle dependency and contamination with speckle noise [52]. In a recent study, we show that speckle statistics are better conserved by applying the 2D analytic signal [50]. Finally, we developed a new approach towards the fusion of the intensity information by estimating the acoustic impedance [55].

Next to mosaicing, we are equally interested in motion modeling from ultrasound. Imaging organs in thorax and abdomen is affected by respiratory motion. For consecutive processing steps, it is often necessary to assign to each image its corresponding breathing phase. In our work, we developed a purely image-based gating system based on manifold learning for the creation of 4D ultrasound [58]. This no longer necessitates the application of external gating systems, which have long setup times, prolong the overall acquisition, are costly, and consequently, rarely used in practice. Moreover, we designed a new approach for the registration of time-resolved images by applying a groupwise registration method [66].

8 Manifold Learning

Computer-aided diagnosis and procedures often imply processing large and high dimensional datasets. Visualization and analysis of such data can be very time demanding for physicians but also very computationally expensive. Fortunately, in many cases the relevant information for an application can be represented in lower dimensional spaces. This is possible using dimensionality reduction methods to decrease the processing time and facilitate any posterior analysis. Up to recent years, dimensionality reduction has relied mainly on linear methods, such as Principal Component Analysis (PCA). Linear methods are however not suitable for handling non-linear complex relationships among the data samples. Non-linear approaches based on manifold learning are a good alternative for dimensionality reduction in such cases [37]. They are simple, flexible, account and have a closed form solution. Furthermore, medical datasets often verify the manifold assumption, i.e. the assumption that the data lies close to a manifold. For instance, the contiguous frames of a video or the slices of a volume vary smoothly; also, the continuous deformation of an organ's shape over time can be considered to form a manifold; and, the variations of an organ over a population can also be expected to lie on a manifold. These facts have recently raised interest in using manifold learning methods for a variety of applications.

We have studied the use of manifold learning for different applications in Computer-aided diagnosis and procedures. Clustering and classification after reducing the dimensionality with manifold learning is usually simpler and more efficient. In [4], images of an endoscopic video were visualized and analyzed in such a dimensionality-reduced space. The obtained representation is suitable for faster navigation in the video, and also for clustering similar scenes or similar imaging conditions. We have also employed manifold learning for classification of biomedical data [51, 43].

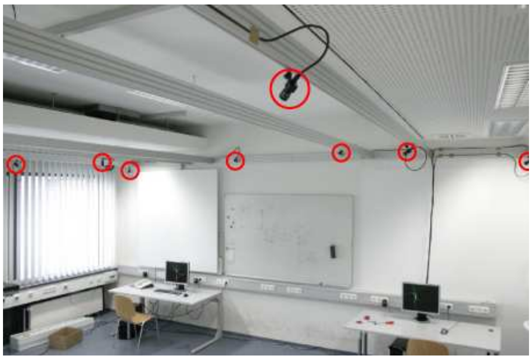


Figure 6. Camera setup of the reconstruction system in our lab [31] and in an interventional room [33]

Manifold learning is also useful for reconstruction of deforming organs from ungated images. In [51], we proposed an image-based gating using LE. The low dimensional representation allowed for the identification of similar images, which were then used for reconstructing 4D ultrasound data from abdominal images affected by breathing motion.

In [54], we apply manifold learning to the multi-modal registration problem. This work relies on the principle that two images of the same organ acquired with different modalities have almost identical intrinsic (self) similarities. Structural representations capturing these self-similarites are computed using LE independently on each image. The resultant representations are then registered with mono-modal methods.

Finally, we have considered the analysis of human motion [45, 46] applied to diagnosis of neurological diseases. The method relies on manifold learning to create a series of low dimensionality representations of activities of interest from motion capture data. Patients can then be equipped with a reduced number of portable sensors that enable long-term analysis. During the test stage, the learned motion models are used to detect the current activity and give an estimate of the pose. The use of other sensors is also possible [44].

9 4D Reconstruction

Real-time 3D-reconstruction has sparked the interest of computer vision researchers for at least the last two decades. However, using a real-time 3D reconstruction system for interventional applications has up to now been a little considered subject. At CAMP we developed a reconstruction system targeted at interventional environments to show that bringing such a system into a clinical environ-

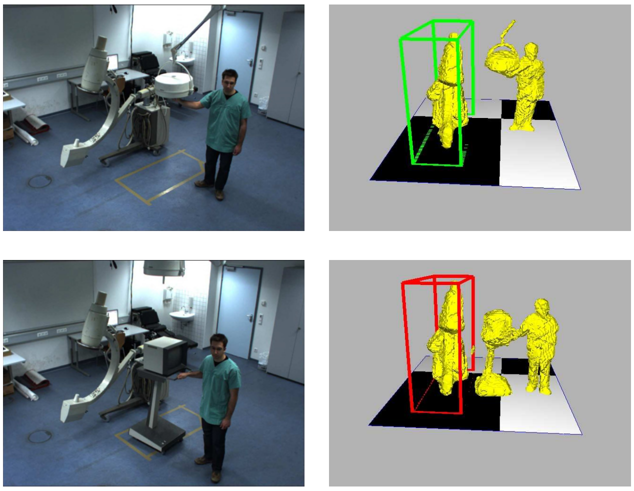


Figure 7. Collision avoidance with medical devices. The red bounding box indicates a danger of collision. [33]

ment opens the door to many new and innovative applications.

Our system is based on a total of 16 synchronized ceiling-mounted cameras observing the scene (see Fig. 6). Using the images acquired by the cameras we perform a 3D-reconstruction. We designed the system with two goals in mind: real-time performance and ease of use in interventional environments. To achieve real-time performance we distributed the computations over multiple PCs making use of modern multi-core architectures and GPU processing [31]. For making the system usable in an interventional setting we adopted an efficient and easy-to-use calibration procedure and a robust background subtraction algorithm which provides the input to the reconstruction algorithm. The reconstruction is performed by either fully computing the visual hull of the scene on the GPU in real-time [31] or by updating the visual hull over time [8].

Based on our system we implemented three interventional applications. In a first application we used the system to automatically detect collisions between automated medical devices such as C-arms and other objects inside the interventional room [33] (see Fig. 7). In a second application we used the 3D-reconstruction of the scene to model a physician's radiation exposure. To this end we track the physician's reconstruction and accumulate the radiation he receives from the X-ray source over time [34]. The result is a color-coded map superimposed on the physician's reconstruction showing the areas of high radiation exposure. Finally, we also used the system to learn and recover the work flow of a surgical procedure [42].

The promising experimental results obtained with these applications show the possible impact of our work for the medical community and illustrate the clinical value of multi-camera systems in the development of intelligent, integrated interventional suites.

In addition to the work directly related to interventional applications we also developed a method for creating high-quality reconstructions from image-collections using an iterative graph-cut approach [32].

10 Real-Time Detection of Low-Textured and Texture-less Objects

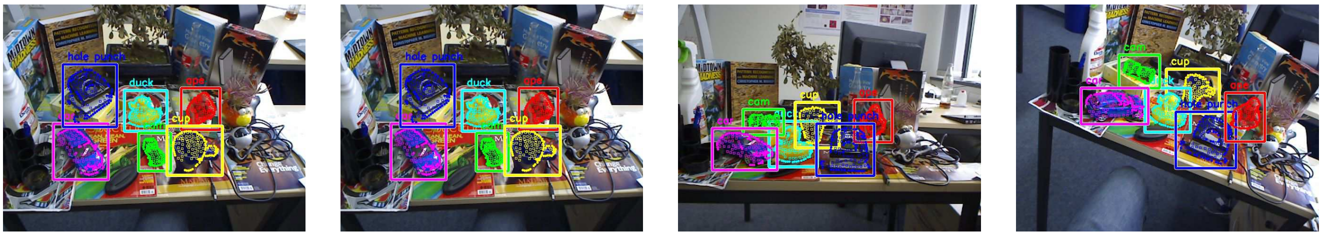
Real-Time detection of known object instances is a key components in various areas of computer vision, e.g. in industrial inspection, augmented reality and robotics. For many applications it has to work robustly and in real-time in order to be fully operational. While real-time detection of well textured objects has already reached a high level of maturity - mainly by using fast keypoint approaches [23] - its application on low-textured or texture-less objects is still an open issue.

The main reasons for that are the lack of robustness to strong background clutter, which lead to a severe degradation of performance or even failure, and the inefficiency during runtime. However, low-textured and texture-less objects play an important role in man made environments which makes it necessary and unavoidable to deal with them in an efficient manner.

We tackle the problem from several directions: for low-textured objects we developed methods based on fast perspective patch rectification [26, 3, 22, 24, 25]. An initial classifier is used to quickly compute a coarse pose estimate which is then refined using a fast template matching algorithm [30]. Computing the similarity between the current image and the reference patch helps to reject outliers and to validate the result. If the reference image is fronto-parallel to the object and the internal parameters are known, one single patch is often enough to precisely estimate the pose. As a result, we can efficiently deal with objects that are significantly less textured than the ones required by state-of-the-art approaches. For detecting texture-less objects, we propose three different approaches: using closed contours on the edge map [28], using fast gradient [27] and normal [29] based template matching methods or using oriented point pair features on the depth map [13]. For the first approach, we propose a robust way to find closed contours in an edge image and to quickly match them to a large database. This method is is invariant to scale changes and robust against planar perspective distortions. Thus, it well suits the detection of texture-less objects as long as closed contours on the object are available.

A more generic approach [27] presents a novel template representation that is designed to be robust to small image transformations. This robustness based on the dominant gradient orientations lets us test only a small subset of all possible pixel locations when parsing the image, and to represent a 3D object with a limited set of templates. Coupled with a binary representation that makes evaluation very fast and a branch-and-bound approach to efficiently scan the image we are able to detect texture-less 3D objects in real-time.

If only the depth map is available, we propose to use a novel method that creates a global model description based on oriented point pair features and matches that model locally using a fast voting scheme [13]. The global model description consists of all model point pair features and represents a mapping from the point pair feature space to the model, where similar features on the model are grouped together. Such representation allows using much sparser object and scene point clouds, resulting in very fast performance. Recognition is done locally using an efficient voting scheme on a reduced two-dimensional search space. Although the recognition process is slower than the ones of [27, 29], it is more robust with respect to partial occlusion.



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

Figure 8. Real-Time Object Detection and Tracking

References

[1] A. Ahmadi, N. Padoy, K. Rybachuk, H. Feussner, S.M. Heining, and N. Navab. Motif discovery in or sensor data with application to surgical workflow analysis and activity detection. In *Proc. MICCAI Workshop Modeling and Monitoring of Computer Assisted Interventions (M2CAI)*, 2009.

[2] A. Ahmadi, T. Sielhorst, R. Stauder, M. Horn, H. Feussner, and N. Navab. Recovery of surgical workflow without explicit models. In *Proc. Int. Conf. Medical Image Computing and Computer Assisted Intervention (MICCAI)*, 2006.

[3] N. Alt, S. Hinterstoisser, and N. Navab. Rapid selection of reliable templates for visual tracking. In *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, 2010.

[4] S. Atasoy, D. Mateus, J. Lallemand, A. Meining, G.Z. Yang, and N. Navab. Endoscopic Video Manifolds (EVMs). In *Proc. Int. Conf. Medical Image Computing and Computer Assisted Intervention (MICCAI)*, 2010.

[5] C. Bichlmeier, E. Euler, T. Blum, and N. Navab. Evaluation of the virtual mirror as a navigational aid for augmented reality driven minimally invasive procedures. In *Proc. IEEE and ACM Int. Symp. Mixed and Augmented Reality (ISMAR)*, 2010.

[6] C. Bichlmeier, S.M. Heining, M. Feuerstein, and N. Navab. The virtual mirror: A new interaction paradigm for augmented reality environments. *IEEE Transaction on Medical Imaging*, 28(9):1498–1510, 2009.

[7] C. Bichlmeier, S. Holdstock, S.M. Heining, S. Weidert, E. Euler, O. Kutter, and N. Navab. Contextual in-situ visualization for port placement in keyhole surgery: Evaluation of three target applications by two surgeons and eighteen medical trainees. In *Proc. IEEE and ACM Int. Symp. Mixed and Augmented Reality (ISMAR)*, 2009.

[8] A. Bigdelou, A. Ladikos, and N. Navab. Incremental visual hull reconstruction. In *Proc. British Machine Vision Conf. (BMVC)*, 2009.

[9] T. Blum, H. Feussner, and N. Navab. Modeling and segmentation of surgical workflow from laparoscopic video. In *Proc. Int. Conf. Medical Image Computing and Computer-Assisted Intervention (MICCAI)*, 2010.

[10] T. Blum, S.M. Heining, O. Kutter, and N. Navab. Advanced training methods using an augmented reality ultrasound simulator. In *Proc. IEEE and ACM Int. Symp. Mixed and Augmented Reality (ISMAR)*, 2009.

[11] T. Blum, N. Padoy, H. Feussner, and N. Navab. Workflow mining for visualization and analysis of surgeries. *International Journal of Computer Assisted Radiology and Surgery*, 3(5):379–386, 2008.

[12] T. Blum, M. Wieczorek, A. Aichert, R. Tibrewal, and N. Navab. The effect of out-of-focus blur on visual discomfort when using stereo displays. In *Proc. IEEE and ACM Int. Symp. Mixed and Augmented Reality (ISMAR)*, 2010.

[13] B. Drost, M. Ulrich, N. Navab, and S. Ilic. Model globally, match locally: Efficient and robust 3D object recognition. In *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, 2010.

[14] B. Glocker, N. Komodakis, N. Paragios, G. Tziritas, and N. Navab. Inter and intra-modal deformable registration: Continuous deformations meet efficient optimal linear programming. In *Information Processing in Medical Imaging (IPMI)*, 2007.

[15] B. Glocker, N. Komodakis, G. Tziritas, N. Navab, and N. Paragios. Dense image registration through mrfs and efficient linear programming. *Medical Image Analysis*, 12(6):731–741, 2008.

[16] B. Glocker, D. Zikic, N. Komodakis, N. Paragios, and N. Navab. Linear image registration through mrf optimization. In *Proc. Int. Symp. Biomedical Imaging: From Nano to Macro (ISBI)*, 2009.

[17] Ben Glocker, Nikos Komodakis, Nikos Paragios, Christian Glaser, Georgios Tziritas, and Nassir Navab. Primal/Dual Linear Programming and Statistical Atlases for Cartilage Segmentation. In *Int. Conf. Medical Image Computing and Computer Assisted Intervention (MICCAI)*, 2007.

[18] M. Groher, F. Bender, R.T. Hoffmann, and N. Navab. Segmentation-driven 2D-3D registration for abdominal catheter interventions. In *Proc. Int. Conf. Medical Image Computing and Computer-Assisted Intervention (MICCAI)*, 2007.

[19] M. Groher, T.F. Jakobs, N. Padoy, and N. Navab. Planning and intraoperative visualization of liver catheterizations: New CTA protocol and 2D-3D registration method. *Academic Radiology*, 14(11):1324–1339, 2007.

[20] M. Groher, D. Zikic, and N. Navab. Deformable 2d-3d registration of vascular structures in a one view scenario. *IEEE Transactions on Medical Imaging*, 28(6):847–860, 2009.

[21] M. Groher, M. Baust D. Zikic, and N. Navab. Monocular deformable model-to-image registration of vascular structures. In *Proc. Int Workshop Biomedical Image Registration (WBIR)*, 2010.

[22] S. Hinterstoisser, S. Benhimane, V. Lepetit, P. Fua, and N. Navab. Simultaneous Recognition and Homography Extraction of Local Patches With a Simple Linear Classifier. In *Proc. British Machine Vision Conf. (BMVC)*, 2008.

[23] S. Hinterstoisser, S. Benhimane, and N. Navab. N3M: Natural 3D Markers for Real-Time Object Detection and Pose Estimation. In *Proc. Int. Conf. Computer Vision (ICCV)*, 2007.

[24] S. Hinterstoisser, S. Benhimane, N. Navab, P. Fua, and V. Lepetit. Online Learning of Patch Perspective Rectification for Efficient Object Detection. In *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, 2008.

[25] S. Hinterstoisser, O. Kutter, N. Navab, P. Fua, and V. Lepetit. Real-Time Learning of Accurate Patch Rectification. In *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, 2009.

[26] S. Hinterstoisser, V. Lepetit, S. Benhimane, P. Fua, and N. Navab. Learning Real-Time Perspective Patch Rectification. *International Journal of Computer Vision*, 2011.

[27] S. Hinterstoisser, V. Lepetit, S. Ilic, P. Fua, and N. Navab. Dominant Orientation Templates for Real-Time Detection of Texture-Less Objects. In *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, 2010.

[28] S. Holzer, S. Hinterstoisser, S. Ilic, and N. Navab. Distance Transform Templates for Object Detection and Pose Estimation. In *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, 2009.

[29] S. Holzer, S. Hinterstoisser, R. B. Rusu, S. Ilic, and N. Navab. Part-based multi-modal template matching for robust real-time object detection. In *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, 2011.

[30] S. Holzer, S. Ilic, and N. Navab. Adaptive linear predictors for real-time tracking. In *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, 2010.

[31] A. Ladikos, S. Benhimane, and N. Navab. Efficient visual hull computation for real-time 3D reconstruction using cuda. In *Proc. IEEE CVPR Workshop Visual Computer Vision on GPUs (CVGPU)*, 2008.

[32] A. Ladikos, S. Benhimane, and N. Navab. Multi-view reconstruction using narrow-band graph-cuts and surface normal optimization. In *Proc. British Machine Vision Conf. (BMVC)*, 2008.

[33] A. Ladikos, S. Benhimane, and N. Navab. Real-time 3D reconstruction for collision avoidance in interventional environments. In *Proc. Int. Conf. Medical Image Computing and Computer-Assisted Intervention (MICCAI)*, 2008.

[34] A. Ladikos, C. Cagniart, R. Gothbi, M. Reiser, and N. Navab. Estimating radiation exposure in interventional environments. In *Proc. Int. Conf. Medical Image Computing and Computer-Assisted Intervention (MICCAI)*, 2010.

[35] T. Lasser, T. Wendler, S. I. Ziegler, and N. Navab. Towards reproducibility of freehand 3d tomographic nuclear imaging. In *Proc. IEEE Medical Imaging Conf. (MIC)*, 2008.

[36] T. Lasser, S. I. Ziegler, and N. Navab. Freehand spect in low uptake situations. In *Proc. SPIE Medical Imaging: Physics of Medical Imaging*, 2011.

[37] D. Mateus, C. Wachinger, S. Atasoy, L. Schwarz, and N. Navab. *Learning manifolds: design analysis for medical applications*. Machine Learning in Computer-Aided Diagnosis: Medical Imaging Intelligence and Analysis. Accepted.

[38] N. Navab, A. Bani-Hashemi, and M. Mitschke. Merging visible and invisible: two camera-augmented mobile c-arm (camc) applications. In *Proc. IEEE and ACM Int Workshop Augmented Reality (IWAR)*, 1999.

[39] N. Navab, S.M. Heining, and J. Traub. Camera augmented mobile c-arm (camc): Calibration, accuracy study and clinical applications. *IEEE Transaction on Medical Imaging*, 29:14121423, 2010.

[40] N. Navab, S. Wiesner, S. Benhimane, E. Euler, and S.M. Heining. Visual servoing for intraoperative positioning and repositioning of mobile c-arms. In *Proc. Int. Conf. Medical Image Computing and Computer-Assisted Intervention (MICCAI)*, 2006.

[41] N. Padoy, T. Blum, A. Ahmadi, H. Feuner, M.O. Berger, and N. Navab. Statistical modeling and recognition of surgical workflow, medical image analysis. *Medical Image Analysis*, 2010.

[42] N. Padoy, D. Mateus, D. Weinland, M.-O. Berger, and N. Navab. Workflow monitoring based on 3D motion features. In *Proc. ICCV Workshop Video-oriented Object and Event Classification*, 2009.

[43] A. Safi, V. Castaneda, T. Lasser, D. Mateus, and N. Navab. Manifold learning for dimensionality reduction and clustering of skin spectroscopy data. In *Proc. SPIE Medical Imaging: Computer-Aided Diagnosis*, 2011.

[44] L. Schwarz, D. Mateus, V. Castaneda, and N. Navab. Manifold learning for tof-based human body tracking and activity recognition. In *Proc. British Machine Vision Conf. (BMVC)*, 2010.

[45] L. Schwarz, D. Mateus, and N. Navab. Discriminative human full-body pose estimation from wearable inertial sensor data. In *Proc. Int. Workshop 3D Physiological Human (3DPH)*, 2009.

[46] L. Schwarz, D. Mateus, and N. Navab. Multiple-activity human body tracking in unconstrained environments. In *Proc. Conf Articulated Motion and Deformable Objects*, 2010.

[47] R. R. Shamir, M. Horn, T. Blum, J. Mehrkens, Y. Shoshan, L. Joskowicz, and N. Navab. Trajectory planning with augmented reality for improved risk assesment in image-guided keyhole neurosurgery. In *Proc. IEEE Int. Symp. Biomedical Imaging: From Nano to Macro (ISBI)*, 2011.

[48] J. Traub, H. Heibel, P. Dressel, S.M. Heining, R. Graumann, and N. Navab. A multi-view opto-xray imaging system: Development and first application in trauma surgery. In *Proc. Int. Conf. Medical Image Computing and Computer-Assisted Intervention (MICCAI)*, 2007.

[49] C. Wachinger, B. Glocker, J. Zeltner, N. Paragios, N. Komodakis, M. Sass Hansen, and N. Navab. Deformable Mosaicing for Whole-body MRI. In *Int. Conf. Medical Image Computing and Computer Assisted Intervention (MICCAI)*, 2008.

[50] C. Wachinger, T. Klein, and N. Navab. The 2d analytic signal on rf and b-mode ultrasound images. In *Proc. Information Processing in Medical Imaging (IPMI)*, 2011.

[51] C. Wachinger, D. Mateus, A. Keil, and N. Navab. Manifold learning for patient position detection in mri. In *Proc. IEEE Int. Symp. Biomedical Imaging: From Nano to Macro (ISBI)*, 2010.

[52] C. Wachinger and N. Navab. Alignment of viewing-angle dependent ultrasound images. In *Proc. Int. Conf. Medical Image Computing and Computer-Assisted Intervention (MICCAI)*, 2009.

[53] C. Wachinger and N. Navab. Similarity metrics and efficient optimization for simultaneous registration. In *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, 2009.

[54] C. Wachinger and N. Navab. Manifold learning for multimodal image registration. In *Proc. British Machine Vision Conf. (BMVC)*, 2010.

[55] C. Wachinger, R. Shams, and N. Navab. Estimation of acoustic impedance from multiple ultrasound images with application to spatial compounding. In *Proc. IEEE Workshop on Mathematical Methods in Biomedical Image Analysis (MMBIA)*, 2008.

[56] C. Wachinger, W. Wein, and N. Navab. Three-dimensional ultrasound mosaicing. In *Proc. Int. Conf. Medical Image Computing and Computer-Assisted Intervention (MICCAI)*, 2007.

[57] C. Wachinger, W. Wein, and N. Navab. Registration strategies and similarity measures for three-dimensional ultrasound mosaicing. *Academic Radiology*, 15:1404–1415, 2008.

[58] C. Wachinger, M. Yigitsoy, and N. Navab. Manifold learning for image-based breathing gating with application to 4d ultrasound. In *Proc. Int. Conf. Medical Image Computing and Computer-Assisted Intervention (MICCAI)*, 2010.

[59] L. Wang, J. Traub, S.M. Heining, S. Benhimane, R. Graumann, E. Euler, and N. Navab. Long bone x-ray image stitching using camera augmented mobile c-arm. In *Proc. Int. Conf. Medical Image Computing and Computer-Assisted*

Intervention (MICCAI), 2008.

[60] L. Wang, J. Traub, S. Weidert, S.M. Heining, E. Euler, and N. Navab. Parallax-free long bone x-ray image stitching. In *Proc. Int. Conf. Medical Image Computing and Computer-Assisted Intervention (MICCAI)*, 2009.

[61] L. Wang, J. Traub, S. Weidert, S.M. Heining, E. Euler, and N. Navab. Parallax-free intra-operative x-ray image stitching. *Medical Image Analysis*, 14(5):674 – 686, 2010.

[62] Lejing Wang, J. Landes, Simon Weidert, Tobias Blum, A. von der Heide, E. Euler, and Nassir Navab. First animal cadaver study for interlocking of intramedullary nails under camera augmented mobile c-arm a surgical workflow based preclinical evaluation. In *Proc. Int. Conf. Information Processing in Computer-Assisted Interventions (IPCAI)*, 2010.

[63] T. Wendler, A. Hartl, T. Lasser, J. Traub, F. Daghighian, S. I. Ziegler, and N. Navab. Towards intra-operative 3d nuclear imaging: reconstruction of 3d radioactive distributions using tracked gamma probes. In *Proc. Int. Conf. Medical Image Computing and Computer-Assisted Interventions (MICCAI)*, 2007.

[64] T. Wendler, K. Herrmann, A. Schnelzer, T. Lasser, J. Traub, O. Kutter, A. Ehlerding, K. Scheidhauer, T. Schuster, M. Kiechle, M. Schwaiger, N. Navab, S. I. Ziegler, and A. K. Buck. First demonstration of 3-d lymphatic mapping in breast cancer using freehand spect. *Eur. J. Nucl. Med. Mol. Imaging*, 37(8):1452–1461, 2010.

[65] T. Wendler, T. Lasser, S. I. Ziegler, and N. Navab. Towards confident 3d tomographic reconstruction for asymmetric, sparse detector geometries. In *Proc. IEEE Medical Imaging Conf. (MIC)*, 2008.

[66] M. Yigitsoy, C. Wachinger, and N. Navab. Temporal groupwise registration for motion modeling. In *Proc. Information Processing in Medical Imaging (IPMI)*, 2011.

[67] D. Zikic, M. Baust, A. Kamen, and N. Navab. Generalization of deformable registration in riemannian sobolev spaces. In *Proc. Int. Conf. Medical Image Computing and Computer-Assisted Intervention (MICCAI)*, 2010.

[68] D. Zikic, B. Glocker, O. Kutter, M. Groher, N. Komodakis, A. Kamen, N. Paragios, and N. Navab. Linear Intensity-based Image Registration by Markov Random Fields and Discrete Optimization. *Medical Image Analysis*, 14(4):550–562, 2010.

[69] D. Zikic, B. Glocker, O. Kutter, M. Groher, N. Komodakis, A. Kamen, N. Paragios, and N. Navab. Markov random field optimization for intensity-based 2d-3d registration. In *Proc. SPIE Medical Imaging: Image Processing*, 2010.

[70] D. Zikic, M. Groher, A. Khamene, and N. Navab. Deformable registration of 3d vessel structures to a single projection image. In *Proc. SPIE Medical Imaging: Image Processing*, 2008.

[71] D. Zikic, A. Kamen, and N. Navab. Natural gradients for deformable registration. In *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, 2010.

[72] D. Zikic, A. Kamen, and N. Navab. Revisiting horn and schunck: Interpretation as gau-newton optimisation. In *Proc. British Machine Vision Conf. (BMVC)*, 2010.

[73] D. Zikic, A. Khamene, and N. Navab. Intensity-unbiased force computation for variational motion estimation. In *Proc. BMVC Workshop Image Registration in Deformable Environments (DEFORM)*, pages 61–70, 2006.