AR Visualization of Thermal 3D Model by Hand-held Cameras

Kazuki Matsumoto[1], Wataru Nakagawa[1], Hideo Saito[1], Maki Sugimoto[1],
Takashi Shibata[2] and Shoji Yachida[2]

[1]*Graduate School of Science and Technology, Keio University, 3-14-1 Hiyoshi, Kohoku-ku, Yokohama, Kanagawa, Japan*

[2]*NEC Corporation, 1753 Shimonumabe, Nakahara-ku, Kawasaki, Kanagawa, Japan*

{*kazuki, nakagawa, saito*}*@hvrl.ics.keio.ac.jp, sugimoto@ics.keio.ac.jp,*
t-shibata@hw.jp.nec.com, s-yachida@bk.jp.nec.com

Keywords: 3D Model, Augmented Reality, Temperature, RGB-D Camera, Thermal Camera, Camera Tracking, Viewpoint Generative Learning.

Abstract: In this paper, we propose a system for AR visualization of thermal distribution on the environment. Our system is based on color 3D model and thermal 3D model of the target scene generated by KinectFusion using a thermal camera coupled with an RGB-D camera. In off-line phase, Viewpoint Generative Learning (VGL) is applied to the colored 3D model for collecting its stable keypoints descriptors. Those descriptors are utilized in camera pose initialization at the start of on-line phase. After that, our proposed camera tracking which combines frame-to-frame camera tracking with VGL based tacking is performed for accurate estimation of the camera pose. From estimated camera pose, the thermal 3D model is finally superimposed to current mobile camera view. As a result, we can observe the wide area thermal map from any viewpoint. Our system is applied for a temperature change visualization system with a thermal camera coupled with an RGB-D camera and it is also enables the smartphone to interactively display thermal distribution of a given scene.

1 INTRODUCTION

Thermal imaging is utilized for various purposes such as recording energy related issues of power equipment and observing body temperature of animals. Recently, a lot of work has been done to combine state-of-the-art computer vision techniques with the thermal imaging. For example, (Szabó et al., 2013) propose a new augmented reality(AR) system of the patient's infrared tissue temperature maps for directly visualizing myocardial ischemia during cardiac surgery. (Kandil et al., 2014) present a method for automatically generating 3D spatio-thermal models, and enables owners and facility managers to quickly get the actual energy performance data for their existing buildings by leveraging recent image-based 3D modeling approaches as well as thermal cameras.

Recently, smartphone attachable thermal imaging devices have started to appear. Since the cost of these devices is considerably less than thermal cameras originally built for military or medical purposes, thermal imaging is starting to be more widely used in consumer applications(Yanai, 2014).

However, the resolution and the field of view of the thermal cameras is limited and it is difficult to monitor large machines and areas. Since the cost of such a device is also high, it makes it hard to use several cameras to cover a large surface. Also, the calibration of these devices is difficult due to the low resolution images obtained from single camera.

In this paper, we propose a system for visualizing wide area temperature map from arbitrary viewpoints. The goal of our paper is AR visualization of a thermal 3D model with ordinary hand-held cameras in order to monitor the spatial temperature distribution of the target scene. Our approach is based on precomputed RGB 3D model and thermal 3D model of the target scene achieved with an RGB-D camera coupled with the thermal camera shown in Figure 1. These 3D models are generated using KinectFusion (Izadi et al., 2011). The colored 3D model is used with the Viewpoint Generative Learning (VGL) (Thachasongtham et al., 2013) algorithm to detect feature points robust to viewpoint changes and to generate a database with corresponding 3D positions and descriptors of these features. We then estimate the pose of the camera by finding keypoint correspondences between the current view and the database. We also combine the frame-to-frame tracking with the VGL based tracking for accurately estimating the camera pose. By knowing the pose of the camera, we are then able to perform AR visualization of thermal 3D model from any viewpoint with a hand-held camera.

As a result, our system has two applications. The first one is temperature change visualization system using an RGB-D camera and a thermal camera. The other is interactive AR visualization of thermal 3D model on smartphone display. The user can reveal the 3D thermal model by touching relevant image regions on the smartphone. The paper is structured as follows. The related works are discussed in Section 2. After describing the detail of our system in Section 3, Section 4 will show the two applications of our method and discuss the accuracy and the runtime of our camera tracking. We finally conclude the paper and describe our future works in Section 5.

Figure 1: Our capture system is composed of the Microsoft KINECT and Optris PI160 thermal camera.

2 RELATED WORKS

The 3D representation of heat distribution has attracted the interest of researchers because of the development of 3D modeling techniques, depth cameras and thermal imaging (Borrmann et al., 2012), (Demisse et al., 2013). These systems reconstruct a thermal 3D model and exploit it for acquiring not only accurate and wide scope thermal data but also geographical information of a building so that the observer can run simulations of thermal distribution and can easily find the areas with abnormal temperatures. They involve a mobile wheeled robot with a laser scanner and a thermal camera for simultaneous acquisition of 3D laser scan data and thermal images. However, this robot is not capable of exploring bumpy ground or confined spaces.

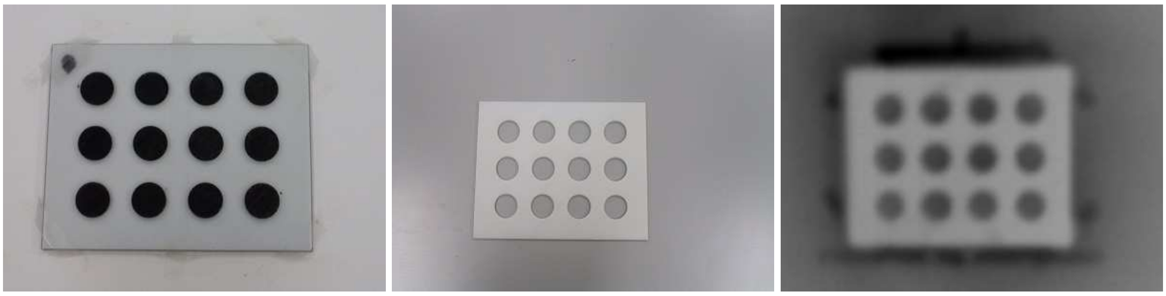
Our work is inspired from a mobile 3D thermal system introduced in (Vidas et al., 2013) which used only two cameras - an RGB-D camera and a thermal camera. This system uses the KinectFusion algorithm (Izadi et al., 2011) for generating dense and high-fidelity 3D thermal model. Inspired from their approach, we also use the KinectFusion for reconstructing 3D thermal model. The major advantages of such approach is its ease of use in confined spaces and its relatively low price when compared with 3D LiDAR and robotics platform.

The problem of 3D pose estimation of rigid objects has been studied for several decades because estimating the pose of a known object is a significant issue in Augmented Reality. (Saito et al., 2014) propose on-line diminished reality system using Viewpoint Generative Learning (VGL) based camera pose estimation. The VGL generates a database of feature descriptors from the 3D model to make the pose estimation robust to viewpoint changes. Therefore, we apply the VGL for tracking the mobile cameras because the purpose of our AR system is to enable the observer to move hand-held camera arbitrarily and to visualize the thermal map in a given scene.

3 PROPOSED METHOD

The overview of our system is shown in Figure 2. As it can be seen, our system pipeline consists of an off-line phase and an on-line phase. In the pre-process stage of this system, we estimate the intrinsic parameters of the RGB-D camera and the thermal camera by using an ordinary circle grid pattern (Zhang, 2000). We also need to calibrate the relative pose of these distinct devices. For this reason we use our own calibration board that makes easier to detect the circle grid pattern with thermal camera. After the preprocessing, we generate two 3D models using Kinect Fusion (Izadi et al., 2011) - one with the RGB information another with the corresponding temperature distribution at the capturing time. The RGB colored 3D model is the source of stable keypoints database stored by Viewpoint Generative Learning in off-line phase and the thermal 3D model will be used for augmented reality in on-line phase. The stable keypoint database will be available for estimating the camera pose in on-line phase.

During the on-line phase, we first initialize the camera pose reference to the RGB 3D model. The initial camera pose is calculated by the correspondences between the stable keypoints in VGL database and h keypoints extracted from the first frame. After this initialization, the camera pose is computed using frame-to-frame tracking in combination with VGL based camera pose estimation. We can then align the thermal 3D model with the current viewpoint and superimpose the thermal information on the current image.



(a) (b) (c)

Figure 3: (a)lower plate (b)upper plate (c) captured image from thermal camera.

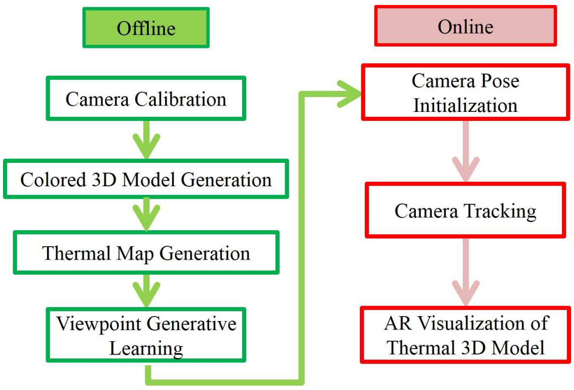


Figure 2: System Overview.

3.1 Camera Calibration

In order simplify the pose estimation of the thermal camera in reference to the RGB-D camera, we use a special calibration board that is visible from both color and thermal cameras. This calibration board is constructed of two plastic plates stacked together. Both details were made with 3D printer. The lower plate is made of a planar surface covered with circular bumps corresponding to the black parts of the circle grid calibration pattern. The upper plate is designed to plug on top of the first one, it is thus made of a planar surface with holes where the black pattern of lower calibration board should appear. Combining both plates creates a flat calibration pattern like the ones commonly used. Just before calibration, we heat the lower plate while the upper one remains at ambient temperature so that the circle grid pattern in thermal image can be detected as shown in Figure 3.

The intrinsic parameters of RGB-D camera and thermal camera are calculated using Zhang's method (Zhang, 2000). In order to estimate the pose of the thermal camera in reference to the RGB-D camera, we obtain a set of 3D-2D correspondences by detecting both 3D positions of black circles captured in RGB-D camera and its corresponding 2D locations in the thermal image. However, the depth map captured with RGB-D camera is contaminated with structural noise especially in black circle areas. Therefore we compute the planar surface equation from acquired 3D points on circle grid and project them onto the estimated plane for accurately estimating their 3D position. We then apply the efficient Perspective-n-Point algorithm (Lepetit et al., 2009) to estimate the extrinsic parameters.

3.2 Colored 3D Model Generation

The KinetFusion algorithm (Izadi et al., 2011) is used to generate the uncolored 3D model of target scene. While KinectFusion is running, we save not only the camera poses of RGB-D camera but also the color image, depth image and thermal image for each frame. Using the pose estimation of each frame, we then generate colored 3D model by projecting RGB data onto the uncolored 3D model.

3.3 Thermal 3D Model Generation

Since the RGB-D camera and the thermal camera are located at slightly separate positions, we need to apply rigid transformation calculated in Section 3.1 to thermal image and deal with occlusions for correctly mapping the thermal data. In order to remove occluded thermal data, we first project the 3D points corresponding to the pixels of the depth image onto the thermal image and generate the depth image from the thermal camera viewpoint. Then, we remove occluded depth values by replacing the neighboring absolutely difference values with the average value of this area. Finally, for each pixel of the RGB-D image, corresponding thermal values can be found while removing occluded area. The process of thermal data mapping is illustrated in Figure 4.

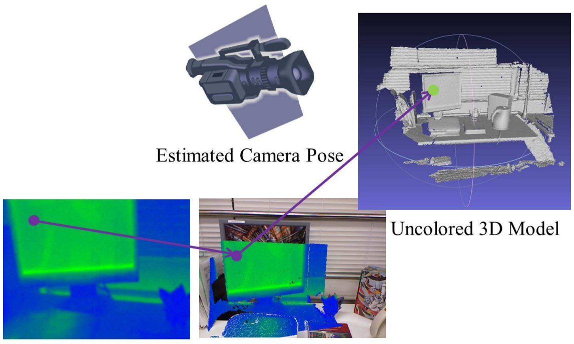


Figure 4: Thermal data mapping from estimated camera pose.

3.4 Viewpoint Generative Learning

Conventional local features such as SIFT and SURF are robust to scale and rotation changes but sensitive to large perspective changes. In order to solve this problem, (Yoshida et al., 2013) proposed a stable keypoint matching method which is robust even under strong perspective changes by using Viewpoint Generative Learning (VGL). However, this method is only focusing on planar surfaces and can not deal with 3D objects. Therefore, (Thachasongtham et al., 2013) modify this algorithm so that they can estimate the pose of a 3D object from stable keypoints stored in VGL database.

During on-line phase, we need a robust camera tracking algorithm against strong viewpoint changes because the user of our system is observing the target scene with a hand-held camera. Therefore, we apply the Viewpoint Generative Learning to the RGB 3D model generated in Section 3.2. In the first step, we generate patterns of the model from various viewpoints using the OpenGL rendering process as shown in Figure 5. For each generated viewpoint, we collect not only the patterns and extracted SIFT features but also the depth and viewpoint of those rendered images. Then, all detected keypoints are projected from pixel coordinate system to 3D coordinate system and conserve only the ones that can be detected over multiple views. We define these features with high repeatability as stable keypoints and collect the corresponding descriptors.

After that, k-means++ (Arthur and Vassilvitskii, 2007) is applied to cluster the set of collected descriptors of each stable keypoint and store the barycenter descriptors and the 3D positions of each stable keypoint in the VGL database.

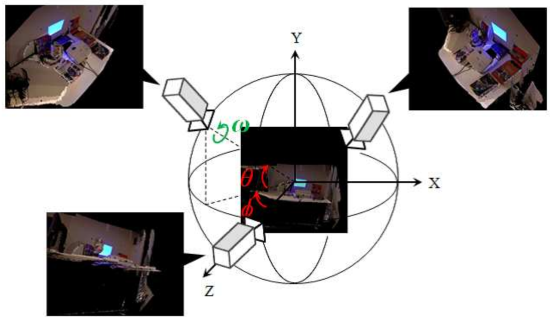


Figure 5: Viewpoint Generative Leaning.

3.5 Camera Pose Initialization

After learning is finished, we first detect SIFT keypoints and extract feature descriptors from the initial frame. For each detected keypoint, we search the two most similar descriptors by evaluating Euclidean distance of their high dimensional value using the Fast Library for Approximate Nearest Neighbors (FLANN) algorithm. Then, we evaluate the ratio of the distance of closest descriptor to that of the second closest descriptor, and if the ratio is under a given threshold we validate the established correspondence. As a result, we can identify the 3D/3D correspondences between the stable keypoints on the model in 3D and the current RGB-D camera view. Finally, the pose of RGB-D camera is deduced with a singular value decomposition associated to RANSAC for excluding wrong correspondences. The accuracy of initialization is evaluated by the ratio between the number of the 3D/3D correspondences and that of extracted keypoints from current image . If the ratio is over the threshold, we assume the initialization is successfully performed and start frame-to-frame tracking from the next frame.

(a) current image (b) camera pose

Figure 6: Camera pose estimation.

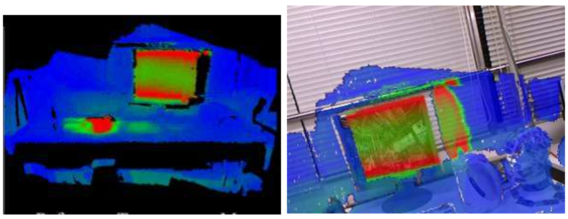
3.6 Camera Tracking

In the frame-to-frame tracking, we continuously extract descriptors from RGB-D frames. Under the assumption that the current camera position is close to the previous one, we search for correspondences with the features from previous frame in their local neighborhood . The matching pairs are evaluated based on Euclidean distance, and the closest pair is selected as matching pair. If the ratio of matched pairs to keypoints extracted in previous frame is over 10 %, the current camera pose is estimated by singular value decomposition and RANSAC (as explained in previous Section), otherwise we apply the VGL based tracking to re-initialize the camera pose.

However, sometimes the frame-to-frame tracking fails even in the case where we can find keypoint correspondences correctly. In order to solve this problem, we evaluate the Euclidean distance of camera position and the rotation of camera poses between current frame and previous frame. If the distance is over 5cm or the rotation is over 10 degrees, we consider the frame-to-frame tracking as wrong estimation and apply the motion model calculated from previous 3 frames for predicting current camera pose. As a result, our camera pose tracking is stable as shown in Figure 6.

3.7 AR Visualization of Thermal Model

During the on-line processing, we superimpose precomputed thermal 3D model on current view from estimated camera pose as shown in Figure 7. The rendering process is performed in GPU with CUDA and OpenGL so that the observer can see the temperature distribution in real-time. As a result, we can visualize the thermal distribution of the scene from any viewpoint.



(a) Off-line generated thermal 3D model (b) AR visualization of thermal model

Figure 7: Examples showing AR visualization.

4 EXPERIMENTS

In this section, we introduce two applications for thermal observation system using AR visualization of thermal 3D model. The first one is AR visualization for detecting the temperature distribution change with an RGB-D camera coupled with a thermal camera. The second one is to interactively visualize the thermal 3D model on smartphone display. For generating thermal 3D model and RGB 3D model, we used Microsoft Kinect(640×480 pixels resolution, 30fps) and Optris PI160 with a resolution of 160×120 pixels and a frame rate at fps. Vertical and horizontal values of the field of view of the PI160 are 21° and 28°, respectively.

4.1 AR Visualization of Temperature Changes Distribution

We demonstrate the use of our AR system by visualizing chansing temperatures of electrical equipment within a scene in real-time. This system can visualize more widespread thermal distribution than our previous work (Nakagawa et al., 2014).

In on-line phase, the user moves same camera set as in the off-line phase and to record current thermal distribution. During camera tracking, this application continuously projects the thermal data onto the off-line generated uncolored model from the estimated viewpoint as shown in Figure 8. Then, we simultaneously superimpose both off-line generated thermal 3D model and on-line rendered thermal map on current view as illustrated in Figure 9.

Additionally, this application enables us to visualize the difference of the current thermal state in respect to the recorded thermal 3D model from the same viewpoint. Figure 9 shows the results by blending the augmented thermal map with current image RGB data int regions of considerable temperature change.

4.2 Quantitative Evaluation

4.2.1 Runtime Evaluation

The experiment was carried out on a PC with 16GB of RAM, an Intel Core i7-4800MQ CPU and a Nvidia GeForce GTX 780M graphics card. Table 1 shows the breakdown of the processing times. We believe that this system can be considered to be running in real-time frame rates. Also, we compare the runtime for camera pose estimation with VGL database based tracking proposed by (Thachasongtham et al., 2013). Their method takes 0.12 seconds for camera pose estimation since requesting the database for finding corresponds keypoints is slower than the local area keypoint searching in frame-to-frame tracking.

Table 1: Breakdown of Processing Time.

Process	runtime (sec)
Total	0.46
Camera pose estimation	0.10
On-line thermal mapping	0.12
Visualization	0.24

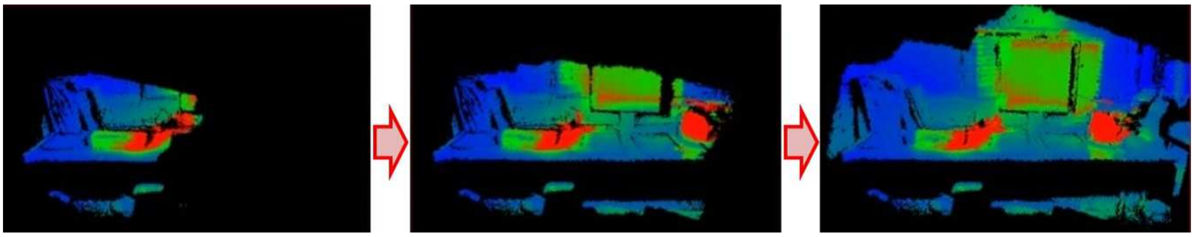


Figure 8: The process of on-line thermal 3D map rendering.

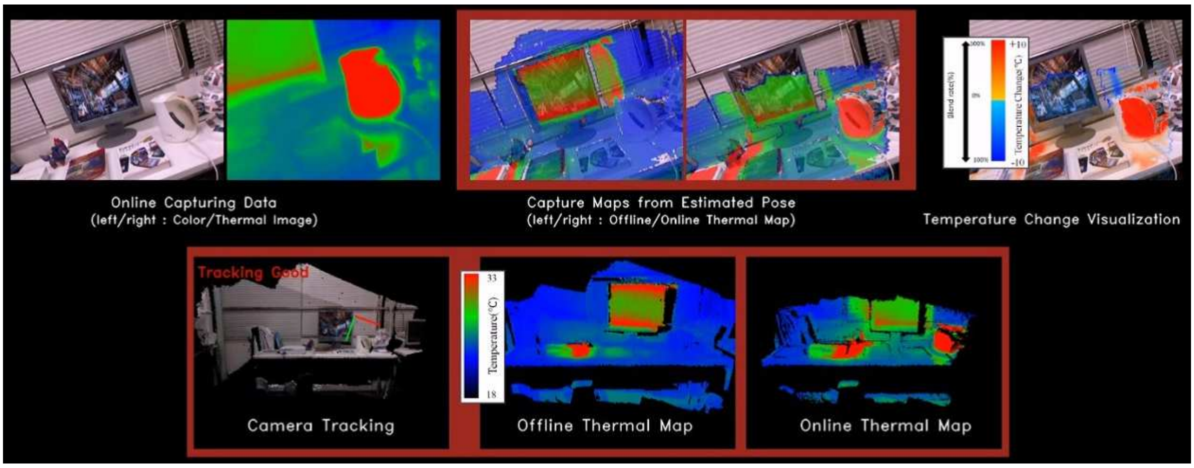


Figure 9: AR temperature change visualization system.

4.2.2 Accuracy Evaluation

In order to evaluate the accuracy of camera pose estimation, we calculate the RMSE score of re-projection error from estimated camera pose and compare it with that of VGL based tracking in 10 frames (Figure 10). As table 10 shows, our proposed method outperforms

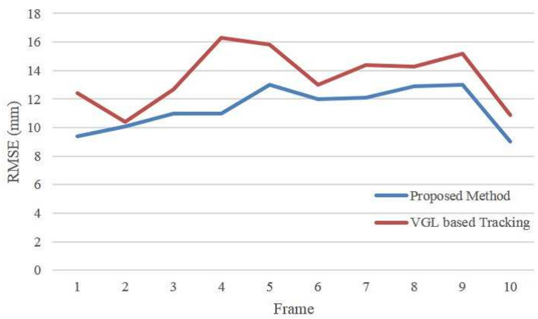


Figure 10: RMSE of re-projection error (mm).

the VGL based tracking in terms of re-projection error. Since our system applies singular value decomposition to the the corredponding 3D-3D keypoints for camera pose estimation, it is more accurate than the VGL based camera pose estimation deduced from 2D-3D correspondences.

Figure 11 shows the Euclidean distances between the camera positions of two consecutive frames. Even when the cameras were moved slowly, the VGL based tracking sometimes fails to track the camera (as highlighted in green circles on the graph). Our method is much more stable, since we combine frame-to-frame tracking, VGL based initialization and motion model for camera pose estimation.

4.3 AR Visualization of Thermal 3D Model on Smartphone

This system consists of a smartphone and a server PC and they are connected via wireless network in order to transfer the video data between those devices. Figure 13 shows communication flow between a smartphone and a server. The server has two threads - one for network operations and one for AR processing. The network thread continuously waits for new frames from the smartphone and buffers them to be used in the AR thread. As the AR thread is rather slow in processing frames, it always retrieves the latest frame in the buffer and drops older frames. The processed frames with AR overlay are buffered in the network thread to be sent back to smartphone. In the server PC, RGB 3D model and thermal 3D model of a target scene are generated and its robust keypoint features are stored in VGL database. In the on-line

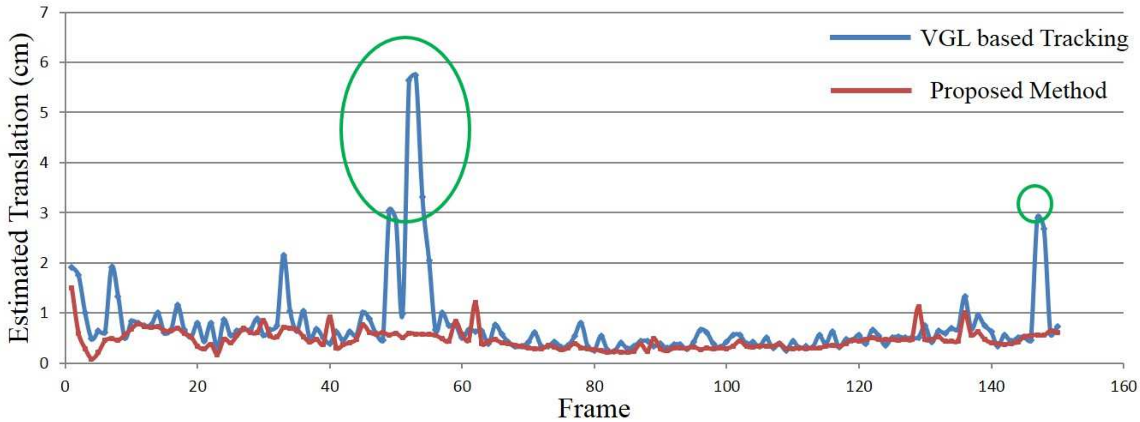


Figure 11: The Euclidean distances between the camera positions of two consecutive frames.

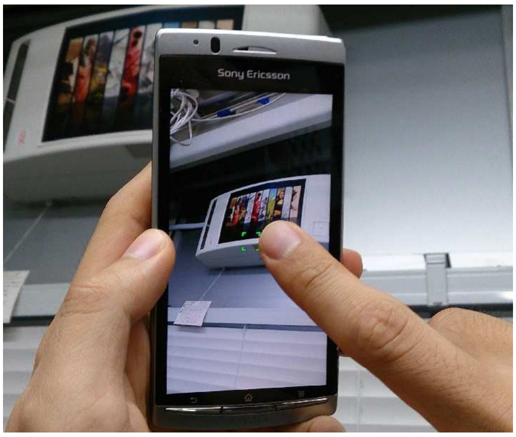


Figure 12: The observer can select the thermal visualization area.

phase, the observer can capture the scene with the smartphone and select target area by touching display of the device (Figure 12). The correspondences between the keypoints on the current image in 2D and stable keypoints of the model in 3D are searched in the same way as the temperature change visualization system described in Section 4.1. Since smartphones can not obtain depth image of current frame, the Perspective-n-Point method (Lepetit et al., 2009) with RANSAC instead of singular value decomposition is applied to the 2D-3D correspondences for deducing the camera pose. We can finally superimpose the thermal 3D object on the target area of smartphone display and visualize the temperature distribution of the area as shown in Figure 14.

The experimental platform was implemented on smartphone with 1.0GHz MSM8255 processor and 512MB of RAM and a laptop with 2.5GHz Intel Core i7-2860QM processor GeForce GTX 560M graphics card and 16GB RAM. The smartphone camera image size is 320×240 pixels.

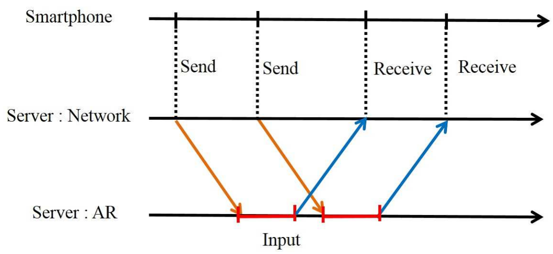
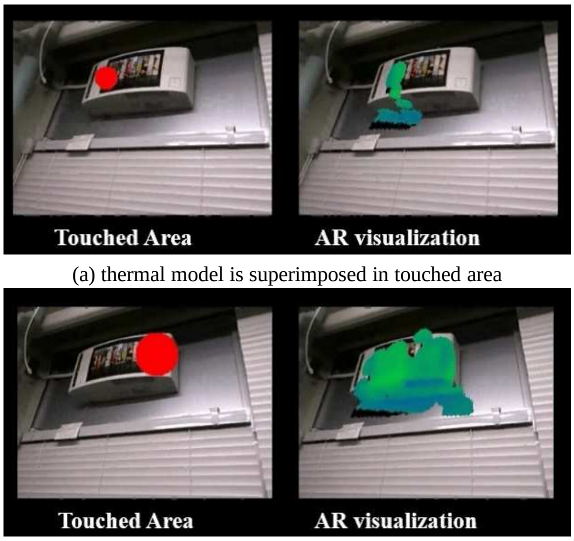


Figure 13: Connection flow between smartphone and server.



(a) thermal model is superimposed in touched area

(b) The target area is increasing

Figure 14: AR visualization of thermal 3D model in smartphone.

5 CONCLUSIONS & FUTURE WORK

In this paper, two systems for visualizing temperature distribution of a given scene using an RGB-D camera and a thermal camera are presented. The first one is temperature change visualization system comparing on-line and off-line thermal 3D models from any viewpoint. Another is the interactive AR visualization of thermal 3D model on smartphone display. Both applications use AR visualization of off-line generated thermal 3D model. In the off-line phase, the uncolored 3D model of a given scene is reconstructed and the poses of the camera with the corresponding color and thermal images are saved by using KinectFusion. After mapping color and thermal images on separate uncolored models, Viewpoint Generative Leaning is applied to the RGB 3D model in order to store the stable keypoints and their clustered descriptors in the VGL database. During the on-line phase, hand-held camera poses are estimated by combining frame-to-frame tracking with the camera pose estimation using correspondences between keypoint descriptors in the current image and in the VGL database. Finally, the thermal 3D model is superimposed on the current hand-held camera view.

Recently, some devices for converting the smartphone camera into thermal camera have appeared in the market such as Therm-App for Android and FLIR ONE for iPhone. We plan to use these devices for getting thermal information from smartphones so that our AR visualization system can detect temperature distribution changes on the fly.

REFERENCES

Arthur, D. and Vassilvitskii, S. (2007). k-means++: The advantages of careful seeding. In *Proceedings of the eighteenth annual ACM-SIAM symposium on Discrete algorithms*, pages 1027–1035. Society for Industrial and Applied Mathematics.

Borrmann, D., Nüchter, A., Dakulovic, M., Maurovic, I., Petrovic, I., Osmankovic, D., and Velagic, J. (2012). The project thermalmapper?thermal 3d mapping of indoor environments for saving energy. In *Proceedings of the 10th International IFAC Symposium on Robot Control (SYROCO)*, volume 10, page 1.

Demisse, G. G., Borrmann, D., and Nuchter, A. (2013). Interpreting thermal 3d models of indoor environments for energy efficiency. In *Advanced Robotics (ICAR), 2013 16th International Conference on*, pages 1–8. IEEE.

Izadi, S., Kim, D., Hilliges, O., Molyneaux, D., Newcombe, R., Kohli, P., Shotton, J., Hodges, S., Freeman, D., Davison, A., et al. (2011). Kinectfusion: real-time 3d reconstruction and interaction using a moving depth camera. In *Proceedings of the 24th annual ACM symposium on User interface software and technology*, pages 559–568. ACM.

Kandil, A., Hastak, M., and Dunston, P. S. (2014). Rapid 3d energy performance modeling of existing buildings using thermal and digital imagery. *Bridges*, 10:9780784412329–100.

Lepetit, V., Moreno-Noguer, F., and Fua, P. (2009). Epnp: An accurate o (n) solution to the pnp problem. *International journal of computer vision*, 81(2):155–166.

Nakagawa, W., Matsumoto, K., de Sorbier, F., Sugimoto, M., Saito, H., Senda, S., Shibata, T., and Iketani, A. (2014). Visualization of temperature change using rgb-d camera and thermal camera. In *Computer Vision–ECCV 2014: 13th European Conference, Zurich, Switzerland, September 6-12, 2014, Proceedings*. Springer.

Saito, H., Honda, T., Nakayama, Y., and de Sorbier, F. (2014). Camera pose estimation for mixed and diminished reality in ftv. In *3DTV-Conference: The True Vision-Capture, Transmission and Display of 3D Video (3DTV-CON), 2014*, pages 1–4. IEEE.

Szabó, Z., Berg, S., Sjökvist, S., Gustafsson, T., Carleberg, P., Uppsäll, M., Wren, J., Ahn, H., and Smedby, Ö. (2013). Real-time intraoperative visualization of myocardial circulation using augmented reality temperature display. *The international journal of cardiovascular imaging*, 29(2):521–528.

Thachasongtham, D., Yoshida, T., de Sorbier, F., and Saito, H. (2013). 3d object pose estimation using viewpoint generative learning. In *Image Analysis*, pages 512–521. Springer.

Vidas, S., Moghadam, P., and Bosse, M. (2013). 3d thermal mapping of building interiors using an rgb-d and thermal camera. In *Robotics and Automation (ICRA), 2013 IEEE International Conference on*, pages 2311–2318. IEEE.

Yanai, O. (2014). Thermal imaging as a smartphone application: exploring and implementing a new concept. In *SPIE Defense+ Security*, pages 90700M–90700M. International Society for Optics and Photonics.

Yoshida, T., Saito, H., Shimizu, M., and Taguchi, A. (2013). Stable keypoint recognition using viewpoint generative learning. In *VISAPP (2)*, pages 310–315.

Zhang, Z. (2000). A flexible new technique for camera calibration. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 22(11):1330–1334.