# 로봇 응용을 위한 협력 및 결합 비전 시스템

# Mixing Collaborative and Hybrid Vision Devices for Robotic Applications

바쟝 정샬[1], 김 성 흠[2], 최 동 걸[2], 이 준 영[2], 권 인 소[†]

Jean-Charles Bazin[1], Sung-Heum Kim[2], Dong-Geol Choi[2], Joon-Young Lee[2], In-So Kweon[†]

**Abstract** This paper studies how to combine devices such as monocular/stereo cameras, motors for panning/tilting, fisheye lens and convex mirrors, in order to solve vision-based robotic problems. To overcome the well-known trade-offs between optical properties, we present two mixed versions of the new systems. The first system is the robot photographer with a conventional pan/tilt perspective camera and fisheye lens. The second system is the omnidirectional detector for a complete 360-degree field-of-view surveillance system. We build an original device that combines a stereo-catadioptric camera and a pan/tilt stereo-perspective camera, and also apply it in the real environment. Compared to the previous systems, we show benefits of two proposed systems in aspects of maintaining both high-speed and high resolution with collaborative moving cameras and having enormous search space with hybrid configuration. The experimental results are provided to show the effectiveness of the mixing collaborative and hybrid systems.

**Keywords:** Collaborative/Hybrid system, Catadioptric , Detection, Tracking, Surveillance, Robotics

## 1. Introduction

Today's robotic systems are able to perform a great number of tasks such as object detection, tracking, grasping, recognition, locomotion and navigation in unknown environments. Applications are not limited to this list, and its success depends on the hardware (the embedded sensors, engines or any mechanical/electronic parts) and the software (the programs to fuse the sensors, and control the servos and engines). It is interesting to note that while the range of robotic applications is enlarging; most systems simply rely on conventional, general equipment that has been invented for different purposes years or even decades ago.

On the contrary, we believe that appropriate equipment must be considered for obtaining a reliable robotic system when the existing equipment does not fit the requirements of the specific target application. Following this motivation, the paper aims at developing new configurations of optical devices.

For example, traditional approaches for solving vision-related problems often show weakness under the limited field of view. There have recently been researches on widening field of view to make vision algorithms more robust, but they also bring

Received : Feb. 15. 2011; Reviewed : Apr. 7. 2011; Accepted : May 16. 2011
※ This work was supported by National Strategic R&D Program for Industrial Technology, Korea.
※ The authors gratefully acknowledge the contribution of Youngcheol Lee and Seunghak Shin for the development of the mobile robot. This research was partially supported by MKE(The Ministry of Knowledge Economy), Korea, under the Human Resources Development Program for Convergence Robot Specialists support program supervised by the NIPA(National IT Industry Promotion Agency) (NIPA-2010-C7000-1001-0007)
† 교신저자 : KAIST 전기 및 전자공학과 정교수
1 동경대학교 산업과학연구소 연구원
2 KAIST 전기 및 전자공학과 박사과정

disadvantages along its advantages when we use only the modified, single optical device. In this sense, we especially focus on how to combine some individual vision sensors, in a complementary way, for building novel, effective collaborative and hybrid vision devices. Among many others, two main applications in real environments have driven to our work: a robot photographer and an omnidirectional surveillance system.

Hence, the paper is divided into two main parts. The first part deals with the development of a robot photographer where we build a vision system mixing a pan/tilt perspective camera and a fisheye camera. The second part is dedicated to an omnidirectional surveillance system where we build an original device that combines a stereo-catadioptric camera and a pan/tilt stereo-perspective camera.

The remainder of this paper is organized as follows: Section 2 discusses the first application of a robot photographer and Section 3 presents the second application of an omnidirectional view detector. Each section starts with a review of existing systems, then we present our proposed system followed by the experimental results in real environments. A closing discussion and summary of this work is given in Section 4.

## 2. Robot Photographer

This section is dedicated to the development of a robot photographer, that is to say a mobile platform that can take pictures of human faces automatically during social events including birthday party, meeting and etc. Our goal is to build a new vision system that permits to facilitate the task of taking face pictures in such situations.

### 2.1 Existing Systems

To give a familiar example in this field, we first remind that Sony has successfully commercialized a camera named “Party Shot” that automatically takes images of people. It is composed of a pan/tilt system with a zoom camera and contains face detection software, so that the system can actively search for human faces in the whole scene. Interesting results can be obtained, but the system moves too slowly and must analyze many images because of the small field-of-view. This is the disappointing point of the fairly recent product.

For example, when a person lies behind the original orientation of the camera, it can spend up to 3 minutes taking a picture of that person, according to our experiments with this camera. Moreover, since the system rotates too slowly, some people outside the current field-of-view can be easily missed. Finally, this sort of camera-only system is impersonal: thus we are rather interested in the human behavior in the presence of robots in order to take pictures of people during the human-robot interaction.

The concept of robot photographer has appeared recently and a few systems have been developed. For example, Lewis is a mobile robot that wanders through a space, while taking pictures of people[1]. The robot alternates between detecting faces and adjusting the camera position to take well-composed photographs. Ahn et al. have proposed another method that can recognize a few events when people wave their hands, move toward them, and take pictures with designated compositions and user-chosen tasks[2].

Although the motivation addressed in this paper might not be original, the core idea of combining different optical devices is new and no previous work on the subject is presented in exactly this way. The implemented system can be also embedded on a mobile robot system that can move autonomously according to obstacle avoidance by using several optical sensors as well as range sensors.

### 2.2 Proposed System

In order to overcome the limitations of the existing systems cited above, we propose a system that combines a wide field-of-view camera and an active camera. We use a fisheye camera for the wide field of view to detect faces in a larger scene than with traditional cameras. The pan/tilt motor is controlled through the serial communication. The fisheye and the perspective cameras are connected to a computer by FireWire port and are vertically aligned, as depicted in Fig. 1-left.

Since fisheye images have low resolution, we combine it with a fast pan/tilt camera to acquire high resolution face images without any distortion. Therefore, two cameras complement each other, and the integrated system goes beyond optical trade-off between resolution and field of view. The details concerning hardware and software parts are explained in the following.

The fisheye camera is composed of the Point Grey's Flea2 (FL2G-13S2C) and the Fujinon's FE185CO-57HA-1 fisheye lens. This system can capture 640 x 480 images at 30 fps provides a field of view (FOV) of 154 x 115 degrees.

The high resolution perspective camera is also Point Grey's Flea2 and is attached to a pan/tilt mechanism with a slip ring for unlimited rotation. The maximum rotation speed of the motor is 680 rpm for no load condition and we limited it to 60 rpm during the experiments. It means the camera can point from a certain direction to the opposite one (180 degree of rotation) in a half second. When an image is acquired with the high-resolution camera, the rotation mechanism is temporarily paused to obtain a clear image.


Fig. 1. Left: our collaborative vision system composed of a pan/tilt perspective high-resolution camera and a fisheye camera. Right: zoom-in view and wide field of view. Note that it is possible to observe objects which do not appear in the traditional perspective camera

### 2.3 Experimental Results

For our experiments, the proposed system had been mounted on a tripod and on a mobile robot as well. This robotic platform permits to automatically navigate in an unknown environment, also interact with the people. Indeed, it is equipped with a microphone and a speech synthesizer so that the human and robot can communicate. We are interested in taking pictures of people during this human-robot interaction, so we set the fisheye camera in front of the robot.

We have performed the intrinsic calibration of the fisheye images by the popular toolbox[3]. Once the calibration parameters are estimated, it is possible to rectify the image, as shown in Fig. 2-right. Face detection is performed on the rectified image using OpenCV library based on Adaboost algorithm[4]. Fig. 3 shows an example of face detection in the rectified fisheye image and the corresponding image acquired by the pan/tilt high-resolution camera. To orientate this camera in the direction of the detected face, it is needed to know the extrinsic calibration between the fisheye and the perspective cameras, and also the rigid transformation between the perspective camera and the pan/tilt rotation center.

The extrinsic calibration is obtained by [3] (stereo case), and the center of the perspective camera sensor

Fig. 2. Left: our mobile platform. Right: Example of fisheye image rectification by [3]. Note that the projections of world lines are now straight in the rectified version.

Fig. 3. Face capture by our robot photographer. Left: face detection and tracking. Right: image acquired by the high resolution pan/tilt camera.

is assumed to lie in the rotating axis of the pan/tilt. It is not perfectly exact but performs correctly with acceptable errors in practice. If needed, more advanced techniques could be used [5].

Detected faces are tracked using particle filter framework in order to select, in a smart way, which face must be acquired and thus avoids taking many pictures of the same person. Readers interested in particle filter may refer to [6] and [7] for detailed information and theoretical justifications. The face images obtained by the proposed system can be further processed for face recognition in the context of classification frameworks such as [8].

## 3. Omnidirectional Surveillance System

This section aims at developing an omnidirectional surveillance system, which is used for monitoring objects and detecting interest target. Our goal is to build a new vision system that permits more robust detection, especially with respect to strong illumination changes.

### 3.1 Existing Systems

Omnidirectional vision is particularly suited for surveillance, and thus several methods have been developed[9-14]. Numerous methods have been developed for foreground/ background segmentation during the last decades. Although it would be beyond the scope of this paper to review all them, readers interested in this may refer to [15], [16] for comparison and reviews of existing methods.

The most popular approach to detect changes is background subtraction[16-19]. The simplest of these models finds moving targets by computing the difference between the current observation and the background model, and large changes are considered as foreground by heuristic thresholding or applying MRF regularization such as standard graph-cuts[20]. In our case, we model the likelihood as the sigmoid function of frame differences, and use the negative log function to convert the problem of maximizing a posterior (MAP) to energy minimization. The whole process can be computed within less than 650ms. The potential challenges for real-time surveillance are dealt with the further time-limited manner.

To speed up overall process with acceptable false positives and true negatives, connected component segmentation is alternatively applied, followed by a threshold on the area size. To take into account slow illumination changes, which is necessary to maintain the long-term background model, the background image is subsequently updated. More advanced methods have been developed to deal with abrupt changes of illumination but they greatly increase the algorithm complexity.

### 3.2 Proposed System

In order to overcome the limitations of the existing systems cited above, we propose combining a stereo-catadioptric single-lens camera (simply referred to as SCC in the following) and a pan/tilt stereo-perspective camera, respectively referred to as SCC and PTSPC in the following. The SCC permits to acquire some stereo omnidirectional images using a single camera. The SCC based on a double lobed mirror has been first suggested in [21] and subsequently improved [22], [23]. Especially[24] has developed a more compact device by folding the upper mirror.

For self-containment of the paper, more information about the SCC can be found[24]. Each stereo image consists of two views of the scene, referred to as the lower and upper views. The system is composed of a manufactured mirror and a Point Grey's Scorpion perspective camera. This stereo-catadioptric camera is used to compute the scene depth map (equivalently referred to as disparity map in the following) easily thanks to the fact that the images are already rectified because the radial directions actually correspond to the epipolar lines. The pan/tilt stereo-perspective camera is the Bumblebee2 camera from Point Grey. The pan/tilt mechanism is the same as in Section 2. It permits to acquire 800x600 images and the associated depth maps at 20 fps using Point Grey's optimized software. The proposed hybrid system is shown in Fig. 4.

In this paper, we suggest mixing collaborative and hybrid vision devices for robotic applications. The key idea of the presented system is summarized in Table 1. Due to the optical limitations nowadays, it is physically impossible to obtain all the desirable features such as wide field of view and high resolution at the same time. We believe the true potential lies in integrating two devices with their complementary advantages and performing the optimized tasks for each module respectively. Especially, as far as we know, no previous work has combined stereo-catadioptic and stereo perspective cameras.

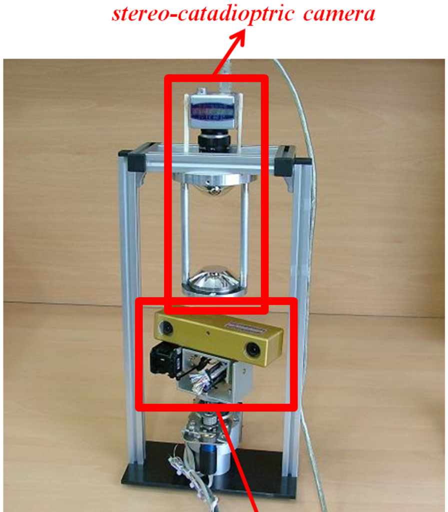


Fig. 4. Our hybrid system composed of a catadioptric-stereo camera with upper/lower convex mirrors and a pan/tilt perspective-stereo

Table 1. Mixing devices for combining tasks

| Features | Main Task(s) | Devices |
|---|---|---|
| Wide field of view | Detection | Fish eye lens, stereo convex mirrors |
| High resolution (with mobility) | Tracking, Recognition | Single / Stereo perspective vision sensors |

Given the background image (composed of its background lower and upper views) obtained by the SCC, we can compute the background depth map. Once the current stereo-image is acquired by using the omni-stereo pair, the associated current depth map can be also computed with the perspective stereo camera. Then, by comparing the background model and current depth maps, we can easily detect the targets. In our experiments, the detection is efficiently performed in the approach similar to the popular background subtraction method, except that the subtraction is applied on the depth maps rather than on the image intensities.

Therefore we consider this approach as background depth map subtraction. This approach has provided interesting results, as shown in the following experiment sub-section. Since the depth maps are estimated using a single image (composed of two views), the depth map is built independently on illumination changes, which provides the robust property.

### 3.3 Experimental Results

Our proposed system has been embedded on a robot in both indoor and outdoor environments shown in Fig. 5. Two kinds of scenarios are applied: the robot can either be 1) set at a specific position or 2) freely navigate in the environment to inspect other places. In both cases, the current depth map is compared to the background depth map acquired at the same position.

To correctly orientate the pan/tilt camera, it is needed to know the transformations between the coordinate systems associated to the SCC, PTSPC and pan/tilt mechanism. The PTSPC is calibrated using [3] (stereo case) and its coordinate system is set in the middle of the two joint cameras. We then compute the rigid transformation between one image of each vision

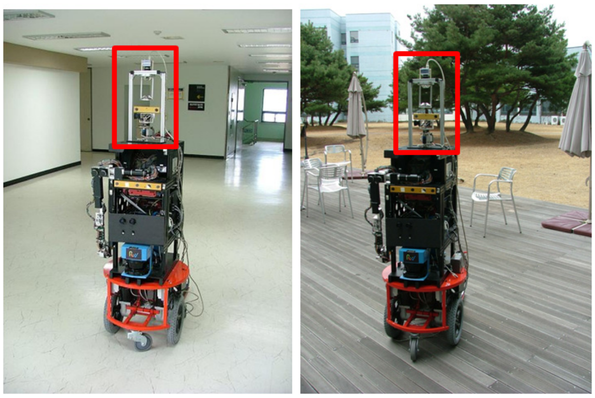

Fig. 5. Our hybrid system composed of a catadioptric-stereo camera and a pan/tilt perspective-stereo

device: the upper panoramic image of the SCC and the left image of the PTSPC (the lower or right images could have been used instead). For the simplification, we assume the pan/tilt center is located at the PTSPC coordinate system. Therefore, given the 3D position of a target object obtained by the SCC, it is possible to orientate the PTSPC towards the same direction using the coordinate system transformations. Experimental results have shown this pan/tilt control performed successfully.

Once we get a pair of catadioptric-stereo images, the stereo image can be converted to the lower and upper panoramic views using straightforward unwarping method as shown in Fig. 6-(b,c). Then, it is possible to compute the depth map associated to these two views using dense stereo algorithms. Many methods have been proposed in the literature (c.f. [25] for a review). Considering time complexity and overall performance, we have shown that the most reasonable results were obtained within 400ms per frame, by using [26], possibly further improved by [27] (c.f. Fig. 6-a).

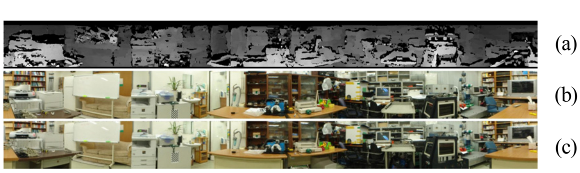


Fig. 6. A pair of panoramic views generated from the omni-stereo images (b),(c) and the corresponding disparity map (a) from[24].

Once we get a pair of catadioptric-stereo images, the stereo image can be converted to the lower and upper panoramic views using straightforward unwarping method as shown in Fig. 6-(b,c). Then, it is possible to compute the depth map associated to these two views using dense stereo algorithms. Many methods have been proposed in the literature (c.f. [25] for a review). Considering time complexity and overall performance, we have shown that the most reasonable results were obtained within 400ms per frame, by using [26], possibly further improved by [27] (c.f. Fig. 6-a).

We performed a qualitative experiment where the system had acquired images every second for several hours, from morning to night. Two types of illumination change occurred: one is smooth and corresponds to the daylight transition, the second one is extremely abrupt and corresponds to the moments when the lights of the room were turned on/off (it could also occur when daylight was not bright enough or people were entering/leaving the room or using an energy-saving light timer). We implemented the widely used approach of background subtraction combined with a background update model (as explained in the sub-section 3-1) and refined the results with the standard graph-cut algorithm. This popular background update can correctly deal with the smooth daylight transition, but often fail when abrupt illumination changes occur, contrary to our depth map-based detection which provides a higher positive detection rate. Depth correspondences can be inferred not only from intensity similarity, but also from invariant texture.

Fig. 7 shows the key steps of the work flow in our

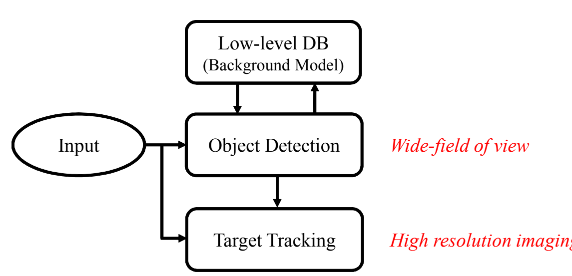


Fig. 7. Flowchart in our approach

approach. The input scene is observed by two different sensors. The device for large-field of view is in charge of detecting region of interest from the panorama depth maps obtained by unwarping the current stereo-catadioptric sequence and background model. Since we have two panoramic views from lower/upper mirrors, the associated depth maps can be computed. By comparing the depth maps and applying a simple threshold operation on small connected areas (for reducing complexity), it is possible to detect the target. Once the target is detected, the active stereo-perspective camera is controlled to automatically face towards the target in order to obtain a high-resolution stereo image, as shown in Fig. 8.

Fig. 9 shows typical results of target detection obtained in outdoor environments. Satisfactory results are achieved with somewhat simple-mind, time-efficient depth map estimation algorithm. We also performed some series of experiments with color light changes. Fig. 10 shows the obtained results in a challenging situation with abrupt color/illumination changes.

In order to simulate the abrupt illumination change, we used a lamp projector attached with a colored filter (blue and red). Typical examples are shown in Fig. 10-(a, b). We applied background subtraction and also background update for the continuous acquisitions. Because of the abrupt change of color light, the popular method, even with the sophisticated color model and MRF optimization is likely to fail in locating the exact

Fig. 8. When a target is detected by the proposed omni-depth map subtraction (top-row), the pan/tilt Bumblebee camera is oriented towards the target direction to obtain a high-resolution stereo image pair (bottom-row).

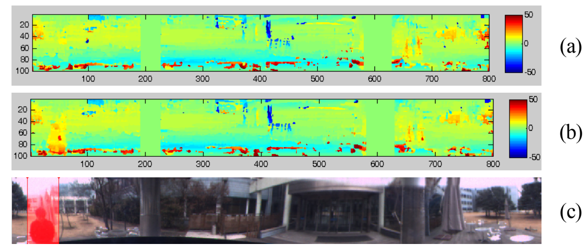


Fig. 9. Experiment in outdoor environment. (a), (b) are examples of the background model (averaging depth in successive input pairs) and the current depth (disparity) maps. (c) shows the detected person displayed in red layer

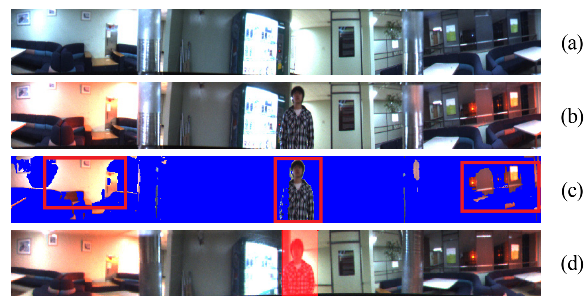


Fig. 10. Object detection with color illumination changes. (a), (b) show the panoramic views in the presence of strong illumination changes. (c) is the result of object detection by standard background subtraction with MRF optimization. (d) shows effectiveness of detection using the proposed method.

target, as depicted in Fig. 10-(c). Some large areas are considered as foreground and thus will not able to be removed by post-processing such as blob-coloring. A typical result obtained by the background depth map subtraction is displayed in Fig. 10-(d). It shows the proposed method can correctly detect the target despite the strong color illumination variations.

It is well-known that any algorithms become more robust when the information to process is more reliable. Since monocular camera-based approaches typically rely on pixel intensities and simple assumptions on surfaces of materials, they obviously suffer from varying illuminations and other types of radiometric noises.

Hence, a feasible solution requires robust low-level information other than visible photometric information. In this sense, we use the scene depth as primary cue for object detection, but often scarify the algorithm components to meet real-time requirement. To balance between accurate performance and feasible computation, some components are replaced with simpler steps. Especially, several heuristics in background subtraction are introduced without any optimization for the practical uses. Depth estimation also has room to improve for more accurate and faster computation.

The analysis on time complexity in Table 2 is conducted under Visual Studio 8.0 on Window 7 platform using Intel® Core™ i7-860 Processor (8M Cache, 2.80 GHz) with SPEC code.

Table 2. Quantitative analysis of computational complexity

| Component | Elapsed Time | Portion |
|---|---|---|
| Loading data | 30 ms | 2.5 % |
| Unwarping | 50 ms | 4 % |
| Background subtracting / updating | 50 ms | 4 % |
| MRF optimization | 600 ms | 50 % |
| Depth map estimation | 400 ms | 33.3 % |
| Post-processing | 70 ms | 5.9 % |
| Motor control | 3 ms/degree | 0.3 % |
| Total | 1.2 s | 100 % |

## 4. Conclusion

In this paper, we present two innovative, collaborative and hybrid vision systems for vision-based robotic applications. Our robot photographer embeds a vision system composed of a collaborative pan/tilt perspective cameras and a fisheye. It not only permits to find more faces thanks to the wide field-of-view, but also overcomes the associated low-resolution problem by the perspective camera that provides images at full, high resolution of the faces.

For the surveillance system, we propose a hybrid system combining a stereo-catadioptric and a pan/tilt stereo-perspective camera. Experimental results in real environments have shown that the stereo information, provided by the stereo-catadioptric camera, facilitates the detection of the target object in the surrounding. The active stereo-perspective camera is then oriented towards the target to acquire a higher-resolution image and possibly refine depth estimation.

The proposed system is thus robust to strong, global illumination changes as well. The algorithm components are individually evaluated in terms of overall performance and time complexity in order to analyze the presented components respectively.

We believe it is worthy to develop the idea of combining vision devices with optical property of particular interest such as wide field of view and high resolution imaging. The presented idea shall encourage achieving other developments of hybrid/ collaborative devices for satisfying their own specific purposes.

## References


[1] Z. Byers, M. Dixon, K. Goodier, W. Smart, and C. Grimm, “Say cheese! experiences with a robot photographer,” AI Magazine, Vol.25, No.2, pp.37–46, 2004

[2] H.-S. Ahn, M.-J. Lee, I.-K. Jeong, and J.-H. Park, “A smart agent for taking pictures,” SIGGRAPH ASIA, 2009

[3] J. Y. Bouguet. Camera calibration toolbox for matlab. URL: http://www.vision.caltech.edu/bouguetj/calib_doc/#examples

[4] Paul Viola and Michael Jones, “Robust real-time face detection,” IJCV, Vol.57, No.2, pp.137–154, 2004

[5] Y.D. Seo, Y.J. Choi and S.W. Lee. A branch-and-bound algorithm for globally optimal calibration of a camera-and-rotation-sensor system. International Conference on Computer Vision, 2009

[6] Branko Ristic, Sanjeev Arulampalam and Neil Gordon. Beyond the Kalman Filter. Artech House, London, 2004

[7] A. Doucet, N. De Freitas and N. Gordon. Sequential Monte Carlo Methods in Practice. Springer-Verlag, 2001

[8] J. Wright, A.Y. Yang, A. Ganesh, S.S. Sastry and Y. Ma, “Robust face recognition via sparse representation,” IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol.31, No.2, pp.210-227, 2009

[9] Y. Onoe, K. Yamazawa, N. Yokoya and H. Takemura, "Visual surveillance and monitoring system using an omnidirectional video camera," International Conference on Pattern Recognition, 1998
[10] Y. Yagi, "Omnidirectional sensing and its applications. Transactions on Information and Systems," pp.568–579, 1999
[11] H. Liu, O. Javed, G. Taylor, X. Cao and N. Haering, "Omni-directional surveillance for unmanned water vehicles," VS, 2008
[12] W. K. Wong, Joanne T. Y. Liew, C. K. Loo and Wei Kin Wong, "Omnidirectional surveillance system for digital home security," ICSAP, 2009
[13] T. E. Boult, X. Gao, R. Micheals and M. Eckmann, "Omni-directional visual surveillance," IVC, Vol.22, No.7, pp.515-534, 2004
[14] S. Morita, K. Yamazawa and N. Yokoya, "Networked video surveillance using multiple omnidirectional cameras," CIRA, 2003
[15] D. Hall, J. Nascimento, P. Ribeiro, E. Andrade, P. Moreno, S. Pesnel, T. List, R. Emonet, R. B. Fisher, J. Santos Victor and J. L. Crowley, "Comparison of target detection algorithms using adaptive background models," PETS, 2005
[16] J. Nascimento and J. Marques, "Performance evaluation of object detection algorithms for video surveillance," IEEE Transactions on Multimedia, 2006
[17] R. Jain and H. Nagel, "On the analysis of accumulative difference pictures from image sequences of real world scenes," IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol.1, No. 2, pp.206–214, 1979
[18] A. Elgammal, D. Harwood and L. Davis, "Non-parametric model for background subtraction," European Conference on Computer Vision, pp.751–767, 2000
[19] C. Stauffer and W. Grimson, "Adaptive background mixture models for real-time tracking," Computer Vision and Pattern Recognition, pp.246–252, 1999
[20] Y. Boykov and V. Kolmogorov, "An experimental comparison of mincut/ max-flow algorithms for energy minimization in vision," IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol.26, No.9, pp.1124-1137, 2004
[21] D. Southwell, A. Basu, M. Fiala, and J. Reyda, "Panoramic stereo," International Conference on Pattern Recognition, 1996
[22] M. Fiala and A. Basu, "Panoramic stereo reconstruction using non-svp optics," International Conference on Pattern Recognition, 2002
[23] E. L. Cabral, J. C. de Souza Junior and M. C. Hunold, "Omnidirectional stereo vision with a hyperbolic double lobed mirror," International Conference on Pattern Recognition, 2004
[24] G.-J. Jang, S.-H. Kim and I.-S. Kweon, "Single camera catadioptric stereo system," 5th Workshop on Omnidirectional Vision, Camera Networks and Non-classical Cameras, 2005.
[25] D. Scharstein, R. Szeliski and R. Zabih, "A taxonomy and evaluation of dense two-frame stereo correspondence algorithms," International Journal of Computer Vision, Vol.47, pp.7-42, 2002
[26] A. S. Ogale and Y. Aloimonos, "A roadmap to the integration of early visual modules," International Journal of Computer Vision, Vol.73. No.1, pp.9-25, 2007
[27] K.-J. Yoon and I.-S. Kweon, "Adaptive support-weight approach for correspondence search," Computer Vision and Pattern Recognition, Vol.28, No.4, pp.650-656, 2006

**바장 정샬**
2005 프랑스 UTC 컴퓨터공학과(학사)
2006 프랑스 UTC 컴퓨터공학과(석사)
2010 KAIST 전기 및 전자공학과(박사)
2010~현재 일본 동경대학교 산업과학 연구소
관심분야 : 로봇 비전, 반사 굴절 비전

**김 성 흠**

2007 연세대학교 전기 및 전자 공학과(학사)

2010 KAIST 전기 및 전자공학과(석사)

2010~현재 KAIST 전기 및 전자공학과 박사과정

관심분야 : 영상처리, 전/배경 분리, 영상편집

**이 준 영**

2007 연세대학교 전기 및 전자 공학과 (학사)

2009 KAIST 전기 및 전자공학과 (석사)

2009~현재 KAIST 전기 및 전자공학과 박사과정

관심분야 : 광원 분석 및 보정, 최적화

**최 동 걸**

2005 한양대학교 전자전기 컴퓨터 공학부(학사)

2007 한양대학교 전자전기제어계측 공학과(석사)

2009~현재 KAIST 전기 및 전자공학과 박사과정

관심분야 : 로봇 비전, 영상기반 항법

**권 인 소**

1981 서울대학교 기계설계학과(학사)

1983 서울대학교 기계설계 학과(석사)

1990 Carnegie Mellon Univ. Robotic Institute(박사).

1991~1992 일본 도시바 중앙연구소 연구원

1992~현재 KAIST 전기 및 전자공학과 정교수