Extended Kalman Filter Based Mobile Robot Localization in Indoor Fire Environments

Jong-Hwan Kim and Gun In Kim
Mechanical & Systems Engineering, Korea Military Academy, Seoul, Republic of Korea
Email: {jongkim, gunin}@kma.ac.kr

***Abstract*—This paper presents localization of a mobile firefighting robot. Sensors that have been widely used for the localization in the past have shown limitations under fire environments due to low visibility and high temperatures. The extended Kalman filter was designed to accurately estimate position and orientation of the robot using relative distances to walls or objects surroundings. In addition, data from a Frequency-Modulated Continuous-Wave (FMCW) Radar, Inertial Measurement Unit (IMU) and encoders that are capable of withstanding fire environments were fused to localize the robot in indoor fire environments. For its validation, an experiment was conducted in a 2 m × 4 m area. The experimental results showed that the proposed localization method was reliable.**

***Index Terms*—firefighting robot, localization, multi-sensor fusion, fire environments, mobile robot**

I. Introduction

Fighting fires is one of the most strenuous and dangerous activities that humans perform. The use of robotics is currently of interest to the military and many public organizations, especially to the US fire department. Due to the dangers of firefighting, the application of robotics is ideal; a robot designed for firefighting activities will not only avoid firefighters from exposure to conditions produced by a fire but also allow for conditions to be monitored in the area close to the fire. In addition, the robot can serve as a tool used by firefighters in helping to reduce the tasks that the firefighter is required to perform. The robot will also be capable of achieving tasks that are not possible by humans. To make the robot accomplish these tasks, the robot will need to navigate on its own and build maps of its surroundings. In order for effective navigation and accurate map-building, position and orientation of the robot must be first known.

Localization is one of the most essential competences applied to a firefighting robot [1]. Hence, localization techniques have constantly received research attention in robotics, and as a result, great advances have been developed on this area. Unfortunately, the sensors that had been widely used for localization such as CCD camera, LIDAR, and sonar, did not function due to dense smoke and high temperature caused by the fire. However, 2.4GHz FMCW Radar (12mm wavelength) was able to work properly under smoke-filled environment [2]-[4]. Also, Inertial Measurement Unit (IMU) and encoder worked properly as well because they were installed inside of robot.

To date, there have been many localization methods. All these methods of localization can be categorized into two areas: the relative and the absolute [5], [6]. The relative (local) method estimates position and the orientation of the robot by integrating information produced by sensors mounted, while the absolute (global) method allows the robot to search its location directly from the mobile system domain [7]. These methods generally build upon navigation beacons, active or passive landmarks, map matching or Global Positioning System (GPS) [7].

A. The Absolute Localization Method

Outdoors, GPS is commonly used for navigation of vehicles to help find its destination and current location. However, this sensor is only able to function under the existing GPS network. To overcome this limitation, indoor GPS, called a geometric beacon has been studied. This beacon can be both dependably monitored in consecutive sensor measurements and accurately shown in a concise geometric parameterization [8]

B. The Relative Localization Method

Use of visual odometer [9] from vision sensors such as CCD camera approximates a robot's position and orientation. Point features on image are matched between pairs of frames and linked into image trajectories at image frame rate. Then, estimation of the camera motion is approximated by the feature tracks. This successive process produces estimates of position and orientation from visual input [9], [10]. Use of point clouds provided by light detection and ranging sensor (LIDAR) has been widely researched due to its accuracy and high sampling rate. One of the scan matching techniques using LIDAR sensor, Iterative Closest Point (ICP) algorithm generates information of position and orientation by scan-matching the actual environment features [11]. Furthermore, these techniques have been developed for Simultaneous Localization and Mapping (SLAM) [12]. Using standard Polaroid sonar sensors is also implemented to localize the robot creating feature-based stochastic maps [13]. Nonetheless, in case of a fire, the above sensors cannot be operated properly; a GPS network is useless indoors due to the lack of signals from satellites, and the beacon could burn out or would not adequately function if its power

Manuscript received May 27, 2015; accepted November 2, 2015.

doi: 10.18178/ijmerr.5.1.62-66

source is damaged. In addition, LIDAR (0.905 μm wavelength) cannot detect any features under dense smoke environments produced by fire because smoke blocks light [14]. The data from sonar sensor varies depending on the temperature which causes a number of errors during localization.

With these limitations of sensor, it was challenge to find sensors which can function properly under fire. A long wave infrared camera is able to see though smokes where a LIDAR sensor is not able, and a FMCW Radar (12mm wavelength) sensor is able to provide distance information between obstacle and the robot under high temperature while ultrasonic sensor is not. Even though an IMU sensor is affected by temperature, this sensor is protected by frames of the robot and all measured data are fully able to be compensated. Because this sensor still function under fire environment, as long as the IMU sensor runs at less than maximum and more than minimum of temperature range.

This paper provides description about the Extended Kalman Filter (EKF) based localization for firefighting robots by fusing data from IMU, FMCW Radar, and encoders. The proposed method was developed for Shipboard Autonomous Firefighting Robot (SAFFiR) [15]-[18], an autonomous humanoid firefighter, but to validate the method, it was first tested on a four-wheel skid-steering mobile robot platform.

II. Fundamentals

A. Mobile Robot Platform

The mobile robot platform in Fig. 1 was built to validate the proposed method before applying it on the humanoid robot SAFFiR [15]-[17]. The dimension of the platform was 0.54 meter in length and 0.56 meter in width to accommodate missions indoors where the doors and hallways are narrow. In addition, four high torch DC motors were installed to support various sensors and the suppression equipment for firefighting tasks. For the robot to autonomously control the DC motors, a microcontroller (Arduino Uno) and a servo controller were used which allowed the robot to move up to 40 cm/sec. To reduce the payload, the frame was built with aluminum. For a forty minute runtime, the robot was equipped with a 24V battery to power the DC motors and three 12V batteries for the sensors.

B. Sensors

The Inertial Measurement Unit (3DM-GX3-25) in Fig. 1 was installed inside of the robot, which provides information about three-axis accelerometer and three-axis gyroscope at a sampling rate of 100Hz. This information is useful for motion determination of the robot and makes localization accurate. Although an IMU has good short-term precision and a high sampling rate, it includes serious errors in long-term usage due to the drift and the algorithm of integration [19], [20]. Thus, additional secondary sensors are needed to complement IMU to construct its system for drift compensation during the long-term measurement [21].

Figure 1. Mobile robot platform (left), inertial measurement unit (center), and FMCW radar (right)

The FMCW Radar used in this work is Sivers IMA RS3400, which uses 1.5 GHz bandwidth, 2.4 GHz carrier frequency with 12 mm wavelength. This sensor plays a role as a complementary sensor during the localization. This sensor measures position at each time stamps and produces linear velocity of the robot. The power spectrum is produced by applying windowed Fast Fourier Transform (FFT) and is processed by a cell average constant false alarm rate [22] to automatically detect peaks. Then, a quadratic least square is used to estimate relative distance and velocity from the peaks. This radar can measure up to 75 meters with sampled points of 1500, which is enough long indoors. This sensor is installed in front of the mobile robot. While the radar generates accurate information to estimate distance and linear velocity of the robot during the go-straight motion, it does not when the robot turns. To solve this problem, an additional sensor, encoder is required.

III. Extended Kalman Filter

The proposed method uses an IMU, FMCW Radar and encoders for estimating orientation and position of the robot. The configuration of the system is shown in Fig. 2. For sensor fusion, EKF was implemented, which is a classic approach to the state estimate problems for a nonlinear stochastic system. In addition, it uses discrete models with first-order approximation for nonlinear systems [23]. The EKF algorithm enables complementary compensation for each sensor's limitations, and the resulting performance of the sensor system is better than individual sensors. The motion model and the observation model in EKF are established using kinematics [24].

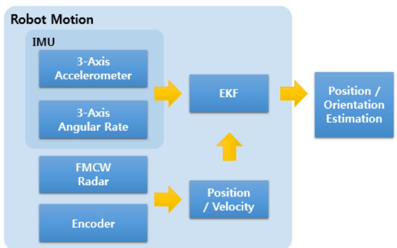

Figure 2. Configuration of the system

$$\begin{aligned} \hat{x}_{k+1} &= f(\hat{x}_k, u_k, w_k), \quad w_k \sim N(0, Q_k) \\ z_k &= H\hat{x}_k + v_k, \qquad\quad v_k \sim N(0, R_k) \end{aligned} \tag{1}$$

As EKF uses discrete models, the first and second lines represent motion model and observation model, respectively. $\hat{x}_{k+1}$ is state value that has nine degrees of freedom; three-axis of position, velocity and Euler angle, and k means the status at time of $\hat{x}$. u_k is input value which has three-axis accelerations and angular rates produced from IMU. w_k and v_k are the process and observation noises, respectively with assumption that these noises follow a Gaussian (or normal) distribution. z_k is observation value that includes robot position and orientation measured at time of k. H is similar to an identity matrix, but its size is different because only information of two-dimension position and yaw angle are used.

$$f(x_k,u_k,w_k)=\begin{bmatrix} {}^{G}P_k \\ {}^{G}V_k \\ {}^{G}\Theta_k \end{bmatrix}+\Delta t\begin{bmatrix} {}^{G}V_k \\ \left({}^{G}_{R}C\right)_k\left({}^{R}A_k\right)+w_k \\ \left({}^{G}_{R}q_{\Theta}\right)_k\left({}^{R}\omega_k\right)+w_k \end{bmatrix} \tag{2}$$

Equation (2) shows the motion model of the EKF system. G and R represent the global frame and local (or robot) frame, respectively. ${}^{G}P_k$ and ${}^{G}V_k$ are a three-axis position and velocity vector based on the global frame. ${}^{G}\Theta_k$ is Euler angles; roll, pitch, and yaw. Equation (3) describes X-Y-Z rotation matrix, where three-axis acceleration data from IMU sensor, which is notated as ${}^{R}A_k$ is transformed from local to global frame. Both $\cos\theta$ and $\sin\theta$ are described as $C\theta$ and $S\theta$, respectively.

$${}^{G}_{R}C=\begin{bmatrix} C\theta C\psi & -S\psi C\phi+C\psi S\phi S\theta & S\phi S\psi+C\psi S\theta C\phi \\ C\theta S\psi & C\phi C\psi+S\theta S\phi S\psi & -S\phi C\psi+S\theta C\phi S\psi \\ -S\theta & C\theta S\phi & C\phi C\theta \end{bmatrix} \tag{3}$$

The three-axis angular velocity, ${}^{R}\omega_k$ is transformed to Euler angle rates by applying the transformation matrix in (4). This transformation matrix makes IMU data suitable to use in the global frame.

$${}^{G}_{R}q_{\Theta}=\begin{bmatrix} 1 & \sin\phi\tan\theta & \cos\phi\tan\theta \\ 0 & \cos\phi & -\sin\phi \\ 0 & \sin\phi\sec\theta & \cos\phi\sec\theta \end{bmatrix} \tag{4}$$

$$z_k=\begin{bmatrix} {}^{R}x_k \\ {}^{R}y_k \\ {}^{R}\varphi_k \end{bmatrix}=\begin{bmatrix} {}^{R}x_{k-1}+\Delta t(V_{linear}\cos(\varphi_{k-1})) \\ {}^{R}y_{k-1}+\Delta t(V_{linear}\sin(\varphi_{k-1})) \\ {}^{R}\varphi_{k-1}+\Delta t(\dot{\varphi}_{k-1}) \end{bmatrix} \tag{5}$$

The data from FMCW Radar and encoder play an important role in observation model described in (5). The velocity calculated by measuring the distance difference with respect to the time difference is a linear velocity, and it is then applied to update the position of the robot. When an obstacle front is present longer than maximum range of the radar or when estimated distance suddenly changes due to the object, data from the encoders were considered instead. Both sensors were used due to their limitations; when the robot turns, encoders installed left and right of wheel are able to produce distance data at each wheel while Radar sensor cannot. In addition, when the robot moves forward encoders have slippage errors while Radar provides accurate distances. A data fusion technique is used to take advantage of both sensors. The robot motion is also monitored by angular rates generated from IMU sensor. Considering that yaw angle changes when the robot turns, if the absolute value of the yaw angle rate is greater than a certain threshold, the encoder data are calculated for the linear velocity, otherwise the radar data are estimated for the linear velocity.

IV. Implementation and Results

The Extended Kalman Filter (EKF) is used to estimate the robot position in two dimensions. There are four steps as shown in Fig. 3; data acquisition, data filtering, calculation, and plotting. First, the data acquisition is applied to obtain data from the sensors mounted on the robot. Second, a filtering process is conducted with curve fitting functions in Matlab [25]. Third, EKF is used to estimate the position and orientation of the robot. Finally, all of estimated positions and orientations are accumulated and plotted. MEX function is designed for EKF code to increase its process speed. As a result, this process repeats every 0.05 sec.

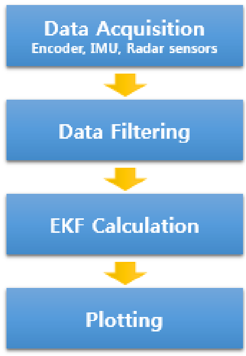

Figure 3. The flow chart for EKF in Matlab code

A. *Data Acquisition*

The data acquisition obtains data from the encoder, IMU, and radar sensors. The square wave shape generated from encoders indicates the rates of wheel rotation. Multiplying angular velocity by radius of the wheel yields its distance. The resolution of the encoder is 16 pulses per a resolution, which is not enough to calculate distance. However, using curve fitting gives approximated distance. The IMU sensor provides three-axis accelerometer and three-axis gyroscope. However, only x-axis linear velocity and z-axis angular rate were picked up to process the EKF localization. The radar sensor also produced linear velocity of the robot. Three linear velocities are compared in Fig. 4. The linear velocity from IMU is increased with respect to time because the linear velocity is calculated by acceleration with constant values. After long usage, IMU accumulates errors. In addition, the radar results in errors during the implementation. Although the encoder shows relatively stable data, the slippage and miss counts still occur. To cope with these problems, curve fitting technique in Matlab is used in the data filtering.

B. *Data Filtering*

IMU has linear velocity that accumulates errors for a long-time experiment as shown Fig. 4. Thus, data filtering is used to handle the problems occurred in the measurement. To calculate linear velocity, the filtered data are differentiated with respect to time. Finally, the filtered data are translated into linear velocity and then used in EKF in the calculation stage.

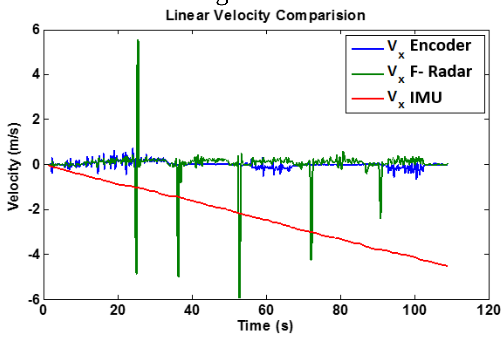

Figure 4. The comparison of linear velocities from the encoder, FMCW Radar and inertial measurement unit (IMU)

C. EKF Calculation

The initial state of the robot is described as (0, 0) in Cartesian coordinates. In the motion model, three-axis of accelerations and three-axis of angular rates from the IMU are used to predict the next position and orientation of the robot. In the observation model, linear velocity and orientation are used to correct the position and orientation predicted in the motion model. The linear velocity is determined depending on the robot motion. For example, when the robot moves forward, data from the radar sensor are prioritized to calculate linear velocity. In contrast, when the robot turns, data from the encoder are prioritized in order to calculate the velocity. The decision for these priorities is calculated from IMU's angular rates at yaw axis. Accelerations and angular rates generated from IMU and the determined linear velocity become input values in EKF. During the EKF process, a Jacobian matrix is created to predict the position and orientation of the robot and that is corrected by observations repeatedly.

D. Plotting

To validate the proposed localization method, an experiment was conducted. The path the robot took was indicated as a gray line on the floor. The test-bed was two meters in width and four meters in length as shown in Fig. 5. In addition, the robot was remotely controlled to move along the path by an operator. During the experiment, the robot moved forward five times, turned left three times, and turned right once. After that, it came back to the start point.

Figure 5. The test-bed for the experiment

Fig. 6 shows the displacement of two encoders and the ultrasonic sensor. Displacement differences between the encoders exist because slippage and friction occur differently on each wheel. Opposite displacement between the two encoders exits when the robot turns, this is because the right and left wheels need to move in different directions to make the turn. The distance on the FMCW Radar decreases as the robot moves forward, and this is shown as slopes in linear velocity. High deviations and non-continuousness are also shown in Fig. 6. Fig. 7 describes angular velocity, which shows the changes of yaw angle providing the number of times and direction of turn that the robot has taken. The data from the encoders, radar sensor, and IMU are processed in EKF to estimate position and orientation of the robot. As a result, Fig. 8 shows the result of localization, producing less than 2 cm difference between start and end position.

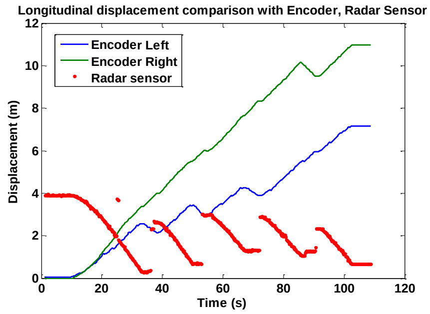

Figure 6. Displacement of both encoders and FMCW Radar

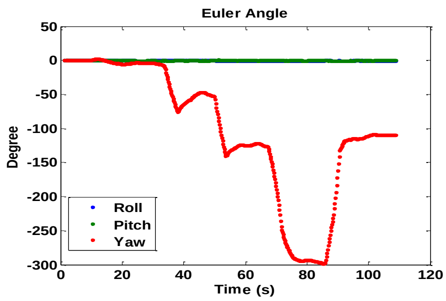

Figure 7. Euler angles of roll, pitch, and yaw from IMU

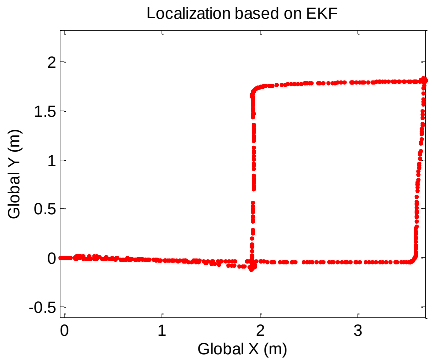

Figure 8. The localization results of the mobile robot

V. CONCLUSION

This paper presented the extended Kalman filter based localization for a firefighting robot. To withstand the conditions caused by fire, FMCW Radar, encoder, and IMU sensors were used. During the test, a mobile robot was remotely controlled to move along the path. EKF was designed to complement each sensor's drawbacks by sensor fusion to obtain accurate position and orientation of the robot. As a result, the localization method shows reliable performance resulting in low errors in the test-bed.

REFERENCES

[1] R. Siegwart, I. R. Nourbakhsh, and D. Scaramuzza, *Introduction to Autonomous Mobile Robots*, 2nd ed., Cambridge, Massachusetts, London, England: The MIT Press, 2011.

[2] M. A. Green, "High efficiency silicon solar cells," in *Proc. Seventh EC Photovoltaic Solar Energy Conference*, 1987, pp. 681-687.

[3] J. W. Starr and B. Lattimer, "Evaluation of navigation sensors in fire smoke environments," *Fire Technology*, pp. 1-23, 2012.

[4] J. H. Kim, J. Starr, and B. Lattimer, "Firefighting robot stereo infrared vision and radar sensor fusion for imaging through smoke," *Fire Technology*, pp. 1-23, 2014.

[5] J. Borenstein and L. Feng, "Measurement and correction of systematic odometry errors in mobile robots," *IEEE Transactions on Robotics and Automation*, vol. 12, pp. 869-880, 1996.

[6] B. Barshan and H. F. Durrant-Whyte, "Inertial navigation systems for mobile robots," *IEEE Transactions on Robotics and Automation*, vol. 11, pp. 328-342, 1995.

[7] F. Kong, Y. Chen, J. Xie, G. Zhang, and Z. Zhou, "Mobile robot localization based on extended kalman filter," in *Proc. Sixth World Congress on Intelligent Control and Automation*, 2006, pp. 9242-9246.

[8] J. J. Leonard and H. F. Durrant-Whyte, "Mobile robot localization by tracking geometric beacons," *IEEE Transactions on Robotics and Automation*, vol. 7, pp. 376-382, 1991.

[9] T. Oskiper, Z. Zhu, S. Samarasekera, and R. Kumar, "Visual odometry system using multiple stereo cameras and inertial measurement unit," in *Proc. IEEE Conference on Computer Vision and Pattern Recognition*, 2007, pp. 1-8.

[10] D. Nistér, O. Naroditsky, and J. Bergen, "Visual odometry for ground vehicle applications," *Journal of Field Robotics*, vol. 23, pp. 3-20, 2006.

[11] X. Yuan, C. X. Zhao, and Z. M. Tang, "Lidar scan-matching for mobile robot localization," *Inform. Technol. J*, vol. 9, pp. 27-33, 2010.

[12] D. Borrmann, J. Elseberg, K. Lingemann, A. Nüchter, and J. Hertzberg, "Globally consistent 3D mapping with scan matching," *Robotics and Autonomous Systems*, vol. 56, pp. 130-142, 2008.

[13] J. D. Tardós, J. Neira, P. M. Newman, and J. J. Leonard, "Robust mapping and localization in indoor environments using sonar data," *The International Journal of Robotics Research*, vol. 21, pp. 311-330, 2002.

[14] J. W. Starrr and B. Y. Lattimer, "A comparison of IR stereo vision and LIDAR for use in fire environments," in *Porc. IEEE Sensors 2012 Conference*, (in Press), 2012.

[15] J. H. Kim, B. Keller, and B. Y. Lattimer, "Sensor fusion based seek-and-find fire algorithm for intelligent firefighting robot," in *Proc. IEEE/ASME International Conference on Advanced Intelligent Mechatronics*, 2013, pp. 1482-1486.

[16] D. Lahr, V. Orekhov, B. Lee, and D. Hong, "Early developments of a parallelly actuated humanoid, SAFFiR," in *Proc. ASME 2013 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, 2013, pp. V06BT07A054-V06BT07A054.

[17] B. Lee, V. Orekhov, D. Lahr, and D. Hong, "Design and measurement error analysis of a low-friction, lightweight linear series elastic actuator," in *Proc. ASME 2013 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, 2013, pp. V06BT07A022-V06BT07A022.

[18] J. H. Kim and B. Y. Lattimer, "Real-time probabilistic classification of fire and smoke using thermal imagery for intelligent firefighting robot," *Fire Safety Journal*, vol. 72, pp. 40-49, 2015.

[19] J. Kelly and G. S. Sukhatme, "Visual-inertial simultaneous localization, mapping and sensor-to-sensor self-calibration," in *Proc. IEEE International Symposium on Computational Intelligence in Robotics and Automation*, 2009, pp. 360-368.

[20] E. Tzoreff and B. Z. Bobrovsky, "A novel approach for modeling land vehicle kinematics to improve GPS performance under urban environment conditions," *IEEE Transactions on Intelligent Transportation Systems*, vol. 13, pp. 344-353, 2012.

[21] S. H. Won, W. W. Melek, and F. Golnaraghi, "A Kalman/particle filter-based position and orientation estimation method using a position sensor/inertial measurement unit hybrid system," *IEEE Transactions on Industrial Electronics*, vol. 57, pp. 1787-1798, 2010.

[22] H. Rohling, "Radar CFAR thresholding in clutter and multiple target situations," *IEEE Transactions on Aerospace and Electronic Systems*, pp. 608-621, 1983.

[23] H. Zhao and Z. Wang, "Motion measurement using inertial sensors, ultrasonic sensors, and magnetometers with extended kalman filter for data fusion," *IEEE Sensors Journal*, vol. 12, pp. 943-953, 2012.

[24] W. J. E. Teskey, M. Elhabiby, N. El-Sheimy, and B. MacIntosh, "Coherence analysis for movement disorder motion captured by six degree-of-freedom inertial sensing," *Journal of Applied Geodesy*, vol. 6, no. 2, 2012.

[25] L. Guan-De, "MATLAB curve fitting toolbox in disposing of experiment data," *Tractor & Farm Transporter*, vol. 4, pp. 40, 2006.

Jong-Hwan Kim received his B.S. degree in applied physics from Korea Military Academy, Seoul, S. Korea in 2001, a M.S. degree in mechanical engineering from New Mexico State University, NM, USA in 2007, and a Ph.D. degree from Virginia Tech in 2014. He has been working on SAFFiR (Shipboard Autonomous Firefighting Robot) since 2012.

He is now an assistant professor in Korea Military Academy in S. Korea. His fields of interest are autonomous mobile robots, obstacle/collision avoidance, advanced firefighting sensor development, intelligent firefighting robot and optimized algorithm development.

Gunin Kim is a professor of Mechanical & Systems Engineering Department in Korea Military Academy, S. Korea. His research is about perception and control theory of mobile robotics, active response system of smart materials, and bulletproof vest and plate of ballistics for the army projects.