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INITIAL PERFORMANCE IMPROVEMENT FOR FUZZY RANSAC ALGORITHM BASED ON WEIGHTED ESTIMATION MODEL

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Abstract. *The computer vision involves many modeling problems with preventing noise caused by disturbance and sensing unit conditions. In order to improve computer vision system performance, a robust modeling technique must be developed for essential models in the system. The random sample consensus (RANSAC) and least median of squares (LMedS) algorithm have been widely applied in such issues. However, the performance deteriorates as the noise ratio increases and the modeling time for algorithms tends to increase in industrial applications. As an effective technique, we proposed a new fuzzy RANSAC method based on reinforcement learning concept for robust modeling. In this study, we proposed a new technique for the fuzzy RANSAC in order to improve learning performance in initial learning stage based on weighted estimation technique. Through modeling synthetic nonlinear data and camera homography experiments, the performance of the technique was evaluated. Their results found the proposed technique to be promising for improving modeling performance in initial learning stage.*
Keywords: Robust estimation, RANSAC algorithm, Fuzzy system, Reinforcement learning, Computer vision, Camera homograpy

1. **Introduction.** In computer vision systems, optical devices such as cameras, lasers, and projectors, are generally utilized to realize non-contact measurement or reconstruction of the target 3-dimensional shapes in the computer. Due to the characteristics of the computer vision systems, noise caused by the disturbance of light, reflection of light, structural variation of parts installation, or optical characteristics of target objects is practically unavoidable. Data used for constructing computer vision system models also often include significant non-negligible optical noises. Therefore, in almost all techniques for computer vision systems, it has been one of the most important issues to prevent the effects of significant outlier noises from processing or model estimation processes. In the computer vision system for 3-dimensional measurement [1,2], the homography modeling process for internal and external camera parameters [3-6] should be performed so that it is invariant to such noise. Furthermore, in reconstructing 3-dimensional shapes from sensing data, dealing with the noise is also indispensable to obtain precise and appropriate shape of the target object.

An important issue exists in developing the robust modeling algorithm for computer vision system problems. The random sample consensus (RANSAC) algorithm [7,8] and the least median of squares (LMedS) [9] have been widely and successfully applied to these problems as essential and effective approaches in computer vision system. These algorithms are simple robust computational estimation algorithms and have good applicability to various modeling problems. However, they need much computational time and the

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precision of the model is not always so high due to their algorithmic features. Moreover, the performance of these algorithms deteriorates as the noise ratio increases. Furthermore, nonlinear modeling such as fuzzy model and neural network model is difficult to deal with practically by the RANSAC sampling. Corresponding to such problems, we proposed a new fuzzy RANSAC method [17] based on fuzzy system concept [15,18] and reinforcement learning concept [14] for modeling in computer vision applications and various other modeling problems. In the fuzzy RANSAC method, the necessary sampling size is varied and the sampling is performed applying reinforcement learning. The evaluation of the model is appropriately performed applying fuzzy system concept. Through numerical experiments based on synthetic data and camera homography experiments, we evaluate the performance of the proposed algorithm and it is found to be quite effective compared with conventional algorithms. As the algorithm is statistic in nature, the performance of the modeling might be deteriorated in the initial stage according to a bad sampling by chance. In this study, in order to improve the fuzzy RANSAC algorithm further, we propose a new technique based on weighted estimation model especially for improvement of performance in initial stage of iterations. Then, we evaluate the technique through experiments of fuzzy modeling of synthetic data and camera homography modeling.

The remainder of the paper is constructed as follows. In Section 2, the computational robust estimation techniques are overviewed. The fuzzy RANSAC method based on reinforcement learning concept is introduced in Section 3. A new technique based on weighted estimation model is also proposed in Section 3. The experimental results of modeling problem and camera homography estimation are presented in Section 4. Finally, conclusions are drawn in Section 5.

2. Computational Robust Estimation Techniques.

2.1. Notation.

In the modeling and control areas such as mechanical control and plant control, although robust estimation techniques for modeling such as M-estimation have been important problems, we can consider that the RANSAC algorithm or LMedS algorithm is a more suitable methodology for various computer vision problems [10] such as estimating homography model preventing various random optical noises. We review the RANSAC algorithm below. It is assumed that some data are measured and collected through calibration works and that the model structure and the method for estimating model parameters are given. The objective of the robust estimation techniques is to estimate the parameters of the model precisely in short computational time period, preventing outlier noise effects.

Let us assume that we have a dataset A by collecting input data vector $\mathbf{x}$ and output y data for modeling as

$$A = \{(\mathbf{x}_1, y_1), \ldots, (\mathbf{x}_i, y_i), \ldots, (\mathbf{x}_N, y_N)\} \tag{1}$$

where N is the number of collected data. The data includes inlier data meeting the model and data of outlier noise. From the dataset, we estimate the model parameter vector θ appropriately expressed as

$$y = f(\mathbf{x}; \theta) \tag{2}$$

applying the computational robust estimation technique, where the structure of model f is known, e.g., linear function in general.

2.2. RANSAC algorithm.

The RANSAC algorithm has been widely used for various modeling problems. The algorithm is simple and generally applicable to various robust estimation problems. The RANSAC algorithm performs the following five steps.

Step1 Selection of a sample randomly from collected data A and have a sample set S. The number of the samples is set as the minimum number for model estimation in general.
Step2 Estimation for the necessary model parameters by using the sample set S.
Step3 Counting the number of data whose estimation error is within constant ε.
Step4 If the number of data within the error constant ε exceeds predefined value γ, the model is estimated using only data within the error constant and the algorithm is terminated.
Step5 If the number of data within the error constant is below predefined value γ, go to Step1 and iterate the procedures.

Before the RANSAC algorithm is started, the parameters ε and γ should be decided appropriately. Based on the procedures, effects from outlier random noises are reduced by random sampling and a valid model is estimated by selecting data. The number of samplings is limited statistically. In Step2, the model parameter vector is estimated minimizing the following objective function by the least squares method when the structure of the model is linear.

$$E_S = \frac{1}{2} \sum_{(\mathbf{x},y)\in S} (y - f(\mathbf{x};\theta))^2 \tag{3}$$

Figure 1 shows the RANSAC algorithm concept as a simple 1-dimensional modeling problem. The model is assumed to be a linear model. The collected dataset is depicted as circles. In the RANSAC procedures, two points are sampled and estimated the parameters as shown in the left side of Figure 1. We evaluate the decided model counting the number of data within the error constant. After several iterations, good inlier data are sampled by chance. Then a good model is estimated as shown in the right side of Figure 1.

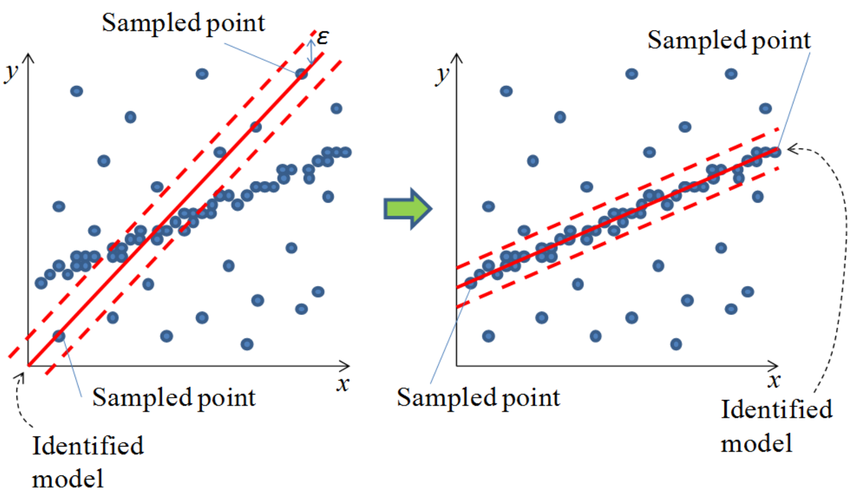

FIGURE 1. Conceptual figure of RANSAC

2.3. **Related works.** In order to improve the RANSAC algorithm, several techniques are proposed and show the effectiveness. The performance of RANSAC such as model accuracy, robustness, and computation time is improved in the hypothesis generation (Step1-Step2) and hypothesis evaluation (Step3-Step5). The methods are called as “RANSAC family” [12].

Chum and Matas proposed a sampling strategy known as PROSAC (Progressive Sample Consensus) [13]. When importance of the collected data is known in advance by some image feature techniques and the rank of data is given, the sampling is performed using the rank information instead of fully random sampling. According to the technique, hypothesis evaluation iteration is expected to be reduced.

Myatt et al. proposed the technique known as NAPSAC (N Adjacent Points Sample Consensus) [19]. In RANSAC procedures, the inlier data is often dense in the input space. By utilizing the nature, a data is sampled and the number of neighborhood points (N adjacent points) of the data is calculated. The RANSAC is performed to the specified dense neighborhood data. Since the ratio of inlier in the dense neighborhood data is increased compared with the original ratio, the RANSAC procedure can be effectively applied. In order to adopt the technique successfully, we need sufficient number of data and the model should be linear.

Chum et al. proposed the technique known as LO-RANSAC (Locally Optimized RANSAC) [20]. In Step4, local optimization process is added to the algorithm. A local optimization such as "inner" RANSAC is applied iteratively to the dataset including data within the error constant. Due to the technique, useless samplings contaminated with outlier data are expected to be reduced.

As another approach, Lee and Kim [11] proposed the technique applying fuzzy clustering to distinguishing the inlier data from outlier data. Though the burden of computation for fuzzy clustering is increased, good filtering performance can be realized.

Although conventional RANSAC family algorithms described above are essential and effective for various modeling problems, there exist some problems in dealing with it. In the techniques of RANSAC family, the number of data in a sample in Step1 is fixed as the minimum number of data for estimating the parameters in the model, in order for a sample to prevent contamination with outlier data. However, the number of data in a sample is difficult to be fixed as a minimal number in order to apply RANSAC estimation to the nonlinear model such as fuzzy model and neural network model practically for stability of numerical computation.

Moreover, in the techniques of RANSAC family, after the sampling in Step1, the model is decided deterministically. Although obvious noise data (outliers) may not affect the modeling result by RANSAC sampling and procedures, estimated model precision is not always improved. This is because the number of data selection is fixed to the minimum value needed for estimation in general. Then we perform sampling varying the number of sampling data in the fuzzy RANSAC algorithm [8,16,17].

Assume that the number of samples is M in RANSAC scheme. Because the model is estimated uniquely from M samples, RANSAC is considered to be a random selection of the best models from among up to ${}_NC_M$ candidate models. In order to increase the number of candidate models, we perform sampling that varies the number of samples randomly to improve the lack of sufficient variation in candidate models. The number of samples h is varied randomly from minimum M to K, where $M < h < K < N$. K is determined in advance. Based on the varied sampling method, the number of candidate models G becomes

$$G \leq \sum_{i=M}^{K} {}_NC_i \tag{4}$$

This leads to improvement of model precision, i.e., optimality. However, the possibility of outlier contamination in the sample becomes higher by the sampling variation. In order to prevent such situation, the data importance is learned by reinforcement learning and inlier data are sampled appropriately in the fuzzy RANSAC algorithm.

3. Fuzzy RANSAC Algorithm Based on Reinforcement Learning.

3.1. Basic concepts and error membership function. In order to improve the modeling precision and computational time, we consider data evaluation through the modeling process in RANSAC method. In the fuzzy RANSAC method, we prepare evaluation value v_i for each measured data and the values are modified by the reinforcement learning algorithm. The evaluation value is desirable to denote goodness of the data (inlier). Also, the sampling is performed effectively based on the evaluation value. Then we consider the following extended dataset from Equation (1):

$$B = \{(\mathbf{x}_1, y_1, v_1), \ldots, (\mathbf{x}_i, y_i, v_i), \ldots, (\mathbf{x}_N, y_N, v_N)\} \tag{5}$$

In order to perform reinforcement learning appropriately, we define a fuzzy set for rewards and evaluation.

In RANSAC algorithm, evaluation of modeling is performed based on the magnitude of each evaluation error by judging whether the absolute error is within predefined ε. However, the modeling performance is affected by the setting ε. In the fuzzy RANSAC, a fuzzy set of the residual error is defined to evaluate the model. The fuzzy set of errors is defined as the triangular type membership function in which center is 0 and width is b. Assuming the modeling error e_i of a measured data, the triangle type membership function is defined as

$$m_i = \begin{cases} |e_i - b|/b; & \text{if } |e_i| \leq b \\ 0; & \text{if } |e_i| > b \end{cases} \tag{6}$$

where m_i is the membership value of the ith data. Figure 2 shows the membership function. It should be noted that the conventional RANSAC is assumed to be crisp set defined on the residual error. The whole evaluation E of the model is calculated by

$$E = \sum_{i=1}^{N} m_i \tag{7}$$

From these definitions, we expect that the above described affection of the parameter ε in the conventional RANSAC will be relaxed. Moreover, the evaluation E can also be utilized to evaluate the estimation performance as an objective function.

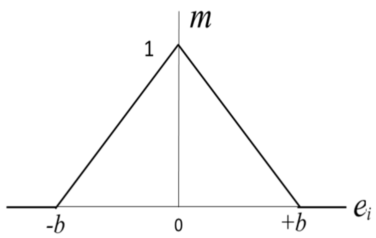

Figure 2. Error membership function

3.2. Sampling strategy and model estimation. Sampling is performed based on v_i applying the ε-roulette strategy [17] to improve exploration and exploitation performance. Namely, with probability ε, we select h data (sampling) uniformly randomly among all data, and with probability $1-\varepsilon$, we select h data applying the roulette strategy based on the evaluation value v. Sampling is performed based on the Monte Carlo method in proportion to evaluation values. Actual sampling is performed proportionally to normalized probability w as follows:

$$w_i = \frac{v_i}{\sum_{j=1}^{N} v_j}, \quad i = 1, \ldots, N \tag{8}$$

In this strategy, data of low evaluation value could also be randomly sampled in low probability. Then model estimation is performed using the sampled data based on Equation (3).

3.3. **Reinforcement learning.** The evaluation value is desirable to denote goodness of the data (inlier). In order to attain this, the evaluation value v is learned based on reinforcement learning [14]. We define the learning algorithm with a necessary reward based on the whole evaluation E in Equation (7) and the membership value m of each data as follows:

$$r = E \tag{9}$$

$$v_i \leftarrow v_i + \alpha(m_i \cdot r - v_i), \quad i = 1, \ldots, N \tag{10}$$

where r is the reward and α is the learning parameter ($0 < \alpha < 1$) in reinforcement learning.

We expect influence caused by outlier noise to be reduced due to the learning mechanism. This may also reduce calculation time for modeling and improve model precision. The modeling process is so simple and applicable that it is applied to various problems in such areas as computer vision and control. Based on the method, the advantages of reinforcement learning that has a good balance of exploration and exploitation are utilized effectively.

3.4. **Initial stage procedure based on weighted estimation model.** Although the modeling performance is drastically improved by the fuzzy RANSAC method compared with the conventional RANSAC, the performance is possible to deteriorate in the initial learning stage because it is possible to perform sampling of only outlier noise data and reinforcement learning is not effectively performed. This problem is similar to "early convergence" problem in the genetic algorithm. Our research objective in this study is to address the problem. The problem is originated from accidental low precision of initial model estimation using only outlier noise data caused by random based methodology.

Then, we propose a new modeling technique for initial stage in fuzzy RANSAC algorithm. We consider estimation technique minimizing the following objective function instead of sampling.

$$E_A = \frac{1}{2} \sum_{(\mathbf{x},y) \in A} W_{\mathbf{x},y} (y - f(\mathbf{x}; \theta))^2 \tag{11}$$

where $W_{\mathbf{x},y}$ is the weight parameter representing goodness of data $(\mathbf{x}, y)$. The model estimation is performed using the whole data. The parameter vector can be estimated immediately minimizing the objective function Equation (11) by weighted least square errors method. If we set appropriate values to the weight parameters, an excellent precise model could be derived immediately. However, it is not realistic to find such ideal values, and we propose using v in Equation (5) for approximating the weight parameter values as

$$E_B = \frac{1}{2} \sum_{(\mathbf{x},y,v) \in B} v (y - f(\mathbf{x}; \theta))^2 \tag{12}$$

By using all data, the initial model is estimated not so badly but fairly. Reinforcement learning is also applied simultaneously. Then v becomes appropriate gradually through learning progress.

We apply the proposed estimation technique in initial stage of iterations in fuzzy RANSAC method. After that, the sampling and estimation are applied as introduced in the previous subsections.

3.5. **Procedures of fuzzy RANSAC algorithm.** The procedures of the fuzzy RANSAC algorithm are as follows. In the first several iterations, the following procedures are employed.

Step1 Estimation of the model using the whole data and the weight parameters.
Step2 Calculation of fuzzy membership function values based on the estimated model.
Step3 Calculation of the evaluation E and rewards for data.
Step4 Employment of reinforcement learning using fuzzy membership values and rewards.

In the latter iterations, the following procedures are employed.

Step1 Decision of the number of samples h randomly ($M \leq h \leq K$).
Step2 Sampling based on the sampling strategy.
Step3 Estimation of the model based on the samples.
Step4 Calculation of fuzzy membership function values based on the estimated model.
Step5 Calculation of the evaluation E and rewards for data.
Step6 Employment of reinforcement learning using fuzzy membership value and rewards.

The procedures are iterated until the predefined number of iterations or a good model is attained. The initial value of v is set to the same small number.

4. **Experimental Results.** We conduct the modeling experiments using synthetic data and camera calibration data to evaluate the proposed improvement method for the fuzzy RANSAC algorithm compared to the conventional fuzzy RANSAC algorithm and traditional RANSAC algorithm.

We evaluated the basic performance of Equation (12) and Equation (10) in advance. We confirmed quite stable learning and modeling performance individually. However, the model precision was limited because of the appropriate weight setting problem. In the following experiments, estimation technique in Equation (12) and Equation (10) is applied in only the first 5 iterations to attaining stable modeling performance.

4.1. **Fuzzy modeling results using synthetic data.** We assume the true model of single input and single output model as shown in Figure 3. The true model is assumed to be a simplified fuzzy model structure [15] using normal triangular membership functions as shown in Figure 4:

$$\begin{cases} \text{IF } x \text{ is Low} & \text{THEN } y = \delta_1 \\ \text{IF } x \text{ is Medium} & \text{THEN } y = \delta_2 \\ \text{IF } x \text{ is Big} & \text{THEN } y = \delta_3 \end{cases} \tag{13}$$

The output of the model $\hat{y}$ is calculated by

$$\hat{y} = \frac{\sum_{i=1}^{3} \mu_i \cdot \delta_i}{\sum_{i=1}^{3} \mu_i} = \sum_{i=1}^{3} \mu_i \cdot \delta_i \tag{14}$$

where μ is the value of the membership function, because the summation of the membership values is always 1.0 in normalized triangular membership functions.

The true values of δ are set as 0.75, 0.25, and 0.75, respectively. Base data are generated by sampling true data randomly and adding a small amount of white noise ($\sim N(0, 0.01^2)$). Random noise data are generated based on 2-dimensional uniform distribution. Then the measured dataset is prepared by mixing 60% of base data with 40% of random noise randomly. The number of data in the measured dataset is 100. We apply the initial stage improvement technique for fuzzy RANSAC algorithm, conventional fuzzy RANSAC algorithm, and the traditional RANSAC algorithm to the measured dataset.

The problem in this experiment is to identify the fuzzy model estimating parameter δ by the least square errors method using the measured dataset. Synthetic measured dataset

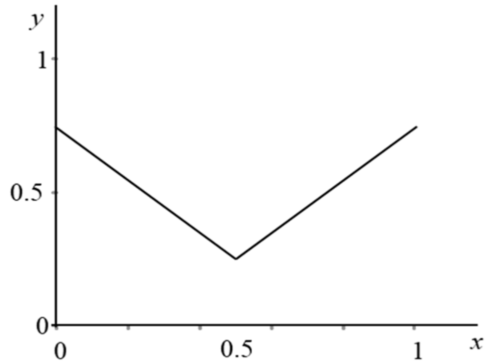

FIGURE 3. True model for synthetic data

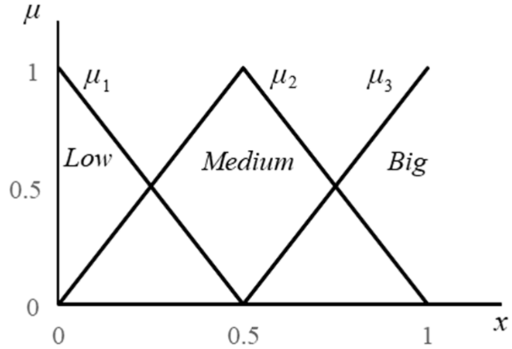

FIGURE 4. Membership functions

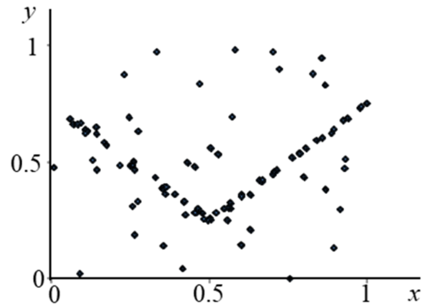

FIGURE 5. Measured dataset for experiments

depicted as points is shown in Figure 5. Though at least 3 samples are required for the problem, estimation calculation of fuzzy model using 3 data falls into unstable situation according to the rank problem due to sparse sample dataset. For the reason, the number of samples is varied randomly from $M = 15$ to $K = 20$ in the modeling.

Since the RANSAC based algorithms are stochastic in nature, it is required to run the algorithm several times in order to evaluate performance. We conduct the 100 modeling trials, including 1,000 iterations of the algorithm using the dataset. Estimation performance is evaluated by the averaged value and minimum value of the best objective function values defined in Equation (7) so far in each simulation trial.

Figure 6 and Figure 7 show results in initial stage of 100 trials. In the figures, "Proposed" denotes the proposed initial learning stage improvement method for fuzzy RANSAC, "F-RANSAC" denotes the conventional fuzzy RANSAC described in Section 3, and "Conventional" denotes the general RANSAC method. In Figure 6, average values of objective

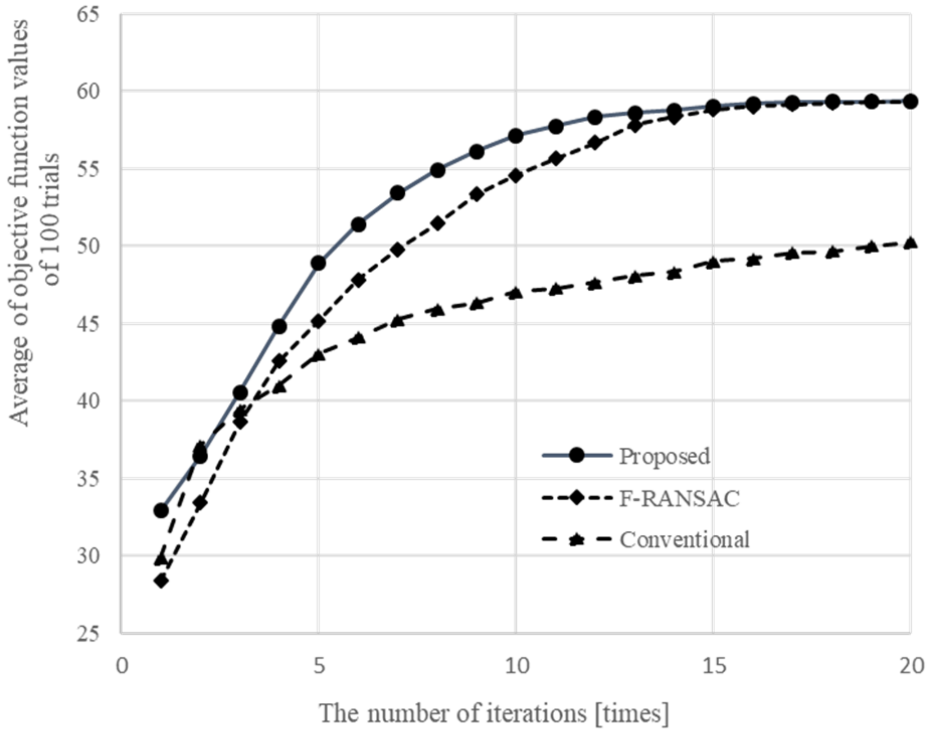

FIGURE 6. Results of average of 100 trials

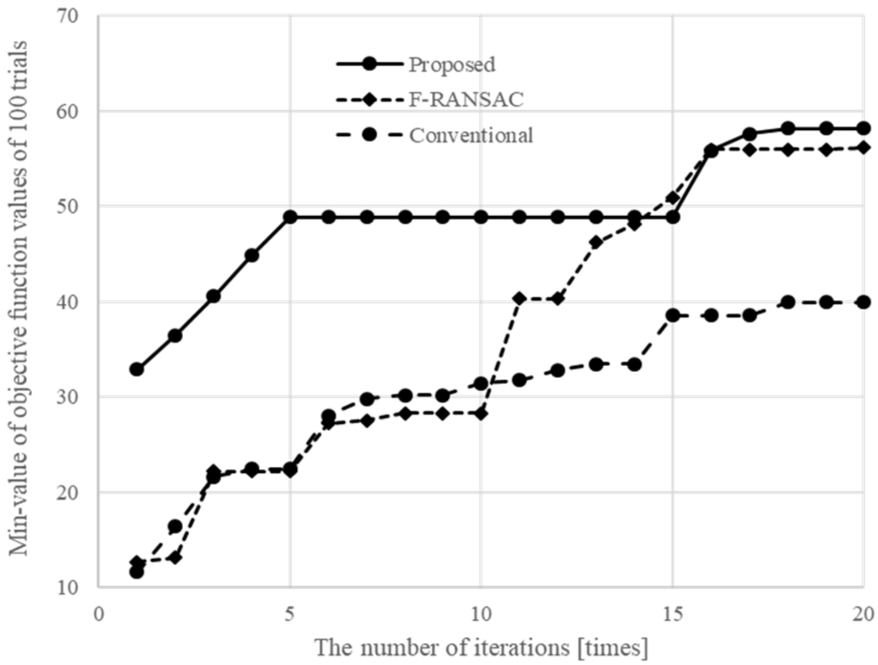

FIGURE 7. Results of the worst case in 100 trials

function value E are evaluated comparatively. In the initial iterations less than the 15th iteration, the performance is improved. In Figure 7, minimum values of objective function value E, i.e., the worst case in 100 trials, are evaluated comparatively. From the results, the performance of the initial stage (less than the 15th iteration) is improved by the proposed method compared with the conventional fuzzy RANSAC method and the traditional method.

4.2. **Results of camera modeling.** We conduct the experiments of camera model estimation using an industrial camera and a calibrator. We evaluate the proposed algorithm compared with the conventional fuzzy RANSAC algorithm and traditional RANSAC.

The camera model is generally expressed as the following essential formulation.

$$\omega \cdot U = \mathbf{P} \cdot W \tag{15}$$
$$U = [u \;\; v \;\; 1]^T, \quad W = [X \;\; Y \;\; Z \;\; 1]^T$$

where $\mathbf{P}$ is the perspective view matrix, (u, v) are image coordinates of the target, (X, Y, Z) are corresponding world coordinates of the target, and ω is the scaling parameter. For application, we should estimate these parameters. Firstly, data pairs of 2D image data and corresponding 3D target coordinates through the camera are collected using the calibrator. Then required parameters such as the perspective view matrix and the scaling parameter are estimated by the least square errors method using collected datasets.

The camera we used in this experiment is a high performance CMOS model with Gigabit Ethernet. Camera resolution is 2,592 × 1,944 pixels. The lens is aspheric with minimal distortion. The checkerboard calibrator shown in Figure 8 is used for collecting data pairs (target 3D points in world coordinates system and corresponding image 2D pixels) for calibration. The number of collected data pairs is 105. We conduct camera homography estimation experiments for 100 simulation trials including 1,000 iterations of the algorithm by using collected dataset.

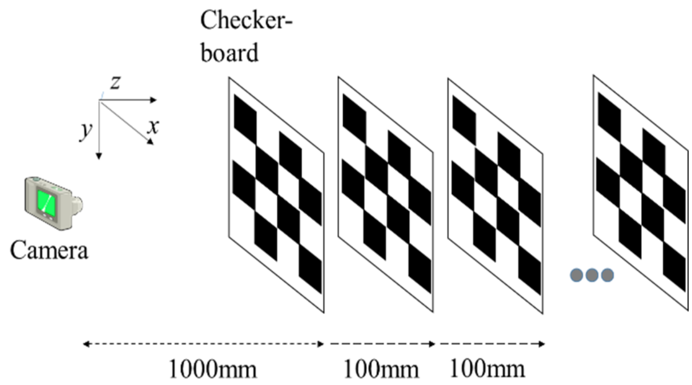

Figure 8. Test field and calibrator

Figure 9 and Figure 10 show results in initial stage of 100 trials. In Figure 9, average values of objective function value E are evaluated comparatively. The average values are improved as shown in Figure 9. In Figure 10, minimum values of objective function value E, i.e., the worst case of 100 trials, are evaluated comparatively. From the results, the performance of the initial stage is improved by the proposed method compared with the conventional method and the traditional method. Especially, the worst case of trials in the early iterations is drastically improved by the proposed method as shown in Figure 10.

We found through experiments that the proposed method is quite effective especially in case the computational time for modeling is limited.

5. **Conclusions.** In this study, we proposed an improvement technique in initial learning stage for fuzzy RANSAC algorithm based on the weighted estimation model and evaluated the technique through modeling synthetic data of fuzzy modeling and camera homography experiments. Their results found the proposed technique to be promising in improving

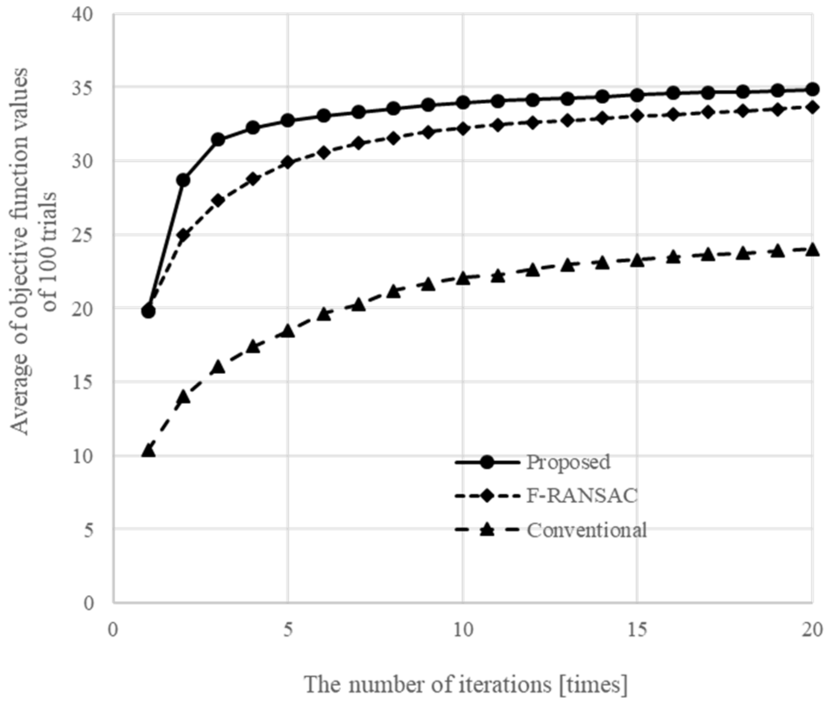

FIGURE 9. Results of average of 100 trials

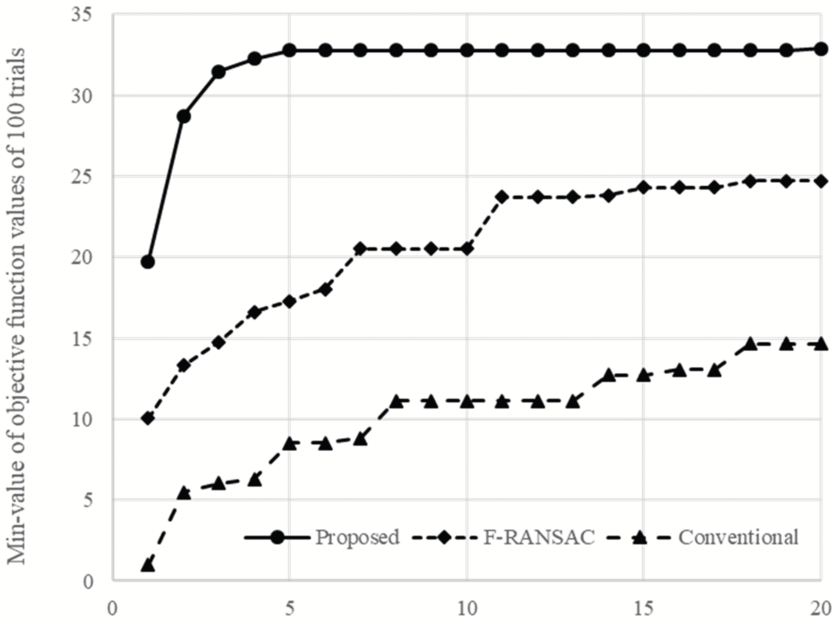

FIGURE 10. Results of the worst case in 100 trials

initial performance of fuzzy RANSAC algorithm. Our future plan includes application of the proposed method to the other modeling problem.

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