Illumination-Invariant Image Matching Based on Simulated Kalman Filter (SKF) Algorithm

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***Abstract*—In this paper, a novel image template matching approach to tackle illumination-invariant problem has been proposed. The traditional algorithm to solve image matching problem takes a lot of memory and computational time. Therefore, the image matching problem is assigned to optimization problem and can be solved precisely. Although there are some methods presented recently for image matching illumination-invariant, all of them have limitations in term of dealing with the pixels complexity and many unknown parameters in a certain algorithm. The search of the image template has been performed exhaustively by using Simulated Kalman Filter (SKF) algorithm. The experiment is conducted using an image taken from the database and the contrast image is changed to get the illumination effect. Experimental results show the comparison between SKF and Particle Swarm Optimization (PSO) to get the performance of the correct matching. The percentage of the matching result for the image within six conditions are 24%, 16%, 16%, 12%, 28% and 4% accordingly, which are higher than the PSO algorithm, which obtained 0% correct matching for all conditions.**

***Index Terms*—Illumination-invariant; Image Template Matching; Simulated Kalman Filter; Optimization.**

I. INTRODUCTION

A major challenge faced in visual localization, navigation and scene classification approaches in outdoor environments is the change in appearance across a wide range of illumination conditions, those encountered during a typical 24-hour day-night cycle [1]. Illumination is the effect of the light on an environment or specific space. Lighting or illumination consists of two sources which are the artificial light source and natural illumination. In case of artificial light source, it includes lamps and natural illumination or also known as ambient light from the sun through window and skylights. Natural illumination is lead to the consumption of energy in the building instead of using the artificial light source. In this paper, the effect of the illumination to the image matching process will be considered. The results of the illumination effect to the image matching algorithm will be explained throughout this paper.

There are many applications that considered the illuminance effect by getting the accurate result. For example, as reported in the [2], for camera calibration application, the ambient light showed the less error compared to the artificial light source.

Template matching is an important image recognizing and processing method. Normalized Cross Correlation (NCC) function, as a similarity measure, is frequently used for this application [3]. It matches the object and the original image with the aid of the relationship between original data like pixel grey value. Nowadays, NCC has better adaption for various images and stronger robustness compared with Sum of Absolute Differences (SAD) and the Sum of Squared Differences (SSD)[4].

Optimization is a process to produce the best result with the least production process. Simulated Kalman Filter (SKF) algorithm is introduced to optimize the result of the image matching application. SKF will reduce the computational time and give the accurate result to the system. There are many types of optimization such as Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO). Every algorithm has their own advantages and disadvantages that could be considered such as the processing time and efficiency of the algorithm. The ability of the algorithm is very important because solving the real-time problem is one of the main goals. As reported in [4], Fruit Fly Optimization (FFO) algorithm has some defects in the optimization process which is in the osphresis phase. Besides, Genetic Algorithm (GA) need many steps such as crossover and mutation. These operators will increase the computational time of the algorithm [5].

The remainder of the paper mainly consists of the following work. The algorithm of the Simulated Kalman Filter is discussed in next section. The discussion of how the SKF and PSO algorithm solves the image matching problem will be discussed in the section after the introduction of the SKF algorithm. The experimental result and performance analysis of the algorithm will be following. The conclusions and future works are contained in the last section.

II. SIMULATED KALMAN FILTER (SKF) ALGORITHM

SKF was presented by Ibrahim *et. al* [6], [7] in 2015. SKF is a population-based metaheuristic algorithm introduced for continuous optimization problem and it is inspired by the estimation capability of Kalman Filter. The SKF algorithm is shown in Figure 1 [8].

The algorithm is started with the initialization of the particles within the search space randomly. In addition, the initial value of error covariance estimate, *P(0)*, the process noise value, *Q*, and measurement noise value, *R* are needed during the initialization stage, which is also needed in Kalman Filter process.

After that, the fitness value of each particle needs to be calculated and the best fitness value of each iteration is recorded as $X_{best}(t)$. Image matching is considered as a maximization problem, therefore Equation (1) is used here.

$$X_{best} = max_{i \in 1,..,n} fit_i\left(X\left(t\right)\right) \tag{1}$$

The updated best in the program known as X_{true}. The X_{true} is updated only if the $X_{best}(t)$ is better than X_{true} which is $X_{best} > X_{true}$ for maximization problem. The next calculations are like Kalman Filter which are a prediction, measurement and estimation.

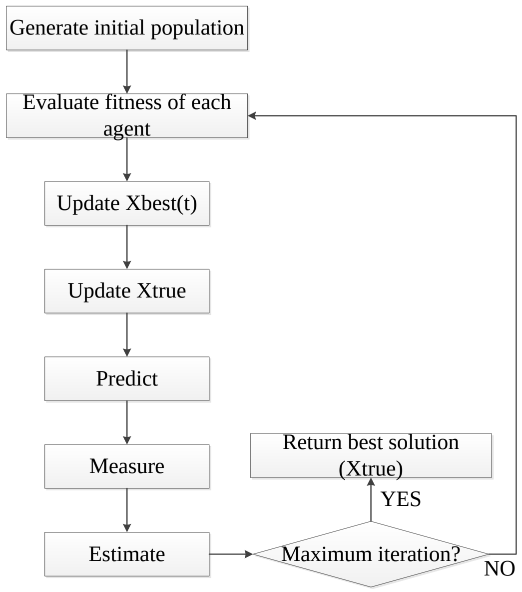

Figure 1: SKF Algorithm

In the prediction stage, the following time-update equations are evaluated in Equation (2) and (3).

$$X_i\left(t \mid t\right) = X_i\left(t\right) \tag{2}$$

$$P\left(t \mid t\right) = P\left(t\right) + Q \tag{3}$$

where $X_i(t|t)$ is the predicted state and $X_i(t)$ is the previous state, $P(t|t)$ and $P(t)$ are predicted error covariance estimate and previous error covariance estimate, respectively and Q is the process noise.

The next step is measurement. It acts as a feedback to the estimation process. Measurement, $Z_i(t)$ of each individual agent is calculated using the Equation (4).

$$Z_i\left(t\right) = X_i\left(t \mid t\right) + sin\left(rand \times 2\pi\right) \times \left|X_i\left(t \mid t\right) - X_{true}\right| \tag{4}$$

where $sin(rand \times 2\pi)$ term gives the stochastic part of SKF and *rand* gives the random number in 0 to 1 range.

The last step is the estimation. Kalman gain is needed in this step and calculated as shown in Equation (5).

$$K\left(t\right) = \frac{P\left(t \mid t\right)}{P\left(t \mid t\right) + R} \tag{5}$$

The estimation of next state is calculated based on Equation (6) and the error covariant is updated based on Equation (7).

$$X_i\left(t+1\right) = X_i\left(t \mid t\right) + K\left(t\right) \times \left(Z_i\left(t\right) - X_i\left(t \mid t\right)\right) \tag{6}$$

$$P\left(t\right) = \left(1 - K\left(t\right)\right) \times P\left(t \mid t\right) \tag{7}$$

Lastly, the algorithm will continue the searching until it meets the stopping condition and in this case, until the maximum iteration reached.

III. IMAGE TEMPLATE MATCHING BY USING OPTIMIZATION ALGORITHMS

The experiment is made with a 256×256 source image and 43×41 template image as shown in Figure 2.

Figure 2: Source image [9] (right) and Template image (left)

The fitness function of the optimization algorithm can be expressed by equation (8) as shown below. It is Normalized Cross-Correlation (NCC) function that had been explained earlier.

$$R\left(i,j\right) = \frac{\sum_{x=1}^{X-1}\sum_{y=1}^{Y-1}\left[S\left(x+i,y+j\right) \times T\left(x,y\right)\right]}{\sqrt{\sum_{x=1}^{X-1}\sum_{y=1}^{Y-1}\left[S\left(x+i,y+j\right)\right]^2 \times \sum_{x=1}^{X-1}\sum_{y=1}^{Y-1}\left[T\left(x,y\right)\right]^2}} \tag{8}$$

where $S(x+i, y+j)$ is random coordinate of the original image grayscale value, $T(x,y)$ is grayscale value of template image, and $R(i,j)$ is the match value. (X,Y) and (x,y) represent size of template and original image respectively. Every $R(i,j)$ will return value between value 0 and 1. The maximum of $R(i,j)$ indicates the best position for T, and thus the matching image is obtained.

A. Simulated Kalman Filter (SKF) Algorithm

Basically, the SKF algorithm is used in this application is same as explained in the previous section. By adding some steps to the algorithm, the good matching result is produced. Figure 3 explained how the algorithm works to this application.

At first, set the parameters of SKF including the initial value of error covariance estimate, the process noise value, and measurement noise value to 1000, 0.5 and 0.5 respectively. The experimental parameters for the algorithm are 5, 10 and 20 particles and 1000 iterations for one run. After that, an image taken from the database website [9] is used throughout the analysis.

The following step is randomly generated the initial population of the SKF algorithm. The population is generated based on a number of particles that initially assigned to the algorithm. The higher the number of the particle assign, more accurate the population generated. Even so, when the number of particles is too big, it will take longer computational time.

After that, the fitness function is evaluated for each particle. In this analysis, the highest fitness value is the fittest agent among all. The value will be taken for the next step and assign to $X_{best}(x)$ value. X_{true} value will update thoroughly for one runtime of the algorithm.

Prediction, measurement and estimation steps will be repeated according to the number of iteration assigned. The equations used already explained clearly in the previous section. The algorithm will end until the iteration is achieved the maximum iteration.

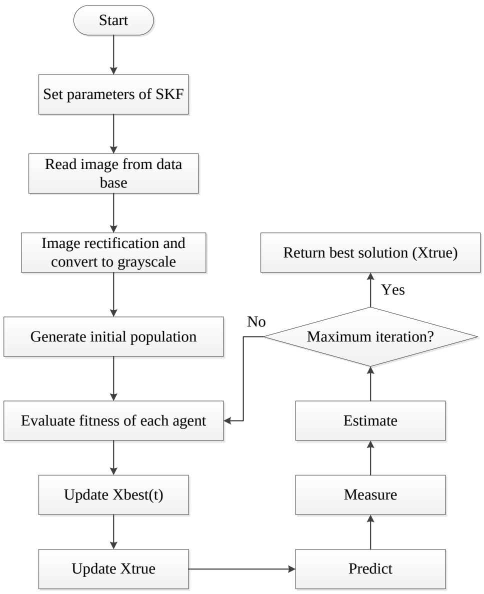

Figure 3: Flowchart for SKF Algorithm with modifications

B. Particle Swarm Optimization (PSO) Algorithm

Like other metaheuristic algorithms, Particle Swarm Optimization (PSO) also evolves according to the adaptability of the individual. PSO algorithm is already applied to solve the image matching problem as reported in [3]. Therefore, the flowchart of the system had been summarized in Figure 4. There is some modification from the traditional PSO. It is by adding a few steps to make the algorithm suitable for this application. It also uses NCC function as the fitness function in the algorithm.

At first, the parameter setting in the PSO algorithm as follows: w_{max} =0.9, w_{min} =0.4, c_1 = 2, c_2 = 2 and the particle dimension is 2. The experimental parameters for the algorithm are 5, 10 and 20 particles and 1000 iterations for one run. After that, an image taken from the database website [9] is also used throughout the analysis.

Next is randomly generated the initial population of the SKF algorithm. The population is generated based on the number of particles that initially assigned to the algorithm.

After that, the fitness function is evaluated for each particle. In this analysis, the highest fitness value is the fittest agent among all. The value will be taken for the next step and assign to P_{best} value. G_{best} value will update thoroughly for one runtime of the algorithm. The algorithm will end until the iteration is achieved the maximum iteration.

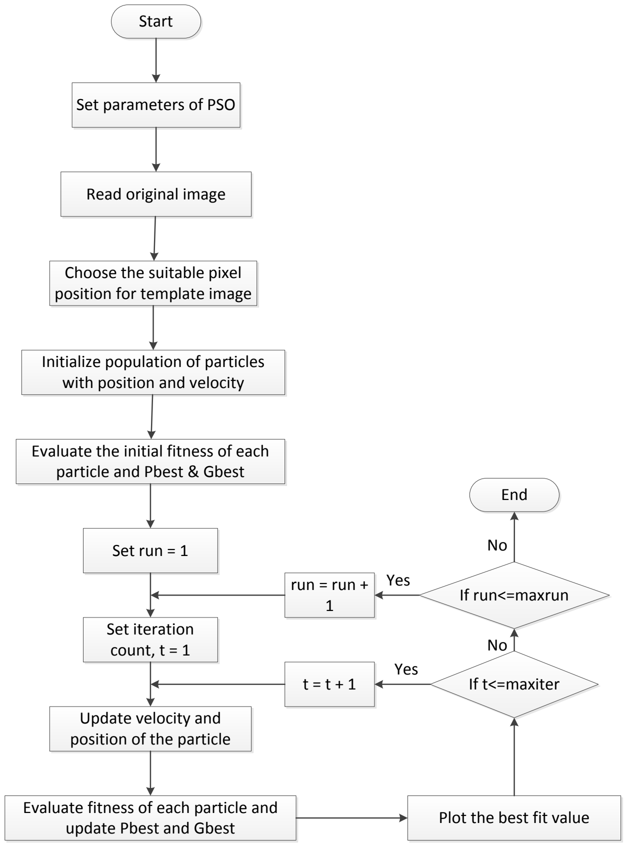

Figure 4: Flowchart of PSO algorithm with modifications

IV. Experimental Result and Performance Analysis

To further analyze the performance of the algorithms based on the illumination-invariant image matching application, 6 images with different intensity is introduced.

As shown in Figure 5, there are six different intensity of the images are produced. Figure 5(a) – (f) had varies contrast range within 0 to 1 which are (a) is the original image, (b) is increase 1% contrast from the contrast image, (c) is within 0.3 to 0.7 contrast range, (d) is within 0.2 to 0.75 contrast range, (e) is within 0.1 to 0.5 contrast range and (f) is within 0.6 to 1.0 contrast range. After getting 6 different images, they will be analyzed to obtain the illumination effect to the image matching application.

Table 1 shows the statistical result for the best fitness value for each image with different intensity as discussed earlier. The first row of the table refers to the label image in Figure 5. As a summary, 20 particles give the best of the fitness value compared to others for the all six different intensities. The best fit value of the analysis is 0.8234 for the image (e) that is between 0.1 to 0.5 contrast range. As we increase the number of particles to 30, the fitness value had decreased. It may be caused by the search space for the original image is low in term of the dimensional image.

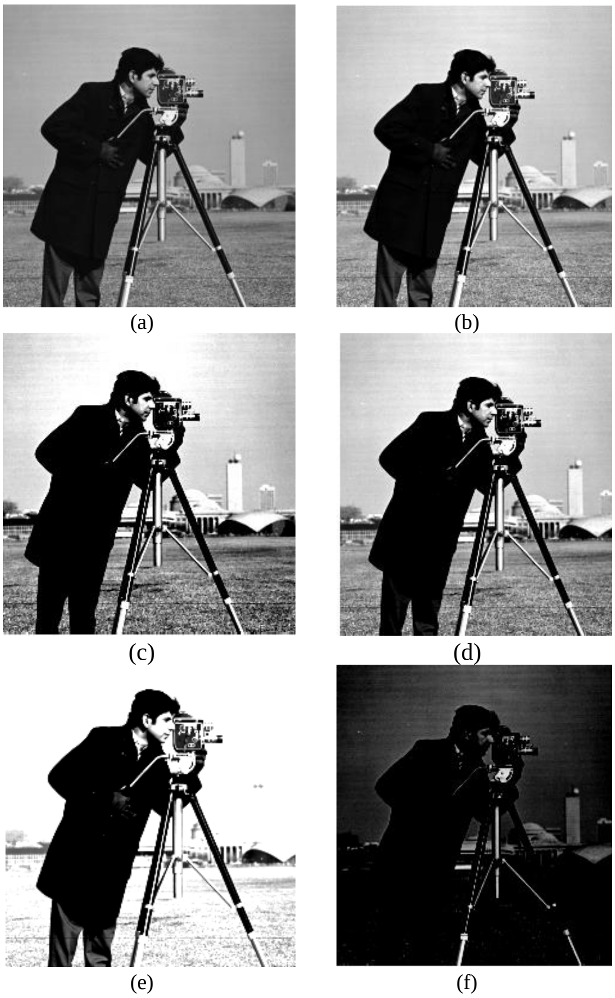

Figure 5: (a) Original Image (b) Increase 1% contrast from original image (c) Contrast range: [0.3 0.7] (d) Contrast range: [0.2 to 0.75] (e) Contrast range: [0.1 to 0.5] (f) Contrast range: [0.6 to 1.0]

Table 1
The Statistical Result for Best Fit Value for each Image with Different Intensity

No. of Particles	Best Fit Value		
	5	10	20
(a)	0.7195	0.7127	0.8006
(b)	0.7131	0.7131	0.8325
(c)	0.7165	0.7162	0.7162
(d)	0.7148	0.7148	0.7145
(e)	0.7141	0.7141	0.8234
(f)	0.7270	0.7270	0.7270

*The highest best fit value is 1

As for Table 2, it discusses the matching position of each image with variant intensity. It will be considered successful when the blue box is detecting the face of the cameraman as per assigned template. The size of the blue box is the same as the template image (43×41). The image matching result is corresponding to the best fitness value. The 20 particles column shows clearly almost all the matching result is a success compared to others.

In addition, Figure 6 shows the difference between two algorithms which are SKF and PSO within 25 independent runs. The analysis shows the correct matching result for both algorithms by using all six illumination-invariant. All trials by PSO algorithms are failed for all conditions. Although the matching result performance is moderate, it still gives the best result compared to PSO.

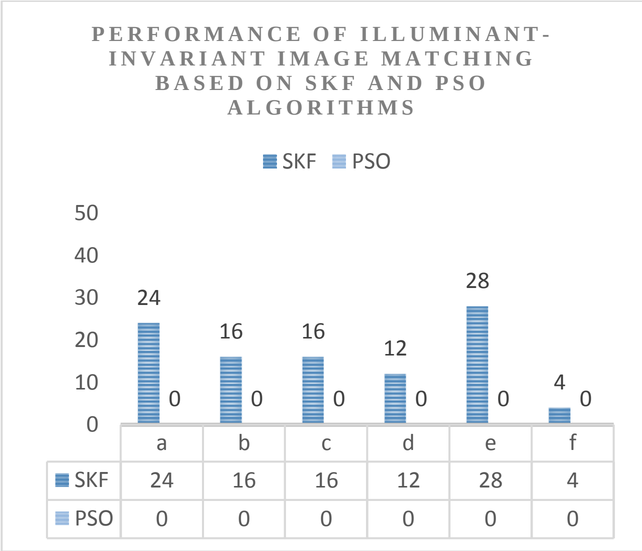

Figure 6: Performance of Illuminant-Invariant Image Matching Based on SKF and PSO Algorithms

As a conclusion, with the varying of image intensity, the proposed image matching algorithm can be applied. The computational time for the algorithm to process each image is just 44 seconds for 5, 10 and 20 particles. As reported in [10], [11], for illumination-invariant image matching analysis, the accuracy and efficiency are more important than the execution time of the experiment. It showed that the algorithm is accurate and precise although apply to different image intensities.

V. Conclusion

This paper presented a novel approach to illuminance-invariant effect towards image matching application by using Simulated Kalman Filter (SKF) algorithm. The percentage of matching result for the image within six conditions are 24%, 16%, 16%, 12%, 28% and 4% accordingly which is higher than PSO algorithm, which is 0% correct matching for all conditions. The computational time is quite low and the image matching application for six different image intensities is successfully matched. Therefore, the proposed algorithm is precise and robust. With the correct parameters assigned to the algorithm, it gives the best result to the six different intensities of images.

For the future work, the real-time application will be considered. Other than that, image matching for a more complex image for the real outdoor and indoor environment will be focused on. With the low computational time and accurate algorithm, there is most probably the algorithm will work with real-time application.

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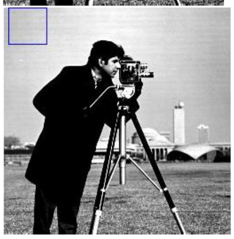
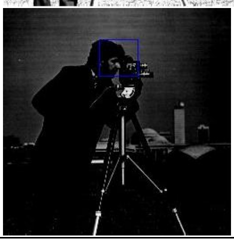
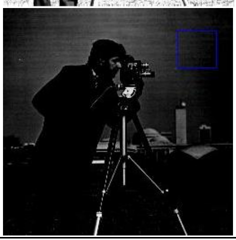
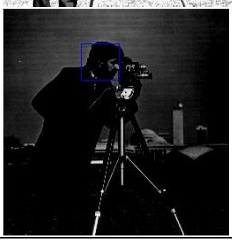
Table 2
Matching Position for each Image with Varied Intensity

No. of Particles	Matching Position		
	5	10	20
(a)			
(b)			
(c)			
(d)			
(e)			
(f)			

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