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Verification of Illumination Tolerance for Clothes Recognition

Ryuki Funakubo[1], Khaing Win Phyu[1], Ryota Hagiwara[1], Hongzhi Tian[1] and Mamoru Minami[1]

[1]Okayama University, Japan
(Tel: 81-86-251-8233, Fax: 81-86-251-8233)
[1]pip62k65@s.okayama-u.ac.jp

Abstract: Recently, robots have been used in clothing industries for mass production with countless merits. However, there remain many challenges for robots in recognition, pose (position and orientation) detection operations, especially when the working object is deformable and every working object has unique shape and color. In this paper, pose detection of clothes through 3D recognition is proposed for the task in which the manipulator should recognize clothes, estimate relative pose and perform pick and place function, where there functions have been thought to be difficult. In proposed cloth recognition system, a variety of models of different clothes with unique shape and color are generated as BMP (bit map file) format extracted from the camera. Recognition experiments under fluorescent light and LED light has been executed, having shown the illumination tolerance of proposed Photo-Model-Based pose recognition system.

Keywords: Genetic Algorithm, Handling, Model-Based-Matching, 3D-Recognition

1 INTRODUCTION

Nowadays, most of the garment companies especially in Japan have been facing with two main inconveniences as follow:

- Growing shortage of labor force because an aging population have been progressing.
- Weak point of human workers are laziness, boring and tiring due to the long working hours.

Recently, IT based technology and Robotics have began to be used in the garment (cloth) companies considering above problems. However, robotics in garment industry are capable of operations only if preconditions are met such as (1) in surrounding operating environment, the light environment is guaranteed not to change in time, (2) the handling object is able to be defined by the shape of object in advance, and (3) the design of the robot hand is predefined based on the object shape. A number of researches concerning robots in recognizing deformable objects especially clothes have been done[9].

In application to cloth handling, the main tasks are to get the purchasing order of clothes from on line customer and classify these clothes and package and place in different box for storage every day. Since clothes are deformable object, no definition of clothes can be predefined in computer. Consequently it is too difficult to handle a wide variety of clothes that are in irregular shape and size. Therefore, we have tried to make a vision-based robot system as shown in Fig.1 to solve the above problems for mass handling of clothes with varieties by robots.

On the other hand, robot control technology using visual information, called as visual servoing, is playing an important role in industry. In our previous works, we have been developing a three-dimensional move on sensing system named 3D-MoS using two cameras as stereo vision sensor. The robot control technology using visual information has been already confirmed in guidance and control of underwater robot (3D-MoS / AUV)[6] and soil decontamination robot system (fully automated robotic system to decontaminate the radioactive contamination soil)[8]. In these previous works, model-based method is used to recognize 3D (three dimensional) pose.

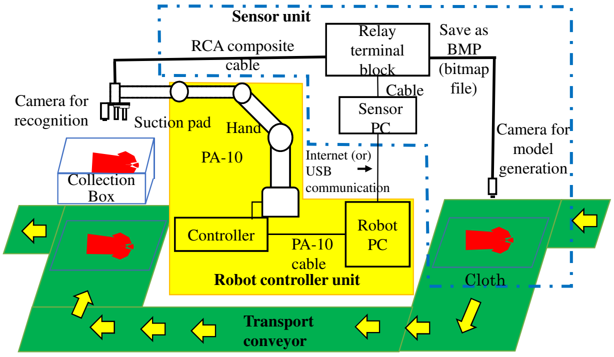

Fig. 1. System configuration

However, in handling application dealing with second-hand clothes in which the manipulator has to pick and place unique-shape-and-color clothes with random appearance in camera images, it is impossible to use models that are predefined for all clothes. Therefore, as a main contribution in this paper, we introduce a new approach to generate models for every clothes during the operation of pick and place. In proposed "Photo-model 3D-MoS," the model of object is automatically created from a photo by robot itself. Then, relative pose estimations of clothes are performed using generated models through model-based clothes recognition. PA10 with 7-DoF (Degree of Freedom) is being used for recognition and pose detection operations.

The configuration of the system is shown in Fig. 1. In this configuration, three cameras are used as vision sensors. First camera is used for model generation. The other two are used for recognition based on the photograph model that are fixed at the end-effector of the mobile manipulator (PA10 robot). The merits of this proposed system are to save the cost of staff and to get the better performance and higher accuracy than workers in the garment distribution company. As the final objective is to pick and place the clothes in/out individual boxes, it is necessary to estimate the pose of the clothes correctly despite environment lighting condition varieties. Therefore, we conducted cloth pose estimation experiments 1000 times for each different twelve cloth and analyzed the recognition accuracy.

2 PROPOSED PHOTOGRAPH MODELING-BASED CLOTHES RECOGNITION

There are two main portions in proposed system. The first portion is cloth model template generation and the latter is relative pose estimation using generated model template through model-based matching method. Here is description of kinematics of stereo-vision before explanation of proposed system in detail.

2.1 Kinematics of Stereo-Vision

Fig. 2 shows the relationships between the world coordinate system of the manipulator Σ_W and the hand coordinate system Σ_H. On the other hand, it can also be called as the coordinate system of 3D-MoS (Move on Sensing) robot. The coordinate system of dual-eyes vision system can be seen in Fig.3. An target object coordinate system is expressed by Σ_M. In the image coordinate system, the coordinate system of the left and right cameras are represented as Σ_{CR} and Σ_{CL}. Σ_{IR} and Σ_{IL} are the coordinate systems of the left and right cameras' images. According to coordinate system, the j-th point of the i-th model can be represented by the following the simultaneous transformation matrix.

- ${}^{CR}\boldsymbol{T}_M$:Homogeneous transformation matrix from right camera coordinate system Σ_{CR} to the object coordinate system Σ_M
- ${}^{M}\boldsymbol{r}_i$: The i-th point coordinates on the model defined by Σ_M, which composes matching model.
- ${}^{CR}\boldsymbol{r}_i$: The i-th point coordinates on matching model based on Σ_{CR}

Therefore, ${}^{CR}\boldsymbol{r}_i$ can be calculated by using Eq. (1)

$$ {}^{CR}\boldsymbol{r}_i = {}^{CR}\boldsymbol{T}_M \, {}^{M}\boldsymbol{r}_i. \tag{1} $$

The homogeneous transformation matrix ${}^{W}\boldsymbol{T}_{CR}$ from world coordinate system Σ_W to the right camera coordinate system Σ_{CR} can be obtained by robots kinematics, and the i-th point coordinates in Σ_W is calculated as,

$$ {}^{W}\boldsymbol{r}_i = {}^{W}\boldsymbol{T}_{CR} \, {}^{CR}\boldsymbol{r}_i. \tag{2} $$

By using projective transformation matrix $\boldsymbol{P}$, the position vector of the i-th point in the right camera image ${}^{IR}\boldsymbol{r}_i$ can be described as Eq. (3). Eq. (4) is described as matrix $\boldsymbol{P}$.

$$ {}^{IR}\boldsymbol{r}_i = \boldsymbol{P} \, {}^{CR}\boldsymbol{r}_i. \tag{3} $$

$$ \boldsymbol{P} = \frac{1}{{}^{C}z_i} \begin{bmatrix} \frac{f}{\eta_x} & 0 & {}^{I}x_0 & 0 \\ 0 & \frac{f}{\eta_y} & {}^{I}y_0 & 0 \end{bmatrix}. \tag{4} $$

Using the same method, it is possible to obtained the position vector of the i-th point in the left camera image ${}^{IL}\boldsymbol{r}_i$.

$$ {}^{CL}\boldsymbol{r}_i = {}^{CL}\boldsymbol{T}_{CR} \, {}^{CR}\boldsymbol{r}_i. \tag{5} $$

$$ {}^{IL}\boldsymbol{r}_i = \boldsymbol{P} \, {}^{CL}\boldsymbol{r}_i. \tag{6} $$

According to Eq. (3) and Eq. (6), the relationship of Eq. (7) connects an arbitrary point on a 3D-model ${}^{M}\boldsymbol{r}_i$ with a pose ${}^{C}\psi_M$ – the pose of Σ_M based on Σ_{CR} and Σ_{CL} – to the projected point on the left camera image ${}^{IL}\boldsymbol{r}_i$ and right camera image ${}^{IR}\boldsymbol{r}_i$ can be written as,

$$ \begin{cases} {}^{IR}\boldsymbol{r}_i = \boldsymbol{f}_R({}^{CR}\boldsymbol{\psi}_M, \, {}^{M}\boldsymbol{r}_i) \\ {}^{IL}\boldsymbol{r}_i = \boldsymbol{f}_L({}^{CL}\boldsymbol{\psi}_M, \, {}^{M}\boldsymbol{r}_i). \end{cases} \tag{7} $$

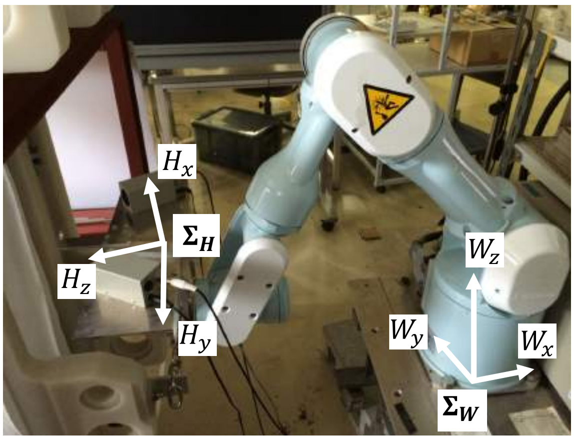

Fig. 2. Coordinate system of 3D-MoS robot

2.2 Fitness Function

A function $P({}^{IR}\boldsymbol{r}_i)$ represents the matched degree of the i-th point of the model on the right image area, ${}^{IR}\boldsymbol{r}_i$.

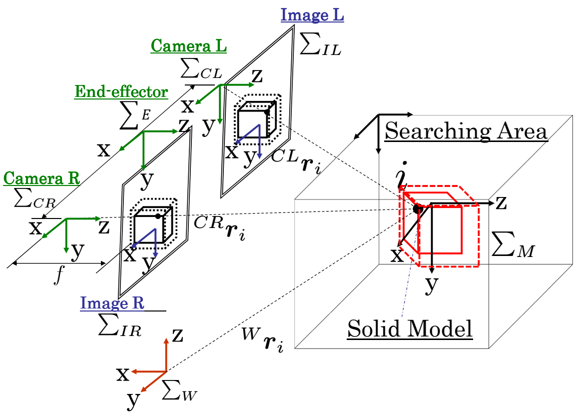

Fig. 3. Coordinate system of dual-eyes

Similarly, the left image area, ${}^{IL}\boldsymbol{r}_i$ represented as a function $P({}^{IL}\boldsymbol{r}_i)$. As shown in Eq.(8), the fitness value will be increase with the voting value of "+2" for every point of clothes in captured images that lies inside of the model frame $S_{R,in}$ and $S_{L,in}$. The fitness value will decrease with the value of "−0.005" for every point of clothes in images whose hue value is similar to average of background and otherwise is "0". As shown in Eq.(9), the fitness value will be increase with the voting value of "+0.1" for every point in outside space of model frame $S_{R,out}$ and $S_{L,out}$ and otherwise is "−0.5". The correlation between the i-th point of the model (the search model) and the image having the evaluation value with such a sign is used the following Eq. (10). The whole evaluation function $F({}^{C}\psi_M)$ is obtained by the average of the fitness function of both left camera image $F_L({}^{CL}\psi_M)$ and right camera image $F_R({}^{CR}\psi_M)$.

$$p_{Rin}({}^{IR}\boldsymbol{r}_i) = \begin{cases} 2 & (|H_{IR}({}^{IR}\boldsymbol{r}_i) - H_{MR}({}^{IR}\boldsymbol{r}_i)| \le 30) \\ -0.005 & (|\overline{H}_B - H_{IR}({}^{IR}\boldsymbol{r}_i)| \le 30) \\ 0 & (otherwise) \end{cases} \quad (8)$$

$$p_{Rout}({}^{IR}\boldsymbol{r}_j) = \begin{cases} 0.1 & (|\overline{H}_B - H_{IR}({}^{IR}\boldsymbol{r}_j)| \le 20) \\ -0.5 & (otherwise) \end{cases} \quad (9)$$

$$\begin{aligned} F({}^{C}\psi_M) &= \Bigg\{ \Bigg(\sum_{\substack{{}^{IR}\boldsymbol{r}_i \in \\ S_{R,in}({}^{CR}\psi_M)}} p({}^{IR}\boldsymbol{r}_i) + \sum_{\substack{{}^{IR}\boldsymbol{r}_i \in \\ S_{R,out}({}^{CR}\psi_M)}} p({}^{IR}\boldsymbol{r}_i) \Bigg) \\ &\quad + \Bigg(\sum_{\substack{{}^{IL}\boldsymbol{r}_i \in \\ S_{L,in}({}^{CL}\psi_M)}} p({}^{IL}\boldsymbol{r}_i) + \sum_{\substack{{}^{IL}\boldsymbol{r}_i \in \\ S_{L,out}({}^{CL}\psi_M)}} p({}^{IL}\boldsymbol{r}_i) \Bigg) \Bigg\} / 2 \\ &= \left\{ F_R({}^{CR}\psi_M) + F_L({}^{CL}\psi_M) \right\} / 2 \end{aligned} \quad (10)$$

2.3 Genetic Algolithm(GA)

Recognition problem of the object can be converted to a searching problem of maximum value $F({}^{C}\psi_M)$. There are various ways in finding the maximum value of the fitness function. The simplest and easiest way is the full search method. It is intended to find the maximum value by scanning all possible pixels. However, it has inefficient drawback in term of computing time. Even though there are powerful optimization methods, GA with long history is selected in this work. By applying the GA evaluation process as an optimization solution, the maximum value search processing can be completed efficiently in a short period of time. In this experiment, GA has 60 individuals representing different poses of model. Each individual chromosome has six variables. Each variable are coded by 12 bits. The former 36 bits represent for the position coordinate of the 3D-model and the last 36bits represent for the orientation of the 3D-model. The characteristics of GA individual is defined as

$$\overbrace{\underbrace{01\cdots01}_{12bit}}^{t_x}\overbrace{\underbrace{00\cdots01}_{12bit}}^{t_y}\overbrace{\underbrace{11\cdots01}_{12bit}}^{t_z}\overbrace{\underbrace{01\cdots01}_{12bit}}^{\epsilon_1}\overbrace{\underbrace{01\cdots11}_{12bit}}^{\epsilon_2}\overbrace{\underbrace{01\cdots10}_{12bit}}^{\epsilon_3}.$$

These 60 chromosomes are evaluated by fitness value. Fitter ones are selected to regenerate next generations. Finally the best chromosome that has the most trustful pose is achieved as shown in Fig.4.

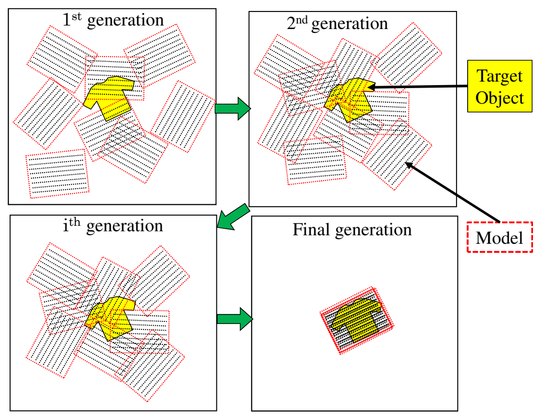

Fig. 4. GA evolution process

2.4 Photo Model Recognition

In our system, three cameras are used as vision sensors. Among these three cameras, the first camera that is fixed in the workspace for capturing photos of clothes is used for cloth model generation. Captured photos are saved as BMP (bit map file) format. Note that generated model is not for just matching between saved ones and current images. Instead, generated model is used to estimate relative pose with respect to end effector using images from two cameras attached together with end effector. In proposed model generation technique, firstly, the background photo is taken as shown in Fig. 5 (a) and average hue value is calculated. Secondly, the cloth (target object) is put on the background and hue value of each point in the image is calculated as shown in Fig. 5 (b). Thirdly, the individual pixel of captured image is compared by scanning with the average of the hue value of the background image to define model frame based on error. Then, inner surface space of model S_{in} is generated by sampling hue value of each point inside defined frame. Finally, the outside space S_{out} of model is generated as shown in Fig. 5 (c).

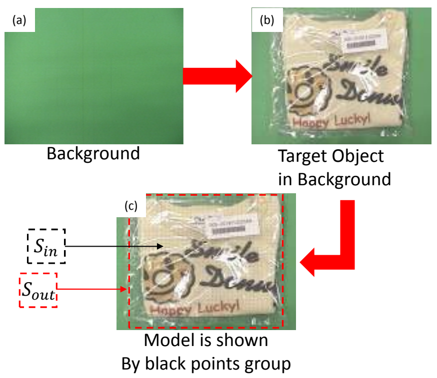

Fig. 5. Model generation technique

2.5 Model-Based Recognition

After generating a model from a bitmap image, the model is used for recognition the cloth (target object). Here, an overview of the recognition method with respect to the camera image is given as a description. 3D pose of the 3D model ${}^{C}\psi_M = [{}^{CR}x_M, {}^{CR}y_M, {}^{CR}z_M, {}^{CR}\epsilon_{1M}, {}^{CR}\epsilon_{2M}, {}^{CR}\epsilon_{3M}]^T$ is determined using model-based matching method. Generated models with different poses are projected from 3D-model in searching area onto the left and right 2D images plane as shown in Fig.6. By comparing the projected models with images from two cameras attached at the end effector, relative pose is estimated by using fitness function $F({}^{C}\psi_M)$ to evaluate. It means the pose of the best model, that is fully matched with captured images from left and right cameras, is selected as estimated pose. The top of Fig. 6 is represented as searching area of a 3D-model named S to search for a cloth(target object). S_{in} is depicted by the space of coordinates on the surface of the model and S_{out} was enveloped the outside space of S_{in}. The left and right 2D searching model are named as S_L and S_R. In order to evaluate, the evaluation and change in hue of the surrounding of the object as shown in the interior region is represented as $S_{R,in}$, $S_{L,in}$ and the outside space enveloping $S_{R,in}$, $S_{L,in}$ is defined as $S_{R,out}$, $S_{L,out}$.

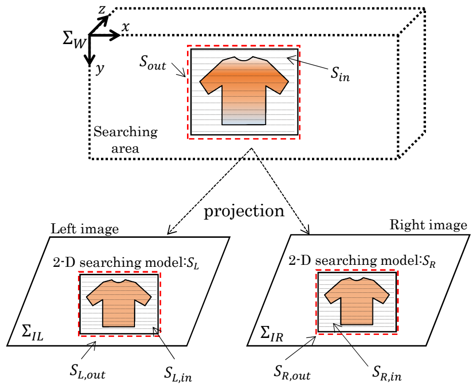

Fig. 6. Searching model

3 EXPERIMENTAL ENVIRONMENT

There are two units in experimental environment. One is for generation cloth model including one camera as shown in Fig. 7. Another one is end effector equiped with two cameras installed in manipulator's end effector as shown in Fig. 8 and Fig. 9. In Fig. 7, the distance from the camera lens to the model creating plane is 400 mm and the plane color is green. The size of clothes models can be up to 250mm $\times$ 200mm. Each coordinate system of the robot and the cloth used in this experiments are shown in Fig. 8 and Fig. 9. The cloth coordinate system is represented as Σ_M and Σ_H is defined as the hand coordinate system of the robot – end effector –. Σ_M can be viewed from (x=0, y=0, z=685mm). It is centered on the recognition range of the position as a reference of the 510mm $\times$ 390mm. After defining about the position, the recognition range of the angles are from 53° to $-53°$. The size of the collection box is a 220mm $\times$ 220mm. However, in this experiment, we mainly emphasized to the recognition experiment and handling experiment is our follow-up work.

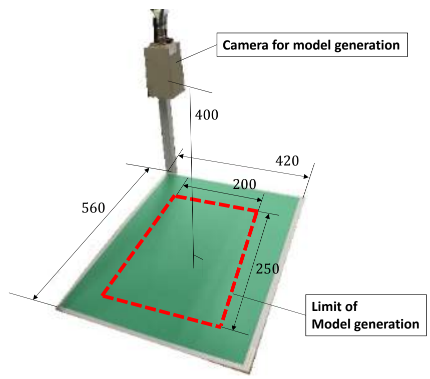

Fig. 7. Coordinate system of target object (unit is mm in Figure 7)

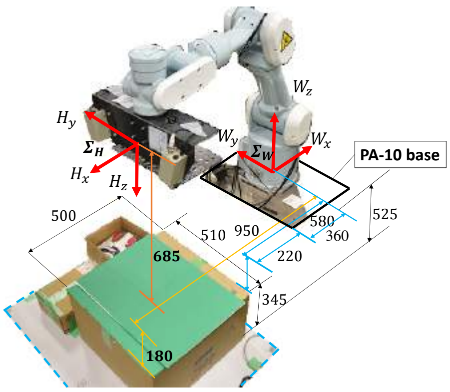

Fig. 8. Environment of model generation (unit is mm in Figure 8)

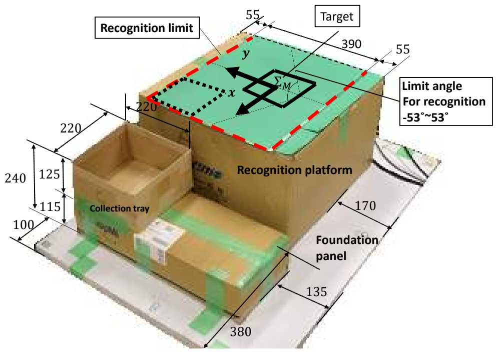

Fig. 9. Coordinate system of robot and end-effector (unit is mm in Figure 9)

4 EXPERIMENTAL CONTENT

We conducted experiments to confirm the influence on GA recognition under fluorescent light and LED light (100Lx, 700Lx, 1300Lx). In this experiment, We use 12 unique clothes (No.1, No.2, ··· , No.12) samples as shown in Fig.10.

The experiment flow is shown below. First, establish the model. Second, set the target object at the center of recognition table in hand coordinate system(x=0, y=0, z=0, θ =0). Third, compare hue value of the model with camera image's hue value to get the fitness function distribution. Last, calculate fitness function distribution and judge whether it is recognizable or not according to the fitness function distribution. This system determines that it can be recognized when maximum fitness function value is larger than 0.3 and there is only one peak of fitness function distribution. We used the model established under fluorescent light when we conduct experiments under fluorescent light and we used the model made under LED light when we conduct experiments under LED light. Fig.11 shows maximum fitness function value under fluorescent light recognition and Fig.12 shows maximum fitness function value under LED light recognition for all clothes. It was demonstrated that clothes can be recognized if it is within the range of indoor illuminance. Furthermore, it was demonstrated that it is possible to recognize if the light environment at the experiment is same as that when the model is established. However, when recognizing some colors such as black and white, which absorbs color and reflects light easily, the fitness function value is low. And, fitness function value is low under both light environments when bright color clothes (e.g. No.11) is recognized. Because hue values of reflected light and white part of clothes are close when we get hue value distribution of camera image.

Fig. 10. Target objects (No.1 ∼ No.12)

5 CONCLUSIONS

In this paper, we introduced new cloth model generation method and pose estimation method using model-based clothes recognition. The merits of the photo-model-based clothes recognition system are shown as follow. First, photo-model-based method can recognize the deformable different clothes recognized automatically. Second, 3D-pose measurement is possible. Third, photo-model-based 3D-pose recognition is not limited to clothing, and any object can recognized with proposed system. By using a photo model of each clothes, the target object with different shape and pattern can be recognized. Even if color of lighting is not general color like fluorescent light, this system can adapt different light environment and recognize clothes. We conducted experiments to confirm the influence on GA recognition under fluorescent light and LED light using 12 clothes with different colorful pattern and multiple size. Illumination tolerance for clothes recognition was analyzed in term of fitness function distribution. According to the experimental results, even if color of lighting is not general color like fluorescent light, this system can adapt it and recognize clothes. Therefore, it can be used in sorting factories.

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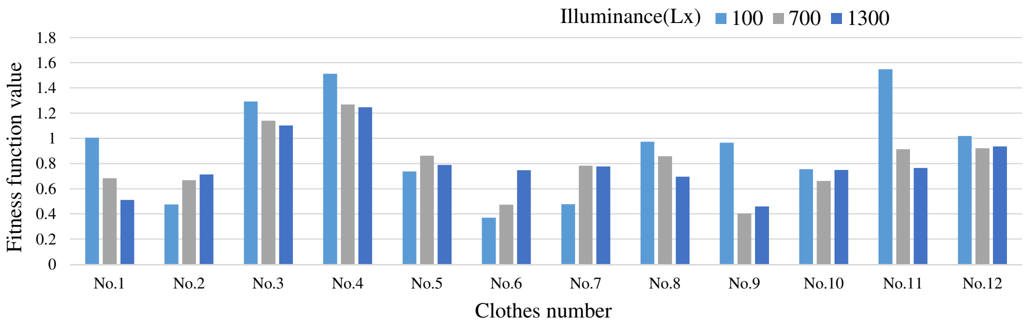

Fig. 11. Fitness function value under fluorescent light

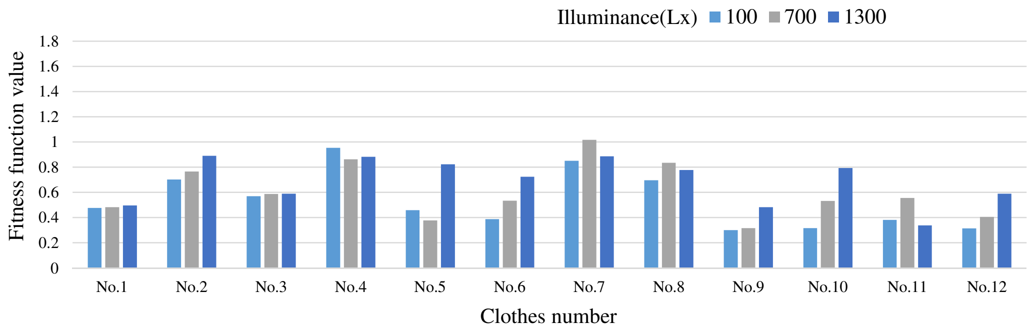

Fig. 12. Fitness function value under LED light

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