Pedestrian Counting based on the Number of Salient Points Considering Non-Linear Effect of Occlusions

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Abstract: In recent studies for video processing-based pedestrian counting, the Albiol method, which is based on the number of salient point detection, is one of the famous pedestrian counting methods. In the Albiol method, a linear relationship is assumed between the number of salient points in a frame and the number of pedestrians. However, the relationship is not always linear because the number of salient points from a pedestrian is decreased when the pedestrian is hidden by another pedestrians in the front, i.e. occlusion. In this paper, to improve estimation accuracy of the Albiol method, we investigate the relationship between the number of salient points and the actual number of pedestrians. We first make a virtual pedestrian model which is an occurrence probability distribution of salient points. We next randomly place virtual pedestrians on a virtual frame, and obtain the regression equations. Then, we propose a pedestrian counting method based on the regression equations. Through evaluations using several actual video sequences, we show that the pedestrian counting accuracy is improved by up to 40% by the proposed method compared to the Albiol method.

Key–Words: pedestrian counting, video processing, occlusion, salient point, video, pedestrian model

1 Introduction

In recent years, the demand for pedestrian counting has been growing for various situations such as the navigation to avoid congestions, marketing survey, and control of transportation systems. The video processing-based pedestrian counting methods [1-7] have some advantages such as flexibility of camera positions and higher counting accuracy compared to simple sensors. They are classified into two methods: detection-based methods [1, 2] and feature-based methods [3-6]. In detection-based methods, regions of pedestrians are directly detected from a frame, and the number of regions is counted. On the other hand, in feature-based methods, the number of pedestrians is estimated based on various features in video sequences and pre-obtained regression equations. They do not directly detect each pedestrian. The latter methods have attracted much attention in recent years since they can estimate the number of pedestrians more accurately in crowded situations.

In the literature [3], Albiol et. al. proposed a method (hereinafter, referred as the Albiol method) for estimating the number of pedestrians in a frame based on the number of salient points. In [3], a salient point is defined as a pixel whose brightness and color are intensely varied compared with the neighbouring pixels. Through a comparative evaluation of counting methods using a common data set in the PETS 2009 workshop [8-10], they showed that the Albiol method can estimate the number of pedestrians more accurately than other counting methods in crowded situations. In the Albiol method, the relationship between the number of pedestrians and the number of salient points are assumed as linear. However, the relationship is not linear in some situations because the number of salient points is decreased when the pedestrian is hidden by another pedestrians in the front, i.e. occlusion. The number of salient points per a pedestrian is affected by the occurrence rate of occlusions. Therefore, there is a room to improve the accuracy of the Albiol method.

In this paper, we improve the accuracy of the Albiol method using the relationship between the number of salient points and the number of pedestrians. To investigate the relationship between the number of salient points and the actual number of pedestrians, we first make a virtual pedestrian model which is an occurrence probability distribution of salient points. We next randomly place virtual pedestrians on a virtual frame, and obtain the regression equations. After that,

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we propose a pedestrian counting method based on the obtained regression equations. Performance evaluation of the proposed method is conducted using several actual video sequences.

The rest of this paper is organized as follows. In section 2, we explain the pedestrian modeling and the simulation method for investigating the relationship between the number of salient points and the number of pedestrians. In section 3, we investigate the relationship using actual video sequences. In section 4, we propose a pedestrian counting method based on the obtained relationship. In section 5, we evaluate performance of the proposed method using actual video sequences. In section 6, we describe conclusions of this paper and future work.

2 Method for Obtaining the Relationship between the Number of Salient Points and the Number of Pedestrians

In this paper, we investigate the relationship between the number of salient points and the number of actual pedestrians by modeling pedestrians and placing virtual pedestrians on a virtual frame. In this section, we explain the placing method. Hereinafter, we refer the i-th frame of video as $f(i)$, and the size of frame as $L_x \times L_y$.

2.1 Extracting Salient Points

First, we extract salient points from all frames of video sequence using a same way in the Albiol method [3]. In the method, we first extract candidate salient points using Harris method [11]. A candidate salient point is a point whose brightness and color are intensely varied compared with the neighbouring pixels. Then, we extract an optical flow whose starting point is a candidate salient point by estimating the corresponding position in frame $f(i-1)$ of the candidate salient point in frame $f(i)$ for all candidate salient points. After that, we exclude a candidate salient point whose length of optical flow is shorter than a threshold since it is considered to be extracted from background parts. We use remaining candidate salient points as salient points. We refer the number of salient points in frame $f(i)$ as $m(i)$.

2.2 Modeling Pedestrian

Next, we make a virtual pedestrian model based on the extracted salient points. Figure 1 shows the flow for constructing a virtual pedestrian model from actual video sequences. At first, we manually set a rectangle

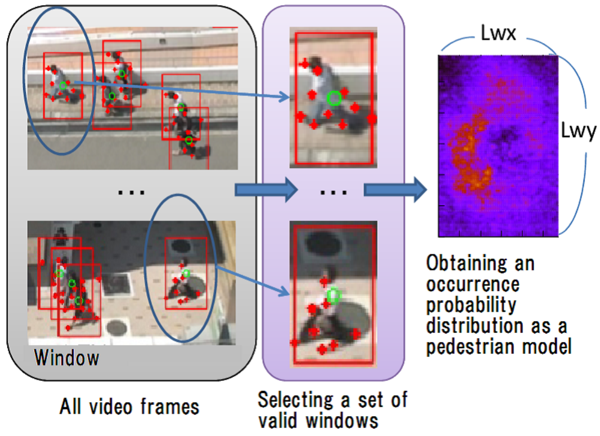

Figure 1: Pedestrian modeling

region called window (red rectangles in Fig. 1) whose size is $L_{wx} \times L_{wy}$ to all pedestrians. The size of window L_{wx} and L_{wy} should be determined as small as possible to enclose all the pedestrians. We refer the set of windows obtained from video sequence as $\mathcal{W}$, coordinates in the coordinate system in a window as $(x_w, y_w)_w$, the u-th window obtained from video sequences as $w(u)$, and the set of salient points in window $w(u)$ as $\mathcal{C}_w(u)$. In addition, we refer the j-th salient point in $\mathcal{C}_w(u)$ as $c_w(u,j)$, and coordinate of salient point $c_w(u,j)$ as $(x_w(u,j), y_w(u,j))_w$.

We next delete a window which overlaps to other any window from the set of window. We refer the remaining set of windows as the set of valid windows $\mathcal{W}_{vld}$. Then, the number of salient points $m_w(x_w, y_w)$ whose coordinate is $(x_w, y_w)_w$ is calculated as follows.

$$m_w(x_w, y_w) = |\{c_w(u,j)\,|c_w(u,j) \in \mathcal{C}_w(u), \\ w(u) \in \mathcal{W}_{vld}, x_w(u,j) = x_w, y_w(u,j) = y_w\}|. \quad (1)$$

The total number of salient points m_{wsum} is also calculated as follows.

$$m_{wsum} = |\{c_w(u,j) \mid c_w(u,j) \in \mathcal{C}_w(u), \\ w(u) \in \mathcal{W}_{vld}\}|. \quad (2)$$

The occurrence probability $p_w(x_w, y_w)$ of salient points in coordinate (x_w, y_w) is given by following equation.

$$p_w(x_w, y_w) = \frac{m_w(x_w, y_w)}{m_{wsum}}. \quad (3)$$

We use the distribution of occurrence probabilities of salient points as the virtual pedestrian. The average

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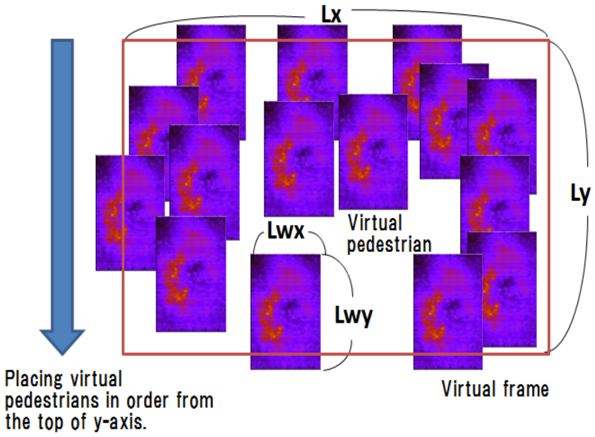


Figure 2: Placing virtual pedestrians on a virtual frame

number of salient points per window g_w is calculated from following equation.

$$g_w = \frac{m_{wsum}}{|\mathcal{W}_{vld}|}. \tag{4}$$

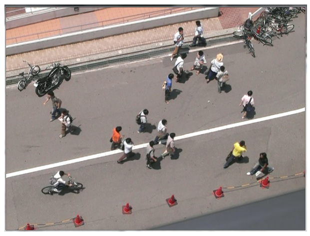
2.3 Placing Virtual Pedestrians on a Virtual Frame

Finally, we obtain the relationship between the number of salient points and the number of pedestrians by placing a number of virtual pedestrians on a virtual frame. In this section, we explain how to place a virtual pedestrian on a virtual frame. Hereinafter, we refer the coordinates in the coordinate system of virtual frame as $(x_v, y_v)_v$, and occurrence probability at the coordinate $(x_v, y_v)_v$ in the virtual frame as $p_v(x_v, y_v)$. The size of virtual frame is $L_x \times L_y$.

Figure 2 shows an example for placing virtual pedestrians on the virtual frame. First, we set zero to all occurrence probabilities $p_v(x_v, y_v)$ in the virtual frame. Next, we determine the location of n_v virtual pedestrians randomly and place the virtual pedestrians on the virtual frame in order from the top of y-axis. When we put virtual pedestrians on the virtual frame, occurrence probabilities of virtual frame $p_v(x_v, y_v)$ are overwritten by occurrence probability of the newly placed virtual pedestrians. This is because a pedestrian located upward in video sequences has higher possibility to locate back. After that, we obtain the number of salient points m_v in the virtual frame as follows.

$$m_v = g_w \sum_{0 \le x_v \le L_x} \sum_{0 \le y_v \le L_y} p_v(x_v, y_v). \tag{5}$$

By changing the number of virtual pedestrians n_v and placing virtual pedestrians on the virtual frame, we can obtain the relationship between the number of salient points and the number of pedestrians. In the next section, we investigate the relationship using actual video sequences.



(a) Video 1

(b) Video 2

(c) Video 3

(d) Video 4

Figure 3: Snapshots of video sequences for obtaining the relationship and evaluation

3 Investigation of the Relationship

In this section, we investigate the relationship between the number of salient points and the number of pedestrians using four video sequences as shown in Fig. 3. The size of the four video sequences is same size and 720×480. Hereinafter, we only show a part of results due to limitation of space.

3.1 Effect of Occlusions

Figure 4 shows virtual pedestrians in color map obtained from each video sequence. The center of virtual pedestrian corresponds to the waist of pedestrian of pedestrians. As shown in Fig. 4, the occurrence probability is low at the center and the edge of virtual pedestrian. This is because the distribution of color around waist of pedestrians is uniform and salient points are rarely extracted around waist. On the other hand, occurrence probability is high at the points which have some distance from the center, since salient points are easily extracted around the border area between a pedestrian and background.

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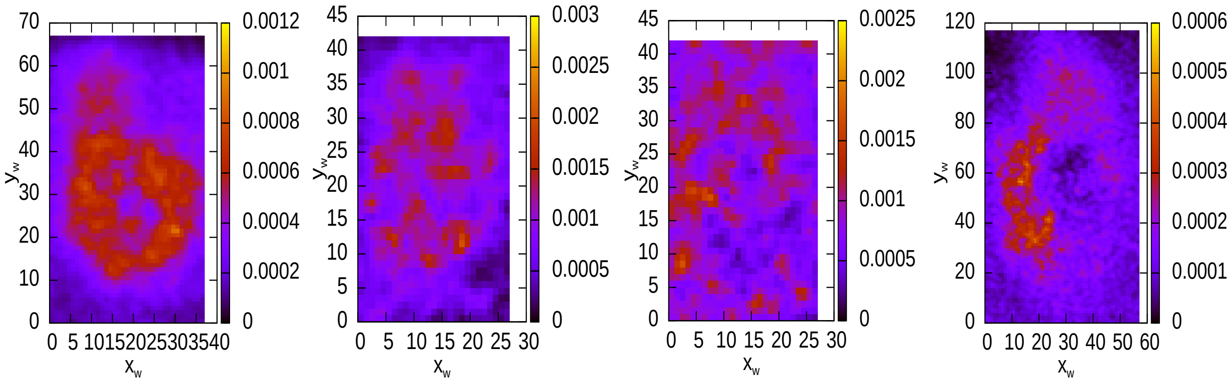

(a) Video 1 (b) Video 2 (c) Video 3 (d) Video 4

Figure 4: Virtual Pedestrian

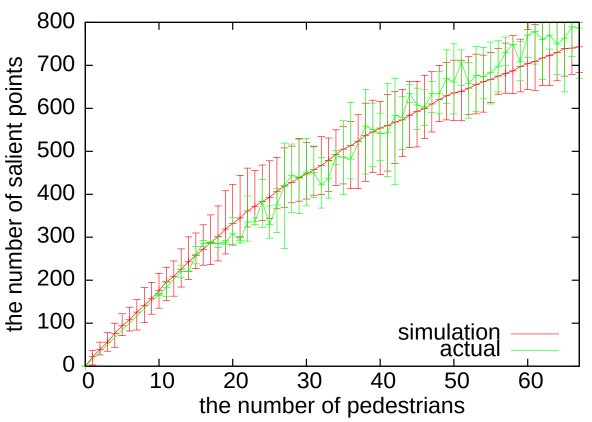

Figure 5: Simulation results and manually-obtained results (Video 4)

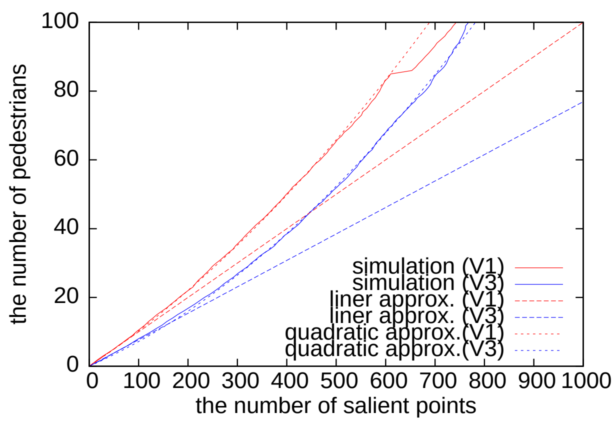

Figure 6: Simulation results and approximated results (Video 1, Video 3)

Figure 5 shows the average number of salient points against the number of pedestrians obtained by placing virtual pedestrians. Hereinafter, we call the results obtaind by placing virtual pedestrians on a virtual frame as simulation resluts. The maximum and the minimum values are shown as error bars. For comparison purpose, manually-obtained relationship is also shown in Fig. 5. As shown in Fig. 5, relationship obtained from simulation is similar to manually-obtained relationship. In addition, the relationship is not linear and the increase rate of salient points decreases when the number of pedestrians increases. This is because pedestrians are hidden by another pedestrians in front by occlusions when the number of pedestrians is high.

In this paper, we assume that the relationship can be modeled as a quadratic approximation equation for simplicity.

$$n_v(i) = \alpha_1 m_v^2(i) + \alpha_2 m_v(i). \tag{6}$$

Here, α_1 and α_2 are coefficients. Figure 6 shows the relationship between the number of salient points obtained from simulation, the liner approximation equation expressed by $m_v(i)/g_w$, and the quadratic approximation equation from Eqn. (6). α_1 and α_2 are obtained from the least-square method using simulation results. As shown in Fig. 6, the relationship using the quadratic approximation equation is more similar to the relationship obtained from simulation than that using the liner approximation equation.

3.2 Effect of the Size of Pedestrian

The number of salient points obtained from a pedestrian is affected by the size of pedestrian. In this pa-

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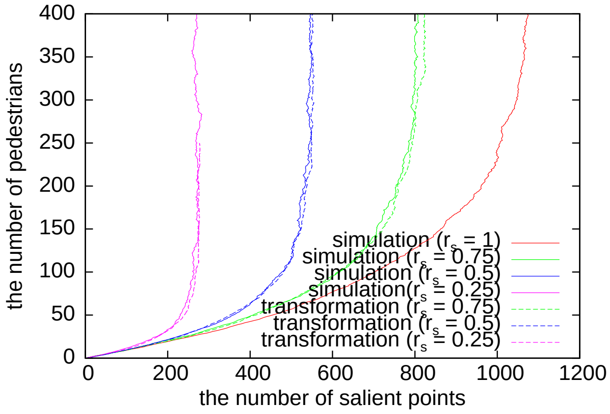

Figure 7: Simulation results and transformed results against the size of passage area (Video 1)

per, we assume that window area ratio, defined as $r_w = L_{wx}L_{wy}/L_xL_y$, influences to coefficients α_1 and α_2. In addition, we assume that the relationship between the window area ratio and coefficients α_1 and α_2 are approximated from following equations.

$$\alpha_1 = \beta_{1,2}r_w^2 + \beta_{1,1}r_w + \beta_{1,0}. \quad (7)$$

$$\alpha_2 = \beta_{2,2}r_w^2 + \beta_{2,1}r_w + \beta_{2,0}. \quad (8)$$

Here, β is coefficient. Coefficient values obtained from the least-square method using simulation results of the four video sequences are as follows: $\beta_{1,2} = 0.0827$, $\beta_{1,1} = 0.000139$, $\beta_{1,0} = 0.0000685$, $\beta_{2,2} = 577$, $\beta_{2,1} = -22.7$, $\beta_{2,0} = 0.241$.

3.3 Effect of the Size of Passage Area

In the previous sections, we assumed that a pedestrian would be present in any position of the virtual frame. However, in actual situations, pedestrians can be present only limited area such as passageway, and they can not be present in some areas such as buildings, sky, obstacles, and so on. In this paper, we call the area where pedestrians can be present as passage area. Since the size of passage area influences the density of pedestrians and the frequency of occlusion, it also influences the relationship between the number of salient points and the number of pedestrians.

To investigate the effects of the size of passage area, we place virtual pedestrians on the virtual frame by changing the size of virtual area $L_x \times L_y$ to 720×480, 624×416, 509×339, 360×240. For each virtual frame, the ratios of the area size of virtual frame to the size 720×480 are 1, 0.75, 0.5, 0.25, respectively. Hereinafter, we refer the ratio as passage area ratio r_s. In addition, we also consider following equation extending Eqn. (6).

$$n_v(i, r_s) = r_s \left(\alpha_1 \left(\frac{m_v(i)}{r_s} \right)^2 + \alpha_2 \frac{m_v(i)}{rs} \right), \quad (9)$$

where coefficient values α_1 and α_2 are based on the results when the passage area ratio is $r_s = 1$.

Figure 7 shows the relationship obtained from simulation and transformations using Eqn. (9) against the passage area ratio r_s. As shown in Fig. 7, the transformed results are similar to the simulation results. Therefore, we can handle effect of passage area ratio by using Eqn. (9).

4 Proposed Counting Method

Based on the discussion and the obtained relationship in the previous section, we propose a pedestrian counting method considering effect of occlusions.

In the proposed method, we first obtain the number of salient points $m(i)$ in frame $f(i)$ from video sequences using the Harris method [3] which is the same way in the Albiol method. Then, we estimate the number of pedestrians using following equation.

$$\hat{n}(i) = \alpha_1 m^2(i) + \alpha_2 m(i), \quad (10)$$

where coefficients α_1 and α_2 are calculated as follows.

$$\alpha_1 = \beta_{1,2}r_w^2 r_s^{-1} + \beta_{1,1}r_w r_s^{-1} + \beta_{1,0}r_s^{-1}. \quad (11)$$

$$\alpha_2 = \beta_{2,2}r_w^2 + \beta_{2,1}r_w + \beta_{2,0}. \quad (12)$$

The passage area ratio r_s and window area ratio r_w should be obtained preliminarily. These parameters are determined depending on installation conditions such as the location and magnification of camera, therefore, they can be easily obtained. In addition, coefficients β should be obtained preliminarily by modeling and placing virtual pedestrians on a virtual frame using sufficient number of video sequences.

5 Performance Evaluation

We evaluate the performance of the proposed method using actual video sequences.

5.1 Evaluation Settings

We use seven video sequences as shown in Figs. 3 and 8. The specifications of video sequences are summarised in Table 1. We use a part of video sequences (Video 1 to Video 4) for obtaining the relationship, and we use all video sequences for evaluation of the proposed method. For each video sequence, window

(a) Video 5 (b) Video 6

(c) Video 7

Figure 8: Snapshots of video sequences for evaluation

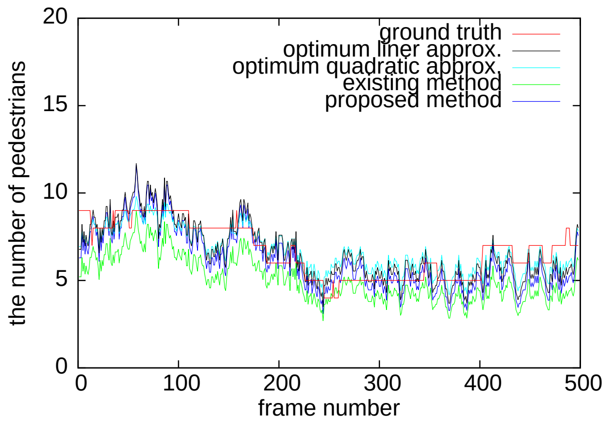

Figure 9: Pedestrian counting results (Video 7)

area ratio r_w is obtained manually. To obtain passage area ratio r_s, we first obtain the foreground region using a background subtraction method for each frame. Then, we consider that the region which is in foreground region in any frame as passage area. The ratio of passage area to the size of video sequence is used as the passage area ratio r_s.

In this paper, we use the mean square error e_{MSE} as performance metrics of the approximation equation, and the relative error e_{RE} as performance metrics of the proposed method.

$$e_{MSE} = \frac{1}{F}\sum_{i=1}^{F}(\hat{n}(i) - n(i))^2, \tag{13}$$

$$e_{RE} = \frac{1}{F}\sum_{i=1}^{F}\frac{|\hat{n}(i) - n(i)|}{n(i)}, \tag{14}$$

where $n(i)$ is the actual number of pedestrians in frame $f(i)$, and F is the last frame number of the video sequence. Smaller e_{MSE} and e_{RE} indicate higher estimation accuracy.

For comparison purpose, we also obtain estimation results using the Albiol method [3]. In the Albiol method, The parameter g which means the number of salient points per one pedestrian, is obtained by prior learning. The number of pedestrians in frame $f(i)$ is estimated by using $\hat{n}(i) = m(i)/g$. In addition, to investigate the upper limit of accuracy using liner and quadratic approximation equations, we also obtain the results using the optimal linear approximation equation and the optimal quadratic approximation equation. In the optimal liner and quadratic approximation equations, coefficients are calculated by the least-square method using manually obtained information from whole frames in a video sequence.

5.2 Results and Discussions

Table 2 shows the mean square error when we use the optimum liner approximation equation, the optimum quadratic approximation equation, the Albiol method and the proposed method for counting pedestrians. Figure 9 shows the number of pedestrians obtained by each method and the actual number of pedestrians (ground truth) in each frame. Table 3 shows the relative error when we use the existing method and the proposed method for counting pedestrians. In Table 3, the reduction rate of the relative error of proposed method to that of the Albiol method is shown. We refer the rate as improved rate.

First, we verify the effectiveness for using a quadratic approximation equation. As show in Table 2, the mean square errors are decreased by using the optimum quadratic approximation equation compared to the optimum liner approximation equation. Therefore, the effectiveness to use a quadratic approximation equation for estimating the number of pedestrians is verified. In particular, the quadratic approximation equation is highly effective for some videos whose occurrence rate of occlusion is large, since the mean square error is greatly reduced in Video 1 and Video 4.

The mean square error of the proposed method is higher than that obtained by the optimum quadratic approximation equation as shown in Table 2. There are two main reasons as follows. Firstly, we treated

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Table 1: Specifications of video sequences

Name	Video 1	Video 2	Video 3	Video 4	Video 5	Video 6	Video 7
Place	Univ.	Univ.	Univ.	Crosswalk	Univ.	Crosswalk	Mall
Size of Video	720×480	720×480	720×480	720×480	720×480	320×200	320×240
The number of frames F	6400	800	800	900	800	300	500
Frame rate [fps]	29.97	29.97	29.97	29.97	29.97	29.97	29.97
Size of window	40×60	30×45	50×80	60×120	50×80	35×80	30×45
Window area ratio r_w	0.00694	0.00391	0.0116	0.0208	0.0116	0.00810	0.00391
Passage area ratio r_s	0.871	0.321	0.327	1	0.669	0.187	0.127
Parameter in the Albiol method g	18.3	6.63	11.3	13.1	15.0	9.59	6.33
The number of pedestrians in frame	2–19	6–16	1–9	4–67	4–19	3–18	4–9
Shooting angle of videos	Large	Large	Middle	Middle	Middle	Small	Large
Occurrence rate of occlusion	Middle	Small	Small	Large	Small	Small	Small

Table 2: Mean square error obtained by each method

Name	Video 1	Video 2	Video 3	Video 4	Video 5	Video 6	Video 7
Optimum liner approx.	6.21	5.92	2.07	30.4	3.73	1.93	1.09
Optimum quadratic approx.	4.28	4.51	1.48	18.1	3.67	1.78	0.89
Existing method	31.0	6.25	4.91	30.5	6.12	5.53	3.53
Proposed method	12.4	7.34	5.25	119	4.10	4.86	1.42

the virtual pedestrian as a rectangle region for simplicity in this paper. However shape of the pedestrian is not rectangle actually, and occlusion does not appear in the edge of the virtual pedestrian. Therefore, it causes errors for obtaining the relationship between the number of salient points and the number of pedestrians. Secondly, we just considered two parameters, i.e. the size of pedestrian and the size of passage area, which affects to the relationship between the number of salient points and the number of pedestrians. However, there are some other parameters which affects to the relationship. For example, if the shooting angle of the camera is small, the occurrence rate of occlusion becomes large, which affects to the relationship. Therefore, we should take into account additional parameters, such as the shooting angle of camera, for the calculation of coefficients in the quadratic approximation equation. Further improvement of the proposed method is considered as one of our future work.

Next, we compare the proposed method and the Albiol method. As shown in Table 3, the relative error of the proposed method is lower than that of the Albiol method for video sequences excluding Video 2. In particular, the relative error of the proposed method is reduced in video sequences from Video 5 to Video 7 which are not used for obtaining the relationship. In Video 7, the relative error is reduced by 40%. By using a quadratic approximation equation, the relative error is decreased in the proposed method.

In Video 1, the relative error of the Albiol method is relatively large compared to that of the proposed method. The reason is as follows. In the Albiol method, the parameter g is set based on the number of pedestrians and the number of salient points in a specific frame which has the maximum number of salient points. Since there is a frame which has a lot of salient points due to shakiness of camera in Video 1, a larger value is set to the parameter g and the accuracy of the Albiol method significantly decreases. On the other hand, parameters of our proposed method, i.e. the window area ratio and the passage area ratio, are determined depending on installation conditions and they are insusceptible to the salient point extraction and pedestrian behaviours. Therefore, in the proposed method, the accuracy does not significantly decrease.

In Video 2, the relative error of the proposed method is higher than that of the Albiol method. In Video 2, the size of pedestrian is small and the shooting angle of camera is large, therefore, occlusion does not frequently occur. In such situations, liner approximation might be sufficient. In addition, we do not take into account the shooting angle of camera in our proposed method, the accuracy decreases when the shooting angle of camera is large and occlusion does not

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Table 3: Relative error obtained by each method

Name	Video 1	Video 2	Video 3	Video 4	Video 5	Video 6	Video 7
Existing method	0.502	0.164	0.327	0.193	0.173	0.172	0.238
Proposed method	0.284	0.204	0.287	0.186	0.159	0.139	0.142
Improved rate [%]	43.4	-24.4	12.2	3.63	8.09	19.2	40.3

frequently occur. Furthermore, we should note that an appropriate value is set to parameter g in the Albiol method.

As shown in Fig. 9, the estimated number of pedestrians is frequently varied compared to the ground truth. This is because that the number of salient points in each frame varied frequently. Since the proposed method uses the quadratic approximation equation, the variation is higher than that of the Albiol method. For example, the variation can be reduced by using information on the previous frames to estimate the number of the pedestrians in current frame. Detailed discussion and evaluation are future work.

6 Conclusions and Future Work

In this paper, we investigated the relationship between the number of salient points and the actual number of pedestrians in crowded situations where occlusions frequently occur. Moreover, we proposed a pedestrian counting method based on the obtained regression equation. Through evaluations using several actual video sequences, we showed that the accuracy is improved by up to 40% compared to the Albiol method by using our proposed method.

In this paper, we treated the virtual pedestrian as a rectangle region for simplicity. It is necessary to extend the virtual pedestrian to handle shape of pedestrians in order to improve the accuracy of the proposed method. Furthermore, we plan to propose a counting method by matching the salient points extracted from a frame and obtained virtual pedestrian.

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