AN EFFECTIVE FLOW ESTIMATION METHOD WITH PARTICLE FILTER BASED ON HELMHOLTZ DECOMPOSITION THEOREM

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ABSTRACT

This paper proposes a novel flow estimation method with a particle filter based on a Helmholtz decomposition theorem. The proposed method extends a model of the Helmholtz decomposition theorem and enables the decomposition of flows into rotational, divergent, and translational components. From the extended model, the proposed method defines a state transition model and an observation model of the particle filter. Furthermore, the proposed method derives an observation density of the particle filter from an energy function based on the Helmholtz decomposition theorem. By utilizing these novel approaches, the proposed method provides a solution to the problem in the traditional ones of not being able to realize an effective flow estimation with the particle filter based on rotation, divergence, and translation, which are important geometric features. Consequently, the proposed method can accurately estimate the flows.

Index Terms— Helmholtz decomposition theorem, Particle filter, Gradient-based method, Flow estimation, Fluid flow.

1. INTRODUCTION

Recently, extensive studies have been carried out on flow estimation because it can be applied to many fields, such as meteorology, oceanography, medicine, etc. Traditionally, many methods to estimate flows from image sequences have been proposed. A gradient-based method [1] is representative of them and improved by [2, 3].

In [2], current flows are estimated by utilizing the previous ones based on relationship between the flows and a disturbance field [4]. However, since the traditional method [2] does not consider estimation errors included in the previous flows, its performance tends to become degraded in the following frames. By introducing a particle filter [3] into the gradient-based method [1], the flow estimation considering the estimation errors included in the previous flows can be achieved. However, it is difficult for a state transition model, an observation model, and an observation density with [1] to realize the flow estimation based on rotation, divergence, and translation, which are important geometric features expressing basic motions of objects. Thus, the particle filter with [1] is not accurate.

This paper proposes a novel flow estimation method with the particle filter based on a Helmholtz decomposition theorem [5]. The proposed method extends a model of the Helmholtz decomposition theorem, which can decompose the flows into rotational and divergent components, in such a way that it can express translational ones. The extended model is utilized for defining the state transition model and the observation model of the particle filter. Furthermore, from an energy function utilized in [5], we derive the observation density of the particle filter. By utilizing these approaches, the proposed method provides a solution to the problem in the traditional ones of not being able to realize an effective flow estimation with the particle filter based on the rotation, the divergence, and the translation, which are the important geometric features. Consequently, the proposed method achieves subjective and quantitative improvement of the flow estimation over the traditional ones.

This paper is organized as follows. In Section 2, we extend the model of the Helmholtz decomposition theorem. Section 3 presents the proposed flow estimation method with the particle filter based on the extended model of the Helmholtz decomposition theorem. Section 4 shows some simulation results to confirm the high performance of the proposed method.

2. EXTENDED MODEL OF THE HELMHOLTZ DECOMPOSITION THEOREM

In this section, we extend the model of the Helmholtz decomposition theorem and enable the decomposition of the flows into the rotational, divergent, and translational components. The traditional method [5] utilizes the following model of the Helmholtz decomposition theorem:

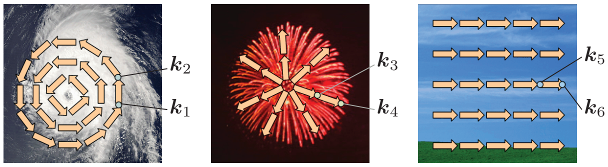
$$\boldsymbol{w} = \boldsymbol{w}^{\mathrm{rot}} + \boldsymbol{w}^{\mathrm{div}}. \tag{1}$$

This equation means that the flow $\boldsymbol{w}$ can be decomposed into the rotational component $\boldsymbol{w}^{\mathrm{rot}}$ ($\boldsymbol{w}^{\mathrm{rot}} = (w_x^{\mathrm{rot}}, w_y^{\mathrm{rot}})$) and the divergent one $\boldsymbol{w}^{\mathrm{div}}$ ($\boldsymbol{w}^{\mathrm{div}} = (w_x^{\mathrm{div}}, w_y^{\mathrm{div}})$). These components satisfy the following equations:

$$\begin{aligned} \mathrm{div}\boldsymbol{w}^{\mathrm{rot}} &= \frac{\partial w_x^{\mathrm{rot}}}{\partial x} + \frac{\partial w_y^{\mathrm{rot}}}{\partial y} \\ &= 0, \end{aligned} \tag{2}$$

$$\begin{aligned} \mathrm{rot}\boldsymbol{w}^{\mathrm{div}} &= -\frac{\partial w_x^{\mathrm{div}}}{\partial y} + \frac{\partial w_y^{\mathrm{div}}}{\partial x} \\ &= 0. \end{aligned} \tag{3}$$

With Eqs. (2) and (3), $\mathrm{div}\boldsymbol{w}$ and $\mathrm{rot}\boldsymbol{w}$ are respectively given by $\mathrm{div}\boldsymbol{w} = \mathrm{div}\boldsymbol{w}^{\mathrm{div}}$ and $\mathrm{rot}\boldsymbol{w} = \mathrm{rot}\boldsymbol{w}^{\mathrm{rot}}$. By utilizing the model shown in Eq. (1), the traditional method [5] realizes the flow estimation based on the Helmholtz decomposition theorem. However, since Eq. (1) in this method does not include a translational component, its performance tends to become degraded when the objects are translated. Therefore, introducing the translational component $\boldsymbol{w}^{\mathrm{tra}}$ into the Helmholtz



(a) (b) (c)

Fig. 1. Properties of the flows: (a) The rotational components satisfy $\boldsymbol{w}_t^{\mathrm{rot}}(\boldsymbol{k}_2) = \boldsymbol{w}_{t-1}^{\mathrm{rot}}(\boldsymbol{k}_2)$, (b) The divergent components satisfy $\boldsymbol{w}_t^{\mathrm{div}}(\boldsymbol{k}_4) = \boldsymbol{w}_{t-1}^{\mathrm{div}}(\boldsymbol{k}_3)$, and (c) The translational components satisfy $\boldsymbol{w}_t^{\mathrm{tra}}(\boldsymbol{k}_6) = \boldsymbol{w}_{t-1}^{\mathrm{tra}}(\boldsymbol{k}_5)$.

decomposition theorem, the proposed method extends the traditional model shown in Eq. (1) as follows:

$$\boldsymbol{w} = \boldsymbol{w}^{\mathrm{rot}} + \boldsymbol{w}^{\mathrm{div}} + \boldsymbol{w}^{\mathrm{tra}}, \tag{4}$$

where $\boldsymbol{w}^{\mathrm{tra}}$ ($\boldsymbol{w}^{\mathrm{tra}} = (w_x^{\mathrm{tra}}, w_y^{\mathrm{tra}})$) satisfies $\frac{\partial w_x^{\mathrm{tra}}}{\partial x} = 0$, $\frac{\partial w_x^{\mathrm{tra}}}{\partial y} = 0$, $\frac{\partial w_y^{\mathrm{tra}}}{\partial x} = 0$, and $\frac{\partial w_y^{\mathrm{tra}}}{\partial y} = 0$. From these four equations, we can see that $\boldsymbol{w}^{\mathrm{tra}}$ in Eq. (4) denotes the translational component.

3. PROPOSED FLOW ESTIMATION METHOD

In this section, we propose a novel flow estimation method with the particle filter based on the Helmholtz decomposition theorem. From the extended model of the Helmholtz decomposition theorem shown in the previous section, we define the state transition model and the observation model of the particle filter whose state variables are the flows. Furthermore, we derive the observation density of the particle filter from the energy function utilized in [5]. With these novel approaches, we can realize the particle filter estimating the flows based on the rotation, the divergence, and the translation, which are the important geometric features expressing the basic motions of the objects. Then, the proposed method can achieve the accurate estimation of the flows.

First, in 3.1, we define the state transition model and the observation model. Next, in 3.2, we propose the estimation method of the flows with the particle filter based on the state transition model and the observation model shown in 3.1.

3.1. Definition of the state transition model and the observation model

In this subsection, we define the state transition model and the observation model based on the extended model of the Helmholtz decomposition theorem shown in the previous section. The proposed method estimates the flow $\boldsymbol{w}_t$ between two successive frames f_{t-1} and f_t ($t = 1, 2, ...$) of the target image sequence f. We utilize $\boldsymbol{w}_t$ as the state variable in the particle filter [3]. Then, we define a process, which provides $\boldsymbol{w}_t$ from $\boldsymbol{w}_{t-1}$, as the following state transition model at each pixel $\boldsymbol{k}$:

$$\boldsymbol{w}_t(\boldsymbol{k}) = \boldsymbol{w}_t^{\mathrm{rot}}(\boldsymbol{k}) + \boldsymbol{w}_t^{\mathrm{div}}(\boldsymbol{k}) + \boldsymbol{w}_t^{\mathrm{tra}}(\boldsymbol{k}), \tag{5}$$

where

$$\boldsymbol{w}_t^{\mathrm{rot}}(\boldsymbol{k}) = \boldsymbol{w}_{t-1}^{\mathrm{rot}}(\boldsymbol{k}) + \boldsymbol{u}_t^1, \tag{6}$$

$$\boldsymbol{w}_t^{\mathrm{div}}(\boldsymbol{k}) = \boldsymbol{w}_{t-1}^{\mathrm{div}}(\boldsymbol{k} + \tilde{\boldsymbol{w}}_{t-1}^{\mathrm{div}}(\boldsymbol{k})) + \boldsymbol{u}_t^2, \tag{7}$$

$$\boldsymbol{w}_t^{\mathrm{tra}}(\boldsymbol{k}) = \boldsymbol{w}_{t-1}^{\mathrm{tra}}(\boldsymbol{k} + \tilde{\boldsymbol{w}}_{t-1}^{\mathrm{tra}}(\boldsymbol{k})) + \boldsymbol{u}_t^3, \tag{8}$$

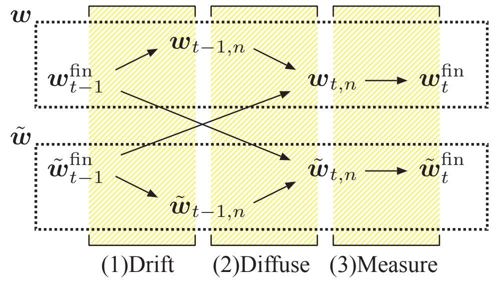
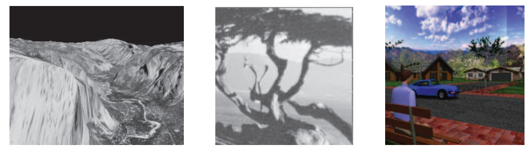


Fig. 2. Procedures of the flow estimation scheme in the proposed method.



(a) (b) (c)

Fig. 3. (a) Yosemite (14 frame), (b) Translating Tree (3 frame), and (c) Street (10 frame).

and $\boldsymbol{u}_t^1 - \boldsymbol{u}_t^3$ are additive noises. Furthermore, $\tilde{\boldsymbol{w}}_{t-1}(\boldsymbol{k})$ ($= \tilde{\boldsymbol{w}}_{t-1}^{\mathrm{rot}}(\boldsymbol{k}) + \tilde{\boldsymbol{w}}_{t-1}^{\mathrm{div}}(\boldsymbol{k}) + \tilde{\boldsymbol{w}}_{t-1}^{\mathrm{tra}}(\boldsymbol{k})$) represents the flow whose direction is opposite to $\boldsymbol{w}_{t-1}(\boldsymbol{k})$ on the time axis. In the proposed method, $\tilde{\boldsymbol{w}}_{t-1}(\boldsymbol{k})$ estimated by the particle filter in the same way as $\boldsymbol{w}_{t-1}(\boldsymbol{k})$ is utilized for calculating the corresponding pixels in Eqs. (7) and (8). Then, Eqs. (6)–(8) are derived from the following properties.

(A) Rotation
In Eq. (6), $\boldsymbol{w}_t^{\mathrm{rot}}(\boldsymbol{k})$ is almost the same as the rotational component of $\boldsymbol{k}$ in the previous frame as shown in Fig. 1 (a).

(B) Divergence and Translation
In Eqs. (7) and (8), $\boldsymbol{w}_t^{\mathrm{div}}(\boldsymbol{k})$ and $\boldsymbol{w}_t^{\mathrm{tra}}(\boldsymbol{k})$ are almost the same as the divergent and translational components of the previous frame's pixels corresponding to $\boldsymbol{k}$ in the current one as shown in Figs. 1 (b) and (c), respectively.

Next, the proposed method defines the observation model. In our method, observations of $\boldsymbol{w}_t$ are $\psi_t = \{f_t, \xi_t^{\mathrm{rot}}, \xi_t^{\mathrm{div}}\}$ and their history is $\Psi_t = \{\psi_1, \psi_2, ..., \psi_t\}$, where scalar fields ξ_t^{rot} and ξ_t^{div} denoting rotational and divergent structures are calculated by [5], respectively. We define the following two processes as the observation model. One is that f_t is generated from f_{t-1} with $\boldsymbol{w}_t$. The other one is that $\boldsymbol{w}_t$ is decomposed into ξ_t^{rot} and ξ_t^{div}. Then, the observation model is defined as follows:

$$f_t = -\bigtriangledown f_{t-1} \cdot \boldsymbol{w}_t + f_{t-1} + v_t^1, \tag{9}$$

$$\xi_t^{\mathrm{rot}} = \mathrm{rot}\boldsymbol{w}_t + v_t^2, \tag{10}$$

$$\xi_t^{\mathrm{div}} = \mathrm{div}\boldsymbol{w}_t + v_t^3, \tag{11}$$

where $v_t^1 - v_t^3$ are the additive noises. When v_t^1, v_t^2, and v_t^3 are zero, Eqs. (9)–(11) become the constraint conditions utilized in [5]. In the same way as Eqs. (9)–(11), the model of $\tilde{\boldsymbol{w}}_t$ is defined.

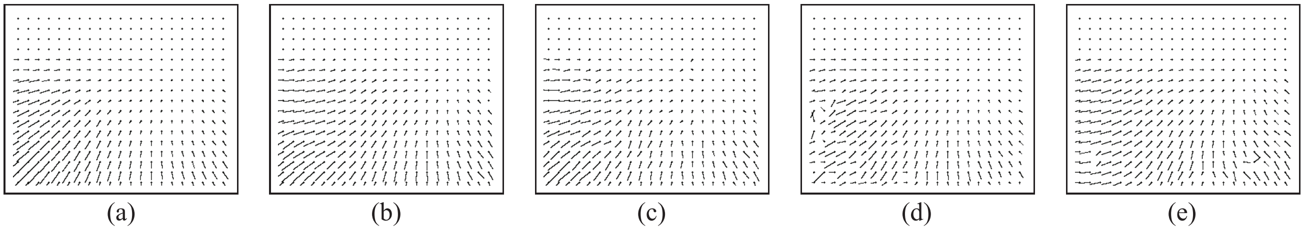


Fig. 4. The estimated flows between 14 and 15 frames (Yosemite): (a) The true flows, (b) Estimation result of the proposed method, (c) Estimation result of the PF with [1], (d) Estimation result of [2], and (e) Estimation result of [5].

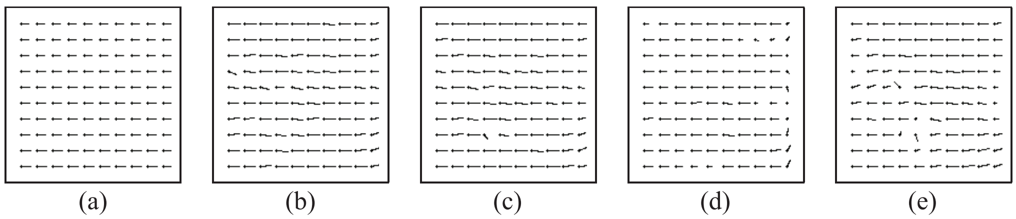


Fig. 5. The estimated flows between 3 and 4 frames (Translating Tree): (a) The true flows, (b) Estimation result of the proposed method, (c) Estimation result of the PF with [1], (d) Estimation result of [2], and (e) Estimation result of [5].

3.2. Flow estimation with Condensation algorithm

In this subsection, we propose the estimation method of the flows with the particle filter based on the state transition model and the observation model shown in the previous subsection. The proposed method estimates $\boldsymbol{w}_t$ with Condensation algorithm [3]. We show the procedures of the flow estimation scheme in Fig. 2 and explain their details as follows.

(1) Drift
For each particle p_n ($n = 1, 2, ..., N$), we select the state variable $\boldsymbol{w}_{t-1,n}$ at time $t-1$ with state density $P(\boldsymbol{w}_{t-1,n}|\Psi_{t-1})$. This procedure is performed in such a way that the estimation errors included in the previous state variables do not affect the estimation of the current state variables [3].

(2) Diffuse
For each particle p_n, the proposed method calculates the state variable $\boldsymbol{w}_{t,n}$ at time t from $\boldsymbol{w}_{t-1,n}$ with Eq. (5).

(3) Measure
From the observation density $P(\psi_t|\boldsymbol{w}_{t,n})$, $P(\boldsymbol{w}_{t,n}|\Psi_t)$ is calculated as follows:

$$P(\boldsymbol{w}_{t,n}|\Psi_t) = \frac{P(\psi_t|\boldsymbol{w}_{t,n})}{\sum_{i=1}^{N} P(\psi_t|\boldsymbol{w}_{t,i})}. \tag{12}$$

By utilizing $P(\boldsymbol{w}_{t,n}|\Psi_t)$, the flow $\boldsymbol{w}_t^{\mathrm{fin}}$ is finally obtained as follows:

$$\boldsymbol{w}_t^{\mathrm{fin}} = \sum_{n=1}^{N} \boldsymbol{w}_{t,n} P(\boldsymbol{w}_{t,n}|\Psi_t). \tag{13}$$

With the above procedures, the proposed method estimates the flows. In the same way, $\tilde{\boldsymbol{w}}_t^{\mathrm{fin}}$ is calculated.

In order to calculate Eq. (12), we have to obtain $P(\psi_t|\boldsymbol{w}_{t,n})$. Therefore, the proposed method defines $P(\psi_t|\boldsymbol{w}_{t,n})$ ($= P(f_t, \xi_t^{\mathrm{rot}}, \xi_t^{\mathrm{div}}|\boldsymbol{w}_{t,n})$) as follows. First, we assume that $P(f_t, \xi_t^{\mathrm{rot}}, \xi_t^{\mathrm{div}}|\boldsymbol{w}_{t,n}) = P(f_{t-1}, f_t, \xi_t^{\mathrm{rot}}, \xi_t^{\mathrm{div}}|\boldsymbol{w}_{t,n})$. Then, based on the Bayes theorem, $P(\psi_t|\boldsymbol{w}_{t,n})$ is given by

$$\begin{aligned} P(\psi_t|\boldsymbol{w}_{t,n}) &= P(f_{t-1}, f_t, \xi_t^{\mathrm{rot}}, \xi_t^{\mathrm{div}}|\boldsymbol{w}_{t,n}) \\ &= \frac{P(\xi_t^{\mathrm{rot}}, \xi_t^{\mathrm{div}}, \boldsymbol{w}_{t,n}|f_{t-1}, f_t) P(f_{t-1}, f_t)}{P(\boldsymbol{w}_{t,n})}. \end{aligned} \tag{14}$$

Next, the proposed method assumes that $P(\boldsymbol{w}_{t,n})$ is constant. Since f_{t-1} and f_t are known, $P(\psi_t|\boldsymbol{w}_{t,n})$ is given by the following equation:

$$P(\psi_t|\boldsymbol{w}_{t,n}) \propto P(\xi_t^{\mathrm{rot}}, \xi_t^{\mathrm{div}}, \boldsymbol{w}_{t,n}|f_{t-1}, f_t). \tag{15}$$

In [5], $P(\xi_t^{\mathrm{rot}}, \xi_t^{\mathrm{div}}, \boldsymbol{w}_{t,n}|f_{t-1}, f_t)$ is defined by utilizing the energy function J as follows:

$$P(\xi_t^{\mathrm{rot}}, \xi_t^{\mathrm{div}}, \boldsymbol{w}_{t,n}|f_{t-1}, f_t) = \frac{1}{Z} \exp\left(-\frac{J}{T}\right), \tag{16}$$

where Z is a normalization constant and T is a temperature. In the proposed method, the observation model of $\boldsymbol{w}_t$ is defined as Eqs. (9)–(11). Furthermore, $\boldsymbol{w}^{\mathrm{tra}}$ satisfies $\frac{\partial w_x^{\mathrm{tra}}}{\partial x} = 0$, $\frac{\partial w_x^{\mathrm{tra}}}{\partial y} = 0$, $\frac{\partial w_y^{\mathrm{tra}}}{\partial x} = 0$, and $\frac{\partial w_y^{\mathrm{tra}}}{\partial y} = 0$ as shown in the previous section. Therefore, we define J as follows:

$$J = J_{\boldsymbol{w}_{t,n}} + \gamma_1 J_{\boldsymbol{w}_{t,n}^{\mathrm{rot}}, \boldsymbol{w}_{t,n}^{\mathrm{div}}} + \gamma_2 J_{\boldsymbol{w}_{t,n}^{\mathrm{tra}}}. \tag{17}$$

In the above equation, $J_{\boldsymbol{w}_{t,n}}$, $J_{\boldsymbol{w}_{t,n}^{\mathrm{rot}}, \boldsymbol{w}_{t,n}^{\mathrm{div}}}$, and $J_{\boldsymbol{w}_{t,n}^{\mathrm{tra}}}$ are respectively obtained by

$$J_{\boldsymbol{w}_{t,n}} = \int_{\Omega} (f_t - f_{t-1} + \triangledown f_{t-1} \cdot \boldsymbol{w}_{t,n})^2 \, d\boldsymbol{k}, \tag{18}$$

$$\begin{aligned} J_{\boldsymbol{w}_{t,n}^{\mathrm{rot}}, \boldsymbol{w}_{t,n}^{\mathrm{div}}} = \int_{\Omega} & (\xi_t^{\mathrm{rot}} - \mathrm{rot}\boldsymbol{w}_{t,n})^2 + \alpha || \triangledown (\mathrm{rot}\boldsymbol{w}_{t,n})||^2 \\ & + (\xi_t^{\mathrm{div}} - \mathrm{div}\boldsymbol{w}_{t,n})^2 + \alpha || \triangledown (\mathrm{div}\boldsymbol{w}_{t,n})||^2 d\boldsymbol{k}, \end{aligned} \tag{19}$$

$$\begin{aligned} J_{\boldsymbol{w}_{t,n}^{\mathrm{tra}}} &= \int_{\Omega} \left(\frac{\partial w_{t,n,x}^{\mathrm{tra}}}{\partial x}\right)^2 + \left(\frac{\partial w_{t,n,x}^{\mathrm{tra}}}{\partial y}\right)^2 \\ &\quad + \left(\frac{\partial w_{t,n,y}^{\mathrm{tra}}}{\partial x}\right)^2 + \left(\frac{\partial w_{t,n,y}^{\mathrm{tra}}}{\partial y}\right)^2 d\boldsymbol{k} \\ &= \int_{\Omega} || \triangledown \boldsymbol{w}_{t,n}^{\mathrm{tra}}||^2 + || \triangledown \boldsymbol{w}_{t,n}^{\mathrm{tra}\perp}||^2 d\boldsymbol{k}, \end{aligned} \tag{20}$$

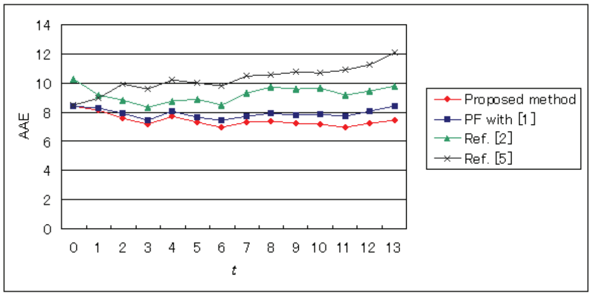


Fig. 6. Performance comparison (AAE) of the proposed method and the traditional ones.

where $\boldsymbol{w}_{t,n}^{\mathrm{tra}} = (w_{t,n,x}^{\mathrm{tra}}, w_{t,n,y}^{\mathrm{tra}})$, $\bigtriangledown \boldsymbol{w}_{t,n}^{\mathrm{tra}} = (\frac{\partial w_{t,n,x}^{\mathrm{tra}}}{\partial x}, \frac{\partial w_{t,n,y}^{\mathrm{tra}}}{\partial y})$, and $\bigtriangledown \boldsymbol{w}_{t,n}^{\mathrm{tra}\perp} = (-\frac{\partial w_{t,n,x}^{\mathrm{tra}}}{\partial y}, \frac{\partial w_{t,n,y}^{\mathrm{tra}}}{\partial x})$. Furthermore, α, γ_1, and γ_2 are the positive constants and Ω is an image plane of f. When γ_2 is zero, J in Eq. (17) becomes the energy function utilized in [5].

The proposed method defines the state transition model and the observation model as shown in Eqs. (5) and (9)–(11). Furthermore, we derive the observation density adjusting to the Helmholtz decomposition theorem from the energy function J in Eq. (17). Thus, we realize the particle filter estimating the flows based on the rotation, the divergence, and the translation, which are the important geometric features expressing the basic motions of the objects. Consequently, an accurate flow estimation can be achieved.

4. EXPERIMENTAL RESULTS

In this section, we show some simulation results in order to confirm the high performance of the proposed method. We utilize Yosemite (316×252 pixels, 8 bits/pixel, 15 frames) and Translating Tree (150×150 pixels, 8 bits/pixel, 20 frames) shown in Figs. 3(a) and (b) for the test image sequences. These image sequences are created by utilizing the true flows. Next, Figs. 4 and 5 show the true flows and the estimated flows by the proposed method, the method utilizing the particle filter based on [1] (PF with [1]), and the traditional ones [2, 5]. The state transition model of the PF with [1] is defined as follows:

$$\boldsymbol{w}_t(\boldsymbol{k}) = \boldsymbol{w}_{t-1}(\boldsymbol{k}) + \boldsymbol{u}_t, \qquad (21)$$

where $\boldsymbol{u}_t = \boldsymbol{u}_t^1 + \boldsymbol{u}_t^2 + \boldsymbol{u}_t^3$. The observation model of the PF with [1] is defined as Eq. (9). In the proposed method, $\boldsymbol{u}_t^m \sim N(0, \sigma^2)$ $(m = 1, 2, 3)$, where $N(0, \sigma^2)$ is the Gaussian whose mean and variance are 0 and σ^2, respectively. We set σ to 0.1 in this simulation. From Figs. 4 and 5, we can see that the proposed method can estimate the flows more successfully than the traditional ones.

In order to evaluate the proposed method quantitatively, we calculate an Average Angular Error (AAE) [6] in the case of Yosemite as shown in Fig. 6. Furthermore, Table 1 denotes the means of the AAE's in the case of Yosemite, Translating Tree, and Street (200×200 pixels, 24 bits/pixel, 20 frames) shown in Fig. 3(c). In Fig. 6, since the traditional methods [2, 5] do not consider the estimation errors of the previous flows, their performance is degraded when $t = 7, 8, ..., 13$. In contrast, the proposed method utilizes the particle filter and its performance is high. From Table 1, we can see that the proposed method has achieved 0.47–0.97° improvement in the case of the best published results in the PF with [1]. Since

Table 1. The means of the AAE's of the proposed method and the traditional ones.

	PF with [1]	Ref. [2]	Ref. [5]	Ours
Yosemite	7.90°	9.25°	10.25°	7.43°
Translating Tree	6.87°	8.29°	8.54°	6.32°
Street	9.29°	10.07°	9.24°	8.32°

we estimate the flows based on the rotation, the divergence, and the translation, which are the important geometric features expressing the basic motion of the objects, the proposed method is more accurate than the PF with [1].

5. CONCLUSIONS

This paper proposes a novel flow estimation method with the particle filter based on the Helmholtz decomposition theorem. The proposed method extends the model of the Helmholtz decomposition theorem and enables the decomposition of the flows into the rotational, divergent, and translational components. Furthermore, the proposed method realizes the introduction of the Helmholtz decomposition theorem into the particle filter. Consequently, an accurate flow estimation based on the rotation, the divergence, and the translation, which are the important geometric features expressing the basic motions of the objects can be achieved. Some simulation results are shown to confirm the high performance of the proposed method.

6. ACKNOWLEDGMENTS

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