WATER LEVEL TRACKING WITH CONDENSATION ALGORITHM

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ABSTRACT

In this report, we propose a tracking method that tracks a water level as a line from a video sequence. This method targets the use in a river surveillance and alarm system. In our proposed method, a line tracking problem is transformed to a point tracking problem by using Hough transformation and the point is tracked with Condensation algorithm. Our proposed method is examined by comparing with the Kalman filtering approach.

1. INTRODUCTION

In this report, we propose a river surface tracking method that targets the use in a river surveillance and alarm system.

As growing the interest of disaster prevention, it is desired to apply the information technology to problems in this area. River water level measurement is very important for river overflow prediction. Generally, it is performed with water level telemeters [1, 2]. To place the water level telemeters is, however, expensive and there are some difficulties in its legal placement in Japan. Thus, there is an increasing demand for measuring the water level by reasonable video cameras and by analyzing the images captured from those cameras.

Therefore, in this report, we propose a method that tracks river surface line in a video sequence from a surveillance camera. Our proposed method adopts the Hough transformation to detect dominant lines [5]. Next these lines are input into the Condensation (conditional density propagation) algorithm, which is a statistical tracking method and yields a estimated line [6]. By using the Hough transformation, a line tracking problem is reduced to a point tracking problem on 2-dimensional plane. Since the Condensation algorithm has sufficient servility to dynamics and robustness to errors, it can provide steady tracking. Although the Condensation algorithm requires relatively high computational cost, our proposed method reduces the computational cost by holding the dimension of state vector to two and by droping the dimension of observation reducing to 1-dimensional.

Our proposed method enables us to estimate the water level from a surveillance video sequence.

In next section, we introduce to the Hough transformation. In Section 3, we explan the overview of the Condensation algorithm. We propose a line tracking method in Section 4. The significance of our proposed method is examined by comparing with the Kalman filtering approach in Section 5 and the conclusions follow.

2. HOUGH TRANSFORMATION

The Hough transformation of lines is used in our proposed method at the and of preprocess.

The Hough transformation is a method that transforms a normal image expressed in rectangular coordinates to one expressed in polar coordinates and detect dominant lines from the polar-coordinate-image [5]. A line on the x-y plane is writen by $y = ax + b$. By using θ and ρ illustrated in Fig. 1(a), the function of a line is expressed as

$$\rho = x\cos\theta + y\sin\theta. \quad (1)$$

The Hough transformation is performed by this equation. A line on x-y plane is transformed to a point on θ-ρ plane and a point on x-y plane is transformed to a sin curve on θ-ρ plane by equation (1). Ranges of θ and ρ are $0 \le \theta < \pi$ and $-w < \rho < \sqrt{w^2 + h^2}$ respectively, where w is width and h is height of the input image.

As shown in Fig. 1, when two points p and q on x-y plane are given, we can obtain each curves on θ-ρ plane by using Eq. (1) and we can find the cross point l. The coordinates (θ_l, ρ_l) of the cross point l with Eq. (1) give us the function $\rho_l = x\cos\theta_l + y\sin\theta_l$. This is the function of the line passing two points p and q.

By using the Hough transformation, it seem that a line on x-y plane can be expressed as a point on θ-ρ plane.

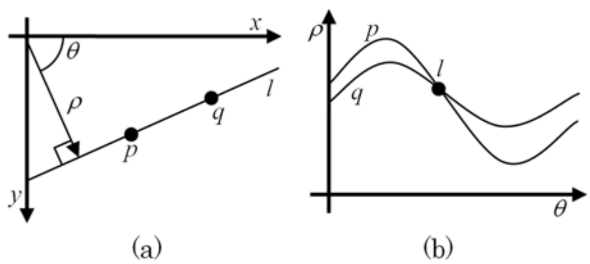


Fig. 1. Hough transformation

3. CONDENSATION ALGORITHM

The Condensation algorithm gives us an framework in order to obtain the posterior distribusion $p(\mathbf{x}_t|Z_t)$ of random variable $\mathbf{x}_t$ from a set $Z_t = \{\mathbf{z}_1, \mathbf{z}_2, \ldots, \mathbf{z}_t\}$ which is a set of datas observed until the time t [6, 7].

3.1. Assumptions for the Condensation Algorithm

The Condensation algorithm assumes the followings.

- The dynamics of the random variable $\mathbf{x}_t$ is Markov chain. Namely,

$$p(\mathbf{x}_t|X_{t-1}) = p(\mathbf{x}_t|\mathbf{x}_{t-1}), \quad (2)$$

  where $X_t = \{\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_t\}$.

- The observation data $\mathbf{z}_t$ depends only on the random variable $\mathbf{x}_t$ and is independent for each time. That is

$$p(Z_t|X_t) = \prod_{i=1}^{t} p(\mathbf{z}_i|\mathbf{x}_i). \quad (3)$$

Under these two assumption, the propagation of probability density is derived.

3.2. Propagation of Probability Density

From Bayes's rule

$$p(\mathbf{x}_t|Z_t) = k_t p(\mathbf{z}_t|\mathbf{x}_t) p(\mathbf{x}_t|Z_{t-1}), \quad (4)$$

where

$$p(\mathbf{x}_t|Z_{t-1}) = \int p(\mathbf{x}_t|\mathbf{x}_{t-1}) p(\mathbf{x}_{t-1}|Z_{t-1}) d\mathbf{x}_{t-1}, \quad (5)$$

and k_t is a normalisation constant that does not depend on $\mathbf{x}_t$.

By Eq. (5), the prior $p(\mathbf{x}_t|Z_{t-1})$ is evaluated from the posterior $p(\mathbf{x}_{t-1}|Z_{t-1})$ which is calculated at previous time step. By the equation (4), the new posterior $p(\mathbf{x}_t|Z_t)$ is decided from the prior $p(\mathbf{x}_t|Z_{t-1})$ and the observation density $p(\mathbf{z}_t|\mathbf{x}_t)$, which depend on the new observation data $\mathbf{z}_t$.

In the Condensation algorithm, the integral of Eq. (5) is not calculated directly, but evaluated approximately by using a sampling method.

3.3. Condensation Algorithm

The Condensation algorithm is one of sampling methods for estimating distribution. The internal representation of the Condensation algorithm is shown in Fig. 2. We have a set of N weighted samples $\left\{\left(\mathbf{s}_t^{(n)}, \pi_t^{(n)}\right); n = 1, \cdots, N\right\}$ and this set approximately represents the posterior $p(\mathbf{x}_t|Z_t)$, where $\mathbf{s}_t^{(n)}$ is a sample of the random variable $\mathbf{x}_t$ and $\pi_t^{(n)}$ is its weight. As a new observation data come in, we can update the weighted sample set through the following three steps and obtain the new posterior.

This algorithm is illustrated in Fig. 3.

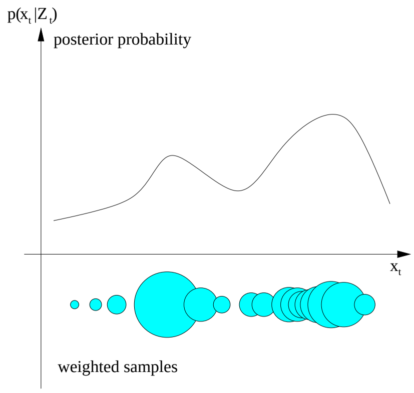


Fig. 2. Internal representation of the Condensation algorithm

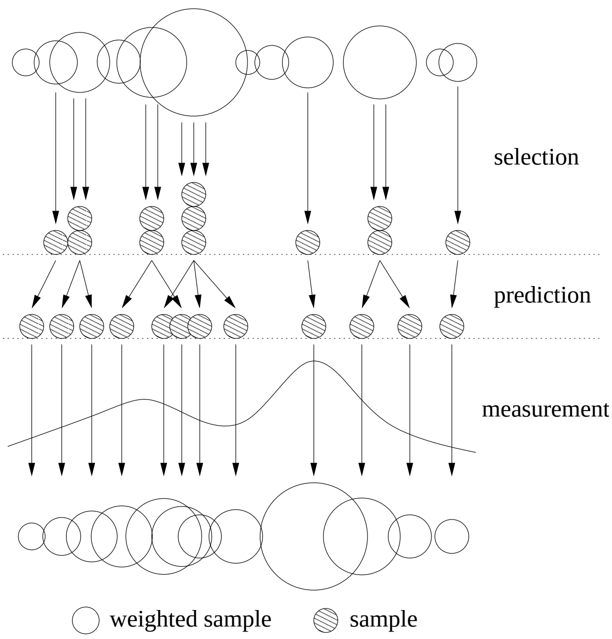


Fig. 3. Condensation algorithm

Step 1: Selection Sample N times from the set $\left\{\mathbf{s}_{t-1}^{(n)}\right\}$ by choosing probability $\pi_t^{(n)}$. In this step, some elements that have especially high weight may be chosen several times and may have identical copy in the new sample set. On the other hand, some elements that have low weight may not be choosen at all. The new sample set is denoted as $\left\{\mathbf{s'}_t^{(n)}\right\}$.

Step 2: Prediction Predict by drawing samples from

$$p\left(\mathbf{x}_t|\mathbf{x}_{t-1} = \mathbf{s'}_t^{(n)}\right) \quad (6)$$

to generate $\left\{\mathbf{s}_t^{(n)}\right\}$. In our proposed method, we assume that the dynamical model is a first-order autoregressive process, consequently predicted sample can be obtained by

$$\mathbf{s}_t^{(n)} = \mathbf{A}\mathbf{s'}_t^{(n)} + \mathbf{B}\mathbf{w}_t, \tag{7}$$

where $\mathbf{w}_t$ is a vector of independent standard normal random variables. Matrices $\mathbf{A}$ and $\mathbf{B}$ represent the deterministic and stochastic components of the dynamical model, respectively.

In this step, the distribution of these samples $\left\{\mathbf{s}_t^{(n)}\right\}$ approximate the prior $p\left(\mathbf{x}_t|Z_{t-1}\right)$.

Step 3: Measurement For each new sample $\mathbf{s}_t^{(n)}$, evaluate the new weight from

$$\pi_t^{(n)} p\left(\mathbf{z}_t|\mathbf{x}_t = \mathbf{s}_t^{n}\right), \tag{8}$$

and normalize to satisfy

$$\sum_{n=1}^{N} \pi_t^{(n)} = 1. \tag{9}$$

In the case that the state vector $\mathbf{x}_t$ is one dimensional,

$$p\left(\mathbf{z}_t|x_t\right) \propto 1 + \frac{1}{\sqrt{2\pi}\sigma\alpha} \sum_m \exp\left\{-\frac{v_m^2}{2\sigma^2}\right\}, \tag{10}$$

where m is the number of observation data, $v_m = z_t^{(m)} - x_t$, σ and α are constants decided from observation accuracy and error rate.

Here we obtain the new weighted sample set $\left\{\left(\mathbf{s}_t^{(n)}, \pi_t^{(n)}\right)\right\}$. The expectational value is calculated from

$$\epsilon\left[\mathbf{x}_t\right] = \sum_{n=1}^{N} \pi_t^{(n)} \mathbf{s}_t^{(n)}. \tag{11}$$

4. PROPOSED WATER LEVEL TRACKING

The structure of our proposed method is shown in Fig.4. The size in these parenthesises is the image size used in the experiment. Each process is explained in the followings.

4.1. Preprocess

At the preprocess, a binary image $I_t^{(\mathrm{bin})}$ is generated from input frame I_t. Next, the Hough transformation is applied to $I_t^{(\mathrm{bin})}$ and dominant lines are extracted.

At first, the difference image $I_t^{(d)}$ is calculated from input frame I_t and a base image $I_t^{(b)}$,

$$I_t^{(d)} = I_t - I_t^{(b)}. \tag{12}$$

The base image $I_t^{(b)}$ is updated by

$$I_{t+1}^{(b)} = \frac{I_t + I_t^{(b)}}{2}. \tag{13}$$

Next, the binary image $I_t^{(\mathrm{bin})}$ is generated from the difference image $I_t^{(d)}$. A threshold value T is used through this

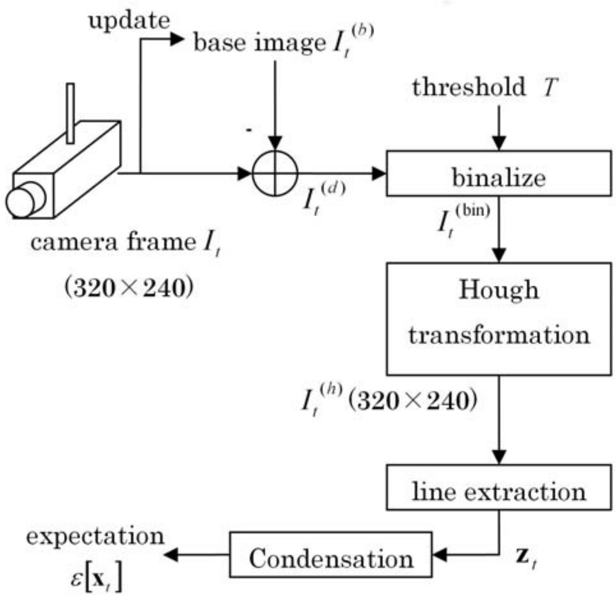


Fig. 4. Structure of our proposed method

(a) Input frame (b) Binary image

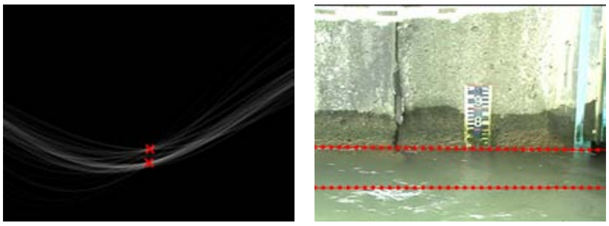
Fig. 5. Binarization of input frame

process. If the absolute value of each pixel in $I_t^{(d)}$ is over the threshold T, corresponding pixel of binary image will be white, otherwise black.

Figure 5 show one input frame and its binarized image. Our proposed method does not employ the simple frame difference method and the base image is weighted average image of input frames, because it is desired to exclude the influence of noise. Since the base image can forget the old input frame information by using Eq. (13) and update the base image, our proposed method possesses adaptability for intensity change.

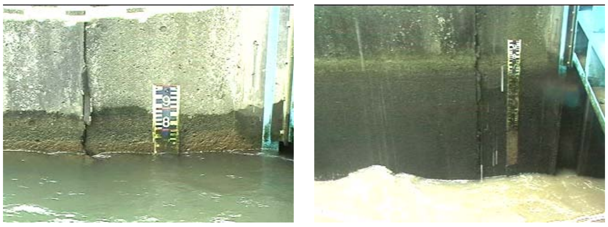
For all white pixels of binary image $I_t^{(\mathrm{bin})}$, the Hough transformation is performed then Hough image $I_t^{(h)}$ is obtained. In the following experiment, $I_t^{(h)}$ is quantized to the same size of the input image for computational convenience. From the Hough image I_h, points corresponding to dominant lines are extracted and the following coordinates set is formed.

$$\mathbf{z}_t = \left\{\mathbf{z}_t^{(m)} = \left(\theta_t^{(m)}, \rho_t^{(m)}\right); m = 1, \cdots, M\right\}. \tag{14}$$



(a) Hough image (b) Extracted lines

Fig. 6. Hough transformation and extracted lines



(a) Sequence 1 (b) Sequence 2

Fig. 7. Snapshots of video sequences)

In our experiment, coordinates quantized onto the Hough image (not parameters of Eq. (1)) are used as $(\theta_t^{(m)}, \rho_t^{(m)})$.

The Hough transformation can be performed for grayscale image, but we use the binary image as input for reducing the computational cost.

The Hough image of the binary image in Fig.5(b) and extracted lines are shown in Fig. 6. Number of dominant lines is not always one. In fact, two lines are extracted in Fig.6. By noise, the Hough transformation may extract wrong lines. Therefore it is necessary to use statistical approach in order to remove this influence. In our proposed method, we use the Condensation algorithm.

4.2. Update of Condensation Sample Set

By the coordinates set $\mathbf{z}_t$, the Condensation sample set is updated and the expectational value $\epsilon[\mathbf{x}_t]$ is evaluated.

Because we assume that the dynamical model is a first-order auto-regressive process, we use Eq. (7) in the Condensation prediction step. To reduce the dimension of observation density to one dimension, we use the following in the measurement step.

$$p(\mathbf{z}_t|\mathbf{x}_t) \propto 1 + \frac{1}{\sqrt{2\pi}\sigma\alpha} \sum_m \exp\left\{ -\frac{d\left(\mathbf{z}_t^{(m)}, \mathbf{x}_t\right)^2}{2\sigma^2} \right\}, \quad (15)$$

where

$$d(\mathbf{x}_1, \mathbf{x}_2) = \sqrt{(\theta_2 - \theta_1)^2 + (\rho_2 - \rho_1)^2}, \quad (16)$$

and $\mathbf{x}_1 = (\theta_1, \rho_1), \mathbf{x}_2 = (\theta_2, \rho_2)$.

5. PERFORMANCE EVALUATION

We use two video sequences for performance evaluation. Snapshots of these sequences are shown in Fig. 7. Table 1 shows some particularities of these video sequences. Sequence 1 is a video sequence of a river in fair weather and the water surface is calm. Sequence 2 is a video of the same river in bad weather. It rains and the water surface is rough.

Table 1. Video Sequences

sequence	frame size	frame rate	number of frames
Seq.1	320x240	30 fps	464
Seq.2	320x240	30 fps	458

As constants of Eq. (7) and (10), we use

$$\begin{aligned} \mathbf{A} &= \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}, \\ \mathbf{B} &= \begin{pmatrix} 5 & 0 \\ 0 & 5 \end{pmatrix}, \\ \sigma &= 1, \\ \alpha &= 0.01, \end{aligned}$$

the binarize threshold $T = 127$ and we experiment on water level tracking with our proposed method for the number of samples $N = 1000$.

To verify the significance, we compare it with the experimental result of the Kalman filtering approach [8]. In the Kalman filter, the state equation and the observation equation are given by

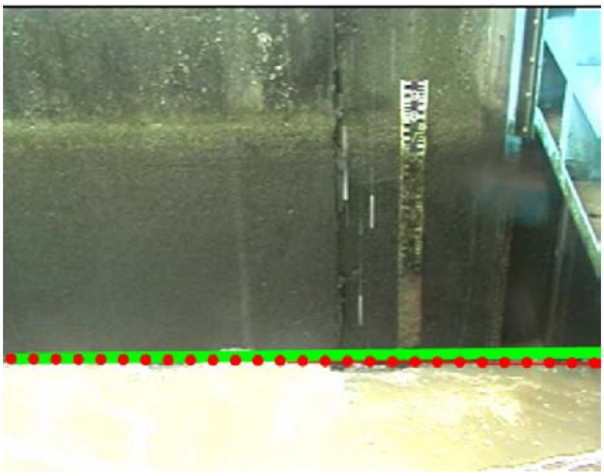
$$\mathbf{x}_t = \mathbf{F}\mathbf{x}_{t-1} + \mathbf{G}\mathbf{w}_t, \quad (17)$$

$$\mathbf{z}_t = \mathbf{H}\mathbf{x}_t + \mathbf{v}_t, \quad (18)$$

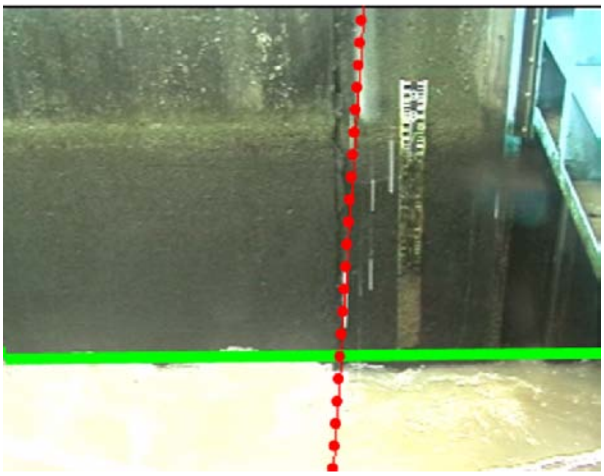
respectively, and constants are set to

$$\begin{aligned} \mathbf{F} &= \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}, \\ \mathbf{G} &= \begin{pmatrix} 5 & 0 \\ 0 & 5 \end{pmatrix}, \\ \mathbf{H} &= \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}, \\ \mathbf{\Sigma}_w &= \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}, \\ \mathbf{\Sigma}_v &= \begin{pmatrix} 10^2 & 0 \\ 0 & 10^2 \end{pmatrix}, \end{aligned}$$

where $\mathbf{w}_t$ and $\mathbf{v}_t$ are vectors of independent standard normal random variables, $\mathbf{\Sigma}_w$ and $\mathbf{\Sigma}_v$ are covariance matrices, respectively.

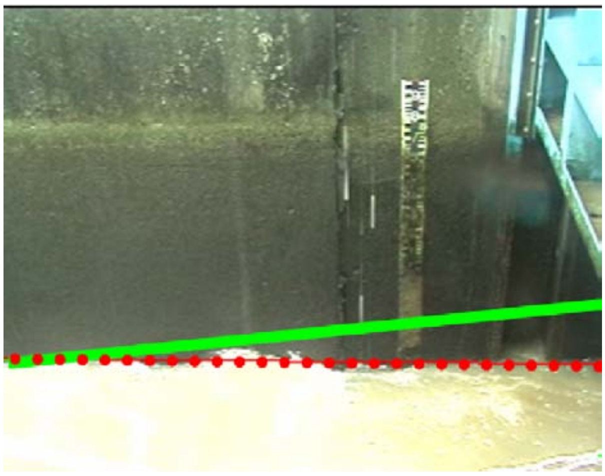


(a) frame 40 of Seq.2

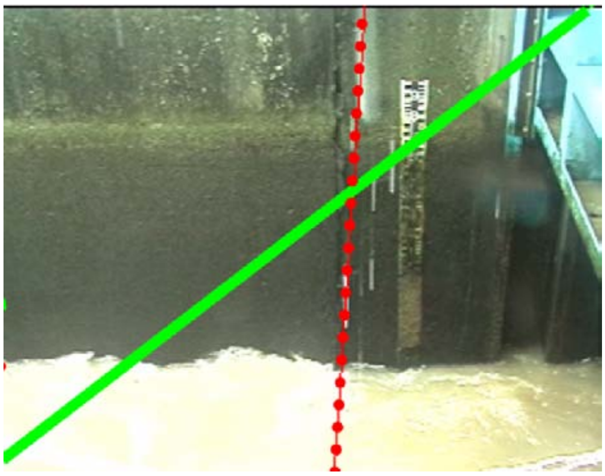


(b) frame 41 of Seq.2

Fig. 8. Simulation result (proposed method)



(a) frame 40 of Seq.2



(b) frame 41 of Seq.2

Fig. 9. Simulation result (Kalman filtering approach)

These results with Seq.2 are shown in Figs. 8 and 9. The dotted lines denote the observation data from the Hough transformation and the solid lines denote the estimated lines at the end.

Both of Figs. 8 and 9 show successive two frames in video sequence 2. From the first frame, almost correct observation is obtained, but wrong observation come in from the other frame due to the rain. In the Kalman filtering approach, the observation error effect the estimation immediately, although, in our proposed method using the Condensation algorithm, the influence is almost not seen. This result from that the Condensation algorithm is designed with considering the observation error. Through the video sequence, both two approaches show almost the same sensitivity in the low observation error part, but in the high error part, our proposed method can obtain more steady tracking than the Kalman filtering approach.

MSE evaluations of proposed method and the Kalman filtering approach is shown in Table 2. Each value in Table 2 shows the mean square error between true water surface lines and estimated lines. True water surface lines are decided manually. Equation (16) is used to calculate errors between true lines and estimated lines.

From Table 2, it is seen that proposed method give us error less tracking for both sequences than the Kalman filtering approach.

6. CONCLUSIONS

In this report, we proposed the water level tracking method in river surveillance video by using the Hough transformation and the Condensation algorithm. From several experimental results, the significance of our proposed method is evaluated with the comparison of our proposed method with

Table 2. Evaluation by MSE

	Condensation	Kalman Filter
Seq. 1	22.46	51.75
Seq. 2	55.24	2925.85

the Kalman filtering approach. There are some assignment for the future such as improvement of preprocess, reduction of the observation error rate and restriction of tracking area.

Acknowledgement

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