Optical Flow Estimation using a Correlation Image Sensor based on FlowNet-based Neural Network

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Abstract: Optical flow estimation is one of a challenging task in computer vision fields. In this paper, we aim to combine correlation image that enables single frame optical flow estimation with deep neural networks. Correlation image sensor captures temporal correlation between incident light intensity and reference signals, that can record intensity variation caused by object motion effectively. We developed FlowNetS-based neural networks for correlation image input. Our experimental results demonstrate proposed neural networks has succeeded in estimating the optical flow.

1 INTRODUCTION

Optical flow is the two-dimensional velocity field that describes the apparent motion of image patterns. It has large applications such as detection and tracking of an object, separation from a background or more generally segmentation, three-dimensional motion computation, etc. One of the most established algorithms for optical flow determination is based on the optical flow constraint (OFC) equation describing the intensity-invariance of moving patterns with regularization term(Horn and Schunck, 1981).

These days a deep neural network methods with convolutional neural networks(CNNs) are applied to estimate optical flow (Weinzaepfel et al., 2013). FlowNet(Dosovitskiy et al., 2015) is one of the successful neural network for optical flow estimation. They adopted FCN-like structure without Fully Connected layers so that their method didn't depends on the input image size. They also proposed good refinement structure, they successfully estimated fine flow fields.

Ando et. al. applied correlation image sensor(Ando and Kimachi, 2003) and weighted integral method(Ando and Nara, 2009) to optical flow estimation(Ando et al., 2009). They started from optical flow partial differential equation(Horn and Schunck, 1981) and formulated exposure time in integral form and developed a sensing system that detects velocity vector distribution on an optical image with a pixel-wise spatial resolution and a frame-wise temporal resolution. Kurihara et. al. implemented fast optical flow estimation algorithm achieving 3ms for 640x512 pixel resolution, and 7.5ms for 1280x1024 pixel resolution using GPU(Kurihara and Ando, 2013). They also applied total variation minimization technique for direct algebraic method of optical flow detection using correlation image sensor(Kurihara and Ando, 2014).

In this paper, we propose to combine correlation image that enables single frame optical flow estimation and deep neural networks. In the following section, we review the correlation image sensor, and show proposed FlowNetS-based neural network for correlation images. Then we showed experimental results.

2 PRINCIPLE

2.1 Correlation Image Sensor

The three-phase correlation image sensor (3PCIS) is the two dimensional imaging device, which outputs a time averaged intensity image $g_0(x,y)$ and a correlation image $g_\omega(x,y)$. The correlation image is the pixel wise temporal correlation over one frame time between the incident light intensity and three external electronic reference signals.

The photo of the 640 $\times$ 512 three-phase correlation image sensor is shown in Figure 1, and its pixel

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Figure 1: Photograph of Correlation Image Sensor(CIS).

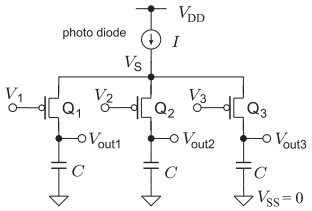


Figure 2: Pixel structure of the correlation image sensor.

structure is shown in Figure 2.

Let T be frame interval and $f(x,y,t)$ be instant brightness of the scene, we have intensity image $g_0(x,y)$ as

$$g_0(x,y) = \int_0^T f(x,y,t)\,dt \tag{1}$$

Let the three reference signals be $v_k(t)$ $(k = 1,2,3)$ where $v_1(t) + v_2(t) + v_3(t) = 0$, the resulting correlation image is written like this equation.

$$c_k(x,y) = \int_0^T f(x,y,t)\,v_k(t)\,dt \tag{2}$$

Here we have three reference signals with one constraint, so that there remains 2 DOF for the basis of the reference signal. We usually choose orthogonal sinusoidal wave pair $(\cos\omega t, \sin\omega t)$ as the basis, which means $v_1(t) = \cos\omega t, v_2(t) = \cos(\omega t + \frac{2}{3}\pi), v_3(t) = \cos(\omega t + \frac{4}{3}\pi)$.

Let the time-varying intensity in each pixel be

$$I(x,y,t) = A(x,y)\cos(\omega t + \phi(x,y)) + B(x,y,t). \tag{3}$$

Here $A(x,y)$ and $\phi(x,y)$ is the amplitude and phase of the frequency component ω, and $B(x,y,t)$ is the other frequency component of the intensity including DC component. Due to the orthogonality, $B(x,y,t)$ doesn't contribute in the outputs c_1, c_2, c_3. Therefore the amplitude and the phase of the frequency ω component can be calculated as follows (Ando and Kimachi, 2003)

$$A(x,y) = \frac{2\sqrt{3}}{3}\sqrt{(c_1-c_2)^2 + (c_2-c_3)^2 + (c_3-c_1)^2} \tag{4}$$

$$\phi(x,y) = \tan^{-1}\frac{\sqrt{3}(c_2-c_3)}{2c_1-c_2-c_3} \tag{5}$$

From the two basis of the reference signal $(\cos n\omega_0 t, \sin n\omega_0 t)$, we can rewrite amplitude and phase using complex equation.

$$g_\omega(x,y) = \int_0^T f(x,y,t)e^{-j\omega t}dt \tag{6}$$

Here $\omega = 2\pi n/T$. $g_\omega(x,y)$ is the complex form of the correlation image, and it is a temporal Fourier coefficient of the periodic input light intensity.

2.2 FlowNet-based Neural Network

We modified FlowNetSimple (Dosovitskiy et al., 2015) for our purpose. The FlowNetSimple requires two color images as input so that it has 6 channels in the input layer. We change number of input channels in the input layer from 6 to 2. It means 2 channels for real part and imaginary part of the complex correlation image. According to this reduction of the input channels, we reduce the channels in latter layers, although we didn't changed the other parameters like kernel size, stride, and activation function. The overall structure is shown in Fig.3. It has nine convolutional layers with stride of 2 and used ReLU activation function after each layer. Convolutional filter sizes decrease towards deeper layers of networks: 7×7 for the first layer, 5×5 for the following two layers and 3×3 for the rest of the layers. The number of feature maps increases in the deeper layers.

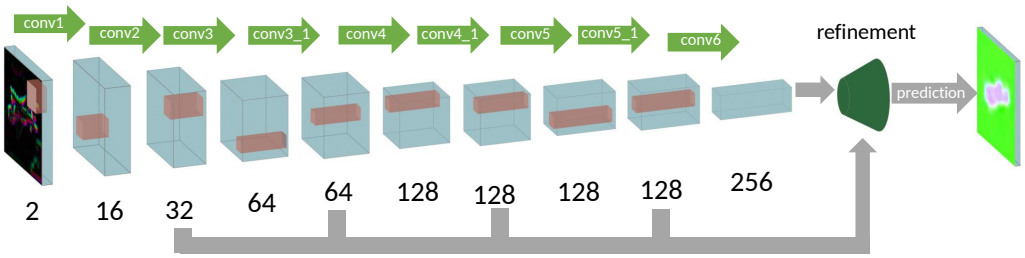
We do not have any fully connected layers, which allows the networks to take images of arbitrary size as input. As training loss we use the endpoint error(EPE), which is used as standard error to measure optical flow estimation. It is the average of Euclidean distance of all pixels between the predicted flow and the ground truth.

Using the same neural network structure, we compared the proposed method with our modified gray scale FlowNetS whose input is two still grayscale images.

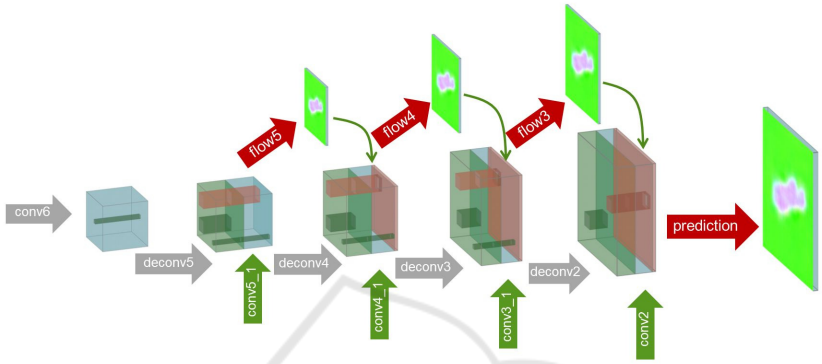
3 EXPERIMENTS

3.1 Dataset

To evaluate our proposed method, we used computer generated correlation images. In this simulation, we



(a)



(b)

Figure 3: Proposed FlowNetS-based Network structure. The number of channels in input layer is reduced from 6 to 2 to receive the correlation image. According to this reduction of the input channels, we reduce the channels in latter layers. Basic structure follows FlowNetS structure. Each scale features are gathered in refinement block. (a)Overal structure, (b) refinement block structure.

overlayed two images. Each image was moved uniformly in a random direction at random speed, in other words each images moved at speed (v_x, v_y). In addition, the upper image was used with mask of alpha channel. Those masks were generated by using Photoshop manually. Examples of the still image are shown in Fig.4.

Figure 4: Examples of the still images and masks used for simulation.

For the simulation, we divided one frame period T into K samples with sampling duration Δ, namely, $T = K\Delta$. The still image $f(x,y)$ were shifted $(v_x\Delta, v_y\Delta)$ at each time-step when we assumed uniform motion. Then we can calculate intensity image as follows,

$$g_0(x,y) = \sum_{k=0}^{K-1} f(x - v_x k\Delta, y - v_y k\Delta). \tag{7}$$

And the correlation image is obtained as follows,

$$g_{\omega_0}(x,y) = \sum_{k=0}^{K-1} f(x - v_x k\Delta, y - v_y k\Delta)\exp(-j\omega_0 k\Delta). \tag{8}$$

Here we overlayed two images, $f_f(x,y)$ as foreground and $f_b(x,y)$ as background, so that $f(x,y)$ is obtained by using foreground mask $m_f(x,y)$ as follows.

$$f(x,y) = f_f(x,y)m_f(x,y) + f_b(x,y)(1 - m_f(x,y)) \tag{9}$$

The shifted image $f(x-\Delta_x, y-\Delta_y)$ is obtained by using Fourier transform as follows.

$$f(x-\Delta_x, y-\Delta_y) = \mathcal{F}^{-1}\left[\exp(ju\Delta_x)\exp(jv\Delta_y)F(u,v)\right] \tag{10}$$

Here Fourier transform of $f(x,y)$ is $F(u,v) = \mathcal{F}[f(x,y)]$, and u, v are spatial frequencies.

We selected two images from 7 still images randomly, and moved each images toward different direction by using uniform random numbers, and generated 4096 sets of intensity image, correlation image and two instant images. The 3276 sets were used for training and the rest 820 sets were used for testing. Figure (5) shows those calculated images.

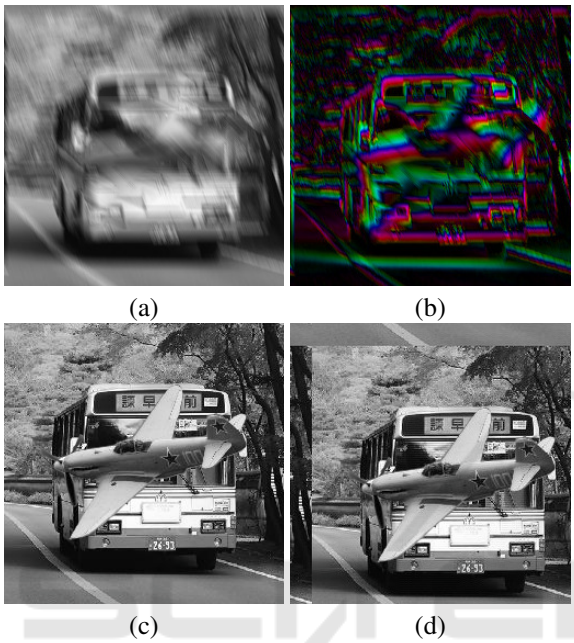


Figure 5: Examples of the simulated images: (a) intensity image, (b) correlation image, In addition, we used instant images to compare the results: (c) instant image at starting time,($k = 0$ in eq.(7)) (d) instant image at ending time($k = K - 1$ in eq.(7)) . In this simulation, foreground image (airplane) moves (-8.25, -3.98) pixels and background image (bus) moves (-7.93, -6.28) pixels during exposure time.

3.2 Training Details

We adopted adam with a learning rate 0.0001 for optimization. We used 300 epochs for training and batch size was set to 8 for 3276 training data. We didn't use data augmentation technique in the experiments. We implemented our models by the PyTorch framework and trained them using a NVIDIA TITAN Xp GPU.

3.3 Results

To demonstrate effect of proposed method, we compared proposed method to FlowNetS-based method. In fact, two compared neural networks have the perfectly the same structure, but input images are different. Proposed method has two input image of real part of correlation image and imaginary part of correlation image, compared method has also has two input images of still images of starting time and ending time.

The minimum EPE for testing data and training are shown in Table 1. The minimum EPE of the proposed method is better than the grayscale FlowNetS.

Table 1: Minimum end poinet error(EPE) over all epoch.

	train	test
Grayscale FlowNetS	0.635	0.727
Proposed	0.601	0.628

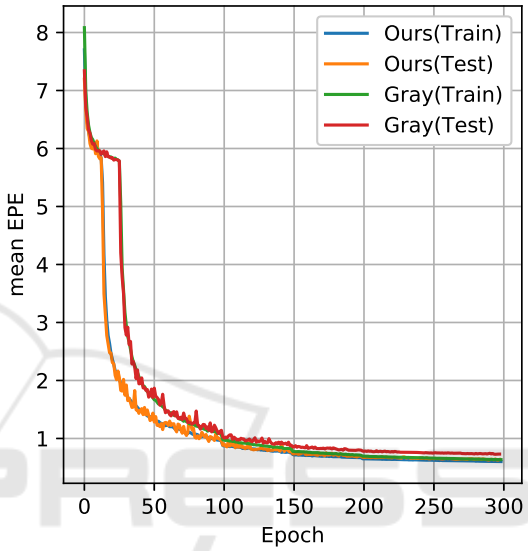
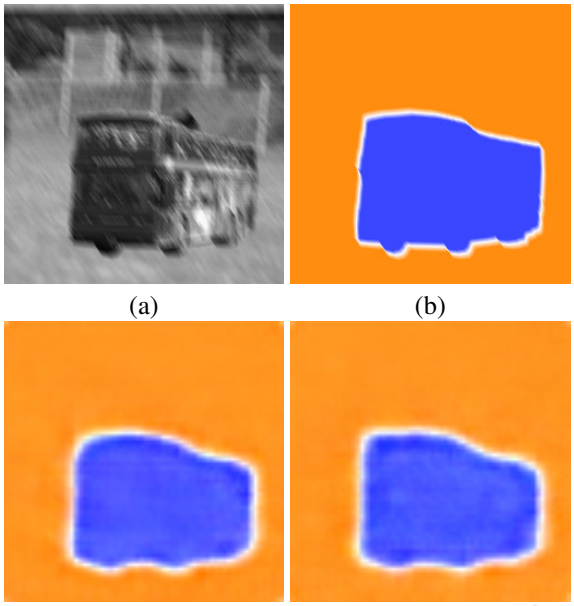


Figure 6: The results of training. (a) Mean end point error (EPE) for training and testing of proposed method and gray method".

The results images are shown in Fig. 7, Fig.8, Fig.9 and Fig.10. As illustrated in the Fig.7, both the proposed method and the compared method looks similar and shows good estimation results compared to the ground truth. Figure 8 shows the best EPE results for both proposed and compared method. The proposed method shows better estimation of the background motion. We consider that the large background area resulted in better EPE, since the second best EPE has also dog foreground. Figure 9 shows the worst EPE results for the proposed method. The wings of the airplane is incomplete in the both methods. Figure 10 shows the worst EPE results for the compared method. Although the velocity estimation of the body of the airplane is wrong for compared method, the proposed method shows better results.

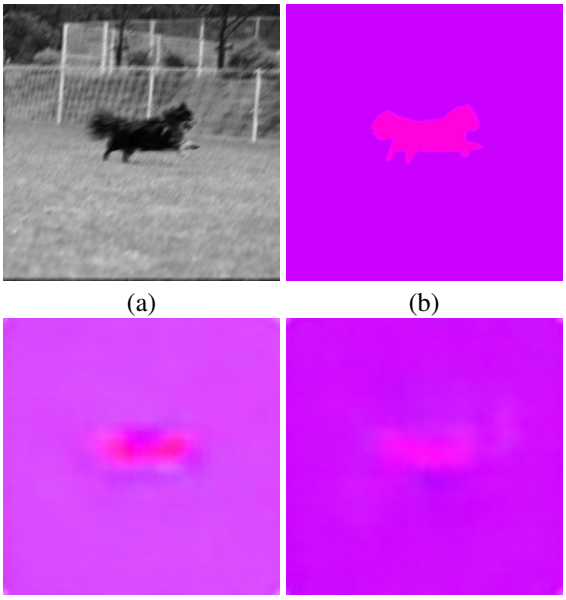
The input images for the grayscale FlowNetS is ideal instant one, which means we didn't consider the effect of motion blur. The faster the motion becomes, more blur will occurs. This phenomenon makes it difficult to find correspondence between the two images. We will investigate this further.



(a) (b)

(c) (d)

Figure 7: Examples of the estimated flow. foreground image (bus) moves (-6.23, -9.10) pixels and background image (dog) moves (-7.93, -6.28) pixels during exposure time: (a) intensity image, (b) ground truth, (c) estimated by using two instant images pair, (d) estimated by using correlation image (proposed).



(a) (b)

(c) (d)

Figure 8: Best mean EPE examples of the estimated flow. (Proposed:0.1596, Gray:0.1902) foreground image (dog) moves (4.47, -2.35) pixels and background image (dog) moves (3.23, -3.96) pixels during exposure time: (a) intensity image, (b) ground truth, (c) estimated by using two instant images pair, (d) estimated by using correlation image (proposed).

4 CONCLUSIONS

We proposed optical flow estimation method using a deep neural network for correlation image. As the input, the complex-valued correlation image is divided in two channels, real value image and imaginary value image. The proposed method enables single-frame optical flow estimation. Right now, the accuracy of the proposed method is similar to the conventional one when we use the same neural network structure. We point out that input images of grayscale FlowNetS are the ideal one, which means there is no motion blur. We need a further investigation about advantages of the proposed method.

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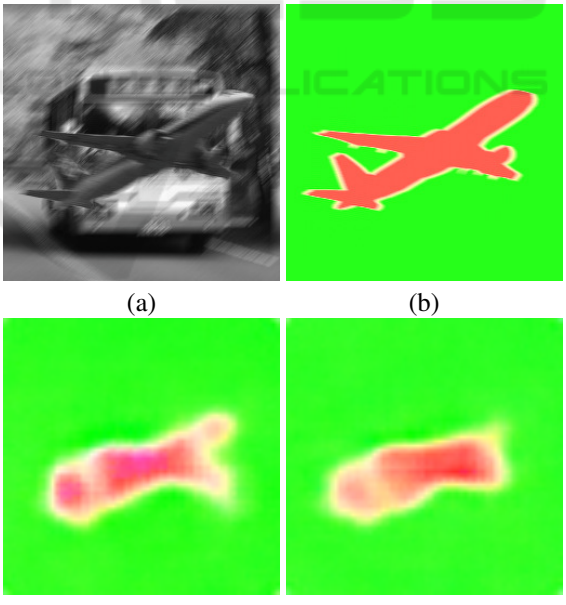
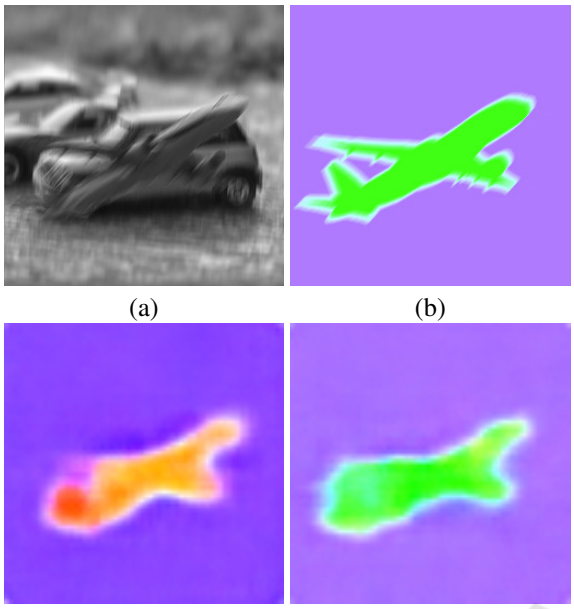


(a) (b)

(c) (d)

Figure 9: Worst mean EPE examples for the proposed method. (Proposed:1.652, Gray:1.687) foreground image (airplane) moves (9.74, 1.49) pixels and background image (dog) moves (-9.63, 8.74) pixels during exposure time: (a) intensity image, (b) ground truth, (c) estimated by using two instant images pair, (d) estimated by using correlation image (proposed).



(a) (b)

(c) (d)

Figure 10: Worst mean EPE examples for the grayscale method. (Proposed:1.370, Gray:2.832) foreground image (airplane) moves (-10.33, 11.25) pixels and background image (car) moves (0.79, -8.56) pixels during exposure time: (a) intensity image, (b) ground truth, (c) estimated by using two instant images pair, (d) estimated by using correlation image (proposed).

REFERENCES

Ando, S. and Kimachi, A. (2003). Correlation image sensor: two-dimensional matched detection of amplitude-modulated light. *IEEE Transactions on Electron Devices*, 50(10):2059–2066.

Ando, S., Kurihara, T., and Wei, D. (2009). Exact algebraic method of optical flow detection via modulated integral imaging –theoretical formulation and real-time implementation using correlation image sensor–. In *Proc. Int. Conf. Computer Vision Theory and Applications (VISAPP 2009)*, pages 480–487.

Ando, S. and Nara, T. (2009). An exact direct method of sinusoidal parameter estimation derived from finite fourier integral of differential equation. *IEEE Transactions on Signal Processing*, 57(9):3317–3329.

Dosovitskiy, A., Fischer, P., Ilg, E., Häusser, P., Hazirbas, C., Golkov, V., v. d. Smagt, P., Cremers, D., and Brox, T. (2015). Flownet: Learning optical flow with convolutional networks. In *2015 IEEE International Conference on Computer Vision (ICCV)*, pages 2758–2766.

Horn, B. K. and Schunck, B. G. (1981). Determining optical flow. *Artificial Intelligence*, 17(1):185 – 203.

Kurihara, T. and Ando, S. (2013). Fast optical flow detection based on weighted integral method using correlation image sensor and gpu(in japanese). volume 3, pages 170–171.

Kurihara, T. and Ando, S. (2014). Tv minimization of direct algebraic method of optical flow detection via modulated integral imaging using correlation image sensor. In *2014 International Conference on Computer Vision Theory and Applications (VISAPP)*, volume 3, pages 705–710.

Weinzaepfel, P., Revaud, J., Harchaoui, Z., and Schmid, C. (2013). Deepflow: Large displacement optical flow with deep matching. In *The IEEE International Conference on Computer Vision (ICCV)*.