15-3

Building Datasets of Aerial Videos Using Drone and Extending Datasets with Chaos Noise

Ryuta YOSHIMURA Yoko UWATE Yoshifumi NISHIO
(Tokushima University)

1. Introduction

The drone is noticed that it is possible to acquire the disaster situation in detail and promptly when natural disasters occur. Last year, 124 people were rescued by drone, such as the discovery of victims left behind in the hill, river and mountainous areas. The drone is easy to deploy in case of disasters and the cost of pilot development can be reduced. At this stage, the rescuer is searching for rescuee through a drone camera manually.

We aim to develop the automated discovery system using CNN, so we constructed the data set which is necessary for learning of CNN. In addition, our method for extending the dataset is to add chaotic noise to the learning data.

2. Proposed method

First, we describe the data collection for data set construction. We obtained videos by letting the drones pass over the sky of the five targets. After that, we cut out the videos into a frame images using openCV, and excluded the images in which the targets were not shown. We divided one-third of the obtained images for testing and others for learning. Next, we added salt and pepper noise to increase the data. The probability of applying noise to each image is the output of the logistic map. The formula of the logistic map is as follows.

$$x_{n+1} = ax_n(1 - x_n) \tag{1}$$

n means the number of steps. When x_n is determined, the next value x_{n+1} is uniquely determined. Similar to x_n and x_{n+1}, there is continuity also in images extracted from moving images, so we expect each image to be affected by the dynamics of this noise. The logistic map takes various values depending on the value of the parameter a. We set the values of a = 4.0 and a = 3.828327 in this study. When a = 4.0, it shows a behavior close to a random number called pure chaos.

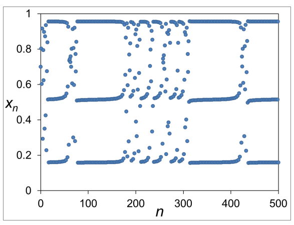

Figure 1: Logistic map at the time when a = 3.828327.

Figure 1 shows a behavior of intermittency chaos which is switching between laminar part and burst part. Laminar means the periodic state and burst means the chaotic state. When we determine the parameter a = 3.828327, the logistic map shows intermittency chaos.

The table shows the parameters and the number of images of the learning data used in this study.

Table 1: The parameters and the number of images of the learning dataset.

Parameter	Number of images
a. basic(not to add noise)	198
b. a=4.0	396
c. a=3.828327	396
d. a=4.0, a=3.828327	594
e. a=4.0(contained)	396
f. a=3.828327(contained)	396
g. a=4.0, a=3.828327(contained)	594

d and g are made to learn two types simultaneously with noise added by each parameter. e, f, g contain the noise application rate from 0 to 10 percent.

In this research, we used a convolution neural network (CNN) widely used for image and video recognition. CNN extracts features by convolution and pooling of the imported image and acquires final output at full connected layer to recognize it. This model consists of an input layer, two convolution layers, two pooling layers, two full connected layers and an output layer.

3. Simulation results

We investigated learning accuracy by learning these data with CNN and how noise influences learning accuracy. The number of learning is 1000 times. Table 2 shows learning accuracy by various parameters.

Table 2: Learning accuracy.

	step=100	step=200	step=500	step=1000
a	0.308081	0.651515	0.752525	0.762626
b	0.333333	0.613636	0.871212	0.886364
c	0.415459	0.649758	0.855072	0.862319
d	0.328076	0.594637	0.818612	0.851735
e	0.534606	0.844869	0.980907	0.988067
f	0.558087	0.936219	0.984055	0.988611
g	0.596970	0.912121	1	1

The learning accuracy improves as the number of times of learning increases. When the number of steps is 200, f is the highest training accuracy, and g is the best after 500 steps.

4. Conclusions

Learning accuracy was improved by increasing data due to noise. However, when learning accuracy converges to 1, it may be over learning.

In the future, we will investigate the generalization ability and judge the existence of over-learning. We will also investigate other parameters and sesame salt noise.