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Estimation of Hazardous Area with Surveillance UAV

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Abstract: Unmanned Aerial Vehicle (UAV) is becoming useful tool for the surveillance of the area where man can't go in. Ideally, UAV should fly fully automatically and some of them are becoming to be able to do this. Autonomous flying UAV can use large amount of data for posture control and navigation during its flight. This paper proposes the method which recycles these data for the purpose of environment recognition. In order to achieve this, we adopt machine learning techniques. Support Vector Machine (SVM) is chosen because it is faster and lighter than other machine learning technique. We demonstrate the method using the UAV made by Hitachi Ltd. and Kawada Industries, Inc. It can fly autonomously using GPS, motion sensor, magnetic sensor. From the flight log obtained by these sensors, SVM can not only classify the space into safe and dangerous area, but also predict undiscovered dangerous area. These areas coincident with the impression of operator who flied the radio control airplane in the same airspace.

Keywords: UAV, Automatic Surveillance, Machine Learning, Data mining, Support Vector Machine

1 INTRODUCTION

There is a growing demands for surveillance using UAV (Unmanned Aerial Vehicle) in disaster area[1][2][3]. For example, at the early stage of the nuclear crisis in Fukushima Daiichi Nuclear Power Station which is caused by Tsunami of 2011 Tohoku earthquake, US military's global hawk flied around and collected valuable data[4].

Ideally, the UAV should fly autonomously, but there are many difficulties for autonomous flight. Compared with the automatic flight of large passenger plane, the status of the flight airspace of UAV is usually unknown because when it is expected to fly above disaster area, the previous information wii be useless.

This paper proposes a method that enables the UAV to recognize the environment using machine learning technique. This method recycles the information from GPS, motion sensor, and so on which is observed originally for flight control.

The following is the contents of this paper. Section 2 introduce the UAV which is used in this research. Section 3 explains our proposed method environment recognition. Section 4 show the results of the recognition from real data. Section 5 concludes this paper.

2 EXPERIMENTAL APPARATUS

The UAV used in this study is made by Hitachi Ltd. and Kawada Industries, Inc. Fig. 1 shows the appearance of the UAV and Table 1 show the specs of the UAV.

The significant feature of the UAV is that it can fly fully autonomously using the hybrid navigation of GPS and INS. In order to achieve that, the UAV equipped various sensors. The following is the information that can be observed.

Table 1. The specs of the UAV used in this research

size	600 x 503 x 163 (mm)
weight	720g
air speed	45 – 70 km/h
duration of flight	15 min
propulsion	propeller propulsion
power	lithium polymer battery
control of flight	autonomous / radio control
camera	1280 x 1024
record	flight data and photo data
takeoff / landing	hand throw / belly-landing

- GPS (position, time)
- acceleration sensor (3-axis acceleration)
- angular velocity sensor (3-axis angular velocity)
- magnetic sensor (direction)
- anemometer (air speed)
- digital camera (photo)

The UAV can send the status to and receive the com-

Fig. 1. The micro UAV used in this research.

mand from the ground station with wireless communication. The flight plan consist of the sequence of waypoints. Hand thrown take off and belly landing enable us to operate the UAV without a runway. It can fly about 15 minutes by the power of lithium-polymer batteries. In autonomous flight, the UAV can't recognize obstacle. Therefore human operator can override the control by radio-control.

3 THE RECOGNITION OF ENVIRONMENT

This section proposes the environment recognition method using support vector machine[6]. SVM is one of the supervised learning method and is used for binary classification.

3.1 Support Vector Machine

SVM has linear separator but the separation is done in the feature space which is produced by kernel function. SVM shows a good performance in non-linear separation problem.

Let the mapping to feature space $\Phi : X \rightarrow H$. Kernel function k can be represented by the inner product of them as $< \Phi(x), \Phi(x') >$.

$$k(x, x') =< \Phi(x), \Phi(x') > \tag{1}$$

In classification problem, SVM divide the hyperplane into two class by

$$< \mathbf{w}, \Phi(x) > +b = 0. \tag{2}$$

Decision function f is

$$f(x) = \mathrm{sign}(< \mathbf{w}, \Phi(x) > +b). \tag{3}$$

The performance of separation is maximum when the margin which is made by hyperplane is maximum.

This problem result in solving constrained quadratic programming. For many kernel functions, the weight can be written as $\mathbf{w} = \sum_i \alpha_i \Phi(x_i)$.

This classification only depends on the data on the margin. These data are called support vectors.

In an attempt to meet the overlapped data, soft margin term ξ can be introduced:

$$\begin{aligned} \text{minimize} \quad & t(\mathbf{w}, \xi) = \tfrac{1}{2}||\mathbf{w}||^2 + \tfrac{C}{m} \textstyle\sum_{i=1}^{m} \xi_i \\ \text{subject to} \quad & y_i(< \Phi(x_i), \mathbf{w} > +b) \geq 1 - \xi_i \\ & \xi_i \geq 0 \ \ (i = 1, \ldots, m) \end{aligned} \tag{4}$$

Here, m is a number of training data and $y_i = \pm 1$.

Solution of SVM $\mathbf{w}$ can be represented as follows:

$$\mathbf{w} = \sum_{i=1}^{m} \alpha_i y_i \Phi(x_i) \tag{5}$$

α_i can be obtained by solving the following duality problem.

$$\begin{aligned} \text{maximize} \quad & W(\alpha) = \textstyle\sum_{i=1}^{m} \alpha_i \\ & -\tfrac{1}{2} \textstyle\sum_{i,j=1}^{m} \alpha_i \alpha_j y_i y_j k(x_i, x_j) \\ \text{subject to} \quad & 0 \leq \alpha_i \leq \tfrac{C}{m} \\ & \textstyle\sum_{i}^{m} \alpha_i y_i = 0 \\ & \xi_i \geq 0 \ \ (i = 1, \ldots, m) \end{aligned} \tag{6}$$

Using duality theorem $\mathbf{w}$ and b can be disappeared and the problem becomes to the maximization problem only for α.

3.2 Data to be Classified

During the flight of our UAV, various kinds of data which is explained in Section 2 is observed and stored in the form of CSV file. The sampling rate is 0.1 sec.

4 EXPERIMENTS

In order to demonstrate our method, some experimental flights have been done. The flight area is the above of the baseball ground in our campus (Fig. 2).

The purpose of this experiment is to find dangerous airspace to flight. Knowing the dangerous airspace is very important for this UAV because it flies fully autonomous.

We set the criteria of dangerous airspace as follows:

- The airspace where large acceleration is observed.
- The airspace where the difference between ground speed and air speed is large.

As we explained in Section 3.2, the UAV gathers a data every 100 msec. Each sampling point checked and marked as "danger" when the above criteria is hold. SVM learned and classify the airspace from these data. Table 2 is a summary of the parameters and results.

The results of estimation are shown from Fig. 3 to Fig. 6. In these figures, each point shows the observation point. Circle is judged as "normal" airspace and triangle is judges as "danger." Black circles and triangles are support vectors.

From the top view (Fig. 3 and Fig. 5), we can see the dangerous airspace is slightly different. This means acceleration based dangerous airspace and speed difference based dangerous airspace is not the same, however the overlapping zone is quite dangerous.

From the side view (Fig. 4 and Fig. 6), we can see the middle of the height is more dangerous than other heights. This result coincidents with the impression of human pilot of radio controlled airplane which flied just before the experiments. This can be thought that there are some air flow around the middle height above the ground. This wind comes from the sea and make a turbulence above the ground because the ground is located on the top of the hill very near from the sea. You can see the location from Fig. 2.

Table 2. Setting parameters and results of support vector machine

experiment	cost parameter	hyperplane parameter	number of support vector	error
Fig. 3	4	4.69	1431	0.336
Fig. 4	8	16.31	1400	0.320
Fig. 5	7	8.96	482	0.059
Fig. 6	7	11.65	424	0.065

5 CONCLUSION

This study proposes a machine learning based method of environment recognition for small UAV in disaster area. This method recycles the information that is obtained originally for autonomous flight into the environment recognition. This method estimates air status of whole airspace from the very little airspace where the UAV fly. As a demonstration, we flied the UAV above the ground of our campus and made the hazard map of the air. The results coincident with the human expert impression. For future works, we need an extension of this method to the realtime estimation (on-flight estimation) and to the coordinated estimation by multiple UAV.

Fig. 2. Map of the experimental field — upper: entire field, lower: zoom up

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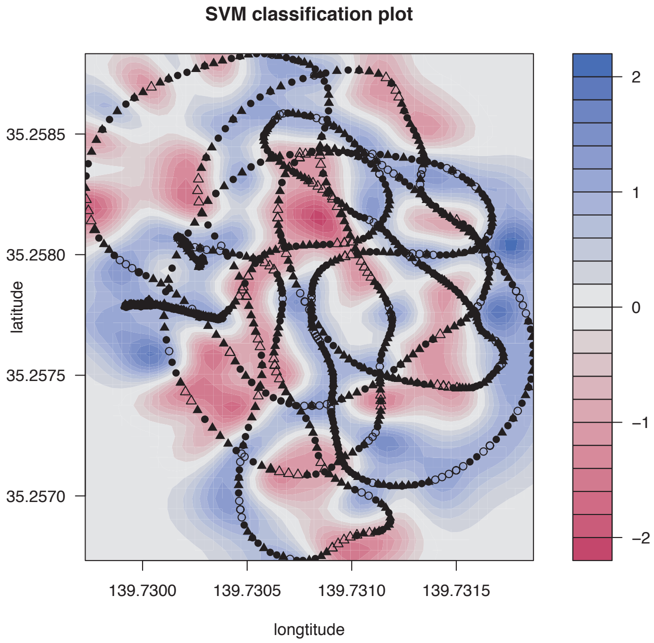

Fig. 3. Classification of the airspace by support vector machine: Classification criteria: large acceleration, View: top view, Date: 27, Aug.

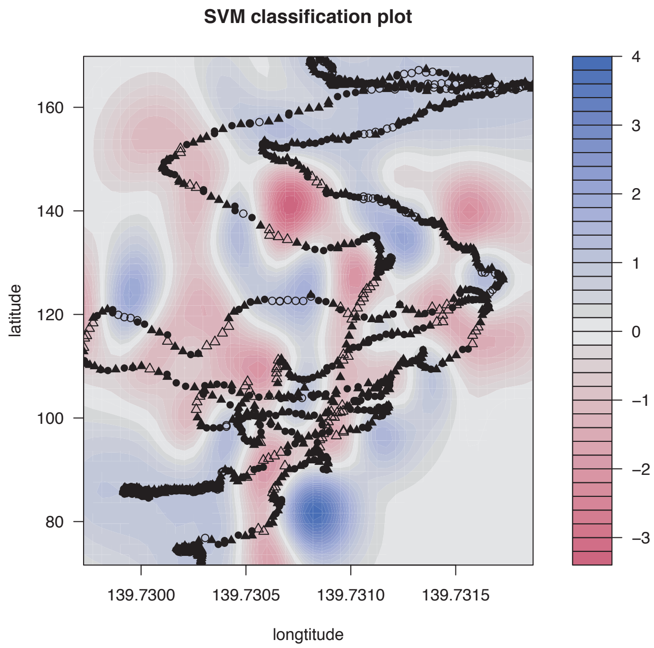

Fig. 4. Classification of the airspace by support vector machine: Classification criteria: large acceleration, View: side view, Date: 27, Aug.

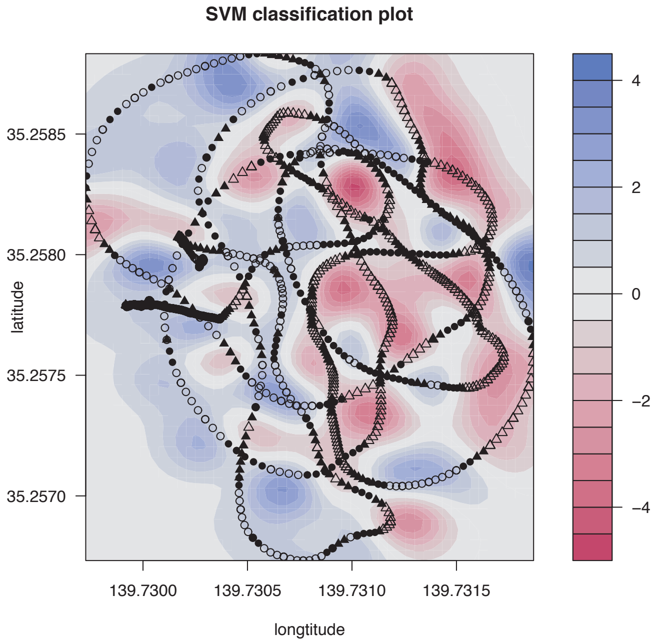

Fig. 5. Classification of the airspace by support vector machine: Classification criteria: large difference between ground speed and air speed, View: top view, Date: 27, Aug.

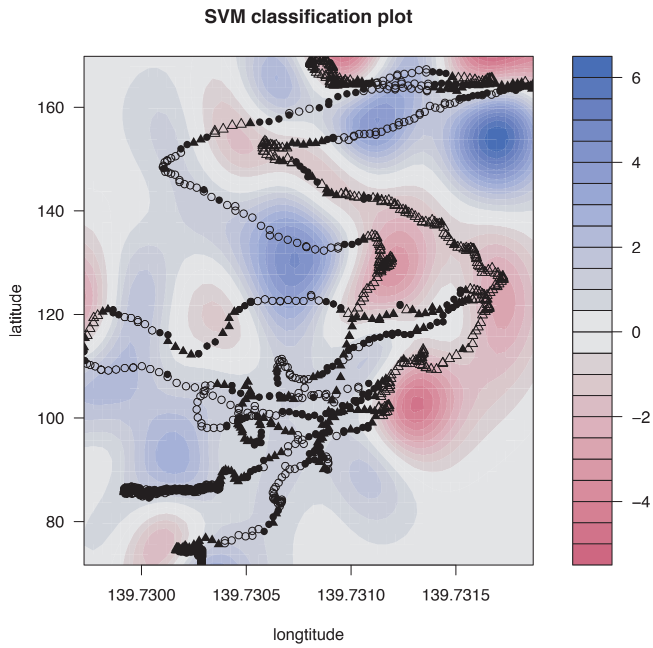

Fig. 6. Classification of the airspace by support vector machine: Classification criteria: large difference between ground speed and air speed, View: side view, Date: 27, Aug.