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LEVEL OF INTEREST IN OBSERVED EXHIBITS IN METAVERSE MUSEUMS

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ABSTRACT

This paper presents a way how to infer the observed exhibits in a Metaverse museum from a movement log. The backgrounds of this research are the expanding demand of Metaverse such as Second Life and the advance of recommendation systems. To use recommendation systems in Metaverse museums, we need some pieces of information to infer which exhibits the user is visiting. We aim to perform this task efficiently and precisely by focusing on the avatar's states in the museum. We divide the avatar's states into 2 kinds of movements by using a Support Vector Machine. We propose a method of inference to determine the state in which the avatar seems to observe some exhibits. The Metaverse museum has a problem that it is hard to get information on acceleration of a visitor, so we introduce key inputs as an additional parameter in movement log. In this study, we could increase the accuracy of inference of observed exhibits.

Key words: Metaverse, Second Life, SVM

1. INTRODUCTION

Demand for Metaverse beginning with the Second Life has been expanding in recent years (Thawonmas and Fukumoto, 2011), and a recommendation system is widely used, so we tried to undertake research in this system as an application of recommendations in the Metaverse. In such a system, accuracy is required in order to provide significant results to the user.

The purpose of this study is to make an estimate of which exhibits are actually observed by the user from their movement logs (Bohnert *et al.*, 2008), and improve the accuracy of the suggestions in the system that recommends the exhibits the user prefers. In general, the fewer possible errors on the data is obtained, the more the accuracy of the system is improved.

In the previous work (Bohnert *et al.*, 2011), they used information of a velocity and the acceleration of a visitor which can be obtained from his or her movement log. However, in the Metaverse museum, it is hard to use it because when the player released the key to go forward, the avatar stopped immediately. So we decided to use information of key inputs as an additional parameter of inference.

2. ENVIRONMENT AND DATA

In this study, we used Second Life that is one of the typical Metaverse as an experimental space. Because there are a lot of museums and we can get movement logs easily by using a script, Second Life is a good environment to perform the research (Warburton, 2009). We used a small museum called Cooper Nest Gallery, which includes 9 exhibits e_1 to e_9, as an experimental space. Figure 1 shows the screen shot of Cooper nest gallery.

Movement log is defined as a time series set which includes *x*-coordinate, *y*-coordinate, and direction of avatar, and key input of moving forwards. *x*-coordinate and *y*-coordinate of the avatar is represented by absolute coordinates in the space. Direction of the avatar is represented by the angle of rotation _ which is defined as in the domain from -π to π and the positive direction of *x*-axis is zero. Key input is represented by the value obtained by the script that returns 1 when the related key is pushed and returns 0 when the related key is not pushed.

Fig. 1. Screen shot of Cooper Nest Gallery

3. METHODS

3.1 Walking and Hovering

When we are visiting the museum and observing an exhibit, it is hard to think that we are staying in the same position for long time. Then, we are able to estimate the state of observing easily by dividing the kind of movement into Walking and Hovering (Bohnert *et al.*, 2011). Walking is the fast movement between an exhibit and another exhibit, not observing some exhibits. Hovering is the slow movement when we are observing an exhibit including staying and turning around the exhibit. The observation of the exhibit is likely to be done when the avatar is Hovering, so we only infer the observed exhibits in the subset which is judged as Hovering.

In general, when the avatar is Walking, the moving speed of avatar is likely to be faster than when it is Hovering. The classification of the state is performed by SVM. We use the library named LibSVM, same as the reference article (Bohnert *et al.*, 2011).

3.2 Parameters of SVM

Parameters used in the SVM in this study are the speed and acceleration of the avatar, and key input of moving forwards. Speed and acceleration of avatar can be calculated from the x-coordinate and y-coordinate of it. In the reference article (Bohnert *et al.*, 2011) using the real museum, there are only two parameters, speed and acceleration of the avatar. However, in Metaverse, we can get and use the information of key inputs. By using this additional information, the accuracy of state classification is expected to improve.

3.3 Inference of exhibits

The observation of the exhibit is likely to be done when the avatar is Hovering, so we only infer the observed exhibits in the subset which is judged as Hovering. The ideal viewing extent of the exhibits are based on a rule of thumb. In this rule of the thumb, the value of the ideal viewing extent tends to be larger when the exhibit is large. The ideal viewing extent means the extent in which the avatar is likely to observe the exhibit.

Step 1: Calculate the centroid of a Hovering subset
Step 2: Calculate the distance between centroid and the ideal viewing extent of each exhibits
Step 3: Calculate the distance between external line of the viewing direction from the avatar and each exhibits
Step 4: Add two distances

Figure 2 shows an illustration of this concept. The dark line means the distance between the centroid and the ideal viewing extent, and the pale line means the distance between the exhibit and the eye line. We assume that the user looks the exhibit which has the smallest value of the sum of dark line and pale line. When the sum is not so different, we assume that the user observes more than two exhibits in the subset.

Furthermore, in order to verify the usefulness of this technique, we compare the result of inference done by this method and the Deemed-Inference, the inference that when the avatar passes around the exhibit, deemed as it is observed.

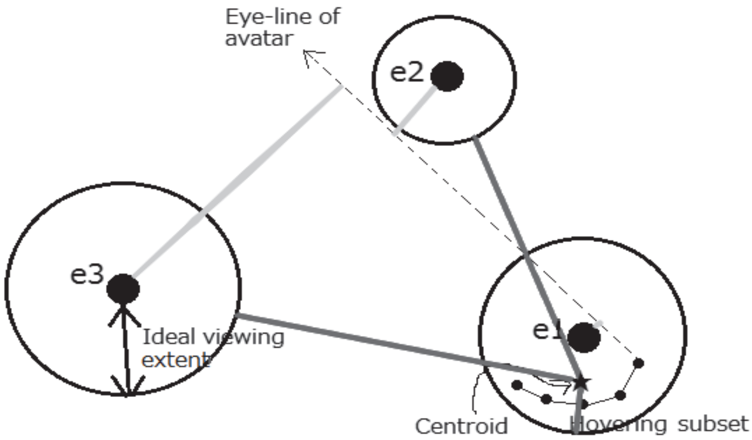

Fig. 2. Inference method of looked Exhibitions

4. EXPERIMENT

4.1 Getting movement logs

When we get movement logs, subjects do the patrol in the museum with the observation of the exhibits. Then, we get a movie of it. Movement log is taken automatically every 0.5[s]. Then, we calculate the speed and acceleration of avatar by using x-coordinate and y- coordinate of taken movement logs. In addition, we do the labeling whether avatar is Walking of Hovering by watching obtained movie data. In this experiment, we get the movement logs from 13 students of our laboratory.

4.2 State classification by SVM

We train the classifier, which parameters are the speed, acceleration, and key inputs. In LibSVM, the label is represented by the value of +1 and -1, so we attach the label of +1 when the subset is judged as Walking, and the label of -1 when the subset is judged as Hovering. Learning of the classifier and the comparison of the accuracy of it is performed in the same time by cross-validation. Output of the result of the state classifications can be carried out by using an application called SVM-predict that is included in LibSVM. We compare two classifiers which has different parameters, whether key input is included or not, to verify the usefulness of the key input as a parameter.

5. RESULTS

5.1 State classification by SVM

First, we describe the parameters that can be adjusted by LibSVM. For the type of SVM, we applied C-SVC, same as the reference article (Bohnert *et al.*, 2011). For the kernel function, we applied Gaussian kernel, same as the reference article (Bohnert *et al.*, 2011). For other parameters, we use the default parameters. Next, for the log data of 13 subjects, we train the classifier by using one data as for validation, and rest 12 data as for training. Two kinds of parameters of the log data are speed/acceleration and speed/acceleration/key input. The correct answer rate of the classification obtained from each classifier is represented by the percentage of data that classified correctly.

Table1 shows the result.

5.2 Inference of Exhibits

We infer the observed exhibits by using the sum of the length of the dark line and the pale line in Figure 2. To verify the effect of classification rate of correct answers, we sorted the data in advance, and the inference is carried out in each data. Then we compare and verify the result of inference done by the proposed method and the Deemed-Inference. The ideal viewing extents D_1 to D_9 are {1.1, 1.3, 1.0, 1.0, 1.0, 1.6, 1.7, and 1.9}. Table 2 shows the result of the inference. The estimated percentages of correct answers about each nine exhibits are represented by the errata of whether the exhibit is actually observed or not.

Table 1. Accuracy of state classification

Data	Key inputs on[%]	Key inputs off[%]
1	63.47	57.59
2	65.51	61.89
3	68.56	62.81
4	71.6	64.87
5	72.65	67.47
6	74.27	68.02
7	75.52	71.97
8	76.21	67.19
9	76.84	72.47
10	77.64	69.22
11	78.89	71.43
12	79.17	73.95
13	83.14	77.18
Average	74.11	68.15
Variance	27.34	25.25

Table 2. Accuracy of inference of observed exhibits

Data	Classification	Inference[%]	Deemed[%]
1	63.47	44.44	66.67
2	65.51	66.67	55.56
3	68.56	55.56	77.78
4	71.6	66.67	66.67
5	72.65	66.67	33.33
6	74.27	77.78	55.56
7	75.52	77.78	77.78
8	76.21	88.89	44.44
9	76.84	77.78	66.67
10	77.64	55.56	33.33
11	78.89	88.89	77.78
12	79.17	100.00	66.67
13	83.14	100.00	55.56
Average	74.11	74.36	59.83
Correlation	27.34	0.91	-0.11

6. DISCUSSIONS

6.1 State classification by SVM

In the average value in Table 1, the data which includes the key inputs exceeded the data which does not include the key inputs by 5.96%. This is almost the expected result of us, and the desired result. From this result, the usefulness of introducing the key input to the movement log as a parameter is proven.There is little difference in the varence between the two data sets.

6.2 Inference of Exhibits

In the average percentage of correct answers for all data in Table 2, the result of proposed method exceeds the result of Deemed-Inference by 14.85%. In addition, as you can see from the value of the correlation coefficient, there is a strong correlation between state classification and inference of exhibit. There are two things we can be seen from this result. The first is the importance of Walking/Hovering state classification in the estimation of the observed exhibits. The second is the usefulness of this method as compared to the Deemed-Inference.

7. CONCLUSION

In this paper, our purpose is to introduce the exhibit inference system using the avatar's state which is used in the real museum to the Metaverse museum. Then, the uniqueness of our study is using key input in the movement log to improve the accuracy of the state classification. In the term of the inference of observed exhibits, the result is better than the Deemed-Inference. From these results, as you can see, our research is very useful.

In this experiment, we measure the ideal viewing extent by a rule of thumb, so it was desirable that it can determined automatically by machine learning. Because there are a lot of terms which require the subjectivity of the experimenter such as state labeling by watching movies, we felt that we should use the method that is objective and experimenter-friendly. In the large museum, there are more than thousands of exhibits, it is impossible for experimenter to do all the work. In addition, there is a problem that the classification is ambiguous when the exhibits are adjacent, so we need to solve this problem.

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