# Measuring the engagement of a museum visitor in interactive museum exhibits

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***Abstract*—Modern interactive museums offer visitors a dynamic learning environment, promoting exploration and encourage the excitement of discovery as visitors learn new concepts, as they are free to interact with the exhibits. In this paper we propose an architecture for an interactive learning environment (ILE) using a collection of commodity devices: a set of displays where different content is presented, a set of mobile devices for each visitor to interact and a Kinect sensor. The engagement affective state is predicted using various classifiers and a database of readings from the Kinect sensor. The architecture also addresses the problem of content distribution among devices. A case study of an interactive exhibit held in classrooms. The participants were students of Technologic Institute of Tijuana. Experimental results show that the proposed approach can predict the engagement affective state.**

***Keywords*—*Interactive, Environment, Kinect 2.0, Affective.***

## I. Introduction

A museum is a public or private institution at the service of the society and its development. These exhibit sets of objects and information that reflect some aspect of human existence or its environment. The museum dates back to the Greco-Roman period, since museums have undergone many changes in terms of how to present the information thanks to technological advances that have emerged, this change has been most noticeable in the last century to date.

In addition to technology there are new techniques and methods to improve the user experience in these museums as interaction, user preferences, virtual and mixed realities among others. Since its beginnings the main objective of museums has been to preserve the cultural heritage, but also make information shown attractive to public in general, this part is a big challenge because each person thinks and assimilates information differently and one of the ways to solve this problem is by making the content adaptive. Interactive museums have been multiplying in recent year, many of which the idea of attracting the public using new technologies, currently there are studies that seek ways to solve the problem of making more attractive exhibits for the museum visitors as it does (aoki 2002; aoki 2002) where their electronic guidebook allows users to share auditory information (They hear each other) using a technologically mediated audio eavesdropping mechanism.

Reilly 2007 uses another approach oriented towards audio-visual experience where literary information shows through high large screens where the user can interact with the museum with touch screens.Others besides dealing with how to present information have involved more with the user from using their personal information to use methods to predict the state of mind. In affective computing there are several affective states but one that goes hand in hand with learning which is the engagement, like all state of mind is difficult to identify.Allen tell us how to design exhibits and how not make it anti-engagement like using lots of content in multiple displays. In this paper we propose the architecture of an interactive environment which consists of the distribution of multimedia content in an exhibit where the content is displayed in sets of learning objects which we call environmental learning object, a simple sequenced implementation which will make the task of a museum guide establishing the order of the learning activities. And finally we use the second-generation Kinect sensor to capture video of the user and predict an emotion based on this catalog the exhibition state as something that engages the user or something that does not engage the user. To test this architecture we conducted an experiment in an interactive museum where we generate a learning activity, at the end of the activity we surveyed the user to obtain information from the user experience and affective state and compare it against the pronostic of the affective state and identify the least interesting activities.

Pending

## II. Background

### A. Interactive museums

Museums at the present are exploring new digital and mobile technologies to enhance the visitor experience. Initiatives go beyond technology within exhibits, but also include more widespread use of technology to create interactive experiences for visitors throughout a museum and remote experiences for those who can not get there.

### B. Intelligent Learning Environments

Intelligent Learning Environments (ILE) are based in learning environments where students and teachers can create knowledge. In other words, the environment represents a cognitive space for a learning community. The ILE seeks to provide adaptive navigation and adaptive sequencing as is commented on [**rondon89**], [10] and [15].The adaptive navigation presents the content of a course in optimized order, where the optimization criteria takes into consideration the learner's backgrounds and performance, whereas adaptive sequencing is defined as the process for selection of learning objects from a digital repository and sequencing them in a way which is appropriated for the targeted learning community or individuals.

### *C. Affective Computing*

Affective computing is the human-computer interaction in which a device has the ability to detect and respond to the emotions of the user and other stimulus properly. A computing device with this capability could gather the signals to the user emotion from a variety of sources. Facial expressions, posture, gestures, speech, strength and pace of keystrokes and temperature changes of hand on a mouse all can mean changes in the emotional state of the user, and these can be detected and interpreted by a computer. A camera is used to capture images of the user and the data is processed algorithms to produce meaningful information. Voice recognition and gesture recognition are some of the other technologies being explored for affective computing applications.

### *D. Learning Objects*

### *E. Kinect 2.0*

## III. Method

This study is divided into 2, the first part was conducted with visitors to the museum's spin tijuana where 21 users divided into 2 groups participated, the first has 10 users between 6 and 11 years 50 % men and 50 % women and the second group consisted of 11 users 11 and older 66 % men 44 % women. In the second part of the study 41 users of the Technological Institute of Tijuana were used aged between 18 and 50 years 66 % men 34 % women.

For this study is required to show images, videos and somehow observe the user, that is why many devices that met these needs as a computer to server, 2 laptops, one 7-inch tablet, headphones, 3 projectors, 2 monitors, cameras, sensors (Kinect 2.0) etc. were used.

Fig 1. User interacting with the environment.

In the first part of the study users immersed in an exhibitor that gave them visual and aural information as shown in Figure 1 on a topic selected based on various criteria, such as the location of the study on this occasion was a interactive museum and the festival of children's day approaching we try to use a simple theme and it will bring awareness so we decided to use the theme of water where information was displayed as the uses of the same, its cycle, forms of energy that could generate, health, and the importance of it for the planet. Each of users are generating an account on the system to register their activity, after that we were made a brief explanation of how it worked the exhibitor others based on observation no longer required this explanation. The user took a tablet that was the how the user interacted with the exhibitor, with which had control of the flow of information, as the information was a sequence at the end of the last activity was a questionnaire on the information received besides a survey.

The second part of the study was very similar to the first one that had some small modifications and additions, now the user no longer had control flow only observe and also to observe the user now will take video and sensor, the theme of the exhibition were video games and film as the age of the users would go for almost 17 years and older could be topics of their interest. In the same way as in the first part each user had an account to record the activity only this occasion the data produced by the sensor and videos captured by the camera would be recorded, and in the same way as in the first part at the end we surveyed the users.

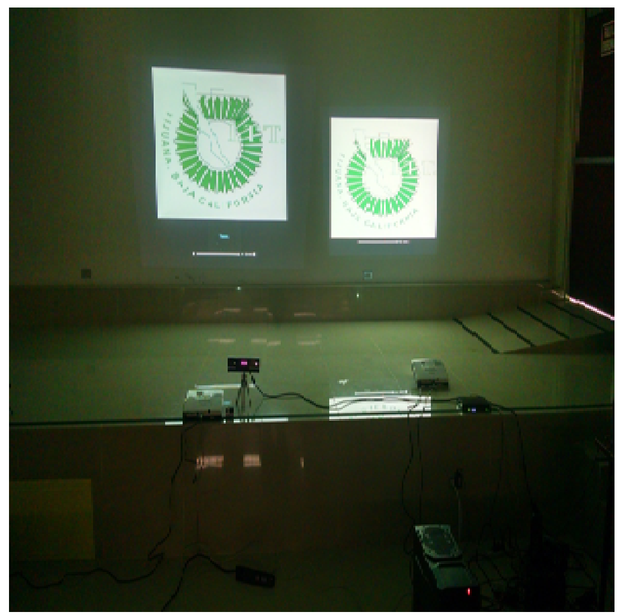

Fig 3. Front display.

For the first part of the study we get data from the survey conducted at the end, in the second they are collected and used data from sensors, this data were a bit more complex, first we need an observer to evaluate the user manually, where the observer determined whether the user was putting attention to what he saw or distracted and based on that assigned a level of attention on a scale of 1 to 3 where 1 is little attention 2 average attention and 3 very attentive. The other way to obtain user information was by Kinect Sensor and is a bit more complex because the sensor provides enough information the sensor detects a user can give:

- engage
- looking away
- happy
- left eye closed
- right eye closed
- mouth open
- mouth moved
- wearing glasses
- yaw pitch and roll of the face

Each of these data the sensor assigned one of the following Yes, No, Maybe and Unknown values; unknown data were discarded since in the sensor documentation was saying that this data could be ”not sensing” and therefore not considered valid data. Only in the face position was a numerical data, the sensor generated an average of 14 records per second of these values sometimes less for a short time when the sensor lost sight of the user but was usually between 1 to 10 seconds.

Fig 2. Front view.

Full activity was carried out in 4 minutes 10 seconds so if the sensor not lose sight of the user throughout the activity It generates about 3500 records. From the above list of data we decided to use only engage, looking away happy and others are captured but used as they are not relevant to what we are measuring. To get textual results perform a normalization by a count of each event every 10 seconds since the data generated by the sensor are textual normalized by assigning numbers to strings for example Yes = 2, Maybe = 1 and No = 0 then for every 10 seconds of activity the Yes, No and Maybe was counted.

As the activity lasted 4:10 we decided to count the sensor event every 10 seconds, at the end we gained an average of 140 records for each period of 10 seconds. Here I was a problem, as the number of records varied by user we had to think about how to normalize this data, as records were recorded and distributed yes, maybe, no the solution was to take a percentage of each of the records obtained by which thus we could handle and sensor data.

## IV. RESULTS

The results as in the other sections are divided into two. The first experiment was carried out at the interactive museum where two user groups were used and obtained the following results Table 1 shows the result of the first 4 survey questions in the second table shown the last 4 questions asked. Recalling that there were 11 respondents users.

TABLE I. : RESULTS OF THE SURVEY TAKEN BY THE GROUP 1 IN THE INTERACTIVE MUSEUM PART 1.

| | Q1 | Q2 | Q3 | Q4 |
|---|---|---|---|---|
| Standard Deviation | 0.504524979 | 0.687551651 | 0.820199532 | 1.009049958 |
| Mean | 4.636363636 | 4.454545455 | 4.454545455 | 4.272727273 |

TABLE II. : RESULTS OF THE SURVEY TAKEN BY THE GROUP 2 IN THE INTERACTIVE MUSEUM PART 2.

| | Q5 | Q6 | Q7 | Q8 |
|---|---|---|---|---|
| Standard Deviation | 0.820199532 | 0.646669791 | 0.687551651 | 0.646669791 |
| Mean | 4.454545455 | 4.727272727 | 4.454545455 | 4.727272727 |

In the second part of the experiment was the second group of surveyed users and the results are shown in Table 3.

TABLE III. : RESULTS OF THE SURVEY TAKEN BY THE GROUP 2 IN THE INTERACTIVE MUSEUM.

| | Q1 | Q2 | Q3 | Q4 |
|---|---|---|---|---|
| Standard Deviation | 0.971825316 | 0.483045892 | 0.483045892 | 0.843274043 |
| Mean | 4.5 | 4.7 | 4.7 | 4.4 |

Decision tree accuracy: 88.42% +/- 5.17% (mikro: 88.44%) kappa: 0.803 +/- 0.088 (mikro: 0.804) KNN accuracy: 87.77% +/- 4.13% (mikro: 87.79%) kappa: 0.792 +/- 0.069 (mikro: 0.7091) Bayes accuracy: 83.69% +/- 4.57% (mikro: 83.71%) kappa: 0.712 +/- 0.079 (mikro: 0.712) Neural Networks accuracy: 91.03% +/- 3.68% (mikro: 88.44%)

TABLE IV. : RESULTS OF THE PREDICTION ON THE LEVEL OF ATTENTION OF THE USER USING DECISION TREE.

| | True Low | True Mid | True High | Class Precision |
|---|---|---|---|---|
| Prediction Low | 141 | 25 | 2 | 83.93% |
| Prediction Mid | 14 | 77 | 16 | 71.96% |
| Prediction High | 3 | 11 | 325 | 95.87% |
| Class Recall | 89.24% | 68.14% | 94.75% | |

TABLE V. : RESULTS OF THE PREDICTION ON THE LEVEL OF ATTENTION OF THE USER USING KNN.

| | True Low | True Mid | True High | Class Precision |
|---|---|---|---|---|
| Prediction Low | 133 | 19 | 3 | 89.13% |
| Prediction Mid | 22 | 78 | 12 | 70.33% |
| Prediction High | 3 | 16 | 328 | 84.94% |
| Class Recall | 84.18% | 69.03% | 495.63% | |

TABLE VI. : RESULTS OF THE PREDICTION ON THE LEVEL OF ATTENTION OF THE USER USING BAYES.

| | True Low | True Mid | True High | Class Precision |
|---|---|---|---|---|
| Prediction Low | 123 | 13 | 2 | 85.81% |
| Prediction Mid | 13 | 88 | 13 | 69.64% |
| Prediction High | 22 | 14 | 327 | 94.52% |
| Class Recall | 84.18% | 69.03% | 95.63% | |

TABLE VII. : RESULTS OF THE PREDICTION ON THE LEVEL OF ATTENTION OF THE USER USING NN.

| | True Low | True Mid | True High | Class Precision |
|---|---|---|---|---|
| Prediction Low | 144 | 11 | 3 | 85.81% |
| Prediction Mid | 12 | 88 | 13 | 69.64% |
| Prediction High | 2 | 14 | 327 | 94.52% |
| Class Recall | 84.18% | 69.03% | 95.63% | |

## V. CONCLUSION

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## APPENDIX A
## PROOF OF THE FIRST ZONKLAR EQUATION

Some text for the appendix.

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