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Multimodal Emotional State Estimation Model for Implementation of Intelligent Exhibition Services*

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Both researchers and practitioners are showing an increased interested in interactive exhibition services. Interactive exhibition services are designed to directly respond to visitor responses in real time, so as to fully engage visitors' interest and enhance their satisfaction. In order to install an effective interactive exhibition service, it is essential to adopt intelligent technologies that enable accurate estimation of a visitor's emotional state from responses to exhibited stimulus. Studies undertaken so far have attempted to estimate the human emotional state, most of them doing so by gauging either facial expressions or audio responses. However, the most recent research suggests that, a multimodal approach that uses people's multiple responses simultaneously may lead to better estimation. Given this context, we propose a new multimodal emotional state estimation model that uses various responses including facial expressions, gestures, and movements measured by the Microsoft Kinect Sensor. In order to effectively handle a large amount of sensory data, we propose to use stratified sampling-based MRA (multiple regression analysis) as our estimation method. To validate the usefulness of the proposed model, we collected 602,599 responses and emotional state data with 274 variables from 15 people. When we applied our model to the data set, we found that our model estimated the levels of valence and arousal in the 10~15% error range. Since our proposed model is simple and stable, we expect that it will be applied not only in intelligent exhibition services, but also in other areas such as e-learning and personalized advertising.

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1. Introduction

Exhibits that allow interaction, that is, two-way communication between visitors and exhibits, are called interactive exhibits. They encourage visitors to experience contents, and to

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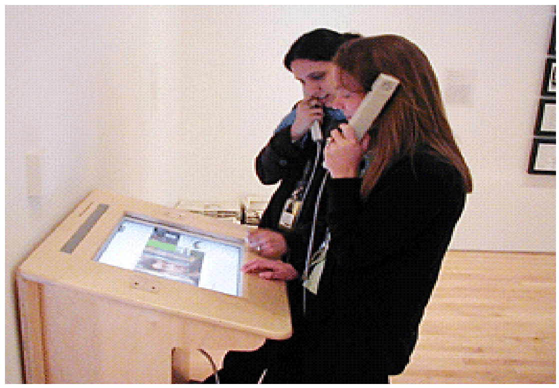
(a) The Victoria and Albert Museum's interactive in-gallery program

(b) The Minneapolis Institute of Arts' off-gallery interactive learning station

(c) The Walker Art Center's interactive dialog table



(d) San Francisco Museum of Modern Art's interactive smart table

〈Figure 1〉 Examples of interactive exhibits; adopted from Sayre(2005)

experiment through selection, hands-on manipulation, and observation of work completed according to the prescribed interaction between visitors and exhibits (Kim, 1996; Jung et al., 2012). They can thus engage visitors' attention more effectively and enhance satisfaction. Interactive exhibition services have been adopted by many art museums or galleries in recent years. <Figure 1> shows some examples of the interactive exhibition services used in major museums across the world (Sayre, 2005).

To meet the needs of this sector, researchers have begun studies on how to improve the quality of interactive exhibition services. Because it is essential to understand visitors' emotions in order to respond to them properly, there is a growing need for studies on emotional state estimation in the exhibition domain. Consequently, several studies have been conducted on this topic in the last five years (Ko et al., 2008; Jung and Kim, 2012; Jung et al., 2012; Kim et al., 2012; Ahn, 2013; Ryoo et al., 2013).

However, these studies have some common limitations: they use only facial responses when estimating emotional states. Other recent studies on emotional state estimation have empirically validated that the use of multiple responses leads to better estimation of emotional states (Wöllmer et al., 2010; 2012; Nicolaou et al., 2011; Hussain et al., 2012; Nicolle et al., 2012). Even in the case of facial responses, recent studies have begun to use 3D or 4D facial expressions in order to estimate human emotions (Sandbach et al., 2012).

We propose a new multimodal emotional state estimation model using various responses including facial expressions, gestures, and movements measured by the Microsoft Kinect Sensor. Kinect Sensor is a motion sensing input device that was first introduced by Microsoft in 2010. It uses three kinds of sensors: an RGB camera, a depth sensor, and a multi-array microphone. Among these, the depth sensor, which consists of an infrared laser projector combined with a monochrome CMOS (Complementary Metal – Oxide – Semiconductor) sensor, can capture video data in 3D, a capability which enables motion or gesture tracking (Wikipedia, 2014). Using the Kinect Sensor, this study estimates peoples' emotional states through their facial expressions and the movements of their head and shoulders.

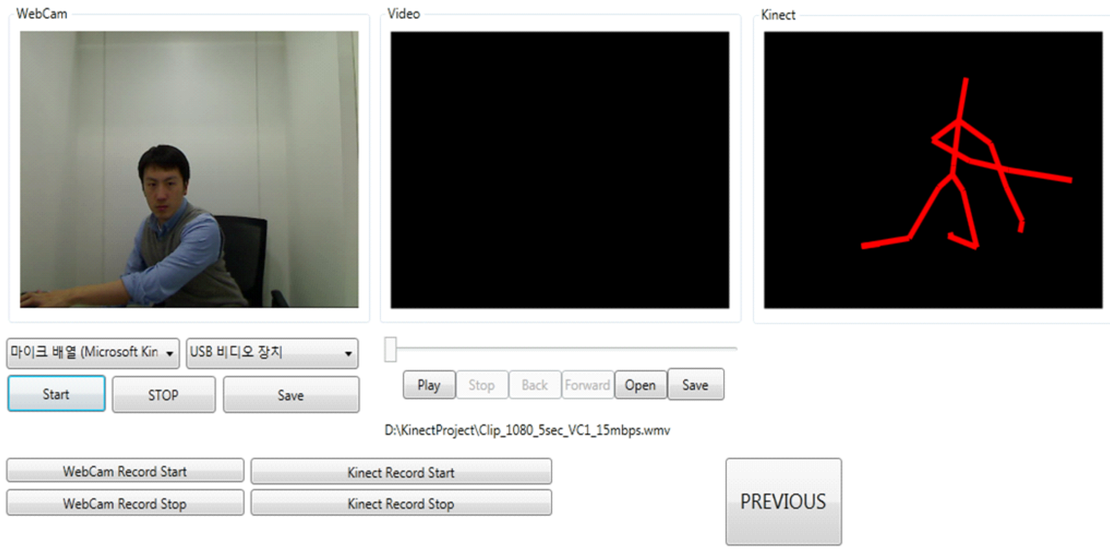
This paper consists of four sections. Section 2 describes our research model thoroughly. The experimental system that enables our proposed model will also be introduced in this section. The data used will be presented in Section 3, followed by the results of our experiment. Finally, Section 4 introduces a practical application of our proposed model. At the end of this section we discuss the contributions and limitations of our study.

2. Research Model

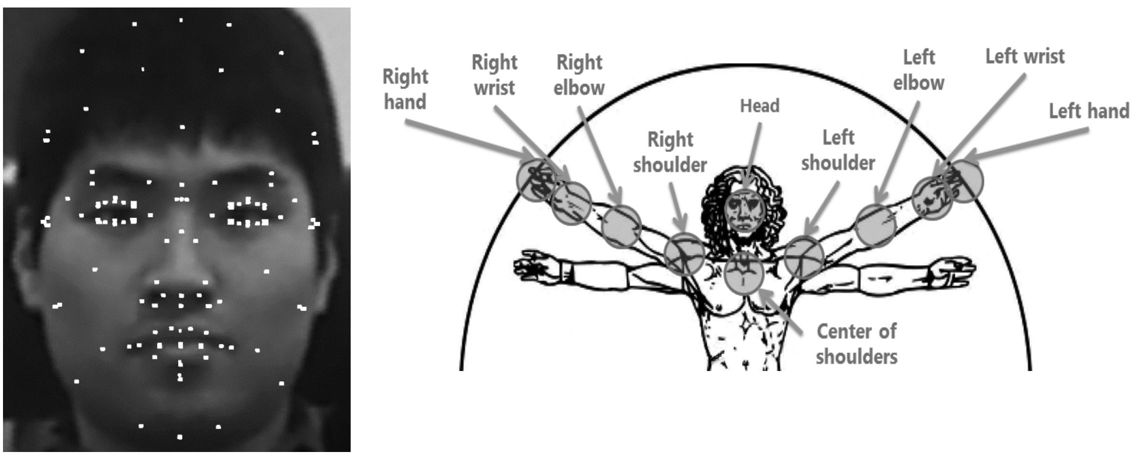
2.1 Measuring Multimodal Responses through the Microsoft Kinect Sensor

As described in the previous section, the Kinect Sensor uses three kinds of sensors including a camera, a depth sensor, and a microphone. We can therefore measure three kinds of responses: facial expressions, body movements, and audio responses. Since museums generally require visitors to maintain silence, in this study, we used only facial expressions and body movements,

To measure multimodal individual responses using the Kinect Sensor, we developed a customized experimental system using the commercial version of Kinect for Windows SDK. The experimental system was developed using C#, and <Figure 2> demonstrates the control screen. Our experimental system is designed to track 121 facial points and 10 body points. Facial points are measured in 2D (x-y axes), while body points are



〈Figure 2〉 Control screen of the experimental system



(a) 121 facial points

(b) 10 body points

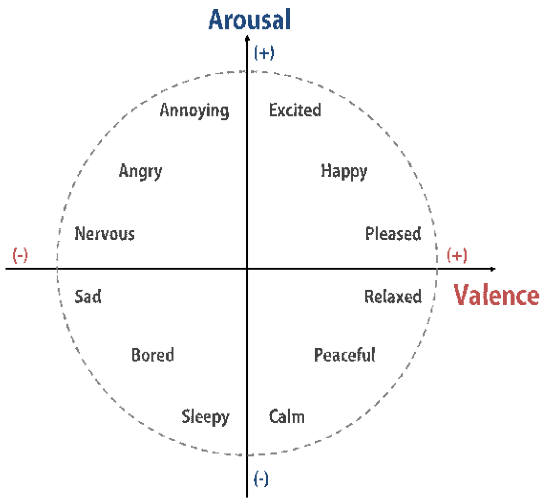
〈Figure 3〉 Positions of the facial and body points to be tracked

measured in 3D (x-y-z axes). <Figure 3> presents the positions of the facial and body points to be tracked. As a result, 272 values (=121×2+10×3) are obtained per frame. The frame rate is set to 30 frames/sec, and the responses are recorded in XML (eXtensible Markup Language) format.

2.2 Measuring the Flow of Emotional States with Feeltrace

The values measured by the Kinect Sensor are used as independent variables in the emotional state estimation model. In order to build the emotional state estimation model we also had to prepare for a dependent variable, that is, individual emotional states. Psychologists have tried to classify human emotional states and have developed classification models. The most popular models are the one proposed by Ekman, which uses six basic emotions, and the V-A (valence-arousal) model. Ekman's model classifies emotions into anger, disgust, fear, happiness, sadness, and surprise. Ekman and Friesen (1978) have also proposed the FACS (Facial Action Coding System) that set out standard facial responses corresponding to each emotional category. Though the FACS has many advantages, it also has one critical problem. Except for happiness, most of the categories represent negative emotional states, which are not particularly useful for business applications (Jung and Kim, 2012). Consequently, recent studies usually adopt the V-A model instead of Ekman's model (Jung and Kim, 2012; Jung et al., 2012; Kim et al., 2012; Ahn, 2013; Ryoo et al., 2013).

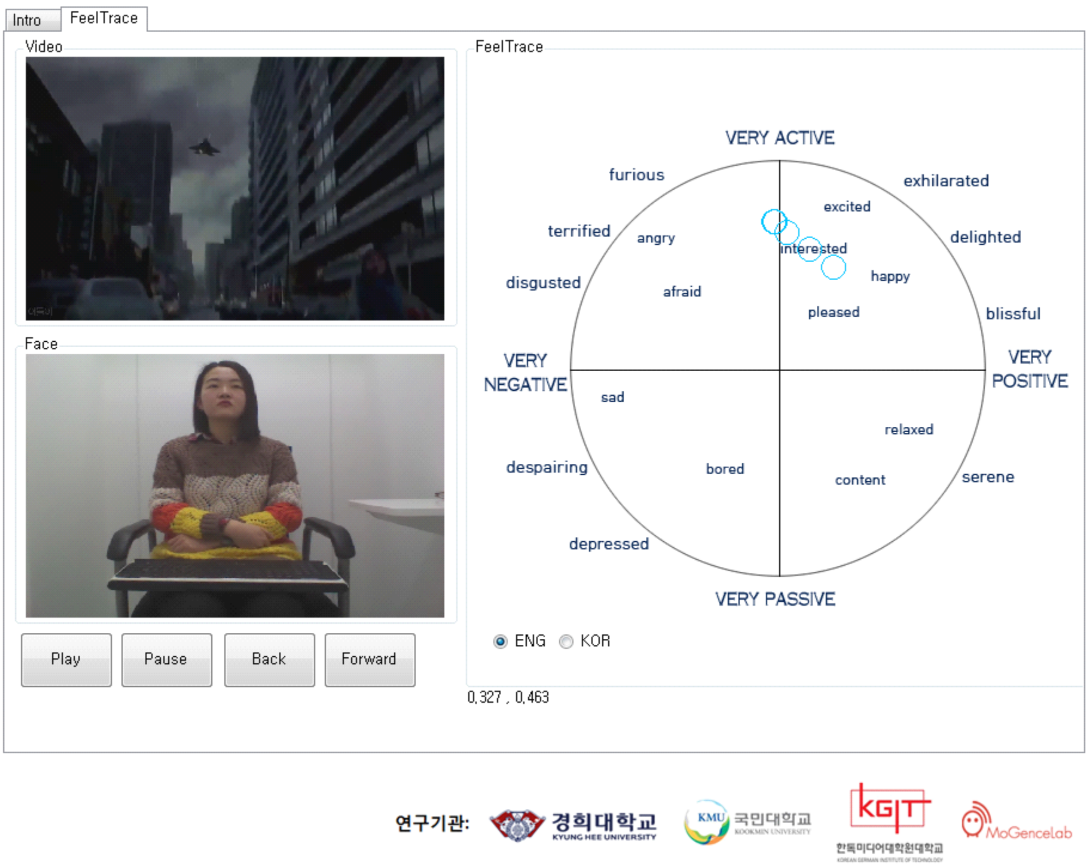
In the V-A model, emotional states are measured using a two-dimensional approach comprising of valence and arousal (Russell, 1980). The valence dimension (V) represents how positive or negative the emotion is, and this ranges from unpleasant to pleasant. The arousal dimension (A)



〈Figure 4〉 Positions of blended emotions in the V-A model

refers to how excited or apathetic the emotion is, and this ranges from sleepiness to frantic excitement (Nicolaou et al., 2011; Jung and Kim, 2012; Ahn, 2013). <Figure 4> shows the two dimensions of the V-A model and the positions of blended emotions.

To make it easier to measure emotional states using the V-A model, a team led by Rody Cowie, Professor of Psychology at Queen's University Belfast, proposed a novel annotation system called 'Feeltrace' (Cowie et al., 2000). Feeltrace allows coders to watch audiovisual recordings and use their mouse to move a pointer in the V-A space confined to [-1,1]. Coders can thus rate their impressions of the emotional state of a subject (Nicolaou et al., 2011). We have used the Feeltrace concept in our study, integrating it into our experiment as shown in <Figure 5>.



〈Figure 5〉 Feeltrace feature of our experimental system

2.3 Building Estimation Models

Our aim is to build estimation models for valence (Y^v) and arousal (Y^a) using the data measured by the Kinect Sensor and Feeltrace as described in 2.1 and 2.2. We propose to build a sampling-based regression model for each of the two response variables, Y^v and Y^a (Quesenberry and Jewell, 1986). Sampling-based regression enables us to efficiently handle the enormous size of the data set. This approach is necessary not only because the amount of the data can barely be loaded into memory when computing, but also because the data can grow in size.

At first, as a preprocessing step, to avoid a potential risk of multicollinearity, we eliminate linearly dependent variables. We then transform Y^v and Y^a by the following rule:

$$\tilde{Y} = \log\left(\frac{Y+1+\tau/2}{2+\tau}\right) \qquad (1)$$

Here, τ is a stabilizing constant, set to 1e-5 in consideration of the scale of Y^v and Y^a. In addition to the stabilizing constant, the transformation works along the lines of the Box-Cox power transformation (Box and Cox, 1964). As in kernel-based regression, we also include non-linear transformations, $\sqrt{x}$ and log(x), of each input variable x.

As the next step, we apply a stratified sampling technique to obtain a sub-data set whose size is one percent of the total data size. The stratified sample is a method to reduce the variability of random sampling (Lange, 2010). We then apply multivariate regression to the normalized sub-data set and repeat the whole procedure many times. As the total number of repetitions grows, the aggregation of the learned models converges to the exact solution.

3. Empirical Validation

3.1 Experimental Data Set and Preprocessing of Data

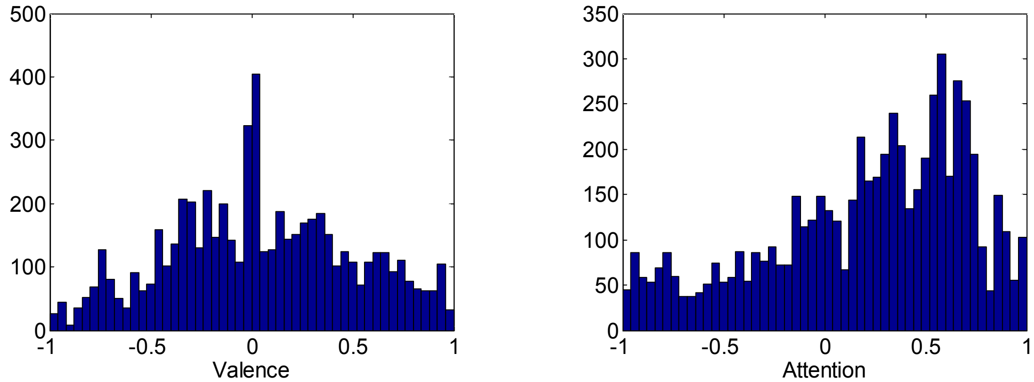
To validate the effectiveness of the proposed model, we collected experimental data from 17 university and graduate school student volunteers from January 14 to 25, 2013. The subjects were exposed to a 23-minute video consisting of five short clips to stimulate various high or low states of valence or arousal. As the subjects watched the video, their responses were measured and recorded by the Kinect Sensor. After watching the video,

〈Table 1〉 Subject profiles and number of observations

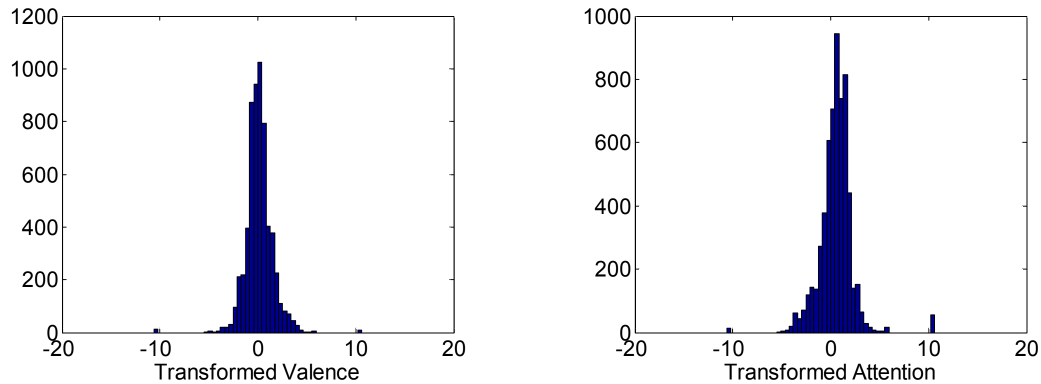
ID	Gender	Age	Observations
201300043	Female	24	41,111
201300046	Male	29	41,472
201300047	Male	26	37,046
201300049	Male	27	40,624
201300050	Female	23	39,363
201300051	Female	24	37,004
201300052	Male	22	41,507
201300053	Male	29	37,774
201300054	Female	26	41,995
201300055	Male	23	41,409
201300056	Female	24	41,644
201300057	Female	23	39,369
201300058	Female	23	40,292
201300059	Male	29	41,029
201300060	Female	24	40,960
Total			602,599

the subjects were asked to use the Feeltrace tool to annotate their emotional state(s) while they were watching the video. Since the responses were measured 30 times per second on average, the data collected was huge. <Table 1> shows the profiles of the subjects and the number of observations they made. As shown here, most subjects were in their 20s, and the male to female ratio was about 47%. In all, 602,599 observations were recorded.

As explained in Section 2.3, to avoid the risk of multicollinearity, we should first eliminate the linearly dependent variables out of the 272 input variables as the preprocessing work. To assess multicollinearity, we examine the ranks of X and X_{-k} where X is the matrix of the input variables, and X_{-k} is the matrix of the input



(a) Original variables



(b) Transformed variables

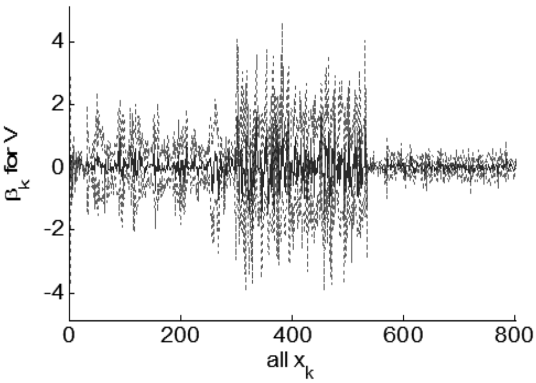
〈Figure 6〉 Histograms of original and transformed dependent variables

variables except for $x_k(k = 1, 2, \cdots, 272)$. In our experiment, rank(X) is found to be 269. Thus, we can eliminate the input variables whose rank(X_{-k} = 269). Here, the 35th, 36th, 101th, 219th, and 220th input variables are found to be linearly correlated and were, therefore, eliminated.

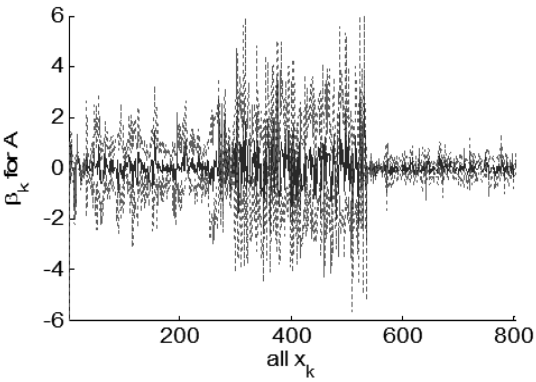
In the next step, we transform Y^v and Y^a by using the transformation function presented in Equation (1). The transformed variables are close to be normally distributed as <Figure 6> shows.

In line with the kernel-based recognition approach, we also include non-linear transformations, $\sqrt{x}$ and log(x), of each input variable x. The resulting 801 variables (3 × 267) are used to build the model.

After preprocessing and transformation of the independent and dependent variables, we apply a stratified sampling technique to obtain a sub-data set of size 6,026, that is, one percent of the data size. Here, we randomly choose one percent of each individual subject's observations and construct an overall sub-data set by adding up all the selected observations. Then, we apply multivariate regression to the normalized sub-data set and repeat the whole procedure 10,000 times. The resulting regression coefficients β_i for $i = 1, 2, \cdots, 801$, including the intercept (β_0), are shown in <Figure 7>. In <Figure 7>, the dark line represents the average, and the bright one represents the empirical 95% confidence intervals.



(a) Regression coefficient of valence

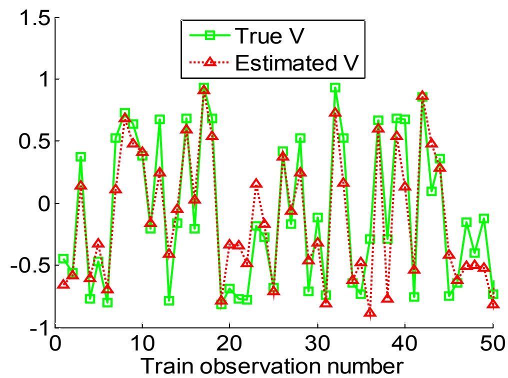


(b) Regression coefficient of arousal

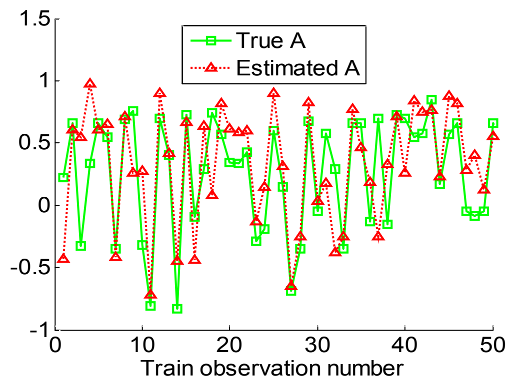
〈Figure 7〉 Regression coefficients through 10,000 sampling iteration

3.2 Experimental Results

We predict the true values of valence and arousal by using the averages of the regression vectors from the sampling-based regression. To illustrate the performance, we randomly choose fifty observations from the data set and predict their values of valence and arousal. The result is shown in <Figure 8>. In this figure, the triangles represent the predicted values, and the rectangles represent true values. As shown here, the predicted values follow the true ones quite closely. Further,



(a) Valence



(b) Arousal

〈Figure 8〉 Experimental results

we report the performance in terms of mean absolute error (MAE) for the training phase, which corresponds to the model building procedures, and the testing phase. The MAE values of valence and arousal for the training phase are 0.219 and 0.478 while those for the testing are 0.234 and 0.292. Considering that the levels of valence and arousal vary from -1 to 1, which means their range is 2, our proposed model estimates the levels of valence and arousal in the error range of 11.7% and 14.6% respectively.

4. Conclusion

This study proposes a novel multimodal emotional state estimation model using human responses measured by the Microsoft Kinect Sensor. Our proposed model estimates time-variant levels of valence and arousal by using 272 input values, 121 facial points in 2D and 10 body points in 3D. The results of empirical tests show that our model estimates the levels of valence and arousal in the 10~15% error range. Based on these promising results, we built a real interactive exhibition system (shown in <Figure 9>) that measures an individual's sensibility by using the model proposed in this study. Our system is currently installed at the DMC Gallery in Sangam-dong, Seoul, Republic of Korea, where visitors from various countries have been experiencing and enjoying it.

Prior studies of interactive or intelligent exhibition services have tried to build more efficient emotional estimation models, but most of them used only facial expressions captured by camera as their inputs. Thus, our study makes an important contribution to this field, since we propose the adoption of a multimodal approach. In addition, as far as we know, there have been no

〈Figure 9〉 Interactive exhibition system 'Sensibility' using the proposed model prior studies that use the Microsoft Kinect Sensor as a tool for collecting multimodal responses. Although this study proposes an emotional state estimation model for the purpose of interactive or intelligent exhibition services, it can also be applied to other domains such as e-learning and personalized advertisements. We expect that future studies in this field will use or develop on our proposed model.

Regardless of its academic and practical contributions, our study also has some limitations. First, our empirical test was based on only 15 people, although the total number of observations was large enough. Moreover, the age, occupation, and background of the subjects were very limited. Future studies should include more variety in this regard.

Second, the test used in our study should be refined. Although we assume that multimodal approach will outperform the uni-modal one, we have not shown any actual empirical evidence that supports our assumption. Though there are prior studies like that of Nicolaou et al. (2011) which support our assumption, further experiments are required to validate the effectiveness of the multimodal approach.

Third, this study adopts a stratified sampling-based MRA as the prediction method. MRA is known to be a computationally simple and stable algorithm, so it was easy for us to convert our proposed model into an actual interactive exhibition system. However, several prior studies have reported that MRA may hinder the accuracy of emotional state estimation models (Jung and Kim, 2012; Kim et al., 2012; Ahn, 2013). Future research should therefore focus on attempts to apply more advanced prediction methods such as neural networks and support vector regressions.

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국문요약

지능형 전시 서비스 구현을 위한 멀티모달 감정 상태 추정 모형

이기천* · 최소윤** · 김재경*** · 안현철****

최근 관람객의 반응에 따라 실시간으로 대응하여 관객의 몰입과 만족도를 증대시키는 인터랙티브 전시 서비스에 대한 학계와 산업계의 관심이 높아지고 있다. 이러한 인터랙티브 전시 서비스를 효과적으로 구현하기 위해서는 관객의 반응을 통해 해당 관객이 느끼는 감정 상태를 추정할 수 있는 지능형 기술의 도입이 요구된다. 인간의 감정 상태를 추정하기 위한 시도들은 많은 연구들에서 이루어져 왔고, 그 중 대부분은 사람의 얼굴 표정이나 소리 반응을 통해 감정 상태를 추정하는 방식을 도입하고 있다. 하지만, 최근 소개되고 있는 연구들에 따르면 단일 반응이 아닌 여러 반응을 종합적으로 고려하는 이른바 멀티 모달(multimodal) 접근을 사용했을 경우, 인간의 감정 상태를 보다 정확하게 추정할 수 있다. 이러한 배경에서 본 연구는 키넥트 센서를 통해 측정되는 관객의 얼굴 표정, 몸짓, 움직임 등을 종합적으로 고려한 새로운 멀티모달 감정 상태 추정 모형을 제안하고 있다. 제안모형의 예측 기법으로는 방대한 양의 데이터를 효과적으로 처리하기 위해, 몬테칼로(Monte Carlo) 방법인 계층화 샘플링(stratified sampling) 방법에 기반한 다중회귀분석을 적용하였다. 제안 모형의 성능을 검증하기 위해, 15명의 피실험자로부터 274개의 독립 및 종속변수들로 구성된 602,599건의 관측 데이터를 수집하여 여기에 제안 모형을 적용해 보았다. 그 결과 10~15% 이내의 평균오차 범위 내에서 피실험자의 쾌/불쾌도(valence) 및 각성도(arousal) 상태를 정확하게 추정할 수 있음을 확인할 수 있었다. 이러한 본 연구의 제안 모형은 비교적 구현이 간단하면서도 안정성이 높아, 향후 지능형 전시 서비스 및 기타 원격학습이나 광고 분야 등에 효과적으로 활용될 수 있을 것으로 기대된다.

주제어 : 감정 상태 추정 모형, 멀티모달 접근법, 지능형 전시 서비스, 키넥트 센서, 계층화 샘플링

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저 자 소 개

이기천
2012년부터 한양대학교 산업공학과 조교수로 또한 한양대학교 기술경영전문대학원의 겸임교수로 일을 하고 있다. 2001년부터 2006년까지 티맥스소프트, 삼성 SDS에서 시스템 소프트웨어 분야에 연구, 개발을 하였고 2010년에 Georgia Institute of Technology의 산업시스템공학과에서 박사학위를 취득하고 Emory 대학교에서 통계적 바이오마커 검출에 대한 내용으로 포닥연구원으로 일하였다. 관심 연구 분야는 데이터마이닝, 통계적 기계학습, 시계열/시퀀스 데이터 분석 등이다.

최소윤
국민대학교에서 경영정보학부에서 학사, 비즈니스IT전문대학원에서 비즈니스IT 전공으로 석사과정에 재학 중이다. 주요 관심분야는 Technical MIS이다.

김재경
서울대학교에서 산업공학 학사, 한국과학기술원에서 경영정보시스템 전공으로 석사 및 박사학위를 취득하였으며 현재 경희대학교 경영대학 교수로 재직하고 있다. 미국 미네소타 주립대학교, 그리고 텍사스 주립대학교(달라스)에서 교환교수를 역임하였다. 주요 관심분야로는 비즈니스 인텔리전스, 추천시스템, 유비쿼터스 서비스 등이 있다. IEEE Transactions on Services Computing, IEEE Transactions on SMC-A, International Journal of Human-Computer Studies, International Journal of Information Management, Technological Forecasting and Social Change, Information and Management 등 다수의 학술지에 논문을 게재하였으며, 또한 한국지능정보시스템학회장, 국가과학기술위원회 서비스 R&D 전문위원, 경희대학교 경영대학 BK21 사업단장, Information Technology and Management(SSCI) AE(Associate Editor)를 역임하였다.

안현철
현재 국민대학교 경영대학 경영정보학부 부교수로 재직 중이다. KAIST에서 산업경영학사를 취득하고, KAIST 테크노경영대학원에서 경영정보시스템을 전공하여 공학석사와 박사를 취득하였다. 주요 관심분야는 금융 및 고객관계관리 분야의 인공지능 응용, 정보시스템 수용과 관련한 행동 모형 등이다.