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Modeling Human Emotions as Reactions to a Dynamical Virtual 3D Face

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Abstract. This paper introduces a comparison of one linear and two nonlinear one-step-ahead predictive models that were used to describe the relationship between human emotional signals (excitement, frustration, and engagement/boredom) and virtual dynamic stimulus (virtual 3D face with changing distance-between-eyes). An input–output model building method is proposed that allows building a stable model with the smallest output prediction error. Validation was performed using the recorded signals of four volunteers. Validation results of the models showed that all three models predict emotional signals in relatively high prediction accuracy.

Key words: 3D face, human emotions, input–output model, parameter estimation, prediction, model validation.

1. Introduction

Virtual environments are already a part of our daily life (work tasks, e-learning, online shopping, etc.). These environments affect the users' emotions in both positive and negative ways. It is important to investigate and describe relationships between various virtual stimuli and human reactions to them. Human state observation is an important task for this purpose. Plenty of bio-signals are used for human state monitoring (Zisook *et al.*, 2013; Suprijanto *et al.*, 2009; Raudonis *et al.*, 2012). EEG-based signals are used because of their reliability and quick response (Sourina and Liu, 2011; Hondrou and Caridakis, 2012). A number of systems and methods are used for emotion recognition, but not so many for emotion control in virtual environment (Hoey *et al.*, 2013; Khushaba *et al.*, 2012).

We have previously investigated linear input–output structure models for exploring human responses (excitement, meditation, frustration, and engagement/boredom) to virtual 3D face features (distance-between-eyes, nose width, and chin width) using EEG-based bio-signals (Vaškevičius *et al.*, 2014; Vidugirienė *et al.*, 2013, 2014).

We continue to use virtual 3D face as stimulus for eliciting human emotions as the majority of information when communicating is transferred by face features (Mehrabian, 1981) and a person is used to react to them in a very short time (Willis and Todorov, 2006).

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In this study we compare a modified linear and two types of nonlinear input–output models to describe the dependencies between human emotions (excitement, frustration, engagement/boredom) and virtual 3D face feature (distance-between-eyes).

2. Observations and Data

A virtual dynamic 3D face with changing distance-between-eyes was used for input as stimulus (shown in a monitor) and EEG-based preprocessed excitement, frustration and engagement/boredom signals of a volunteer was measured as output (Fig. 1). The output signals were recorded using Emotiv Epoc device that records EEG inputs from 14 channels (according to international 10–20 locations): AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4 (Emotiv Epoc specifications).

A dynamic stimulus was formed from a changing woman face. One 3D face created with Autodesc MAYA was used as a "neutral" one (Fig. 2, middle). Other 3D faces were formed by changing distance-between-eyes in an extreme manner (Fig. 2, top, bottom). The transitions between normal and extreme stages were programmed. Experiment plan for input is shown in Fig. 2.

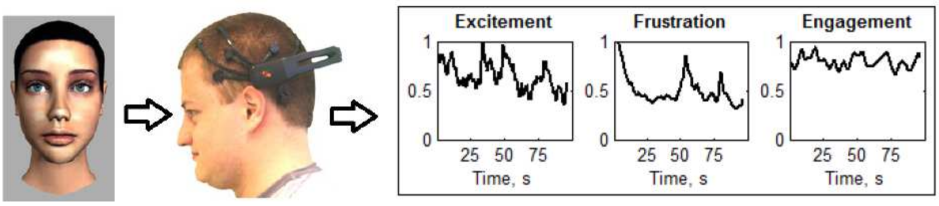

Fig. 1. Input–output scheme for the experiments.

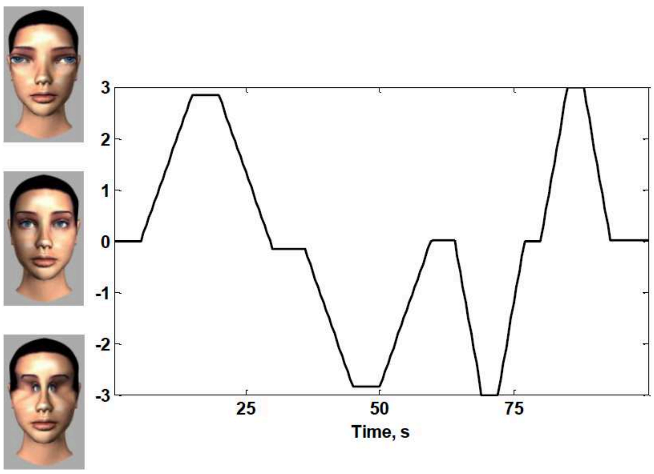

Fig. 2. Input signal: experiment plan.

At first "neutral" face was shown for 5 s, then the distance-between-eyes was increased continuously and in 10 s the largest distance between eyes was reached, then 5 s of steady face was shown and after that the face came back to "normal" in 10 s. Then "normal" face was shown for 5 s, followed by 10 s of continuous change to the face with the smallest distance between eyes, again 5 s of steady face was shown and in the next 10 s the face came back to "normal". The experiment was continued in the same way further using 3 s time intervals for steady face and 5 s for continuous change. "Neutral" face has 0 value, largest distance-between-eyes corresponds to value 3 and smallest distance-between-eyes corresponds to value -3. Values of the output signals (excitement, frustration and engagement/boredom) vary from 0 to 1. If excitement, frustration or engagement is low, the value is close to 0 and if it is high, the value is close to 1. The signals were recorded with the sampling period of $T_0 = 0.5$ s.

Four volunteers (three males – volunteers Nos. 1–3, and one female – volunteer No. 4) were tested. Each volunteer was watching one animated scene of approximately 100 s, and EEG-based signals were measured and recorded simultaneously.

3. Building of Mathematical Models

Dependencies between human emotion signals (excitement, frustration, and engagement/boredom) as reactions to virtual 3D face feature (distance-between-eyes) changes are described by input–output structure dynamical model (Kaminskas, 1982):

$$A(z^{-1})y_t = \theta_0 + B(z^{-1})f(x_t) + \varepsilon_t, \tag{1}$$

where

$$B(z^{-1}) = \sum_{j=0}^{m} b_j z^{-j}, \qquad A(z^{-1}) = 1 + \sum_{i=1}^{n} a_i z^{-1} \tag{2}$$

and

$$f(x_t) = x_t, \tag{3}$$

$$f(x_t) = |x_t|, \tag{4}$$

$$f(x_t) = x_t^2, \tag{5}$$

where $f(x_t)$ is a linear, absolute or square transform function of input, y_t is an output (excitement, frustration, or engagement/boredom), x_t is an input (distance-between-eyes) signal respectively expressed as

$$y_t = y(tT_0), \qquad x_t = x(tT_0) \tag{6}$$

with sampling period T_0, θ_0 is a constant value (which indicate that the values of human reaction signals are positive), ε_t corresponds to white-noise signal, and z^{-1} is the backward shift operator ($z^{-1}x_t = x_{t-1}$). A sign | | denotes absolute value.

This type of function $f(x_t)$ was chosen to examine if a volunteer reacts to the changes of a 3D face (increase or decrease of distance-between-eyes) directly (3) or the reaction depends on the change of the amplitude and not on the direction of the change (4)–(5).

Parameters (coefficients of the polynomials (2)), orders (degrees m and n of the polynomials (2)) and constant θ_0 of the models (1)–(5) are unknown. They have to be estimated according to the observations obtained during the experiments with the volunteers.

Equation (1) can be expressed in the following form:

$$y_t = \theta_0 + \sum_{j=0}^{m} b_j f(x_{t-j}) - \sum_{i=1}^{n} a_i y_{t-i} + \varepsilon_t. \tag{7}$$

It is not difficult to see that (7) can be expressed as the linear regression equation:

$$y_t = \mathbf{d}_t^T \mathbf{c} + \varepsilon_t \tag{8}$$

where

$$\mathbf{d}_t^T = \left[1, f(x_t), f(x_{t-1}), \ldots, f(x_{t-m}), -y_{t-1}, \ldots, -y_{t-n}\right], \tag{9}$$

and

$$\mathbf{c}^T = [\theta_0, b_0, b_1, \ldots, b_m, a_1, a_2, \ldots, a_n], \tag{10}$$

T is a vector transpose sign.

For the estimation of unknown parameter vector $\mathbf{c}$ we use a method of least squares (Kaminskas, 1982):

$$\hat{\mathbf{c}} = \mathbf{Q}^{-1}\mathbf{q}, \tag{11}$$

where $\mathbf{Q}$ and $\mathbf{q}$ are expressed as follows

$$\mathbf{Q} = \sum_{t=1}^{M} \mathbf{d}_t \mathbf{d}_t^T, \qquad \mathbf{q} = \sum_{t=1}^{M} y_t \mathbf{d}_t \tag{12}$$

and M is a number of observation values that are used to build a model. After calculating the estimates of model parameters, stability condition of a model is verified (Kaminskas, 1982). It means that the roots

$$z_i^A: \quad \hat{A}_M(z) = 0, \quad i = 1, 2, \ldots, n \tag{13}$$

of the following polynomial

$$\hat{A}_M(z) = z^n \hat{A}_M\left(z^{-1}\right) = z^n + \sum_{i=1}^{n} \hat{a}_i^M z^{n-i} \tag{14}$$

have to be in the stability domain, i.e. in the unit disk

$$\left|z_i^A\right| < 1. \tag{15}$$

If the condition (15) is not satisfied, coefficients of polynomial $\hat{A}_M(z^{-1})$ are projected

$$\hat{a}_i = \gamma \hat{a}_i^M, \quad 0 < \gamma \leqslant 1, \; i = 1, 2, \ldots, n, \tag{16}$$

to the stability domain. It is easy to calculate γ constant when $n \leqslant 2$, because the stability domain is defined by:

$$-1 < \hat{a}_1 < 1, \quad \text{if } n = 1, \tag{17}$$

$$\begin{cases} 1 + \hat{a}_1 + \hat{a}_2 > 0, \\ 1 - \hat{a}_1 + \hat{a}_2 > 0, \quad \text{if } n = 2 \\ -1 < \hat{a}_2 < 1, \end{cases} \tag{18}$$

and

$$\gamma = \min\left\{1, \gamma_1^{(1)}\right\}, \quad \text{if } n = 1, \tag{19}$$

$$\gamma_1^{(1)} = \frac{1}{|\hat{a}_1^M|} - \gamma_0, \tag{20}$$

$$\gamma = \min\left\{1, \gamma_1^{(2)}, \gamma_2^{(2)}, \gamma_3^{(2)}\right\}, \quad \text{if } n = 2, \tag{21}$$

$$\gamma_1^{(2)} = \begin{cases} -\frac{1}{\hat{a}_1^M + \hat{a}_2^M} - \gamma_0, & \text{if } \hat{a}_1^M + \hat{a}_2^M < 0, \\ 1, & \text{in other cases,} \end{cases} \tag{22}$$

$$\gamma_2^{(2)} = \begin{cases} -\frac{1}{\hat{a}_2^M - \hat{a}_1^M} - \gamma_0, & \text{if } \hat{a}_2^M - \hat{a}_1^M < 0, \\ 1, & \text{in other cases,} \end{cases} \tag{23}$$

$$\gamma_3^{(2)} = \frac{1}{|\hat{a}_2^M|} - \gamma_0 \tag{24}$$

where positive constant $\gamma_0 \in [0.001, 0.01]$. When $n \geqslant 3$, nonlinear inequalities appear in the system of inequalities that define the stability domain and the calculation of γ becomes more complex.

Estimates of the model orders – $\hat{m}$ and $\hat{n}$ – are defined from the following conditions (Kaminskas, 1982):

$$\hat{n}: \quad \left|\frac{\sigma_\varepsilon[m, n+1] - \sigma_\varepsilon[m, n]}{\sigma_\varepsilon[m, n]}\right| \leqslant \delta, \quad n = 1, 2, \ldots \tag{25}$$

$$\hat{m}: \quad \left|\frac{\sigma_\varepsilon[m+1, n] - \sigma_\varepsilon[m, n]}{\sigma_\varepsilon[m, n]}\right| \leqslant \delta, \quad m = 1, 2, \ldots, n \tag{26}$$

where

$$\sigma_{\varepsilon}[m,n] = \sqrt{\frac{1}{N}\sum_{t=1}^{N}\hat{\varepsilon}_t^2[m,n]} \tag{27}$$

is one-step-ahead output prediction error standard deviation,

$$\hat{\varepsilon}_t[m,n] = y_t - \hat{y}_{t|t-1}[m,n] \tag{28}$$

is one-step-ahead output prediction error,

$$\hat{y}_{t|t-1} = \hat{\theta}_0 + z\big[1 - \hat{A}\big(z^{-1}\big)\big]y_{t-1} + \hat{B}\big(z^{-1}\big)f(x_t) \tag{29}$$

is one-step-ahead output prediction (Kaminskas, 1982, 2007), z is the forward shift operator ($zy_t = y_{t+1}$) and $\delta > 0$ is a chosen constant value. Usually in identification practice $\delta \in [0.01 \div 0.1]$ what corresponds to a relative variation of prediction error standard deviation from 1% to 10%.

This way stable input–output models are built that ensure the best one-step-ahead output signal prediction.

4. Validation of Models

Validation of the models (1)–(5) was performed for each of 4 volunteers (three males and one female). Each model is selected from nine possible models (when $n = 1, 2, 3$, $m = 0, 1, 2, 3$) using the rules (25)–(26). Figure 3 demonstrate prediction error standard deviations for an input–output pairs for one male (volunteer No. 2) and one female (volunteer No. 4) using the linear model (1)–(3). The analysis of data showed that relations between distance-between-eyes input and excitement output signal can be modelled when model order is $\hat{m} = 0$, $\hat{n} = 1$, frustration output signal can be modelled when model order is $\hat{m} = 0$, $\hat{n} = 2$, and engagement/boredom output signal can be modelled when model order is $\hat{m} = 0$, $\hat{n} = 3$. According to data analysis results, one-step-ahead prediction of output signals for every model can be performed using the following expressions

$$\hat{y}_{t+1|t} = \hat{\theta}_0 - \hat{a}_1 y_t + \hat{b}_0 f(x_{t+1}) \tag{30}$$

in the case of excitement output signal,

$$\hat{y}_{t+1|t} = \hat{\theta}_0 - \hat{a}_1 y_t - \hat{a}_2 y_{t-1} + \hat{b}_0 f(x_{t+1}) + \hat{b}_1 f(x_t) \tag{31}$$

in the case of frustration output signal, and

$$\hat{y}_{t+1|t} = \hat{\theta}_0 - \hat{a}_1 y_t - \hat{a}_2 y_{t-1} - \hat{a}_3 y_{t-2} + \hat{b}_0 f(x_{t+1}) \tag{32}$$

in engagement/boredom output signal case.

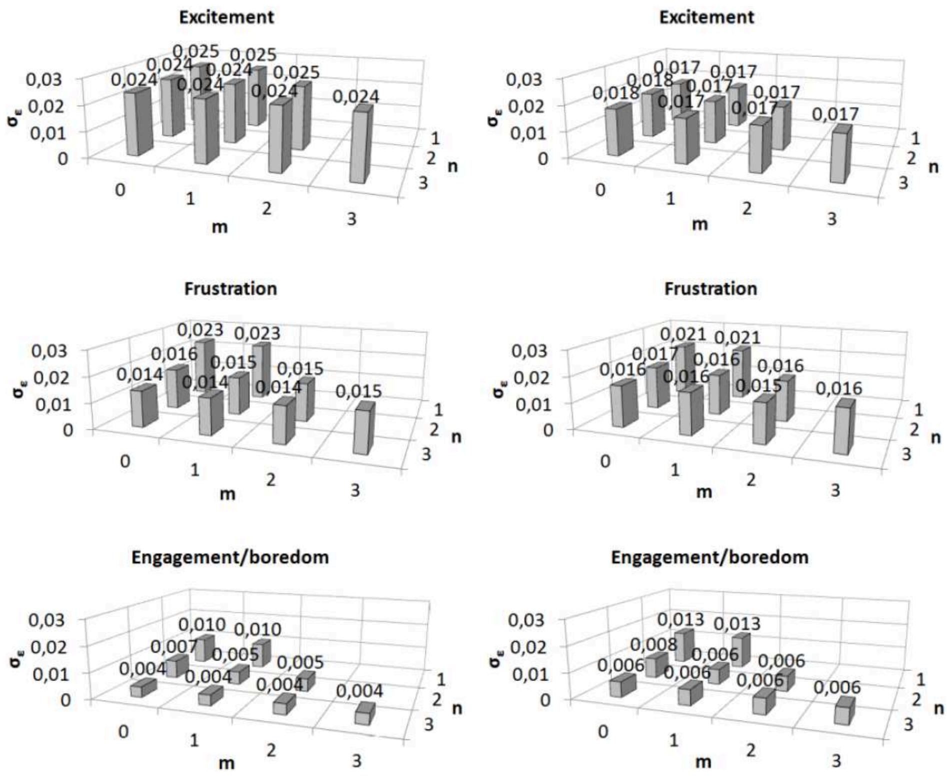

Fig. 3. Prediction error standard deviations for emotional signals with different model orders using linear model (1)–(3) for volunteer No. 2 (left), and volunteer No. 4 (right).

Prediction accuracies were evaluated using the following measures:

– prediction error standard deviation

$$\sigma_\varepsilon = \sqrt{\frac{1}{N}\sum_{t=0}^{N-1}(y_{t+1} - \hat{y}_{t+1|t})^2}, \tag{33}$$

– relative prediction error standard deviation

$$\tilde{\sigma}_\varepsilon = \sqrt{\frac{1}{N}\sum_{t=0}^{N-1}(y_{t+1} - \hat{y}_{t+1|t})^2}, \tag{34}$$

– and average absolute relative prediction error

$$|\bar{\varepsilon}| = \frac{1}{N}\sum_{t=0}^{N-1}\left|\frac{y_{t+1} - \hat{y}_{t+1|t}}{y_{t+1}}\right| * 100\%. \tag{35}$$

One-step-ahead predictions (30)–(32) were performed using the observation data that were used to build a model ($M = 124$, in (12)) and the additional ones that were not used to build a model (in total $N = 200$, in (33)–(35)). Prediction accuracy measures are provided in Table 1.

Figures 4–7 show one-step-ahead prediction results when using all models (1)–(5) for all four volunteers. Thick solid line denotes an observed signal, thick dotted line denotes

Table 1
Prediction accuracy measures.

Vol. No.	Output	$f(x_t) = x_t$ σ_ε	$\tilde{\sigma}_\varepsilon$ (%)	$\lvert\bar{\varepsilon}\rvert$ (%)	$f(x_t) = \lvert x_t\rvert$ σ_ε	$\tilde{\sigma}_\varepsilon$ (%)	$\lvert\bar{\varepsilon}\rvert$ (%)	$f(x_t) = x_t^2$ σ_ε	$\tilde{\sigma}_\varepsilon$ (%)	$\lvert\bar{\varepsilon}\rvert$ (%)
1	Excitement	0.045	7.2	5.7	0.045	7.2	5.8	0.045	7.2	5.8
	Frustration	0.015	2.7	1.8	0.015	2.7	1.9	0.015	2.8	1.9
	Engagement	0.006	0.8	0.6	0.006	0.8	0.6	0.006	0.8	0.6
2	Excitement	0.025	9.9	7.2	0.025	10.3	7.5	0.025	10.3	7.5
	Frustration	0.015	3.5	2.6	0.015	3.6	2.6	0.015	3.6	2.7
	Boredom	0.004	0.7	0.5	0.004	0.7	0.5	0.004	0.7	0.5
3	Excitement	0.036	11.8	9.0	0.036	11.7	9.1	0.036	11.8	9.1
	Frustration	0.012	2.2	1.6	0.012	2.2	1.6	0.012	2.2	1.6
	Boredom	0.004	0.5	0.4	0.004	0.5	0.4	0.004	0.5	0.4
4	Excitement	0.017	9.0	5.7	0.018	9.0	5.7	0.018	9.0	5.7
	Frustration	0.016	3.2	2.4	0.016	3.1	2.3	0.016	3.1	2.3
	Boredom	0.006	0.8	0.6	0.006	0.8	0.6	0.006	0.8	0.6

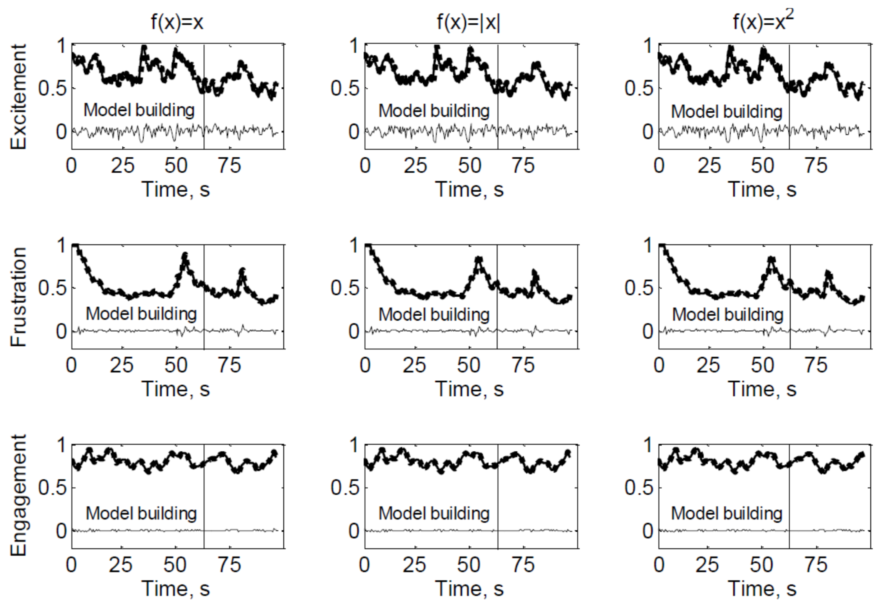

Fig. 4. One-step-ahead prediction results when using models (1)–(5) for volunteer No. 1.

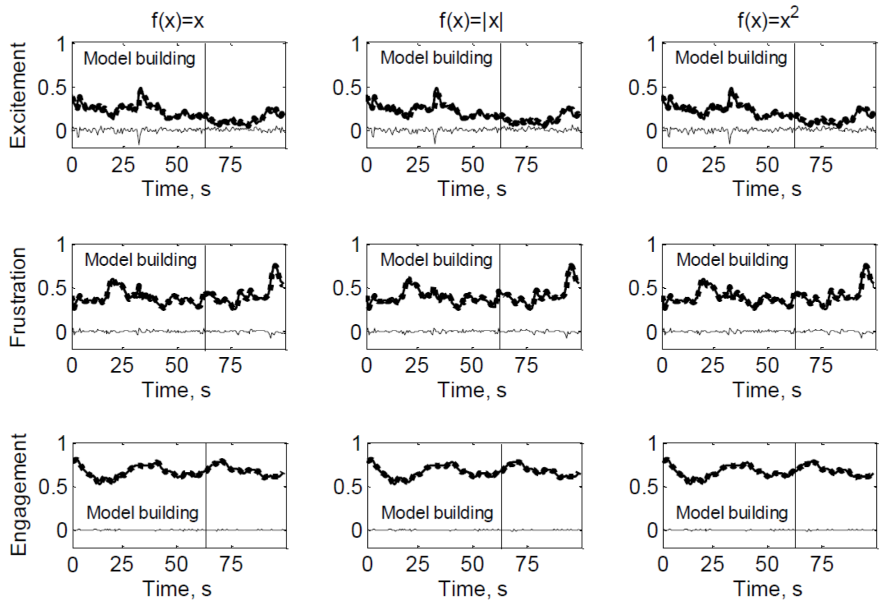

Fig. 5. One-step-ahead prediction results when using models (1)–(5) for volunteer No. 2.

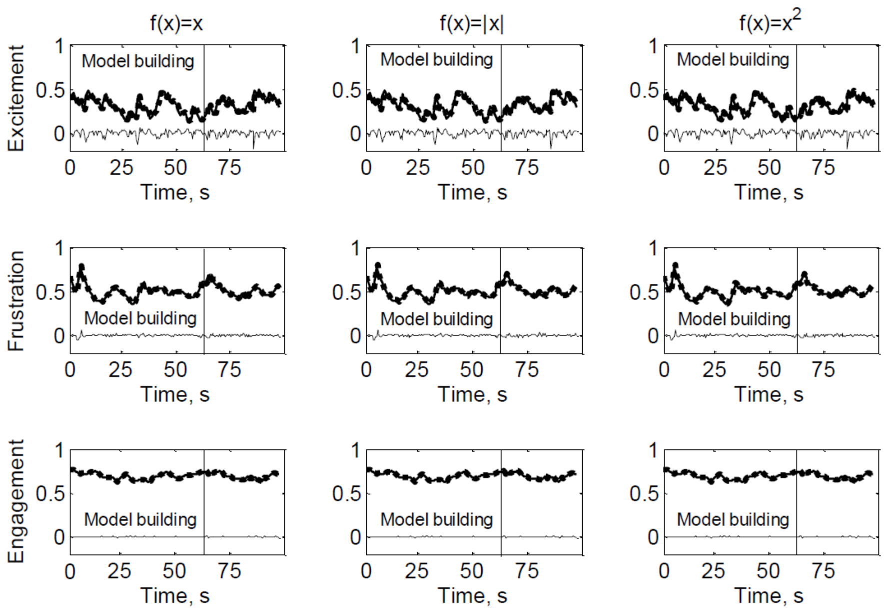

Fig. 6. One-step-ahead prediction results when using models (1)–(5) for volunteer No. 3.

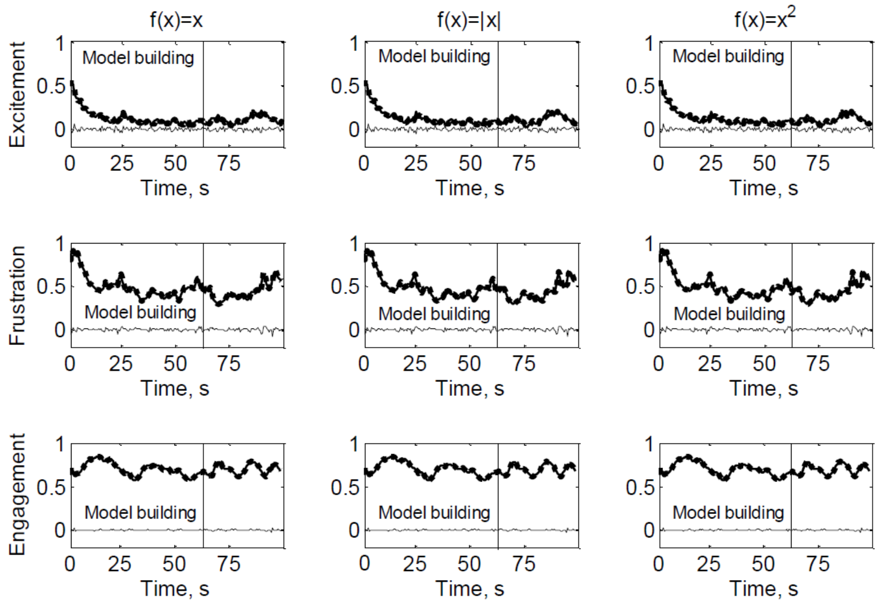

Fig. 7. One-step-ahead prediction results when using models (1)–(5) for volunteer No. 4.

Table 2
Estimated parameters for excitement signal prediction using first order model (30).

$f(x_t)$		x_t	$\lvert x_t \rvert$	x_t^2
Volunteer	$\hat{b}_0$	0.0012	−0.0042	−0.0016
No. 2	$\hat{a}_1$	−0.9139	−0.8898	0.8868
(male)	$\hat{\theta}_0$	0.0189	0.0303	0.0302
Volunteer	$\hat{b}_0$	0.0007	−0.0006	−0.0002
No. 4	$\hat{a}_1$	−0.9097	−0.9099	−0.9099
(female)	$\hat{\theta}_0$	0.0085	0.0093	0.0092

Table 3
Estimated parameters for frustration signal prediction using second order model (31).

$f(x_t)$		x_t	$\lvert x_t \rvert$	x_t^2
Volunteer	$\hat{b}_0$	−0.0049	0.0121	0.0001
No. 3	$\hat{b}_1$	0.0044	−0.0142	−0.0007
(male)	$\hat{a}_1$	−1.7377	−1.7277	−1.7375
	$\hat{a}_2$	0.8113	0.8131	0.8162
	$\hat{\theta}_0$	0.0367	0.0454	0.0408
Volunteer	$\hat{b}_0$	−0.0088	−0.0140	−0.0035
No. 4	$\hat{b}_1$	0.0092	0.0135	0.0034
(female)	$\hat{a}_1$	−1.5874	−1.5825	−1.5805
	$\hat{a}_2$	0.6131	0.6084	0.6065
	$\hat{\theta}_0$	0.0118	0.0126	0.0122

Table 4
Estimated parameters for engagement/boredom signal prediction using third order model (32)

$f(x_t)$		x_t	$\lvert x_t \rvert$	x_t^2
Volunteer	$\hat{b}_0$	0.0001	0.0022	0.0007
No. 1	$\hat{a}_1$	−2.3133	−2.2207	−2.2331
(male)	$\hat{a}_2$	1.9004	1.7634	1.8847
	$\hat{a}_3$	−0.5582	−0.4881	−0.5018
	$\hat{\theta}_0$	0.0232	0.0409	0.0379
Volunteer	$\hat{b}_0$	0.0007	0.0008	0.0003
No. 4	$\hat{a}_1$	−1.9525	−1.9745	−1.9730
(female)	$\hat{a}_2$	1.1013	1.1392	1.1320
	$\hat{a}_3$	−0.1208	−0.1364	−0.1312
	$\hat{\theta}_0$	0.0197	0.0187	0.0187

predicted signal and thin solid line denotes prediction error at every time moment. Vertical line denotes M position as model parameters were estimated in the interval from 0 to M (equal to 124). As sampling period $T_0 = 0.5$ s, M is 62 s.

Examples of parameter estimates of the models (30)–(32) are given in Tables 2–4.

The prediction results show that excitement can be predicted with less than 9%, frustration – with less than 3% and engagement/boredom – with less than 1% absolute relative prediction error. According to the prediction accuracy, all three models (1)–(5) are similar. These models are more accurate than previously investigated linear models (Vaškevičius *et al.*, 2014; Vidugirienė *et al.*, 2013, 2014).

5. Conclusions

Three alternative models – one linear and two nonlinear – were proposed to describe the dependencies between human emotional signals (excitement, frustration, and engagement/boredom) and 3D face feature (distance-between-eyes). The linear model describes the reaction of a volunteer to the direct changes of a 3D face (increase or decrease of distance-between-eyes). The second and the third models describe the reaction to the amplitude of a change of a 3D face and not to the direction of the change.

A method for building input–output models was proposed that allows building stable models for one-step-ahead predictions of excitement, frustration, and engagement/boredom signals with the smallest prediction errors.

Validation of the models showed that each volunteer has an individual reaction to the given stimuli, and the reactions can be described using first order ($n = 1$, $m = 0$) model for excitement signals, second order ($n = 2$, $m = 1$) model for frustration signals and third order ($n = 3$, $m = 0$) model for engagement/boredom signals. These three models with different input transform function (linear, absolute, and quadratic) are similar in respect to prediction accuracies.

Engagement/boredom signal was predicted with the least absolute relative prediction error (less than 1%). Frustration signal was predicted with less than 3% absolute relative prediction error. Excitement signal was predicted with the largest prediction error, but less than 9%.

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Žmogaus emocijų, kaip reakcijų į virtualų kintantį trimatį veidą, modeliavimas

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Šiame straipsnyje pateikiamas vieno tiesinio ir dviejų netiesinių modelių, kurie aprašo sąryšius tarp žmogaus emocinių signalų (susijaudinimo, susierzinimo ir susidomėjimo/nuobodulio) ir virtualaus dinaminio stimulo (virtualaus trimačio veido su besikeičiančiu atstumu tarp akių), palyginimas. Pasiūlytas „įėjimas–išėjimas“ tipo modelių, kurie yra stabilūs ir prognozuoja išėjimo signalą su mažiausia paklaida, sudarymo metodas. Modelių validavimas buvo atliktas naudojant keturių tiriamųjų signalus. Validavimo rezultatai parodė, kad visi trys modeliai prognozuoja emocinius signalus santykinai aukštu tikslumu.