

Predictor-based Control of Human Emotions When Reacting to a Dynamic Virtual 3D Face Stimulus

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Abstract: This paper introduces how predictor-based control principles are applied to the control of human emotion – excitement and frustration – signals. We use changing distance-between-eyes in a virtual 3D face as a control signal. A predictor-based control law is synthesized by minimizing control quality criterion in an admissible domain. Admissible domain is composed of input signal boundaries. Relatively high control quality of excitement and frustration signals is demonstrated by modelling results. Input signal boundaries allow decreasing variation of changes in a virtual 3D face.

1 INTRODUCTION

As virtual environment already became a part of our daily life including computer games, learning environments, social networks and their games, there is a need to prevent children and adults from harmful effects that can cause addiction to virtual environment or even various mental diseases (Calvo et al, 2015, Scherer et al, 2010). For this purpose, a control mechanism for human state regulation is needed. Brain-computer interfaces and applications are one of the means that help to regulate human state and emotions in different environments and circumstances (Graumann et al, 2011, Tan and Nijholt, 2010). We use EEG-based signals because of their reliability and quick response (Sourina and Liu, 2011; Hondrou and Caridakis, 2012).

We have investigated predictive input-output structure models for exploring dependencies between virtual 3D face features and human reaction to them in Kaminskas et al. (2014), and Vaškevičius et al. (2014) as a person is used to react quickly to the smallest face feature changes (Willis and Todorov, 2006). Predictive models are necessary in the design of predictor-based control systems (Åström and Wittenmark, 1997, Clarke, 1994, Kaminskas, 2007)

This paper introduces how predictor-based control principles are applied to the control of human emotion signals (excitement and frustration). We use changing distance-between-eyes in a virtual 3D face as a control signal.

2 INPUT-OUTPUT CONTROL PLANT

A virtual 3D face with changing distance-between-eyes was used for input as stimulus (shown in a computer monitor to a volunteer) and EEG-based pre-processed excitement and frustration signals of a volunteer were measured as output (Figure 1). The output signals were recorded with 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. A 3D face created with Autodesk MAYA was used as a “neutral” one (Figure 1, left).

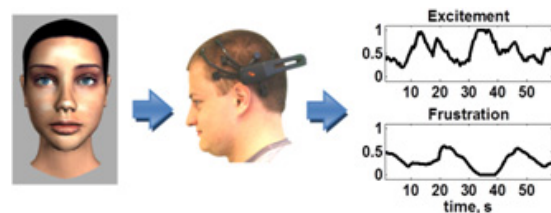


Figure 1: Input-Output scheme.

Other 3D faces were formed by changing distance-between-eyes in an extreme manner (Figure 2). The transitions between normal and extreme stages were programmed. “Neutral” face has 0 value, largest distance-between-eyes

corresponds to value 3 and smallest distance-between-eyes corresponds to value -3.

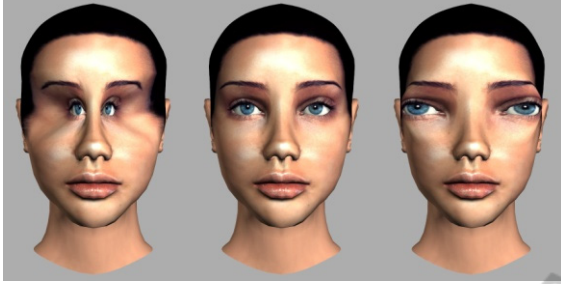


Figure 2: A 3D virtual face with the smallest (left), normal (middle) and the largest (right) distance-between-eyes.

Values of the output signals – excitement and frustration – vary from 0 to 1. If excitement and frustration are low, their values are close to 0 and if they are high, their values are close to 1. The signals were recorded with the sampling period of $T_0=0.5$ s.

Dependency between virtual 3D face feature (distance-between-eyes) and human emotions (excitement or frustration) are described by input-output structure linear model (Kaminskas et al, 2014):

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

where

$$B(z^{-1}) = \sum_{j=0}^m b_j z^{-j}, \quad (2)$$

$$A(z^{-1}) = 1 + \sum_{i=1}^n a_i z^{-i},$$

y_t is an output (excitement or frustration), x_t is an input (distance-between-eyes) signals respectively expressed as

$$y_t = y(tT_0), \quad x_t = x(tT_0) \quad (3)$$

with sampling period T_0 , θ_0 is a constant value, ε_t corresponds to noise signal, and z^{-1} is the backward-shift operator ($z^{-1}x_t = x_{t-1}$).

Eq. (1) can be expressed in the following form:

$$y_t = \theta_0 + \sum_{j=0}^m b_j x_{t-j} - \sum_{i=1}^n a_i y_{t-i} + \varepsilon_t, \quad (4)$$

Parameters (coefficients b_j and a_i , degrees m and n of the polynomials (2) and constant θ_0) of the model (1) are unknown. They have to be estimated according to the observations obtained during the experiments with the volunteers (Kaminskas et al., 2014).

3 DIGITAL PREDICTOR-BASED CONTROL WITH CONSTRAINTS

A predictor-based control law is synthesized by minimizing control quality criterion $Q_t(x_{t+1})$ in an admissible domain Ω_x (Kaminskas, 2007):

$$x_{t+1}^*: Q_t(x_{t+1}) \rightarrow \min_{x_{t+1} \in \Omega_x} \quad (5)$$

$$Q_t(x_{t+1}) = M\{y_{t+1} - y_{t+1}^*\}^2 \quad (6)$$

$$\Omega_x = \{x_{t+1}: x_{min} \leq x_{t+1} \leq x_{max}, |x_{t+1} - x_t^*| < \delta_t\} \quad (7)$$

where M is a mathematical expectation sign, y_{t+1}^* is a reference signal (reference trajectory for emotion signal), x_{min} and x_{max} are input signal boundaries (smallest and largest distance-between-eyes), $\delta_t > 0$ are the restriction values for the change rate of the input signal, and $\text{sign} | \cdot |$ denotes absolute value.

Then solving the minimization problem (5)-(7) for one-step prediction model

$$y_{t+1|t} = \theta_0 + L(z^{-1})y_t + B(z^{-1})x_{t+1} \quad (8)$$

the control law is described by equations

$$x_{t+1}^* = \begin{cases} \min\{x_{max}, x_t^* + \delta_t, \tilde{x}_{t+1}\}, & \text{if } \tilde{x}_{t+1} \geq x_t^* \\ \max\{x_{min}, x_t^* - \delta_t, \tilde{x}_{t+1}\}, & \text{if } \tilde{x}_{t+1} < x_t^* \end{cases} \quad (9)$$

$$B(z^{-1})\tilde{x}_{t+1} = -L(z^{-1})y_t + y_{t+1}^* - \theta_0, \quad (10)$$

$$L(z^{-1}) = z[1 - A(z^{-1})] \quad (11)$$

where z is a forward-shift operator ($zy_t = y_{t+1}$).

If the roots of polynomial

$$B(z) = z^m B(z^{-1}) \quad (12)$$

are in the unity disk

$$|z_j^B| < 1, \quad z_j^B: B(z) = 0, j = 1, \dots, m, \quad (13)$$

then from (10) and (11) the following equation is correct

$$\tilde{x}_{t+1} = \frac{1}{b_0} \left\{ \sum_{i=1}^n a_i y_{t+1-i} + y_{t+1}^* - \theta_0 - \sum_{j=1}^m b_j x_{t+1-j} \right\}. \quad (14)$$

If a part or all of polynomial (12) roots do not belong to the unity disk, factorization of

polynomial $B(z^{-1})$ is performed (Åström and Wittenmark, 1997).

4 MODELLING RESULTS

Experiments consisted of two phases. In the first phase human emotional signals (excitement and frustration) as reactions to three types of dynamical 3D face stimuli (testing input) were observed. According to these observations input-output model

(1) parameter estimates were calculated. Using these estimates in the second phase, dynamical virtual 3D face features were formed according to control law (9)-(11) (control input). The control tasks were to maintain high excitement levels and low frustration levels (reference signals). In this case control efficiency can be evaluated by a relative measure:

$$\Delta y = \frac{|\bar{y}_C - \bar{y}_T|}{\bar{y}_T} * 100\% \tag{15}$$

where \bar{y}_T is an average of output y_t^T (excitement or

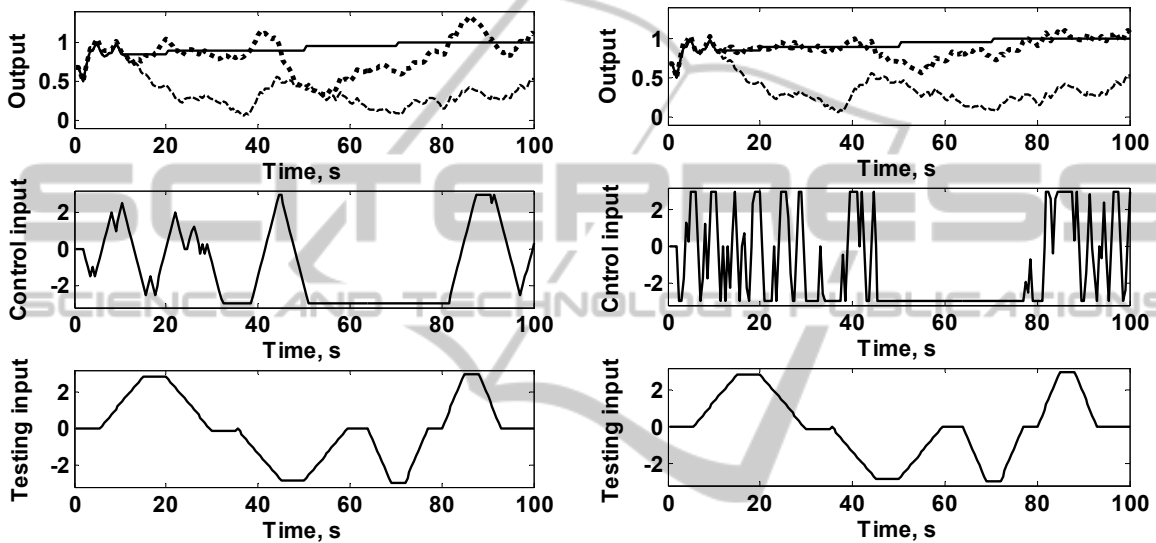


Figure 3: Excitement control (volunteer no. 1, female), when $\delta_t = 1/s$ (left) and $\delta_t = 6/s$ (right). Top: solid lines denote reference signals y_t^* , dotted lines denote output y_t^C (excitement), and dashed lines denote output y_t^T ; middle: control input x_t (distance-between-eyes); bottom: testing input x_t (distance-between-eyes).

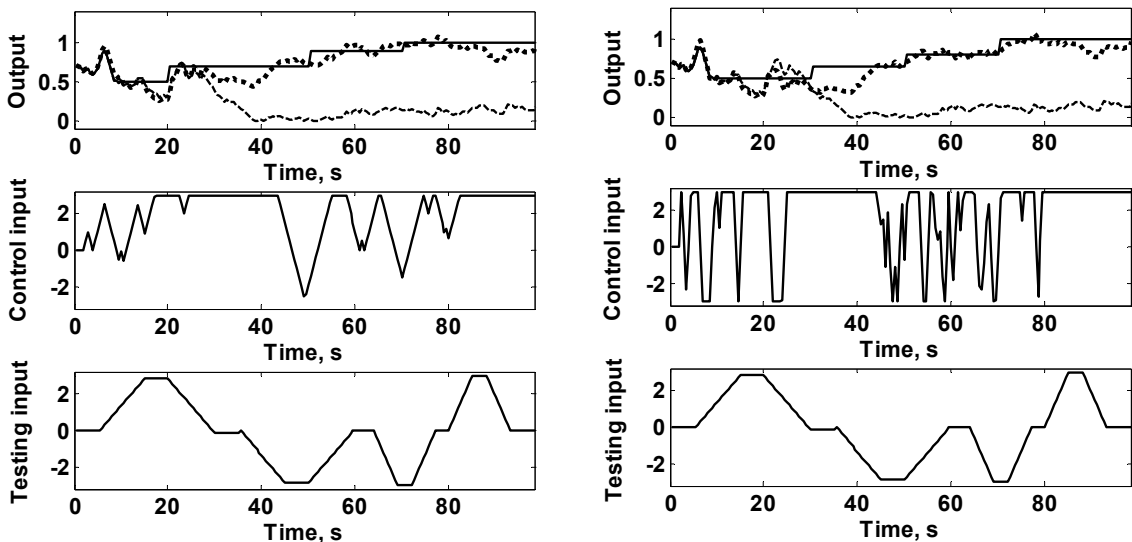


Figure 4: Excitement control (volunteer no. 3, male), when $\delta_t = 1/s$ (left) and $\delta_t = 6/s$ (right). Top: solid lines denote reference signals y_t^* , dotted lines denote output y_t^C (excitement), and dashed lines denote output y_t^T ; middle: control input x_t (distance-between-eyes); bottom: testing input x_t (distance-between-eyes).

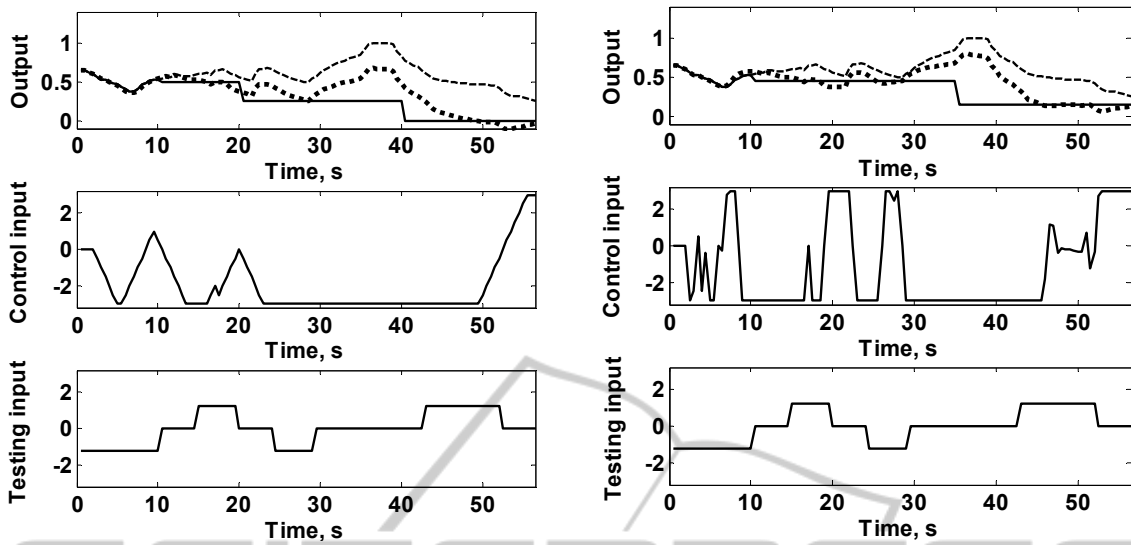


Figure 5: Frustration control (volunteer no. 4, female), when $\delta_t = 1/s$ (left) and $\delta_t = 6/s$ (right). Top: solid lines denote reference signals y_t^* , dotted lines denote output y_t^C (frustration), and dashed lines denote output y_t^T ; middle: control input x_t (distance-between-eyes); bottom: testing input x_t (distance-between-eyes).

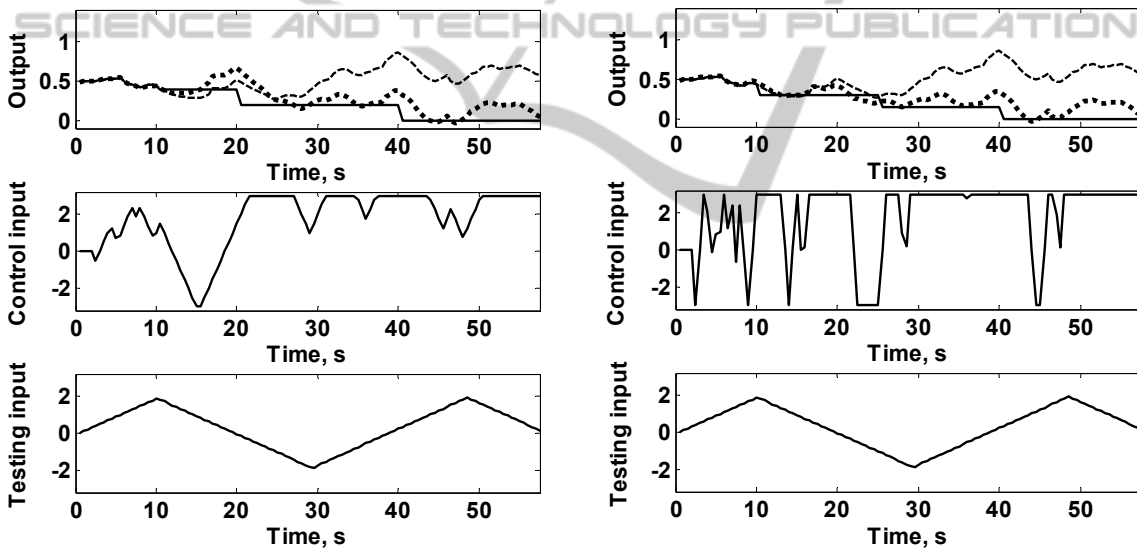


Figure 6: Frustration control (volunteer no. 5, male), when $\delta_t = 1/s$ (left) and $\delta_t = 6/s$ (right). Top: solid lines denote reference signals y_t^* , dotted lines denote output y_t^C (frustration), and dashed lines denote output y_t^T ; middle: control input x_t (distance-between-eyes); bottom: testing input x_t (distance-between-eyes).

frustration) as a reaction to testing input, and \bar{y}_C is an average of output y_t^C (excitement or frustration) as a reaction to control input. These measures are given in Table1 and Table2.

Table 1: Efficiency of excitement control.

Volunteer no.		$\Delta y, \%$	
		$\delta_t = 1/s$	$\delta_t = 6/s$
1	(female)	119.9	133.6
2	(male)	90.1	103.6
3	(male)	205.6	205.5

Table 2: Efficiency of frustration control.

Volunteer no.		$\Delta y, \%$	
		$\delta_t = 1/s$	$\delta_t = 6/s$
1	(female)	35.8	35.1
4	(female)	39.0	36.6
5	(male)	40.3	40.8
6	(male)	27.4	30.4

Excitement and frustration control results are shown in Figs. 3-7.

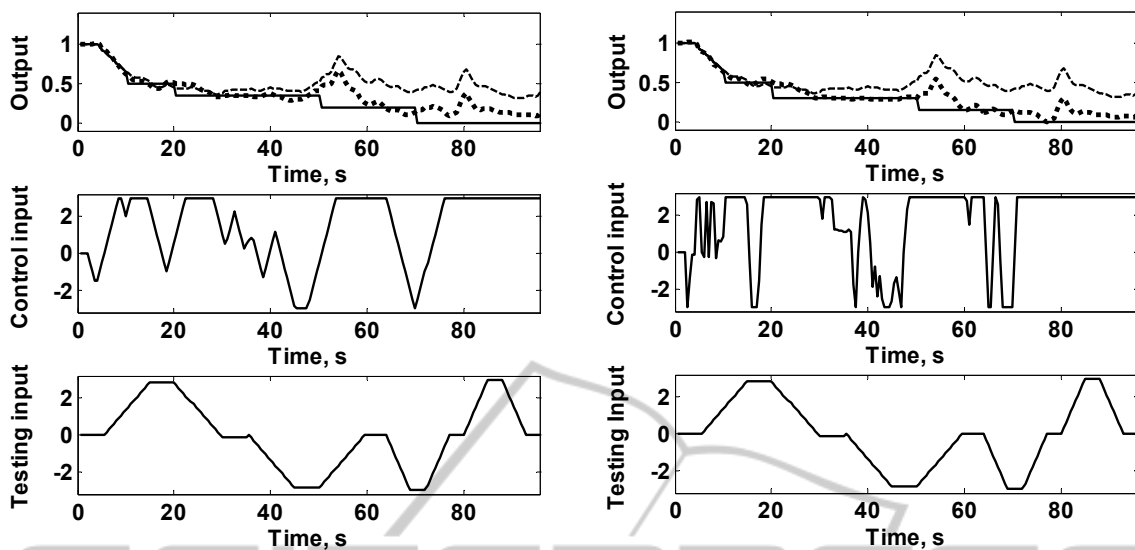


Figure 7: Frustration control (volunteer no. 6, male), when $\delta_t = 1/s$ (left) and $\delta_t = 6/s$ (right). Top: solid lines denote reference signals y_t^* , dotted lines denote output y_t^C (frustration), and dashed lines denote output y_t^I ; middle: control input x_t (distance-between-eyes); bottom: testing input x_t (distance-between-eyes).

Modelling results show that using predictor-based control with constraints a sufficiently good quality of human emotional signals control can be reached. Excitement level can be raised up to 2 times in comparison with testing input, and frustration level can be lowered by 1/3 in comparison with testing input. Control quality is influenced by a control signal variation speed which is limited by the parameter δ_t of the admissible domain. This parameter allows decreasing control signal variation which is usually high in predictor-based control systems without constraints.

5 CONCLUSIONS

Predictor-based control with constraints was applied for controlling human emotions (excitement and frustration) when reacting to a dynamic stimulus (virtual 3D face with changing distance-between-eyes).

Sufficiently good control quality of excitement and frustration signals is demonstrated by modelling results. Input signal boundaries allow decreasing variation of changes in a virtual 3D face.

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REFERENCES

- Åström, K.J., and Wittenmark, B., 1997. Computer Controlled Systems – Theory and Design. 3rd ed. Prentice Hall Inc.
- Calvo, R.A., D’Mello, S.K., Gratch, J., Kappas, A., (editors), 2015. The Oxford Handbook of Affective Computing. Oxford library of psychology. Oxford University Press, 2015.
- Clarke, D.W., 1994. Advances in Model Predictive Control. Oxford Science Publications, UK, 1994.
- Hondrou, C., Caridakis, G., 2012. Affective, Natural Interaction Using EEG: Sensors, Application and Future Directions. In *Artificial Intelligence: Theories and Applications*, Vol. 7297, p. 331-338. Springer-Verlag Berlin Heidelberg.
- Emotiv EPOC specifications. Brain-computer interface technology. Available at: <http://www.emotiv.com/upload/manual/sdk/EPOCSpecifications.pdf>.
- Graimann, B., Allison, B., Pfurtscheller, G., (editors), 2011. Brain-computer interfaces. Revolutionizing human-computer interaction. *The Frontiers Collection*. Springer-Verlag Berlin Heidelberg, 2011.
- Kaminskas, V., 2007. Predictor-based self tuning control with constraints. In: *Model and Algorithms for Global Optimization, Optimization and Its Applications* Vol. 4, Springer, p. 333-341.

- Kaminskas, V., Vaškevičius, E., Vidugirienė, A., 2014. Modeling Human Emotions as Reactions to a Dynamical Virtual 3D Face. *Vilnius University, INFORMATICA*, 2014, Vol. 25, No. 3, p. 425–437.
- Scherer, K.R., Bänziger, T., Roesch, E.B., (editors), 2010. *Blueprint for Affective Computing, a sourcebook*. Series in Affective Science. Oxford university press, 2010.
- Sourina, O., Liu, Y., 2011. A Fractal-based Algorithm of Emotion Recognition from EEG using Arousal-valence model. In *Proc. Biosignals*, p. 209-214.
- Tan, D.S., Nijholt, A., (editors), 2010. *Brain-computer interfaces. Applying our minds to human-computer interaction*, *Human-computer interaction series*. Springer-Verlag Berlin Heidelberg, 2010.
- Vaškevičius, E., Vidugirienė, A., Kaminskas, V., 2014. Identification of Human Response to Virtual 3D Face Stimuli. *Information Technologies and Control*, Vol. 43, No. 1. p. 47 – 56.
- Willis, J., and Todorov, A., 2006. First Impressions: Making Up Your Mind After a 100-Ms Exposure to a Face. *Psychological science*, Vol.17, No.7. 2006. p.592-598.

