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# Estimating Muscle Activation Patterns using a Surrogate Model of Facial Biomechanics

Tim Wu, Harald Martens, Peter Hunter, and Kumar Mithraratne

*Abstract*—**Analyzing the muscle activities that drive the expressive facial gestures can be a useful tool in assessing one's emotional state of mind. Since the skin motion is much easier to measure in comparison to the actual electrical excitation signal of facial muscles, a biomechanical model of the human face driven by these muscles can be a useful tool in relating the geometric information to the muscle activity. However, long computational time often hinders its practicality. The objective of this study was to replace the precise but computationally demanding biomechanical model by a much faster multivariate meta-model (surrogate model), such that a significant speedup (real-time interactive speed) can be achieved and data from the biomechanical model can be practically exploited. Using the proposed surrogate, muscle activation patterns of six key facial expressions were estimated in the iterative fit from the structured-light scanned geometric information.**

## I. Introduction

Facial expressions have been the subject of scientific investigation for nearly four centuries. One of the first studies that link facial expressions to state of mind was published by John Bulwer in the late 1640s [1]. This initial work was later extended by Charles Darwin [2], who demonstrated the universality of expressions and the commonality between man and animals. Another significant work on facial expressions was by Duchenne [3], in which for the first time, the electrical activities of muscles were linked to expressive facial motions. These early researchers have sowed the seeds for hundreds of years of research into behavioral biology, and from their works, there is no question that facial expressions provide distinctive measurement to a person's state of mind.

The expressive motions of the face are intrinsically linked to the activity of facial muscles, and therefore, by measuring the electrical signals through electromyographic (EMG) techniques, the emotional state of mind can be accurately determined (see e.g. [4, 5]). However, measuring facial EMG signals can be a time-consuming and cumbersome task. Moreover, the number of muscles that can be measured is restricted by how many electrodes that can be attached to the face. Hence the practicality of using facial EMG is limited.

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T. Wu, P. Hunter and K. Mithraratne are with the Auckland Bioengineering Institute, University of Auckland, Auckland, New Zealand (phone: +64-9-373-7599; e-mails: twu051@aucklanduni.ac.nz, [p.hunter, p.mithraratne]@auckland.ac.nz).

H. Martens is with the Nofima AS, Norwegian Institute of Food, Fisheries and Aquaculture Research, 1430 Ås, Norway and the Centre for Integrative Genetics, Norwegian University of Life Science, 1430 Ås, Norway (e-mail: harald.martens@nofima.no).

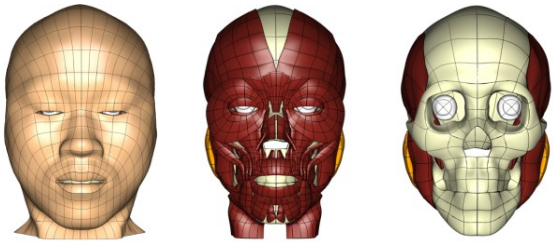

Figure 1. Volume meshes of the superficial soft tissue continuum (left), muscles of facial expression (center) and deep structures (right).

Alternatively, the emotional state of a person can also be inferred through visually recognizing and analyzing different facial motions (see e.g. [6, 7]). Nevertheless, these geometric interpretations are only descriptive, and do not provide physiological meaning to the movements that they measure.

Here we present a methodology to determine the physiologically relevant muscular activities from geometrical information that can be easily obtained. To achieve this, we employed a highly detailed, muscle-driven, biomechanical model of the face that was previously developed [8] (Fig. 1). This biomechanical model can reliably generate a wide range of expressive movements; however, its long computational time inhibits using it for estimating muscle activities from experimental measurements. In order to address this, a surrogate-based modelling approach was undertaken that included the following steps: (a) the system is emulated statistically by developing a multivariate partial least squares regression (PLSR) meta-model based on the data from a simulation experiment, and (b) the original biomechanical model is replaced by the meta-model which is then used to determine the muscle activation levels by performing an iterative fit to the empirical geometric measurements.

## II. Methods

The biomechanical model of the face is controlled by a set of 18 input parameters (corresponding to the 18 muscles of facial expressions that were considered). Through physically-based equations, it yields output parameters that describe the geometric deformation of the facial mesh. A surrogate model (or multivariate meta-model) of the biomechanical system is based on a statistical modelling approach, where the exact physical relationship between the inputs and the corresponding outputs is more or less ignored. Instead, its behavior is characterized using a relatively simple mathematical function, fitted from a sample of simulation results that was obtained from a statistically designed numerical experiment (Fig. 2).

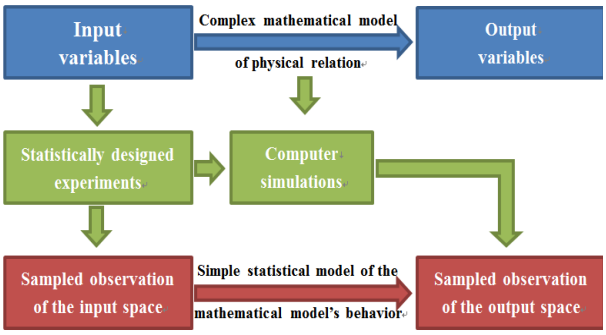


Figure 2. Diagrammatic representation of a conventional deterministic physical model (blue path), and its adaptation to the data-driven surrogate model (red path) via designed computer simulations and statistical regression modelling of the simulation data.

### A. *Design of Experiment*

One of the main challenges in the surrogate-based modelling approach is to determine an optimal design of experiment (DOE) that captures the statistical characteristics of the system while requiring the minimal investment in obtaining new simulations. In this study, a multilevel extension to the $2^{K-P}$ factorial design was created using the multilevel binary replacement (MBR) method proposed by Martens et al. [9], and optimized for both space-spanning and space-filling [10]. Multilevel factorial design was employed, as it is believed that, compared to e.g. random sampling, the factorial approach in general facilitates the spanning of the high-dimensional input factor space more readily. Moreover, it also accommodates the modelling of nonlinear input-output relationships by splitting the parameter variables into equally spaced levels.

In the factorial design, each factor in the input space (i.e. the level of muscle activation for each of the considered muscle), was discretized into four levels, and therefore making a total of $4^{18}$ possible combinations. Due to the limited computer resources, a strongly reduced simulation design with only 128 parameter combinations was employed. To extend this sparse design, converged intermediate solutions obtained from the stepping of activation parameters were also used, providing a total of 6081 observations of the system.

### B. *Modeling input-output relationship*

In this study, the input-output relationship was emulated using a regression approach based on the principle of partial least squares (PLS; the acronym has later been explained as projection to latent structures). The two-block PLS regression [11] approach allows particularly relevant subspaces to be extracted from two or more data matrices. To avoid confusion with other PLS – based methods, Martens and Naes [12] named it "PLSR"; some authors simply write "PLS", for short.

The PLSR is a method for summarizing systematic relations between two sets of observed variables by means of estimated latent variables [13]. In contrast to traditional full-rank least squares methods that can cause a serious variance inflation problem and misleading parameter estimates [14], PLSR reduces the dimension of the system while preserving the most significant information (i.e. a shrinkage estimator), and uses intercorrelations among the variables for model stabilization. Here, PLSR is used for the classical (forward) meta-modelling context where the output solution is estimated statistically from a set of input variables, i.e. Outputs=*f*(Inputs).

In order to model the nonlinearity and interaction of the input parameters, the input space ( $\mathbf{x} \in \mathrm{R}^K$ ) is often mapped to a higher dimensional feature space ( $\phi(\mathbf{x}) = \boldsymbol{\varphi} \in \mathrm{R}^{K^*}$ , with $K^* > K$ ). In this study, a quadratic surface projection [15] was used, with the 18-dimensional input space being mapped to a 189- dimensional feature space. Specifically, the original input data were extended by considering the squares and cross products of the entries.

$$\mathbf{x} = (x_1,...,x_K) \rightarrow \boldsymbol{\varphi} = (x_1,...,x_K, x_1^2,...,x_K^2, x_1x_2,...,x_{K-1}x_K) \tag{1}$$

The PLS method decomposes mean-centred $\boldsymbol{\Phi}$ (input data that was transformed to the feature space) and $\mathbf{Y}$ (output data) matrices into bilinear structure models consisting linear combinations of score and loading matrices.

$$\begin{aligned} \boldsymbol{\Phi} &= \mathbf{T}\mathbf{P}^{\mathrm{T}} + \mathbf{E} \\ \mathbf{Y} &= \mathbf{U}\mathbf{Q}^{\mathrm{T}} + \mathbf{F} \end{aligned} \tag{2}$$

where $\mathbf{T}$ and $\mathbf{U}$ are the orthogonal score matrices (i.e. latent projection of $\boldsymbol{\Phi}$ and $\mathbf{Y}$ respectively), $\mathbf{P}$ and $\mathbf{Q}$ are the loading matrices, and $\mathbf{E}$ and $\mathbf{F}$ are residual matrices (i.e. the unexplained parts of $\boldsymbol{\Phi}$ and $\mathbf{Y}$ respectively). The classical PLS method assumes that a linear inner relation between the scores exists (i.e. $\mathbf{U}=\mathbf{TD}+\mathbf{H}$, where $\mathbf{D}$ is the diagonal matrix of regression coefficients and $\mathbf{H}$ denotes the matrix of residual that results from the linear inner relation mapping). The present polynomial PLSR combines the linear inner relation with (1). Replacing $\mathbf{U}$ by predictor $\mathbf{TD}$ gives the PLSR model.

$$\mathbf{Y} = \boldsymbol{\Phi}\mathbf{W}\left(\mathbf{P}^{\mathrm{T}}\mathbf{W}\right)^{-1}\mathbf{D}\mathbf{Q}^{\mathrm{T}} + \mathbf{F}^* \tag{3}$$

in which $\mathbf{W}$ is an orthogonal weight matrix [16] and $\mathbf{F}^*=\mathbf{H}\mathbf{Q}^{\mathrm{T}}+\mathbf{F}$ (assumes $\mathbf{E}$ is negligible) is the combined residuals from the PLS decomposition and the inner relation mapping. To determine the parameter matrices ($\mathbf{W}$, $\mathbf{P}$, $\mathbf{D}$ and $\mathbf{Q}$) from the training data, the non-linear iterative partial least squares (NIPALS) algorithm [17] was employed. Following this, given a new set of input data $\mathbf{X}$, the corresponding output $\mathbf{Y}$ can be predicted.

### C. *Cross-Validation and rank optimization*

Theoretically, for linear input-output systems, or for meta-model that is suitably extended to handle nonlinearities, a perfect prediction of the model's outputs $\mathbf{Y}$ from its inputs $\mathbf{X}$ should be possible, since the $\mathbf{X}$ data and $\mathbf{Y}$ data are error free (apart from algorithmic problems such as inadequate convergence, round-off errors etc.). However, the problem is, if the statistical estimation process has estimated too many independent surrogate parameters, compared to the information content of the available training data, over-fitting

(due to over-parameterization) may arise. This means that small irrelevant variations in the input-output relationship are built into the model, whereby its predictive ability deteriorates.

One of the main advantages of PLSR is that its rank can be managed via removing insignificant scores from the model. To determine the optimal rank, and hence reducing the possibility of over-parameterization, a four-fold cross-validation was used [12]. The optimal rank was chosen as the rank with highest predictive ability in **Y**. In the present study, a model with rank of 153 (i.e. the first 153 scores) was employed. If future tests reveal that the model is over-fitted and gives inadequate predictions in some parts of the parameter space, the PLSR model may then be improved with better nonlinearity handling and a new cross-validation study.

Once the fast PLSR meta-model has been established, it replaces the original biomechanical model in a conventional iterative data fitting process [18] to estimate the model parameters **X** that give the empirically determined output **Y**.

## III. Results

The experimental data for the analysis were obtained using the Mephisto® EX-PRO structured-light scanner (http://www.4ddynamics.com). Using this scanner, surface data of six key facial expressions were obtained (Fig. 3a). The average CPU time for computing a forward solution (input to output) using the described PSLR surrogate was approximately 100ms (On a standard quad-core 2.4GHz computer). As an error measure, the structured-light scanned data were projected onto the surface of the surrogate-deformed mesh. This metric was subsequently used in an iterative nonlinear optimizer which minimizes the RMS projection error. Table I summarizes the optimized muscle activation parameters. The converged RMS errors were 0.56mm, 0.69mm, 0.86mm, 0.94mm, 1.24mm and 1.39mm for smiling with eyes closed, smiling with mouth opened, sad, terror, pain and crying expressions respectively. The deformed configuration for each expression is depicted in Fig. 3b.

## IV. Conclusion & Discussion

The CPU time for computing a forward simulation using the surrogate model (100ms) was a significant speedup compared to the original biomechanical model, which takes an average of 2 hours per solution. As a result of this speedup, it became viable to apply the system to estimate muscle activation parameters from structured-light scanned surface data, which required multiple iterative forward solves. Following from this, the estimated muscle activation values can be associated with facial electromyographic (EMG) signal with a variety of applications, such as measuring emotional reaction for market research [19] and human-computer interactions [20].

Nevertheless, unlike facial EMG signal, the estimation of activation parameters from the surrogate model can be sensitive to a number of factors such as the noise in the scanned data, the initial registration of the data cloud to the mesh, and the simplifying assumptions of the underlying biomechanical model. Some of these factors can be addressed by incorporating experimental data on the trajectory path of the skin material points (e.g. with motion capturing technology), and to improve accuracy of the underlying biomechanical model. These improvements are the current direction of our research.


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TABLE I. Estimated muscle activation values.

| Muscle list | Expressions | | | | | |
|---|---|---|---|---|---|---|
| | *Smiling (eyes closed)* | *Smiling (mouth opened)* | *Sad* | *Terror* | *Pain* | *Crying* |
| Buccinator | 0.84 | 0.08 | 0.00 | 0.00 | 0.63 | 0.11 |
| Corrugator supercilii | 0.12 | 0.01 | 1.00 | 0.20 | 0.70 | 0.85 |
| Depressor anguli oris | 0.00 | 0.04 | 1.00 | 1.00 | 0.23 | 1.00 |
| Depressor labii inferioris | 0.00 | 0.26 | 0.00 | 0.99 | 0.00 | 0.01 |
| Depressor supercilii | 0.02 | 0.00 | 0.00 | 0.00 | 1.00 | 0.64 |
| Frontalis | 0.00 | 0.03 | 0.14 | 0.27 | 0.00 | 0.00 |
| Levator anguli oris | 0.18 | 1.00 | 0.00 | 0.04 | 1.00 | 0.55 |
| Levator labii superioris | 0.08 | 0.16 | 0.01 | 0.01 | 0.28 | 0.91 |
| Levator labii superioris alaeque nasi | 0.00 | 0.21 | 0.00 | 0.00 | 0.00 | 1.00 |
| Mentalis | 0.08 | 0.00 | 0.22 | 0.01 | 0.20 | 0.06 |
| Orbicularis oculi (orbital part) | 0.04 | 0.05 | 0.04 | 0.00 | 0.99 | 0.99 |
| Orbicularis oculi (palpebral part) | 0.28 | 0.00 | 0.00 | 0.00 | 0.13 | 0.10 |
| Orbicularis oris | 0.00 | 0.00 | 0.21 | 0.00 | 0.01 | 0.00 |
| Platysma | 0.00 | 0.04 | 0.31 | 1.00 | 0.49 | 1.00 |
| Procerus | 0.00 | 0.00 | 0.20 | 0.00 | 0.23 | 0.45 |
| Risorius | 0.10 | 0.01 | 1.00 | 0.88 | 0.29 | 0.16 |
| Zygomaticus major | 1.00 | 1.00 | 0.00 | 0.00 | 0.39 | 0.41 |
| Zygomaticus minor | 0.39 | 0.52 | 0.00 | 0.00 | 1.00 | 1.00 |

* The muscle activation values are normalized between 0 and 1.

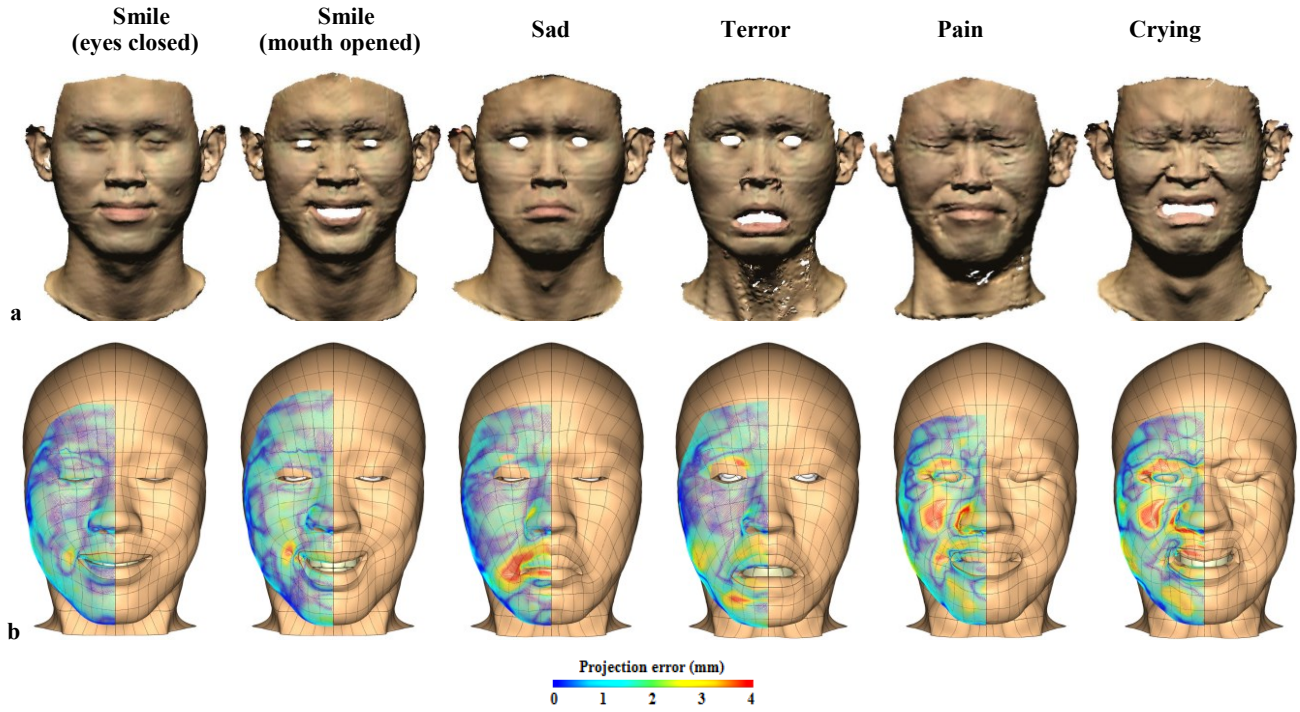


Figure 3. Optimization of muscle activation pattern, showing (a) 3-D surface data of facial expressions obtained from structured-light scanner, and (b) the surrogate-based simulations of corresponding expressions with the optimized muscle activation. The 3-D surface data are projected onto the deformed mesh displaying the Euclidean distance of the projections.

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