Author(s) Rantanen, Ville; Venesvirta, Hanna; Spakov, Oleg; Verho, Jarmo; Vetek, Akos; Surakka, Veikko; Lekkala, Jukka

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Capacitive Measurement of Facial Activity Intensity

Ville Rantanen, *Student Member, IEEE,* Hanna Venesvirta, Oleg Špakov, Jarmo Verho, Akos Vetek, Veikko Surakka, and Jukka Lekkala

***Abstract*—The measurement of the intensity of facial muscle activity can be used in several applications such as human–computer interaction and behavioural science. A new method for the intensity measurement is presented. It is based on a contactless, capacitive measurement of the movements that the facial activity produces. The muscles responsible for raising the eyebrows, lowering the eyebrows, raising the mouth corners, and pulling down the mouth corners were measured simultaneously with the capacitive method and electromyography (EMG) during controlled experiments. Each muscle was activated by 10 participants at three different intensity levels (low, medium, and high), 10 repetitions at each level. The capacitive intensity values were in good agreement with the ones registered with the EMG: average mean absolute errors were between 7–12% of the observed intensity range. However, compared to the EMG, the capacitive intensity values were noticed to have offsets that may be partly caused by the measurement itself and partly by the EMG reference. As a result, the measurement may require a calibration for more intensity values than just the maximum. In the case of the capacitive method it is also required to distinguish between the muscle activations originating from the same facial regions to determine which activation is taking place. This was done with an almost perfect performance by using hierarchical clustering to cluster the intensity values.**

***Index Terms*—capacitive measurement, distance measurement, electromyography (EMG), facial activity measurement, muscle activation intensity measurement**

I. INTRODUCTION

THE human facial activity can be a source of a vast amount of information. Both voluntary and spontaneous activity can be registered. Applications for the measurement of voluntary facial activity includes human–computer and human–technology interaction where it can be used as control signals [1], [2], [3], [4], [5], [6]. Spontaneous activity, on the other hand, can provide invaluable information for example for behavioural science and medicine [7], [8], [9], [10], [11], [12]. While detecting the facial activations correctly may be sufficient in some applications, distinguishing between different intensity levels of the activity can provide additional value in others.

One method to measure facial activity is surface electromyography (EMG) that measures the electrical activity of the muscles and the intensity of the activity. EMG has a high temporal resolution which makes it good for the measurement of spontaneous activity that has a rapid onset and a short duration [9]. A notable benefit of the EMG is that the processing of the signals to find out the activation intensities is simple and computationally efficient [13], [14, ch. 5]. Another advantage is the possibility to detect facial activity when it is not even visible [9].

The major drawbacks of the EMG are caused by the requirement to physically attach the electrodes to the face. The preparation of the electrode sites includes cleaning and abrasion of the skin, and the application of electrode paste to achieve good electrical contact [13]. The electrodes are mildly intrusive and may inhibit movements [9]. Further, the measured spontaneous behaviour may be altered when the person becomes self-conscious about the attached electrodes [9], [13]. The measurement may also be affected by loosening of the electrodes caused by facial movements [9]. Due to the space requirement of the electrodes and the electrode leads, the number of measurable channels is limited [9]. Even if EMG is used to measure the activation intensities of single muscles, its specificity is considered to be low [9]. It suffers from crosstalk which means that the activity of neighbouring muscles and muscles whose fibres interweave with those of the target muscle are also measured [9], [13]. Some variation in the placement of the electrodes between experiments is also always present despite the guidelines of the measurement locations for different muscles [11].

A second option to measure facial activity consists of vision-based methods. Probably the most comprehensive one is Facial Action Coding System (FACS) that describes facial activity based on all the movements that the human anatomy allows [9], [15], [16]. Each possible movement caused by a single muscle or a few muscles is called an action unit. The latest version of FACS includes a 6-point scale for the intensity of the action units from not visible to extreme [16]. Originally FACS included manual coding of the facial activity by an expert that viewed slow-motion video recordings of the face [15], [16]. More recently, automated methods that rely on machine vision have been developed to carry out the coding [8], [9], [11], [12]. In addition to automatically recognising the activity, there are studies where the intensity information has been extracted for some action units such as the ones

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V. Rantanen, J. Verho, and J. Lekkala are with the Sensor Technology and Biomeasurements, Department of Automation Science and Engineering, Tampere University of Technology, Tampere, Finland (email: ville.rantanen@tut.fi, jarmo.verho@tut.fi, jukka.lekkala@tut.fi).

H. Venesvirta, O. Špakov, and V. Surakka are with the Research Group for Emotions, Sociality, and Computing, Tampere Unit for Computer-Human Interaction, School of Information Sciences, University of Tampere, Tampere, Finland (email: hanna.venesvirta@uta.fi, oleg.spakov@uta.fi, veikko.surakka@uta.fi).

A. Vetek is with the Media Technologies Laboratory, Nokia Research Center, Espoo, Finland (email: akos.vetek@nokia.com).

responsible for smiling [9], [17], [18]. In a more recent study, the intensity information was obtained and reported for 15 action units but its accuracy was not evaluated [12]. Nevertheless, the intensity information provided by FACS is highly similar to the one by the EMG, and a high correlation ($r = 0.85$) between the two have been reported when using manual coding [9].

The drawbacks of automated measurement of facial activity with machine vision methods are mainly caused by the computational requirements. The general workflow of the image processing includes preprocessing, face detection and feature extraction to find tracked features, image alignment to compensate for the pose and the camera locations, and action unit recognition [8], [9], [12]. Other drawbacks are introduced by the cameras. The measurement is susceptible to environmental lighting conditions, and it requires the user to be relatively still as it relies on remotely placed cameras.

A third option to measure facial activity is a capacitive method that applies a contactless measurement of the movement of the facial tissue [5]. The measurement electrodes for the capacitive measurement need to be supported close to the targeted facial tissue to register the movements [5]. The measurement can be integrated to wearable devices, and it has mostly been used as a simple detector of the facial activity [6], [19], [20], [21]. These studies only measured a few channels with electrodes on fixed locations on eyeglass-like prototypes. The signal processing for the detection was done with a computationally efficient algorithm [5], [19]. Later, the number of channels have been increased to 22 with a prototype device that had the electrodes mounted on adjustable extensions on a headset [22]. The prototype was used to locate simple facial movements to correct facial regions based on a multichannel measurement with a wearable prototype device and principal component analysis of the data [22].

The drawbacks of the capacitive method have not been extensively reported because it has mostly been used as a simple detector. However, the measurement has been mentioned to be slightly sensitive to the movement of the measurement device on the head and that this movement cannot necessarily be distinguished from the one of the targeted facial tissue [22].

Based on the discussed properties of the facial activity measurement methods, the capacitive method has advantages compared to EMG and vision-based ones. Compared to EMG, the number of channels that can be measured simultaneously is larger. The capacitive measurement is contactless, and, thus, more comfortable than EMG, and it does not inhibit the targeted movements. The lack of physical contact to the face may also introduce less self-conscious behaviour when measuring spontaneous activity [13] even though the measurement is not completely unintrusive. Compared to automatic vision-based methods, the computational requirements are lighter, the measurement is not susceptible to changes in environmental lighting conditions, and it is usable in mobile applications.

The goal of this study was to evaluate the capacitive facial activity measurement as a new method to determine the activity intensity. A wearable prototype device was used to measure facial activity with a multichannel capacitive measurement. Simultaneous EMG measurements were carried out to obtain reference values for the intensities. Experiments were conducted to collect data from activations of the muscles *Frontalis* (that raises the eyebrows), *Corrugator supercilii* (that lowers the eyebrows), *Zygomaticus major* (that raises the mouth corners), and *Triangularis* (aka *Depressor anguli oris* that pulls the mouth corners down). Data was analysed to evaluate the performance of the capacitive intensity measurement relative to the EMG measurement. Further, because a single capacitive channel cannot be expected to only respond to the activity of a specific muscle, hierarchical clustering with the Ward's method was used to distinguish between the muscle activations that originated from the different muscles at the same facial regions.

II. METHODS

A. Capacitive Measurement of Facial Activity

The used method for measuring the intensity of facial activity is based on the capacitive measurement of facial movements. It can be considered a distance measurement between a measurement electrode and the facial tissue [5], [22]. The measurement has the same principle as capacitive push buttons and touchpads, and a single channel requires only a single electrode. The electrode produces an electric field that is used to measure the movement of conducting objects in its proximity by measuring the capacitance due to the capacitive coupling between the electrode and the object.

B. Capacitance Measurement Equipment

The capacitance measurement in this study is carried out with a programmable controller for capacitance touch sensors (AD7147 by Analog Devices) that applies a multichannel measurement. The same controller and its older version (AD7142) have been used for the task before [5], [19], [22]. A controller (AD7143) from the same product range has also been used for a distance measurement in automotive applications [23]. The controllers AD7142 and AD7143 measure the capacitances between a transmitter electrode and receiver electrodes, but AD7147 operates in a single-electrode mode that uses only one electrode in the measurement [24]. The measurement range of the controller is reported to be ± 8 pF with a femtofarad resolution [24]. An excitation signal at 250 kHz charges a measurement electrode, and a sigma-delta (Σ-Δ) modulator continuously samples the flowing charge that changes due to the capacitive coupling between the electrode and the measurement target [24]. Further, the controller produces an active shield signal that can be used to shield the sensor traces to avoid stray capacitances. The shield has the same waveform as the excitation signal, and, thus, the capacitance between the electrodes and the shield does not affect the measured capacitances [24]. The combination of shielding the electrodes and their traces and using the sigma-delta modulation effectively eliminates noise and other interferences and makes the measurement of very low capacitance values possible.

C. Prototype Device

The wireless, head-mounted prototype device is seen in Fig. 1. The construction of the prototype follows that of acoustic hearing protectors. The wearability, weight, and comfortability are on a par with those of the protectors. The prototype earmuffs include the electronics and the extensions in front of the face house the electrodes for the capacitive measurement. There are a total of 22 channels for the measurement: 11 for each side of the face. The electrodes used in the measurement are printed circuit board pieces with a size of 12 x 20 mm. The pieces are double sided and their backplanes are connected to the shield signal of the AD7147 controller. Thin coaxial cables are used to shield the sensor traces by connecting also the cable sheaths to the shield signal. Two controllers are used, one for each side of the face. The sampling frequency of the capacitance measurement is limited by the number of measured channels and was 29 Hz in this case.

The device also measures EMG signals as a bipolar measurement without a separate grounding electrode. It is done with basic three-amplifier instrumentation amplifiers that have antialiasing filters with a cut-off frequency of 150 Hz. The signals were sampled at 435 Hz. Since the content of the EMG is known to mostly reside between 10 and 200 Hz [13], the measurement registers most of the EMG activity. The wires to the EMG electrodes are coaxial wires that shield the signals with a constant potential.

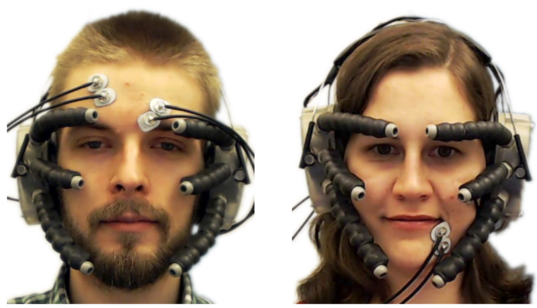
The wireless operation of the device is achieved with a Li-ion battery and a Bluetooth module (RN-41 by Roving Networks). The device also has additional functionality such as inertial measurements that were not used in this study. The operation of the device is handled by a microcontroller (ATMega168P by Atmel).

Figure 1. The head-mounted measurement device. The numbers represent the different measurement channels on the extensions. The electrodes are at the numbered locations facing the face.

D. Experiments

Twenty successful trials to collect data were carried out by voluntary participants. Ten trials included *Frontalis* and *Corrugator supercilii* activations and ten included *Zygomaticus major* and *Triangularis* activations. Each muscle was activated at three intensity levels: low, medium, and high. The number of participants was 14 (8 female and 6 male, ages 19–44, mean age 32), and 6 of them carried out both the upper face and the lower face trials. The selection of the participants was not strictly controlled. The only requirements were their willingness, necessary skills in carrying out the voluntary muscle activations, and sufficient eyesight to see onscreen information during the trials.

The experimental procedure was started by asking the participant a written consent to use the collected data, and explaining how the trial proceeds. The facial skin was prepared for the attachment of the EMG electrodes to proper locations for the measurement of the target muscles of that trial. The attachment was done according to the guidelines provided in [13]. The electrodes for the capacitance measurements were adjusted to be approximately at a distance of 1 cm from the face when the facial expression was neutral. The top extension channels targeted the eyebrows, the middle ones the cheek bone areas, and the bottom ones the mouth corner and the jaw areas. Since the EMG electrodes disturb the capacitance measurements, the capacitances were measured from the right side of the face and the EMG signals from the muscles on the left side of the face. The only exception was the *Frontalis* muscle for which the standard measurement location for EMG is on the forehead so that it could also be measured from the right side of the face. Fig. 2 shows the device on participants during the trials.



(a) Upper face trials: *Frontalis* and *Corrugator supercilii* measurements

(b) Lower face trials: *Zygomaticus major* and *Triangularis* measurements

Figure 2. The device on participants during the trials.

After setting up the device, the maximum EMG intensity levels, i.e. maximum voluntary contraction levels, were determined. The average of 5 EMG intensity peak maxima during maximum voluntary contractions was considered as the maximum level. At the same time, the experimenter verified that the muscle activations were carried out without excessive activation of other muscles than the target muscle. The target intensity levels during the actual trial were defined as percentages of the determined maximum. The low level was considered to be 20-40%, the medium 40-60%, and the high 60-80%. The upper limit of the high level was selected to be less than 100% because the maximum voluntary contraction cannot be expected to be easily produced multiple times. Before the actual trial was started, the participant was allowed to try activating the muscles and holding the activations at the target levels in a short practice session.

In the actual trial, the participant activated the muscles according to instructions given as synthesized speech. Each instruction stated the activation and the target intensity. Then a beep sound was played to indicate that the activation task started. A vertical bar whose height indicated the current activation intensity was shown to the participant, and the target level was highlighted as shown in Fig. 3. After the participant had held the muscle activation in the target level for 2 seconds, another beep sound was played to indicate the successful completion of the task. Participants were given 10 seconds for completing each task, and between tasks they were instructed to relax for 5 seconds. Ten repetitions of each of the three intensities of the two target muscles of that trial were performed in randomized order. This resulted in a total length of 20 minutes for the trial.

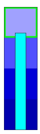


Figure 3. The visual feedback of the EMG activation intensity that was shown to the participant during the experiments. The different background colors show the different intensities (none, low, medium, and high), the cyan vertical bar shows the current level, and the green highlighting shows the target level of the task.

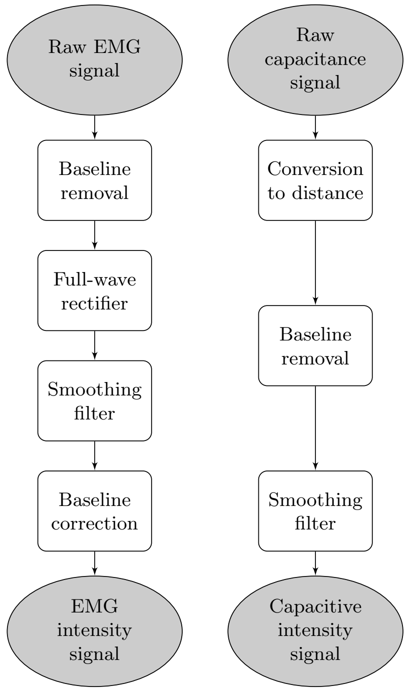


Figure 4. Block diagram presentation of the signal processing of the EMG and capacitance signals.

E. Signal Processing

The signal processing for converting raw signals to signals that represent the intensity of facial movements is shown in Fig. 4. Examples of the signal processing are shown in Fig. 5.

1) EMG Signal Processing:

a) Baseline removal: The raw EMG signals were input to a single-pole high-pass filter with a time constant of 35 ms for removing their baselines. In the offline analysis this filter was applied as a zero-phase forward and reverse filter.

b) Full-wave rectifier: The signals after the baseline removal were fed to a full-wave rectifier.

c) Smoothing filter: A smoothing filter was used to convert the rectified signals to intensity signals. A 500 ms moving root mean square (RMS) filter was used for the task in the offline analysis, but the online filter that was applied during the trials was a single-pole low-pass filter with a time constant of 500 ms. Computational efficiency was desired for the online use and better smoothing and more accurate EMG amplitude estimation for the offline one. Either the average rectified value or the RMS value are considered to be good estimates for the true EMG amplitude [14, ch. 5].

d) Baseline correction: The effect of the noise on the EMG intensity signal was decreased by carrying out a baseline correction for the smoothed signal. A moving window minimum filter with a window length of 15 s was used for the task. It took the minimum value of each window, and further applied a 10 s moving average filter to the solved baseline before subtracting it from the smoothed signal. The length of the window for the minimum filter was determined based on the fact that participants had 10 s of time to carry out each activation task. Baseline correction was not done in the online processing which may cause small differences between the EMG intensity levels that were registered online and the ones that were solved offline.

2) Capacitance Signal Processing:

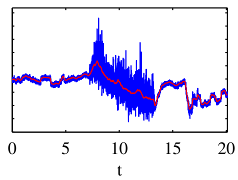
a) Conversion to distance: The raw capacitance signals were converted to distance signals, or, more precisely, to signals that were proportional to the distance between the facial tissue and the measurement electrode. The capacitance of each channel was modelled with the equation for a parallel-plate capacitor:

$$C = \frac{\epsilon A}{d}, \tag{1}$$

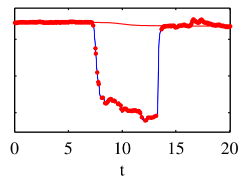
where ϵ is the permittivity of the substance between the capacitor plates, A the plate area, and d the distance between the plates. One plate of the capacitor is the measurement electrode and the other the facial tissue facing the electrode. The measure proportional to the distance becomes

$$d_p = \frac{1}{C} = \frac{1}{C_s - C_b}, \tag{2}$$

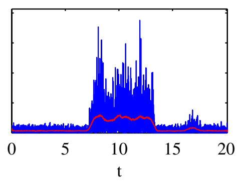
where C_s is the value of the capacitance sample and C_b is the base level of the capacitance channel. The subtraction of



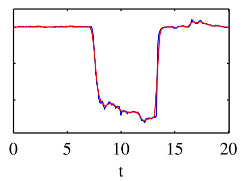
(a) EMG signal baseline removal: blue is the signal and red its baseline.



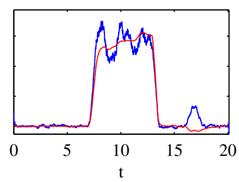
(b) Capacitive signal baseline removal: blue is the signal, red dots the baseline candidates, and red line the baseline.



(c) EMG signal smoothing: blue is the rectified signal and red the smoothed signal.



(d) Capacitive signal smoothing: blue is the signal and red the smoothed signal.



(e) Smoothed EMG and capacitive signals: blue is the EMG and red the capacitance. Capacitive signal y-axis is reversed, and the signals are normalised and aligned for the illustration.

Figure 5. Examples of the signal processing.

the base level is required because the channels have unique offsets that are affected by their electrical connections and surroundings of their electrodes. The base levels were measured when the measurement electrodes were directed away from conducting objects.

b) Baseline removal: To further convert the distance signals to indicate relative changes in the distance, baseline removal was carried out. The signals may have stepwise changes and drift due to small movements of the device on the head, and a slow drift has occasionally also been observed to be introduced in the measurement electronics. A median filter was chosen to find the baseline because it follows stepwise changes and the drift well but is unaffected by short-duration peaks that the facial activity often produces. A window length of 30 s was chosen for the filter based on the length of the activation tasks. However, the median filtering was enhanced by not including all the signal samples in it, but selecting only a part of the samples as baseline candidates by applying a constant false alarm rate (CFAR) processor.

The CFAR processor calculates an adaptive threshold based on the noise characteristics of the processed signal [25, ch. 5], [26]. The distance signal was first pre-processed with a differentiator, a single-pole low-pass filter with a time constant of 20 ms, and a full-wave rectifier to be suitable for the CFAR processor. The differentiator and the low-pass filter were implemented as a single zero-phase forward and reverse filter. The CFAR processor took the current pre-processed sample as a test sample and samples from its both sides as reference samples. Some samples adjacent to the test sample were left out as guard samples to reduce the information overlap between the test and reference samples. Samples within 1 second from the test sample were considered the guard samples and the following 14 seconds the reference samples. The adaptive threshold was calculated as the mean of the reference samples. The mean could be multiplied by a sensitivity parameter, but in this case the parameter was chosen to be 1. The threshold was then used to determine which samples did not exceed it. The corresponding samples of the input distance signal were included in the calculation of the median to solve the baseline value.

The calculated median signal was further smoothed with a 2-second moving average before it was subtracted as the baseline from the distance signal.

c) Smoothing filter: The capacitive intensity signals were calculated with a smoothing filter after the baseline removal. A 500 ms moving average was used for the smoothing.

3) Signal Alignment: The calculated EMG and capacitance intensity signals were aligned in time. This was done because the processing of the signals introduces delays of variable length. To be able to compare the signals, the filtered EMG signals were first downsampled to 29 Hz by taking every 15th sample from them. Then the alignment was done based on the highest cross-correlation between the capacitance channels and the EMG channels, and delaying all the capacitance signals with the corresponding delay.

4) Activation Intensity Calculation: The noise levels of the EMG and capacitance signals are not constant all the time due to different noise sources. EMG suffers from powerline noise and electrode movement artefacts. The noises of the capacitive intensity signals are affected by the exact initial distance of the electrodes to the face. Noise introduces differences in the waveforms of the two intensity signal types. Thus, the EMG and the capacitive intensity signals were not compared directly, but the activation intensity for each channel was chosen to be the mean of the intensity signal during the 2-second interval that the participant held the target intensity. This efficiently removes the effect that noise might have on momentary intensity.

F. Performance of the Capacitive Facial Activity Intensity Measurement

Linear regression was computed for the activation intensities to find out how the capacitive intensity compares to the EMG one. Correlation coefficients and intensity estimation errors of the capacitive channels were calculated for the different muscles. The errors of the capacitive intensity values from a fitted regression line are represented with the mean absolute error (MAE) and the 95th percentile of the absolute error.

The intensities were normalised by dividing the EMG intensities with the maximum intensity value within the trial. The normalised intensity range $[0,1]$ then is the range of intensities that is likely to be encountered. The intensity ranges in this scale become 0.25-0.50 for low, 0.50-0.75 for medium, and 0.75-1.00 for high. The capacitive values were normalised by mapping the normalised EMG intensities $[0,1]$ to $[C_0, C_0+1]$ by using the regression equations of the channels.

The capacitive intensity value C_0 at the EMG intensity 0 is an offset that each capacitive channel has. The offset indicates how small intensities can be registered with the capacitive measurement. The offset values were normalised by multiplying them by the signs of the correlation coefficients because their interpretation would otherwise depend on the signs. A negative normalised offset represents the activation intensity level that is required for the activation to produce visible changes in the capacitively measured intensity. A positive offset on the other hand means that small changes are easily distinguishable from the signal. However, it should be noted that EMG crosstalk also affects the observed offsets.

In the comparison of the intensity values, the capacitive intensity needs to be represented based on the multichannel data. A single capacitance channel per muscle was chosen as an indicator of the activation intensity. The channel with the best average regression coefficient during the tasks of a muscle was selected to represent the intensity of that muscle.

G. Distinguishing Activations of Different Muscles from the Capacitance Data

The capacitance intensity signals are produced by the movement of the facial tissue. The same measurement channel can respond to the activation of different muscles. Thus, the activations need to be distinguished from one another to know which muscle's activation intensity is represented by the registered capacitance at any given time. To estimate how well the two movements of each trial could be distinguished from one another, the solved activation intensities (the means during the 2-second intervals) were clustered. The face was divided into two regions for the clustering. Only the intensities of the capacitance signals from the top extensions were included when doing the clustering for the upper face trials, and both middle and bottom extensions when doing the clustering for the lower face trials.

Hierarchical clustering was chosen to always have the same results for the same set of data. The linkage of the clustering was done with the Ward's method that forms clusters by minimising the increase in the total within-cluster variance about the cluster centre [27], [28]. A fixed number of 9 clusters were formed. The number was selected based on what the data was expected to be. Each trial had 6 different events, i.e. 2 movements and 3 intensities. In addition, the movements of the face cannot be expected to always be the same when performing repetitions of the same activation, and the data for the different intensities of the same muscle can be expected to be elongated to a certain direction. Ward's method is not good at handling elongated clusters and outliers [28], and, thus, 3 additional clusters were included to account for possible spread in the data.

The performance of distinguishing the activations from one another was calculated for each muscle. It was chosen to be presented with the percentages of the activations that were clustered to clusters specific to the muscle in question. A cluster was considered to be specific to a certain muscle when majority of activations clustered to it were from that muscle.

H. Visual Inspection

Visual inspection of videos of the participants recorded during the trials was carried to support the analysis of the data. Essential information that affected the results was logged during the inspection. This included information if the participants carried out the movements as instructed, about the symmetry of the movements, and about the fit and placement of the device on the head. Unusually small movements even with the highest activation intensities were also noted.

III. Results

The percentages of successfully performed muscle activation tasks in the trials are shown in Table I. Since the maximum number of successful tasks was 10 for each intensity, one task corresponds to 10%. Percentages for single participants are always higher than 70% because otherwise the trial was considered unsuccessful and discarded from the analysis. The amount of such trials was four for upper face trials and two for lower face ones.

Table I
THE MEANS AND STANDARD DEVIATIONS OF THE PERCENTAGES OF SUCCESSFULLY PERFORMED MUSCLE ACTIVATION TASKS IN THE TRIALS.

	Contraction intensity		
	Low	Medium	High
Frontalis	99.0 ± 3.2	100.0 ± 0.0	94.0 ± 10.7
Corrugator supercilii	99.0 ± 3.2	100.0 ± 0.0	98.0 ± 4.2
Zygomaticus major	100.0 ± 0.0	99.0 ± 3.2	96.0 ± 9.7
Triangularis	100.0 ± 0.0	98.0 ± 4.2	87.0 ± 13.4

A. Performance of the Capacitive Facial Activity Intensity Measurement

Fig. 6 shows an example of the linear regression for the solved activation intensities. The figure shows how the relationship between the capacitive and EMG intensities can be approximated to be linear within the range of the observed intensities.

The results of the performance estimation are shown in Table II. The locations of the channels are shown in Fig. 1.

The capacitive intensity measurements of the *Frontalis* muscle have strong correlations (absolute values > 0.8) with the EMG measurement with all the participants. The correlations of the *Corrugator supercilii* intensity measurement are strong with 7 out of the 8 participants that were not considered outliers. The *Zygomaticus major* measurements have a strong correlation with all the 7 participants that are not considered outliers. The correlations in the *Triangularis* measurements are strong with 3 out of the 6 participants that were not considered outliers.

While none of the participants were considered outliers in the *Frontalis* tasks, two were considered such in the *Corrugator supercilii* tasks. Participant 2 had simultaneous activation

Table II
THE PERFORMANCE OF THE CAPACITIVE INTENSITY MEASUREMENT. PARTICIPANTS 1 TO 6 WERE THE SAME IN BOTH THE UPPER AND THE LOWER FACE TRIALS. THE LETTERS U AND L REFER TO PARTICIPANTS THAT CARRIED OUT ONLY EITHER THE UPPER OR THE LOWER FACE TRIALS, RESPECTIVELY. PARTICIPANTS CONSIDERED AS OUTLIERS ARE MARKED WITH AN ASTERISK. CORRELATION COEFFICIENT r BETWEEN THE EMG AND CAPACITIVE INTENSITY SIGNALS, CAPACITIVE OFFSET $C_0 \cdot \mathrm{sgn}(r)$ THAT IS INDEPENDENT OF THE SIGN OF THE CORRELATION COEFFICIENT, MEAN ABSOLUTE ERROR (MAE), AND 95TH PERCENTILE P_{95} OF THE ABSOLUTE ERROR ARE SHOWN. DUE TO THE NORMALISATION, THE ERRORS ARE PROPORTIONS OF THE EFFECTIVE MEASUREMENT RANGE, AND THE OFFSET IS ALSO RELATIVE TO THE RANGE. THE MEANS AND STANDARD DEVIATIONS ARE CALCULATED WITHOUT THE OUTLIERS, AND IN THE CASE OF THE CORRELATION COEFFICIENT FROM THE ABSOLUTE VALUE.

Part.	r	$C_0 \cdot \mathrm{sgn}(r)$	MAE	P_{95}
1	0.96	-0.04	0.06	0.13
2	0.83	-0.29	0.09	0.19
3	0.97	-0.02	0.06	0.12
4	0.94	0.12	0.07	0.20
5	0.96	-0.01	0.07	0.17
6	0.92	-0.54	0.09	0.26
7u	0.95	-0.02	0.07	0.21
8u	0.95	-0.15	0.06	0.15
9u	0.95	0.12	0.07	0.15
10u	0.96	-0.39	0.04	0.11
Mean	0.94 ± 0.04	-0.12 ± 0.22	0.07 ± 0.01	0.17 ± 0.04

(a) *Frontalis* from the channel top right 2

Part.	r	$C_0 \cdot \mathrm{sgn}(r)$	MAE	P_{95}
1	0.96	-0.28	0.05	0.11
2 *	0.85	-0.11	0.11	0.35
3	0.88	-0.30	0.08	0.19
4	-0.78	-0.10	0.12	0.40
5 *	0.57	-0.09	0.31	0.64
6	0.96	-0.14	0.06	0.12
7u	0.94	-0.21	0.07	0.14
8u	0.90	0.23	0.10	0.23
9u	0.96	-0.04	0.05	0.14
10u	0.94	-0.11	0.06	0.17
Mean	0.92 ± 0.06	-0.12 ± 0.17	0.07 ± 0.02	0.19 ± 0.10

(b) *Corrugator supercilii* from the channel top right 2

Part.	r	$C_0 \cdot \mathrm{sgn}(r)$	MAE	P_{95}
1	-0.94	0.20	0.07	0.16
2 *	-0.74	0.60	0.19	0.53
3	-0.96	0.70	0.05	0.13
4	-0.90	0.44	0.12	0.24
5	-0.91	-0.03	0.08	0.17
6	-0.90	0.03	0.11	0.22
7l	-0.85	0.03	0.12	0.32
8l *	-0.74	-0.45	0.18	0.35
9l	-0.96	-0.26	0.06	0.14
10l*	-0.33	15.08	0.50	1.11
Mean	0.92 ± 0.04	0.16 ± 0.32	0.09 ± 0.03	0.20 ± 0.07

(c) *Zygomaticus major* from the channel middle right 1

Part.	r	$C_0 \cdot \mathrm{sgn}(r)$	MAE	P_{95}
1	-0.76	-0.26	0.15	0.34
2 *	0.23	-0.81	0.64	1.59
3	-0.83	0.90	0.09	0.24
4 *	-0.05	-10.58	3.30	8.94
5	-0.90	0.34	0.09	0.20
6	-0.88	-0.04	0.09	0.29
7l	-0.91	0.29	0.08	0.16
8l *	0.71	0.19	0.18	0.38
9l *	-0.05	20.26	3.70	7.78
10l	-0.65	0.08	0.20	0.54
Mean	0.82 ± 0.10	0.22 ± 0.40	0.12 ± 0.05	0.29 ± 0.13

(d) *Triangularis* from the channel bottom right 2

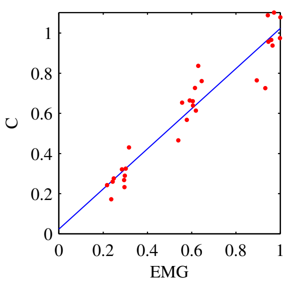


Figure 6. An example of the relationship between the EMG and the capacitive intensity values with the measured activation intensities from a single participant. The EMG has been normalized to the range [0,1] and the corresponding capacitive values to the range [C_o,C_o+1].

of the *Frontalis* in the tasks. With participant 5, the problem was the fit of the device: the extensions could not reach the *Corrugator supercilii* area to register its movements. In the *Zygomaticus major* tasks, three participants were considered outliers. Participant 2 made several of the activations asymmetrically. Participant 8l activated the *Triangularis* simultaneously with the target muscle. For participant 10l, the fit of the device was also so that the middle extensions could not reach in front of the cheek bone region well enough to register the movements the same way as with other participants. In the *Triangularis* tasks, participant 2 was considered an outlier due to simultaneous activation of *Zygomaticus major*. Participant 4 made only *Zygomaticus major* activations even during *Triangularis* tasks. With participant 8l, the movement was the same as in the *Zygomaticus major* tasks, i.e. both the muscles of the trial activated. Participant 9l had asymmetries in the movements, especially at the stronger intensities.

It was also observed that the movement range of the activations was really small with participants 1 and 10l even during the maximum activation intensities of the *Triangularis*. However, this was not considered to fulfil the set outlier criteria.

B. Distinguishing Activations of Different Muscles from the Capacitance Data

The results of distinguishing the activations of different muscles from one another are shown in Table III. The participants that could not activate the muscles of the trial separately as instructed were considered outliers.

IV. DISCUSSION

Generally, the capacitive intensity measurement achieved high correlations with the EMG intensity measurement. The

Table III
THE PERFORMANCE OF DISTINGUISHING THE ACTIVATIONS FROM ONE ANOTHER FOR THE TWO PAIRS OF THE MUSCLE ACTIVATIONS. THE PERCENTAGES OF THE ACTIVATIONS THAT WERE CLUSTERED TO CLUSTERS SPECIFIC TO THE MUSCLE IN QUESTION ARE SHOWN.

Part.	*Front.*	*Corr.*
1	100.0	100.0
2 *	60.0	100.0
3	100.0	100.0
4	100.0	100.0
5	100.0	100.0
6	100.0	93.3
7u	100.0	100.0
8u	96.3	100.0
9u	100.0	100.0
10u	83.3	100.0
Mean	97.7 ± 5.5	99.3 ± 2.2

(a) Upper face trials: *Frontalis* and *Corrugator supercilii*

Part.	*Zyg.*	*Triang.*
1	100.0	100.0
2 *	100.0	96.6
3	100.0	100.0
4 *	37.9	100.0
5	100.0	100.0
6	100.0	100.0
7l	100.0	100.0
8l *	23.3	100.0
9l	100.0	100.0
10l	100.0	100.0
Mean	100.0 ± 0.0	100.0 ± 0.0

(b) Lower face trials: *Zygomaticus major* and *Triangularis*

weakest correlation values were obtained for the *Triangularis* muscle that is difficult to measure with the capacitive method due to the movement that its activation produces. The movement is mostly tangential relative to the surface of the face as opposed to normal that would be more easily detected. Also, very small movement ranges were encountered with some participants. Other issues that affected the calculated correlation values were also encountered. In the case of the *Corrugator supercilii* muscle, the correlation value of participant 4 was not strong and was also of opposite sign compared to the other participants. This was caused by slightly unsuitable positioning of the device on the head. The top extensions were too low for the measurement which caused the movement to be registered differently than with the other participants. The two other correlation values that had an opposite sign compared to the values of other participants were encountered in the *Triangularis* tasks with the outlier participants. In these the reason was that the participants actually contracted the antagonist muscle during the tasks.

Even if the relationship between the capacitive and EMG signals was linear within the range of the measured intensities, the solved capacitive offset values indicated that the range from the background signal level (0) to the minimum measured intensity was not always linear. The magnitudes of the normalised offsets describe the capacitance changes that occur within this range. They should be larger than -0.25 for the measurement to be able to measure the entire range beginning from the EMG intensity value 0.25 that was considered the lower end of the low intensity range. The negative offset values of the *Frontalis* muscle indicated problems in the measurement of that muscle with participants 2, 6, and 10u. An apparent reason for the offsets with participants 2 and 10u could not be pointed out, but the negative values for both were large enough to render the capacitive measurement unusable in the low intensity range. The offset of participant 6 resulted from unexpected changes in the capacitive signals during the activations. Different activation intensities caused the signal to change to different directions. The lowest intensity activations introduced negative intensity values while the medium and high activations caused positive ones. These unexpected changes affected only two of the measured channels: top right 1 and 2. The offsets were better in the *Corrugator supercilii* tasks. Still, two participants had negative offsets close to -0.30 which means that capacitance started to respond to the activation after the intensity was already above the lowest fifth of the defined low intensity range. In the *Zygomaticus major* tasks, the participants not considered outliers all had such offsets that even the low intensity range is measurable. The same applied to the *Triangularis* tasks. However, similar unexpected changes in the signals that were encountered with participant 6 in the *Frontalis* tasks were met with participant 2 in the *Triangularis* tasks. In this case the reason was the activation of the *Zygomaticus major* simultaneously.

The intensity estimation errors as described by the mean absolute error can be considered acceptable with all muscles for most participants that were not considered outliers. MAEs less than or equal to 0.10 on average were obtained for all muscles except the *Triangularis*. The average P_{95} values were less than or equal to 0.20 for all other muscles but the *Triangularis*. In the *Frontalis* tasks, a high value was met with participant 6 who was already noticed to introduce some unusual changes to capacitive signals. In the *Corrugator supercilii* tasks, the very high P_{95} value with participant 4 could be explained with the unsuitable positioning of the device on the head as described earlier. In the *Zygomaticus major* tasks, an evident explanation for the high value with participant 7l could not be given, but the value may have been affected by the positioning of the middle extensions relative to the movements that the *Zygomaticus major* produces with that specific anatomy of the face. Finally, the *Triangularis* had the highest overall P_{95} values that can be considered to result from the already discussed difficulties in measuring its movements.

The observed performance of the capacitive method may be influenced by a few issues that can make the results appear worse than the performance truly is. The noise of the reference EMG measurement may have affected the results. The noise levels varied a bit between the channels and the trials and in some cases even within a trial. The noise characteristics may be such that the simple baseline correction that was done to the EMG intensity signal was not sufficient to correct the effect of the noise. EMG crosstalk may also contribute and especially the observed offsets may be caused by it. The way that the capacitive measurement registers the activity may also affect the observed performance. Some movement of the device in the head may occur during the muscle activations, which changes the way the activations are seen in the signals. Other facial movements than those caused by the target muscle also affect the measurements. Further, the absolute distances of the capacitance measurement electrodes to the face may affect the measurement because the parallel-plate capacitor model that was used in the calculations assumes that the distance is really small compared to the plate area. The conversion of capacitance signals to distance signals further assumes that each capacitance is introduced by the parallel plates. However, the facial tissue is not always clearly a plate.

The capacitive channel to represent the activation intensity of each muscle was chosen based on which channel had the best average correlation. In actual use, this information is not available without measuring the EMG as well, but the channel selection needs to be justified in other ways. The physical positioning of the capacitance channels with respect to the movements that the targeted activations introduce may be used as a basis for it. The channels with the best average correlation correspond with the locations where each muscle activation is seen to cause distinct movements.

The results of distinguishing between the different movements were really good. When the outlier participants were left out from the analysis, only a small number of activations were the cause of the decreased performance. All these ambiguously clustered activations were low-intensity ones. The low-intensity activations of the different muscles are close to each other in the data and may be problematic at times.

An important issue that affects the feasibility of the capacitive measurement method is the adjustment of the electrode locations. It affects how the movements are registered. An expert made the adjustment in this study, and it was noticed that the adjustment could be made easier. The movement ranges of the electrode extensions, currently adjustable with the ball-and-socket joints, could be far less to achieve the necessary adjustability while simplifying proper positioning. Also, a calibration phase could be used to instruct the adjustment of the electrodes to optimal locations.

To measure different intensities, the calibration phase is obligatory for determining the maximum activity levels. The offset should also be calibrated unless further studies show that the offsets observed in this study were mainly caused by the noise and crosstalk related to the EMG reference signals. For distinguishing between different muscle activations in real-time use cases, the calibration phase can be used to collect data to be used for classification. The clustering could be used as a basis for simple classification, for example, by mapping data to clusters formed in the calibration phase based on which cluster centre the data point is closest to. Real classifiers could also be used. These could consider the temporal content of the intensity signals in addition to the current intensity values.

This study revealed that the capacitive method for measuring activation intensity has properties that are very similar to those of the EMG. The correlations between the intensities measured with the two methods were mostly strong. The signals also have a very similar temporal content meaning that the capacitive method should function well in determining the onset and duration of spontaneous facial activity. On the other hand, also the drawbacks of the methods are similar. Both can be considered to suffer from crosstalk. In EMG, it is caused by the electrical activity of surrounding muscles and also by the electrode placement. In the capacitive method, the crosstalk is caused by the facial movements that interfering muscles cause when activated, and also by the possible small movements of the measurement device on the head. The capacitive method also has a similar property as the automated FACS: it requires to determine which muscles are active similarly as FACS needs a classifier to solve the active action units [8], [29], [30], [12].

V. Conclusions

A new capacitive method for measuring the intensity of facial activity was presented. The measurement that has previously been used to detect and locate facial activity was shown to be able to register the activation intensities of the muscles *Frontalis*, *Corrugator supercilii*, *Zygomaticus major*, and *Triangularis*. The intensity estimation errors compared to the EMG were small except for the *Triangularis* muscle. Additionally, the linear relationship between the EMG and the capacitive intensity values was in some cases noticed to have an offset while in the ideal case a zero EMG intensity value should correspond to a zero capacitive value. This might cause difficulties in distinguishing the low intensity activations from the baseline. A more complex calibration procedure may also be necessary because of the offset. However, the distinction between the different facial activations based on the capacitive intensity data appears more straightforward and in this study could be done almost perfectly for all the target muscles.

Future developments of the method should include verification measurements to find out if the noticed offsets of the capacitive intensity measurement were affected by the EMG reference. A calibration phase should be developed to calibrate the measurement for different intensities, and the movements should be classified also in real-time. Calibration could include an automated instruction phase to instruct the user to adjust the electrodes to the desired distance from the face to achieve optimal operation. Finally, a modified implementation of the signal processing algorithms should be made to utilise the intensity information in real-time.

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Ville Rantanen received his M.Sc. degree (2007) in biomedical engineering from the Tampere University of Technology. After that he has carried out postgraduate studies in measurement technology at the same university. His research interests include developing measurement methods and sensors for biomedical applications.

Hanna Venesvirta received her M.Sc. degree (2012) in interactive technology from the University of Tampere. After that she has been working towards her Ph.D in interactive technology at the same university. Her research interests include developing interaction methods for technology mediated nonverbal communication.

Oleg Špakov received his Ph.D. degree (2008) in interactive technologies from the University of Tampere. After that he continued his research in studying and applying eye movements in human-computer interaction at the same university. His research interests include developing gaze-based uni- and multi-modal applications and interaction modeling.

Jarmo Verho is working as a research assistant at the Department of Automation Science and Engineering, Tampere University of Technology. He is specialized in low-noise electronics design and embedded systems. His other research interests include sensor networks, radio networks, short range inductive links, and capacitive sensing techniques.

Akos Vetek is a Principal Researcher at the Media Technologies Laboratory of Nokia Research Center. His research interests include multimodal interaction, intelligent user interfaces, sensors and wearables.

Veikko Surakka PhD is a professor in interactive technology at the University of Tampere, School of Information Sciences. He has MA, Psych. Lic., and doctoral degrees in psychology. He is the head of the Research Group for Emotions, Sociality, and Computing that focuses especially in research on emotions in human-technology interaction.

Jukka Lekkala received his M.Sc. degree in electronics and D.Tech. degree in biomedical engineering from the Tampere University of Technology, Finland, in 1979 and 1984, respectively. Since 1991, he has been a docent of bioelectronics at the University of Oulu, and a docent of biomedical engineering at the Tampere University of Technology. Currently, he is a professor of automation technology at the Tampere University of Technology, Department of Automation Science and Engineering. His research activities include sensors and biosensors, sensor materials, measurement systems, and modelling.