Estimation of Mathematical Anxiety Using Psycho-Physiological Data

Andrej Košir[1], Urban Burnik[1], Janez Zaletelj[1], Samo Jean[1], Peter Janjušević[2] and Gregor Strle[1]

[1]*University of Ljubljana, Faculty of Electrical Engineering, Tržaška 25, SI-1000 Ljubljana, Slovenia*

[2]*The Counselling Centre for Children, Adolescents and Parents Ljubljana, Gotska 18, SI-1000 Ljubljana, Slovenia*

Abstract

This work addresses the question of how to estimate mathematical anxiety from psycho-physiological data in real-time applicable to primary school pupils. Besides establishing machine learning and statistical learning architecture, the intrusion of wearable sensors and the feasibility of test dataset collection are considered. From the psychological aspect, the framework of mathematical anxiety estimation was established within the CoolKids program. It provides an established and verified program of helping pupils with mathematical anxiety and the instruments to estimate mathematical anxiety without technology. As such it also provides the measurement scenario. Measurement and estimation system architecture and an early-stage research design are given only.

Keywords

psycho-physiological signals, mathematical anxiety, sensors, machine learning, social signal processing

1. Introduction

Mathematics anxiety (MA) is described as "a feeling of tension and anxiety that interferes with the manipulation of numbers and the solving of mathematical problems in a wide variety of ordinary life and academic situations." [1].

According to Luttenberger [2], anxiety disorders are some of the most widespread mental health issues worldwide involving nearly 17% of the population. MA is spread across all ages. Studies of the USA population revealed 95% of the population experienced some MA and 17% experienced high levels of anxiety. We were not able to find reliable data on the situation in Central Europe or Slovenia.

An important finding is that the research showed mathematical anxiety is not necessarily linked to lower mathematical abilities and can be caused by numerous other factors as pointed out by Mammarella et. al. [3]. Also, according to Luttenberger [2] math anxiety is different from anxieties in other school subjects or general test anxiety.

MA framework is a complex one and it interacts with environment-related and person-related variables. According to Luttenberger [2], citation "antecedents of MA may be environment-related and include culture, the characteristics of educational systems, as well as parents' and

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andrej.kosir@fe.uni-lj.si (A. Košir); urban.burnik@fe.uni-lj.si (U. Burnik); janez.zaletelj@fe.uni-lj.si (J. Zaletelj); samo.jean@lucami.fe.uni-lj.si (S. Jean); peter.janjusevic@scoms-lj.si (P. Janjušević); gregor.strle@fe.uni-lj.si (G. Strle)

teachers' attitudes toward math and their students and children. Furthermore, antecedents of math anxiety may be person related and include aspects such as trait anxiety or gender". Furthermore, variables that interact reciprocally with math anxiety are self-efficacy, self-concept, and motivation. As a consequence, there is a need for the objective measurement of MA in real time using modern technology.

In this paper, the first step of the mathematical anxiety (MA) measurement and estimation system is given. We present the study design including the measurement procedure and mathematical anxiety ground truth determination. A reliable feasibility study is one of the main goals including sensor intrusion measurement.

2. Related Work

2.1. Mathematical anxiety

A primary interest of this study is to estimate mathematical anxiety (MA) from real-time measurement and to obtain ground truth values best available today. Therefore, models of mathematical anxiety are the first to be examined. There are several models of mathematical anxiety studied, among them, MA as a personality construct, MA as a cognitive construct, MA as a sociocultural construct, and MA as a neuro-biological construct as indicated by Mammarella et. al. [3]. In principle, the cognitive construct led to a ground truth determination instrument and procedure, and the neuro-biological construct led to a psycho-psychological measurement design. Since the ground truth determination instruments and procedures are taken as ready to go from the Cool Kids program, we focus primarily on psycho-physiological sensors and signals, and related machine learning procedures applicable to automatically estimate MA in real-time.

2.2. CoolKids program

The Cool Kids Anxiety Management Program has been developed, designed, and established by Ron Rapee and his colleagues at Macquarie University. It is been running and further developed since 1993, [4]. The program consists of 10 sessions running for 10 weeks. Parents and children (ages 7-17 years) attend sessions to better cope with and manage their child's anxiety. The program can be run with individuals or in a group, in a clinical or school setting [5].

The theoretical basis of the Cool Kids Anxiety Program is derived from Cognitive Behavioural Therapy (CBT), with a focus on teaching practical skills. There are a number of research and scientific studies evaluating the efficiency of the program available. The development of the program followed these studies. Past studies showed that the majority of attendees of the program show significant improvement. There were indications of improvements in terms of an increase in school attendance, academic achievement, confidence, and decreases in worry, shyness, and fear. The many aspect verifications of the program are crucial for our research since it assures the best available ground truth values of MA entered into statistical analysis and machine learning procedures.

Slovenian language versions of procedures materials and instruments were developed and made available by a consortium of four child and adolescent mental health centers (SCOMS

Ljubljana and Maribor and Community Health Centres Ljubljana and Velenje), through funding by the Ministry of Health of Republic of Slovenia while obtaining Cool Kids license [6].

2.3. Psycho-physiological signals and mathematical anxiety

Since MA may be affected by any aspect of cognitive processing, we examined promising studies from a wider area of processes such as fatigue, affect, and emotion.

Physiological signals were used to estimate users' fatigue [7][8]. Estimation of human activity can be assessed from sensors using data fusion and machine learning [9]. Activity recognition using body-mounted sensors utilizing machine learning provides promising results [10][11]. Affect and emotion detection is well studied in physiological signals analysis [12][13][14] also utilizing heterogeneous multi-modal data using fusion approaches [15].

To the best of our knowledge, no study on MA estimation from psycho-physiological sensors is available. However, there were studies on the association of psycho-physiological signals to MA such as heart rate (HR) and electro-dermal activity (EDA), see [16][17][17]. Only low effect-size associations were found indicating the automatic estimation of MA from these signals is a difficult task.

2.4. Psycho-physiological sensors, signals and mathematical anxiety

Since sensors applicable to a given measurement scenario is a major design-deciding factor, we present psycho-psychological signals grouped by sensors primarily selected in this research. According to the previous studies' results, see Subsec. 3.4, we selected three sensors briefly described below.

2.4.1. Empatica E4

The Empatica E4 bracelet [18] is a state-of-the-art sensor for the real-time measurement of wrist psycho-psychological signals. Among others, it covers skin electro-dermal activity (EDA), heart rate, accelerometer, gyroscope, and others. It is important to point out 200 Hz sampling rate allows for algorithmically separating EDA signal into a phasic and a tonic signal component.

2.4.2. Tobii glasses 3

Tobii pro glasses 3 [19] supports eye tracking, pupil diameter measurement, head acceleration, and other measurements. The intrusiveness of eye-tracking glasses was reduced considerably by a novel design. The calibration procedure is not required for each individual measurement. Also, it allows selecting lenses with a selected diopter. The Samling rate of eye tracking can be set to $50Hz$ or $100Hz$.

2.4.3. Edge computing Camera R50

Edge computing camera R50 [20] was selected to track the pupil's skeleton in real-time. The OAK-D baseboard has three on-board cameras which implement stereo and RGB vision, piped directly into the OAK SoM for depth and AI processing. The data is then output to a host via USB 3.1 Gen1 (Type-C).

3. Methodology and proposed solution

In this section, we provide an outline of the measurement and mathematical anxiety estimation operation procedure and PC-based application including selected psycho-physiological sensors.

3.1. System architecture

3.1.1. System requirements

System requirements were derived from research goals and research questions mainly directed toward the feasibility of automatic mathematical anxiety estimation:

1. Measurement device (to which sensors are connected) might not be the same as the device presenting estimation results in real-time;
2. Near-real-time measurement and anxiety estimation, delays under 1 second are acceptable;
3. Psycho-physiological sensor connection - there is no applicable standard for sensor connection and a specific solution for each sensor must be provided;
4. Reliability and end-to-end delay: reliability is of crucial importance and will be regularly verified (see Sec. 3.1.3). End-to-end delay (measurement, processing, MA estimation) is not critical, a delay of 1 sec. is acceptable.

3.1.2. Proposed solution

Considering also ethical (including GDPR) requirements we decided the architecture system architecture is based on a client-server architecture built around node.js run-time environment [21] and real-time database InfluxDB [22]. Specifically:

1. Client/server architecture based on node.js run-time environment;
2. User interface must support 1. real-time interaction of a session supervisor, 2. real-time visualization of measured signals to monitor sensor ”burn-in” period (for instance, the bracelet for EDA must get to the right temperature), and to make sure the measurement system is operating properly;
3. Measurement device is Windows PC as it allows the simplest development environment;
4. Measured signals database: we selected the real-time database InfluxDB meeting all requirements;
5. Candidate sensors are given in Subsection 2.4.

The resulting architecture is given in Fig 1

The outline of the operation is the following: First, we run a script that starts up the sensors. Data from sensors has to be collected and sent to the server database. This is done with the help of a python program that turns on the sensors and triggers the sensors to start measuring. It also sends data to the server database. Values that are sent represent sensor measurements and are written in JSON format. Next, the database receives the JSON strings that contain sensor measurements. It stores them in a table that contains a timestamp to maintain the necessary relations between different sources. This information is later used to calculate which values pertain to the measured event. Afterward, the server's main assignment is to maintain

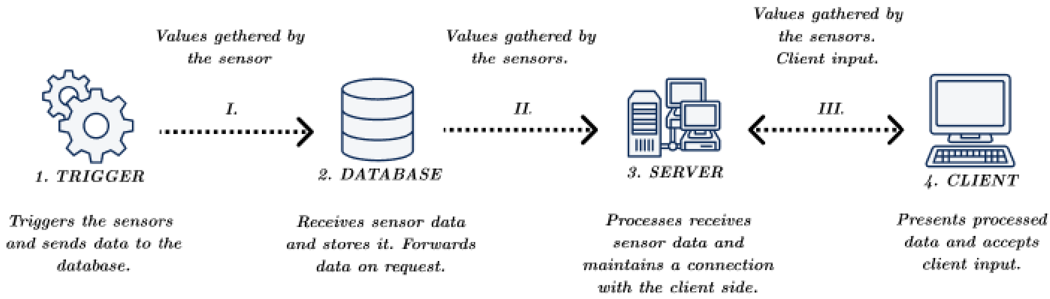

Figure 1: Measurement and estimation system architecture. The connection between the trigger and the database only goes one way (I.). The connection between the database and the server is used to transfer measured and now prepared data to the server (II). The connection between the client and server side is a two-way connection (III.)

a connection between the back-end and front-end. It receives client input which determines the state of the data-gathering process. Based on client input and values from the database it calculates the level of anxiety. Calculated data is then forwarded to the client side where it is presented. The connection between the client and server side is a two-way connection. Its job is to maintain a connection between the two parts. It forwards the state of the data-gathering process from the client side and forwards calculation results from the server side. Note that client is responsible for taking user input that defines the state of the data-gathering process and forwarding it to the server side. It also presents calculated results from the server side.

3.1.3. Reliability and end-to-end delay verification

Reliability verification will be implemented in terms of

1. Regular arrival data points from sensors: are sensors fully functional?
2. Missing data points from sensors: is the proportion of missing values low enough?
3. Correctness of machine-learning algorithms for MA estimation: do we receive correct MA estimation results?

According to our experience with similar systems, the wireless connections (WIFi and Bluetooth) of sensors to the measurement device is the main source of reliability issues. Reliability will be verified during the usage of the system regularly once per month.

End-to-end delay will be measured on three different test persons through automatic analysis of system log files. In the verification mode, the system will be logging the following events: data point arrivals from sensors, each estimation of MA and user interface refresh. All events will be time-stamped.

3.2. Mathematical anxiety measurement scenario

The measurement scenario is taken from the Cool Kids format. As an established and verified program, our goal was to modify it as little as possible. The time frame is given by carefully designed and structured ten sessions each pupil attends. Sessions are one-to-one and supervised by certificated psychologists.

We plan to measure two out of ten sessions as identified by the field experts. The session will be upgraded by a standard explanation of the study purpose to the participants and their parents and sensor mounting. The online measurements and MA estimation results are not planned to be shown to the participants. For a fair comparison of results, the rest of the Cool Kids [4] session procedure will remain as unchanged as possible.

3.3. Ground truth determination

To label our measured data on real subjects with estimated mathematical anxiety we also lean on Cool Kids program [4] and its instruments of mathematical anxiety determination. Such labels are required to equip machine learning testing datasets. Before the session, the participants will fill out a short self-report measure of MA (to be decided later between several different scales in consideration at the moment).

During the process of the session, the participant's (pupil's) mathematical anxiety is measured several times using a single-dimensional 10-level anxiety level scale as a pupil self-report. The participant estimates and reports her anxiety by looking at the graphical representation of the scale attached to the wall.

The number of Likert scale levels of MA as a ground truth will be determined according to the distribution of obtained values on the 10-level scale. The starting point is a 10-level scale.

After the session, participants will again fill out a short self-report measure of MA (to be decided later between several different scales in consideration at the moment).

3.4. Statistical and machine learning

To the best of our knowledge, automatic estimation of Mathematical anxiety in real-time from psycho-physiological signals was not reported yet. However, useful algorithms were reported and described from likely related estimations including stress and attention estimation.

Literature review shows machine and statistical learning algorithms are selected and optimized according to the selected psycho-physiological signals and features extracted from them. As such, feature extraction is the main challenge of information extraction from physiological signals [23][24][25][26]. Since measuring the time dynamics of our test participants, we will pay special attention to time-local features. Signal-specific feature extraction yields the best results. Regarding EDA, decomposition to tonic and phasic components is of key importance [27]. Standard feature extraction includes the number of peaks, variability, and spectral-based features. There are specific feature extraction techniques. Observing EDA at different frequencies is studied in [28]. Authors of [29] focus on time and frequency domain features followed by information-based feature selection approaches including maximization of mutual information and input symmetrical relevance. Chaspari et al [30] proposed a multidimensional EDA fingerprint as a model of effective feature extraction. Authors of [31] focus on multi-modal feature extraction proposing 40 features designed for fear classification but applicable to other tasks.

Regarding heart signals, authors of [32] propose dimensionality reduction and salient features approach to ECG signal directly linked to feature selection and machine learning methods. Ebrahimzadeh propose lime-local features of ECG signal evaluated for sudden cardiac death [33]. Authors of [34] focus on fusion-based feature extraction of ECG signal applicable as general purpose framework. Van Gent et. al pay special attention to noisy heart rate signals [35] also providing a Python toolbox. A systematic review of deep learning-based methods is given in [36] covering 154 research papers. Machine learning techniques are usually linked to specific signals and their features [37].

Studies directed into mathematical anxiety estimation are summarised in [16]. As a framework, the human autonomous response system is described. The most reliable measurement pointed out was salivary cortisol level which is not applicable in real-time measurement. There were several studies on hart rate (HR) correlation to MA and one study [17] reported a negative correlation to the Anxiety Toward Mathematics Scale with low effect size. Other studies did not find correlations. Regarding Skin conductance (as a part of Electro-dermal activity) one study found a positive correlation to the Anxiety Toward Mathematics Scale and to the Mathematics Anxiety Rating Scale [17]. No pupil diameter relations to MA were reported.

Several Python toolkit are available, we will base our work on Tsfresh [24], PySiology [25], Neurokit2 [38] and PyHeart [35].

3.5. Analysis of measured data

The measured psycho-physiological signals will be reprocessed (missing values, outliers etc.), time-synchronized, and labeled by the MA ground truth. To make machine learning model evaluation possible, we will extract candidate psycho-physiological signal features and visualize them. According to the addressed research question, the following data analysis is planned.

1. *Which signal features are associated with MA?* A one-way ANOVA design will be applied. Since signal features are typically not distributed normally, we will use Kruskal-Wallis ANOVA when necessary.
2. *Which statistical model explains most of the MA variability?* To test linear and nonlinear models, we will statistically test the null hypothesis $H_0 = [R^2 = 0]$ for each tested model. R^2 stands for the Coefficient of determination.
3. *Which machine learning model performs the best classification on MA classes?* For practical application of MA estimation, classification of MA into predefined classes may be more effective compared to regression models (ad 2.). We will analyze the distribution of ground truth values of MA, group them into three or more classes, and evaluate ML classification algorithms using Area Under ROC measure.

4. Discussion and Conclusion

The problem of real-time mathematical anxiety (MA) estimation is posed and the outline of the solution in terms of technology, procedure, and ground truth of MA determination is proposed.

A plan of statistical analysis is also provided. As the research project is in an early stage, no experimental results on measurements or machine learning algorithms' performance are presented.

Future work includes measurement application implementation and verification (currently in progress), two-phase measurement of real subjects, selection and adaptation of most effective machine learning algorithms, and the evaluation of the results. Note that the research is primarily focused on the feasibility of the automatic MA estimation using sensors. Performance in terms of reliability and end-to-end delay is scheduled first. Based on a small-scale study of five participants, we will select classic instruments to measure MA later utilized as machine learning test labels. Experimental results will be presented in the form of a feasibility study in terms of machine learning and measurement (sensor intrusion included).

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