Detection and analysis of a programmer's confidence

A multimodal approach

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CONTENTS OF THIS PRESENTATION

1. State of the art:
    - By peripheral used
        - Keystroke features analysis
        - Mouse features analysis
        - Multi-modal approaches
    - By the analysed input
        - Free text analysis
        - Fixed text analysis

2. Our model: » A multimodal approach, combining:
    - Keystroke analysis
    - Mouse click analysis
    - Program execution data

    » A free-text analysis model

Motivation and goals

Confidence level measurement is very useful in many real-life cases. In this way, our study is motivated by the following needs that we encountered:

- The need of studying what improves or decreases the concentration, mood, and thus CONFIDENCE of a programmer.
- The need for combating the chronic fatigue during and after the working hours.
- A method for keeping the students attentive through classes
- A way of differentiation between participants at technical interviews

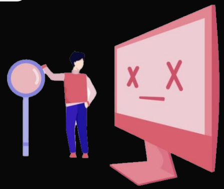
Goals:

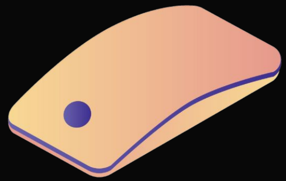
Going from programmers who are fatigued

or suffer from impostor syndrome

to healthy and CONFIDENT developers

Motivation and goals





WHY keystroke

WHY compiler errors?

WHY mouse movements?

- Non-intrusive approaches
- Meant for long-term users' supervision
- Multi-modal approaches have higher rates of success

STATE OF THE ART

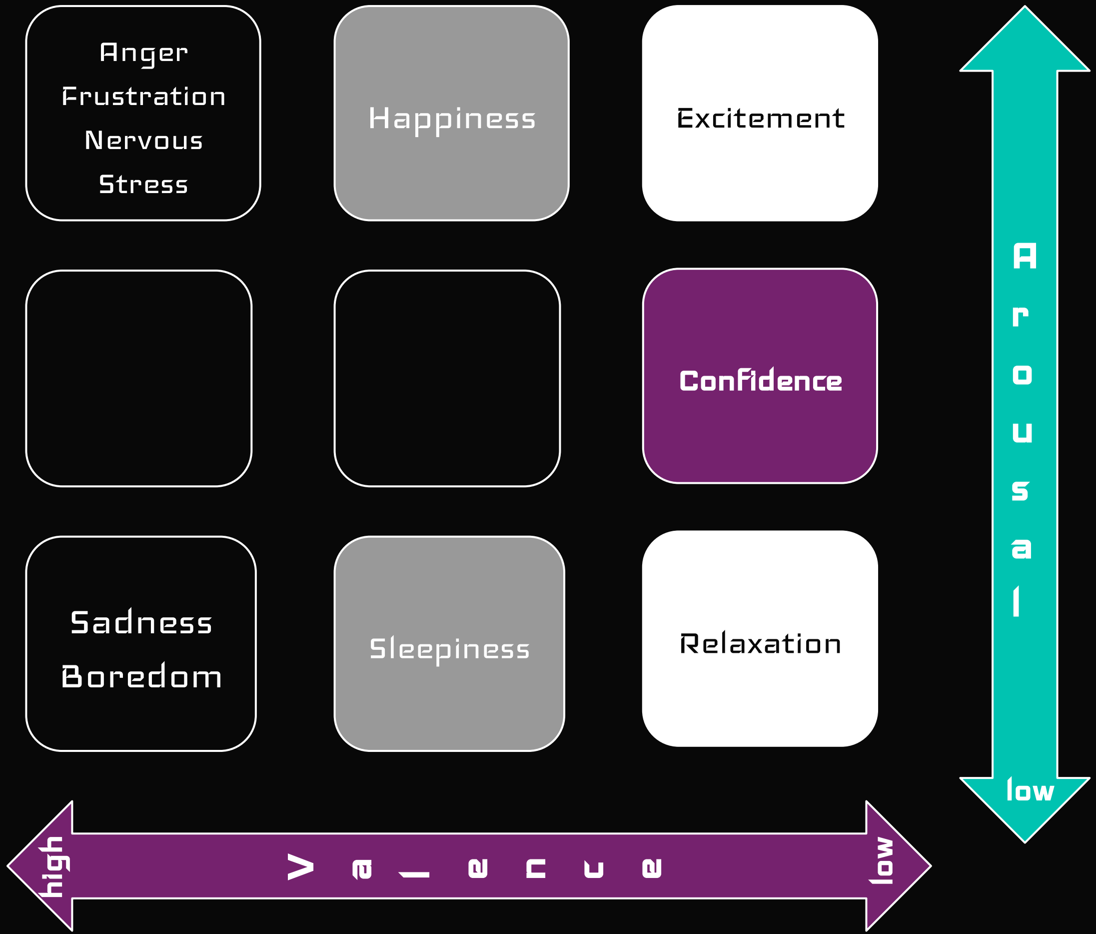
ANALYSIS OF PREVIOUS WORK

04.

STATE OF THE ART: METHODS USED BEFORE FOR IDENTIFYING EMOTIONS

- KEYSTROKE FEATURES FOR IDENTIFYING CONFIDENCE
- KEYSTROKE FEATURES FOR IDENTIFYING STRESS
- KEYSTROKE FEATURES + FACIAL FEEDBACK FOR IDENTIFYING POSITIVE AND NEGATIVE EMOTIONS
- KEYSTROKE + LANGUAGE FEATURES FOR IDENTIFYING EMOTIONS
- MOUSE MOVEMENTS ANALYSIS FOR IDENTIFYING STRESS

Ref.	Emotion analyzed	Peripherals	Analysis Text	Method	Results
[2]	Confidence	keystroke	Free+Fixed Text	Decision Trees	Classification accuracy: 86.2% for fixed text, Free text results ignored
[3]	Positive and negative	keystroke + facial feedback	Fixed Text	Statistical analysis	Significant differences in the typing patterns under positive and negative emotions for all subjects.
[5]	Stress	keystroke + language parameters	Free text	Decision trees, support vector machine, k-NN, AdaBoost, neural networks	75.0% for cognitive stress (k-NN), 62.5% for physical stress (AdaBoost, SVM, neural networks) conclusion: number of mistakes made while typing decreases under stress
[10]	Stress	keystroke + mouse features	Free Text	Linear Discriminant Analysis, feature vector, 5-NN, SVM, NB	Overall accuracy: 74.5%



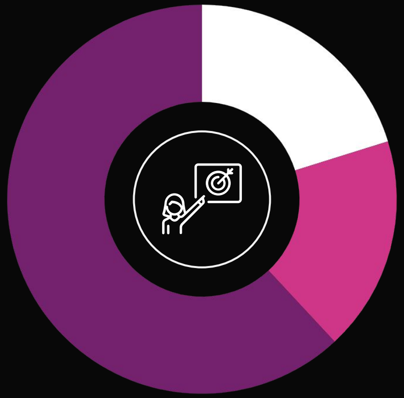
- **Arousal** : intensity of the feeling, the excitement of the person
- **Valence**: the feeling is positive or negative

From the valence values:

» Positive emotions mark a great level of confidence;

» Negative emotions mark low level of confidence

RESULTS OF PREVIOUS WORK



20.22%

Keystroke

Identifies emotional states by ECG signals.

17.88%

Mouse

Identifies a set of 8 emotions

61.92%

Multimodal

Identifies complex emotions through facial expressions

OUR MODEL

A MULTIMODAL APPROACH

02.

Previous work:

+ shows great results for multimodal approaches
- shows not so good results on free text analysis
+ many resources talking about keystroke analysis or mouse movements
+ they used different stimuli to generate emotional reactions

The approach we want to make use of:

+ a non-intrusive one, based on previous results and studies.
+ a mirrored view of previous work: knowing the moments in which the user is "emotional" and only then identifying if the emotion he/she is feeling is a good or bad emotion.

The element of novelty:

+ it consists of combining keystroke analysis, mouse movements and compiler errors identification and counting.
+ enough accurate results=> we can say that good emotions will show a great level of confidence, and bad emotions will mark a low level of confidence.
+ will bring a great difference in the results

BRIEF ANALYSIS OF OUR MODEL

INPUT DATA

We extract keyboard and mouse input and compiler errors

DELIVERABLES

Command-line utility that records keyboard and mouse input data

CONFIDENCE

We deduce confidence from the identified emotions of the programmer

INTEGRATION

Integrated Visual Studio Code extension that records the occurrences of compilation errors and warnings.

THE THREE MAIN STAGES OF THE RESEARCH

1

Data gathering and labeling

- How to gather the data?
- Which data to collect?
- How to induce the emotional state?

2

Extracting Features From data

- Keystroke features
- Mouse features

3

Training the system

What algorithms should be applied to train a classifier of emotional states?

OUR EXPERIMENT

1

Warm up session

- 5 minutes
- Trivial tasks

2

Control block

- induce a high level of confidence
- simple tasks

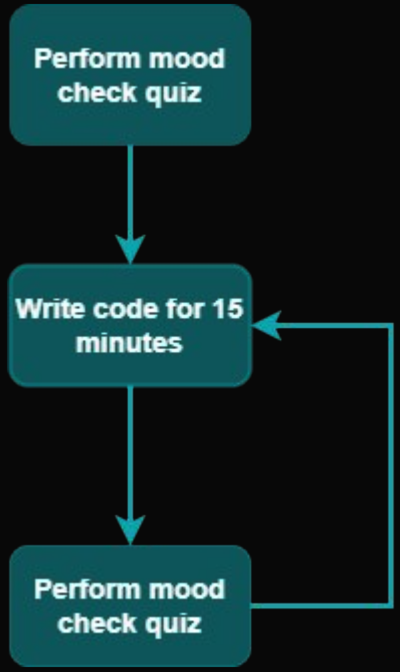
3

Experimental block

- reduce the level of confidence
- more challenging and thoughtful tasks

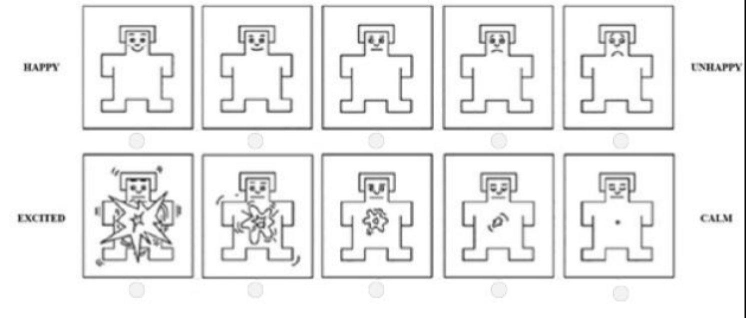
Methodology

- First, the participants were asked to fill out a questionnaire about their arousal and valence at that moment and provide information about their programming background
- The participants were assigned problems based on their skills and knowledge.
- Once every 15 minutes the participants were required to report their perceived valence, arousal and confidence level by filling out a questionnaire



The questionnaire

- We used the 5-Point Self-Assessment Manikin, which has been extensively used for self-reporting arousal and valence, along with two additional questions:
    - “How mentally demanding was the task?”
    - “How confident are you that the task was solved correctly?” with a 5-Point precision.
- It allowed us to determine whether or not the levels of confidence were successfully induced,
- It provides an opportunity to analyze changes in mouse and keystroke behavior elicited by the prior priming task by comparing the data collected during an easy (control) session with the data collected during the difficult (experimental) session.



Results and study

The study consisted of 24 participants, out of which 2 had to be disqualified due to improper data collection. Most participants were Computer Science students or IT industry professionals with at least 2-5 years of experience, because our research is targeting the programming world and we wanted the results to be as accurate and relevant in finding a solution as possible. They were all relatively young adults, with ages varying between 20 and 40. The metrics recorded were the number of keystrokes, the average keystroke duration, the number of mouse clicks, the number of backspace and delete key presses, as well as the number of program executions, all of which were extracted from 15-minute coding sessions.

Results and study

After combining the recorded metrics and quiz results with the help of a decision tree, the result is computed as a number on a scale from 1 to 5, with 1 indicating a lack of confidence, and 5 indicating high confidence.

To compute the model's accuracy, this prediction is compared against the participant's self-reported confidence during the quiz.

68.72%

Accuracy

Understanding results

~30h recorded data

Results - Correlations

High levels of confidence detected by our system were correlated with a calm state and feeling that the task was not mentally demanding.

The number of backspace key-press events grew smaller as the levels of confidence grew higher.

Conclusion

- Overall accuracy: 68.4%

- Improvements: created a more user-friendly environment, since the experiment was not realized in a laboratory setting. Our model can be used from home, school, or work, without any restrictions, and is a useful tool for one's confidence level identification, thus a mood improver.

- Limitations: small dataset gives relative results=> an increasing of the dataset would help the accuracy increase significantly

- Results: a step closer to more non-intrusive, accessible methods of confidence detection.

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