# Data mining of Facial Emotional Responses in spontaneous contexts for Parkinson's disease progression

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**Abstract**

Epidemiology of neurodegenerative disorder such as Parkinson disease (PD) and Alzheimer disease (AD) is still largely unknown (De Lau, et al., 2018). Current knowledge stands that non-genetic factors with interaction with susceptibility genes are the causation. This study tested the hypothesis that facial emotional responses (FER) are impaired in pre-dementia Parkinson's disease. FER measure was based on the Facial Action Coding System (FACS) proposed by (Ekman & Rosenberg, 1997) and implemented in the experimental clinical software. Our preliminary results reveal that there are distinguishing differences in FER factors intensity between the pre-clinical PD patients and control participants. Thus, this method could be relevant in the context of machine learning as a model that provides accuracy superior to reference cognitive tests for early Parkinson's disease diagnosis.

# 1 Introduction

PD is a neurodegenerative disease that typically begins about age 60 and causes slowness of movement (bradykinesia), muscular stiffness (rigidity), tremor, poor postural stability, soft voice, shuffling gait, sudden cessation of the movement called freezing, and a paucity of spontaneous movements (akinesia) (Fahn, 2003). Motor manifestations typically begin on one side of the body, only later affecting the other side as well (Rajput et al., 1991). Underlying degeneration of dopaminergic nigrostriatal neurons with subsequent striatal dopamine deficiency forms the basis for pharmacotherapy (McColl et al., 2002). Thus, people with PD tend to develop reduced spontaneous facial expression and a mask-like face.

AD symptoms start to be observed in the same age as PD in the mid-60s, memory problems are typically one of the first signs of cognitive impairment related to AD. The first symptoms vary from person to person, for many, decline in non-memory aspects of cognition, such as word-finding, vision/spatial issues, and impaired reasoning or judgment, may signal the very early stages of AD. As the disease progresses, people experience greater memory loss and other cognitive difficulties. Problems can include wandering and getting lost, repeating questions, taking longer to complete normal daily tasks, personality and behaviour changes. Afterwards damage occurs in areas of the brain that control language, reasoning, sensory processing, and conscious thought.

The correlation between the PD/AD and the emotions have been investigated in previous studies (Braak & Braak, 1991) (Gray, et al., 2010) which revealed that the perception and expression of the emotions among the people who suffer from PD and AD are disturbed due to damage to the structures of the limbic system, including basal ganglia and amygdala. This phenomenon is called hypomimia, and it is a cardinal sign of the disease often presented in its early stages (Vinokurov et al., 2015). The syndrome is characterized by a marked diminution of expressive gestures of the face, including brow movements that accompany speech and facial emotional responses.

This study introduces experimental clinical software which relies on the computer vision system for stimulus presentation and emotion recognition. The purpose of the study is to investigate the reaction of the extrapyramidal system and the primary motor cortex involved in the facial expressions, both intended and spontaneous (Rinn & William, 1984). As an outcome, we would like to conclude whether data gathered during the experiment is relevant and could be used as an input for the machine learning models.

# 2 Methods

Central Clinical Hospital of the MSWiA in Warsaw, which participates in the described project, shared a laboratory in which research equipment has been installed. Examined group (N=10) consists of five patients with negligible or mild motor impairment (CSF Parkinson's disease biomarker-positive data) and five healthy control participants, without predestination for PD, in the age between 25 and 35 years old.. The whole experiment was divided into two major phases that covered (2.1) neurological and neuropsychological tests aligned with the (2.2) digital stimulus and FER registration.

## 2.1 Neurological and neuropsychological examination

The primary task for the patient was to undertake a set of neurological and neuropsychological examinations that provide an overview of their mental, cognitive and motoric state. The selection of tests was implemented due to earlier research. For example, the Epworth test is being used because affective disturbances and changes in sleep-wake cycles have been recognised in both disorders. Furthermore, it is commonly accepted (Reijnders, et al., 2008) that clinically important depressive disorders occur in 40–50% of patients with PD and they influence many other clinical aspects of the disease, thus the Beck Depression Inventory was introduced. The whole set consists of the six tests, enumerated as follows.

- Epworth sleepiness scale (ESS) provides a measurement of the subject's general level of daytime sleepiness (Johns, 1991).
- The Montreal Cognitive Assessment (MoCA), is a brief measure of global cognitive function; originally developed to detect mild cognitive impairment (Nasreddine & et al., 2005).

- The Stroop Color and Word Test (SCWT) assesses the ability to inhibit cognitive interference, which occurs when the processing of a stimulus feature affects the simultaneous processing of another attribute of the same stimulus (Stroop, 1935).
- Parkinson's Disease Questionnaire Short Form (PDQ-8) is a disease-specific measurement of overall health status (Jenkinson, 1997).
- Beck Depression Inventory (BDI-II) is one of the most widely used psychometric tests for measuring the severity of depression (Beck, et al., 1996).
- Trail Making Test (TMT) provides information on the visual search, scanning, speed of processing, mental flexibility, and executive functions (Tombaugh, 2004).

## 2.2 Facial Emotional Responses evaluation

The second part of the project involved the setup of a high-quality USB camera, a high-performance desktop computer and developed software designed for our research. The application allowed us to design a study in which the researcher has an ability to present the stimulus for the respondents and record their reactions.

A stimulus was a movie that presented several people who express varied emotions. Every presented person was captured in a spontaneous emotional situation, so the smooth transition from neutral to the emotional stimulus occurred. In total 14 faces has been presented. Every presented scene was a representation of one of the six basic emotions (enjoyment, fear, disgust, anger, sadness, surprise) and neutral appearance. The stimulus is presented on the 1920 x 1080 (23") screen where the whole area is covered by the movie, without distractors. The respondent was not aware of what kind of emotion would be presented in advance.

During stimulus presentation, we recorded a video of the patients' face with the Logitech BRIO camera (1280 x 720px, 35fps). The recorded data was timestamped therefore we were able to match specific reactions with the displayed stimulus on the frame-level.

The task relies on the paradigm that the observation of emotion of others also recruits regions involved in experiencing similar emotions (Bastiaansen et al., 2009). Thus, subconscious reproduction should be revealed on the patients' face.

To measure basic emotions, we have used the state-of-the-art library OpenFace (Baltrušaitis, et al., 2018). OpenFace, therefore, relies on the Facial Action Coding System (FACS) (Ekman & Rosenberg, 1997). FACS is a system to taxonomize human facial movements by their appearance on the face. Movements of individual facial muscles are encoded by FACS from slightly different instant changes in facial appearance. Using FACS it is possible to code nearly any anatomically possible facial expression, deconstructing it into the specific Action Units (AU) that produced the expression. It is a common standard to objectively describe facial expressions.

Intensities of FACS are annotated by appending letters A–E (for minimal-maximal intensity) to the action unit number (e.g. AU 1A is the weakest trace of AU 1 and AU 1E is the maximum intensity possible for the individual person).

- A: Trace
- B: Slight
- C: Marked or pronounced
- D: Severe or extreme
- E: Maximum

**Figure 1 – Selected examples of the presented stimulus**.
This collage shows selected parts of the film during
which the most expression occurred.

There are other modifiers present in FACS codes for emotional expressions, such as "R" which represents an action that occurs on the right side of the face and "L" for actions which occur on the left. An action which is unilateral (occurs on only one side of the face) but has no specific side is indicated with a "U" and an action which is unilateral but has a stronger side is indicated with an "A."

OpenFace is able to recognize a subset of AUs, specifically: *1, 2, 4, 5, 6, 7, 9, 10, 12, 14, 15, 17, 20, 23, 25, 26, 28, and 45*. Every AU is denoted by two values:

1. *Presence* - if AU is visible in the face (for example AU01_c)
2. *Intensity* - how intense is the AU (minimal to maximal) on a 5-point scale

To obtain the basic emotions from the AUs, we need to build a formula based on proposed sets of AUs according to each emotion. In our research, we are utilizing later descriptors.

| $e_i$ | Emotion | Action Units |
|---|---|---|
| $e_0$ | Surprise | { "AU01", "AU02", "AU05", "AU15", "AU20", "AU26" } |
| $e_1$ | Fear | { "AU01", "AU02", "AU04", "AU05", "AU15", "AU20", "AU26" } |
| $e_2$ | Disgust | { "AU02", "AU04", "AU09", "AU15", "AU17" } |
| $e_3$ | Anger | { "AU02", "AU04", "AU07", "AU09", "AU10", "AU20", "AU26" } |
| $e_4$ | Happiness | { "AU01", "AU06", "AU12", "AU14" } |
| $e_5$ | Sadness | { "AU01", "AU04", "AU15", "AU23" } |

**Table 1 - Emotion - Action Units Mapping.** This combination has been selected based on the best match with the recognition capabilities of Action Units in the OpenFace library.

The intensity and presence predictors have been trained separately and on slightly different datasets, this means that the predictions of both might not always be consistent. Therefore, we introduced an additional model which concludes the value of every set of AUs to get most reliable scores.

# 3 Results

Using methods describe in (2.2) we were able to register and identify PD patients' and Control Group Facial Emotional Responses based on occurrence of a set of AUs, mapped accordingly to Table 1. Results of measured Facial Emotional Responses of PD patients are presented in a histogram plots, that show all the AUs that are a component of every emotion. Then analogic histogram for response of control group participant is shown for reference.

Emotion Surprise presentd on Figure 2 is composed of 6 AUs: {"AU01", "AU02", "AU05", "AU15", "AU20", "AU26"} from which for PD Patient FER we registered 171 AUs occurrences that is 1.26 % of all registered AUs for this emotion. AUs occurrences in control group for this emotion is equal to 1209 in total this stands for 16.81%

Emotion Fear presentd on Figure 2 is composed of 7 AUs: {"AU01", "AU02", "AU04", "AU05", "AU15", "AU20", "AU26"} dominating AU in this emotion for PD Patient FER is AU04 that represent movement of Brow Lowering – 2256 occurrences it is 93 % of active responses among all AUs. In control group participant response mostly occurred through AU05 - Upper Lid Lifting but it is not as dominating as for PD Patient – is equal to 69.8 % of active response for this emotion.

Emotion Anger presented on Figure 3 is composed of 7 AUs: {"AU02", "AU04", "AU07", "AU09", "AU10", "AU20", "AU26"} this emotion is one of the best responded one, 5 out of 7 AUs are present, the occurrences are distributed as follows: AU02: 3.01%, AU04: 30.24%, AU07: 30.61%, AU09: 0%, AU10: 30.84%, AU20: 0%, AU26: 5.3%. For control group response is even higher 6 out of 7 AUs are present with contribution: AU02: 1.74%, AU04: 2.28%, AU07: 41.8%, AU09: 0.08%, AU10: 51.44%, AU20: 0%, AU26: 2.66%. For control group participant, the highest response is through AU10 - more than 50 % in contrary to PD patient whose response is divided by 3 AUS with 30% range between AU04, AU07 and AU10.

Emotion Happiness presented on Figure 03 is well populated for PD patient 04 comparing it with average resopnse of PD patients. Patient 04 AUs % occurance: AU01: 4.46%, AU06: 100%, AU12: 100%, AU14: 100%, while average AUs % occurrence in PD group is: AU01: 3.09%, AU06: 41.3%, AU12: 4,94%, AU14: 9.68%. To compare average AUs % occurrence for control group is: AU01: 2.2%, AU06: 22.58%, AU12: 45.19%, AU14: 68.93%. Response of CG is more intense at AU12 and AU14.

Emotions disgust is composed of 5 AUs: {"AU02", "AU04", "AU09", "AU15", "AU17"}. Results of FER on Figure 4 are presented for PD patient 04 and CG participant 03 both individuals are good representative of their population comparing to average of AUs occurrence in each group. The general tendency is that for PD group AU02 and AU15 have low level of distribution with high count of AU04 and none at AU09. The average tendency in CG is low occurrence in all AUs.

Emotion Sadnes is composed of 4 AUs: {"AU01", "AU04", "AU15", "AU23"} plots presented on Figure 4 are valid representation of average count of AUs distributed among CG and PD. Count of average of occurrences in each AUs are as follow. For PD: AU01: 77.6, AU04: 2497.8, AU15: 82.4, AU23: 441.2. For CG: AU01: 31.8, AU04: 43.0, AU15: 29.2, AU23: 1424.2.

Comparing the results for PD patients' and Control Group the primary observation is the tendency that in CG there is more active response across nearly all of AUs, while the response for PD patients is distributed for less AUs

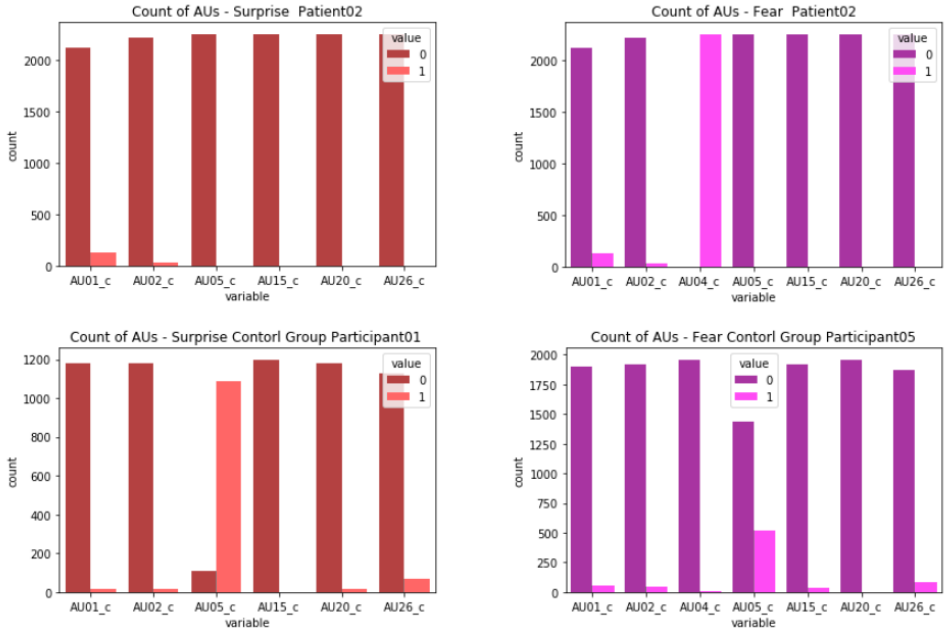


**Figure 2 - Histogram plot of AUs for Surprise and Fear.** 1 stands for appearance of AUs, 0 means lack of AUs. Top charts are representing the score of the patient and bottom one's control group participant.

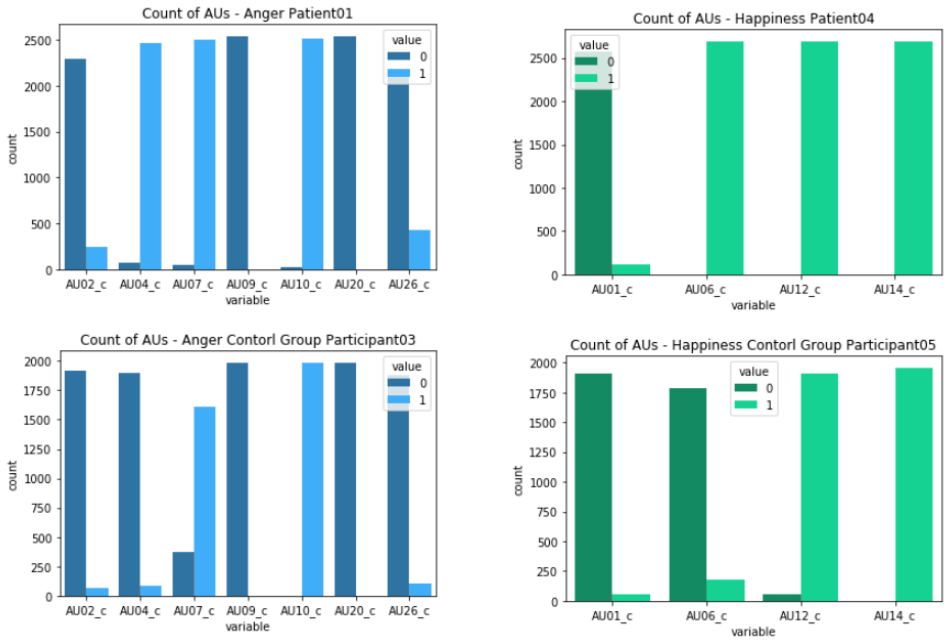


**Figure 3 - Histogram plot of AUs for Anger and Happiness.** 1 stands for appearance of AUs, 0 means lack of AUs. Top charts are representing the score of the patient and bottom one's control group participant.

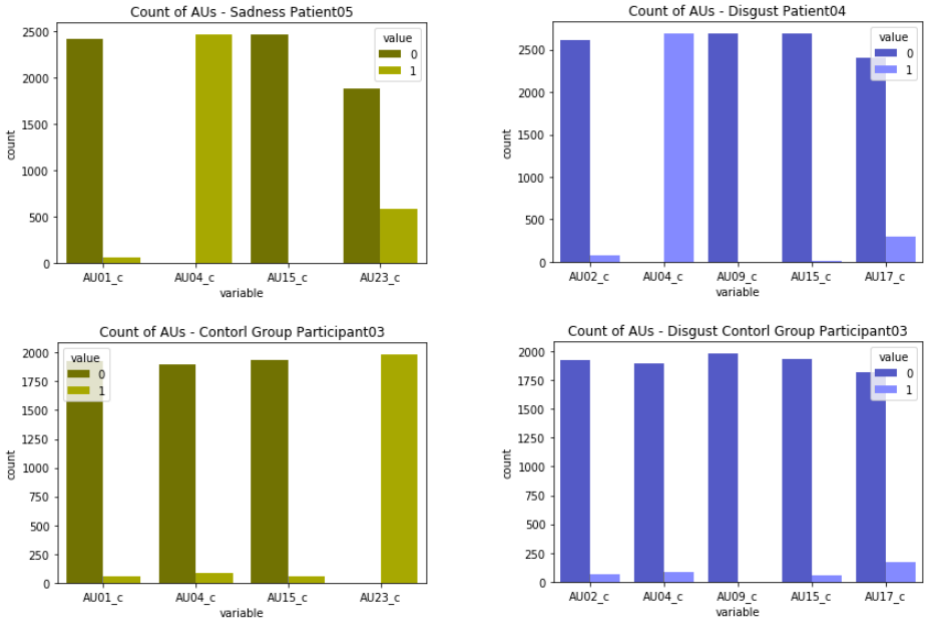


**Figure 4 - Histogram plot of AUs for Sadness and Disgust.** 1 stands for appearance of AUs, 0 means lack of AUs. Top charts are representing the score of the patient and bottom one's control group participant.

# 4 Discussion

People vary substantially in their combination of symptoms, a rate of progression, and reaction to treatment. Averaging patients' symptoms on different stages of the disease give very rough approximations of results. If we want to improve such investigations, we need to take into account an extreme diversity of patients' symptoms and the light effects of cares and therapies in distinctive cases. These problems are well-described in the famous statement: "No two people face Parkinson's in quite the same way".

Nevertheless, the purpose of this study is to go even deeper into symptoms of the individuals that are in the pre-clinical stage of the disease. We are going to deal with the unknown land of attributes which are being so ambiguous and complex to detect even for the experienced neurologist. Substantial diversification of data mining and machine learning methods should ensure us therefore rules based on such subtle correlates that only specialized devices combined with artificial intelligence would be able to explore.

One of those signs is disturbed perception and expression of facial emotional responses. Based on our preliminary result we see this tendency among examined PD patients, unlike to control group. Results shown that data gathered during the experiment is relevant and could be used as an input for the machine learning models.

# Ethics Statement

This study was carried out in accordance with the recommendations of Bioethics Committee of Central Clinical Hospital of the MSWiA in Warsaw with written informed consent from all subjects. All subjects gave written informed consent in accordance with the Declaration of Helsinki. The Bioethics Committee of Central Clinical Hospital of the MSWiA in Warsaw approved the protocol.

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