# Automatic Behaviour Understanding in Medicine

Michel Valstar
School of Computer Science
University of Nottingham
michel.valstar@nottingham.ac.uk

## ABSTRACT

As Affective Computing and Social Signal Processing methods are becoming increasingly robust and accurate, novel areas of applications with significant societal impact are opening up for exploration. Perhaps one of the most promising areas is the application of automatic expressive behaviour understanding to help diagnose, monitor, and treat medical conditions that themselves alter a person's social and affective signals. This work argues that this is now essentially a new area of research. It gives a definition of the area, discusses the most important groups of medical conditions that could benefit from this, and makes suggestions for future directions.

## Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous; D.2.8 [**Software Engineering**]: Metrics—*complexity measures, performance measures*

## General Terms

Affective Computing, Social Signal Processing, Medicine

## 1. INTRODUCTION

Medical applications have always been a driving force in Affective Computing and Social Signal Processing (AC/SSP). Research in automatic facial action detection for example was motivated by speeding up the process of manual coding of face video so larger and more reliable psychology trials could be carried out [7]. Rosalind Picard's book introducing Affective Computing already mentioned potential medical applications [24]. And in particular in the study of Autism Spectrum Disorder (ASD), techniques from AC and SSP have long been applied [10].

Over the years, a number of remarkable contributions have been made, which have served to proof that some aspects of AC/SSP are now mature enough to be used in such medical applications. For example, both Philips' vital signs camera and Poh et al.'s medical mirror include an algorithm that can detect heart rate from variations in the luminance of someone's face [25, 29]. Researchers at the University of Pennsylvania have already applied a basic facial expression analysis algorithm to distinguish between patients with Schizophrenia and healthy controls [15, 35]. Early studies that addressed the topic of estimating the severity of depression from social and affective cues were e.g. [8, 35]. Recently two challenges were held to measure severity of depression on a benchmark database [33, 34]. The winner of the first challenge, a team from the MIT Lincoln Lab [36], attained an average error of 6.53 on a severity of depression score ranging between 0 and 43, indicating that even the first approaches in this direction have some predictive value.

We can argue that there exists now in effect a novel interdisciplinary domain that combines the goals and methods of Affective Computing, Social Signal Processing, and Medicine, for reasons outlined below in detail. One way of naming this would be *Behaviomedics*, which is short for 'automatic expressive behaviour analysis and synthesis for medicine'. Behaviomedics can thus be defined to be:

> **Behaviomedics** - The application of automatic analysis and synthesis of affective and social signals to aid objective diagnosis, monitoring, and treatment of medical conditions that alter one's affective and socially expressive behaviour.

In behaviomedics experts in AC/SSP but without specialised medical training would work together with clinicians open to innovation to develop groundbreaking new technology addressing serious medical issues. This is not a novel field in the sense that many respected researchers have been performing exactly this type of research for a long period of time already. Of course, we can only speak of the possibility of a new area of research when a certain critical mass of work has been reached in that area. However, there are a number of reasons why it is timely to term this as a separate area of research:

- *Breadth* - it is becoming clear that the number of medical conditions that could potentially benefit is vast and much broader than anticipated.
- *Focus* - traditional AC and SSP are concerned with the detection of generic affective and social signals, with the focus at relatively low-level signal processing. In *behaviomedics* the focus shifts to employing or adapting existing AC/SSP techniques to diagnose, monitor, and treat specific medical conditions.


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- *Disciplines* - behaviomedics requires interdisciplinary research involving at least two disciplines: Computer Science and Medicine. While AC and SSP don't exclude medicine, it's not a required component either.

- *Funding* - having a specific field spanning two disciplines will ease obtaining research funding from both.

Whereas the cause of social and affective signals lies in people's felt emotion and interactive goals, in behaviomedics causality is even more complex with the addition of one or more medical conditions causing expressive signalling. It is already accepted that inference of felt emotion from observable signals, such as facial muscle actions or tone of voice, is a hard problem, not least because of the near-impossibility of obtaining real ground truth of felt emotion. The addition of medical factors only makes this a harder problem, in particular given the fact that many medical conditions are comorbid (i.e. occur together), often resulting in similar deviations in expressive behaviour.

The remainder of this manuscript is structured around a taxonomy of a few of the medical areas that are most likely to benefit from Behaviomedics. Related work will thus be discussed where topically applicable. Due to a lack of space, the taxonomy is not complete, focusing rather on the areas for which the largest amount of prior work exists.

# 2. MEDICAL CONDITIONS THAT ALTER BEHAVIOUR

Not all medical conditions where technology can make a difference are the subject of interest in *behaviomedics.* The defining feature of a behaviomedical condition is that it alters a person's expressive behaviour, in such a way that this deviation from either one's personal or a population norm can be measured objectively by non-invasive sensors such as cameras and microphones. Below we discuss three groupings of such conditions that have to date received the largest amount of interest from the AC/SSP communities. Groupings not discussed below (due to a lack of space) include personality disorders, changes in behaviour due to paralysis, and common conditions, among others.

## 2.1 Mood and anxiety disorders

Mood disorders are inherently related to emotion. Originally even termed 'Affective disorders' [22], they were later redefined as mood disorders to better capture the longitudinal temporal changes in underlying emotion [4]. For example, the behaviour of people suffering from mood disorders such as unipolar depression shows a strong temporal correlation with the affective dimensions valence and arousal [34].

There are many mood disorders, grouped by the Diagnostic and Statistical Manual of Mental Disorders [1] into depressive disorders (including unipolar depression), bipolar disorders, substance induced mood disorders, mood disorders due to general medical conditions, and mood orders not otherwise specified. Anxiety disorders are grouped separately, although some automatic behaviour understanding researchers address them as a similar group [30] .

As a consequence of the conditions' direct effect on emotion, psychologists and psychiatrists report on changes in expressive facial and vocal cues. However, such cues are rarely included in official diagnosis. Instead, in the case of depression, clinician-administered self-report questionnaires such as the Hamilton Rating Scale for Depression [14] or the Structured Clinical Interview for DSM-IV (SCID) [11] are the current gold standard [2, 38] (for assessment of severity and diagnosis of depression, respectively). Being self-report questionnaires, such instruments pay little or no attention to observable expressive behaviour. This may well be because of the desire to practise evidence-led medicine, with clinicians' observations of social and affective signals considered to be too subjective and impossible to quantify reliably. This is exactly where behaviomedics could make a significant contribution by adding objective, repeatable and reliable measures of expressive behaviour to complement existing diagnostic and monitoring procedures in clinical assessment.

Early attempts at automatic analysis of the effects of depression on expressive behaviour are e.g. [35, 8]. More recently, Girard et al. [12] performed a longitudinal study of manual and automatic facial expressions during semi-structured clinical interviews of 34 clinically depressed patients. They found that for both manual and automatic facial muscle activity analysis, participants with high symptom severity produced more expressions associated with contempt, smile less, and the smiles that were made were more likely to be related to contempt. Yang et al [37] analysed the vocal prosody of 57 participants of the same study. They found moderate predictability of the depression scores based on a combination of $F_0$ and switching pauses. Both studies used the Hamilton Rating Scale for Depression. Scherer et al. [30] studied the correlation between automatic gaze, head pose, and smile detection and three mental health conditions (Depression, Post-Traumatic Stress Disorder and Anxiety). Splitting 111 participants into three groups based on their self-reported distress, they found significant differences for the automatically detected behavioural descriptors between the highest and lowest distressed groups. Recently Scherer et al. [31] also reported on gender differences, reporting that for some indicators depression effected behaviour significantly differently (e.g. activation of AU4 (brow lowering), displays of disgust and contempt). For the brow lowerer the effect was even in opposite direction: causing increased activation in men and decreased activation in women.

## 2.2 Neuro-developmental disorders

Neuro-developmental disorders signify impairments of the growth and development of the brain or central nervous system. A narrower interpretation limits it as disorders of brain function that affects emotion, learning ability, self-control and memory, which unfold as the individual grows. Sometimes it is incorrectly associated with Autism Spectrum Disorders (ASD) only, while in fact it is a rather large group of disorders, including: schizophrenia, Foetal Alcohol Spectrum disorder, tic disorders, fragile-X syndrome, Down syndrome, and Attention Deficit Hyperactivity Disorder (ADHD).

Clearly, the effects on emotion and self-control would result in observable behaviour that can be analysed automatically. However, whereas for mood and anxiety disorders it is theoretically possible to measure the deviation from the norm within a specific individual (provided this normal behaviour is somehow captured before the onset of the condition), neuro-development disorders tend to be present from birth and so only comparisons with the general population are possible. This makes inference much harder as now variations caused by e.g personality or culture are included in the causes for the displayed behaviour.

Work on the automatic analysis of neuro-developmental disorders includes measurement of biophysical signals such as electrodermal conductivity, as proposed by Picard [26]. Hoque [18] analysed speech pattern differences between neurotypical people and those diagnosed with ASD or Down syndrome, finding a range of differences particularly in pitch, intensity, and formants between the two groups. Other studies focus on technology to support interventions, for example by recording interventions and providing basic activity analysis visualisation [17]. For the neurodevelopmental condition of schizophrenia, two works exist that use facial expression analysis algorithms to distinguish between patients with schizophrenia and healthy controls [35, 15].

## 2.3 Pain

Pain in itself is generally a symptom not a medical condition, although clinical conditions exist that are entirely pain related (e.g. chronic pain syndrome or complex regional pain syndrome). Either way, pain more often than not results in clearly observable expressive signals. One of the most widely applied observational frameworks of pain behaviour is proposed by Keefe & Block [20] who identified five distinctive action-based categories (guarding, bracing, rubbing, grimacing and sighing) which incorporates all pain behaviour. A further categorisation was proposed by Sullivan et al. who identified two functions of the observed behaviour [32]: protective and communicative. Of the two, communicative behaviour is most relevant to behaviomedics.

In communicative behaviour the predominant manifestations are facial expressions (i.e. grimacing), vocalisations and gestural body movements. This is defined as deliberate or non-deliberate overt displays in order to communicate one's state and distress to observers [27, 13, 5]. There has been a large volume of work on the facial expressions of pain [26], and early work in general emotion research [21] showed distinct expressions that accompany acute episodes of pain. Craig & Patrick [9] characterised the pain faces based on the Facial Action Coding System.

Automatic recognition of pain focuses almost entirely on cues from the face. Lucey et al. report baseline recognition models based on AAM features and Support Vector Machine (SVM) classifiers to recognise pain versus non pain with an area under the ROC curve (AUC) score of 83.9% on the UNBC-McMaster dataset [23]. Many further studies on this dataset followed, e.g. [19, 16]. Of particular interest is the work of Romera-Paredes et al. [28], who applied a novel Multi-task learning framework with a transfer learning capability to account for idiosyncrasies between subjects, outperforming traditional user-bias reduction methods.

Studies on other facial pain expression datasets include Chen et al. [6] where the authors apply rule based classification to AAM features on imagery of lung cancer patients undergoing sitting, standing up, recline and walking tasks. A recent study by Bartlett et al. [3] showed that the use of face action dynamics with non linear SVMs can classify real versus fake pain expression better than human observers.

In comparison to face cues, the effect of body motion and audio cues remains little studied in research on automated pain recognition.

# 3. FUTURE DIRECTIONS

This work describes the emergence of what could possibly be a new field of research. Behaviomedics combines Affective Computing, Social Signal Processing, and Medicine to provide novel technological solutions to medical conditions that alter expressive behaviour. The paper discusses a few major groups of medical conditions that would benefit from this. This list is not complete and future work should provide a full taxonomy of medical conditions that would apply, including an overview of their comorbidities and explanations of how exactly they alter behaviour. Neither is the list of AC/SSP works applied to such medical conditions complete, again due to space constraints. Having a full survey of such works would greatly benefit this emerging community.

Automatic behaviour understanding is not easy even in the absence of medical conditions that alter it. The extra complexities introduced by (possibly comorbid) medical conditions ensures that there's a large body of work that remains to be done in this area. At the same time, the need for medical knowledge means that the most successful teams in this area will either be multi-disciplinary, or consist of people trained in this novel multidisciplinary context.

Given the breadth of the medical conditions that could potentially benefit, many of which are life-long conditions, it is hard to overestimate the potential impact that contributions to this domain might have.

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