Machine understanding of facial expression of pain

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Abstract: An automated system for monitoring facial expressions could increase the reliability, sensitivity, and precision of the research on the relationship between facial signs and experiences of pain, and it could lead to new insights and diagnostic methods. This commentary examines whether the research on facial expression of pain, as reported by Williams, provides a sufficient basis for machine understanding of pain-associated facial expressions.

Automatic analysis of facial expressions is rapidly becoming an area of intense interest in computer vision and artificial intelligence research communities. The major impulse to investigate the machine vision problems of detecting, tracking, and interpreting human facial expressions comes from the potential benefits that could accrue from these efforts. Automated systems that sense, process, and interpret human facial signals have important commercial potential; they seem to have a natural place in commercial products such as computer systems for video conferencing, video telephony, video surveillance, face and visual speech synthesis, and pervasive perceptual man-machine interfaces. Furthermore, monitoring and interpreting facial signals are important to lawyers, the police, and security agents, who are often interested in issues concerning deception and attitude. Finally, basic research that uses measures of facial behavior including behavioral science, medicine, neurology, and psychiatry, would reap substantial benefits from inexpensive, reliable, and rapid facial-expression measurement tools. Such tools could greatly advance the quality of research in these fields by providing an increased reliability, sensitivity, and precision of facial measurements, by shortening the time to conduct research that is now lengthy and laborious, and by enabling many more researchers, who are presently inhibited by its expense and complexity, to use facial measurements. It is this potential improvement of basic research, including the research on the relationship between facial expressions and experiences of pain, that forms our major motivation to discuss here whether the research reported by Williams provides a sufficient basis for machine understanding of pain-associated facial expressions.

The problem of automatic facial expression analysis from images of faces is usually divided into three subproblem areas: (i) detecting the face and its permanent features such as eyebrows, eyes, and mouth in an input image, (ii) detecting the changes in the shape and location of the permanent facial features by making a comparison with an expressionless face of the observed subject, and (iii) interpreting these changes in terms of some interpretation categories such as the Action Units (AUs) categories defined in the Facial Action Coding System (FACS; Ekman & Friesen, 1978) and/or in terms of affect-descriptive categories. For exhaustive reviews of the past attempts to solve these problems, the readers are referred to: Samal & Iyengar (1992) for an overview of early works, Donato et al. (1999) for a review of techniques for detecting micro facial actions (i.e., AUs of the FACS system), and Pantic & Rothkrantz (2000) for a survey of current efforts. The first two problem areas mentioned above concern issues typical for visual processing and have, therefore, little relevance for this commentary. What is of true interest here is whether the research reported by Williams provides well-defined rules based on which facial expression of pain and its intensity can be distinguished from other facial expressions by using the currently available facial-expression processing technology.

From the previous work done on automating FACS coding, the automatic AU analyzers presented by Tian et al. (2001) and Pantic (2001) perform the best: They code 16 and, respectively, 29 AUs occurring alone or in a combination in face images. Both systems can automatically detect AU4, AU6, AU7, AU9, AU10, AU12, AU20, AU25, AU26, and AU27, in terms of which Williams defines the facial expression of pain. In addition, Pantic (2001) proposed a self-adaptive facial-expression analyzer that classifies detected facial muscle activity into multiple, quantified, user-defined interpretation categories. By interacting with the user, the pertinent system is able to learn interpretations (e.g., “pain”) that the user associates with different facial expressions. Nevertheless, a number of requirements must be met if a valuable automatic classification of AU codes into one or more quantified interpretation categories is to be accomplished.

1) *Each interpretation category must be uniquely defined* in terms of one or more AUs that underlie the facial expression characteristically classified in the interpretation category in question. AUs in terms of which Williams defines the facial expression of pain are also micro components of facial expressions that are typically depicted as *anger*, *fear*, and *disgust* (Ekman & Friesen 1975). In addition, the combination of these AUs is usually interpreted as *disgust* (Ekman & Friesen 1975) or more freely as *loathing* or *yucky*. Hence, a unique definition of an “acute pain” interpretation category requisite for machine recognition of facial expression of pain cannot be obtained based upon the research results reported by Williams.

2) *The knowledge about the “influence” that each AU has* for the produced facial expression to be classified in a certain interpretation category must be available. Based on this knowledge, quantification of an interpretation label generated by an automated facial expression analyzer can be accomplished. So, for example, does an activation of AU6 have the same influence as an activation of AU10 on the detection of pain by human observers? Williams reported that an observed patient can control the intensity and frequency of AU6 activation if he or she wishes to suppress or augment facial expression of pain. The same has not been reported for AU10. Hence, we can speculate that an evidence of AU10 activation should have more influence than an evidence of AU6 activation on the detection of pain by human observers. However, this is a mere

speculation. A minimal set of AUs – their frequency, intensity, and overall temporal dynamics – and the relevant importance of each of those occurrences for human observers to detect pain, have not been clearly defined within Williams' report. Therefore, even if a unique "acute pain" interpretation category could be defined for the purposes of machine understanding of facial expression (see the discussion above), the knowledge needed to accomplish automatic quantification of such an interpretation label cannot be obtained from Williams' report.

In summary, the research presented by Williams does not provide clearly defined rules based on which facial expression of acute pain and its intensity can be distinguished from other facial expressions by an automated facial expression analyzer. The AUs in terms of which Williams defines the facial expression of pain occur also in facial expressions interpreted usually as *disgust*, *anger*, and *fear*. The frequency of their occurrences, their intensity, and the related overall temporal dynamics relevant for detection of facial expression of pain either by human observers or by a computer system cannot be extracted from the target report.

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