AI-based Facial Recognition in Emotional Detection

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Facial recognition is a method of identifying a human face with the help of computer vision (CV). The popularity of smart gadgets and the advancement of cameras' capabilities have caused facial recognition to become a hot topic among academia and practitioners. Besides the traditional facial data gathered from surveillance systems, commercial facial recognition systems for measuring emotional states have recently become popular. These systems are often AI-based and use facial recognition algorithms, along with biometrics, to map facial features and motions from an image or through a live stream. The aim of this paper is to study the ability of these systems to detect emotion accurately. Humans have complex personalities that are often present in our facial expressions and do not necessarily reflect specific feelings. Additionally, those with personality disorders, such as narcissistic or histrionic personality disorder, have different facial expressions than the general public. Those expressions are not representative of the emotions that would be detected through the diagnostic systems. Therefore, complementary technologies and solutions are needed to make such measurements more accurate.

1. Introduction

Emotional measurements based on facial recognition (FR) have become very popular, specifically as a supplement for usability and user experience data. In addition, many companies have promoted their facial recognition solution to enhance sales and improve customer relationships [1]. The advancement of these devices is mainly due to the significant improvements in related technologies, such as HD cameras and facial recognition algorithms, which include Fisherfaces [2], Local Binary Patterns Histograms (LBPH) [3], Deep Neural Network (DNW) [4], Rectified Linear Units Layer (ReLU) [4], and Convolutional Neural Network (CNN) [5]. These algorithms are widely used by industries.

Facial recognition applications have become very popular among both companies and consumers. They are accessible even for children and can be seen in programs like Snapchat, which is based on computer vision (CV), the widely-used Google search engine, which utilizes pattern recognition, and Facebook, which detects human faces present in users' pictures [6]. These examples combine artificial intelligence methods and computer vision [7] to teach the algorithm to make more accurate measurements. Many products, such as iMotions, FaceReader, and Deepface, strive to measure emotion through facial recognition.

The measurement of emotion can be achieved using three main approaches; subjective, behavioral, and physiological [8]. Behavioral measurements assess user behavior and are used in programs like the Facial Action Coding System (FACS) [9] [10], which measures facial poses. Physiological measurements monitor emotional change through methods such as monitoring the autonomic nervous system [11] or detecting galvanic skin responses via sensors.

The purpose of this paper is to investigate the efficiency of the latest facial recognition-based emotional detection. This study includes a literature review in which we demonstrate that human personality impacts facial expression. The result of this research will aid practitioners in gauging the reliability of AI-based facial recognition and will suggest further investigations on this topic to academics.

2. Related Research

Facial Recognition

The term Computer Vision (CV) refers to the field of research within the realm of artificial intelligence (AI) that aims to enable computers to see and process the content of images and videos. Object detection within an image, detailing what is seen and where it is located, is the main task of the CV algorithm. Additionally, this algorithm must identify the properties of the object; for example, whether it is a face, a building, or a door. In most cases, these identified images are stored and then compared new objects, and CV enables us to have multiple metrics for the selected objects. This research has been utilized in various sectors, such as safety, health, security, entertainment, cars, robotics, and sports.

Facial recognition is a subset of the CV techniques used by computer algorithms to identify or verify a face through images and has existed for decades. The importance of facial recognition has become evident with the popularity of social media and networking. Figure 1 represents the process of the facial recognition:

Fig. 1. Facial Recognition process

The applications for FR are widespread, being used in security systems, marketing, and as an identification and clearance system. In addition, facial recognition is commonly applied in expression assessments. Facial expressions and emotion measurements were studied in 1993 [12] by Ekman. The facial experience measure was used to study the non-verbal expressions and behaviors of the participant. The aim was to identify the invoked emotions through observing changes on the face. Ekman's [13] FACS measured the basic emotions (e.g., happy, anger, fear, and surprise) in order to evaluate the emotional reaction invoked by the user's interaction with the product.

FR is done through verification and identification. During verification, the system compares the given object with the existing stored objects, while in identification, the system identifies the object and ranks the possible matches. In both cases, the biggest and most complex step is teaching the machine to recognize faces. The FR technology implementation consists of several stages: image acquisition, image processing, characteristic identifications (e.g., eye sockets, nose shape), template creation, and template matching [14]. Facial recognition algorithms often measure the distance between the eyes, the width of the nose, the depth of the eye sockets, the cheekbones, and the chin. Many pictures are needed for the training data that enables the machine to learn how to differentiate faces. Different algorithms can be utilized, with some using a statistical approach or search pattern and others using a neural network. The major facial recognition algorithms are detailed below.

Emotion and Feeling

Darwin noted that emotions are a product of evolution, having developed through adaption with our surroundings. Psychiatric and neuroscience studies have proven that humans are equipped with a basic sets of emotions [15] [16]. Each emotion is associated with psychological and physiological behaviors. Whereas traditional approaches to human higher–order cognitive processes ignore emotions, emerging neuroscientific evidence suggests that rational decision-making depends on emotional processing [17]. For example, fear is the automatic and subconscious result of unpleasant emotion, and our neocortex interprets this emotional signal as conscious feelings [18]. Furthermore, Ekman and Friesen [19] studied a method to recognize the facial expression masks that reflect basic emotions. Their findings indicated that basic emotions are expressed through the same facial expressions universally. Habibi and Damasio [20] defined feelings as mental experiences that are connected to an activity in a certain brain region that maps body states. In alignment with this definition, Damasio [18] considered feelings as a mental representation of the physiological changes that accompany emotions.

Personal Disorder and Facial Expressions

Lynch et. al [21] studied emotional sensitivity in those with Borderline Personality Disorder (BPD). The authors demonstrated that for BPD participants, facial expressions change from neutral to maximum very quickly in comparison to healthy participants. Furthermore, those with BPD are more sensitive when identifying emotional expressions. Pelc et. al [22] conducted a study with Attention-Deficit Hyperactivity Disorder (ADHD) participants regarding the impact of facial expression reactions on basic emotions. Their findings indicated that there was a correlation between interpersonal problems and emotional facial expression decoding impairment for angry expressions. The authors [22] found that nonverbal decoding abilities had implications during therapy sessions for ADHD. Thomas et. al also noted that children with anxiety disorder showed and exaggerated fearful faces. And Marissen, Deen, and Franken [23] illustrated that a person with Narcissistic Personality Disorder (NPD) performed worse in facial emotion recognition tasks.

Subjective, behavioral, and physiological approaches can be used to measure the elicitation of emotion [8]. Behavioral measurements cover versatile approaches that are used to gauge user behavior. Two examples are FACS [9], which measures facial poses (e.g., when we are happy, we tend to smile), and the Specific Affect Coding System (SPAFF) [24], which measures emotions during interactions; for example, those between couples. Physiological measurements identify how the body behaves when emotions change, such as alterations in the autonomic nervous system [11]. An example of a physiological measurement is detecting galvanic skin response via a sensor, which may be indicative of emotions such as happiness, surprise, disgust, anger, or fear [25].

Researchers often employ subjective measurements to behavior using instruments such as questionnaires, rating scales, and experimental sampling. Scholars have also developed systematic subjective behavior measurement approaches, including the Positive and Negative Affect Schedule [26]. In such systems, users are asked how they currently feel (e.g., nervous, scared, inspired). Other methods, like the Stress Appraisal Measure [27] , measure the user's stress level. Finally, an attempt to capture people's emotions can be made through experience sampling methods [28].

3. A Complementary Approach on Emotional Detection

In the facial recognition testing environment, there are many emotions, such as enjoyment, curiosity, interest, hope, anger, anxiety, shame, confusion, frustration or even boredom, that participants frequently experience. Calder and Young [29] demonstrated that faces contain social signals and identity the functional and neural levels, and attempts to detect emotions through them have a long history. For many decades, therapists in psychotherapy sessions have monitored the behavior and body language of the patient in addition to their verbal communications. Non-verbal communications complement facial expressions. Kulkarni and Bagal [30] noted that accurately interpreting facial expressions is critically important for non-human primates that rely on non-verbal signals.

However, there are variables that impact expression. Personality disorders inhibit both facial expression and facial expression interpretations. For example, Surguladze et. al [31] stated that those with major depression have different facial stimuli for sad, happy, and neutral expressions in comparison with healthy people. Additionally, culture, social context, and financial status also influence facial expressions, as Turner and Stets [32] revealed.

The reviewed literature indicates that facial recognition algorithms or physiological measurements alone are not sufficient to accurately detect emotion. To achieve optimal and reliable results, complementary solutions and approaches to the existing methods and tools must be identified. We are investigating additional technologies that help existing FR systems to detect personality disorders, which may help the facial recognition and biometric systems more accurately measure emotions. The details of such new technological solutions are beyond the scope of this paper and will be published once the efficiency of the systems are proven.

4. Discussion

Although FR is effective in some situations, such as recognizing users' happy, neutral, or unhappy expressions, it also has several drawbacks. Firstly, the facial cues of those suffering from personality disorders differ from other populations, making the reliability of emotional recognition problematic. Many people have appeared happy is social situations while suffering from depression. For example, the public was very surprised when the comedian and actor Jim Carrey revealed his long struggle with depression (Mental Health Daily, 2014). This exemplifies the difficulty of recognizing emotional states even in those who are under close public scrutiny. Thus, all emotional cues cannot be identified without analyzing the accompanying behavior in different contexts as well. Additionally, if it was possible to connect other biometric data to facial information, it would improve the reliability of FR analysis.

Secondly, there are still several technological limitations in FR. Cameras can recognize faces if people move directly toward them, with their head frontally visible, but not if they simply pass by. For example, Allgovision technology allows for only a 20-degree tilt in both the x- and y-directions. It is probable that similar limitations would be present in the algorithms of other technology developers. The FR algorithms have been crafted to recognize different targets (such as eyes, noses, or mouths), their distances, and micro expressions on a face. If faces are scanned from different angles, the machine learning algorithms cannot receive all the data needed for reliable processing.

However, FR technologies are developing fast. Current facial recognition is very accurate when dealing with high quality two-dimensional images that do not require complicated or detailed results. NIST's reports [33] stated that the most accurate facial recognition algorithms will find matching entries among 12 million individual images, with error rates below 0.2%. The report also revealed that FR technologies have significantly developed between 2013 and 2018. The authors stated that there is now at least one patented algorithm with the ability to recognize twins, which was once impossible. Nevertheless, all of these excellent results are only valid with high-quality photos where faces are visible frontally; in other words, clear, two-dimensional images that do not move. NIST [33] did not comment on the accuracy of emotional detection.

Privacy concerns are also an unresolved issue when developing facial recognition for retail stores, malls, and other public locations. For example, like many facial recognition technologies, Azure Face API [34] can recognize gender and age. It finds similar faces from catalogs and can identify a person if it already has his or her facial image. Thus, a person could be immediately recognized when they enter a building or other location. If the owner of the location included emotion recognition in their FR technology, they could also collect information about the emotional state of the person during that timeframe. Buzzfeed.com states the thousands of U.S. retailers are purchasing and implementing facial recognition for security purposes. It is, however, a short step from identifying consumers to scanning their emotional states, particularly considering that the goal of service providers is for the customer to leave happier than when they arrived. There are initiatives in China, for instance, to identify customers when they enter stores and connect them with purchase, preference, and network data [35]. Although, customers in other countries are more open to the privacy issues than others, it is still unclear how the facial recognition could analyze the emotions related to the purchase behavior of different customer segments. Detecting the emotional purchasing behavior of customers from their data or from social media would, in all likelihood, be more reliable than utilizing FR emotional measurements.

5. Conclusions

Emotional detection devices have recently become popular in the marketing sector. However, these devices are not reliably accurate, especially for those with personality disorders. Measuring emotion through facial expressions is a complex process that will require extensive study, as a facial gesture often does not correlate with a specific feeling. In the future, the authors of this paper aim to investigate further and develop a proper solution to complement existing devices.

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