Automated Detection of Human Emotion

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Abstract

An automated method to identify human emotions using electronic visual data has been pursued in hopes of advancing human-computer interaction and various other commercial needs. While previous ventures into this area have proven successful, the majority of them require high-end equipment which keeps this technology out of reach for most casual uses. By utilizing an easily accessible web camera and python, an inexpensive alternative can be created with hopefully the same level of accuracy as more expensive attempts.

Introduction

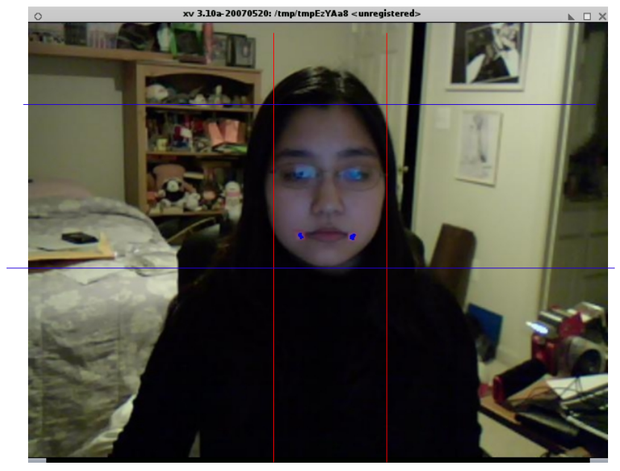
This project will explore the limitations of using low-end equipment to accurately track facial movement to identify emotions. By researching previous expensive attempts, a variety of tracking techniques can be found and utilized. The results of this project can then be used to expand human-computer interaction, or expand the commercial use of this technology, possibly in the standard household.

Background

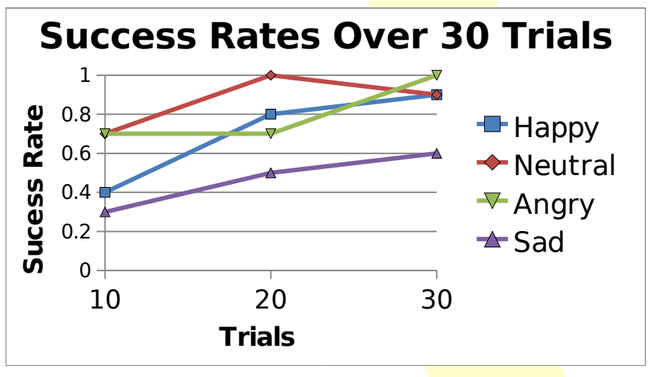
The ability to read human emotions automatically and efficiently has been a goal for both computer scientists and commercial entities. Human-Computer interaction is a quickly expanding field where this information is vital. Commercial uses include advancing automated product testing, and various uses in the entertainment industry. However, various different approaches have been previously used in previous experiments. Some rely on both visual and auditory data while others rely on one or the other. Visually based experiments also utilize different techniques such as tracking placed markers and analyzing shadow placement. However, most of these experiments utilized high end equipment while I am attempting to recreate the same results at a much cheaper price.

Facial Action Coding System

The Facial Action Coding System (FACS) was developed by Paul Ekman and Wallace Friesen in 1976 and is used as the standard for determining emotions by psychologists and animators. FACS works by identifying action units that associated with certain muscle movements. When a certain combination of action units are seen together, emotions can be narrowed down and identified.

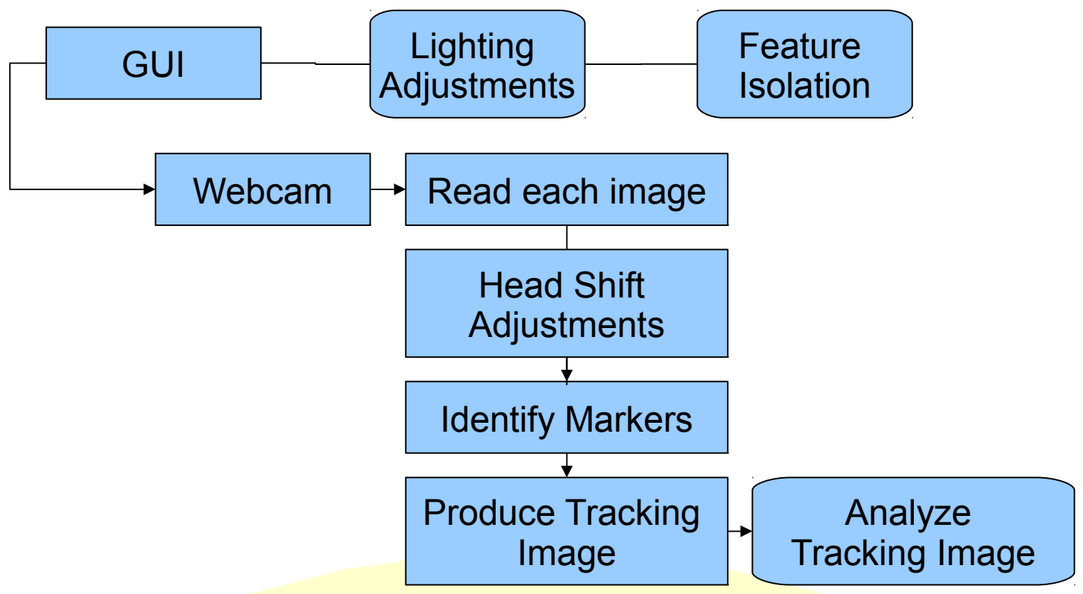


Marker recognition and guideline marking.



Development

Development consisted of three stages: tracking, emotion recognition, and GUI development. Each of these stages begin very simply and then expand into more complicated code after extensive testing. The entire project was coded using Python with the OpenCV package to receive webcam information and the PIL package to analyze the visual data.



Results

Emotional Classifications After 30 Trials				
	Happy	Neutral	Angry	Sad
Happy	0.9	0.1	0	0
Neutral	0	0.9	0	0.1
Angry	0	0	1	0
Sad	0	0.3	0.1	0.6

Results, after thirty trial runs, show that the program is relatively successful when classifying all four emotions with the exception of sadness. Plotting the success rate over time also shows how the backpropogation greatly increased the success rate over time.

Discussion

While the results of the emotion classification was at first rather inaccurate, after 30 trials, the results greatly improved. The high success rate for happy and angry can be attributed to the relatively large displacement of both markers when expressing those emotions. The neutral emotion, on the other hand, also has a large success rate due to the lack of displacement of the markers. However, sadness had the lowest success rate due to its overlap with the anger and neutral emotions. An extremely notable problem with my experiment is that it was only tested with myself. Thus, results may be completely off when testing with other people. However, because of the backpropogation technique and society's general consensus on what a smile is (no one smiles by frowning) I am confident the program would reach similar success rates after a good number of runs.