Recognizing emotions with technology and starting discussions

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Abstract

According to Waag Society and the Research Group Crossmedia, recent studies have shown that young adults are hard to reach when it comes down to (cultural) heritage. Waag Society is researching how cultural heritage institutions can connect to these groups and how heritage objects can be relevant to (young) people. Both parties believe that a better understanding of the emotions people have, is very important to learn more about the way people value cultural heritage. Therefore, Waag Society and the Research Group Crossmedia asked students of the HvA to design an interactive tool that captures young adults emotions and enables them to discuss these emotions with their peers when looking at (cultural) heritage.

1. Keywords

Facial recognition, prototype, emotions, heritage, discussion, expressions

2. Introduction

During the minor 'Research in Emerging Technologies', we've chosen the project 'Emotions in Heritage' that is commissioned by the Research Group Crossmedia (HvA) and the Waag Society. The Waag Society explores emerging technologies not only related to the internet, but also related to biotechnology and cognitive sciences. Art and culture often plays a central role in our research as well.

Our project involves systematically collecting the different emotions people experience when they perceive (cultural) heritage, and use this information to spark meaningful conversations between different parties by visualizing the different emotions. Cultural heritage could, for example, mean a painting, a building, or even a tradition. Earlier research regarding emotion recognition has already been conducted. However, these researches were mostly conducted from a psychological point of view; what emotions are being expressed and why do young adults express a specific emotion? As such, models to define the emotions already exist. Currently, there is a lack of instrumentation to capture these emotions and allow young adults to openly discuss their emotions regarding heritage.

There are many options available to recognize emotions. For example, facial expression recognition, voice recognition, text recognition, and wireless signals. Initially, we did research regarding these different methods. We found a paper [1] which contained the various recognition methods and also included the accuracy with which they were able to recognize emotions. Using these measurements, we made the choice to limit how our project will recognize emotions to the method with the highest accuracy. The result of this research concluded that facial expression recognition had the highest accuracy at an average of 94.48%

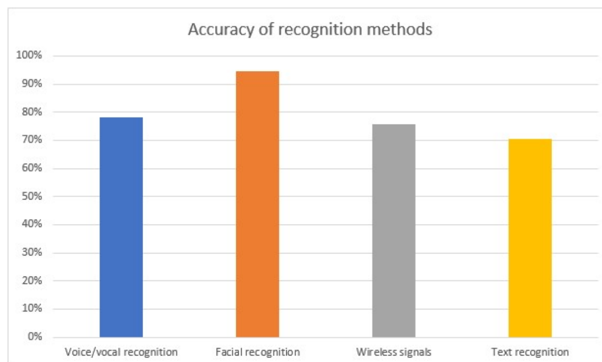

Figure 1: Accuracy of recognition methods

Besides accuracy, two more restraints are defined:

(1) If at all possible, all code and libraries used must be open source.
(2) The prototype has to display the predicted emotions in an interactive way.

Due to these requirements, and our choice to use facial expression recognition, the main research question of this paper is: *Does the visualization of emotions of young people (aged 16-26) by facial expression recognition software, lead to discussion regarding the displayed content?*

By working towards answering this question, we are developing a prototype that collects the relevant information that is required for the goal of the project: starting a meaningful conversation between young adults, regarding a specific subject. Furthermore, if the prototype proves to be useful and provides valid data, it might be used in subsequent research as a tool for collecting data.

3. Related work

Our project, as defined by the Waag Society, is already based on two previous research projects. The first project explores a method to sympathize with other people's emotions around heritage objects. Young people, teachers, and heritage professionals each map their emotions around a certain heritage topic and use that mapping as a starting point for discussion [6]. The goal of this research is very similar to our own, however the means to reach that goal differ, in that our research aims to use technology to read the emotions of the participants, as opposed to mapping them themselves.

The second project examines how participation, narratives, digital media, and atmosphere affect museum visitors when visiting an exhibition and how exhibition makers can influence these visitor experiences. One of the research questions is how people are emotionally affected when encountering one of these means []. Just like the first project, our research differs due to our focus on the technological aspect of detecting emotions.

Besides the above two project which were already defined at the start of the project, we've also found research conducted towards facial expression recognition [1]. This research focuses solely on detecting emotions using a camera. We also had the opportunity to try out the software created during this research. Unlike this research, our research also seeks to visualize these predicted emotions in a meaningful way in order to spark a discussion.

Lastly, we found a series of articles that aim to create open source facial expression recognition software [7]. All of the chosen libraries and datasets were open source or easily available. We have chosen these articles as the basis for our own prototype.

4. Material

Before creating the prototype, we were free in choosing *how* we were going to implement the emotion recognition. However, there were a couple restrictions and requirements. First, a very limited time span to create the prototype in. The prototype had to be up and running in roughly 8 weeks so that we could use it to perform our research. Secondly, preferable everything about the prototype had to be open source, as requested by the Waag Society. Because of prior desk-research, combined with the above restrictions, we chose to use facial expression recognition using a camera as the basis for our prototype. This decision was further solidified upon the discovery of several articles regarding open source facial expression software using Python, OpenCV, Dlib, and Facial Landmarks [7].

Aside from the facial expression recognition part of the project, the prototype had to be able to visualize the emotions to allow participants to reflect on their emotions and spark a discussion. The goal of the visualization is to show the user of the prototype their emotions over a certain time span, and allow the user to navigate through this time span. One of our clients, the Waag Society, had already done work regarding this subject, including the classification of emotions [5] which we will use, and a possible model for the visualization. We have used both the classification, as well as the model as a basis for our prototype. The emotions we have used in our prototype are as follows: *sadness, anger, contempt, disgust, fear, happiness, neutral, and surprise.*

In order to support our user research, the prototype has to go through a number of steps. Below, each of these steps is explained in more detail:

(1) Show a video to the research subject, and start filming at the same time. Store the video for analysis.
(2) Once the video is done, analyze the video and store the results of the analysis.
(3) Visualize the generated model on-screen when the user is ready.

The first step, recording and storing the video, is done with OpenCV[1] to allow video capture from the webcam. The prototype records at 10 frames per second (FPS). Next, the video captures are stored locally on disk. Displaying the video that the user of the prototype watches while he is being recorded, is considered part of the visualization, and will be discussed later in this chapter.

The analysis and prediction of emotion from video frames is largely the same as described in the series of articles written by Paul van Gent [7]. We use a trained, linear SVM machine learning model to predict the emotions on someone's face, based on 68 specific facial landmarks. The linear SVM machine learning model was created with scikit-learn[2], an open source machine learning library for Python. In order to train the SVM model, we needed a suitable dataset of images, labeled with the accompanying emotions. For this, we used the Cohn-Kanade and Extended Cohn-Kanade [2, 4] data sets. Each image in the dataset is preprocessed before being used to train the SVM model. This includes detecting a face on each image, cropping and resizing the face to a common size, removing all color, and using OpenCV's CLAHE algorithm. Once the preprocessing and sorting of the images is done, we use Dlib's [3] shape predictor to fetch the 68 specific facial landmarks. These landmarks, together with the label describing the emotion on the face, are then used to train the SVM model. The total dataset used to train the model contains 834 images. Using a larger dataset will likely result in a more accurate, stable, result.

The recorded video from our prototype is analyzed frame by frame. Each frame goes through the same preprocessing steps as the dataset used to train the SVM model. Once preprocessed, the 68 landmarks from each frame are then sent through the SVM model. Since this is a probabilistic model, the percentage chance for each of the 8 emotions is returned as a result. We found that these results could fluctuate fairly rapidly in a short number of frames. In order to get a more stable result, we've used the average of 5 each emotion over a span of 5 frames (half a second). This means that our final prototype predicts the emotions for every half a second of recorded video. Once the predictions are made for the entire video, the results are stored in an Sqlite database to be used later for the visualization. This also allows us to store the results for analysis later in our research.

[1] https://opencv.org
[2] https://scikit-learn.org
[3] https://dlib.net

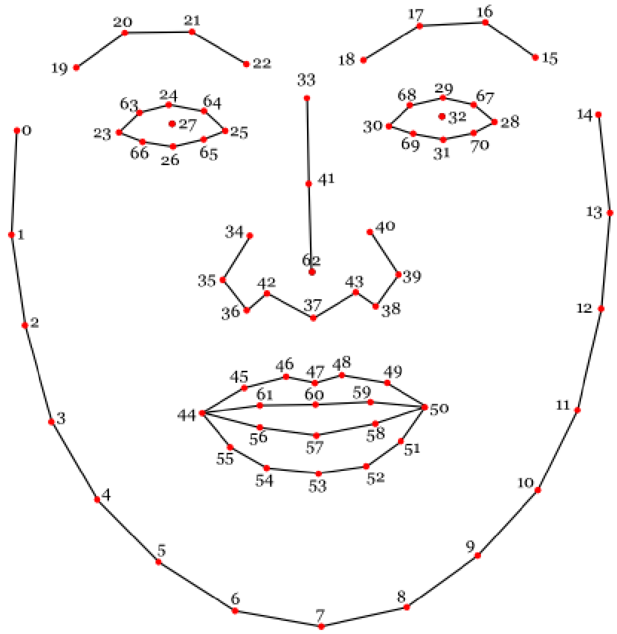

Figure 2: 68 facial landmarks

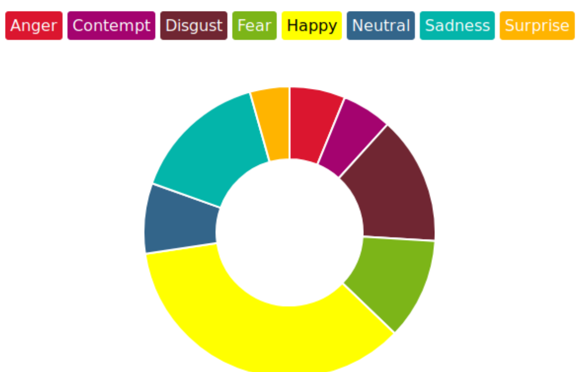

Figure 3: Visualized model as generated by the prototype

The visualization itself is a web application. A Flask[4] webserver is used to allow API access to the rest of the prototype. HTML, CSS and Javascript are then used to create the user interface for the prototype, including the visualization of the model. Initially, we wanted to use Qt[5], a C++ UI library, but due to a lack of time and expertise on our side, we decided to opt for something more familiar, which in this case resulted in a web application. The user interface consists of four pages. One to display the video (and start the recording), one to manage the sessions with our research participants, one to create a new session, and lastly, one to show the visualization. The visualization page uses doughnut charts for each recorded participants. The charts are generated using Chart.js[6], a Javascript library for creating a multitude of charts. The predicted emotions are displayed half a second at a time, with a time line slider to allow the participant to scroll through the predictions throughout the video.

[4]http://flask.pocoo.org
[5]https://qt.io

5. Method

After thoroughly testing the prototype on every aspect, working towards answering the main question was imminent. *Does the visualization of emotions of young people (aged 16-26) by facial expression recognition software, lead to discussion regarding the displayed content?*

The research that we performed was qualitative research. Our prototype was built for testing purposes, and not as an end-product. Therefore, we greatly value any feedback and improvement suggestions for our prototype from our research participants, as this can be used in future development. Because we are researching different emotional reactions of users, we're looking for very specific results. This means that our research design is very specific as well. The research design has the following requirements:

- Users of the prototype have to be in a closed-off room to prevent any distractions which can affect test results.
- Users of the prototype will not be given any information regarding the purpose or operation of the prototype, since this can affect their emotional reactions and therefore the test results.
- Users will be asked to use the prototype one-by-one.
- Users of the prototype will be asked a set of questions which will be focused on accuracy and improvement of the prototype.
- Each video shown by the prototype has a maximum length of one minute due to technical restrictions.

5.1. Participants

The participants are aged between 16-26 years old, and were scouted at the Amsterdam University of Applied Sciences. The participants were invited into a reserved, closed-off classroom, located at the Wibautstraat, where they were able to test the prototype. Our goal was to invite at least 20 participants. Unfortunately, due to technical difficulties and time restrictions, we've only managed to get 13 participants.

5.2. Content

The video had to provoke a measurable reaction from the subjects. Therefore, it is important that we show content that is doing just that. Research conducted by the Journal of Social Psychology [3] has shown that the strongest emotional reaction by people is caused by showing pictures of traumatic events. However, we wanted our subjects to show multiple emotions, and not just the ones that are associated with traumatic events, like *fear* and *disgust*. Therefore, we decided to show the subjects content that is, in any way, provoking.

[6]http://chartjs.org

We have selected three videos which have been edited to last roughly one minute:

(1) Roast of Giel Beelen (Peter Pannekoek roast)
(2) Asian longnecks: Why does this culture consider this beauty?
(3) Failarmy, best fails of 2017

6. Results

As described in 5, we have conducted prototype testing sessions with 13 participants. For each of these participants, we have two pieces of data:

- Predicted emotions during the shown video, created by the prototype
- Results from the interview we had with each participant during the testing

Furthermore, for every of the three available videos, we have expectations regarding the emotions at certain times of the video. Using these pieces of data, we are interested in the following information from analyzing the results:

(1) Do the participants agree with the emotions predicted by the prototype?
(2) Do the predicted emotions coincide with the expectations we had for certain videos?

The first questions can be answered by cross-checking the data that the prototype generated, against the answers from the participants during the interview. The second question can be verified by checking the expected emotions at certain times in a video, against the average of all the participants who watched that video. This will make it clear whether the expected emotion is also the dominant emotion at that time. Finally, we can combine questions 1 and 2. If both results are positive; that is, the predicted emotions by the prototype match up with our expectations, and are valid according to the participant, then we can conclude that it's highly likely to be accurate.

6.1. Test results

We present a table with the results of the interview. The table gives an overview of the answers given by the participants regarding the accuracy of the prototype. Furthermore, several line charts are given which show the average emotions of all participants from each video, and the expected emotions as a dashed vertical line.

The analyzing of the data generated by the prototype was done using some custom code. This analyzer tool was created using Python and the matplotlib[7] library to generate the charts. The analysis tool is available as well: https://github.com/drtheuns/minor_riet_analysis

7. Discussion

To be added

8. Conclusion

To be added

[7]https://matplotlib.org

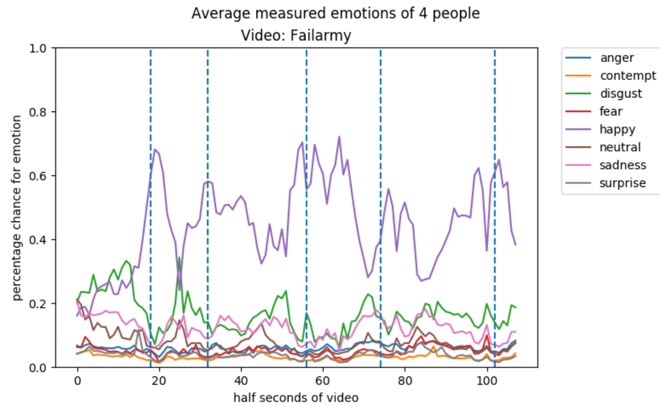

Figure 4: Average emotions of participants with video "Failarmy"

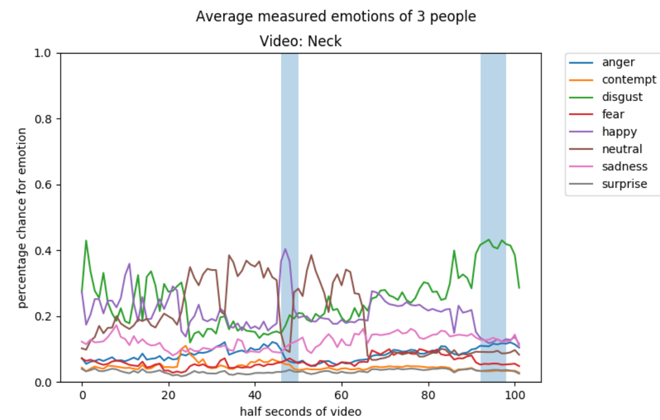

Figure 5: Average emotions of participants with video "Neck"

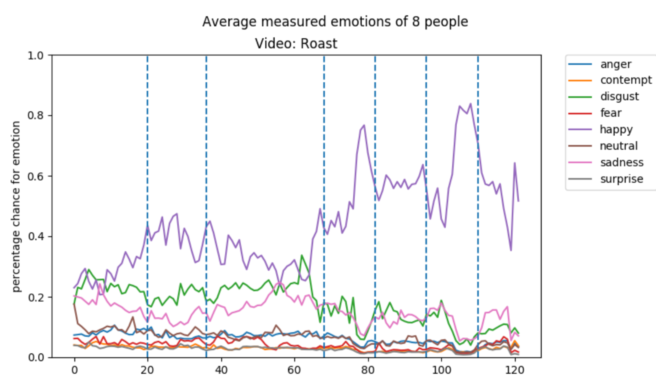

Figure 6: Average emotions of participants with video "Roast"

9. Acknowledgment

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