EYE MOVEMENT BEHAVIOUR VARIES WITH EMOTIONAL CUES

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It is certified that the final copy of MS Thesis written by *Usman Khalid* (Registration No. NUST-2015-MS-RIME-00000119520), of Department of Robotics and Intelligent Machine Engineering (SMME) has been vetted by undersigned, found complete in all respects as per NUST statutes / regulations, is free from plagiarism, errors and mistakes and is accepted as a partial fulfilment for award of MS Degree. It is further certified that necessary amendments as pointed out by GEC members of the scholar have also been incorporated in this dissertation.

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Declaration

I certify that this research work titled "*EYE MOVEMENT BEHAVIOUR VARIES WITH EMOTIONAL CUES"* is my own work. The work has not been presented elsewhere for assessment. The material that has been used from other sources, it has been properly acknowledged / referred.

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Abstract

A basic question in vision research asks where people look in complex scenes and how this influences their performance in various tasks. Research with static images has confirmed a close link between where people look and what they remember. Here, we examined the pattern of eye movements when participants watching neutral and emotional (happy and sad) clips from Hollywood-style movies. Participants were shown 1-min-long neutral and emotional movie clips. Fixations locations and duration was recorded for total of 10 movies (with 30 clips) over 24 participants, using Tobii T120 eye tracker. Post experiment, clips were segmented into three regions of interest; face, upper body, and other. This was done to access the subject's viewing behavior in response to different types of stimuli. The fixation locations and duration were analyzed for all the clip types and showed significant differences in observed pattern. In conclusion, the longest fixation mean was for the neutral clips with the smallest fixation for the happy clips and mean fixation for the sad clips lied between before neutral and happy clips. In another conclusion, participants were paying more attention to faces for emotional content in comparison to neutral clips. However, emotional clips showed more fixations in other regions as compared to neutral clips.

Key Words: *Computer Vision, Human Cognition, attention; emotional movie clips; eye movements*

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CHAPTER 1: INTRODUCTION

When a robot (Arnold Schwarzenegger) from future returns to the past. Then enters the bar, and start scanning the bar full of people. He accesses the records of the people is the famous scene of the movie Terminator 2: Judgement Day. So, the viewer watching the scene as the gaze of the viewer is concentrated on the robot and his action instead of concentrating their gaze towards the other part of the scene that is the bar appearance. Hence, we are going to investigate “whether the emotions affect the fixation duration and location varies with different emotional cures?”.

Figure 1 A frame from Film Terminator 2

A lot of investigations have been made in the using the images to find the relationship where the human sees and what they remember. Using this approach has produced numerous findings to understand how the visual cognition system of human systems works. But there is need to study the eye movement behavior varies with different emotional cues. For investigating above the question, considering images is a not a suitable option because they are cannot offer emotional cues. The images might bring some emotions on the face of the human, but they are static in nature, so they do not have emotional cues in it. So instead of using images, we opt to use videos as a primary tool to investigate our question. In our experiment, the images are not considered as a source to be used for investigation. Images are a static view of the scene where we can only study the situation for a moment of time. It does not provide any source where we can study the dynamically changing the scene. To counter this shortcoming of side of the images, we opt to consider video as primary source because they can capture dynamically changing scene. But video can of many sources, video made from the camera, any video consisting of the images made using software or any movie. So, we use movies as a standard. Movies provide us the situation that humans face in the real life. It will help us understand the question of where human looks are whether affected by the emotional cues. There is another reason that we are using movies because the professional movie makers use highly intelligent techniques that would drive the attention and gaze of the observers. They have a strong narrative with editing techniques that effect the observers viewing. Movies also offer multiple emotional moods like happy, fun surprise, sad, gloomy etc. Hollywood style movies provide us a variety of the emotional moods. From a long list of emotional moods, we select three emotional moods for movies of one-minute duration because we cannot include films as it would offer a huge amount of data and also, we have to put a lot of assumptions to process the data. There are multiples genre of films likes romantic, action, adventure, horror, romance, comedy or animated. The genre is defined by the certain type of emotions elicited by the viewers, for example a romantic movie may make viewers laugh, but may have some scene where there are no emotions like the scene is neutral.

1.1 Bio Inspired Computer Vision

The word ‘Bio’ means life. The life of the living things that consists of animals and human beings. There have been many inventions that were invented based on the inspiration from the human being or animals for example the first airplane invented by the Wright brothers had direction control of an airplane based on the principle how the birds changed the directions using their wings. [1]

Bio-Inspired Computer Vision has been a popular research area for the last decade, as they are suggested new approaches to solve the problems that occurs in the field of computer vision. Apart from the inventions, computational models of biological vision can help in the design of computer vision algorithms. [2] In the history, the camera is developed on the principle as the human eye works. The bats use ultrasonic waves to navigate through the caves. So, the ultrasonic sensors are developed on the same principle that is used by bats.

In the current period, biological visual systems perform all these tasks with both high sensitivity and strong reliability given the fact that natural images are highly noisy, cluttered, highly variable and ambiguous. In the near future this field will be working with perception, motion planning to get the robots to their required destination. [2]

Visual Cognitive System falls under the category of the Bio Inspired Computer Vision. The system has a great importance to humans and animals. Humans see using the eye and extract the information from the scene using the brain known as a cognitive system. So is the case with the animals, they use vision plus other sensing capability like smelling, seeing etc. To gather information from the surrounding and process them to take desired action.

1.2 Visual Cognitive System

Visual according to the dictionary means that is related to the site. Vision is one of the five sense that human is used in their common life. Eyes is the organ that is used by humans to relate to vision.

Cognitive according to the dictionary means the process that relates to cognition. The cognition is related to the brain where it acquires information from the surrounding or recall the old information learned from experience.

Visual Cognition is the process of developing elements that might be a picture or not a picture. The elements may consist of dots representing a letter or a cloud of star appearing a shape that may be close or far away. They may be a choice among an infinity of possibilities, chosen based on likelihood, bias, or a whim, but chosen by rejecting other valid competitors. Sometimes, it may be static like a picture hanging on the wall to dynamic structure that emerged over short time like the moon orbiting a planet. There is clearly some large-scale information processing system that accumulates and oversees these visual computation [3].

1.3 Emotion Elicitation

Emotion Elicitation means to provoke the emotions. To get the required psychological behavior, there is a need of the high impact of manipulations and deceptions. The advantage of using this kind of the method is that we can avoid many pitfalls. Such as participants come aware of the experiment that might affect the experimental results. [36]

CHAPTER 2: LITERATURE REVIEW

In 1995, a dataset of films was created for the use with American audiences. It did not offer the effectiveness as it did not include the students from the college. So, address the shortcoming of the previously designed data set, a new dataset was created in 2011. It proposed a novel circle of short clips that would aid in researching regarding emotion elicitation. Factors taken into account in validation were intensity, discreteness, valence, and arousal. The finding suggested that these variables impact the participants' rating of various emotions significantly and systematically. So, these variables should be considered in emotion. [33]

2.1 Visual Saliency

Visual salient means the region where the viewer fixates his vision in a scene. There are some objects in a scene that are distinct from the surrounding which captures our attention based on a distinct subjective perceptual quality. [7]

There are different types of visual information that is used by a viewer in a scene that are following [4]:

1. Bottom-up stimulus-based information
2. Top-down memory-based knowledge.

2.1.1 Bottom-up stimulus-based information

In this type process, the stimulus is the fixated by the viewer in a scene [4]. So that, all the information is collected by the perception. Hence, it is a data drive process. For example, when a person focuses his sight towards the flower so information about the flower and all the information about the stimulus are carried from the retina to the visual cortex in the brain. The signal travels in one direction. [5].

2.1.2 Top-down memory-based knowledge

In this type of knowledge, human eye not only draws the present accessible visual input, but also relies on more than a few cognitive systems, including short-term memory for same scene previously or stored information about the other similar scene inform of visual, spatial and semantic information and the goals and plans of the viewer. [4] For instance, you are presented with a paragraph written with difficult handwriting. It is easier to understand what the writer wants to convey if you read the whole paragraph rather than reading the words in separate terms. The brain may be able to perceive and understand the gist of the paragraph due to the context supplied by the surrounding words. [5]

2.2 Visual Saliency computational models

There are a number of computational models formed in the past for understanding the working of the human visual cognition system. Following is the name of the computational models:

1. Bottom up: feature driven
2. Top down: Task driven.

2.2.1 Bottom up method

It is also known as Itti and Koch algorithm that works in the following way as shown in the below diagram.

- Computing bottom-up
    a. Itti et al. Algorithm- uses center, surround filters
    b. Torralba et al. – Explicitly model statistics of features
    c. Rosenholtz – Gaussian modeling of features

2.2.1.1 ITTI model

The Ittii model is divided into four stages [8]

- Feature maps

  Compute strength of individual features

- Conspicuity maps

  Compute saliency of individual features through center surround

- Saliency maps

  Combines saliency from different features

- Inhibition of return

  Models covert attention

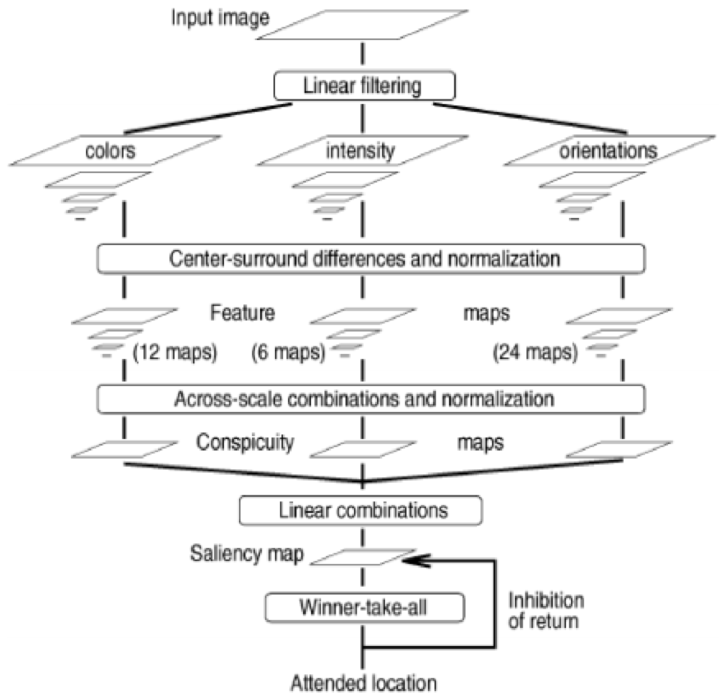

Figure 2 Itti Model

Visual features are computed using linear filtering at eight spatial scales, followed by the center-surround differences, which compute local spatial contrast in each feature dimension for a total of 42 maps. An iterative lateral inhibition scheme instantiates competition for salience within each feature map. After the competition, feature maps are combined into a single ‘conspicuity map’ for each feature type. The three conspicuity maps, then are summed into the unique topographic saliency map. The saliency map is implemented as a 2-D sheet of Integrate-and-Fire (I&F) neurons. The WTA, also implemented using I&F neurons, detects the most salient locations and directs attention towards it. An inhibition-of-return mechanism transiently suppresses this location in the saliency map, such that attention is autonomously directed to the next most salient image location. [26]

2.2.1.2 Contextual Guidance Model

The design of the Contextual Guidance Model is shown in the below diagram. The system works in two parallel stages. In the first stage, the salient features are computed parallel with the second stage where the global features are computed in a feed forward manner. When there is a search task that need top-down control where sometimes system has the prior knowledge learned from the experience or learn new knowledge through learning. Saliency map is based on the information available in the context of the scene. Might be the context is a pedestrian walking on the road. Probability of target presence by integration of task constraints and global and local image information. [12]

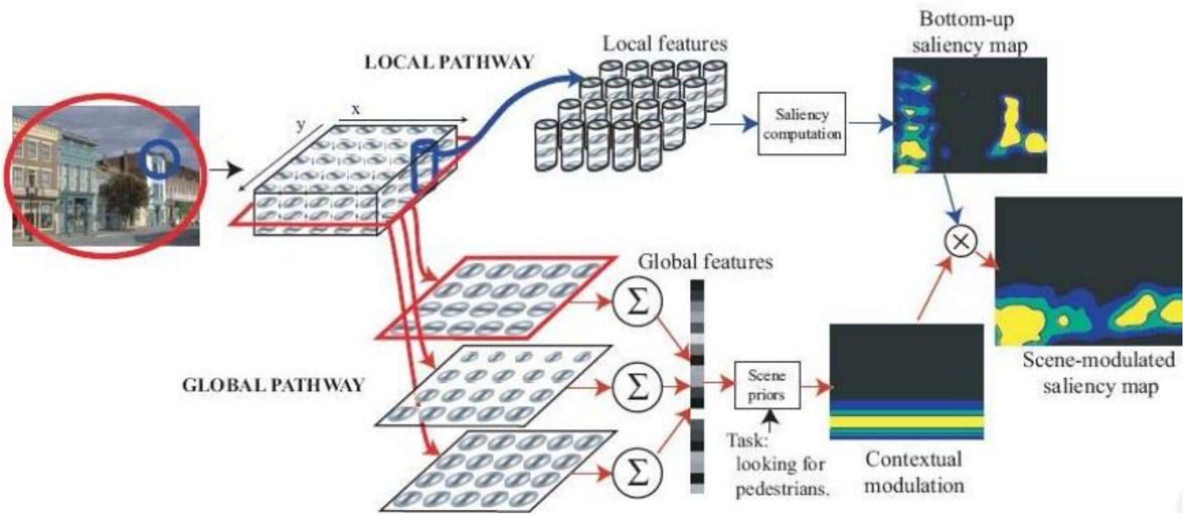

Figure 3 Contextual Guidance model

2.2.2 Statistical approach to saliency

In this approach we apply statistics to differentiate objects from the background. The areas which are different from the neighboring areas are likely to have more information as compared to near regions. The informative regions may likely to appear as objects. Each color channel, passed through a bank of multi scale-oriented filters (e.g. Steerable pyramid) to extract local features/Model distribution of features using multivariate power exponential distributions.

Below is the formula that is used to apply statistics to the image to find out the saliency map of the image.

i. Normalization constant k
ii. Exponent α
iii. Mean η
iv. Covariance Δ

$$\log p(L) = \log k - \frac{1}{2}[(L-\eta)^t \Delta^{-1}(L-\eta)]^\alpha$$

$$\frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) Gaussian$$

Figure Statistical approach to saliency

2.3 Top down knowledge

There are three different types of top down knowledges: [4]

1. Episodic Scene knowledge

   The knowledge learnt in two types of time of period

- Short term of a scene

  It includes information previously attended information in the current scene, that includes an example is the personal computer

- Long-term encounter of a scene.

  Long-term episodic knowledge is based on the information about a particular that is learned over a long period of time, for example, such as aware of the location of office clock that it is residing on the filing cabinet.

2. Scene-schema knowledge

   It includes information about the objects in following categories:

- specific category of scene

  "E.g. Kitchens typically contain ovens"

- Spatial regularities associated with a scene category

  "E.g. pages are typically found on desks"

- Generic world knowledge about science

  "E.g. Chairs do not float in the air"

3. Task-related knowledge

   It can involve a strategy relevant to a given task, such as periodically fixating the reflection in the rear-view mirror while driving, and moment-to moment control decisions based on ongoing perceptual and cognitive needs.

2.4 Images

It is an artifact that may be picture or a drawing that depicts visual perception which enables a person to interpret the picture. In terms of computer vision, it is a two-dimensional picture. In the starting days of the film industry, there were black and white pictures. With the development of the technology, the images were captured in multi-color. With the passage of time, the images converted into films.

2.5 Films

Films is known as motions of the picture. The rate at which the pictures are moved to form a film may be 30 fps or 60 fps or 120 fps. Fps stand for frames per second. A Film consists of shots and cuts. Shot consist of scene and sometimes one scene transitions into another scene. There are two types of transitions between scene

1. Abrupt transition
2. Gradual transition

2.5.1 Abrupt transition

In this type of transition, the scene suddenly changes into another scene. In other words, the last frame of the first shot is immediately followed by the first frame of the next shot. Cut falls in this category.

2.5.2 Gradual transition

In this type of transitions, the scene changes into another very slowly over time. There are three types of gradual transitions:

1. Fade in/ fade out
   Slowly fading to black and starting from black
2. Dissolve
   A short period in which the two images are superimposed
3. Wipe
   A translation of one image with a vertical/ horizontal line while the next image slowly moves in

2.5.3 Emotional states

According to the encyclopedia, it means a state of arousal characterized by alteration of feeling tone and by physiologic behavioral changes [34]. There are many emotions that have been discovered by medical science. Some of the emotions are following

1. Joy
2. Fear
3. Anger
4. Grief
5. Crying
6. Laughing
7. Blushing

Work has been done since the days of Greek philosopher Aristotle in his famous book named Rhetoric. He has stated emotions are divided in the following categories

1. Anger
2. Friendship
3. Fear
4. Shame
5. Kindness
6. Pity
7. Indignation
8. Envy
9. Love

In latest work by Robert Plutchik, he has identified eight basic emotions

1. Fear
2. Anger
3. Sadness
4. Joy
5. Disgust
6. Surprise
7. Trust
8. Anticipation

2.6 Recent Work

In the early twentieth century, Carney Landis introduced emotion elicitation by placing fire cracker under the seat of the participants while they had to execute the rat or sometimes place the hand of the participants in the bucket of live frogs that was unknown to the participant. These methods were not acceptable so there was a need of standardization of the methods for example FMRI help in understanding how emotions affects the brain or heart rate can describe the psychological effects of emotion on the body. The emotion elicitation procedures can help to study emotion. Emotion is considered as independent variables in the studies that study the effect of several emotional states on numerous behavioral and psychological tasks. [33] There are multiples method to introduce the emotions, but we are focusing on the video clips and images.

2.6.1 Image data set

Image sets a standout amongst the most ordinarily utilized strategies as they offer standardization and ease of use. Some famous sets that were established are following and others, contain only images of faces exhibiting different emotions [33].

- In 1976 an image dataset was developed by Paul Ekman and Wallace V. Friesen.
- The Research Network on Early Experience and Brain Development developed the MacArthur Network Face Stimuli Set.
- The Karolinska Institute established an image data set in 1988 by Lundqvist, Flykt, & Ohman.
- Bradley, Lang, and Cuthbert produced International Affective Picture System (IAPS) which contained pictures of "snakes, babies, household objects, mutilated bodies and nature to induce a broad spectrum of emotions".

The images are good sources of eliciting the emotions. But there are other methods to elicit emotion which can be sets of sounds, music clips, words, and bodies of text designed to elicit emotion. The problem with these methods is that they can create the situation closer to the real-life, but to create a standard is a problem.

2.6.2 Film Dataset

The advantages of using the films as emotional stimuli are following: [33]

- The finest features of each of the emotion elicitation techniques can be combined together.
- Great scale of standardization across research centers and experiments.
- Integrating both pictorial and audio information, allows the viewer to simultaneously receive emotional cues from more than one sensory modality. The experience brings the emotional experience of everyday life close to the participant as it involves more than one modality to attain a bigger grade of ecological validity.
- It provides a lot of contextual information about the emotional subject as compared to the picture.
- Film dataset has a large capacity as compared to the capacity of image sets by presenting the emotions and situations, creating strong emotional behavior for the viewer along with the other emotional signs provided by music and sound creates a lifelike emotional experience.
- Film clips are less apt to be perceived as deceptive or manipulative that have also been shown to elicit strong behavioral and physiological responses that have outdone other emotion elicitation methods.
- Participants often genuinely enjoy watching film clips, increasing their investment in the experiment. (Rottenberg, Ray & Gross, 2007).

The already worked in the field of the emotion elicitation based on the films are listed below

- In 1990, a study was conducted which included sixteen approaches for the elicitation of broadly optimistic or adverse moods
- Westermann, Spies, Stahl and Hesse in 1996 observed in a meta-analysis that “the presentation of films or stories was the most effective mood induction technique out of the eleven techniques studied”.

Above mentioned methods were focusing on the wide-mode rather than a specific emotion, nor the effect of the face or image set are considered in comparison to their results, the results are promising.

- In a 1998, experiment was conducted to study how emotion effects the breathing system, for example, F.A. Boiten faced difficulties with the film.

Several problems have made the validation of films a problem due to following reasons: [33]

- Developing clips from films is a relatively difficult to develop.
- As the cultural preferences and norms are rapidly changing with the modern times.
- Films are produced in a specific time period, perhaps more than any other emotion induction stimuli.

The efforts of the researchers for creating of the emotion elicitation using the films in the past are summarized below.

- The first film was developed in 1930 by John Scott to elicit anger, fear and sexual arousal in studying emotion effects in systolic blood pressure. [33]
- In 1982, McHugo with Smith, and Lanzetta created foremost set of experimentally authenticated film clips. The experiment rated fourteen different clips into categories of affirmative, pessimistic, and neutral using a modified version of the DES (Differential Emotion Scale by Izard developed in 1974) by the people participated. The result of the study was that film clips fall into three types of groups: fearful/anxious, disgusted/scornful, and amused/warmhearted.
- Pierre Philippot in 1993 made a study which included newer film clips which were colored and also included had pre-selected film clips. The study contained analysis that was based on the distinct emotional state they were anticipated to stimulate, twelve films were inspected in this investigation- two for every one of the six anticipated feeling (anger, disgust, fear, happiness, neutral, and sadness).
- Gross and Levenson in 1995 created a best film dataset that included 78 movies that were analyzed into eight target emotions: amusement, anger, contentment, disgust, fear, neutral, sadness, and

surprise. This examination, one of only a handful few directed in English-talking populaces, fills in as the reason for a significant part of the present research.

- In 2007, Sato, Noguchi, & Yoshikawa conducted an experiment for Japanese population. The films examined in the study are several decades old, but it met with success and also widely cited in the literature.
- In Germany, Hagemann et al. (1997) and Hewig et al. (2005) generated and verified two film sets that were established on a mix of the abovementioned film sets created in 1990. "All three of these experiments examined clips so that the confounding effect is avoided during the EEG (electroencephalographic) experiment".
- Hewig et al. (2005) added neutral film clips to the data set that were similar to the non-neutral clips in terms of content and source. "In the previous studies' short clips of view or theoretical shapes were used as neutral stimuli".
- In 2007, Von Leupoldt make an effort to create a little set of films especially used for kids. Unfortunately, the investigation just inspected one broad positive, negative, and neutral film clip instead of the clips intended to produce specific emotions, so results are restricted.
- The most recent study that specifically aims to validate film clips was conducted by Schaefer, Nils, Sanchez, and Philippot in 2010. 70 film clips were examined for target emotions of fear, anger, sadness, disgust, amusement, tenderness, and neutral using McHugo's modified DES scales and the PANAS (Positive and Negative Affect Scales) (Watson, Clark, & Tellegen, 1988).

Above mentioned data set had many shortcomings like some were limited to a specific region, that could not be used in another region. The already existing dataset had old films so a new dataset was established in 2014 that elicit intense and discrete emotions in a laboratory. [33]

2.6.3 Work done in the field of the emotion elicitation

- In [37], Pictures and film clips are widely used and accepted stimuli to elicit emotions. The aim of the present study was to compare pictures and films in terms of their capacity to induce emotions verified by means of explicit measures. Stimuli were
  - Single pictures presented for 6s
  - A set of three consecutive pictures with emotionally congruent contents presented for 2s each
  - Short film clips with a duration of 6s

  A total of 144 participants rated their emotion and arousal states following stimulus presentation. The outcome of the research was followed:

- Short film clips seem to be an effective method for eliciting emotions.
- Film clips do not appear to be better than pictures at evoking emotion and arousal states.

- In [38], the experiment was about to study the question about gender differences in both emotional experience and expressivity. The participants watched 16 video clips that induced eight different emotions i.e. Sadness, anger, horror, disgust, neutrality, amuse, surprise and pleasure while Heart rate (HR) was noted as an indicator of the emotional experience. The findings of the experiment were following:
  - When watching recordings that instigate a passionate reaction, men frequently have progressively exceptional enthusiastic encounters, though ladies have higher passionate expressivity, especially for negative feelings.
  - The gender differences rely upon the particular feeling type yet not the valence.
- In another experiment, [39] about 123 participants took part to find whether a set of film clips with certain emotions were capable to elicit measurable objective physiological responses. The participants were asked to see a set of emotional film clip that might induce seven emotions: anger, fear, sadness, disgust, amusement, tenderness and neutral state.

  The following factors were recorded while the participants watching film clip: Skin conductance level (SCL), heart rate (HR) and subjective emotional responses. The findings were as SCL was significantly higher for fear clip as compared to neutral clips and HR was higher for the fear films and anger films. The findings suggest that physiological activation would be more easily induced by emotion-eliciting films that tap into emotions with higher subjective arousal such as anger and fear.
- In this paper [40], the study was made to compare the effectiveness of two types of internal versus external MI across multiple discrete emotions. In this experiment, 40 students took part. In the first part, they had to take part in the task related to external procedure which was to watch the film clips. In the next part they have to complete the internal procedure that was to recall personal events i.e. Internal procedure inducing 4 basic emotions that were fear, anger, joy, sadness and later completed a self-report questionnaire. Both the procedures elicited target emotions. When contrasting the intensity of target emotions, both techniques showed no significant differences, with the exception of Joy, which was more intensely elicited by the internal procedure. A more detailed investigation of the data suggests that recalling personal events (a type of internal procedure) generates more negative and mixed blends of emotions, which might account for the overall higher intensity of the internal mood induction.

- About 49473 participants took place. There were about 4946 effects were included that elicited the discrete emotions of happiness, sadness, anger, and anxiety as independent variables with adults. Picture presentations were overall the most effective elicitor of discrete emotions. [41]
- In this experiment, IAPS Database of images was used. The pictures in form of pleasant, unpleasant and neutral. The images were flawless or stage mixed structure. Pictures were superimposed by a glinting showcase of moving arbitrary spots, which comprised the essential undertaking and empowered us to record steady-state visual evoked potentials (SSVEPs) as a constant proportion of attentional asset designation coordinated to the assignment. Subjects were required to take care of the spots and to recognize short interims of lucid movement while overlooking the foundation pictures. We found that charming and disagreeable in respect to unbiased pictures all the more unequivocally impacted undertaking related handling as reflected in a noteworthy lessening in SSVEP amplitudes and target identification rates, both covering a period window of a few hundred milliseconds. [43]
- To study the eye movement patterns of different subjects when free viewing dynamic natural scenes? A number of 54 participants took part to record 18 videos of outdoor scenes measured their variability using the Normalized Scanpath Saliency, which we extended to the temporal domain. Eye movements on natural movies were then compared with eye movements in several control conditions. Hollywood action movie trailers were used to probe the upper limit of eye movement coherence. The results demonstrate a few precise contrasts between conditions, both for general eye movement parameters, for example, saccade amplitude and fixation duration and for eye development changeability. Eye developments on Hollywood motion pictures are essentially more intelligible than those on natural films. [44]
- To study the probability of eye movements when seeing high-goals, regular recordings, three recently published gaze data sets were used. The set included a wide scope of the film, from scenes of practically a still-life character to expertly made, quick paced promotions and motion picture trailers. Between subject look inconstancy varies altogether between informational collections, with changeability being most minimal for the expert motion pictures. We at that point assess three cutting edge saliency models on these informational collections. A model that depends on the invariants of the structure tensor and that joins nonexclusive, meager video portrayals with AI strategies beats the two reference models; execution is additionally improved for two informational collections when the model is stretched out to a perceptually enlivened shading space. At long last, a joint investigation of look inconstancy and consistency demonstrates that eye developments on the expertly made motion pictures are the most intelligible (because of

certain look direction methodologies of the film chiefs), yet the least unsurprising (apparently because of the continuous cuts). [45]

- We estimated long haul memory for an account film. Amid the analysis, members watched 27 min long motion picture scene. Amid the test session, managed at a defer running from 3 hours to 9 months after the examination session, long haul memory for the motion picture was tested utilizing a modernized poll that surveyed signaled review, acknowledgment, and metamemory of film occasions inspected ∼20 sec separated. The execution of each gathering of members was estimated at a solitary time point as it were. The members recollected numerous occasions in the motion picture even a very long time in the wake of watching it. Examination of execution, utilizing different measures, demonstrates contrasts between later (weeks) and remote (months) memory. Examination of various substance components in the motion picture uncovered differential memory execution profiles as indicated by time since encoding. [46]
- Magnification around the most significant purpose of a film scene (the focus of intrigue - COI) may help individuals with visual impedances that reason goals misfortune. This will be compelling just if the vast majority take a gander at a similar spot when viewing a motion picture. We recorded the eye developments of 20 regularly located subjects as each watched 6 motion picture cuts, totaling 37.5 minutes. The greater part of the time the circulation of subject look focuses fell inside a region measurement that was under 12% of the film scene. Male and more established subjects were bound to look at a similar spot than female and more youthful subjects, separately. We infer that the between-subject understanding is adequate to make the methodology useful.

CHAPTER 3: ANALYTICAL MODELS AND NUMERICAL METHODOLOGY

A lot of Visual Cognitive models have established to understand the working of the human visual cognitive system. In the first step, the faces of the actors were identified along with the upper body. In the next step, the bounding box was used to identify the point in which region.

3.1 Analytical methods

The following methods were used during the experiment

3.1.1 Face detector

The Maltab face detector is used to identify the face in the video clips. It is the code that was adopted from paper [27]. When a clip is passed to the Matlab face detector, it returns the coordinates of the face in following format. The algorithms return a matrix as an M-by-4 element matrix. Each row of the output matrix contains a four-element vector, [x y, width height], that specifies in pixels, the upper-left corner and size of a bounding box [28].

3.1.2 Upper body detector

Calvin established an algorithm for detecting the upper body. The resulting detector returns bounding-boxes fitting the head and upper half of the torso of the person. [29]. It is based on the successful part-based object detection framework [30] and contains a model to detect near-frontal upper-bodies, trained from the data of [31]. The resulting detector returns bounding-boxes fitting the head and upper half of the torso of the person.

3.1.3 Shot detection

Open source [32] was used to analyze the cut in the film so that it can be used in further in the experiment.

3.1.4 Bounding Box algorithm

The algorithm was developed in the paper [49] to check whether the point lies in the polygon region or not. The function is provided by the point to be checked and the boundaries of the polygon and in return the function return with 1 or 0. One means that the point lies on the polygon and zero means point does not lie in the polygon. The algorithm is as follows:

$$"function\ [in, on] = inpolygon(x, y, xv, yv)$$

$$\%\ The\ edge\ loops\ defining\ each\ contour\ are\ checked\ for\ closure, and\ if$$

$$\%\ necessary\ they\ are\ closed\ .$$

$$if\ \sim isvector(xv)\ ||\ \sim isvector(yv)$$

$$error(message('MATLAB{:}inpolygon{:}PolygonVecDef'));$$

$$end$$

$$xv = xv(:);$$

$$yv = yv(:);$$

$$inputSize = size(x);$$

$$x = x(:).';$$

$$y = y(:).';$$

$$mask = (x >= min(xv)) \,\&\, (x <= max(xv)) \,\&\, (y >= min(yv)) \,\&\, (y <= max(yv));$$

$$if \sim any(mask)$$

$$in = false(inputSize);$$

$$on = in;$$

$$return$$

$$end$$

$$[xv, yv] = close\_loops(xv, yv);$$

$$Nv = length(xv);$$

$$\% \; Issue\ a\ warning\ if\ the\ bounding\ box\ is\ outside\ the\ modeling\ world\ that$$

$$\% \; we\ can\ accurately\ represent.$$

$$xrange = max(xv) - min(xv);$$

$$yrange = max(yv) - min(yv);$$

$$min\_safe\_limit = 1.0e - 15;$$

$$max\_safe\_limit = 1.0e150;$$

$$if\ xrange < min\_safe\_limit \;||\; yrange < min\_safe\_limit$$

$$warning(message('MATLAB{:}inpolygon{:}ModelingWorldLower'));$$

$$end$$

$$if\ xrange > max\_safe\_limit \;||\; yrange > max\_safe\_limit$$

$$warning(message('MATLAB{:}inpolygon{:}ModelingWorldUpper'));$$

$$end$$

$$inbounds = find(mask);$$

$$x = x(mask);$$

$$y = y(mask);$$

$$\% \; Choose\ block\_length\ to\ keep\ memory\ usage\ of\ vec\_inpolygon\ around$$

$$\% \; 10\ Megabytes.$$

```
block_length = 1e5;
M = numel(x);
if M * Nv < block_length
if nargout > 1
[in, on] = vec_inpolygon(Nv, x, y, xv, yv);
else
in = vec_inpolygon(Nv, x, y, xv, yv);
end
else
% Process at most N elements at a time
N = ceil(block_length/Nv);
in = false(1, M);
if nargout > 1
on = false(1, M);
end
n2 = 0;
while n2 < M,
n1 = n2 + 1;
n2 = n1 + N;
if n2 > M,
n2 = M;
end
if nargout > 1
[in(n1:n2), on(n1:n2)] = vec_inpolygon(Nv, x(n1:n2), y(n1:n2), xv, yv);
else
in(n1:n2) = vec_inpolygon(Nv, x(n1:n2), y(n1:n2), xv, yv);
end
end
end
if nargout > 1
onmask = mask;
onmask(inbounds(~on)) = 0;
on = reshape(onmask, inputSize);
```

$$end$$

$$mask(inbounds(\sim in)) \ = \ 0;$$

$$\% \ Reshape \ output \ matrix.$$

$$in \ = \ reshape(mask, inputSize);"$$

[IN ON] = INPOLYGON (X, Y, XV, YV) returns a second matrix,

ON, which is the size of X and Y.

ON (p, q) = 1

If the point (X (p, q), Y (p, q)) is on the edge of the polygonal region;

Otherwise ON (p, q) = 0.

Code of Bounding Box Algorithm

3.2 Regions

In this part of an experiment, we are going to identify the three regions as per fixation location of the viewer is concerned. The three regions are mentioned below

1. Face

   The face of living thing, i.e. Human or cartoon character in a clip
2. Upper body

   This region includes the area that includes the region from head to shoulder in which we are excluding the face.
3. Other region

   A region that is then faced and upper body

In the first portion of this experiment, we noted the fixation location and duration of first five fixation. Then for every clip, we calculated means and standard deviation for first five fixation and then based on the three emotional cues, the mean and standard deviation was calculated for first five fixations are calculated. The results are mentioned in the next section.

3.3 Fixation Duration

In this part of the experiment, we are going to consider fixation with a duration from a range of 50 millisecond to 1000 milliseconds. The rest of fixations are ignored.

Chapter 4: RESULT

4.1 Filtering of Fixation based on duration

The fixation data are summarized in the diagram in the below diagram

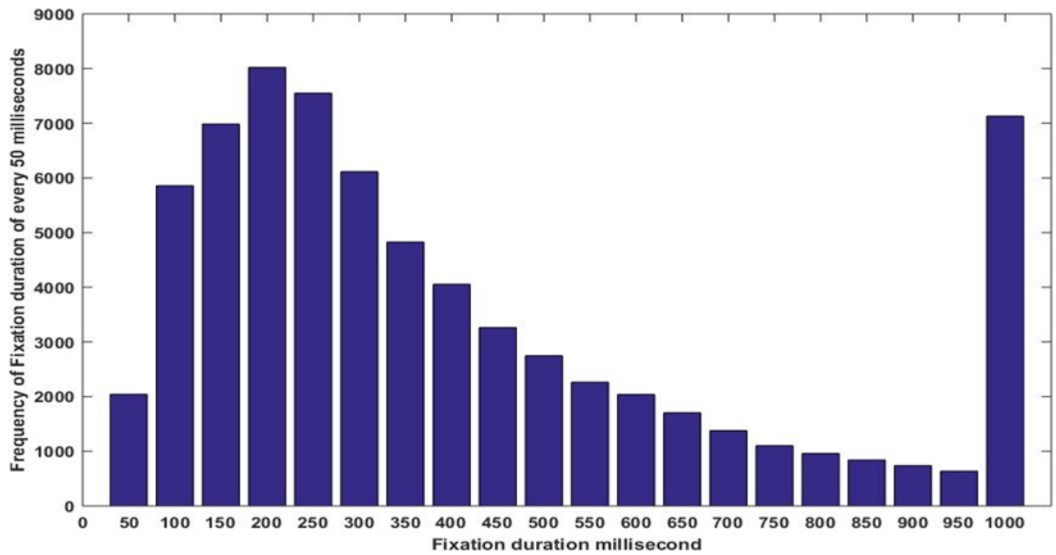

Figure 4 Summarized data of all fixation duration

4.2 Shot detection Result

The result given by the shot detection is shown below with the clip number and frame number on which the scene is changing

Clip	Shot change frame no
1	{265;322;577;744}
2	{346;438;632;761;887};
3	{83;188;241;260;274;496;538;581;769;858;920;1025;1062;1115;1180;1245;1306};
4	{249;341;409;495;626;704;791;873;959;1024;1139;1196;1272;1336;1438;1501;1559;1581;1615;1659;1708;1818;1851;1928;1962;2026};
5	{72;123;235;299;426;512;582;649;701;766;835;982;1080;1199;1289;1545;1621;1725;1803;1863;1931;2124};
6	{25;54;73;90;114;140;183;236;374;433;569;617;642;694;745;781;879;913;1009;1069;1115};
7	{79;162;195;312;351;424;461;534;580;668;699;774;825;836;857;892;940;981;1000;1022;1054;1215;1276;1324;1363;1386};
8	217
9	{53;96;174;211;272;289;345;389;469;505;572;633;665;677;739;770;826;894;951;1048;1165;1352};
10	{152;262;291;384;459;604;667;715;773;868};
11	241;285;350;401;569;660;962;1205};
12	5;117;264;342;437;515;583;601;633;696;755;805;930;1100;1504;1538};

13	{75;157;216;301};
14	{227;324;440;598;651;711;1021;1222;1266;1335;1452;1527;1576;1638;1702;1832;1980};
15	123;202;338;461;529;627;696;752;848;922;957;1075;1180};
16	{57;133;156;212;254;395;483;1623;1704};
17	{67;153;294;762;852;952;981;1023;1054;1381;1694;1787;1894;1978;2073;2253;2353;2829};
18	{258;349;412;472;652;717;897;1028};
19	{123;193;351;713;803;912;1216;1315};
20	{18;46;54;71;79;174;256};
21	46;86;144;225;274;305;515;545;724;788;847;963;1092;1162;1231
22	{101;184;232;262;336;364;418;443;471;488;543;575;618;647;676;709;747;789;819;913;979;1029;1067;1111;1193;1238;1278;1306;1346;1384;1451;1487;1525;1544;1590;1645};
23	{54;158;198;241;347;447;505;591;660;727;826;900;1002;1028;1040;1070;1134;1192;1209;1232;1329;1451;1507;1582;1700};
24	{78;122;215;309;487;560;846};
25	{51;156;194;667;725;782;869;904;1025;1121;1175;1344};
26	{112;160;222;259;417;452;532;659;944;995;1192;1524;1604;1646;1682;1728;1826;1968;2009};
27	{71;588};
28	{45;217;280;404;465;496;560;712;769;868;977};
29	{55;140;207;274;298;315;459;627;658;694;762;822;1077;1101;1179;1239;1338;1481;1532;1552};
30	{149;236;401;495;728;792;851;1306;1346;1504;1677}

Table 1 Scene change in every clip

4.3 First Five Fixations

4.3.1 Mean of first five fixations according to Emotion type

Clip type	Fixation 1	Fixation 2	Fixation 3	Fixation 4	Fixation 5
Sad	0.35537 0.02048	0.36526 0.01225	0.364360 0.020229	0.365820 0.016546	0.351740 0.015715
Happy	0.35696 0.05088	0.36409 0.04134	0.35912 0.04183	0.34764 0.03842	0.33721 0.05848
Neutral	0.34973 0.03153	0.35172 0.02360	0.36974 0.02001	0.35555 0.0186	0.35507 0.02424

Table 2 Average Time of First Five Fixations for Three Emotions Type

4.3.2 Summary of first five fixations locations

Clip type	Face	Upper Body	Other Region
Sad	1785	1222	7050
Happy	1957	988	8502
Neutral	1256	430	3642

Table 3 First Five Fixation Concentration on three regions for Emotional Clips

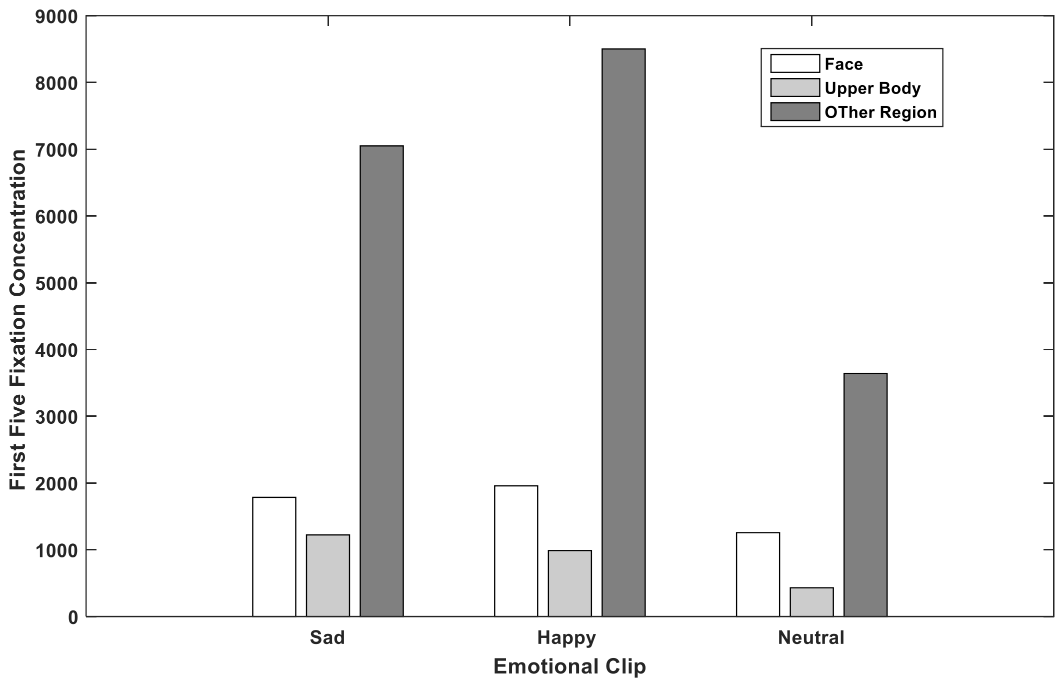

Figure 5 First Five Fixation location on three regions summary based on emotional clips

Clip type	Face	Non-Face
Sad	3007	7050
Happy	2945	8502
Neutral	1686	3642

Table 4 First Five Fixation Concentration on two regions for Emotional Clips

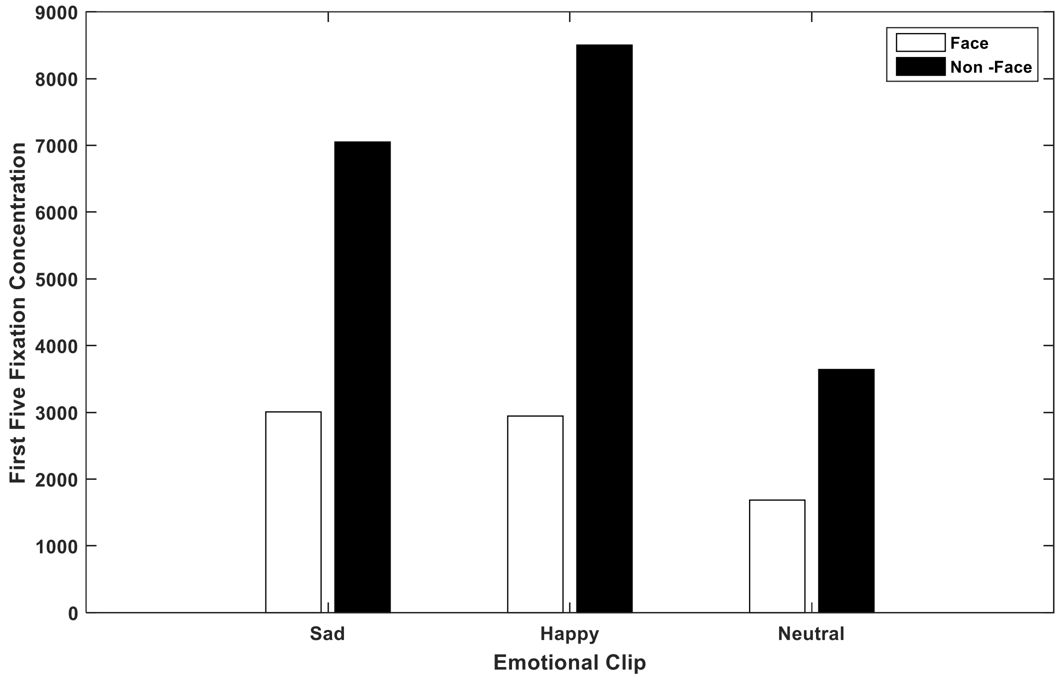

Figure 6 First Five Fixation location on two regions summary based on emotional clips

4.4 First Ten Fixations

4.4.1 Mean and Standard Deviation of First Ten Fixation Based on Emotions

Clip	**Fix1**	**Fix2**	**Fix 3**	**Fix4**	**Fix 5**	**Fix 6**	**Fix 7**	**Fix 8**	**Fix 9**	**Fix 10**
Sad	0.35282 0.02036	0.36175 0.0119	0.35773 0.01797	0.36156 0.01761	0.3482300 0.018500	0.3395400 0.020964	0.333500 0.02802	0.3309800 0.03899	0.3251900 0.04023	0.2991800 0.05466
Happy	0.35492 0.0515	0.36622 0.0418	0.35987 0.0395	0.35056 0.0354	0.34128 0.0573	0.33846 0.0384	0.33646 0.0449	0.32898 0.0383	0.33085 0.0464	0.33626 0.0495
Neutral	0.34998 0.031	0.35192 0.0235	0.36895 0.0190	0.35583 0.0186	0.35497 0.0241	0.36701 0.0432	0.36149 0.0324	0.34208 0.0404	0.34583 0.0391	0.34336 0.0253

Table 5 Mean and standard deviation of first ten fixations according to the different emotion

4.4.2 Summary of First Ten Fixation Location

Clip type	**Face**	**Upper Body**	**Other Region**
Sad	2410	1668	10215
Happy	2703	1221	10842
Neutral	1941	664	5196

Table 6 First Ten fixation location summary for Three type of clips on three regions

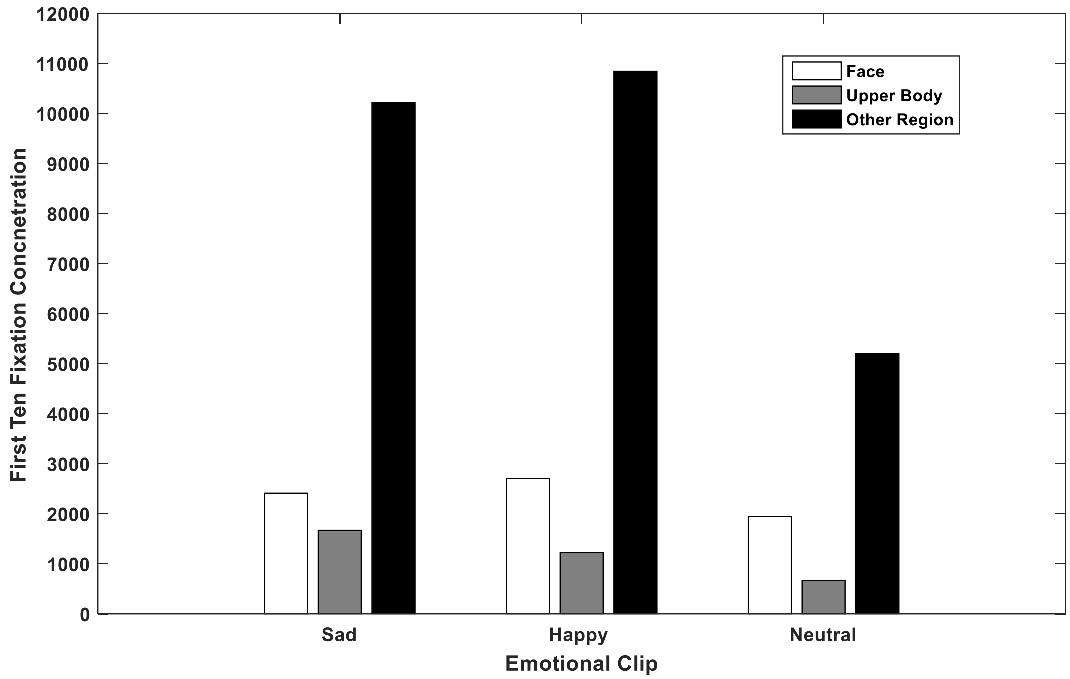

Figure 7 First Ten Fixation location on three regions summary based on emotional clips

Clip type	**Face**	**Non-Face**
Sad	4078	10215
Happy	3924	10842
Neutral	2605	5196

Table 7 First Ten fixation location summary for Three type of clips on two regions

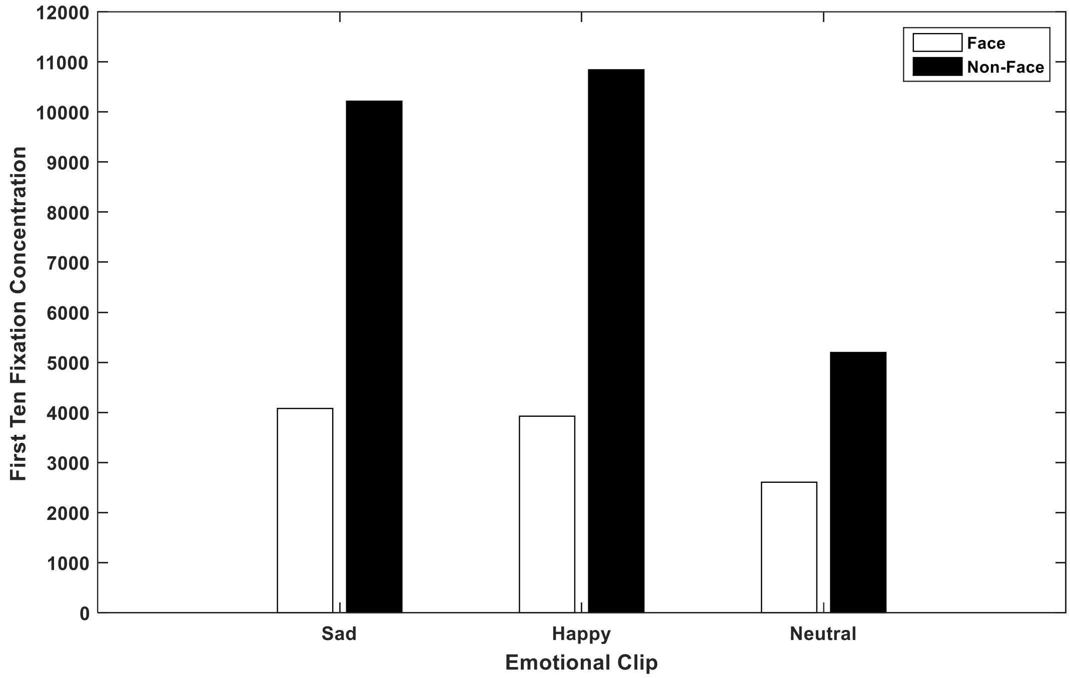

Figure 8 First Ten Fixation location on two region summary based on emotional clips

4.5 Total Fixation

4.5.1 Summary of Total Fixation Location

Clip type	Face	Upper Body	Other Region
Sad	3717	2968	18054
Happy	3160	2426	17414
Neutral	3315	1498	8924

Table 8 total fixation location summary for Three type of clips on three regions

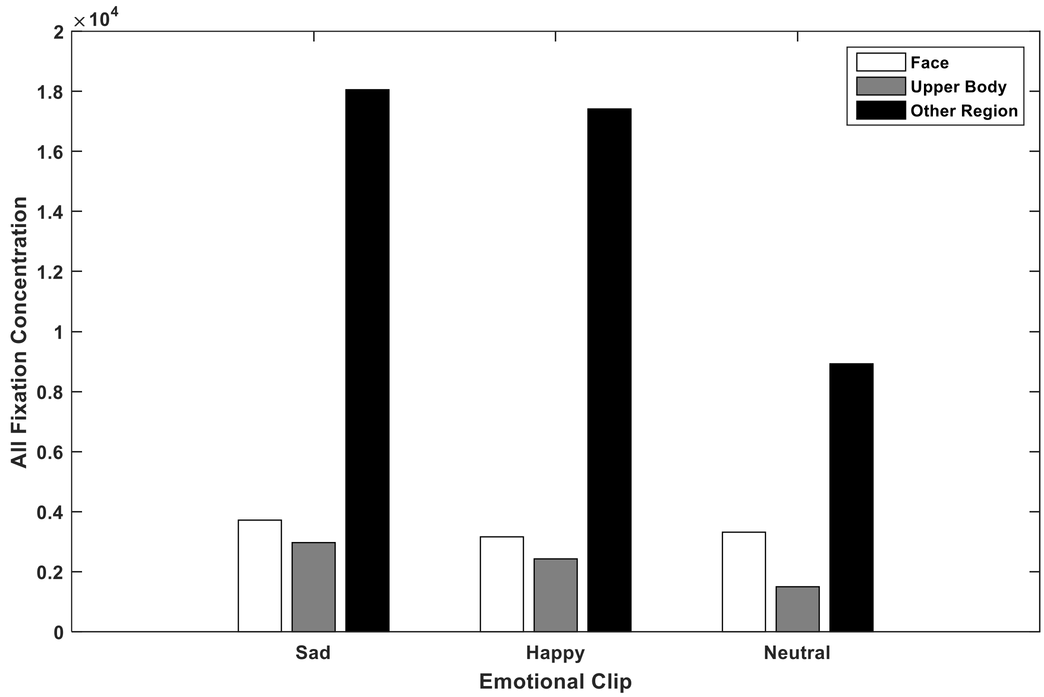

Figure 9 All Fixation location summary on three regions based on emotional clips

Clip type	**Face**	**Non-Face**
Sad	4078	18054
Happy	5586	17414
Neutral	6685	8924

Table 9 total fixation location summary for Three type of clips on two region

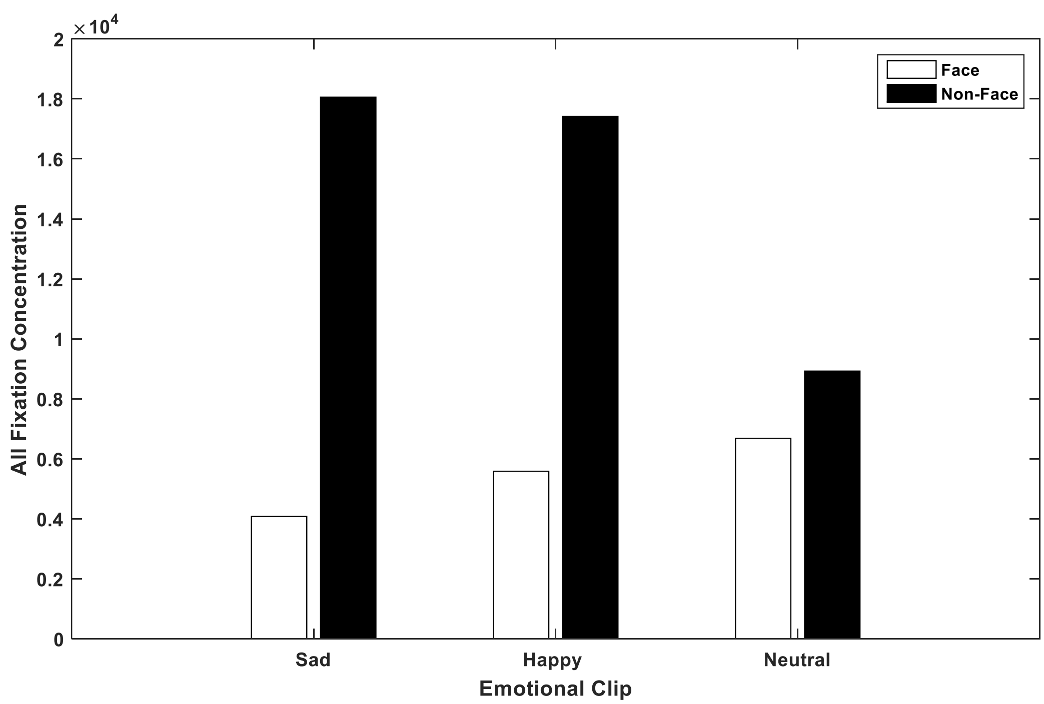

Figure 10 All Fixation location summary on two regions based on emotional cl

CHAPTER 5 DISCUSSION AND CONCLUCION

5.1 Discussion

After the calculating the Anova test for the first five fixation for the three different types of emotional clips. The result concluded that the mean fixation duration for the first five fixation for three emotional types of clips i.e. Sad, happy and neutral was same. Hence, we can conclude that there is no change in mean duration of first five fixation when the emotional type of clips changes. The means duration of first five fixation of sad clips was 356 ms, following the value of mean duration for the happy clips was 355 ms and the value for neutral clips was. 356 ms. The p value was greater than. 05. The result is mentioned in Appendix B.

After the calculating the Anova test for the first ten fixation for the three different types of emotional clips. The result concluded that the mean fixation duration for the first five fixation for three emotional types of clips i.e. sad, happy and neutral was same. Hence, we can conclude that there is no change in mean duration of first ten fixation when emotional type of clips changes. The means duration of first ten fixations of sad clips was 341×10^{-3}ms, following the value of mean duration for the happy clips was 344×10^{-3}ms and the value for neutral clips was 354×10^{-3}ms. The p value was greater than .05. The result is mentioned in Appendix B.

When the paired hoc t test was applied on the all fixation based on emotional clips [15]. The finding was as follow: Fixation rate difference was found between neutral and positive $(\mathrm{t}\,(23) = -2.2136, \mathrm{p} < 0.05)$ and also found between positive and negative$(\mathrm{t}\,(23) = -3.531, \mathrm{p} < 0.005\,)$. It was not for the found for neutral and negative stimuli$(\mathrm{t}\,(23) = -1.0066, \mathrm{n.s.})$. The mean for positive clips was 496.6 ms. The mean for sad clips was 541 ms. The mean for neutral clips was 496.6 ms.

In the second part of our investigation, we checked whether the fixation locations changed with change in emotional clips. We proceeded in three steps:

1. First Five locations
2. First Ten locations
3. All Fixations.

When the T test was applied for first five fixation the finding was following:

There was no significant difference when fixation location i.e. head was tested first five fixations for different emotional clips. $T(18) = -0.79521$ was the value for the Neutral and sad stimuli which lie in the range from $-2.1\ to\ 2.1$. The value for sad and happy stimuli was $T(18) = -0.20623$ which is le in the range $-2.1\ to\ 2.1$. The neutral and happy stimuli have a value of $T(18) = -1.1$ which also lie in the range $-2.1\ to\ 2.1$.

The second fixation location was upper body. The value for sad and happy stimuli was $T\ (18) = 0.574$, for sad and neutral stimuli was $T\ (18) = 2.0153$ and for happy and neutral stimuli was $(18) = 1.833112$. The difference was seen for the happy and neutral stimuli that was out of the range from - $-2.1\ to\ 2.1$. The third location was other region i.e. surrounding area. The values found using the T test was : for sad and happy stimuli was $T(18) = -2.5167$, for neutral and happy stimuli has a value of $T(18) = -3.622$ and for sad and happy stimuli has a value of $T(18) = -0.942$.

In the next step, the first ten fixations were considered and the results are following:

In the first part, we divided fixation location into three regions: Face, Upper Body and Other Region. The T test applied for three regions for three type of emotional clips: happy, sad and neutral. The findings for the face was: The value for happy and sad stimuli was $T(18) = -0.28403$, the value for sad and neutral stimuli was $T(18) = 0.535783$ and the value for positive and neutral stimuli was $T(18) = 0.893234$. The values for the face lied in the range of -2.1 to 2.1. Second region was Upper body and the values of different stimuli were: The value for happy and sad stimuli was $T(18) = 0.759381$, the value for sad and neutral stimuli was $T(18) = 1.77987$ and the value for positive and neutral stimuli was $T(18) = 1.351669$. The values for the Upper Body lied in the range of -2.1 to 2.1. Third region was Other Region and the values of different stimuli were: The value for happy and sad stimuli was $T(18) = -0.28098$, the value for sad and neutral stimuli was $T(18) = 2.481345$ and the value for positive and neutral stimuli was $T(18) = 3.101985$. Two values for the Upper Body did not lie in the range of -2.1 to 2.1 and only one value lied in the range.

In the last step, all fixations were considered and the results are following:

In the first part, we divided fixation location into three regions: Face, Upper Body and Other Region. The T test applied for three regions for three type of emotional clips: happy, sad and neutral. The findings for the face was: The value for happy and sad stimuli was $(18) = 0.421617$, the value for sad and neutral stimuli was $T(18) = -0.30534$ and the value for positive and neutral stimuli was $T(18) = 0.122984$. The values for the face lied in the range of -2.1 to 2.1. Second region was Upper body and the values of different stimuli were : The value for happy and sad stimuli was $T(18) = 0.482689$, the value for sad and neutral stimuli was $T(18) = -1.56594$ and the value for positive and neutral stimuli was $T(18) = -0.90422$. The values for the Upper Body lied in the range of -2.1 to 2.1. Third region was Other Region and the values of different stimuli were : The value for happy and sad stimuli was$T(18) = 0.196142$, the value for sad and neutral stimuli was $T(18) = -2.75636$ and the value for positive and neutral stimuli was $T(18) = -4.30197$. Two values for the Upper Body did not lie in the range of -2.1 to $2.1$and only one value lied in the range.

Emotional clips got more fixations in other region as compared to neutral clip for the first ten locations and all fixations locations. The number of first ten fixation fixated in other region in neutral clips was 5196, for sad clips was 10215 and for happy clips was 10842. The number of all fixation fixated in other region in neutral clips was 8924, for sad clips was 18054 and for happy clips was 17414. The possibly explanations for the behavior can be following: [50]

1. According to Busewell, “Eye movements are the unconscious adjust to the demand of the attentions during visual experience”.
2. In 1974 , “Fixations on informative areas are concentrated towards initial few seconds of viewing while later greater proportion of fixations are fixated in less informative areas”.

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APPENDIX A

Clip number	Face	Upper Body	Other region
1	149	38	160
2	230	154	10
3	268	114	745
4	629	174	721
5	640	144	748
6	118	13	664
7	89	168	1125
8	52	0	51
9	91	74	943
10	84	198	271
11	198	123	362
12	126	384	634
13	29	108	184
14	344	26	709
15	100	16	875
16	97	224	260
17	20	158	1121
18	176	1	335
19	164	35	538
20	27	48	263
21	60	102	1043
22	102	104	689
23	331	79	1283
24	295	37	385
25	123	16	831
26	215	73	883
27	4	0	202
28	185	0	852
29	51	2	1230
30	1	27	1077

Table 10 First Five Fixation Concentration on three regions

Clip number	Face	Non face
1	149+38	160
2	230+154	10
3	268+114	745
4	629+174	721
5	640+144	748
6	118+13	664
7	89+168	1125
8	52	51
9	91+74	943
10	84+198	271
11	198+123	362
12	126+384	634
13	29+108	184

14	344+26	709
15	100+16	875
16	97+224	260
17	20+158	1121
18	176+1	335
19	164+35	538
20	27+48	263
21	60+102	1043
22	104+102	689
23	331+79	1283
24	297+37	385
25	123+16	831
26	215+73	883
27	4	202
28	185	852
29	51+2	1230
30	1+27	1077

Table 11First Five Fixation Concentration on two regions

Clip number	Fix 1	Fix 2	Fix 3	Fix 4	Fix 5
Clip 1	0.2970 ± 0.1787	0.3664 ± 0.2320	0.4043 ± 0.2498	0.3038 ± 0.2013	0.3489 ± 0.2183
2	0.3888 ± 0.2752	0.3705 ± 0.2240	0.3978 ± 0.2437	0.3664 ± 0.2412	0.3731 ± 0.2529
3	0.3615 ± 0.2220	0.3659 ± 0.2181	0.3623 ± 0.2115	0.3476 ± 0.2083	0.3064 ± 0.1907
4	0.3551 ± 0.2092	0.3776 ± 0.2145	0.3548 ± 0.1953	0.3633 ± 0.1948	0.3343 ± 0.2052
5	0.3846 ± 0.2285	0.3937 ± 0.2236	0.4045 ± 0.2061	0.3704 ± 0.2064	0.3581 ± 0.1988
6	0.3590 ± 0.2078	0.3398 ± 0.2059	0.3722 ± 0.2201	0.3846 ± 0.2304	0.3381 ± 0.1831
7	0.3572 ± 0.2171	0.3433 ± 0.2079	0.3328 ± 0.2004	0.3118 ± 0.1940	0.3687 ± 0.2426
8	0.4709 ± 0.2777	0.4050 ± 0.2541	0.3892 ± 0.2373	0.4199 ± 0.2428	0.4423 ± 0.2241
9	0.3587 ± 0.2253	0.4059 ± 0.2338	0.3792 ± 0.2344	0.3903 ± 0.2362	0.3928 ± 0.2030
10	0.3374 ± 0.1946	0.3037 ± 0.2010	0.3379 ± 0.2017	0.3096 ± 0.2072	0.3089 ± 0.2175
11	0.3832 ± 0.2060	0.3678 ± 0.2166	0.3568 ± 0.1991	0.3899 ± 0.2241	0.3337 ± 0.1980
12	0.3095 ± 0.2095	0.3070 ± 0.2019	0.3174 ± 0.2225	0.3224 ± 0.2006	0.2663 ± 0.1976
13	0.4127 ± 0.2491	0.4085 ± 0.2477	0.4202 ± 0.2300	0.3752 ± 0.1827	0.3596 ± 0.1593
14	0.3952 ± 0.2159	0.4082 ± 0.2164	0.4200 ± 0.2212	0.3846 ± 0.1924	0.3968 ± 0.2145

15	0.3719 ± 0.2084	0.3911 ± 0.2032	0.3867 ± 0.2127	0.3665 ± 0.2030	0.3786 ± 0.1936
16	0.3247 ± 0.1763	0.3412 ± 0.2120	0.3119 ± 0.1841	0.3280 ± 0.2121	0.3103 ± 0.1711
17	0.3240 ± 0.2207	0.3370 ± 0.2167	0.3142 ± 0.1975	0.3352 ± 0.2147	0.3369 ± 0.2212
18	0.3550 ± 0.2260	0.3375 ± 0.2377	0.3440 ± 0.2291	0.2957 ± 0.1881	0.3073 ± 0.2131
19	0.3264 ± 0.1993	0.3331 ± 0.1977	0.3257 ± 0.1779	0.3498 ± 0.2150	0.3482 ± 0.1853
20	0.3816 ± 0.2119	0.3809 ± 0.2244	0.3672 ± 0.2030	0.3980 ± 0.2060	0.3538 ± 0.2076
21	0.3685 ± 0.2159	0.3449 ± 0.2073	0.3418 ± 0.2001	0.3006 ± 0.1616	0.2929 ± 0.1688
22	0.3779 ± 0.2352	0.3882 ± 0.2343	0.3924 ± 0.2441	0.3630 ± 0.2170	0.3562 ± 0.2240
23	0.3467 ± 0.1918	0.3828 ± 0.2129	0.3762 ± 0.2094	0.3781 ± 0.1994	0.3578 ± 0.1881
24	0.3169 ± 0.1881	0.3460 ± 0.2028	0.3624 ± 0.2157	0.3435 ± 0.1955	0.3410 ± 0.1947
25	0.3506 ± 0.1985	0.3760 ± 0.2228	0.3700 ± 0.2048	0.3505 ± 0.2018	0.3355 ± 0.1824
26	0.3316 ± 0.2121	0.3285 ± 0.2113	0.3597 ± 0.2208	0.3650± 0.2260	0.3503± 0.2169
27	0.3083 ± 0.1823	0.3228 ± 0.1886	0.3906 ± 0.2307	0.4326 ± 0.2199	0.4121± 0.2425
28	0.3137 ± 0.2067	0.3544 ± 0.2002	0.3509 ± 0.2249	0.3408 ± 0.2103	0.3443 ± 0.1957
29	0.3207 ± 0.1902	0.3342 ± 0.2108	0.3482 ± 0.2001	0.3330 ± 0.1961	0.3301 ± 0.1874
30	0.3313 ± 0.2078	0.3488 ± 0.1970	0.3409 ± 0.1883	0.3700 ± 0.2141	0.3569± 0.2069

Table 12 Average Time of First Five Fixations for Every Clip

Clip	Fix1	Fix2	Fix 3	Fix4	Fix 5	Fix 6	Fix 7	Fix 8	Fix 9	Fix 10
1	0.2970 0.1787	0.3664 0.2320	0.4043 0.2498	0.3038 0.2013	0.3489 0.2183	0.3411 0.2404	0.3227 0.1943	0.3544 0.2245	0.3165 0.1901	0.3122 0.2443
2	0.3888 0.2752	0.3705 0.2240	0.3978 0.2437	0.3664 0.2412	0.3731 0.2529	0.3635 0.2415	0.3673 0.2377	0.3631 0.2276	0.3383 0.2480	0.3383 0.2267
3	0.3615 0.2220	0.3659 0.2181	0.3630 0.2112	0.3476 0.2083	0.3064 0.1907	0.3556 0.2094	0.3463 0.2026	0.3271 0.1916	0.3598 0.2250	0.3156 0.1927
4	0.3551 0.2092	0.3776 0.2145	0.3548 0.1953	0.3633 0.1948	0.3343 0.2052	0.3454 0.1896	0.3393 0.1854	0.3479 0.1822	0.3677 0.1623	0.2702 0.1815
5	0.3853 0.2281	0.3941 0.2234	0.3976 0.2059	0.3704 0.2064	0.3581 0.1988	0.3613 0.1881	0.3560 0.2161	0.3703 0.1940	0.2903 0.1592	0.3219 0.1984
6	0.3590	0.3398	0.3702	0.3846	0.3381	0.4684	0.4195	0.3728	0.4402	0.3759

	0.2078	0.2059	0.2206	0.2304	0.1831	0.2959	0.2415	0.1893	0.2675	0.2123
7	0.3578 0.2168	0.3442 0.2076	0.3256 0.1996	0.3141 0.1936	0.3687 0.2426	0.3087 0.1695	0.3282 0.1790	0.2718 0.1632	0.3052 0.2111	0.3226 0.1563
8	0.4709 0.2777	0.4050 0.2541	0.3892 0.2373	0.4199 0.2428	0.4423 0.2241	0.4233 0.2764	0.4655 0.2451	0.4164 0.2803	0.3843 0.2483	0.4253 0.1918
9	0.3603 0.2266	0.4059 0.2338	0.3734 0.2313	0.3919 0.2363	0.3928 0.2030	0.2961 0.1934	0.3386 0.1717	0.3643 0.2462	0.3665 0.1773	0.2582 0.1025
10	0.3399 0.1965	0.3057 0.2015	0.3436 0.2094	0.3124 0.2076	0.3079 0.2161	0.2766 0.1640	0.3671 0.2251	0.2504 0.1275	0.2346 0.1370	0.2637 0.1829
11	0.3832 0.2060	0.3678 0.2166	0.3556 0.1989	0.3899 0.2241	0.3337 0.1980	0.3299 0.1883	0.3341 0.2090	0.3127 0.1566	0.3310 0.1917	0.4211 0.1874
12	0.3095 0.2095	0.3070 0.2019	0.3174 0.2225	0.3224 0.2006	0.2663 0.1976	0.3073 0.2188	0.2745 0.1705	0.3351 0.2052	0.3020 0.2151	0.2505 0.1758
13	0.4127 0.2491	0.4085 0.2477	0.4198 0.2282	0.3752 0.1827	0.3596 0.1593	0.4181 0.2074	0.3608 0.1644	0.3372 0.1700	0.4187 0.1926	0.3947 0.2458
14	0.3949 0.2156	0.4081 0.2160	0.4124 0.2217	0.3839 0.1921	0.3990 0.2134	0.3911 0.2221	0.3748 0.1960	0.3545 0.1773	0.3911 0.2074	0.4020 0.2338
15	0.3719 0.2084	0.3903 0.2039	0.3811 0.2124	0.3665 0.2030	0.3786 0.1936	0.3158 0.1765	0.3477 0.1803	0.3709 0.2463	0.3955 0.2187	0.3508 0.1857
16	0.3247 0.1763	0.3412 0.2120	0.3119 0.1841	0.3280 0.2121	0.3103 0.1711	0.3597 0.2225	0.2803 0.1826	0.2610 0.1458	0.2799 0.1270	0.3264 0.1832
17	0.3240 0.2207	0.3370 0.2167	0.3142 0.1975	0.3352 0.2147	0.3369 0.2212	0.3330 0.2031	0.3132 0.2161	0.2949 0.1650	0.3050 0.1823	0.3120 0.1916
18	0.3550 0.2260	0.3375 0.2377	0.3440 0.2291	0.2957 0.1881	0.3073 0.2131	0.3586 0.2464	0.2637 0.1767	0.3379 0.1970	0.2621 0.1556	0.3267 0.1760
19	0.3264 0.1993	0.3331 0.1977	0.3239 0.1786	0.3498 0.2150	0.3482 0.1853	0.3465 0.1968	0.3420 0.1715	0.3370 0.2205	0.3008 0.2014	0.3400 0.2018
20	0.3816 0.2119	0.3809 0.2244	0.3737 0.2080	0.3980 0.2060	0.3538 0.2076	0.3343 0.1749	0.3663 0.2120	0.2788 0.1215	0.2717 0.1287	0.3293 0.2053
21	0.3464 0.1972	0.3694 0.2040	0.3765 0.2325	0.3280 0.1987	0.3367 0.1966	0.3349 0.2002	0.3341 0.1774	0.3640 0.2098	0.3228 0.2088	0.3602 0.2519
22	0.3512 0.2094	0.3516 0.1975	0.3390 0.2003	0.3184 0.1951	0.3189 0.1814	0.3164 0.2203	0.2933 0.1376	0.2608 0.1458	0.2040 0.1218	0.1750 0.0594
23	0.3471 0.1916	0.3791 0.2108	0.3688 0.2101	0.3776 0.1955	0.3547 0.1851	0.3604 0.2024	0.3357 0.1855	0.3366 0.1764	0.3383 0.1830	0.3495 0.1890
24	0.3169 0.1881	0.3460 0.2028	0.3590 0.2149	0.3435 0.1955	0.3410 0.1947	0.3531 0.2063	0.3505 0.2161	0.3441 0.2077	0.3437 0.2219	0.3611 0.2149
25	0.3506 0.1985	0.3760 0.2228	0.3704 0.2044	0.3505 0.2018	0.3355 0.1824	0.3586 0.2025	0.3584 0.1809	0.3485 0.1914	0.3605 0.2065	0.3361 0.1737
26	0.3316 0.2121	0.3285 0.2113	0.3597 0.2208	0.3650 0.2260	0.3503 0.2169	0.3422 0.2253	0.3274 0.1926	0.3579 0.2259	0.3522 0.2105	0.3220 0.1993
27	0.3083 0.1823	0.3228 0.1886	0.3863 0.2294	0.4326 0.2199	0.4121 0.2425	0.3813 0.2334	0.3964 0.2534	0.3688 0.2283	0.4444 0.2210	0.3317 0.2038

28	0.3137 0.2067	0.3544 0.2002	0.3492 0.2269	0.3408 0.2103	0.3443 0.1957	0.3031 0.1679	0.3267 0.1945	0.3018 0.1864	0.3130 0.2064	0.3023 0.1746
29	0.3207 0.1902	0.3342 0.2108	0.3482 0.2001	0.3330 0.1961	0.3301 0.1874	0.2997 0.1754	0.3438 0.1998	0.3269 0.1788	0.3252 0.2024	0.2584 0.1456
30	0.3312 0.2074	0.3504 0.1980	0.3349 0.1872	0.3711 0.2141	0.3569 0.2069	0.3661 0.2317	0.3403 0.2024	0.3525 0.2001	0.3534 0.2138	0.3343 0.1940

Table 13Mean and standard deviation of first ten fixations

Clip number	**Face**	**Upper Body**	**Other region**
1	236	85	228
2	319	221	15
3	397	170	950
4	731	186	897
5	820	167	966
6	156	13	779
7	91	169	1380
8	92	0	85
9	104	87	1088
10	99	255	379
11	230	193	554
12	217	577	881
13	35	151	272
14	518	36	964
15	131	16	1155
16	109	320	335
17	24	203	1758
18	258	2	429
19	266	68	846
20	34	66	412
21	266	68	846
22	178	110	1230
23	406	88	1826
24	511	89	572
25	173	24	1194
26	285	118	1213
27	20	1	361
28	268	0	1245
29	80	6	1636
30	0	64	1757

Table 14 Concentration of First Ten Fixation on Three Different Region

Clip	Face	Non face
1	236+85	228
2	319+221	15
3	397+170	950
4	731+186	897

5	820+167	966
6	156+13	779
7	91+169	1380
8	92	85
9	104+87	1088
10	99+255	379
11	230+193	554
12	217+577	881
13	35+151	272
14	518+36	964
15	131+16	1155
16	109+320	335
17	24+203	1758
18	258+2	429
19	266+68	846
20	34+66	412
21	80+118	1153
22	178+110	1230
23	406+88	1826
24	511+89	572
25	173+24	1194
26	285+118	1213
27	20+1	361
28	268	1245
29	80+8	1636
30	8+64	1757

Table 15 First Ten Fixation Concentration over Two regions: Face and Non-Face

Clip Number	**Face**	**Upper Region**	**Other Region**
1	565	248	554
2	471	489	233
3	620	340	2024
4	992	221	1261
5	937	230	1341
6	233	18	990
7	109	210	1781
8	208	0	361
9	130	123	1416
10	117	390	583
11	292	311	1281
12	313	828	1379
13	89	519	950
14	708	76	1518
15	145	16	1543
16	148	927	1188
17	55	346	3252
18	323	4	550
19	382	174	1430

20	220	433	2172
21	97	195	1523
22	255	143	1599
23	503	160	2264
24	1003	115	762
25	210	27	2239
26	541	177	1831
27	64	27	867
28	331	3	1877
29	99	10	2230
30	32	132	3393

Table 16 Concentration of all fixation on three different regions

clip	Faces	Non-Faces
1	565+248	554
2	471+489	233
3	620+340	2024
4	992+221	1261
5	937+230	1341
6	233+18	990
7	109+210	1781
8	208	361
9	130+123	1416
10	117+390	583
11	292+311	1281
12	313+828	1379
13	89+519	950
14	708+76	1518
15	145+16	1543
16	148+927	1188
17	55+346	3252
18	323+4	880
19	382+174	1430
20	220+433	2172
21	97+195	1523
22	255+143	1599
23	503+160	2264
24	1003+115	762
25	210+27	2239
26	541+177	1831
27	64+27	867
28	331+3	1877
29	99+10	2230
30	32+132	3393

Table 17 Concentration of all fixation on two different regions

APPENDIX B

"t-Test: Two-Sample Assuming Equal Variances"

	Sad	*Happy*
"Mean"	0.36051	0.353004
"Variance"	4.22E-05	0.000114
"Observations"	5	5
"Hypothesized Mean Difference"	0	
"Df"	7	
"t Stat"	1.344769	
"P(T<=t) one-tail"	0.110319	
"t Critical one-tail"	1.894579	
"P(T<=t) two-tail"	0.220639	
"t Critical two-tail"	2.364624	

"t-Test: Two-Sample Assuming Equal Variances"

	Sad	*neutral*
"Mean"	0.36051	0.356362
"Variance"	4.22E-05	6.17E-05
"Observations"	5	5
"Pooled Variance"	5.2E-05	
"Hypothesized Mean Difference"	0	
"df"	8	
"t Stat"	0.909788	
"P(T<=t) one-tail"	0.194761	
"t Critical one-tail"	1.859548	
"P(T<=t) two-tail"	0.389521	
"t Critical two-tail"	2.306004	

"t-Test: Two-Sample Assuming Equal Variances"

	Happy	*neutral*
"Mean"	0.353004	0.356362
"Variance"	0.000114	6.17E-05
"Observations"	5	5
"Pooled Variance"	8.76E-05	
"Hypothesized Mean Difference"	0	
"df"	8	
"t Stat"	-0.5672	
"P(T<=t) one-tail"	0.29307	
"t Critical one-tail"	1.859548	
"P(T<=t) two-tail"	0.586139	
"t Critical two-tail"	2.306004	

SUMMARY				
Groups	*Count*	*Sum*	*Average*	*Variance*

Sad	5	1.80255	0.36051	4.22E-05
Happy	5	1.76502	0.353004	0.000114
Neutral	5	1.78181	0.356362	6.17E-05

ANOVA						
"Source of Variation"	*"SS"*	*"df"*	*"MS"*	*"F"*	*"P-value"*	*"F crit"*
"Between Groups"	0.000141	2	7.07E-05	0.975054	0.405156	3.885294
"Within Groups"	0.00087	12	7.25E-05			
"Total"	0.001011	14				

"t-Test: Two-Sample Assuming Equal Variances"

	Sad	*Happy*
"Mean"	0.341048	0.344386
"Variance"	0.000387	0.000162
"Observations"	10	10
"Pooled Variance"	0.000275	
"Hypothesized Mean Difference"	0	
"df"	18	
"t Stat"	-0.45044	
"P(T<=t) one-tail"	0.328887	
"t Critical one-tail"	1.734064	
"P(T<=t) two-tail"	0.657774	
"t Critical two-tail"	2.100922	

"t-Test: Two-Sample Assuming Equal Variances"

	Sad	*nentral*
"Mean"	0.341048	0.354142
"Variance"	0.000387	8.84E-05
"Observations"	10	10
"Pooled Variance"	0.000238	
"Hypothesized Mean Difference"	0	
"df"	18	
"t Stat"	-1.89915	
"P(T<=t) one-tail"	0.036846	
"t Critical one-tail"	1.734064	
"P(T<=t) two-tail"	0.073692	
"t Critical two-tail"	2.100922	

SUMMARY				
"Groups	*Count*	*Sum*	*Average*	*Variance*
Sad	10	3.41048	0.341048	0.000387
Happy	10	3.44386	0.344386	0.000162
Neutral	10	3.54142	0.354142	8.84E-05

"ANOVA"						
"Source of Variation"	*"SS"*	*"df"*	*"MS"*	*"F"*	*"P-value"*	*"F crit"*

Between Groups	0.000926	2	0.000463	2.17843	0.132715	3.354131
Within Groups	0.005738	27	0.000213			
Total	0.006664	29				

Five fixations

Face

“t-Test: Two-Sample Assuming Equal Variances”

	neutral	*sad*
“Mean”	125.6	178.5
“Variance”	7567.822	36685.61
“Observations”	10	10
“Pooled Variance”	22126.72	
“Hypothesized Mean Difference”	0	
“df”	18	
“t Stat”	-0.79521	
“P(T<=t) one-tail”	0.218426	
“t Critical one-tail”	1.734064	
“P(T<=t) two-tail”	0.436852	
“t Critical two-tail”	2.100922	

“t-Test: Two-Sample Assuming Equal Variances”

	sad	*happy*
“Mean”	178.5	195.7
“Variance”	36685.61	32873.79
“Observations”	10	10
“Pooled Variance”	34779.7	
“Hypothesized Mean Difference”	0	
“df”	18	
“t Stat”	-0.20623	
“P(T<=t) one-tail”	0.419463	
“t Critical one-tail”	1.734064	
“P(T<=t) two-tail”	0.838926	
“t Critical two-tail”	2.100922	

“t-Test: Two-Sample Assuming Equal Variances”

	neutral	*happy*
“Mean”	125.6	195.7
“Variance”	7567.822	32873.79
“Observations”	10	10
“Pooled Variance”	20220.81	
“Hypothesized Mean Difference”	0	
“df”	18	
“t Stat”	-1.10231	
“P(T<=t) one-tail”	0.142424	
“t Critical one-tail”	1.734064	
“P(T<=t) two-tail”	0.284848	
“t Critical two-tail”	2.100922	

Upper body

"t-Test: Two-Sample Assuming Equal Variances"

	sad	*happy*
"Mean"	122.2	98.8
"Variance"	11379.29	5200.844
"Observations"	10	10
"Pooled Variance"	8290.067	
"Hypothesized Mean Difference"	0	
"df"	18	
"t Stat"	0.574674	
"P(T<=t) one-tail"	0.286312	
"t Critical one-tail"	1.734064	
"P(T<=t) two-tail"	0.572625	
"t Critical two-tail"	2.100922	

"t-Test: Two-Sample Assuming Equal Variances"

	sad	*neutral*
"Mean"	122.2	43
"Variance"	11379.29	4065.111
"Observations"	10	10
"Pooled Variance"	7722.2	
"Hypothesized Mean Difference"	0	
"df"	18	
"t Stat"	2.0153	
"P(T<=t) one-tail"	0.029528	
"t Critical one-tail"	1.734064	
"P(T<=t) two-tail"	0.059056	
"t Critical two-tail"	2.100922	

"t-Test: Two-Sample Assuming Equal Variances"

	happy	*neutral*
"Mean"	98.8	43
"Variance"	5200.844	4065.111
"Observations"	10	10
"Pooled Variance"	4632.978	
"Hypothesized Mean Difference"	0	
"df"	18	
"t Stat"	1.833112	
"P(T<=t) one-tail"	0.041689	
"t Critical one-tail"	1.734064	
"P(T<=t) two-tail"	0.083379	
"t Critical two-tail"	2.100922	

Other region

"t-Test: Two-Sample Assuming Equal Variances"

	neutral	*sad*
"Mean"	364.2	705
"Variance"	62953.29	120414
"Observations"	10	10
"Pooled Variance"	91683.64	
"Hypothesized Mean Difference"	0	
"df"	18	
"t Stat"	-2.51674	
"P(T<=t) one-tail"	0.010772	
"t Critical one-tail"	1.734064	
"P(T<=t) two-tail"	0.021544	
"t Critical two-tail"	2.100922	

"t-Test: Two-Sample Assuming Equal Variances"

	neutral	*happy*
"Mean"	364.2	850.2
"Variance"	62953.29	117046.8
"Observations"	10	10
"Pooled Variance"	90000.07	
"Hypothesized Mean Difference"	0	
"df"	18	
"t Stat"	-3.62243	
"P(T<=t) one-tail"	0.000974	
"t Critical one-tail"	1.734064	
"P(T<=t) two-tail"	0.001948	
"t Critical two-tail"	2.100922	

"t-Test: Two-Sample Assuming Equal Variances"

	sad	*happy*
"Mean"	705	850.2
"Variance"	120414	117046.8
"Observations"	10	10
"Pooled Variance"	118730.4	
"Hypothesized Mean Difference"	0	
"df"	18	
"t Stat"	-0.94226	
"P(T<=t) one-tail"	0.179268	
"t Critical one-tail"	1.734064	
"P(T<=t) two-tail"	0.358535	
"t Critical two-tail"	2.100922	

Face

"t-Test: Two-Sample Assuming Equal Variances"

	neutral	*sad*
"Mean"	168.6	300.7
"Variance"	9362.489	52862.01
"Observations"	10	10
"Pooled Variance"	31112.25	
"Hypothesized Mean Difference"	0	
"df"	18	
"t Stat"	-1.67464	
"P(T<=t) one-tail"	0.055645	
"t Critical one-tail"	1.734064	
"P(T<=t) two-tail"	0.11129	
"t Critical two-tail"	2.100922	

"t-Test: Two-Sample Assuming Equal Variances"

	neutral	*happy*
"Mean"	168.6	294.5
"Variance"	9362.489	43926.5
"Observations"	10	10
"Pooled Variance"	26644.49	
"Hypothesized Mean Difference"	0	
"df"	18	
"t Stat"	-1.72467	
"P(T<=t) one-tail"	0.050858	
"t Critical one-tail"	1.734064	
"P(T<=t) two-tail"	0.101716	
"t Critical two-tail"	2.100922	

"t-Test: Two-Sample Assuming Equal Variances"

	sad	*happy*
"Mean"	300.7	294.5
"Variance"	52862.01	43926.5
"Observations"	10	10
"Pooled Variance"	48394.26	
"Hypothesized Mean Difference"	0	
"df"	18	
"t Stat"	0.06302	
"P(T<=t) one-tail"	0.475222	
"t Critical one-tail"	1.734064	
"P(T<=t) two-tail"	0.950445	
"t Critical two-tail"	2.100922	

First ten fixation\
Face

"t-Test: Two-Sample Assuming Equal Variances"

	sad	*happy*
"Mean"	241	270.3
"Variance"	55131.33	51281.34
"Observations"	10	10
"Pooled Variance"	53206.34	
"Hypothesized Mean Difference"	0	
"df"	18	
"t Stat"	-0.28403	
"P(T<=t) one-tail"	0.389813	
"t Critical one-tail"	1.734064	
"P(T<=t) two-tail"	0.779625	
"t Critical two-tail"	2.100922	

"t-Test: Two-Sample Assuming Equal Variances"

	sad	*neutral*
"Mean"	241	194.1
"Variance"	55131.33	21493.21
"Observations"	10	10
"Pooled Variance"	38312.27	
"Hypothesized Mean Difference"	0	
"df"	18	
"t Stat"	0.535783	
"P(T<=t) one-tail"	0.299334	
"t Critical one-tail"	1.734064	
"P(T<=t) two-tail"	0.598667	
"t Critical two-tail"	2.100922	

"t-Test: Two-Sample Assuming Equal Variances"

	happy	*neutral*
"Mean"	270.3	194.1
"Variance"	51281.34	21493.21
"Observations"	10	10
"Pooled Variance"	36387.28	
"Hypothesized Mean Difference"	0	
"df"	18	
"t Stat"	0.893234	
"P(T<=t) one-tail"	0.19176	
"t Critical one-tail"	1.734064	
"P(T<=t) two-tail"	0.383519	
"t Critical two-tail"	2.100922	

Upper body

"t-Test: Two-Sample Assuming Equal Variances"

	sad	*happy*
"Mean"	166.8	122.1
"Variance"	24743.73	9905.656
"Observations"	10	10
"Pooled Variance"	17324.69	
"Hypothesized Mean Difference"	0	
"df"	18	
"t Stat"	0.759381	
"P(T<=t) one-tail"	0.228728	
"t Critical one-tail"	1.734064	
"P(T<=t) two-tail"	0.457455	
"t Critical two-tail"	2.100922	

"t-Test: Two-Sample Assuming Equal Variances"

	sad	*neutral*
"Mean"	166.8	66.4
"Variance"	24743.73	7075.6
"Observations"	10	10
"Pooled Variance"	15909.67	
"Hypothesized Mean Difference"	0	
"df"	18	
"t Stat"	1.77987	
"P(T<=t) one-tail"	0.045993	
"t Critical one-tail"	1.734064	
"P(T<=t) two-tail"	0.091986	
"t Critical two-tail"	2.100922	

“t-Test: Two-Sample Assuming Equal Variances”

	happy	*neutral*
“Mean”	122.1	66.4
“Variance”	9905.656	7075.6
“Observations”	10	10
“Pooled Variance”	8490.628	
“Hypothesized Mean Difference”	0	
“df”	18	
“t Stat”	1.351669	
“P(T<=t) one-tail”	0.096612	
“t Critical one-tail”	1.734064	
“P(T<=t) two-tail”	0.193224	
“t Critical two-tail”	2.100922	

Other region

“t-Test: Two-Sample Assuming Equal Variances”

	sad	*happy*
“Mean”	1021.5	1084.2
“Variance”	287893.2	210050
“Observations”	10	10
“Pooled Variance”	248971.6	
“Hypothesized Mean Difference”	0	
“df”	18	
“t Stat”	-0.28098	
“P(T<=t) one-tail”	0.390964	
“t Critical one-tail”	1.734064	
“P(T<=t) two-tail”	0.781929	
“t Critical two-tail”	2.100922	

“t-Test: Two-Sample Assuming Equal Variances”

	sad	*neutral*
“Mean”	1021.5	519.6
“Variance”	287893.2	121235.6
“Observations”	10	10
“Pooled Variance”	204564.4	
“Hypothesized Mean Difference”	0	
“df”	18	
“t Stat”	2.481345	
“P(T<=t) one-tail”	0.011595	
“t Critical one-tail”	1.734064	
“P(T<=t) two-tail”	0.023189	
“t Critical two-tail”	2.100922	

“t-Test: Two-Sample Assuming Equal Variances”

	happy	*neutral*
“Mean”	1084.2	519.6
“Variance”	210050	121235.6
“Observations”	10	10

“Pooled Variance”	165642.8
“Hypothesized Mean Difference”	0
“df”	18
“t Stat”	3.101985
“P(T<=t) one-tail”	0.003076
“t Critical one-tail”	1.734064
“P(T<=t) two-tail”	0.006153
“t Critical two-tail”	2.100922

Face

“t-Test: Two-Sample Assuming Equal Variances”

	sad	*happy*
“Mean”	407.8	392.4
“Variance”	83810.18	67761.82
“Observations”	10	10
“Pooled Variance”	75786	
“Hypothesized Mean Difference”	0	
“df”	18	
“t Stat”	0.125087	
“P(T<=t) one-tail”	0.450921	
“t Critical one-tail”	1.734064	
“P(T<=t) two-tail”	0.901841	
“t Critical two-tail”	2.100922	

“t-Test: Two-Sample Assuming Equal Variances”

	sad	*neutral*
“Mean”	407.8	260.5
“Variance”	83810.18	25866.28
“Observations”	10	10
“Pooled Variance”	54838.23	
“Hypothesized Mean Difference”	0	
“df”	18	
“t Stat”	1.40652	
“P(T<=t) one-tail”	0.0883	
“t Critical one-tail”	1.734064	
“P(T<=t) two-tail”	0.1766	
“t Critical two-tail”	2.100922	

“t-Test: Two-Sample Assuming Equal Variances”

	happy	*neutral*
“Mean”	392.4	260.5
“Variance”	67761.82	25866.28
“Observations”	10	10
“Pooled Variance”	46814.05	
“Hypothesized Mean Difference”	0	
“df”	18	
“t Stat”	1.363144	
“P(T<=t) one-tail”	0.094823	
“t Critical one-tail”	1.734064	
“P(T<=t) two-tail”	0.189647	
“t Critical two-tail”	2.100922	

All fixation

face

"t-Test: Two-Sample Assuming Equal Variances"

	neutral	*sad*
"Mean"	331.5	371.7
"Variance"	78820.5	94509.34
"Observations"	10	10
"Pooled Variance"	86664.92	
"Hypothesized Mean Difference"	0	
"df"	18	
"t Stat"	-0.30534	
"P(T<=t) one-tail"	0.381804	
"t Critical one-tail"	1.734064	
"P(T<=t) two-tail"	0.763607	
"t Critical two-tail"	2.100922	

"t-Test: Two-Sample Assuming Equal Variances"

	neutral	*happy*
"Mean"	331.5	316
"Variance"	78820.5	80022.44
"Observations"	10	10
"Pooled Variance"	79421.47	
"Hypothesized Mean Difference"	0	
"df"	18	
"t Stat"	0.122984	
"P(T<=t) one-tail"	0.451741	
"t Critical one-tail"	1.734064	
"P(T<=t) two-tail"	0.903483	
"t Critical two-tail"	2.100922	

"t-Test: Two-Sample Assuming Equal Variances"

	sad	*happy*
"Mean"	371.7	316
"Variance"	94509.34	80022.44
"Observations"	10	10
"Pooled Variance"	87265.89	
"Hypothesized Mean Difference"	0	
"df"	18	
"t Stat"	0.421617	
"P(T<=t) one-tail"	0.339148	
"t Critical one-tail"	1.734064	
"P(T<=t) two-tail"	0.678297	
"t Critical two-tail"	2.100922	

Upper body

"t-Test: Two-Sample Assuming Equal Variances"

	neutral	*sad*
"Mean"	149.8	296.8
"Variance"	33682.62	54439.51
"Observations"	10	10
"Pooled Variance"	44061.07	
"Hypothesized Mean Difference"	0	
"df"	18	
"t Stat"	-1.56594	
"P(T<=t) one-tail"	0.067387	
"t Critical one-tail"	1.734064	
"P(T<=t) two-tail"	0.134774	
"t Critical two-tail"	2.100922	

"t-Test: Two-Sample Assuming Equal Variances"

	neutral	*happy*
"Mean"	149.8	242.6
"Variance"	33682.62	71645.82
"Observations"	10	10
"Pooled Variance"	52664.22	
"Hypothesized Mean Difference"	0	
"df"	18	
"t Stat"	-0.90422	
"P(T<=t) one-tail"	0.18891	
"t Critical one-tail"	1.734064	
"P(T<=t) two-tail"	0.377821	
"t Critical two-tail"	2.100922	

"t-Test: Two-Sample Assuming Equal Variances"

	sad	*happy*
Mean	296.8	242.6
"Mean"	54439.51	71645.82
"Variance"	10	10
"Observations"	63042.67	
"Pooled Variance"	0	
"Hypothesized Mean Difference"	18	
"df"	0.482689	
"t Stat"	0.317567	
"P(T<=t) one-tail"	1.734064	
"t Critical one-tail"	0.635135	
"P(T<=t) two-tail"	2.100922	

Other region

"t-Test: Two-Sample Assuming Equal Variances"

	neutral	*sad*
"Mean"	892.4	1805.4
"Variance"	210978.9	886182
"Observations"	10	10
"Pooled Variance"	548580.5	
"Hypothesized Mean Difference"	0	
"df"	18	
"t Stat"	-2.75636	
"P(T<=t) one-tail"	0.006497	
"t Critical one-tail"	1.734064	

“P(T<=t) two-tail”	0.012995
“t Critical two-tail”	2.100922

“t-Test: Two-Sample Assuming Equal Variances”

	neutral	*happy*
“Mean”	892.4	1741.4
“Variance”	210978.9	178497.6
“Observations”	10	10
“Pooled Variance”	194738.3	
“Hypothesized Mean Difference”	0	
“df”	18	
“t Stat”	-4.30197	
“P(T<=t) one-tail”	0.000215	
“t Critical one-tail”	1.734064	
“P(T<=t) two-tail”	0.000429	
“t Critical two-tail”	2.100922	

“t-Test: Two-Sample Assuming Equal Variances”

	sad	*happy*
“Mean”	1805.4	1741.4
“Variance”	886182	178497.6
“Observations”	10	10
“Pooled Variance”	532339.8	
“Hypothesized Mean Difference”	0	
“df”	18	
“t Stat”	0.196142	
“P(T<=t) one-tail”	0.423348	
“t Critical one-tail”	1.734064	
“P(T<=t) two-tail”	0.846696	
“t Critical two-tail”	2.100922	

Face

“t-Test: Two-Sample Assuming Equal Variances”

	neutral	*sad*
“Mean”	481.3	668.5
“Variance”	95919.57	132514.1
“Observations”	10	10
“Pooled Variance”	114216.8	
“Hypothesized Mean Difference”	0	
“df”	18	
“t Stat”	-1.23859	
“P(T<=t) one-tail”	0.115705	
“t Critical one-tail”	1.734064	
“P(T<=t) two-tail”	0.231409	
“t Critical two-tail”	2.100922	

“t-Test: Two-Sample Assuming Equal Variances”

	neutral	*happy*
“Mean”	481.3	558.6
“Variance”	95919.57	155883.2

“Observations”	10	10
“Pooled Variance”	125901.4	
“Hypothesized Mean Difference”	0	
“df”	18	
“t Stat”	-0.48713	
“P(T<=t) one-tail”	0.316021	
“t Critical one-tail”	1.734064	
“P(T<=t) two-tail”	0.632042	
“t Critical two-tail”	2.100922	

“t-Test: Two-Sample Assuming Equal Variances”

	sad	*happy*
“Mean”	668.5	558.6
“Variance”	132514.1	155883.2
“Observations”	10	10
“Pooled Variance”	144198.6	
“Hypothesized Mean Difference”	0	
“df”	18	
“t Stat”	0.647146	
“P(T<=t) one-tail”	0.262853	
“t Critical one-tail”	1.734064	
“P(T<=t) two-tail”	0.525705	
“t Critical two-tail”	2.100922	