Predicting Movie Ratings from Audience Behaviors

Rajitha Navarathna\textsuperscript{1}, Patrick Lucey\textsuperscript{1}, Peter Carr\textsuperscript{1}, Elizabeth Carter\textsuperscript{1,2}, Sridha Sridharan\textsuperscript{3}, Iain Matthews\textsuperscript{1}

\textsuperscript{1}Disney Research, Pittsburgh, USA

\textsuperscript{2}Carnegie Mellon University, USA, \textsuperscript{3}Queensland University of Technology, Australia

\{rajitha.navarathna,patrick.lucey,peter.carr,iainm\}@disneyresearch.com

lizcarter@cmu.edu, s.sridharan@qut.edu.au

Abstract

We propose a method of representing audience behavior through facial and body motions from a single video stream, and use these motions to predict the rating for feature-length movies. This is a very challenging problem as: i) the movie viewing environment is dark and contains views of people at different scales and viewpoints; ii) the duration of feature-length movies is long (80-120 mins) so tracking people uninterrupted for this length of time is an unsolved problem; and iii) expressions and motions of audience members are subtle, short and sparse making labeling of activities unreliable. To circumvent these issues, we use an infra-red illuminated test-bed to obtain a visually uniform input. We then utilize motion-history features which capture the subtle movements of a person within a pre-defined volume, and then form a group representation of the audience by a histogram of pair-wise correlations over small time windows. Using this group representation, we learn a movie rating classifier from crowd-sourced ratings collected by rotten-tomatoes.com and show our prediction capability on audiences from 30 movies across 250 subjects (> 50 hours).

1. Introduction

Having the ability to objectively measure group experience would be of major benefit within the educational, marketing, advertising and behavioral science domains. However, due to the complexities of the observed environments and task, the de-facto standard of measuring audience or group experience is still via self-report \cite{4}. As self-report measures are subjective, labor intensive, and do not provide feedback at precise time-stamps; an automated and objective measure is desirable. In an attempt to provide an objective measure, Madan et al. \cite{19} utilized a wearable device which measured audio, head movement and galvanic skin responses of a group interacting. Eagle and Pentland \cite{7} developed a system using a PDA which required continuous user input. While both are interesting approaches, our goal is to implement a less invasive solution.

For measuring reactions to consumer products, almost all ratings are via self-report (i.e., “likes” or a Likert-type scale \cite{5}). Given enough crowd-sourced ratings (100K’s), useful measures can be obtained which can be used to predict other products that a person maybe interested in based on their previous behavior. Such recommendation systems are often based on matrix factorization approaches. Pandora\textsuperscript{1} (songs), Netflix\textsuperscript{2} (movies/tv-shows) and Amazon\textsuperscript{3} (products) are popular examples for content-based and collaborative filtering approaches \cite{15}.

For movies, Rotten Tomatoes \cite{1} have both critic and crowd-sourced audience ratings. Such information is only useful at a coarse level as it captures the overall global reaction to the stimuli and does not contain any specific local “interest” information. For long continuous time-series signals like movies, knowing which parts the audience (or sub-groups of the audience) like and do not like would be very beneficial to writers/directors/marketers/advertisers. Achieving this through self-report is subjective and diffi-
cult, as it would require a person to consciously think and document about what they are watching (most likely causing subject to miss important parts of the movie). Similarly, subjects could be instrumented with a myriad of wearable sensors, but such approaches are invasive and unnatural which may not be a good indicator of the actual rating.

In this paper, we use a single camera as our input sensor and use face and body motion features to predict and summarize audience ratings of full-length movies (see Figure 1). Our work is motivated by the noted film editor Walter Murch who speculates in his book “In the Blink of an Eye” [22], that the engagement of an audience can be gauged through the synchrony of audience motion. Apart from the very dark environment, monitoring an audience from a single vantage point for a full-length feature film is a challenging problem because: i) it spans a very long time period (typically movies normally range from 80-150 minutes) which is an enormous amount of video data to process; ii) people are at different vantage points and resolutions; iii) we required frame-based measurements to measure synchrony; and iv) getting ground-truth labels of activity is subjective and time-consuming.

To counter these issues, we calculate the motion-history features of each audience member within a 3D volume to capture his/her face and body movements. We then propose an entropy of pair-wise correlations measure to gauge the collective behavior of the audience. We show that our approach outperforms human-annotated labels which do not pick up on these fine details. Using the audience ratings from rotten tomatoes.com, we then use this feature to predict the movie rating solely from audience behaviors. Additionally, we use change-point detection to temporally cluster and summarize audience behaviors into a series of interest segments.

2. Related Work

A survey of recent work in automatically measuring a person’s behavior using vision-based approaches is presented in [33]. Much of this work has centered on recognizing an individual’s facial expression, with notable progress made in the areas of smile detection in consumer electronics [32], pain detection [17] and human-computer-interaction [29]. An emerging area of research over the last couple of years is the use of affective computing for marketing and advertising purposes. When a user watches video clips or listens to music, they may experience certain feelings and emotions [14] which manifest through gestural and physiological cues such as laughter. These emotional responses to multimedia content have been studied in the research community [25]. Shan et al., [25] studied the relationship between music features and emotions from film music. In a recent study, Joho et al., [13] showed that facial expression is a good feature to predict personal highlights in media content. Hoque et al., [11] further showed that these facial behaviors vary from the laboratory setting to real-world.

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This prior work was applied only to individuals and limited to stimuli of short duration (i.e., $10 - 60$ seconds), with the exception of [10]. We expand this research to include simultaneous recording of multiple individuals and continuous tracking over long periods of time (e.g., up to 2 hours). Automatic long-term monitoring of human behavior is difficult: tracking people for this period of time is still an unsolved problem in vision (see Section 4). Additionally, being in a group environment introduces extra variability as behavior can be altered by other audience members as well as by the stimuli.

3. Experimental Setup

3.1. InfraRed Illuminated Testbed

Observing people watching visual stimuli from a screen is difficult because: 1) the environment is very dark, and 2) the reflected lights from the visual stimuli causes a non-uniform illumination environment. Wide aperture lenses and sensor sensitivity are two important features to consider when selecting a good camera to capture the objects in low-light conditions. We instrumented a test-bed with an infra-red (IR) sensitive low-light camera (Allied Vision GX 1920 with a 2/3” Sony ICX674 CCD sensor and a f/1.4 9mm wide angle lens), two IR illuminators (Bosch

![Figure 2. A schematic of the audience-test bed used in this work.](image-url)
UFLED95-8BD AEGIS illuminators with 850 nm wavelength and 95 degree wide beam pattern, and an IR band-pass filter to reduce reflections from the viewing screen (850nm ± 5nm). The resulting images are 1936 × 1456 pixels captured at 15 frames per second. The schematic diagram of the infra-red illuminated test-bed and effects of those instruments are shown in Figure 2 and in Figure 3 respectively.

### 3.2. Audience Footage

We used [www.rottentomatoes.com](http://www.rottentomatoes.com) [1] to select movies from the genre “Animation, Comedy, Kids & Family”. Out of a total of 62 movies (year 1998 – 2013) in that genre, we selected a subset of ten movies (refer to Table 1) with varying crowd-sourced audience ratings again from [1]. To do this, we chose three good movies (ratings greater than 80%), three average movies (ratings from 60% to 80%), and four bad movies (ratings below 60%).

For this study we sought subjects (age 18-70) to be apart of an audience ranging in size of 5-10 people (mean 8 people). This work was approved by an Institutional Review Board, and participants were compensated for their time. We screened the movies at the same time (6.00pm) and for each screening, only participants who had not seen the movie previously, and had normal or corrected-to-normal vision and hearing were used. We had three sessions for each movie (total 30 sessions) and each subject could only participant once. At the completion of each session, every participant completed a survey asking about their overall rating of the movie (similar to a self-report), age, gender, movie genre preference, and expectation/recommendation of the movie. A comparison of movie ratings using the self-report method from our audience (mean 67.3) to the rotten-tomatoes.com users (mean 65.1) for each movie is given in Figure 4. As shown in Figure 4, our audience had a reasonably good compatibility compared to the crowd-sourced measure.

To get a sense of how many different actions and activities a person normally performs while viewing a movie, we selected a subset of sessions for human annotation. As we were interested in both facial expressions and body movements, we manually annotated the following gestures at the frame-level. A description of these actions and activities are...
4. Extracting Audience Features

To extract features from each audience member, we first register the image region that he or she occupies over the course of the movie, and then extract motion features. The following section describes each method.

4.1. Registering Audience Members

Despite a person remaining relatively stationary whilst watching a movie, continuous tracking is a challenging because there are considerable appearance changes due to out-of-plane head motion or self-occlusion (e.g., hands on the face). While face tracking is a mature area of research, most of the previous work has only looked at videos of small periods of time (i.e., up to one minute). In contrast, our problem represents a paradigm shift in this area called long-term face tracking. To illustrate the issues in this method, we provide the following example. First, the intuitive method of registering each audience member would be to use a “off-the-shelf face-detector on each frame and then track each detection. As can be seen in Figure 6, this approach works well in ideal conditions but not so well in our test-bed because we are capturing faces from a different viewpoint (i.e., camera is looking down on the audience), we are operating in the infra-red spectrum, and the resolution of faces can be small.

An example of the “off-the-shelf” face detector performance is given in Figure 7(a). Alternatively, we could use a template update method, where we register an initial face and then update the template at every frame [3, 18]. This works reasonably well, but it tends to drift over long periods of time (Figure 7(b)). New methods that use a dictionary of templates have worked reasonably well, especially those of the \( l_1 \) variety [12]. However, as shown in Figure 7(c), they perform worse when there is considerable change in appearance or pose - i.e., when a key frame is not in the dictionary. A solution to this is to have prior knowledge of the key frames in the dictionary, but this is not ideal as it requires manual intervention (Figure 7(d)).

But this begs the question: do we actually need to track each person? As the person does not move substantially during the movie - they are basically restricted within the confines of their volume to maintain space between other audience members - a more reliable solution is to pre-define a volume that the person occupies throughout the movie. In this work, we implemented such an approach by using the first frame to define a volume that the person would occupy. Across the 250 subjects, we found that this method worked very well, even in cases where the person left to go to the bathroom, as our feature extraction was robust to this issue. In this work, we implemented such an approach and it was much more reliable than the tracking approach, which constantly failed.

4.2. Motion Features

In terms of recognizing individual and specific actions, there is a plethora of research which has solely focussed on this domain, with excellent progress being made [2]. Efros et. al., [8] used optical flow features to recognize actions from ballet, soccer and tennis. More recently, Rodriguez et. al., [23] used similar features to analyze crowds.

Note that this process was very time consume (annotation time was > 90 hours per session).
Figure 8. (Top) An example of the magnitude of the optical flow of an audience member, (bottom) compared to the magnitude of the motion-history features which had over 85% correlation.

Motion History Images: Using optical flow is very computationally expensive to compute\(^5\) which limits the usefulness of this approach for this work. In order to overcome the computation time from the optical flow method, we used an aggregated real-time approach to represent the spatiotemporal motion that recursively integrates into a single motion history images [6]. This is done by layering the threshold differences between consecutive frames one over the other. This represents how motion in the image is moving opposed to where, which is our interest. These motion history images can be calculated as follows:

\[
H_s(x, y, t) = \begin{cases} 
\gamma & \text{if } D(x, y, t) = 0 \\
\max(0, H_s(x, y, t-1) - 1) & \text{otherwise}
\end{cases}
\]

where, \(D(x, y, t)\) is a binary image sequence indicating regions of motion at pixel \((x, y)\) in time \(t\) and parameter \(\gamma\) is the temporal duration of the motion history images. Then, we calculate the normalized local 3D energy for person \(q\) as,

\[E_q.t = \frac{1}{a_q} \sum H_s(x, y, t).\]

The normalized energy from optical flow and motion history can be vectorized over the duration of the movie time \(T\) as \(e_q = [E_{q,1}, E_{q,2}, \cdots, E_{q,T}]\). Finally, we define a aggregate normalized measure of overall audience engagement over the movie time \(T\) as \(e_{\text{movie}} = \frac{1}{N} \sum_{q=1}^{N} e_q.\)

Comparison: To see how reliable each feature was, we analyzed the correlation between flow features (i.e optical flow features and motion history images) for a one movie. An example of an individual flow-field for an audience member using these features is given in Figure 8. We observed 85\% of average cross-correlation between motion history features and optical flow magnitudes.

\(^5\) Calculating the optical flow of an audience for a 2-hour feature length movie took more than 2-3 days on a high-performance computing cluster which is not tractable for our application
5. Predicting Movie Ratings

To gauge how much the general public likes a particular movie, rotten tomatoes.com has an interactive feature which allows people to go online and give a rating. Over time the number of ratings aggregate (100k’s) and based on these crowd-sourced ratings, they generate an “audience measure”. Based on these scores, an average audience measure is obtained, with a movie rating 75% or higher being deemed a good movie, a movie rating between 50-75% being ok and below 50% denotes a bad movie.

Achieving this using self-report is difficult as it would require a person to consciously think and document what they are watching and subjects may miss important parts of the movie, due to distractions. Similarly, subjects could be instrumented with a myriad of wearable sensors, but such approaches are invasive and unnatural and therefore may not result in good indicators of the actual rating. Alternatively, we derive the following representations of individual audience members as well as the entire group solely on the audience reaction to predict movie ratings.

5.1. Individual Representation

To represent the individual behavior, we used individual motion features $e_i$ using motion history images. Given an audience energy signal smoothed over 6 seconds, we generate histogram distribution $X = p(e_i)$, which allows us to represent a measure of each audience behavior during the movie. Given this representation and known movie ratings $y$ from [1], we learn a regression model to predict the movie ratings solely on the individual audience reaction as shown in Figure 9.

5.2. Group Representation

5.2.1 Joint Representation

We develop an objective measure using the facial expressions and body motion of audience members to gauge the synchrony of behavior. In order to represent the group, we initially used the joint distribution of the audience. We used an aggregate normalized measure of overall audience engagement over 30-second temporal segments, $e_{movie}$. Once we derive the aggregate measure, we generate the joint distribution/histogram $X = p(e_{movie})$ for all audience members (similar to Figure 9) that is used for prediction.

5.2.2 Mid-Level Representation

We utilized an entropy of pair-wise similarity between each audience member at the local-level (i.e. pair-wise comparison) as well as the global-level (i.e. compared to the whole group). In this regard, we first compare the small feature segment between two audience members, $e_1$ and $e_2$, and calculate the pair-wise similarity by using,

$$C_{e_1e_2} = \exp \left( -\frac{\|e_1 - e_2\|^2}{2\sigma^2} \right)$$

where $\sigma$ is an adjustable parameter for each similarity matrix. We then exhaustively calculated all of the pairwise correlations between audience members, yielding a similarity matrix. When everyone is doing something at the same time (e.g., laughing/smiling) the cohesion is high; similarly, when everyone is doing nothing, the audience cohesion is still high. Given that the similarity matrix of piece-wise correlations can be represented by $S$, we can generate a probability distribution of $S$ for that time segment $p(S)$, allowing us to gain a measure of audience disorder via entropy [26]

$$H(S) = -\sum_{i=0}^{N-1} p(i) \log p(i)$$

A high value of entropy means that there is great disorder (i.e., random behavior), while a low value of entropy means that there is cohesion or predictability of behavior. Finally, we generate a probability distribution $X = p(H(S))$ to gain a measure of synchrony of audience for predicting movie ratings. The system is shown in Figure 10.
5.3. Performance Evaluation

Once we extract the features from individual and group representation, we used those features to learn audience behaviors from a library of movies (See Table 1) and use these features to predict the audience rating for an unseen movie. We analyzed this prediction using different predictors such as linear, logistic and support vector regression (SVR). There was not a big discrepancy between these methods, and we present the results for SVR. Given the feature representation $X$ and known movie ratings $y$ from [1], we learn $w$ for SVR by minimizing the following objective function,

$$\arg\min_w \frac{1}{2} \|w\|^2 + C \sum_{i=1}^n (\xi_i + \xi_i^*)$$

subject to $y_i - w^T x_i - b \leq \epsilon + \xi_i$,

$$w^T x_i + b - y_i \leq \epsilon + \xi_i^*$$

$$\xi_i \geq 0, \xi_i^* \geq 0$$

where $C > 0$ is a parameter to control the amount of the influence and $\xi_i, \xi_i^*$ are slack variables.

We validate our framework using a leave-one-out cross validation strategy (leaving out entire an movie). The parameters for SVR were chosen using a cross-validation method as described in [31] with a polynomial kernel. For a quantitative assessment, we compute the root mean squared error (RMSE) between the predicted rating value $\hat{y}_i$ and the audience rating $y_i$ such that:

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (\hat{y}_i - y_i)^2}{n}} \quad (6)$$

For the mid-level group representation, we tested different timing window segments (i.e 30, 45, 60, 120 seconds) to obtain pair-wise entropy values and different $\sigma$ values. We observed that 30 second window segments with $\sigma = 0.5$ gave the best prediction values.

The experimental results for leaving out an entire movie in terms of average RMSE are shown in Table 2. As shown in Table 2, audience behavior (i.e., synchrony/coherency of audience motion) for a group is more robust than for each individual. Overall, our framework showed that we can predict movie ratings solely using audience behaviors, a potential solution to the problems with current standard self-report measures. Using the mid-level group representation and SVR, we show our average movie prediction (i.e., average from all the 3 sessions for a movie) results for a movie in Figure 11. As can be seen from this result, we get a reasonable approximation to the rottentomatoes.com crowdsourced ratings.

Finally, we also compared our automatic prediction from audience behavior to their (our viewers) self-report audience rating, as shown in Figure 12. The average RMSE value compared to the viewer’s self-report rating is 16.95. In this environment, the result makes sense: self-report is subjective and difficult as it would require an audience to consciously think about what they were watching. In addition, it does not contain feedback at precise timestamps [24].

5.4. Temporal Window Analysis

During the movie, audience members tend to move and react. In this work, we are interested in the synchrony of audience behavior (i.e., is everyone doing a particular thing at the same time?). We looked at what is the optimal timing window in which the audience behaves in an interesting way? To do this analysis, we selected different window sizes from 10sec – 5min. For these different windows sizes, we generated group representations and predicted movie ratings. The average RMSE with different window sizes is given in Figure 13. We observed that we can capture interesting audience behaviors using 30-second increments.

![Figure 11. Average results of our automatic approach compared to the crowd-sourced ones from rottentomatoes.com.](image1)

![Figure 12. Average results of our automatic audience rating measure compared to the viewer’s self-report measure.](image2)

![Figure 13. Variation of average RMSE with respect to different temporal window sizes.](image3)
6. Movie Summarization

As feature-length movies are very long in duration, often it is beneficial for a domain expert to quickly skim through the behaviors of an audience. Finally, to summarize the reaction of the audience to a movie signal $e_q$ (smoothed over a 6-second window), we chunk the movie into 1-minute windows, and we find for each window the strongest audience change-point (i.e., zero-crossing values in audience signal $e_q$). Using that as our index, we use a 1-second window centered at that change-point to summarize the audience behavior over that minute. We piece this together to form a summarization of the audience behavior, allowing someone to assess a 90-minute movie over the course of 90 seconds. Qualitatively, we found that we could find engaging and disengaging segments during the movie using this approach. Visual examples are given in Figure 14.

7. Summary

We proposed an automatic method of measuring, summarizing and predicting audience behavior using face and body motions from a single video stream. Due to the complexity and difficulty of this task, no one has previously looked at this problem. To do this: (i) we introduce an IR based test-bed as the movie viewing environment is dark and contains views of many people at different scales and viewpoints, and we use more than $> 50$ hours of audience data; (ii) we then utilize motion-history features that can pick up on the subtle movements of a person within a predefined volume; (iii) we propose a method to learn individual and group behaviors; and (iv) we use these representations to learn our movie rating classifier from crowd-sourced ratings collected by rotten-tomatoes.com and show our prediction capability on audiences from 30 movies and 250 viewers. We showed that we can give a reasonable approximation solely from audience behavior to the rotten-tomatoes.com crowd-sourced ratings.

References


Figure 14. An example of movie summarization for a: (a) good movie and (b) bad movie. The green boxes show examples of similar activities while red boxes illustrate random activities.