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A MACHINE LEARNING APPROACH TO AUTOMATICALLY CAPTURE DESIGNERS' AFFECTIVE STATES DURING PROTOTYPING ACTIVITIES

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ABSTRACT

Prototyping helps design teams explore multiple approaches and ideas, hereby reducing risk and ensuring that all the design requirements are met. The iterative prototyping process can be time-consuming as well as physically and mentally demanding. It has been shown that positive affective states such as happiness, excitement or interest influence productivity. Most studies show a positive relationship between a designer's engagement or "interest" and productivity during the prototyping process. Interest in a particular prototyping task can sometimes be the deciding factor in the success of the final product. In order to increase growth and sustainability of design teams by promoting productivity, it is important to measure affective states such as interest of designers. Though interest during the prototyping process is important, the use of power- operated machines and other such equipment require designers to be comfortable with using this kind of equipment. Comfort and interest can be measured in various ways such as filling out surveys or questionnaires at the end of a particular task. However, these methods are disadvantageous as they do not provide real-time feedback and have cost as well as scalability concerns. Addressing these issues, semi-automated/automated technologies have been developed to capture designers' internal representations using text, speech or body language. However, analyzing designers' internal representations using these modalities may be impractical due to interference with the task at hand. To mitigate this challenge, this thesis proposes a machine learning approach to model designers' affective states such as interest and comfort by capturing their facial expressions. Automatic prediction of these affective states will provide real-time feedback and thus help in building intelligent systems which have the potential to improve efficiency and productivity during the prototyping process. Moreover, they will be extremely useful in the preparation of workforce training protocols used to train the new engineering design workforce. A machine learning approach is proposed to detect these affective states using trained Support Vector Machines (SVMs). An SVM classification model is used to predict interest and the accuracy is found to be 72%. An SVM regression model is used to predict comfort and it yielded an R^2 value of 0.68. The two case studies illustrate that the prediction of affective states such as interest and comfort is possible with a reasonably good accuracy. This thesis has the potential to transform the manner in which design teams utilize engineering equipment, towards more efficient concept generation and prototype creation processes.

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I would also like to thank my colleagues of the Design Analysis Technology Advancement (D.A.T.A.) lab for their constant help and encouragement, which helped transform this thesis topic into a reality. Last but not the least, I would like to take this opportunity to thank my family, Sudesh Bezawada, Rama Bezawada and my sister Saina, for always being there for me and believing in me.

CHAPTER 1

INTRODUCTION

Design concept generation is a critical step of the engineering design process. If this step is not understood well, it leads to undesirable outcomes such as design fixation that refers to designers' inability or reluctance to establish and solve a design need in multiple ways (Linsey et al., 2010). Also, design concepts affect the quality and efficiency of production, as they lead to different manufacturing processes (i.e., mass production, lean production or manual production)(Wang, Shen, Xie, Neelamkavil & Pardasani, 2002). Methods such as brainstorming, parallel thinking and technology probes are used to create design concepts (Powers & Jones-Walker, 2005) (Hutchinson et al., 2003). A significant correlation exists between the quantity of brainstormed ideas and the quality of design outcomes (Yang, 2009). After design conceptualization, design prototypes are created (often in an iterative manner) to test the feasibility of the design concepts.

Prototyping helps design teams explore multiple approaches and ideas, hereby reducing risk and ensuring that all the design requirements are met. Prototyping typically involves iterations that include feedback pertaining to either the prototype itself or the process by which a designer creates the prototype. The iterative prototyping process can be time-consuming as well as physically and mentally draining. It has been shown that positive affective states such as happiness, excitement or interest influence productivity (Kraiger et al., 1989). Most studies show a positive relationship between a designer's engagement or interest in the task at hand and productivity (Markos and Sridevi, 2010). Interest in a particular prototyping task can sometimes be the deciding factor in the success of the final product. It has the potential to affect efficiency as well as team loyalty (Lockwood, 2007). In order to increase growth and sustainability of design teams by promoting productivity, it is important to measure affective states such as interest of designers. The prototyping process involves the use of power-operated machines and other such equipment. Using this kind of equipment requires caution as well as experience. In order to achieve faster and more efficient prototyping processes, it is important that designers feel comfortable while using engineering equipment in order to minimize risks associated with incomplete prototypes or injuries during their creation. Proper equipment performance is difficult to guarantee without proper attention given to human factors and safety (Fadier & De la Garza, 2006). Comfort also influences performance because designers must be comfortable with the tools and equipment that they use on a regular basis in order to perform their tasks efficiently (Teizer et al., 2008). Therefore, apart from the widely known affective states such as happiness and excitement, interest and comfort are equally important in influencing productivity.

Surveys and questionnaires have been used in the past to measure interest and comfort of designers. However, these methods are disadvantageous as they do not provide real time feedback and have cost as well as scalability concerns. Addressing these issues, semi-automated/automated technologies have been developed to capture designers' internal representations using text (Dong et al., 2003), speech (Stempfle and Badke-Schaub, 2002) or body language (Behoora and Tucker, 2015). For example, individuals' internal representation can be captured and mined through textual data in order to model individuals' responses to external stimuli (Munoz and Tucker, 2014). However, analyzing designers' internal representations using text may be impractical in a design workshop environment because it may interfere with the required task at hand. Speech analysis may also be a challenging solution, as the noise levels of the engineering equipment may interfere with the audio frequencies projected by designers' voices. Other data modalities may be explored to mitigate the limitations of using audio or textual information to assess designers' interaction with engineering machines. For example, Behoora and Tucker explored the use of non-wearable sensing systems to capture designers' body language during design team interactions to infer designers' affective state (Behoora and Tucker, 2015). However, body language exhibited during the prototyping phase of design is dependent on the task, rather than designers' particular comfort with the given engineering equipment.

To mitigate the aforementioned challenges, this thesis proposes a machine learning approach to model designers' comfort levels with engineering equipment and interest expressed by designers with the task at hand by capturing their facial expressions. Facial data is explored for several reasons:

- Unlike other body parts such as hands and feet, a designers' face is typically unobstructed during the prototype creation phase
- Facial expressions exhibited by a designer can be mapped to internal affective states
- Facial key points can be automatically captured and mined using machine learning algorithms

Facial expressions can be used to detect the affective states such as interest and comfort using affective computing. It aims to bridge the gap between humans and the computer by developing computational systems that recognize and respond to the affective states (Pantic and Rothkrantz, 2000). These computational systems which have the ability to recognize affect can be applied in many domains including gaming, mental health, and learning technologies (Kapoor and Picard, 2005). Advancements in the field of affective computing have the potential to also enhance certain engineering design activities that benefit from automation and real-time performance feedback. Previous work in the field of affective computing involves the identification of six main affective states otherwise known as universal affective states: happiness, anger, sadness, fear, disgust and surprise. This thesis aims to detect the lesser known affective states such as interest and comfort. Incorporation of these detection systems in intelligent monitoring systems have the potential to influence productivity in the field of engineering design.

This thesis is organized as follows: The introduction section provides motivation to incorporate interest and comfort level measurement in intelligent monitoring systems which have the potential to improve productivity and efficiency during the prototyping process. It also highlights the shortcomings of the methods used in the past to identify these affective states and how affective computing can be used to solve these problems. Section 2 describes the previous work on affective state recognition using facial expressions and describes common models used in affective state recognition. Section 3 outlines the methodology proposed to predict interest and level of comfort using facial expressions. Section 4 presents two case studies which illustrates how interest and the level of comfort can be predicted using machine learning algorithms. The results obtained from the case studies and their applications in the field of engineering design are discussed in Section 5. Section 6 provides the conclusions drawn and outlines directions for future work.

CHAPTER 2

LITERATURE REVIEW

The literature review is divided into two sub-sections. The first section presents the recent work in affective computing and how it can be applied in the field of engineering design. The second section provides motivation for the importance of predicting comfort level and interest in designers during the prototyping phase.

2.1 Previous Work in Affective Computing

2.1.1 Affective State Detection and Classification

This section summarizes the work done in the identification and classification of affective states. Ekman et al. conducted various experiments on human judgment of deliberately posed facial expressions and concluded that there were six affective states that could be recognized universally: anger, happiness, surprise, disgust, sadness and surprise (Ekman et al., 2013). Early work on affective state classification and affective state detection primarily focused on the six universal affective states. However, interest, pain, anxiety and comfort also represent affective states that can be identified using facial expressions (Mortillaro et al., 2011). Ekman's work on the topic focused exclusively on posed images of emotional expression. Yet in real-life interactions, the display of affective states is much more intricate, including displays of affective states such as interest, awe and calm, which can be reliably identified by human observers (Mortillaro et al., 2011). Despite their ability to be read from the face, these more intricate states were not identified as having universally clear displays. This may be because of their interactive nature, which makes them more difficult to accurately and precisely interpret from facial expressions or they have variability in their displays. Also, cultural differences in expressing these emotions also makes them less "universal" (Koda et al., 2009). A complete review of recent affective state recognition systems based on facial expressions is provided by Pantic et al. (Pantic and Rothkrantz, 2000).

The previous work done in affective computing mainly focuses on the identification of the six universal emotions: anger, happiness, surprise, disgust, sadness and surprise. Very little work has been done to identify lesser known affective states such as interest, pain, comfort, anxiety, etc. Detection of these states will be helpful in building intelligent systems which have the potential to improve productivity and efficiency, especially in the field of engineering design. Affective states such as interest and comfort play a critical role during the prototyping phase. Hence, a system which can detect and predict these affective states will be useful in order to achieve faster and more efficient prototyping activities.

2.1.2 Prediction of Universal Affective States

The location and movement of prominent features on the face represent the static characteristics and dynamic characteristics form the foundation of facial expression recognition (Zhang and Tjondronegoro, 2011). Mase proposed the use of directions of movement of facial muscles to build an affective state recognition system. The system identified four affective states: happiness, anger, disgust and surprise with an accuracy of 80% (Mase, 1991). Yacoob et al. also proposed a similar method and classified the six universal affective states by using the rule-based system with an accuracy of 88% (Yacoob and Davis, 1994). Cohen et al. used a Naïve Bayes classifier along with Hidden Markov Models (HMM) to classify the universal affective states such as anger, happiness, surprise, disgust, sadness and surprise using facial expressions (Cohen et al., 2003). Zhang and Tjondronegoro used the Support Vector Machine (SVM) algorithm along with Gabor Wavelet filters for feature extraction and classification of the universal affective states using facial expressions (Zhang and Tjondronegoro, 2011).

The most commonly used machine learning algorithms to identify affective states are Naïve Bayes algorithm, Support Vector Machines and Hidden Markov Models. In the case of engineering design, generalizability is an important property the algorithm should possess as it helps in scalability. Therefore, SVMs are best suited to model affective states of designers during the prototyping phase.

2.1.3 Applications of Affective State Computing

Affective states can be detected in many different ways (Example- surveys, body language, facial expressions, etc.) and applied in several fields such as gaming, mental health, education and advertising. Jiamsanguanwong and Umemuro examined the effect of affective states on hazard perception of warning signs (Jiamsanguanwong and Umemuro, 2014). Yuan et al. focused on positive psychological states, traits and behaviors of employees to improve job satisfaction (Yuan et al., 2015). Beer et al. tried to consider the capabilities and limitations of people with respect to the tasks and equipment in home health care from a human systems perspective (Beer et al., 2014). Kirchhubel et al. investigated the usage of speech cues in detecting deception (Kirchhübel and Howard, 2013). Zeng et al. explored ways for a computer to recognize users' affective states (e.g. interest, boredom, frustration and confusion) and to apply the corresponding feedback strategy (Zeng et al., 2006). Khan et al. presented a concept to identify learning styles and affective states of a learner and use it to develop a web-based learning management systems (Khan et al., 2009).

Affective computing has been used in many fields such as education, gaming and healthcare as mentioned above. It has great potential in improving engineering design activities such as prototyping. It will ensure that designers follow safety protocols at all times and will build confidence in them as they perfect their design and prototyping skills.

2.2 Prediction of Affective States such as Interest and Comfort

Given the iterative nature of prototyping, it is important that designers feel comfortable while using engineering equipment in order to minimize risks associated with incomplete prototypes or injuries during their creation. Proper equipment performance is difficult to guarantee without the careful focus on human factors and safety (Fadier & De la Garza, 2006). Furthermore, the ergonomics of the machines themselves could be assessed towards more user-friendly designs (Pavlovic-Veselinovic, 2014). Apart from comfort, most studies show a positive relationship between a designer's engagement or "interest" in the task at hand and productivity (Markos and Sridevi, 2010). Interest in a particular prototyping task can sometimes be the deciding factor in the success of the final product. It has the potential to affect efficiency as well as team loyalty (Lockwood, 2007).

Lesser known affective states such as interest and comfort have not been as widely explored as the universal affective states. However, there has been some work been done in predicting interest as an affective state in the past. For example, Yeasin et al. used the optical flow method for feature extraction and a HMM to recognize the six universal affective states and used the results to approximate the levels of personal interest in each individual. The recognized levels of the affective states were transformed into an intensity score. The level of interest was approximated from the intensity score of the apex frame. While the researchers had tested their model for prediction of the six universal affective states, no validation was provided for the prediction of the interest level (Yeasin et al., 2006). Kapoor and Picard proposed a multi-sensor recognition system and classified interest in children trying to solve an educational puzzle on a computer. This work requires special instrumentation (special sensing chair) and a specific model of the difficulty levels of the interactive program. They achieved an accuracy of 86% (Kapoor and Picard, 2005). Sagonas et al. predicted interactive interest from audio-visual cues as opposed to just facial expressions. But their work is based on the SEMAINE Database which primarily consists of conversations between participants and an avatar. This work is useful in predicting interactive interest (Sagonas et al., 2015).

The aforementioned studies emphasize the importance of power-operated equipment during the iterative prototyping phase. However, there exists a knowledge gap in terms of how to provide designers with personalized feedback during the prototyping phases of design. The methodology presented in this thesis aims to mitigate these challenges by exploring the use of automated facial feedback capture systems that model and predict designers' comfort or engagement with engineering equipment during the physical prototyping process. In this thesis, the focus is solely on designers during the prototyping phase and how the facial expressions of these designers can be used to automatically gauge interest and comfort. The methodology requires only video data of a quality easily available from commodity webcams or even modern smartphones, thereby reducing cost and increasing scalability.

CHAPTER 3

METHODOLOGY

The engineering prototyping process is iterative and hence can be time-consuming as well as physically and mentally demanding. In order to make the prototyping process faster and more efficient, it is imperative to ensure designers are engaged or “interested” and comfortable during the prototyping process. This thesis proposes a machine learning model to predict the level of comfort and interest as affective states. In this thesis, facial key points are captured automatically by video recording systems and mined using machine learning algorithms to predict the affective states of interest and comfort. The detailed steps of the methodology for predicting interest as well as comfort are presented in Figure 1. The methodology consists of four major steps: Data Collection, Facial Key Point Extraction, Model Building and Model Evaluation.

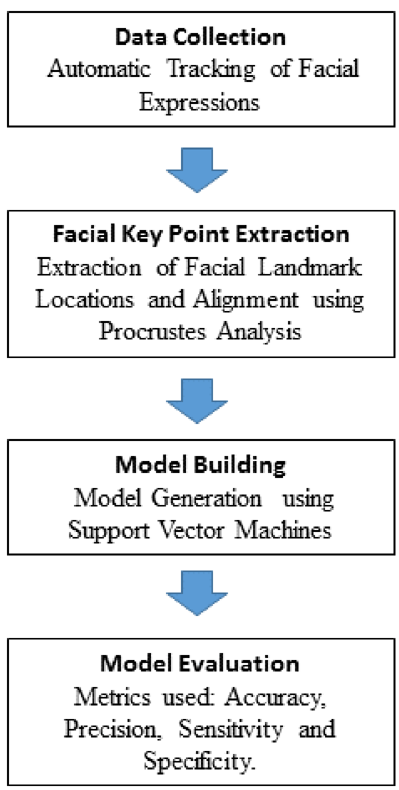


Figure 1: Outline of Methodology

3.1 Data Collection

The video clips can be recorded in a wide range of settings using standard video recording equipment. The equipment can range from Standard Definition such as a webcam to higher resolutions such as High Definition (HD) or 4K cameras. While recording the videos, individuals should be facing the camera so that the expressions exhibited on their face can be fully captured. From the videos recorded, clips are extracted such that the faces of the individuals are visible clearly.

3.2 Facial Key Point Extraction

The video to be classified is split into frames, with the facial landmarks or features of each frame extracted using facial analysis software (Saragih et al., 2010). For example, the Regularized Mean-Shift Algorithm can be used to extract the key points on the face. These key points are major landmark locations which provide information about the emotional state of a person. These facial key points are reported in the two-dimensional space of the image, and hence are in the form of (x, y).

The location of the facial image, its size and its tilt are characteristics of an individual's pose and location, relative to the camera and not aspects of the individual’s affective state. Ordinary Procrustes Analysis is performed on the features obtained from each frame. The idea behind Ordinary Procrustes Analysis is to match all the faces in the frames as closely as possible to a specified reference frame by uniform rotation, translation and scaling (Stegmann and Gomez, 2002).

After alignment, reduction of dimensionality is crucial, as higher dimensional data might result in misleading predictions. The predictions might be misleading due to the following reasons: 1) It is challenging for the machine learning algorithm to identify patterns from sparse data and 2) Higher dimensionality might add noise which leads to inaccurate results (Yeasin et al., 2006). Dimensionality reduction is done using Principal Component Analysis (PCA). It is a multivariate technique that extracts linear combinations of components that maximize variance explained and represents it as a new set orthogonal vectors (Jolliffe, 2014). The *N* features or the set of facial feature points are transformed into a new set of *N* orthogonal feature vectors (or principal components). PCA orders the components in order of the proportion of variance explained. Only the components that explain the maximum variance in the facial feature data are considered and used as the input to the predictive models.

3.3 Model Building

3.3.1 Machine Learning Model for Predicting Interest

Analyses that might not be possible with just a human observer can be performed using automated classification. The classifiers are trained using a training set of frames. Each of the frames are rated as 0 indicating "not interested" and 1 indicating "interested". The ground-truth data is required to test the model performance. The major steps involved in model building are training of the models followed by testing and validation. An overview of the model training process is illustrated in Figure 2.

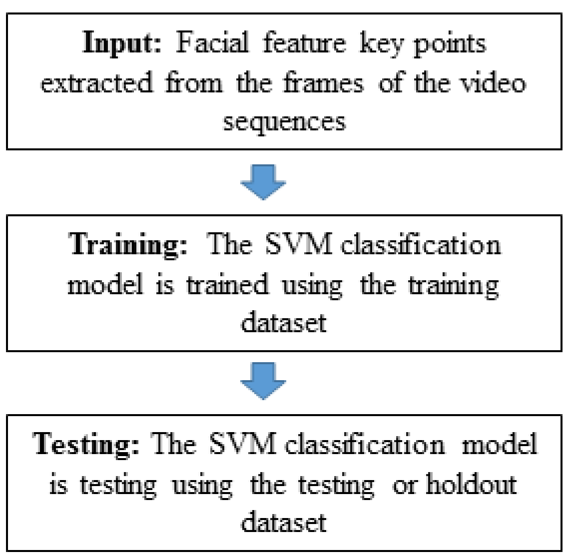


Figure 2: Overview of Model Building

A Support Vector Machine (SVM) is used to perform the classification. An SVM is a classification algorithm that locates a hyper plane which divides the data points with respect to their class by maximizing the distance between the data points of the same class and the hyper-plane (Burges, 1998). An SVM is chosen for the following reasons: 1) the kernel function of the SVM contains a non-linear transformation and hence, no assumptions to make the data linearly separable are necessary. 2) SVMs generalize well, if the parameters are appropriately chosen. They can be robust, even when there is some bias in the training set. For a more detailed explanation, please refer to the review of Support Vector Machines provided by Burges (Burges, 1998).

3.3.2 Machine Learning Model for Predicting Level of Comfort

Non-linear regression is conducted using the Support Vector Machine (SVM) algorithm to predict the level of comfort using facial expressions. The SVM regression model is chosen as the level of comfort was rated on a scale of 1-10. The 1-10 scale ratings will be more beneficial to provide feedback to the designers as the severity of the discomfort with the machine or other equipment can be thoroughly assessed. SVMs are best suited as they perform well with continuous variables in high dimensional spaces (Smola & Vapnik, 1997). In this case, the predictors for the model are the means and the standard deviations of the normalized key points across all the frames in a particular video clip. The mean and standard deviation of the rotation parameter of the Procrustes Analysis are also used as predictors along with the means and standard deviations of the facial key points. The dependent variable for the model is the level of comfort, which is rated by designers on a scale of 1- 10. It is important to note that this rating is provided only once by each designer to establish ground truth data for the machine learning algorithm.

For the SVM model, hyper-parameter optimization chooses the best parameters for the model by training multiple models. The two parameters to be estimated are Epsilon (ε) and Cost (C). Epsilon (ε) controls the width of the ε-insensitive zone used for fitting the training data. The Cost (C) determines the tradeoff between the model complexity and the degree to which deviations larger than ε are tolerated in the optimization formulation with different epsilon (ε) and cost (C) values. The mathematical formulation of the SVM is presented below:

Minimize $\frac{1}{2}\|\boldsymbol{w}\|^2 + C\sum_{i=1}^{N}(\xi_i + \xi_i^*)$ (1)

Subject to $y_i - \boldsymbol{w}g(x_i) - b \leq \varepsilon + \xi_i$ (2)

$\boldsymbol{w}g(x_i) + b - y_i \leq \varepsilon + \xi_i^*$ (3)

$\xi_i, \xi_i^* \geq 0$ (4)

Where,

x_i - Training sample of facial key points acquired from designers,

y_i - The dependent variable *comfort* that is based on a scale of 1-10, where 1 represents "least comfortable" and 10 represents "most comfortable", $i = 1, \dots, N$

w - Normal Vector to the Hyperplane

ε - Tolerable Error

C - Cost of error

ξ_i, ξ_i^* - Deviation outside epsilon intensive band, $i = 1, \dots, N$

$g(x_i)$ - Nonlinear transformation, $i = 1, \dots, N$

b - Bias Term

SVM regression uses an epsilon intensive loss function to allow deviation from the true value within distance and at the same time reach global minimum. Specifically, the points within the epsilon intensive band have no cost of errors and the cost of error outside the band are measured by parameter C. Slack variables ξ_i, ξ_i^* are introduced to measure the deviation outside the epsilon intensive band. Figure 3 is a conceptual representation of a one dimensional nonlinear SVM regression model with an epsilon intensive band. The epsilon intensive band boundaries are determined by the parameter ε. The SVM regression model is employed to determine the relationship between the facial key points acquired from a designer and their comfort levels with different pieces of engineering equipment.

The Support Vector Machine classification and regression algorithms predict interest and comfort using facial key points data as the input. The facial key points are extracted using the CSIRO face-tracking algorithm and is modeled using the SVM algorithm after normalization. The SVM reduces overfitting i.e. it is able to generalize quickly and hence interest and comfort can be predicted reliably using this model across different designers.

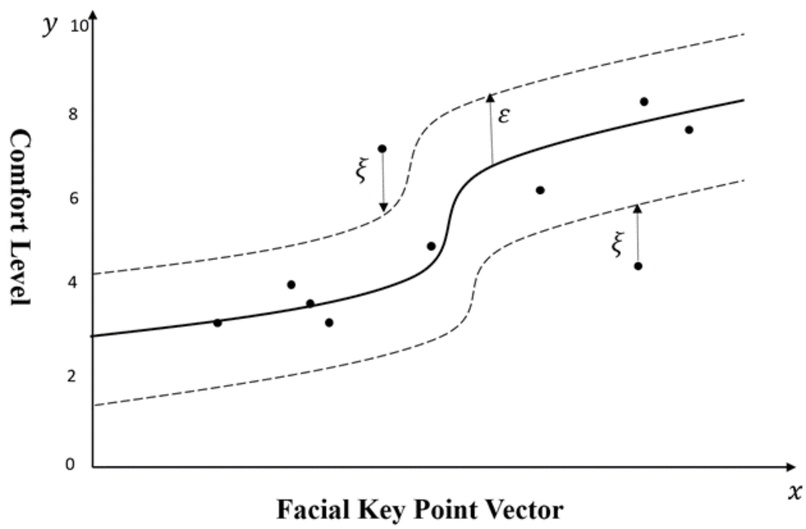


Figure 3: One Dimensional Non-Linear Regression with Epsilon Intensive Band

3.4 Model Evaluation

3.4.1 Model Evaluation for SVM Classification Model

The confusion matrix as shown in Table 1 is a table used to test the performance of the SVM classification model. Performance metrics used to test the predictive power of the classifier are accuracy, precision, sensitivity and specificity. Accuracy is the proportion of instances (frames in this case) classified correctly in the entire dataset used for testing. Precision is the proportion of predicted true instances i.e the number of frames which are rated "interested" that are classified correctly. Sensitivity is the proportion of true positives classified correctly (true positives are shown in Table 1). Specificity is the proportion of true negatives classified correctly (true negatives are shown in Table 1). Mathematical representations of these metrics are presented in Table 2.

Table 1: Confusion Matrix

Predicted Values	**Actual Values**	
	Interested	**Not Interested**
Interested	True Positive (TP)	False Positive (FP)
Not Interested	False Negative (FN)	True Negative (TN)

Table 2: Mathematical Expressions for the Performance Metrics of the SVM

Performance Metrics	**Mathematical Expression**
Accuracy	$\frac{TP + TN}{TP + FP + TN + FN}$
Precision	$\frac{TP}{TP + FP}$
Sensitivity	$\frac{TP}{TP + FN}$
Specificity	$\frac{TN}{TN + FP}$

3.4.2 Model Evaluation for SVM Regression Model

The SVM regression model is tested using measures such as Coefficient of Determination, Adjusted R^2 Value, Mean Squared Error, Root Mean Squared Error, Relative Absolute Error and Root Relative

Absolute Error. The Coefficient of Determination or R^2 value represents the proportion of the variance explained by the facial key points. An R^2 value modified based on the number of predictors (facial key points) is known as adjusted R^2 value. This value only increases if the model performance improves more than chance and not because of the addition of extra predictors (facial key points). Mean Squared Error and Root Mean Squared Error measure the difference between the actual value of comfort and the predicted value of comfort. Relative Absolute Error and Root Relative Absolute Error measure the magnitude of the difference between predicted and actual values of comfort level.

In summary, the methodology involves four major steps: Data Collection, Facial Key Point Extraction, Model Building and Model Evaluation. The facial key points extracted from the video clips are used to predict interest and level of comfort by using SVM algorithms. The models built using these algorithms are tested for their predictive ability using performance metrics.

CHAPTER 4

CASE STUDIES

4.1 CASE STUDY 1: AUTOMATIC PREDICTION OF INTEREST

In this case study, it has been demonstrated that more intricate and potentially informative constructs such as interest can be detected using machine learning algorithms. The results of the case study can be applied to a wide variety of fields, especially in the field of engineering design. The results pave the way for building intelligent monitoring systems which can detect interest and provide feedback accordingly. Novice designers undergoing training or creating prototypes will find this study useful as training instructors can improve the quality of their training based on the feedback. Moreover, safety also will be ensured during the prototyping process as these intelligent systems will be able to detect when designers are not paying attention to the equipment they are using during the prototyping phase. Further, it has been demonstrated that interest can be classified automatically using machine learning tools with a reasonable amount of accuracy.

4.1.1 Data Collection

A data set of 41 five-second clips of front-facing facial expression data collected for a previous video-conference experiment was acquired. The equipment used included a Standard Definition webcam (640 x 480 pixels, 30 Hz). In the experiment, participants engaged in dyadic videoconference conversations in which one or the other participant was instructed to tell a story about a time they experienced a specific affective state (e.g., "Talk about a time when you felt sad."). The clips were rated as “interested” or “not interested” by experts. Figure 4 illustrates the first four frames of the video sequence which are used as the input for the classification model. 41 five-second clips were selected from these conversations because they contained displays of affective states, but not for their specific display of interest.

Figure 4: Snapshot of Video Sequence used for Prediction of Interest

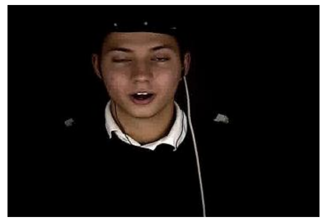


Figure 5: Example Frame Rated "Not Interested

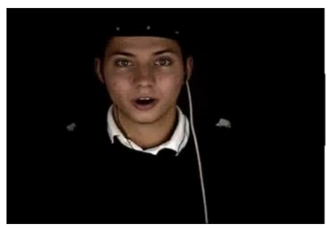


Figure 6: Example Frame Rated “Interested"

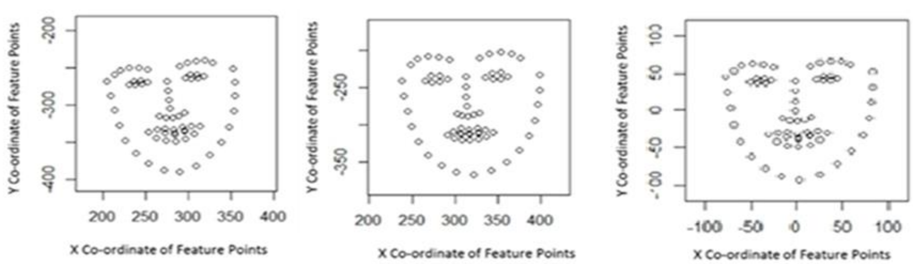


Figure 7: Procrustes Analysis. From Left to Right: Frame to be Normalized, Reference Frame and the Normalized Frame

Each clip shows only a single individual, and no individual appeared in more than one clip. Clips were manually rated on a frame-by-frame basis as either displaying or not displaying interest. Five clips (650 frames) were selected at random and set aside as a hold-out test set. Importantly, as no single individual appeared in more than one clip, no single person from the training set also appears in the hold-out set. Figure 5 and Figure 6 illustrate example frames rated as not interested and interested respectively.

4.1.2 Facial Key Point Extraction

Each five-second clip is made up of approximately 141 frames of video. 66 feature location points were extracted from each frame using the Face Modeling GUI and the CSIRO Face Analysis SDK (Saragih et al., 2010). Each feature had an X and Y co-ordinate, resulting in 132 features per frame. Ordinary Procrustes Analysis was performed to align all faces to a canonical orientation and scale defined by the arithmetic mean across all observed faces, centered at the origin, as illustrated in Figure 7. PCA reduced the 132 feature vectors in the resulting dataset to 16 vectors of component scores. A sufficient number of components that explained 99% of the total variation in point locations (in this case 16 components) were retained. While 132 features may not be considered a large feature space in certain domains, a feature space reduction to 16 components that explain 99 % of the variance drastically reduces the time taken for modeling.

4.1.3 Model Building

To demonstrate the reliable prediction of the display of interest using facial expressions, a machine learning methodology was proposed to classify interest as a distinct affective state. A Support Vector Machine was chosen to perform the classification not only because it is robust but also does not assume linearity and has an in-built regularization parameter. The SVM was implemented in R, a statistical programming language using the package “e1071” (Dimitriadou et al., 2008). The frames obtained from 36 of the videos are used to train the SVM. A radial kernel is used and the SVM is fit using the training data. Fitting refers to the selection of the best set of parameters to fit the training set. After choosing the best values for the parameters based on cross-validation to train the model, it is tested using the test set. The model's predictive ability is assessed using classification accuracy, precision, specificity and sensitivity.

4.1.4 Model Evaluation

The set of videos which were not included in the training set were used as the test set. It consisted of frames from the remaining 5 videos (36 videos were used for training). The model was tested and a confusion matrix was obtained. The confusion matrix for the SVM classifier is provided in Table 3 and Table 4 summarizes the performance metrics of the SVM classification model. The overall accuracy for the SVM was calculated to be 72%. This indicates that the SVM model classified only 72% of the total frames used for model testing correctly. The sensitivity was found to be 78.7% i.e. only 78.7% of the total frames rated interested were classified correctly. The specificity was found to be 86.2% i.e. only 86.2% of the total frames rated not interested were classified correctly.

Table 3: Confusion Matrix for SVM classification

Predicted Values	Actual Values	
	Interested	**Not Interested**
Interested	174	47
Not Interested	134	295

Table 4: Performance Metrics for SVM

Measure	Value for SVM (%)
Accuracy	72
Precision	56.4
Sensitivity	78.7
Specificity	86.2

4.2 CASE STUDY 2: AUTOMATIC PREDICTION OF LEVEL OF COMFORT

Apart from interest, comfort of a designer during the prototyping phase is also important in order to achieve faster and more efficient prototyping processes. In this study, it has been demonstrated that it possible to predict the level of the comfort of the designer during the prototyping phase. Most studies show that a decrease in the level of comfort increases the probability of accidents, especially while using power-driven equipment. This case study demonstrates that the level of comfort can be predicted with good accuracy using machine learning algorithms. It will help in building intelligent monitoring systems which can prevent equipment related accidents during the prototyping phase as help can be rendered when the level of comfort drops below a certain threshold.

4.2.1 Data Collection

The data for the study was collected in an engineering workshop at Penn State. Participants included engineering design students from the course, Introduction to Engineering Design (EDGSN 100). During the concept generation and prototype stages of design, designers frequently utilize the engineering workshop to iteratively create and refine prototypes. For this study, three engineering equipment stations were set up. Station 1 was the power saw station, Station 2 was the drilling machine station, and Station 3 was the scissors station. Video recording equipment was set up at each engineering equipment station such that the face of the participant performing the task could be seen clearly. The experimental layout is shown in Figure 8.

Cardboard pieces of uniform size (21cm x 9 cm) were used for designing two tasks at each engineering equipment station. The first task at station 1 (power saw) and station 3 (scissors) consisted of cutting along a straight line drawn along the middle of the piece of cardboard. The second task consisted of cutting along the shape of the figure ‘8’. At station 2 (drill), the first task consisted of drilling a hole in the center of the piece of cardboard and the second task consisted of drilling two holes 1 cm apart along a line parallel to the edge of the cardboard. The participants had to ensure that the two holes did not join together while drilling. At station 3, participants performed the same tasks as those at Station 1. Approximate task instructions are shown in Figures 9 and 10.

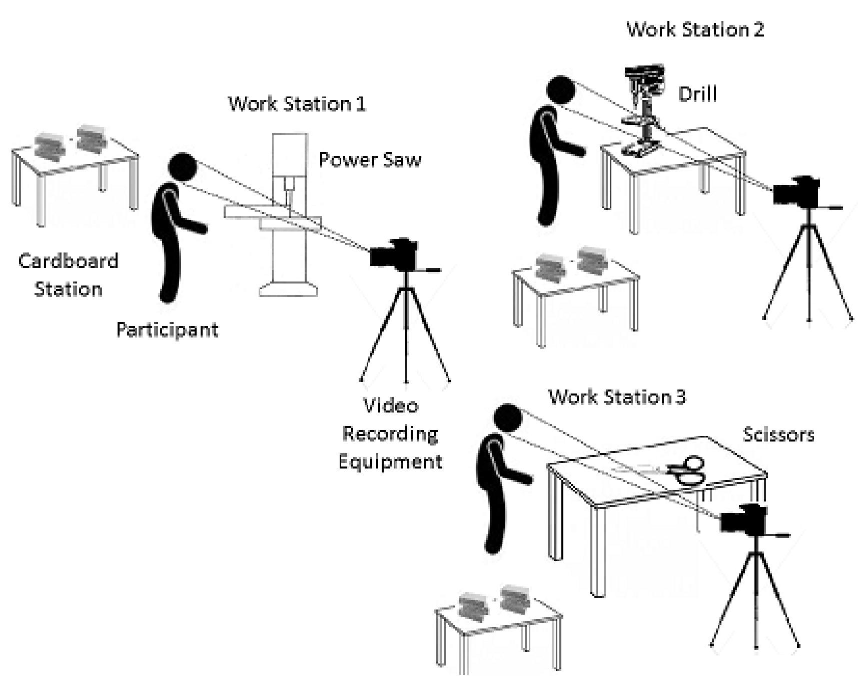


Figure 8: Experimental Layout

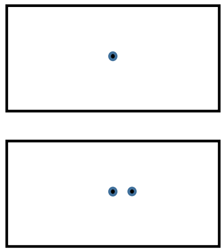


Figure 10: Tasks to be performed at the Drill Station

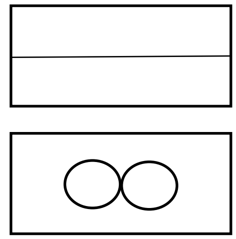


Figure 9: Tasks to be performed with the Power Saw as well as Scissors Stations

An initial questionnaire asked participants to rate their current affective state based on a series of emotional words. Participants rated the degree to which they were currently experiencing the emotion on a scale of 0-10. Participants also completed the Personality Minimarker, which evaluates personality according to the Big Five traits (Block, 1995). Participants were also asked about their knowledge and comfort of workshop machinery and laboratory tasks. Lastly, participants provided their gender, age, and race.

Participants completed one task-specific questionnaire after each task. The task-specific questionnaire consisted of the same emotional items as the initial questionnaire. In addition, the questions asked participants about perceived danger of the specific machine. Lastly, the task-specific questionnaire asked participants to evaluate their performance on the task and report their level of focus. Once participants provided signed consent, they completed the initial questionnaire. Upon completing the initial questionnaire, an experimenter assigned each participant to a randomized order of work stations. Participants were then instructed to complete a task-specific questionnaire after they finished each task. Therefore, each participant provided six task-specific questionnaires: two (one for each task) per station for three stations.

The participants in the study were all freshman engineering students enrolled in EDGSN 100 (Introduction to Engineering Design). The participant summary is shown in Table 5. This experiment was performed in accordance with IRB guidelines as per Penn State's IRB 3029: "Real Time Observation, Inference and Intervention of Co-robot Systems towards Individually Customized Performance Feedback Based on Students' Affective States". All participants provided informed consent. Participation in the study was voluntary.

Table 5: Participant Summary

Participant Summary	
Number of Paricipants	40
Age of Participants	18-19 years
Undergraduate Year	Freshman
% of Female Participants	27.5

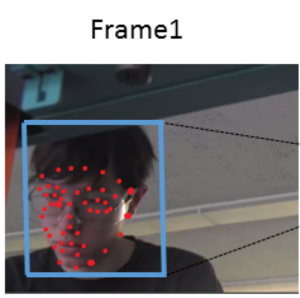
The participants entered the machine shop in groups of three, with a different participant assigned to each workstation. There was no interaction or communication between participants. After providing consent, each participant completed an initial questionnaire to assess their emotional state prior to the use of the equipment, and was then assigned a specific order such that no participant was kept waiting at any engineering equipment station. The participants were recorded while performing the two tasks at each station. Each participant completed a questionnaire to assess their emotional state and level of comfort after completion of each task. After completion of both tasks, participants were rotated to the next machine so that each participant completed all six tasks.

Videos were edited such that the final clips used for analysis consisted of the participants performing the two tasks at the three different work stations (Figure 11 shows an example of the video recording of a participant using the power saw in station 1).

Figure 11: Snapshot of Video Sequence of Participant using the Power Saw

4.2.2 Facial Key Point Extraction

A total of 60 clips were used for the study. The clips were chosen such that the face was not hidden by the equipment. The clips consist of a diverse mix of participants performing the two tasks at each of the three engineering equipment stations. Some of the clips were omitted, as the participants in most of the frames were blocked by the equipment or were out of range of the video recording equipment. Therefore, while the data collection started with 40 participants, only 37 were actually used in the model generation. The number of frames in each clip varied as the time taken for each task by the participant differed. 66 facial key points were extracted using the CSIRO Face Analysis SDK (Saragih et al., 2010) and the Face Modeling GUI. 66 facial key points are extracted using this software (see Figure 12). Ordinary Procrustes Analysis was performed to align all faces to a canonical orientation and scale centered at the origin and scaled to unit variance, as explained Section 3.2.



Frame	Facial Keypoint 1	Facial Keypoint 2	....	Facial Keypoint 66
1	128.66	-195.88		176.65
2	132.9	-185.7		178.01
3	145	-176.32		175.82

Figure 12: Extraction of Facial Key Points from Video Sequences

4.2.3 Model Building

SVM regression was used to predict self-reported level of comfort from mean and standard deviations of facial key points and Procrustes alignment parameters using the R package ‘e1071’ (Dimitriadou et al., 2006). Grid search determined that C = 1 and ε = 0.01 were the optimal parameters to minimize the cost function of the SVM model. The metric used for hyper-parameter optimization was the accuracy. The parameters were chosen so that they yielded the maximum model accuracy. Box-Cox transformations were performed to equalize the variance for both the positively and negatively skewed predictors. The model performance was tested using regression model performance metrics, as explained further in the next section.

4.2.4 Model Evaluation

The SVM regression model was tested using the test set or hold-out set which consisted of 18 video clips. The Coefficient of Determination (R^2 value) was found to be 0.68, which indicates that 68% of the variation in level of comfort is explained by the facial key points. The Mean Squared Error (MSE), Relative Absolute Error (RAE) and the Root Relative Absolute Error (RRAE) were calculated and are presented in Table 6. MSE was calculated to be 1.157 which indicates that each of the predicted values of the comfort level were approximately a value of 1.157 away from the actual level of comfort. RAE and RRAE which measure the magnitude of the difference between predicted and actual values of comfort level were calculated to be 0.41 and 0.23 respectively.

Table 6: Evaluation of SVM Regression Model

Metric	Value
Correlation Coefficient	0.83
Adjusted R squared Value	0.68
Mean Squared Error	1.157
Root Mean Squared Error	1.32
Relative Absolute Error	0.41
Root Relative Squared Error	0.23

CHAPTER 5

CASE STUDY RESULTS AND DISCUSSION

A positive relationship between a designer's engagement or "interest" and productivity has been established and shown in a number of studies. Interest in a particular prototyping task can sometimes be the deciding factor in the success of the final product. Apart from interest, comfort also influences performance because designers must be comfortable with the tools and equipment that they use on a regular basis in order to perform their tasks efficiently. In order to promote growth and sustainability of design teams, it is important to measure affective states such as interest and comfort of designers. Intelligent monitoring systems which have the ability to detect affective states such as interest and comfort have the potential to improve efficiency during the prototyping process. They can provide personalized feedback to each designer to help them successfully complete the task at hand during the prototyping process.

The results for the two case studies which can potentially help build sophisticated intelligent systems are presented in this chapter. They demonstrate that affective states such as interest and comfort can be detected using machine learning algorithms with a reasonable amount of accuracy. Section 5.1 discusses the results of the first case study in which machine learning models were used to predict interest and Section 5.2 discusses the results of the second case study in which the comfort level was predicted.

5.1 Case Study 1: Automatic Prediction of Interest

The results indicate that interest can be reliably detected by an automatic classifier operating on videos of natural facial expressions. The current classification model can be used for classifying interest in real-time on live video as it is computationally efficient because of the reduced number of facial features used.

The SVM classification model is more accurate in predicting disinterest rather than interest. This can have application in improving the effectiveness of the mandatory online training modules designers have to complete during their training process. It is crucial to identify disinterest in designers so that the instructor can modify the content accordingly. This helps in gaining insight into determining what areas can be improved upon based on designers' disinterest. It can also help in detecting when designers are not paying attention while using power-driven equipment or other engineering equipment, thus minimizing accidents during the prototyping phase.

Significant improvements in accuracy can be made using a larger data set and more advanced classification systems. The classification accuracy can also be improved by incorporating more data from diverse databases. Future experiments might test this experiment by including dynamic information in a traditionally static classification system using procedures such as time-delay embedding in an SVM.

In this study, it has been demonstrated that interest can be classified automatically using machine learning tools with a reasonable amount of accuracy. The findings in this study can be successfully applied to develop intelligent monitoring systems which have the potential to alert designers when they are not paying attention while using power-driven equipment or other engineering equipment during the prototyping process.

5.2 Case Study 2: Automatic Prediction of Level of Comfort

The objective of this case study is to predict comfort level, regardless of the piece of engineering equipment or designer in the engineering workspace. As can be imagined, this is a complex objective, given the variations that exist in machine complexity, designer experience, etc. However, in the absence of engineering-equipment-specific data, the general model can be used as a baseline model, while additional ground-truth data is being acquired for the new design prototype scenario. The results indicate that 68% of the variation in level of comfort is explained by the facial key points. Each of the predicted values of the comfort level were approximately a value of 1.157 away from the actual level of comfort. This can be attributed to the fact that the levels of comfort were rated by the participants themselves on a scale of 1-10. This indicates that the level of comfort used as “ground-truth” is subjective, resulting in high variance across participants. Another factor that may have contributed to lower accuracy is missing facial key point data for some engineering tasks. During data collection, the participants’ face might have been hidden by the equipment while performing the task for a short period of time or may have moved away from the focus of the video recording equipment.

It is expected that with a larger data set and more advanced modeling algorithms, the accuracies of the proposed methodology will improve. Future experiments will explore these research questions by using dynamic classification engines like Gaussian Process Models.

The results indicate that an automatic classifier operating on videos of natural facial expressions is able to predict the level of comfort of an individual. The results show that the data collected through non-invasive data capture techniques while designers are at work, can be used to effectively model and predict their comfort level. During design conceptualization and prototyping, designers would not need to be disturbed and could continue with the task at hand, while the proposed system modeled and predicted their comfort level. Design teams could choose if/when intervention feedback would be provided which can enhance designer efficiency, while minimizing distraction and injury.

CHAPTER 6

CONCLUSION

Developing prototypes is an essential step in the design process. The current design landscape calls for enhanced productivity and efficiency. Most studies show a positive relationship between a designer's engagement or "interest" and productivity during the prototyping process. Interest in a particular prototyping task can sometimes be the deciding factor in the success of the final product. Though interest in the task at hand during the prototyping process is important, the use of power-operated machines and other such engineering equipment requires designers to be comfortable with using this kind of equipment. Therefore, it is important to measure affective states such as interest and comfort of designers in order to increase growth and sustainability of design teams. In this study, it has been demonstrated that both interest and the level of comfort can be classified automatically using machine learning tools with a reasonable amount of accuracy. The SVM classification model used to predict interest had an accuracy of 72% and the SVM regression model used to predict comfort had an R^2 value of 0.68. Though this study is promising, it has many limitations. Firstly, the designer has to be constantly monitored which leads to an exponential increase in the amount of data to be analyzed. The intelligent systems built to detect comfort and interest will have to be sophisticated due to the increase in data volume, which raises scalability as well as cost concerns. With the increase in the amount of data available, real-time feedback might not be possible with the current system. Constant monitoring also leads to an increase in the noise in the data collected, which might affect the prediction accuracy of the predictive models.

Future scope of this study involves the building of sophisticated intelligent monitoring systems which can help designers become more efficient during the prototyping process by alerting them when they are not paying attention to the task at hand. It can also provide help when they are not comfortable with using a particular type of equipment during the process of prototyping. This thesis provides the preliminary groundwork required for building such intelligent feedback systems to help enhance productivity and efficiency during the prototyping process. These intelligent systems will be able to detect if the person is distracted or not comfortable during the prototyping process. Automatic feedback systems also benefit workforce training, engineering laboratory teaching and other domains. They can help increase the efficiency of learning processes by providing assistance as needed. In addition, intelligent monitoring systems will ensure that individuals follow safety protocols at all times during the prototyping process. Feedback from these systems will build confidence in individuals as they perfect their design and prototyping skills. More self-esteem in engineering and designers has the potential to induce more confidence in projects and influence productivity.

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