Automatic Facial Expression Recognition and Operator Functional State

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Abstract. The prevalence of human error in safety-critical occupations remains a major challenge to mission success despite increasing automation in control processes. Although various methods have been proposed to prevent incidences of human error, none of these have been developed to employ the detection and regulation of Operator Functional State (OFS), or the optimal condition of the operator while performing a task, in work environments due to drawbacks such as obtrusiveness and impracticality. A video-based system with the ability to infer an individual's emotional state from facial feature patterning mitigates some of the problems associated with other methods of detecting OFS, like obtrusiveness and impracticality in integration with the mission environment. This paper explores the utility of facial expression recognition as a technology for inferring OFS by first expounding on the intricacies of OFS and the scientific background behind emotion and its relationship with an individual's state. Then, descriptions of the feedback loop and the emotion protocols proposed for the facial recognition program are explained. A basic version of the facial expression recognition program uses Haar classifiers and OpenCV libraries to automatically locate key facial landmarks during a live video stream. Various methods of creating facial expression recognition software are reviewed to guide future extensions of the program. The paper concludes with an examination of the steps necessary in the research of emotion and recommendations for the creation of an automatic facial expression recognition program for use in real-time, safety-critical missions.

1.0 Introduction

The increasing mechanization of control processes in the modern world has lessened the gross total workload of the operator and has increased the breadth of tasks that humans can accomplish. However, despite the operator shouldering an objectively smaller workload than before the advent of automation, human error still accounts for the largest percentage of actions leading to the prevention of mission success. When affected by emotional and environmental influences, the operator can falter in the execution of critical tasks. In order to combat the negative consequences of a sub-optimal operator state, it becomes necessary to create a system that both evaluates the operator and influences him or her into embracing an optimal emotional state. Operator Functional State (OFS) defines the current theory of what constitutes an optimal state: "the multidimensional pattern of human psycho-physiological conditions that mediates performance in relation to physiological and psychological costs, [and] results from the synthesis of operator characteristics, current operator conditions, and the operator's interaction with operational requirements."[13] OFS does not place value judgments on a specific aspect of state, but rather looks at its holistic representation and effect on the operator. The regulation of OFS in operators could help to spot and prevent any human errors from occurring.

Various techniques have been proposed and utilized to measure OFS in real-time, such as electroencephalography (EEG), eye activity, and core temperature measurements.[13] The implementation of these techniques allows for the least noisy sources of data; however, each method only measures a single aspect that affects OFS, and the implementation of the multiple apparatuses measuring these different methods onto a single person would cause considerable discomfort and diminishing returns in respect to the amount of useful data acquired. The most important component of assessing OFS becomes finding a measurement that can take multiple factors into account while extrapolating from a single source of information. This source of information can be found in the human face.

Humans have residual information about their current activities and emotions stored in their face for a variable length of time, and can be charted through tracing muscle movements. Researchers have employed electromyography (EMG) in order to measure muscle activity in the face because of its reliability in detecting facial muscle movement.[9] However, the method uses electrodes attached to the face, which has several technical and practical drawbacks.[9] In the setting of a flight deck, for example, the inconvenience of attached electrodes overshadows the benefits. A potential non-obtrusive system comes in the form of monitoring an operator through live-video streams, and by using facial expression as a measure of state. This paper overviews the science behind facial expressions, their link to emotions, and describes stress, fatigue, and complacency: three psycho-physiological states that promote sub-optimal OFS. Next follows a description of the feedback loop video system, along with the suggested protocols and models for the regulation of an operator's state in the case of stress, fatigue, and complacency. Then, a description of the basic program created by the author, and an explanation of the computer algorithms and statistical models available to create a facial expression recognition program shows the extent of the possibilities in computer vision.

2.0 Emotion and OFS

Darwin's work, *The Expressions of Emotion in Man and Animals,* postulates that human emotions, and subsequently the physical generation of emotion through facial expressions, are "evolved and adaptive." Darwin proposes that human emotion and its expression could not be the product of societal constructs, but represent the culmination of millions of years of evolution selected to benefit the species.[8] As social creatures even before the advent of human speech, ancestral humans could communicate their emotions and intentions to others through their facial expressions.[8] Despite the formation of language, humans keep their ability to show their emotional state through the face. Ekman and his colleagues later revived interest in Darwin's theory of universality of emotion by continuing cross-cultural studies and noting the similarity of emotional expressions throughout the world. Ekman and his colleagues agreed with Darwin and proclaim that facial expressions, and the emotions displayed by each facial expression, are universal.[10] In order to create a scientific and methodological manner of determining a facial expression, Ekman also created the Facial Action Coding System (FACS), which uses facial muscle movements, defined as Action Units (AUs), to discern emotion. Vetted by the scientific community, FACS presents a foundation for all measures of facial expression and continues to be a measuring scale for human emotion. FACS allows the scientific examination of facial muscles in facial expression analysis, which can be used to measure OFS after examining the effects of emotion.

Emotion has a continual effect on an operator's perception of a task and on his or her OFS. Studies have shown that emotional arousal has an effect on the general reactivity and decision-making abilities of an individual, despite the emotion's valence.[16] The impact of emotion on cognitive tasks elevates it to an aspect of state to be examined. The face allows a unique combination of both physiological and psychological changes in the body. For example, the perception of happiness in an individual connotes an emotional recognition fueled by the physiological conformation of different muscles in the face. The universality of facial expressions also validates the creation of a facial recognition system focused on the determination of sub-optimal OFS since it would not have to be calibrated for each individual operator. The different conformation of muscles can be measured through the FACS, which already decoded the different potential muscle movements in the face. Although different states of sub-optimal OFS exist, the following three incorporate a large spectrum of the challenges faced by operators and will be concentrated.

2.1 Stress

The Lazarus definition of stress, "the process of appraising [negative or cumbersome] events, of assessing one's potential to control or cope with the event, and continuing reappraisal as new information becomes available," defines stress as a process for dealing with harmful, emotional events rather than a strict emotional state in itself.[14] Stress does not constitute an emotion, but rather combines an amalgam of emotions in reaction to a situation. Stress can arise from a time-restricted and work-intensive environment, like those found in safety-critical missions, and has both psychological and physiological effects on the body that leads to a sub-optimal OFS.

In terms of the psychological effects of stress, the brain attempts to mount multiple defensive measures, such as a reflexive completion of tasks without cognitive input, in order to reduce stress.[14] However, following the failure or lack of initialization of these defensive measures, the mind suffers from a reduced ability to process the environment due to the high workload.

Subsequently, stress affects an individual's physical state as well. Selye's General Adaptation Syndrome (GAS) represents the process in which stress manifests in the physiology of an organism. GAS defines the "progressive responses to prolonged stress in which an organism mobilizes for action and compensates for stress," and its component, Alarm, Resistance, and Exhaustion (ARE), shown in Fig. 1, delineates the stages of the response.[14] The GAS shows the general wearing down of an organism in the face of stress. Ultimately, when stress fails to be mitigated, the organism reaches exhaustion and becomes unable to respond

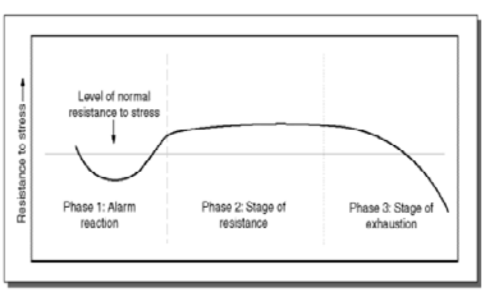

Figure 1. Alarm, Resistance, Exhaustion (ARE).[14] Figure shows the three stages of Selye's General Adaptation Syndrome (GAS).

appropriately to the environment. The culmination of stress, psychologically and physiologically, creates an error-prone environment for the operator due to his or her inability to cope with high-load tasks.

2.2 Fatigue

Fatigue colloquially describes "feelings of fatigue, exhaustion, and to problems of attention and motivation."[5] However, the amorphous boundaries of this definition of fatigue encompass a multitude of other emotional states like drowsiness and intense hunger. In the context of work-related fatigue, fatigue defines a "normal, healthy response to an oncoming depletion of resources, caused by the execution of physical and mental tasks," which highlights the fact that humans are not meant to concentrate on a task for an extended period time without regard for their overall state of being.[5] Work-related fatigue does not include the effects of outside influence like lack of sleep, although these factors can be confounded and mistaken as fatigue. Fatigue occurs in a work environment due to extended interaction with a task without any breaks or change of requirements in the task. Fatigue affects the operator's psycho-physiological state by inducing a state of tiredness usually followed by a decrease in cognitive function.

The effects of fatigue lead to the operator being unable to completely process his or her environment. The monotony of the task causes the operator to revert to more energy-saving strategies. For example, in response to the decrease in awareness, the operator either continues the task at his or her current pace and makes mistakes, or slows down the process in an attempt to reduce the mistakes.[5] Essentially, the operator has to take the time to evaluate different work strategies to combat the side effects of fatigue.

2.3 Complacency

Complacency, in the terms of safety-critical missions, defines the tendency for operators to blindly trust automation without monitoring, and often renders the operator unable to quickly respond to any malfunctions.[12] Complacency also results when the operator works in a highly reliable and automated environment, and the operator's sole task is to stay vigilant in case of occasional error.[15] Although automation has increased the capability of an operator in a multitude of environments, it has also caused an unbalanced mental workload and reduced situational awareness in operators.[12][15] Complacency differs from boredom due to the implicit trust in the automation; complacency lulls the operator into a false sense of security due to trust. While an operator may be bored because of the absence of a task, a complacent operator can also be bored due to the trust given to the automation. A complacent operator appropriates a small cognitive investment in his or her environment, and can lead to overlooking any number of mistakes in the automation.

Complacency does not necessary increase the number of errors committed by the operator, but rather causes the operator to ignore potentially dangerous situations due to a lack of cognitive awareness. Complacency leads to a reduced reaction time if any errors occur, or an inability to spot any errors at all. If an error occurs while the operator is complacent, the operator could be sent into a panic while attempting to discover and fix the problem occurring in the task simultaneously.

3.0 Video Systems and Facial Expression Recognition

3.1 The Feedback Loop

The use of a feedback loop allows information gathered from the user to be analyzed in real-time and sent back to inform him or her to modify or continue his or her current actions. The proposed feedback loop, as shown in Fig. 2, notifies the user about their state based on the data analyzed from the facial expression

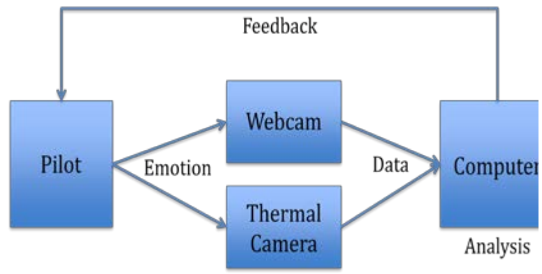

Figure 2. The Feedback Loop. The feedback loop utilized in the potential facial recognition system in order to aid pilots and other critical-safety task

recognition program. The program then sends the product of the data analysis back to the user in the form of useful information regarding their current state. For example, when the subject displays a sub-optimal state of awareness, the feedback loops allow this information to be sent back to the user. Users can then modify their state based on their newly acquired knowledge, or, if they lack the ability due to extreme conditions, allow other protocols to be put into place. The feedback sent to the operator would depend on the emotion he or she displayed, and would be designed to combat that specific sub-optimal state. The different protocols that would be assigned to the three main sub-optimal OFS, and the make-up of the physical systems in the feedback loop, are explained further.

3.2 Suggested Protocols for Sub-Optimal States

3.2.1 Stress Protocol Description

The weight of stress on an operator leads to a variety of negative emotional responses such as fear, anger, disgust, distress, and helplessness.[4][11] Although a distinct stress progression does not project itself directly onto the face, the stress can be traced through the shifts between negative emotions on the face in response to high-load work. The program would monitor the operator for any sequence of negative facial expressions over a period of time. Current research shows that the detection of stress through live-video streams is both possible and improving and could be an integral part of assessing OFS.[4]

The program would constantly monitor for an emotional reaction to stressors, like a sudden change in the environment, and note the duration of the emotional response. If stress episodes are infrequent and short in duration, the program will not report those results to the operator. However, once the length or frequency of the episodes increase, then the program would report the findings to the operator through voice-command or through a notice in one of the display monitors. The program then prompts the operator to commence a relaxation technique, such as deep breathing or voluntary and directed muscle contraction. The implementation of the stress protocol hopes to reduce stress as it begins, rather then allowing the operator to reach maximum stress levels at any point. However, if the levels of stress are deemed to be overwhelming the operator, then the program will suggest replacing the operator if possible.

3.2.2 Fatigue Protocol Description

Although the measurement of fatigue should not include the symptoms of sleep loss or an out-of-sync circadian rhythm, the outward manifestation of these states are similar.[5] Therefore, for the purposes of the fatigue protocol, all states that manifest similarly to fatigue will be considered as such. However, while fatigue can be alleviated through the implementation of short breaks or modifying the task, the curing of symptoms caused by sleep loss require more intensive recovery. In light of the similarities between the states, the program will also pay attention to the duration that the emotion outwardly affects the operator.

Although the current literature does not describe the facial expressions associated with fatigue, the proposed program looks for characteristics like heavy-lidded eyes combined with a neutral expression and possibly the inability to detect the operator's face for increments of time due to head-nodding or complete eye closure. The program monitors the operator for their level of fatigue throughout the task. The goal of the program is to squash any signs of fatigue before they affect the operator in a fundamental way and reduce work efficiency. If the level of fatigue passes a level to be determined, the program would inform the operator and instruct them to take a break, focus on another task, or instruct the task-manager to appropriate another task to the operator.

3.2.3 Complacency Protocol Description

Complacency generally manifests itself in ways similar to boredom. In terms of OFS, complacency usually occurs from the under-load experienced due to automation. Research shows that the most effective way to place the operator back into experiencing the appropriate level of load comes in the form of adaptive automation.[12] Adaptive automation refers to the ability to reallocate the level of automation from the operator to the environment depending on the operator's state.[12]

The current literature does not describe the facial expressions associated with complacency, however, for the purposes of the program, complacency will be discerned through the formation of a neutral face, combined with the appearance of cues like constant pupil movement away from potential locations of display monitors. If the operator appears complacent, then the program will alert the adaptive automation system to return some function back to the operator. The transfer of work back to the operator will allow them to regain focus and invest some cognitive awareness into his or her environment.

3.3 The Physical Components
3.3.1 Webcam

Since their introduction, webcams have improved in both their popularity and their capabilities; however, they still suffer from a multitude of technological shortcomings, such as the maximum number of frames per second and megapixels. The webcam also experiences some practical limitations, like the inability to function well in poorly lit environments.[9] However, despite these setbacks, webcams allow an inexpensive alternative to expensive video equipment; webcams are built to stream video live onto another source, while more traditional video equipment solely stores video for later use. Webcams also have the advantage of size, and the introduction of a webcam into the work environment will be almost unnoticeable due to their small size.

3.3.2 Thermal Camera

Preliminary research shows that thermal cameras present another non-obtrusive way to detect facial muscle movement.[9] By analyzing the muscles delineated in the FACS, the researchers found that the production of AUs creates an increase in the temperature in certain areas of the face while decreasing other areas, and shows a promising method of evaluating facial muscle movement.[9] Programs that rely on webcams suffer from the camera's inability to register images correctly when the subjects are under poor lighting. Thermal cameras, however, do not require any light at all; the images form through the analysis of heat emanating from a surface. A drawback of thermal cameras comes from the camera's inability to see through other objects. For example, if an operator had to wear goggles, the thermal camera would only reflect the heat of the goggles rather than any of the eye muscles due to the goggles occluding the eyes. The occlusion occurs for all objects, regardless of transparency, so any accessories that cover the face will have to either be removed or redesigned to prevent facial occlusion.

The combination of both standard webcams and thermal cameras in the system would allow for both the continual monitoring of the operator despite lighting conditions and the ability to corroborate facial muscle movements between the webcam and the thermal camera when the operator sits under good lighting. The utilization of both methods would help to cover some of the drawbacks of either method and create a more balanced system.

4.0 Computer Algorithms for Deciphering Facial Expressions

The current iteration of the automatic facial recognition program, created in Visual C++, utilizes Open Computer Vision (OpenCV) libraries and Haar cascades, and tracks a human face in a live video-feed. After identifying a human face, the program then subsequently identifies some key facial landmarks: the eyes, pupils, nose, mouth, and the corners of the mouth. Some of the limitations of the program, both intentional and unintentional, are as follows: the program currently only tracks one individual at a time, has a slight delay due to the application of the facial landmark identification boxes onto a live-stream video, does not include thermal camera integration, and can only identify facial features deviating 30 degrees either to the left or right from facing the camera directly.

The program also lacks a key component: facial expression recognition. The current state of computer vision allows for the utilization of a multitude of algorithms to create a program that automatically recognizes facial expression. The most prominent algorithms seen in recent years are Haar cascades, Active Shape Models, Active Appearance Models, and the Piecewise Bézier Volume Deformation Model.

4.1 Haar Cascades

Haar cascades, described by Viola and Jones [2001], describe a method to quickly identify images using feature-detection. Haar cascades rely on Haar-like features that detect the change in contrast values between adjacent rectangular groups of pixels, rather than the intensity values of a pixel itself.[19] Although the use of Haar-like features reduces computing time drastically, comparing every feature in an image in order to find an object creates unnecessary work.[19] The cascading of classifiers allows the further reduction of necessary computing power. Cascading refers to the utilization of a degenerate decision tree that processes images through a series of comparison tests, and rejecting the image if it fails any one of the tests.[18] For example, if the part of the image being compared matches the feature in the first sub-window but does not match the second, then the cascade rejects that portion of the image and moves to the next feature. The degenerate decision tree allows for the comparison of all pixels without an unnecessarily complete classifier comparison, and results in the rejection of most negative images and the approval of most positive images.

In order for a Haar classifier cascade to identify a particular object, the algorithm has to be trained. The training of the algorithm requires a large library of both positive and negative images. The positive images contain the object that the user wants the algorithm to detect, while the negative images consist of random images without the object.[18] The robustness of the algorithm has a positive relationship with the number of images used for training; however, this positive relationship occurs due to the larger probability of variety in larger samples. In the case of facial feature detection, the sample images would have to span across ages, genders, and races.

For facial expression detection, however, Haar cascades create some difficulty. Facial expressions, while universal, can also be repressed or faked to some degree. While noses and eyes vary solely in shape and size, facial expressions vary in the totality of their expressions, from the arch of the brow to the movement of the mouth, and the differences between two different emotions could be too subtle for the Haar cascade to differentiate between. Instead of whole-face facial expression recognition, it could be possible to track more emotive landmarks of the face, like the eyebrows, and then create a program that would note the locations of facial features in relation to the proportions of the face, and then process that information for emotional detection. However, that process would be tedious and probably inaccurate for the subtleties of emotional expression.

4.2 Active Shape Models (ASM)

Cootes and Taylor's [1995] ASMs illustrate a trained statistical modeling algorithm that utilizes Point Distribution Models (PDMs) to rapidly locate the desired structure.[3] PDMs describe a training set of images dotted with landmark points. The training sets have multiple instances of the same object, but with some natural variation. The mean position of the landmark points in relation to the object, and then the points that show how each object in the training set deviates from the calculated mean, are determined.[3] After the establishment of the PDMs, the ASM performs an iterative search to locate the shapes of the structures in different images.[3] The ASMs result in the ability to fit the model to the image after a finite number of iterations.

The human face, although variable, generally follows a model format with the same number of facial features. The general shapes of the facial features are also the same, although the size of these features in relation to each other, and in general, can change. ASMs then provide a non-rigid modeling approach to identify and conform to different facial expressions. The measured facial expressions would be trained by different sets of PDMs and then the conformation of certain ASMs would denote that expression.

However, the use of ASMs in order to describe human emotion runs into similar problems as Haars cascades – although ASMs require less training, they only identify models defined in their training sets. Therefore, a PDM would have to be created for each emotion. Even though ASMs are more forgiving than Haars cascades when conforming to images, the complexities of an emotion would have too much deviation from the mean. For example, the manifestation of a smile can range from the open mouth smile to the Duchenne smile. Each variation of the smile still constitutes a smile; however, the difference between a closed-mouth smile and an open-mouth smile, combined with the appearance of teeth, only constitute a portion of the variation.

4.3 Active Appearance Models (AAM)

AAM, also created by Cootes and Taylor [2001], shows a statistical modeling method similar to ASM, but diverges from tracking a specific object and moves toward matching a class of deformable objects.[2] AAM works similarly to ASM by requiring a training set marked with points. An image in the training set, after being marked, has its points aligned; the subsequent wrapping of the images around the mean of the training set then creates a "shape-free patch," which lacks any texture.[2] The process is repeated for each image in the set, training the model to conform to a variety of shapes of a similar class. The "shape-free patch" is raster scanned into a texture vector and then applied with Eigen-analysis to build a texture model.[2] Lastly, the correlations between shape and texture generate a combination of the shape and the texture to create a combined appearance model.[2]

The ability to follow deformable objects, such as a face with any expression, bestows the ability to identify the expression without specific training, allowing AAMs to surpass AAMs in facial expression recognition. AAM works slightly slower than ASM, but the added robustness and the reduction in different training sets for different emotions overrules any advantages of ASM in terms of identifying facial expression.[2] AAM, however, does require a large set of images for training, and the availability of large facial databases are limited.[17] Until more high-quality databases are established, AAMs will not be able to attain the robustness capable of the model.

4.4 Piecewise Bézier Volume Deformation Model (PBVDM)

The PBVDM utilizes the Connected Linear Deformation Method (CDLM), from the work of Tao and Huang [2003] and defines a model consisting of multiple deformable 2D patches whose movements are determined by a set of different vibration modes.[7] Vibration modes refer to the different displacement vectors that determine the deformation of a particular patch. These patches are connected together with hinges that work to maintain the spatial relationships between the patches and prevent any drifting. CDLM can therefore be used to track and model the movements of facial muscles, which would be represented as different vibrations of the patches.[7]

The PBVDM creates Bézier volumes across specified areas of the face, with a section of the surface model, or facial mesh, in between the top and bottom volume layers. The movement of the Bézier volumes deforms the surface model, and in the case of facial mesh, shows the movement of facial muscles in that region. PBVDM can utilize the AUs of the FACS to define the available facial movements. Therefore, the PBVDM allows a more specific analysis of desired facial muscle movements in real-time.[6]

The use of PBVDM in facial expression recognition allows a more scientific approach. The other models require training sets to tell the model what constitutes an emotion, and then the models can only identify those trained emotions. PBVDM, on the other hand, allows an analysis of muscle movements through the use of individual volume patches without training sets. PBVDM can be made to be analogous with a FACS analysis of a face. Current PBVDM facial meshes do not cover the complexity of facial muscle movement covered by FACS, or the ability to decipher emotions as effectively as a human can, but the accuracy of the algorithms is improving.

5.0 Discussion

Currently, the research surrounding the emotional states of boredom and fatigue are limited in both their breadth and depth. More research into the states and facial expressions associated with fatigue and complacency would be helpful in creating algorithms to define those emotional states. A potential method of determining the facial expressions associated with fatigue and complacency would be to conduct a study where individuals would be exposed to situations that lead to those emotional states, and then facial expression would be analyzed to search for commonalities, similar to the current studies on stress.[4]

The current iteration of the program developed by the author allows for the detection of some facial landmarks, which represents the first step in automatic facial expression recognition. The program could be extended even further to recognize other landmarks like the eyebrows. In the future, the actual creation of an automatic facial expression recognition program for use in human factor's experiments will help in the tracking of sub-optimal states of awareness in operators. The facial expression recognition program should be created through the use of either AAMs or PBVDM due to their robustness and ability to reliably deform to the human face. Unless more facial databases come into fruition, the use of PBVDM would be optimal due to its ability to deform to the human face without the need for high quality training sets.

After the creation of a proper facial expression recognition program, a complete study to evaluate the emotion protocols and their effect on the frequency of errors during flight would help to determine the efficacy of the system.

6.0 Conclusion

The study of OFS requires the consideration of a large number of variables in order to find the optimal OFS. However, the use of automatic facial expression recognition could help to reduce the number of accidents due to human error by helping to reduce sub-optimal states of OFS before they overtake the operator. The use of video systems in lieu of more obtrusive methods of determining state allows the practical implementation of state-measuring devices into the operator's environment. The implementation of video-systems in a work environment would help to increase the safety experienced by both operators and their charges, and lead to a safer world.

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