Physiologically Attentive User Interface for Robot Teleoperation

Real Time Emotional State Estimation and Interface Modification using Physiology, Facial Expressions and Eye Movements

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Abstract: We developed a framework for Physiologically Attentive User Interfaces, to reduce the interaction gap between humans and machines in life critical robot teleoperations. Our system utilizes emotional state awareness capabilities of psychophysiology and classifies three emotional states (*Resting, Stress,* and *Workload*) by analysing physiological data along with facial expression and eye movement analysis. This emotional state estimation is then used to create a dynamic interface that updates in real time with respect to user's emotional state. The results of a preliminary evaluation of the developed emotional state classifier for robot teleoperation are presented, along with its future possibilities are discussed.

1 INTRODUCTION

Due to many fold increase in computing capabilities, we have seen tremendous evolution in Human-Computer Interaction (HCI). And through technological improvements and robotics evolution; we are witnessing another form of interaction which is between Humans and Robots; and widely known as Human-Robot Interaction (HRI). No matter if it is HCI or HRI, the ways we are interacting with machines have evolved to such an extent that science is now looking for methods that help understand human intentions without much need of physical input from humans.

From the emergence of computers to the development of personal computers, and then becoming an ubiquitous entity, the relationship between humans and computers shifted from many-to-one to one-to-one, and now it is one-to-many. This technological shift brings in the demand for smarter Human-Computer Interfaces.

To optimize HCI, Vertegaal (2003) proposed a framework for Attentive User Interfaces (AUI). AUI uses sensing, communication, augmentation, control, and availability of human to strategically optimize communication between Humans and Machines. AUIs designed by different authors (Vertegaal, 2003; Siewiorek et al., 2003; Vertegaal et al., 2006) use sociable forms of interaction by sensing user's attention levels for their surroundings and more preciously for the Interface itself.

However, current AUIs depend on overt measurements of user's attention, such as eye contact, which may not always accurately indicate user's availability for notifications or interruptions. Although overt measures of user's attention may tell us that a user is performing a given task, they do not necessarily indicate the covert state of mind.

Due to this one-to-many relationship between humans and computer systems, traditionally designed approaches are not capable enough to convey information from these devices to humans in a precisely uninterrupted way. On the opposite, these information hungry devices trigger un-timely notifications and information delivery, and they are becoming heavier and more demanding with time (Dirican & Gokturk, 2009).

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Alongside, robot teleoperation also caught into this attention's demand created by interface and robot operations. This eventually creates lots of workload and stress on operators, and sometimes operators also experience boredom, interest loss, and focus issues. Drones like Global Hawks from US Air Force have such a sophisticated system that they need more attention and mental presence than normally flying a plane. In other situations these drones do not require attention and mental focus every single time, which creates windows of unawareness and lack of attention which decreases performance and could cause problems. Secondly, the complexity of these systems could be very high in some situations, leading to very high mental workload and induced stress on operators.

Fortunately, we have improved cognitive abilities to understand covert emotional states that are particularly not possible for current Graphic User Interfaces (GUIs) or Attentive User Interfaces (AUIs) (Dirican & Göktürk, 2011). Psychophysiological activities provide a quiet, hidden, and implicit way to understand cognitive and affective states of users with respect to their mind-body relationship (Dirican & Göktürk, 2011). Human physiology is highly affected by the activity of the Central Nervous System (CNS) and the Autonomic Nervous System (ANS), and reflects physiology in the form of physical signals generated by human body in real time (Sapa, 2011; Dirican & Göktürk, 2011), which could be helpful in telling emotional state of a person.

We explored the field of Psychophysiology to understand covert states of human mind alongside integrated this with overt measurements of facial expressions and eye movements, and prepared an Artificially Intelligent system to precisely detect three Emotional states (*Resting*, *Stress*, and *Workload*).

These emotional predictions were then used in real time to create a *Physiologically Attentive User Interface* (PAUI) that changes dynamically with respect to the emotional state of the person in real time.

However, this generated PAUI developed over an older GUI to reduce the complexity (e.g. reducing the amount of information provided) and to increase both usability and development flexibility for a closed system. In which the older GUI was a frozen 12 years old interface with very complex user interaction and feedback view. This new interface reduces the complexity of the older one by displaying only the more relevant information (reducing unnecessary user's cognitive overload) and updates itself in real time with respect to the emotional state of the person. In addition, it will also communicate with the older GUI, via a picture-driven computing approach e.g. (Silva et al., 2016), to eliminate the need of creating a new interactive system from scratch.

Following in this paper we have discussed current state of physiologically driven interfaces and Human-Machine interactions. Then explained the solution we developed for PAUI creation and the framework designed. Then next, emotion classification processes, experiments, and there results are discussed. It is then followed by the conclusion and its future perspective.

2 REVIEW

Due to emotional state awareness capabilities of Psychophysiological measures, they are catching lot of attention these days in areas like Autonomous systems, Military, Medicine, among others. Few of them relevant to the project were studied and their findings are discussed below.

Bulling (2016) provides an analytical and projective view on current and future aspects of User Interfaces, with an insight to the possibilities and requirements for Pervasive Attentive User Interfaces. User interfaces will shift their focus from being an attention demanding to attention managing systems; interfaces adapt for amount, type, and time of information delivery on the basis of current attention capacities of the users. Bulling (2016) defined Unobtrusiveness, Accuracy, Large scale, Long-lividness, Seamlessness, and Context awareness are 6 important categories that defines new Pervasive Attentive User Interfaces.

Chen & Vertegaal (2004) used LF spectral components for mental workload and analyzed EEG for motor activity to find four distinguish states of user, and use them to predict the availability of the user for interrupts. These four states have interruption costs for speech and motor related activities. And by using user's physiological state and cost of interruption (calculated by user's preferences for mode of interrupt for email, IM, and calls in all four states), system decides if the user has to be interrupted or not. First state of this system exhibits very lower degree of attention, in which user is not actively engaged with any task and could be interrupted for having relatively very low interruption cost. However, this was not generalized with other relaxing states where interruption cost could be high. Second state has low interruption cost for audio related interrupts but has high interruption cost for motor related interrupts like messaging. This state is associated with transit activities like walking or running. Third state is mental engagement while at rest which results into high cost for auditory interrupts that could interface with mental state of the user. And the fourth state is of higher activity engagement in which interrupt cost of any kind is high and should not be disturbed.

A Human-Computer Interface (HCI) was developed by (Chapin et al., 1999; Wessberg, 2000) in Duke University to establish communication between a Monkey's brain and a Robot arm. To achieve this communication they used multiple EEG electrodes implanted over a greater area of monkey's brain. Neural activity of large population of monkey's brain was recorded and then decoded the arm movements out of them. This information was then used to reproduce the movements in robot arm.

Another example of Brain-Machine communication was demonstrated jointly by Honda Research Institute Japan, Advanced Telecommunications Research Institute International (ATR) and Shimadzu Corporation in March 2009, in which a Robot was controlled only by Human thoughts. They measured electric signals and blood flow changes in the brain while imagining body part movements and used these to predict user's thought process. These predicted motions are then supplied to Honda's ASIMO humanoid robot to perform similar movements like raising its arm. More than 90% of accuracy rate was achieved (Zhang et al., 2010).

Caproni et al. (2009) has developed a comprehensive hemodynamic pattern classification framework to enhance Human-Robot Interaction (HCI) for medical robotics using Near-Infrared BCI. Caproni et al. (2009) studied different simulations for Motor Imagery (MI) and Non-Motor Imagery (NMI) frameworks. Simulation combinations depends on three channel combinations i.e. left, right, and all channels; two classifier i.e. Support Vector Machine (SVM) and AdaBoost; and three aggregation policies i.e. Majority Voting, Weighted Majority Voting, and Correcting Classifiers. Out of which they found NMI as a best performer. After scrutinizing all of their experiments and their results, Caproni et al. (2009) concluded Near InfraRed Spectroscopy (NIRS) based Brain Computer Interfaces has a huge potential to help enhance existing Human-Machine Interfaces.

3 PAUI

3.1 Approach

We created a basic Physiologically Attentive User Interface (PAUI) to read and understand user's Psychophysiology in real time with an intention to classify three different emotional states (*Resting*, *Stress*, and *Workload*) of a person while teleoperating a robot. These classification results are then use to change the interface in such a way that improves user performance in the task and ease the process of robot teleoperation.

3.2 Apparatus Used and Placement

We are using Bitalino by Plux (Bitalino, 2017) for reading biosignals that are Electroencephalography, Electrocardiogram, Electrodermal activity, and Electromyography. For eye tracking, we use Tobii 4c from Tobii Technologies (Tobii Technologies, 2017) and a normal webcam to extract facial emotions.

Once the person is at the station s(he) will be attached with Ag/AgCl electrodes under right clavicula (Plus), under left musculus pectoralis major (Minus), and under left clavicula (Neutral) for ECG's best suggested placement by (Němcová et al., 2016); for EDA two electrodes were used on left palm; for EMG negative and positive electrode are placed at Abductor pollicis brevis muscle of left hand and reference electrode at left arm's Head of ulna; and for EEG negative and positive electrodes were placed at forehead and reference electrode at left earlobe.

3.3 Architecture

PAUI application's architecture shown in figure 1 is divided into three sub modules that work alongside to achieve overall goal of creating Physiologically Attentive User Interface (PAUI) for robot teleoperation. The three sub modules are *Emotional State Estimator (ESE)*, *Attentive User Interface (AUI)*, and *System Integrator (SI)*.

ESE interacts with external hardware modules to extract covert and overt data of the user and process that for emotion prediction. This predicted emotional state is then fed to AUI that makes changes to its interface with respect to that. And SI is helping in filling the communication gap between old GUI and new PAUI. Moreover, communication between *Hardware layer – ESE* and *ESE – AUI* is one way, but between *AUI – SI* and *SI – Old GUI* is two way.

3.3.1 Emotional State Estimator (ESE)

This module is sub divided into 4 parallel threads: *Bitalino* thread extracts data at 1000 Hz for processing physiological signal; *Camera* thread processes camera images and extracts facial emotions at 15 Hz; *Tobii* thread extracts data at 90 Hz for tracking eye movements; and the *Classifier* thread runs at 2000 Hz that reads data from Bitalino, Camera, and Tobii thread, and performs emotion extraction and provides predicted emotion.

Bitalino thread processes ECG signal for Heart Rate (HR), Heart Rate Variability i.e. Standard Deviation of Normal to Normal (SDNN) and Root Mean Square of the Successive Differences (RMSSD), and Frequency components i.e. Very Low Frequency (VLF from 0.0033 to 0.04), Low Frequency (LF from 0.04 to 0.15 Hz), and High Frequency (HF from 0.15 to 0.4 Hz). It processes EEG for Delta (0.5 – 3.5 Hz), Theta (3.5 – 8 Hz), Alpha (8 – 13 Hz), Beta (13 – 30 Hz), Gamma (30 – 45 Hz), and Engagement (Engagement = Beta / (Alpha + Theta)) suggested by McMahan et al. (2015). Processes EDA for Skin Conductance Level, Skin Conductance Response. And EMG is processed for Muscle Fiber Excitation (MFE). Table 1 contains the list of parameters extracted from each device. The camera thread uses common webcam and Emotion SDK from Affectiva (Affectiva, 2017) to processes image frames and extracts emotions from

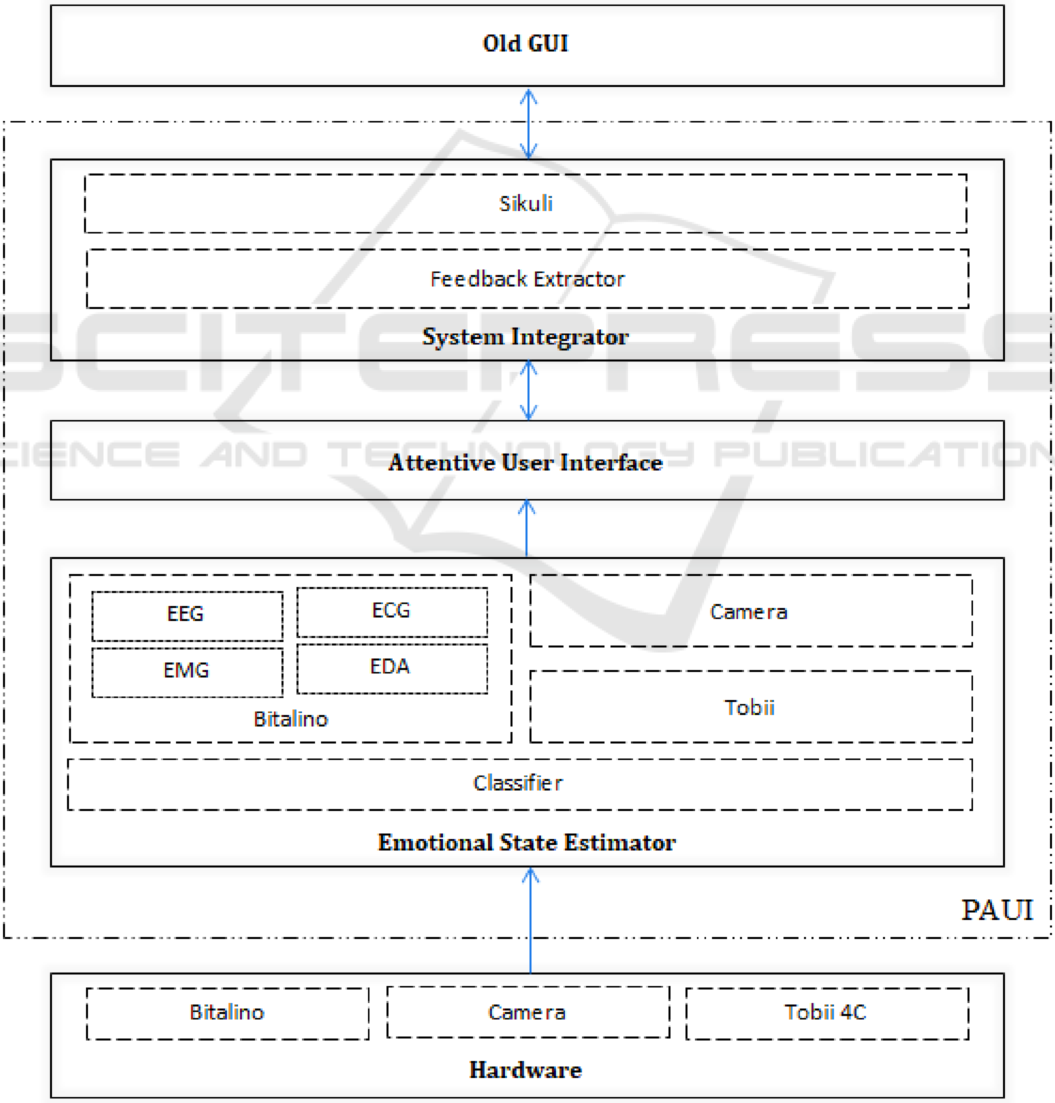

Figure 1: PAUI Architecture.

faces present in the frames. In that we are extracting 9 facial emotions, 21 facial expressions, and facial orientation information.

Tobii thread is continuously monitoring eye movements on the screen and keeps on updating custom designed data set for fixations map on the screen. It contains comprehensive information of fixation map like average fixation, biggest fixation at, among fixation specific information like number of fixations at particular location, fixation coming from and fixation going to, and so on.

Classifier thread works above all three threads, it takes data from them approximately every 500 micro seconds, do the average of data of 3 seconds and use this averaged data with trained Support Vector Machine (SVM) classifier for Emotion prediction out of three trained emotional states (i.e. *Resting*, *Stress*, and *Workload*).

Table 1: Extracted parameters from all three sensors.

Sensor	Category	Features
Bitalino	ECG	▪ HR ▪ SDNN ▪ RMSSD ▪ VLF ▪ LF ▪ HF
	EEG	▪ Delta ▪ Theta ▪ Alpha ▪ Beta ▪ Gamma ▪ Engagement
	EMG	▪ Number of Peaks ▪ Total Peak Time ▪ Max Peak Magnitude ▪ Current Peak Magnitude
	EDA	▪ SCL ▪ SCR
Tobii	General Fixation Information	▪ Number of Fixations ▪ Total Time ▪ Total Fixation Duration ▪ Average Fixation Duration ▪ Repeated Fixations ▪ Biggest Fixation At ▪ Maximum Visited Counts ▪ Maximum Visited At
	Fixation Map *Containing information for each fixation	▪ Number of Visits ▪ Start Time ▪ Fixation Duration ▪ Total Fixation Duration ▪ Total Interval Between Visits ▪ List of Locations Coming From and its count ▪ List of Locations Going To and its count
Camera	Emotions	▪ Joy ▪ Fear ▪ Disgust ▪ Sadness ▪ Anger ▪ Surprise ▪ Contempt ▪ Valence ▪ Engagement
	Expressions	▪ Smile ▪ Inner Brow Raise ▪ Brow Raise ▪ Brow Furrow ▪ Nose Wrinkle ▪ Upper Lip Raise ▪ Lip Corner Depressor ▪ Chin Raise ▪ Lip Pucker ▪ Lip Press ▪ Lip Suck ▪ Mouth Open ▪ Cheek Raise ▪ Dimplier ▪ Eye Widen ▪ Jaw Drop ▪ Lip Tighten ▪ Lip Stretch ▪ Smirk ▪ Eye Closure ▪ Attention
	Face Orientation	▪ Pan ▪ Tilt ▪ Yaw

3.3.2 Attentive User Interface (AUI)

This is the interactive interface with which user is meant to interact and it changes with respect to users psychophysiological state predicted by Emotional State Estimator (ESE). It keeps on reading psychophysiological state predicted by ESE along with data provided by Tobii, and performs required changes in its design along with sending required operations to SI for old GUI.

3.3.3 System Integrator (SI)

System Integrator (SI) is the communication bridge between new Physiologically Attentive User Interface (PAUI) and any old GUI (used for robot teleoperation in our example, figure 2). It needs to perform two basic functionalities in between PAUI and old GUI. One is to extract data from old GUI in a reliable and continuous manner to provide working information to the user (*Feedback Extractor* sub-layer). And secondly, it needs to take action commands from AUI and perform required activities on old GUI using Sikuli's task automation properties (*Sikuli* sub-layer).

Figure 2: Old GUI for robot teleoperation.

3.4 Experiment Setup

3.4.1 Virtual Environment Experiments

Experiments were divided into two categories: Virtual Environment and Robot Teleoperation. To get initial understanding of the data and to perform preliminary tests, we created a virtual setup using games that help generating emotional stimulus in subjects.

In virtual environment experiments the subject were given 2 minutes of relaxing time in the beginning, afterwards s(he) needs to perform *Relaxing* task for 5 minutes. It was then followed by self-assessment in NASA-TLX and SAM. Afterwards, the person was either put on *Workload* or *Stress* task randomly.

In the Workload task, subjects were asked to perform 3 tasks in Rigs of Rods (Rigsofrods.org, 2017) for 5 minutes each, in which difficulty was increased linearly. These 3 sessions of workload were separated by 0.30 minute of break and self-assessment on NASA-TLX.

The *Stress* test is also divided into 3 sessions on a modified Tetris game to make it very hard for whole time play. All three sessions of *Stress* were separated by 0.30 minutes of self-assessment on SAM and break alongside.

After finishing first session of Workload or Stress task, subjects were introduced to Relaxing session for 5 minutes and then again put on either Workload or Stress task. The Workload and Stress sessions were pseudo randomized in such a way that if the first session is of Workload then the second should be of Stress and same should be other way around.

3.4.2 Robot Teleoperation Experiments

After conducting preliminary experiments on virtual environments, we performed experiments on robot teleoperation while imitating search and rescue operations of Fire fighters.

In which *Resting* was performed by driving the robot from one end to other end in a long room for five minutes at minimum speed, to simulate inactivity and lack of mental and physical demand. Then in the *Stress* task subjects need to teleoperate the robot through a very difficult environment and have to finish this task within 5 minutes. And in the *Workload* task, subjects have to search for five items in the environment alongside answering basic arithmetic operations.

However, to keep things unbiased we randomized the whole testing procedure. Each subject has to perform 2 sessions of each task in a randomly controlled way. A home like test setup was used for the experiments that contains a bedroom, living room, and a Kitchen; installed in our lab. Alongside, this home like test setup, we also used some parts of the lab for these experiments. And for Stress tests, 2 specially designed areas in the lab were used to intensify task difficulty and to elevate stress.

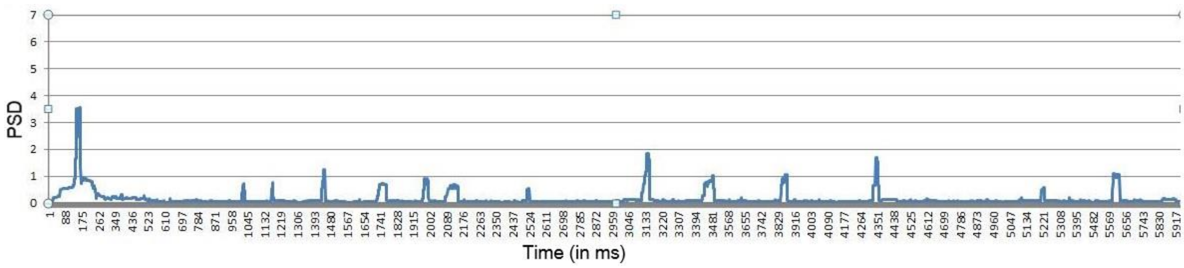

Figure 3: Graph containing engagement data from resting test in virtual environment experiments, in which engagement value shows very less intensity.

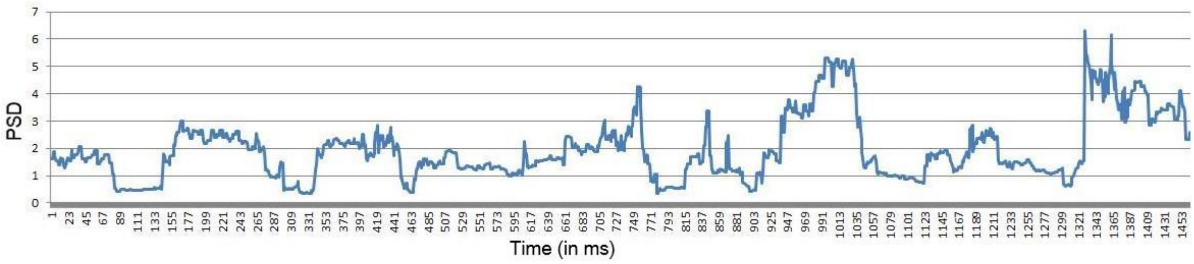

Figure 4: Graph containing engagement data from stress test in virtual environment experiments, in which engagement value shows very high intensity.

After attaching all required electrodes and test them thoroughly, each subject then put onto realisation session, in which they introduced with the tests and robot controls, and let them play with the robot for five minutes. Then out of 6 sequential combinations of resting, stress, and workload test, a random combination was chosen and performed with five minutes of wash away time in between each session, in which they also needed to fill NASA-TLX questionnaire for workload and 5 scale Self-Assessment Manikin (SAM) containing Valence and Arousal for stress. After completing the combination of three tests, another combination was selected out of remaining 5 combinations. Then for the next subject only remaining combinations were used and this continued until all 6 combinations were used.

As proof of concept for this project, five subjects participated and performed two sessions of each task (*Resting, Stress,* and *Workload*) by each subject.

4 CLASSIFICATION AND RESULTS

For benchmarking of our system we performed K-Nearest Neighbour (KNN) and Support Vector Machine (SVM) classification on data from both Virtual Environment Experiments (VEE) and Robot Teleoperation Experiments (RTE). And out of all extracted features we used 46 features (without normalization or scaling) for each vector space

As the physiological data is dependent on task and varies from person to person, we try to evaluate both the conditions. The data from VEE and RTE were arranged into three different categories: *Task Specific* (Gaming and Teleoperation) and *Person Specific*, which then classified and evaluated.

In *Task Specific*, data from VEE and RTE were trained and tested separately with SVM and KNN. In which, 70% of VEE data was used for training SVM and KNN and remaining 30% of VEE data was used for testing, similar training and testing percentage was used with RTE data. Thus the classification results of SVM outperformed KNN in both the tasks. With VEE data SVM gave 80.00% of accuracy and KNN gave 77.63% of accuracy. And with RTE data SVM gave 84.75% of accuracy and KNN gave 79.84% of accuracy.

In *Person Specific*, data of single subject from RTE was used. In which, both SVM and KNN were trained with 70% data and tested with remaining 30% of data. As the data represent only one single person, classifiers performed relatively better than *Task Specific*, and gave 88.37% of accuracy by SVM and 82.95% of accuracy by KNN. Please refer table 2 for classification results.

Table 2: Classification Results.

DATA	SVM	KNN
Task Specific (VEE)	80.00%	77.63%
Task Specific (RTE)	84.75%	79.84%
Person Specific	88.37%	82.95%

As we conducted a validatory research, to support the framework for Physiologically Attentive User Interface, small amount of training data was used which may have interfered with the classification accuracy. Nevertheless, SVM gave expectedly good results to support the framework for real time emotional state processing.

Alongside, the engagement data from resting and stress tests conducted in virtual environment experiments shows clear differences in the patters and intensity in both the measurements. Intensity of engagement value in stress test is relatively very high as compared to resting, and it also stayed high in whole stress session, shown in figure 3 and 4.

5 CONCLUSIONS AND FUTURE PERSPECTIVE

User's psychophysiological state was measured and predicted in real time and autonomy is provided to the system to improve its interface dynamically with respect to the mental workload and stress level on the user. A PAUI was created, that performs dynamic updations to its interface and helps in decelerating the effects of workload and stress.

Moreover, the classification findings are quite impressive. We have explored different aspects of psychophysiology and combined them with external emotional and attentional clues. Getting 88.37% of accuracy in *Person* specific data and 84.75% accuracy in *Task* specific data with this small amount of training samples gives a valid indication of having huge potential of improvement.

Current findings clearly suggest that the use of Deep learning techniques could be a promising measure to achieve higher degree of accuracy in emotion classification.

Future aspects of this research are with the improvements in emotion classification techniques with current state of the art classifiers. One important field to scrutinize is with Recurrent Neural Networks that could be helpful in understanding the changing patterns of the data and make prediction on them. And to introduce more emotional states for classification which helps in bring more dynamicity and understandability to PAUI.

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