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Research paper

SWIFT cognitive behavioral assessment model built on cognitive analytics of empirical mode internet of things

P. V. V. Kishore [1] *, Sk. Azma1, K. Gayathri [1], A. S. C. S. Sastry [1], E. Kiran Kumar [1], D. Anil Kumar [1]

[1] *Biomechanics and Vision Computing Research Centre, Department of Electronics and Communication Engineering, KLEF Deemed-to-be-University, Andhra Pradesh, India*
**Corresponding author E-mail: pvvkishore@kluniversity.in*

Abstract

This paper introduces a study and analysis to predict the present human behaviour through his/her object interactions in the physical environment. The physical environment consists of a door, chair and telephone with accelerometer sensors attached to them and connected to computer using a raspberry pi IoT (Internet of Things) kit. Two other parameters used for assessment are human voice intensities and human motion analysis through a motion capture camera with inbuilt microphone and Wi-Fi module. The dataset is a collection of accelerometer data from chair and telephone, human interaction with door through camera and voice sample of a word 'Hello'. These 4 parameter measurements are collected from 15 test subjects in the age group 19-21 without their knowledge. We used the dataset to train and test 3 predominant behaviours in the chosen age group namely, excitable, assertive and pleasant on an artificial neural network with backpropagation training algorithm. The overall recognition accuracy is 84.89% based on the physical assessment from a physiatrist of all the test subjects. This study can help individuals, doctors and machines to predict the current human emotional state and provide feedback to modify unpleasant current state of behaviour to a pleasant state to maximize human performance.

Keywords: *Cognitive Behavior Assessment; Signal Processing; Pattern Classification; Artificial Neural Networks (ANN); Internet of Things (IoT).*

1. Introduction

Understanding human brain falls in the category of unsolved challenges of modern technological world. Research is on from past few centuries and with emerging technologies in the past two decades provided a greater insight into the function of human brain. Complete understanding of the human brain may take time. But the driving question of our research is, can the knowledge acquired till now is enough to re-program human brain to alter their cognitive behavior based on the situations they encounter. This study attempts to answer this question using human cognition analysis with emerging IoT and Artificial Intelligence models.
This work "Swift Cognitive Behavioral Assessment Model Built on Cognitive Analytics of Empirical Mode Internet of Things" answers the question. The aim is to develop a computer application that advices individuals to transform their cognitive behaviors by assessing their present cognitive behavior. This analysis achieves the goal using the sensors connected to Internet of Things (IoT) and Neural network machine classifier. Thus in this paper the following activities has been taken up:

1) Understand and Model Human Interactions with Objects of daily use.
2) Make a list of common objects and their cognitive behavior during interactions.
3) Identifying sensors and placing them in/with the objects for information capture.
4) Develop an Internet of things (IoT) architecture connecting daily useable things by people with sensors that can measure human interaction.
5) An Algorithm that can classify the present cognitive state of human mind based on present and past interaction with objects. The algorithm is based on Artificial Neural Networks.
6) The assessment with possible behavioral changes is transformed to the user's mobile phone as an e-mail. This is not attempted in this work.

Finally testing is done by using expert human psychologist to confirm the results obtained from the model outcomes. This is important to test the model for active human application. For testing the target age group is between 19yrs to 21yrs with 15 male and female test subjects.
In this fast paced life style most of the human brains act unconsciously to situation of stress which produces undesirable outcomes for them and others. For example, let us assume a person driving car at rush hour to get to the office. He encounters traffic and some unusual drivers on his way. His mind is anxious after an hour long drive. For his brain to directly concentrate on the job becomes difficult and the outcomes for most of the humans always end in disasters. It is impossible for the mind to control these undesired effects instantaneously till a disaster happens such as shouting on co-workers, misbehaving and breaking objects.
At this breaking point, this study asks, can technology help to predict the unfavourable situation and revert back to the individual before the situation deteriorates? We use in this work, smart technology that can help to possibly predict the current cognitive behavioural or emotional state of the mind as the situation demands. This can help humans make meaningful decisions for themselves and the others around them instantaneously.
Few research questions on this will introduce the true importance of this work. One is how can you understand the present cognitive state of the human being in any situation without self-

Consciousness. Second, you somehow found his present cognitive state, how to change the behavior instantaneously.
The answer for the first question comes from IOT (Internet of Things) and Artificial Neural Networks (ANN) for cognitive state assessment and state transformation in real time. Why this concept as there are powerful tools to understanding human cognitive system.
Cognitive behaviours of human beings can be best judged based on the reactions of the mind in dealing with day to day activities performed by the people. Most the behaviors are reactions of the mind to the stimulus at that point in time. The responses of the mind depend on the people's previous cognitive history such as social, cultural, educational, religion, physical and family issues. Most of the responses are a sudden surge in emotions to on external stimulus. The Fig.1, shows the cognitive behaviour of two persons handling the telephone receiver in first two rows and in the last row, the first two figures show door interaction and last three columns a T.V. remote handling.

Fig. 1: First Two Rows Showing Interaction of People with Telephone Receiver. Last Row First Two Columns Show Door Handling and Last Three Columns T.V. Remote Handling.

The first row of the fig.1 shows a human test subjects interaction with the telephone receiver is quite different from the person handling the receiver in second row. Similar distinction can be found in first two columns of last row where the first picture shows the person pushing the door hard compared to the second person.
The problem that is addressed by most of the people in cognitive science relates to failure of a human brain to function normally due to issues of memory [1], learning [2] [3] [4] and concentration [5] [6]. The cognitive analytic therapy (CAT) [7] [8] deals with studying [9] [10] and improving the performance of the human brain under controlled environments [11] [12] [13] such as clinics with resources to test these conditions. What we observe during lab visits the human brain behaves normally due its presence in the environment. The question that drives is how one can know about a human brain with a controlled set of test stimulus [14] [15]. The answer defines the problem of this research study.
This paper aims to study the cognitive behaviors of humans in real world and use this data to transform them to react differently during critical emotional situations. This can have a greater implication for people to transform certain cultural, social, driving, public talking, regional and educational behaviors.

2. Current CBT methods

The current cognitive assessment is human dependent, meaning that the human brain knows that his cognitive analysis is being monitored and assessed and the brain somehow reacts consciously to the external stimulus. The following CBT methods [16] [17] are currently in use.

a) Physical Analysis and Human Interaction to identify the problem, if a person suffers and wanted to see a doctor. Disadvantages, Too Much Time, Patient forgets the therapy once he or she goes back to the problem environment, Financially Draining. – Still most popular technique for CBT [4].
b) Project VIBE is a new and innovative research study being conducted by M. Tracie Shea, PhD, Madhavi Reddy, PhD, Ana Abrantes, PhD and Benjamin Greenberg, MD, PhD for improving well-being and quality of life in Veterans diagnosed with PTSD. Post-Traumatic Stress Disorder MRI Study. Center for Neurorestoration and Neurotechnology [18].
c) CBT Worksheets and Questionnaire. Too Boring and difficult to answer because of the previous states of the brain [19].
d) Use of technology, such as EEG. Again not a cost effective solution to identify the causes of cognitive behaviours and treatments. Too Much Time (TMT) [20].

Most of the testing happens in labs using, fMRI, EEG Caps and Questionnaire on certain things and trying to make an assessment based on the score. Out of these fMRI and EEG are most widely used, and are costly. The questionnaire will always give inconclusive results, because it depends on present cognition state of brain irrespective of questionnaire. This proposed method originated form the need to help humans manage their cognitive behaviors properly for their own good. It can also helps predict human behaviors to establish their personality.

3. Proposed method

The methodologies used will comprehend the objectives defined for this work. The generalised outline of the proposed methodology is shown in Fig.2.

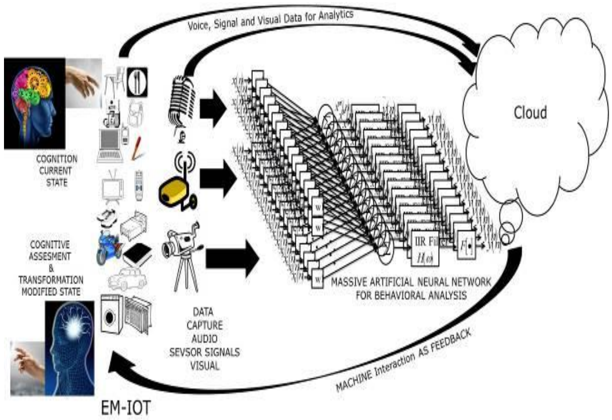
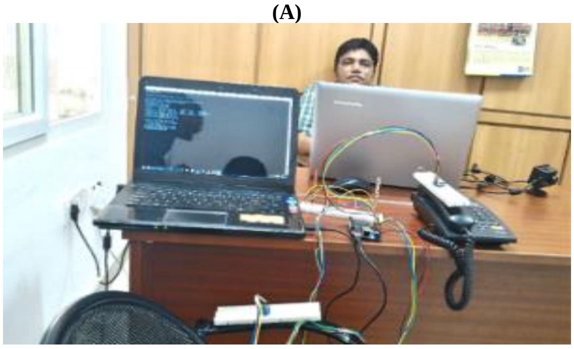


Fig. 2: Architecture of Proposed Method.

The first objective is to build internet of things (IoT) with objects that humans interact regularly. For accomplishing this task, we plan to execute the following methodology. Put sensor (such as pressure, motion, vision and sound) interfaces on objects of interaction. Connect these sensors with raspberry pi, IoT Development KIT. Use cloud on KLU campus to connect these devices with our computer. Collect data from theses sensors as human interactions happen in real time. Human identification is based on biometrics such as fingerprinting and face recognition and mobile codecs.
The data is multi modal, having sound signals, sensor signals, images, videos. This huge data set is stored on the cloud under a particular human code that gets generated when a human comes in contact with the cloud for the first time using their mobile phones. This huge data is pre-processed and conditioned using filtering and enhancement algorithms.
The second objective is to build a neural network algorithm that can classify human cognition. Neural networks [21] [22] [23] can take any kind of data (1D, 2D or 3D) to meaningful patterns in the

data. Networks parameters (such as Weight and bias, etc.) are initialized randomly the first time and from previous results then on. This neural network will exhibit the characteristics of a human brain which is an excellent cognitive tool.
The outcome at this stage is a set of human behaviors that are formulated through interaction with objects around them. Some of these behaviors we are looking at are laughing, blushing, Altruism, Superstition, self-destructive, nasty, carve ornamentation, lie, cheat, steal and stress. In this application we focused on only three behaviors for training and testing the network which are dominant in the age group 19 to 21.
Finally, a mobile application with the proposed model can be constructed to help human beings assess and transform their cognitive behaviors when it matters most. The app will identify the human by generating a reference code on the cloud. The user can set a time frame for the analysis. In that time frame the system tries to access all the information available on the cloud to assess the instantaneous cognitive level of the human and giving suggestions for behaviorl transformations.
This kind of technology has a large potential to build better societies and better mental health care. For example, the doctor Psychiatrist can get information on their computer about the next patient's cognitive behaviour before he even talks to them. This technology can also have negative side, where it can give behavioural information to un desired parties.
The experimental setup, hardware and software module arrangement in our laboratory for testing the cognitive behavior of people is shown in Fig.3.

(A)



(B)

Fig. 3: Our Laboratory Setup. A) Proposed Project Model. B) Cognitive Assessment Hardware and Software Module.

Figure 3 shows a 3 axis digital output low power accelerometer MMA7455 attached to phone receiver and another one attached to chair arm. The third accelerometer is attached to door in the room. Raspberry Pi, BCM2836 soc with a 1.2GHz 32 bit, quad core ARM cortex A-7 processor with 256KB L2 cache connects them along with a microphone and a camera. We have in our experimental set up data from five sensors. The door accelerometer failed due to speed of movement of the door by some test subjects and the door interactions are measured using high speed camera sensor.
The raspberry Pi 3 in this project is equipped with 1.2GHz processer and 1GB Ram. It also houses on board Wi-Fi 802.11n which is accessed by Laptop. The sensor data is send through KLU cloud to laptop and stored in various excel files for further processing. This linking of raspberry pi3 to sensors is programed in python software. The processing on varies data item such on video feature extraction and voice processing is done in Matlab. The ANN classifier is also built in Matlab software.

4. Results and discussion

We tested our proposed model to monitor the human interaction with telephone receiver, chair, door and human. The human interactions with Telephone receiver and chair are communicated back using accelerometer data. Door and chair interaction with visual sensor data. Human voice samples are collected using microphone. Figure 4 shows frames from a video captured during experimentation of a test subject. The observation shows, the process of interaction of the test subject with the door and chair.
The test subjects are completely unaware of this experimentation being performed for analysis of cognitive behaviours in real world conditions. After the experiment they have been informed to avoid ethical issues. Test subjects are students at K.L. University associated with applied signal processing Lab. Figure 5 shows the velocity features projected onto the original frames. Velocity features capture the motion of moving objects between consecutive frames using optical flow algorithm [24][25]. Here we use Horn schunck optical flow model to extract velocity features in x and y directions of the moving objects.

Fig.4: Camera Sensor O/P for Kamila Devi_Test_Sub_1.

Fig. 5: Video Sensor -1 Outputs of Test_Sub_1.

Velocity vectors from consecutive frames form the feature vector for pattern classifier. Figures 6 and 7 show the same results from another test subject. Here door velocity vectors and human velocity vectors are separated using connected component analysis. In this velocity vectors are considered connected in a 3×3 neighbourhood based on their magnitude and direction. The door velocity vectors are almost fixed in the direction as their magnitude varies based on the force applied on the door. All door velocity vectors are stored in database for each test subject. This is also applied to chair. But the vector magnitude is weak and hence these visual features are discarded in this work and chair accelerometer data is used.

Similarly, telephone receiver accelerometer and chair accelerometer data for the corresponding test subjects are plotted in figure 8 and 9 respectively. Figure 8 shows accelerometer sensor plots of 15 test subjects during their interaction with telephone receiver. Figure 9 plots the accelerometer information of chair movements during test subject interaction with chair. Figure 10 shows the two voice samples of the word ‘Hello’ and their Fourier transform plots when they meet me during experimentation. The frequency samples are thresholded with average sample values and their magnitude response is represented as feature vector for individual test subject. All sensors are calibrated for a sampling rate of 0.4 seconds.

Fig. 6: Camera Sensor O/P for Manikanta_Test_Sub_2.

Fig. 7: Video Sensor -1 Outputs Test Sub_2.

Similarly, telephone receiver accelerometer and chair accelerometer data for the corresponding test subjects are plotted in figure 8 and 9 respectively. Figure 8 shows accelerometer sensor plots of 15 test subjects during their interaction with telephone receiver. Figure 9 plots the accelerometer information of chair movements during test subject interaction with chair. Figure 10 shows the two voice samples of the word ‘Hello’ and their Fourier transform plots when they meet me during experimentation. The frequency samples are thresholded with average sample values and their magnitude response is represented as feature vector for individual test subject. All sensors are calibrated for a sampling rate of 0.4 seconds.

The input feature Vector has 4 Attributes from 2 Accelerometers, one Image Feature from Video sensors and 1 voice sensor output having 720 test values from 15 people repeating the same task 10 times at different time steps. The training data is having 720 samples from these 4 attributes. 25% of the input vector will be used for testing the ANN classifier’s performance. Hence the feature matrix is 4×720 vector each column representing sensor data of 15 people who participated in the experiment. Increasing the number of training samples further with multiple representations for a single test subject provide better classification of test subjects.

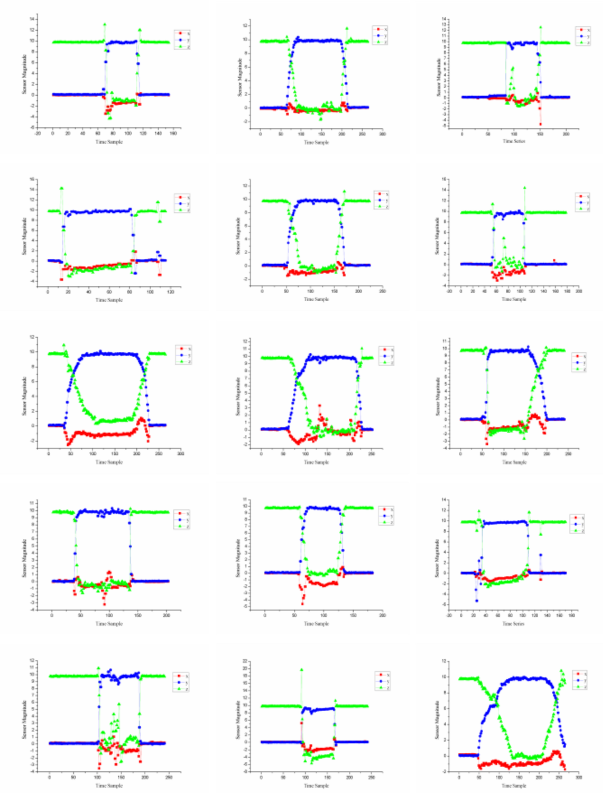


Fig. 8: Sensor Plots of Phone Accelerometer Data during Test Subject Interaction with Chair. A Total of 15 Samples are Collected as Shown.

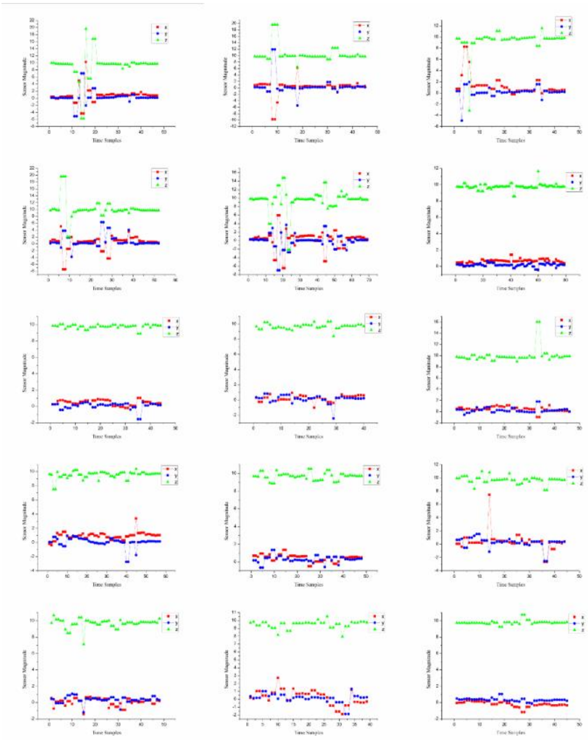


Fig. 9: Output Plots of Chair Accelerometer Data Obtained of 15 Test Subjects.

Figure 11 shows the three behaviors for classification of the 15 test subjects based on the sensor data. In the first experiment we provided the neural network in figure 12 with one sample of 4×720 feature matrix. The network trains using error backpropagation algorithm, where the network outputs are feedback to modify the weights and bias, making the error between inputs and outputs to reach a specified minimum value. More information on backpropagation training can be found in our work at [26] [27] [28]. The network is trained with one sample and 100 hidden neurons. Error threshold is set at 0.0001 for a learning rate of 0.2. Initial weights and biases are randomly selected.

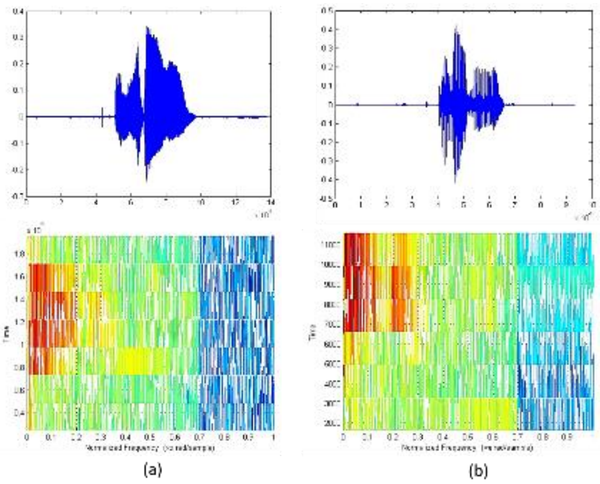


Fig. 10: Voice Samples for the Word Hello from the Two Test Subjects Along with Their Extracted Spectrums. A) Voice Samples Test_1 (Female) B) Voice Sample Test_2(Male).

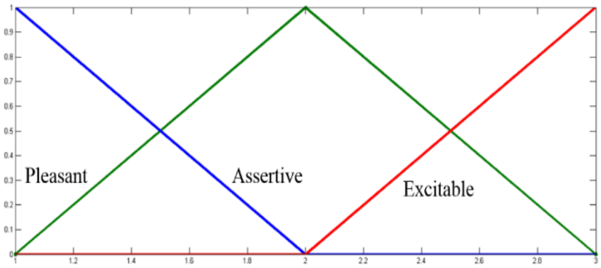


Fig. 11: Behaviours to Be Identified.

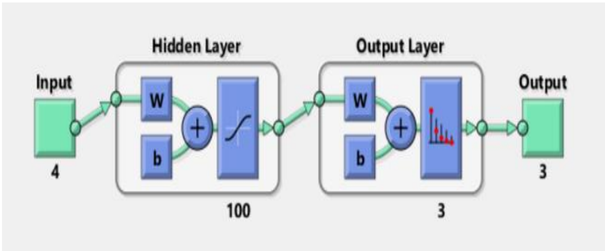


Fig. 12: Neural Network Model for Behavioural Analysis.

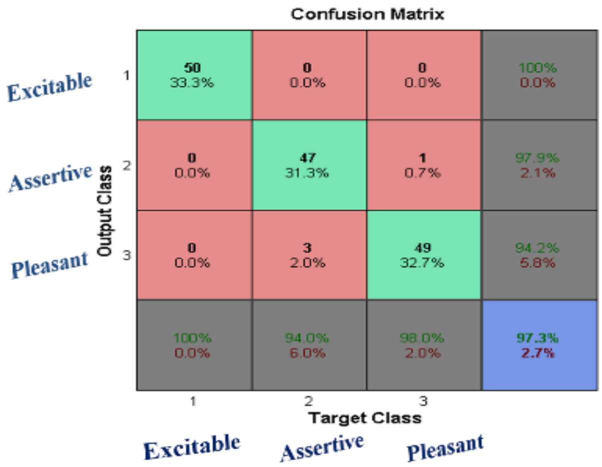


Fig. 13: Confusion Matrix with Max Size Training Vector.

The three output behaviors are modeled with same sized binary vector of size 3×720 samples. Each binary string represents a behavior namely, pleasant, assertive and excitable. The network iterated for 121 iterations producing a correct matching of 61.2%. The correctness is validated by testing each subject based on psychiatrist evaluation. Further increasing the size of the training sample to thrice the initial size to 4×2160 produced a matching of 74.5%. Finally, a sample size of 4×5760 produced a recognition rate of 97.5%. Figure 12 shows the neural network model used for classification. The resultant confusion matrix produced from 8 sample training and 7 sample testing is in figure 13. Averaging on multiple training and testing iterations for the same network produces a true behavior classification rate of 84.89%. The results of individual test subjects are tabulated as shown in table 1.

Figure 14 shows various test subjects participated in this analysis and their interaction with door and chair. We find the results encouraging and a thorough investigation is carried out at Applied signal processing lab, Department of Electronics and Communication Engineering, K.L. University.

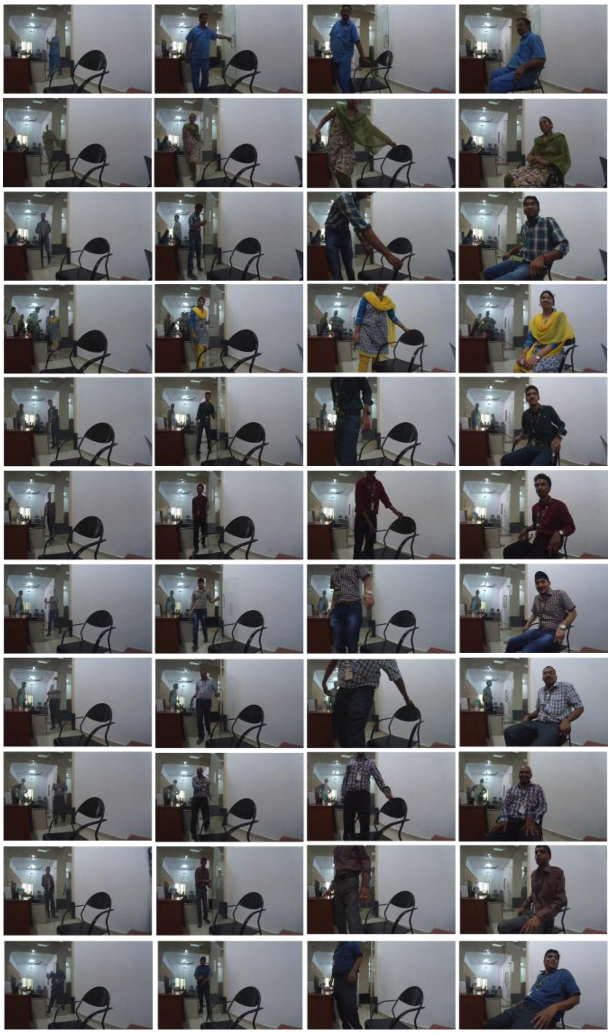


Fig. 14: Video Frames of Test Subjects Door and Chair Interactions Captured at 240 Frames Per Second High Speed Motion Capture Camera.

Table 1 shows behaviour percentage matching between the proposed sensor based model and the psychiatrist doctor practicing from 20 years. She conducted exclusive tests and her team classified the entire 15 test subjects into three behavioural categories as shown in table 1. The code for test subjects in table as F_HTS_1 indicates a Female_Human Test Subject_Number and for M_HTS_1 indicates a Male Human Test subject. The average matching is around 84.89% from multiple testings of the same test subject. The classification is near perfect for excitable behavior when compared to pleasant and assertive. Pleasant and Assertive behaviors are closely related and the features are misclassified in more than few instances. In future more number of sensors and large number of test subjects with different behaviors.

Table 1: Test Validation

Sl. No.	Test Subject	Behaviour Assessment from Proposed System	Doctor Evaluation (Validation)	Behaviour Matching Percentage
1	F_HTS_1	Excitable	Excitable	100
2	M_HTS_1	Pleasant	Pleasant	90
3	M_HTS_2	Pleasant	Assertive	50
4	M_HTS_3	Assertive	Assertive	90
5	M_HTS_4	Excitable	Excitable	100
6	M_HTS_5	Assertive	Assertive	90
7	M_HTS_6	Pleasant	Pleasant	80
8	M_HTS_7	Excitable	Excitable	100
9	M_HTS_8	Assertive	Pleasant	40
10	F_HTS_2	Pleasant	Pleasant	90
11	F_HTS_3	Excitable	Excitable	100
12	F_HTS_4	Assertive	Assertive	90
13	F_HTS_5	Pleasant	Pleasant	90
14	F_HTS_6	Pleasant	Pleasant	90
15	M_HTS_9	Excitable	Excitable	100

5. Conclusions

Currently, the Cognitive Behavioral Therapy – CBT totally depends on the human being's interaction with questionnaire or EEG with offline stimulus, or fMRI with offline stimulus or with cognitive experts. In all the situations the person under test knows he/she is being watched and hence we believe the results provide a confusing picture about the individual to the doctor. Therefore, a system "Swift Cognitive Behavioral Assessment Model Built on Cognitive Analytics of Empirical Mode Internet of Things" can assess the Cognitive Human Behavior without human conscience. This paper presents a model based on IOT and experimental results to prove that such a system can be built. This cognitive model can be used by individual human for active behavioral changes to reduce the risk of failure in the day to day tasks. There are a number of applications for this technology like, hospitals to health monitoring, schools to monitor the student behavior, crime understanding, digital forensics, better management for drivers, offices to name a few, for human cognitive analysis based on the human IOT-object interactions.

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