HOW DO EMOTIONAL STIMULI INFLUENCE THE LEARNER'S BRAIN ACTIVITY?

Tracking the Brainwave Frequency Bands Amplitudes

Alicia Heraz and Claude Frasson

HERON Lab, University of Montréal, CP 6128 succ., Centre Ville, Montréal QC, Canada

Keywords: Electrical Brain Activity, Machine Learning Techniques, Learner Brainwaves Model.

Abstract: In this paper we discuss how learner's electrical brain activity can be influenced by emotional stimuli. We conducted an experimentation in which we exposed a group of 17 learners to a series of pictures from the International Affective Picture System (IAPS) while their electrical brain activity was recorded. We got 33.106 recordings. In an exploratory study we examined the influence of 24 picture categories from the IAPS on the amplitude variations of the 4 brainwaves frequency bands: δ, φ, α and β. We used machine learning techniques to track the amplitudes in order to predict the dominant frequency band which inform about the learner mental and emotional states. Correlation and regression analyses show a significant impact of the emotional stimuli on the amplitudes of the brainwave frequency bands. Standard classification techniques were used to assess the reliability of the automatic prediction of the dominant frequency band. The reached accuracy was 90%. We discuss the prospects of extending our actual Brainwave-Sensing Multi Agent System to be integrated to an intelligent tutoring system (ITS) in the future.

1 INTRODUCTION

Innovative Research is rapidly expanding the level of control that is achievable in Human-Machine Interactions. Scientists have been experimenting with non-invasive brain-computer interfaces that read brain signals with an electroencephalogram (EEG). EEG-based brain-computer interfaces use sensors placed on the head to detect brainwaves and feed them into a computer as input (Palke, 2004). To close the performance gap between the user and the computer, many research focused on the user modelling (Conati, 2002); (Kort & al., 2001).

Most of the work in this field has focused on identifying the user's emotions as they interact with computer systems such as tutoring systems (Fan & al., 2003) or educational games (Conati, 2002; 2004). The importance of the systematic study of emotions has become more present in several disciplines (Ekman, 1992); (Mandler, 1999); (Panksepp, 1998); (Picard, 1997) since it was largely ignored until the late 20th century.

Kort, Reilly and Picard (2001) proposed a comprehensive four-quadrant model that explicitly links learning and affective states; this model has not yet been supported by empirical data from human learners. Conati (2002) has developed a probabilistic system that can reliably track multiple emotions of the learner during interactions with an educational game. Their system relies on dynamic decision networks to assess the affective states of joy, distress, admiration, and reproach. The performance of their system has been measured on the basis of learner self reports (Conati, 2004) and inaccuracies that were identified have been corrected by updating their model (Conati, 2005). D'Mello (2005) study reports data to integrate affect-sensing capabilities into an intelligent tutoring system with tutorial dialogue, namely AutoTutor. They identified affective states that occur frequently during learning. They applied various classification algorithms towards the automatic detection of the learners affect from the dialogue patterns manifested in AutoTutor's log files.

Unfortunately, many of these of systems lack precision because they are based on learner self reports, or use tools to analyze the learner external behaviour like facial expression (Fan et al., 2003), vocal tones (D'Mello et al., 2005) or gesture

Heraz A. and Frasson C. (2009).
HOW DO EMOTIONAL STIMULI INFLUENCE THE LEARNER'S BRAIN ACTIVITY? - Tracking the Brainwave Frequency Bands Amplitudes .
In *Proceedings of the International Conference on Agents and Artificial Intelligence*, pages 14-20
DOI: 10.5220/0001558100140020

recognition (Kort & al., 2001). In addition, one affective state is not sufficient to encompass the whole gamut of learning (Conati, 2002).

Our previous work (Heraz & al., 2008); (Heraz & al., 2007) indicated that an EEG is an efficient info source to detect emotions. Results show that the student's affect (Anger, Boredom, Confusion, Contempt, Curious, Disgust, Eureka, and Frustration) can be accurately detected (82%) from brainwaves (Heraz & al., 2007). We have also conducted an experimentation in which we explored the link between brainwaves and emotional assessment on the SAM scale (pleasure, arousal and domination). Results were promising, with 73.55%, 74.86% and 75.16% for pleasure, arousal and dominance respectively (Heraz & al., 2007). Those results support the claim that all rating classes for the three emotional dimensions (pleasure, arousal and domination) can be automatically predicted with good accuracy through the nearest neighbour algorithm.

As a contrast to the learner self reports and use tools to analyze the learner external behaviour; our previous work is directed towards measuring emotions from the learner brainwave activity to track the learner's emotional states transitions. But what is the influence of feeling emotions on Brainwaves? What impact has emotional stimuli on the amplitudes of the brainwaves frequency bands?

In this paper, we focus on 4 different frequency bands: delta, theta, alpha and beta. We measure their amplitudes to identify the predominant learner mental state corresponding to the highest amplitude. We use the International Affective Picture System to induce emotions and we aim to how these effects the brainwaves amplitudes.

2 BRAINWAVES AND EEG

In the human brain, each individual neuron communicates with the other by sending tiny electrochemical signals. When millions of neurons are activated, each contributing its small electrical current, they generate a signal that is strong enough to be detected by an electroencephalogram (EEG) device (Bear et al., 2001); (Cantor, 1999).

The EEG used in this experimentation is Pendant EEG. Commonly, Brainwaves are categorized into 4 different frequency bands, or types, known as delta, theta, alpha, and beta waves. Each of these wave types often correlates with different mental states. Table 1 lists the different frequency bands and their associated mental states.

Table 1: Brainwaves Categories.

Brainwave	Frequency	Mental State
Delta (δ)	0-4 Hz	Deep sleep
Theta (θ)	4-8 Hz	Creativity, dream sleep, drifting thoughts
Alpha (α)	8-12 Hz	Relaxation, calmness, abstract thinking
Beta (β)	+12 Hz	Relaxed focus, high alertness, agitation

Delta frequency band is associated with deep sleep. Theta is dominant during dream sleep, meditation, and creative inspiration. Alpha brainwave is associated with tranquillity and relaxation. By closing one's eyes can generate increased alpha brainwaves. Beta frequency band is associated with an alert state of mind, concentration, and mental activity (Palke, 2004).

The electrical signal recorded by the EEG is sampled, digitized and filter to divide it into 4 different frequency bands: Beta, Alpha, Theta and Delta (Figure 1).

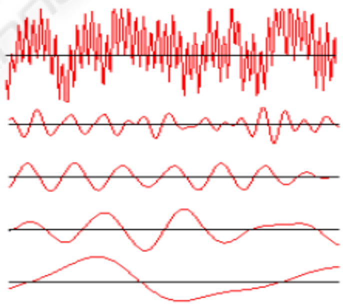

Figure 1: A raw EEG sample and its filtered component frequencies. Respectively (from the top): Beta, Alpha, Theta and Delta Brainwaves (Palke, 2004).

3 CATEGORIES IN THE IAPS

The International Affective Picture System (IAPS) is a large colored bank of pictures. It provides the ratings of emotions. It includes contents across a wide range of semantic categories. IAPS is developed and distributed by the NIMH Center for Emotion and Attention (CSEA) at the University of Florida in order to provide standardized database that are available to researchers in the study of emotion and attention. IAPS has been characterized primarily along the dimensions of valence, arousal, and dominance. Even though research has shown that the IAPS is useful in the study of discrete emotions, the categorical structure of the IAPS has not been characterized thoroughly. Mickels (2005) experimentation consisted of collecting descriptive emotional category data on subsets of the IAPS in an effort to identify pictures that elicit one discrete emotion more than others. Results revealed multiple emotional categories for the pictures and indicated that this picture set has great potential in the investigation of discrete emotions (Mikels & al., 2005).

This study provided categorical data that allows the IAPS to be used more generally in the study of emotion from a discrete categorical perspective. In accord with previous reports (Bradley & al., 2001), gender differences in the emotional categorization of the IAPS images were minimal. These data show that there are numerous images that elicit single discrete emotions and, furthermore, that overall, a majority of the images elicit either single discrete emotions or emotions that represent a blend of discrete emotions, also in accord with previous reports.

Table 3 shows the categories identified by Mikel's study

Table 2: Mikel's categories for the IAPS.

Category	Description
A	Anger
D	Disgust
F	Fear
U	Undifferentiated
S	Sadness
Am	Amusement
Aw	Awe
C	Contentment
U	Undifferentiated
†	Pictures that are outside two standard deviations from the overall mean and may thus be blends of positive and negative emotions.

4 EXPERIMENTATION

In our experimentation we use Pendant EEG (McMilan, 2006), a portable wireless electroencephalograph. Electrode placement was determined according to the \10-20 International System of Electrode Placement." This system is based on the location of the cerebral cortical regions Electrodes were placed on PCz, A1 and A2 (Palke, 2004). Pendant EEG sends the electrical signals to the machine via an infrared connection. Light and easy to carry, it is not cumbersome and can easily be forgotten within a few minutes. The learner wearing Pendant EEG is completely free of his movements: no cable connects them to the machine. The experiment included 17 learners selected from the Computer Science Department of University of Montreal. In order to induce the emotions which occur during learning, we use IAPS.

The participant is connected to Pendant EEG. The duration of the experimentation for each participant varies between 15 and 20 minutes. This one is free to stop when he wishes. He's invited to indicate his emotions any time, whenever it changes (figure 2).

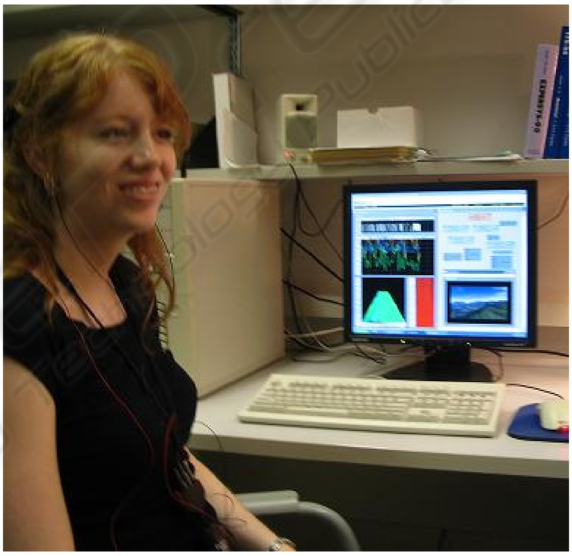

Figure 2: A learner wearing Pendant EEG.

The purpose of the experimentation is to record the emotions at each change of brainwave amplitude. The recording set size is 33106.

5 DATA TREATMENT

Before using the database as an input to several learning algorithms, preliminary treatments of formatting, cleaning and selection had to be applied to it. The initial database was composed of 33106 tuples that contained the user id and the picture category from IAPS. The first treatment that was applied to the database was to extract a dataset of tuples that contain the picture category and the transition from two vectors $Amp_t(\delta_1,\theta_1,\alpha_1,\beta_1)$ and $Amp_{t+\Delta t}(\delta_2,\theta_2,\alpha_2,\beta_2)$, where $Amp_t(\ )$ is the amplitudes recorded at instant t and $Amp_{t+\Delta t}(\ )$is the amplitude at $t+\Delta t$. Δt (in sec) is the time between each modification in one of the 4 brainwaves amplitudes.

We also applied some few data cleaning with respect to picture categories frequencies by removing every picture categories that had a frequency inferior to 6. The most represented image category in the dataset is U (Undifferentiated) which is more than 4 times more frequent than S (Sadness), which is the next most frequent one, but since undifferentiated images appear in the case of transitions from emotion 5 (disgust) to another, we decided to keep that category in the dataset. Figure 3 shows the repartition of pictures categories in the dataset.

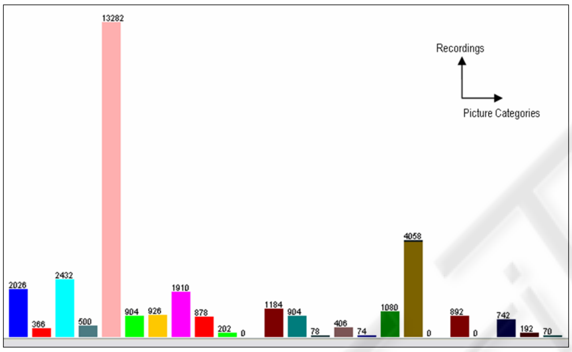

Figure 3: Repartition of picture categories in the dataset; three empty categories were removed.

The empty categories were: AwAwC, ADF and AS. They were removed. Most of pictures that the learners saw were in the categories: U (13282), S (4058), D (2432), DF (2026) and AwE (1910).

In addition, we created the class $dominance$. It gives the order of the brainwaves amplitudes. Since we have 4 types of brainwaves frequency bands, $dominance$ takes 4! =24 different values from the set $\{dtab, dtba, ..., btad\}$. The value $btda$ means that the first highest amplitude recorded is for beta brainwave, the second is for theta, the third is for delta and the fourth one is for alpha. This means that the predominant mental state is the one associated to beta. Most of time, $b***$ values are predominant, figure 4 shows that fact.

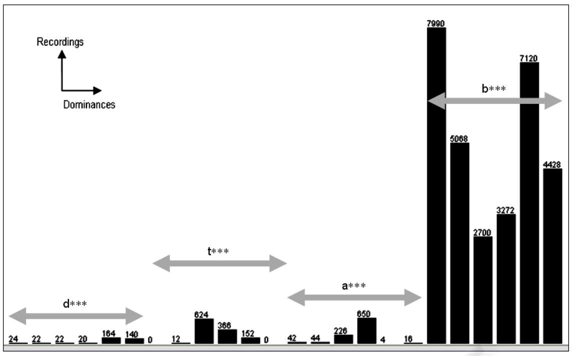

Figure 4: Dominance Values Repartition.

The percentage of predominance of Delta, Theta, Alpha and Beta on the 33106 recordings were respectively: 1,2%, 3,5%, 3% and 92,2%.

6 PREDICTION RESULTS

Determining the impact of emotional stimuli on the brainwaves is a multi-class classification problem. The mapping function is:

$$f:(\delta,\theta,\alpha,\beta,pictureCat)\rightarrow dominance$$

For classification we used Weka a collection of machine learning algorithms for solving data mining problems implemented in Java and open sourced under the GPL (Witten & al., 2005).

Many classification algorithms were tested. Best results were given by Naïve Bayes, K-Nearest Neighbor and Decision trees (Quinlan, 1993). Table 4 shows the overall classification results using k-fold cross-validation5 (k = 10). In k-fold cross-validation the data set (N) is divided into k subsets of approximately equal size (N/k). The classifier is trained on (k-1) of the subsets and evaluated on the remaining subset. Accuracy statistics are measured. The process is repeated k times. The overall accuracy is the average of the k training iterations. The various classification algorithms were successful in detecting the new dominant value from the four brainwaves amplitudes and the picture category. Classification accuracy varies from 78.02% to 93.82%. Kappa statistic measures the proportion of agreement between two rates with correction for chance. Kappa scores ranging from 0.4 – 0.6 are considered to be fair, 0.6 – 0.75 are good, and scores greater than 0.75 are excellent (Robson, 1993). In the case of the algorithms we tested Kappa scores vary from 0.73 to 0.92 (good to excellent). Results are shown on table 4.

Table 3: the Best Results.

Algorithm	Accuracy	Kappa
Naïve Bayes	78.02%	0.73
k-NN (k=1)	92.52%	0.91
Decision Tree	93.82%	0.93

For the decision tree Algorithm, table 4 shows the details of classification accuracy among the 24 values of the class Dominance.

Table 4: Detailed Accuracy by Class.

Precision	Recall	F-Measure	Class
0.783	0.75	0.766	dtab
0.708	0.773	0.739	dtba
0.6	0.682	0.638	datb
0.737	0.7	0.718	dabt
0.873	0.841	0.857	dbat
0.831	0.771	0.8	dbta
~~0~~	~~0~~	~~0~~	~~tdab~~
0.818	0.75	0.783	tdba
0.904	0.893	0.898	tbad
0.898	0.885	0.891	tbda
0.938	0.895	0.916	tabd
~~0~~	~~0~~	~~0~~	~~tadb~~
0.976	0.952	0.952	atdb
0.907	0.886	0.897	atbd
0.925	0.872	0.897	abdt
0.89	0.871	0.88	abtd
0.5	0.5	0.5	adtb
0.938	0.938	0.938	adbt
0.954	0.957	0.956	btad
0.943	0.94	0.942	btda
0.927	0.922	0.924	bdat
0.93	0.935	0.933	bdta
0.944	0.946	0.945	batd
0.934	0.942	0.938	badt

For the decision tree algorithm and according to table 4, we calculated the Youden's J-index to increase the weight to the rating classes with minority instances (Youden, 1961) as the following formula:

$$JIndex = Card(RC)^{-1} \sum_{e \in RC} \Pr ecision_e$$

With $Card(RC)$ is the cardinality of rating classes list and is 22 (24-2; we removed the 2 classes $tdab$ and $tadb$ since they are empty). The JIndex value is 73.32% which is less (but still good) than the classification prediction shown in table 4 (93.82%). This result supports the claim that all rating classes for the 22 classes can be automatically detected with good accuracy (73.32%) through the decision tree algorithm.

Figure 5 shows the Confusion Matrix.

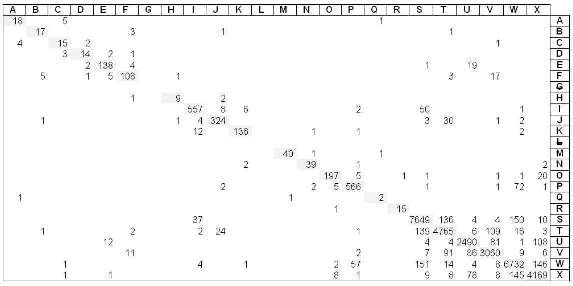

Figure 5: The confusion Matrix.

The highest classification rates appear on the Matrix Diagonal. Two classes were removed: G=$tdab$ and L=$tadb$. They are empty.

7 FUTURE INTEGRATION

In our previous works, we conceived the Architecture of a multi agent System (MAS) for 3 agents that assess emotional parameters from brainwaves. Via the JADE (Java Agent Development Framework) platform (Bellifemine, 1999) and according to the communication language FIPA-ACL, these agents communicate with the planner located in the tutoring module of an ITS. They send to the latter the predicted emotional state. To complete this work, we aim by doing this experimentation to extend our MAS in the future and add the Brainwave Dominance Predictor (BDP) Agent. BDP Agent will induce emotional stimuli to regulate the Brainwave Activity. New pedagogical strategies will be implemented and suggested to an ITS to improve the learning conditions. Figure 6 shows the overall architecture.

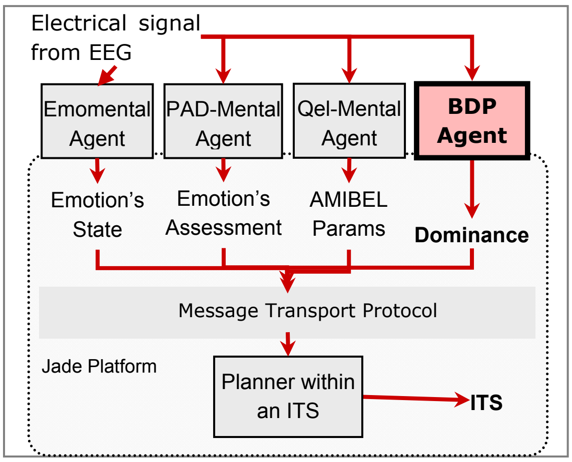

Figure 6: Extended Architecture of the Multi-Agent Brain-Sensitive System.

The BDP Agent will be implemented within the MAS in the future.

8 CONCLUSIONS

This study has presented machine learning techniques to follow and track the learner's brainwaves frequency bands amplitudes. It completes many previous works that assess emotional parameters from brainwaves by using an EEG. This can be useful for some particular learners as taciturn, impassive and disabled learners. We do not consider the whole cases of disabled learners. We will consider only disabled learner who cannot express facial emotions or body gestures due to an accident or a surgery and also those who lost their voice or cannot talk. Here we are talking about physical disability and not mental disability. This procedure allowed us to record the brainwaves amplitudes of the learners exposed to emotional stimuli from the International Picture System. These data were used to predict the future dominant amplitude knowing the picture category and the actual brainwaves frequency band amplitudes.

We acknowledge that the use of EEG has some potential limitations. In fact, any movement can cause noise that is detected by the electrodes and interpreted as brain activity by Pendant EEG. Nevertheless, we gave a very strict instructions to our participants. They were asked to remain silent, immobile and calm. We believe that the instructions given to our participants, their number (17) and the database size (33106 records) can considerably reduce this eventual noise. Results are encouraging, a potential significant impact of emotional stimuli and the brainwave amplitudes. The decision tree analyses resulted in accurate predictions 93.82% and the Yuden's J-Index is 73.22%. If the method described above proves to be effective in tracking the learner's brainwaves amplitudes, we can direct our focus to a second stage. An ITS would select an adequate pedagogical strategy that adapt to certain learner's mental states correlated to the brainwaves frequency bands in addition to cognitive and emotional states. This adaptation would increase the bandwidth of communication and allow an ITS to respond at a better level. If this hypothesis holds in future replication, then it would give indications on how to help those learners to induce positive mental states during learning.

ACKNOWLEDGEMENTS

We acknowledge the support of the FQRSC (Fonds Québécois de la Recherche sur la Société et la Culture) and NSERC (National Science and Engineering Research Council) for this work.

REFERENCES

Bear, M.F., Connors, B.W., Paradiso, M. A, 2001. *Neuroscience: Exploring the Brain, second ed.* Lippincott Williams & Williams, Baltimore, MD.

Bellifemine, F., Poggi, A., Rimassa, G., 1999. JADE - A FIPA-compliant Agent Framework, In *PAAM'99*, London, UK.

Bradley, M.M., Codispoti, M., Cuthbert, B.N., Lang, P.J., 2001. *Emotion and motivation: Defensive and appetitive reactions in picture processing*. Emotion, 1.

Cantor, D.S., 1999. *An overview of quantitative EEG and its applications to neurofeedback. In Introduction to Quantitative EEG and Neurofeedback*. J. R. Evans and A. Abarbanel, Eds. Academic Press.

Conati, C., 2002. Probabilistic assessment of user's emotions in educational games. *Journal of Applied Artificial Intelligence*.

Conati, C., 2004, How to evaluate models of user affect? In *Proceedings of ADS 04, Tutorial and Research Workshop on Affective Dialogue Systems*. Kloster Irsee, Germany.

Conati, C., Mclaren H., 2005. Data-driven Refinement of a Probabilistic Model of User Affect. In *Proceedings of UM2005 User Modeling: Proceedings of the Tenth International Conference, Lecture Notes in Computer Science*, Springer Berlin / Heidelberg..

D'Mello, S.K., Craig, S.D., Gholson, B., Franklin, S., Picard, R.W., Graesser, A.C., 2005. Integrating Affect Sensors in an Intelligent Tutoring System. In *Affective Interactions: The Computer in the Affective Loop Workshop at 2005 International conference on Intelligent User Interfaces*. AMC Press, New York.

Ekman, P., 1992. *Are there basic emotions?* Psychological Review.

Fan, C., Sarrafzadeh, A., Overmyer, S., Hosseini, H. G., Biglari-Abhari, M., Bigdeli, A., 2003. *A fuzzy approach to facial expression analysis in intelligent tutoring systems*. In Antonio Méndez-Vilas and J.A.Mesa González Eds.

Heraz, A., Frasson, C., 2008. Predicting the three major dimensions of the learner's emotions from brainwaves. *International Journal of Computer Science*.

Heraz, A., Razaki, R. Frasson, C., 2007. Using machine learning to predict learner emotional state from brainwaves. *7th IEEE conference on Advanced Learning Technologies: ICALT2007*, Niigata, Japan.

Kort, B., Reilly, R., Picard, R., 2001. An affective model of interplay between emotions and learning: Reengineering educational pedagogy—building a learning companion. In *T. Okamoto, R. Hartley,* *Kinshuk, & J. P. Klus (Eds.), Proceedings IEEE International Conference on Advanced Learning Technology*.

Mandler, G., 1999. *Emotion*. In B. M. Bly & D. E. Rumelhart (Eds.), Cognitive science. Handbook of perception and cognition 2nd ed. San Diego, CA: Academic Press.

McMilan, B., 2006. www.pocket-neurobics.com.

Mikels J.A., Fredrickson, B. L., Larkin, G.R., Lindberg, C.M., Maglio, S.J., Reuter-Lorenz, P.A., 2005. *Emotional category data on images from the International Affective Picture System*, Behav Res Methods 37.

Palke, A., 2004. *Brainathlon: Enhancing Brainwave Control Through Brain-Controlled Game Play*. Master thesis, Mills College, Oakland, California, USA.

Panksepp, J., 1998. *Affective neuroscience: The foundations of human and animal emotion*. New York: Oxford University Press.

Picard, R. W., 1997. *Affective computing*. Cambridge, Mass: MIT Press.

Quinlan, R., 1993. *C4.5: Programs for Machine Learning*. San Mateo, CA: Morgan Kaufmann Publishers.

Robson C., 1993. *Real word research: A resource for social scientist and practitioner researchers*. Oxford: Blackwell.

Witten, I.H., Frank, E., 2005. *Data Mining: Practical Machine Learning Tools and Techniques with Java Implementations*. Morgan Kaufmann, San Francisco.

Youden, W.J., 1961. *How to evaluate accuracy*. Materials Research and Standards, ASTM.