First Insights into Hybrid AI-Fuzzy Tutoring System for Boredom Identification

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Abstract: In this paper, we introduce the Hybrid AI-Fuzzy Intelligent Control (HAFiC) system prototype. The proposed model is the add-on to online learning-tutoring environments to proactively detect learners' emotional states by measuring performance gaining or degradation in a game-like form. We introduce a system model and experimental results implementing recently proposed Simple Algorithm for Boredom Identification (SABI) (Zagorskis et al.,2019) along with the Fuzzy Intelligent control approach to evaluate whether proposed indirect data acquisition method allows retrieving performance data variability in correspondence to real user emotional states. In the proposed system, the AI part cares about Image Processing and Text Recognition gathered from mobile-handwriting devices. In contrast, Fuzzy Expert System part organises users' performance data utilisation and decision making based on adaptive fuzzy inference approach. First experiment results described.

1 INTRODUCTION

This paper introduces with experience of a building of hybrid intelligent learning-tutoring system mock-up powered by Artificial Intelligence (AI), Machine Learning (ML) (Russell and Norvig, 2016), and Fuzzy Logic (Siddique, 2013) techniques.

Learning environments centered on the student can help to address some weaknesses of traditional education models such as complexity in learner's performance management and generation of personalized learning environments (Lugo et al., 2015). Respectively, there is a need in solutions that would meet the learners' needs, interests, rhythms and styles. According to the latest trends in e-learning education market, personalized content is presented as an intelligent machine response to learner's requirements. Therefore, design of a personalized learning environment makes it necessary to cover the following set of characteristics: understanding the situation of the student in terms of emotional and cognitive states, previous knowledge background, skills, interests, response to situations related to the teaching learning process and learning style (Lugo et al., 2015). Individual learning style directly characterizes student's behavior and plays a key-role in building predictive model according to cognitive state analysis. For example, sensing students prefer facts, data and experimentation whereas intuitive students prefer principles and theories. Sensing students are patient with detail but do not like complications, whereas intuitive students are bored with detail and welcome complications (Li and Rahman, 2018).

In this paper, we give insights into the implementation of Simple Algorithm for Boredom Identification (SABI) (Zagorskis et al., 2019) in the experimental mockup. The essence of the SABI algorithm is boredom identification analyzing periodic handwriting on mobile surfaces. Afterwards, we validate SABI algorithm operation in action.

Aim of the research is to evaluate whether indirect data acquisition method realized through SABI algorithm, AI-based and Fuzzy Intelligent control methods allows getting data variability suitable for a successful boredom detection and optimization of e-learning ecosystem architecture and technology respectively. Hypothesis is formulated based on the results from previous research (Zagorskis et al., 2019).

The paper has been organized as follows: Section 2 contains the reflection of related theories, methods, and approaches; in Section 3, which is the most

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important part of the research, we propose design of the hybrid Fuzzy-logic based tutoring system; in Section 4, we describe the experimental results; Section 5 concludes the paper.

2 PRELIMINARIES

2.1 Identifying Learners' Activity

Each learner's individual characteristics like motivation, attitude, learning style, background knowledge, ability to apply preliminary skills and the number of asked questions - affect the learning process (Graf et al., 2010). In the e-learning environment, knowing specific characteristics of user activity, it is possible to reveal hidden personality features like a tendency to be bored or being engaged in the learning process. Compared with other emotions, such as anxiety, boredom can be considered a relatively 'silent' emotion (Tze et al., 2016). Summing up the facts above, our research covers an evaluation of the relationship between student's academic boredom and potential learning outcomes.

Analysis of user's activity data will allow us to apply AI or ML methods to identify the user's learning style. Moreover, by conducting user self-assessment and emotional states surveys, we will get one more data tensor for analysis and supervising of machine methods. Comparing both data, we can make conclusions regarding user behaviour patterns, emotional conditions and learning styles.

Nowadays, instructional designers follow state-of-the-art practices to engage learners by new instructional design and content. It has been noted that even the same content enveloped in different frames can have a disparate impact on learners attention time. Learners' activity and engagement defined by interaction environment settings gains better user experience (UX) and instructional design in a game-like approach.

2.2 Recent Boredom Detection Methods

There are at least two methods for boredom detection: direct (or explicit) and implicit method. Explicit implementation of surveys (or interviewing) is a kind of intelligent methods involving post-processing of the textual, audio, and video data. It is applicable for the usage in small-scale environments while for large-scaled online learning environments automated and implicit methods are more relevant.

Environments. In recent years boredom detection based on automatically inferring user behaviour activities from mobile phone usage has been actively studied. M.Pielot et al. introduce the user-independent machine-learning model of boredom-leveraging features related to (1) recency of communication, (2) usage intensity, (3) time of a day, and demographics (Pielot et al., 2015). As results show, M.Pielot et al. 's experiments infer boredom with an accuracy of up to 82.9%. Before that, Bixler and D'Mello show that the most popular methods for boredom detection are: (1) facial expressions, (2) speech and voice features, text analysis, and physiological signals from mobile devices (Bixler and D'Mello, 2013).

Self-Assessment Manikin (SAM) method (Bradley and Lang, 1994) evaluates the pleasure, arousal and dominance in one scale. In SAM method, the perceived users' emotions are obtained by questionnaires and recorded in three-dimensional spaces (valence, arousal, and dominance). Each space has five ranking levels giving the capability to identify 15 different emotions. Although the boredom is not given in the emotions list, the new methods can be elaborated modifying SAM method. For example, fuzzy Hidden Markov Chains (FHMC) we find as one of possible research directions in the future (Wang et al., 2014), (Cannarile et al., 2018).

Stochastic Multi-player Games (SMGs). Another way of modelling stochastic processes is the usage of games-based methods. For example, for stochastic two-player game modelling two competing entities can be used: a) a user working on it's mobile device, and b) machine or host operating according to its own or general strategy.

To specify the system evolution by the decisions of multiple players taking into account the presence of their probabilistic behaviour, we constrain our attention to turn-based to stochastic games, in which a single player controls

Definition One. (Stochastic Multi-player Game)
A stochastic multi-player game (SMG) is a tuple $\mathbb{G} := (\Pi, S, (S_i)_{i\in\Pi}, s, A, \delta, L)$, where:

- Π is a finite set of *players*,
- S is a finite state of *states*,
- $(S_i)_{i\in\Pi}$ is a partition of S,
- $\bar{s} \in S$ is an initial state,
- A is a finite state of *actions*,
- $\delta : S \times A \to Dist(S)$ is a probabilistic transition function,
- $L : S \to 2^{AP}$ is a labeling function mapping states to sets of atomic propositions.

Probabilistic behaviour typically coexists with non-determinism. Both non-determinism and probability (in discrete state space) are present in the classical model of Markov decision processes (MDPs), which typically expressed in temporal logics (Kwiatkowska, 2013).

Markov decision processes (MDPs) represent the case when SMG contains only one player - $\Pi := \{1\}$. Most common and widely studied class of SMG models involve two-players ($\Pi := \{1,2\}$).

Definition Two. (Strategy) A strategy for player $i \in \Pi$ in SMG $\mathbb{G}$ is a function $\sigma_i : (SA) \cdot S_i \to Dist(A)$.

Summing up the above facts, we formulate the following research question: RQ - does indirect data acquisition method allow getting data variability related to the SABI algorithm?

About Intelligent Control Methods. Notably that intelligent control systems are not defined in terms of specific algorithms (Siddique, 2013), and therefore are suitably aimed at processes that are complex, nonlinear, time-varying, and stochastic. The area of intelligent control is inter-disciplinary and combines methods from other disciplines, including modern adaptive and optimal control, learning theory, fuzzy logic, and artificial intelligence (Zaknich, 2006). Neural networks, fuzzy logic and genetic algorithms are the constituent techniques of the methods in a non-classical control engineering.

Another applicable methods belong to the dynamic programming (DP) class. In dynamic programming exist subclass of reinforcement learning-based techniques such as Q-learning, R-learning, and action-dependent heuristic dynamic programming belonging to model-free methods. Much of the recent research on continuous-time reinforcement learning has focused on model-free methods promising for the future studies (Kamalapurkar et al., 2018).

Methods for Stated Problem. To continue experiment with SABI algorithm (Zagorskis et al., 2019) in a hybrid environment, we select appropriate Fuzzy Intelligent control methods. One of those methods is an ANFIS - adaptive neuro-fuzzy inference system (Jang, 1993). Motivated by the need to accommodate uncertainties in system model, much of the our research has focused on Fuzzy methods.

For our experimental setup, we started revealing the level of boredom according to Bixler and D'Mello, arguing that there are methods how to detect boredom during writing tasks through logging the writers' keystrokes. As authors mentioned, keystrokes had comparably low predictive power - roughly 11% above chance - for discriminating engagement-neutral and boredom-neutral states. By adding stable traits of the learners to the model, as Bixler and D'Mello argue, prediction performance could be notably improved.

3 HYBRID SYSTEM DESIGN AND EXPERIMENTAL SETUP

In this section, we describe the proof of the concept of a hybrid boredom detection system based on fuzzy logic methods.

The system setup involves an approach that during the learning process organized in a game-like manner, learners are given small regular assignments with a content that matches learning objectives. Learner's interaction with learning content is required. Afterwards, learners apply feedback to the learning environment. The response is partially processed, analyzed, and sent to an application running machine-learning algorithm to identify specific behavior patterns. The approach is: learners use the mobile surface screens with several simultaneous data channels providing Mobile device - Host communication. In our experimental test-bed, the host sends instructional data (JSON format) to the application deployed and started on a mobile client device. Similarly, data produced on a mobile device is preliminarily processed and sent to the host for analysis and control.

In our approach (Figure 1), we organize acquisition and data processing based on mobile surface touching events logs. We measure user's activity time from users' typewriting, drawing, and screen scrolling. The proposed scheme is applicable to each user-machine interacting experiment (a game round). To clarify interaction model, we follow notation; we use subscript index: i - for user-machine interaction rounds counting.

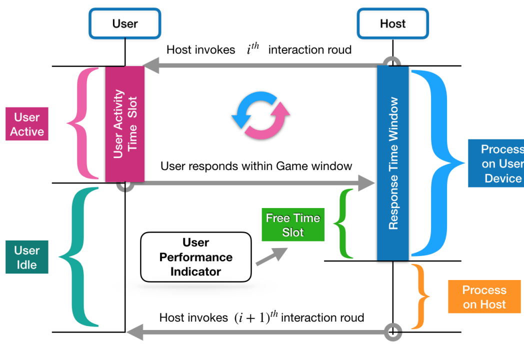

Figure 1: Simplified user-machine interaction protocol. One interaction round.

In our model, a time spent by a user for the interaction with different learning objects (LOs) may vary in an arbitrary time slot. During interaction we define the user behaviour as a signal $S(t)$ with independent variable t - time. The signal for user k is defined as follows:

$$S^k(t) = S_C^k(t) + N_E^k(t) + N_B^k(t) \qquad (1)$$

Now, we clarify notation. The k^{th} learner's conscious response to assigned task S_C is a process $S_C^k(t)$ mixed with simultaneously upcoming noise signals like emotional noise $N_E^k(t)$ and behavioural noise $N_B^k(t)$. Equation 1 defines learner's answer (a signal) model responding on a learning task.

Emotional Modality detection from learner's data involves both measuring of attention time, spent on LO, and reply classified as right or wrong answer interacting with LOs. Since learners' behaviour data is encoded with a noise signal

$$N(t) = N_E(t) + N_B(t) \qquad (2)$$

, decoding process, in general, lead to signal $S_C(t)$ detection errors due to noise stochastic characteristics. Hence, user boredom detection problem relates to the correct decoding of a signal transferred over a noisy environment. Here, optimal filtering techniques can be applied.

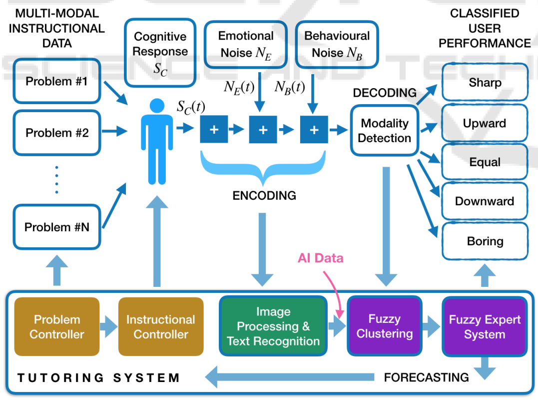

Figure 2: Hybrid AI-Fuzzy Intelligent Control (HAFiC) system. The model of learner's cognitive signal $S_C(t)$ degradation due to impact of emotional $N_E(t)$ and behavioural $N_B(t)$ noise. Since behavioural data contains varied hidden noise sources, decoding can lead to cognitive response data detection errors.

To continue with experimental setup description, we clarify algorithm named as Simple Algorithm for Boredom Identification (SABI) recently proposed in (Zagorskis et al., 2019). Also, we reveal crucial experimental settings structure, components, and usage aspects before model validation experiment.

To rebuild the SABI algorithm ready for modelling, authors follow the best findings and practice in the adaptive mobile learning (Cinquin et al., 2019),(FOX, 2016). Also, into consideration are taken some relevant findings starting from initial ideas (Tappert et al., 1990), following through the pitfalls, issues and challenges (Abuzaraida et al., 2013) to recent achievements (Wang et al., 2016), that researchers figured out in handwriting recognition.

In Figure 2, we illustrate components interaction protocol for the Hybrid AI-Fuzzy Intelligent Control (HAFiC) system - the addon to online learning-tutoring environment. During the learning process, users interact with LOs producing a batch of vector or raster–graphics data. AI and Fuzzy extensions to SABI algorithm operate, allowing build sustainable hybrid system with feedback and, what is essential, forecasting options.

During the experiment calibration process, user behaviour information is gathered and stored on the host. Obtained data is also sent to the Fuzzy Expert system. The goal of calibration is to determine specific, time-related user behaviour traits. In particular, to identify an average (or problem-specific) response time window, we provide experiments in game-like approach (Figure 3). Gaming element is to control, restrict, or just identify user response time window in a sequence of organized experiments. Once Learner's Response Time increases in comparison to in calibration stored "normal" response time - the learner is classified as bored if his/her interaction quality additionally classified as diligent. Diligence detection is also one of the objectives of the problem landscape. Here, the fuzzy approach is helpful for experimenting.

4 RESULTS AND DISCUSSION

In this section, we give insights into experimental data on decision making in a fuzzy-logic equipped environment. We represent student's activity, which is grouped into five classes based on recommendations from 1) AI vector or raster–graphics data recognition system, 2) AI learners' diligence detection system, and 3) explicit learners polling regarding their feelings being bored (see Figure 4). We perform fuzzification as a mapping from an observed input space to fuzzy sets in a time universe of discourse. In our model, a time spent on a task is mapped to the enumeration of linguistically expressed emotional states (bored, slow, active, fast, sharp).

Firstly, to represent the experiment data, we apply Fuzzy C-Means Clustering Algorithm to classify

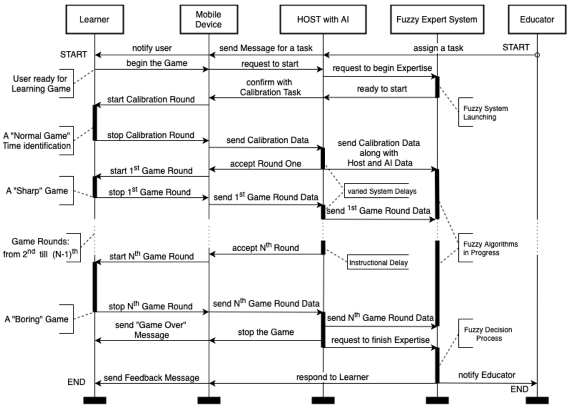

Figure 3: SABI algorithm in Hybrid AI-Fuzzy Intelligent Control (HAFiC) system. Example work-path: educator invokes N-rounds Learning Game. Calibration Round starts: 1) learner responds within user-specific time interval. 2) response time is recorded as a "normal" for the user. Round One: a similar or equal task is assigned. 1) SABI algorithm identifies a gain of user-machine interaction performance - user finishes task before calibrated time window ends. 2) Fuzzy-Expert system algorithms compute learner's performance indicators and can respond with a feedback. Round N_{th}: a similar problem. 1) the user being bored - interaction is slow or ignored. 2) SABI algorithm identifies "*significant*" time increase comparing to calibrated value. As a result, 1) Fuzzy-Expert system responds to learners and educators by giving a feedback, and 2) learner performance model updates in HAFiC settings.

outcomes among the five subsets of the A set. The "sharp" value corresponds to the fastest response time and correct answer on assigned task, whereas "bored" state indicates the slow - non-responsive or discursive or disjointed actions. Next, we use Gaussian Fuzzy approximation method applied to each subset.

Finally, we depict one experiment results (Figure 3). Here, on horizontal axis yellow curve indicates maximum value at 1400 ms, which is the mean value of data from all the games, and all the game rounds classified as "Active" since the first - calibration round. Also, it should be mentioned that in each individual game-case "normal" response time is different and depends on two factors: problem complexity and learner's personality traits. Also, in presented experiment data, "bored" class is characterized by task completion time greater than 2 sec.

Next, on Figure 5, after data classification and re-scaling, we identify an unusual value of membership function associated with the emotional state "Slow". Such a result can be explained by an insufficient amount of data - as it was already mentioned, in our experiment (n=54). The reason for such a limitation lays within the boundaries of experiment - a limited number of involved students (54) and a one task in an assignment.

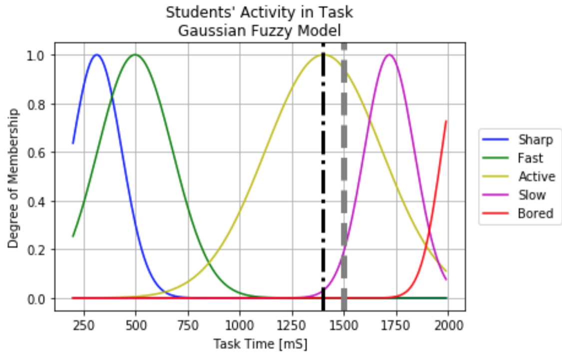

Figure 4: Students' activity results. Five diverse judgements about user emotional states on the universe of task completion time. Dashed line identifies educator expectations regarding average task completion time. The dotted line is the mean value of a data class "normal activity". In this experiment, learners are more productive comparing to educators forecast.

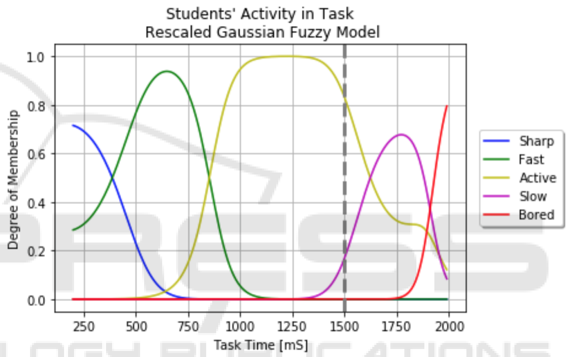

Figure 5: Students' activity results. Five diverse judgements about user emotional performance on the universe of task completion time. Degree of membership normalized and rescaled. The dashed line identifies educator expectations regarding average task completion time.

Before the experiment, assignment outcomes also estimated by experts' council suggesting outcome equal (on the average) to 1500 ms.

On another hand, during the experiment, we identify average learners' performance improvement - "active" rescaled curve (on Figure 5) is wider and shifted towards better performance (approx. 1200 ms).

Ultimately, comparing students' emotional states after each experiment round (using an explicit questionnaire method) with data classified from the output of the experimental Fuzzy Intelligent system mockup, we acquired the level of confidence close to 70%.

5 CONCLUSIONS

Experimental validation of SABI algorithm implementation in Hybrid AI-Fuzzy mockup system has shown that such a hybrid system operates and is capable of solving aimed problems. Although, for building an accurate model with higher accuracy level, there should be a sufficient amount of input data.

Summing up the results, we can conclude that AI-Fuzzy models with simple components are comparatively easy to implement and use but they do not always provide good accuracy. This finding can be explained by algorithm's dependence on the number of students involved in the experiment, the number of assigned tasks on the host side, as well as the honest answers, difficulty, and fuzziness, to classify boredom by students themselves.

The accuracy of experimental model can also be improved by the usage of complex components and advanced system architecture but those models are difficult to implement.

An optimal choice of components for the fuzzy model element design is especially important when implementing the model in low-end hardware. Further research will involve experimenting with more data sources, wider range of tasks' completion time variety, ensuring feedback automatizing process and work on the increase of data intelligence efficiency.

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REFERENCES

Abuzaraida, M. A., Zeki, A. M., and Zeki, A. M. (2013). Problems of writing on digital surfaces in online handwriting recognition systems. *2013 5th International Conference on Information and Communication Technology for the Muslim World, ICT4M 2013*, pages 1–5.

Bixler, R. and D'Mello, S. (2013). Detecting boredom and engagement during writing with keystroke analysis, task appraisals, and stable traits. In *Proceedings of the 2013 international conference on Intelligent user interfaces - IUI '13*, page 225, New York, New York, USA. ACM Press.

Bradley, M. M. and Lang, P. J. (1994). Measuring emotion: the self-assessment manikin and the semantic differential. *Journal of behavior therapy and experimental psychiatry*, 25 1:49–59.

Cannarile, F., Compare, M., Baraldi, P., Di Maio, F., and Zio, E. (2018). Homogeneous Continuous-Time, Finite-State Hidden Semi-Markov Modeling for Enhancing Empirical Classification System Diagnostics of Industrial Components. *Machines*, 6(3):34.

Cinquin, P.-A., Guitton, P., and Sauzéon, H. (2019). Online e-learning and cognitive disabilities: A systematic review. *Computers & Education*, 130:152–167.

FOX, A. M. Y. (2016). Microlearning for Effective Performance Management. (cover story). *TD: Talent Development*.

Graf, S., Liu, T.-C., and Kinshuk (2010). Analysis of learners' navigational behaviour and their learning styles in an online course. *J. Comp. Assisted Learning*, 26:116–131.

Jang, J. . R. (1993). Anfis: adaptive-network-based fuzzy inference system. *IEEE Transactions on Systems, Man, and Cybernetics*, 23(3):665–685.

Kamalapurkar, R., Walters, P., Rosenfeld, J., and Dixon, W. (2018). *Reinforcement Learning for Optimal Feedback Control: A Lyapunov-Based Approach*. Communications and Control Engineering. Springer International Publishing.

Kwiatkowska, M. Z. (2013). Advances in quantitative verification for ubiquitous computing. In *ICTAC*.

Li, L. X. and Rahman, S. S. A. (2018). Students' learning style detection using tree augmented naive bayes. In *Royal Society open science*.

Lugo, G. S., Rodríguez, L.-F., López, R. I. G., Macías-Estrada, A., and Echeverría, M. R. (2015). Behavioral patterns for automatic detection of learning styles in learning management systems: a case study. *Research in Computing Science*, 106:69–77.

Pielot, M., Dingler, T., Pedro, J. S., and Oliver, N. (2015). When attention is not scarce - detecting boredom from mobile phone usage. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, pages 825–836, Osaka. ACM.

Russell, S. and Norvig, P. (2016). *Artificial Intelligence: A Modern Approach*. Always learning. Pearson.

Siddique, N. (2013). *Intelligent Control: A Hybrid Approach Based on Fuzzy Logic, Neural Networks and Genetic Algorithms*. Studies in Computational Intelligence. Springer International Publishing.

Tappert, C. C., Suen, C. Y., and Wakahara, T. (1990). The State of the Art in On-Line Handwriting Recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence*.

Tze, V. M. C., Daniels, L. M., and Klassen, R. M. (2016). Evaluating the relationship between boredom and academic outcomes: A meta-analysis. *Educational Psychology Review*, 28:119–144.

Wang, G., Zhang, X., Tang, S., Zheng, H., and Zhao, B. Y. (2016). Unsupervised Clickstream Clustering for User Behavior Analysis. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems - CHI '16*.

Wang, N., Sun, S. D., Cai, Z. Q., Zhang, S., and Saygin, C. (2014). A hidden semi-markov model with durationdependent state transition probabilities for prognostics. *Mathematical Problems in Engineering*, 2014(1).

Zagorskis, V., Kapenieks, A., and Gorbunovs, A. (2019). Emotions identification utilizing periodic handwriting on mobile surfaces. *Periodicals of Engineering and Natural Sciences (PEN)*, 7(1):IC18.

Zaknich, A. (2006). *Principles of Adaptive Filters and Self-learning Systems*. Advanced Textbooks in Control and Signal Processing. Springer London.