Vilniaus universitetas
Duomenų mokslo ir skaitmeninių technologijų institutas
L I E T U V A

INFORMATIKOS INŽINERIJA (T007)

VISUAL LEARNING OBJECTS SIMULATION AND MODIFICATION RESEARCH TO PERSONALISE LEARNING

Viktorija Dvareckienė

2019 m. spalis

Mokslinė ataskaita DMSTI-DS-T007-19-03

VU Duomenų mokslo ir skaitmeninių technologijų institutas, Akademijos g. 4,
Vilnius LT-08412
www.mii.lt

Abstract

The report presents an original method of identifying suitable Augmented Reality (AR)-based learning systems including learning content (i.e. learning objects) and activities necessary for particular user/learner. AR is often used in education to enhance students' motivation by visualizing learning content and activities. The method is aimed to personalise learning by applying well-known Felder Silverman learning styles model and intelligent technologies and thus to ensure that suitable AR based learning systems should be selected for particular users to improve their learning motivation and thus – quality and efficiency. The method of identifying students preferring to actively use AR-based learning systems is based on identification of probabilistic suitability indexes to choose the most suitable AR-based learning systems for particular students and acquire these products in the market. The research is multidisciplinary, including education, computer science, engineering, operational research and psychology areas. Application of the personalisation method presented here may be used to improve human-computer interaction and may be extended beyond the education area and used in e.g. e-commerce to apply AR for particular customers' needs.

Keywords: learning personalisation, augmented reality, user needs, learner models, intelligent technologies

Contents

Contents

Introduction

The report aims to analyse a particular area of Augmented Reality (AR) research and application development that demonstrate the capacity of AR to change radically the commerce and shopping experience in the near future. This area is education, e.g. environmental education where AR applications seem to be very helpful. AR market for education is increasing dramatically during the last several years, and research on optimisation of acquisition of AR-based systems for educational institutions to enhance learning motivation, quality and efficiency becomes very relevant.

Research on AR-based learning systems (incl. learning objects and activities) becomes more and more demanded in scientific literature. Possibilities of AR application in education are very wide and bring many advantages to students of all ages, although much needs to be done.

However, only several studies directly address personalisation question of AR-based systems in education. Many authors agree that the problem of personalisation of AR-based learning systems and resources is relevant and should be further analysed.

Therefore, original personalisation method of AR-based learning systems, based on applying learners' profiles/models and intelligent technologies, is formulated and presented in the report. Implementation of this method in real educational practice should optimise acquisition of AR-based systems for educational institutions according to users' (i.e. students') needs.

Personalisation of learning became very popular topic in scientific literature during last years. Application of learners' profiles /models based on different learning styles models and intelligent (smart) technologies to personalise learning are recognised to be effective in terms of improving learning quality and efficiency.

Research Methodology

According to Squire and Klopfer (2007), all learning process (e.g. learning activities or learning units / scenarios) should be personalised according to the main characteristics/needs of the learners/users.

In order to personalise any learning components (learning units/scenarios consisting of learning objects, learning activities and learning environments) according to students' learning styles, expert evaluation methods and techniques should be used.

To perform current research, the authors have selected quite simple and convenient expert evaluation method based on application of trapezoidal fuzzy numbers.

First of all, the authors have prepared a questionnaire for expert evaluation on suitability of Felder-Silverman learning styles (Felder and Silverman, 1988) and learning activities based on application of AR.

According to numerous resources (e.g. Jevsikova *et al*., 2017; Kurilovas *et al*., 2016; Kurilovas, 2019)), Felder Silverman learning styles model (FSLSM) (Felder and Silverman, 1988) is the best model for application in Science, Technology, Engineering and mathematics (STEM).

The following question was formulated: "What do you think is suitability level of learning systems based on application of AR to Felder-Silverman learning styles (excellent, good, fair, poor, or bad)" (Table 1).

Table 1. Questionnaire for expert evaluation

Felder-Silverman learning styles		Suitability to learning systems based on application of Augmented Reality				
By information type	**Sensory**	Excellent	Good	Fair	Poor	Bad
	Intuitive	Excellent	Good	Fair	Poor	Bad
By sensory channel	**Visual**	Excellent	Good	Fair	Poor	Bad
	Verbal	Excellent	Good	Fair	Poor	Bad
By information processing	**Active**	Excellent	Good	Fair	Poor	Bad
	Reflective	Excellent	Good	Fair	Poor	Bad
By understanding	**Sequential**	Excellent	Good	Fair	Poor	Bad
	Global	Excellent	Good	Fair	Poor	Bad

After that, details explaining Felder-Silverman learning styles model (Felder and Silverman, 1988) were provided for the experts. According to FSLSM, all students could be divided into four dimensions and eight learning styles:

- By information type: Sensory (SEN) Vs Intuitive (INT);
- By sensory channel: Visual (VIS) Vs Verbal (VER);
- By information processing: Active (ACT) Vs Reflective (REF);
- By understanding: Sequential (SEQ) Vs Global (GLO).

After filling in the questionnaire, the authors could easily calculate the average values of suitability of Felder-Silverman learning styles and learning systems applying AR.

These values of suitability can be calculated using conversion of linguistic variables into triangular (Kurilovas, 2009) or trapezoidal non-fuzzy values (Kurilovas, 2018) that will be used in this report:

- "Excellent" – 1.000,
- "Good" – 0.800,
- "Fair" – 0.500,
- "Poor" – 0.200,
- "Bad" – 0.000.

The average values of suitability should be easily calculated by division of the total sum of all non-fuzzy values by the number of experts.

According to Kurilovas *et al.* (2016), an example could be obtained by filling in Soloman and Felder's Index of Learning Styles Questionnaire [28]. If a student answers e.g. 7 questions favourable to the Sensory learning style, and 4 questions favourable to the Intuitive learning style, then $PR_{SEN} = 7 / 11 = 0.64$, and $PRI_{INT} = 4 / 11 = 0.36$, and further on to all dimensions of FSLSM. Thus, we could obtain e.g. the following learning styles initially stored in student profile/model (Table 2).

Table 2 Example of learning style initially stored in student profile/model

Learning styles							
By Information type		By Sensory channel		By Information processing		By Understanding	
SEN	INT	VIS	VER	ACT	REF	SEQ	GLO
0.636	0.364	0.818	0.182	0.727	0.273	0.455	0.545

If we should multiply probabilistic values of particular students' learning styles according to Table 2 (PR) by AR-based learning systems and learning styles suitability values according to Table 1 (V), we would obtain probabilistic values (SI) of suitability of particular AR-based learning systems to particular student according to Formula 1:

$$SI_{ACT} = PR_{ACT} \times V_{ACT} \quad (1)$$

This is the example of Active learning style of the particular student. In the same way, we could calculate probabilistic suitability indexes of all learning styles of particular student according to Table 2.

Results and Discussion

3 experts (researchers from Vilnius University Education systems research group with solid experience in technology-enhanced learning and personalisation) have filled in the questionnaire by selecting one of the linguistic variables. The results are presented in Table 3.

Table 3. Expert evaluation results

Learning Style	SEN	INT	VIS	VER	ACT	REF	SEQ	GLO
Average value	0.866	0.933	1.000	0.400	0.700	0.133	0.600	0.700

In Table 3, the experts have expressed their opinion on suitability of AR-based learning systems to all FSLSM-based learning styles.

If we want to calculate probabilistic indexes of suitability of these learning systems to particular students described by Table 2, we should use the methodology of creating probabilistic suitability indexes (Kurilovas *et al.,* 2016) presented in Section 3 and calculate these suitability indexes according to Formula 1, i.e. to calculate the indexes of particular learning component's (e.g., learning objects / activities / environments) suitability to FSLSM-based learning styles described by Table 3.

We will demonstrate the application of the method with the group of 6 students of Bachelor study programme of Technical University analysed by the authors Mamcenko and Kurilovas (2017), Kurilovas (2019).

The respondents have filled out Soloman and Felder's Index of Learning Styles Questionnaire (44 questions) (Soloman and Felder, 2019) translated into Lithuanian. The results (Table 4) have shown that:

- 4 respondents prefer to process information in Active way, and 2 in Reflective;
- 4 respondents are mostly Sensory, and 2 Intuitive learners by information type;
- 4 respondents are mostly Visuals and 2 Verbal learners by sensorial channel; and
- 1 respondent is clear Sensorial and 1 is clear Global learner by understanding.

Table 4. Respondents' learning styles (%) according to the questionnaire results

No.	Information Type		Sensorial Channel		Information Processing		Understanding	
	SEN	INT	VIS	VER	ACT	REF	SEQ	GLO
1	54.5	45.5	72.7	27.3	72.7	27.3	54.5	45.5
2	27.3	72.7	100.0	0.0	45.5	54.5	18.2	81.8
3	36.4	63.6	36.4	63.6	72.7	27.3	45.5	54.5
4	63.6	36.4	27.3	72.7	72.7	27.3	45.5	54.5
5	72.7	27.3	54.5	45.5	63.6	36.4	45.5	54.5
6	72.2	27.3	90.9	9.1	27.3	72.2	72.7	27.3

In (Mamcenko and Kurilovas, 2017), the methodology has been applied to evaluate virtual learning environment Moodle course activities' suitability for students' leaning styles, and here we apply it to evaluate AR learning systems suitability to particular students according to their learning style preferences.

By applying suitability indexes obtained from the experts' evaluation (Table 3), we generate AR suitability for each student (Table 5).

Table 5. AR suitability indexes for the respondents

AR suitability for Student ID						
	1	2	3	4	5	6
Average	36.542	37.344	34.084	33.174	34.493	35.457
Max	72.700	100.000	59.339	55.078	62.958	90.900

Suitability indexes, presented in Table 5, are: 1) average values taking into account each component of learning style (by Information type, Sensorial channel, Information processing, and Understanding) and 2) maximum values, taking into account only one dominant style (e.g. Visual or Active). In practice, student has more than one learning style preference, and all the preferences should be considered. However, maximum value for one dominant preference and most suitable for AR based learning systems, may help to identify students who could benefit most from using AR learning systems.

In Table 5, we see that AR-based learning systems are most suitable for students 1, 2 and 6.

These suitability indexes should be included in recommender system, and all learning components (e.g., learning objects, activities or environments) should be linked to particular students according to those suitability indexes. The higher suitability index the better the learning component fits particular student's needs, and vice versa.

Expert evaluation, linking learning systems and students by probabilistic suitability indexes, and recommender system are the main intelligent technologies applied to personalise learning.

An optimal learning unit/scenario (i.e. learning unit/scenario of the highest quality) for particular student means a methodological sequence of learning components (learning objects to be learnt, learning activities how to learn and learning environment) having the highest probabilistic suitability indexes. According to Kurilovas (2016), the level of students' competences, i.e. knowledge / understanding, skills and attitudes/values directly depends on the level of application of optimal learning units / scenarios in real pedagogical practice.

Expert evaluation results presented in Table 3 have shown that learning systems based on application of Augmented Reality are:

- the most suitable for Visual (value 1.000), Intuitive (value 0.93) and Sensor (value 0.866) learners, and
- the most unsuitable for Verbal (value 0.400) and Reflective (value 0.133) learners. The results also show that there is almost no difference in preferences on using AR for learning styles by Understanding dimension (Sequential Vs Global).

AR learning systems are suitable for Activist learners (value 0.700), however this value could be higher if we specified certain types of AR, e.g. AR involving to act within the learning scenario. Therefore, in order to strengthen these students' motivation and improve their learning results, optimal learning scenarios based on active use of AR should be created and used in their learning process.

According to Felder and Silverman (1988), most people of college age and older are visual. Visual learners remember best what they see but not hear. If something is simply said to them they will probably forget it.

The same was confirmed by the study of students of medicine faculty, presented in (Kurilovas *et al.*, 2016). The results of this study have shown that among target group of 22 final year students of Faculty of Medicine of Vilnius University (77.27% female, 22.73% male):

- 50% of students had medium preference to learning styles, whereas even 45% had a strong reference to a certain learning style. The majority of tested students prefer Active (59.1%), Sensory (72.7%), Visual (86.4%) and Sequential (54.5%) learning styles. The majority of students have medium to strong preference to learning styles: Visual (13 – 59.1%), Active (6 – 27.3%), Sensory (6 – 27.3%), and Sequential (4 – 12.2%).
- Multimodal students (students having preferences to more than one mode) included 14 (63.6%) students. 9 (40.1%) have preference to two learning styles, and 5 (22.7%) have preference to 3 learning styles at the same time. 2 (9.1%) students have strong preference to multimodal learning style.
- Only 1 student has no significant preferences for any of the learning styles.
- Dominant learning styles were as follows: 59.1% students were evaluated as Active, 86.4% Visual, 72.7% Sensory, and 54.5% Sequential. There was no significant difference in preference for learning style between genders.

Thus, AR is extremely suitable for Visual learners while Verbal learners prefer written and spoken explanations. Verbal learners remember and learn well from discussions, prefer verbal explanation to visual demonstration, and learn effectively by explaining things to others.

Therefore, for Visual learners, the optimal learning scenarios should include e.g. visual representations of presented material – pictures, films, diagrams, time lines, flow charts, demonstrations.

On the other hand, according to Felder and Silverman (1988), Active learners learn by trying things out, working with others. They do not learn much from lectures because they require them to receive information passively. They work and learn better in situations that allow for group work and hands on experimentation. They prefer to actively use AR while Reflective learners learn by thinking things through, working alone. Active learners do not learn much in situations that require them to be passive. An Active learner is someone who feels more comfortable with, or is better at, active experimentation than reflective observation. Active experimentation involves doing something in the external world with the information – discussing it or explaining it or testing it in some way.

On the opposite, according to Felder and Silverman (1988), Reflective learners require situations that provide opportunity to think about the information being presented, and they work well alone and do not requite to actively use AR.

It is obvious that for hypothetic student described by Table 1 and student 1 described by Table 4 AR activities are very suitable (they are Visual learners), but, as an Activists, they prefer mostly learning units/scenarios based on active use of AR. For the respondents 2 and 6 described by Table 4 AR activities are suitable as for Visual learners, while other learning preferences of these students may give more information on what kind of AR activities and sequences the students would prefer. Thus, while student 6 is Visual and Reflective, AR could be useful for the presentation of new material, giving place for student's reflective practice.

Thus, if an educational institution (e.g. University) has a majority of Visual, Intuitive or Sensor students/users, the institution should actively acquire AR-based systems for their learners. If there is a majority of Active learners in the educational institution, "active" (e.g. simulation, not demonstrational) AR systems should be acquired and actively used in real pedagogical practice.

Conclusion

In this report, original method of identifying users preferring to use AR-based learning systems is presented. The method is aimed to personalise learning by applying Felder-Silverman learning styles model and intelligent technologies and thus to improve learning motivation, quality and effectiveness.

Presented method of identifying students preferring to actively use AR-based learning systems is based on identification of these learning systems' suitability indexes to particular users/students according to their learning styles.

Expert evaluation results have shown that learning systems based on application of AR are most suitable for Visual, Intuitive and Sensor learners, and most unsuitable for Verbal and Reflective learners.

The level of students' competences, i.e. knowledge / understanding, skills and attitudes / values directly depends on the level of application of these optimal (i.e. the highest Suitability Indexes–based) learning scenarios in real pedagogical practice. The presented method is to be used in learning recommendation system.

Research results had shown that the problem of acquisition of AR for educational purposes highly depends on learning institutions' students' learning needs and it should be more effective if corresponding probabilistic suitability indexes should be taken into account.

The method presented is not limited to AR application in education area, but can be successfully transferred into the e.g. area of ecommerce and used to present AR according to the customer's shopping style and preferences.

Future work should include analysis of different kinds of AR and their suitability to particular users/students of particular educational institutions. The other relevant area of future research is analysis and creation of ontologies-based recommender system to propose particular users/students the most suitable AR-based learning components. Learning analytics and artificial neural networks could be also actively applied while creating optimal learning scenarios for particular users.

References

JUSKEVICIENE A., JASUTE E., KURILOVAS E., MAMCENKO J. Application of 1:1 Mobile Learning Scenarios in Computer Engineering Education. International Journal of Engineering Education 32 (3) 2016, pp. 1087–1096.

JEVSIKOVA T., BERNIUKEVIČIUS A., KURILOVAS E. Application of Resource Description Framework to Personalise Learning: Systematic Review and Methodology. Informatics in Education, vol. 16(1) 2017, pp. 61–82 .

YOSHIOKA, S.R.I., ISHITANI, L. An Adaptive Test Analysis Based on Students' Motivation. Informatics in Education, vol. 17(2) 2018, pp.381–404.

KITCHENHAM B. Procedures for performing systematic reviews. Joint technical report Software Engineering Group, Keele University, United Kingdom and Empirical Software Engineering, National ICT Australia Ltd, Australia, 2004.

KURILOVAS E., DVARECKIENĖ V., JEVSIKOVA T. Augmented Reality-Based Learning Systems: Personalisation Framework. In: Proceedings of 15th European Conference on eLearning (ECEL 2016). Prague, October 27–28 2016, pp 391–398.

AZUMA R., BAILLOT Y., BEHRINGER R., FEINER S., JULIER S., MACINTYRE B. Recent Advances in Augmented Reality. IEEE Computer Graphics & Applications, vol. 21(6) 2001, pp. 34–47.

PETERSEN N., STRICKER D. Cognitive Augmented Reality. Computers & Graphics, vol. 53 2015, pp. 82–91.

DIEGMANN P., SCHMIDT-KRAEPELIN M., VAN DEN EYNDEN S., BASTEN D. Benefits of Augmented Reality in Educational Environments-A Systematic Literature Review. In: Wirtschaftsinformatik Proceedings 2015, pp. 1542–1556.

RADU I. Augmented reality in education: a meta-review and cross-media analysis. Personal and Ubiquitous Computing , vol. 18(6) 2014, pp. 1533–1543.

BACCA J., GESA R.F., GRAF S., KINSHUK, NAVARRO S.M. Augmented Reality Trends in Education: A Systematic Review of Research and Applications. Journal of Educational Technology & Society, vol. 17(4) 2014, pp.133–149.

WU H., LEE S.W., CHANG H., LIANG J. Current status, opportunities and challenges of augmented reality in education. Computers & Education, vol. 62 2013, pp.41–49.

KAUFMANN H., SCHMALSTIEG D. Mathematics and geometry education with collaborative augmented reality. Computers & Graphics, vol. 27 2003, pp. 339–345.

DIAZ C., HINCAPIE M., MORENO G. How the Type of Content in Educative Augmented Reality Application Affects the Learning Experience. Procedia Computer Science, vol. 75 2015, pp. 205–212.

HUANG T.C., SHU Y., YEH T.C., ZENG P.Y. Get lost in the library? An innovative application of augmented reality and indoor positioning technologies. The Electronic Library, vol. 34(1) 2016, pp. 99–115.

CALDERON R.R., ARBESU R.S. Augmented Reality in Automation. Procedia Computer Science, vol. 75 2015, pp.123–128.

TOBAR-MUNOZ H., BALDIRIS S., FABREGAT R. Augmented Reality Game-Based Learning: Enriching Students' Experience During Reading Comprehension Activities. Journal of Educational Computing Research, vol. 55(7) 2017, pp. 901–936

SQUIRE K., KLOPFER E. Augmented reality simulations on handheld computers. Journal of the Learning Sciences, vol. 16(3) 2007, pp. 371–413.

CHIANG T.H., YANG S.J., HWANG G.J. Students' online interactive patterns in augmented reality-based inquiry activities. Computers & Education, vol. 78 2014, pp. 97–108.

DUNLEAVY M., DEDE C., MITCHELL R. Affordances and limitations of immersive participatory augmented reality simulations for teaching and learning. Journal of Science Education and Technology, vol. 18(1) 2009, pp. 7–22.

KURILOVAS E. Evaluation of Quality and Personalisation of VR/AR/MR Learning Systems. Behaviour & Information Technology, vol. 35(11) 2016, pp.998–1007.

HE J., REN J., ZHU G., CAI S., CHEN G. Mobile-Based AR Application Helps to Promote EFL Children's Vocabulary Study. In: Proceedings of ICALT: 2014 IEEE 14th International Conference on Advanced Learning Technologies 2014, pp. 431–433.

WEI X.D., WENG D.D., LIU Y., WANG Y.T. Teaching based on augmented reality for a technical creative design course. Computers & Education, vol. 81 2015, pp. 221– 234.

KURILOVAS E., ZILINSKIENE I., DAGIENE V. Recommending Suitable Learning Paths According to Learners’ Preferences: Experimental Research Results. Computers in Human Behavior, vol. 51 2015, pp. 945–951.

FELDER R.M., SILVERMAN L.K. Learning and Teaching Styles in Engineering Education. Engineering Education, vol. 78(7) 1988, pp. 674–681.

KURILOVAS E. Evaluation and Optimisation of e-Learning Software Packages: Learning Object Repositories. Proceedings of the 4th International Conference on Software Engineering Advances (ICSEA 2009). Porto, Portugal, September 20–25 2009, pp. 477–483.

KURILOVAS E. On Data-Driven Decision-Making for Quality Education. Computers in Human Behavior 2018, in press, DOI: 10.1016/j.chb.2018.11.003

KURILOVAS E., KURILOVA J., ANDRUSKEVIC T. On Suitability Index to Create Optimal Personalised Learning Packages. In: Dregvaite G, Damasevicius R (Eds): ICIST 2016, Communications in Computer and Information Science (CCIS), vol. 639 2016, pp. 479–490.

SOLOMAN B.A., FELDER R.M. Index of Learning Styles Questionnaire. http://www.engr.ncsu.edu/learningstyles/ilsweb.html. Accessed on February 2, 2019.

MAMCENKO J., KURILOVAS E. On Using Learning Analytics to Personalise Learning in Virtual Learning Environments. In: Proceeding of 16th European Conference on e-Learning (ECEL 2017), Porto, Portugal, October 26-27 2017, pp 353–361.

KURILOVAS E. Advanced Machine Learning Approaches to Personalise Learning: Learning Analytics and Decision Making. Behaviour & Information Technology, vol. 38(4), 2019, pp. 410–421.

KURILOVAS E., KURILOVA J., KURILOVA I., MELESKO J. Personalised Learning System Based on Students' Learning Styles and Application of Intelligent Technologies. In: Proceedings of the 9th International Conference of Education, Research and Innovation (ICERI 2016). Seville, Spain, November 14–16 2016, pp. 6976–6986.