Biologically Inspired Cognitive Architectures 25 (2018) 37–42

Contents lists available at ScienceDirect

Biologically Inspired Cognitive Architectures

journal homepage: www.elsevier.com/locate/bica

Research article

Semantic-map-based analysis of insight problem solving

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ARTICLE INFO

Keywords:
Creative assistant
Cognitive architecture
Self-regulated learning
Social-emotional intelligence
Human-friendly AI

ABSTRACT

Intelligent agents and co-robots, or cobots, become increasingly popular today as assistants of creators of arts. They can be also expected to become popular in the near future as assistants in other creative work, including research and, in particular, insight problem solving. Arguably, the success of such tools is linked to their social-emotional intelligence. This work continues the previous study of the concept of a cobot-assistant of an insight problem solver (Kuznetsova & Samsonovich, Procedia Computer Science 123:258–64, 2018). The concept is based on a semantic map, that represents cognitive and emotional states and attitudes. The previously constructed semantic map is used here to study the dynamics of human cognitive and emotional states during insight problem solving. It is found here that subjects solving an insight problem become more excited and try to take more radical approaches, and also become slightly more confident, as they approach the insight moment, regardless of whether they actually succeed. This finding should help to formulate rules and cognitive schemas to be tested in future studies of the proposed insight problem solver assistant. The expected impact is on the anticipated emergence of general-purpose virtual cobots-assistants, unleashing higher creativity in their users.

Introduction

Background and significance

Intelligent cognitive assistants in the form of physical or virtual human-friendly collaborative robots (cobots) will become ubiquitous in a near future (Samsonovich, 2018; Veloso, Biswas, Coltin, & Rosenthal, 2015). They will serve as extensions of human minds and bodies into physical and virtual worlds, together facing challenges that today only humans can solve. One such challenge is represented by the domain of *insight problems*, the solution of each of which involves the "Aha!" moment (an insight experience). Insight problem solving is traditionally linked to general fluid intelligence (Jaeggi, Buschkuehl, Jonides, & Perrig, 2008): the ability to successfully deal with new, unexpected challenging situations, where prior knowledge does not help. Contrary to common belief, this natural human capacity can be enhanced by training of working memory (Jaeggi et al., 2008). It can also be augmented by scaffolding and guidance, provided by artificial intelligence (AI) tools such as computer-based learning environments (Azevedo, 2002; Desmarais & Baker, 2012; Roscoe, Segedy, Sulcer, Jeong, & Biswas, 2013) and cobots (Timms, 2016). The latter built for this purpose are frequently based on self-regulated learning (SRL) frameworks (Winne & Nesbit, 2009; Zimmerman, 2008) couched in a cognitive architecture framework (e.g., Samsonovich et al., 2008). It remains to add that many data from psychological studies suggest that emotionality plays a key role in development of insight (Malekzadeh, Mustafa, & Lahsasna, 2015; Wen, Butler, & Koutstaal, 2013). This observation encourages thinking of a potential for application of emotional cognitive architectures (Eidlin & Samsonovich, 2018; Hudlicka, 2011).

Toward a creative cobot-assistant: Previous work and the present task

Our general approach to designing the creative cognitive assistant of an insight problem solver in the form of a virtual cobot was outlined in the previous work (Kuznetsova & Samsonovich, 2018). In essence, it is based on a simplified form of the emotional Biologically Inspired Cognitive Architecture eBICA (Samsonovich, 2013, 2018) with a weak semantic map (Ascoli & Samsonovich, 2012; Samsonovich, 2018; Samsonovich, Goldin, & Ascoli, 2010) at its heart. For the present purposes, the semantic map is built as a two-dimensional vector space, used to represent the cognitive-emotional flavor of the momentary psychic state of the problem solver. The same space is also used to map a database of available general cognitive strategies, that are potentially applicable to a cognitive problem of any sort. The cobot does not know the problem and its solution, and does not perceive the line of reasoning of the user whom it assists. All the cobot receives on input at each time step is the choice of a general strategy currently made by the user and the user's self-evaluation of own progress and attitude toward the

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https://doi.org/10.1016/j.bica.2018.07.017
Received 4 July 2018; Received in revised form 12 July 2018; Accepted 12 July 2018
2212-683X/

problem (with the possibility to add real-time psychometric and neuroimaging data). This information is processed and used to represent the current position of the user on the semantic map. The result in turn can be used to select map coordinates of the short list of strategies that will be offered to the user as a guidance. The process of selection is governed by the currently active *cognitive schema* in the cobot. The ultimate choice is made by the user, who can accept or reject the cobot advice. One of the goals for the cobot is to maintain a socio-emotional contact with the user, based on a mutual understanding and trust. The main objective for both, the cobot and the user, is to find a solution to the problem.

This conceptual model has not been implemented yet. As the first step to its realization, in the previous work (Kuznetsova & Samsonovich, 2018) a list of strategies was collected from various sources. Then, the *semantic map* was constructed from them as follows. Each strategy was evaluated by human subjects on 10 different semantic scales: *conservative-revolutionary, passive-aggressive, concrete-abstract, easy-difficult, detail-level vs. meta-level, condition-oriented vs. solution-oriented, weak-strong, opening-closing, basic-extra, prospective-retrospective*. The resultant ten-dimensional distribution was reduced to two main principal components, that were selected as map coordinates. Semantics of these coordinates was evaluated by experts and used to interpret the map data (Fig. 1).

The second step, which was the main task for the present study, was to accumulate and analyze phenomenological data on human behavior during insight problem solving, interpreted in terms of the semantic map. This study is necessary to formulate a set of cognitive schemas (see above) as hypotheses, that will be tested in future experimental studies with cobots-assistants. The second-step study was performed, yielding an interesting finding about human insight problem solving, and is presented below.

Materials and methods

Semantic map

The list of SRL strategies borrowed from various sources together with the weak semantic map built of them were constructed in the previous work (Kuznetsova & Samsonovich, 2018). The resultant semantic map is represented in Fig. 1.

Strategies: 1. Understand what is given. **2.** Understand the statement of the problem. **3.** Understand and separate the conditions. **4.** Try to reformulate the problem (once again). **5.** Try to prove the impossibility of solution. **6.** Find a contradiction in the problem statement. **7.** Understand whether the given data is sufficient. **8.** Reject an intuitive interpretation/solution. **9.** Divide the problem into parts. **10.** Set an intermediate subgoal. **11.** Solve a particular case of the problem. **12.** Examine particular cases in sequence. **13.** Try to achieve a bigger goal. **14.** Try to solve a more general problem. **15.** Try to solve an analogous problem. **16.** Use a similar problem with known solution. **17.** Use a known formula. **18.** Apply a given means in an unconventional way. **19.** Visualize the given situation/statement. **20.** Use a symmetry or mirror reflection. **21.** Use a known mathematical fact. **22.** Introduce variables. **23.** Write down an equation or system of equations. **24.** Get rid of redundant data. **25.** Could additional data lead to the solution? **26.** Try to use all given information. **27.** Enumerate all possibilities. **28.** Find a pattern. **29.** Make a list. **30.** Make a table **31.** Introduce convenient notation. **32.** Try to solve the problem backwards. **33.** Use logical reasoning. **34.** Draw a diagram. **35.** Introduce additional elements. **36.** Read the statement attentively once again. **37.** Make a plan. **38.** Follow the plan. **39.** Validate every step. **40.** Recall definitions. **41.** Analyze the result of each step. **42.** Could the result be obtained in another way? **43.** Can the obtained result solve the problem? **44.** Understand the causes of failures of problem comprehension/solution. **45.** Get ready to take it easy.

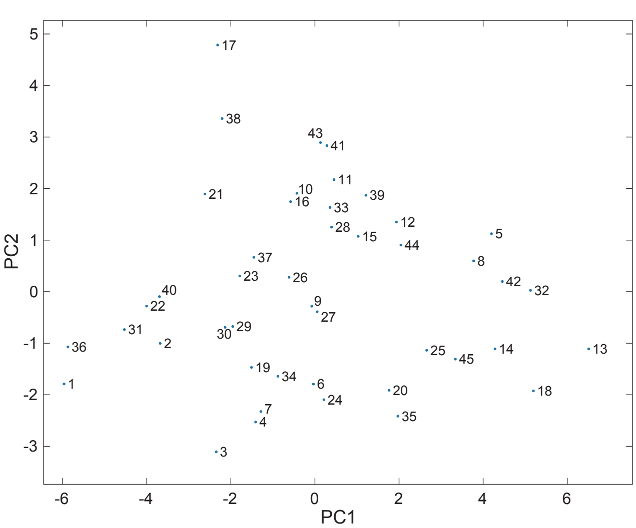

Fig. 1. Semantic map constructed of the 45 strategies (Kuznetsova & Samsonovich, 2018). Coordinates are main principal components of the distribution. The semantics of PC1 can be interpreted as *Aggressiveness, Arousal, Activity*. PC2 can be interpreted as *Valence, Confidence*. Strategies are represented by numbered dots and listed in text according to their numbers.

Semantic interpretation of coordinates PC1, PC2 in Fig. 1 is approximate and to a large extent subjective. PC1 can be interpreted as *Aggressiveness, Arousal, Activity*. PC2 can be interpreted as *Valence, Confidence*. Parameters of the distribution in PC1, PC2 are evaluated as follows. The center of the distribution is set to zero by the Principal Component Analysis. The standard deviations are: 2.94 in PC1 and 1.78 in PC2. Units are determined by the units of the original Likert scale (Kuznetsova & Samsonovich, 2018).

Insight problems

In total, eight insight problems presented below were offered to participants in this study, plus several additional, simpler problems not presented here were used for warm-up. Problems were acquired from various known sources, as indicated. Some of the problems were modified to match the level of difficulty used in this study, and are presented here as they were used in this study. All problems are known to be difficult for an average adult, yet they do not require for their solution any special knowledge beyond the high school program, and can be solved without any mathematical calculations. Solutions are intentionally not included here, except for one problem, for which the expected solution may be disputable. The rest have a clearly acceptable, valid solution each (while this fact cannot be used as a part of the reasoning scheme in finding the solution to the problem).

Problem 1: Two string problem (Fig. 2)

Given: a subject (a boy) in an empty room, where two strings are hanging from the ceiling at a distance from each other, so that the subject cannot grab them simultaneously. There are also a dome light, a chair, and plyers on the floor in that room. The subject holds an end of one string in one hand and tries to reach for the other string with the other hand, but cannot succeed. The original figure caption says: *"As hard as the subject tries, he can't grab the second string. How can he tie the two strings together? (Note: Just using the chair doesn't work!)"* (Goldstein, 2015; Maier, 1931).

Problem 2 (Fig. 3A), based on (Dawra, 2017): The line

Given: a line on the plane and a line segment parallel to the line. The task is to divide the segment into two equal parts.

Conditions: you are not allowed to perform any measurements or calculations, to copy objects, distances or angles. Only the following actions are permitted:

Fig. 2. The Two String Problem (reproduced with permission from Goldstein, 2015, p. 339).

- Select a random point on the plane or on a line.
- Select an intersection of lines or an end of the segment.
- Draw up to five straight lines through selected pairs of points.

Problem 3 (Fig. 3B), based on (Dawra, 2017): The circle

Given: a circle, a chord in it, and the marked middle of the chord. The task is to mark two points on the chord, located inside the circle at equal distances from the middle of the chord.

Conditions: you are not allowed to perform any measurements or calculations, to copy objects, distances or angles. Only the following actions are permitted:

- Select a random point on the plane, on any line or on the circle.
- Select an intersection, an end or the middle of the chord.
- Draw up to five straight lines through selected pairs of points.

Problem 4 (Fig. 4), based on (Dawra, 2017): The triangle

Given: (Fig. 4A) an equilateral triangle, a random point inside the triangle connected to its vertices by line segments *a, b, c*. The angle between segments *a* and *c* is α. Another triangle (Fig. 4B) is assembled from segments *a*, *b* and *c*. The angle between *a* and *c* in this triangle is β. The values of *a*, *b*, *c*, α and β are not specified. The task is to find the numerical value of the difference of two angles, α and β.

Conditions: you are not allowed to perform any measurements or calculations, either with numbers or with variables. You are also not allowed to copy given objects, distances or angles, to perform their rotation, reflection, or superposition. However, you are allowed to draw any diagrams that support your reasoning.

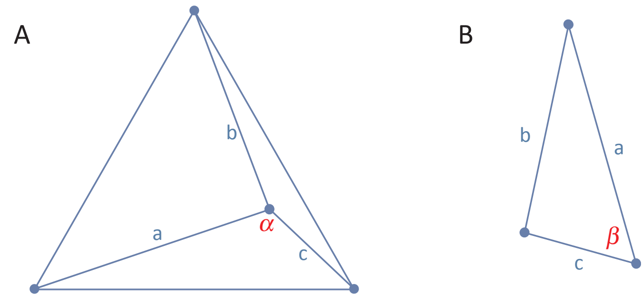

Fig. 4. The triangle problem. Two triangles are made of the same segments *a, b, c* in two different ways. A: The big triangle is equilateral. The angles and lengths of *a, b, c* are unknown. B: The lengths of *a, b, c* are the same as in A. The task is to find the difference α-β.

Problem 5 (Fig. 5), based on (Spiridonov, 2006). The square

Given: the cross, assembled from matchsticks, as shown in the figure. The task is to move one matchstick in order to obtain a square. Conditions: you cannot break matchsticks.

Problem 6 (Fig. 6), based on (Spiridonov, 2006)

Given: the wrong equality, assembled from matchsticks. The task is to move only one matchstick in order to obtain a valid equality. Conditions: you cannot break matchsticks.

Problem 7, based on (Spiridonov, 2006)

Given is the following phrase:

—“A hamster can eat a kilogram of oats, and a horse cannot.”

The task is to explain why this is a general fact (the presented version was in Russian; the phrase given above is the exact Google Translate of the original Russian phrase).

Problem 8 (see Samsonovich & Ascoli, 2005, for solution and discussion). Twenty questions game

This is one of the many well-known twenty-questions-game stories. The participant is given an incomplete story. Their task is to guess missing details, so that the story would make sense. The storyteller knows the answer. The participant can ask the storyteller any questions about the story, usually up to 20 questions. The storyteller must tell the truth, but can only have three options for an answer: “yes”, “no”, or “irrelevant”. The story given to the participant initially is the following.

> *“A man cannot sleep. He gets up, picks a phone and makes a call. When the other party answers, he hangs up and goes to bed. Now he sleeps well.”*

Fig. 3. Two problems in planar geometry. A: the line problem. B: the circle problem.

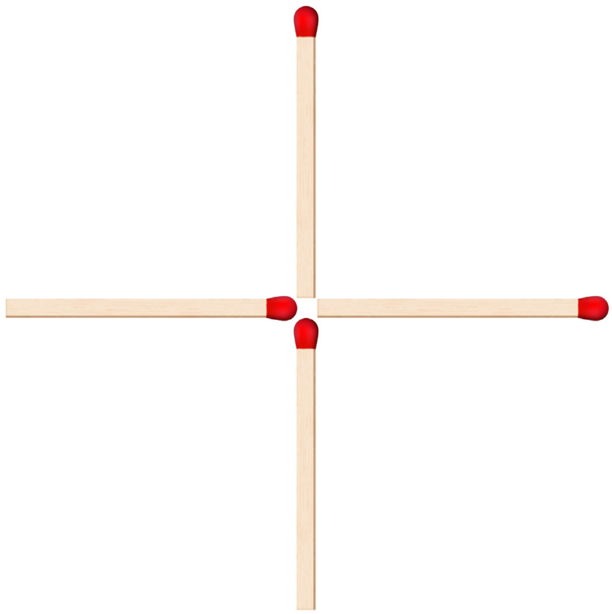

Fig. 5. A cross made of matchsticks. Based on (Spiridonov, 2006).

Comment

The last two problems, 7 and 8, may not be sufficiently explained here. Because problems were presented in Russian, the answer to Problem 7 was possible to find, based on an unusual way of parsing the phrase. The "right" answer was that hamsters do not eat horses. Of course, the applicability of this answer to the given phrase in English can be disputed. The purpose, however, was to create a challenging situation for participants, leaving the possibility of "solving" the challenge, while the "solution" was not easy to find. As to Problem 8, the reader is referred to the previous work (Samsonovich & Ascoli, 2005).

Human subjects and procedures

In total, 35 Master Students of NRNU MEPhI voluntarily participated in this study. The age of all was above 18 and below 28. All of them were full-time students studying Program Engineering at the NRNU MEPhI Cybernetics Department. They all indicated Russian as their native language. 14 of them were females and 21 were males. All participants signed the informed consent form. Participation was strictly voluntary.

The procedure was the following. Each participant was given blank paper, a pen, and a set of 45 SRL strategies (see above) printed on one page either as a list or as a two-dimensional set of randomly scattered text labels (the two groups were of approximately equal size; there was no significant differences found in results of the two groups). Participants were asked to read and to understand the given strategies before they received the problems. Participants were instructed to select and use, if possible, strategies from the given set, when working on the problems.

When participants were given a problem (presented on a slide and explained verbally), they were instructed to write down the number of each selected strategy as soon as they start following it, and also to mark whether any progress toward a solution was achieved while using or trying to use this strategy. When they thought that they found a solution, they had to represent it graphically or write in words on paper and show to the experimenter. Then the experimenter informed them whether the solution they found was right or wrong. Participants continued working on the problem for up to 15 or 20 min or until the expected solution was found. The process of problem solving, except for Problem 8, did not involve any need for information communicated by the experimenter after the problem was explained and before the answer was confirmed.

Results

Overall in this study, 35 subjects solved 8 problems using 45 strategies. Not all subjects solved or attempted to solve all problems, and not all trials were based on any of the 45 strategies and therefore recorded. Out of 280 possible trials, there were 202 recorded trials, of which only 121 had map trajectories of nonzero length (the other trials were based on a single strategy each). Of these 121, successful were 41, and 80 failed.

Examples of map trajectories in two selected trials – a failed trial and a successful trial – are represented in Fig. 7. Here, as discussed above, PC1 can be interpreted as *Arousal, Aggressiveness*, and PC2 can be interpreted as *Valence, Confidence*. All trajectories cover the plane uniformly. Significant observations are summarized in Table 1.

At the same time, there was not found any significant difference between winning and losing trials (ANOVA $P > 0.43$ for PC1, $P > 0.91$ for PC2). Also, there was no significant correlation between increments in PC1 and in PC2 ($P > 0.24$). Similarly, there was found no significant differences among results across individual subjects as well as across individual problems (ANOVA P-value > 0.21 and 0.76 for PC1 and PC2, respectively). This fact allowed us to merge all trials for all subjects and problems together in the presented analysis.

Discussion

The main finding of this study is that the semantic map trajectory of a participant solving an insight problem on average moves to the right and slightly upwards on the map (Table 1, Fig. 8). In other words, both PC1 and PC2 coordinates increase during the course of solution finding, with the PC1 increase being much more significant compared to PC2. Stated differently, the subject solving an insight problem becomes more excited and tries to take more radical approaches toward the end of the process, regardless of whether they succeeds at the end.

This observation is interesting in the context of related work on insight problem solving (e.g., Spiridonov & Lifanova, 2013). For example, it was found in other studies (Shen, Yuan, Liu, & Luo, 2016) that the "Aha!" moment is associated with the experience of happiness, clarity, ease and certainty. In other words, in terms of the semantic map (Fig. 1), the last step on the map trajectory should be upwards, like in Fig. 8B. This last step was not possible to capture by our methodology, because the endpoint on the recorded trajectory corresponds to selection of a strategy *before* the progress using this strategy was made.

The finding of Shen et al. (2016) may seem trivial: intuitively, almost everybody knows from own experience that succeeding in solving a difficult problem gives a moment of happiness and enlightenment: this is what an insight is about. In contrast, the moment of finding a

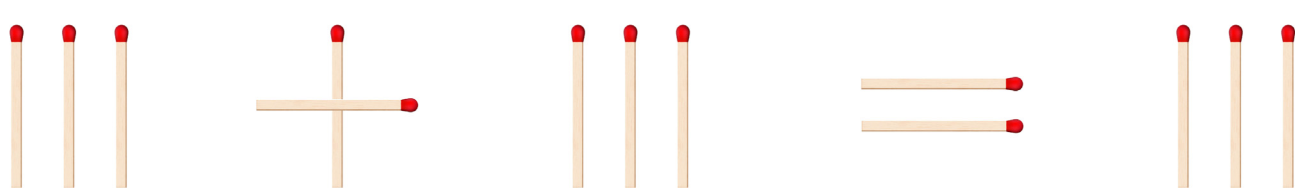

Fig. 6. The wrong equality made of matchsticks. Based on (Spiridonov, 2006).

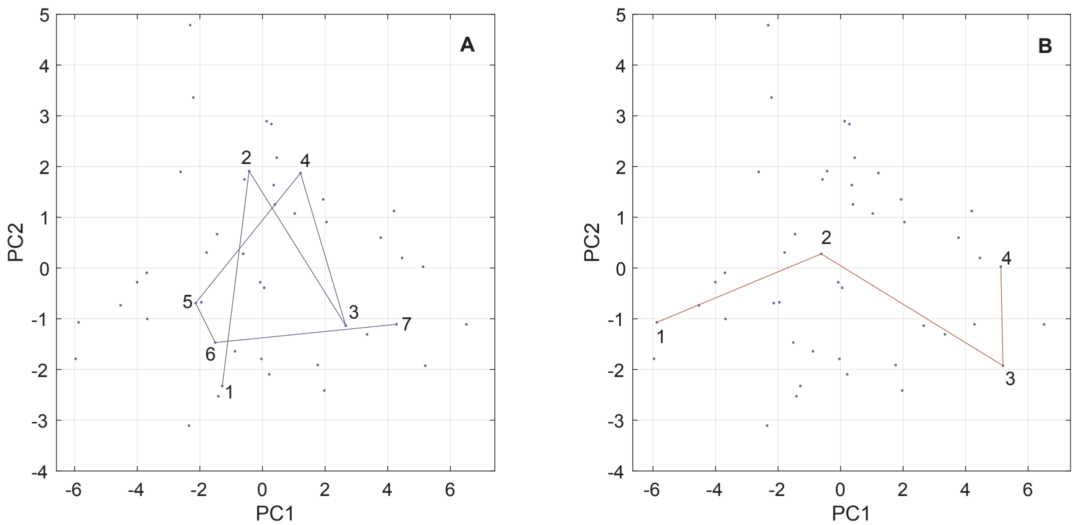

Fig. 7. Examples of map trajectories. Numbers represent the order in which strategies were selected by participants. A: solution was not found. B: solution was found. The subjects did not see the actual map, and therefore could not use map-based spatial reasoning in their choices.

Table 1
Characteristics of the 121 map trajectories.

Measure	Mean	Standard Error	P-value
Displacement along the trajectory, PC1	1.91	0.44	$P < 3e-5$
Displacement along the trajectory, PC2	0.42	0.21	$P < 0.043$
Displacement in the last jump, PC1	1.41	0.38	$P < 3e-4$
Displacement in the last jump, PC2	0.48	0.19	$P < 0.012$

solution of a difficult non-insight problem is not associated with sensations of happiness or clarity (Shen et al.. 2016).

A much more interesting question was addressed in the present work: What sort of cognitive and emotional experience is associated with the process of finding a path toward the solution of an insight problem? This question is important for designing an intelligent assistant to insight problem solvers. Here we give an answer to this question: the flavor of this experience can be characterized by aggressiveness, excitement, and taking active control. On average, this is true about the entire map trajectory as well as about the last step on this trajectory. For comparison, we did not see this effect in solutions of relatively easy or non-insight warm-up problems (not presented here).

It is interesting to note in this context that another study (Korovkin, Vladimirov, & Savinova, 2014) found a significant increase in working memory load just *before* the final stage of insight problem solving, as revealed by measurements of the reaction time. In contrast, the increase was absent for non-insight problems. These observations indicate that something significant happens before the subject comes to an idea of a solution, and here cognitive processes as well as emotional attitudes become involved.

In conclusion, the concept of a creative cobot-assistant of an insight problem solver outlined in Section “Toward a creative cobot-assistant: Previous work and the present task” can be implemented based on a semantic map of SRL strategies (Fig. 1) and a cognitive schema of an insight solution. There is a hope that the outcome will be successful, if the schema will be designed to generate an advice of the cobot taking the user in the right direction on the map: from the left to the right, and slightly upwards. For this purpose, at a certain moment the cobot should offer strategies located to the right of the map coordinates of the current cognitive and psychic state of the subject, or offer strategies taken from the rightmost edge of the distribution. This sort of an advice,

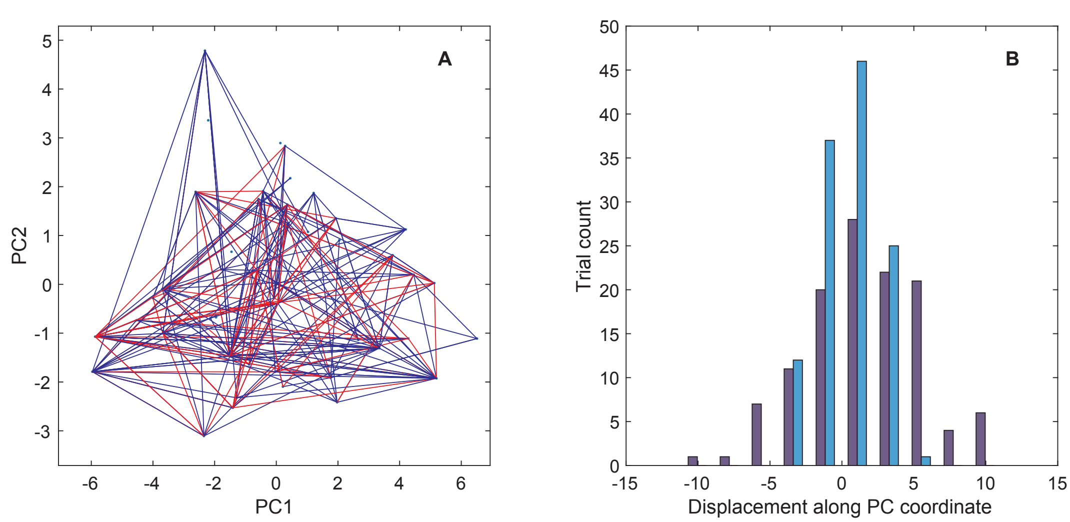

Fig. 8. Results for All 121 trials. A: all map trajectories are superimposed. Red lines represent successful trials, blue lines represent unsuccessful trials. Almost every strategy was used. B: Histograms of the displacements along the map trajectory in individual trials. Dark-blue: PC1, light-blue: PC2. On average, both are positive (see Table 1).

if given at the right moment, may trigger an insight. The cognitive schema formulated as a mathematical rule for picking strategies should be treated as a hypothesis and will need to be verified in future studies. The outlined rule for selecting strategies can be used in future virtual cobots-assistants. However, it remains to be determined whether the proposed rule is effective from the point of view of the success in insight problem solving, and therefore further studies are needed. The main finding of this work is limited to the human insight problem solving, and consists in establishing a new law for the semantic map trajectory in this case.

Intelligent virtual cognitive cobots are expected to become increasingly popular in the near future as assistants in creative work, including research and, in particular, insight problem solving. They will also become very useful beyond these domains (Campbell & Weihl, 2018). It appears that their effectiveness can be linked to their emotional intelligence (Samsonovich, 2018). In this work we used a semantic map constructed from SRL strategies to study the laws of finding a path toward an insight problem solution. It is expected that the findings presented here will be useful in design of virtual cobots-assistants, that will give higher productivity and higher creativity to their users.

Acknowledgments

This work was supported by the Russian Science Foundation Grant #18-11-00336. The authors are grateful to the NRNU MEPhI Academic Excellence Project for providing computing resources and facilities to perform the experiments and data analysis. The authors are also very grateful to all NRNU MEPhI Students who participated in this study.

References

Ascoli, G. A. and Samsonovich, A. V. (2012). Semantic Cognitive Map. US Patent No. 8, 190,422 B2, issued on May 29, 2012. Washington, DC: U.S. Patent and Trademark Office.

Azevedo, R. (2002). Beyond intelligent tutoring systems: Using computers as METAcognitive tools to enhance learning? *Instructional Science, 30*(1), 31–45. https://doi.org/10.1023/a:1013592216234.

Campbell, K., & Weihl, C. (2018). Cobots: Man and machine team up for workplace productivity; industry leaders discuss how human-robot collaboration is shaping the future of manufacturing. *Welding Journal, 97*(5), 34–39.

Dawra, N. (August 25, 2017). Simple Math Problems to Fool the Best: Video posted on YouTube at https://www.youtube.com/watch?v=Db3CwFh7qng&t=6s.

Desmarais, M. C., & Baker, R. (2012). A review of recent advances in learner and skill modeling in intelligent learning environments. *User Modeling and User-Adapted Interaction, 22*(1–2), 9–38. https://doi.org/10.1007/s11257-011-9106-8.

Eidlin, A. A., & Samsonovich, A. V. (2018). A roadmap to emotionally intelligent creative virtual assistants. *Advances in Intelligent Systems and Computing: vol. 636*, (pp. 47–56). Cham, Switzerland: Springer Nature.

Goldstein, E. B. (2015). (4th ed.). *Cognitive psychology: Connecting mind, research, and everyday experience*Stamford, CT: Cengage Learning ISBN-13: 978-1-285-76702-4.

Hudlicka, E. (2011). Guidelines for designing computa-tional models of emotions. *International Journal of Synthetic Emotions, 2*(1), 26–79.

Jaeggi, S. M., Buschkuehl, M., Jonides, J., & Perrig, W. J. (2008). Improving fluid intelligence with training on working memory. *Proceedings of the National Academy of Sciences of the United States of America, 105*(19), 6829–6833.

Korovkin, S. Yu, Vladimirov, I. Yu, & Savinova, A. D. (2014). The dynamics of working memory load in insight problem solving. *Russian Journal of Cognitive Science, 1*(4), 67–81.

Kuznetsova, K., & Samsonovich, A. V. (2018). Semantic-map-based approach to designing an insight problem solving assistant. *Procedia Computer Science, 123*, 258–264.

Maier, N. R. F. (1931). Reasoning in humans: II. The solution of a problem and its appearance in consciousness. *Journal of Comparative Psychology, 12*, 181–194.

Malekzadeh, M., Mustafa, M. B., & Lahsasna, A. (2015). A review of emotion regulation in intelligent tutoring systems. *Educational Technology & Society, 18*(4), 435–445.

Roscoe, R. D., Segedy, J. R., Sulcer, B., Jeong, H., & Biswas, G. (2013). Shallow strategy development in a teachable agent environment designed to support self-regulated learning. *Computers & Education, 62*, 286–297. https://doi.org/10.1016/j.compedu.2012.11.008.

Samsonovich, A. V. (2013). Emotional biologically inspired cognitive architecture. *Biologically Inspired Cognitive Architectures, 6*, 109–125.

Samsonovich, A. V. (2018). On semantic map as a key component in socially-emotional BICA. *Biologically Inspired Cognitive Architectures, 23*, 1–6.

Samsonovich, A. V., & Ascoli, G. A. (2005). A simple neural network model of the hippocampus suggesting its pathfinding role in episodic memory retrieval. *Learning & Memory, 12*(2), 193–208.

Samsonovich, A. V., De Jong, K. A., Kitsantas, A., Peters, E. E., Dabbagh, N., & Kalbfleisch, M. L. (2008). Cognitive constructor: An intelligent tutoring system based on a biologically inspired cognitive architecture (BICA). In P. Wang, B. Goertzel, & S. Franklin (Eds.). *Artificial General Intelligence*(pp. 311–325).

Samsonovich, A. V., Goldin, R. F., & Ascoli, G. A. (2010). Toward a semantic general theory of everything. *Complexity, 15*(4), 12–18.

Shen, W., Yuan, Y., Liu, C., & Luo, J. (2016). In search of the "Aha!" experience: Elucidating the emotionality of insight problem solving. *British Journal of Psychology, 107*, 281–298. https://doi.org/10.1111/bjop.12142.

Spiridonov, V. F. (2006). *The psychology of thinking: Problem solving.* Moscow: Genesis (Russian).

Spiridonov, V. F., & Lifanova, S. S. (2013). Insight and mental operators, or whether it is possible to solve an insight problem step-by-step. Psychology. *Journal of the Higher School of Economics, 10*(3), 54–63.

Timms, M. J. (2016). Letting artificial intelligence in education out of the box: Educational cobots and smart classrooms. *International Journal of Artificial Intelligence in Education, 26*(2), 701–712.

Veloso, M., Biswas, J., Coltin, B., & Rosenthal, S. (2015). CoBots: Robust symbiotic autonomous mobile service robots. *IJCAI International Joint Conference on Artificial Intelligence*(pp. 4423–4429). January.

Wen, M. C., Butler, L. T., & Koutstaal, W. (2013). Improving insight and non-insight problem solving with brief interventions. *British Journal of Psychology, 104*(1), 97–118.

Winne, P. H., & Nesbit, J. C. (2009). Supporting self-regulated learning with cognitive tools. In D. J. Hacker, J. Dunlosky, & A. C. Graesser (Eds.). *Handbook of Metacognition in Education*Mahwah, NJ: Erlbaum.

Zimmerman, B. J. (2008). Investigating self-regulation and motivation: Historical background, methodological developments, and future prospects. *American Educational Research Journal, 45*(1), 166–183.