Dynamic stress profile generation for crisis situations training

Luca Pelissero-Witoslawski, Domitile Lourdeaux, Dominique Lenne

2021 IEEE International Conference on Systems, Man, and Cybernetics (SMC)
17-20 October, 2021. Melbourne, Australia

Dynamic stress profile generation for crisis situations training

Luca PELISSERO-WITOSLAWSKI[1], Domitile LOURDEAUX[2], Dominique LENNE[3]

2021 IEEE International Conference on Systems, Man, and Cybernetics (SMC) | 978-1-6654-4207-7/21/$31.00 ©2021 IEEE | DOI: 10.1109/SMC52423.2021.9659295

Abstract— **Our work focuses on improving the management of stressful situations using virtual environments. We hypothesise that learners can improve how they deal with these situations by being confronted with a wide variety of scenarios. We want to create customised situations using different stressors, which is why we are interested in the representation and diagnosis of the learner ability to cope with said stressors. The diagnosis of a stress profile is carried out using stress sensors which provide measurements. However, these measurements are not quite spotless and uncertainties are present. Moreover, the situations we generate are complex and involve stressors that can impact each learner differently. Hence, many uncertainties also impact the diagnosis. In order to take these uncertainties into account, we rely on the transferable belief model, and we come up with stressors depicted in the form of a taxonomy that can be configured by the instructor. This will allow them to explore different levels of granularity.**

I. INTRODUCTION

Training in a virtual environment allows instructors to set up complex situations that would be difficult to reproduce in the context of conventional training, such as crisis situations (terrorist attack, armed conflicts, natural disaster, health crisis). In addition, virtual reality for training makes it possible to confront the learner with a wide variety of situations. Crisis situations are particularly stressful for people who have to work in similar real-life conditions. We hypothesise that increasing the number of confrontations with increasingly complex and/or stressful situations would allow learners to better regulate their stress. We then place ourselves within the framework of the constructivist current. However, each individual is unique. A potential development situation for one learner might turn out to be difficult to overcome for another, consequently putting them in failure. Likewise, people are stressed by different stimuli.

We propose a system which aims at generating a dynamic and personalised profile for each learner. The learner profile reflects their ability to manage stressful elements, using a representation of Vygotsky's zone of proximal development in the form of n-dimensional spaces, where each dimension is linked to a stressful element. Thus, each point from this space represents a class of situations involving stressful elements, and our system is able to advise next class of situations to train in order to progressively expand the learner's zone of proximal development.

*This work is funded by the Hauts-de-France Region and the European Regional Development Fund (ERDF) 2014/2020 as well as the Labex MS2T.

Alliance Sorbonne Universite, Universite de technologie de Compiegne, CNRS, Heudiasyc UMR 7253 - 57 avenue de Landshut 60203 Compiegne Cedex, France

[1] luca.pelissero-witoslawski@hds.utc.fr
[2] domitile.lourdeaux@hds.utc.fr
[3] dominique.lenne@hds.utc.fr

The profile is generated using data from physiological sensors. However, their measurements are not quite spotless and uncertainties are present. In addition to the uncertainty associated with potential measurement errors, signals used in real time to detect an individual's state of stress are influenced by many factors, phenomena or actions that are frequently found with the utilisation of a virtual reality headset such as fatigue, movement or simulator sickness. It is also difficult to isolate the factor at the origin of this stress as there are multiple causes inducing it. This is why our system is based on the theory of transferable beliefs as well as on a knowledge model to allow semantic reasoning on uncertain data.

In addition, there are specific needs to work at different levels of granularity of situation for each instructor. To take into account their different strategies to explore and work on skills, our system offers such levels through a transfer of belief.

This profile is used in conjunction with a dynamic planner based on narrative theories to generate personalised training situations. The profile is used to determine which stressors will be played out in the virtual environment.

These scenarios must be adapted to each learner. It is important to modulate the situations we present them during a training session. By this mean, we intend not only to diagnose the effects of a given situation during its execution, but also for future sessions. Therefore, we are interested in an adaptation of the scenario both at microscenaristic and mesoscenaristic levels.

II. LEARNER PROFILE

Our goal is to allow learners to work on the skills they already acquired by offering in addition stressful situations illustrating these skills. To this end, we carry out a diagnosis of their skills through data obtained thanks to biological sensors. This offers them situations in line with their profile. This profile also allows us to make predictions about their ability to manage their stress in new situations. Our diagnosis method is therefore both a descriptive and a predicative model.

This description and prediction problem has been the subject of numerous studies. We describe in this section some existing examples of learner diagnosis and uncertainties modelling to represent learner skills mastering state.

A. Uncertainties modelling

In order to establish our diagnosis, we must think about the method we can use to represent the knowledge of the learner, and to predict the state of this knowledge. Thus, we wish to be able to model a set of data which may turn out to be false (see III.A Data). In other words, we need to use a model to represent beliefs with uncertainties. We have examined several theories in the literature to model these beliefs: set theory; fuzzy set theory [1]; possibility theory [2], [3]; Bayesian networks [4]; belief functions theory [5]; transferable belief model [6]. All these models allow us to represent the imprecision in a data set.

So as to position our work, we have also studied several examples of methods for generating a learner profile in the literature.

B. Existing learner profiles

We compared three existing methods: an ontology-based profile [7], a Bayesian network based profile [8] and a transferable belief based profile. [9].

1) Ontology-based profile: Ontologies are used to describe numerous elements in development of learner profile. For example, ON-SMMILE [7] uses ontologies to describe learning objectives, knowledge object as well as learner performance during lessons.

Ontologies offer powerful representing and reasoning tools. ON-SMMILE uses ontology reasoning as a diagnostic system to create learner profile. This approach is easily adaptable to different learning environments, and offers an easily understandable system for instructors.

However, uncertainties in learner profile are not taken into account innately.

2) Bayesian network based profile: Bayesian networks are used to represent conditional independence among variables of interest, like learner skills mastering rate. Uncertainties can be described using both static Bayesian networks or dynamic Bayesian networks. Probabilistic inferences are possible using this theory. The structure can also be based on knowledge or data, making Bayesian networks greatly adaptable to correspond to most of the needs in representation.

However, Bayesian networks are hardly adaptable to multiple learning environments. Another drawback is the difficulty of reliably defining the conditional probabilities, and defining other system parameters for the instructor.

3) Transferable belief based profile: TAILOR [9] uses transferable belief theory to describe currently mastered skills and skills that are close to be mastered through a graphical representation of most of the encounterable situations in the learning environment.

This system can also be used to represent skills that have no hierarchical relationship.

However, the representation used by TAILOR can become complex to understand, involving n-dimensional spaces. In addition, since each skill must first be defined in the system, it can be complex to define a representation that can be used in several learning environments.

Although it can be hard for instructors to update the model by themselves, as in a Bayesian network based profile, TAILOR proposes a modelling method that can be adapted to our goal: the stress management skills representation.

C. Positioning

We studied both uncertainties modelling theories and some methods for generating a learner profile. This helped us to choose the theory which may suit our needs, as well as ideas for creating our own learner stress profile.

We finally chose the theory of transferable beliefs. This theory encompasses all of the other theories that we have listed, and also allows us to represent conflicts between information sources, as well as lack of knowledge. This formal framework also offers tools for merging information from several sources, as well as tools for making inferences about the values of a variable presenting a lack of knowledge (see III.C Profile).

III. CONTRIBUTION

We propose a system allowing to dynamically generate a profile of the stress of a learner, i.e. all the stressful situations involving skills the learner has mastered, with the aim of being used in stress management training. This profile is established from physiological data from sensors and constructed according to a taxonomy of skills that can be edited by instructors.

A. Data

To establish the profile, the system needs a source of information on the user physical reactions when the user is under a stressor. We also analyse how the learner handles proposed situations to create new beliefs on the state of their skills.

There are many analysable signals. However, the system must meet strong constraints in terms of execution speed, and must operate all of its actions in less than a second, a value named the interactive time. We must also exclude sensors that would be difficult to use with a virtual reality headset.

Two sensors satisfy our criteria, giving us the capacity to obtain information on electrodermal activity (EDA) and electrical activity of the heart (ECG) respectively [10], both varying on exposure to a stressor and governed by the sympathetic nervous system. The analysis of the variation of the electrical potential, of the electrical resistance as well as of the variability of the heart rate allows us to quantify for an individual the way their body will respond to a stressful element. We consider that the less important the response to the stimulus is, the more successfully the learner has coped with the stressful situation.

Signals from EDA and ECG analyses may be affected by stimuli other than stressors. For example, the physical activity of the body leads to an increase in both cardiac and electrodermal activity. In addition, both cognitive overload and simulator sickness, a disorder manifesting itself in a situation presenting a mismatch between the vestibular system and visual perception, can also act on the signals we analyse. These problems, which are very common when using a virtual reality device, create uncertainty in our measurements. Moreover, sensors can produce measurement errors, depending on an error rate that we have to take into account. This is why we use multi-sensor data fusion to improve the reliability of our data.

Other problems can arise when diagnosing the learner over time and the various training sessions in which they take part. In particular, it is possible that data analyses are contradictory among several workouts. It is also possible that the data analyses are different between two workouts within the same scenario. The interactive time measurement of stress is still a research problem to this day. Each individual has different physiological signals, there is no universal threshold to define the state of stress. The duration of response to a stimulus is also variable among individuals, and the time to regain a basal level in the signals we analyse can be quite long. All of these constraints bring additional uncertainty to our measurements.

Finally, it is difficult to imagine that a learner can carry out training on each situation that can be trained to. We must therefore also take into account this lack of information on situations that will never be explored through our diagnosis.

To acknowledge these problems during our diagnosis, we must use a mathematical model characterising the knowledge resulting from the analysis of the data coming from several sources of information, while allowing to materialise uncertainties as well as contradictions and lack of information. This method is similar to the resolution of problem and to the acknowledgement of the result of this resolution.

B. Stressors representation

Dougall and Baum [11] propose a model allowing a categorisation of stressors, which can be represented in the form of an ontology, or a taxonomy. According to this categorisation, these stressors can be organisational (specific to a setting or an activity) or acute (ephemeral and sudden and may not be linked to the individual undergoing the stressor).

Our objective being to confront the learner with stressors similar to those they can cope with according to our system, we use this taxonomy to define semantic distances between stressors. The handling and modification of a taxonomy being easy, we put the expert or the instructor at the heart of the development of the hierarchy.

We propose an ordering between the stressors. We might intuitively think that it is more complex to deal with certain stressors. However, we consider that it is impossible to find a universal ordering of stressors because of the uniqueness of each learner.

For example, we might think that an adult cries are less stressful than a child cries. But depending on the context, this assumption may be altered. The cries of an adult could, for a particular learner, remind them of a traumatic episode, causing them greater stress.

To link the concepts of taxonomy together, we introduce a measure of semantic similarity between two nodes. We rely on the measure of semantic similarity of Wu and Palmer [12], which has the advantage of relying only on the distance between the nodes without taking into account the information related to the nodes. We denote by $h(X)$ the distance separating node X from the root of the taxonomy ($h(root) = 1$).

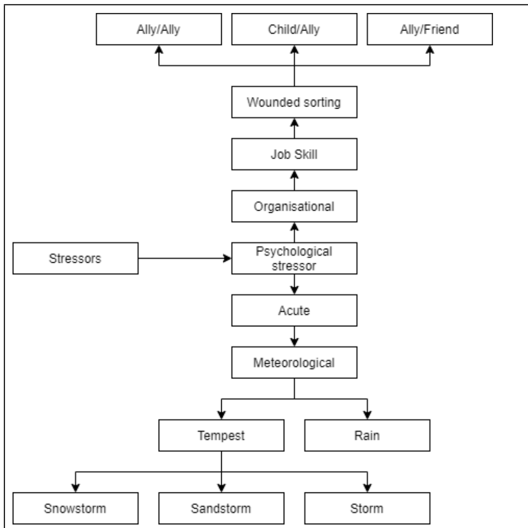

Fig. 1. Taxonomic representation of acute and job stressors

Let N and M be two nodes of the taxonomy. We denote by P the first parent node common to N and M ($N \neq M$). We denote by sim the semantic similarity between N and M such that:

$$sim(N, M) = \frac{2 \times h(P)}{h(N) + h(M)}$$

The greater the semantic similarity (i.s. closer to 1) is, the deeper the nodes are in the taxonomy. Thus, the structure of the taxonomy is of great importance from its development, and must be created taking the calculation to be performed into account. This semantic similarity is used in the propagation of belief within the dynamic profile of the learner (see III.C Profile).

C. Profile

We are interested in job skill training through stressful situations. One of our goals is to provide personalised training scenarios in which the training situations involve skills under stressful conditions. As the ability to manage stress is unique to each learner, our second objective is to gradually expand the development area of each learner profile, which are generated by our system.

We can therefore equate our objectives with the representation and expansion of the zone of proximal development from Vygotsky.

The Zone of Proximal Development (ZPD) refers to the ”distance between current level of development (ZDA), as could be determined by the child abilities to solve problems on their own, and the level of potential development, as could be determined through this child problem-solving, when it is helped by adults or collaborates with initiated peers.”, [13].

We want to be able to account for the present level of development of capacities of a learner to cope with stressors through the dynamic stress profile. We also want to be able to represent their level of potential development and be able to advise the instructor on new stressors to work on. In addition, we want to give the instructor some control over the training settings, as well as the visualisation of the learner profile.

We hypothesise it is possible to train skills without initiated peers thanks to a system based on Vygotsky's ZPD. Moreover, this system can help learners come over situations they have trouble handling.

Carpentier has propose a representation of the ZPD called zpd-space, based on the model of transferable beliefs [9] (see Figure 2). We propose to extend this model to diagnose the evolution of the learner at different hierarchical skill levels in parallel. This diagnosis will be based on physiological data from our sensors.

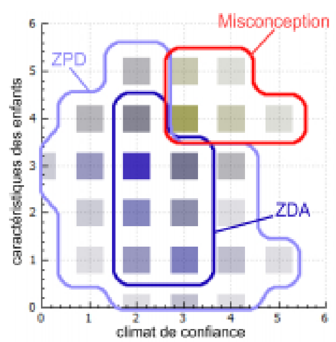

Fig. 2. ZPD representation in [9]

1) Zpd-space by stressor: The learning domain is represented through the use of classes of situations. A class of situations is an "abstract representation of a set of situations presenting common properties called descriptors. A descriptor is an element used to describe a variant". We associate the vector σ to the class of situations S, such that:

$$\sigma = (\sigma_1, \sigma_2, ..., \sigma_n)$$

with σ_i the value corresponding to the descriptor i.

These descriptors let us differentiate the classes of situations from one another.

In our representation of the ZPD in the form of zpd-space, an axis (or dimension) can represent:

- A job skill. Descriptors correspond to didactic variables or skills.
- A stressor taxonomy leaf, i.e. a stressor. Descriptors of this kind of axis are the three possible levels of intensity of a stressor : low, medium and hard. They are arranged arbitrarily.
- A node of the taxonomy which is not a leaf, i.e. a set of stressors. Descriptors of this kind of axis are the children of the node. They are not arranged.

We generate a zpd-space for each node of our taxonomy. Each zpd-space contains n dimensions ($n \in N^*$). A dimension represents either a job skill, a stressor, or a set of stressors.

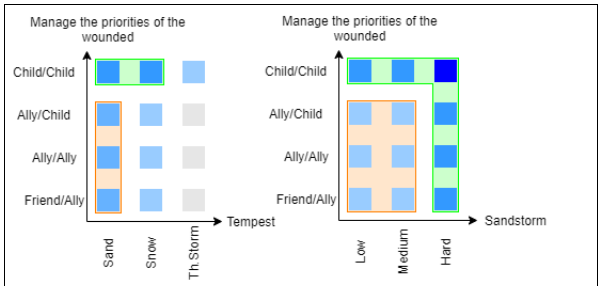

Fig. 3. Example of two-dimensional zpd-space generated from a leaf (Sandstorm) or non-leaf node (Tempest) of the taxonomy

By formalising the theory of belief functions, we associate to each class of situations a belief mass distribution $(a(S_i), d(S_i), c(S_i), i(S_i))$ according to a discernment framework Ω representing the set of assumptions that are based on the state of the learner's skills such as, for a hypothesis B:

$$m^{\Omega(S_i)} : 2^{\Omega(S_i)} \rightarrow [0, 1]$$
$$B \mapsto m^{\Omega(S_i)}(B)$$

checking:

$$\sum_{B \subseteq \Omega} m^{\Omega}(B) = 1$$

$2^{\Omega(S_i)}$ contains all possible subsets formed by hypotheses and unions of hypotheses of $\Omega(S_i)$ with:

$$\Omega(S_i) = \{Ability(S_i), Disability(S_i)\}$$

Ability is the hypothesis according to which the learner is able to manage a situation belonging to a class of situations S_i, while *Disability* is the hypothesis according to which the learner is incapable of handling a situation falling within a class of situations S_i.

By applying the belief mass distribution function to its Ω discernment framework, we associate with each class of situations a n-tuple made up of four belief masses such as:

- $m^{\Omega(S_i)}(\{Ability\})$ is the belief mass according to which the learner is able to cope with a situation falling within the class S_i, named $a(S_i)$.
- $m^{\Omega(S_i)}(\{Disability\})$ is the belief mass according to which the learner isn't able to cope with a situation falling within the class S_i, named $d(S_i)$.
- $m^{\Omega(S_i)}(\{Ability, Disability\})$ is the belief mass according to which the system can't determine the learner ability or inability to cope with a situation falling within the class S_i, named $i(S_i)$.
- $m^{\Omega(S_i)}(\{\emptyset\})$ is the belief mass reflecting the conflict created when two sources of information conflict about the learner ability or inability to cope with a situation falling within the class S_i, named $c(S_i)$.

Thereby:

$$\sum_{B \subseteq \Omega(S_i)} m^{\Omega(S_i)}(B) = a(S_i) + d(S_i) + c(S_i) + i(S_i) = 1$$

These masses are calculated beforehand from the data of the physiological sensors that are used. Initially, $i(S_i) = 1$ because there is no information exploited, which corresponds to ignorance.

D. Mastering new situations

The system offers a situation before each training session to extend the learner ZDA and ZPD.

For each situation S, if $a(S) > 0.85$ and $d(S) < 0.1$, then the situation integrates the learner ZDA: they master the situation. If $a(S) > 0.65$ then the situation integrates the learner ZPD: competence is close to being acquired, either from training or from the propagation of beliefs from similar situations. In the Figure 3, the ZDA is represented by the green area, while the ZPD is represented in orange. The colour gradient of the situation classes varies here according to $a(S)$.

Mastering new situations comes down to studying new situations, or situations of the ZPD, in order to extend the ZDA. This situation must then be the subject of one or more training sessions. We are interested in the algorithms allowing our system to suggest the next situation to be implemented within a training. The objective is to maximise the expansion of the ZPD with a minimum of training.

We must therefore use an algorithm going through all of our classes of situations and selecting the one that is the most suitable for training. We have studied several algorithms to meet these needs.

1) Arbitrary selection in the ZPD: One of the solutions to extend the ZDA would be to choose an arbitrary class of situations located on the edge of the ZPD. The advantage of such an algorithm is that it ensures a linear training course, and always close to the skills already acquired by the learner. However, such a method does not take full advantage of the use of belief functions.

2) Greedy search algorithm: The greedy algorithm consists in calculating a local optimum choice for each element of the search space. This optimum choice is itself governed by a function.

In our case, this function calculates the input of new sets of information within the zpd-space. The objective is then to extend the learner's ZPD with a minimum of training sessions. In this case, we take full advantage of beliefs.

The greedy route can be done on two sets:

- all the classes of situations, allowing an extension of the learner ZDA and ZPD in several distinct zones of the zpd-space.
- a subset of the ZPD situation classes, allowing the ZDA and ZPD to be extended from a single zone of the zpd-space.

3) Nearest neighbour search algorithm: In order to offer a configurable system, we could let the instructor select a class of situations, and suggest the other closest classes. The instructor would then be able to restrict stress management training to a close set of stressors, allowing them to center the training around any situation, which may even be outside the ZPD or the ZDA.

This problem can be translated into a search for the nearest neighbours. For a given class of situations, the algorithm searches for its k nearest neighbours ($k \in N^*$), k being determined by the instructor or by the system. This solution is particularly suitable when the search space is partitioned. The kd-tree structure is particularly applicable to our taxonomy for this search, but other algorithms for finding k nearest neighbours are applicable.

This algorithm can also use an information input maximisation function. The system then performs a scheduling in the k nearest neighbours, and returns the most efficient neighbour to extend the ZPD.

E. Beliefs propagation

We rely on the propagation function in order to propagate beliefs between the classes of situations, through the whole taxonomy.

We denote $\Phi(\mathrm{S_A},\mathrm{S_B})$ the propagated belief from $\mathrm{S_A}$ to $\mathrm{S_B}$ according to a propagation function Φ using Shafer's simple weakening rule [5].

$$\begin{aligned} m^{\alpha}(A) &= (1-\alpha) \times m(A), \forall A \subset \Omega \\ m^{\alpha}(\Omega) &= (1-\alpha) \times m(\Omega) + \alpha \end{aligned}$$

Thereby:

$$\begin{aligned} a_{S_A \to S_B} &= \Phi_a(S_A, S_B) = (1-\alpha)^d \times a_{S_A} \\ d_{S_A \to S_B} &= \Phi_d(S_A, S_B) = (1-\alpha)^d \times d_{S_A} \\ c_{S_A \to S_B} &= \Phi_c(S_A, S_B) = (1-\alpha)^d \times c_{S_A} \\ i_{S_A \to S_B} &= \Phi_i(S_A, S_B) = (1-\alpha)^d \times (i_{S_A} - 1) + 1 \end{aligned}$$

with d the Manhattan distance [14] between to class of situations S_A and S_B such that:

$$d(S_A, S_B) = \sum_{i=1}^{n} |\sigma_1^i - \sigma_2^i|$$

This propagation allows the system to make assumptions about the control of a class of situations close to another class. We hypothesise that the learner partially masters a situation involving descriptors used in situations they are already familiar with.

However, the Manhattan distance used by Carpentier is not applicable in our context, as we want to be able to extend beliefs between different levels of hierarchy, i.e. between different subsets. The semantic similarity being calculated thanks to the distance in the taxonomy between two nodes, we modify the formula, with $\alpha = 1 - sim(A, B)$, such as:

$$\begin{aligned} a_{S_A \to S_B} &= \Phi_a(S_A, S_B) = sim(A, B) \times a_{S_A} \\ d_{S_A \to S_B} &= \Phi_d(S_A, S_B) = sim(A, B) \times d_{S_A} \\ c_{S_A \to S_B} &= \Phi_c(S_A, S_B) = sim(A, B) \times c_{S_A} \\ i_{S_A \to S_B} &= \Phi_i(S_A, S_B) = sim(A, B) \times (i_{S_A} - 1) + 1 \end{aligned}$$

If two belief masses characterise the same class of situations after propagation, the system then proceeds to a fusion of these belief masses by applying Shafer's conjunctive combination rule. The fusion of two belief mass distributions m_1 and m_2 forms a new belief mass distribution m_R such that:

$$
\begin{aligned}
a_R &= a_1 \times a_2 + i_1 \times a_2 + i_2 \times a_1 \\
d_R &= d_1 \times d_2 + i_1 \times d_2 + i_2 \times d_1 \\
i_R &= i_1 \times i_2 \\
c_R &= 1 - a_R - d_R - i_R
\end{aligned}
$$

IV. EXAMPLE

We place ourselves in the case of the training proposed in the framework of VICTEAMS [15], a virtual environment for non-technical skills training for medical team leaders in crisis situations.

In this example, the trainer wishes to train the learner in stressful situations involving casualty sorting in the presence of various stressors, according to the reduced taxonomy presented in Figure 2. The current profile of the learner is as illustrated in Figure 3. We place ourselves in a simple case where the profile does not contain any conflicts.

For the next training session, the system determines the situation that most effectively extends the learner's ZDA. The algorithms determine that the ideal candidate is the class of situations corresponding to a sorting between an ally and a friend (noted F/A) in the context of an intense (noted I) sandstorm (noted S). This storm is characterised by a reduced field of vision in the virtual environment, increased noise and the inability to request an emergency evacuation.

At the end of the training session, the system collects and analyses the data from the sensors, as well as the observables indicating the success or failure of the task. It determines a belief mass reflecting the outcome of the session which is propagated to the rest of the situation classes.

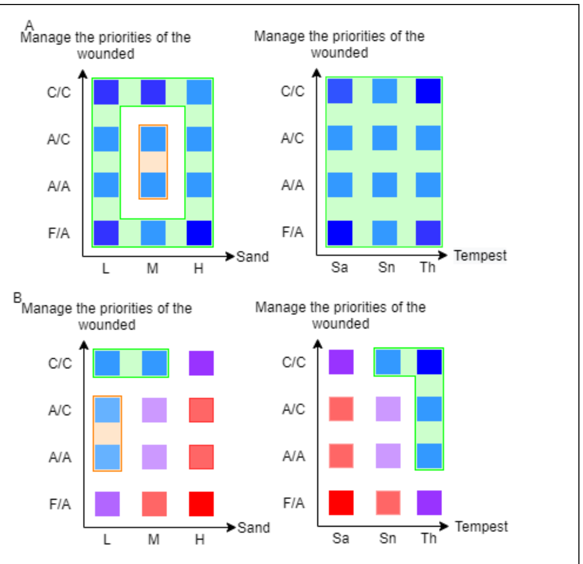

Fig. 4. Zpd-space generated at the end of the session

- the training is a success (case A). The situation class, as well as the close classes, integrate the ZDA, thanks to the propagation of beliefs.
- the training is a failure (case B). The belief mass of the situation class is updated (in red), and its propagation generates conflict (in purple) with the already existing masses. This conflict must therefore be removed by new training. The ZDA is affected by this conflict.

V. CONCLUSIONS

We have presented an approach allowing to generate a dynamic profile of the stress of a learner, based on physiological data and using the Transferable Beliefs model in order to make assumptions about the control of various stressful situations. Our approach has the advantage of being configurable and adaptable by the instructor.

This system is coupled with a planner, which is not the subject of this article, in order to generate personalised training scenarios according to each stress profile.

Our work has been strongly impacted by the current global health crisis. The experiments we have planned require the presence of people, as well as wearing a set of sensors and wearing a virtual reality headset. This equipment normally requires a heavy and strict sanitary protocol, and is now very complex to set up. Thus our system was only tested with simulated data. Our contribution will be evaluated to demonstrate the quality of the evolution of the profile. We also want to assess the capacity of our system to infer correct beliefs about the learner abilities and to propose an optimal path to extend the learner ZPD in as few training sessions as possible.

REFERENCES

[1] L. A. Zadeh, "Fuzzy sets," in *Fuzzy sets, fuzzy logic, and fuzzy systems: selected papers by Lotfi A Zadeh*, pp. 394–432, World Scientific, 1996.
[2] L. A. Zadeh, "Fuzzy sets as a basis for a theory of possibility," *Fuzzy sets and systems*, vol. 1, no. 1, pp. 3–28, 1978.
[3] D. Dubois and H. Prade, *Possibility theory: an approach to computerized processing of uncertainty*. Springer Science & Business Media, 2012.
[4] J. Pearl, *Probabilistic reasoning in intelligent systems: networks of plausible inference*. Elsevier, 2014.
[5] G. Shafer, *A mathematical theory of evidence*, vol. 42. Princeton university press, 1976.
[6] P. Smets and R. Kennes, "The transferable belief model," *Artificial intelligence*, vol. 66, no. 2, pp. 191–234, 1994.
[7] H. Yago, J. Clemente, D. Rodriguez, and P. Fernandez-de Cordoba, "On-smmile: Ontology network-based student model for multiple learning environments," *Data & Knowledge Engineering*, vol. 115, pp. 48–67, 2018.
[8] C. Conati, "Bayesian student modeling," in *Advances in intelligent tutoring systems*, pp. 281–299, Springer, 2010.
[9] K. Carpentier and D. Lourdeaux, "Generation of learning situations according to the learners profile within a virtual environment," in *international conference on agents and artificial intelligence*, pp. 245–260, Springer, 2013.
[10] P. Schmidt, A. Reiss, R. Duerichen, C. Marberger, and K. Van Laerhoven, "Introducing wesad, a multimodal dataset for wearable stress and affect detection," in *Proceedings of the 20th ACM international conference on multimodal interaction*, pp. 400–408, 2018.
[11] A. L. Dougall and A. Baum, "Stress, health, and illness.," 2012.
[12] A. Tchechmedjiev, "State of the art: Local semantic similarity measures and global algorithmes for knowledge-based word sense disambiguation," in *Proceedings of the Joint Conference JEP-TALN-RECITAL 2012, volume 3: RECITAL*, pp. 295–308, 2012.
[13] L. S. Vygotsky, *Mind in society: The development of higher psychological processes*. Harvard university press, 1980.
[14] H. Minkowski, *Geometrie der zahlen*, vol. 2. , 2016.
[15] D. Lourdeaux, Z. Afoutni, M.-H. Ferrer, N. Sabouret, V. Demulier, J.-C. Martin, L. Bolot, V. Boccara, and R. Lelong, "Victeams: a virtual environment to train medical team leaders to interact with virtual subordinates," in *Proceedings of the 19th ACM International Conference on IVA*, pp. 241–243, 2019.